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

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Abstract

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

Using a comprehensive cross-section and time-series of bond returns assembled from multiple data sources, we analyze whether commonly analyzed equity return predictors also predict bond returns. We find that many predictors such as size, value, and past equity returns do predict bond returns, but others such as accruals and earnings surprises do not. We uncover a surprisingly strong monthly lead from equity to bond returns, indicating that new information gets reflected in the equity market first. Net equity issues are positively priced in the bond market, consistent with the notion that equity is preferred when bond market is undervalued. Profitability is negatively priced while idiosyncratic volatility is positively priced in the corporate bond market, suggesting that profitable and relatively less volatile firms are more attractive to bond investors, thus requiring lower returns. Our results generally accord with the notion that the bond markets attract clienteles that are sophisticated enough to price risk, but also are susceptible to delayed information transmission relative to equities.

1 Introduction

Public 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 required returns on debt and equity components. However, we do not observe the required return on debt and equity claims directly, but observe only the realized returns. Some recently documented predictors of realized 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)) while that of past returns to overreaction (Cooper (1999)), which is motivated by the psychological biases of overconfidence and self-attribution (Daniel, Hirshleifer, and Subrahmanyam (1998)).

While a voluminous literature documents "anomalies" (empirical deviations from the RR paradigm) in equity markets (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. Whether such anomalies should exist in the bond market and whether the signs of the predictors should match those for the equity market are open issues. For example, it may be that bond markets are insufficiently volatile to attract individual investors (Kumar (2009)), and thus be more efficiently priced than stock markets. Alternatively, it may be that bonds might get mispriced, but on account of thinness and illiquidity, not attract enough arbitrageurs, and thus exhibit anomalous behavior. Further, if bonds lag equities on account of the fact that they are insufficiently liquid to attract informed traders, then the ensuing positive cross-autocorrelations could more than offset the short-horizon reversals documented for the stock market by Jegadeesh (1990). Finally, predictors like net equity issuance are associated with market timing (Pontiff and Woodgate (2008)) which implies issuing equity when equity markets are overvalued, and, by the same token, when debt markets are undervalued. Therefore net equity issues may predict equity and bond returns in opposite directions.

In this paper, we empirically examine whether equity return predictors also forecast corporate bond returns. We borrow from the rich literature on equity anomalies to identify variables that forecast equity returns. Our extensive panel data of corporate bonds from 1973 to 2011, assembled from four different data sets, namely, the Lehman Brothers Fixed Income Database, TRACE, Mergent FISD/NAIC, and DataStream, makes 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. This way, 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 without worrying about the interactions with changes in treasury yields.

We start our analysis by sorting corporate bonds into decile portfolios based on equity characteristics. Since junk bonds are more expensive to trade, we sort investment-grade bonds and junk bonds separately to make sure the anomalies are pervasive across rating categories. We find that many equity anomalies are significant forecasters of bond returns: size, value, lagged equity returns, equity volatility, 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.

We also find that the variation in excess returns on these portfolios is not explained by several asset pricing models. In particular, we check alphas from the one-factor CAPM, the five-factor Fama and French (1993) model (including bond factors), and a two-factor model proposed by Nozawa (2013). We find that none of these models materially reduces the magnitudes of alphas. We conclude that risk-based explanations are unable to account for the variation in corporate bond returns.

Next, we ask whether these equity characteristics have incremental predictive power in multivariate context. We run Fama and MacBeth (1973) cross-sectional regressions of bonds returns on lagged equity characteristics. As in portfolio sorts, we run separate regressions for investment grade bonds and junk bonds to check if the result is driven only by junk bonds.

In multivariate regressions, we find that size, value momentum, lagged equity returns, profitability, and idiosyncratic volatility forecast bond returns. 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. Similarly, if highly profitable firms are less risky, 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.

Chordia, Sarkar, and Subrahmanyam (2011) demonstrate the role of large firm liquidity in explaining the lead from large stocks to small stocks. To further examine the role of liquidity in corporate bonds and how liquidity affects the bond return predictability based on lagged equity return, we construct several liquidity measures on corporate bonds including trading volume, turnover, Amihud (2002) measure, Pástor and Stambaugh (2003) measure, and Bao, Pan, and Wang (2011) measure. We find that none of these proxies for bond liquidity drives out the lead-lag effect in the cross-sectional regression of bond returns on lagged equity return, lagged bond liquidity, and an interaction term.

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) find that Merton model predicts the sensitivities of corporate bond returns to equity returns correctly 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 Merton model. All these papers focus on realized returns while we study expected returns. Moreover, 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 their bankruptcy indicators to forecast stock returns. Anginer and Yildizhan (2013) find credit spreads of corporate bonds produce a variation in equity risk premium in the cross-section and Friewald, Wagner, and Zechner (2013) find that credit risk premium implied from CDS spreads is priced in equities. We complement these studies by, instead, forecasting bond returns based on equity anomalies.

Our work is the first to examine the relationship between bonds and equities from the perspective of expected returns. We believe our work has implications for theories of rational and behavioral asset pricing that seek to explain the cross-section of asset returns. Specifically, any theory that explains, say, the cross-section of returns in equities, ideally, should also be adapted to explain that in corporate bonds within a coherent framework.

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 risk-based and illiquidity-based explanations 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 four 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 choose to include matrix prices in our main result to maximize the power of the test. However, we also repeat the main exercise in Appendix and show that our results are robust to the exclusion of matrix prices. Second, from 1994 to 2011, we use the Mergent FISD/NAIC Database. This database consists of actual transaction prices reported by insurance companies. Third, from 2002 to 2011, we use TRACE data which 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. 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 negative prices; second, we remove the observations if the prices bounce back such that the product of the two consecutive monthly returns are less than -0.04; third, we remove the observations if the prices do not change for more than three months.

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 and DataStream. As Jostova, Nikolova, Philipov, and Stahel (2012) (JNPS) find, the degree of overlap is not large relative to the total size of the dataset, with the largest overlap between TRACE and Mergent FISD being 3.3% 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[1] provide the 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 callable 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 by adding fixed effects for callable bonds in our main tests in Appendix and show that our results are not sensistive to this feature of the data.

We merge all four 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

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

observations, we have an unbalanced panel of 895,415 bond-month return observations with 17,675 bonds issued by 3,109 firms over 468 months. Our sample size is lower than that of JNPS as our sample from DataStream is smaller and we use only the 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.

2.2 Bond Returns

We define the return on corporate bond i as:

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

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 as a function of both the price of a treasury bond and the firm-specific default risk. Since equity anomalies should work via firm's default risk, we need to adjust corporate bond returns for treasury returns. To this end, 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:

$$R_{it}^{f} \equiv \frac{P_{it}^{f} + AI_{it} + Coupon_{it}}{P_{it-1}^{f} + AI_{it-1}} - 1 \,, \tag{2}$$

where P_{it}^f 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:

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

Since the synthetic treasury bond has the same future cash flow as the corporate bond, R_{it} is not affected by any movements in treasury yield curve. In other words, by examining R_{it}, we focus on the bond return due to shocks to the firm's fundamentals.

To construct the matching treasury bond price P_{it}^f 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.[2] We add all the discounted cash flows to obtain the synthetic treasury bond price which matches 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 has 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. In our case, using a maturity-matched treasury bond will cause excess returns to move mechanically because of shocks to treasury yield curves, since the 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

[2]We match the maturity of the zero coupon treasury prices to the cash flow exactly by linearly interpolating continuously compounded forward rates.

a treasury yield curve and thus more suitable for our study on the bond-equity relationship.[3]

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).

We study the characteristics of bonds separately by credit ratings for the following reasons. First, according to structural models of a debt such as Merton (1974), a bond that is close to default should behave more like equities while high-credit bonds should be relatively less sensitive to a shock to firm fundamentals. Thus, it is reasonable to conjecture that the effect of equity anomalies on corporate bonds differs across credit ratings. 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 in reality. 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 0.106% for all bonds and is higher for bonds with lower credit ratings. Junk bond returns are more volatile than IG bond returns as evidenced in their higher standard deviation and thicker tails of the distribution.

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

[3] 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 still use this matching method as other alternative methods are also subject to the same problem due to the accelerated payments upon default.

more observations on IG bonds (732,365, or 81.8% of the total number of observations) relative to Junk bonds (155,846, or 17.4% of the total number of observations). The number of observations with zero price change indicates liquidity of bonds. Overall, only 1.6% of observations correspond to zero price change observations.[4] 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 have higher market values (83.2% of the total bond market capitalization in our sample) than Junk bonds (16.5%). This means that value-weighted bond portfolios, that we study later in the paper, will be more representative of IG bonds than will be equal-weighted bond portfolios. However, as the ratio of the number of observations across the two categories 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 slightly shorter time-to-maturity.

The correlation between equity returns and bond excess returns is modest. The average correlation is 0.14 for the entire sample, 0.10 for IG bonds, and 0.23 for Junk bonds. The higher correlation for Junk bonds suggests that low-grade bonds may show a stronger link with equities than do high-grade bonds. Low correlation in bond and equity realized returns, consistent with Collin-Dufresne, Goldstein, and Martin (2001), does not a priori rule out a link between bonds and equity expected returns. For example, bond market specific factors may affect unexpected returns, leaving expected returns determined solely by firm fundamentals.

We also look at the characteristics of the issuers of bonds. We classify issuers as Micro if their market-cap is below the 20th percentile, as Small if their market-cap is between the

[4]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.

20th and 50th percentiles, and Big if their market-cap is above the 50th percentile market cap (the percentiles are calculated using only NYSE stocks). Most of the bonds in our sample are issued by big firms; 84.2% of observations are associated with big firms, 12.1% with small firms, and only 3.7% with micro firms. We find that Junk bonds are issued more often by smaller firms; 15.2% 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 weaker or no predictability for big stocks. This observation leads to a caveat in our study; namely, that some equity anomalies may not forecast bond returns simply because corporate bonds are issued mostly by big firms in our sample.

3 Equity Anomalies 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. Lead-Lag (R_{eq}(1)): the monthly return on equity. See Jegadeesh (1991)

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).

8. Gross Profitability (GP/A): the ratio of gross profit to total assets. See Novy-Marx (2013).

9. 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).

10. 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).

11. Equity Volatility ($TotalVol$): the annualized equity volatility calculated using daily data over each month. See Ang, Hodrick, Xing, and Zhang (2006).

12. 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).

Table 2 shows the summary statistics on our anomaly 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. 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 anomaly variables are related to bond excess returns based both on the entire sample and on the breakdown using credit ratings.

3.1 Portfolio Sorts

We start our analysis by considering the univariate relation between equity anomaly variables and bond returns via portfolio sorts. Forming portfolios is equivalent to non-parametric estimation of expected return as a function of security characteristics. 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. We sort at the end of June of every year and hold these portfolios for one year for the anomaly variables $\log MC$, $\log B/M$, Ac/A, dA/A, Y/B, GP/A, NS, 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), $TotalVol$, and $IdioVol$.

Table 3 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 for brevity.

Equity size, $\log MC$, yields significant variation in average excess returns on corporate bonds. The equal- and value-weighted returns on the hedge portfolio are -0.39% and -0.37%, respectively, with high statistical significance. 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. Since there is sufficient variation in equity size within the subsample of Junk bonds, equity size effect is strong for Junk bonds too with hedge portfolios returns of -0.32% and -0.29%.

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 hedge portfolio returns are between 0.15% and 0.53%. 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.

Equity momentum, R_{eq}(2,12), works 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 anomaly that we find. The hedge portfolio returns range from 0.30% to 0.95%, and are strongly statistically significant. The effect is more pronounced for Junk bonds but IG bonds also show a significant lead-lag effect. The positive relationship between lagged equity returns and bond returns at the monthly horizon is interesting given the evidence of reversal in monthly stock returns in Jegadeesh (1990). The lagged response of bond returns can potentially arise due to illiquidity of corporate bonds which prevents investors to trade quickly on firm-specific news. We will examine the issue of liquidity more in detail in Section 4.

Three accounting variables, dA/A, Y/B, and NS, show some predictive power for future bond excess returns. The impact of dA/A is economically small and marginally statistically significant for Junk bonds but not for IG bonds. Y/B yields significant variation in average excess returns 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.

On second glance, however, the result for NS is consistent with intuition from behavioral arguments. 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, by the same token, that debt is undervalued. So we would in fact expect NS to predict debt returns positively. 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.

Three accounting variables, Ac/A, GP/A, and SUE, do not have predictive power for future bond returns. Thus, we drop these three variables in the following multivariate analysis.

Equity volatility, $TotalVol$ or $IdioVol$, both forecast bond excess returns well. 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 bond market, possibly due to a more sophisticated clientele in this market. Since $TotalVol$ and $IdioVol$ are highly correlated and lead to similar results, we drop $TotalVol$ from the rest of our analysis.

3.2 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 Fama and MacBeth (1973) regressions for this analysis. We assume that expected returns are linear in characteristics though there are no theories that support such parametric assumptions. However, regressions are more efficient than portfolios and can handle multiple characteristics at the same time.

In determining the functional form, we are guided by the results of portfolio sorts in Table 3. $\log MC$, $\log B/M$, $R_{eq}(1)$, Y/B, and $TotalVol$ have a fairly monotone relationship with average excess returns and thus we impose linearity on these anomalies. There is a discrete jump in average excess returns between negative values of NS and non-negative values. Thus, we use a dummy variable for the negative NS in the regression. Finally, when we assume linearity on R_{eq}(2,12) in running multivariate regression and sort the residuals based on R_{eq}(2,12), we find that the average residuals do not show significant non-linearity. Thus, despite some evidence of non-linearity for R_{eq}(2,12) in the univariate portfolio sorts, we impose linearity on this momentum variable as well.

Even though our interest lies in the relation between bond returns and equity characteristics, we also include some control variables related to bonds to ensure that the influence of equity-based variables is robust. In particular, we include last-month bond return, last 11-month bonds return (skipping the most recent month), and a distance-to-default (DD) measure to control for default likelihood of the bond. Thus, our regression specification is:

$$R_{it} = \gamma_{0t} + \gamma_{1t}' Zeq_{it-1} + \gamma_{2t} R_{it-1} + \gamma_{3t} R_{it-2:t-12} + \gamma_{4t} DD_{it-1} + \epsilon_{it}, \tag{4}$$

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. In addition, we also report the result of value-weighted cross-sectional 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.

Table 4 shows the results from regressing excess bond returns on lagged equity anomaly variables. We run regressions using the full sample as well as the subsamples containing only IG bonds or Junk bonds. As mentioned above, we report both equal-weighted (EW) and value-weighted (VW) regressions for the sample of all stocks. We report only the results of EW regressions for IG and Junk bonds. Finally, we report only the coefficients of interest, γ_1, from equation (4).[5]

Economically, $\log MC$ and $\log B/M$ both have fairly strong forecasting power. Their predictability is weaker, and statistically insignificant, for IG bonds, as compared to junk bonds. A difference-of-means test of coefficients between these two categories of bonds is statistically significant for both these variables. Therefore, size and book-to-market help forecast only Junk bond returns but not IG bond returns.

Equity momentum, $R_{eq}(2,12)$ becomes statistically significant in the multivariate regression though it is insignificant in the univariate sort (Table 3). 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 $\log MC$ 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. At the same time, momentum 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 12.07 is the highest amongst all the 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 and the slope coefficient has a t-statistic of 8.77.

[5]While we do not report the coefficients on bond market predictors for brevity and because our focus is on equity return predictors, we find that the past month's bond return negatively forecasts the current month's bond return, as in Jegadeesh (1990), and the past two-to-twelve month return is also negatively (albeit marginally) related to the contemporaneous month's return. These results are available from the authors upon request.

Two accounting variables, dA/A and $NegNS$, lose their significance in regressions. Profitability, Y/B, remains statistically significant, although only for the sample of Junk bonds. $IdioVol$ is also highly significant predictor of bond excess returns both economically and statistically. The predictive power is again limited to Junk bonds only.

To summarize the results from this section, we find that many anomaly variables, such as size, book-to-market, momentum, lead-lag, profitability, and volatility, have significant predictive power of bond returns. While some of these variables predict bond returns the same way as they do stock returns, the predictive power of other variables for bond returns is opposite to that for stock returns. These variables tend to be risk-based; it may be argued that low Y/B firms are closer to bankruptcy, and high $IdioVol$ firms are more risky; both arguments imply higher returns, which is what we find. We also find that predictability is stronger for the relatively riskier junk bonds than for IG bonds.

In the next section, we examine the role of risk factors or bond illiquidity in the cross-section of bond returns.

4 The Roles of Risk and Illiquidity

4.1 Risk-Based Models and the Cross-Section of Expected Bond Returns

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

$$R_{it} = \alpha_i + \beta_i' f_t + \varepsilon_{it}. \tag{5}$$

We use three different factor models. The first is 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). The third model is from Nozawa (2013), who uses the first two principal components of the excess returns on ten portfolios of corporate bonds sorted on credit spreads.

Table 5 shows the alpha from these time-series regressions for the value-weighted H−L hedge portfolio. 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 sample of all, IG, and Junk bonds. We drop dA/A and $NegNS$ variables from this analysis because of the lack of their statistical power in Table 4.

Looking across the anomaly variables, the CAPM and the five-factor model do not explain the variation in average excess returns on these portfolios. It may seem surprising that the inclusion of the bond factors in the five-factor models 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.[6] 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 related to size and book-to-market.

The first two principal component factors of Nozawa (2013) do better in explaining the variation in average excess returns on portfolios sorted on $\log MC$, $\log B/M$, Y/B, and $IdioVol$. However, this factor model fares worse in explaining $R_{eq}(2{,}12)$. The lead-lag effect, $R_{eq}(1)$, still remains after testing against all the three asset pricing models. Finally, even the

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

principal component factors do not help explain the hedge portfolio returns for any anomaly variables for the sample of Junk bonds. Thus, overall, the ability of risk-based models to explain the performance of equity market predictors for bond returns is circumscribed.

4.2 Bond Market Liquidity and the Lead-Lag Relation Between Stock and Bond Returns

One-month lagged equity returns are the strongest predictor of corporate bond returns. As corporate bonds are traded in OTC market, liquidity may affect their price movements significantly. If there is a delay in bond markets' reaction to information about firms' fundamentals, the lead-lag effect should be stronger for illiquid bonds than liquid bonds.

The challenge in studying the liquidity and its effects in bond markets is limited data. As most of the liquidity measures proposed in the literature require either transaction volume data or high frequency (daily) price data, we have to limit our data to Mergent FISD and TRACE. To construct a liquidity measure, we use all the observations in these two datasets. This subsample runs from 1994 to 2011 and covers fewer bonds before the full implementation of TRACE, which starts to cover all transactions from 2005. We construct the following liquidity measures:

1. Dollar transaction volume (L^{Volume}). This is the dollar transaction volume in month t. See Brennan, Chordia and Subrahmanyam (1998) and Chordia, Subrahmanyam and Anshuman (2001).

2. Turnover (L^{Turn}). This is calculated as the dollar transaction volume of the bonds in month t divided by the amount outstanding at the end of month $t-1$. See Brennan, Chordia and Subrahmanyam (1998) and Chordia, Subrahmanyam and Anshuman (2001).

3. Bao, Pan, and Wang (2011) measure (L^{BPW}): This calculated as the autocovariance

of excess bond returns.

$$L_{it}^{BPW} = \mathrm{cov}_t\left(R_{itd+1}, R_{itd}\right) \ ,$$

where R_{itd} is the excess return on bond i on day d of month t.

4. Pástor and Stambaugh (2003) measure (L^{PS}): This is calculated via the following regression:

$$R_{itd+1} = a + bR_{itd} + L_{it}^{PS}\mathrm{sign}(R_{itd})V_{itd} + \varepsilon_{itd+1} \ ,$$

where V_{itd} is the dollar volume on day d of month t.

5. Amihud (2002) measure (L^{Amihud}):

$$L_{it}^{Amihud} = \frac{1}{D}\sum_{d=1}^{D}\frac{|R_{itd}|}{V_{itd}} \ ,$$

where D is the number of the days in month t.

To reduce noise in the estimates of L_{it}^{PS} and L_{it}^{BPW}, we use all observations between month $t-3$ and t and eliminate bonds that have fewer than 10 observations during the period. We take natural logarithms of volume, turnover and Amihud measure as these measures show significant positive skewness. We also add negative sign to the (log) Amihud measure so that the positive values imply liquidity for all the variables that we use. To complement the bond liquidity measures above, we also compute Amihud measure using equity returns, denoted $L_{it}^{eAmihud}$.

The summary statistics of the panel data of bond liquidity measures are provided in Table 6. The number of observations for L^{BPW} and L^{PS} is fewer than that for other variables due to more stringent requirement for data availability. The use of log transformation reduces the skewness of liquidity measures.

Using these liquidity measures, we run the following cross-sectional regression:

$$R_{it} = a_t + b_{1t} R_{eq,it-1} + b_{2t} L_{it-2} + b_{3t} R_{eq,it-1} L_{it-2} + \varepsilon_{it} \ , \tag{6}$$

where L_{it-2} is the liquidity measure observed two months before the current month, and $R_{eq,it-1}$ is the last-month equity return. We winsorize each liquidity measure at the 0.5th and 99.5th percentiles and scale it by its standard deviation so we can compare the economic significance of the estimated coefficients. If investors require a reward for holding illiquid bonds, the coefficient b_2 should be negative. The interaction term coefficient, b_3, measures whether predictability due to lagged equity returns is related to bond liquidity. Since L is a proxy for liquidity, we expect b_3 to be negative.

Table 7 reports the results from estimating equation (6). Each panel has three columns, corresponding to coefficients b_1, b_2, and b_3. We run equal-weighted (EW) and value-weighted (VW) regressions. To value-weight, we multiply both sides of the equation by the square-root of the market value of a bond in month $t-1$.

Regarding the direct effect of liquidity, L, we find that the estimated coefficients are negative in all specifications except L^{PS} in EW regressions. Thus, a more liquid bond earns lower average excess returns than a less liquid bond. These findings are consistent with Chordia, Subrahmanyam, and Anshuman (2001) who find that stock returns are negatively related to trading volume and turnover.

The coefficient, b_3, for the interaction term, on the other hand, presents a rather mixed result. The signs vary across different measures of liquidity. The estimates are mostly insignificant with the exception of equity Amihud measure. Therefore, we find no clear supports for the claim that the lead-lag effect of corporate bond and equity returns are due to illiquidity of corporate bonds.

Our main interest is in the coefficient b_1 for the lead-lag effect. We find that this coefficient remains statistically significant in almost all the specifications in Table 7. Thus, we do not find convincing evidence for the claim that $R_{eq}(1)$ is a proxy for bond illiquidity. A caveat is that this result may be affected by the limited sample size or noise in our liquidity proxies for liquidity. Thus, the lead-lag effect cannot be explained by either a risk-based model or by bond illiquidity.

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, value, 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. There is some evidence that net equity issues positively predict bond returns (unlike for equity returns), which accords with the market timing notion that equity is preferred when equity is overvalued and debt is undervalued. 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 volatility are considered more risky by bond market investors, so that the bonds command higher required returns.

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 result in Table 4, we run a series of robustness tests and report the results in Table A1.

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 14.11 from 12.07 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. The coefficient on $R_{eq}(2,12)$ is also statistically significantly higher in the sample without matrix prices than that in the main sample. 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 results in Panel B show that the value effect becomes weak and statistically insignificant in the new sample. The inferences on all the other anomaly variables are the same as those in the main sample; differences between the coefficients from the full sample and the sub-sample are statistically insignificant for other anomaly variables.

Sample with Reverse Priority: For our main results, we prioritize the four datasets in the following order: the Lehman Brothers Fixed Income Database, TRACE, Mergent FISD/NAIC, 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, 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.

Checking Non-linearity: Sort of Residuals of Cross-sectional Regressions: In the cross-sectional regressions in Table 4, we assume that expected returns are linear in the characteristics we use. To check the validity of the assumption, we sort the residuals of the regressions into equal-weighted portfolios based on the underlying characteristics. If there is significant non-linearity, we may be able to see the pattern in the average residuals along some anomaly variables.

Table A2 shows average residuals. The estimated average residuals are very small in general. The largest spread between the first and tenth deciles is 0.16% per month (and is associated with NS).

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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. '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										
				Percentiles							
	Mean	Median	SDev	1%	5%	10%	25%	75%	90%	95%	99%
All	0.106	0.080	2.653	-7.605	-3.975	-2.548	-0.973	1.144	2.762	4.228	8.098
IG	0.055	0.052	2.453	-7.068	-3.769	-2.433	-0.953	1.041	2.551	3.900	7.126
AA+	0.012	0.026	2.425	-6.718	-3.833	-2.519	-1.013	0.991	2.509	3.880	6.905
A	0.043	0.035	2.391	-6.892	-3.689	-2.405	-0.959	1.020	2.506	3.840	6.928
BBB	0.099	0.090	2.540	-7.468	-3.833	-2.418	-0.901	1.101	2.634	3.980	7.608
Junk	0.332	0.251	3.389	-9.367	-5.005	-3.121	-1.087	1.673	3.757	5.737	12.065

	Nobs	No Price Change	% Market Value	Mat	Corr	%Issuers Equity Size		
						Micro	Small	Big
All	895,415	14,703	100.0	11.4	0.14	3.7	12.1	84.2
IG	732,365	7,644	83.2	11.8	0.10	1.0	8.5	90.5
AA+	167,903	2,639	24.4	12.8	0.09	0.6	7.5	92.0
A	306,571	3,268	32.1	12.1	0.09	0.8	8.5	90.7
BBB	257,891	1,737	26.7	10.9	0.11	1.5	9.3	89.2
Junk	155,846	6,790	16.5	9.4	0.23	15.2	28.2	56.6

Table 2: Summary Statistics of Equity Anomaly Variables

The table presents summary statistics of all 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. $\log MC$ is the natural log of market value (in millions) of the issuer's equity; $\log B/M$ is the ratio of book value to the current market value; $R_{eq}(2, 12)$ (momentum) is the issuer's equity returns from month $t-12$ to $t-2$; $R_{eq}(1)$ is the issuer's equity returns in month $t-1$; Ac/A (accruals) 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; dA/A (growth in assets) is the percentage change in total assets; Y/B (profitability) is the ratio of equity income (income before extraordinary items − dividend on preferred shares + deferred taxes) to book equity; GP/A (gross profitability) is the ratio of gross profit to total assets; SUE (earnings surprise) is the change in (split-adjusted) earnings over the same quarter in the last fiscal year divided by the current price; NS (net stock issues) is the change in the natural log of the split-adjusted shares outstanding; $TotalVol$ (equity volatility) is the annualized equity volatility calculated using daily data over each month; and $IdioVol$ (idiosyncratic volatility) 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. 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
$\log MC$	1,149,328	7.5	7.6	1.5	8.0	8.0	1.2	6.2	6.3	1.4
$\log B/M$	1,102,471	-0.3	-0.3	0.7	-0.4	-0.3	0.6	-0.2	-0.1	0.9
$R_{eq}(2,12)$	1,138,074	13.2	10.4	33.2	12.8	11.3	23.6	14.1	7.8	48.9
$R_{eq}(1)$	1,149,328	1.0	0.8	9.0	1.0	0.8	6.9	1.1	0.4	12.7
Ac/A	866,599	-3.9	-3.7	4.8	-3.9	-3.7	3.9	-3.9	-3.7	6.6
dA/A	1,100,476	12.7	7.2	26.6	11.2	7.1	20.5	15.8	6.8	37.4
Y/B	1,095,586	-3.4	3.2	45.1	2.4	4.0	20.5	-18.2	-2.0	74.7
GP/A	1,114,128	21.5	16.2	17.6	21.8	16.6	17.3	23.4	18.0	19.3
NS	1,115,679	3.8	1.1	9.8	3.0	1.0	8.5	4.9	1.5	12.4
SUE	1,094,112	-0.2	0.1	9.3	0.0	0.1	4.3	-0.7	0.2	16.1
$TotalVol$	1,149,291	32.6	28.1	19.0	28.0	25.6	12.4	46.1	39.8	26.9
$IdioVol$	1,149,291	26.1	21.7	17.6	21.7	19.5	10.9	38.9	32.3	25.4

Table 3: Average Excess Bond Returns for Portfolios Formed Using 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 $\log MC$, $\log B/M$, Ac/A, dA/A, Y/B, GP/A, NS, 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), $TotalVol$, 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 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
$\log MC$	4.81	6.08	6.67	7.11	7.50	7.87	8.22	8.59	9.04	9.97	5.17	4.24	4.51
EW	0.44	0.21	0.17	0.17	0.09	0.09	0.09	0.04	0.05	0.05	-0.39	-0.04	-0.32
	(4.81)	(2.61)	(2.11)	(2.10)	(1.18)	(1.16)	(1.15)	(0.56)	(0.62)	(0.73)	(-5.96)	(-1.14)	(-3.43)
VW	0.40	0.19	0.17	0.15	0.08	0.07	0.10	0.04	0.01	0.03	-0.37	-0.03	-0.29
	(4.26)	(2.29)	(2.07)	(1.90)	(1.04)	(0.88)	(1.18)	(0.49)	(0.13)	(0.42)	(-5.28)	(-0.74)	(-2.94)
$\log B/M$	-1.53	-0.91	-0.64	-0.46	-0.32	-0.20	-0.07	0.07	0.25	0.75	2.28	2.04	2.81
EW	0.08	0.07	0.13	0.08	0.11	0.08	0.10	0.12	0.15	0.40	0.32	0.15	0.53
	(1.21)	(0.97)	(1.82)	(1.10)	(1.41)	(1.08)	(1.22)	(1.46)	(1.82)	(4.13)	(5.50)	(3.89)	(5.61)
VW	0.04	0.04	0.12	0.05	0.08	0.03	0.06	0.08	0.11	0.30	0.26	0.17	0.48
	(0.53)	(0.60)	(1.57)	(0.67)	(0.98)	(0.44)	(0.69)	(1.00)	(1.26)	(2.99)	(3.96)	(2.85)	(4.28)
R_{eq}(2,12)	-30.74	-11.80	-3.47	2.66	8.00	13.13	18.75	25.61	36.64	68.62	99.35	77.78	140.98
EW	0.28	0.08	0.11	0.09	0.11	0.08	0.08	0.15	0.15	0.28	0.00	0.15	0.09
	(2.93)	(0.93)	(1.35)	(1.18)	(1.43)	(1.08)	(1.10)	(1.98)	(2.04)	(3.72)	(-0.01)	(4.15)	(0.84)
VW	0.16	0.03	0.06	0.07	0.07	0.05	0.04	0.14	0.11	0.24	0.08	0.18	0.13
	(1.74)	(0.41)	(0.76)	(0.84)	(0.97)	(0.58)	(0.47)	(1.79)	(1.46)	(2.97)	(1.43)	(4.17)	(1.14)
R_{eq}(1)	-12.25	-5.90	-3.34	-1.48	0.08	1.60	3.25	5.24	8.10	15.54	27.80	22.83	38.18
EW	0.02	0.07	0.06	0.07	0.09	0.11	0.16	0.16	0.18	0.49	0.48	0.30	0.95
	(0.20)	(0.86)	(0.81)	(0.91)	(1.22)	(1.40)	(2.03)	(2.12)	(2.27)	(5.62)	(10.85)	(9.63)	(10.01)
VW	-0.05	0.02	0.03	0.07	0.05	0.07	0.12	0.12	0.13	0.37	0.42	0.32	0.93
	(-0.63)	(0.26)	(0.40)	(0.85)	(0.58)	(0.95)	(1.50)	(1.60)	(1.68)	(4.45)	(9.18)	(8.75)	(8.90)

	1	2	3	4	5	6	7	8	9	10	H−L	H−L IG	H−L Junk
Ac/A	-11.83	-7.55	-5.88	-4.86	-4.05	-3.34	-2.67	-1.91	-0.68	3.74	15.58	13.63	20.44
EW	0.20	0.14	0.13	0.11	0.12	0.10	0.10	0.14	0.14	0.18	-0.02	0.05	0.06
	(2.45)	(1.74)	(1.67)	(1.36)	(1.50)	(1.21)	(1.20)	(1.73)	(1.81)	(2.41)	(-0.71)	(1.60)	(1.05)
VW	0.09	0.08	0.09	0.08	0.08	0.06	0.07	0.09	0.09	0.11	0.02	0.07	0.12
	(1.07)	(0.97)	(1.07)	(0.98)	(1.05)	(0.71)	(0.84)	(1.10)	(1.17)	(1.47)	(0.71)	(2.44)	(1.84)
dA/A	-10.05	-1.06	1.87	4.01	5.99	8.19	11.05	15.47	24.42	57.71	67.76	55.95	95.80
EW	0.26	0.14	0.14	0.13	0.10	0.11	0.13	0.14	0.10	0.15	-0.11	0.00	-0.14
	(3.31)	(1.88)	(1.71)	(1.60)	(1.31)	(1.42)	(1.65)	(1.78)	(1.29)	(2.00)	(-3.49)	(-0.03)	(-2.03)
VW	0.17	0.10	0.09	0.07	0.05	0.06	0.09	0.11	0.07	0.10	-0.08	0.00	-0.13
	(2.15)	(1.28)	(1.13)	(0.89)	(0.64)	(0.74)	(1.11)	(1.34)	(0.86)	(1.25)	(-2.01)	(0.06)	(-1.54)
Y/B	-51.61	-9.97	-3.63	-0.18	2.29	4.29	6.35	8.82	12.36	21.81	73.41	45.10	132.82
EW	0.33	0.14	0.16	0.09	0.14	0.09	0.11	0.10	0.08	0.11	-0.21	-0.03	-0.28
	(3.76)	(1.66)	(1.91)	(1.17)	(1.75)	(1.14)	(1.44)	(1.29)	(1.11)	(1.67)	(-4.69)	(-0.89)	(-4.35)
VW	0.21	0.09	0.10	0.04	0.10	0.08	0.10	0.06	0.02	0.07	-0.15	-0.03	-0.24
	(2.48)	(1.09)	(1.15)	(0.52)	(1.17)	(0.97)	(1.19)	(0.80)	(0.30)	(1.00)	(-3.12)	(-0.98)	(-2.81)
GP/A	3.78	7.64	10.22	12.54	14.91	17.52	21.11	27.89	38.43	60.74	56.97	56.55	58.75
EW	0.22	0.13	0.13	0.15	0.13	0.11	0.15	0.13	0.10	0.14	-0.08	-0.01	-0.03
	(2.85)	(1.66)	(1.56)	(1.80)	(1.57)	(1.35)	(1.86)	(1.73)	(1.39)	(1.92)	(-2.26)	(-0.40)	(-0.40)
VW	0.16	0.09	0.08	0.10	0.12	0.06	0.09	0.07	0.05	0.08	-0.08	-0.06	-0.04
	(2.14)	(1.19)	(0.94)	(1.17)	(1.43)	(0.69)	(1.12)	(0.92)	(0.62)	(1.08)	(-1.95)	(-1.11)	(-0.51)

	1	2	3	4	5	6	7	8	9	10	H−L	H−L IG	H−L Junk
SUE	-7.55	-1.42	-0.55	-0.17	0.05	0.23	0.42	0.73	1.39	6.19	13.74	7.85	29.26
EW	0.33	0.12	0.10	0.11	0.09	0.06	0.07	0.08	0.12	0.29	-0.04	0.06	0.07
	(3.74)	(1.44)	(1.28)	(1.46)	(1.21)	(0.86)	(0.96)	(1.04)	(1.52)	(3.35)	(-1.05)	(1.72)	(0.80)
VW	0.20	0.06	0.07	0.09	0.05	0.02	0.04	0.05	0.07	0.21	0.00	0.08	0.16
	(2.40)	(0.77)	(0.85)	(1.12)	(0.67)	(0.29)	(0.50)	(0.67)	(0.95)	(2.40)	(0.12)	(1.91)	(1.75)
NS	-5.34	-1.53	-0.48	0.11	0.68	1.56	3.13	5.16	9.40	23.51	28.85	25.22	36.44
EW	-0.02	-0.01	0.21	0.25	0.19	0.12	0.15	0.14	0.18	0.20	0.22	0.20	0.33
	(-0.29)	(-0.13)	(2.76)	(3.21)	(2.38)	(1.55)	(1.89)	(1.72)	(2.09)	(2.38)	(6.11)	(5.85)	(4.13)
VW	-0.03	-0.05	0.15	0.18	0.15	0.07	0.09	0.09	0.14	0.16	0.19	0.17	0.34
	(-0.44)	(-0.68)	(1.93)	(2.20)	(1.94)	(0.91)	(1.07)	(1.07)	(1.59)	(1.92)	(4.66)	(4.35)	(3.56)
$TotalVol$	14.69	18.45	21.14	23.63	26.19	29.03	32.36	36.74	43.71	66.95	52.26	36.84	75.13
EW	0.06	0.03	0.08	0.07	0.07	0.09	0.12	0.16	0.19	0.53	0.47	0.06	0.92
	(0.80)	(0.44)	(1.11)	(0.84)	(0.87)	(1.18)	(1.60)	(1.97)	(2.31)	(5.64)	(7.28)	(1.46)	(9.44)
VW	0.04	0.00	0.06	0.05	0.02	0.09	0.07	0.12	0.13	0.40	0.36	0.05	0.84
	(0.51)	(-0.06)	(0.75)	(0.68)	(0.20)	(1.15)	(0.94)	(1.49)	(1.60)	(4.38)	(5.43)	(0.98)	(7.86)
$IdioVol$	10.97	13.94	16.07	18.09	20.18	22.48	25.26	29.04	35.31	57.62	46.64	31.38	68.99
EW	0.04	0.06	0.07	0.07	0.07	0.10	0.10	0.14	0.25	0.52	0.48	0.09	0.81
	(0.52)	(0.79)	(0.95)	(0.87)	(0.96)	(1.24)	(1.23)	(1.76)	(3.03)	(5.54)	(7.37)	(2.24)	(8.32)
VW	0.02	0.04	0.05	0.04	0.04	0.07	0.05	0.10	0.20	0.40	0.38	0.08	0.76
	(0.21)	(0.50)	(0.58)	(0.49)	(0.52)	(0.96)	(0.63)	(1.22)	(2.48)	(4.36)	(5.68)	(1.60)	(6.83)

Table 4: Average Slopes from Monthly Cross-Sectional Regressions

We run the following cross-sectional regression each month

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

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), and DD is the distance-to-default. 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 $t-1$. We also present EW estimates on subsamples of investment grade (IG) and speculative grade (Junk) bonds. t-statistics are given in parenthesis below the coefficients. The sample period is 1973 to 2011.

	All		IG	Junk	IG−Junk
	EW	VW	EW	EW	EW
$\log MC$	-3.73	-3.19	-0.32	-6.08	5.76
	(-2.36)	(-1.76)	(-0.13)	(-2.34)	(1.62)
$\log B/M$	3.66	2.20	2.01	7.29	-5.28
	(2.68)	(1.36)	(0.91)	(3.02)	(-2.31)
R_{eq}(2,12)	4.36	3.90	2.89	6.97	-4.08
	(3.42)	(2.50)	(1.81)	(3.23)	(-0.88)
$R_{eq}(1)$	12.07	12.18	5.08	21.73	-16.65
	(9.15)	(8.98)	(3.01)	(8.77)	(-6.88)
dA/A	-1.29	-1.09	2.08	-1.85	3.93
	(-1.18)	(-0.90)	(1.33)	(-1.09)	(0.62)
Y/B	-5.19	-5.45	0.63	-8.60	9.23
	(-3.83)	(-3.97)	(0.48)	(-4.33)	(3.42)
$NegNS$	-0.96	-2.85	1.21	-1.65	2.86
	(-0.54)	(-1.46)	(0.54)	(-0.50)	(0.11)
$IdioVol$	5.95	5.33	0.95	7.59	-6.64
	(4.16)	(3.58)	(0.70)	(3.40)	(-2.88)

Table 5: Asset Pricing Alphas of Bond Portfolios

Equity anomaly variables are described in Table 2. We form value-weighted portfolios as described in Table 3. 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). PC are the two-factors calculated as principal components of the excess returns on the ten portfolios of corporate bonds sorted on credit spreads, following Nozawa (2013). 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}	α_{PC}	$\overline{R}$	α_{CAPM}	α_{FF}	α_{PC}	$\overline{R}$	α_{CAPM}	α_{FF}	α_{PC}
$\log MC$	-0.37	-0.33	-0.33	-0.04	-0.03	-0.03	-0.02	0.01	-0.29	-0.31	-0.29	-0.15
	(-5.28)	(-4.89)	(-5.82)	(-0.87)	(-0.74)	(-0.72)	(-0.45)	(0.35)	(-2.94)	(-3.21)	(-3.17)	(-1.59)
$\log B/M$	0.26	0.21	0.20	0.09	0.17	0.13	0.14	0.07	0.48	0.49	0.43	0.39
	(3.96)	(3.56)	(3.30)	(1.54)	(2.85)	(2.35)	(2.47)	(1.21)	(4.28)	(4.41)	(3.78)	(3.43)
R_{eq}(2,12)	0.08	0.10	0.10	0.19	0.18	0.20	0.19	0.25	0.13	0.15	0.20	0.27
	(1.43)	(1.83)	(1.69)	(3.58)	(4.17)	(4.32)	(3.91)	(5.36)	(1.14)	(1.32)	(1.64)	(2.46)
$R_{eq}(1)$	0.42	0.44	0.45	0.44	0.32	0.33	0.34	0.35	0.93	0.96	0.99	0.93
	(9.18)	(9.43)	(9.29)	(8.23)	(8.75)	(8.83)	(8.76)	(8.56)	(8.90)	(9.25)	(9.35)	(8.93)
Y/B	-0.15	-0.11	-0.12	0.02	-0.03	-0.02	0.00	0.01	-0.24	-0.21	-0.19	-0.09
	(-3.12)	(-2.47)	(-2.56)	(0.45)	(-0.98)	(-0.52)	(0.02)	(0.40)	(-2.81)	(-2.48)	(-2.30)	(-1.07)
$IdioVol$	0.38	0.35	0.36	0.08	0.08	0.07	0.08	-0.04	0.76	0.72	0.70	0.46
	(5.68)	(5.38)	(5.93)	(1.79)	(1.60)	(1.29)	(1.40)	(-0.82)	(6.83)	(6.77)	(6.63)	(4.74)

Table 6: Summary Statistics for Corporate Bond Liquidity Measures

L^{Volume} is the dollar transaction volume in month t. L^{Turn} is the dollar transaction volume of the bonds in month t divided by the amount outstanding at the end of month $t-1$. L^{BPW} is the autocovariance of daily returns computed from months $t-3$ to t. L^{PS} is the coefficient of the regression of bond returns on product of lagged volume and sign on the lagged returns. L^{Amihud} is the mean bond returns in absolute values divided by dollar volume. All statistics are first calculated as cross-sectional averages and the table then presents time-series averages of these statistics. The sample period is 1994 to 2011.

	Nobs	Mean	SDev	Percentiles						
				1%	10%	25%	50%	75%	90%	99%
$\log L^{Volume}$	280,267	8.76	1.88	3.50	6.23	7.71	8.99	10.05	10.93	12.28
$\log L^{Turn}$	280,288	-3.88	1.71	-8.76	-7.17	-4.82	-3.66	-2.73	-1.93	-0.63
L^{BPW}	184,918	-0.30	0.50	-2.44	-0.80	-0.35	-0.13	-0.04	0.00	0.17
L^{PS}	184,904	-0.06	1.92	-5.53	-0.54	-0.14	0.00	0.15	0.51	4.04
$-\log L^{Amihud}$	244,863	7.63	2.04	3.24	5.07	6.21	7.56	9.00	10.30	12.37
$-\log L^{eAmihud}$	412,454	10.49	1.88	4.32	8.05	9.56	10.81	11.82	12.61	13.29

Table 7: Average Slopes from Monthly Cross-sectional Regressions on Lagged Equity Returns and Liquidity Measures

The table shows average slopes and their standard errors from monthly cross-sectional regressions to predict bond excess returns.

$$R_{it} = a_t + b_{1t} R_{eq,it-1} + b_{2t} L_{it-2} + b_{3t} R_{eq,it-1} L_{it-2} + \varepsilon_{it} \ ,$$

where L_{it-2} is the liquidity measure observed two months before the current month, and $R_{eq,it-1}$ is the last-month equity return. L^{Turn} is the dollar transaction volume of the bonds in month t divided by the amount outstanding at the end of month $t-1$. L^{Volume} is the dollar transaction volume in month t. L^{BPW} is the autocovariance of daily returns computed from months $t-3$ to t. L^{PS} is the coefficient of the regression of bond returns on product of lagged volume and sign on the lagged returns. L^{Amihud} is the mean bond returns in absolute values divided by dollar volume. We winsorize each liquidity measure at the 0.5th and 99.5th percentiles and scale it by its standard deviation. We run equal-weighted (EW) and value-weighted (VW) regressions. To value-weight, we multiply both sides of the equation by the square-root of the market value of a bond in month $t-1$. Numbers in parentheses are t-statistics of the corresponding coefficient. The sample period is 1994 to 2011.

	$R_{eq}(1)$	L	$R_{eq}(1)L$	$R_{eq}(1)$	L	$R_{eq}(1)L$	$R_{eq}(1)$	L	$R_{eq}(1)L$
	$\log L^{Turn}$			$\log L^{Volume}$			L^{BPW}		
EW	22.42	-4.96	2.10	20.12	-6.02	-0.37	19.65	-25.39	-12.34
	(4.42)	(-2.29)	(1.18)	(2.30)	(-2.62)	(-0.19)	(5.04)	(-3.20)	(-0.59)
VW	23.22	-7.34	3.63	6.91	-6.43	2.34	18.71	-22.14	-11.73
	(3.90)	(-2.43)	(1.77)	(0.60)	(-2.09)	(0.85)	(4.45)	(-2.83)	(-0.56)
	$-\log L^{Amihud}$			L^{PS}			$-\log L^{eAmihud}$		
EW	45.65	-8.32	-5.86	18.07	-15.66	-6.30	42.96	-12.59	-5.92
	(2.71)	(-3.01)	(-1.85)	(4.60)	(-1.63)	(-0.61)	(5.75)	(-3.99)	(-3.53)
VW	30.61	-9.15	-2.53	16.34	-20.93	-7.66	34.56	-8.06	-4.04
	(1.71)	(-2.80)	(-0.69)	(4.41)	(-1.99)	(-0.64)	(4.16)	(-2.04)	(-2.08)

Table A1: Average Slopes from Monthly Cross-sectional Regressions: Robustness Checks

We run the following cross-sectional regression each month:

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

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), and DD is the distance-to-default. 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 4. 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
$\log MC$	-4.53	-2.24	-0.80	0.95	-6.63	-5.52	-2.90	-2.33
	(-2.25)	(-0.90)	(-0.62)	(0.94)	(-4.20)	(-3.38)	(-1.09)	(-0.47)
$\log B/M$	4.63	3.82	0.97	1.62	1.24	0.77	-2.42	-1.43
	(2.52)	(1.67)	(0.61)	(1.12)	(0.98)	(0.62)	(-0.51)	(-0.21)
R_{eq}(2,12)	6.01	5.06	1.65	1.16	3.80	4.24	-0.56	0.34
	(4.14)	(3.00)	(2.17)	(1.69)	(3.20)	(3.18)	(-0.76)	(-0.33)
R_{eq}(1)	14.11	13.51	2.04	1.33	9.56	9.57	-2.51	-2.61
	(9.08)	(8.56)	(2.88)	(2.45)	(8.82)	(8.49)	(-0.09)	(-0.47)
dA/A	-0.96	-0.74	0.33	0.35	0.38	0.39	1.67	1.48
	(-0.74)	(-0.54)	(0.16)	(0.27)	(0.50)	(0.48)	(1.04)	(1.42)
Y/B	-7.03	-6.31	-1.84	-0.86	-5.26	-5.85	-0.07	-0.40
	(-3.97)	(-3.79)	(-1.52)	(-0.71)	(-4.17)	(-4.32)	(-0.25)	(-0.33)
$NegNS$	7.47	6.78	1.52	1.45	5.73	4.74	-0.22	-0.59
	(4.09)	(3.57)	(1.41)	(1.33)	(4.49)	(3.91)	(-0.89)	(-1.33)

	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
$\log MC$	-3.50	-2.84	0.23	0.35	-3.99	-3.28	-0.26	-0.09
	(-1.98)	(-1.33)	(0.25)	(0.30)	(-2.45)	(-1.76)	(-1.07)	(-0.30)
$\log B/M$	2.71	2.16	-0.95	-0.04	3.67	2.18	0.01	-0.02
	(2.03)	(1.35)	(-1.31)	(-0.03)	(2.64)	(1.34)	(0.09)	(-0.09)
R_{eq}(2,12)	4.01	3.86	-0.35	-0.04	4.15	3.78	-0.21	-0.12
	(2.76)	(2.31)	(-0.37)	(-0.04)	(3.17)	(2.38)	(-1.17)	(-0.62)
$R_{eq}(1)$	11.26	12.03	-0.81	-0.15	12.20	12.24	0.13	0.06
	(7.80)	(8.20)	(-1.02)	(-0.18)	(9.12)	(8.91)	(0.68)	(0.31)
dA/A	-1.18	-1.08	0.11	0.01	-1.41	-1.21	-0.12	-0.12
	(-1.03)	(-1.01)	(0.11)	(0.02)	(-1.25)	(-0.98)	(-0.55)	(-0.48)
Y/B	-3.92	-4.21	1.27	1.24	-5.19	-5.47	0.00	-0.02
	(-2.88)	(-2.94)	(1.65)	(1.05)	(-3.88)	(-4.01)	(0.01)	(-0.11)
$NegNS$	5.51	4.67	-0.44	-0.66	5.79	5.31	-0.16	-0.02
	(3.17)	(2.96)	(-0.39)	(-0.50)	(4.02)	(3.48)	(-0.75)	(-0.09)
$IdioVol$	-2.35	-3.69	1.89	2.07	-4.16	-5.63	0.08	0.13
	(-0.89)	(-1.28)	(1.29)	(1.18)	(-1.89)	(-2.24)	(0.30)	(0.46)

Table A2: Equal-Weighted Average Residuals from the Cross-Sectional Regressions

Equity anomaly variables are described in Table 2. This table shows average residuals in basis points and their t-statistics in parenthesis from monthly cross-sectional equal-weighted regressions to predict bond excess returns. Standard errors are given in parenthesis below the averages. The sample period is 1973 to 2011.

	1	2	3	4	5	6	7	8	9	10	H–L
$\log MC$	2.48	-1.14	0.19	-0.41	-3.84	-3.46	-2.13	-2.87	2.34	9.39	6.91
	(1.67)	(-0.74)	(0.12)	(-0.28)	(-2.90)	(-2.16)	(-1.34)	(-2.34)	(1.83)	(7.06)	(4.36)
$\log B/M$	1.57	0.47	-1.62	-3.37	-1.03	1.24	-0.07	-1.68	-0.39	6.05	4.48
	(1.28)	(0.41)	(-1.13)	(-2.41)	(-0.75)	(0.85)	(-0.05)	(-1.13)	(-0.25)	(3.63)	(3.27)
R_{eq}(2,12)	-2.36	-0.31	0.72	1.37	-0.32	-1.24	-2.8	0.8	1.42	1.4	3.76
	(-1.45)	(-0.20)	(0.54)	(0.76)	(-0.27)	(-0.81)	(-1.99)	(0.61)	(1.20)	(1.09)	(2.13)
R_{eq}(1)	-3.49	4.88	2.88	-0.99	2.45	-0.79	2.27	-3.14	-4.5	0.32	3.81
	(-2.97)	(3.23)	(2.12)	(-0.66)	(1.97)	(-0.53)	(1.77)	(-2.16)	(-3.54)	(0.24)	(2.90)
dA/A	-0.27	1.27	-1.83	0.37	0.2	-5.38	0.26	2.02	-0.06	4.8	5.07
	(-0.15)	(0.93)	(-1.33)	(0.26)	(0.15)	(-3.54)	(0.18)	(1.18)	(-0.04)	(4.12)	(2.50)
Y/B	0.37	-0.14	-1.98	-4.2	-1.87	-2.06	-0.83	1.91	1.63	6.64	6.27
	(0.23)	(-0.08)	(-1.46)	(-2.51)	(-1.35)	(-1.38)	(-0.62)	(1.38)	(1.20)	(4.23)	(3.37)
NS	-9.4	-5.39	6.18	6.06	-1.31	-1.36	0.89	0.13	1.21	3.89	13.3
	(-6.01)	(-3.08)	(3.86)	(3.42)	(-0.86)	(-0.95)	(0.69)	(0.09)	(0.80)	(2.27)	(6.03)
$IdioVol$	-0.96	3.3	-0.77	1.16	-0.68	-1.87	-2.26	-1.26	0.18	3.28	4.24
	(-0.68)	(2.47)	(-0.55)	(0.92)	(-0.59)	(-1.43)	(-1.63)	(-0.79)	(0.10)	(2.78)	(2.57)