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Abstract

Is the Cross-Section of Expected Bond Returns Influenced by Equity Return Predictors?

This paper studies whether the commonly analyzed equity return predictors also predict corporate bond returns. Bond markets do price risk, but are also susceptible to delayed information transmission relative to equities. Firm size and profitability are negatively priced while idiosyncratic volatility is positively priced, suggesting that large firms, more profitable firms and relatively less volatile firms are more attractive to bond investors, thus requiring lower returns. Consistent with a relatively sophisticated institutional clientele, bonds are efficiently priced in that none of the behaviorally-motivated variables provide profitable trading strategies after accounting for transactions costs, though some risk-based variables continue to do so.

1 Introduction

Firms finance their assets by a mixture of debt and equity claims. As per the risk-reward (RR) paradigm exposited in neoclassical asset pricing models, the required return on a firm represents a reward for risk borne by investors in the firm and is the weighted average of the expected returns on debt and equity components. Some recently documented predictors of average equity returns are hard to rationalize in the context of the RR paradigm, and seem to represent anomalous deviations from the paradigm. Thus, for example, the predictive power of accounting accruals and earnings surprises has been attributed to limited attention (Hirshleifer and Teoh (2003); Hirshleifer, Lim, and Teoh (2011)). Short-term (monthly and weekly) reversals documented by Jegadeesh (1990) and Lehmann (1990) have been attributed to overreaction (Cooper (1999)) while predictability due to longer-term returns has been motivated by the psychological biases of overconfidence and self-attribution (Daniel, Hirshleifer, and Subrahmanyam (1998)) as well as the conservatism bias and the representativeness heuristic (Barberis, Shleifer and Vishny (1998)). Other anomalies including asset growth, profitability and idiosyncratic volatility are attributed to investor overreaction or underreaction.

While a voluminous literature documents anomalies in equities (see Harvey, Liu, and Zhu (2013) for an excellent summary), there is as yet only limited evidence for the existence of such anomalies in the bond market. We fill this void by empirically examining whether variables capturing equity return anomalies also forecast corporate bond returns. There are a few arguments for why analogs of equity anomalies might or might not exist in the bond market: (1) Both bond and stock market investors have cognitive biases that are reflected in both the stock market and the bond market, and arbitrage is partially effective.[1] (2) Bond market investors have cognitive biases, and arbitrage is completely ineffective. (3) Bond market investors are quite sophisticated, leading to a bond market free of anomalous behavior. The three situations above have different implications for the statistical and economic significance of anomalies. In Case (1) we expect statistically significant anomalies which disappear net of transaction costs, in Case (2) we expect anomalies that are profitable net of transaction costs, while in Case (3) we expect no discernible anomalies at all.[2]

One reason that investor biases may *not* manifest themselves in the corporate bond market is because this market is dominated by institutions, and Barber et al. (2009) suggest that institutions tend to be more sophisticated than individuals.[3] Indeed, Edwards, Harris, and Piwowar (2007) document a median trade size of $632,700 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.[4] While this *a priori* reasoning is suggestive that the market for corporate bonds may in fact be more efficient than that for stocks, our empirical tests are able to shed specific light on which of the three cases above is supported by the data.

We borrow from the rich literature on equity anomalies to identify several prominent

[1] Edwards, Harris, and Piwowar (2007) show that on average bonds trade on only 53% of the days in their sample with an average number of trades per day of 2.4. Bao, Pan, and Wang (2011) also document substantial illiquidity in the bond market and also show that this illiquidity impacts yield spreads. Dick-Nielsen, Feldhutter, and Lando (2012) and Friewald, Jankowitsch, and Subrahmanyam (2012) also document the impact of illiquidity on yield spreads and show that this impact increases during the recent financial crisis. These papers suggest that illiquidity in the corporate bond market may preclude arbitrage from being fully effective.

[2] There is a fourth reason for why anomalies might exist in the corporate bond market. Investor biases might affect only stock prices but this could impact bond prices through the credit risk channel. For instance, past stock returns are likely to change leverage levels and thus impact bond prices. We address this in our tests by controlling for the distance to default as well as leverage.

[3] On the other hand, a number of 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), Cici (2012), Ye (2014).

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

variables that forecast equity returns, and test relations between these variables and expected bond returns, using an extensive panel of corporate bonds from 1973 to 2011. Our data are assembled from five distinct data sets, namely, the Lehman Brothers Fixed Income Database, TRACE, Mergent FISD/NAIC, Merill Lynch, and DataStream, and make it possible to estimate expected returns on corporate bonds precisely. 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 isolate returns on corporate bonds due to shocks to issuer's default risk from Treasury bond returns, which allows us to focus on the bond-equity relationship while abstracting from the interactions with changes in treasury yields.

We start our analysis by sorting corporate bonds into decile portfolios based on equity characteristics. We differentiate between investment-grade bonds and junk bonds, and investigate whether our findings are pervasive across rating categories. Variation in excess returns on these portfolios is not explained by asset pricing models. We check alphas from the one-factor CAPM and the five-factor Fama and French (1993) model (including bond factors) to find that none of these models materially reduces the magnitudes of alphas. In our univariate portfolio sorts, many equity anomalies are significant forecasters of bond returns: size, value, lagged equity returns, idiosyncratic volatility and net stock issues forecast bond returns across credit ratings. Equity momentum works for investment grade bonds only while accruals and profitability forecast junk bond returns.

Do these equity characteristics have incremental predictive power in a multivariate context? We run Fama and MacBeth (1973) cross-sectional regressions of bonds excess returns on lagged equity characteristics separately for investment grade and junk bonds. In multivariate regressions, size, momentum, lagged equity returns, profitability, and idiosyncratic volatility forecast bond returns, but other variables such as accruals, asset growth, SUE, and net issues 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. In particular, the signs of the coefficients on lagged equity returns (Jegadeesh (1990)) and idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang (2006)) are positive while the sign of the coefficient on profitability (Fama and French (2008)) is negative.

The positive coefficient on the one-month lagged equity return is consistent with the notion that information flows to stocks first, followed by bonds. Further, if highly profitable firms are less risky[5] and if firms with higher idiosyncratic volatility are riskier then the 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.

Finally, we examine the full impact of transaction costs (including bid-ask spreads and commissions) on the economic significance of bond return predictors. After controlling for transaction costs, risk-based variables (size,[6] profitability, and idiosyncratic volatility) continue to yield evidence of predictability, whereas the effect of predictive variables motivated by behavioral or friction-based arguments disappears. This implies that bond markets tend to be efficiently priced up to transactions costs, in that they do not appear to permit arbitrage opportunities. Thus, the totality of the evidence indicates a picture consistent with Case (1) above, i.e., a corporate bond market efficient up to transactions costs.

[5]Highly profitable firms likely have more accumulated cash and thus a reduced likelihood of default.
[6]Large firms are generally considered less risk than small firms.

Our paper is related to the literature that studies the pricing relationship between corporate bonds and equities. Based on Merton (1974), Collin-Dufresne, Goldstein and Martin (2001) regress 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. None of these studies analyze the relation between equity characteristics and corporate bond returns.

Our paper is also partly related to papers that analyze 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 (2013) 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. After completing work on our paper, we became aware of a closely related paper by Choi and Kim (2014). These authors consider the impact of a limited set of four anomalies on the cross-section of corporate bond returns. We use a slightly longer sample period, about three times as many observations,[7] and a broader set of anomalies. Our results are different as a consequence. Thus, unlike these authors, who do not find that profitability is priced in bonds, we find that profitability is negatively priced (consistent with the notion that profitable firms are less risky), and also document a strong lead from monthly equity

[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. They have a total of about 325,000 observations in their sample. In contrast, we use five distinct data sets to construct a comprehensive sample consisting of more than one million observations spanning the period 1973-2011.

returns to monthly bond returns.

Finally, a related paper is 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 no own-momentum for corporate bond returns in excess of that on matching Treasury bonds, in presence of other equity anomaly variables (though there is momentum in gross corporate bond returns). Thus, momentum in JNPS appears to arise from momentum in the Treasury bond market.

Overall, we believe our work to be among the first to examine the relationship between bonds and equities from the perspective of examining commonalities in the cross-section of expected returns in equities and corporate bonds. Our results indicate that there is a room for a unified theory that simultaneously explains differences in the cross-sectional predictability of returns across the stock and bond markets.

The rest of this paper is organized as follows. Section 2 discusses the corporate bond data and our construction of bond returns. Section 3 presents the main results on the relation between equity characteristics and corporate bond returns. We analyze the role of institutional investors and trading costs in Section 4 and conclude in Section 5.

2 Corporate Bond Data and Bond Returns

2.1 Data

We obtain monthly prices of senior unsecured corporate bonds from the following five data sources. First, 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 it, 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. In the Lehman Brothers Fixed Income Database, some observations are dealers' quotes while others are matrix prices. Matrix prices are set using algorithms based on the quoted prices of other bonds with similar characteristics. Though matrix prices are less reliable than actual dealer quotes (Warga and Welch (1993)), we include these prices in our main result to maximize the power of our tests. However, in the Appendix, we show that our results are robust to the exclusion of matrix prices. Second, from 1994 to 2011, we use the Mergent FISD/NAIC data. This database consists of actual transaction prices reported by insurance companies. Third, from 2002 to 2011, we use the TRACE data which also provides actual transaction prices. TRACE covers more than 99 percent of the OTC activities in the US corporate bond markets after 2005. The data from Mergent FISD/NAIC and TRACE are transaction-based data and, therefore, the observations are not 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 latest one and treat it as the month-end observation. Fourth, we use the Merrill Lynch database which provides month-end quotes from 1997 to 2011. The Merrill Lynch database covers only relatively liquid bonds, as the bonds in the database are required to have fixed coupon rates and a minimum amount outstanding of $100 million for junk bonds and $150 million for investment grade bonds. Lastly, we use the DataStream database which provides month-end quotes from 1990 to 2011.

To remove data that seem unreasonable, we apply the following three filters: first, we remove prices that are less than one cent per dollar, or more than the prices of matching Treasury bonds; second, we remove observations if the prices appear to bounce back in an extreme fashion; specifically if the product of the two consecutive monthly returns is less than -0.04; and third, we remove observations if prices do not change for more than three months.

Since our data comes from different sources, we check for differences / similarities across the different data sources. Table A1 in the appendix shows that the Merrill Lynch sample has higher returns and positive autocorrelations whereas the other datasets have negative correlations in the bond excess returns. Since the Merrill Lynch dataset is different from the others, we have verified that our results remain qualitatively unchanged when we drop the Merrill Lynch sample from the analysis.

Since there are overlapping observations among the four databases, we prioritize in the following order: the Lehman Brothers Fixed Income Database, TRACE, Mergent FISD/NAIC, Merill Lynch, and DataStream. As JNPS (2013) find, the degree of overlap is not large relative to the total size of the dataset, with the largest overlap between TRACE and Merill Lynch being 6.1% of the non-overlapping observations. To check data consistency, we examine the effect of our priority ordering by reversing the priority. We show in the Appendix that our main empirical findings are not sensitive to the ordering choice of the four datasets.

The Lehman Brothers Fixed Income Database and Mergent FISD[8] provide other characteristics specific to the issuer of bonds, such as the maturity dates, credit ratings, coupon rates, and optionalities of the bonds. We remove bonds with floating rates and with any option features other than callable bonds. Until the late 1980s, there are very few bonds that are non-callable. Removing callable bonds would reduce 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 value, the return on these bonds may behave differently from the return on non-callable bonds. We address this concern in the Appendix by adding fixed effects for callable bonds, and show that our results are not sensitive to this feature of the data.

We merge all five bond databases using the CUSIP identifiers at the firm and at the issue level. 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 slightly over one million bond-month return observations with 18,850 bonds issued by 3,588 firms over 468 months. Our sample size is smaller than that of JNPS (2013) as our sample from DataStream is smaller and we only use observations that can be matched to equity returns and accounting information. We also find that there are many missing values in DataStream and the prices often do not change for more than several months. We show in the Appendix that our main results are robust to the exclusion of Datastream data from our sample.

[8] Mergent FISD provides relatively limited price information but provides bond characteristic information for most of the bonds since 1994.

2.2 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. The price of a corporate bond can be considered to be a function of both the price of a treasury bond and the firm-specific default risk. 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 treasury bond whose construction we explain below. Then the excess bond return that we use for our analysis is:

$$R_{it} \equiv R^b_{it} - R^f_{it}\,. \tag{3}$$

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 due to shocks to the firm's fundamentals.

To construct the matching treasury bond price 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. At each month and for each corporate bond in the dataset, we construct the future cash flow schedule from the coupon and principal payments. Then we 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. 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.

Our definition of excess returns differs from other methods to account for the effect of treasury yields. Other studies (for example, Collin-Dufresne, Goldstein, and Martin (2001)) 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.[9]

[9]Strictly speaking, the cash flow matching is still not perfect for a corporate bond that is close to default. If the bond is close to default, its cash flow 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 other alternative methods are also subject to the same problem due to the accelerated payments upon default.

2.3 Descriptive Statistics

Table 1 shows the summary statistics of excess returns on corporate bonds in the sample. 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 bonds ($AA+$), A-rated bonds (A) and BBB-rated bonds (BBB).

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 default should behave more like equities while high-credit bonds should be relatively closer to riskless debt in its behavior.[10] 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 high grade bonds (Chen, Lesmond, and Wei (2007)). Therefore, if the equity anomalies only affect junk bonds but not IG bonds, then such predictability may be expensive to exploit. Thus, 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 0.120% for all bonds and it decreases monotonically with bond rating. Investment grade bonds earn lower excess returns. Junk bond returns are more volatile than IG bond returns as evidenced in their higher standard deviation and thicker tails of the distribution. The first order autocorrelation, AR1, is generally negative. AR1 increases with credit rating, from -0.27 for AA+ to -0.01 for junk bonds. The sum of the first six autocorrelations also

[10] See Baker and Wurglur (2012).

increases monotonically with ratings, from -0.31 for AA+ bonds to 0.06 for junk bonds. The negative AR1 is consistent with overreaction and 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. As there are more IG bonds outstanding and they are more frequently traded, we have more observations on IG bonds (784,770 or 78.4% of the total number of observations) relative to junk bonds (207,658, or 21.6% of the total number of observations). The number of observations with zero price change is a measure of bond liquidity. Overall, only 2.1% of observations correspond to zero price change observations.[11] This low ratio shows that the corporate bond prices in our sample are fairly variable and likely to be informative about the link between bonds and equities.

IG bonds also constitute a larger fraction of the sample (73.3% of the total bond market capitalization in our sample) than junk bonds (26.3%). This means that value-weighted bond portfolios, that we study later in the paper, are likely to be more representative of IG bonds than the equal-weighted bond portfolios. However, as the ratio of the number of observations is not very different from the ratio of the market values across the two categories, 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. The average correlation is 0.22 for the entire sample, which is consistent with Collin-Dufresne,

[11] Chen, Lesmond, and Wei (2007) use zero return observations to measure liquidity. Due to accrued interest, in general a return is not zero even when the price does not change at all. In Table 1 we show the number of observations with no price change rather than a zero return.

Goldstein, and Martin (2001).

We also look at the 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). Most of the bonds in our sample are issued by big firms; 79.6% of observations are associated with big firms, 14.3% with small firms, and only 6.1% with micro firms. We find that junk bonds are issued more often by smaller firms; 18.7% of observations for junk bonds are from micro issuers.

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 the total of 3,060 firms are micro stocks and only 626 firms are big stocks. They also find that some anomaly variables (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.

3 Equity Return Predictors and Corporate Bond Expected Returns

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 the market related variables (returns and prices) are assumed to be known immediately. We construct the following anomaly variables.

1. Size ($\log MC$): the natural logarithm of the market value of the equity of the firm (in million 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}(2,12)): the cumulative 11-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 + 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).[12]

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 over the same quarter in the last fiscal year divided by price. See Ball and Brown (1968) and Livnat and Mendenhall (2006).

[12]We also used gross profitability calculated as the ratio of gross profit to total assets (Novy-Marx (2013)). Our results are weaker using this measure of profitability.

10. Idiosyncratic Volatility ($IdioVol$): the annualized volatility of the residuals from market model regression for the issuer's equity over 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 the expected signs of these variables under two categories of arguments: (i) behavioral misreactions/frictions and (ii) the risk-reward paradigm. Focusing first on the risk-reward (RR) paradigm, the signs appear unambiguous in only a few cases. First, 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 thus require lower returns, we would expect Y/B should have a negative coefficient in the bond markets.[13] Given that investors do not hold diversified portfolios, higher equity 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 the volatility variables. It would seem that net equity issues should reduce leverage and thus reduce risk suggesting that the sign on NS should be negative. However, we control for the distance to default (a good risk proxy) which would leave the sign on NS unspecified.[14] The role for the other variables under the RR paradigm appears hard to predict, so we leave these signs unspecified as well.

[13]Novy-Marx (2013) and Fama and French (2013), however, find that more profitable firms earn higher equity returns.

[14]In unreported results we have also controlled for leverage (defined by book value of debt over market value of equity) and our results remain unchanged.

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 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, an underreaction to idiosyncratic volatility could would result in a negative coefficient on $IdioVol$. If investors prefer the bonds of large, growth firms, we would expect a negative coefficient on firm size and a positive coefficient on the book-to-market ratio. We predict NS to have a positive coefficient in the bond market (but a negative one in the equity market), because the market timing hypothesis predicts 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. As for $R_{eq}(1)$, under the behavioral/friction hypothesis of overreaction and correction (Cooper (1999)), 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, we would expect $R_{eq}(1)$ to also predict bond returns with a negative sign, even after controlling for the lagged bond return if the latter is measured with error, due to stale prices, for instance.[15] However, if bond markets react to stock markets with a lag, the coefficient of $R_{eq}(1)$ will 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 2, the expected impact of the firm characteristics on bond returns is often different based on whether it is the RR paradigm or the be-

[15]In our later tests, we do in fact control for lagged bond returns.

havioral/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, asset growth, accruals, earnings surprise and equity issues cannot be determined under the RR paradigm, the behavioral/friction paradigm provides clear signs. The Fama-MacBeth (1973) regressions (to follow) allow us to shed light the question of whether institutions, who are more active and are likely the marginal traders in the bond markets, are subject to behavioral biases.

3.1 Summary Statistics

Table 3 provides the 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. Most of the equity anomaly variables have greater standard deviation for the sample of junk bonds than they do for the sample of 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 slope coefficient in a regression of bond returns on these equity characteristics could be sensitive to junk bond observations. Thus, it is important to check whether equity return predictors are related to bond excess returns based both on the entire sample and on the breakdown using credit ratings.

Even though our variables have been shown in the prior literature to be related to equity returns, it is important to check their predictive power in our sample. We do this by sorting stocks into deciles and calculating equal- and value-weighted post-formation returns for these portfolios. We sort at the end of June of every year and hold these portfolios for one year for the anomaly variables $\log MC$, $\log B/M$, Y/B, NS, Ac/A, dA/A, and SUE. We sort at the end of each month and hold the portfolio for the subsequent month for the anomaly variables R_{eq}(2,12), R_{eq}(1), and $IdioVol$. We repeat this procedure for three different samples. The first sample consists of all available stocks. The second sample consists of only big capitalization stocks (defined as stocks above the median NYSE capitalization). The third sample consists of those stocks for which we have the matched sample of bonds. It is important to check the predictability in these different samples because Fama and French (2008) show that many anomaly variables work poorly in the sample of large stocks; Table 1 shows that bonds are issued primarily by large companies.

Table 4 shows that almost all anomaly variables have strong predictive power for future stock returns in the full sample. As expected, the predictability is weaker amongst big stocks. Unlike the sample for all stocks, the large firm sample does not exhibit significant returns for profitability, new equity issues, accruals, earnings surprise and idiosyncratic volatility. The results are generally weaker for the value-weighted portfolios. Since many of the anomalies do not obtain in the equity market, it is quite likely that they will not be manifested in bonds as well.

3.2 Portfolio Sorts for Expected Bond Returns

We start our analysis by considering the univariate relation between equity anomaly variables and bond returns via portfolio sorts. We sort bonds into decile portfolios and calculate both equal-weighted and value-weighted returns. Value-weighting is done using the prior month's market capitalization of the bond. The sorting procedure is the same as that for equity returns described in the previous subsection.

Table 5 shows the results of these portfolio sorts. Each block has five rows. The first row is the equal-weighted average characteristics that we use to sort the bonds. The second and the third row show the equal-weighted average excess return (EW) and its t-statistic. The fourth and fifth row show the value-weighted excess return (VW) and its t-statistic. The column entitled H−L shows the hedge portfolio return that is long in the tenth decile and short in the first decile. We repeat the same exercise for subsamples of IG and junk bonds but report the returns only on the hedge portfolio.

Equity 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 −0.34% and −0.33%, respectively. In annual terms, the hedge portfolio 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 and statistically insignificant for IG bonds. This result is not surprising as the large variation in equity size comes from the variation across all bonds rather than within each credit-rating category. However, since there is sufficient variation in equity size within the subsample of junk bonds, the equity size effect is strong for junk bonds with equal and value weighted hedge portfolios returns of −0.31% and −0.32%, respectively.

The value effect, $\log B/M$, is also a strong predictor of bond returns both for the full sample as well as the subsample of IG and junk bonds. The monthly hedge portfolio returns are between 0.11% and 0.57%. Once again, the predictability is stronger for junk bonds than it is for IG bonds, partly reflecting the greater variation in book-to-market for issuers of junk bonds than that for the issuers of IG bonds.

The impact of equity momentum, R_{eq}(2,12), obtains for IG bonds but not for junk bonds. The existence of equity momentum effect on IG bonds is consistent with Gebhardt, Hvidkjaer, and Swaminathan (2005b) who find an equity momentum effect using only investment grade bonds. The new finding in this article is that there is no equity momentum effect in junk bonds and that this effect also disappears in the full sample. Although we have fewer observations for junk bonds, these observations tend to end up in the extreme deciles. For example, the extreme losers portfolio for the full sample is mostly populated by junk bonds. Since average excess returns for junk bonds are higher than those on IG bonds, the first decile using the full sample earns high average excess returns, erasing the momentum effect for the sample of all bonds.

The lead-lag effect, $R_{eq}(1)$, is the strongest effect that we find. The monthly hedge portfolio returns range from 0.21% to 0.71% (2.5% to 8.5% annually) and are strongly statistically significant. The effect is more pronounced for junk bonds but IG bonds also show a significant lead-lag effect. Earlier we had postulated the delayed reaction hypothesis and the overreaction hypothesis, which predicted opposite (respectively, positive and negative) signs on $R_{eq}(1)$. The result in Table 5 supports the former hypothesis.

Two accounting variables, Ac/A and SUE, have statistically significant predictive power for IG bonds, but the economic significance seems to be small. The variables dA/A, Y/B, and NS, show some predictive power for future bond excess returns. The impact of dA/A and Y/B is significant for junk bonds but not for IG bonds. On the other hand, NS forecasts bond returns for both IG and junk bonds. These findings are consistent with Fama and French (2008) who find that NS is a strong forecaster of equity returns across all size categories while Y/B works only for small and micro stocks. What is interesting, however, is that these variables predict bond returns with a sign opposite to that for stock return prediction, Y/B is negatively associated with bond returns whereas the opposite is true for NS suggesting that these effects are probably not being driven by investor behavioral biases. The signs of the coefficients on NS and Y/B are consistent with the rational pricing. Thus, net issuance of equity as opposed to debt, as per the market timing rationale (Baker and Wurgler (2002)), might mean that equity is overvalued, or that debt is undervalued. Thus, NS is expected to positively predict bond returns. The coefficient for Y/B is consistent with the notion that the bond market considers low Y/B firms to be more risky (closer to distress), and thus requires higher returns from such firms.

The pattern in the average characteristics across Y/B portfolios is also worth a note. For Y/B, most of the variation in average excess returns happens across the first and the second deciles. The first decile has extreme negative profitability on average. As the average excess returns are fairly flat between the second and the tenth deciles, it seems that there is something unique about firms with very large negative profits, which is intuitive, because these are the firms that are the closest to financial distress, requiring higher returns. A similar non-linear pattern can be found for NS sorted bonds. There is a distinct jump in average excess returns between the second and third deciles. The firms in the first two deciles repurchase stocks, on average, while the firms in the third decile do not materially repurchase or issue equities.

Equity volatility, $IdioVol$, forecasts bond excess returns positively, again in a manner consistent with the RR paradigm. High equity volatility implies higher probability of default in the Merton (1974) model. Thus, it is reasonable that bonds of issuers with high equity volatility earn higher excess returns on average. On the other hand, Ang, Hodrick, Xing, and Zhang (2006) show that idiosyncratic volatility forecasts stock returns negatively in the cross-section of stock returns. Our finding of a positive relation between average bond returns and idiosyncratic volatility is consistent with a pricing of risk in the bond market, possibly due to a more sophisticated clientele in this market.

In Figure 1, we plot the average bond returns to the equal-weighted decile portfolios for the variables $\log MC$, $\log B/M$, R_{eq}(2,12), R_{eq}(1), Y/B, and $IdioVol$, separately for IG and junk bonds. The predictive effect of the variables is clearly more pronounced in junk bonds. The figure also shows that the predictive ability of R_{eq}(2,12) is present only for IG bonds, whereas the Y/B effect is more clearly apparent in junk bonds. Some of the effects are large, for example the portfolio with the largest values of $IdioVol$ and $R_{eq}(1)$ earn returns about eight to nine times greater than those with the smallest values of these variables.

3.3 Factor Model Alphas

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

$$R_{it} = \alpha_i + \beta_i' f_t + \varepsilon_{it}. \tag{4}$$

We use two different factor models. The first is the CAPM which includes only the equity market factor (MktmRf). The second is the five-factor model of Fama and French (1993). This includes three equity factors (MktmRf, SMB, and HML) and two bond factors (Term and Def). Term is the difference in returns between long-term treasury bonds and T-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).

Table 6 shows 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 samples of all, IG, and junk bonds.

Given that the alphas are very similar to the average excess returns across the anomalies, we conclude that the CAPM and the five-factor model do not explain the variation in average excess returns on these portfolios. Overall, the ability of the factor models to explain the performance of equity market predictors for bond returns is limited. It may seem surprising that the inclusion of the bond factors in the five-factor model does not reduce the intercepts. In this regard, two points are noteworthy. First, since we analyze bond returns in *excess* of those on cash-flow matched treasury bonds, the role of the Term factor in explaining returns is naturally limited. Second, over the sample period between 1973 and 2011, Def earns a premium of only −0.02% per month.[16] Since default risk is only weakly priced, this additional factor may have limited explanatory power for returns on the test assets analyzed in this paper. At the same time, it is surprising that the stock market factors SMB and HML are unable to explain the variation in junk bond returns since junk bond returns are more closely aligned with stock returns.

3.4 Fama-MacBeth Regressions

We now turn to multivariate analysis to see which equity anomalies have marginal power to predict bond returns. Since sorts involving multiple variables are infeasible, we use the Fama and MacBeth (1973) methodology for this analysis. While our regressions do impose linearity, they can handle multiple characteristics at the same time. Recall

[16] This risk premium is lower than that reported in Fama and French (1993). However, our sample includes the financial crisis of 2008.

that Table 5 shows a distinct jump in bond returns as one moves from deciles one/two to higher deciles for Y/B and NS sorted portfolios. This suggests that using a dummy variable for negative Y/B and/or NS might lead to higher power. In unreported results, we find that using dummy variables instead of continuous variables for these two characteristics does not materially alter our results, so we preserve the linear specification for these variables.

One source of the anomaly based returns could be investor misperceptions about credit risk and the impact of this misperception on bond returns. Thus, we include bond-related variables in the Fama-MacBeth regressions. In particular, we include the last-month's bond return, the last 11 months bonds return (skipping the most recent month), and the distance-to-default (DD) measure to control for default likelihood of the bond. Finally, we also include the Amihud measure of liquidity constructed using equity returns and volume to control for possible liquidity effects. Our regression specification is:

$$R_{it} = \gamma_{0t} + \gamma_{1t}' Zeq_{it-1} + \gamma_{2t} R_{it-1} + \gamma_{3t} R_{it-2:t-12} + \gamma_{4t} DD_{it-1} + \gamma_{5t} L_{it-1}^{eAmihud} + \epsilon_{it}, \quad (5)$$

where R_{it} is the excess bond return and Zeq_{it-1} are lagged equity characteristics (the momentum returns are lagged by an additional month). An OLS regression puts equal weight on each observation in each month. Thus, the estimated slopes are sensitive to outliers which tend to be small and illiquid bonds. To deal with the issue of outliers, we winsorize all the right-hand-side variables at the 0.5th and 99.5th percentile each month.

Table 7 shows the results from regressing excess bond returns on lagged equity anomaly variables. In Panel A we first present the results of regressions where bond returns are regressed on one predictor at a time (2nd column), and then present results when bond market predictors plus bond control and equity liquidity are added to these regressions (3rd column). Panel B uses subsets of variables, as well as the full set of variables, whereas Panel C reports the results of regressions for all of the variables, for the full sample as well as subsamples containing only IG bonds or junk bonds.

Considering Panel A first, we see from the 2nd column that consistent with the portfolio sorts, $\log MC$, $\log B/M$, $R_{eq}(1)$, Y/B, and $IdioVol$ all predict bond returns at the 5% level, whereas a few other variables are significant at the 10% level. Note that NS (as in the portfolio sorts) and SUE have the opposite sign to that of equities). Controlling for bond predictors in the third column, $R_{eq}(1)$, Y/B, and $IdioVol$ preserve their sign and significance, but $\log MC$ loses significance, and $\log B/M$, while significant, changes its direction of prediction. Unreported analysis indicates that the distance-to-default (DD) variable plays a key role in the attenuation and reversal of the $\log B/M$ effect. This supports the notion that $\log B/M$, at least partially, proxies for distress risk in the bond market. We also find that the $\log MC$ effect is largely captured by the Amihud measure of (equity) liquidity, suggesting that illiquidity partially proxies for the market cap effect.

Turning now to Panel B, the first regression in this panel shows that size is negatively priced when it is included along with book/market. The coefficient of $\log MC$ reduces considerably when bond controls are included in the second regression (as in Panel A), but the sign is preserved. The third and fourth regressions demonstrate that the positive coefficient on the lagged one-month equity return is strongly significant whether the bond market variables are included or not. However, the positive coefficient on longer-term equity returns is significant only when the bond market variables are included. Thus, equity momentum, $R_{eq}(2,12)$ becomes statistically significant in the multivariate regression though it is insignificant in the univariate sort (Table 5). In univariate sorts, the equity momentum effect is erased by junk bond losers that earn high average returns in the future. In multivariate analysis, other variables such as $\log MC$ and DD control for the variation due to credit risk and leave the pure equity momentum effect. As a result, equity momentum works better in the multivariate regression than univariate analysis. The next four regressions demonstrate that the negative coefficient of Y/B and the positive coefficient of $IdioVol$ are also robust to whether bond market variables are included. NS is not significant in the regressions, unlike in the portfolio sorts. The last column presents results including all of the variables, and confirms the robustness of the lagged equity returns, Y/B, and $IdioVol$.

In economic terms, a one standard deviation increase in market capitalization decreases corporate bond returns, in the cross-section, by 9 basis points per month; a one standard deviation increase in R_{eq}(2,12) (R_{eq}(1)) increases returns by 1.25% (0.76%); a one standard deviation increase in Y/B ($IdioVol$) decreases (increases) corporate bond returns by 2.14% (0.69%). Thus, the impact of the equity anomaly variables on the cross-section of corporate bond returns is economically large.

In terms of the bond market controls, we find, interestingly, that the lagged one-month bond return has a negative and strongly significant coefficient, whereas the lagged one-month equity return has a positive coefficient, which is also strongly significant. It is possible that illiquidity in the corporate bond market causes an overreaction to bond market trades which is subsequently corrected giving rise to the bond reversal effect. The negative coefficient on past two to twelve month returns also point 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}(2,12) is the result of the subsequent correction of the overreaction. Finally, the distance to default variable is positive and significant, which is consistent with its interpretation as a default risk proxy, which has a positive influence on required returns.

In Panel C, which uses all of the variables, we also report the results of value-weighted (VW) cross-sectional regressions, in addition to reporting the OLS (i.e, equal-weighted, or EW) regressions. To value-weight, we multiply both sides of the equation by the square-root of the market value of a bond in month $t-1$. As value-weighted regression puts more weight on large bonds, the resulting slope should be less sensitive to outliers than OLS estimates. We also standardize each anomaly variable with its cross-sectional standard deviation each month so that the economic magnitude of the slope estimates are comparable to each other. For brevity, we report only the results of EW regressions for IG and junk bonds.

The estimated coefficient on $\log MC$ is statistically significant and is weaker for IG bonds, as compared to junk bonds. A difference-of-means test of coefficients between these two categories of bonds is statistically insignificant for size. Similarly, the impact of past two to twelve month equity returns is weaker for IG bonds than it is for junk bonds, although the difference in coefficients for these two categories is not statistically significant. Echoing the portfolio sort results, the lead-lag variable, $R_{eq}(1)$ has the strongest predictive power. Its slope coefficient at around nine is the highest amongst all the equity variables that we examine (recall that we standardize all variables so that slope estimates are comparable to each other). The predictability is even stronger for junk bonds.

The accounting variables, Ac/A, dA/A, SUE, and NS, are not significant in the presence of other variables.[17] The coefficient estimate of profitability, Y/B, is nega-

[17]These variables are significant at the 10% level in at least one column of Table 7, Panel A. SUE has the wrong sign relative to the equity market which disappears after the additional controls in Panel A, so we do not discuss it further. Additional analysis reveals that Y/B is crucial in making

tive and remains statistically significant, although only for the sample of junk bonds. The coefficient on $IdioVol$ is positive and statistically significant, suggesting that idiosyncratic volatility is also a highly significant predictor of bond excess returns. Note that the signs of the coefficients on Y/B and $IdioVol$ are inconsistent with the behavioral arguments discussed in the context of Table 2 but are consistent with the RR arguments as more profitable firms are likely to be less risky and higher idiosyncratic volatility firms are likely to more risky leading to the positive and negative signs on the coefficient estimates of $IdioVol$ and Y/B, respectively. Moreover, the fact that accruals, asset growth, earnings surprise and new equity issues are also insignificant, is also inconsistent with the behavioral arguments of Table 2.

As before the lagged bond returns are negatively related to future bond returns and the effect is stronger for the IG bonds. This suggests that the corporate bond markets are illiquid and overreact to return shocks. Consistent with the risk arguments the coefficient on distance to default, DD, is positive. Stock market liquidity does not impact bond returns.

To summarize the results from this section, we find that many anomaly variables, such as size, momentum, lead-lag, profitability, and idiosyncratic volatility, have significant predictive power for bond returns. Stock returns over the past two to twelve months are positively related to bond returns. The negative coefficient on the two to twelve month bond returns points to overreaction, but is only marginally significant. The positive coefficient of $R_{eq}(1)$ is consistent with a lead-lag relationship from equities to bonds. The large negative coefficient on the one month lagged bond returns is

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NS and Ac/A insignificant, suggesting that unprofitable firms have less internal cash and issue more equity, and also have high non-cash accruals, so that Y/B proxies for NS and Ac/A. Also, Y/B and equity momentum are crucial in lessening the significance of asset growth. This is consistent with the notion that profitable firms have high asset growth, and high past returns, so that Y/B captures these variables.

consistent with inventory-based reversals due to high illiquidity in the corporate bond market. The positive coefficient on idiosyncratic volatility and the negative coefficients on profitability and distance to default are consistent with the risk-return paradigm. In general, the coefficient estimates are larger for the relatively riskier junk bonds than for IG bonds.

3.5 A Robustness Check

One concern is that different firms have different number of bonds outstanding. Thus, firms with more bonds outstanding can have a larger impact on the cross-sectional relations that we are testing. For instance, large firms like General Motors may have had a large number of bonds outstanding and given that it went through restructuring, its financial distress could have a large impact on the cross-sectional relation between bond-excess returns and characteristics such as the book-to-market ratio, 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 three 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 and (iii) we choose the most recent bond issue. The second and third procedures are based on Bao, Pan and Wang (2011), who show that the most recent issue and the issue with the shortest maturity are in fact the most liquid ones. Table 8 presents the results.

We find that the coefficient estimates are larger for $log(MC)$, $R_{eq}(1)$, Y/B and $IdioVol$ and the significance pattern remains largely unchanged relative to that in

Table 7. The coefficients of R_{eq}(2,12) are smaller and often statistically insignificant. For bond characteristics, the coefficients of R_{bd}(2,12) are statistically significant only for the value-weighted regressions. Also, the distance to default is significant only for the shortest maturity bonds. The overall conclusion, however, is that using different number of bonds for different firms does not have a material impact on the results. Specifically, idiosyncratic volatility and profitability continue to exert material influences on bond returns in a manner consistent with the risk-return paradigm, while there continues to be a material lead from equity returns to bond returns.

In the next section, we examine the role of institutions and trading costs in the cross-section of bond returns.

4 The Role of Institutions and Trading Costs

4.1 Institutional Holdings

We start by analyzing whether the equity anomaly variables have differential predictive power across different categories of stocks which differ on the dimension of institutional holdings. The idea is that if institutions are not subject to behavioral biases then the bonds of firms whose equity has larger institutional holdings, are likely to be more efficiently priced. The percentage institutional holdings for the corresponding equities are obtained from Thomson/Reuters. We split the sample into two by the most recently available median value of institutional holdings and run separate cross-sectional regressions for each sub-category of firms. Table 9 presents the results.

The impact of firm size, lagged one month equity and bond returns and the lagged two to twelve month equity and bond returns is the same across firms with high and low institutional holdings. The difference obtains in the case of profitability, Y/B, and idiosyncratic volatility where it is indeed the case that the coefficient estimates are significantly larger in absolute terms for firms with lower institutional holdings. The difference between the coefficients of accruals for firms with high and low institutional holdings is informative. The coefficient estimate is positive (albeit insignificant) for firms with low institutional holdings but is negative (also insignificant) for firms with high institutional holdings. However, the difference in the coefficient estimates between the firms with low and high institutional holdings is significant at the 5% level for the equally-weighted regressions and at the 10% level for the value-weighted regressions. The negative coefficient estimate on accruals, Ac/A, for the firms with high institutional holdings suggests that institutions are less likely to be fooled by accruals-based earnings management. The impact of distance to default is larger for bonds of firms with higher institutional holdings suggesting that institutions are more sensitive to credit risk possibly because they often have restrictions on holding non-investment grade bonds.

We now examine the impact of transactions costs in relation to the anomaly based trading profits.

4.2 Hedge Portfolio Profits After Transaction Costs

Though equity anomalies help forecast bond returns in the cross-section, 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 documented in Section 3.1, we estimate the portfolio transaction costs using the Bao, Pan, and Wang (2011) measure (L^{BPW}). 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. L^{BPW} is the Roll (1984) measure of the bid-ask spreads. Bao, Pan and Wang show that the Roll measure provides more conservative estimates of effective transaction costs than quoted bid-ask spreads or the liquidity measures of Edwards, Harris and Piwowar (2007). Also, the Roll measure is easier to compute and covers more bonds in the sample compared with the transaction cost estimates of Feldhutter (2012).

We compute L_{it}^{BPW} whenever the data are available, and compute its cross-sectional average for each portfolio every month. The time-series average of the illiquidity measure, multiplied by the time-series average of the portfolio turnover rate is reported as TransCosts in Table 10. Thus, we implicitly assume that the bonds without L_{it}^{BPW} have on average the same level of transaction costs as the bonds with L_{it}^{BPW} in the same portfolio. The illiquidity measure is only available for the subsample starting from 1994.

Table 10 shows that the estimated transaction costs are relatively small for the portfolios sorted annually, while they are large for the portfolios sorted monthly. For the full sample, using the results from Table 5, we find that average hedge portfolio returns dominate transaction costs for $\log MC$, $\log B/M$, Y/B, and $IdioVol$, while the transaction costs dominate returns for $R_{eq}(2, 12)$, $R_{eq}(1)$, dA/A, and NS. For instance, in the case of junk bonds, the long-short hedge portfolio formed on $R_{eq}(1)$ yields a value-weighted monthly return of 0.71% but transaction costs amount to 2.90% per month. Thus, despite its strong significance, the lead-lag effect does not provide profitable trading opportunities for investors net of transaction costs. In contrast, size, profitability, and volatility variables seem to survive transaction costs.

Recall from Table 7 that the impact of past two to twelve month equity returns, $R_{eq}(2,12)$, became large and statistically significant in cross-sectional regressions after the introduction of the bond specific variables including the past bond returns and the distance to default. Thus, instead of assessing the post-transaction-cost, univariate profitability of trading based on $R_{eq}(2,12)$ we assess (in unreported results) the post-transaction-cost profitability based on double sorts based on (i) the past two to twelve month equity and bond returns, (ii) the past two to twelve month equity returns and the past one month bond return and (iii) the past two to twelve month equity returns and the distance to default. In each case, the transaction costs are larger than the potential momentum-based trading strategy profits.

Interestingly, the bond return predictors that do survive transactions costs can, at least, in part motivated by the rational risk-reward paradigm. Thus, size, profitability, and idiosyncratic volatility are all linked to distress likelihood or risk, whereas the ones that do not survive transaction costs (past one month and the two to twelve month returns) are largely behaviorally motivated.[18] Since risk-based predictors do not present a true arbitrage opportunity, our overall findings are consistent with the notion that bonds are efficiently priced up to transactions costs.

[18]In unreported tests, we have ascertained that the bond variables, $R_{bd}(2,12)$, $R_{bd}(1)$, 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. Full results are available upon request.

5 Conclusion

We conduct an empirical analysis of whether cross-sectional equity return predictors also predict bond returns. The answer is mixed. Some predictors such as size, profitability, and past equity returns are strong predictors of bond returns and some others like accounting accruals and earnings surprises are not.

Among the more notable results, we find that there is a strong lead from stocks to bonds at the monthly horizon, which is consistent with the notion that common information is reflected sooner in the more liquid equity market. We also find that profitability and equity return volatility negatively and positively predict bond returns, respectively. This evidence is consistent with the view that firms with low or negative profits and high idiosyncratic volatility are considered more risky by bond market investors, so that the bonds command higher required returns. After accounting for transaction costs in bond markets, only the variables with a risk-based rationale continue to yield profits. This is consistent with the view that institutions, that are likely to be the marginal traders in the corporate bond market, price corporate bonds quite efficiently (within transaction cost bounds).

We believe our work suggests many extensions. For example, our work illustrates the point that the pricing of risk depends on the clientele holding a security and this notion can be extended to other securities such as warrants and preferred stock. In addition, whether our cross-sectional predictors of bond returns extend to other countries remains an open question. Finally, theoretical developments that accord with our findings and suggest new testable implications also remain a fruitful area for future research.

Appendix: Further Robustness Checks

To ascertain the robustness of the results in Table 7, we run a series of robustness tests and report the results 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 responding 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 anomaly variables 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, Merill Lynch, and DataStream. To check the sensitivity of our result to this priority, we reverse this order. Specifically, we reconstruct our sample based on the following order: DataStream, Merill Lynch, Mergent FISD/NAIC, TRACE, and the Lehman Brothers Fixed Income Database. 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.

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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 speculative grade (junk) category. IG bonds are further sub-divided into AA+, A, and BB 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. Nobs is the total number of observations. 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 2011.

	Excess returns						
	Mean	SDev	Median	AR1	AR2	AR3	AR1-AR6
All	0.12	2.84	0.09	-0.15	-0.04	0.10	-0.10
IG	0.05	2.49	0.05	-0.23	-0.07	0.11	-0.21
AA+	0.00	2.44	0.01	-0.27	-0.11	0.10	-0.31
A	0.04	2.42	0.03	-0.27	-0.08	0.11	-0.25
BBB	0.10	2.60	0.09	-0.17	-0.03	0.12	-0.11
Junk	0.38	3.84	0.28	-0.01	0.01	0.07	0.06

	Nobs	No Price Change	% Market Value	Mat	Corr	%Issuers Equity Size		
						Micro	Small	Big
All	1,001,479	20,942	100.0	11.9	0.22	6.1	14.3	79.6
IG	784,770	9,222	73.3	13.1	0.22	1.7	9.3	89.1
AA+	176,869	3,424	14.8	14.9	0.29	0.9	7.5	91.6
A	322,074	3,782	28.0	13.4	0.22	1.3	8.9	89.8
BBB	285,827	2,016	30.5	11.6	0.18	2.6	10.8	86.6
Junk	207,658	10,473	26.3	8.3	0.22	18.7	29.2	52.1

Table 2: Expected Signs on Equity Characteristics 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. 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 ($R_{eq}(2{,}12)$) is the cumulative 11-month return on equity, starting from the 2nd 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.

Variable	Behavioral/Frictions	Risk-Return
Size ($\log MC$)	-	-
Value ($\log B/M$)	+	+
Momentum ($R_{eq}(2{,}12)$)	+	?
Lead-Lag ($R_{eq}(1)$)	−/+	?
Profitability (Y/B)	+	−
Net Stock Issues (NS)	+	?
Accruals (Ac/A)	−	?
Asset Growth (dA/A)	−	?
Earnings Surprise (SUE)	+	?
Idiosyncratic Volatility ($IdioVol$)	−	+

Table 3: Summary Statistics of Equity Anomaly Variables

Equity anomaly variables are described in Table 2. The table presents summary statistics of these equity anomaly variables used to predict the corresponding bond returns. Statistics are presented for all bonds as well as for investment grade (IG) and speculative grade (junk) category. All statistics are first calculated as cross-sectional averages and the table then presents time-series averages of these statistics. The sample period is 1973 to 2011.

		All bonds			IG			junk		
	Nobs	Mean	Median	SDev	Mean	Median	SDev	Mean	Median	SDev
$\log MC$	1,234,573	7.5	7.6	1.5	7.9	7.9	1.3	6.3	6.4	1.5
$\log B/M$	1,181,763	-0.3	-0.3	0.7	-0.4	-0.3	0.6	-0.2	-0.1	0.9
$R_{eq}(2,12)$	1,219,890	13.7	10.7	33.5	13.1	11.1	25.3	14.6	8.4	48.0
$R_{eq}(1)$	1,234,573	1.1	0.8	9.0	1.2	0.9	7.3	1.2	0.5	12.3
Y/B	1,174,748	-3.2	3.3	45.4	1.9	4.2	24.4	-16.1	-0.8	72.6
NS	1,198,197	3.7	1.1	9.8	3.1	1.0	8.6	4.7	1.4	12.2
Ac/A	931,647	-3.9	-3.7	4.8	-3.8	-3.7	4.1	-3.9	-3.6	6.6
dA/A	1,180,282	12.7	7.3	26.2	11.7	7.3	21.3	15.1	6.9	36.3
SUE	1,175,243	-0.2	0.1	9.1	-0.1	0.1	5.2	-0.5	0.2	15.1
$IdioVol$	1,234,537	26.2	21.9	17.3	22.7	20.2	11.9	37.5	31.3	24.5

Table 4: Equity Returns from Sorts on Equity Anomaly Variables

Equity anomaly variables are described in Table 2. We sort stocks into deciles and calculate both equal-weighted and value-weighted returns. Value weighting is done using the prior month's market capitalization. We sort at the end of June of every year and hold these portfolios for one year for the anomaly variables $\log MC$, $\log B/M$, Y/B, NS, Ac/A, dA/A, and SUE. We sort at the end of each month and hold these portfolios for one month for the anomaly variables R_{eq}(2,12), R_{eq}(1), and $IdioVol$. The table reports returns on a hedge portfolio that is long in the tenth decile and short in the first decile. All returns are in percentage per month. The numbers in parenthesis are the t-statistics of the corresponding returns. We calculate these returns for the sample of all stocks, the sample of big stocks (those above the median NYSE market capitalization), and for a sample of stocks matched to the bond sample. The sample period is 1973 to 2011.

	Equal-weighted returns			Value-weighted returns		
	All stocks	Big stocks	Matched sample	All stocks	Big stocks	Matched sample
$\log MC$	-1.35	-0.25	-0.53	-0.37	-0.35	-0.48
	(-4.71)	(-1.35)	(-2.12)	(-1.35)	(-1.70)	(-2.02)
$\log B/M$	1.42	0.79	0.54	0.47	0.43	0.44
	(6.04)	(3.21)	(2.02)	(1.86)	(1.81)	(1.66)
$R_{eq}(2,12)$	0.59	1.02	0.88	1.78	0.96	0.78
	(1.52)	(2.96)	(2.14)	(4.31)	(2.73)	(1.91)
$R_{eq}(1)$	-2.96	-0.58	-0.47	-0.63	-0.24	0.04
	(-8.76)	(-2.16)	(-1.68)	(-1.83)	(-0.85)	(0.13)
Y/B	-0.18	0.05	-0.13	0.16	0.08	0.10
	(-0.69)	(0.25)	(-0.49)	(0.58)	(0.39)	(0.38)
NS	-0.97	-0.87	-0.23	-0.77	-0.69	-0.21
	(-5.32)	(-5.28)	(-1.29)	(-5.51)	(-4.93)	(-0.98)
Ac/A	-0.70	-0.57	-0.14	-0.37	-0.43	-0.15
	(-5.72)	(-4.73)	(-0.80)	(-1.82)	(-2.44)	(-0.69)
dA/A	-1.39	-0.81	-0.61	-0.53	-0.54	-0.45
	(-7.50)	(-5.59)	(-3.21)	(-3.10)	(-3.21)	(-2.20)
SUE	0.51	0.51	-0.15	0.32	0.30	0.00
	(4.13)	(3.86)	(-0.67)	(1.60)	(1.75)	(0.00)
$IdioVol$	0.22	-0.47	0.34	-0.40	-0.15	0.06
	(0.58)	(-1.42)	(1.09)	(-1.08)	(-0.46)	(0.21)

Table 5: Bond Returns from Sorts on Equity Anomaly Variables

Equity anomaly variables are described in Table 2. 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. 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 June of every year and hold these portfolios for one year for the anomaly variables $\log MC$, $\log B/M$, Y/B, NS, Ac/A, dA/A, and SUE. We sort at the end of each month and hold these portfolios for one month for the anomaly variables R_{eq}(2,12), R_{eq}(1), and $IdioVol$. We also 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. All returns are in percentage per month. The numbers in parenthesis are the Newey-West corrected (using 12 lags) t-statistics of the corresponding returns. The first row of each block is the average characteristics used in sorting. The sample period is 1973 to 2011.

	1	2	3	4	5	6	7	8	9	10	H−L	H−L IG	H−L junk
$\log MC$	4.79	6.04	6.61	7.05	7.45	7.81	8.16	8.53	8.98	9.94	5.16	4.52	4.78
EW	0.39	0.18	0.15	0.16	0.10	0.11	0.08	0.07	0.03	0.05	-0.34	-0.02	-0.31
	(3.50)	(2.17)	(1.94)	(1.98)	(1.26)	(1.60)	(1.08)	(1.03)	(0.51)	(1.01)	(-4.62)	(-0.87)	(-3.50)
VW	0.36	0.17	0.15	0.14	0.08	0.09	0.07	0.06	0.01	0.03	-0.33	-0.02	-0.32
	(3.30)	(1.99)	(1.90)	(1.76)	(1.08)	(1.35)	(0.93)	(0.90)	(0.21)	(0.51)	(-4.75)	(-0.68)	(-3.83)
$\log B/M$	-1.54	-0.89	-0.63	-0.45	-0.30	-0.18	-0.05	0.07	0.25	0.72	2.26	2.05	2.82
EW	0.10	0.08	0.08	0.08	0.10	0.11	0.10	0.11	0.13	0.36	0.26	0.11	0.54
	(1.71)	(1.13)	(1.22)	(1.26)	(1.38)	(1.55)	(1.36)	(1.42)	(1.51)	(3.32)	(3.94)	(2.85)	(4.82)
VW	0.04	0.05	0.06	0.06	0.06	0.08	0.04	0.07	0.07	0.29	0.25	0.11	0.57
	(0.78)	(0.81)	(0.91)	(0.91)	(0.91)	(1.11)	(0.59)	(0.95)	(0.86)	(2.96)	(4.42)	(2.59)	(4.63)
$R_{eq}(2,12)$	-30.46	-11.54	-3.27	2.80	8.12	13.31	18.91	25.96	36.85	77.10	107.56	84.94	157.19
EW	0.26	0.10	0.08	0.06	0.08	0.08	0.10	0.09	0.14	0.21	-0.05	0.08	-0.09
	(2.19)	(1.23)	(1.09)	(0.87)	(1.17)	(1.11)	(1.53)	(1.43)	(2.13)	(2.68)	(-0.73)	(2.22)	(-0.84)
VW	0.15	0.06	0.05	0.03	0.04	0.04	0.06	0.07	0.09	0.16	0.01	0.10	-0.03
	(1.52)	(0.77)	(0.66)	(0.41)	(0.70)	(0.61)	(0.98)	(1.10)	(1.43)	(2.22)	(0.12)	(2.56)	(-0.34)
$R_{eq}(1)$	-12.65	-5.85	-3.30	-1.46	0.12	1.62	3.26	5.27	8.10	16.86	29.51	24.77	41.29
EW	0.02	0.05	0.05	0.07	0.10	0.10	0.12	0.14	0.17	0.38	0.36	0.21	0.67
	(0.26)	(0.73)	(0.71)	(1.00)	(1.53)	(1.41)	(1.62)	(1.87)	(2.12)	(3.74)	(7.21)	(6.55)	(6.68)
VW	-0.05	0.02	0.01	0.06	0.05	0.06	0.09	0.09	0.12	0.30	0.35	0.24	0.71
	(-0.65)	(0.33)	(0.16)	(0.93)	(0.70)	(0.99)	(1.29)	(1.35)	(1.65)	(3.41)	(7.50)	(7.88)	(6.62)
Y/B	-70.07	-9.80	-3.43	-0.04	2.40	4.46	6.55	9.09	12.49	23.53	93.59	62.12	170.01
EW	0.30	0.15	0.14	0.09	0.13	0.09	0.09	0.10	0.07	0.10	-0.20	-0.02	-0.26
	(2.84)	(1.71)	(1.71)	(1.27)	(1.73)	(1.28)	(1.38)	(1.44)	(1.00)	(1.66)	(-3.65)	(-0.70)	(-3.32)
VW	0.21	0.10	0.08	0.04	0.09	0.07	0.06	0.05	0.02	0.06	-0.16	0.00	-0.26
	(2.21)	(1.21)	(1.12)	(0.57)	(1.28)	(0.95)	(1.00)	(0.73)	(0.38)	(0.96)	(-3.39)	(-0.14)	(-3.02)

	1	2	3	4	5	6	7	8	9	10	H−L	H−L IG	H−L junk
NS	-6.04	-1.54	-0.45	0.14	0.69	1.57	3.12	5.05	8.81	24.51	30.55	27.23	39.71
EW	-0.02	0.00	0.18	0.21	0.20	0.12	0.17	0.11	0.17	0.18	0.20	0.16	0.33
	(-0.21)	(-0.01)	(2.19)	(2.33)	(2.71)	(1.69)	(1.99)	(1.44)	(1.94)	(2.11)	(4.76)	(3.36)	(3.66)
VW	-0.04	-0.04	0.13	0.16	0.15	0.05	0.12	0.08	0.13	0.14	0.17	0.14	0.39
	(-0.47)	(-0.57)	(1.65)	(1.78)	(2.17)	(0.84)	(1.45)	(1.03)	(1.61)	(1.76)	(5.16)	(3.76)	(3.71)
Ac/A	-12.28	-7.55	-5.88	-4.84	-4.02	-3.32	-2.63	-1.82	-0.56	4.47	16.74	14.81	22.86
EW	0.19	0.14	0.14	0.10	0.09	0.12	0.11	0.16	0.13	0.15	-0.04	0.03	-0.01
	(2.34)	(1.77)	(1.90)	(1.36)	(1.15)	(1.76)	(1.38)	(2.06)	(1.87)	(2.01)	(-1.61)	(1.77)	(-0.26)
VW	0.11	0.08	0.10	0.07	0.05	0.08	0.04	0.12	0.07	0.10	-0.01	0.04	0.07
	(1.49)	(1.11)	(1.46)	(1.04)	(0.66)	(1.22)	(0.61)	(1.57)	(1.12)	(1.49)	(-0.38)	(2.07)	(1.14)
dA/A	-11.08	-1.06	1.96	4.09	6.11	8.30	11.26	15.45	23.84	65.88	76.97	66.34	111.63
EW	0.28	0.13	0.14	0.09	0.11	0.10	0.11	0.12	0.09	0.14	-0.14	-0.02	-0.29
	(2.98)	(1.61)	(1.82)	(1.25)	(1.51)	(1.48)	(1.56)	(1.64)	(1.23)	(1.80)	(-4.87)	(-1.17)	(-4.53)
VW	0.19	0.09	0.11	0.05	0.05	0.06	0.07	0.05	0.04	0.08	-0.11	-0.01	-0.29
	(2.36)	(1.22)	(1.44)	(0.76)	(0.79)	(0.92)	(1.07)	(0.80)	(0.61)	(1.19)	(-4.22)	(-0.60)	(-3.68)
SUE	-7.91	-1.24	-0.49	-0.15	0.05	0.22	0.40	0.65	1.20	6.60	14.50	7.84	31.79
EW	0.28	0.12	0.09	0.06	0.09	0.09	0.08	0.10	0.12	0.27	-0.01	0.08	-0.06
	(2.57)	(1.45)	(1.19)	(0.87)	(1.33)	(1.43)	(1.31)	(1.51)	(1.77)	(2.99)	(-0.23)	(3.42)	(-0.78)
VW	0.20	0.07	0.04	0.04	0.04	0.05	0.04	0.08	0.08	0.21	0.01	0.12	-0.11
	(2.00)	(0.96)	(0.61)	(0.55)	(0.69)	(0.78)	(0.64)	(1.26)	(1.14)	(2.42)	(0.48)	(5.19)	(-1.35)
$IdioVol$	10.35	13.25	15.24	17.16	19.11	21.30	24.07	27.62	33.35	54.98	44.63	32.41	67.50
EW	0.04	0.05	0.08	0.09	0.09	0.08	0.11	0.13	0.23	0.43	0.39	0.10	0.75
	(0.69)	(0.87)	(1.23)	(1.33)	(1.21)	(1.16)	(1.44)	(1.60)	(2.47)	(3.63)	(5.56)	(2.68)	(7.85)
VW	0.01	0.02	0.04	0.06	0.04	0.07	0.07	0.09	0.18	0.35	0.33	0.10	0.69
	(0.18)	(0.27)	(0.60)	(0.96)	(0.57)	(0.98)	(0.92)	(1.23)	(2.08)	(3.05)	(4.72)	(2.20)	(6.88)

Table 6: Asset Pricing Alphas of Bond Portfolios

Equity anomaly variables are described in Table 2. We form value-weighted portfolios as described in Table 5. The table gives statistics on H−L portfolios for each sort. We show average excess returns as well as the intercept of the time-series regressions, $R^e_{i,t} = \alpha_i + \beta_i' F_t + \epsilon_{i,t}$, where F_t are the factor used in the asset pricing model. For the CAPM, the factor is market factor. FF is the five-factor model with market factor, stock size- and value-factors, and two bond factors (Term, return on long-term treasury bonds in excess of T-bills; and Def, return on corporate bond market portfolio in excess of long-term treasury bond). Newey-West corrected (using 12 lags) t-statistics are given in parenthesis below the returns/alphas. The sample period is 1973 to 2011.

	All			IG			Junk		
	$\overline{R}$	α_{CAPM}	α_{FF}	$\overline{R}$	α_{CAPM}	α_{FF}	$\overline{R}$	α_{CAPM}	α_{FF}
$\log MC$	-0.33	-0.28	-0.29	-0.02	-0.02	0.00	-0.32	-0.30	-0.32
	(-4.75)	(-4.59)	(-4.31)	(-0.68)	(-0.53)	(0.02)	(-3.83)	(-3.69)	(-4.05)
$\log B/M$	0.25	0.21	0.19	0.11	0.08	0.08	0.57	0.55	0.48
	(4.42)	(3.97)	(3.44)	(2.59)	(2.28)	(2.17)	(4.63)	(4.55)	(4.08)
$R_{eq}(2,12)$	0.01	0.02	0.01	0.10	0.11	0.10	-0.03	-0.02	-0.03
	(0.12)	(0.38)	(0.15)	(2.56)	(3.03)	(2.85)	(-0.34)	(-0.25)	(-0.36)
$R_{eq}(1)$	0.35	0.36	0.36	0.24	0.25	0.25	0.71	0.73	0.76
	(7.50)	(7.35)	(6.99)	(7.88)	(7.84)	(7.49)	(6.62)	(7.05)	(7.10)
Y/B	-0.16	-0.13	-0.12	0.00	0.01	0.03	-0.26	-0.24	-0.21
	(-3.39)	(-3.05)	(-2.43)	(-0.14)	(0.56)	(1.14)	(-3.02)	(-2.73)	(-2.57)
NS	0.17	0.16	0.16	0.14	0.13	0.12	0.39	0.38	0.38
	(5.16)	(4.34)	(4.34)	(3.76)	(3.26)	(3.01)	(3.71)	(3.57)	(3.44)
Ac/A	-0.01	0.00	0.01	0.04	0.05	0.05	0.07	0.07	0.07
	(-0.38)	(0.09)	(0.40)	(2.07)	(2.50)	(3.06)	(1.14)	(1.13)	(0.95)
dA/A	-0.11	-0.10	-0.08	-0.01	-0.01	0.00	-0.29	-0.27	-0.25
	(-4.22)	(-4.24)	(-3.61)	(-0.60)	(-0.81)	(-0.02)	(-3.68)	(-3.74)	(-3.72)
SUE	0.01	0.02	0.02	0.12	0.12	0.13	-0.11	-0.10	-0.08
	(0.48)	(0.66)	(0.80)	(5.19)	(5.72)	(5.29)	(-1.35)	(-1.30)	(-0.99)
$IdioVol$	0.33	0.29	0.30	0.10	0.09	0.08	0.69	0.65	0.63
	(4.72)	(4.65)	(3.95)	(2.20)	(2.11)	(1.78)	(6.88)	(6.55)	(5.63)

Table 7: Monthly Cross-Sectional Regressions for Bond Returns

We run the following cross-sectional regression each month

$$R_{it} = \gamma_{0t} + \gamma_{1t}' Zeq_{it-1} + \gamma_{2t} R_{it-1} + \gamma_{3t} R_{it-2:t-12} + \gamma_{4t} DD_{it-1} + \gamma_{5t} \log L_{it-1}^{eAmihud} + \epsilon_{it},$$

where R_{it} is the excess bond return, Zeq_{it-1} are lagged equity anomaly variables (the momentum returns are lagged by an additional month), DD is the distance-to-default, and $L^{eAmihud}$ is equity Amihud illiquidity. Equity anomaly variables are described in Table 2. Panel A presents the results for using one equity variable one at a time. Panel B presents the OLS results for using subsets of variables for the sample of all bonds. Panel C presents further results using all variables. EW is the OLS estimates while VW is the estimates based on value-weighted regressions. To value-weight, we multiply the square-root of the market value of a bond in month $t-1$ with both its excess return in month t and the independent variables in month $t-1$. We also present EW estimates on subsamples of investment grade (IG) and speculative grade (junk) bonds. Newey-West corrected (using 12 lags) t-statistics are given in parenthesis below the coefficients. The sample period is 1973 to 2011.

Panel A: One variable		
	Without controls	With controls
$\log MC$	-7.63	-2.07
	(-4.32)	(-0.98)
$\log B/M$	2.90	-2.09
	(2.07)	(-2.67)
$R_{eq}(2,12)$	0.17	3.33
	(0.12)	(3.26)
$R_{eq}(1)$	9.09	8.90
	(5.85)	(7.23)
Y/B	-5.71	-4.11
	(-4.75)	(-4.21)
NS	1.40	0.79
	(1.79)	(1.13)
Ac/A	-1.06	-0.70
	(-1.83)	(-1.19)
dA/A	-0.96	-0.93
	(-1.29)	(-1.25)
SUE	-1.48	0.98
	(-1.74)	(1.37)
$IdioVol$	8.25	4.14
	(4.18)	(2.96)

Panel B: Subsets of variables									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log MC$	-7.27	-2.97							-6.07
	(-4.65)	(-1.53)							(-3.09)
$\log B/M$	1.10	-1.77							0.12
	(0.89)	(-2.04)							(0.15)
$R_{eq}(2,12)$			0.31	3.28					3.72
			(0.21)	(3.22)					(4.33)
$R_{eq}(1)$			8.99	9.38					8.48
			(6.55)	(8.07)					(6.32)
Y/B					-5.36	-4.31			-4.71
					(-4.68)	(-4.81)			(-4.18)
NS					0.67	0.12			1.07
					(0.93)	(0.17)			(1.36)
Ac/A							-0.47	-0.49	0.31
							(-0.92)	(-0.79)	(0.57)
dA/A							-1.55	-0.99	-0.81
							(-2.20)	(-1.31)	(-0.87)
SUE							0.00	0.79	-0.37
							(0.00)	(0.96)	(-0.44)
$IdioVol$							9.55	4.80	3.97
							(4.19)	(3.38)	(3.32)
$R_{bd}(2,12)$		-2.97		-3.57		-3.20		-3.82	-4.99
		(-1.25)		(-1.46)		(-1.37)		(-1.61)	(-2.05)
$R_{bd}(1)$		-26.75		-27.71		-26.79		-29.20	-30.44
		(-7.09)		(-7.30)		(-7.10)		(-7.36)	(-7.60)
DD		-4.91		-4.81		-3.90		-3.62	-2.37
		(-3.22)		(-3.25)		(-2.58)		(-2.96)	(-2.45)
$\log L^{eAmihud}$		-3.27		-5.69		-5.17		-3.87	1.36
		(-1.90)		(-5.45)		(-4.84)		(-4.01)	(0.81)

Panel C: All variables					
	All		IG	Junk	IG−Junk
	EW	VW	EW	EW	EW
$\log MC$	-6.07	-3.85	-3.94	-11.01	7.07
	(-3.09)	(-1.93)	(-2.44)	(-2.23)	(1.32)
$\log B/M$	0.12	-0.53	-0.80	2.97	-3.77
	(0.15)	(-0.64)	(-1.13)	(1.45)	(-1.82)
$R_{eq}(2,12)$	3.72	3.86	3.50	5.47	-1.97
	(4.33)	(4.64)	(6.07)	(2.20)	(-0.75)
$R_{eq}(1)$	8.48	8.93	3.89	18.26	-14.37
	(6.32)	(6.68)	(5.06)	(6.69)	(-5.85)
Y/B	-4.71	-5.20	0.20	-8.44	8.64
	(-4.18)	(-4.62)	(0.32)	(-3.09)	(3.11)
NS	1.07	1.19	-0.10	2.81	-2.91
	(1.36)	(1.76)	(-0.14)	(1.48)	(-1.54)
Ac/A	0.31	0.12	-0.59	-0.87	0.28
	(0.57)	(0.20)	(-1.43)	(-0.55)	(0.17)
dA/A	-0.81	-0.76	-0.19	-0.38	0.19
	(-0.87)	(-0.87)	(-0.24)	(-0.22)	(0.11)
SUE	-0.37	0.07	-0.37	-1.20	0.83
	(-0.44)	(0.07)	(-0.42)	(-0.57)	(0.38)
$IdioVol$	3.97	2.82	-0.66	3.28	-3.94
	(3.32)	(2.26)	(-1.14)	(1.39)	(-1.72)
$R_{bd}(2,12)$	-4.99	-6.87	-9.19	-5.03	-4.16
	(-2.05)	(-2.72)	(-4.29)	(-1.37)	(-1.28)
$R_{bd}(1)$	-30.44	-36.28	-36.66	-28.02	-8.64
	(-7.60)	(-10.38)	(-11.14)	(-4.33)	(-1.31)
DD	-2.37	-2.25	-1.81	-6.55	4.74
	(-2.45)	(-2.12)	(-1.80)	(-3.27)	(2.11)
$\log L^{eAmihud}$	1.36	-0.38	1.52	6.08	-4.56
	(0.81)	(-0.24)	(1.15)	(1.16)	(-0.82)

Table 8: Cross-Sectional Regressions: Single Bond Return per Firm

We run the following cross-sectional regression each month

$$R_{it} = \gamma_{0t} + \gamma_{1t}' Zeq_{it-1} + \gamma_{2t} R_{it-1} + \gamma_{3t} R_{it-2:t-12} + \gamma_{4t} DD_{it-1} + \gamma_{5t} \log L_{it-1}^{eAmihud} + \epsilon_{it},$$

where R_{it} is the excess bond return, Zeq_{it-1} are lagged equity anomaly variables (the momentum returns are lagged by an additional month), DD is the distance-to-default, and $L^{eAmihud}$ is equity Amihud illiquidity. Equity anomaly variables are described in Table 2. The table shows only the average slopes, γ_1. EW is the OLS estimates while VW is the estimates based on value-weighted regressions. To value-weight, we multiply the square-root of the market value of a bond in month $t-1$ with both its excess return in month t and the independent variables in month $t-1$. Newey-West corrected (using 12 lags) t-statistics are given in parenthesis below the coefficients. We run the regression using only bond per firm. This bond is chosen at random, or the one with the shortest maturity, or the one with lowest age. The sample period is 1973 to 2011.

	Random		Shortest maturity		Lowest age	
	EW	VW	EW	VW	EW	VW
$\log MC$	-9.66	-4.38	-8.75	-4.00	-9.22	-5.71
	(-3.63)	(-1.44)	(-3.39)	(-1.64)	(-3.32)	(-1.98)
$\log B/M$	-2.16	-2.24	-0.82	-1.02	-2.60	-2.21
	(-1.42)	(-1.73)	(-0.68)	(-0.83)	(-1.45)	(-1.42)
$R_{eq}(2,12)$	1.90	2.47	2.04	2.36	1.57	2.03
	(1.34)	(1.69)	(1.88)	(2.08)	(1.23)	(1.32)
$R_{eq}(1)$	13.05	13.67	10.59	10.17	11.41	11.52
	(6.10)	(7.01)	(6.68)	(6.93)	(5.49)	(6.69)
Y/B	-4.86	-5.80	-5.37	-6.21	-8.49	-9.35
	(-2.08)	(-2.55)	(-3.50)	(-4.32)	(-4.09)	(-4.86)
NS	2.44	2.02	1.79	2.06	1.58	0.97
	(2.02)	(1.45)	(1.63)	(1.75)	(1.36)	(0.81)
Ac/A	-1.52	-1.25	-0.53	-0.23	-1.64	-1.18
	(-1.35)	(-1.03)	(-0.63)	(-0.28)	(-1.38)	(-1.01)
dA/A	-3.22	-2.35	-2.16	-2.02	-1.56	-0.54
	(-1.88)	(-1.25)	(-1.63)	(-1.45)	(-1.28)	(-0.46)
SUE	-1.26	0.91	-1.27	-0.12	-0.50	1.14
	(-0.66)	(0.39)	(-0.98)	(-0.08)	(-0.33)	(0.72)
$IdioVol$	6.76	6.20	4.33	4.21	5.31	5.85
	(3.60)	(2.85)	(2.60)	(2.48)	(2.69)	(2.82)
$R_{bd}(2,12)$	-4.20	-7.76	-4.04	-5.82	-4.60	-6.09
	(-1.60)	(-2.60)	(-1.63)	(-2.33)	(-1.66)	(-2.03)
$R_{bd}(1)$	-29.02	-34.56	-26.42	-31.33	-30.62	-36.27
	(-6.16)	(-8.75)	(-6.91)	(-9.14)	(-7.39)	(-9.57)
DD	-1.90	-1.17	-2.98	-2.71	-2.03	-1.98
	(-1.17)	(-0.71)	(-2.67)	(-2.83)	(-1.42)	(-1.27)
$\log L^{eAmihud}$	2.00	-3.46	2.48	-1.88	2.61	-0.25
	(0.74)	(-1.26)	(1.07)	(-0.86)	(0.97)	(-0.09)

Table 9: Subsample Cross-Sectional Regressions for Bond Returns

We run the following cross-sectional regression each month

$$R_{it} = \gamma_{0t} + \gamma_{1t}' Zeq_{it-1} + \gamma_{2t} R_{it-1} + \gamma_{3t} R_{it-2:t-12} + \gamma_{4t} DD_{it-1} + \gamma_{5t} \log L_{it-1}^{eAmihud} + \epsilon_{it},$$

where R_{it} is the excess bond return, Zeq_{it-1} are lagged equity anomaly variables (the momentum returns are lagged by an additional month), DD is the distance-to-default, and $L^{eAmihud}$ is equity Amihud illiquidity. Equity anomaly variables are described in Table 2. The table shows only the average slopes, γ_1. EW is the OLS estimates while VW is the estimates based on value-weighted regressions. To value-weight, we multiply the square-root of the market value of a bond in month $t-1$ with both its excess return in month t and the independent variables in month $t-1$. Newey-West corrected (using 12 lags) t-statistics are given in parenthesis below the coefficients. The sample period is 1973 to 2011. The sample is split in two based on the most recently available institutional holdings.

	EW	VW	EW	VW	EW	VW
	Low holdings		High holdings		Difference	
$\log MC$	-6.07	-3.85	-6.19	-5.55	0.12	1.70
	(-3.09)	(-1.93)	(-1.93)	(-1.53)	(0.04)	(0.59)
$\log B/M$	0.12	-0.53	-1.51	-2.59	1.63	2.06
	(0.15)	(-0.64)	(-1.21)	(-1.96)	(1.55)	(1.72)
$R_{eq}(2,12)$	3.72	3.86	5.73	4.57	-2.01	-0.71
	(4.33)	(4.64)	(3.52)	(2.66)	(-1.18)	(-0.41)
$R_{eq}(1)$	8.48	8.93	6.18	6.71	2.30	2.22
	(6.32)	(6.68)	(3.10)	(3.26)	(1.49)	(1.43)
Y/B	-4.71	-5.20	-0.24	-0.32	-4.47	-4.88
	(-4.18)	(-4.62)	(-0.16)	(-0.20)	(-2.50)	(-2.77)
NS	1.07	1.19	1.17	0.60	-0.10	0.59
	(1.36)	(1.76)	(0.93)	(0.46)	(-0.09)	(0.43)
Ac/A	0.31	0.12	-1.76	-2.22	2.07	2.34
	(0.57)	(0.20)	(-1.41)	(-1.63)	(1.99)	(1.83)
dA/A	-0.81	-0.76	2.08	1.41	-2.89	-2.17
	(-0.87)	(-0.87)	(1.40)	(0.95)	(-2.34)	(-1.43)
SUE	-0.37	0.07	1.62	1.70	-1.99	-1.63
	(-0.44)	(0.07)	(1.20)	(1.11)	(-1.37)	(-0.91)
$IdioVol$	3.97	2.82	0.98	0.96	2.99	1.86
	(3.32)	(2.26)	(0.97)	(0.83)	(2.56)	(1.38)
$R_{bd}(2,12)$	-4.99	-6.87	-6.87	-7.76	1.88	0.89
	(-2.05)	(-2.72)	(-2.77)	(-2.85)	(0.94)	(0.54)
$R_{bd}(1)$	-30.44	-36.28	-30.09	-36.04	-0.35	-0.24
	(-7.60)	(-10.38)	(-5.92)	(-8.31)	(-0.16)	(-0.12)
DD	-2.37	-2.25	-5.29	-5.04	2.92	2.79
	(-2.45)	(-2.12)	(-3.42)	(-4.07)	(1.73)	(2.01)
$\log L^{eAmihud}$	1.36	-0.38	-0.92	0.20	2.28	-0.58
	(0.81)	(-0.24)	(-0.32)	(0.07)	(0.88)	(-0.22)

Table 10: Transaction Costs for Bond Portfolios

Equity anomaly variables are described in Table 2. We sort bonds into deciles and calculate equal-weighted costs. We compute L_{it}^{BPW} whenever the data is available, and compute the average for each portfolio every month. The time-series average of the illiquidity measure, multiplied by the time-series average of the portfolio turnover rate is reported as TransCosts. We sort at the end of June of every year and hold these portfolios for one year for the anomaly variables $\log MC$, $\log B/M$, Y/B, NS, Ac/A, dA/A, and SUE. We sort at the end of each month and hold these portfolios for one month for the anomaly variables R_{eq}(2,12), $R_{eq}(1)$, and $IdioVol$. 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 costs for the subsamples. All bid-ask spreads and TransCosts are in percentage per month. The sample period is 1994 to 2011.

		1	2	3	4	5	6	7	8	9	10	H−L	H−L IG	H−L Junk
$\log MC$	BidAsk	1.63	1.45	1.14	1.79	1.18	1.20	1.00	1.02	0.90	0.80			
	Turnover	0.01	0.03	0.04	0.04	0.04	0.04	0.04	0.04	0.03	0.01			
	TransCosts	0.02	0.04	0.04	0.07	0.05	0.05	0.04	0.04	0.03	0.01	0.03	0.03	0.08
$\log B/M$	BidAsk	0.88	0.94	0.93	0.93	0.93	1.10	1.10	1.18	1.37	1.44			
	Turnover	0.02	0.05	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.04			
	TransCosts	0.02	0.05	0.05	0.06	0.06	0.07	0.07	0.07	0.08	0.05	0.07	0.10	0.14
$R_{eq}(2,12)$	BidAsk	1.63	1.11	1.07	0.97	1.00	1.14	0.91	0.98	1.00	0.98			
	Turnover	0.29	0.58	0.68	0.73	0.75	0.75	0.73	0.69	0.60	0.30			
	TransCosts	0.47	0.65	0.73	0.70	0.75	0.85	0.67	0.68	0.60	0.29	0.77	0.72	0.93
$R_{eq}(1)$	BidAsk	1.32	1.10	0.99	0.93	1.02	1.01	1.13	1.06	1.07	1.39			
	Turnover	0.84	0.91	0.90	0.89	0.89	0.89	0.89	0.89	0.91	0.87			
	TransCosts	1.12	1.00	0.90	0.83	0.90	0.89	1.01	0.95	0.97	1.21	2.33	1.93	2.90
Y/B	BidAsk	1.59	1.06	0.97	1.10	1.08	1.15	0.99	0.95	1.01	0.99			
	Turnover	0.04	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.05	0.03			
	TransCosts	0.07	0.06	0.06	0.07	0.07	0.07	0.06	0.06	0.05	0.03	0.10	0.07	0.14

		1	2	3	4	5	6	7	8	9	10	H−L	H−L IG	H−L Junk
NS	BidAsk	0.98	0.97	1.07	1.07	1.25	0.98	1.12	1.07	1.26	1.21			
	Turnover	0.05	0.06	0.06	0.06	0.07	0.07	0.07	0.07	0.07	0.06			
	TransCosts	0.05	0.06	0.07	0.07	0.09	0.07	0.07	0.07	0.08	0.08	0.13	0.12	0.17
Ac/A	BidAsk	1.06	1.06	0.99	1.03	1.02	1.14	0.99	1.06	1.04	1.11			
	Turnover	0.05	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.06			
	TransCosts	0.06	0.07	0.07	0.07	0.08	0.08	0.07	0.07	0.07	0.07	0.12	0.11	0.14
dA/A	BidAsk	1.20	1.08	0.98	0.93	0.97	1.07	1.19	1.15	1.20	1.10			
	Turnover	0.06	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.06			
	TransCosts	0.07	0.07	0.07	0.07	0.07	0.07	0.09	0.08	0.08	0.07	0.14	0.12	0.17
SUE	BidAsk	1.37	1.25	1.05	0.99	0.98	0.91	0.95	1.09	1.05	1.19			
	Turnover	0.07	0.08	0.08	0.07	0.07	0.07	0.07	0.07	0.08	0.07			
	TransCosts	0.10	0.09	0.08	0.07	0.07	0.06	0.07	0.08	0.08	0.09	0.19	0.16	0.24
$IdioVol$	BidAsk	0.90	0.92	0.92	1.00	1.01	1.02	1.06	1.39	1.34	1.79			
	Turnover	0.06	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.05			
	TransCosts	0.06	0.06	0.07	0.07	0.07	0.08	0.08	0.10	0.09	0.09	0.15	0.12	0.17

Table A1: Summary Statistics by Data Source

The table presents summary statistics of all bonds used in the paper. Bonds are also divided into investment grade (IG) and speculative grade (Junk) category. 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. Nobs is the total number of observations. 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 2011.

	Nobs	No price Change	% Market Value	Mat	Excess returns				
					Mean	SDev	Median	AR1	AR1-AR6
					All				
All	1,001,479	20,942	100.0	11.9	0.12	2.84	0.09	-0.15	-0.10
IG	784,770	9,222	73.3	13.1	0.05	2.49	0.05	-0.23	-0.21
Junk	207,658	10,473	26.3	8.3	0.38	3.84	0.28	-0.01	0.06
					Lehman Brothers				
All	684,907	13,567	61.8	11.8	0.12	2.75	0.08	-0.17	-0.12
IG	551,000	6,673	45.8	12.9	0.06	2.47	0.05	-0.24	-0.22
Junk	127,804	5,973	15.7	8.4	0.40	3.65	0.26	-0.04	0.04
					TRACE				
All	87,303	1,639	12.0	12.8	0.10	2.73	0.08	-0.19	-0.15
IG	69,800	823	10.0	14.0	0.05	2.51	0.04	-0.25	-0.21
Junk	16,447	698	2.0	8.9	0.32	3.45	0.24	-0.07	-0.02
					Mergent				
All	15,892	299	1.4	13.0	0.09	2.71	0.07	-0.18	-0.09
IG	12,859	171	1.1	14.1	0.04	2.49	0.04	-0.25	-0.23
Junk	2,876	112	0.3	9.1	0.34	3.46	0.25	-0.01	0.22
					Datastream				
All	121,174	2,386	11.5	12.6	0.12	2.75	0.08	-0.18	-0.14
IG	96,282	11,58	8.5	13.7	0.05	2.52	0.05	-0.24	-0.20
Junk	23,525	1,082	2.9	9.0	0.36	3.50	0.26	-0.07	-0.05
					Merrill Lynch				
All	56,354	2,262	9.6	9.7	0.17	3.91	0.20	0.11	0.15
IG	26,878	37	5.3	12.9	0.00	2.75	0.05	-0.05	0.01
Junk	29,476	2,224	4.3	7.0	0.33	4.72	0.40	0.16	0.18

Table A2: Monthly Cross-Sectional Regressions of Bond Returns: Robustness Checks

We run the following cross-sectional regression each month:

$$R_{it} = \gamma_{0t} + \gamma_{1t}' Zeq_{it-1} + \gamma_{2t} R_{it} + \gamma_{3t} R_{it-2:t-12} + \gamma_{4t} DD_{it-1} + \gamma_{5t} \log L_{it-1}^{eAmihud} + \epsilon_{it},$$

where R_{it} is the excess bond return, Zeq_{it-1} are lagged equity anomaly variables (the momentum returns are lagged by an additional month), DD is the distance-to-default, and $L^{eAmihud}$ is equity Amihud illiquidity. Equity anomaly variables are described in Table 2. The table shows only the average slopes, γ_1. EW is the OLS estimates while VW is the estimates based on value-weighted regressions. To value-weight, we multiply the square-root of the market value of a bond in month $t-1$ with both its excess return in month t and the independent variables in month $t-1$. 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 7. t-statistics are given in parenthesis below the coefficients. The sample period is 1973 to 2011.

	Panel A: Without matrix prices				Panel B: Without Datastream			
	New sample		Difference from full-sample		New sample		Difference from full-sample	
	EW	VW	EW	VW	EW	VW	EW	VW
$\log MC$	-4.12	-2.94	-1.95	-0.91	-3.87	-5.44	-2.20	1.59
	(-1.63)	(-1.12)	(-1.07)	(-0.49)	(-1.80)	(-2.08)	(-1.09)	(0.70)
$\log B/M$	1.01	-0.68	-0.89	0.15	-1.35	-2.37	1.47	1.84
	(0.73)	(-0.58)	(-0.95)	(0.20)	(-1.00)	(-1.69)	(1.16)	(1.40)
$R_{eq}(2,12)$	3.95	3.33	-0.23	0.53	3.14	2.92	0.58	0.94
	(2.60)	(2.68)	(-0.20)	(0.62)	(2.61)	(2.52)	(0.80)	(1.33)
$R_{eq}(1)$	11.26	10.71	-2.78	-1.78	7.69	9.00	0.79	-0.07
	(5.70)	(5.26)	(-2.66)	(-1.52)	(5.72)	(7.00)	(0.56)	(-0.07)
Y/B	-5.41	-6.05	0.70	0.85	-4.38	-3.94	-0.33	-1.26
	(-3.67)	(-4.38)	(0.70)	(1.11)	(-3.39)	(-3.13)	(-0.37)	(-1.45)
NS	0.04	0.07	1.03	1.12	1.22	1.30	-0.15	-0.11
	(0.04)	(0.06)	(1.30)	(1.52)	(1.10)	(1.22)	(-0.17)	(-0.14)
Ac/A	0.91	0.25	-0.60	-0.13	-0.79	-0.54	1.10	0.66
	(0.92)	(0.26)	(-0.70)	(-0.16)	(-1.05)	(-0.76)	(1.56)	(1.12)
dA/A	0.10	0.35	-0.91	-1.11	0.79	0.74	-1.60	-1.50
	(0.09)	(0.29)	(-1.37)	(-1.78)	(0.43)	(0.42)	(-0.93)	(-0.93)
SUE	1.00	1.02	-1.37	-0.95	-0.74	-1.30	0.37	1.37
	(0.76)	(0.67)	(-1.32)	(-0.90)	(-0.65)	(-1.17)	(0.47)	(1.70)
$IdioVol$	3.34	2.10	0.63	0.72	2.69	2.26	1.28	0.56
	(1.55)	(0.99)	(0.41)	(0.55)	(1.81)	(1.56)	(0.96)	(0.58)
$R_{bd}(2,12)$	-3.51	-4.32	-1.48	-2.55	-1.88	-3.37	-3.11	-3.50
	(-1.38)	(-1.60)	(-0.93)	(-1.41)	(-0.80)	(-1.40)	(-1.87)	(-2.41)
$R_{bd}(1)$	-34.08	-40.30	3.64	4.02	-24.93	-30.37	-5.51	-5.91
	(-8.23)	(-10.30)	(1.73)	(2.50)	(-5.30)	(-6.66)	(-2.93)	(-2.95)
DD	-2.24	-2.84	-0.13	0.59	-3.94	-3.82	1.57	1.57
	(-1.51)	(-1.95)	(-0.13)	(0.63)	(-3.57)	(-3.35)	(1.71)	(1.65)
$\log L^{eAmihud}$	-1.19	-1.29	2.55	0.91	0.27	1.47	1.09	-1.85
	(-0.55)	(-0.58)	(1.54)	(0.54)	(0.13)	(0.64)	(0.52)	(-0.88)

	Panel C: With reverse ordering of databases				Panel D: With fixed effects for callable bonds			
	New sample		Difference from full-sample		New sample		Difference from full-sample	
	EW	VW	EW	VW	EW	VW	EW	VW
$\log MC$	-5.14	-4.13	-0.93	0.28	-6.04	-3.90	0.03	-0.05
	(-2.64)	(-2.00)	(-1.10)	(0.25)	(-3.08)	(-1.96)	(0.22)	(-0.43)
$\log B/M$	0.19	-0.34	-0.07	-0.19	0.21	-0.60	0.09	-0.07
	(0.20)	(-0.40)	(-0.19)	(-0.46)	(0.25)	(-0.74)	(0.65)	(-0.67)
$R_{eq}(2,12)$	3.82	4.14	-0.10	-0.28	3.77	3.87	0.05	0.01
	(3.87)	(4.66)	(-0.23)	(-0.61)	(4.22)	(4.48)	(0.44)	(0.08)
$R_{eq}(1)$	8.84	9.92	-0.36	-0.99	8.60	9.01	0.12	0.08
	(5.99)	(6.83)	(-0.86)	(-2.33)	(6.50)	(6.85)	(1.41)	(0.85)
Y/B	-4.70	-4.45	-0.01	-0.75	-4.96	-5.38	-0.25	-0.18
	(-3.94)	(-3.48)	(-0.02)	(-1.57)	(-4.44)	(-4.84)	(-1.79)	(-1.38)
NS	0.35	0.45	0.72	0.74	1.11	1.23	0.04	0.04
	(0.37)	(0.54)	(1.86)	(1.90)	(1.46)	(1.83)	(0.37)	(0.37)
Ac/A	-0.05	0.09	0.36	0.03	0.38	0.09	0.07	-0.03
	(-0.09)	(0.12)	(1.23)	(0.10)	(0.70)	(0.15)	(1.15)	(-0.37)
dA/A	-0.54	-0.75	-0.27	-0.01	-0.92	-0.81	-0.11	-0.05
	(-0.49)	(-0.74)	(-0.85)	(-0.03)	(-1.00)	(-0.95)	(-1.00)	(-0.40)
SUE	-0.44	-0.22	0.07	0.29	-0.41	0.00	-0.04	-0.07
	(-0.48)	(-0.20)	(0.19)	(0.78)	(-0.48)	(0.00)	(-0.59)	(-0.73)
$IdioVol$	4.24	3.04	-0.27	-0.22	3.83	2.76	-0.14	-0.06
	(3.09)	(2.10)	(-0.55)	(-0.39)	(3.24)	(2.20)	(-1.41)	(-0.83)
$R_{bd}(2,12)$	-2.64	-4.13	-2.35	-2.74	-5.01	-6.92	-0.02	-0.05
	(-1.20)	(-1.80)	(-2.92)	(-2.47)	(-2.11)	(-2.81)	(-0.07)	(-0.17)
$R_{bd}(1)$	-22.48	-28.40	-7.96	-7.88	-30.89	-36.93	-0.45	-0.65
	(-4.95)	(-7.36)	(-4.75)	(-5.03)	(-7.67)	(-10.67)	(-1.45)	(-1.93)
DD	-2.26	-2.03	-0.11	-0.22	-2.28	-2.23	0.09	0.02
	(-2.18)	(-1.72)	(-0.29)	(-0.44)	(-2.40)	(-2.13)	(0.53)	(0.12)
$\log L^{eAmihud}$	0.63	-0.13	0.73	-0.25	1.05	-0.62	-0.31	-0.24
	(0.38)	(-0.08)	(1.20)	(-0.35)	(0.62)	(-0.39)	(-1.32)	(-1.23)

Figure 1: Portfolio Returns for IG Bonds and junk Bonds Portfolios

Equity anomaly variables 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 June of every year and hold these portfolios for one year for the anomaly variables $\log MC$, $\log B/M$, Y/B. We sort at the end of each month and hold these portfolios for one month for the anomaly variables $R_{eq}(2{,}12)$, $R_{eq}(1)$, and $IdioVol$. 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 2011.