Trend Momentum in Corporate Bonds

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Abstract

This paper investigates bond momentum by utilizing all trend signals in the short-, intermediate- and long-term simultaneously. Using this informationally efficient strategy, we uncover, for the first time, economically significant momentum for corporate bonds across all ratings. Bond momentum has little correlation with stock momentum, and is robust to various controls. It is stronger in the post-TRACE era and during periods with low sentiment and growth. The bond momentum presents the most pronounced cross-sectional anomaly in the corporate bond market to date that challenges the existing rational pricing theory.

JEL classification: G12; G14;

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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 devoted to this important issue.[1] In a comprehensive study of stock market anomalies, Schwert (2003) concludes that the momentum anomaly is one of the most persistent and robust anomalies. However, to date the literature of momentum has focused on the stock market and much less is known for the corporate bond market, which is larger than the former in capitalization and is the primary source of long-term capital in the US. A question that naturally arises is whether momentum exists in the corporate bond market. This issue is important not only for pricing corporate bonds and managing portfolios, but also for understanding what really drives momentum.

Gebhardt, Hvidkjaer and Swaminathan (2005a) seem the first to investigate this issue and find no evidence of momentum in investment-grade bond returns. When extending the data to high-yield bonds, Jostova, Nikolova, Philipov and Stahel (2013) find evidence of momentum in noninvestment-grade bonds. However, since the value of high-yield bonds accounts only for about 8% of the corporate bond market, the finding of momentum for this sector appears to be of limited significance. The fundamental question remains whether there is momentum in the entire corporate bond market. Recently, Choi and Kim (2016), and Chordia, Goyal, Nozawa, Subramanyam and Tong (2016) examine the cross-sectional return predictability for corporate bond with various characteristics, but still find little evidence of bond momentum. In a study subsequent to ours, van Zundert (2016) uses volatility-weighting instead of equal-weighting, and finds larger bond momentum. Nevertheless, the magnitude of the momentum for investment-grade bonds documented in his study is only 20 basis points per month, hardly significant economically after transaction costs.

[1]For example, the latest number of Google citations of Jegadeesh and Titman (1993) is over 9000.

In this paper, we find, for the first time, strong momentum for all rated bonds that is no less than the stock momentum return, by using an efficient method that captures all available important information to form momentum portfolios. Following Haugen and Baker (1996), we estimate the expected corporate bond returns using a cross-sectional regression approach that utilizes multiple price signals. This approach differs from the existing procedure that sorts bond returns based on only one signal. The signals used in this approach include price trends of bonds over short-, intermediate- and long-term investment horizons. Analogous to Han, Zhou and Zhu (2016), the trends are captured by moving averages of prices scaled by the current price at different lags, which in the bond market are comparable to yields, over different horizons.[2] A number of studies have provided economic rationales, both theoretically and empirically, as to 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; Neely, Rapach, Tu and Zhou, 2014). Since our procedure uses the trend signals over different return horizons simultaneously, it has much higher power to detect bond momentum than the conventional one-signal sorting approach used in past momentum studies.

A substanitial body of research work has suggested that return predictability is horizon dependent. Researchers have uncovered a number of horizon-dependent patterns of return predictability that are difficult to explain by conventional risk-factor models: Short-term autocorrelation of returns at daily, weekly and monthly levels (Lehmann, 1990; Lo and MacKinlay, 1990), momentum in 6-12 month horizons (Jegadeesh and Titman, 1993), and long-term reversals in 3-5 year horizons (DeBondt and Thaler, 1985). These patterns imply that asset returns contain predictive components in different investment horizons, and also suggest that price information in the short-, intermediate- and long-term horizons can help predict returns. Recent studies lend support to this contention. Daniel, Hirshleifer and Sun (2017) show that that different factors predict short- and long-horizon returns and Akbas, Jiang and Koch (2017) find that different investment horizons contain distinct

[2] While Han, Zhou and Zhu (2016) is the first to use such moving averages to forecast stock returns, we are the first to apply them to corporate bonds.

information for future returns. Thus, it is important to incorporate price information in different investment horizons in order to maximize the efficiency of predicting future returns.

Using a comprehensive sample of corporate bonds from January 1973 to September 2015, we construct the momentum portfolio following the convention that is long in the bonds with the highest expected returns and short in those with the lowest expected returns, except that we estimate the expected returns by the aforementioned efficient method. Using this new method, we document several important findings. First, there is strong momentum in not only speculative-grade bonds, but also investment-grade bonds in every rating category. For clarity, we shall name the momentum detected by our method as *trend* momentum, for which multiple trend signals are used, while the traditional momentum is simply referred to as momentum. Although existing studies were able to discover limited momentum profits, typically less than 30 basis points, for investment-grade bonds, we find that the trend momentum profits range from 110 basis points (for AAA bonds) to 143 basis points (for BBB bonds). As to speculative-grade bonds, while Jostova et al. (2013) detect a momentum profit of 121 basis points per month, we find the trend momentum yields a profit of 158 points per month, which is 30% higher. [3]

Second, the trend momentum profit is higher 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 profits in the corporate bond market. However, in contrast to the findings in the equity market, we find that trend momentum profits of bonds are not primarily derived from taking the short position. Furthermore, the trend momentum profits depend on bond characteristics. The momentum tends to be stronger for bonds with smaller issue size, higher coupon rates and yields, and newer bonds (on-the-run). While bond characteristics matter, the trend momentum remains highly significant after controlling for various firm characteristics in out-of-sample forecasting tests.

Third, the trend momentum cannot be explained by standard risk factors, bond characteristics and transaction costs, and the unexplained trend portfolio returns are higher for speculative-grade

[3] Trend momentum profits reported here are based on decile portfolio sorts.

bonds. Including the information for bond characteristics does not help to improve cross-sectional bond return prediction either. While there are over 80 cross-sectional anomalies in the stock market (see, for example, Hou, Xue and Zhang, 2015), the trend momentum appears to be the only one that is significant across the corporate bond market. For speculative-grade bonds, the momentum may be explained by the gradual information diffusion of Hong and Stein (1999). But this explanation does not extend to large and more transparent firms in our sample. The trend momentum anomaly challenges the existing rational bond pricing theory.

Fourth, the trend momentum varies over time. It is stronger after TRACE (the Trade Reporting and Compliance Engine) is established that improves 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 rather than decrease it. In addition, the trend momentum is stronger in the periods of low market sentiment and slow economic growth. The trend momentum profits over these periods is much larger for speculative-grade bonds.

Our paper addresses the issue of cross-sectional predictability of corporate bond returns. This is differentiated from the traditional studies on time-series predictability that is linked to the time-varying bond risk premia. Keim and Stambaugh (1986) present the first study on predicting corporate bond returns using the past information. Fama and French (1989) find that lagged default spreads, term spreads and dividend yields are important predictors for corporate bond returns. Subsequently, 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) apply an iterated combination approach to a large set of predictors and find that this approach significantly improves the out-of-sample forecasting performance. The approaches for dealing with cross-sectional predictability and time-series predictability are quite different, but both provide valuable insights that improve our understanding of asset pricing in the corporate 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 and

Section 5 conducts additional robustness tests. Finally, Section 6 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 make use of all past important information at every possible time length, we employ the moving averages of past prices from short to long horizons to draw price signals. More specifically, we extract the signals 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. We then 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 for predicting 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

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

where Y_j^t is the closing yield for bond j in month t and L is the lag length. We construct the moving average using 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 can complicate the time-series analysis. 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 use this valuable information.

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:

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

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-, and 48-months in month $t-1$. These MA signals represent 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 using the past trend 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 (L) is referred to as the return on the trend factor in a way similar to the construction of the traditional momentum factor. The trend factor portfolio longs bonds with the highest expected returns and shorts bonds with the lowest expected returns. This sorting approach is similar in spirit 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 the past return in a fixed horizon, we sort bonds by their expected returns which are forecast by using multiple trend signals. In particular, the traditional 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 method is more general and can potentially capture the important information for the short-, intermediate- and long-term predictive components of bond returns.

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.[4] 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.

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.[5] We exclude bonds with maturity less than two years and longer than 30 years and bonds with

[4]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.

[5] This return is transformed to the log return in the forecast, so that monthly log returns could be added together to

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.[6]

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 over time, 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 profits across different ratings. We next turn to empirical tests.

[Insert Table 1 here]

4 Empirical results

4.1 Returns of bond trend portfolios

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 forecast by the trend 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 97 basis points, which is significant at the 1% level (t = 8.12).[7] The bonds included in the high quintile portfolio consist of more low-grade

get a return of longer horizon conveniently.

[6]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.

[7]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. Unreported results show high quintile portfolio has more junk bonds (12.63%) than the low quintile portfolio (9.29%). Results imply that high returns of the top quintile 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 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, indicating 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 profit captured by our trend momentum strategy is much larger. Using the traditional momentum strategy based solely on the price information in the past six months, Jostova et al. (2013) report a momentum profit of 121 basis points for non-investment grade bonds. In contrast, using the multiple price signals in the short, intermediate and long terms, we find a much larger momentum profit of 158 basis points for speculative-grade bonds, which is more than 25% higher than their estimate for the one-month holding period. The higher momentum profits generated from our momentum strategy suggest that past prices in the short and long terms contain useful information for cross-sectional return predictions over and beyond the intermediate term (6 months).

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 is 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 over different investment horizons, we uncover, for the first time, significant trend momentum in investment-grade bonds. Results show that momentum is pervasive in the corporate bond market, not just limited to a small subset of high-yield bonds.

There is evidence 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 of momentum concentration in the stocks and bonds with speculative grade, our results show a very different picture. In particular, trend momentum does not concentrate in the bonds with speculative grades in the Low portfolio. Unreported results (omitted for brevity) 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 for speculative-grade 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 portfolio and low trend 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 come primarily from the long position, instead of the short position. This pattern holds not just for high-grade bonds but also for the low-grade bonds.

[Insert Table 2]

Several recent studies have documented abnormal returns in the corporate bond market (see Chordia, et al., 2016; Choi and Kim, 2016; Bai, Bali and Wen, 2016). Sorting all bonds into deciles by firm 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 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 do 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.

Figure 1 plots the time series of returns for the trend factor (H-L) over the entire sample period. It shows that trend momentum is quite stable over time. Moreover, the trend momentum exhibits similar patterns across bonds of different ratings. Results again show that 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 momentum factor has positive returns in this period. The bond market does not exhibit a "momentum crash" as in the stock market.[8]

Panel A of Table 3 reports the summary statistics and extreme values of bond trend factor portfolio (H-L). For comparison, we also report the results of stock market momentum factor portfolio (MOM). The trend factor portfolios have lower standard deviations and much higher Sharpe ratios than MOM. They also have positive skewness and large kurtosis. These findings

[8]The mean H-L portfolio returns during the financial crisis period (December 2007 to June 2009) are 2.79%, 1.81%, 2.72%, 3.45%, 5.71% and 3.81% for all, AAA, AA, A, BBB and junk bonds respectively.

are similar to the stock trend momentum factor documented in Han, Zhou and Zhu (2016). The minimum returns of the trend factor portfolios decrease with ratings. However, they are still much greater than that of MOM. For example, the minimum value of MOM during the sample period is -34.58%, whereas it is only -16.53% for the trend momentum portfolio of junk bonds. The trend factor portfolios also have a smaller number of extreme negative value observations. There is no observation below two standard deviations for the whole bond sample. The trend factor portfolio of junk bonds has six observations below two standard deviations, and one observation below three standard deviations. By contrast, the number of observations below two and three standard deviations are nine and three, respectively for MOM.

In Panel B of Table 3, we report the correlations between the trend momentum factor and other risk factors. The correlations are close to zero and negative in a number of cases. This finding suggests a potential diversification benefit in investing in both bond trend factor portfolios and stock factor portfolios (MKT, SMB, HML and MOM). This issue is further explored later.

[Insert Table 3]

We also calculate the value-weighted returns of bond trend portfolios. Unreported results show that value-weighted H-L return of all bonds is 0.93% with a t-value of 8.13 if quantile portfolios are constructed, and is 1.33% with a t-value of 10.26 if decile portfolios are constructed. The results are close to those reported in Table 2. The results of the value-weighted returns of bond trend portfolios of different ratings are similar. The results suggest that the trend momentum documented in this paper is robust to the choice of portfolio weight.

4.2 Alpha of bond trend portfolios

We next examine whether the trend portfolios formed by MA signals consistently earn abnormal returns. In this analysis, we run the time-series regressions of portfolio 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 H-L return spreads $r^e_{p,t} = r_{H,t} - r_{L,t}$, $\mathbf{F_t}$ is a vector of conventional risk factors, and the intercept, α_p, measures the risk-adjusted return. A significant α_p suggests that the conventional 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 use differenced term and default factors as explanatory variables. $\Delta TERM_t = (TERM_t - TERM_{t-1})$ and $\Delta DEF_t = (DEF_t - DEF_{t-1})$. $mTERM_t = \Delta TERM_t/(1 + TERM_{t-1})$, and $mDEF_t = \Delta DEF_t/(1 + DEF_{t-1})$. 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.[9] We calculate

[9]We also run the time series regression using Fama-French (2015) five factors. The results are similar and available

the test statistics of Gibbons, Ross and Shanken (GRS, 1989) to test the null hypothesis that all the intercepts are zero.

Table 4 reports alphas of time-series regressions for the whole sample. Results clearly show that the risk-adjusted returns of Low portfolios are all negative, while those of High portfolios are all positive. The α_p's of H-L portfolios are all positive and highly significant. Results suggest that the returns of trend factor portfolios (H-L) cannot be explained by standard risk factors. GRS test statistics soundly reject the null hypothesis that all intercepts are zero. Introducing more factors improves the explanatory power of the model but does not help to reduce alpha values.

[Insert Table 4]

Table 5 reports regression results by bond rating. The H-L portfolio alphas are again all highly significant across ratings. A substantial proportion of the trend portfolio return cannot be explained 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 5]

4.3 Economic gains of trend factor portfolios

An important question is how much economic gain could be achieved by using the trend factor portfolios. We address this question in two ways. First, following Gibbons, Ross and Shanken (1989), we examine the improvement in the maximum Sharpe ratio by using trend factor portfolios. We calculate the maximum Sharpe ratio of using stock factor portfolios only (θ_p) and using stock factor portfolios and bond trend factor portfolios jointly (θ^*). The difference between these two Sharpe ratios provide a measure of economic gains for using bond trend momentum portfolios.

upon request.

Panel A of Table 6 reports the maximum Sharpe ratios.[10] When using only stock factor portfolios, we find that the maximum monthly Sharpe ratios are all smaller than 0.30. For example, the θ_ps of MKT+SMB+HML and MKT+SMB+HML+MOM are only 0.22 and 0.29, respectively. The values increase dramatically to around 0.80 when trend factor portfolios are included. The monthly θ^* by using trend factor portfolios jointly with MKT, SMB, HML and MOM is 0.86 or 2.98 ($0.86 \times \sqrt{12}$) per annum. This is a highly significant Sharpe ratio. Using bond trend factor portfolios increases the monthly Sharpe ratio by more than 0.60 for most cases (2.08 per annum). Results show that there are substantial economic gains by using bond trend momentum factor in investment portfolios.

As a comparison, we calculate the change of maximum Sharpe ratio by using bond index portfolios of different ratings. In each month we calculate the equal-weighted portfolio returns of each rating, and use them to construct the optimal risky portfolio with stock factor portfolios. The maximum Sharpe ratio using bond index portfolios with MKT+SMB+HML+MOM is 0.32. The increase over the θ_p of MKT+SMB+HML+MOM is only 0.03. The results suggest that the economic gains provided by bond trend factor portfolios are not driven by the benefit of introducing corporate bond market into the portfolio construction.

Second, we investigate whether the trend momentum survives transaction costs. We first calculate turnover rates of portfolios each month and report turnover ratios of both high and low trend momentum portfolios. Then, following the literature (e.g., Grundy and Martin, 2001; Barroso and Santa-Clara, 2015; Han, Zhou and Zhu, 2016), 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 factor portfolio using the risk factors in model (8) of Tables 4 and 5. By contrast, the insignificant BETCs are transaction costs that make the raw returns or the risk-adjusted returns of the trend factor portfolio insignificantly different from zero at the 5% level.

[10] To obtain these ratios, we need to calculate $\alpha'\Sigma^{-1}\alpha$, where Σ is the variance-covariance matrix of the residuals across bond trend portfolios.

Panel B of Table 6 reports the results for turnover rates and break-even transaction costs for the whole sample and different rating categories. The results 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 factor portfolio is not dominated by either long or short side. The right side of Table 8 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 1.30% to make it become statistically insignificant at the 5% level. For risk-adjusted returns, it takes transaction costs of 1.73% and 1.48%, respectively. The results by ratings show that break-even 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) report a BETC of 1.03% over the period from 1926 to 1995 for a completely dominant stock momentum portfolio. Han, Zhou and Zhu (2016) report a BETC of 1.24% to render zero returns for the stock trend portfolio. The estimates of BETCs also suggest that trend momentum 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). Thus, the trend momentum profit survives ransaction cost.

Overall, results show that the profit of the trend factor portfolio is of economic significance and survives trading cost. Moreover, trend momentum profits of corporate bonds are much higher than that of stock momentum or stock trend momentum.

[Insert Table 6]

4.4 Properties of bond trend portfolios

In this section, we explore the properties of bond trend portfolios. We first investigate the bond characteristics in each trend portfolio. Following this, we report the past six-month return distribution of bonds in each trend portfolio.

4.4.1 Bond characteristics of trend portfolio

Does the trend portfolio exhibit particular characteristics? We answer this question by summarizing the bond characteristics in each trend portfolio. Table 7 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 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 are highest in absolute value. In contrast, the spreads in average bond yields (past 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 portfolios have more bonds with higher yields and coupon rates, lower issuance amount and younger age.

[Insert Table 7 here]

4.4.2 Past six-month return distribution of trend portfolio

An interesting question is whether the return predictability shown above is driven by the conventional bond momentum. One way to answer this question is to investigate the composition of trend portfolios. If bond momentum (e.g., over the 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.

Table 8 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. Results show that bond momentum is not a driver for 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. The 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 8]

4.5 Bivariate portfolio analysis

4.5.1 Bivariate portfolios analysis using MAs and historical bond returns

We next investigate whether trend momentum will persist after controlling for the conventional bond momentum. We perform bivariate portfolio sorts. We first sort bonds into quintiles (Loser, 2, Medium, 4 and Winner) based on the past six-month returns. Then for 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. We calculate the return of each trend portfolio by averaging across all five momentum portfolios. The resulting trend momentum portfolios have perfect control for the momentum effect because each trend portfolio has an identical distribution of bonds with different past returns (bond momentum).

The first two columns of Table 9 reports the results of trend portfolio returns. 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. The mean return of the H-L portfolio of junk bonds is 94 bps. Results show that trend momentum is not driven by conventional bond momentum.

4.5.2 Bivariate portfolios analysis using MAs and other bond characteristics

The analysis above shows that the trend portfolios have different bond characteristics (see Table 7). This raises a concern that trend portfolio returns may simply reflect the effects of bond characteristics. To address this concern, we perform bivariate sorts 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 yield 25 portfolios. For each quintile trend portfolio, we average across quintiles of bond characteristics to obtain trend portfolio returns. The resulting trend portfolios have a similar distribution of bond characteristics. We consider four bond characteristics: bond issue size, age, coupon rate and average past yield from month $t-6$ to $t-1$ ($yld_{-6,-1}$).

Table 9 reports the results of controlling for the effects of bond characteristics. Results continue to show highly significant H-L trend portfolio returns across the board. The trend momentum persists even after controlling for the effects of characteristics and this effect is stronger as the rating decreases. For example, controlling for the effect of bond issue size, the H-L portfolio return of AAA is 84 bps, and 123 bps for junk bonds. Results for controlling age, coupon and $yld_{-6,-1}$ share a similar pattern. Thus, trend momentum is robust to controls for bond characteristics.

[Insert Table 9]

4.6 Cross-sectional regression analysis

To further investigate the robustness of 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 has an advantage of control for multiple characteristic variables. We regress monthly returns of individual corporate bonds on the expected returns predicted by MA signals and characteristic 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.[11] The weights used are the inverse of variance of corporate bond returns estimated using the whole sample data. We consider six regression models with different controls:

(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.

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 is significantly positive, suggesting that the MA signals have predictive power for future corporate bond returns cross-sectionally. The predictive power of MA signals is robust to control for bond characteristics. As shown, z_1 remains significant in model (6) that uses all control variables. Moreover, z_1 tends to increase as the rating decreases. The larger z_1 for lower-grade bonds is consistent with the finding in the

[11] We have also used ordinary least squares (OLS) and found similar results.

portfolio analysis earlier that momentum strategies based on MA signals are more profitable for low-grade bonds.

Bond characteristic variables help explain returns cross-sectionally. When no bond characteristic variable is used (model (1)), the adjusted R-squared 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 robust to controls for bond characteristics.

Past returns (average bond returns in the past six months) help to 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_1s for AAA and junk bonds have value of 0.30 and 0.35, respectively. This finding suggest a potential interactive effect of conventional 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 conventional bond momentum.

[Insert Table 10]

5 Additional tests

5.1 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 11 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 affect the cross-sectional predictability of returns. In light of the literature, we examine whether investor sentiment plays a role in trend momentum in the cross section of bond returns.

We divide the whole sample period into three subperiods using the investor sentiment index proposed by Baker and Wurgler (2006, 2007, BW). The results in Table 11 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 of 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 11 report 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. 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, 2016).

[Insert Table 11]

5.2 Trend momentum of cash flow matched excess returns

Chordia, et al. (2016) show that bond momentum becomes insignificant if the cash flow matched excess return is used to calculate the momentum return. We test whether our trend momentum is robust to the use of cash flow matched excess returns. To calculate the cash flow matched excess return, we first obtain the price of the equivalent bond that has the same coupon and maturity as the corporate bond by discounting the coupons with the Treasury spot rates matching the time of each coupon and the principal payment. The spot rates are taken from Gurkaynak, Sack and Wright (2007). We then subtract the return of this riskless equivalent bond from the return of corporate bond to generate the cash flow match excess return. Specifically, the cash flow matched excess return equals the return of the portfolio with a long position in the corporate bond and a short position in a riskfree bond that has the same coupon and maturity structure as the corporate bond.

Table 12 shows that the trend momentum is robust to the use of the cash flow matched excess return to calculate the momentum profit. The H-L portfolio return for the sample that includes all bonds is 1.06%, and significant at the one percent level. This result is somewhat stronger than that reported in Table 2. The results by rating also show significant H-L returns. The H-L returns of investment-grate bonds are slightly greater than the results using gross returns reported in Table 2, while the H-L return of junk bonds is lower than that using gross returns. The interest rate factor is not useful for explaining the trend momentum of gross returns for investment-grade bonds, but could partly explain the trend momentum of junk bonds.

[Insert Table 12]

5.3 Trend portfolios forecast by 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

$$r_{j,t} = \beta_{0,t} + \sum_k \gamma_{k,t} B_{k,jt-1} + \varepsilon_{j,t}, \quad j = 1, ..., n. \tag{8}$$

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

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

where $E_t[\gamma_{k,t+1}] = \frac{1}{12}\sum_{m=1}^{12} \gamma_{k,t+1-m}$. 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 four different cross-sectional regressions in the first step by using different bond characteristics:

(1) bond issue size;

(2) bond age;

(3) coupon rate;

(4) issue size, age and coupon rate.

Table 13 reports the returns of H-L portfolios. Models (1), (2) and (3) use bond issue size, age and coupon rates, respectively, and Model (4) uses all characteristics. Results show that none of the returns of H-L portfolios is significant. Results suggest that using these bond characteristics to predict bond returns fails to generate significant economic profits.

[Insert Table 13]

5.4 Bond trend portfolios with different holding horizons

To examine the sensitivity of results to different holding horizons, we calculate trend momentum returns for three-month $[t+1, t+3]$ and six-month $[t+1, t+6]$ holding horizons. Table 14 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. The trend momentum weakens for the longer holding horizon but it remains significant.

Turning to the results by rating, we find significant trend momentum across all rating categories. Again, low-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 horizon, confirming that the low-grade bonds have significantly higher trend momentum than the high-grade bonds.

[Insert Table 14]

5.5 Trend momentum of public firms

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 firms that have both stocks and bonds outstanding. Using the same two-step procedure, we perform return forecasts.

Panel A of Table 15 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 15, 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 little evidence that the trend momentum is weaker for public firms.

Chordia, et al. (2016) and Choi and Kim (2016) show that stock market anomaly variables have the ability to predict the cross-sectional variations of expected corporate bond returns. We next examine the robustness of our results to control for these variables. Following Chordia, et al. (2016) and Choi and Kim (2016), we construct the following stock market anomaly 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 Fama-French 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 anomaly variables. We sort the firm-level returns each month by an individual stock market variable into three groups (Low, Medium and High), and in each group we further sort the bonds into trend quintile portfolios. For each trend quintile portfolio, we then average returns across the three groups of stock market variables.

Panel B of Table 15 reports the results of bivariate portfolio analysis. For simplicity, we only report the results using all bonds.[12] All H-L portfolio returns are significantly positive. Results continue to show strong trend momentum across the board, suggesting that the trend momentum in the corporate bond market is not driven by stock market variables.

We next run the cross-sectional regression of firm-level bond returns on their return forecasts with and without stock market variables each month. Panel C of Table 15 reports the mean, *t*-stats of coefficients of return forecast (expected return) and the mean adjusted R-squared of cross-sectional regressions. The results continue to show that there is significant relationship between bonds' return forecasts and their future returns even after controlling for the stock market anomaly variables.

[Insert Table 15]

5.6 Momentum spillover between stocks and bonds

Gebhardt et al. (2005b) find no momentum spillover from corporate bonds to stocks. Their finding suggests that the historical corporate bond return information is not useful for predicting

[12]We also run the test for investment-grade and junk bonds separately. Unreported results show that the results for investment-grade bonds are stronger. This implies stock market variables explain the cross-sectional returns of junk bonds more than the cross-sectional returns of investment-grade bonds, which is consistent with the view that junk bonds behave more like stocks. The results are available upon request.

stock returns cross-sectionally. However, given that our trend momentum seems to contain more information than the conventional momentum, it might capture some information in past corporate bond returns that is useful for predicting stock returns. In this section, we investigate this possibility by using the trend momentum which includes past corporate bond price information from short to long horizons.

In each month, we sort the stocks into quintile portfolios by their firm-level expected corporate bond returns based on the information from MA signals. We then calculate the return for each stock portfolio and the return spread (H-L) between the stock portfolios with the highest and lowest expected corporate bond returns. Table 16 (left panel) reports the H-L return spreads for the sample that includes all rated firms and for the subsamples with different ratings. As shown, none of the H-L spreads is significant at the conventional level. Results show no momentum spillover from bonds to stocks even when we use bond trend information.

For comparative purposes, we also investigate the stock momentum and momentum spillover from stocks to bonds using the same sample. Following Daniel and Moskowitz (2016), we sort the stocks into quintile portfolios using their past [-12, -2] returns. The right panel of Table 16 reports the results where H-L is the return difference between the stock (bond) portfolios with the highest and lowest past own stock returns. We find significant stock momentum for the whole sample. However, this momentum appears to be driven predominantly by firms with a speculative grade. The results for the portfolios by rating show that only the stocks of the firms with a speculative grade have significant stock momentum. This phenomenon is consistent with the finding of Avramov et al. (2013) that stock market momentum exists only for high-risk firms with a speculative grade.

Consistent with Gebhardt, Hvidkjaer and Swaminathan (2005a), Lin, Wang and Wu (2013) and Chordia et al. (2016), we document significant momentum spillover from stocks to bonds. The H-L bond portfolio generates a monthly return of 16 basis points that is significant at the 1% level for the sample that includes all bonds. Momentum spillover is stronger among firms with lower ratings. However, these results are much weaker than those reported in Table 2, which again shows the superior power of using bond MAs in forecasting the cross-sectional bond returns.

To firmly test the hypothesis of momentum spillover between corporate bonds and stocks, we use the method of Zheng, Shi and Zhang (2012) to calculate the generalized measure of correlation (GMC) between the bond trend factor portfolios and the stock MOM portfolio. These GMCs are then used to run the Granger causality test for the bond trend factor and the stock MOM. The advantage of using the GMC over the traditional Granger causality test is that the former is able to deal with asymmetry in explained variance,[13] and the linear or nonlinear relationship between random variables. As such, GMC is more general in addressing the dependency issue in causality tests. The test statistics follow a standard normal distribution under the null hypothesis of no Granger causality relationship.

Panel B of Table 16 reports the test results. There is strong evidence that MOM Granger-causes bond trend factor. All test statistics are significant at the one percent level. On the other hand, the bond trend momentum factor does not Granger-causes MOM. As indicated, none of the test statistics is significant. Results strongly suggest an information spillover from stocks to bonds, but not vice versa.

[Insert Table 16]

6 Conclusion

In this paper, we employ a new methodology to investigate momentum in the corporate bond market. This methodology includes trend signals over different investment horizons, which is more general than the conventional momentum methodology that uses only one lagged return over a fixed horizon. As a result, our method is more informationally efficient and capable of uncovering a significant momentum in the corporate bond market across bond ratings, which has not been detected by the more restrictive conventional method.

[13]This is asymmetry in the variation explained by a random variable in the regression involved with two random variables.

Empirical evidence strongly suggests that there is a significant trend momentum effect not only for speculative-grade bonds, but also for investment-grade bonds. The momentum profits survive transaction costs, and are of economic significance. Previous studies find no evidence of momentum for investment-grade bonds largely because they rely on a less efficient method which uses only one price 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. The trend momentum is by far the most significant cross-sectional corporate bond anomaly that challenges the existing rational pricing theory.

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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. Returns of trend portfolios

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-, and 48-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. Trend factor portfolio: Summary statistics and correlations

Panel A reports the summary statistics of the trend factor portfolio returns (H-L). Panel B reports their correlations with other factors. 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 $\Delta DEF_t = (DEF_t - DEF_{t-1})$.

Panel A. Summary statistics

	Summary statistics				Extreme values		
	Std. (%)	Sharpe ratio	Skewness	Kurtosis	Min. (%)	$n(< -2Std.)$	$n(< -3Std.)$
ALL	1.30	0.74	1.20	4.62	-2.53	0	0
AAA	1.60	0.53	0.71	3.31	-5.28	6	1
AA	1.38	0.56	0.76	5.14	-4.40	3	1
A	1.59	0.62	3.11	28.26	-3.16	0	0
BBB	2.25	0.47	2.36	12.00	-6.71	5	0
Junk	3.01	0.40	1.03	10.04	-16.53	6	1
MOM	4.54	0.15	-1.44	11.37	-34.58	9	3

Panel B. Correlation

	MKT	SMB	HML	MOM	$\Delta TERM$	ΔDEF
ALL	0.07	0.1	0.05	0.13	0.14	0.09
AAA	-0.06	-0.01	-0.07	-0.06	0.02	0.01
AA	0.04	0.01	-0.02	-0.14	-0.1	-0.05
A	0.01	0.01	0.02	-0.14	-0.01	0.12
BBB	-0.02	0.05	0.01	-0.15	0.03	0.16
Junk	0.11	0.06	-0.01	-0.06	0.07	0.02

Table 4. Alphas: All bonds

This table reports alphas from eight factor models: (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) $\Delta TERM, \Delta DEF, MKT, SMB, HML, MOM$; where 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 $\Delta DEF_t = (DEF_t - DEF_{t-1})$; $mTERM_t = \Delta TERM_t/(1+TERM_{t-1})$; $mDEF_t = \Delta DEF_t/(1+DEF_{t-1})$. GRS is the test statistics of Gibbons, Ross and Shanken (1989) with null hypothesis that all the alphas are zero. [a] denotes the significance at the 1% level.

Model	Low	2	3	4	High	H-L	t-stats	$Adj.R^2$ (%)	GRS
1	-0.12	0.15	0.28	0.43	0.85	0.97	14.68	1.34	45.48[a]
2	-0.13	0.15	0.28	0.43	0.85	0.97	14.67	0.85	45.78[a]
3	-0.12	0.15	0.28	0.43	0.85	0.97	14.71	2.08	45.90[a]
4	-0.23	0.04	0.18	0.32	0.70	0.94	13.85	2.22	40.79[a]
5	-0.24	0.03	0.16	0.31	0.74	0.98	14.35	4.50	40.05[a]
6	-0.24	0.03	0.17	0.31	0.70	0.93	13.91	4.27	40.75[a]
7	-0.23	0.03	0.15	0.31	0.74	0.97	14.33	6.15	43.62[a]
8	-0.23	0.03	0.15	0.31	0.74	0.97	14.33	6.17	43.64[a]

Table 5. Alphas: Across ratings
This table reports the same alphas as the previous table except applied to bonds of different ratings.

	Model	Low	2	3	4	High	H-L	t-stats	R^2 (%)	GRS
AAA	1	-0.14	0.13	0.25	0.36	0.72	0.86	11.16	0.07	26.07[a]
	2	-0.15	0.13	0.24	0.36	0.71	0.86	11.17	0.00	26.12[a]
	3	-0.14	0.13	0.24	0.36	0.72	0.86	11.15	0.07	26.40[a]
	4	-0.21	0.08	0.18	0.30	0.68	0.90	11.45	1.35	26.66[a]
	5	-0.23	0.05	0.15	0.27	0.66	0.89	11.13	1.40	25.16[a]
	6	-0.23	0.06	0.16	0.29	0.67	0.90	11.43	1.47	26.87[a]
	7	-0.24	0.04	0.14	0.26	0.65	0.89	11.09	1.54	25.31[a]
	8	-0.24	0.04	0.14	0.26	0.65	0.89	11.09	1.52	25.31[a]
AA	1	-0.07	0.11	0.25	0.37	0.72	0.79	11.94	0.96	30.33[a]
	2	-0.07	0.11	0.25	0.37	0.71	0.79	11.88	0.21	29.79[a]
	3	-0.07	0.11	0.25	0.37	0.72	0.79	11.94	1.13	30.33[a]
	4	-0.15	0.01	0.17	0.28	0.63	0.78	11.45	0.19	26.84[a]
	5	-0.17	0.00	0.15	0.27	0.65	0.82	11.96	2.43	29.90[a]
	6	-0.16	0.00	0.16	0.28	0.62	0.78	11.50	1.31	27.40[a]
	7	-0.17	-0.01	0.15	0.27	0.65	0.83	12.10	4.04	31.20[a]
	8	-0.17	-0.01	0.15	0.27	0.65	0.83	12.10	4.06	31.19[a]
A	1	-0.13	0.12	0.24	0.39	0.85	0.97	12.59	0.01	39.93[a]
	2	-0.13	0.12	0.24	0.39	0.84	0.97	12.67	1.37	40.16[a]
	3	-0.13	0.12	0.24	0.39	0.85	0.97	12.66	1.39	40.32[a]
	4	-0.23	0.01	0.13	0.27	0.74	0.96	12.17	0.10	36.73[a]
	5	-0.23	-0.01	0.12	0.27	0.78	1.01	12.60	2.04	38.51[a]
	6	-0.23	0.00	0.12	0.27	0.72	0.96	12.15	1.60	36.48[a]
	7	-0.23	-0.01	0.11	0.27	0.77	1.00	12.60	3.57	38.28[a]
	8	-0.23	-0.01	0.11	0.27	0.77	1.00	12.60	3.57	38.29[a]
BBB	1	-0.12	0.20	0.35	0.50	0.95	1.06	9.72	0.08	22.02[a]
	2	-0.12	0.20	0.35	0.49	0.94	1.06	9.83	2.50	22.33[a]
	3	-0.12	0.20	0.35	0.50	0.95	1.06	9.82	2.54	22.39[a]
	4	-0.28	0.09	0.23	0.37	0.79	1.07	9.53	0.48	20.26[a]
	5	-0.30	0.08	0.22	0.36	0.84	1.14	10.15	3.25	23.03[a]
	6	-0.28	0.09	0.23	0.36	0.78	1.06	9.54	3.11	20.01[a]
	7	-0.29	0.09	0.23	0.36	0.84	1.13	10.15	5.74	22.79[a]
	8	-0.29	0.09	0.23	0.36	0.84	1.13	10.15	5.75	22.81[a]
Junk	1	-0.10	0.12	0.35	0.65	1.12	1.22	8.35	0.51	20.50[a]
	2	-0.10	0.12	0.35	0.65	1.12	1.22	8.35	0.05	20.54[a]
	3	-0.10	0.12	0.35	0.65	1.12	1.22	8.34	0.55	20.54[a]
	4	-0.28	-0.08	0.15	0.45	0.86	1.15	7.72	1.68	16.87[a]
	5	-0.25	-0.07	0.19	0.48	0.93	1.18	7.77	1.92	18.24[a]
	6	-0.28	-0.08	0.16	0.44	0.87	1.15	7.70	2.23	16.54[a]
	7	-0.23	-0.06	0.21	0.49	0.94	1.17	7.72	2.39	18.04[a]
	8	-0.23	-0.06	0.21	0.49	0.94	1.17	7.72	2.41	18.04[a]

Table 6. Economic significance

This reports reports the economic significance of the trend factor portfolios. Panel A reports the change of maximum Sharpe ratio by using the trend factor portfolios (H-L) of different ratings jointly with stock market factor portfolios. We follow Gibbons, Ross and Shanken (1989) to calculate the maximum Sharpe ratios using stock factor portfolios only (θ_p) and using stock factor portfolios and trend factor portfolios jointly (θ^*). Panel B reports the turnover ratios 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 4 and 5. 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.

Panel A. Change of maximum Sharpe ratio

Stock factor portfolio	θ_p	θ^*	Diff.
MKT	0.14	0.79	0.65
SMB	0.07	0.78	0.71
HML	0.09	0.78	0.69
MOM	0.15	0.81	0.66
MKT+SMB+HML	0.22	0.81	0.59
MKT+SMB+HML+MOM	0.29	0.86	0.57

Panel B.Turnover ratio and BETCs

	Turnover ratio (%)			BETCs (%)			
				Zero return		Insignificance	
Rating	High	Low	H-L	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 7. Characteristics of bond trend portfolios

This table reports the characteristics of trend portfolios including bond size, age, coupon rate, yield in the last month (yld_{-1}) and average yield over the last six months ($yld_{-6,-1}$). 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-, and 48-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
yld_{-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
($yld_{-6,-1}$(%)	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 8. Past six-month return distribution of bond trend portfolios

This table summarizes the distribution of bonds in each trend portfolio by bonds' past six-month returns. 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 9. Bivariate portfolio analysis using MAs and bond characteristics

This table reports the returns of portfolios sorted by the bond's expected return and characteristic. 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. The bond characteristics considered are bond's historical six-month returns ($r_{-6,-1}$), bond size, age, coupon rate and historical six-month mean yield level ($yld_{t-6,t-1}$). 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.

	$r_{-6,-1}$		Bond size		Age		Coupon		$yld_{t-1,t-6}$	
Rating	H-L	t-stats	H-L	t-stats	H-L	t-stats	H-L	t-stats	H-L	t-stats
All	0.64	5.41	0.96	8.07	0.98	8.09	0.96	8.00	0.91	7.91
AAA	0.79	6.29	0.84	6.63	0.77	6.25	0.74	5.99	0.75	5.92
AA	0.70	6.30	0.75	6.76	0.77	6.82	0.80	7.06	0.74	6.68
A	0.84	6.88	0.95	7.25	0.96	7.33	0.96	7.29	0.90	7.12
BBB	0.96	6.94	1.07	7.23	1.06	7.60	1.05	7.63	0.93	6.96
Junk	0.94	5.72	1.23	6.94	1.26	7.36	1.33	7.57	1.05	6.72

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. Trend momentum of 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-, and 48-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 12. Trend momentum of cash flow matched excess returns

This table reports the cash flow matched excess returns of portfolios sorted by bonds' expected excess returns. We follow a two-step procedure to forecast an individual bond's expected cah flow matched excess 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-, and 48-months. We then sort all bonds into quintile portfolios (Low, 2, 3, 4, and High). 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.

	Return						
Rating	Low	2	3	4	High	H-L	t-stats
All	0.08	0.39	0.53	0.69	1.14	1.06	10.14
AAA	0.08	0.38	0.46	0.57	0.89	0.81	8.61
AA	0.11	0.31	0.47	0.60	0.99	0.88	10.49
A	0.08	0.37	0.53	0.64	1.08	1.00	9.22
BBB	0.10	0.48	0.62	0.71	1.20	1.10	7.70
Junk	0.33	0.53	0.62	0.91	1.39	1.06	5.52

Table 13. Trend momentum by bond characteristics

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

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

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

$$E_t[r_{j,t+1}] = \sum_k E_t[\gamma_{k,t+1}] B_{k,jt},$$

where $E_t[\gamma_{k,t+1}] = \frac{1}{12}\sum_{m=1}^{12} \gamma_{k,t+1-m}$. Bond characteristics include issue size, age and coupon rate. 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. 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 four different cross-sectional regressions in the first step by using different bond characteristics:
(1) bond issue size;
(2) bond age;
(3) coupon rate;
(4) 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

Table 14. 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-, and 48-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 15. Trend momentum of public firms

This table reports the trend momentum of public firms. Panel A reports returns of portfolios sorted by bonds' expected returns. Table B reports the results of trend momentum of all public firms controlling for stock market variables. Following Chordia, et al. (2016) 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). Then in each group we further sort the bonds into trend quintile portfolios. For each trend quintile portfolio, we then average returns across the three groups of stock market variables. 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. In panel C, we 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 C.

The sample period is from January 1973 to September 2015.

Panel A. Univariate portfolio analysis

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. Bivariate portfolio analysis

Stock variable	H-L	t-stats	Stock variable	H-L	t-stats
Size	0.61	5.51	Value	0.58	5.00
Accruals	0.56	4.73	Asset growth	0.54	4.69
Profitability	0.61	5.25	Net stock issuance	0.57	4.82
Earning surprise	0.63	5.45	Idiosyncratic volatility	0.63	5.54

Panel C. Cross-sectional regression

Without controlling variables			With controlling variables		
Coefficient	t-stat	$Adj.R^2$ (%)	Coefficient	t-stat	$Adj.R^2$ (%)
0.60	9.53	8.33	0.71	11.03	16.35

Table 16. Momentum spillover between stocks and bonds

Panel A reports the results of bond trend momentum spillover to stock returns, and the stock momentum and momentum spillover from stocks to bonds using the past stock returns at the [-12, -2] interval. The left panel reports the results of stock portfolio returns by sorting the stocks into quintile portfolios using their bonds' MAs information. In the right panel, we sort the stocks or bonds using their past stock returns at the [-12, -2] interval. H-L is the return difference between the portfolios with high and low expected returns. Panel B reports the Granger causality relationship between the bond trend factor portfolio and stock momentum factor portfolio MOM. We use the generalized measure of correlation (GMC) proposed by Zheng, Shi and Zhang (2012) in the test. [a] denotes significance at the 1% level.

Panel A. Portfolio analysis

	Using bond MAs		Using [-12, -2] stock returns			
	stock		stock		bond	
Rating	H-L	t-stats	H-L	t-stats	H-L	t-stats
ALL	-0.09	-0.25	0.54	2.14	0.16	3.49
AAA	-0.82	-1.14	1.18	1.34	-0.18	-0.89
AA	0.15	0.39	0.43	1.46	0.09	1.42
A	0.14	0.40	0.32	1.32	0.13	3.03
BBB	-0.14	-0.33	0.46	1.99	0.16	3.16
Junk	-0.58	-0.90	0.90	2.96	0.32	3.52

Panel B. Granger causality test

X	Y	X does not Granger causes Y	Y does not Granger causes X
ALL	MOM	-5.00	5.48[a]
AAA	MOM	-0.54	4.10[a]
AA	MOM	-1.89	10.17[a]
A	MOM	-2.01	10.78[a]
BBB	MOM	-1.64	4.39[a]
Junk	MOM	1.41	2.98[a]

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