# Does Momentum Exist in Bonds of Different Ratings?

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### Abstract

This paper investigates whether momentum exists in the corporate bond market. Instead of relying on the price information from just a single time horizon, we incorporate all trend signals in the short, intermediate and long terms simultaneously. Using this informationally efficient strategy, we uncover for the first time strong and significant momentum for all bonds across ratings. Interestingly, bond momentum earns roughly the same amount of return as stock momentum, but has little correlation with the latter. The effect of bond momentum is robust to various controls of risk factors, bond characteristics, and transaction costs, and is stronger after the establishment of TRACE and during periods with low sentiment or low growth. Overall, momentum appears to be the most pronounced cross-sectional anomaly emerged from the bond market that challenges the existing rational pricing theory of corporate bonds.



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# 1 Introduction

Since the seminal work of Jegadeesh and Titman (1993), it has been well known that in the stock market, winners (losers) over the past six months or a year tend to be winners (losers) over the next six months or a year. Because of its profound implications for asset pricing theory and market efficiency, a vast literature has been developed to study this important issue and to find theoretical reasons.[1] In his comprehensive study of anomalies, Schwert (2003) concludes that the momentum anomaly is one of the most robust and persistent anomalies.

The extant literature of momentum has largely focused on the stock market and much less is known for the corporate bond market, which is in fact larger than the stock market in capitalization and is the primary source of long-term capital in the US. Since corporate bonds and stocks are different claims to the same underlying cash flows of assets and are affected by the fundamentals of the same firms, a question that naturally arises is whether there exists momentum in the corporate bonds market similar to that of the stock market. This question is important not only for pricing corporate bonds and managing portfolios, but also for understanding what really drives momentum. Surprisingly, this issue has not been addressed until fairly recently. Gebhardt, Hvidkjaer and Swaminathan (2005) are the first to investigate this issue and find that there is no momentum in investment-grade bond returns. However, by extending the data sample to high-yield bonds, Jostova, Nikolova, Philipov and Stahel (2013) find evidence of momentum in noninvestment grade bonds. Since the value of high-yield bonds accounts only for about 8% of the corporate bond market, this finding seems not an anomaly as significant as the stock market. A question of fundamental importance that remains unanswered is whether there is momentum in the entire corporate bond market or why only high-yield bonds have momentum.

In this paper, following Haugen and Baker (1996), we estimate the expected bond returns using a cross-sectional regression approach that utilizes multiple price signals. This approach contrasts sharply with the existing procedure that sorts bond returns to form buy and sell portfolios based

[1] For example, the latest number of Google citations of Jegadeesh and Titman (1993) is over 7730.

on only one price signal. Our multiple signals are the price trends of corporate bonds over short-, intermediate- and long-term investment horizons. Following Han, Zhou and Zhu (2015), we use moving averages of prices scaled by the current price at different lags, which are analytically equivalent to bond yields over different investment horizons.[2] A number of studies have provided economic rationales, both theoretically and empirically, for why the moving average returns contain information beyond a single past return (see, for example, Treynor and Ferguson, 1985; Brown and Jennings, 1989; Brock, Lakonishok and LeBaron, 1992; Hong and Stein, 1999; Lo, Mamaysky and Wang, 2000; Fung and Hsieh, 2001; Cespa and Vives, 2012). Since our procedure uses the trend signals across different return horizons simultaneously in a unified framework, it has much higher power to detect momentum not captured by the conventional one-signal sorting approach.

Using a comprehensive sample of corporate bonds over a long span, we construct the momentum portfolio in the standard way as the traditional spread portfolio of buying bonds with the highest expected returns (the first decile) and shorting those with the lowest expected returns (the last decile). Using this momentum strategy, we document several important findings for the corporate bond market. First, we find strong evidence of momentum not only in speculative-grade bonds but also in investment-grade bonds in every rating category. For clarity, we will name the momentum detected by our method as *trend* momentum as trend signals are used, while referring to what identified by the conventional method simply as momentum. While no existing studies were able to discover momentum profits for investment-grade bonds, we find that the trend momentum profits range from 124 basis points for AAA bonds to 143 basis points for BBB bonds. In addition, although Jostova et al. (2013) detect a momentum profit of 121 basis points per month for speculative-grade bonds, we find a trend momentum profit of 158 points.

Second, the trend momentum effect is stronger for bonds with a lower rating. Consistent with the findings in the equity market (Avramov, Chordia, Jostova and Philipov, 2007, 2013), our results show that credit risk plays a critical role in driving the momentum effect in the corporate bond

[2]While Han, Zhou and Zhu (2015) is the first to use such moving averages to forecast stock returns, we are the first to apply them in the context of corporate bonds.

market. However, we find that momentum profits are not exclusively derived from taking the short position in the worst-rated bonds. Furthermore, the trend momentum effect depends on bond characteristics. It tends to be stronger for newer bonds with smaller issue size, and higher coupon rates and yields. While bond characteristics matter, overall the trend momentum effect is robust to the controls for the effects of these characteristics in out-of-sample forecasts.

Third, the trend momentum effect varies over time. The trend momentum is stronger after TRACE (the Trade Reporting and Compliance Engine) was established to improve dissemination of trading information in the corporate bond market. This finding suggests that availability of trading information increases cross-sectional predictability of corporate bond returns. Also, the trend momentum effect is stronger in the period of low market sentiment and slow economic growth. The increase in the trend momentum effect over these periods is much larger for speculative-grade bonds.

Fourth, the trend momentum effect cannot be explained by standard risk factors, bond characteristics and transaction costs, and the unexplained trend portfolio returns are higher for speculative-grade bonds. Including the information for bond characteristics does not help to improve cross-sectional bond return prediction either. There are over 80 cross-section anomalies in the stock market (see, e.g., Hou, Xue and Zhang, 2015). Although Jostova et al. (2013) discovers first the momentum effect for speculative-grade bonds, the effect is small in the entire market and much of it, as discussed in their paper, can be potentially explained by the gradual diffusion of information story of Hong and Stein (1999). But that explanation does not apply to large and more transparent firms. Recently, Choi and Kim (2016) and Chordia, Goyal, Nozawa, Subramanyam and Tong (2016) document limited evidence of corporate bond return anomaly using stock variables, while Bai, Bali and Wen (2016) shows that the distributional characteristics of corporate bonds are powerful determinants of the cross-sectional differences in future corporate bond returns. Our trend momentum returns are much stronger than those reported in the literature. Therefore, the trend anomaly appears truly the strongest cross-section anomaly in the corporate bond market. Our empirical results clearly challenge existing bond pricing theory which does not allow the possibility of cross-section predictability.

Our paper is about cross-sectional predictability of corporate bond returns. This is different from literature of time-series predictability that explains the time-varying bond risk premia. For example, Keim and Stambaugh (1986) present the first major study on predicting corporate bond returns. Fama and French (1989) find that default spreads, term spreads and dividend yields are valuable predictors of corporate bond returns. Later on, Greenwood and Hanson (2013) and Lin, Wang and Wu (2014) identify issuer quality and liquidity and forward rate factors, separately, as useful predictors for corporate bond returns. Lin, Wu and Zhou (2016) propose an iterated combination approach to a large set of predictors and find that this approach significantly improves the forecasting performance. Cross-sectional predictability and time-series predictability are quite different, but both provide valuable insights into understanding corproate bond market.

The remainder of the paper is organized as follows. Section 2 presents empirical methodology and Section 3 discusses the data. Section 4 reports empirical results for trend momentum, assesses the robustness of momentum effect to bond characteristics and traditional momentum, and performs subperiod analysis. Section 5 examines whether the trend momentum effect can be explained by standard risk factors and bond characteristics. Section 6 investigates the robustness of trend momentum to transaction cost and evaluates the predictive power of bond characteristics. We compare the effects of stock and bond trend momentum and assess the trend momentum effect of bonds issued by public firms. Additionally, we investigate the issue of whether there is a trend momentum spillover from stocks to bonds. Finally, Section 7 summarizes our major findings and concludes the paper.

# 2 Methodology

The key idea behind our empirical methodology is to obtain useful information from the past and current data to form the optimal momentum strategies. To achieve this goal, we extract multiple price signals based on moving averages of past prices. The literature has shown that moving averages (MAs) of past prices have predictive power on asset returns. The predictive power of MA trends can be due to differences in the timing of receiving information and differences in the response to information by heterogeneous investors, behavior biases or feedback trading.

To ensure that we capture all past important information at every possible time length, we use the moving averages of past prices from short to long horizons to draw price signals. More specifically, the signals can be extracted from the moving averages of past prices from one month to four years to capture the information in the short-, intermediate- and long-term price trends. The moving averages (MAs) constructed over various time horizons enable us to retrieve all potentially useful information in the past to form optimal momentum strategies. After constructing moving averages, we run a cross-sectional regression of bond returns on the MA signals at different lags. This cross-sectional regression scheme enables us to obtain a weighted average of MA signals to come up with an optimal forecaster to predict cross-sectional bond returns.

To form momentum strategies based on trend signals, we first calculate the moving average (MA) yield each month. The MA of lag $L$ in month $t$ for bond $j$ is defined as

$$MA_{jt,L} = \frac{Y_j^{t-L+1} + Y_j^{t-L+2} + ... + Y_j^t}{L} \tag{1}$$

where $Y_j^t$ is the closing yield for bond $j$ on month $t$ and $L$ is the lag length. We construct the moving average signal based on bond yields rather than prices for several reasons. First, almost all conventional fixed-income pricing, market timing and trading decisions on sector or issue basis begin with some sort of yield analysis. Second, yields provide market participants a nice summary figure for comparing different bonds. Cash flows are not directly comparable in any simple way and so are prices which depend on cash flows and are hence subject to the scale or size effect. Third, bond prices are nonstationary, which complicates the empirical analysis based on the time series of observed prices. Last, it has been shown in the literature that past and current yields contain substantial information for future bond returns (see Lin, Wang and Wu, 2014; Joslin, Priebsch and Singleton, 2014). Thus, from a cross-sectional forecasting perspective, it is important to make good use of this valuable information in bond return predictions.

We use a two-step estimation procedure to predict monthly expected bond returns cross-sectionally. In the first step, we run the following cross-sectional regression of bond returns on the MAs to obtain the time-series of the coefficients on the moving average signals:

$$r_{j,t} = \beta_{0,t} + \sum_i \beta_{i,t} MA_{jt-1,L_i} + \varepsilon_{j,t}, j = 1,...,n \tag{2}$$

where $MA_{jt-1,L_i}$ is the trend signal at the end of month $t-1$ on bond $j$ with lag $L_i$, $\beta_{i,t}$ is the coefficient of the trend signal with lag $L_i$ in month $t$, $\beta_{0,t}$ is the intercept, $r_{j,t}$ is bond returns and $n$ is the number of bonds. In this cross-sectional regression, only the past information is used on the right hand side. We consider the MAs of lag lengths 1-, 3-, 6-, 12-, 24-, 36-, 48-, and 60-months in month $t-1$. These MA signals capture the price trends of bonds from the short to long horizons. The betas obtained from the above regression reflect the correlations between the past MA signals and future returns. The strength of correlation determines the relative importance of MA signals at different lags calculated in month $t-1$ in forming expectations in month $t$ to predict returns in month $t+1$.

In the second-step, we estimate the bond's expected return in month $t+1$ by

$$E_t[r_{j,t+1}] = \sum_i E_t[\beta_{i,t+1}] MA_{jt,L_i}, \tag{3}$$

where $E_t[r_{j,t+1}]$ is bond $j$'s expected return for month $t+1$, and $E_t[\beta_{i,t+1}]$ is the estimated expected coefficient of the trend signal with lag $L_i$ which is given by

$$E_t[\beta_{i,t+1}] = \frac{1}{12} \sum_{m=1}^{12} \beta_{i,t+1-m}. \tag{4}$$

That is, we use the average of estimated loadings on a trend signal at particular lag $i$ over the past 12 months as the expected coefficient for the next month. We do not include an intercept in the above formulation as it is the same for all bonds in the cross-sectional regression and thus not useful in ranking the bonds as discussed below. Also, since only the information available in month $t$ is used to forecast the return in month $t+1$, this is completely an out-of-sample analysis.

We then sort all bonds into quintile portfolios by their expected returns. We construct the equal-weighted portfolio and rebalance it each month. These portfolios are called trend portfolios as they are formed by the past trend or moving average signals. Portfolio returns are calculated for each month. The return difference between the last quintile portfolio with the highest expected returns (H) and the first quintile portfolio with the lowest expected return is referred to as the return on the trend factor in a way similar to the construction of the traditional momentum factor in the literature. By construction, the trend factor portfolio longs bonds with the highest expected returns and shorts bonds with the lowest expected returns. This sorting approach is similar to the conventional momentum portfolio analysis of Jegadeesh and Titman (1993), Gebhardt, Hvidkjaer and Swaminathan (2005a, 2005b), Jostova, Nikolova, Philipov, and Stahel (2013), among many others. The main difference is that instead of sorting assets by firm/bond characteristics or the past return in a fixed horizon, we sort bonds by their expected returns which are forecast by the moving average signals. In particular, the standard momentum factor can be viewed as the degenerated case of our trend factor under the constraint that there is only one trend signal, i.e., the past one-year (or six-month) return, and the beta coefficient is equal to one. Thus, our trend portfolio analysis is more general and can potentially capture important information for the predictive return components in the short, intermediate and long terms.

# 3 Data

Corporate bond data are from several sources: the Lehman Brothers Fixed Income (LBFI) database, Datastream, the National Association of Insurance Commissioners (NAIC) database, the Trade Reporting and Compliance Engine (TRACE) database and Mergent's Fixed Investment Securities Database (FISD). The LBFI database covers monthly data for corporate bond issues from January 1973 to March 1998. The data include month-end prices, accrued interest, rating, issue date, maturity and other bond characteristics. Datastream reports the daily corporate bond price averaged across all dealers for that bond on a given day. We choose US dollar-denominated bonds with regular coupons and obtain the data up to September 2015.

NAIC and TRACE databases contain corporate bond transaction data. The TRACE coverage begins in July 2002 while the NAIC data start from January 1994. TRACE initially covers only a subset of corporate bonds traded in the over-the-counter market and we supplement it by the NAIC dataset, which covers transactions primarily by insurance companies.[3] FISD provides issue- and issuer-specific data such as coupon rates, issue date, maturity date, issue amount, ratings, provisions and other bond characteristics. We merge data from all sources. To avoid overlapping data, we keep only one return record if the same bond is covered in different databases. We discard Datastream data whenever bond data are available from other sources. Also, when both transaction and non-transaction data are available, we opt for the transaction-based data.

We construct monthly returns from the data other than LBFI which has already provided monthly returns. Month-end prices are used to calculate monthly returns. The monthly corporate bond return as of time $t$ is

$$r_t = \frac{(P_t + AI_t) + C_t - (P_{t-1} + AI_{t-1})}{P_{t-1} + AI_{t-1}}, \tag{5}$$

where $P_t$ is the bond price, $AI_t$ is accrued interest and $C_t$ is the coupon payment, if any, in month $t$.[4] We exclude bonds with maturity less than one year and longer than 30 years and bonds with a floater or odd frequency of coupon payments. We use primarily the Moody's rating but if it is unavailable, we use the Standard and Poor's rating when possible. The sample period is from January 1973 to September 2015.[5]

[3]The procedure of Bessembinder, Kahle, Maxwell and Xu (2009) is used to filter out canceled, corrected and commission trades and daily prices are trade size-weighted average of intraday prices over the day.

[4] This return is transformed to the log return in the forecast, so that monthly log returns could be added together to get a return of longer horizon conveniently.

[5]We screen data by deleting the observations with prices more than 150 or less than 50. We use the last available price if there is no transaction on the last day of each month. We drop the data if last trade is is more than six months away from the current trade.

Table 1 summarizes the data by rating, maturity and source. In terms of ratings, A-rated bonds account for the largest proportion of data observations. The distribution by maturity is fairly even, with bonds with maturity less or equal to 5 years accounting for the highest proportion of the sample. Among the four data sources, TRACE contributes the most to the entire sample, followed by LBFI, Datastream, and NAIC. The sample consists of a wide dispersion of credit quality which facilitates analysis of momentum effects across different ratings. We next turn to empirical tests.

[Insert Table 1 here]

# 4 Empirical results

## 4.1 Trend portfolio returns and characteristics

Panel A of Table 2 reports the returns of quintile portfolios for the one-month holding horizon. Low (L) represents the portfolio of bonds with the lowest expected returns, and High (H) is the portfolio of bonds with the highest expected returns. The results clearly show that the bonds with high expected return based on the MA signals have high returns ex post. The return differences between High and Low (H-L) portfolios are all significant. For example, for the sample including all bonds (first row), the H-L (trend factor) return is 0.97%, which is significant at the 1% level ($t$ = 8.12). [6] The bonds included in the high quintile portfolio consist of more low-grade bonds. Unreported results show high quintile portfolio has more junk bonds (12.63%) than the low quintile portfolio (9.29%). Results imply that high returns in the High portfolio are partly driven by risky bonds.

To see the results for different rated bonds, we perform portfolio sorts by rating. Results show that MA or trend signals have high predictive power for cross-sectional returns across all ratings. A distinct pattern is that the H-L return difference is higher for low-grade bonds than for high-grade

[6] We use Newey-West (1987) standard error when calculating the $t$-stats of three months and six months to account for data overlapping issue.

bonds. The H-L return differences range from 0.85% for AAA bonds to 1.21% for junk bonds, all significant at the one percent level. The return spread increases as the rating decreases. The difference between the H-L returns of junk and AAA bonds is 0.36%, which is significant at the 5% level.

To make our results more comparable to Jostova et al. (2013), we also sort the bonds into deciles. Panel B of Table 2 reports the results of decile portfolio. The H-L returns are higher than those reported in Panel A, which show a stronger trend effect for finer portfolio sorts. Consistent with previous findings for bond momentum (Jostova et al., 2013), we find momentum in speculative-grade bonds. However, the momentum effect captured by our trend momentum strategy is much stronger than that previously documented by the traditional momentum method. Using the traditional momentum strategy based solely on the price information in the past six months, Jostova et al. (2013) report a momentum profit estimate of 121 basis points for non-investment grade bonds. In contrast, by forming portfolios based on multiple price signals in the short, intermediate and long terms, we find a much larger momentum effect with a profit of 158 basis points for one-month holding period for speculative-grade bonds, which is more than 25% higher than their estimate. The higher momentum profits generated from our momentum strategy suggest that past prices in the short and long terms contain additional useful information for cross-sectional return predictions beyond that in the intermediate term of 6 months. The trend factor formed by multiple price signals contain additional important information and thus significantly improves momentum profits.

The advantage of using the trend momentum strategy is even more apparent when comparing with previous momentum studies for investment-grade bonds. Gebhardt, Hvidkjaer and Swaminathan (2005b) find no evidence of momentum in investment-grade bond returns. Using more recent data, Jostova et al. (2013) report the momentum profit of only 10 basis points per month for investment-grade bonds, which is also statistically insignificant. In contrast, we find strong evidence of momentum in investment-grade bonds. The trend momentum profit averages 124 basis points for the one-month holding period, which are only a little below the momentum profit of speculative-grade bonds. Results show substantial economic gains by combining all useful information across short, intermediate and long horizons in forming momentum strategies. By incorporating simultaneously all past price information at different investment horizons, we uncover for the first time significant trend momentum in investment-grade bonds. Results show that momentum effects are pervasive in the corporate bond market, not just limited to a small subset of high-yield bonds.

Importantly, our evidence suggests that credit risk plays a role in momentum of corporate bond returns. As shown in Panel B of Table 2, momentum profits increase monotonically as the rating decreases. The importance of credit risk for momentum strategies is consistent with the findings in the equity market (see Avramov et al., 2007, 2013). However, unlike previous findings that momentum concentrates in the stocks and bonds with junk ratings, our results show a different picture. In particular, trend momentum does not concentrate in the bonds with speculative grades in the Low portfolio. Unreported results show the proportion of junk bonds in the Low portfolio is only 9.29% and investment-grade bonds account for the remaining 90.71%. In contrast, the proportion of junk bonds is 21.92 in the High portfolio, which is significantly higher than that in the Low portfolio. There is no evidence that the Low trend portfolio contain more junk bonds than other trend portfolios. Thus, trend momentum profits are not derived primarily from shorting the worst-rated bonds.

In stark contrast to previous studies, we find that momentum is everywhere in the corporate bond market, not just concentrating in the worst-rated bonds. Another important finding in our study is that the profits of momentum strategies are not deriving predominantly from taking short positions in high credit risk firms that experience deteriorating credit conditions. Quite contrary, the results in Table 2 show just the opposite: both the high trend momentum portfolio and low trend momentum portfolio have positive returns. The trend momentum strategies do involve taking a long position in the high-momentum bonds and shorting a position in the low-momentum bonds but the profits are derived primarily from the long position, instead of the short position. This pattern holds not just for high-grade bonds but also for the worst-rated bonds.

[Insert Table 2]

We next compare our portfolio returns with those reported in Chordia, et al. (2016), Choi and Kim (2016) and Bai, Bali and Wen (2016). Sorting all bonds into deciles using size, asset growth, profitability and distance to default, Chordia, et al. (2016) report the H-L portfolio returns of -0.41%, -0.19%, -0.14% and -0.42%, respectively. Separately, Choi and Kim (2016) report -0.32%, -0.24%, and 0.21%, respectively for the equal-weighted H-L portfolios sorted by asset growth, investment, and book-to-market ratio. In contrast, our portfolios sorted by MA signals in Panel B of Table 2 generate much larger return spreads than these studies. Bai, Bali and Wen (2016) sort corporate bond into quintiles based on the 60-month rolling estimates of variance, skewness and kurtosis, and report the H-L portfolio returns of 0.64%, -0.24% and 0.37%, respectively. Our results in Panel A of Table 2 based on the quintile portfolios are also much stronger than their high-low portfolio return spreads.[7]

Figure 1 plots the time series of returns for the trend factor (H-L) over the entire sample period. It shows that trend momentum effects are quite stable over the sample period. Moreover, the trend momentum exhibits similar patterns across bonds of different ratings. Results again clearly show that the trend momentum is pervasive, not just limited to a particular rating class. Unlike the negative returns of stock momentum strategies documented by a number of studies during the crisis period (e.g., Daniel, Jagannathan and Kim, 2012; Barroso and Santa-Clara, 2015), the trend factor has relatively high positive returns in this period. Thus, the bond market does not exhibit a ”momentum crash” as in the stock market.

Does the trend portfolio exhibit particular characteristics? We answer this question by summarizing the bond characteristics in each trend portfolio. Table 3 reports the characteristics of trend portfolios, including bond issuance size, age, coupon rate, and the moving average of yields in the last one and six months. For the whole sample (All), the portfolios with high expected bond returns tend to be associated with firms with smaller issue size and newer (younger) bonds. These

[7]In order to test whether the trend momentum is robust of the firm variables, we re-run the trend momentum analysis controlling for these variables in section 7.

portfolios also tend to have higher coupon rates and historical yields. Most of the differences in the characteristics between High and Low portfolios (H-L) have values significant at the conventional level. Turning to the results by rating, some interesting patterns emerge. For issue size and age, the differences in these characteristics between high and low trend portfolios tend to decline as the rating decreases, For example, for AAA bonds, the spreads (or dispersion) in issue size and age is highest in absolute value. In contrast, the spreads in average bond yields at last one and six months between High and Low trend portfolios tend to increase as the rating decreases. On the other hand, the pattern of H-L spreads in coupon rates show no clear pattern.

In summary, bond returns show significant trend momentum and trend portfolios exhibit different characteristics. High trend momentum portfolios have more bonds with higher yields and coupon rates, lower issuance amount and younger age. By incorporating the trend signals over short, intermediate and long terms, we find that bond portfolios with high (forecast) expected returns consistently earn high future returns. Results show that trend signals at various time horizons provide important information for forecasting future bond returns.

[Insert Table 3 here]

## 4.2 Trend portfolio and bond momentum

An interesting question is whether the predictability by moving averages is driven by the conventional bond momentum. To see whether bond momentum is the driver of this cross-sectional predictability, we perform two types of analysis. The first analysis is to investigate the composition of trend portfolios. If bond momentum (e.g., at six-month horizon) is the driving force behind the predictability, then we shall observe that a large proportion of bonds in the High (Low) portfolio have high (low) historical bond returns in the past six months. The second analysis is to check if trend momentum persists even after controlling for the conventional bond momentum effect. If the trend momentum persists after controlling for bond momentum, then the latter will unlikely be the driver of the former.

Table 4 reports the distribution of bonds in each trend portfolio based on the past six-month returns. We divide the bonds by their past six-month returns into quintiles (Loser, 2, Medium, 4 and Winner portfolios). We then calculate the percentage of bonds in each trend portfolios that fall in each bond momentum quintile. The results show that bond momentum is not a factor driving the cross-sectional return predictability. There is no evidence that the High trend portfolio has a larger percentage of bonds that fall in the Winner group, and the Low trend portfolio has a larger percentage of bonds in the Loser group. In fact, we find that bonds in the High trend portfolio tend to have low past returns, whereas the bonds in the Low trend portfolio tend to have high past returns. Results by rating are similar with a somewhat polarized pattern for the AAA and junk bonds. Thus, conventional bond momentum does not appear to be the source of cross-sectional return predictability uncovered by the trend momentum strategy.

[Insert Table 4]

The second analysis employs a double-sorting portfolio approach. We first sort bonds into quintiles (Loser, 2, Medium, 4 and Winner) based on the past six-month returns. Then in each of these quintile portfolios, we further sort bonds into quintiles based on the expected returns forecast by MA signals. The intersection of momentum and expected return sorts results in 25 (5 x 5) portfolios. If the conventional bond momentum overlaps with trend momentum, the return difference between High and Low trend portfolios should become insignificant after the past bond return, or the effect of bond momentum, is controlled. Conversely, if the return difference between High and Low trend portfolios remains significant after the past return is controlled, it would suggest that MA signals provide independent information important for the cross-sectional predictability of corporate bond returns.

Table 5 reports the results of bivariate sorts for the monthly horizon. For the interest of brevity, we only report the distribution of trend momentum portfolios for loser (Low), winner (High) and medium momentum groups. Results show that the H-L trend portfolio return remains highly significant even after controlling for the momentum effect. For example, for the sample that includes all bonds, the H-L returns are 0.92%, 0.47% and 0.77% respectively for Loser, Medium and Winner groups, all significant at the 1% level. The significance of H-L return differences is clearly robust to the control of past bond momentum returns. Results again suggest that conventional bond momentum is not a source of predictability uncovered by the trend momentum strategy.

We also report the results of bivariate portfolio sorts by rating in Table 5. Results show all H-L returns are highly significant across ratings. Controlling for the effect of bond momentum, the H-L trend portfolio returns are higher for low-grade bonds than for high-grade bonds, indicating that trend momentum is higher for the former. The relation between the trend momentum effect and credit risk remains strong even after controlling for the effect of conventional bond momentum.

In the bivariate sort, given a trend portfolio, there are five momentum quintile portfolios. By construction, each trend portfolio has an identical distribution of bonds in momentum portfolios. We calculate the trend portfolio return by averaging across all five momentum portfolios. The resulting trend portfolios have perfect control for the momentum effect because each trend portfolio has an identical distribution of bonds with different past returns (price momentum). The bottom of Table 5 reports the results of trend portfolio returns after averaging across bond momentum portfolios. Results continue to show significant trend momentum even after controlling for the effect of bond momentum. The H-L trend portfolio returns are all highly significant for the whole sample as well as for each rating category. For example, the spread of the H-L portfolio returns is 64 bps which is significant at the one percent level for the sample that includes all bonds. Moreover, the H-L returns increase as the rating decreases for the results by rating. Results show that the pattern of trend momentum is not derived from the conventional bond momentum.

[Insert Table 5]

## 4.3 Trend portfolios with different holding horizons

To examine the sensitivity of results to different holding horizons, we calculate momentum returns for three-month $[t+1, t+3]$ and six-months $[t+1, t+6]$ holding horizons. Table 6 reports the results for these horizons. Results continue to show significant cross-sectional predictability by moving averages over these holding horizons. The trend factor (H-L) returns are overwhelmingly significant. For the sample including all bonds, the H-L returns of $[t+1,t+3]$ and $[t+1,t+6]$ are 44 and 24 basis points per month respectively, all significant at the 1% level. Thus, the significance of trend portfolio returns is robust to different return horizons.

Turning to the results of different ratings, we find significant trend momentum across all ratings at different horizons. Again, lower-grade bonds tend to have higher trend momentum than high-grade bonds. For AAA bonds, the H-L spread is 37 and 23 basis points per month for the three- and six-month holding periods, respectively. For junk bonds, the corresponding returns are 52 and 31 basis points, which are about 40% and 35% higher. The differences in the H-L returns between junk and AAA bonds are significant at the 1% level for three month holding horizons, indicating that the low-grade bonds have significantly higher trend momentum than the high-grade bonds.

[Insert Table 6]

## 4.4 Trend portfolio and bond characteristics

The analysis above shows that the trend portfolios have different bond characteristics (see Table 2). This raises a concern that trend portfolio returns may simply reflect the effects of bond characteristics. To address this concern, we follow a double-sorting approach similar to the momentum diagnosis above to control for the effects of bond characteristics. In each month, we first sort bonds into quintiles by a bond characteristic and then further sort bonds in each quintile into five trend portfolios to construct 25 portfolios at the interaction of characteristics and expected return rankings. We consider four bond characteristics: bond issue size, age, coupon rate and average past yield from month $t-6$ to $t-1$.

Table 7 reports the results of bivariate portfolio sorts. For brevity, we report the results of H-L returns only. The first three panels (upper) report H-L trend portfolio returns for low, medium and high characteristic groups. Results strongly show that MA signals predict corporate bond returns cross-sectionally even after controlling for the effects of bond characteristics. The H-L returns are all significantly positive for the whole sample and across bond ratings. When the effect of issue size is controlled, H-L returns are higher among the bonds with small issue size. For the full sample that includes all bonds, the return of H-L is 1.14% for the small bond issues, while it is only 0.69% for the large bond issues. The results for different ratings show a similar patterns of issue size effect. Within each size group (small, medium and large), the H-L return tends to increase as the rating decreases, consistent with the results in previous tables. The remaining three column report results associated with bond age, coupon rate and past yields. Results show a similar pattern in that H-L spreads are higher for low-grade bonds. The returns of H-L are also all highly significant and quite stable for portfolio sorts based on these characteristics.

The bottom of Table 7 reports the H-L trend portfolio returns, averaged across quintile characteristic portfolios, for the sample as a whole and for each rating category. These trend portfolios again contain identical distribution of characteristics and hence are completely controlled for their effects. Results continue to show highly significant H-L trend portfolio returns across the board. The trend momentum effect persists even after controlling for the effects of characteristics and this effect is stronger as the rating decreases. Thus, there is strong evidence that trend momentum is robust to controls for bond characteristics.

[Insert Table 7]

## 4.5 Subperiod analysis

Previous studies in the equity market have shown that the momentum effect varies over time. An important issue then is whether the cross-sectional bond return prediction or trend momentum is sensitive to different subperiods. To address this issue, we investigate the behavior of trend momentum profits for different subperiods. We first divide the sample into three subperiods using the two important events associated with disseminating corporate bond trading data as the cutoffs. One is January 1994 when NAIC started reporting bond transactions by insurance companies, and the other is July 2002 when TRACE was established. As an improvement in the reporting system increases the transparency of corporate bond market and makes trading data more readily available, they could enhance cross-sectional predictability of bond returns using past price information.

The left column of Table 8 reports H-L returns for the three subperiods. Results show that the initiation of TRACE has the largest impact on cross-sectional return predictability. As shown, the returns of H-L portfolios are much higher in the third subperiod compared with those in the first subperiod. For the full sample including all bonds, the H-L return in the first subperiod is only 0.59% with a $t$-value of 2.79, while it is 1.60% with a $t$-value of 8.25 in the third subperiod. Results show that introducing TRACE significantly increases cross-sectional return predictability of corporate bond returns. The TRACE disclosure increases return predictability for each rating category while its impacts are larger for lower-grade bonds (e.g., BBB and junk), which implies a greater benefit of information disclosure for risky bonds. One possible reason for higher return predictability of low-grade bonds is that TRACE improves the data coverage over time and the improvement is greater for these bonds.

The literature has shown that investor sentiment affects return predictability. Baker and Wurgler (2006, 2007) find that high investor sentiment predicts low returns in the cross section for stocks that are speculative and hard to arbitrage. Stambaugh, Yu, and Yuan (2012) find that investor sentiment is a strong predictor for the short leg of long-short investment strategies. Baker, Wurgler and Yuan (2012) document international evidence that investor sentiment has high power for forecasting stock returns. Huang, Jiang, Tu and Zhou (2015) find that investor sentiment is a powerful predictor for US stock market returns. These findings suggest that investment sentiment can drive the cross-sectional predictability of returns. In light of this literature, we examine whether investor sentiment play a role in trend momentum in the cross section of bond returns.

We divide the whole sample period into three subperiods using the popular investor sentiment indexes proposed by Baker and Wurgler (2006, 2007, BW). The results in Table 8 show that cross-sectional predictability is more pronounced in the period of low investor sentiment. For example, the return of H-L portfolio for the sample including all bonds is 1.18% with a $t$-value of 4.81 in the low sentiment subperiod. It drops to 0.92% with a $t$-value of 4.62 in the high sentiment subperiod. When we divide the full sample of bonds into different ratings, we find that the pattern for the overall impact of market sentiment is similar across ratings but within each sentiment regime, the H-L returns are larger for lower-grade bonds, suggesting that trend momentum is significantly higher for these bonds, particularly when market sentiment is low. As a example, the return of H-L is 1.59% for BBB bonds in the period of low investor sentiment and only 0.76% in the low sentiment period. Results show a temporal variation in the cross-sectional predictability that depends on the market investor sentiment.

The literature has also shown that return predictability change with macroeconomic conditions. Returns tend to be more predictable in bad economy than in good economy (see Rapach, Strauss and Zhou, 2010). There is also substantial evidence that macroeconomic fundamentals are the driving force for time variations in risk premiums and return predictability (Lin, Wu and Zhou, 2016). To see if macroeconomic conditions play a role in trend momentum, we next examine the relationship between cross-sectional predictability and macroeconomic conditions.

We divide the sample into three subperiods using the smooth recession probability (SRP) of Chauvet (1998) and the real GDP growth rate reported by the Federal Reserve Bank at St. Louis. The smooth recession probability is estimated by a dynamic Markov-switching factor model of Chauvet (1998) using monthly coincident indexes of non-farm payroll employment, industrial production, real personal income, and real manufacturing and trade sales. The last two columns of Table 8 reports the results. For the sample including all bonds, the H-L returns for the high recession probability period and low-growth period are 1.11% and 1.21% respectively, which are substantially higher than those for the low recession probability and high-growth period (0.84% and 0.83% respectively). All H-L spreads are significant at the one percent level. The results by rating show a similar pattern, other than that cross-sectional return predictability is higher for lower-grade bonds across the board. Results suggest that cross-sectional return predictability by MA signals is stronger when economic growth is low. This evidence is consistent with the findings of time-series return predictability studies that asset returns are more predictable when economic conditions are poor (see Rapach, Strauss and Zhou, 2010; Lin, Wu and Zhou, 2015).

[Insert Table 8]

# 5 Regression analysis

While the portfolio analysis provides intuitive insights for return predictability, the regression approach allows us to accommodate effects of more characteristics or signals and have better multiple controls. It also allows us to assess the relative importance of different characteristics. In this section, we conduct regression analysis for trend momentum. We first run time-series regressions to test whether the returns of trend portfolios can be explained by systematic risk factors suggested in the asset pricing literature. We then explore the role of MA signals in the cross-sectional predictability of corporate bond returns by controlling for the effects of multiple characteristic variables.

## 5.1 Time-series regressions

We begin by examining whether the momentum portfolios formed by MA signals consistently earn abnormal returns. In this analysis, we run the time-series regressions of these portfolios' excess returns on different factors and test the significance of the intercept,

$$r^e_{p,t} = \alpha_p + \beta_{\mathbf{p}}^{'}\mathbf{F_t} + e_{p,t}, \tag{6}$$

where $r^e_{p,t} = r_{p,t} - r_{f,t}$ is the trend portfolio's excess return over the risk-free rate or the trend strategy return $r^e_{p,t} = r_{H,t} - r_{L,t}$, $\mathbf{F_t}$ is a vector of risk factors, and the intercept, $\alpha_p$, measures the risk-adjusted return. A significant $\alpha_p$ suggests that the risk factors cannot explain away the excess returns of trend portfolios. We consider eight different sets of explanatory variables for $\mathbf{F_t}$:

(1) $mTERM$;

(2) $mDEF$;

(3) $mTERM, mDEF$;

(4) $MKT, SMB, HML$;

(5) $MKT, SMB, HML, MOM$;

(6) $mTERM, mDEF, MKT, SMB, HML$;

(7)$mTERM, mDEF, MKT, SMB, HML, MOM$;

(8) $\Delta TERM, \Delta DEF, MKT, SMB, HML, MOM$;

$MKT, SMB, HML$ are the returns of the market, size, and book-to-market factors of Fama and French (1993). $MOM$ is the momentum factor of Carhart (1997). $TERM_t$ is the difference between long-term government bond yield and Treasury bill rate. $DEF_t$ is the difference between BAA and AAA corporate bond yields. We also try differenced factors as explanatory variables. $\Delta TERM_t = (TERM_t - TERM_{t-1})$ and $\Delta DEF_t = (DEF_t - DEF_{t-1})$. $mTERM_t = \Delta TERM_t/(1 + TERM_{t-1})$, $mDEF_t = \Delta DEF_t/(1 + DEF_{t-1})$. The data for these risk factors are from Amit Goyal and Kenneth R. French's websites. Similar variables are used by Jostova et al. (2013) to examine the effects of systematic risk factors on bond momentum portfolio returns.

Table 9 reports alphas of time-series regressions. Panels A and B report the results for the whole sample and by rating, respectively. Results clearly show that the risk-adjusted returns of Low portfolios are all negative, while those of High portfolios are all positive. The $\alpha_p$'s of H-L portfolios are all positive and highly significant with large $t$-values. Results suggest that the returns of trend portfolios, H-L, cannot be explained by standard risk factors. Introducing more factors improves the explanatory power of the model but does not help reduce alpha values.

Panel B reports regression results by bond rating. The H-L portfolio alphas are again all highly significant across ratings. Results show that a considerable proportion of the trend portfolio return is unexplained by standard risk factors. Alphas of H-L portfolios tend to increase as the rating decreases. Overall, results show that trend portfolio returns or momentum profits cannot be explained by systematic risk factors and the unexplained excess returns tend to be larger for lower-grade bonds.

[Insert Table 9]

## 5.2 Cross-sectional regressions

To investigate the robustness of the return predictability by MA signals, we run cross-sectional regressions to control for the effects of other variables using the Fama-MacBeth (1973) method. The cross-sectional regression gives better controls for the effects of multiple characteristic variables. We regress monthly returns of individual corporate bonds on the expected returns predicted by MA signals and other bond-specific variables,

$$r_{j.t+1} = z_0 + z_1 E_t[r_{j,t+1}] + \sum_{k=1}^{m} f_k B_{j,kt} + \varepsilon_{j,t+1}, \tag{7}$$

where $E_t[r_{j,t+1}]$ is the return of bond $j$ forecast by MA signals, and $B_{j,kt}, k = 1, ..., m$ are bond characteristic variables. Following Shanken and Zhou (2007), we use weighted least square (WLS) in the first step.[8] The weights used are the inverse of variance of corporate bond returns estimated using the whole sample data. We consider six models with different explanatory variables in the regression,

(1) No bond-specific variable;

(2) Bond issue size;

(3) Issue size and age;

(4) Issue size, age and coupon rate;

(5) Issue size, age, coupon rate and moving average yields of past six months ($MA_{jt-1,6}$);

(6) Issue size, age, coupon rate, $MA_{jt-1,6}$ and average bond returns of past six months.

[8] We also tried ordinary least square (OLS) and found the results are robust.

Table 10 reports the results of Fama-MacBeth regressions. For brevity, we only report the estimates of $z_1$ which is of primary interest. Results show $z_1$ has a significant and positive coefficient, suggesting that the MA signals have predictive power for future corporate bond returns cross-sectionally. The predictive power of MA signals are robust to controls of bond characteristic variables. As shown, $z_1$ remains significant in model (6) that uses all control variables. Moreover, $z_1$ tend to increase as the rating decreases. The larger $z_1$ for lower-grade bonds is consistent with the finding in the portfolio analysis earlier that momentum strategies based on MA signals are more profitable for low-grade bonds.

Bond-specific variables help explain returns cross-sectionally. When no bond-specific variable is used (model (1)), the adjusted R square is only 20.91% for the sample that includes all bonds. It gradually increases and reaches 41.92% when all characteristic variables are used. Results (omitted for brevity) show that $MA_{jt-1,6}$ and past bond returns can predict the bond returns in the next month cross-sectionally. Most important, inclusion of the characteristic variables (except past returns) in the cross-sectional regression has little impact on the significance of $z_1$ which remains highly significant in all controls. Results show that the effect of trend momentum factor is quite robust to controls for bond characteristics.

Interestingly, past returns (average bond returns in the past six months) help explain the difference in $z_1$ estimates between high- and low-grade bonds. For example, in model (1), $z_1$ is 0.30 for AAA, and 0.57 for junk bonds which is substantially higher. This pattern does not change much until past returns are introduced in model (6). In model (6), the difference in coefficient estimates narrows considerably, where the $z_1$s for AAA and junk bonds have value of 0.30 and 0.35, respectively. This finding suggest a potential interactive effect of momentum and the moving average signal. Nevertheless, $z_1$ continues to be very significant for the whole sample and each rating category, suggesting that the MA signals have important effects beyond that of traditional bond momentum.

[Insert Table 10]

# 6 Additional tests

In this section, we further examine the robustness of our results and conduct additional tests. We first investigate the robustness of momentum returns to transaction costs. Following this, we explore whether bond characteristics can provide additional information beyond the MA signals to predict bond returns in the cross section. Finally, we assess the relative strength of stock and bond momentum and examine whether there is a trend momentum spillover from stocks to bonds.

## 6.1 Transaction costs

A question of fundamental importance is whether transaction costs can explain the trend momentum effect. To address this issue, we first calculate turnover rates of portfolios each month and report turnover rates of both high and low trend portfolios. Then, following the literature (e.g., Grundy and Martin (2001), Barroso and Santa-Clara (2015) and Han, Zhou and Zhu (2015)), we calculate the break-even transaction costs (BETCs). We construct two measures of BETCs. Zero-return BETCs are transaction costs that completely offset the raw returns or the risk-adjusted returns of the trend portfolio using the risk factors in model (8) of Table 9. By contrast, the insignificant BETCs are transaction costs that make the raw returns or the risk-adjusted returns of the trend portfolio insignificantly different from zero at the 5% level.

Table 11 reports the results for turnover rates and break-even transaction costs for the whole sample and different rating categories. The results reported on the left side show that turnover rates of the H-L portfolio are on average about 55% cross rating categories. They are almost equally distributed between high and low portfolios, suggesting that the turnover of the trend portfolio is not dominated by either long or short side. The right side of Table 11 reports the BETCs results. For the full sample including all bonds, it takes a transaction cost of 1.72% to completely offsets the raw returns, and 2.30% to make it become statistically insignificant at the 5% level. For adjusted returns, it takes transaction costs of 1.73% and 1.48%, respectively. The results by ratings show that transaction costs (BETCs) are higher as the rating decreases, consistent with the pattern of momentum returns reported earlier.

The BETCs estimates for corporate bonds are much higher than those using stock market data. For example, Grundy and Martin (2001) reported a BETC of 1.03% over the period from 1926 to 1995 for a completely dominant momentum portfolio. Han, Zhou and Zhu (2015) reported a BETC of 1.24% to render zero returns for the stock trend portfolio. Results for the estimates of BETCs suggest that trend momemntum profit is higher than the transaction cost for corporate bonds. Edwards, Harris and Piwowar (2007) report average transaction cost of about 24 basis points per dollar trading for a median size of corporate bond trade (or a round-trip cost of 48 basis points). Based on this estimate, the trend momentum profit survives the transaction cost.

Overall, results show that the profit of the trend portfolio is of economic significance and difficult to be explained by normal trading cost. Moreover, trend momentum profits of corporate bonds are much higher than that of stock momentum or stock trend momentum.

[Insert Table 11]

## 6.2 Trend portfolios forecast by MAs and bond characteristic variables

We next investigate the usefulness of bond characteristic variables for constructing trend portfolios. Again, we employ a two-step procedure to forecast bond returns. In the first step, we run the cross-sectional regression of bond returns on bond characteristics and MA signals,

$$r_{j,t} = \beta_{0,t} + \sum_i \beta_{i,t} MA_{jt-1,L_i} + \sum_k \gamma_{k,t} B_{k,jt-1} + \varepsilon_{j,t},\ j = 1, \ldots, n \tag{8}$$

In the second step, we estimate the bond's expected return for month $t+1$ by

$$E_t[r_{j,t+1}] = \sum_i E_t[\beta_{i,t+1}] MA_{jt,L_i} + \sum_k E_t[\gamma_{k,t+1}] B_{k,jt}, \tag{9}$$

where $E_t[\beta_{i,t+1}] = \frac{1}{12}\sum_{m=1}^{12}\beta_{i,t+1-m}$, and $E_t[\gamma_{k,t+1}] = \frac{1}{12}\sum_{m=1}^{12}\gamma_{k,t+1-m}$. The bond characteristics used are bond issue size, age and coupon rate. We then sort the bonds into quintile portfolios (Low, 2, 3, 4, and High) based on their expected returns and calculate the H-L returns. We consider five different cross-sectional regressions in the first step by using different sets of bond characteristics and MAs,

(1) bond issue size;

(2) bond age;

(3) coupon rate;

(4) issue size, age and coupon rate;

(5) MA signals and issue size, age and coupon rate.

Table 12 reports the returns of H-L portfolios. Models (1), (2) and (3) use bond issue size, age and coupon rate respectively, Model (4) uses all characteristics and finally model (5) use both MA signals and all characteristics. Results show that none of the returns of H-L portfolios for the first four models is significant. Results strongly suggest that using these bond characteristics to predict bond returns fails to generate significant economic profits. This finding is in sharp contrast with their in-sample statistically significant results reported in Table 10. Thus, variables with good in-sample explanatory power does not guarantee good performance in out-of-sample forecasts.

Model (5) of Table 12 reports the results using both MAs and bond characteristics. The H-L spreads (momentum profits) are very close to those reported in Table 2. Adding the MA signals significantly increases the momentum profits. Overall, results show that MA signals remain highly statistically significant and economically important even after controlling for the effects of bond characteristics, while the contribution by introducing bond characteristic variables to the cross-section return prediction appears quite limited.

[Insert Table 12]

## 6.3 Bond and stock trend portfolios

Whether a firm is a public or private may affect the performance of bond portfolios. For example, Jostova et al. (2013) show that bond momentum profits are larger among private firms. It is therefore of interest to investigate whether the trend portfolio returns are lower among public firms. In this analysis, we only use the bonds of public firms or the stocks that have bonds outstanding. Using the same two-step procedure, we perform return forecasts.

Panel A of Table 13 reports the results of trend portfolio returns for bonds which are issued by public firms. As shown, the results are comparable to those reported in Table 2 that include both public and private firms. For example, the return of H-L portfolio based on the full sample of all bonds is 0.92% with a $t$-value of 7.5 in Panel A of Table 13, while it is 0.97% with a $t$-value of 8.12 in Panel A of Table 2. The results of other rated bonds are similar. Results show no evidence that the trend momentum effect is weaker for public firms.

Panel B of Table 13 reports the returns of stock trend portfolios using the stocks that match bond price information. All H-L returns are statistically significant. Consistent with the finding of Han, Zhou and Zhou (2015), results show a significant stock trend momentum effect. Panel C of Table 13 reports the correlation between bond and stock trend portfolio returns. Most correlation coefficients are small and negative and the correlations for lower rating bonds are more negative. Results show little correlation between bond and stock trend momentum returns. Thus, bond trend momentum is not driven by stock trend momentum. The finding of low correlation suggests a potential diversification benefit by investing in both bond and stock trend portfolios.

[Inset Table 13]

## 6.4 Bond and stock momentum

Gebhardt, Hvidkjaer and Swaminathan (2005b) document a momentum spillover effect in which bond momentum portfolios formed by past six-month stock returns earn abnormal profits. Since the trend momentum strategy use more sophisticated price signals than the conventional momentum strategy, it is unclear whether the momentum spillover effect will still exist in this new momentum strategy. To investigate this possibility, we first use both MA signals of stocks and bonds to forecast expected returns and form trend portfolios based on these expected returns. We then examine whether stock MA signals can enhance the effect of trend momentum.

Panel D of Table 13 reports the results using both stock and bond MA signals in expected return forecasts. Results show that including the stock MA signals does not improve the profitability of the trend momentum strategy. Compared with the results in Panel A which use only MA signals of corporate bonds, the momentum profits (H-L) are either lower or little changed for the full sample and by rating. Result show no evidence that adding stock trend signals improves the bond momentum profits.

Another way to control for the effect of stock trend momentum on the bond trend momentum is to adjust the bond return by the effect of stock momentum. To obtain this ”stock-adjusted” return, for each firm-level bond return, we subtract the average monthly return of bonds in the quintile of stock returns (formed by stock MA signals) to which the bond belongs. The firm-level bond returns are the returns averaged across all bonds issued by the firm weighted by issuing size. Using this adjustment method, we control the effect of stock trend momentum on the firm-level bond trend momentum. [9]

Panel E of Table 13 reports the results of portfolio sorts based on the raw firm-level bond returns and ”stock-adjusted” firm-level bond returns. Results show that adjusting the effect of stock trend momentum does not weaken the bond trend momentum effect. The H-L portfolio returns continue to be highly significant for the full sample and the subsamples by rating. The bond trend momentum once again shows a monotonic pattern that the profit increases as the rating decreases.

[9] We also follow Gebhardt, Hvidkjaer and Swaminathan (2005b) by using the regression approach to calculate the stock-adjusted bond returns. For each bond in month $t$, we run regression of the bond return on the stock return using their last five years data, $r_{i,t} = \alpha_i + \beta_i r_{i,st} + e_t$, where $r_{i,st}$ is firm $i$'s stock return in month $t$. We then calculate the stock-adjusted bond return in month $t$ by $r_{i,t} - \hat{\beta}_i r_{i,st}$. The results are similar to those adjusted by stock portfolio returns and are available upon request.

We further analyze the interactions of bond and stock trend momentum by performing bivariate portfolio sorts. Bond returns are independently sorted into 5 x 5 portfolios based on bond and stock MA signals, respectively. Panel F of Table 13 reports the average returns of the 25 portfolios over the one-month holding period. Results based on the full sample show that bond trend momentum is present in all stock MA quintiles. Bond trend momentum profits range from 1.08 to 1.37 percent monthly. There is no systematic pattern across the stock momentum quintiles. We find no significant trend momentum spillover from stocks to bonds at the five percent level. The spillover is slightly larger for the high bond quintile portfolio, which is only significant at the ten percent level. When we divide the full sample into different rating categories, we find a similar pattern. The only discernible difference is that the trend momentum spillover is stronger for speculative-grade bonds where it is significant at the five percent for the 2nd bond quintile and the high bond quintile. Results show that the trend momentum spillover can vary for bonds with different ratings. However, there are pervasive bond trend momentum effects which are not resulting from stock trend momentum.

We next perform the regression analysis which permits multiple controls for other variables. We run the Fama-MacBeth cross-sectional regressions of monthly bond returns against the expected bond returns using both bond and stock MAs, lagged bond returns and past ratings. Specifically, we run the following cross-sectional regression for each month:

$$r_{i,t} = c_{0,t} + c_{1,t}E_r^B + c_{2,t}E_r^S + c_{3,t}r_{i,t-1} + c_{4,t}Rating_{i,t-1} + e_{i,t}$$

where $E_r^B$ is the expected bond return using bond MA signals, $E_r^S$ is the expected bond return using stock MA signals, $r_{i,t-1}$is the lagged bond returns and $Rating_{i,t-1}$ is the past bond rating.

Panel G of Table 13 reports the results of cross-sectional regressions. The top of the table show the results based on the full sample (All). Consistent with the portfolio analysis, results in row 1 show that bond MAs have a highly significant coefficient. When using stock MAs as an explanatory variable, we find that the coefficient is also significant at the one percent level but the size of coefficient is much smaller than that of the bond MAs. Also, the adjusted R-squares va;ie is only 1.6 %. When both bond and stock MAs are included in the regression, the coefficient of stock MAs drops a little but the coefficient of bond MAs is not decreased. The coefficient of bond MAs is much larger that of stock MAs, indicating that bond MAs have a much stronger effect than stock MAs on bond returns.

When we further add the lagged bond return, it has a negative coefficient which is statistically significant, suggesting a return reversal. The rating has a significant positive effect on bond returns when used alone in the regression. However, it becomes insignificant when we include it along with other explanatory variables.

The results of cross-sectional regressions by rating reveal additional information. When used alone, stock MAs have no significant effect for high-quality bonds (AAA) but have a significant effect for other bonds. The size of stock MAs coefficient increases as the rating decreases, suggesting that the trend momentum spillover is more pronounced for lower-grade bonds. When used with bond MAs, the effect of stock MAs is significant for bonds with a rating of A and below. The return reversal tends to be stronger for junk bonds. Ratings have no significant effect when used with other variables in the regression.

Overall, the results show that bond trend momentum is not driven by stock trend momentum and suggest that the former represents an independent effect. However, we also find some evidence of trend momentum spillover from stocks to bonds. This finding suggests that some information or events for the firm affect both stock and bond returns. The effect of stock trend momentum is stronger for lower-grade bonds, consistent with the traditional view that lower-grade bonds are more like stocks. More importantly, all results clearly show that bond MAs contain important information for predicting future bond returns and this finding is robust to different controls for credit rating and past bond and stock returns.

# 7 Stock market anomaly and trend momentum

Chordia, et al. (2014) and Choi and Kim (2016) show that stock market variables have the ability to predict the cross-sectional variations of expected corporate bond returns. In this section, we examine the robustness of our results to controls for these variables. Following Chordia, et al. (2014) and Choi and Kim (2016), we construct the following stock market variables for each firm in our sample:

- Size: the natural logarithm of the market value of firm equity.
- Value: the ratio of book value to market value of equity.
- Accruals: the ratio of accruals to assets. Accruals are calculated by change in (current assets − cash and short-term investment − current liabilities + debt in current liabilities + income tax payable) − depreciation.
- Asset growth: the percentage change in total assets.
- Profitability: the ratio of equity income to book equity. Equity income is defined as income before extraordinary items − dividends on preferred shares + deferred taxes.
- Net stock issues: the change in the natural log of the split-adjusted shares outstanding.
- Earnings surprise: the change in split-adjusted earnings per shares divided by price.
- Idiosyncratic volatility: the residuals from three factor model regression for the issuer's equity over each month.

We first perform a bivariate portfolio analysis to control for the impact of stock market variables. We sort the firm-level returns each month by an individual stock market variable into three groups (Low, Medium and High). For each group, we conduct the trend momentum analysis. If the trend momentum is driven by these stock market variables, we should not find significant trend momentum once the effects of these variables are controlled.

Panel A of Table 14 reports the results of bivariate portfolio analysis. Results continue to show strong trend momentum in each group, suggesting that the trend momentum in corporate bond market is not driven by stock market variables. The results for investment-grade bonds are much stronger than for junk bonds. These results are different from those without controlling for stock market variables. This implies stock market variables explain the cross-section of junk bonds more than the cross-sectional of investment-grade bonds, which is consistent with the view that junk bonds behave more like stocks.

We next run the cross-sectional regression of firm-level bond returns on their return forecasts with and without stock market variables as controls each month. Panel B of Table 14 reports the mean, $t$-stats of coefficients of return forecast and the mean adjusted R-squares of cross-sectional regressions. The results continue to show that there is significant relationship between bonds' return forecasts and their future returns with and without the stock market control variables. The increase in adjusted R-squares by adding stock market variables is more significant for speculative-grade bonds than for investment-grade bonds, which again shows more important role played by stock market variables in the high-yield bond market.

[Insert Table 14]

# 8 Conclusion

In this paper, we employ a new methodology to investigate the momentum effect in the corporate bond market. This methodology includes multiple moving averages or trend signals over different investment horizons, which is more general than the conventional momentum methodology that uses only one trend signal in a fixed horizon. As a result, our method is able to uncover a significant momentum effect in the corporate bond market which has not been detected by the more restrictive conventional method.

Using this new method, we document strong evidence of momentum in the corporate bond market across all ratings. Empirical evidence clearly shows significant trend momentum effects not only for speculative-grade bonds but also for investment-grade bonds. The momentum profits survive transaction costs. Previous studies find no evidence of momentum for investment-grade bonds largely because they rely on a method which uses only one trend signal over a predetermined horizon and thus misses out the momentum effect existing in different investment horizons. Overall, our results strongly suggest that the cross-sectional returns of corporate bonds are predictable across all rating categories and this predictability increases as credit rating decreases.

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Table 1. Sample distribution

This table reports the sample distribution of corporate bond data. The data are merged from different sources: the Lehman Brothers Fixed Income (LBFI) database, Datastream (DTSM), the National Association of Insurance Commissioners (NAIC) database, the Trade Reporting and Compliance Engine (TRACE) database, and Mergent's Fixed Investment Securities Database (FISD). The combined corporate bond data cover the period from January 1973 to September 2015. The cut-off values for maturities are 5, 7, and 10 years.

| | Maturity | | | | Data source | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Rate | Short | 2 | 3 | Long | DTSM | LBFI | NAIC | TRACE | Total |
| AAA | 28944 | 10561 | 13877 | 12229 | 8291 | 15537 | 25878 | 15905 | 65611 |
| AA+ | 10513 | 2371 | 3152 | 5024 | 8151 | 4114 | 1233 | 7562 | 21060 |
| AA | 24893 | 9689 | 10098 | 14142 | 7638 | 21015 | 3984 | 26185 | 58822 |
| AA- | 39160 | 12847 | 15102 | 9191 | 8155 | 17048 | 9486 | 41611 | 76300 |
| A+ | 46515 | 17435 | 22063 | 23379 | 8089 | 32303 | 11913 | 57087 | 109392 |
| A | 69329 | 25574 | 34506 | 43399 | 17737 | 49954 | 16351 | 88766 | 172808 |
| A- | 39178 | 15680 | 21901 | 30661 | 15910 | 32990 | 10860 | 47660 | 107420 |
| BBB+ | 29195 | 13956 | 21739 | 33256 | 23883 | 21885 | 8240 | 44138 | 98146 |
| BBB | 29782 | 13731 | 22704 | 26719 | 15493 | 25538 | 7140 | 44765 | 92936 |
| BBB- | 15088 | 7466 | 14899 | 19468 | 10886 | 17886 | 7109 | 21040 | 56921 |
| BB+ | 11119 | 4102 | 5049 | 7959 | 5515 | 6012 | 2666 | 14036 | 28229 |
| BB | 4458 | 3087 | 4486 | 3433 | 3111 | 3519 | 1756 | 7078 | 15464 |
| BB- | 4188 | 3016 | 4103 | 2850 | 2070 | 3100 | 1541 | 7446 | 14157 |
| B+ | 5043 | 3469 | 3819 | 3931 | 4410 | 3137 | 847 | 7868 | 16262 |
| B | 2357 | 2275 | 2475 | 1695 | 1110 | 1193 | 701 | 5798 | 8802 |
| B- | 2600 | 2615 | 1839 | 1746 | 1523 | 762 | 432 | 6083 | 8800 |
| CCC+ | 1560 | 1842 | 1143 | 3243 | 2898 | 69 | 221 | 4600 | 7788 |
| CCC | 1127 | 833 | 483 | 402 | 469 | 308 | 171 | 1897 | 2845 |
| CCC- | 277 | 100 | 109 | 68 | 46 | 2 | 73 | 433 | 554 |
| CC | 475 | 194 | 149 | 356 | 25 | 178 | 108 | 863 | 1174 |
| C | 341 | 89 | 144 | 80 | 52 | 53 | 8 | 541 | 654 |
| D | 2149 | 918 | 948 | 1186 | 0 | 5201 | 0 | 0 | 5201 |
| Total | 368291 | 151850 | 204788 | 244417 | 145462 | 261804 | 110718 | 451362 | 969346 |

Table 2. Summary statistics

This table reports the returns of portfolios sorted by bonds' expected returns. We follow a two-step procedure to forecast an individual bond's expected return using the information from MA signals. The MA signals include the bond's moving average yields of lag lengths 1-, 3-, 6-, 12-, 24-, 36-, 48-, and 60-months. We then sort all bonds into quintile portfolios (Low, 2, 3, 4, and High) in Panel A and decile portfolios in Panel B based on their expected returns. H-L is the difference between High and Low portfolios. The portfolios are equally weighted and rebalanced each month. The $t$-statistics measure the significance of H-L returns. The sample period is from January 1973 to September 2015.

Panel A. Quintile portfolios

| | | Return | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Horizon | Rating | Low | 2 | 3 | 4 | High | H-L | $t$-stats |
| One month: $[t+1, t+1]$ | All | 0.26 | 0.53 | 0.66 | 0.81 | 1.23 | 0.97 | 8.12 |
| | AAA | 0.24 | 0.51 | 0.63 | 0.74 | 1.10 | 0.85 | 6.96 |
| | AA | 0.31 | 0.49 | 0.64 | 0.75 | 1.09 | 0.78 | 6.93 |
| | A | 0.25 | 0.50 | 0.63 | 0.78 | 1.23 | 0.98 | 7.39 |
| | BBB | 0.26 | 0.58 | 0.73 | 0.88 | 1.32 | 1.06 | 6.74 |
| | Junk | 0.27 | 0.50 | 0.73 | 1.03 | 1.49 | 1.21 | 6.90 |

Panel B. Decile portfolios

| | Return | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Rating | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | H-L | $t$-stats |
| All | 0.11 | 0.40 | 0.49 | 0.58 | 0.63 | 0.69 | 0.77 | 0.86 | 0.99 | 1.48 | 1.37 | 10.45 |
| AAA | 0.14 | 0.47 | 0.48 | 0.58 | 0.55 | 0.67 | 0.69 | 0.78 | 0.82 | 1.24 | 1.10 | 9.60 |
| AA | 0.22 | 0.41 | 0.47 | 0.52 | 0.60 | 0.67 | 0.70 | 0.80 | 0.90 | 1.29 | 1.07 | 9.41 |
| A | 0.13 | 0.38 | 0.47 | 0.53 | 0.59 | 0.66 | 0.72 | 0.83 | 1.00 | 1.47 | 1.34 | 9.41 |
| BBB | 0.08 | 0.46 | 0.53 | 0.63 | 0.68 | 0.78 | 0.83 | 0.93 | 1.12 | 1.52 | 1.43 | 8.12 |
| Junk | 0.23 | 0.34 | 0.47 | 0.56 | 0.67 | 0.79 | 0.95 | 1.10 | 1.19 | 1.80 | 1.58 | 7.08 |

Table 3. Characteristics of trend portfolios

This table reports the characteristics of trend portfolios including bond size, age, coupon rate, moving average of yield over the last month ($MA_{t-1,t-1}$) and the last six months ($MA_{t-1,t-6}$). We use a two-step procedure to forecast the individual bond's expected return using the information from MA signals. The MA signals include the bond's moving average yields of lagged 1-, 3-, 6-, 12-, 24-, 36-, 48-, and 60-months. We then sort the bonds into five portfolios (Low, 2, 3, 4, and High) based on their expected returns and report average values of issue size, age, coupon rate and past one- and six-month yields for each trend portfolio. H-L is the difference between High and Low portfolios. The portfolios are equally weighted and rebalanced each month. the $t$-statistic measures the significance of H-L. The sample period is from January 1973 to September 2015.

| | | Trend portfolios | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Characteristic | Rating | Low | 2 | 3 | 4 | High | H-L | $t$-stats |
| Bond size (Mil.) | All | 456.22 | 447.49 | 390.90 | 370.97 | 343.36 | -112.86 | -3.02 |
| | AAA | 2203.89 | 1903.17 | 1928.26 | 1780.53 | 1729.10 | -474.79 | -2.56 |
| | AA | 312.25 | 330.84 | 329.75 | 320.58 | 292.64 | -19.61 | -1.13 |
| | A | 240.33 | 248.83 | 237.29 | 226.88 | 202.59 | -37.74 | -3.49 |
| | BBB | 200.49 | 195.40 | 188.68 | 181.48 | 179.59 | -20.90 | -2.35 |
| | Junk | 199.63 | 203.60 | 199.41 | 207.80 | 180.91 | -18.72 | -1.76 |
| Age (Yrs.) | All | 8.55 | 7.97 | 7.81 | 7.57 | 7.70 | -0.85 | -1.51 |
| | AAA | 9.64 | 10.42 | 10.95 | 10.12 | 11.12 | 1.47 | 1.49 |
| | AA | 9.82 | 8.15 | 7.93 | 7.38 | 8.35 | -1.47 | -2.27 |
| | A | 8.56 | 8.23 | 7.49 | 6.98 | 6.87 | -1.70 | -2.89 |
| | BBB | 9.13 | 8.50 | 8.21 | 8.74 | 8.53 | -0.60 | -0.85 |
| | Junk | 5.78 | 5.62 | 5.63 | 5.90 | 6.17 | 0.40 | 1.50 |
| Coupon (%) | All | 6.55 | 6.53 | 6.77 | 7.10 | 7.68 | 1.13 | 8.54 |
| | AAA | 6.25 | 6.12 | 6.12 | 6.15 | 6.51 | 0.26 | 1.75 |
| | AA | 5.80 | 5.92 | 6.11 | 6.44 | 6.74 | 0.94 | 6.70 |
| | A | 6.32 | 6.48 | 6.79 | 7.04 | 7.36 | 1.04 | 7.79 |
| | BBB | 7.25 | 7.20 | 7.34 | 7.49 | 7.51 | 0.27 | 1.81 |
| | Junk | 8.30 | 8.32 | 8.49 | 8.59 | 8.87 | 0.57 | 3.97 |
| $MA_{t-1,t-1}(\%)$ | All | 7.10 | 7.20 | 7.46 | 7.78 | 8.99 | 1.89 | 9.70 |
| | AAA | 6.32 | 6.52 | 6.66 | 6.77 | 7.04 | 0.72 | 3.32 |
| | AA | 6.35 | 6.76 | 7.00 | 7.22 | 7.51 | 1.15 | 5.31 |
| | A | 6.82 | 7.11 | 7.38 | 7.66 | 8.21 | 1.39 | 6.87 |
| | BBB | 7.71 | 7.81 | 8.03 | 8.34 | 9.06 | 1.35 | 6.15 |
| | Junk | 9.39 | 9.20 | 9.47 | 10.04 | 12.36 | 2.97 | 12.62 |
| $MA_{t-1,t-6}(\%)$ | All | 7.42 | 7.32 | 7.50 | 7.75 | 8.67 | 1.25 | 6.49 |
| | AAA | 6.55 | 6.62 | 6.70 | 6.75 | 6.89 | 0.34 | 1.59 |
| | AA | 6.58 | 6.86 | 7.04 | 7.20 | 7.32 | 0.74 | 3.48 |
| | A | 7.08 | 7.23 | 7.42 | 7.63 | 7.96 | 0.88 | 4.45 |
| | BBB | 8.02 | 7.94 | 8.06 | 8.28 | 8.72 | 0.69 | 3.28 |
| | Junk | 9.82 | 9.33 | 9.49 | 9.92 | 11.68 | 1.85 | 8.28 |

Table 4. Composition of trend portfolios by past six-month returns

This table summarizes the distribution of bonds in each trend portfolio by bonds' past six-month returns. We use a two-step procedure to forecast the individual bond's expected return using the information from MA signals. The MA signals include the bond's moving average yield of lagged 1-, 3-, 6-, 12-, 24-, 36-, 48-, and 60-months. We sort the bonds into quintile portfolios (Low, 2, Medium, 4, and High) based on their expected returns. We also sort the bonds into five groups (Loser, 2, Medium, 4, Winner) based on their historical returns over the past six months. We calculate the percentage of bonds in each portfolio that are in the Loser, Medium and Winner groups. The data period is from January 1973 to September 2015.

| | | Trend portfolios | | | | |
|---|---|---|---|---|---|---|
| Rating | $r_{-6,-1}$ | Low | 2 | Medium | 4 | High |
| | Loser | 17.76 | 13.81 | 14.46 | 18.63 | 32.99 |
| All | Median | 18.46 | 23.72 | 24.76 | 21.16 | 13.99 |
| | Winner | 23.84 | 17.26 | 16.54 | 18.98 | 20.97 |
| | Loser | 13.47 | 15.16 | 16.32 | 21.06 | 36.54 |
| AAA | Median | 17.41 | 21.95 | 23.89 | 21.52 | 15.22 |
| | Winner | 30.74 | 22.01 | 16.71 | 15.18 | 13.09 |
| | Loser | 19.61 | 15.02 | 13.72 | 18.41 | 34.05 |
| AA | Median | 16.49 | 21.41 | 25.16 | 22.77 | 14.13 |
| | Winner | 25.27 | 20.45 | 17.30 | 16.87 | 19.38 |
| | Loser | 20.58 | 15.15 | 14.56 | 18.04 | 31.95 |
| A | Median | 16.57 | 22.61 | 24.95 | 22.26 | 13.59 |
| | Winner | 25.17 | 18.29 | 16.29 | 17.73 | 22.25 |
| | Loser | 17.06 | 14.04 | 14.50 | 19.39 | 35.46 |
| BBB | Median | 17.95 | 23.53 | 24.26 | 20.44 | 13.82 |
| | Winner | 25.85 | 18.51 | 17.66 | 18.85 | 18.72 |
| | Loser | 13.94 | 14.32 | 16.28 | 21.29 | 35.26 |
| Junk | Median | 19.38 | 22.94 | 22.70 | 20.76 | 14.13 |
| | Winner | 27.11 | 20.09 | 16.73 | 16.02 | 19.11 |

Table 5. Controls for momentum effects

This table reports the returns of portfolios sorted by the bond's expected return and its historical return over the past six months. We follow a two-step procedure to forecast the individual bond's expected return using the information from MA signals. The MA signals include the bond's moving average yields of lagged 1-, 3-, 6-, 12-, 24-, 36-, 48-, and 60-months.We first sort bonds by their historical returns into quintiles, and then in each quintile we further sort the bonds into trend quintile portfolios. We then average the resulting 5 $\times$ 5 trend quintile portfolios across the five quintiles of historical returns to form five average trend quintile portfolios, each has a identical distribution of bonds in quintile portfolios sorted by historical returns. H-L is the difference between High and Low portfolios. The portfolios are equally weighted and rebalanced each month. The investment horizon is monthly. The $t$-statistics measure the significance of H-L returns. The sample period is from January 1973 to September 2015.

| $r_{-6,-1}$ | Rating | Low | 2 | 3 | 4 | High | H-L | $t$-stats |
|---|---|---|---|---|---|---|---|---|
| Loser | All | 0.71 | 0.89 | 1.12 | 1.21 | 1.63 | 0.92 | 5.58 |
| | AAA | 0.50 | 0.74 | 0.80 | 1.16 | 1.64 | 1.13 | 6.22 |
| | AA | 0.50 | 0.69 | 0.83 | 1.06 | 1.55 | 1.05 | 7.58 |
| | A | 0.56 | 0.77 | 0.93 | 1.14 | 1.83 | 1.27 | 7.26 |
| | BBB | 0.71 | 0.89 | 1.14 | 1.31 | 1.98 | 1.27 | 6.24 |
| | Junk | 0.84 | 0.87 | 1.26 | 1.57 | 2.39 | 1.56 | 4.69 |
| Medium | All | 0.45 | 0.60 | 0.75 | 0.75 | 0.93 | 0.47 | 4.14 |
| | AAA | 0.40 | 0.61 | 0.62 | 0.72 | 0.97 | 0.57 | 4.17 |
| | AA | 0.40 | 0.54 | 0.66 | 0.73 | 0.93 | 0.53 | 4.72 |
| | A | 0.36 | 0.51 | 0.65 | 0.70 | 0.98 | 0.61 | 5.01 |
| | BBB | 0.38 | 0.62 | 0.81 | 0.78 | 1.15 | 0.77 | 5.54 |
| | Junk | 0.39 | 0.54 | 0.74 | 0.86 | 1.08 | 0.69 | 3.34 |
| Winner | All | 0.05 | 0.44 | 0.60 | 0.65 | 0.82 | 0.77 | 5.77 |
| | AAA | -0.17 | 0.19 | 0.30 | 0.57 | 0.84 | 1.01 | 6.40 |
| | AA | 0.04 | 0.27 | 0.45 | 0.56 | 0.77 | 0.73 | 5.40 |
| | A | -0.04 | 0.27 | 0.49 | 0.58 | 0.84 | 0.88 | 6.62 |
| | BBB | -0.15 | 0.27 | 0.56 | 0.65 | 0.89 | 1.04 | 6.14 |
| | Junk | -0.17 | 0.30 | 0.54 | 0.86 | 0.97 | 1.14 | 3.84 |
| Average | All | 0.41 | 0.63 | 0.78 | 0.83 | 1.05 | 0.64 | 5.41 |
| | AAA | 0.30 | 0.54 | 0.61 | 0.79 | 1.09 | 0.79 | 6.29 |
| | AA | 0.34 | 0.51 | 0.64 | 0.76 | 1.04 | 0.70 | 6.30 |
| | A | 0.30 | 0.51 | 0.66 | 0.79 | 1.15 | 0.84 | 6.88 |
| | BBB | 0.34 | 0.60 | 0.78 | 0.88 | 1.30 | 0.96 | 6.94 |
| | Junk | 0.40 | 0.58 | 0.81 | 1.03 | 1.34 | 0.94 | 5.72 |

Table 6. Trend momentum over different investment horizons

This table reports the returns of portfolios sorted by bonds' expected returns over different investment horizon. We use a two-step procedure to forecast the individual bond's expected return using the information from MA signals. The MA signals include the bond's moving average yields of lagged 1-, 3-, 6-, 12-, 24-, 36-, 48-, and 60-months. We then sort all bonds into quintile portfolios (Low, 2, 3, 4, and High) by their expected returns. H-L is the difference between High and Low trend portfolios. The portfolios are equally weighted and rebalanced each month. We use the Newey-West (1987) standard errors to calculate the $t$-values when the investment horizons are three and six months to account for the data overlapping effect. The sample period is from January 1973 to September 2015.

| Horizon | Rating | Low | 2 | 3 | 4 | High | H-L | $t$-stats |
|---|---|---|---|---|---|---|---|---|
| Three months: $[t+1, t+3]$ | All | 0.50 | 0.63 | 0.68 | 0.76 | 0.94 | 0.44 | 5.77 |
| | AAA | 0.46 | 0.61 | 0.63 | 0.68 | 0.84 | 0.37 | 4.93 |
| | AA | 0.49 | 0.57 | 0.64 | 0.69 | 0.84 | 0.35 | 4.80 |
| | A | 0.46 | 0.59 | 0.65 | 0.74 | 0.96 | 0.51 | 6.32 |
| | BBB | 0.54 | 0.68 | 0.74 | 0.82 | 1.04 | 0.50 | 5.20 |
| | Junk | 0.63 | 0.66 | 0.77 | 0.83 | 1.14 | 0.52 | 4.48 |
| Six months: $[t+1, t+6]$ | All | 0.58 | 0.64 | 0.68 | 0.71 | 0.82 | 0.24 | 4.25 |
| | AAA | 0.52 | 0.60 | 0.64 | 0.67 | 0.75 | 0.23 | 4.13 |
| | AA | 0.53 | 0.59 | 0.63 | 0.67 | 0.77 | 0.24 | 4.54 |
| | A | 0.52 | 0.60 | 0.66 | 0.71 | 0.83 | 0.31 | 5.43 |
| | BBB | 0.63 | 0.72 | 0.72 | 0.78 | 0.88 | 0.25 | 3.68 |
| | Junk | 0.76 | 0.68 | 0.74 | 0.79 | 1.07 | 0.31 | 2.29 |

Table 7. Trend portfolio returns and bond characteristics

This table reports the returns of portfolios sorted by the bond's expected return and characteristic. We use a two-step procedure to forecast the individual bond's expected return using the information from MA signals. The MA signals include the bond's moving average yields of lagged 1-, 3-, 6-, 12-, 24-, 36-, 48-, and 60-months. We first sort bonds by their characteristics into five quintile groups, and then in each quintile we further sort the bonds to construct five trend quintile portfolios. We then average the resulting 5 × 5 trend quintile portfolios across the five quintiles of bond characteristics to form five new trend quintile portfolios, all of which should have similar level of bond characteristics. H-L is the difference between High and Low portfolios. Portfolios are equally weighted and rebalanced each month. The $t$-statistics measure the significance of H-L returns. The sample period is from January 1973 to September 2015.

| | Bond size | | Age | | Coupon | | $MA_{t-1,t-6}$ | |
|---|---|---|---|---|---|---|---|---|
| Rating | H-L | $t$-stats | H-L | $t$-stats | H-L | $t$-stats | H-L | $t$-stats |
| | Small | | Young | | Low | | Low | |
| All | 1.14 | 8.25 | 0.90 | 7.48 | 0.95 | 7.97 | 0.65 | 6.72 |
| AAA | 0.88 | 5.07 | 0.52 | 3.79 | 0.71 | 5.50 | 0.65 | 4.72 |
| AA | 0.94 | 6.82 | 0.67 | 5.58 | 0.72 | 6.73 | 0.44 | 4.24 |
| A | 1.03 | 6.96 | 0.85 | 6.20 | 0.89 | 7.12 | 0.68 | 5.67 |
| BBB | 1.19 | 5.91 | 0.93 | 5.32 | 1.24 | 7.07 | 0.64 | 5.51 |
| Junk | 1.70 | 6.95 | 1.58 | 6.28 | 1.15 | 5.21 | 0.61 | 2.66 |
| | Medium | | Medium | | Medium | | Medium | |
| All | 1.04 | 8.42 | 1.00 | 7.37 | 1.00 | 7.16 | 0.89 | 7.24 |
| AAA | 0.59 | 4.27 | 0.80 | 5.37 | 0.85 | 5.61 | 0.59 | 4.04 |
| AA | 0.80 | 6.81 | 0.75 | 5.95 | 0.89 | 6.75 | 0.70 | 5.97 |
| A | 1.05 | 8.06 | 1.02 | 7.32 | 0.97 | 6.37 | 0.88 | 6.82 |
| BBB | 1.05 | 6.74 | 1.27 | 7.74 | 1.01 | 6.82 | 0.85 | 5.91 |
| Junk | 1.18 | 4.20 | 1.15 | 4.06 | 1.46 | 5.04 | 1.28 | 6.16 |
| | Large | | Old | | High | | High | |
| All | 0.69 | 6.25 | 1.02 | 7.37 | 0.98 | 7.12 | 1.24 | 7.29 |
| AAA | 0.89 | 6.38 | 1.05 | 6.24 | 0.83 | 4.89 | 1.03 | 5.11 |
| AA | 0.56 | 4.99 | 0.87 | 6.86 | 0.78 | 5.83 | 0.96 | 6.27 |
| A | 0.72 | 5.08 | 1.05 | 7.28 | 1.01 | 7.25 | 1.26 | 7.01 |
| BBB | 0.77 | 4.89 | 1.14 | 7.07 | 0.98 | 7.24 | 1.23 | 5.85 |
| Junk | 1.02 | 3.99 | 1.06 | 4.01 | 1.43 | 4.88 | 1.29 | 3.75 |
| | Average | | Average | | Average | | Average | |
| All | 0.96 | 8.07 | 0.98 | 8.09 | 0.96 | 8.00 | 0.91 | 7.91 |
| AAA | 0.84 | 6.63 | 0.77 | 6.25 | 0.74 | 5.99 | 0.75 | 5.92 |
| AA | 0.75 | 6.76 | 0.77 | 6.82 | 0.80 | 7.06 | 0.74 | 6.68 |
| A | 0.95 | 7.25 | 0.96 | 7.33 | 0.96 | 7.29 | 0.90 | 7.12 |
| BBB | 1.07 | 7.23 | 1.06 | 7.60 | 1.05 | 7.63 | 0.93 | 6.96 |
| Junk | 1.23 | 6.94 | 1.26 | 7.36 | 1.33 | 7.57 | 1.05 | 6.72 |

Table 8. Trend momentum returns for different subperiods

This table reports the returns of portfolios sorted by bonds' expected returns for different subperiods. We use a two-step procedure to forecast the individual bond's expected return using the information from MA signals. The MA signals include the bond's moving average yields with lag length of 1-, 3-, 6-, 12-, 24-, 36-, 48-, and 60-months. We then sort the bonds into quintile portfolios (Low, 2, 3, 4, and High) by their expected returns for three subperiods. The three subperiods are based on the three stages of corporate bond coverage: NAIC (January 1994-June 2002) and TRACE (July 2002-current), the level of Baker-Wurgler (2006, 2007) sentiment index (Sentiment: BK), the level of smooth recession probability (SRP), and the real GDP growth rate, respectively. The real GDP growth rate is from Federal Reserve at St. Louis. There are 15 portfolios at the intersection of trend portfolio sorts and subperiods. H-L is the return difference between High and Low portfolios. The portfolios are equally weighted and rebalanced each month. The $t$-statistics measure the significance of H-L returns. The sample period is from January 1973 to September 2015.

| | Bond data periods | | Sentiment: BW | | SRP | | GDP growth rate | |
|---|---|---|---|---|---|---|---|---|
| Rating | H-L | $t$-stats | H-L | $t$-stats | H-L | $t$-stats | H-L | $t$-stats |
| | Jan. 1973- Dec. 1993 | | Low | | Low | | Low | |
| All | 0.59 | 2.79 | 1.18 | 4.81 | 0.84 | 5.52 | 1.21 | 4.04 |
| AAA | 0.42 | 1.80 | 1.05 | 4.52 | 0.65 | 3.80 | 1.04 | 4.09 |
| AA | 0.32 | 1.51 | 1.05 | 4.59 | 0.65 | 4.47 | 1.04 | 4.12 |
| A | 0.44 | 1.96 | 1.24 | 4.74 | 0.74 | 4.81 | 1.22 | 3.85 |
| BBB | 0.58 | 2.16 | 1.59 | 4.74 | 0.87 | 4.24 | 1.33 | 3.60 |
| Junk | 1.02 | 3.30 | 1.13 | 3.02 | 1.03 | 4.57 | 1.46 | 2.88 |
| | Jan. 1994-July 2002 | | Medium | | Medium | | Medium | |
| All | 0.67 | 3.65 | 0.84 | 4.57 | 0.97 | 6.32 | 0.87 | 5.88 |
| AAA | 0.85 | 4.33 | 0.78 | 5.02 | 0.84 | 4.23 | 0.94 | 5.64 |
| AA | 0.71 | 3.63 | 0.74 | 4.57 | 0.77 | 5.10 | 0.83 | 6.03 |
| A | 0.75 | 3.85 | 0.87 | 3.93 | 0.97 | 5.92 | 1.00 | 6.31 |
| BBB | 0.46 | 2.26 | 0.89 | 3.69 | 1.06 | 5.71 | 0.99 | 5.73 |
| Junk | 0.59 | 2.91 | 1.37 | 5.08 | 1.37 | 5.30 | 1.08 | 4.80 |
| | Aug. 2002-Sept. 2015 | | High | | High | | High | |
| All | 1.60 | 8.25 | 0.92 | 4.62 | 1.11 | 3.97 | 0.83 | 5.42 |
| AAA | 1.35 | 7.86 | 0.77 | 3.12 | 1.07 | 4.19 | 0.57 | 2.83 |
| AA | 1.35 | 8.85 | 0.60 | 3.06 | 0.92 | 3.56 | 0.46 | 2.73 |
| A | 1.73 | 7.63 | 0.83 | 3.83 | 1.23 | 3.83 | 0.72 | 4.09 |
| BBB | 1.99 | 7.14 | 0.76 | 3.05 | 1.26 | 3.37 | 0.85 | 3.65 |
| Junk | 1.83 | 5.86 | 1.16 | 4.13 | 1.24 | 3.13 | 1.10 | 5.17 |

Table 9. Alphas of corporate bond trend portfolios

Trend portfolio returns are computed using the same procedure as in Table 2 from January 1979 to September 2015. We then run time-series regressions of the portfolio excess returns on systematic factors:

$$r^e_{p,t} = \alpha_p + \beta'_{\mathbf{p}}\mathbf{F_t} + e_{p,t},$$

where $r^e_{p,t} = r_{p,t} - r_{f,t}$ is the trend portfolio excess return over the risk-free rate or the trend strategy return $r^e_{p,t} = r_{H,t} - r_{L,t}$. $\mathbf{F_t}$ is a vector of risk factors. We consider eight different model specifications of $\mathbf{F_t}$ including :

(1) $mTERM$;

(2) $mDEF$;

(3) $mTERM, mDEF$;

(4) $MKT, SMB, HML$;

(5) $MKT, SMB, HML, MOM$;

(6) $mTERM, mDEF, MKT, SMB, HML$;

(7)$mTERM, mDEF, MKT, SMB, HML, MOM$;

(8) $\Delta TERM, \Delta DEF, MKT, SMB, HML, MOM$.

$MKT, SMB, HML$ are the returns of the market, size, and book-to-market portfolios of Fama and French (1993). $MOM$ is the momentum factor of Carhart (1997). $TERM_t$ is the difference between the long-term government bond yield and Treasury bill rate. $DEF_t$ is the difference between BAA and AAA corporate bond yields. $\Delta TERM_t = (TERM_t - TERM_{t-1})$ and $\Delta DEF_t = (DEF_t - DEF_{t-1})$. $mTERM_t = \Delta TERM_t/(1 + TERM_{t-1})$, $mDEF_t = \Delta DEF_t/(1 + DEF_{t-1})$. Panels A and B report the results for all bonds, and bonds with different ratings, respectively.

Panel A. Alpha: all bonds

| Model | Low | 2 | 3 | 4 | High | H-L | $t$-stats | $Adj.R^2$ (%) |
|---|---|---|---|---|---|---|---|---|
| 1 | -0.12 | 0.15 | 0.28 | 0.43 | 0.85 | 0.97 | 14.68 | 1.34 |
| 2 | -0.13 | 0.15 | 0.28 | 0.43 | 0.85 | 0.97 | 14.67 | 0.85 |
| 3 | -0.12 | 0.15 | 0.28 | 0.43 | 0.85 | 0.97 | 14.71 | 2.08 |
| 4 | -0.23 | 0.04 | 0.18 | 0.32 | 0.70 | 0.94 | 13.85 | 2.22 |
| 5 | -0.24 | 0.03 | 0.16 | 0.31 | 0.74 | 0.98 | 14.35 | 4.50 |
| 6 | -0.24 | 0.03 | 0.17 | 0.31 | 0.70 | 0.93 | 13.91 | 4.27 |
| 7 | -0.23 | 0.03 | 0.15 | 0.31 | 0.74 | 0.97 | 14.33 | 6.15 |
| 8 | -0.23 | 0.03 | 0.15 | 0.31 | 0.74 | 0.97 | 14.33 | 6.17 |

Panel B. Alpha by rating

| | Model | Low | 2 | 3 | 4 | High | H-L | $t$-stats | $R^2$ (%) |
|---|---|---|---|---|---|---|---|---|---|
| AAA | 1 | -0.14 | 0.13 | 0.25 | 0.36 | 0.72 | 0.86 | 11.16 | 0.07 |
| | 2 | -0.15 | 0.13 | 0.24 | 0.36 | 0.71 | 0.86 | 11.17 | 0.00 |
| | 3 | -0.14 | 0.13 | 0.24 | 0.36 | 0.72 | 0.86 | 11.15 | 0.07 |
| | 4 | -0.21 | 0.08 | 0.18 | 0.30 | 0.68 | 0.90 | 11.45 | 1.35 |
| | 5 | -0.23 | 0.05 | 0.15 | 0.27 | 0.66 | 0.89 | 11.13 | 1.40 |
| | 6 | -0.23 | 0.06 | 0.16 | 0.29 | 0.67 | 0.90 | 11.43 | 1.47 |
| | 7 | -0.24 | 0.04 | 0.14 | 0.26 | 0.65 | 0.89 | 11.09 | 1.54 |
| | 8 | -0.24 | 0.04 | 0.14 | 0.26 | 0.65 | 0.89 | 11.09 | 1.52 |
| AA | 1 | -0.07 | 0.11 | 0.25 | 0.37 | 0.72 | 0.79 | 11.94 | 0.96 |
| | 2 | -0.07 | 0.11 | 0.25 | 0.37 | 0.71 | 0.79 | 11.88 | 0.21 |
| | 3 | -0.07 | 0.11 | 0.25 | 0.37 | 0.72 | 0.79 | 11.94 | 1.13 |
| | 4 | -0.15 | 0.01 | 0.17 | 0.28 | 0.63 | 0.78 | 11.45 | 0.19 |
| | 5 | -0.17 | 0.00 | 0.15 | 0.27 | 0.65 | 0.82 | 11.96 | 2.43 |
| | 6 | -0.16 | 0.00 | 0.16 | 0.28 | 0.62 | 0.78 | 11.50 | 1.31 |
| | 7 | -0.17 | -0.01 | 0.15 | 0.27 | 0.65 | 0.83 | 12.10 | 4.04 |
| | 8 | -0.17 | -0.01 | 0.15 | 0.27 | 0.65 | 0.83 | 12.10 | 4.06 |
| A | 1 | -0.13 | 0.12 | 0.24 | 0.39 | 0.85 | 0.97 | 12.59 | 0.01 |
| | 2 | -0.13 | 0.12 | 0.24 | 0.39 | 0.84 | 0.97 | 12.67 | 1.37 |
| | 3 | -0.13 | 0.12 | 0.24 | 0.39 | 0.85 | 0.97 | 12.66 | 1.39 |
| | 4 | -0.23 | 0.01 | 0.13 | 0.27 | 0.74 | 0.96 | 12.17 | 0.10 |
| | 5 | -0.23 | -0.01 | 0.12 | 0.27 | 0.78 | 1.01 | 12.60 | 2.04 |
| | 6 | -0.23 | 0.00 | 0.12 | 0.27 | 0.72 | 0.96 | 12.15 | 1.60 |
| | 7 | -0.23 | -0.01 | 0.11 | 0.27 | 0.77 | 1.00 | 12.60 | 3.57 |
| | 8 | -0.23 | -0.01 | 0.11 | 0.27 | 0.77 | 1.00 | 12.60 | 3.57 |
| BBB | 1 | -0.12 | 0.20 | 0.35 | 0.50 | 0.95 | 1.06 | 9.72 | 0.08 |
| | 2 | -0.12 | 0.20 | 0.35 | 0.49 | 0.94 | 1.06 | 9.83 | 2.50 |
| | 3 | -0.12 | 0.20 | 0.35 | 0.50 | 0.95 | 1.06 | 9.82 | 2.54 |
| | 4 | -0.28 | 0.09 | 0.23 | 0.37 | 0.79 | 1.07 | 9.53 | 0.48 |
| | 5 | -0.30 | 0.08 | 0.22 | 0.36 | 0.84 | 1.14 | 10.15 | 3.25 |
| | 6 | -0.28 | 0.09 | 0.23 | 0.36 | 0.78 | 1.06 | 9.54 | 3.11 |
| | 7 | -0.29 | 0.09 | 0.23 | 0.36 | 0.84 | 1.13 | 10.15 | 5.74 |
| | 8 | -0.29 | 0.09 | 0.23 | 0.36 | 0.84 | 1.13 | 10.15 | 5.75 |
| Junk | 1 | -0.10 | 0.12 | 0.35 | 0.65 | 1.12 | 1.22 | 8.35 | 0.51 |
| | 2 | -0.10 | 0.12 | 0.35 | 0.65 | 1.12 | 1.22 | 8.35 | 0.05 |
| | 3 | -0.10 | 0.12 | 0.35 | 0.65 | 1.12 | 1.22 | 8.34 | 0.55 |
| | 4 | -0.28 | -0.08 | 0.15 | 0.45 | 0.86 | 1.15 | 7.72 | 1.68 |
| | 5 | -0.25 | -0.07 | 0.19 | 0.48 | 0.93 | 1.18 | 7.77 | 1.92 |
| | 6 | -0.28 | -0.08 | 0.16 | 0.44 | 0.87 | 1.15 | 7.70 | 2.23 |
| | 7 | -0.23 | -0.06 | 0.21 | 0.49 | 0.94 | 1.17 | 7.72 | 2.39 |
| | 8 | -0.23 | -0.06 | 0.21 | 0.49 | 0.94 | 1.17 | 7.72 | 2.41 |

Table 10. Cross-sectional regressions

This table reports the results of cross-sectional regressions of monthly returns of individual corporate bonds on the expected return predicted by MA signals, and other bond-specific variables.

$$r_{j.t+1} = z_0 + z_1 E_t[r_{j,t+1}] + \sum_{k=1}^{m} f_k B_{j,kt} + \varepsilon_{j,t+1},$$

where $E_t[r_{j,t+1}]$ is the forecast future $(t+1)$ return of bond $j$ by MA signals in month $t$, and $B_{j,kt}, k = 1,...,m$ are bond characteristic variables. The regression is a Fama-MacBeth cross-sectional regression with weighted least squares (WLS) in the first step. The weights used are the inverse of variance of corporate bond returns estimated using the whole sample data as suggested by Shanken and Zhou (2007). We consider six models that use different bond characteristics in the regression:

(1) No bond-specific variable;
(2) bond size;
(3) bond size and age;
(4) bond size, age and coupon rate;
(5) bond size, age, coupon rate and moving average yield of last six months ($MA_{jt-1,6}$);
(6) bond size, age, coupon rate, $MA_{jt-1,6}$ and average bond return of last six months.

For brevity, we only report the estimates of the coefficient of expected returns $z_1$. The sample period is from January 1973 to September 2015.

| | | All | AAA | AA | A | BBB | Junk |
|---|---|---|---|---|---|---|---|
| Model (1) | $z_1$ | 0.57 | 0.30 | 0.42 | 0.47 | 0.43 | 0.57 |
| | $t$-stats | 10.39 | 6.92 | 7.82 | 6.38 | 6.29 | 11.83 |
| | $adj.R^2$ (%) | 20.91 | 13.36 | 17.62 | 17.20 | 13.37 | 15.78 |
| Model (2) | $z_1$ | 0.55 | 0.30 | 0.44 | 0.49 | 0.43 | 0.52 |
| | $t$-stats | 11.02 | 7.14 | 8.42 | 7.49 | 6.32 | 12.10 |
| | $adj.R^2$ (%) | 26.56 | 21.33 | 22.13 | 22.05 | 19.31 | 21.37 |
| Model (3) | $z_1$ | 0.55 | 0.32 | 0.44 | 0.50 | 0.43 | 0.51 |
| | $t$-stats | 11.68 | 7.30 | 8.73 | 7.60 | 6.30 | 11.67 |
| | $adj.R^2$ (%) | 29.29 | 25.01 | 24.67 | 25.00 | 22.75 | 22.72 |
| Model (4) | $z_1$ | 0.46 | 0.34 | 0.47 | 0.49 | 0.45 | 0.51 |
| | $t$-stats | 7.91 | 7.47 | 9.51 | 7.37 | 6.42 | 10.55 |
| | $adj.R^2$ (%) | 33.89 | 30.51 | 31.88 | 28.63 | 26.16 | 24.97 |
| Model (5) | $z_1$ | 0.34 | 0.29 | 0.47 | 0.56 | 0.43 | 0.44 |
| | $t$-stats | 4.21 | 4.81 | 12.60 | 11.76 | 5.99 | 7.09 |
| | $adj.R^2$ (%) | 37.55 | 35.27 | 39.25 | 35.30 | 32.39 | 28.23 |
| Model (6) | $z_1$ | 0.26 | 0.30 | 0.42 | 0.52 | 0.40 | 0.35 |
| | $t$-stats | 4.22 | 5.15 | 11.90 | 12.11 | 7.51 | 6.62 |
| | $adj.R^2$ (%) | 41.92 | 41.11 | 43.65 | 39.20 | 37.19 | 30.36 |

Table 11. Turnover rates and break-even transaction costs (BETCs)

This table reports the turnover rates of the trend factor portfolio (H-L) and the corresponding break-even transaction costs (BETCs). We report the turnover rates of high and low portfolios and the H-L portfolio that longs high and shorts low trend portfolios (H-L). The zero return BETCs are the transaction costs that completely offset the returns or the risk-adjusted returns of the trend factor portfolio using the risk factors in model (8) of Table 9. The insignificant BETCs are the costs that make the returns or risk-adjusted returns of H-L insignificantly different from zero at the 5% level.

| | Turnover rates (%) | | | BETCs (%) | | | |
|---|---|---|---|---|---|---|---|
| Rating | High | Low | H-L | Zero return | | Insignificance | |
| | | | | Raw return | Adjusted return | Raw return | Adjusted return |
| ALL | 28.93 | 27.61 | 56.54 | 1.72 | 1.72 | 1.30 | 1.48 |
| AAA | 30.15 | 29.39 | 59.54 | 1.44 | 1.49 | 1.03 | 1.37 |
| AA | 26.03 | 25.60 | 51.64 | 1.51 | 1.61 | 1.08 | 1.38 |
| A | 27.36 | 26.83 | 54.19 | 1.81 | 1.85 | 1.33 | 1.16 |
| BBB | 28.77 | 28.02 | 56.79 | 1.87 | 1.99 | 1.32 | 1.26 |
| Junk | 27.86 | 27.21 | 55.07 | 2.20 | 2.12 | 1.58 | 1.51 |

Table 12. Trend momentum by MAs and bond characteristics

This table reports the return of portfolios sorted by bonds' expected returns forecast by MA signals and bond characteristics. We use a two-step procedure to forecast the individual bond's expected return using the information from bond characteristics and MA signals. In the first step, we run the cross-sectional regression of bond returns on bond characteristics and MA signals,

$$r_{j,t} = \beta_{0,t} + \sum_i \beta_{i,t} MA_{jt-1,L_i} + \sum_k \gamma_{k,t} B_{k,jt-1} + \varepsilon_{j,t}, \, j = 1,...,n$$

In the second step, we estimate the bond's expected return for month $t+1$ by

$$E_t[r_{j,t+1}] = \sum_i E_t[\beta_{i,t+1}] MA_{jt,L_i} + \sum_k E_t[\gamma_{k,t+1}] B_{k,jt},$$

where $E_t[\beta_{i,t+1}] = \frac{1}{12}\sum_{m=1}^{12} \beta_{i,t+1-m}$, and $E_t[\gamma_{k,t+1}] = \frac{1}{12}\sum_{m=1}^{12} \gamma_{k,t+1-m}$. Bond characteristics include issue size, age and coupon rate. The MA signals include the bond's moving average yields with lag length of 1-, 3-, 6-, 12-, 24-, 36-, 48-, and 60-months. We then sort the bonds into quintile portfolios (Low, 2, 3, 4, and High) based on their expected returns. H-L is the return difference between High and Low portfolios, and Junk-AAA is the difference between speculative and AAA bonds. Portfolios are equally weighted and rebalanced each month. the $t$-statistics measure the significance of H-L returns. The sample period is from January 1973 to September 2015. We consider five different cross-sectional regressions in the first step by using different bond characteristics and MAs:

(1) bond issue size;

(2) bond age;

(3) coupon rate;

(4) issue size, age and coupon rate;

(5) MA signals and issue size, age and coupon rate.

| Model | | All | AAA | AA | A | BBB | Junk |
|---|---|---|---|---|---|---|---|
| Model (1) | H-L | 0.01 | 0.05 | -0.10 | 0.02 | -0.13 | 0.06 |
| | $t$-stats | 0.08 | 0.39 | -0.82 | 0.17 | -0.93 | 0.39 |
| Model (2) | H-L | 0.02 | 0.03 | -0.03 | 0.04 | 0.03 | -0.08 |
| | $t$-stats | 0.19 | 0.25 | -0.32 | 0.31 | 0.22 | -0.53 |
| Model (3) | H-L | 0.02 | -0.05 | 0.07 | 0.13 | 0.12 | 0.10 |
| | $t$-stats | 0.14 | -0.46 | 0.64 | 1.05 | 0.87 | 0.69 |
| Model (4) | H-L | 0.08 | 0.02 | -0.02 | 0.08 | 0.03 | 0.04 |
| | $t$-stats | 0.71 | 0.16 | -0.16 | 0.66 | 0.24 | 0.27 |
| Model (5) | H-L | 0.95 | 0.83 | 0.80 | 0.97 | 1.01 | 1.29 |
| | $t$-stats | 7.99 | 6.82 | 7.00 | 7.36 | 6.63 | 7.15 |

Table 13. Bond and stock trend momentum

This table reports the returns of quintile bond (stock) portfolios sorted by bond (stock) expected returns. We only use the bonds of public firms or the stocks that have bonds outstanding in this analysis. For bonds, the MA signals include the bond's moving average yields with lag length of 1-, 3-, 6-, 12-, 24-, 36-, 48-, and 60-months. The MA signals for stocks include the stock's MAs with lag length of 3-, 5-, 10-, 20-, 50-, 100-, 200- 400-, 600-, 800- and 1000-days. We then sort the bonds (stocks) into quintile portfolios (Low, 2, 3, 4, and High) based on their expected returns. H-L is the return difference between High and Low portfolios. Portfolios are equally weighted and rebalanced in every month. the $t$-statistics measure the significance of H-L returns. The sample period of bonds is from January 1973 to September 2015, while the sample period of stocks is from January 1973 to December 2014. Panel A and B report the results of bond and stock trend portfolios, respectively. Panel C reports the correlation between the bond and stock trend portfolios. Panel D reports the results of bond trend portfolios using both bond and stock's MAs. Panel E reports the results using firm-level bond returns and stock-adjusted bond returns. Monthly firm-level bond returns are averages return across all available bonds weighted by issuing size. The stock-adjusted bond return is calculated by subtracting the average monthly bond return of the expected return decile to which the bond belongs in that month using stock MAs from each bond-month return. Panel F reports the returns of 5×5 independently sorted portfolios based on bond and stock MAs respectively. In panel G, we run the monthly Fama-MacBeth cross-sectional regressions of monthly bond returns on expected bond returns using bond MAs ($E_r^B$), expected returns using stock MAs ($E_r^S$), lagged bond returns ($r_{i,t-1}$) and lagged bond numeric ratings ($Rating_{i,t-1}$):

$$r_{i,t} = c_{0,t} + c_{1,t}E_r^B + c_{2,t}E_r^S + c_{3,t}r_{i,t-1} + c_{4,t}Rating_{i,t-1} + e_{i,t}.$$

The numeric ratings are defined as $1 = AAA, 2 = AA+, 3 = AA, , 20 = CC, 21 = C$ and below. We do not use $Rating_{i,t-1}$ for the regressions within AAA since they are all one. Panel G reports the time-series averages of the cross-sectional regression coefficients with $t$-statistics and average adjusted R squares. $^a$, $^b$, and $^c$ indicate the significance level of 1%, 5% and 10%, respectively.

Panel A. Bond portfolios

| Rating | Low | 2 | 3 | 4 | High | H-L | $t$-stats |
|---|---|---|---|---|---|---|---|
| All | 0.29 | 0.54 | 0.67 | 0.80 | 1.21 | 0.92 | 7.50 |
| AAA | 0.30 | 0.54 | 0.61 | 0.69 | 1.04 | 0.74 | 5.38 |
| AA | 0.31 | 0.53 | 0.62 | 0.74 | 1.05 | 0.74 | 6.62 |
| A | 0.27 | 0.51 | 0.62 | 0.76 | 1.21 | 0.94 | 7.07 |
| BBB | 0.29 | 0.60 | 0.74 | 0.85 | 1.22 | 0.93 | 5.97 |
| Junk | 0.37 | 0.62 | 0.80 | 1.06 | 1.55 | 1.18 | 5.99 |

Panel B. Stock portfolios

| Rating | Low | 2 | 3 | 4 | High | H-L | $t$-stats |
|---|---|---|---|---|---|---|---|
| All | 1.08 | 1.21 | 1.33 | 1.56 | 2.12 | 1.04 | 2.57 |
| AAA | 0.61 | 1.54 | 1.32 | 1.63 | 1.96 | 1.35 | 1.84 |
| AA | 1.08 | 1.14 | 1.41 | 1.54 | 1.85 | 0.77 | 1.75 |
| A | 1.25 | 1.17 | 1.39 | 1.51 | 1.97 | 0.71 | 2.02 |
| BBB | 1.16 | 1.26 | 1.40 | 1.62 | 1.99 | 0.84 | 2.26 |
| Junk | 1.05 | 1.25 | 1.20 | 1.59 | 2.14 | 1.09 | 2.14 |

Panel C. Correlation between bond and stock trend portfolio returns

| | All | AAA | AA | A | BBB | Junk |
|---|---|---|---|---|---|---|
| Correlation | -0.06 | -0.03 | 0.04 | 0.04 | -0.15[a] | -0.03 |

Panel D. Bond portfolios by MAs of bonds and stocks

| Rating | Low | 2 | 3 | 4 | High | H-L | $t$-stats |
|---|---|---|---|---|---|---|---|
| All | 0.32 | 0.53 | 0.65 | 0.81 | 1.24 | 0.92 | 6.92 |
| AAA | 0.52 | 0.47 | 0.60 | 0.70 | 0.83 | 0.32 | 2.46 |
| AA | 0.36 | 0.50 | 0.63 | 0.75 | 1.04 | 0.68 | 6.00 |
| A | 0.30 | 0.49 | 0.62 | 0.76 | 1.20 | 0.90 | 7.22 |
| BBB | 0.41 | 0.54 | 0.65 | 0.84 | 1.31 | 0.90 | 6.39 |
| Junk | 0.44 | 0.64 | 0.83 | 1.03 | 1.48 | 1.04 | 6.31 |

Panel E. Firm-level bond returns and stock-adjusted bond returns

| | Firm-level bond returns | | | | Stock-adjusted bond returns | | | |
|---|---|---|---|---|---|---|---|---|
| Rating | Low | High | H-L | $t$-stats | Low | High | H-L | $t$-stats |
| All | 0.40 | 1.11 | 0.71 | 6.23 | -0.40 | 0.51 | 0.91 | 17.66 |
| AAA | 0.48 | 0.97 | 0.49 | 3.51 | -0.28 | 0.40 | 0.68 | 10.20 |
| AA | 0.41 | 0.94 | 0.53 | 4.80 | -0.32 | 0.40 | 0.72 | 15.45 |
| A | 0.39 | 1.07 | 0.68 | 5.29 | -0.39 | 0.53 | 0.92 | 17.07 |
| BBB | 0.38 | 1.16 | 0.78 | 6.11 | -0.39 | 0.52 | 0.91 | 12.27 |
| Junk | 0.48 | 1.41 | 0.94 | 4.83 | -0.38 | 0.83 | 1.20 | 8.14 |

Panel F. Bivariate portfolio returns

| | Stock quintiles | Bond quintiles Low | 2 | 3 | 4 | High | H-L | $t$-stats |
|---|---|---|---|---|---|---|---|---|
| All | L | 0.18 | 0.51 | 0.59 | 0.71 | 1.08 | 0.91 | 6.21 |
| | 2 | 0.30 | 0.55 | 0.64 | 0.91 | 1.24 | 0.93 | 6.66 |
| | 3 | 0.23 | 0.47 | 0.65 | 0.83 | 1.13 | 0.90 | 6.08 |
| | 4 | 0.32 | 0.57 | 0.74 | 0.86 | 1.28 | 0.96 | 7.51 |
| | H | 0.35 | 0.65 | 0.70 | 0.87 | 1.37 | 1.02 | 7.75 |
| | H-L | 0.18 | 0.15 | 0.10 | 0.16 | 0.29 | | |
| | $t$-stats | 1.38 | 1.20 | 0.80 | 1.21 | 1.93 | | |
| AAA | L | 0.32 | 0.52 | 0.58 | 0.74 | 1.20 | 0.87 | 5.51 |
| | 2 | 0.08 | 0.37 | 0.45 | 0.48 | 1.00 | 0.92 | 4.62 |
| | 3 | 0.48 | 0.60 | 0.54 | 0.94 | 1.02 | 0.54 | 2.09 |
| | 4 | 0.43 | 0.56 | 0.47 | 0.74 | 1.02 | 0.60 | 2.80 |
| | H | 0.33 | 0.63 | 0.53 | 0.72 | 1.24 | 0.90 | 3.89 |
| | H-L | 0.01 | 0.11 | -0.05 | -0.02 | 0.04 | | |
| | $t$-stats | 0.06 | 0.65 | -0.29 | -0.09 | 0.18 | | |
| AA | L | 0.33 | 0.51 | 0.63 | 0.75 | 1.08 | 0.75 | 6.01 |
| | 2 | 0.31 | 0.49 | 0.59 | 0.70 | 0.99 | 0.68 | 5.36 |
| | 3 | 0.24 | 0.49 | 0.59 | 0.67 | 1.04 | 0.81 | 6.42 |
| | 4 | 0.26 | 0.52 | 0.66 | 0.74 | 1.08 | 0.82 | 6.26 |
| | H | 0.26 | 0.47 | 0.64 | 0.71 | 1.06 | 0.80 | 6.38 |
| | H-L | -0.07 | -0.03 | 0.00 | -0.03 | -0.02 | | |
| | $t$-stats | -0.62 | -0.28 | 0.04 | -0.26 | -0.16 | | |
| A | L | 0.25 | 0.44 | 0.51 | 0.71 | 1.13 | 0.88 | 5.59 |
| | 2 | 0.22 | 0.54 | 0.68 | 0.72 | 1.22 | 1.00 | 7.09 |
| | 3 | 0.19 | 0.49 | 0.61 | 0.73 | 1.22 | 1.03 | 7.34 |
| | 4 | 0.23 | 0.54 | 0.66 | 0.76 | 1.32 | 1.08 | 7.44 |
| | H | 0.36 | 0.53 | 0.69 | 0.85 | 1.44 | 1.08 | 7.43 |
| | H-L | 0.11 | 0.09 | 0.18 | 0.14 | 0.30 | | |
| | $t$-stats | 0.85 | 0.71 | 1.36 | 1.05 | 1.80 | | |
| BBB | L | 0.27 | 0.65 | 0.64 | 0.65 | 1.15 | 0.88 | 4.06 |
| | 2 | 0.13 | 0.55 | 0.70 | 0.80 | 1.38 | 1.25 | 7.11 |
| | 3 | 0.35 | 0.61 | 0.72 | 0.87 | 1.42 | 1.07 | 6.95 |
| | 4 | 0.29 | 0.56 | 0.70 | 0.89 | 1.50 | 1.21 | 7.74 |
| | H | 0.35 | 0.62 | 0.82 | 0.96 | 1.55 | 1.20 | 6.79 |
| | H-L | 0.08 | -0.03 | 0.18 | 0.31 | 0.40 | | |
| | $t$-stats | 0.41 | -0.18 | 1.21 | 1.81 | 1.96 | | |
| Junk | L | 0.16 | 0.09 | 0.45 | 0.97 | 1.24 | 1.08 | 3.90 |
| | 2 | 0.44 | 0.72 | 0.91 | 1.22 | 2.07 | 1.63 | 5.17 |
| | 3 | 0.09 | 0.39 | 0.94 | 1.00 | 1.68 | 1.59 | 6.00 |
| | 4 | 0.37 | 0.47 | 0.85 | 0.92 | 1.52 | 1.15 | 4.66 |
| | H | 0.32 | 0.74 | 0.87 | 1.13 | 1.68 | 1.36 | 3.86 |
| | H-L | 0.17 | 0.65 | 0.42 | 0.16 | 0.44 | | |
| | $t$-stats | 0.64 | 2.76 | 1.66 | 0.62 | 2.20 | | |

Panel G. Cross-sectional regressions of bond returns on bond and stock MA signals

| Model | $c_0$ | $t$-stats | $E_r^B$ | $t$-stats | $E_r^S$ | $t$-stats | $r_{i,t-1}$ | $t$-stats | Rating | $t$-stats | $adj.R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | All | | | | | |
| 1 | 0.14 | (1.50) | 0.65 | (13.23) | | | | | | | 8.98 |
| 2 | 1.67 | (8.25) | | | 0.26 | (4.59) | | | | | 1.58 |
| 3 | 1.19 | (5.34) | 0.68 | (14.34) | 0.24 | (4.26) | | | | | 10.42 |
| 4 | 1.38 | (6.25) | 0.56 | (11.29) | 0.25 | (4.57) | -0.08 | (-5.23) | | | 16.69 |
| 5 | 0.57 | (8.22) | | | | | | | 0.02 | (3.57) | 2.75 |
| 6 | 1.21 | (5.89) | 0.61 | (11.91) | 0.24 | (4.75) | -0.08 | (-5.39) | 0.00 | (-0.31) | 18.65 |
| | | | | | | AAA | | | | | |
| 1 | 0.00 | (-0.01) | 0.43 | (9.21) | | | | | | | 11.92 |
| 2 | 6.75 | (2.14) | | | 0.08 | (1.69) | | | | | 4.12 |
| 3 | 4.29 | (1.01) | 0.44 | (9.71) | 0.11 | (1.64) | | | | | 16.30 |
| 4 | -3.26 | (-0.88) | 0.31 | (5.34) | 0.06 | (0.88) | -0.22 | (-4.65) | | | 29.61 |
| | | | | | | AA | | | | | |
| 1 | -0.30 | (-2.64) | 0.64 | (12.10) | | | | | | | 14.64 |
| 2 | 0.89 | (3.54) | | | 0.08 | (2.14) | | | | | 1.53 |
| 3 | -0.15 | (-0.53) | 0.65 | (12.02) | 0.07 | (1.69) | | | | | 16.25 |
| 4 | 0.09 | (0.34) | 0.59 | (11.34) | 0.04 | (1.07) | -0.09 | (-4.63) | | | 25.53 |
| 5 | 0.64 | (8.19) | | | | | | | 0.00 | (-0.26) | 1.36 |
| 6 | 0.11 | (0.40) | 0.59 | (11.41) | 0.05 | (1.35) | -0.09 | (-4.68) | -0.00 | (-0.03) | 26.27 |
| | | | | | | A | | | | | |
| 1 | -0.43 | (-3.07) | 0.68 | (11.19) | | | | | | | 14.04 |
| 2 | 0.91 | (3.81) | | | 0.11 | (2.18) | | | | | 1.24 |
| 3 | -0.56 | (-1.92) | 0.69 | (11.40) | 0.16 | (3.04) | | | | | 15.40 |
| 4 | -0.35 | (-1.24) | 0.64 | (11.02) | 0.21 | (3.97) | -0.07 | (-3.82) | | | 22.93 |
| 5 | 0.49 | (4.79) | | | | | | | 0.05 | (2.26) | 1.46 |
| 6 | -0.37 | (-1.29) | 0.64 | (11.09) | 0.19 | (3.89) | -0.07 | (-3.85) | 0.00 | (0.08) | 24.04 |
| | | | | | | BBB | | | | | |
| 1 | -0.02 | (-0.12) | 0.52 | (8.14) | | | | | | | 13.54 |
| 2 | 1.72 | (2.79) | | | 0.18 | (3.09) | | | | | 3.55 |
| 3 | -0.47 | (-0.71) | 0.55 | (8.32) | 0.34 | (4.57) | | | | | 16.73 |
| 4 | -1.63 | (-2.17) | 0.52 | (8.63) | 0.22 | (3.70) | -0.01 | (-0.17) | | | 25.21 |
| 5 | 0.73 | (4.55) | | | | | | | 0.03 | (1.81) | 0.55 |
| 6 | -1.02 | (-1.37) | 0.52 | (8.56) | 0.22 | (3.60) | 0.01 | (0.29) | 0.01 | (0.60) | 25.33 |
| | | | | | | Junk | | | | | |
| 1 | 0.14 | (0.86) | 0.39 | (7.88) | | | | | | | 10.05 |
| 2 | -5.46 | (-2.75) | | | 0.26 | (4.72) | | | | | 5.22 |
| 3 | -3.55 | (-2.34) | 0.42 | (8.12) | 0.23 | (4.33) | | | | | 14.28 |
| 4 | -2.13 | (-1.55) | 0.23 | (3.65) | 0.23 | (4.44) | -0.13 | (-4.14) | | | 19.17 |
| 5 | 0.60 | (2.71) | | | | | | | 0.03 | (1.89) | 4.15 |
| 6 | -0.92 | (-0.45) | 0.25 | (3.72) | 0.20 | (3.68) | -0.19 | (-3.59) | 0.01 | (0.47) | 20.43 |

Table 14. Stock market variables and trend momentum

This table report the results of trend momentum controlling for stock market variables. Following Chordia, et al. (2014) and Choi and Kim (2016), we consider eight stock market anomaly variables including the size, value, accruals, asset growth, profitability, net stock issuance, earnings surprise, and idiosyncratic volatility. We sort the firm-level return observations in each month by their individual stock market variables into three groups (Low, Medium and High). In each group we run the trend momentum analysis to calculate the H-L returns. Panel A report these results. We next run the cross-sectional regression of firm-level bond returns on their return forecasts with and without the stock market variables as controls each month. The mean, $t$-stats of coefficients of return forecast and the mean adjusted R-squares of cross-sectional regression are reported in Panel B.

Panel A. Trend portfolios controlling for firm characteristic variables

| | Low | | Medium | | High | | Low | | Medium | | High | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | H-L | $t$-stats | H-L | $t$-stats | H-L | $t$-stats | H-L | $t$-stats | H-L | $t$-stats | H-L | $t$-stats |
| | | | Size | | | | | | Value | | | |
| ALL | 0.72 | 5.9 | 0.55 | 4.43 | 0.57 | 5.08 | 0.64 | 5.2 | 0.64 | 5.16 | 0.46 | 3.66 |
| IG | 0.75 | 6.12 | 0.63 | 4.88 | 0.52 | 4.63 | 0.65 | 5.29 | 0.64 | 5.38 | 0.59 | 4.83 |
| Junk | 0.61 | 2.69 | 0.99 | 3.29 | 0.57 | 2.22 | 0.6 | 2.63 | 0.38 | 1.8 | 0.05 | 0.19 |
| | | | Accruals | | | | | | Asset growth | | | |
| ALL | 0.42 | 3.31 | 0.6 | 4.85 | 0.54 | 4.15 | 0.5 | 3.94 | 0.61 | 5.14 | 0.52 | 4.1 |
| IG | 0.56 | 4.34 | 0.61 | 4.96 | 0.72 | 5.66 | 0.61 | 5.14 | 0.63 | 5.31 | 0.64 | 5.17 |
| Junk | -0.32 | -1.29 | 0.02 | 0.1 | 0.15 | 0.59 | 0.39 | 1.76 | 0.36 | 1.21 | 0.54 | 2.68 |
| | | | Profitability | | | | | | Net stock issuance | | | |
| ALL | 0.55 | 4.44 | 0.70 | 5.55 | 0.56 | 4.78 | 0.59 | 4.89 | 0.49 | 3.91 | 0.62 | 4.72 |
| IG | 0.59 | 4.67 | 0.72 | 5.72 | 0.66 | 5.65 | 0.62 | 5.28 | 0.69 | 5.65 | 0.56 | 4.33 |
| Junk | 0.33 | 1.73 | 0.65 | 2.73 | 0.02 | 0.09 | 0.60 | 2.48 | 0.29 | 1.12 | 0.61 | 2.00 |
| | | | Earnings surprise | | | | | | Idiosyncratic volatility | | | |
| ALL | 0.49 | 3.86 | 0.73 | 6.03 | 0.68 | 5.43 | 0.70 | 6.26 | 0.52 | 4.16 | 0.68 | 5.18 |
| IG | 0.65 | 5.32 | 0.68 | 5.53 | 0.59 | 4.62 | 0.72 | 6.35 | 0.55 | 4.28 | 0.64 | 5.06 |
| Junk | 0.43 | 1.66 | 0.33 | 1.40 | 0.58 | 2.68 | 0.43 | 1.74 | 0.45 | 1.90 | 0.59 | 2.08 |

Panel B. Regression

| | Without controlling variables | | | With controlling variables | | |
|---|---|---|---|---|---|---|
| | Coefficient | $t$-stats | $Adj.R^2$ | Coefficient | $t$-stats | $Adj.R^2$ |
| All | 0.60 | 9.53 | 8.35 | 0.71 | 11.03 | 16.35 |
| IG | 0.78 | 11.90 | 10.17 | 0.83 | 11.50 | 15.72 |
| Junk | 0.44 | 2.18 | 7.52 | 0.71 | 1.98 | 18.74 |

Figure 1. Portfolio return
This graph plots the returns of trend momentum portfolios.