Cross-Sectional Predictability of Corporate Bond Returns

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First draft: February, 2016

Current version: Tuesday 12th March, 2019

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We thank Hengjie Ai, Bo Becker, Ivan Brick, Hui Chen, Tarun Chordia, Zhi Da, Jens Dick-Nielsen, 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 Georgia State University, Monash University, National Taiwan University, Peking University, Renmin University of China, Rutgers University, Shanghai University of Finance and Economics, 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, 2017 China International Conference in Finance, 2018 New Zealand Finance Colloquium, 2018 Conference on Financial Predictability and Data Science and 2018 European Finance Association Annual Meeting for helpful suggestions and comments.

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Abstract

While there are hundreds of cross-sectional predictors in the equity market, whether corporate bonds are predictable in the cross-section is an open question. This paper proposes to use trend signals in returns, which exploit short-, intermediate- and long-term trends simultaneously, to predict future bond returns. We provide new evidence that there is statistically significant and economically important predictability in the cross-section of corporate bond returns. This predictability is robust to various controls and stronger for lower-rated bonds. The pronounced bond market anomaly uncovered in this study joins a host of equity anomalies that challenges existing rational pricing models.

JEL classification: G12; G14

Keywords: trend signals; moving averages; cross-sectional predictability; corporate bond returns.

1 Introduction

A central issue in finance is to explain why assets have different expected returns. The size and book-to-market factors of Fama and French (1993) are well known equity predictors: small size or high book-to-market firms have greater average returns in the future. The momentum factor of Jegadeesh and Titman (1993) is another important equity predictor, out of hundreds of firm characteristics that have predictive power on future stock returns (see, e.g., Hou, Xue, and Zhang, 2018). The study of cross-sectional predictors is important not only for understanding market efficiency and improving investment performance, but also for stimulating new theories for explaining their existence. In the corporate bond market, which is comparable in capitalization to the stock market and is the primary source of long-term capital in the US, there is, however, little evidence for its cross-sectional predictability. After testing a comprehensive set of equity characteristics, Chordia, Goyal, Nozawa, Subrahmanyam, and Tong (2017) find that only a few of them have some predictive power, but not economically significant. This finding is echoed in recent studies by Choi and Kim (2018) and Bai, Bali, and Wen (2018). Hence, whether corporate bonds are predictable in the cross section remains an open question.

In this paper, we propose to use trend signals in returns as a predictor for corporate bond returns. We approximate returns by bond yields. Cochrane and Piazzesi (2005) is one of the major studies that use average yields of one- to five-year Treasury bonds to predict future Treasury returns, and they find that past yields contain important information for bond premia. Instead of using only one yield average, we take the averages over short-, intermediate- and long-term holding maturities, and use all the resulting predictors instead of a single one. There are two reasons for this specification. First, it is difficult to argument which yield average is the one a representative bond investor uses. Surveys and interviews indicate that many investors follow return trends across financial markets, but some may follow short-term trends and others may follow long-term trends. This pattern can arise rationally due to limited information or from an anchoring behavioral bias (Avramov, Kaplanski, and Subrahmanyam, 2019). Han, Zhou, and Zhu (2016) demomstrate theoretically that historical averages of various horizons have predictive power for future returns even in equilibrium due to the presence of heterogeneous trend-following traders. Second, it is difficult to select ex ante which yield average is the best one to use as a predictor. Our use of multiple predictors, which captures short-, intermediate- and long-term return trends, is econometrically sound as it permits the data to determine the relative importance of these predictors.

We use the econometric method of Haugen and Baker (1996) to exploit the information in all the predictors. We first estimate bond expected returns cross-sectionally using the multiple trend signals. We then long bonds with the highest expected returns and short those with the lowest. The spread portfolio earns a statistically significant premium of 0.97% per month using quintile portfolio sorts, and 1.37% per month using decile portfolios. In economic terms, this trend premium is as sizable as the momentum premium in the equity market.

The trend premium evidence is robust. Its magnitude is little changed with a more general forecasting model. Since the set of our cross-sectional predictors is large that reflect return trends over short-, intermediate-, and long-term investment horizons, there is a potential concern of over-fitting in the multivariate regression model of Haugen and Baker (1996). To address this concern, we empoly the partial least squares (PLS) approach of Light, Maslov, and Rytchkov (2017) which is a robust procedure that applies to large cross-sectional and possibly closely correlated predictors. With the PLS forecasts, we find that the magnitude and statistical significance of the trend premium remain almost intact.

Further analysis reveals that trading profits are not primarily driven by shorting the worst-rated bonds. Profits are however characteristic-dependent and stronger for bonds with smaller issue size, higher coupon rates and yields, and for newer bonds (on-the-run). While firm characteristics matter, the trend premium remains highly significant after controlling for them. Additionally, following Lewellen (2015), we examine the predictability of trend signals by computing the predictive slope of realized returns on our predicted returns. The slope is highly significant, again confirming the predictive power of our trend signals.

The trend premium cannot be explained by standard risk factors, bond characteristics, and transaction costs. The trend premium varies over time. It increases after the establishment of TRACE (the Trade Reporting and Compliance Engine), which improved transparency and lowered trading costs in the corporate bond market. Moreover, profits are higher in periods of slow economic growth and recession, a finding consistent with the literature which shows return predictability is linked to business conditions.

The evidence of trend premium uncovered in this paper has important implications for asset pricing, besides being a profitable trading strategy for bond investors. It is an anomaly across diverse bond categories in the corporate bond market, similar to the well-known Jegadeesh and Titman (1993) momentum phenomenon in the stock market. Interestingly, while there are over hundreds of anomalies in the stock market, trend premium appears to be the most significant anomaly identified to date in the corporate bond market in terms of the size of abnormal returns. The high trend premium challenges rational bond pricing theories. Moreover, the bond trend premium is comparable in magnitude to the momentum premium in the stock market, suggesting that trend-following by bond investors is as strong as that by stock investors, despite that the former is presumed to be more sophisticated institutional investors that dominate the bond market.

The cross-sectional predictability documented by this paper is different from the bond momentum identified by Jostova, Nikolova, Philipov, and Stahel (2013). First, Jostova et al. (2013) find that momentum only exists in speculative-grade bonds, but our evidence of return predictability covers the entire universe of bonds. Second, while momentum strategies identify only the high or low past return group using information over a fixed time horizon, our methodology provides the expected values on all bonds based on the information over different horizons. Theoretically, similar to bond momentum studies, the trend premium appears to be partially explained by the gradual information diffusion model of Hong and Stein (1999). Due to slow transmission of information, the market can experience trends, suggesting that slow incorporation of good or bad news on bond prices is a plausible source of return predictability.

Our paper is about the cross-sectional predictability of corporate bond returns, which is differentiated from the time-series return predictability investigated by many other studies. Keim and Stambaugh (1986) is perhaps the first study on time-varying risk premia of corporate bonds. Fama and French (1989) find that lagged default spreads, term spreads, and dividend yields are important time-series predictors of bond returns. Subsequently, Greenwood and Hanson (2013) and Lin, Wang, and Wu (2014) identify issuer quality, and liquidity and forward rate factors, separately, as useful predictors. Lin, Wu, and Zhou (2018) apply an iterated combination approach to improving 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 shows empirical evidence for cross-sectional predictability in corporate bond returns 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 empirical methodology, which involves two stages. First, we identify new predictors for corporate bond returns, making use of all information in the short-, intermediate-, and long-term return horizons. Second, we employ an econometric procedure that incorporates multiple predictors to forecast returns cross-sectionally. The spread portfolio formed by the forecasted returns then constitutes the bond trend factor.

2.1 Trend signals

Treynor and Ferguson (1985), Brown and Jennings (1989) and Cespa and Vives (2011) show theoretically that past returns have predictive power on future returns due to differences in receiving and responding to information by heterogeneous investors. Recently, based on behavioral theory, Greenwood and Shleifer (2014) and Hirshleifer, Li, and Yu (2015) show that, when investors extrapolate expectations from the past, return trends should reflect expected returns. Building on the evidence of trend-following by hedge funds and top traders, Han et al. (2016) show that moving averages (MAs) of past prices scaled by the current price, which capture past return trends, have predictive power for future returns in equilibrium with both informed and technical traders. On the empirical front, Brock, Lakonishok, and LeBaron (1992), Lo, Mamaysky, and Wang (2000), and Neely, Rapach, Tu, and Zhou (2014), among others, provide evidence that past return trends can predict stock returns. This paper is the first to document that similar trend signals have predictive power for corporate bond returns.

Unlike equity market studies, a unique feature in this study is our use of the MAs of bond yields rather than prices to predict returns. There are several reasons for using bond yields. 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 et al., 2014; Joslin, Priebsch, and Singleton, 2014). Thus, in adapting the MA analysis from stocks to bonds, we use bond yields instead of prices.

To obtain the trend signals over a time horizon, we calculate the moving average yield of lag L in month t for bond j,

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

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 the MAs of lag lengths 1-, 3-, 6-, 12-, 24-, 36-, and 48-months. These MA signals essentially represent the return trends of bonds from short to long horizons.

2.2 Two-pass regressions

Using the multiple MA signals as return predictors, we 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, in each month we run the following cross-sectional regression of bond returns in month t on the MAs in month $t-1$ to obtain the time-series of slope coefficients for each moving average signal:

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

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 with returns determines the relative importance of MA signals at different lags in forming investors' expectations in month t to predict returns in month $t+1$.

In the second-step, we project a 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 $t+1$, MA_{jt,L_i} is the trend signal at the end of month t with lag L_i, 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 a particular lag L_i over the past 12 months as the expected beta coefficient for the next month. Averaging the coefficients of a trend signal reduces the noise in beta estimates. In short, 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 Eq. (2).[1] The magnitude of a beta reflects the relevance of a particular trend signal to 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 bonds in portfolio analysis. Also, since only the information available in month t is used to predict the return in month $t+1$, the formation process of expectations is completely out of sample.

2.3 The partial least squares approach

We use the MA signals simultaneously in Eq. (2) to forecast a bond's return in our main empirical analysis. However, since there are multiple correlated regressors, a potential concern is that the simple regression may overfit the MA signals. To address this concern, we also estimate expected returns using the partial least squares (PLS) approach of Light et al. (2017) that is designed to handle large cross-sectional and potentially correlated predictors.

Following Light et al. (2017), we forecast a bond's expected return in two steps. First, we run separate cross-sectional regressions of bond return r_{jt}, $j = 1, ..., n$, on each MA signal, MA_{jt-1,L_i}, for $L_i = 1, 3, 6, 12, 24, 36, 48$, and obtain their slopes as $\lambda_t^{L_i}$. Second, for each bond j, we run a regression of MA_{jt,L_i} on the average $\lambda_t^{L_i}$ of the last 12 months and obtain the slope $\hat{\mu}_{jt}$. We then use $\hat{\mu}_{jt}$ as the forecast of bond j's expected return in month $t+1$. Using this PLS forecast as an alternative to Eq. (3), we check the robustness of our results to correlation in MA predictors.

2.4 Portfolio analysis

We sort bonds into quintile portfolios by their expected returns, and form the equal-weighted portfolios and rebalance them monthly. These portfolios are dubbed trend portfolios as they are

[1] In the appendix, we show that the trend signal is a weighted combination of historical monthly yield levels.

constructed using trend signals. 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 factor, similar in spirit to the construction of the momentum factor. Essentially, the trend factor portfolio longs bonds with the highest expected returns and shorts bonds with the lowest expected returns. This procedure for constructing the trend portfolio resembles that of Jegadeesh and Titman (1993), Gebhardt, Hvidkjaer, and Swaminathan (2005a,b), and Jostova et al. (2013), among many others. The main difference is that instead of sorting assets on their past returns in a predetermined fixed horizon, we sort bonds on their expected returns based on multiple trend signals. While focusing on quintile portfolio sorts, we also construct decile portfolios which are common in equity studies.

In general, the traditional momentum factor can be viewed as a 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 future prices always falls within a particular time horizon (e.g., the past six months). This assumption is quite stringent in a dynamic world where various economic forces can alter trend signals for future market performance over different horizons (see Han et al., 2016; Daniel, Hirshleifer, and Sun, 2017). Hence, limiting the use of return signals to a restricted time horizon is likely to underestimate the predictability of bond premiums. In contrast, by accounting for differences in the timing of receiving and processing information or heterogeneous information diffusion, we form a trend factor which captures information for the short-, intermediate- and long-term predictive components of bond returns. Our methodology can detect information signals over different investment horizons more effectively to determine whether return predictability indeed exists in the corporate bond market.

3 Data

Our 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 the 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 data set, which mainly covers transactions of insurance companies.[2] 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.[3] We exclude bonds with maturity less than two years or longer than 30 years, and bonds with

[2] The procedure of Bessembinder, Kahle, Maxwell, and Xu (2008) is used to filter out canceled, corrected and commission trades. Prices are the trade size-weighted average of intraday prices over the day.

[3] Note that when there is a coupon payment in month t, AI is dropped. The bond return is transformed to the log

a floater or odd frequency of coupon payments. We primarily use the Moody's rating, but if it is unavailable, we use the Standard and Poor's rating whenever possible. The sample period runs from January 1973 to September 2015.[4]

Table 1 reports the summary statistics of the data. Panel A of 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 trend premium across different ratings.

Panel B of Table 1 reports the summary statistics of the returns. We report both gross returns and cash flow matched excess returns. To calculate cash flow matched excess returns, we first obtain the price of a riskfree equivalent bond that has the same coupon and maturity as the corporate bond by discounting the cash flows 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.

Both gross returns and cash flow matched excess returns are higher when ratings are lower. The mean cash flow matched returns of AAA bonds are close to zero. However, standard deviation of AAA returns is close to 1, suggesting that the long-short portfolio returns can be high. We next turn to empirical tests.

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return in the forecast so that monthly log returns can be conveniently added together to obtain a return over a longer horizon.

[4]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 and linearly interpolate the prices between months. We drop the data if last observation is more than six months ago from the current one.

[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 return forecasted by 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 (the first row), the H-L (trend factor) return is 0.97%, which is significant at the 1% level (t-stats = 8.12).[5] The bonds included 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 trend 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. The monthly H-L return differences range from 0.85% for AAA bonds to 1.21% for junk bonds, all significant at the 1% level. The return spread increases as the rating decreases. The difference between the monthly H-L returns of junk and AAA bonds is 0.36%, which is significant at the 5% level.

Panel B of Table 2 reports the returns of trend portfolios when we use the PLS method to form expectations of returns. The results are slightly weaker than those reported in Table 2. Nev-

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

ertheless, all of the H-L returns remain significant at the 1% level. The monthly H-L return is 0.63% using all bonds, and is significant at the 1% level. The results show the robustness of trend premium estimation to the use of an alternative and perhaps more general approach to extract information from the MA signals. Thus, the correlation among predictors does not appear to be a serious concern here.

[Insert Table 2]

Table 3 reports the results when we sort the bonds into deciles. The H-L returns are higher than those reported in Table 2, indicating a stronger trend effect for finer portfolio sorts. Consistent with previous findings for bond momentum (Jostova et al., 2013), we find significant trend premium in speculative-grade bonds. However, the profit captured by our trend 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 profit of 1.21% for non-investment grade bonds. In contrast, using multiple price signals in the short-, intermediate- and long-term simultaneously, we find a much larger profit of 1.58% for speculative-grade bonds, which is about 30% higher than their estimate for the one-month holding period return. Using the PLS method also generates a significant profit of 1.45%. The higher profits generated from our trading strategy suggest that trend signals 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.

Why is there a trend premium even for the investment-grade bonds? To provide some insight as to the possible source of return spreads, we first analyze the temporal pattern of cross-sectional variations in returns using AAA bonds as an example. Figure 1 plots the time series of the 10th and 90th percentile of AAA bond returns each month. Results show that the cross-sectional variations are large within the AAA category, with an average standard deviation of 1.35%. Hence, the ex post decile spread portfolio can have an average return of 4.37%, which is much greater than 1.10% earned by the decile H-L portfolio in the AAA category. Of course, that is not achievable in real markets with frictions. As shown, our efficient forecasting approach can only generate the H-L portfolio return of 1.10%. The point in this illustration is that it is plausible to derive profits from the return dynamics even for premium AAA bonds using an efficient signal extraction method like ours.

[Insert Figure 1]

The trend premium increases monotonically as a bond's rating decreases. This pattern is consistent with the findings of stock momentum in the equity market (see Avramov, Chordia, Jostova, and Philipov, 2007, 2013). However, unlike previous findings of momentum concentrated in speculative-grade stocks and bonds, our results show a dramatically different picture: the trend premium does not concentrate on 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 portfolio contains more junk bonds than other trend portfolios. Thus, trend premiums are not derived primarily from shorting the worst-rated bonds.

In stark contrast to previous studies (e.g., Jostova et al., 2013), we find that the trend premium is everywhere in the corporate bond universe, not just limited to speculative-grade bonds. Another important finding in this study is that the profits of trend 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 Tables 2 and 3 show just the opposite: both High and Low trend portfolios have positive returns. Trend strategies do involve taking a long position in the high-trend bonds and shorting low-trend 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 3]

Several recent studies find some evidence of abnormal returns in the corporate bond market (see Chordia et al., 2017; Choi and Kim, 2018; Bai et al., 2018). Sorting all bonds into deciles on stock momentum (MOM), bond momentum, asset growth, and profitability, Chordia et al. (2017) report monthly H-L bond portfolio returns of 0.13%, 0.16%, -0.19%, and -0.14%, respectively. Separately, Choi and Kim (2018) report -0.32%, -0.24%, and 0.21% returns per month for the H-L portfolios sorted on asset growth, investment, and book-to-market ratio, respectively. In contrast, our portfolios sorted on MA signals in Table 3 generate much larger bond return spreads than do these studies. Bai et al. (2018) sort corporate bonds into quintiles 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 on return distribution characteristics. The trend anomaly uncovered in this study hence poses an even bigger challenge to rational asset pricing theories in the corporate bond market.

Figure 2 plots the time series of returns for the trend factor (H-L) over the entire sample period. It shows that the trend premium is quite stable over time. Moreover, the trend premium exhibits similar patterns across bonds of different ratings. This set of results again shows that the trend premium is pervasive, not just limited to a particular rating class. Further, unlike the negative returns of stock momentum strategies during the crisis period documented by a number of studies (e.g., Daniel, Jagannathan, and Kim, 2012; Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016), the trend factor has positive returns in this period. The bond market does not appear to behave similarly to the stock market which experienced a momentum crash during the subprime crisis.[6]

[Insert Figure 2]

Panel A of Table 4 reports 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 find-

[6]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.

ings are similar to the behavior of the stock trend factor documented by Han et al. (2016). The minimum returns of the trend factor 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 factor portfolio of junk bonds. The trend factor portfolios also have a smaller number of extreme negative observations. There is no observation below two standard deviations for the whole bond sample. The trend factor portfolio of junk bonds has six observations below two standard deviations and one observation below three standard deviations. By contrast, the number of observations below two and three standard deviations is nine and three, respectively, for MOM.

In Panel B of Table 4, we report the correlations between the trend factor and other risk factors. The correlations are close to zero and negative in many 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 4]

We also calculate the value-weighted returns of bond trend portfolios. Unreported results show that the mean value-weighted H-L return of all bonds is 0.93% with a t-value of 8.13 if quintile portfolios are constructed, and 1.33% with a t-value of 10.26 if decile portfolios are constructed. The results are close to those reported in Tables 2 and 3. The results of the value-weighted returns of bond trend portfolios of different ratings are similar. Thus, the trend premium of bonds is robust to the choice of portfolio weights.

4.2 Alphas 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 regression 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 nine 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) MKT, SMB, HML, RMW, CVA;

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

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

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

MKT, SMB, HML, RMW, CVA are the returns of the market, size, book-to-market, profitability and investment factors in Fama and French (1993) and Fama and French (2015). MOM is Carhart (1997)'s 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 the Amit Goyal and Kenneth R. French websites. Similar variables are used by Jostova et al. (2013) to examine the effects of systematic risk factors on bond momentum portfolio returns. We calculate the Gibbons, Ross, and Shanken (1989) (GRS) statistics to test the null hypothesis that all intercepts are zero.

Table 5 reports the alphas of time-series regressions for the whole sample. Results show that the risk-adjusted returns of Low portfolios are all negative, while those of High portfolios are all positive. The α_ps 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 5]

Table 6 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, the results show that trend portfolio returns or trend premiums cannot be explained by systematic risk factors and that unexplained excess returns are larger for lower-grade bonds.

[Insert Table 6]

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 improvement in the Sharpe ratio and investigate whether the H-L returns survive transaction costs. First, following Gibbons et al. (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 portfolios.

Panel A of Table 7 reports the maximum Sharpe ratios.[7] 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 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 rating portfolio returns 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 indexes of the corporate bond market in the portfolio construction.

Second, we investigate whether the trend premium survives transaction costs. We first calculate the turnover ratios of both high and low trend portfolios. Then, following the literature (e.g., Grundy and Martin, 2001; Barroso and Santa-Clara, 2015), we calculate the break-even transaction costs (BETCs) of H-L returns. It is sufficient to consider the most comprehensive factor model with factors $\Delta TERM, \Delta DEF, MKT, SMB, HML, MOM$, or Model (9) in Tables 5 and 6. We construct two 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. 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.

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

Panel B of Table 7 reports the results of 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 portfolios 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 7 reports the BETCs results. For the full sample including all bonds, it takes a transaction cost of 1.72% to completely offset the H-L returns, and 1.30% to make H-L returns statistically insignificant at the 5% level. For H-L 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 trend 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 et al. (2016) report that a BETC of 1.24% is required to render zero return for such portfolio. The estimates of BETCs suggest that the trend premium is higher than transaction cost of 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 premium of bonds easily survives transaction cost.

Overall, our results show that the profit of the trend strategy is of economic significance and much larger than typical trading costs of bonds. 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 portfolio, which has a Sharpe ratio about three times larger. This provides a stimulus for further research on developing theories to understand fully the economic forces behind it.

[Insert Table 7]

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 8 reports the characteristics of the bonds in each trend portfolio, including bond issue size, age, coupon rate, and the moving average of yields in the last month ($MA_{t-1,1}$) and six months ($MA_{t-1,6}$). For the whole sample (All), the portfolios that have high expected bond returns tend to be associated with bonds 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 the 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 H-L spreads in coupon rates show no clear pattern across ratings.

In summary, bond returns show a significant trend premium, and trend portfolios consist of bonds with different characteristics. High trend portfolios have more bonds with higher yields and coupon rates, lower issuance amount and younger age.

[Insert Table 8 here]

4.4.2 Past six-month return distribution of trend portfolios

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 9 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). 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 predictability 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 driver of cross-sectional return predictability uncovered by the trend strategy.

[Insert Table 9]

Figure 3 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. The result shows that the trend premium we document here is not due to high bond returns in the past month.

[Insert Figure 3 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 momentum and bond characteristics.

4.5.1 Bivariate portfolios analysis using MAs and historical bond returns

To firmly establish the robustness of cross-sectional return predictability 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 return forecasts 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 portfolios have effective control for the conventional bond momentum effect.

The first two columns of Table 10 report the results. Results continue to show a significant trend premium even after controlling for the effect of conventional bond momentum. The H-L 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 0.64%, which is significant at the 1% level for the full sample that includes all bonds. Moreover, the H-L returns increase as bond ratings decrease. The mean return of the H-L portfolio of junk bonds is 0.94%. These results suggest that the trend premium 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 characteristics (see Table 8). This raises a concern that trend portfolio returns could 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 on a bond characteristic and then further sort bonds in each quintile into five trend portfolios to yield 5x5 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* ($MA_{t-1,6}$).

Table 10 reports the results of controlling for the effects of bond characteristics. Results continue to show highly significant H-L portfolio returns across the board. The trend premium persists even after controlling for bond characteristics, and the effect strengthens as bond rating decreases. For example, controlling for the effect of bond issue size, the H-L portfolio return is 0.84% for AAA bonds and 1.23% for junk bonds. The results of controlling for age, coupon and past yields $MA_{t-1,6}$ share a similar pattern. Thus, the trend premium is robust to controlling for bond characteristics.

The expected return can be approximated by $Er_{j,t+1} \simeq y_{j,t} \times \Delta t - MD_{j,t} \times \Delta y_{j,t+1}$, where $MD_{j,t}$ is the modified duration of bond j 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 bivariate portfolio analysis using the yield level in the month *t-1* as the control variable. The results are very close to those using $MA_{t-1,6}$ as the control variable in Table 10, 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, the results suggest that trend signals contain important information beyond that in bond yields over the past one or six month horizons.

[Insert Table 10]

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 and 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,[8] 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 ($MA_{t-1,6}$);

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

Table 11 reports the results of the Fama-MacBeth regressions. For brevity, we only report the estimates of z_1, the coefficient of expected return forecasts by the MA signals, which is 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, the predictive power of MA signals is robust to controlling 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. Larger z_1 for lower-grade bonds is consistent with the finding in our portfolio analysis that trend strategies based on MA signals are more profitable for higher-risk bonds.

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

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 $MA_{t-1,6}$ and past bond returns can predict the bond returns in the next month cross-sectionally. Most important, the 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 after controlling for these effects. Results show that the effect of MA signals is robust to controlling for bond characteristics.

Past returns (the 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 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 11]

5 Additional tests

5.1 Subperiod analysis

Previous studies in the equity market have shown that the momentum effect varies over time. This evidence brings up the issue of whether cross-sectional bond return prediction or the trend premium is sensitive to different subperiods. To address this issue, we examine the trend premium 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 12 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 the trend premium increases over time in the corporate bond market. This post-TRACE increasing trend premium pattern is similar to the finding of Jostova et al. (2013) for the pattern in the 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 et al., 2018). To see if macroeconomic conditions play a role in trend premium, we next examine the relationship between cross-sectional predictability and macroeconomic conditions.

We divide the sample into three subperiods using the Chauvet (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 12 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 1% level. The results by rating show a similar pattern, except that the cross-sectional return predictability is higher for lower-grade bonds. Thus, 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 et al., 2010; Lin et al., 2018).

[Insert Table 12]

5.2 Trend premium using different returns

Table 13 reports the trend premiums using different returns. First, we test whether the trend premium is robust to the use of cash flow matched excess returns.[9] Panel A of Table 13 reports the results. The trend premium is robust to the use of the cash flow matched excess return to calculate the profit. The average H-L portfolio return using all bonds is 0.97%, and significant at the 1% level. This result is the same as that reported in Table 2. The results by rating also show significant H-L returns. Comparing these results with Table 2, we find that the H-L spreads do not change much. These results suggest that the interest rate factor is not useful for explaining the trend premium of corporate bonds. Second, we calculate the returns using capital gain and loss only. Panel B of Table 13 reports the results. Results continue to show significant trend premium effect when the coupon is excluded from return calculation.

Corporate bonds generally trade much less frequently than stocks. We address the robustness of our results to infrequent trading in two ways. First, we drop bonds that do not have trading in past three months to address the potential concern of infrequent trading. Panel C of Table 13 shows that the results are similar to those reported in Table 2.

A second concern from infrequent trading is the potential look-ahead bias. In constructing the long-short portfolios in month t, we exclude those bonds that do not have trading in month $t+1$ in our portfolio return calculation, which may result in a forward looking bias. To examine whether

[9] 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.

our results are robust to this bias, for bonds that are traded in month t but not in month $t+1$, we replace them with zero returns in month $t+1$. Panel D of Table 13 reports the results of this alternative specification. Although the trend premium becomes somewhat weaker after we control for the forward looking bias, they remain highly significant. Thus, our finding of trend premium appears to be robust to controlling for infrequent trading.

[Insert Table 13]

5.3 Trend portfolios forecasted by bond characteristic variables

Previous studies have shown that bond characteristics can explain the cross-section of bond returns (see Gebhardt et al., 2005a). This raises a possibility that bond characteristics could 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 $E_t[\gamma_{k,t+1}] = \frac{1}{12}\sum_{m=1}^{12} \gamma_{k,t+1-m}$ and characteristics include bond issue size, age, and coupon rate. After obtaining the returns forecast by characteristics, we sort bonds into quintile portfolios (Low, 2, 3, 4, and High) based on their expected returns and calculate the H-L return spreads. We consider four cross-sectional regressions in the first step by using different bond characteristics:

(1) bond issue size;

(2) bond age;

(3) coupon rate; and

(4) issue size, age and coupon rate.

Table 14 reports H-L portfolio returns. The 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.[10]

[Insert Table 14]

Lewellen (2015) shows that the predictive slope coefficient of cross-sectional returns regressed on their forecasts is a good measure on how a forecasting model performs. The mean-squared-error (MSE) of the forecast is smaller than the null forecast that all assets have the same expected return if the predictive slope is greater than 0.50. Testing whether the predictive slope is greater than 0 is equivalent to testing whether putting a positive weight on the forecasts helps to reduce the MSE relative to the null forecast. Following Lewellen (2015), we run Fama-MacBeth (FM) regression of out-of-sample cross-sectional return forecasts from different models. Figure 4 plots the time-series averages of the FM slope coefficients and their 95% confidence intervals. If bond size, age, and coupon rate are used to forecast bond returns, the slope coefficients are close to zero. Most of the 95% confidence intervals include zero, suggesting that these predictive slopes are not significantly different from zero statistically. We observe a dramatic increase of the predictive slope when including the moving average signals as one predictor. Most of the coefficients are around 2 and significantly greater than 0.5. This evidence again suggests that the MA signals contain important information of the cross-sectional bond expected returns.

[Insert Figure 4]

[10]We have also tried the cross-sectional PLS method to predict corporate bond returns using these bond characteristics. The results continue to be insignificant.

5.4 Bond trend portfolios with different holding horizons

To examine the sensitivity of our results to different investment holding horizons, we calculate the trend premium for the three-month $[t+1, t+3]$ and six-month $[t+1, t+6]$ holding horizons. Table 15 shows 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 0.44% and 0.24% per month, respectively, both significant at the 1% level. The trend premium weakens for the longer holding horizon of six months, but it remains significant.

Turning to the results by rating, we find a significant trend premium across all rating categories. Again, low-grade bonds tend to have a higher trend premium than high-grade bonds. For AAA bonds, the H-L spread is 0.37% per month for the three-month holding period and 0.23% for the six-month holding period. In contrast, for junk bonds, the corresponding returns are 0.52% and 0.31%, which are about 40% and 35% higher, respectively. The difference in the H-L returns between junk and AAA bonds is significant at the 1% level for three-month holding horizon, confirming that low-grade bonds have a significantly higher trend premium than high-grade bonds.

[Insert Table 15]

5.5 The trend premium 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 16 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 0.92% with a t-value of 7.50 in Panel A of Table 16, while it is 0.97% with a t-value of 8.12 in Panel A of Table 2. The results of other rated bonds are similar. Results, therefore, show little evidence that trend premium is weaker for public firms.

5.6 Robustness to stock market anomaly variables

Chordia et al. (2017) and Choi and Kim (2018) show that some stock market anomaly variables can 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 (2018), 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 the stock price;
- Idiosyncratic volatility: standard deviation of daily return residuals relative to the Fama-French three-factor model in the past one 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 anomaly variable into three groups (Low, Medium and High), and within 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 anomaly variables.

Panel B of Table 16 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. The results continue to show a strong trend premium across the board, suggesting that the trend premium in the corporate bond market is not driven by the 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 anomaly variables each month.[12] For brevity, we focus on the coefficient of expected bond returns. Panel C of Table 16 reports the mean, t-statistics of the coefficients of return forecasts (expected returns) and mean adjusted R-squared of cross-sectional regressions. The results continue to show a significant relation between bonds' return forecasts and their future returns, even after controlling for the effects of stock market anomaly variables. This evidence suggests that MA signals have important independent predictive power over and beyond that of stock market anomaly variables.

[Insert Table 16]

5.7 Information 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 factor seems to contain more information than the conventional momentum factor, 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 signal which includes past corporate bond price information in short to long horizons to

[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 anomaly 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. We report these results in the internet appendix.

[12] The firm-level bond returns are the returns averaged across all bonds issued by the firm weighted by issuing size.

predict stock returns.

In each month, we sort stocks into quintile portfolios on their firm-level expected 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. Panel A of Table 17 (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 information spillover from bonds to stocks, even when we use bond trend information as a predictor.

For comparative purposes, we also investigate stock momentum and information 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 Panel A of Table 17 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 in line with the finding of Avramov et al. (2013) that stock market momentum exists only for high-risk firms with a speculative grade.

We next sort bonds into quintile portfolios using past stock returns. Consistent with Gebhardt et al. (2005b), Lin, Wang, and Wu (2013) and Chordia et al. (2017), we document significant information spillover from stocks to bonds. The H-L bond portfolio generates a monthly return of 0.16% that is significant at the 1% level for the sample that includes all bonds. Information spillover is stronger among firms with lower ratings. However, these spillover effects are much weaker than the trend premium reported in Table 2, which again shows the superior power of using bond MAs in predicting cross-sectional bond returns. In an internet appendix, we show that adding the stock market momentum factor in bond portfolio formation does not improve the predictability of returns using the bond trend returns as the predictor alone.

To firmly establish the hypothesis of information 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 can deal with asymmetry in the explained variance,[13] 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 17 reports the test results. There is strong evidence that the MOM factor Granger-causes the bond trend factor. All test statistics are significant at the 1% level. On the other hand, the bond trend factor does not Granger-causes the MOM factor. As indicated, none of the test statistics is significant. Results suggest an information spillover from stocks to bonds, but not vice versa. This finding explains why the trend signals of corporate bonds have little predictive power for stock returns as reported in Panel A of Table 17.[14]

[Insert Table 17]

6 Conclusion

In this paper, we employ a new methodology to investigate the cross-sectional predictability in the corporate bond market by incorporating trend signals over multiple return horizons, which generates much richer information for expected returns than the conventional methodology that uses only one lagged signal over a fixed horizon. As a result, it is more informationally efficient and capable of detecting return predictability in the corporate bond market across all bond ratings,

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

[14]We also report more results of bond and stock trend spillover in the internet appendix.

which is missing in the existing literature.

We find convincing evidence that there is a significant trend premium, not only in speculative-grade bond returns but also in investment-grade bonds returns. The trend premium is stronger for bonds with smaller issue size, higher coupon rates and yields, and newer issuance. The trend premiums in all rating categories survive transaction costs and are of economic significance. Conventional risk factors and bond characteristics cannot explain these returns. The trend-based trading strategy earns higher returns in periods of slow economic growth and recession.

Our results are robust to using alternative estimation methods, such as the generalized PLS method of Light et al. (2017). Applying the predictive slope analysis of Lewellen (2015) to our data also confirms that bond trend signals have high predictive power. The results are robust to different measures of excess returns and to controlling for bond characteristics and risk factors. Moreover, the trend premium has little relation to the conventional bond momentum that is based on a single past return predictor, nor is it connected to the spillover of stock momentum.

Our finding strongly suggests the existence of return predictability across the entire corporate bond market; the trend premium is pronounced and not limited only to the speculative grade. It will be interesting to explore further the relation of bond market return predictability to stock market return predictability and various stock anomalies in future studies. In addition, our methodology can be useful for exploring the trend premium in other asset classes, such as the currencies and carry-trades, where interest rates play a similar role as bond yields.

References

Avramov, D., Chordia, T., Jostova, G., Philipov, A., 2007. Momentum and credit rating. Journal of Finance 62, 2503–2520.

Avramov, D., Chordia, T., Jostova, G., Philipov, A., 2013. Anomalies and financial distress. Journal of Financial Economics 108, 139–159.

Avramov, D., Kaplanski, G., Subrahmanyam, A., 2019. Stock return predictability: New evidence from moving averages of prices and firm fundamentals. Working paper, SSRN.

Bai, J., Bali, T., Wen, Q., 2018. Common risk factors in the cross-section of corporate bond returns. Journal of Financial Economics, Forthcoming.

Barroso, P., Santa-Clara, P., 2015. Momentum has its moments. Journal of Financial Economics 116, 111–120.

Bessembinder, H., Kahle, K. M., Maxwell, W. F., Xu, D., 2008. Measuring abnormal bond performance. Review of Financial Studies 22, 4219–4258.

Brock, W., Lakonishok, J., LeBaron, B., 1992. Simple technical trading rules and the stochastic properties of stock returns. Journal of Finance 47, 1731–1764.

Brown, D. P., Jennings, R. H., 1989. On technical analysis. Review of Financial Studies 2, 527–551.

Carhart, M. M., 1997. On persistence in mutual fund performance. Journal of Finance 52, 57–82.

Cespa, G., Vives, X., 2011. Dynamic trading and asset prices: Keynes vs. Hayek. Review of Economic Studies 79, 539–580.

Chauvet, M., 1998. An econometric characterization of business cycle dynamics with factor structure and regime switching. International Economic Review 39, 969–996.

Choi, J., Kim, Y., 2018. Anomalies and market (dis) integration. Journal of Monetary Economics, Forthcoming.

Chordia, T., Goyal, A., Nozawa, Y., Subrahmanyam, A., Tong, Q., 2017. Are capital market anomalies common to equity and corporate bond markets? An empirical investigation. Journal of Financial and Quantitative Analysis 52, 1301–1342.

Cochrane, J. H., Piazzesi, M., 2005. Bond risk premia. American Economic Review 95, 138–160.

Daniel, K., Hirshleifer, D., Sun, L., 2017. Short and long horizon behavioral factors. Working paper, National Bureau of Economic Research.

Daniel, K., Jagannathan, R., Kim, S., 2012. Tail risk in momentum strategy returns. Working paper, National Bureau of Economic Research.

Daniel, K., Moskowitz, T. J., 2016. Momentum crashes. Journal of Financial Economics 122, 221–247.

Edwards, A. K., Harris, L. E., Piwowar, M. S., 2007. Corporate bond market transaction costs and transparency. Journal of Finance 62, 1421–1451.

Fama, E. F., French, K. R., 1989. Business conditions and expected returns on stocks and bonds. Journal of Financial Economics 25, 23–49.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.

Fama, E. F., French, K. R., 2015. A five-factor asset pricing model. Journal of Financial Economics 116, 1 – 22.

Fama, E. F., MacBeth, J. D., 1973. Risk, return, and equilibrium: Empirical tests. Journal of Political Economy 81, 607–636.

Gebhardt, W. R., Hvidkjaer, S., Swaminathan, B., 2005a. The cross-section of expected corporate bond returns: Betas or characteristics? Journal of Financial Economics 75, 85–114.

Gebhardt, W. R., Hvidkjaer, S., Swaminathan, B., 2005b. Stock and bond market interaction: Does momentum spill over? Journal of Financial Economics 75, 651–690.

Gibbons, M. R., Ross, S. A., Shanken, J., 1989. A test of the efficiency of a given portfolio. Econometrica 57, 1121–1152.

Greenwood, R., Hanson, S. G., 2013. Issuer quality and corporate bond returns. Review of Financial Studies 26, 1483–1525.

Greenwood, R., Shleifer, A., 2014. Expectations of returns and expected returns. Review of Financial Studies 27, 714–746.

Grundy, B. D., Martin, J. S., 2001. Understanding the nature of the risks and the source of the rewards to momentum investing. Review of Financial Studies 14, 29–78.

Gürkaynak, R. S., Sack, B., Wright, J. H., 2007. The US Treasury yield curve: 1961 to the present. Journal of Monetary Economics 54, 2291–2304.

Han, Y., Zhou, G., Zhu, Y., 2016. A trend factor: Any economic gains from using information over investment horizons? Journal of Financial Economics 122, 352–375.

Haugen, R. A., Baker, N. L., 1996. Commonality in the determinants of expected stock returns. Journal of Financial Economics 41, 401–439.

Hirshleifer, D., Li, J., Yu, J., 2015. Asset pricing in production economies with extrapolative expectations. Journal of Monetary Economics 76, 87–106.

Hong, H., Stein, J. C., 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. Journal of Finance 54, 2143–2184.

Hou, K., Xue, C., Zhang, L., 2018. Replicating anomalies. Review of Financial Studies, Forthcoming.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. Journal of Finance 48, 65–91.

Joslin, S., Priebsch, M., Singleton, K. J., 2014. Risk premiums in dynamic term structure models with unspanned macro risks. Journal of Finance 69, 1197–1233.

Jostova, G., Nikolova, S., Philipov, A., Stahel, C. W., 2013. Momentum in corporate bond returns. Review of Financial Studies 26, 1649–1693.

Keim, D. B., Stambaugh, R. F., 1986. Predicting returns in the stock and bond markets. Journal of Financial Economics 17, 357–390.

Lewellen, J., 2015. The cross-section of expected stock returns. Critical Finance Review 4, 1–44.

Light, N., Maslov, D., Rytchkov, O., 2017. Aggregation of information about the cross section of stock returns: A latent variable approach. Review of Financial Studies 30, 1339–1381.

Lin, H., Wang, J., Wu, C., 2013. Liquidity risk and momentum spillover from stocks to bonds. Journal of Fixed Income 23, 5–42.

Lin, H., Wang, J., Wu, C., 2014. Predictions of corporate bond excess returns. Journal of Financial Markets 21, 123–152.

Lin, H., Wu, C., Zhou, G., 2018. Forecasting corporate bond returns with a large set of predictors: An iterated combination approach. Management Science 64, 4128–4238.

Lo, A. W., Mamaysky, H., Wang, J., 2000. Foundations of technical analysis: Computational algorithms, statistical inference, and empirical implementation. Journal of Finance 55, 1705–1765.

Neely, C. J., Rapach, D. E., Tu, J., Zhou, G., 2014. Forecasting the equity risk premium: The role of technical indicators. Management Science 60, 1772–1791.

Newey, W. K., West, K. D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.

Rapach, D. E., Strauss, J. K., Zhou, G., 2010. Out-of-sample equity premium prediction: Combination forecasts and links to the real economy. Review of Financial Studies 23, 821–862.

Shanken, J., Zhou, G., 2007. Estimating and testing beta pricing models: Alternative methods and their performance in simulations. Journal of Financial Economics 84, 40–86.

Treynor, J. L., Ferguson, R., 1985. In defense of technical analysis. Journal of Finance 40, 757–773.

Zheng, S., Shi, N.-Z., Zhang, Z., 2012. Generalized measures of correlation for asymmetry, nonlinearity, and beyond. Journal of the American Statistical Association 107, 1239–1252.

Table 1. Summary statistics

This table reports the summary statistics of the data used in our analysis. Panel A 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 ten years. Panel B reports the summary statistics of returns, including gross returns and cash flow matched excess returns.

Panel A. Sample distribution

	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

Panel B. Summary statistics of returns

	Gross return				Cash flow matched excess return			
Rate	Mean (%)	S.D. (%)	Skewness	Kurtosis	Return (%)	S.D. (%)	Skewness	Kurtosis
All	0.67	1.63	0.11	4.28	0.08	1.09	-0.13	6.69
AAA	0.61	1.69	0.43	4.34	0.02	0.96	0.09	6.18
AA	0.63	1.60	0.42	5.73	0.04	0.96	0.05	8.90
A	0.64	1.72	-0.11	4.98	0.06	1.13	-0.84	13.06
BBB	0.70	1.91	-0.83	6.59	0.09	1.50	-0.75	8.32
Junk	0.78	2.06	-0.47	4.08	0.19	1.87	-0.34	4.85

Table 2. Returns of trend portfolios: Quintile portfolios

This table reports the returns of portfolios sorted by bonds' expected returns. We 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. In Panel A we use the MA signals simultaneously in Eq. (2) to forecast a bond's return. In Panel B, we apply Light et al. (2017) PLS approach to estimate expected returns. We then sort all bonds into quintile portfolios (Low, 2, 3, 4, and High). H-L is the difference in the returns between High and Low portfolios in the one-month holding horizon. 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. Using the MA signals simultaneously in Eq. (2)

		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. The PLS method

		Return						
	Rating	Low	2	3	4	High	H-L	t-stats
One month:$[t+1, t+1]$	All	0.42	0.60	0.69	0.79	1.05	0.63	5.13
	AAA	0.29	0.56	0.61	0.69	1.13	0.83	6.25
	AA	0.36	0.56	0.66	0.76	0.94	0.59	5.17
	A	0.35	0.57	0.67	0.80	1.04	0.69	5.23
	BBB	0.43	0.64	0.76	0.86	1.22	0.79	5.51
	Junk	0.42	0.63	0.70	0.99	1.40	0.98	4.99

Table 3. Returns of trend portfolios: Decile portfolios

This table reports the returns of portfolios sorted by bonds' expected returns. We 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. In Panel A we use the MA signals simultaneously in Eq. (2) to forecast a bond's return. In Panel B, we apply Light et al. (2017) PLS approach to estimate expected returns. We then sort all bonds into decile portfolios. H-L is the difference in the returns between High and Low portfolios in the one-month holding horizon. 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. Using the MA signals simultaneously in Eq. (2)

	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

Panel B. The PLS method

	Return											
Rating	Low	2	3	4	5	6	7	8	9	High	H-L	t-stats
All	0.37	0.47	0.60	0.61	0.67	0.72	0.77	0.81	0.86	1.23	0.86	6.37
AAA	0.14	0.43	0.48	0.57	0.57	0.59	0.70	0.67	0.90	1.36	1.22	7.94
AA	0.26	0.46	0.51	0.60	0.62	0.70	0.75	0.78	0.81	1.09	0.83	7.12
A	0.27	0.44	0.55	0.59	0.65	0.70	0.77	0.82	0.92	1.17	0.90	6.35
BBB	0.34	0.51	0.61	0.67	0.77	0.75	0.84	0.90	1.04	1.43	1.09	6.56
Junk	0.35	0.54	0.49	0.80	0.65	0.73	0.95	1.03	1.01	1.80	1.45	5.52

Table 4. 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 5. Alphas: All bonds

This table reports alphas from nine factor models: (1) $mTERM$; (2) $mDEF$; (3) $mTERM, mDEF$; (4) MKT, SMB, HML; (5) MKT, SMB, HML, MOM; (6) MKT, SMB, HML, RMW, CVA; (7) $mTERM, mDEF, MKT, SMB, HML$; (8) $mTERM, mDEF, MKT, SMB, HML, MOM$; (9) $\Delta TERM, \Delta DEF, MKT, SMB, HML, MOM$. MKT, SMB, HML, RMW, CVA are the returns of the market, size, book-to-market, profitability and investment portfolios of Fama and French (1993) and Fama and French (2015); 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 et al. (1989) with null hypothesis that all the alphas are zero. The dependent variable can be the excess return of a trend portfolio or the High-Low (H-L) return spread. The symbol ^{a} denotes 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	-0.22	0.05	0.17	0.32	0.77	1.00	14.11	4.86	43.73^a
7	-0.24	0.03	0.17	0.31	0.70	0.93	13.91	4.27	40.75^a
8	-0.23	0.03	0.15	0.31	0.74	0.97	14.33	6.15	43.62^a
9	-0.23	0.03	0.15	0.31	0.74	0.97	14.33	6.17	43.64^a

Table 6. 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	-0.24	0.06	0.15	0.26	0.66	0.90	10.94	1.59	24.91[a]
	7	-0.23	0.06	0.16	0.29	0.67	0.90	11.43	1.47	26.87[a]
	8	-0.24	0.04	0.14	0.26	0.65	0.89	11.09	1.54	25.31[a]
	9	-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	0.02	0.17	0.28	0.66	0.82	11.59	2.46	29.25[a]
	7	-0.16	0.00	0.16	0.28	0.62	0.78	11.50	1.31	27.40[a]
	8	-0.17	-0.01	0.15	0.27	0.65	0.83	12.10	4.04	31.20[a]
	9	-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	-0.22	0.01	0.13	0.28	0.80	1.02	12.36	2.53	38.67[a]
	7	-0.23	0.00	0.12	0.27	0.72	0.96	12.15	1.60	36.48[a]
	8	-0.23	-0.01	0.11	0.27	0.77	1.00	12.60	3.57	38.28[a]
	9	-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	-0.25	0.09	0.24	0.37	0.87	1.11	9.55	3.60	21.03[a]
	7	-0.28	0.09	0.23	0.36	0.78	1.06	9.54	3.11	20.01[a]
	8	-0.29	0.09	0.23	0.36	0.84	1.13	10.15	5.74	22.79[a]
	9	-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	-0.22	-0.04	0.23	0.51	0.97	1.18	7.54	1.99	18.11[a]
	7	-0.28	-0.08	0.16	0.44	0.87	1.15	7.70	2.23	16.54[a]
	8	-0.23	-0.06	0.21	0.49	0.94	1.17	7.72	2.39	18.04[a]
	9	-0.23	-0.06	0.21	0.49	0.94	1.17	7.72	2.41	18.04[a]

Table 7. 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 et al. (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 portfolios (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 portfolios using the risk factors in Model (9) in Tables 5 and 6. The insignificant BETCs are the costs that make the returns or the risk-adjusted returns of H-L portfolios 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 (%)			BETCs (%)			
				Zero return		Insignificance	
	High	Low	H-L	H-L return	H-L Adjusted return	H-L return	H-L Adjusted return
ALL	28.93	27.61	56.54	1.72	1.73	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 8. Characteristics of bond trend portfolios

This table reports the characteristics of trend portfolios including bond size, age, coupon rate, yield in the last month ($MA_{t-1,1}$) and average yield over the last six months ($MA_{t-1,6}$). We use 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 the bonds into quintile 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
$MA_{t-1,1}$ (%)	All	7.10	7.20	7.46	7.78	8.99	1.89	9.70
	AAA	6.32	6.52	6.66	6.77	7.04	0.72	3.32
	AA	6.35	6.76	7.00	7.22	7.51	1.15	5.31
	A	6.82	7.11	7.38	7.66	8.21	1.39	6.87
	BBB	7.71	7.81	8.03	8.34	9.06	1.35	6.15
	Junk	9.39	9.20	9.47	10.04	12.36	2.97	12.62
$MA_{t-1,6}$(%)	All	7.42	7.32	7.50	7.75	8.67	1.25	6.49
	AAA	6.55	6.62	6.70	6.75	6.89	0.34	1.59
	AA	6.58	6.86	7.04	7.20	7.32	0.74	3.48
	A	7.08	7.23	7.42	7.63	7.96	0.88	4.45
	BBB	8.02	7.94	8.06	8.28	8.72	0.69	3.28
	Junk	9.82	9.33	9.49	9.92	11.68	1.85	8.28

Table 9. 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, 3, 4, and High) based on their expected returns. We also sort the bonds into quintile 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	3	4	High
All	Loser	17.76	13.81	14.46	18.63	32.99
	Medium	18.46	23.72	24.76	21.16	13.99
	Winner	23.84	17.26	16.54	18.98	20.97
AAA	Loser	13.47	15.16	16.32	21.06	36.54
	Medium	17.41	21.95	23.89	21.52	15.22
	Winner	30.74	22.01	16.71	15.18	13.09
AA	Loser	19.61	15.02	13.72	18.41	34.05
	Medium	16.49	21.41	25.16	22.77	14.13
	Winner	25.27	20.45	17.30	16.87	19.38
A	Loser	20.58	15.15	14.56	18.04	31.95
	Medium	16.57	22.61	24.95	22.26	13.59
	Winner	25.17	18.29	16.29	17.73	22.25
BBB	Loser	17.06	14.04	14.50	19.39	35.46
	Medium	17.95	23.53	24.26	20.44	13.82
	Winner	25.85	18.51	17.66	18.85	18.72
Junk	Loser	13.94	14.32	16.28	21.29	35.26
	Medium	19.38	22.94	22.70	20.76	14.13
	Winner	27.11	20.09	16.73	16.02	19.11

Table 10. 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 quintile groups, and then in each quintile, we further sort the bonds to construct quintile trend portfolios. We then average the resulting 5 $\times$ 5 trend portfolios across the quintiles of bond characteristics to form new quintile trend portfolios, all of which should have a 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 average yield level ($MA_{t-1,6}$). 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		$MA_{t-1,6}$	
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 11. 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 (month $t+1$) 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 the 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 ($MA_{t-1,6}$);

(6) bond size, age, coupon rate, $MA_{t-1,6}$ and the average bond return of last six months ($r_{-6,-1}$).

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 12. Trend premium 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 an individual bond's expected return using the information from MA signals. The MA signals include the bond's moving average yields with the lag lengths 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 13. Trend premium using different returns

This table reports the trend premium of the corporate bond market using different returns. Panel A uses the cash flow matched excess returns. Panel B uses the capital gain returns. Panel C uses the returns calculated from the price data within three months. Panel D reports the results by replacing missing observations with zero returns. We 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). 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. Cash flow matched excess returns

	Return						
Rating	Low	2	3	4	High	H-L	t-stats
All	-0.38	-0.08	0.03	0.16	0.59	0.97	9.50
AAA	-0.39	-0.11	0.00	0.13	0.40	0.80	8.06
AA	-0.32	-0.12	-0.02	0.10	0.50	0.82	10.25
A	-0.36	-0.12	0.01	0.13	0.54	0.91	8.56
BBB	-0.34	-0.07	0.09	0.15	0.68	1.02	7.29
Junk	-0.32	-0.09	0.05	0.35	0.87	1.20	6.27

Panel B. Capital gain returns

	Return						
Rating	Low	2	3	4	High	H-L	t-stats
All	-0.31	-0.02	0.12	0.23	0.59	0.90	7.43
AAA	-0.27	0.05	0.10	0.21	0.56	0.83	6.56
AA	-0.21	0.00	0.13	0.22	0.55	0.76	6.73
A	-0.30	-0.05	0.08	0.22	0.63	0.93	6.88
BBB	-0.35	-0.01	0.13	0.26	0.70	1.05	6.44
Junk	-0.41	-0.16	-0.03	0.28	0.65	1.06	5.91

Panel C. Returns using price data within three months

	Return						
Rating	Low	2	3	4	High	H-L	t-stats
All	0.26	0.54	0.66	0.80	1.21	0.96	7.97
AAA	0.24	0.52	0.60	0.72	1.12	0.88	7.20
AA	0.31	0.50	0.63	0.74	1.08	0.78	6.90
A	0.26	0.50	0.61	0.78	1.21	0.95	7.23
BBB	0.25	0.59	0.73	0.87	1.31	1.06	6.81
Junk	0.22	0.54	0.73	1.01	1.49	1.26	7.20

Panel D. Replace missing observations with zero returns

	Return						
Rating	Low	2	3	4	High	H-L	t-stats
All	0.27	0.52	0.62	0.76	1.11	0.84	7.83
AAA	0.24	0.48	0.57	0.66	0.96	0.72	6.38
AA	0.31	0.48	0.58	0.69	0.97	0.66	6.38
A	0.27	0.47	0.59	0.72	1.10	0.83	7.13
BBB	0.29	0.55	0.71	0.84	1.19	0.90	6.40
Junk	0.32	0.49	0.71	0.96	1.37	1.05	6.57

Table 14. Trend premium by bond characteristics

This table reports the returns of portfolios sorted by bonds' expected return forecasts using bond characteristics. We use a two-step procedure to forecast an 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 a bond's expected return for month $t+1$ by

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

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 15. Trend premium 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 an 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 and 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 16. Trend premium of public firms
This table reports the trend premium of public firms. Panel A reports the returns of portfolios sorted by bonds' expected returns. Table B reports the results of trend premium of all public firms controlling for stock market anomaly variables. Following Chordia et al. (2017) and Choi and Kim (2018), 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 stock market anomaly 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 anomaly 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 anomaly variables as controls each month. The mean, t-stats of coefficients of return forecast and the mean adjusted R-squared 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 17. Information spillover between stocks and bonds

Panel A reports the results of bond trend 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 et al. (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. 10th and 90th percentile of AAA bond returns
This figure plots the time series of the 10th and 90th percentile of AAA bond returns in each month.

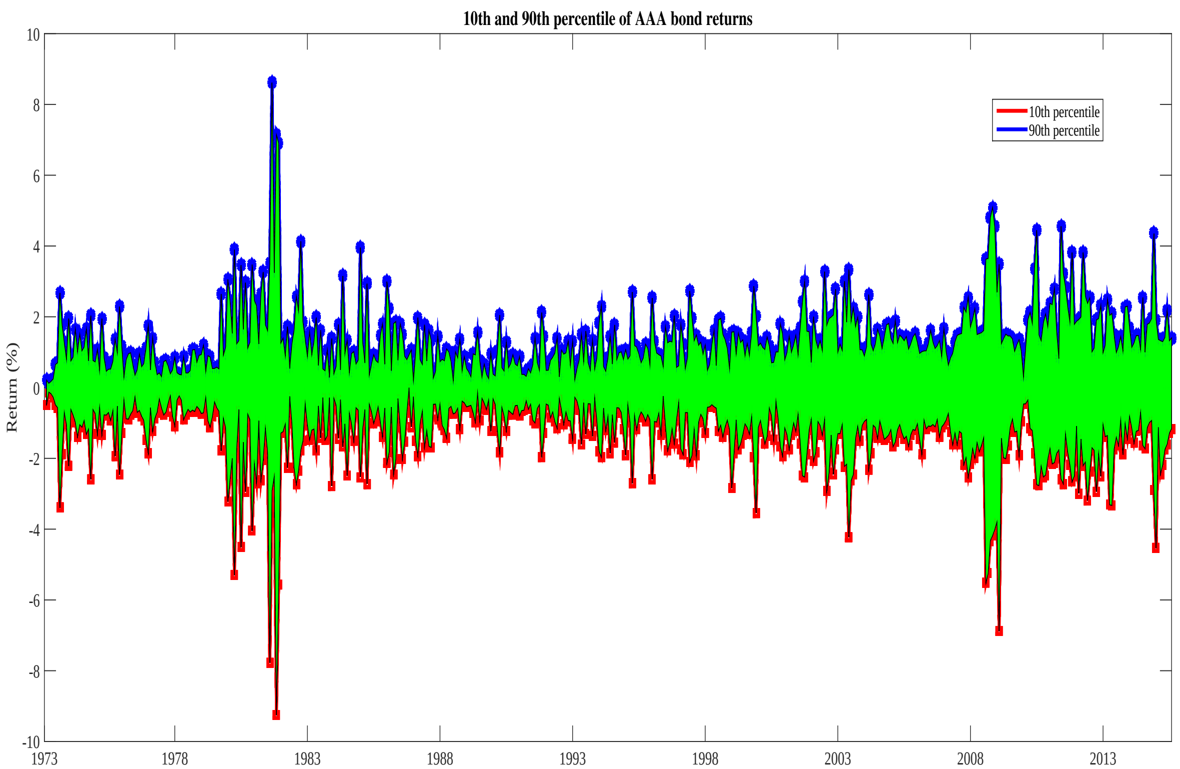


Figure 2. Portfolio returns
This figure plots the returns of trend factor portfolios.

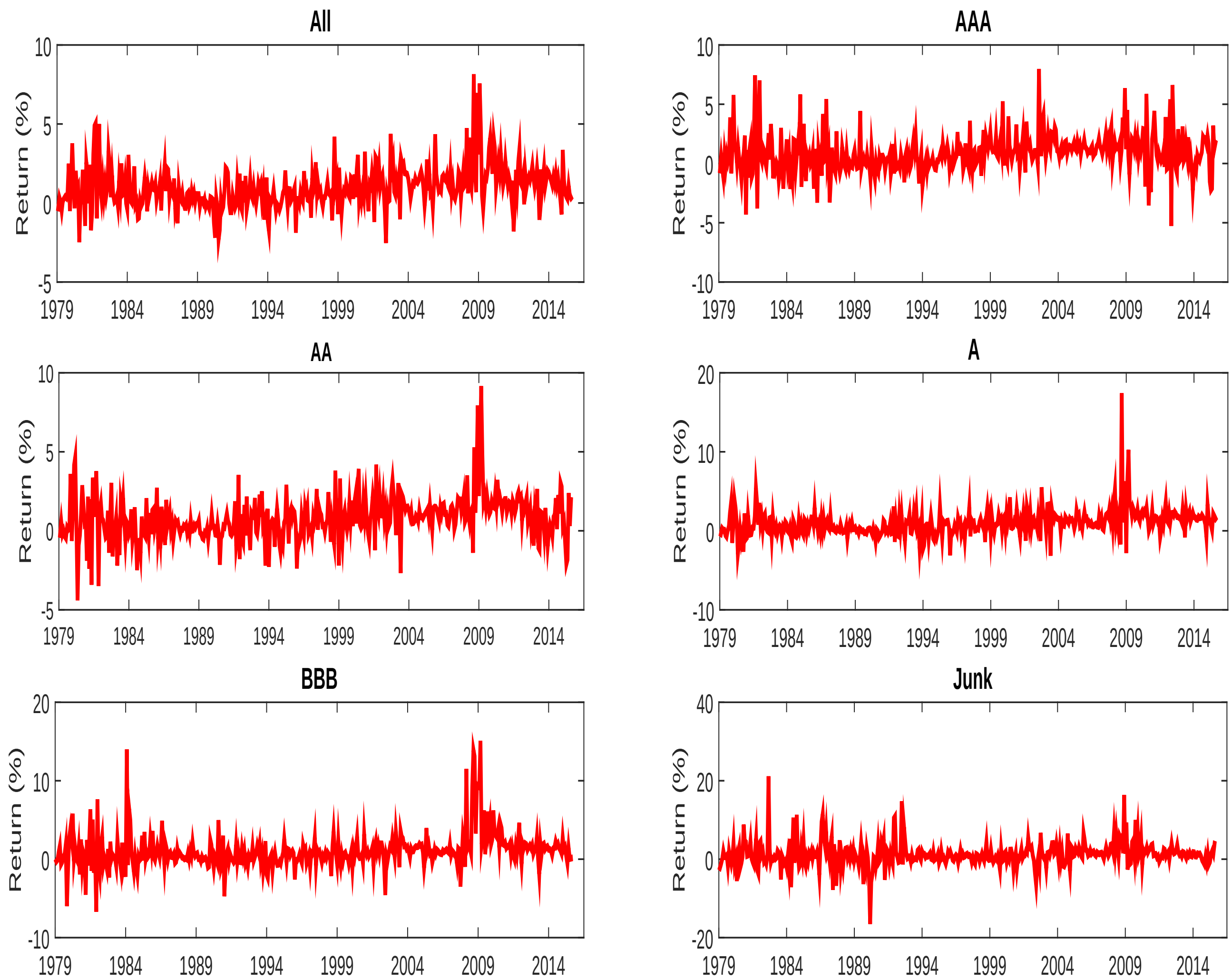


Figure 3. Average trend factor portfolio returns in months $-1, 0, 1, \ldots, 6$
This figure plots the average trend factor portfolio returns in months $-1, 0, 1, \ldots, 6$. Month 0 is the portfolio formation month.

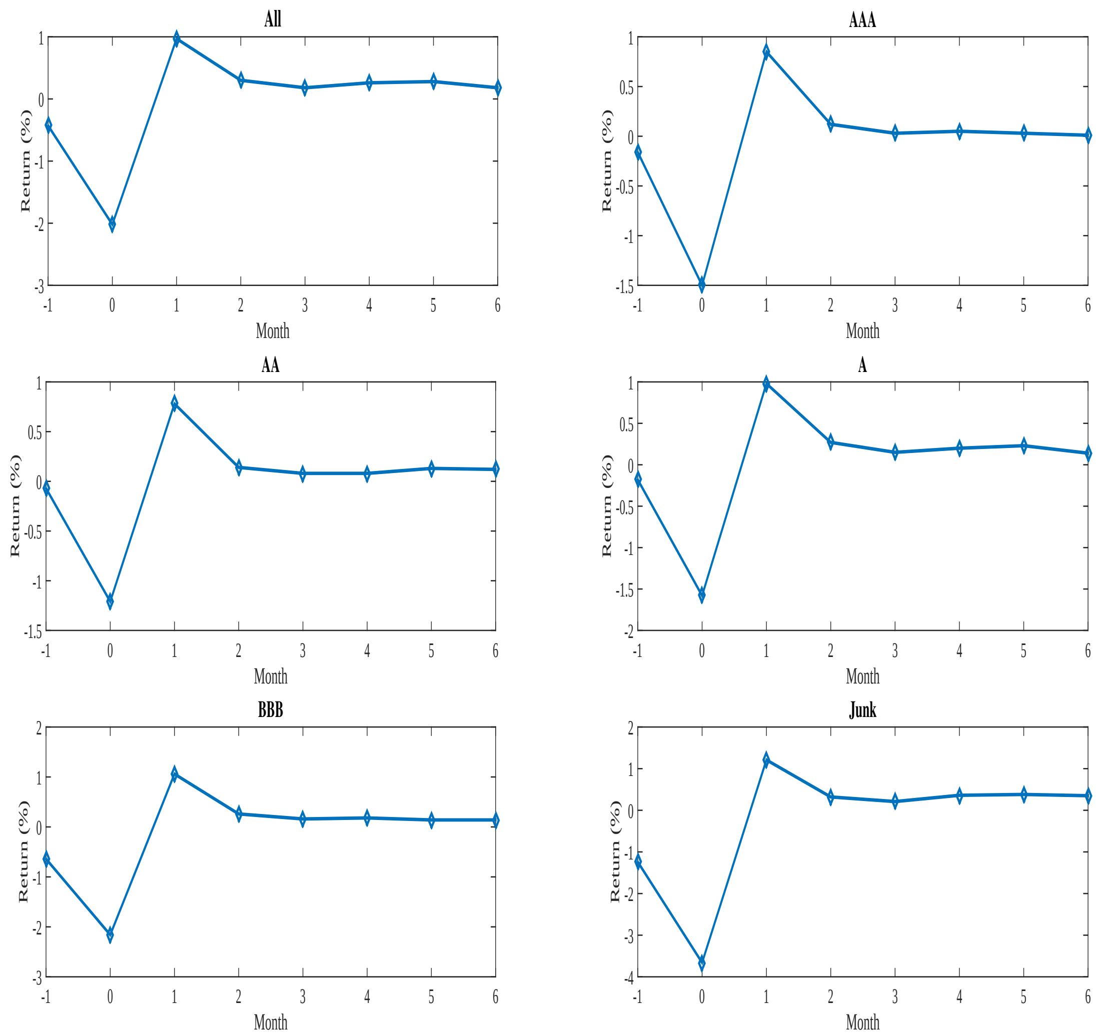
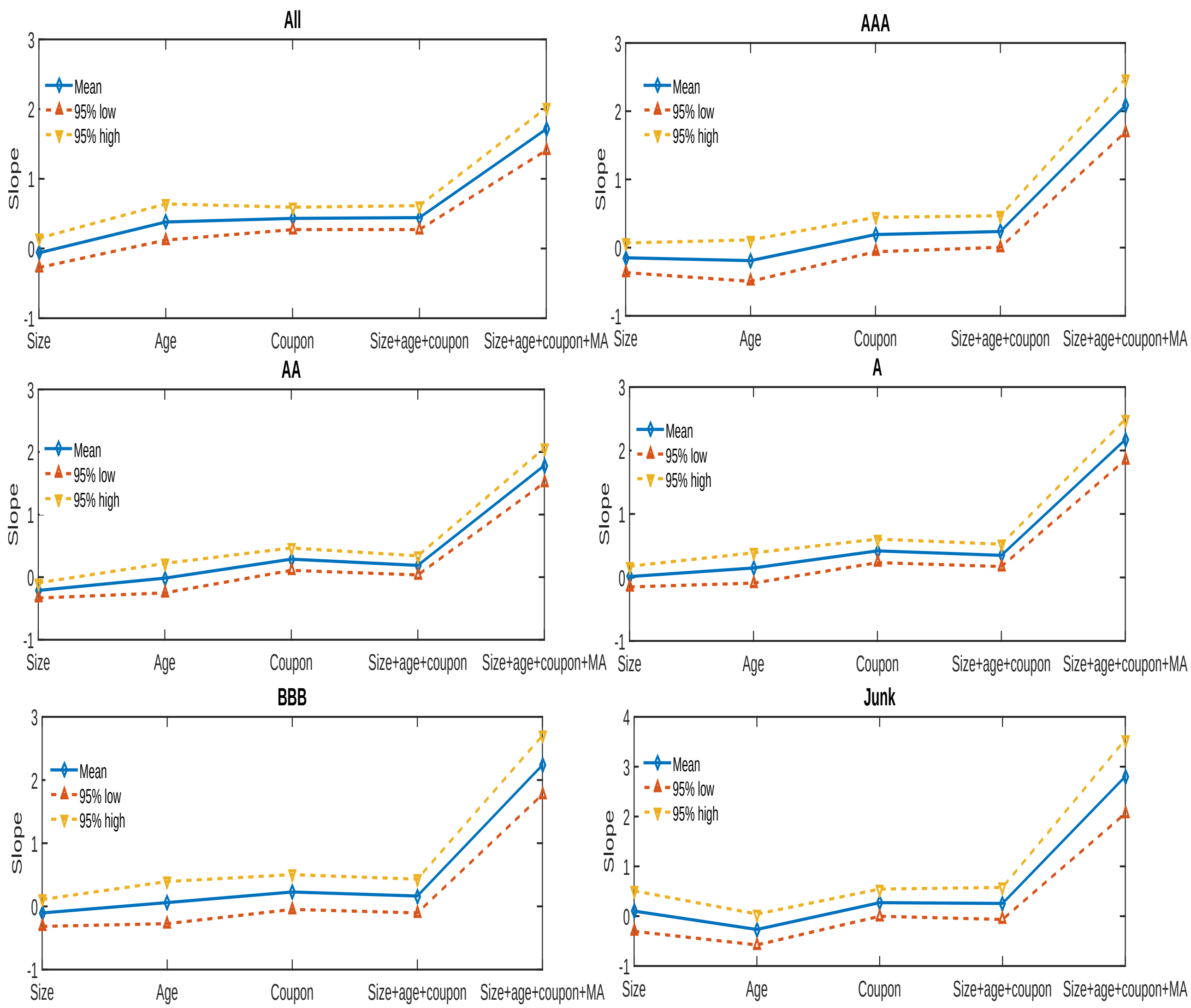


Figure 4. FM slopes of cross-sectional forecasts
This figure plots the FM slopes of different cross-sectional bond return forecasts. We run Fama-MacBeth regression of out-of-sample cross-sectional return forecasts based on different models. This figure plots the time-series averages of the slope coefficients and their 95% confidence intervals.



Appendix: Rearrangement of trend signals

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

From Eq. (3), we have

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

Rearranging the right terms, we have

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

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. 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.

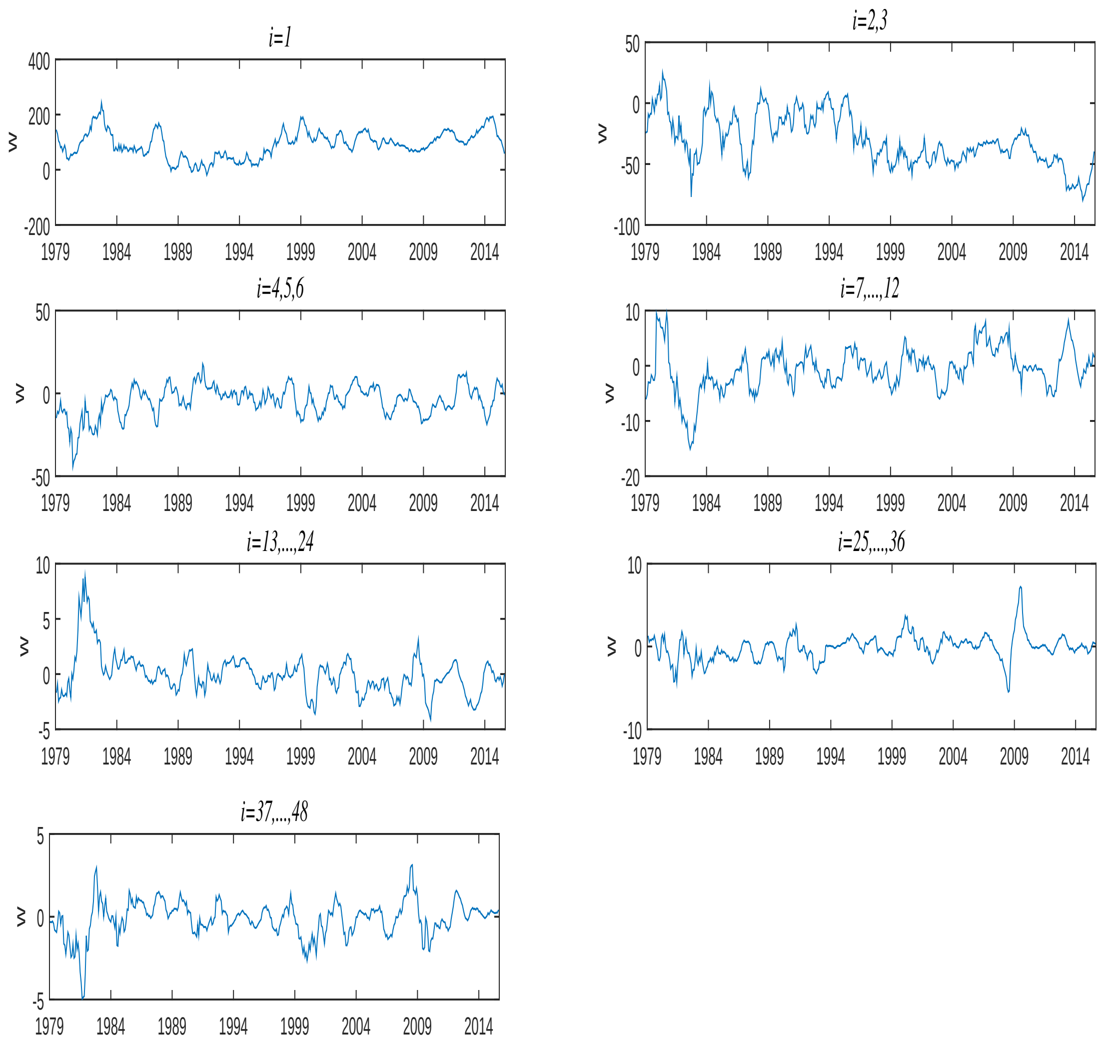
[Insert Table A here]

[Insert Figure A here]

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

	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.



Internet Appendix to “Cross-Sectional Predictability of Corporate Bond Returns”

Tuesday 12$^{\text{th}}$ March, 2019

In this internet appendix, we provide the following results.

- Table A1: Bond and stock trend premium spillover discussed in Section 5.7 of the paper
- Table A2: Stock market anomaly variables and bond trend premium discussed in footnote 11 of the paper
- Table A3: Bond risk, characteristics and cross-sectional expected bond returns

1 Bond and stock trend premium spillover

Panel A of Table A1 reports the returns of stock trend portfolios using the stocks that match bond price information. All H-L returns are statistically significant. Consistent with the finding of Han, Zhou, and Zhu (2016), results show a significant stock trend premium effect. Panel B of Table A1 reports the correlation between bond and stock trend factor portfolio returns. Most correlation coefficients are small and negative and the correlations for lower rating bonds are more negative. Results show little correlation between bond and stock trend factor returns. Thus, bond trend premium is not driven by stock trend premium. The finding of low correlation suggests a potential diversification benefit by investing in both bond and stock trend portfolios.

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

Panel C of Table A1 reports the results using both stock and bond MA signals in the return forecasts. Results show that including the stock MA signals does not improve the profitability of the trend premium strategy. Compared with the results in Table 15 which use only MA signals of corporate bonds, the profits (H-L) are either lower or little changed for the full sample and by rating. Result show no evidence that adding stock trend signals improves the profits.

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

Using this adjustment method, we control the effect of stock trend premium on the firm-level bond trend premium.[1]

Panel D of Table A1 reports the results of the raw firm-level bond returns and "stock-adjusted" firm-level bond returns. Results show that adjusting the effect of stock trend premium does not weaken the bond trend premium effect. The H-L portfolio returns continue to be highly significant for the full sample and the subsamples by rating. The bond trend premium once again shows a monotonic pattern that the profit increases as the rating decreases.

We further analyze the interactions of bond and stock trend premium by performing bivariate portfolio sorts. Bond returns are independently sorted into 5 x 5 portfolios based on bond and stock MA signals, respectively. Panel E of Table A1 reports the average returns of the portfolios over the one-month holding period. Results based on the full sample show that bond trend premium is present in all stock MA quintiles. Bond trend profits range from 0.90 to 1.02 percent monthly. There is no systematic pattern across the stock trend quintiles. We find no significant trend premium spillover from stocks to bonds at the 5% level. The spillover is slightly larger for the high bond quintile portfolio, which is only significant at the 10% level. When we divide the full sample into different rating categories, we find a similar pattern. The only discernible difference is that the trend premium spillover is stronger for speculative-grade bonds where it is significant at the 5% level for the second bond quintile and the high bond quintile. Results show that the trend premium spillover can vary for bonds with different ratings. However, there are pervasive bond trend premium effects which are not resulting from stock trend premium spillover.

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

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

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

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

Panel F of Table A1 reports the results of cross-sectional regressions. The top of the table show the results based on the full sample (All). Consistent with the portfolio analysis, results in row 1 show that bond MAs have a highly significant coefficient. When using stock MAs as an explanatory variable, we find that the coefficient is also significant at the 1% level but the size of coefficient is much smaller than that of the bond MAs. Also, the adjusted R-squares is only 1.58%. When both bond and stock MAs are included in the regression, the coefficient of stock MAs drops a little but the coefficient of bond MAs remains intact. The coefficient of bond MAs is much larger that of stock MAs, indicating that bond MAs have a much stronger effect than stock MAs on bond returns.

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

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

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

[Inset Table A1]

2 Stock market anomaly and trend premium

Chordia, Goyal, Nozawa, Subrahmanyam, and Tong (2017) and Choi and Kim (2018) show that stock market anomaly variables have the ability to predict the cross-sectional variations of expected corporate bond returns. In this section, we examine the robustness of our results to controls for these variables. Following Chordia et al. (2017) and Choi and Kim (2018), we construct the following stock market anomaly variables for each firm in our sample:

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

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

Panel A of Table A2 reports the results of bivariate portfolio analysis. Results continue to show strong trend premium in each group, suggesting that the trend premium in corporate bond market is not driven by stock market anomaly variables. The results for investment-grade bonds are much stronger than for junk bonds. These results are different from those without controlling for stock market anomaly variables. This implies stock market anomaly variables explain the cross-section of junk bonds more than the cross-sectional of investment-grade bonds, which is consistent with the view that junk bonds behave more like stocks.

We next run the cross-sectional regression of firm-level bond returns on their return forecasts with and without stock market anomaly variables as controls each month. Panel B of Table A2 reports the mean, t-stats of coefficients of return forecast and the mean adjusted R-squared of cross-sectional regressions. The results continue to show that there is significant relationship between bonds' return forecasts and their future returns with and without the stock market control variables. The increase in adjusted R-squared by adding stock market anomaly variables is more significant for speculative-grade bonds than for investment-grade bonds, which again shows more important role played by stock market anomaly variables in the high-yield bond market.

[Insert Table A2]

3 Bond risk, characteristics and cross-sectional expected bond returns

One question of great interest is to understand why the cross-sectional expected bond returns using bond trend signals could forecast the bond returns well. One possible reason is that the expected bond returns reflect the information about bond risk and characteristics. For example, the bonds with high bond trend returns might have high risks. They might also have bond characteristics that tend to generate high expected returns. We address this question by running the WLS Fama-Macbeth cross-sectional regression of bond expected returns on bond risk and characteristics. 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 use the beta of term, default, Fama-French three factor and momentum factor to measure the risk of individual bonds. The betas are estimated using time series regression of last five years data. We only choose the bonds that have at least twenty observations used in the regressions. The bond characteristics variables include bond indiosyncratic volatility (Ivol), age, maturity, size, coupon rate and bond rating. All the betas and characteristic variables are standardized in each month to have mean of zero and variance of one.[2]

Table A3 reports the cross-sectional results. When only term beta (β_{TERM}) is used, the coefficient is significantly positive and explains up to 7.84% of the cross-sectional expected bond returns. Default beta (β_{DEF}) is also significantly positive and explains 5.33% of the cross-sectional expected bond returns. Term beta and default beta jointly explain 12.84% of the cross-sectional expected bond returns. The betas of Fama-French three factor and momentum factor also help explain the cross-sectional bond expected returns. The mean adjusted R-squared increase to 23.40% when they are used in the regressions. The coefficient of indiosyncratic volatility (Ivol) is highly positive and significant. The use of Ivol increases the adjusted R-squared by more than 4%.

Introducing other bond characteristic variables including age, maturity, size, coupon rate and bond rating significantly increases the explanatory power from 27.48% to 46.74%. All coefficients of bond characteristic variables are significant and consistent with the literature. For example, the coefficient of size is negative, which implies that bonds with high trend tend to be small. The coefficient of coupon rate is positive, and suggests that bonds with high trend tend to pay high coupon. The coefficients of term and default beta become insignificant once the bond characteristic

[2] We also control the standardized variables to be between -10 and 10.

variables are used in the regressions. Overall, both bond risks and characteristic variables explain nearly half of the cross-sectional expected bond returns. This leaves a future research question about how to explain the other half.

[Insert Table A3]

References

Choi, J., Kim, Y., 2018. Anomalies and market (dis) integration. Journal of Monetary Economics, Forthcoming.

Chordia, T., Goyal, A., Nozawa, Y., Subrahmanyam, A., Tong, Q., 2017. Are capital market anomalies common to equity and corporate bond markets? An empirical investigation. Journal of Financial and Quantitative Analysis 52, 1301–1342.

Gebhardt, W. R., Hvidkjaer, S., Swaminathan, B., 2005. Stock and bond market interaction: Does momentum spill over? Journal of Financial Economics 75, 651–690.

Han, Y., Zhou, G., Zhu, Y., 2016. A trend factor: Any economic gains from using information over investment horizons? Journal of Financial Economics 122, 352–375.

Shanken, J., Zhou, G., 2007. Estimating and testing beta pricing models: Alternative methods and their performance in simulations. Journal of Financial Economics 84, 40–86.

Table A1. Bond and stock trend premium spillover

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

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

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

Panel A. Stock portfolios

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

Panel B. Correlation between bond and stock trend factor portfolio returns

	All	AAA	AA	A	BBB	Junk
Correlation	-0.06	-0.03	0.04	0.04	-0.15^a	-0.03

Panel C. Bond portfolios by MAs of bonds and stocks

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

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

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

Panel E. Bivariate portfolio returns

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

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

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

Table A2. Stock market anomaly variables and bond trend premium

This table report the results of bond trend premium controlling for stock market anomaly variables. Following Chordia et al. (2017) and Choi and Kim (2018), we consider eight stock market anomaly variables including the size, value, accruals, asset growth, profitability, net stock issuance, earnings surprise, and idiosyncratic volatility. We sort the firm-level return observations in each month by their individual stock market anomaly variables into three groups (Low, Medium and High). In each group we run the bond trend premium analysis to calculate the H-L returns. Panel A report these results. We next run the cross-sectional regression of firm-level bond returns on their return forecasts with and without the stock market anomaly variables as controls each month. The mean, t-stats of coefficients of return forecast and the mean adjusted R-squared of cross-sectional regressions are reported in Panel B.

Panel A. Trend portfolios controlling for firm characteristic variables

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

Panel B. Regression

	Without controlling variables			With controlling variables		
	Coefficient	t-stats	$Adj.R^2$	Coefficient	t-stats	$Adj.R^2$
All	0.60	9.53	8.33	0.71	11.03	16.35
IG	0.78	11.90	10.17	0.83	11.50	15.72
Junk	0.44	2.18	7.52	0.71	1.98	18.74

Table A3. Bond risk, characteristics and cross-sectional of expected bond returns.

This table reports the results of weighted least squares (WLS) Fama-Macbeth cross-sectional regression of monthly expected bond returns on bond risk and characteristics. 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). Bond risk measures include term beta (β_{TERM}), default beta (β_{DEF}), Fama-French three factor beta (β_{MKT},β_{SMB} and β_{HML}) and momentum factor beta (β_{MOM}). The betas at time t are estimated using the information between $t-60$ and t. Bond characteristics variables include bond return indiosyncratic volatility (Ivol), Age, maturity (Mat.), size, coupon rate, and bond rating. The indiosyncratic volatilities at time t are measured by the standard deviation of the residuals from the time series regression of bond returns on term, default, Fama-French three factors and momentum factor using last five years data. The sample period is from January 1973 to September 2015.

	β_{TERM}	β_{DEF}	β_{MKT}	β_{SMB}	β_{HML}	β_{MOM}	Ivol	Age	Mat.	Size	Coupon	Rate	$Adj.R^2$ (%)
Coef.	0.04												7.84
t-stats	(6.40)												
Coef.		0.05											5.33
t-stats		(3.64)											
Coef.	0.05	0.05											12.84
t-stats	(7.38)	(3.57)											
Coef.	0.05	0.07	0.07	0.03	-0.01	-0.04							23.40
t-stats	(5.88)	(4.48)	(4.00)	(1.77)	(-0.54)	(-2.15)							
Coef.	0.04	0.04	0.03	0.01	-0.01	-0.03	0.10						27.48
t-stats	(5.41)	(2.63)	(1.36)	(0.77)	(-0.34)	(-1.83)	(8.90)						
Coef.	-0.01	-0.01	0.02	0.02	0.01	0.01	0.03	-0.03	0.09	-0.02	0.03	0.03	46.74
t-stats	(-1.08)	(-0.64)	(1.76)	(3.55)	(1.64)	(2.05)	(4.78)	(-4.59)	(7.86)	(-4.98)	(3.38)	(6.93)	