Trend Momentum in Corporate Bonds

Hai Lin

Victoria University of Wellington

Chunchi Wu

State University of New York at Buffalo

and

Guofu Zhou

Washington University in St. Louis and CAFR*

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*Correspondence: Guofu Zhou, Olin School of Business, Washington University, St. Louis, MO 63130. Phone: (314) 935-6384 and e-mail: zhou@wustl.edu. We thank Hengjie Ai, Bo Becker, Ivan Brick, Hui Chen, Tarun Chordia, Zhi Da, Serdar Dinc, Douglas J. Fairhurst, Adlai Fisher, Vidhan Goyal, Gerard Hoberg, Qianqian Huang, Jerry Kallberg, Elizabeth Kempf, Jin-Mo Kim, Cheng F. Lee, Tao Li, Abhiroop Mukherjee, Daniela Osterrieder, Darius Palia, Oded Palmon, George Panayotov, Neil Pearson, Junbo Wang, Xueping Wu, Oleg Sokolinskiy, Brian McTier, Thomas Schmid, Denis Sosyura, Jason Turkiela, Selale Tuzel, Jeroen van Zundert, Yangru Wu, Zhenlong Zheng, Ken Zhong and seminar participants at Monash University, National Taiwan University, Rutgers University, Southwest Jiaotong University, Temple University, Tsinghua University, University of Newcastle, University of Sydney, University of Technology Sydney, Washington University in St. Louis, Xiamen University, 2017 Hong Kong International Finance Conference on Corporate Finance and Financial Markets at City University of Hong Kong, and 2017 China International Conference in Finance for helpful suggestions and comments.

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Abstract

This paper investigates bond momentum by exploiting 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 effects for corporate bonds in all rating categories. Bond trend momentum has little correlation with stock momentum, and is robust to various controls. It is stronger for low-grade bonds and in the post-TRACE era, and in periods with slow economic growth. The significant bond return momentum documented in this study presents the most pronounced cross-sectional anomaly in the corporate bond market to date that challenges existing rational pricing models.

JEL classification: G12; G14;

Keywords: Trend signals; moving averages; cross-sectional predictability; corporate bond returns; momentum strategies

1 Introduction

Since the seminal work of Jegadeesh and Titman (1993), it has been well known that there is momentum in the stock market—-winners (losers) over the past six months or a year tend to remain winners (losers) over the next six months or a year. Because of the profound implications for asset pricing theory and market efficiency, a vast literature has been devoted to the study of 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 in asset pricing. However, to date, the literature of momentum has focused on the stock market. Much less is known about the corporate bond market, which is comparable 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 managing corporate bond portfolios, but also for understanding what really drives bond expected returns.

Gebhardt, Hvidkjaer and Swaminathan (2005a) appear to be the first researchers to investigate corporate bond momentum. While they do not find it in investment-grade bond returns, Jostova, Nikolova, Philipov and Stahel (2013) document evidence of momentum in non-investment grade bonds. However, the value of high-yield bonds accounts only for about 8% of the market, and so the question remains whether there is momentum in the whole universe of corporate bonds. Recently, Choi and Kim (2016), and Chordia, Goyal, Nozawa, Subramanyam and Tong (2017) examine cross-sectional return predictability for corporate bonds 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 that the momentum for investment-grade bonds can be as high as 20 basis points per month, which also does not seem economically significant after transaction costs.[2]

In this paper, we uncover, for the first time, pronounced momentum for the entire corporate

[1] For example, the latest number of Google citations of Jegadeesh and Titman (1993) is over 9510.

[2] For example, Edwards, Harris and Piwowar (2007) report an average transaction cost of 24 basis points per dollar trading for a median size of corporate bond trade.

bond market that is stronger than stock momentum. In contrast to past studies that sort bonds by a single signal, we use an efficient method that can incorporate multiple return trends over short-, intermediate- and long-term investment horizons, in forming the momentum spread portfolio. Theoretically, from the behavioral models of Greenwood and Shleifer (2014) and Hirshleifer, Li, and Yu (2015), return trends contain information on future returns when investors extrapolate expectations from the past. This is also the case, as shown by Han, Zhou and Zhu (2016), in a model with technical traders. Our choice of multiple trend signals as preferred return predictors is consistent with Daniel, Hirshleifer and Sun (2017) and Akbas, Jiang and Koch (2017) who show that different factors predict short- and long-horizon returns and trading over different investment horizons contains distinct information for future returns. A point of departure from the conventional literature is that we use multiple signals (return trends), rather than using just one (say a past return), to identify the momentum in the corporate bond market. For ease of reference, we refer to the momentum identified by our methodology as *trend momentum* throughout this paper.

We document several interesting findings, using a comprehensive sample of corporate bonds from January 1973 to September 2015. First, we uncover strong evidence of trend momentum not only in speculative-grade bonds, but also in investment-grade bonds in every rating category. For investment-grade bonds, the trend momentum profits range from 110 basis points (for AAA bonds) to 143 basis points (for BBB bonds) when portfolios are sorted into deciles. This contrasts sharply with the findings of previous studies, which show limited momentum profits: typically less than 30 basis points. For speculative-grade bonds, we also find a trend momentum profit of 158 basis points per month, which is 30% higher than the 121 basis points documented by Jostova, Nikolova, Philipov and Stahel (2013) using the conventional momentum strategy.

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 momentum profits in the corporate bond market. However, the trend momentum profits are not primarily driven from the short leg of the momentum strategy. Moreover, the profits are characteristic dependent, which are stronger for bonds with smaller issue size, higher coupon rates and yields, and for newer bonds (on-the-run). While characteristics matter, the trend momentum remains highly significant even after controlling for all bond characteristics.

Third, the trend momentum cannot be explained by standard risk factors, bond characteristics and transaction costs, and the unexplained returns are much higher for speculative-grade bonds. Fourth, the trend momentum profit varies over time. It increases after the establishment of TRACE (the Trade Reporting and Compliance Engine), which lowers transaction costs in the corporate bond market. Moreover, the profit is higher in periods of slow economic growth and recession, consistent with the literature that return predictability is linked to business conditions.

The evidence of trend momentum we uncover in this paper has important implications for asset pricing, besides being a profitable trading strategy to bond investors. It is an anomaly across diverse bond categories in the corporate bond market, similar to the well-known Jegadeesh-Titman (1993) momentum phenomenon in the stock market. Interestingly, while there are over 80 anomalies in the stock market (see, for example, Hou, Xue and Zhang, 2015), the trend momentum appears to be the most significant anomaly to date identified in the corporate bond market. The high trend momentum return challenges the rational bond pricing theories. In line with Jostova, Nikolova, Philipov and Stahel (2013), the momentum of corporate bonds may be explained by the gradual information diffusion model of Hong and Stein (1999). Also, our evidence of consistent momentum returns across all rating classes leaves the possibility that investors' extrapolative learning or the presence of technical traders may explain the persistence of trend momentum. However, as the case of equity momentum, it remains an open problem to develop equilibrium models to explain the size of momentum returns and identify the risk premium.

The central issue in our paper is about the cross-sectional predictability of corporate bond returns, which differs from the time-series return predictability investigated by many other studies. Keim and Stambaugh (1986) is perhaps the first study on the time-varying risk premia. Fama and French (1989) find that lagged default spreads, term spreads and dividend yields are important time-series predictors. Subsequently, Greenwood and Hanson (2013) and Lin, Wang and Wu

(2014) identify issuer quality, and liquidity and forward rate factors separately, as useful predictors. Lin, Wu and Zhou (2016) apply an iterated combination approach to improve out-of-sample forecasting performance. While cross-sectional and time-series predictability are different issues, both strands of research provide valuable insights that improve our understanding of asset pricing in the corporate bond market.

The remainder of this paper is organized as follows. Section 2 presents our empirical methodology and Section 3 discusses the data. Section 4 reports empirical results for trend momentum and Section 5 conducts robustness tests. Finally, Section 6 summarizes our major findings and concludes the paper.

2 Methodology

In this section, we describe our research methodology, which involves two stages. First, based on existing theories and empirical evidence, we propose new predictors for corporate bond returns. Second, we employ an econometric procedure that incorporates multiple predictors to forecast returns cross-sectionally. Then, the spread portfolio formed from the forecasted returns constitutes the bond trend momentum factor.

Treynor and Ferguson (1985), Brown and Jennings (1989) and Cespa and Vives (2012), among others, show theoretically that past returns have predictive power on on future returns due to differences in receiving and responding to information by heterogeneous investors. Recently, based on behavioral evidence, Greenwood and Shleifer (2014) and Hirshleifer, Li, and Yu (2015) show that, when investors extrapolate expectations from the past, return trends should matter for expected returns. Building on the evidence of trend-following by hedge funds and top traders, Han, Zhou and Zhu (2016) show that moving averages (MAs) of past prices scaled by the current price, which capture past return trends, have predictive power in an equilibrium with both informed and technical traders. Empirically, Brock, Lakonishok, and LeBaron (1992), Lo, Mamaysky, and Wang (2000), and Neely, Rapach, Tu, and Zhou (2014), among others, provide the predictive evidence on stock returns. Our paper is the first to confirm that similar trend signals have predictive power for corporate bond returns.

In contrast to equity market studies, a new feature in our paper is that we use the MAs of bond yields rather than prices. There are several important reasons for this use. First, almost all conventional fixed-income pricing, market timing and trading decisions begin with some sort of yield analysis. Second, yields provide market participants with a consistent summary figure for comparing different bonds. Cash flows are not directly comparable, and neither are prices, which depend on cash flows and are hence subject to the scale effect. Third, 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, to adapt the MAs of prices from equity to bonds, it is important to use the bond yields instead of prices.

To form the trend signals, we first calculate the moving average (MA) yield of lag L in month t for bond j from

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

where Y_j^t is the closing yield for bond j in month t and L is the lag length. To make use of past important information, we consider below the MAs of lag lengths 1-, 3-, 6-, 12-, 24-, 36-, and 48-months in month $t-1$. These MA signals essentially represent the return trends of bonds from short to long horizons.

With the available multiple predictors, we now need to incorporate them to form cross-sectional expected returns. Following Haugen and Baker (1996), we use a two-step procedure to extract return expectations. In the first step, each month we run the following cross-sectional regression of bond returns on the MAs to obtain the time-series of slope coefficients for 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, $\beta_{0,t}$ is the intercept, $r_{j,t}$ is bond returns and n is the number of bonds in month t. Note that only past yield information appears on the right hand side of the equation. 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 $t+1$ with

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

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 beta coefficient for the next month. Averaging reduces the noise in beta estimates. In essence, the expectation for future returns is derived from the combination of past trend signals at different lags where the weights for these signals are averaged betas obtained from the cross-sectional regression in (2). The magnitude of a beta reflects the relevance of a particular trend signal for expectations of future returns. A larger beta implies that a particular trend signal contains more information for expected future returns. We do not include an intercept in the above formulation for return expectations 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.

Bonds are sorted into quintile portfolios by their expected returns. We construct the equal-weighted portfolio and rebalance it each month. These portfolios are dubbed trend portfolios as they are constructed using the past price trend signals. Portfolio returns are calculated each month. The return difference between the last quintile portfolio with the highest expected return (H) and the first quintile portfolio with the lowest expected return (L) is referred to as the return on the trend momentum factor, similar in spirit to the construction of the conventional momentum factor. Essentially, the trend factor portfolio longs bonds with the highest expected returns and shorts bonds with the lowest expected returns. This procedure of constructing the momentum portfolio resembles that of Jegadeesh and Titman (1993), Gebhardt, Hvidkjaer and Swaminathan (2005a, 2005b), and Jostova, Nikolova, Philipov, and Stahel (2013), among many others. The main difference is that instead of sorting assets by their past returns in a predetermined fixed horizon, we sort bonds by their expected returns based on multiple trend signals.

In general, 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 of this trend signal is equal to one. The traditional momentum model implicitly assumes that the relevant signal contained in past returns for predicting future prices always falls within a particular time horizon (e.g., the past six months). This assumption is quite restrictive in a dynamic world where various economic forces can alter trend signals for future market performance at different horizons (see Han et al., 2016; Daniel et al., 2017). Hence, limiting the use of return signals to a restricted time horizon is likely to under-estimate the predictability of bond returns. In contrast, by accounting for differences in the timing of receiving and processing information or heterogeneous information diffusion, we form a momentum factor which captures the information for the short-, intermediate- and long-term predictive components of bond returns. Our methodology can detect more information efficiently to find out whether momentum indeed exists in the corporate bond market.

3 Data

Corporate bond data come 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. This data set includes 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 data up to September 2015.

The NAIC and TRACE databases contain corporate bond transaction data. TRACE coverage begins in July 2002 while the NAIC data set starts in January 1994. TRACE initially covers only a subset of corporate bonds traded in the over-the-counter market, and we supplement it with the NAIC dataset, which mainly covers transactions of insurance companies.[3] FISD provides issue- and issuer-specific data such as coupon rates, issue date, maturity date, issue amount, ratings, provisions and other bond characteristics. We merge the 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.[4] We exclude bonds with maturity less than two years and longer than 30 years and bonds with

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

[4] This return is transformed to the log return in the forecast, so that monthly log returns can be conveniently added

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 runs from January 1973 to September 2015.[5]

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 of maturity less than 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 ex post quintile portfolios sorted by expected returns for the one-month holding horizon. Low (L) represents the portfolio of bonds with the lowest expected returns, and High (H) denotes the portfolio of bonds with the highest expected returns. The results clearly show that the bonds with high expected returns forecast by the trend signals have high returns ex post. The return differences between High and Low (H-L) portfolios are all highly 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 ($t = 8.12$).[6] The bonds included

together to obtain a return of longer horizon.

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

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

in the high quintile portfolio consist of more low-grade bonds. Unreported results show the high quintile portfolio has more junk bonds (12.63%) than the low quintile portfolio (9.29%). These results imply that the high returns of the top quintile portfolio are partly driven by the performance of risky bonds.

To see the momentum effects for differently rated bonds, we further report the results of portfolio sorts by rating category. Results show that trend signals have high predictive power for cross-sectional bond returns across all ratings. Results also reveal a distinct pattern in which the H-L return difference is higher for low-grade bonds than for high-grade bonds. The monthly H-L return differences range from 85 bps for AAA bonds to 121 bps for junk bonds, all significant at the one percent level. The return spread increases as the rating decreases. The difference between the monthly H-L returns of junk and AAA bonds is 36 bps, which is significant at the 5% level.

To make our results more comparable to those of Jostova et al. (2013), we also sort the bonds into deciles. Panel B of Table 2 reports the results of the decile portfolio sorts. 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 significant 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 price information over the past six months, Jostova et al. (2013) report a momentum profit of 121 basis points for noninvestment-grade bonds. In contrast, using multiple price signals in the short, intermediate and long term, we find a much larger momentum profit of 158 basis points for speculative-grade bonds, which is about 30% higher than their estimate for the one-month holding period return. The higher profits generated from our momentum strategy suggest that past prices in both the short and long term contain important information for the cross section of expected returns over and beyond the information in the intermediate term (6 months) which is the focus of the Jostova et al. (2013) study.

Gebhardt, Hvidkjaer and Swaminathan (2005b) find no evidence of momentum in investment-grade bond returns. Using more recent data, Jostova et al. (2013) report a very small momentum profit of only 10 basis points per month for investment-grade bonds, which is statistically insignificant. In stark contrast, we document 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 smaller than the momentum profit of speculative-grade bonds. Results show substantial economic gains from combining all useful information over the short, intermediate and long horizons. Using this momentum strategy, we uncover, for the first time, significant trend momentum in investment-grade bonds. Results show that return momentum is pervasive in the corporate bond market, not just limited to a small subset of high-yield bonds. Previous studies find no momentum in investment-grade bonds because they rely only on past price information in the intermediate return horizon of 6 to 12 months and neglect the important information in other horizons.

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

In sharp contrast to previous studies, we find that momentum is everywhere in the corporate bond market, not just limited to speculative-grade bonds. Another important finding in this study is that the profits of momentum strategies do not derive predominantly from taking short positions in high credit risk firms that experience deteriorating credit conditions. To the contrary, the results in Table 2 show just the opposite: both the high trend portfolio and low trend portfolio have positive returns. Trend momentum strategies do involve taking a long position in the high-momentum bonds and shorting low-momentum bonds, but the profits come primarily from the long position, rather than the short position. This pattern holds not just for high-grade bonds, but also for low-grade bonds.

[Insert Table 2]

Several recent studies find some evidence of abnormal returns in the corporate bond market (see Chordia et al., 2017; Choi and Kim, 2016; Bai, Bali and Wen, 2016). Sorting all bonds into deciles by stock momentum (MOM), bond momentum, asset growth, and profitability, Chordia et al. (2017) report monthly H-L portfolio returns of 0.13%, 0.16%, -0.19%, -0.14% and -0.42%, respectively. Separately, Choi and Kim (2016) report -0.32%, -0.24%, and 0.21% returns per month for the H-L portfolios sorted by asset growth, investment, and book-to-market ratio, respectively. 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 bonds into quintiles based on the 60-month rolling estimates of variance, skewness and kurtosis, and report H-L portfolio returns of 0.64%, -0.24% and 0.37%, respectively. Results in Panel A of Table 2, based on our quintile portfolios, are also much stronger than their high-low portfolio return spreads sorted by return distribution characteristic. The momentum anomaly uncovered in this study hence poses an even bigger challenge to rational asset pricing theories in the corporate bond market.

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. This set of results again shows that trend momentum is pervasive, not just limited to a particular rating class. Unlike the negative returns of stock momentum strategies documented by a number of studies during the crisis period (e.g., Daniel, Jagannathan and Kim, 2012; Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016), the trend momentum factor has positive returns in this period. The bond market does not appear to have a "momentum crash" as in the stock market.[7]

[7] 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 bonds and AAA, AA, A, BBB and junk bonds, respectively.

Panel A of Table 3 reports the summary statistics and extreme values of the trend factor portfolios of bonds (H-L). For comparison, we also report the results of the momentum factor portfolio of stocks (MOM). The trend factor portfolios of bonds have lower standard deviations and much higher Sharpe ratios than MOM. They also have positive skewness and high kurtosis. These findings are similar to the behavior of the stock trend momentum factor documented by Han, Zhou and Zhu (2016). The minimum returns of the trend momentum portfolios of bonds 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 observations. There is no value 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 points to a potential diversification benefit of investing in both bond trend factor portfolios and stock factor portfolios (MKT, SMB, HML and MOM). This issue will be further explored later.

[Insert Table 3]

We also calculate the value-weighted returns of bond trend portfolios. Unreported results show that the value-weighted H-L return of all bonds is 93 bps with a t-value of 8.13 if quintile portfolios are constructed, and 133 bps 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. Thus, the trend momentum of bonds is robust to the choice of portfolio weights.

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 the dependent variable can be $r^e_{p,t} = r_{p,t} - r_{f,t}$, the trend portfolio's excess return over the risk-free rate, or $r^e_{p,t} = r_{H,t} - r_{L,t}$, the H-L return spreads, $\mathbf{F_t}$ 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 in Fama and French (1993). MOM is Carhart's (1997) momentum factor. $TERM_t$ 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 come 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.[8] We calculate the Gibbons-Ross-Shanken (GRS, 1989) statistics to test the null hypothesis that all intercepts are zero.

Table 4 reports the 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. Moreover, the 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 bond momentum profits cannot be explained by systematic risk factors and that unexplained excess returns are larger for lower-grade bonds.

[Insert Table 5]

4.3 Economic gains of trend factor portfolios

An important issue is how much economic gain can be achieved by incorporating the trend factor portfolios in the trading strategy. To address this issue, we calculate the Sharpe ratio and net momentum portfolio returns after transaction costs. First, following Gibbons, Ross and Shanken

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

(1989), we examine the improvement in the Sharpe ratio from the strategy of combining the trend factor portfolios and stock factor portfolios. We calculate the maximum Sharpe ratios for stock factor portfolios only (θ_p), and for the strategy combining both stock factor portfolios and bond trend factor portfolios (θ^*). The difference between these two Sharpe ratios indicates the incremental gain from adding bond trend momentum portfolios.

Panel A of Table 6 reports the maximum Sharpe ratios.[9] 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 of bonds are included. The monthly θ^* of combining the trend factor portfolios with MKT, SMB, HML and MOM is 0.86 or 2.98 ($0.86 \times \sqrt{12}$) per annum. This is a highly economically significant Sharpe ratio. Incorporating bond trend factor portfolios increases the monthly Sharpe ratio by more than 0.60 for most cases (2.08 per annum). Results show substantial economic gains from adding the trend momentum factor of bonds in investment portfolios. For comparative purposes, we also report the change in the maximum Sharpe ratio by combining bond index portfolios of different ratings. In each month we calculate the equal-weighted portfolio returns of each rating index and construct the optimal risky portfolio by combining them with stock factor portfolios. The maximum Sharpe ratio for the strategy of combining bond index portfolios with the four stock factors is 0.32. The increase over the θ_p of MKT+SMB+HML+MOM is only 0.03. These results suggest that the economic gains contributed by bond trend factor portfolios are not derived from the benefit of including the index returns of the corporate bond market in the portfolio construction.

Second, we investigate whether 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), we calculate the break-even transaction costs (BETCs). We construct two

[9]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.

measures of BETCs. Zero-return BETCs are transaction costs that completely offset the raw return or the risk-adjusted return 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 return or the risk-adjusted return of the trend factor portfolio insignificantly different from zero at the 5% level.

Panel B of Table 6 reports the results for turnover rates and break-even transaction costs for the whole sample as well as for different rating categories. The results on the left side show that the turnover rates of the H-L portfolio are on average about 55% across all 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 the long or the 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 offset the raw returns, and 1.30% to make raw returns become statistically insignificant at the 5% level. For risk-adjusted returns, it takes transaction costs of 1.73% and 1.48%, respectively. For the results by rating, break-even transaction costs (BETCs) grow higher as bond ratings decrease, consistent with the pattern of momentum returns reported earlier.

The BETCs estimates for corporate bonds are much higher than for stocks. For example, Grundy and Martin (2001) report a BETC of 1.03% over the period from 1926 to 1995 for a completely stock-dominant portfolio. For a stock trend portfolio, Han, Zhou and Zhu (2016) report that a BETC of 1.24% is required to render zero return for such portfolio. The estimates of BETCs suggest that trend momentum profit is higher than the transaction cost for corporate bonds. Edwards, Harris and Piwowar (2007) report an average transaction cost of about 24 basis points per dollar trading for a median-sized corporate bond trade (or a round-trip cost of 48 basis points). Thus, the trend momentum profit of bonds easily survives transaction cost.

Overall, our results show that the profit of the trend momentum strategy is of economic significance and much larger than the trading cost of bonds. Moreover, the trend momentum of corporate bonds is stronger than that of stock momentum or stock trend momentum. Asset pricing theories grappling with an aggregate equity Sharpe ratio of 0.3 face a much greater challenge when considering a combination with a bond trend momentum portfolio, which has a Sharpe ratio about three times larger.

[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 characteristics of the bonds in each trend portfolio. Following this, we report the return distribution of bonds over the past six months in each trend portfolio.

4.4.1 Bond characteristics of trend portfolios

Does a trend portfolio of bonds exhibit certain characteristics? We answer this question by summarizing the characteristics of the bonds in each trend portfolio. Table 7 reports the characteristics of the bonds in each trend portfolio, including bond issuance size, age, coupon rate, and the moving average of yields in the last month (yld_{-1}) and six months ($yld_{-6,-1}$). For the whole sample (All), the portfolios that have 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 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 between High and Low trend portfolios over the past one and six months 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 consist the bonds of 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

A question of particular interest is whether the return predictability that we have uncovered is driven by conventional bond momentum. One way to answer this question is to investigate the composition of trend portfolios. If conventional momentum (e.g., over the six-month horizon) is behind the cross-sectional return predictability of bonds, we shall observe that a large proportion of bonds in the High (Low) trend portfolios have high (low) bond returns over the past six months.

Table 8 reports the distribution of bonds in each trend portfolio based on the returns of past six months. We divide the bonds by their returns over the past six months into quintiles (Loser, 2, Medium, 4 and Winner portfolios). We then calculate the percentage of bonds in a trend portfolio that fall in each bond momentum quintile. Results show that bond momentum is not a driver for the cross-sectional return predictive pattern generated from trend signals. There is no evidence that the High trend portfolio has a larger percentage of bonds that fall in the Winner group and that 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]

Figure 2 plots the average trend factor portfolio returns in month $-1, 0, 1, \ldots, 6$. Month 0 is the month when the trend portfolio was constructed. The graph shows that the bond trend factor portfolio has negative returns in month -1 and month 0. This pattern holds across all ratings. Result show that the trend momentum we document here is not due to high returns in the past month.

[Insert Figure 2 here]

4.5 Bivariate portfolio analysis

In this section, we conduct robustness checks using bivariate portfolio sorts, in which we control for potential cross-sectional pricing effects of conventional momentum and bond characteristics.

4.5.1 Bivariate portfolios analysis using MAs and historical bond returns

To firmly establish the robustness of trend momentum to the effect of conventional bond momentum, we perform bivariate portfolio sorts by directly controlling for this effect. We first sort bonds into quintiles (Loser, 2, Medium, 4 and Winner) based on their returns over the past six months. Then, for each of these quintile momentum portfolios, we further sort bonds into quintiles based on their 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 conventional bond momentum effect.

The first two columns of Table 9 report the results of trend portfolio returns. Results continue to show significant trend momentum even after controlling for the effect of conventional 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 full sample that includes all bonds. Moreover, the H-L returns increase as bond ratings decrease for the results of bivariate sorts by rating. The mean return of the H-L portfolio of junk bonds is 94 bps. These results suggest that trend momentum is not driven by conventional bond momentum.

4.5.2 Bivariate portfolio analysis using MAs and other bond characteristics

The analysis in the preceding section shows that trend portfolios contain bonds of 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 to control for the effects of bond characteristics. In each month, we first sort bonds into quintiles by 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 characteristic portfolios to obtain trend portfolio returns. The resulting trend portfolios all 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 bond characteristics and it strengthens as bond rating decreases. For example, controlling for the effect of bond issue size, the H-L portfolio return of AAA bonds is 84 bps, and 123 bps for junk bonds. Results for controlling age, coupon and past yields $yld_{-6,-1}$ share a similar pattern. Thus, trend momentum is robust to controlling for bond characteristics.

The expected return can be approximated by $Er_{i,t+1} \simeq y_t \times \Delta t - MD_{i,t} \times \Delta y_{i,t+1}$, where $MD_{i,t}$ is the modified duration of bond i at time t. Thus, the source of predictive power for future returns could be either the past yield level or the expected yield change. To see if the return predictability comes from the short-term past yield, we conduct an additional bivariate portfolio analysis using the yield level in month $t-1$ as the control variable. The results are very close to those using $yld_{-6,-1}$ as the control variable in Table 9, confirming that the predictive power of trend signals for cross-sectional bond returns is not driven by the yield level in the past month. Overall, results suggest that trend signals contain important information beyond that in bond yields over just the past one or six month horizons.

[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 the advantage of being able to control for the effects of 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 squares (WLS) in the first step,[10] where the weights used are the inverse of the variance of corporate bond returns estimated from 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 over the past six months ($MA_{jt-1,6}$);

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

Table 10 reports the results of the Fama-MacBeth regressions. For brevity, we only report the estimates of z_1, the coefficient of expected returns forecast by the MA signals, which constitutes our primary interest. Results show a significantly positive z_1, again suggesting that the MA signals have predictive power for future corporate bond returns cross-sectionally. More importantly,

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

the predictive power of MA signals is robust to control for all bond characteristics. As shown, z_1 remains significant in model (6), which includes 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 our portfolio analysis that momentum strategies based on MA signals are more profitable for higher-risk bonds.

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

Past returns (average bond returns over 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 bonds, and 0.57 for junk bonds, which is substantially higher. This pattern does not change much until past bond returns are introduced in model (6). In model (6), the difference in z_1 coefficient estimates narrows considerably, where the z_1s for AAA and junk bonds have values of 0.30 and 0.35, respectively. This finding suggests a potential interaction effect of conventional momentum and the moving-average signals. Nevertheless, z_1 continues to be very significant for the whole sample and each rating category, suggesting that the MA signals have an important effect on future returns beyond the conventional bond momentum effect.

[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. This brings up the issue of whether the cross-sectional bond return prediction or trend momentum is sensitive to different subperiods. To address this issue, we examine the trend momentum profits for different sampling periods. We first divide the sample into three subperiods using 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.

The left column of Table 11 reports H-L returns for the three subperiods. Results show that the initiation of TRACE coverage 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, whereas it is 1.60% with a t-value of 8.25 in the third subperiod. The increase in predictability is larger for lower-grade bonds (BBB and junk). Results show that trend momentum increases over time in the corporate bond market. This post-TRACE increasing trend momentum pattern is consistent with the finding of Jostova et al. (2013) for conventional momentum of junk bonds.

The literature has also shown that return predictability changes with macroeconomic conditions. Returns tend to be more predictable in a bad economy than in a 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 Chauvet's (1998) smooth recession probability (SRP) measure and the real GDP growth rate reported by the Federal Reserve Bank of St. Louis. The smooth recession probability is estimated via a dynamic Markov-switching factor model 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 periods associated with different macroeconomic conditions. For the sample including all bonds, the H-L returns for the high-recession probability and low-growth periods are 1.11% and 1.21% respectively, which are substantially higher than those for the low-recession probability and high-growth periods (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, except that cross-sectional return predictability is higher for lower-grade bonds. This suggests 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. (2017) show that momentum of junk bonds becomes insignificant if the cash flow matched excess return is used to calculate the momentum return. To check the sensitivity of our results to this effect, we test whether our trend momentum is robust to the use of cash flow matched excess returns. To calculate cash flow matched excess returns, we first obtain the price of an equivalent bond that has the same coupon and maturity as the corporate bond by discounting the coupons with Treasury spot rates matching the time of each coupon and the principal payment. Treasury spot rates are taken from Gürkaynak, Sack and Wright (2007), which have been updated to the present moment on the Federal Reserve Bank (FRB) website. We then subtract the return of this riskless equivalent bond from the return of the corporate bond to generate the cash flow matched 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 equivalent 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 trend 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-grade 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 those using gross returns. Overall, results show that the interest rate factor is not useful for explaining the trend momentum of investment-grade bonds, but could partially explain the trend momentum of junk bonds.

[Insert Table 12]

5.3 Trend portfolios forecast by bond characteristic variables

Previous studies have shown that bond characteristics can explain the cross section of bond returns (see Gebhart et al., 2005a). This raises a possibility that bond characteristics may contain predictive information for future bond returns. We next investigate this possibility by examining 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 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 a 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 characteristics used here 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. Results show that none of the returns of H-L portfolios is significant, suggesting that using these bond characteristics to predict bond returns fails to generate significant gains in economic profits.

[Insert Table 13]

5.4 Bond trend portfolios with different holding horizons

To examine the sensitivity of our results to different investment holding horizons, we calculate trend momentum returns for the 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 of returns by moving-average signals over different holding horizons. The trend factor (H-L) returns are all highly 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, both significant at the 1% level. The trend momentum weakens for the longer holding horizon of six months, 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 basis points per month for the three-month holding period and 23 basis points for the six-month holding period. In contrast, for junk bonds, the corresponding returns are 52 and 31 basis points, which are about 40% and 35% higher, respectively. 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 low-grade bonds have significantly higher trend momentum than high-grade bonds.

[Insert Table 14]

5.5 Trend momentum of public firms

Whether a firm is 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 useful to investigate whether trend portfolio returns are lower among public firms. In this analysis, we only use the bonds of public firms or of firms that have both stocks and bonds outstanding. Using the same two-step procedure, we perform return forecasts for public firms.

Panel A of Table 15 reports the results of trend portfolio returns for bonds issued by public firms. As shown, the results are comparable to those reported in Table 2, which include both public and private firms. For example, the return of the H-L portfolio based on the full sample of all bonds is 92 bps with a t-value of 7.5 in Panel A of Table 15, while it is 97 bps with a t-value of 8.12 in Panel A of Table 2. The results of other rated bonds are similar. Results therefore show little evidence that trend momentum is weaker for public firms.

Chordia et al. (2017) 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. (2017) 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 measured by changes 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 the 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 bond 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 quintile trend portfolios. For each quintile trend portfolio, we then average returns across the three portfolios formed by stock market variables.

Panel B of Table 15 reports the results of bivariate portfolio sorts. For simplicity, we only report the results using all bonds.[11] 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 anomaly variables.

Finally, we run a 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-statistics of the coefficients of return forecasts (expected returns) and the mean adjusted R-squares of cross-sectional regressions. Results continue to show that there is a significant relationship

[11] 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 that stock market variables have higher explanatory power for the cross-sectional returns of junk bonds than for investment-grade bonds, which is consistent with the view that junk bonds behave more like stocks. The results are available upon request.

between bonds' return forecasts and their future returns, even after controlling for the effects of 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 past corporate bond return information is not useful for predicting stock returns cross-sectionally. However, given that our trend momentum portfolio seems to contain more information than conventional momentum, it might capture some information in past corporate bond returns that is useful for predicting stock returns. In this section, we check this possibility by using the trend momentum portfolio which includes past corporate bond price information in short and long horizons to predict stock returns.

In each month, we sort the stocks into quintile portfolios according to their firm-level expected corporate bond returns estimated by MA signals. We then calculate the return for each stock portfolio as well as 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 as a predictor.

For comparative purposes, we also investigate 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 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. (2017), 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 momentum spillover effects are much weaker than those reported in Table 2, which again shows the superior power of using bond MAs in predicting cross-sectional bond returns.

To firmly establish 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 portfolio and the stock MOM portfolio. These GMCs are then used to run the Granger causality test for these portfolios. The advantage of using the GMC over the traditional Granger causality test is that the former is able to deal with asymmetry in the explained variance,[12] and is robust to the nonlinear relationship between random variables. As such, the GMC test is more powerful for detecting the dependency of variables in causality tests. The test statistics have 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 the MOM factor Granger-causes the bond trend momentum factor. All test statistics are significant at the one percent level. On the other hand, the bond trend momentum factor does not Granger-causes the MOM factor. As indicated, none of the test statistics is significant. Results strongly suggest an information spillover from stocks to bonds, but not vice versa. This finding explains why the trend portfolio returns of corporate bonds have little predictive power for stock returns as reported in Panel A of Table 16.

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

[Insert Table 16]

6 Conclusion

In this paper, we employ a new methodology to investigate momentum in the corporate bond market. This methodology accounts for trend signals over multiple return horizons, which generates much richer information than the conventional momentum methodology that uses only one lagged return signal over a fixed horizon, to predict future returns. As a result, this method is more informationally efficient and capable of uncovering momentum in the corporate bond market across different bond ratings, which has not been detected by the more restrictive conventional momentum method.

Empirical evidence strongly suggests that there is significant trend momentum not only in speculative-grade bond returns, but also in investment-grade bonds returns. Momentum returns are higher for bonds with smaller issue size, higher coupon rates and yields, and for newer bonds. Bond momentum profits in all rating categories survive transaction costs, and are of economic significance. The conventional risk factors and bond characteristics cannot explain the momentum returns that we uncover in this paper. Bond momentum is as pronounced as stock momentum and does not exhibit a momentum crash as in the stock market. In fact, bond momentum returns are higher in periods of slow economic growth and recession. There is no evidence that trend momentum of corporate bonds is driven by conventional bond momentum or the spillover of stock market momentum.

Results show that the trend signals extracted from past returns over different horizons have strong predictive power for the cross section of corporate bond returns. Our finding suggests that returns over different investment horizons contain important information for future returns. This finding is consistent with the prediction of the theoretical models of Greenwood and Shleifer (2014) and Hirshleifer, Li, and Yu (2015), which suggest that return trends contain the information for future returns when investors extrapolate expectations from the past. Our results are robust to different measurements of excess returns and controlling for bond characteristics and risk factors. Previous studies find no evidence of momentum for investment-grade bonds largely because they rely on a less efficient method which uses only one return signal over a predetermined horizon and thus misses out on the important momentum information existing in other return horizons.

Overall, our results strongly suggest that the cross-sectional returns of corporate bonds are predictable across all rating categories and that this predictability increases as the credit rating decreases. The existence of trend momentum seems by far the most significant cross-sectional corporate bond anomaly ever discovered in this market and it poses a challenge to existing rational pricing theories.

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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	-0.10	-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) $\Delta TERM, \Delta DEF, MKT, SMB, HML, MOM$. 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: Bonds of different 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 table 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

Rating	Turnover ratio (%) High	Turnover ratio (%) Low	Turnover ratio (%) H-L	BETCs (%) Zero return Raw return	BETCs (%) Zero return Adjusted return	BETCs (%) Insignificance Raw return	BETCs (%) Insignificance 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-statistics measure 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 trend portfolio that fall in each bond momentum quintile. 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 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		SRP		GDP growth rate	
Rating	H-L	t-stats	H-L	t-stats	H-L	t-stats
	Jan. 1973- Dec. 1993		Low		Low	
All	0.59	2.79	0.84	5.52	1.21	4.04
AAA	0.42	1.80	0.65	3.80	1.04	4.09
AA	0.32	1.51	0.65	4.47	1.04	4.12
A	0.44	1.96	0.74	4.81	1.22	3.85
BBB	0.58	2.16	0.87	4.24	1.33	3.60
Junk	1.02	3.30	1.03	4.57	1.46	2.88
	Jan. 1994-July 2002		Medium		Medium	
All	0.67	3.65	0.97	6.32	0.87	5.88
AAA	0.85	4.33	0.84	4.23	0.94	5.64
AA	0.71	3.63	0.77	5.10	0.83	6.03
A	0.75	3.85	0.97	5.92	1.00	6.31
BBB	0.46	2.26	1.06	5.71	0.99	5.73
Junk	0.59	2.91	1.37	5.30	1.08	4.80
	Aug. 2002-Sept. 2015		High		High	
All	1.60	8.25	1.11	3.97	0.83	5.42
AAA	1.35	7.86	1.07	4.19	0.57	2.83
AA	1.35	8.85	0.92	3.56	0.46	2.73
A	1.73	7.63	1.23	3.83	0.72	4.09
BBB	1.99	7.14	1.26	3.37	0.85	3.65
Junk	1.83	5.86	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 cash 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 returns 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 the 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. (2017) 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 bond returns 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. The symbol "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 figure plots the returns of trend factor portfolios.

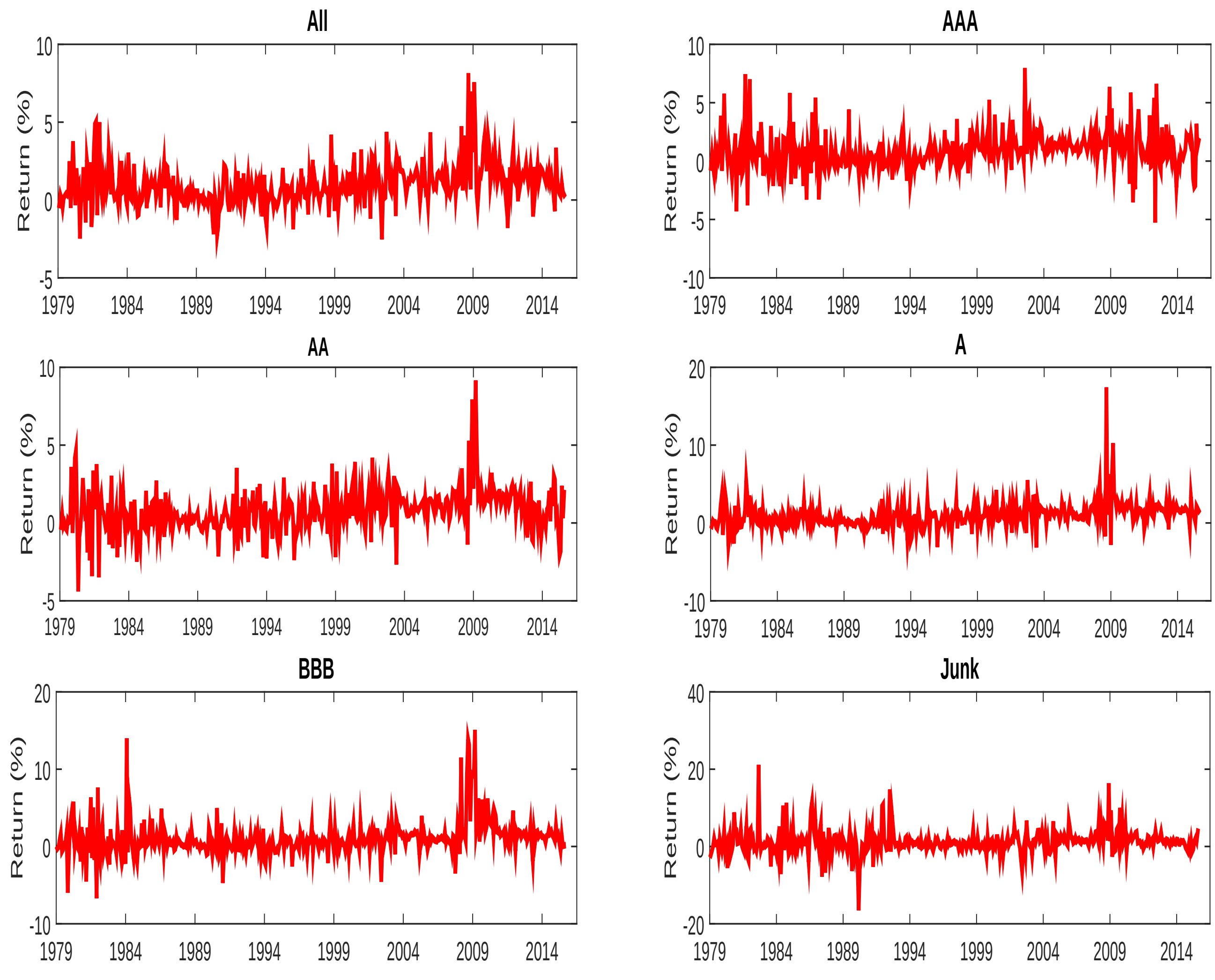
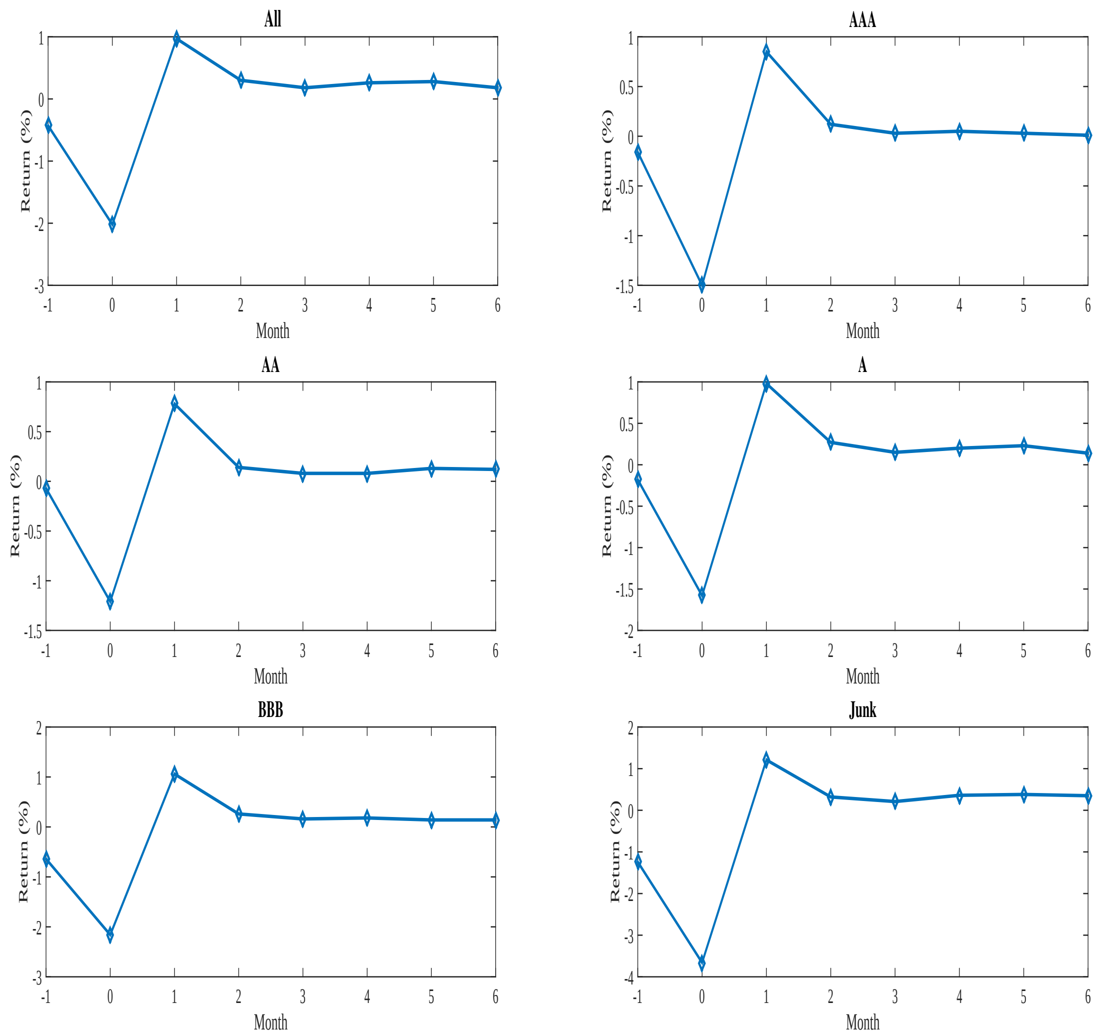


Figure 2. Average trend portfolio returns in months $-1, 0, 1, \ldots, 6$
This figure plots the average trend portfolio returns in months $-1, 0, 1, \ldots, 6$. Month 0 is the portfolio formation month.



Appendix: Rearrangement of trend signals

In this appendix, we show that the trend signal is the weighted combination of historical monthly yield levels.

From (3), we have

$$E_t(r_{j,t+1}) = E_t(\beta_{1,t+1})Y_j^t + E_t(\beta_{3,t+1})\frac{Y_j^t + Y_j^{t-1} + Y_j^{t-2}}{3} + E_t(\beta_{6,t+1})\frac{Y_j^t + ...Y_j^{t-5}}{6}$$
$$+ E_t(\beta_{12,t+1})\frac{Y_j^t + ...Y_j^{t-11}}{12} + E_t(\beta_{24,t+1})\frac{Y_j^t + ...Y_j^{t-23}}{24} + E_t(\beta_{36,t+1})\frac{Y_j^t + ...Y_j^{t-35}}{36}$$
$$+ E_t(\beta_{48,t+1})\frac{Y_j^t + ...Y_j^{t-47}}{48}. \quad (10)$$

Rearranging the right terms, we have

$$E_t(r_{j,t+1}) = \sum_{i=1}^{i=48} \omega_{i,t} Y_{j,t-i+1}, \quad (11)$$

where

$$\omega_{i,t} = \begin{cases} E_t(\beta_{1,t+1}) + \frac{E_t(\beta_{3,t+1})}{3} + ... + \frac{E_t(\beta_{48,t+1})}{48}, i = 1 \\ \frac{E_t(\beta_{3,t+1})}{3} + ... + \frac{E_t(\beta_{48,t+1})}{48}, i = 2,3 \\ \frac{E_t(\beta_{6,t+1})}{6} + ... + \frac{E_t(\beta_{48,t+1})}{48}, i = 4,5,6 \\ \frac{E_t(\beta_{12,t+1})}{12} + ... + \frac{E_t(\beta_{48,t+1})}{48}, i = 7,...,12 \\ \frac{E_t(\beta_{24,t+1})}{24} + ... + \frac{E_t(\beta_{48,t+1})}{48}, i = 13,...,24 \\ \frac{E_t(\beta_{36,t+1})}{36} + \frac{E_t(\beta_{48,t+1})}{48}, i = 25,...,36 \\ \frac{E_t(\beta_{48,t+1})}{48}, i = 37,...,48 \end{cases}$$

This shows that the trend signal is a weighted combination of monthly yield levels in the last four years. It is of interest to see the weight of each historical yield in the trend signal. Table A reports the mean weight of each yield level in last four years in the trend signal extracted from all bonds in the sample. We also report the t-statistics of these weights to see whether they are significantly different from zero. There are several observations. First, most mean coefficients (weights) are significant, suggesting that the yield levels at different time contribute to the trend signal jointly. Second, the absolute weights of yields decrease with time, i.e., more recent yields have larger weights in the trend signal. Third, the weights of current yields are positive, while those of historical yields are mostly negative. Finally, for AAA bonds, the absolute weights for the yields at longer lags are larger than those of junk bonds. For example, the weight of the yield level three to four years ago in the trend signal is -2.76 for AAA bonds, whereas it is only -0.57 for junk bonds. Figure A plots the time series of weights for each historical yield in the trend signal.

[Insert Table A here]

[Insert Figure A here]

Table A. Weights of the past yield levels in the trend signal
This table reports the mean weight for each yield of the past four years in the trend signal extracted from all bonds.

	Weight: ω_{it}						
	$i=1$	$i=2,3$	$i=4,5,6$	$i=7,...,12$	$i=13,...,24$	$i=25,...,36$	$i=37,...,48$
All	92.62	-30.55	-4.42	-0.61	-0.03	-0.14	-0.12
t-stats	40.62	-31.39	-10.26	-3.27	-0.39	-1.98	-2.37
AAA	199.39	-99.48	-17.38	0.01	-0.72	0.98	-2.76
t-stats	29.84	-13.80	-8.15	0.01	-1.77	3.04	-14.60
AA	138.87	-41.18	-6.68	-0.91	-0.34	0.44	-0.63
t-stats	44.55	-36.88	-12.30	-3.04	-2.93	2.73	-3.96
A	126.41	-35.03	-8.48	-0.04	-0.28	-0.10	-0.23
t-stats	35.16	-23.96	-16.08	-0.15	-2.73	-0.73	-3.42
BBB	123.52	-36.30	-8.86	0.37	-1.10	-0.68	1.26
t-stats	36.57	-26.97	-8.73	0.90	-3.18	-2.61	3.62
Junk	86.89	-38.78	3.97	-0.71	-0.51	0.69	-0.57
t-stats	30.31	-18.10	4.16	-1.96	-3.53	4.16	-5.14

Figure A. Time series of weights for each historical yield in the trend signal
This figure plots the time series of weights for each historical yield in the trend signal extracted from all bonds.