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

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Abstract

We investigate whether the cross-section of corporate bond returns exhibit anomalies similar to those in stocks. Equity market capitalization, profitability, and asset growth negatively predict corporate bond returns, and equity returns positively predict one-month-ahead bond returns. Since smaller, unprofitable firms should be more risky, and firms with high asset growth (or high real investment) should have lower required returns, the evidence indicates that corporate bond returns accord with the risk-reward paradigm. Stock markets lead bond markets, consistent with equities aggregating diverse information and transmitting it to bonds. Overall, however, bonds are efficiently priced within our estimated transaction cost bounds, and equity predictor-based Sharpe ratio magnitudes are largely consistent with risk-based pricing.

Firms finance their assets using a mixture of debt and equity claims. As per the neoclassical risk-reward (RR) paradigm, the required return on a firm represents a reward for risk borne by investors in the firm and thus depends on returns expected on both debt and equity. There is a large literature exploring the determinants of average equity returns. This literature generally attributes the predictive ability of various characteristics to risk, frictions, or behavioral aspects of investors. For example, the book/market effect is attributed to distress risk in Fama and French (1993). Return predictors linked to asset growth (Cooper, Gulen, and Schill (2008)) and profitability (Fama and French (2008)) have been rationalized within the RR paradigm, in the context of the q-theory of the firm (Hou, Xue, and Zhang (2014)). 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) and Nagel (2012)). Hirshleifer and Teoh (2003) and Hirshleifer, Lim, and Teoh (2011) attribute the ability of accounting accruals and earnings surprises to predict returns to limited attention. Momentum over three 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 anomaly discovered by Ang, Hodrick, Xing, and Zhang (2006) has also been attributed to investor misreaction in Stambaugh, Yu, and Yuan (2015).

While a voluminous body of work documents characteristics that predict equity returns (see Harvey, Liu, and Zhu (2015) for a comprehensive summary), there is as yet only limited evidence for whether these predictors also apply to the bond market. Motivated by this observation, we examine whether equity return predictors also explain cross-sectional variation in average bond returns. We seek to answer the following research questions: Do corporate bond returns exhibit anomalous behavior similar to that in equities? And, if so, are the anomalies 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?

Regarding the role of investor biases in explaining average returns, we note at the outset that one reason for why such biases may *not* manifest themselves in the corporate bond market is because this market is dominated by institutions, and Barber, Lee, Liu, and Odean (2009) suggest that institutions tend to be more sophisticated than individuals.[1] Indeed, Edwards, Harris, and Piwowar (2007, EHP henceforth) document a median trade size of $240,600 in the corporate bond market and find that transaction costs are lower for larger trades suggesting that institutions are likely to be the typical traders in bonds.[2] While this a priori reasoning is suggestive that the market for corporate bonds may in fact be quite efficient, our empirical tests are able to shed light on whether this is actually the case.

In our analysis, we examine the relation between equity return predictors and expected bond returns, while controlling for bond return determinants, using an extensive panel of corporate bonds from 1973 to 2014. Our data are assembled from four distinct data sets, namely, the Lehman Brothers Fixed Income Database, TRACE, Mergent FISD/NAIC, and Datastream. To establish a clear link between corporate bonds and equities, 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. Unlike maturity matching or duration matching, our measure of excess returns is in principle not affected by any change in Treasury yield curves. Thus, we are able to isolate returns on corporate bonds due to shocks to issuer's default risk from Treasury bond returns. This allows us to focus on the bond-equity relationship while abstracting from interactions of bond returns with Treasury yields. To our knowledge, a comprehensive analysis of the cross-section of average bond returns and its link to stock-market-based anomalies has not previously been conducted.

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[1] On the other hand, some papers have suggested that institutions and other sophisticated agents are also subject to behavioral biases. See, for instance, Haigh and List (2005), Locke and Mann (2005), Pope and Schweitzer (2011), Jin and Scherbina (2011) and Cici (2012).

[2] This may be the case because bonds are insufficiently volatile to attract individual investors (Kumar (2009)).

We run Fama and MacBeth (1973, FM henceforth) regressions and perform long-short portfolio analyses of excess bond returns on lagged equity characteristics. The robust results across regressions and portfolio analyses are that size, momentum, lagged equity returns, profitability, and asset growth forecast bond returns, but other variables such as accruals, SUE, 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. Thus, the sign of the coefficient on lagged equity returns is positive while the sign of the coefficient on profitability is negative.

The positive sign on the one-month lagged equity return is consistent with the notion that stocks aggregate diverse information (Hellwig (1980)) and transmit it to bonds.[3] The negative sign on asset growth has been rationalized by Hou, Xue, and Zhang (2015) in the context of the q-theory of the firm. The idea is that firms are likely to invest heavily 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. If large firms and highly profitable firms are less risky,[4] then our profitability results also are consistent with the view that risk is positively priced in the bond market, possibly due to this market's more sophisticated clientele.

While these arguments suggest risk is priced in bond markets, we do control for standard risk factors, and find that our results survive. We regress hedge portfolio returns on the Fama and French (1993) factors (the bond-market-related term and default factors as well as the equity market, firm size, and value factors), the Fama and French (2015) factors (market, firm size, value, investment, and profitability factors) and the Pástor and Stambaugh (2003)

[3]Even if debt market investors are more sophisticated than those in the stock market, the stock market, with its greater liquidity and larger clientele, can aggregate information beyond that possessed by bond market investors (Subrahmanyam and Titman (1999)).

[4]Highly profitable firms are more likely to generate healthy amounts of cash from operations and thus have a reduced likelihood of default.

liquidity factor,[5] and find that the alphas of the portfolios are essentially unchanged from the raw returns. Further, in FM regressions, after controlling for a distance-to-default measure and adjusting returns for risk via factor models, we continue to find evidence of characteristic-based predictability.

The fact that our results survive after standard risk controls suggests that these controls might be incomplete. Therefore, we investigate whether the magnitudes of Sharpe ratios obtained from hedge portfolio returns and alphas accord with risk-based arguments. We do this by statistically comparing Sharpe ratios to the MacKinlay (1995) threshold, below which the ratio accords with missing risk factors. We find that only the lagged monthly equity return yields a Sharpe ratio that robustly exceeds the MacKinlay threshold.

We also examine the impact of transaction costs on the economic significance of bond return predictors. We use two different estimates of transaction costs. First, we use effective bid-ask spreads calculated from autocovariances of bond returns following Bao, Pan, and Wang (2011, BPW henceforth). Second, we use effective trading costs estimated from an econometric model by EHP (2007). We find that after adjusting for transaction costs, the strategy based on lagged equity returns yields mostly negative returns (an exception is positive, albeit statistically insignificant at 5% level, returns in the sample of junk bonds from one-month lagged equity return using EHP cost estimates). After accounting for trading frictions, only firm size continues to consistently yield positive average returns. However, none of the Sharpe ratios net of transaction costs are statistically higher than the MacKinlay (1995) threshold. All of this evidence implies that bond markets tend to be efficiently priced up to transactions costs, although predictors of corporate bond returns do share commonalities with those of equity returns.

In two papers most closely linked to ours, Gebhardt, Hvidkjaer, and Swaminathan (2005a,

[5] For our extended sample period, bond liquidity measures are not readily available as we do not have data at greater than a monthly frequency for part of the sample. However, since 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.

2005b) also consider the cross-section of expected bond returns. The major differences between their work and ours is that they use a subset of our data (the Lehman Brothers database from 1973 to 1996), and do not 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.[6] Thus, we adjust corporate bond returns for risk by considering the cross-sectional determinants of risk-adjusted returns, as in Brennan, Chordia, and Subrahmanyam (1998). Like Gebhardt, Hvidkjaer, and Swaminathan (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.

After completing work on the initial version of our paper, we became aware of an independent but closely related paper by Choi and Kim (2014). These authors consider the impact of six 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. We use a longer sample period and a broader set of equity return predictors.[7] Our results are different as a consequence. Thus, in our sample, while asset growth does predict corporate bond returns, profitability is also priced; in addition, we document a strong lead from monthly equity returns to monthly bond returns.

There is a related literature that studies the pricing relationship between corporate bonds and equities. Based on Merton (1974), Collin-Dufresne, Goldstein, and Martin (2001) regress

[6]Gebhardt, Hvidkjaer, and Swaminathan (2005a) also consider duration and ratings. However, since we consider corporate bond returns net of those on matching Treasury bonds, the need to control for interest rate sensitivity is mitigated in our analysis. To allow for the fact that ratings have an important impact on bond returns we control for the distance to default in our analysis. In addition, we present results separately for investment grade and junk bonds.

[7]Choi and Kim (2014) use the Reuters Fixed Income Database and the Lehman Brothers Fixed Income database for their sample spanning 1979 to 2012. We use four 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.

changes in credit spreads on equity returns and other state variables, and find that the explanatory power of these regressions is rather low. Schaefer and Strebulaev (2008) and Bao and Hou (2013) find that the empirical patterns in the comovements of short-term and long-term bonds with equities are consistent with the Merton model. Bai, Bali, and Wen (2014) analyze the relation between bond return moments and bond returns. In contrast to these papers, our principal focus is the relation between *equity* characteristics and corporate bond returns.

In addition, our paper 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 distance-to-default while Campbell, Hilscher, and Szilagyi (2008) construct bankruptcy indicators to forecast stock returns. Anginer and Yildizhan (2013) find 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 CDS spreads are priced in equity markets. We complement these studies by, instead, linking bond returns to equity return predictors.

Another related paper is Jostova, Nikolova, Philipov, and Stahel (2013) (henceforth, JNPS), which shows that there is significant momentum in corporate bond returns (gross of corresponding Treasury 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. However, in our multivariate analysis, we find that there is limited evidence of own-momentum for corporate bond returns in excess of that on matching Treasury bonds in the presence of other equity return predictors (though there is momentum in gross corporate bond returns). Thus, the results of JNPS are quite robust, but are influenced by momentum in the Treasury bond market.

Overall, our work distinguishes itself from earlier research by examining several potential sources of commonalities in the determinants of average bond and equity returns. Perhaps the most relevant message is that the empirical relevance of rational risk-reward models in a class of securities may depend on the sophistication of the clientele holding those securities. Specifically, our evidence suggests that the relatively sophisticated institutions who dominate corporate bond markets price risk in the neoclassical sense.

The rest of this paper is organized as follows. Section 1 discusses the corporate bond data and our construction of bond returns. Section 2 presents the main results on the relation between equity characteristics and corporate bond returns. We analyze the Sharpe ratios of hedge portfolios and the impact of trading costs on portfolio returns in Section 3, and conclude in Section 4.

1 Corporate Bond Data and Bond Returns

1.1 Data

We obtain prices of senior unsecured corporate bonds from the following four data sources: (1) From 1973 to 1997, we use the Lehman Brothers Fixed Income Database which provides month-end bid prices. Since Lehman Brothers used these prices to construct the Lehman Brothers bond index while simultaneously trading the index components, the traders at Lehman Brothers had an incentive to provide correct quotes. Thus, 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 while others are matrix prices. Matrix prices are set using algorithms based on quoted prices of other bonds with similar characteristics. Though matrix prices are less reliable than dealer quotes (Warga and Welch (1993)), we include these prices to maximize the power of our tests.[8] (2) From 1994 to 2011, we use the Mergent FISD/NAIC data. This database consists of actual transaction prices reported by insurance companies. (3) From 2002 to 2014, we use

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

the TRACE data which also provides transaction prices. TRACE covers more than 99% of the OTC activities in the US corporate bond markets after 2005. The data from Mergent FISD/NAIC and TRACE are transaction-based, and the observations may not be exactly at the end of the month. We use only the observations that are in the last five days of each month. If there are multiple observations in the last five days, we use the last one and treat it as the month-end observation. (4) Finally, we obtain month-end quotes from 1990 to 2011 from the Datastream database.

To remove data that seem unreasonable, we apply the following three filters: (i) we remove prices that are less than one cent per dollar, or more than the prices of matching Treasury bonds; (ii) we remove observations if the prices appear to bounce back in an extreme fashion relative to preceding days; specifically, denoting R_t as the date t return, we exclude an observation at date t if $R_t R_{t-k} < -0.02$ for $k = 1, \ldots, 12$; and (iii) we remove observations if prices do not change for more than three months. The filters above reduce our sample sizes by 9.5%, 1.3%, and 7.2%, respectively.

As our data obtain 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 that those in the other datasets. 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 among the four databases, we prioritize in the following order: the Lehman Brothers Fixed Income Database, TRACE, Mergent FISD/NAIC, and Datastream. As JNPS (2013) find, the degree of overlap is not large relative to the total size of the dataset, with the overlap being less than 6% across all the datasets. To check data consistency, we examine the effect of our ordering by reversing the priority. We show in the 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.[9] 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 non-callable. Removing callable bonds reduces the length of the sample period significantly and, therefore, we include these bonds in our sample. As the callable bond price reflects the discount due to the call option, the return on these bonds may behave differently from the return on non-callable bonds. We address this concern by adding fixed effects for callable bonds, and show in the Appendix Table A2 that our results are not sensitive to this feature of the data.

We merge all four bond databases using the CUSIP identifiers at both the firm and issue levels. Since CUSIP identifiers vary over time, we also use historical CUSIP of CRSP and the RatingXpress of Compustat to match issuers and issues. Finally, we manually match remaining issuers based on the ticker information provided by Bloomberg's 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 JNPS (2013) as 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 one bond per firm. For this second category, we require at least 50 firms per month to run our regressions. After applying our filtering criteria, owing to irregularities in Mergent FISD/NAIC and Datastream, we omit the period from May 1998 to March 2001 for the robustness check, during which we do not have enough firms in our sample to run

[9]Mergent FISD provides relatively limited price information but does provide comprehensive information on bond characteristics since 1994.

the regressions reliably.

1.2 Bond Returns

The return on corporate bond i is:

$$R^b_{it} \equiv \frac{P_{it} + AI_{it} + Coupon_{it}}{P_{it-1} + AI_{it-1}} - 1\,, \tag{1}$$

where P_{it} is the price of corporate bond i at time t, AI_{it} is the accrued interest, and $Coupon_{it}$ is the paid coupon. To obtain a clear relationship between corporate bonds and equities, we need to account for variation in the risk-free return. In order to abstract from Treasury bond returns, we construct an "excess return" on corporate bonds. First, we define the return on a synthetic Treasury bond that has the same coupon rate and the repayment schedule as the ith corporate bond as:

$$R^f_{it} \equiv \frac{P^f_{it} + AI_{it} + Coupon_{it}}{P^f_{it-1} + AI_{it-1}} - 1\,, \tag{2}$$

where P^f_{it} is the price of the synthetic matching Treasury bond. To construct P^f_{it} for all corporate bonds in the sample, 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 dataset, 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 exactly match those of the corporate bond. We repeat this process for all corporate bonds at each month to obtain the panel data of matching Treasury bond prices.

The excess bond return that we use for our analysis is:

$$R_{it} \equiv R_{it}^{b} - R_{it}^{f} \,. \tag{3}$$

Since the synthetic Treasury bond has the same future cash flow as the corporate bond, R_{it} is not affected by any movements in Treasury yield curve. In other words, by examining R_{it}, we focus on the bond return driven by influences specific to the corporate bond market. 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. Using a maturity-matched Treasury bond can cause excess returns to move mechanically because of shocks to Treasury yield curves, since 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 unaffected by any change in a Treasury yield curve and thus more suitable for our study on the bond-equity relationship.[10]

1.3 Descriptive Statistics

Table 1 presents the summary statistics of excess returns on corporate bonds. The table shows the aggregate statistics, as well as 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.

Bond characteristics are presented separately by credit ratings for the following reasons. First, according to structural models of debt such as Merton (1974), a bond that is close to

[10]Strictly speaking, cash flow matching is still not perfect for a corporate bond that is close to default. The cash flow of such a bond is likely to be accelerated rather than paid as scheduled. This acceleration can invalidate the cash flow matching process. We nonetheless use this matching method as we are not able to identify an alternative method not susceptible to the issue arising from accelerated payments upon default.

default should behave more like equity while a high-rated bond should be relatively closer to riskless debt in its behavior (Baker and Wurgler (2012)). Thus, it is reasonable to conjecture that the effect of equity anomalies on corporate bonds differs across credit ratings and that investor biases are more likely to manifest themselves in junk bonds. Second, transaction costs for low-grade bonds tend to be higher than those for high grade bonds (Chen, Lesmond, and Wei (2007)). If the equity anomalies only affect junk bonds but not IG bonds, then such predictability may be expensive to exploit. For the above reasons, it is important to check whether the anomalous returns are pervasive across credit ratings.

The top panel of Table 1 shows 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 bond rating. IG bonds earn lower excess returns than junk bonds. Returns on junk bonds are more volatile than IG bond returns as evidenced in their higher standard deviation. The first order autocorrelation, AR1, is generally negative. AR1 drops in magnitude with credit rating, from -0.29 for AA+ to -0.01 for junk bonds. The sum of the first six autocorrelations also increases monotonically with ratings, from -0.29 for AA+ bonds to 0.02 for junk bonds. The negative AR1 suggests monthly reversals. We will test this more formally in a multivariate setting.

The bottom panel 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. As 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 correspond to zero price changes.[11] This low ratio shows that the corporate

[11] While bonds are thinly traded (e.g., EHP (2007)), prices can change without trading due to quote updating. Also, while Chen, Lesmond, and Wei (2007) use zero return observations to measure liquidity, due to accrued interest, a return is not zero even when the price does not change. So, in Table 1 we show the number of observations with no price change rather than a zero return.

bond prices in our sample are fairly variable and likely to be informative about the link between bonds and equities.

IG bonds also 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, as 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 not be that significant (this is not the case for micro-cap and large stocks in Fama and French (2008)). Time-to-maturity (Mat) seems to differ little across rating categories, though 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, Goldstein, and Martin (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 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. We find that junk bonds are issued more often by smaller firms; 20.1% of the observations for junk bonds are from the micro-cap firms as compared to 1.1% of IG bonds.

Our bond sample is, thus, strikingly different from the equity sample of Fama and French (2008). Fama and French 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 (such as 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.

2 Equity Return Predictors and Corporate Bond Expected Returns

Our sample consists of all publicly traded firms with a bond issue.[12] We obtain equity returns from CRSP and accounting information from Compustat. All accounting variables are assumed to become available six months after the fiscal-year end while market-related variables (returns and prices) are assumed to be known immediately. We construct the following equity return predictors.

1. Size ($\log MC$): the natural logarithm of the market value of the equity of the firm (in millions of dollars). See Banz (1981) and Fama and French (1992).

2. Value ($\log B/M$): 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). See Chan, Hamao, and Lakonishok (1991) and Fama and French (1992).

3. Momentum (R_{eq}(2,6)): the cumulative 5-month return on equity. See Jegadeesh and Titman (1993).

4. Past month's equity return (R_{eq}(1)): the stock's return, lagged one month. See Jegadeesh (1990).

5. Accruals (Ac/A): the ratio of accruals to assets where accruals are defined as the change in (current assets $-$ cash and short-term investments $-$ current liabilities $+$

[12] Our results are virtually unchanged when we exclude financial firms (SIC codes between 6000 and 6499, and between 6700 and 6999).

short-term debt + taxes payable) less depreciation. See Sloan (1996).

6. Asset Growth (dA/A): the percentage change in total assets. See Cooper, Gulen, and Schill (2008).

7. Profitability (Y/B): the ratio of equity income (income before extraordinary items − dividend on preferred shares + deferred taxes) to book equity. See Cohen, Gompers, and Vuolteenaho (2002) and Fama and French (2008).[13]

8. Net Stock Issues (NS): the change in the natural log of the split-adjusted shares outstanding. See Pontiff and Woodgate (2008) and Fama and French (2008).

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

10. Idiosyncratic Volatility ($IdioVol$): 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, Hodrick, Xing, and Zhang (2006) (using total equity volatility instead of idiosyncratic volatility has no material impact on any of the results in this paper).

Table 2 provides summary statistics on our equity return predictor variables for the bond-equity matched sample of all bonds, as well as the subsamples of IG and junk bonds. All of the equity market variables have greater standard deviations for junk bonds than they do for IG bonds. Also, the junk bond sample has high average idiosyncratic volatility and is unprofitable while the IG sample has lower average idiosyncratic volatility and is profitable. As a result, if we sort corporate bonds into portfolios based on these equity characteristics, the extreme portfolios are likely to have more junk bonds than IG bonds. Also, the estimated

[13] In unreported analysis, we also use gross profitability calculated as the ratio of gross profit to total assets (Novy-Marx (2013)). Our results are weaker using this measure of profitability

slope coefficient in a regression of bond returns on these equity characteristics could be sensitive to junk bond observations.

Panel B of Table 2 presents time-series averages of cross-sectional correlations between the equity return predictors. We also include controls that are used in our regressions, namely, the one month lagged bond return, the two to six month lagged bond return, and the distance-to-default (DD), as well as the Amihud (2002)-based liquidity measure from the equity market.[14]

Among the more noteworthy results from Panel B are the correlations of DD with equity market variables. Specifically, idiosyncratic volatility and book/market are negatively related to DD, whereas profitability and market capitalization are positively related to DD. Further, larger firms have lower idiosyncratic volatility and firms with higher asset growth also have higher net equity issues. These correlations are all statistically different from zero.

2.1 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, $R_{eq,t+1}$ and $R_{bd,t+1}$, respectively, at time $t+1$, are driven by a single factor whose realization at time $t+1$ is ε_{t+1}:

$$\begin{aligned} R_{eq,t+1} &= \mu_{eq,t} + \Delta_{eq,t}\varepsilon_{t+1} \\ R_{bd,t+1} &= \mu_{bd,t} + \Delta_{bd,t}\varepsilon_{t+1} \ , \end{aligned} \tag{4}$$

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

[14]It is not feasible to construct a similar bond liquidity measure as we have daily data on only a small subsample of bonds.

a setting with a representative agent). Then the Euler equations imply that:

$$
\begin{aligned}
\mu_{eq,t} &= \frac{1}{\mathrm{E}_t m_{t+1}} \mathrm{Cov}_t\left(m_{t+1}, R_{eq,t+1}\right) = \frac{\Delta_{eq,t}}{\mathrm{E}_t m_{t+1}} \mathrm{Cov}_t\left(m_{t+1}, \varepsilon_{t+1}\right) \\
\mu_{bd,t} &= \frac{1}{\mathrm{E}_t m_{t+1}} \mathrm{Cov}_t\left(m_{t+1}, R_{bd,t+1}\right) = \frac{\Delta_{bd,t}}{\mathrm{E}_t m_{t+1}} \mathrm{Cov}_t\left(m_{t+1}, \varepsilon_{t+1}\right) \ .
\end{aligned} \tag{5}
$$

Combining these two Euler equations, we have:

$$
\mu_{bd,t} = h_t \cdot \mu_{eq,t} \ , \tag{6}
$$

where the hedge ratio, h_t, is defined by $h_t = \Delta_{bd,t}/\Delta_{eq,t}$. Equation (6) implies that in the rational, representative agent setting, equity characteristics can affect the bond risk premium in two ways. First, if equity characteristics are associated with the equity risk premium, $\mu_{eq,t}$, then holding h_t constant, these variables will affect $\mu_{bd,t}$. Second, the equity anomaly variables can be related to the hedge ratio, h_t. Holding the equity risk premium constant and assuming that $\mu_{eq,t} > 0$, a larger value of h_t leads to a larger bond premium, $\mu_{bd,t}$. The net effect of equity anomalies on bond risk premiums is ambiguous or even zero, if the anomalies forecast equity returns and hedge ratios in opposite directions.

While Merton's (1974) structural model is an elegant framework for analyzing equity and bond returns simultaneously, we discuss realistic scenarios below, that lead us to adopt a reduced-form approach instead.

First, the anomaly literature suggests that a number of the equity characteristics listed above 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)). Thus, based on the available evidence, the scenario of complete rationality in equity markets is unrealistic. Based on this observation, suppose that the equity expected returns deviate from Eq. (5)

for behavioral reasons (such as overconfidence or limited attention). In this scenario, bond returns might deviate from Eq. (5) in similar ways, provided investors have common biases across the two markets. Eq. (6) would not hold because, under the behavioral paradigm, the Euler equations would not apply. We might, however, see behaviorally-motivated predictors, such as accruals, influence returns in bond markets with the same sign as in equities.

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 Eq. (5) to hold for bonds but not for equities (Eq. (6) 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 above, 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) and Grossman and Miller (1988)).

Overall we propose that market segmentation, investor biases and frictions would violate the assumptions underlying (5) and call tests of (6) into question.[15] We reiterate that Eq. (6) does not, in any case, provide unambiguous predictions of anomaly variables on bond returns. Thus, given the lack of clear predictions from Merton model framework in Eqns. (4) to (6), we directly study the impact of equity characteristics on bond returns.

We consider two categories of possible reasons for bond return predictability from equity characteristics: (i) the risk-reward paradigm, and (ii) behavioral misreactions and frictions (including market segmentation). Table 3 provides the expected signs of the firm characteristics (in the context of the FM regressions to follow) as bond return predictors, and justifies

[15] Not surprisingly, Choi and Kim (2014) reject Eq. (6) for portfolios sorted on some equity characteristics.

them in Sections 2.1.1 and 2.1.2. Further, after presenting the regression coefficients and portfolio analyses in Sections 2.3-2.4, in Section 3 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.

2.1.1 The Risk-Reward Paradigm

The RR arguments link characteristic-based predictability to risk compensation. In our empirical work, while we control for the distance-to-default (DD),[16] and for risk factors, risk-related variables could still be priced as long as DD and our factor models do not completely capture risk in the corporate bond market. We now discuss the likely direction of prediction for each of the variables under the notion that our risk controls are imperfect.

The signs appear unambiguous in only a few cases under the RR paradigm. Thus, if size and book/market 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 as firms with higher distress risk (small firms and high book-to-market ratio firms) should require higher bond returns. Further, under the plausible conjecture that profitable firms are less risky and require lower returns, we would expect Y/B to have a negative coefficient in the bond markets.[17] If investors do not hold diversified portfolios, higher idiosyncratic volatility ($IdioVol$) 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 $IdioVol$. Of course, if investors hold well-diversified portfolios then the coefficient on $IdioVol$ should be close to zero.

[16] To allay concerns that equity return predictors affect realized equity returns, which in turn, affect leverage, and hence, required return on debt, in unreported results we control for leverage (defined by book value of debt over market value of equity) and our results remain unchanged.

[17] From the perspective of stock investors, Hou, Xue, and Zhang (2015) use q-theory to argue that more profitable firms have higher discount rates, else they would invest in less profitable projects. Novy-Marx (2013) and Fama and French (2015) do find that more profitable firms earn higher equity returns. But, more profitable firms are likely to generate more cash from operations and thus are likely to be less risky from the perspective of the bondholders.

It would seem that net equity issues should reduce leverage and thus reduce risk suggesting that the sign on NS should be negative. However, once we control for the distance-to-default (we have also controlled for leverage and the results are similar to those presented) the sign on NS becomes indeterminate from the risk-return perspective. Further, asset growth should provide more collateral to bondholders and thus reduce risk suggesting that the sign on dA/A should also be negative. Further, Hou, Xue, and Zhang (2015) argue that firms with higher investment (and consequently higher asset growth) must be those with lower equity and bond expected returns. The role for the other variables under the RR paradigm appears hard to predict, so we leave these signs unspecified.

2.1.2 Behavioral/Frictions

Turning now to the behavioral/frictions hypotheses, we expect all variables except Net Stock Issues (NS) and Lead-lag ($R_{eq}(1)$) to have the same sign as that for equities. 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, positive future 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 $IdioVol$. Barberis, Shleifer and Vishny (1998) and Daniel, Hirshleifer and Subrahmanyam (1998) have argued that behavioral biases 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, Hvidkjaer and Swaminathan (2005b), then we would expect a positive coefficient on $R_{eq}(2,6)$.

If the behavioral arguments of Barberis and Huang (2001), or Daniel, Hirshleifer, and Subrahmanyam (1998) also apply in the bond market, we expect a negative (positive) coefficient on firm size (book-to-market ratio). We expect NS to have a positive coefficient in the bond market (but a negative one in the equity market), because the market timing hypothesis posits a preference for equity over debt when equities are overvalued and/or the debt is *undervalued*, which implies a *positive* sign for NS as a predictor of bond returns.

We now turn to $R_{eq}(1)$. 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 (owing to errors induced by stale prices, for example), then we might expect $R_{eq}(1)$ to predict bond returns with a negative sign, even after controlling for the lagged bond return. However, while bond markets consist of more sophisticated investors than stock markets (EHP (2007)), it may still be the case that the larger number of traders in the stock market allow the stock price to aggregate a large number of diverse opinions (Hellwig (1980)) and convey information to the bond market. In this scenario, bond markets could react to stock markets with a lag, and the coefficient of $R_{eq}(1)$ might be positive. Hence the sign of the coefficient of $R_{eq}(1)$ can be positive or negative, depending on the relative validity of the overreaction and the delay-based arguments.

Thus, as noted in Table 3, the expected impact of the firm characteristics on bond returns is often different based on whether it is the RR paradigm or the behavioral/friction paradigm that has the marginal impact. For instance, the coefficients on profitability and idiosyncratic volatility have opposite signs depending on which paradigm drives bond returns. Also, while the signs of the coefficients for momentum, past one month return, accruals, and earnings surprises cannot be determined under the RR paradigm, the behavioral/friction paradigm provides clear signs.

2.2 Fama-MacBeth Regressions

To begin our analysis, it is first necessary to demonstrate that our equity return predictors actually are related to average *equity* returns. Accordingly, 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 percentile 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 per month.

Table 4 presents the FM coefficient estimates from the following cross-sectional regression each month:

$$R_{it}^{eq} = \gamma_{0t} + \gamma_{1t}' Zeq_{it-1} + \epsilon_{it}, \tag{7}$$

where R_{it}^{eq} is the excess stock return and Zeq_{it-1} are lagged equity return predictors (the momentum returns are lagged by an additional month). The predictors are described in Table 2. Newey and West (19987) corrected (using 12 lags) t-statistics are given in parentheses. 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.

In the full sample, we find that all of the firm characteristics impact the cross-section of stock returns, and the signs are consistent with those in the earlier literature. This is to be expected given that these are standard, well-established anomalies. However, in the sample matched with corporate bond data, we find that value, momentum, profitability, accruals, and idiosyncratic volatility are not significant. We note that our corporate bond sample, in market capitalization, is much closer to the full sample of equities, rather than the matched sample in Table 4. Thus, for example, the median firm in the full sample has a equity market capitalization of \$134 million, whereas the corresponding number for the matched sample is as high as \$2 billion. The median bond issue, on the other hand has a market value of \$102 million, putting it much closer to the median equity market capitalization for the full sample. Given the reliable positive relation between the extent of equity return predictability and market capitalization documented in Fama and French (2008), we therefore expect bond return predictability to mimic that in the full sample of equities, rather than the matched sample.

We now turn to an analysis of which equity anomalies have marginal power to predict bond returns. Since an OLS regression puts equal weight on each observation in each month, the estimated slopes are sensitive to outliers which tend to be small and illiquid bonds. To address this issue, as before, we winsorize all the right-hand-side variables at the 0.5th and 99.5th percentile each month. Since momentum and reversals in the bond market could influence the impact of equity returns on bond returns (due to a contemporaneous correlation between bond and equity returns) we include bond-related variables in the FM regressions. In particular, we include a distance-to-default (DD) measure to control for the default likelihood of the bond, the last-month's bond return and the last five months' bonds return (skipping the most recent month). Finally, we also include the Amihud measure of liquidity constructed using equity returns and trading volume to control for possible liquidity effects. Our regression specification is:

$$R_{it} = \gamma_{0t} + \gamma_{1t}' Zeq_{it-1} + \gamma_{2t} R_{it-1} + \gamma_{3t} R_{it-2:t-6} + \gamma_{4t} DD_{it-1} + \gamma_{5t} L_{it-1}^{eAmihud} + \epsilon_{it}, \tag{8}$$

where R_{it} is the excess bond return.

Table 5 presents the results from regressing excess bond returns on lagged equity return predictors. The first regression shows that $\log MC$ and $\log B/M$ are negatively priced when both are included in the regression. In univariate regressions (not shown) $\log B/M$ is positively priced. The coefficient of $\log B/M$ becomes even more negative and significant when the bond variables (especially the distance-to-default) are included in the cross-sectional regressions. The third and fourth regressions demonstrate that the positive coefficients on the lagged one-month equity return and the longer-term equity returns, R_{eq}(2,6), become more strongly significant when the bond market variables are included. The next four regressions demonstrate that the negative coefficients on profitability, Y/B, and asset growth, dA/A, are robust to the inclusion of the bond market variables while the positive coefficient on idiosyncratic volatility, $IdioVol$ is not.[18] The last column presents results including all of the variables, and confirms the robustness of $\log MC$, the lagged equity returns, Y/B, and dA/A.

The final regression of Table 5 documents that a one standard deviation changes in $\log MC$, $R_{eq}(1)$, R_{eq}(2,6), Y/B and dA/A impact bond market returns by 4.28, 13.61, 9.06, 4.48, and 2.33 basis points per month, respectively. Thus, the impact of the equity return predictors on the cross-section of corporate bond returns, though not overwhelmingly large, is economically material.

In terms of the bond market controls, we find that the coefficient on lagged one-month bond return is negative and strongly significant with a t-statistic of -10.79, whereas the lagged one-month equity return has a positive coefficient, which is also strongly significant. The former effect 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 two to six month bond returns points to an overreaction that is subsequently corrected. It is possible that investors overreact to improvements or deterioration in credit risk and the negative coefficient on R_{bd}(2,6) is the result of the subsequent correction of the overreaction. The coefficient on DD is negative and significant, which is consistent with its interpretation as an inverse default risk proxy. Finally, the coefficient on the equity liquidity variable, $L^{eAmihud}$, is 3.75 with a t-statistic of 2.67. Thus, returns are higher for bonds with

[18] Panel B of Table 2 shows that the unconditional cross-sectional correlation of DD with Y/B, dA/A, and $IdioVol$ is 0.27, -0.01, and -0.55, respectively.

illiquid shares.

Note that the signs of the coefficients on Y/B and dA/A are consistent with risk-reward arguments (as long as the risk controls in the regressions are less than perfect). This is because more profitable firms and firms that invest a lot are likely to be less risky and earn lower bond returns. 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.

In unreported results, we apply factor models to adjust bond returns for risk. Specifically, we use the three Fama-French (1993) stock factors plus the $Term$ and Def factors,[19] and, in turn, the five-factor model of Fama and French (2015) plus the Pástor and Stambaugh (2003) liquidity factor, and apply Brennan, Chordia, and Subrahmanyam (1998) methodology to risk-adjust bond returns. We use full sample betas and only bonds with at least 24 months of data. We also include total equity volatility and bond volatility (using a 60 month rolling window to estimate standard deviations) as additional risk controls. While this exercise causes a loss of sample size, results obtained using these procedures are substantially similar to those in the paper.

Overall, the results indicate that the cross-section of expected bond returns behaves differently from that of stock returns, so that a common pricing kernel does not appear to apply to both stock and bond returns. In addition, the direction of prediction of some of the variables suggests that bond markets price risk in a manner consistent with the RR paradigm, under the proviso that the existing methods of risk-adjustment are imperfect.

[19] $Term$ 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).

2.3 A Robustness Check

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 such firms experience a material event like restructuring, their financial distress could have a large impact on the cross-sectional relation between bond returns and variables such as book-to-market and DD, since we treat each individual bond as a separate cross-sectional observation.

To address the above issue, we now report the results of cross-sectional regressions that use one bond per firm. For firms that have more than one 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 one year, (iii) we choose the most recent bond issue and (iv) we use the equal-weighted average the bond returns across each firm. The second and third procedures are motivated by BPW (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. The only exceptions are the negative and significant coefficient of $\log B/M$ and the positive coefficient of NS, which is not always robust.

2.4 Portfolio Sorts and Factor Alphas

Since the FM regressions assume linearity, we now present results for the relation between equity return predictors and bond returns using portfolio sorts. We sort bonds into deciles based on the equity 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. Most of the equity market variables have greater standard deviations for junk bonds than they do for IG bonds. As a result, if we sort corporate bonds into portfolios based on these equity characteristics, the extreme portfolios are likely to have more junk bonds than IG bonds. Thus, we check the relation between equity return predictors and bond excess returns both for the entire sample and subsamples of IG and junk bonds. Panel A of Table 7 presents the results for the long-short (H−L) portfolios that is long the tenth decile and short the first. For brevity, we focus only on the equity characteristics that are significant in the multivariate context, namely, at the 5% level in the last column of Table 5.

Firm size, $\log MC$, yields significant variation in average excess returns on corporate bonds. The monthly equal- and value-weighted returns on the hedge portfolio are −0.41% and −0.34%, respectively. In annual terms, the hedge portfolio value-weighted return is about 4%. However, the equity size effect is not pervasive across rating categories. The average excess returns on the hedge portfolios are economically small for IG bonds. This result is not surprising as the large variation in equity size comes from the variation across junk bonds. Thus, the equity size effect is strong for junk bonds with equal- and value-weighted hedge portfolios returns of −0.45% and −0.30%, respectively. This pattern, where the hedge portfolio returns are higher for the junk bonds holds for all the equity variables in Table 7.

The lead-lag effect, $R_{eq}(1)$, is the strongest one that we find. The monthly hedge portfolio returns range from 0.22% to 0.77% (2.6% to 9.2% annually) and are strongly statistically significant. The effect is more pronounced for junk bonds but IG bonds also show a significant lead-lag effect. In Section 2.1.2, we proposed the delayed reaction hypothesis and the overreaction hypothesis, which postulated opposite (respectively, positive and negative) signs on $R_{eq}(1)$. The result in Table 7 supports the former hypothesis.

In general, the hedge portfolio results are consistent with the FM regression results of Table 5. In Figure 1, we plot the average bond returns to the equal-weighted decile portfolios for the variables $\log MC$, $R_{eq}(2{,}6)$, $R_{eq}(1)$, Y/B, and dA/A, separately for IG and junk bonds. The predictive effect of the variables is clearly more pronounced in junk bonds.

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

$$R_{it} = \alpha_i + \sum_k \beta_{ik} f_{kt} + \varepsilon_{it}. \tag{9}$$

We use two different factor models. The first consists of the five factors proposed by Fama and French (1993). These are comprised of three equity factors ($MktmRf$, SMB, and HML) and two bond factors ($Term$ and Def). The second model is the five-factor model of Fama and French (2015), augmented by the Pástor and Stambaugh (2003) liquidity factor. Panel B of Table 7 presents the alphas from these time-series regressions for the value-weighted H−L hedge portfolios. (The results using equal-weighted portfolios are very similar to the ones reported here and are thus omitted.) We show the results separately for the full sample and subsamples of IG and junk bonds.

The pattern of results is similar to that of Panel A with the raw returns. The exceptions are the following: the alphas for returns sorted on $\log MC$ and for Y/B are not significant for the IG bonds. The alphas are generally lower than the raw returns and, moreover, the absolute alphas and their statistical significance are generally lower when the six-factor model is used. For instance, in the case of all bonds, the alpha for $\log MC$ is -0.30 (t-statistic $=$ -4.22) with the five-factor model and -0.21 (t-statistic $= -2.89$) for the six-factor model.[20]

In the next section, we investigate whether profits from anomaly-based bond market strategies survive transaction cost considerations, and also consider the reward to risk ratios of these strategies.

[20]We also calculate alphas by including factors constructed from bond returns. For each of the characteristic, Y/B and dA/A, we form three portfolios separately for IG and junk bonds and then take average of the two hedge portfolio excess returns to construct the bond factor. We add these bond factors to the five- and six-factor model and calculate alphas from the augmented model. In unreported results, we find that new alphas are mostly similar to those reported in Table 7. The only noteworthy exceptions are for portfolios sorted on Y/B and dA/A, for which the augmented alphas are slightly lower (and statistically insignificant) than the five-factor alphas for the subsample of junk bonds.

3 Hedge Portfolio Profits After Transaction Costs and Sharpe Ratios

3.1 The Effect of Trading Costs on Hedge Portfolio Profits

Although equity anomalies help us forecast bond returns in the cross-section, the high transaction costs of corporate bonds may prevent investors from taking advantage of the predictability. To check the significance of average returns after costs on the hedge portfolios in Section 2.4, we estimate portfolio transaction costs using two approaches.

We first use the BPW (2011) measure (L^{BPW}) of bid-ask spreads. This is calculated as the autocovariance of excess bond returns:

$$L_{it}^{BPW} = \left(-\text{cov}_t\left(\Delta p_{itd+1}, \Delta p_{itd}\right)\right)^{0.5},$$

where Δp_{itd} is the log price change on bond i on day d of month t, and L^{BPW} is the Roll (1984) measure of the effective bid-ask spread. BPW show that the Roll measure provides more conservative estimates of effective transaction costs than quoted bid-ask spreads. Also, the Roll measure is easier to compute and is able to cover more bonds in the sample compared with the price-pressure-based cost estimates of Feldhütter (2012).

We calculate L_{it}^{BPW} using daily data starting in 2002 and then compute its cross-sectional average for each portfolio every month. The time-series average of the effective bid-ask spread is reported as trading costs. We compute the transaction costs as the product of the portfolio turnover and the average bid-ask spreads, and then compute the net returns as the difference of the gross returns and these transaction costs. We report portfolio turnover, trading costs, and net returns for only the hedge portfolios in Panel A of Table 8. For ease of interpretation, we normalize all hedge portfolio gross returns to be positive; that is, for example, the $R_{eq}(1)$-based strategy is long high $R_{eq}(1)$ firms and short low $R_{eq}(1)$ firms, the Y/B-based strategy shorts the most profitable firms and goes long on the least profitable firms, and so on.

Panel A shows that, unsurprisingly, portfolio turnover is relatively small for portfolios sorted annually but high for portfolios sorted monthly. This leads to lower transaction costs for annually-sorted portfolios than those for monthly-sorted portfolios. For the full sample, we find that net returns are positive only for $\log MC$. The net returns are strongly and statistically significantly negative for $R_{eq}(2,6)$ and $R_{eq}(1)$. For instance, in the case of junk bonds, the long-short hedge portfolio formed on $R_{eq}(1)$ yields a value-weighted net monthly return of -2.04%. Thus, despite its strong significance, the lead-lag effect does not provide profitable trading opportunities for investors net of transaction costs.

Large institutional investors may be able to trade at costs lower than the effective spreads. Thus, the cost estimates based on BPW (2011) effective bid-ask spreads could be treated as the higher end of the range of costs. As an alternative approach, we use trading costs of EHP (2007). EHP use an econometric model to estimate effective trading costs. They report these trading costs for different trade sizes and for different bond characteristics such as the credit rating of the bond. In our analysis, we use EHP estimates for an institutional order size of \$1 billion (EHP report a median institutional order size of \$1.15 billion). The relevant numbers from EHP for our bonds are trading costs of 18bps for all bonds, 16bps for IG bonds, and 30bps for junk bonds. Using these trading costs, we repeat the earlier analysis of calculating transaction costs as the product of portfolio turnover and trading costs, and net returns as the difference of gross returns and transaction costs. The results are reported in Panel B of Table 8.

Since EHP (2007) trading costs are lower than those of BPW (2011), the net returns are higher in Panel B than those in Panel A. Nevertheless, the net returns are still negative for $R_{eq}(2,6)$. The net returns are consistently and significantly positive only for hedge portfolios sorted on $\log MC$. The net returns are positive for the sample of all and junk bonds for portfolios sorted on $R_{eq}(1)$ and Y/B. The returns are also positive for the sample of all and

IG bonds for dA/A.

Interestingly, the bond return predictor that robustly survives transactions costs, equity market capitalization, can be motivated by the RR paradigm, in that it is linked to the likelihood of distress (Fama and French (1993, 2008)). In unreported tests, we have ascertained that the bond variables, $R_{bd}(2,6)$, $R_{bd}(1)$, and the Amihud illiquidity measure, also do not yield positive profits net of transaction costs. DD does but, again, it has a risk-based interpretation. Since 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 large arbitrage opportunities.

3.2 Sharpe Ratios of Hedge Portfolios

Our analysis thus far shows that many equity characteristics yield significant portfolio returns, and while most of these returns survive standard risk adjustment (Panels A and B of Table 7), they are not robust to transaction cost considerations. There remains the question, however, of whether the magnitude of the predictability documented in Section 2.4 is consistent with risk pricing or a behavioral model. To address this issue, we follow MacKinlay (1995) in calculating the Sharpe ratios of the characteristics-based hedge portfolios.[21] The exact methodology is as follows. For each characteristic, we form value-weighted decile portfolios as described earlier. We then calculate alphas for each decile using the five- and six-factor models as in Panel B of Table 7. The Sharpe ratio using the raw returns is defined simply as the ratio of average returns to the standard deviation of the returns. We also calculate the Sharpe ratios using alphas as the ratio of alpha to the standard deviation of the residuals from the time-series regression. This Sharpe ratio using alphas 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

[21] See also Gebhardt, Hvidkjaer, and Swaminathan (2005a).

(see MacKinlay 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. Henceforth we term this bound M. We calculate the p-value of the upper tail probability associated with this null of M. To calculate the p-value, the standard errors of Sharpe ratios are calculated by applying the delta method to the Sharpe ratio and using the Newey and West (1987) correction with 12 lags. For ease of interpretation, we again normalize all hedge portfolio returns and alphas to be positive.

Table 9 shows the Sharpe ratios and the p-values associated with the null. We present this analysis separately for all bonds, IG bonds, and Junk bonds. Panel A presents the results for gross (of transaction costs) returns. The results show that the highest Sharpe ratios are obtained for the long-short portfolio sorted on $R_{eq}(1)$. For the sample of all bonds the Sharpe ratio based on the five factor alpha is 0.50 and is significantly larger than M. In the case of $R_{eq}(1)$, the Sharpe ratio based on the raw returns as well on the alphas is significantly higher than M for the IG and the Junk bonds as well. The Sharpe ratio of all other characteristic based portfolios is not significantly higher than M. Overall, of the five characteristics under consideration, only one characteristic, $R_{eq}(1)$, has robustly high Sharpe ratios across the sample of all bonds as well as IG and Junk bonds. However, the average returns yielded by the strategy based on $R_{eq}(1)$ do not survive transactions costs, as described in Section 3.1.

More generally, the previous subsection illustrates that most characteristics do not survive transactions costs. Accordingly, we repeat the analysis using net returns using BPW (2011) estimates in Panel B and using EHP (2007) estimates in Panel C. The results show that, none of the net Sharpe ratios are significantly larger than M. 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.

4 Conclusion

Do bond markets exhibit return anomalies similar to those in stocks? Size, profitability, and asset growth do predict bond returns, but other predictors like accruals, earnings surprise, and idiosyncratic volatility do not. While size and asset growth effects in bonds are 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 that small firms and those with low or negative profits are considered more risky by bond market investors, so that their bonds command higher required returns.

The preceding evidence indicates that the relatively sophisticated institutions in the bond market (EHP(2007)) price risk rationally. Interestingly, however, we also find there is a statistically significant lead from stocks to bonds at the monthly horizon, which indicates new information is reflected in stock markets first. This is consistent with the notion that while bond market investors are likely more sophisticated, the stock market aggregates diverse information from a larger mass of heterogeneously informed investors, and this information is subsequently transmitted to bond market prices.

We statistically compare anomaly-based Sharpe ratios to the bound suggested by MacKinlay (1995), below which a ratio accords with missing risk factors. We find that only the lagged monthly equity return-based strategy yields a ratio that is reliably higher than the MacKinlay bound, but the profitability from this strategy does not survive transaction cost considerations. This indicates that overall, bonds are priced efficiently (within transaction cost bounds). Our work suggests many extensions. The results suggest that the degree to which prices adhere to the risk-reward 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

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 are similar to those from the full sample. Surprisingly, the coefficient for $R_{eq}(1)$ without matrix prices increases to 11.05 from 8.35 with matrix prices in EW regressions. Even without matrix prices, this lead-lag effect is the most significant forecaster of bond returns. 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 sub-sample without matrix prices.

Sample Excluding Datastream: We exclude Datastream data from the sample. The inferences on all the other equity return predictors remain largely the same as those in the main sample; differences between the coefficients from the full sample and the sub-sample are statistically insignificant for all variables except Y/B, whose effect is exacerbated.

Sample with Reverse Priority: For our main results, we prioritize the five datasets in the following order: the Lehman Brothers Fixed Income Database, TRACE, Mergent FISD/NAIC, Merrill Lynch, and Datastream. We now reverse this order. Panel C shows that the difference 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, however, shows that this has virtually no impact on the main results.

References

Amihud, Yakov, 2002, Illiquidity and Stock Returns: Cross-Section and Time-Series Effects, *Journal of Financial Markets* 5, 31–56.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The Cross-Section of Volatility and Expected Returns, *Journal of Finance* 61, 259–299.

Anginer, Deniz, and Celim Yildizhan, 2013, Is There a Distress Risk Anomaly? Pricing of Systematic Default Risk in the Cross Section of Equity Returns, Working paper available at http://ssrn.com/abstract=1344745.

Bai, Jenni, Turan G. Bali, and Quan Wen, 2014, Do Distributional Characteristics of Corporate Bonds Predict Their Future Returns?, working paper, Georgetown University, Washington, DC.

Baker, Malcolm, and Jeffrey Wurgler, 2012, Comovement and Predictability Relationships Between Bonds and the Cross-Section of Stocks, *Review of Asset Pricing Studies* 2, 57-87.

Ball, Ray, and Philip Brown, 1968, An Empirical Evaluation Of Accounting Income Numbers, *Journal of Accounting Research* 6, 159–177.

Banz, Rolf W., 1981, The Relationship Between Return and Market Value of Common Stocks, *Journal of Financial Economics* 9, 3–18.

Bao, Jack, and Kewei Hou, 2013, Comovement of Corporate Bonds and Equities, Working paper available at http://ssrn.com/abstract=2293027.

Bao, Jack, Jun Pan, and Jiang Wang, 2011, The Illiquidity of Corporate Bonds, *Journal of Finance* 66, 911–946.

Barber, Brad, Yi-Tsung Lee, Yu-Jane Liu, and Terrance Odean, 2009, Just How Much Do Individual Investors Lose by Trading?, *Review of Financial Studies* 22, 609–632.

Barberis, Nicholas and Ming Huang, 2001, Mental Accounting, Loss Aversion, and Individual

Stock Returns, *Journal of Finance* 56, 1247-1292.

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny, 1998, A Model of Investor Sentiment, *Journal of Financial Economics* 49, 307–343.

Brennan, Michael J., Tarun Chordia, and Avanidhar Subrahmanyam, 1998, Alternative Factor Specifications, Security Characteristics, and the Cross-Section of Expected Stock Returns, *Journal of Financial Economics* 49, 345–373.

Campbell, John Y., Jens Hilscher, and Jan Szilagyi, 2008, In Search of Distress Risk, *Journal of Finance* 63, 2899–2939.

Chen, Long, David A. Lesmond, and Jason Wei, 2007, Corporate Yield Spread and Bond Liquidity, *Journal of Finance* 62, 119–149.

Chen, Louis C.K., Yasushi Hamao, and Josef Lakonishok, 1991, Fundamentals and Stock Returns in Japan, *Journal of Finance* 46, 1739–1764.

Choi, Jaewon, and Yongjun Kim, 2014, Anomalies and Market (Dis)Integration, working paper, University of Illinois, Champaign, IL.

Cici, Gjergji, 2012, The Prevalence of Disposition Effect in Mutual Funds' Trades, *Journal of Financial and Quantitative Analysis* 47, 795-820.

Cohen, Randolph B., Paul A. Gompers, and Tuomo Vuolteenaho, 2002, Who Underreacts to Cash-Flow News? Evidence from Trading between Individuals and Institutions, *Journal of Financial Economics* 66, 409–462.

Collin-Dufresne, Pierre, Robert S. Goldstein, and J. Spencer Martin, 2001, The Determinants of Credit Spread Changes, *Journal of Finance* 56, 2177–2207.

Cooper, Michael, 1999, Filter Rules Based on Price and Volume in Individual Security Overreaction, *Review of Financial Studies* 12, 901–935.

Cooper, Michael, Husayin Gulen, and Michael Schill, 2008, Asset Growth and the Cross-Section of Stock Returns, *Journal of Finance* 63, 1609–1651.

Crawford, Steven, Pietro Perotti, Richard A. Price, and Christopher J. Skousen, 2015, Accounting-Based Anomalies in the Bond Market, working paper available at http://ssrn.com/abstract=2423850.

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor Psychology and Security Market Under- and Overreactions, *Journal of Finance* 53, 1839–1885.

Edwards Amy K., Lawrence E. Harris, and Michael S. Piwowar, 2007, Corporate Bond Market Transaction Costs and Transparency, *Journal of Finance* 62, 1421–1451.

Fama, Eugene F., and Kenneth R. French, 1992, The Cross-Section of Expected Stock Returns, *Journal of Finance* 47, 427–465.

Fama, Eugene F., and Kenneth R. French, 1993, Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics* 33, 23–49.

Fama, Eugene F., and Kenneth R. French, 2008, Dissecting Anomalies, *Journal of Finance* 63, 1653–1678.

Fama, Eugene F., and Kenneth R. French, 2015, A Five-Factor Asset Pricing Model, *Journal of Financial Economics* 116, 1–22.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, Return and Equilibrium: Empirical Tests, *Journal of Political Economy* 81, 607–636.

Feldhütter, Peter, 2012, The Same Bond at Different Prices: Identifying Search Frictions and Selling Pressures, *Review of Financial Studies* 25, 1155–1206.

Friewald, Nils, Christian Wagner, and Josef Zechner, 2014, The Cross-Section of Credit Risk Premia and Equity Returns, *Journal of Finance* 69, 2419–2469.

Gebhardt, William R., Soeren Hvidkjaer, and Bhaskaran Swaminathan, 2005a, The Cross-Section of Expected Corporate Bond Returns: Betas or Characteristics?, *Journal of Financial Economics* 75, 85–114.

Gebhardt, William R., Soeren Hvidkjaer, and Bhaskaran Swaminathan, 2005b, Stock and Bond Market Interaction: Does Momentum Spill Over?, *Journal of Financial Economics* 75, 651–690.

Grossman, Sanford J., and Merton H. Miller, 1988, Liquidity and Market Structure, *Journal of Finance* 43, 617–633.

Haigh, Michael, and John List, 2005, Do Professional Traders Exhibit Myopic Loss Aversion? An Experimental Analysis, *Journal of Finance* 60, 523–534.

Harvey, Campbell R., Yan Liu, and Heqing Zhu, 2015, ... and the Cross-Section of Expected Returns, *Review of Financial Studies* 29, 5–68.

Hellwig, Martin F., 1980, On the Aggregation of Information in Competitive Markets, *Journal of Economic Theory* 22, 477–498.

Hirshleifer, David, and Siew Hong Teoh, 2003, Limited Attention, Information Disclosure, and Financial Reporting, *Journal of Accounting and Economics* 36, 337–386.

Hirshleifer, David, Sonya S. Lim, and Siew Hong Teoh, 2011, Limited Investor Attention and Stock Market Misreactions to Accounting Information, *Review of Asset Pricing Studies* 1, 35–73.

Hong, Gwangheon, and Arthur Warga, 2000, An Empirical Study of Bond Market Transactions, *Financial Analysts Journal* 56, 32–46.

Hou, Kewei, Chen Xue, and Lu Zhang, 2015, Digesting Anomalies: An Investment Approach, *Review of Financial Studies* 28, 650–705.

Jegadeesh, Narasimhan, 1990, Evidence of Predictable Behavior of Security Returns, *Journal of Finance* 45, 881–898.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *Journal of Finance* 48, 65–91.

Jegadeesh, Narasimhan, and Sheridan Titman, 1995, Short-Horizon Return Reversals and the Bid-Ask Spread, *Journal of Financial Intermediation* 4, 116–132.

Jin, Li, and Anna Scherbina, 2011, Inheriting Losers, *Review of Financial Studies* 24, 786–820.

Jostova, Gergana, Stanislava Nikolova, Alexander Philipov and Christof W. Stahel, 2013, Momentum in Corporate Bond Returns, *Review of Financial Studies* 26, 1649–1693.

Kumar, Alok, 2009, Who Gambles in the Stock Market?, *Journal of Finance* 64, 1889-1933.

Lehmann, Bruce, 1990, Fads, Martingales, and Market Efficiency, *Quarterly Journal of Economics* 105, 1–28.

Livnat, Joshua, and Richard R. Mendenhall, 2006, Comparing the Post-Earnings Announcement Drift for Surprises Calculated from Analyst and Time Series Forecasts, *Journal of Accounting Research* 44, 177–205.

Locke, Peter, and Steven Mann, 2005, Professional Trader Discipline and Trade Disposition, *Journal of Financial Economics* 76, 404–444.

MacKinlay, A. Craig, 1995, Multifactor Models do not Explain Deviations From the CAPM, *Journal of Financial Economics* 38, 3–28.

Maslar, David A., 2013, Illiquidity Spillover: The Cross-Market Price Impact of Firm Level Illiquidity, working paper, University of Tennessee.

Merton, Robert C., 1974, On the Pricing of Corporate Debt: The Risk Structure of Interest Rates, *Journal of Finance* 29, 449–470.

Nagel, Stefan, 2012, Evaporating liquidity, *Review of Financial Studies* 25, 2005-2039.

Newey, Whitney, and Kenneth West, 1987, A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica* 55, 703–708.

Novy-Marx, Robert, 2013, The Other Side of Value: The Gross Profitability Premium, *Journal* *of Financial Economics* 108, 1–28.

Pástor, Ľuboš, and Robert F. Stambaugh, 2003, Liquidity Risk and Expected Stock Returns, *Journal of Political Economy* 111, 642–685.

Pontiff, Jeffrey, and Artemiza Woodgate, 2008, Share Issuance and Cross-Sectional Returns, *Journal of Finance* 63, 921–945.

Pope, Devin, and Maurice Schweitzer, 2011, Is Tiger Woods Loss Averse? Persistent Bias in the Face of Experience, Competition, and High Stakes, *American Economic Review* 101, 129–157.

Roll, Richard, 1984, A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market, *Journal of Finance* 39, 1127–1139.

Schaefer, Stephen, and Ilya A. Strebulaev, 2008, Structural Models of Credit Risk are Useful: Evidence from Hedge Ratios on Corporate Bonds, *Journal of Financial Economics* 90, 1–19.

Sloan, Richard G., 1996, Do Stock Prices Fully Reflect Information in Accruals and Cash Flows About Future Earnings? *The Accounting Review* 71, 289–315.

Stambaugh, Robert F., Jianfeng Yu, and Yu Yuan, 2015, Arbitrage Asymmetry and the Idiosyncratic Volatility Puzzle, *Journal of Finance* 70, 1903–1948.

Subrahmanyam, Avanidhar, and Sheridan Titman, 1999, The Going-Public Decision and the Development of Financial Markets, *Journal of Finance* 54, 1045–1082.

Vassalou, Maria, and Yuhang Xing, 2004, Default Risk in Equity Returns, *Journal of Finance* 59, 831–868.

Warga, Arthur, and Ivo Welch, 1993, Bondholder Losses in Leveraged Buyouts, *Review of Financial Studies* 6, 959–982.

Table 1: Summary Statistics on Bond Returns and Characteristics

The table presents summary statistics of all bonds used in the paper. Bonds are also divided into investment grade (IG) and junk categories. IG bonds are further sub-divided into AA+, A, and BBB categories. Excess return is calculated in excess of the matching Treasury bond which has the same coupons and repayment schedule. AR1 to AR3 are the autocorrelation coefficients at lags one to three, and AR1-AR6 is the sum of the first six 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 observations in a rating category. %Issuers Equity Size is the ratio of issuers whose market value of equity is below the 20 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 NYSE stocks). The sample period is 1973 to 2014.

	Excess returns						
	Mean	SDev	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

	N	No Price Change	% Market Value	Mat	Corr	%Issuers Equity Size		
						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

Table 2: Summary Statistics of Equity Return Predictors

The table presents summary statistics of equity return predictors used to predict the corresponding bond returns. Size ($\log MC$) is the natural logarithm of the market value of the equity of the firm. Value ($\log B/M$) is the natural logarithm of the ratio of the book value of equity to the market value of equity. Momentum (R_{eq}(2,6)) is the cumulative 5-month return on equity, starting from the second month prior to the current month. Lead-Lag (R_{eq}(1)) is the lagged monthly return on equity. Profitability (Y/B) is the ratio of equity income (income before extraordinary items − dividend on preferred shares + deferred taxes) to book equity. Net Stock Issues (NS) is the change in the natural log of the split-adjusted shares outstanding. Accruals (Ac/A) 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 (dA/A) is the percentage change in total assets. Earnings Surprise (SUE) is the change in (split-adjusted) earnings over the same quarter in the last fiscal year divided by price. Idiosyncratic Volatility ($IdioVol$) is the annualized volatility of the residuals from market model regression for the issuer's equity over each month. Accounting variables are assumed to become available six 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 cross-sectional regressions. DD is the distance-to-default and $L^{eAmihud}$ is the Amihud illiquidity measure's logarithm. We compute the correlations each month and report the time-series average of these correlations. The sample period is 1973 to 2014.

Panel A: Descriptive statistics

		All Bonds			IG			Junk		
	N	Mean	Median	SDev	Mean	Median	SDev	Mean	Median	SDev
Size ($\log MC$)	1,159,522	7.6	7.7	1.5	8.1	8.2	1.2	6.3	6.3	1.5
Value ($\log B/M$)	1,109,230	−0.3	−0.3	0.7	−0.4	−0.3	0.6	−0.2	−0.1	0.9
Momentum ($R_{eq}(2,6)$)	1,155,128	5.8	4.7	20.5	5.8	5.1	14.9	5.9	3.4	29.8
Lead-Lag ($R_{eq}(1)$)	1,159,522	1.1	0.9	9.1	1.2	1.0	6.8	1.1	0.5	13.0
Profitability (Y/B)	1,102,671	−3.5	3.3	48.2	3.2	4.6	20.0	−20.5	−2.4	81.7
Net Stock Issues (NS)	1,127,472	3.6	1.2	9.9	2.8	1.0	8.4	4.9	1.4	12.6
Accruals (Ac/A)	872,184	−3.9	−3.7	4.8	−3.8	−3.6	3.9	−4.1	−3.8	6.7
Asset Growth (dA/A)	1,111,863	12.4	7.0	26.4	10.8	7.0	19.9	15.2	6.5	36.8
Earnings Surprise (SUE)	1,106,417	−0.3	0.1	10.4	−0.1	0.1	4.3	−0.8	0.2	18.1
Idiosyncratic Volatility ($IdioVol$)	1,159,488	26.2	21.6	18.3	21.4	19.3	10.7	39.4	32.2	26.8

Panel B: Cross-sectional correlations													
	$\log B/M$	$R_{eq}(2,6)$	$R_{eq}(1)$	Y/B	NS	Ac/A	dA/A	SUE	$IdioVol$	$R_b(2,6)$	$R_b(1)$	DD	$L^{eAmihud}$
$\log MC$	−0.34	0.10	0.05	0.21	−0.04	−0.02	0.02	0.08	−0.42	−0.06	−0.03	0.50	−0.29
$\log B/M$		−0.23	−0.11	0.00	0.04	0.01	−0.11	−0.14	0.11	−0.05	−0.01	−0.30	0.11
$R_{eq}(2,6)$			0.01	−0.01	−0.05	−0.02	−0.06	0.14	−0.13	0.20	0.04	0.08	−0.06
$R_{eq}(1)$				0.00	−0.03	0.00	−0.03	0.03	0.04	0.02	0.11	0.03	−0.02
Y/B					−0.04	0.24	0.13	−0.10	−0.24	−0.07	−0.03	0.27	−0.11
NS						0.08	0.43	0.00	0.04	0.00	0.00	−0.06	−0.02
Ac/A							0.23	−0.04	−0.05	−0.01	−0.01	0.04	0.00
dA/A								−0.05	0.04	−0.03	−0.01	−0.01	−0.04
SUE									−0.12	0.07	0.02	0.07	−0.06
$IdioVol$										0.01	0.01	−0.55	0.28
$R_b(2,6)$											−0.09	−0.07	0.02
$R_b(1)$												−0.03	0.00
DD													−0.15

Table 3: Expected Signs of Equity Variables as Bond Return Predictors

This table 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/Frictions
Size ($\log MC$)	−	−
Value ($\log B/M$)	+	+
Momentum (R_{eq}(2,6))	?	+
Lead-Lag (R_{eq}(1))	?	−/+
Profitability (Y/B)	−	+
Net Stock Issues (NS)	?	+
Accruals (Ac/A)	?	−/+
Asset Growth (dA/A)	−	−
Earnings Surprise (SUE)	?	+
Idiosyncratic Volatility ($IdioVol$)	+/0	−

Table 4: Monthly Cross-Sectional Regressions for Stock Returns

We run the following cross-sectional regression each month:

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

where R_{it}^{eq} is the excess stock return and Zeq_{it-1} are lagged equity return predictors (the momentum returns are lagged by an additional month). Equity return predictors are described in Table 2. Newey-West (19987) corrected (using 12 lags) t-statistics are given in parentheses. We denote statistical significance at the 10% and 5% level with one and two asterisks, respectively. The column entitled 'Full sample' shows results for all stocks with price greater than \$1. The column entitled 'Matched sample' shows results for only those stocks for which we have corresponding bond returns. The sample period is 1973 to 2014, excluding the months between May 1998 to March 2001, in which we do not have enough firm observations to run the regressions in the matched sample.

	Full sample	Matched sample
$\log MC$	−21.00**	−13.51**
	(−3.47)	(−2.56)
$\log B/M$	17.37**	7.82
	(3.03)	(1.45)
$R_{eq}(2,6)$	16.05**	1.23
	(2.88)	(0.17)
$R_{eq}(1)$	−59.75**	−24.11**
	(−10.20)	(−4.08)
Y/B	10.13**	2.37
	(3.10)	(0.41)
NS	−14.09**	−12.93**
	(−5.64)	(−3.19)
Ac/A	−12.17**	−3.15
	(−5.98)	(−0.96)
dA/A	−16.74**	−8.17**
	(−6.11)	(−2.32)
SUE	30.44**	11.78**
	(12.05)	(2.09)
$IdioVol$	−23.90**	−6.09
	(−4.15)	(−0.93)

Table 5: Monthly Cross-Sectional Regressions for Bond Returns

We run the following cross-sectional regression each month:

$$R_{it} = \gamma_{0t} + \gamma'_{1t} Zeq_{it-1} + \gamma_{2t} R_{it-1} + \gamma_{3t} R_{it-2:t-6} + \gamma_{4t} DD_{it-1} + \gamma_{5t} L^{eAmihud}_{it-1} + \epsilon_{it},$$

where R_{it} is the excess bond return, Zeq_{it-1} are lagged equity return predictors (the momentum returns are lagged by an additional month), DD is the distance-to-default, and $L^{eAmihud}$ is the Amihud illiquidity measure's logarithm. All returns are in basis points per month. Equity return predictors are described in Table 2. Newey-West (19987) corrected (using 12 lags) t-statistics are given in parentheses. We denote statistical significance at the 10% and 5% level with one and two asterisks, respectively. The sample period is 1973 to 2014.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log MC$	−7.35**	−4.75**							−4.28**
	(−4.77)	(−3.12)							(−2.72)
$\log B/M$	−1.40	−3.44**							−1.20
	(−1.31)	(−3.41)							(−1.36)
$R_{eq}(2,6)$			4.31**	8.96**					9.06**
			(4.13)	(7.68)					(8.02)
$R_{eq}(1)$			10.62**	13.87**					13.61**
			(7.39)	(7.48)					(7.11)
Y/B					−6.64**	−5.64**			−4.48**
					(−4.78)	(−5.96)			(−3.62)
NS					−0.14	−0.45			0.95
					(−0.15)	(−0.45)			(0.54)
Ac/A							−0.25	−0.05	1.15
							(−0.39)	(−0.07)	(0.95)
dA/A							−3.23**	−3.38**	−2.33**
							(−3.29)	(−3.06)	(−1.98)
SUE							1.04	1.38	0.31
							(0.86)	(0.91)	(0.21)
$IdioVol$							5.85**	1.07	−1.91
							(2.90)	(0.60)	(−0.90)
$R_{bd}(2,6)$		−9.55**		−11.69**		−9.89**		−9.10**	−12.53**
		(−3.96)		(−4.60)		(−3.97)		(−3.93)	(−4.97)
$R_{bd}(1)$		−39.80**		−42.13**		−39.59**		−41.01**	−44.38**
		(−10.00)		(−10.21)		(−10.08)		(−10.64)	(−10.79)
DD		−4.44**		−7.24**		−3.91**		−5.08**	−5.77**
		(−3.01)		(−4.59)		(−2.30)		(−3.52)	(−3.48)
$L^{eAmihud}$		3.00**		5.18**		3.62**		4.11**	3.75**
		(2.72)		(4.45)		(3.45)		(3.36)	(2.67)

Table 6: Cross-Sectional Regressions: Single Bond Return per Firm

We run the following cross-sectional regression each month:

$$R_{it} = \gamma_{0t} + \gamma_{1t}' Zeq_{it-1} + \gamma_{2t} R_{it-1} + \gamma_{3t} R_{it-2:t-6} + \gamma_{4t} DD_{it-1} + \gamma_{5t} L_{it-1}^{eAmihud} + \epsilon_{it},$$

where R_{it} is the excess bond return, Zeq_{it-1} are lagged equity return predictors (the momentum returns are lagged by an additional month), DD is the distance-to-default, and $L^{eAmihud}$ is the Amihud illiquidity measure's logarithm. Equity return predictors are described in Table 2. Newey and West (1987) corrected (using 12 lags) t-statistics are given in parentheses. We denote statistical significance at the 10% and 5% level with one and two asterisks, respectively. We run the regression using only one 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 a value-weighted average of all bond returns for a given firm in a given month. The sample period is 1973 to 2014, excluding the months between May 1998 to March 2001, in which we do not have enough firm observations to run the regressions.

	Randomly chosen	Shortest maturity	Lowest age	Average within firm
$\log MC$	−6.61**	−5.80**	−4.58**	−6.54**
	(−5.22)	(−3.65)	(−2.02)	(−4.74)
$\log B/M$	−3.36**	−2.85**	−4.09**	−3.58**
	(−3.23)	(−3.15)	(−3.80)	(−4.12)
$R_{eq}(2,6)$	5.86**	6.12**	8.88**	7.19**
	(8.42)	(7.46)	(7.04)	(8.47)
$R_{eq}(1)$	11.35**	12.06**	15.64**	12.97**
	(9.25)	(9.42)	(9.75)	(9.40)
Y/B	−3.17**	−2.88**	−3.69**	−3.33**
	(−3.29)	(−3.07)	(−3.23)	(−3.76)
NS	1.75**	2.11**	1.65*	1.94**
	(2.17)	(3.18)	(1.86)	(3.00)
Ac/A	−0.27	0.36	−0.11	0.10
	(−0.46)	(0.57)	(−0.16)	(0.17)
dA/A	−2.63**	−2.71**	−2.86**	−2.95**
	(−2.45)	(−2.90)	(−2.72)	(−3.45)
SUE	0.66	0.43	0.80	1.03
	(0.77)	(0.48)	(0.68)	(1.20)
$IdioVol$	−0.28	−0.07	−0.10	−0.38
	(−0.18)	(−0.05)	(−0.07)	(−0.28)
$R_{bd}(2,6)$	−6.07**	−8.83**	−9.75**	−9.47**
	(−3.88)	(−4.03)	(−3.17)	(−4.89)
$R_{bd}(1)$	−23.31**	−35.40**	−44.10**	−30.35**
	(−10.58)	(−11.64)	(−13.46)	(−11.05)
DD	−3.66**	−5.03**	−6.17**	−4.77**
	(−2.80)	(−5.20)	(−3.52)	(−4.11)
$L^{eAmihud}$	2.08*	2.34*	2.70**	2.28*
	(1.74)	(1.87)	(2.03)	(1.89)

Table 7: Bond Returns from Sorts on Equity Return Predictors

Equity return predictors are described in Table 2. In Panel A, we sort bonds into deciles and calculate both equal-weighted (EW) and value-weighted (VW) returns. 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 one year for the variables $\log MC$, Y/B, and dA/A. We sort at the end of each month and hold these portfolios for one month for the variables R_{eq}(2,6) and $R_{eq}(1)$. 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 tenth decile and short in the first decile. We form all 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, $R^e_{i,t} = \alpha_i + \beta_i' F_t + \epsilon_{i,t}$, where F_t are the factors used in the asset pricing model. α_5 is calculated from Fama and French (1993) five-factor model with the market factor, stock size- and value-factors, and two bond factors ($Term$ and Def), and α_6 is calculated from a six-factor model with Fama and French (2015) five-factor model with market factor, firm size, value, investment and profitability factors, and the Pástor and Stambaugh (2003) liquidity factor. $Term$ is the return on long-term Treasury bonds in excess of T-bills and Def is the return on corporate bond market portfolio in excess of long-term Treasury bond. All returns and alphas are in percentage per month. The numbers in parentheses are the Newey-West (1987) corrected (using 12 lags) t-statistics. We denote statistical significance at the 10% and 5% level with one and two asterisks, respectively. The sample period is 1973 to 2014.

Panel A: Bond Returns						
	Equal-weighted returns			Value-weighted returns		
	All	IG	Junk	All	IG	Junk
$\log MC$	−0.41**	−0.10**	−0.45**	−0.34**	−0.09**	−0.30**
	(−4.51)	(−2.83)	(−3.29)	(−4.19)	(−2.44)	(−3.35)
$R_{eq}(2,6)$	0.13**	0.10**	0.42**	0.14**	0.10**	0.52**
	(2.14)	(3.01)	(3.84)	(2.54)	(2.68)	(4.32)
$R_{eq}(1)$	0.49**	0.22**	0.75**	0.45**	0.23**	0.77**
	(6.85)	(5.53)	(6.51)	(8.08)	(5.60)	(7.62)
Y/B	−0.19**	−0.05**	−0.38**	−0.11**	−0.05*	−0.22**
	(−4.06)	(−1.68)	(−2.92)	(−2.06)	(−1.76)	(−2.47)
dA/A	−0.14**	−0.08**	−0.19**	−0.11**	−0.07**	−0.04
	(−5.26)	(−4.02)	(−3.07)	(−3.90)	(−2.90)	(−0.41)

Panel B: Bond Alphas						
	All		IG		Junk	
	α_5	α_6	α_5	α_6	α_5	α_6
$\log MC$	−0.30**	−0.21**	−0.04	−0.02	−0.29**	−0.22**
	(−4.22)	(−2.89)	(−1.15)	(−0.66)	(−3.23)	(−2.29)
$R_{eq}(2,6)$	0.13**	0.13**	0.12**	0.11**	0.54**	0.53**
	(2.52)	(2.27)	(3.81)	(3.18)	(4.23)	(4.18)
$R_{eq}(1)$	0.48**	0.45**	0.26**	0.24**	0.77**	0.79**
	(7.25)	(7.56)	(5.06)	(5.92)	(8.19)	(7.67)
Y/B	−0.11**	−0.07	−0.03	0.00	−0.18**	−0.09
	(−2.37)	(−1.54)	(−0.75)	(−0.02)	(−2.03)	(−0.92)
dA/A	−0.09**	−0.06*	−0.07**	−0.07**	−0.12**	−0.10
	(−2.57)	(−1.65)	(−3.22)	(−2.75)	(−1.97)	(−1.61)

Table 8: Transaction Costs for Bond Portfolios

Equity return predictors are described in Table 2. We form value-weighted decile portfolios as described in Table 7. We calculate returns on a hedge portfolio (H−L) that is long in the tenth decile and short in the first 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, Pan, and Wang (2011) in Panel A and following Edwards, Harris, and Piwowar (2007) in Panel B. Portfolio transaction costs are calculated as the product of the portfolio turnover and the trading costs. The table reports the returns net of these transaction costs. All returns are in percentage per month. The numbers in parentheses are the Newey-West (1987) corrected (using 12 lags) t-statistics. We denote statistical significance for positive net returns at the 10% and 5% level with one and two asterisks, respectively. The sample period is 1973 to 2014.

	Turnover	Trading costs			Net returns		
		All	IG	Junk	All	IG	Junk
Panel A: Trading costs from Bao, Pan, and Wang (2011)							
$\log MC$	0.02	1.35	1.24	1.56	0.31**	0.05**	0.23**
					(3.78)	(1.36)	(2.51)
$R_{eq}(2,6)$	0.87	1.32	1.04	1.60	−1.01	−0.84	−0.91
					(−18.32)	(−23.17)	(−7.58)
$R_{eq}(1)$	1.76	1.31	1.02	1.62	−1.84	−1.56	−2.04
					(−32.84)	(−38.13)	(−20.32)
Y/B	0.08	1.25	1.00	1.43	0.01	−0.02	0.08
					(0.23)	(−0.81)	(0.93)
dA/A	0.12	1.09	0.94	1.28	−0.02	−0.04	−0.13
					(−0.59)	(−1.74)	(−1.51)
Panel B: Trading costs from Edward, Harris, and Piwowar (2007)							
$\log MC$	0.02	0.18	0.16	0.30	0.33**	0.08**	0.29**
					(4.13)	(2.30)	(3.19)
$R_{eq}(2,6)$	0.87	0.18	0.16	0.30	−0.02	−0.05	0.25
					(−0.30)	(−1.31)	(2.09)
$R_{eq}(1)$	1.76	0.18	0.16	0.30	0.14**	−0.05	0.25**
					(2.45)	(−1.26)	(2.44)
Y/B	0.08	0.18	0.16	0.30	0.09*	0.04	0.19**
					(1.80)	(1.35)	(2.15)
dA/A	0.12	0.18	0.16	0.30	0.09**	0.05**	0.00
					(3.16)	(2.11)	(−0.04)

Table 9: Sharpe Ratios of Hedge Portfolios

Equity anomaly variables are described in Table 2. We form value-weighted decile portfolios as described in Table 7 and calculate raw returns and alphas for these portfolios. α_5 is calculated from the Fama and French (1993) five-factor model with the market factor, stock size- and value-factors, and two bond factors ($Term$ and Def), and α_6 is calculated from a six-factor model which adds the Pástor and Stambaugh (1999) liquidity factor. [$Term$ is the return on long-term treasury bonds in excess of T-bills and Def is the return on corporate bond market portfolio in excess of long-term treasury bond.] The table reports monthly Sharpe ratios of the extreme long-short (H−L) portfolios 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. Standard errors of Sharpe ratios are calculated by applying the delta method and the Newey and West (1987) correction using 12 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 parenthesis below the Sharpe ratio. Panel A presents the results using gross returns, Panel B presents the results using net returns after adjusting for trading costs from Bao, Pan, and Wang (2011), and Panel C presents the results using net returns after adjusting for the trading costs from Edwards, Harris, and Piwowar (2007). $SR(R)$ represents the Sharpe ratio based on raw returns, whereas $SR(\alpha_n)$, $n = \{5, 6\}$ represents the alpha-based Sharpe ratio using the relevant n-factor model. We denote statistical significance at the 10% and 5% level with one and two asterisks, respectively. The sample period is 1973 to 2014.

	All			IG			Junk		
	$SR(R)$	$SR(\alpha_5)$	$SR(\alpha_6)$	$SR(R)$	$SR(\alpha_5)$	$SR(\alpha_6)$	$SR(R)$	$SR(\alpha_5)$	$SR(\alpha_6)$
Panel A: Gross Returns/Alphas									
$\log MC$	0.20	0.22	0.14	0.11	0.06	0.03	0.16	0.16	0.12
	(0.26)	(0.16)	(0.73)	(0.91)	(0.99)	(1.00)	(0.63)	(0.59)	(0.87)
$R_{eq}(2,6)$	0.12	0.11	0.12	0.11	0.15	0.14	0.26	0.27	0.27
	(0.88)	(0.91)	(0.86)	(0.90)	(0.72)	(0.79)	(0.04)	(0.08)	(0.17)
$R_{eq}(1)$	0.46**	0.50**	0.46**	0.31**	0.36**	0.33**	0.39**	0.43**	0.44**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Y/B	0.10	0.13	0.08	0.05	0.03	0.00	0.12	0.11	0.05
	(0.91)	(0.82)	(0.97)	(1.00)	(1.00)	(1.00)	(0.84)	(0.85)	(0.98)
dA/A	0.14	0.12	0.08	0.10	0.14	0.13	0.02	0.08	0.07
	(0.77)	(0.82)	(0.96)	(0.97)	(0.77)	(0.86)	(1.00)	(0.98)	(0.99)

	All			IG			Junk		
	$SR(R)$	$SR(\alpha_5)$	$SR(\alpha_6)$	$SR(R)$	$SR(\alpha_5)$	$SR(\alpha_6)$	$SR(R)$	$SR(\alpha_5)$	$SR(\alpha_6)$
Panel B: Net Returns/Alphas from Bao, Pan, and Wang (2007) trading costs									
$\log MC$	0.18	0.19	0.12	0.06	0.00	−0.02	0.12	0.12	0.08
	(0.43)	(0.33)	(0.85)	(0.99)	(1.00)	(1.00)	(0.86)	(0.85)	(0.98)
$R_{eq}(2,6)$	−0.85	−0.88	−0.88	−0.97	−1.03	−1.02	−0.45	−0.46	−0.45
	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
$R_{eq}(1)$	−1.86	−1.87	−1.92	−2.08	−2.16	−2.18	−1.04	−1.15	−1.11
	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
Y/B	0.01	0.01	−0.03	−0.02	−0.05	−0.08	0.05	0.03	−0.03
	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(0.99)	(0.99)	(1.00)
dA/A	−0.02	−0.05	−0.09	−0.06	−0.08	−0.09	−0.07	−0.04	−0.04
	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
Panel C: Net Returns/Alphas from Edwards, Harris, and Piwowar (2011) trading costs									
$\log MC$	0.20	0.21	0.14	0.10	0.05	0.03	0.15	0.15	0.11
	(0.29)	(0.18)	(0.74)	(0.93)	(0.99)	(1.00)	(0.68)	(0.65)	(0.90)
$R_{eq}(2,6)$	−0.01	−0.02	−0.02	−0.06	−0.03	−0.04	0.12	0.14	0.13
	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(0.85)	(0.69)	(0.65)
$R_{eq}(1)$	0.14	0.17	0.14	−0.07	−0.03	−0.06	0.12	0.14	0.15
	(0.77)	(0.52)	(0.71)	(1.00)	(1.00)	(1.00)	(0.80)	(0.71)	(0.60)
Y/B	0.09	0.11	0.06	0.04	0.02	−0.01	0.10	0.10	0.04
	(0.95)	(0.89)	(0.98)	(1.00)	(1.00)	(1.00)	(0.90)	(0.91)	(0.99)
dA/A	0.11	0.09	0.05	0.07	0.10	0.09	0.00	0.06	0.04
	(0.90)	(0.92)	(0.99)	(0.99)	(0.95)	(0.97)	(1.00)	(1.00)	(1.00)

Table A1: Summary Statistics on Bond Returns by Data Source

The table 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 which has the same coupons and repayment schedule. AR1 is the first autocorrelation coefficient and AR1-AR6 is the sum of the first six 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 to 2014.

	N	No price Change	% Market Value	Mat	Excess returns				
					Mean	SDev	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

Table A2: Monthly Cross-Sectional Regressions of Bond Returns: Robustness Checks
We run the following cross-sectional regression each month:

$$R_{it} = \gamma_{0t} + \gamma'_{1t} Zeq_{it-1} + \gamma_{2t} R_{it} + \gamma_{3t} R_{it-2:t-6} + \gamma_{4t} DD_{it-1} + \gamma_{5t} L^{eAmihud}_{it-1} + \epsilon_{it},$$

where R_{it} is the excess bond return, Zeq_{it-1} are lagged equity return predictors (the momentum returns are lagged by an additional month), DD is the distance-to-default, and $L^{eAmihud}$ is the Amihud illiquidity measure's logarithm. Equity return predictors are described in Table 2. Panel A shows the results when we do not include matrix prices in the bond sample. Panel B shows the results when we do not include Datastream in the bond sample. Panel C shows the results when we prioritize the databases in the following order: the Lehman Brothers Fixed Income Database, TRACE, Mergent FISD/NAIC, and Datastream. Panel D shows the results when we include fixed effects for callable bonds in cross-sectional regressions. In each panel, the columns entitled "Difference from full-sample" show the difference of these results from those presented in Table 5. Newey-West (19987) corrected (using 12 lags) t-statistics are given in parentheses. We denote statistical significance at the 10% and 5% level with one and two asterisks, respectively. The sample period is 1973 to 2014.

	Without matrix prices		Without Datastream		With reverse ordering of databases		With fixed effects for callable bonds	
	New	Difference	New	Difference	New	Difference	New	Difference
$\log MC$	−3.82**	−0.46	−4.20**	−0.08	−3.44*	−0.84	−5.02**	0.74
	(−2.14)	(−0.52)	(−2.67)	(−0.09)	(−1.84)	(−0.59)	(−3.37)	(1.43)
$\log B/M$	−1.64	0.44	0.05	−1.25	1.77	−2.97	−1.50*	0.31
	(−0.92)	(0.31)	(0.04)	(−1.17)	(0.71)	(−1.23)	(−1.89)	(0.68)
$R_{eq}(2,6)$	10.21**	−1.15	7.72**	1.33**	10.17**	−1.11	9.39**	−0.33*
	(5.20)	(−0.71)	(8.26)	(3.43)	(4.73)	(−0.68)	(7.98)	(−1.68)
$R_{eq}(1)$	15.03**	−1.41	11.62**	1.99**	13.49**	0.12	13.53**	0.08
	(6.91)	(−1.21)	(6.92)	(2.58)	(6.27)	(0.14)	(7.09)	(0.46)
Y/B	−4.14*	−0.34	−3.64**	−0.84	−0.08	−4.40	−4.40**	−0.08
	(−1.89)	(−0.16)	(−3.61)	(−1.16)	(−0.02)	(−1.20)	(−3.68)	(−0.41)
NS	0.29	0.66	2.82**	−1.86**	−0.11	1.06	1.01	−0.06
	(0.16)	(0.72)	(3.08)	(−4.09)	(−0.05)	(1.06)	(0.61)	(−0.23)
Ac/A	1.26	−0.11	1.01	0.14	−0.76	1.91	1.02	0.13
	(0.97)	(−0.08)	(1.59)	(0.25)	(−0.45)	(0.81)	(0.84)	(0.99)
dA/A	−3.54	1.21	−2.69	0.36	−1.32	−1.01	−2.05	−0.28
	(−1.60)	(0.62)	(−2.49)	(0.70)	(−0.84)	(−1.32)	(−1.56)	(−1.08)
SUE	−0.12	0.44	1.77	−1.46	−1.22	1.53	−0.12	0.43
	(−0.04)	(0.18)	(1.29)	(−1.20)	(−0.54)	(0.79)	(−0.08)	(1.11)
$IdioVol$	−2.61	0.70	1.56	−3.48	1.13	−3.05	−2.24	0.33
	(−1.33)	(0.57)	(0.71)	(−2.48)	(0.56)	(−1.11)	(−0.92)	(0.61)
$R_{bd}(2,6)$	−16.42**	3.89**	−15.23**	2.70	−12.22**	−0.31	−12.84**	0.31
	(−5.52)	(1.99)	(−4.61)	(1.27)	(−5.35)	(−0.28)	(−5.20)	(0.91)
$R_{bd}(1)$	−50.13**	5.76**	−45.50**	1.12	−33.51**	−10.87**	−45.22**	0.84**
	(−12.34)	(3.66)	(−8.35)	(0.34)	(−10.50)	(−2.90)	(−10.79)	(2.49)
DD	−5.78**	0.01	−2.62**	−3.15**	−4.12**	−1.65**	−5.89**	0.12
	(−3.94)	(0.01)	(−1.96)	(−2.31)	(−2.92)	(−2.27)	(−3.46)	(0.48)
$L^{eAmihud}$	6.54**	−2.80*	6.24	−2.49	4.13**	−0.39	4.13**	−0.38*
	(2.92)	(−1.74)	(1.59)	(−0.67)	(2.89)	(−0.64)	(2.65)	(−1.74)

Figure 1: Hedge Portfolio Returns for Investment Grade and Junk Bonds

Equity return predictors are described in Table 2. 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 one year for the variables log MC, Y/B, and dA/A. We sort at the end of each month and hold these portfolios for one month for the variables $R_{eq}(2{,}6)$ and $R_{eq}(1)$. 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. The figure shows the returns on these decile portfolios. All returns are in percentage per month. The sample period is 1973 to 2014.