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Predictive information in corporate bond yields☆

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ABSTRACT

We document strong evidence of the cross-sectional predictability of corporate bond returns based on a set of yield predictors that capture the information in the yields of past 1, 3, 6, 12, 24, 36, and 48 months. Return predictability is economically and statistically significant, and is robust to various controls. The uncovered predictability presents the most pronounced anomaly in the corporate bond literature that challenges rational pricing models.

1. Introduction

A central mission in finance research is to explain why assets have different expected returns. While there are hundreds of studies on cross-section stock return predictability, there are only a few on the cross-sectional predictability of corporate bonds (e.g., Pospisil and Zhang, 2010; Kim et al., 2012; Chordia et al., 2017; Choi and Kim, 2018; Ho and Wang, 2018; Israel et al., 2018; Bektić and Regele, 2018; Huang and Shi, 2021; Bali et al., 2021). Corporate bond return predictability is an important issue because the bond market is comparable in capitalization to the stock market and is the primary source of raising long-term capital in the United States. Hence, it is of interest to understand the efficiency and predictability of the corporate bond market. However, while much progress has been made, the documented predictability evidence in the corporate bond literature is weak: it is either significant only for specific junk-grade bonds or insignificant for all bonds after controlling for transaction costs.

In this paper, we use a set of seven bond average yields as predictors that capture the yield information from months 1 to 48 (up to four years) and apply the Fama–MacBeth (1973) regression method to further investigate cross-sectional predictability in

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corporate bond returns out-of-sample. There are three motivations for our choice of these predictors for bond returns. The first motivation is Cochrane and Piazzesi (2005). Exploiting the correlation of interest rates with business cycles, these authors show that on average, Treasury bond yields over the past five years strongly predict the yield curve. We extend their time series forecast strategies to the cross-section of individual bonds, which in spirit align with the approach of Goyal and Jegadeesh (2018). There are several differences between our method and that of Cochrane and Piazzesi (2005). First, we do not use the term structure information at each time t as in Cochrane and Piazzesi (2005), which includes bonds with different maturities at the same time point. Instead, we obtain the moving average of yields for the same individual bond over time. Although the maturity for the bond changes over time, this is not the same as the term structure. Second, we utilize the average yields of corporate bonds, rather than average Treasury bond yields, as predictors. Third, while Cochrane and Piazzesi (2005) use a single average yield signal to capture the information in the entire Treasury yield curve, we employ multiple average corporate bond yields instead, as multiple yield predictors are likely to capture more relevant predictive information than a single predictor.[1]

The second motivation is extrapolated beliefs and sticky expectations. Building on behavioral theory, Greenwood and Shleifer (2014) and Hirshleifer et al. (2015) show that when investors extrapolate expectations from their past experience, historical average returns contain information for expected returns. In the context of corporate bonds, this implies that in the presence of extrapolated beliefs, historical average yields will convey information for expected bond returns. According to belief extrapolation theory, positive past trends inflate prices (prices overshoot fundamentals), resulting in subsequent lower returns when price inflation is corrected. On the other hand, the sticky expectation theory of Bouchaud et al. (2019) suggests that investors with sticky expectations under-react to positive past trends and so returns are subsequently higher. Using a comprehensive data set of corporate bonds spanning from January 1973 to September 2019, we find both positive and negative coefficients of past yield signals in the forecast of expected returns, which are in line with both extrapolated beliefs and sticky expectations hypotheses.

The third motivation is technical analysis. Treynor and Ferguson (1985), Brown and Jennings (1989), Cespa and Vives (2011), among others, demonstrate theoretically, and Brock et al. (1992), Lo et al. (2000), Neely et al. (2014) show empirically, that past returns have predictive power for future returns due to market imperfections, such as differences in receiving and responding to information by heterogeneous investors. In the corporate bond market, past trends are better represented by average yields over various horizons than returns. Since it is difficult to tell ex ante which investment horizon is focused on by investors, we construct, for each corporate bond, a trend predictor (average yield) over a plausible range of horizons with a lagged length from 1, 3, 6, 12, 24, 36, to 48 months, similar to studies in Brock et al. (1992) and Han et al. (2016), to retrieve this information.

We find the predictors constructed from the corporate bond yields contain important signals for future bond returns out-of-sample. There is strong evidence of predictability in the cross-section of corporate bond returns. We use the multiple regression method of Haugen and Baker (1996) to exploit the information in the seven predictors as sorting by all predictors is infeasible.[2] We first run a multiple regression of the bond returns cross-sectionally on all yield predictors. Using the regression slope coefficients, we estimate expected bond returns from the yield predictors and sort them into quintiles or deciles to perform portfolio analysis. Following most studies, we use the performance of the long–short (H–L) portfolio to measure cross-sectional return predictability. A trading strategy that longs bonds with the highest expected returns (H) and shorts those with the lowest expected returns (L) earns an average of 0.96% per month based on quintile portfolio sorts. This return spread is highly statistically significant and comparable in size to the momentum premium of Jegadeesh and Titman (1993) in the equity market.

The magnitude and breadth (across the entire bond universe) of predictability far exceeds any findings in the corporate bond literature. The large abnormal return cannot be explained by traditional risk factors and thus presents a new anomaly, which we refer to as the *yield anomaly*, following the convention in the equity market to name the anomaly after the predictor. The yield anomaly we uncover appears to be the most pronounced anomaly documented so far in the corporate bond market.

The predictive power of the yield predictors is robust. Besides the gross returns obtained from consecutive monthly prices, we find that using the cash flow matched excess returns or other return measures continue to show high return predictability. Harvey et al. (2016) propose a new multiple testing method and provide modified cutoff points for establishing the significance of cross-sectional tests. They suggest using multiple test hurdles of 2.78 at the 5% significance level and 3.39 at the 1% significance level. Hou et al. (2020) find that the majority of equity anomalies documented in the literature fail to hold up to acceptable standards when using these new cutoff points in empirical tests. Treating yield predictors as factors, our t-statistics from using these predictors surpass the robust test hurdles of Harvey et al. (2016). Unlike many equity anomalies, bond trading profits are not driven mainly by the short leg of the spread portfolio. While firm characteristics matter, the long–short portfolio returns remain highly significant after controlling for their effects. The abnormal return cannot be explained by standard risk factors, bond characteristics, or transaction costs.

We find an important source of the predictive power of yield predictors is their ability to predict changes in bond fundamentals that affect ratings and expected bond returns. The return predictability of corporate bonds varies over time. Returns are more predictable during periods of slow economic growth and recession, a finding consistent with the literature that shows return predictability is linked to business conditions (Rapach et al., 2010). Return predictability generally increases after the establishment of TRACE (the Trade Reporting and Compliance Engine) except for junk bonds, which improved transparency and lowered trading costs in the corporate bond market.

[1] Our results hold with yield predictors up to five years, although we limit them to four years to retain a large sample size of bonds to be comparable with other studies.

[2] As one robustness test, we use all 48 average yield signals as the predictors and apply one widely used machine learning approach, the elastic-net (e-Net) method, to circumvent over-fitting by shrinkage of predictors. The results are similar.

Our paper is the first to show that corporate bond return predictability is both economically and statistically significant for *all* rating bonds, after accounting for transaction costs. Using a comprehensive set of firm characteristics, Chordia et al. (2017) find that a few variables have predictive power for bond returns over the short-term horizon. But none of them could survive the transaction costs, which is echoed by Choi and Kim (2018).

Bali et al. (2021) identify a long-term return reversal pattern. Their results of different credit ratings show that return reversal only exists for low rating bonds. Our paper documents a predictor that is both statistically and economically significant across the whole corporate bond universe, even after controlling for transaction costs.

Our evidence of predictability has important implications for asset pricing. While there are hundreds of anomalies in the stock market (see, Hou et al., 2020), and the cross-sectional predictability of corporate bond returns has been documented in the bond literature, the yield anomaly we identify appears to be the most significant anomaly that permeates all categories in the corporate bond market, and is not just limited to junk bonds, and survives the transaction costs.[3] In terms of magnitude, it delivers a level of abnormal returns comparable to the momentum anomaly of the stock market. Our finding calls for the development of theoretical models of corporate bonds to explain such a pronounced anomaly and other milder ones documented in the bond literature.

Our paper is about the cross-sectional predictability of corporate bond returns, which is differentiated from time series predictability. The former focuses on the relative cross-sectional performance of individual bonds while the latter predicts the return of a given bond over time.[4] Keim and Stambaugh (1986) are perhaps the first to study the 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 et al. (2014) identify issuer quality, and liquidity and forward rate factors, respectively, as useful predictors, and Lin et al. (2018) apply an iterated combination approach to improving out-of-sample forecasting performance using more predictors. While cross-sectional and time series predictability are different, both strands of research provide valuable insights that improve our understanding of asset pricing in general.

The remainder of this paper is organized as follows. In Section 2, we present our empirical methodology, and in Section 3, we discuss the data. In Section 4, we present empirical evidence for cross-sectional predictability in corporate bond returns, and in Section 5, we provide additional tests. Finally, in Section 6, we summarize our main findings and conclude the paper.

2. Methodology

Our empirical methodology involves a two-stage implementation procedure. In the first stage, we identify new predictors for corporate bond returns, making use of all information in the short-, intermediate-, and long-term segments of corporate bond yields. In the second stage, we employ a two-pass regression procedure that incorporates multiple predictors to forecast returns cross-sectionally. The spread (H–L) portfolio formed by the forecasted returns then constitutes the yield trend factor.

2.1. Yield trend signals

Unlike equity return predictability studies, a unique feature in our study is the use of the moving averages (MAs) of bond yields rather than prices to predict returns. There are several reasons for using past yields as predictors of bond returns. 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, bond yields reflect ex ante expected returns. Previous studies show that past and current yields contain information for future bond returns (see Lin et al., 2014; Joslin et al., 2014). Thus, in adapting the moving average or trend analysis from stocks to bonds, we turn to bond yields instead of prices.

To obtain the future return 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 that well cover the forecast horizons used in the return predictability literature (e.g., DeBondt and Thaler, 1985; Jegadeesh and Titman, 1993; Bali et al., 2021). These MAs thus capture rich information in the yields over a sufficient length of historical horizons.

[3] In a recent paper, Guo et al. (2021) propose a bond investor sentiment measure and find it significantly predicts the cross-section of corporate bond returns. While both papers study cross-sectional predictability of corporate bond returns, their motivations are completely different. Guo et al. (2021) is based on the behavior bias driven by sentiment, while this paper focuses on the information content of technical signals.

[4] Goyal and Jegadeesh (2018) discuss the differences and relations in the stock market.

2.2. Two-pass regressions

Using the multiple MA yield signals as return predictors, we project cross-sectional expected returns. Following Haugen and Baker (1996), we use a two-step procedure to extract return expectations. In the first step, each month we run the following cross-sectional regression of bond returns in month t on the MAs in month $t-1$ to obtain the time series of slope coefficients for each moving average signal:

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

where $MA_{jt-1,L}$ is the trend signal at the end of month $t-1$ on bond j with lag L, $\beta_{L,t}$ is the coefficient of the trend signal with lag L, $\beta_{0,t}$ is the intercept, $r_{j,t}$ is the bond return, and n is the number of bonds in month t.[5] 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

$$E_t[r_{j,t+1}] = \sum_{L} E_t[\beta_{L,t+1}] MA_{jt,L}, \tag{3}$$

where $E_t[r_{j,t+1}]$ is bond j's expected return for month $t+1$, $MA_{jt,L}$ is the yield trend signal at the end of month t with lag L, and $E_t[\beta_{L,t+1}]$ is the estimated expected coefficient of the trend signal with lag L, which is given by:

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

That is, we use the average of estimated loadings on a yield trend signal at a particular lag L over the past 12 months as the expected beta coefficient for the next month. Averaging the loadings reduces the noise in the beta estimation. In short, the expectation for future returns is derived from the combination of past yield trend signals at different lags, where the weights for these signals are averaged betas obtained from the cross-sectional regression in Eq. (2). 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 of 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 expectations formation process is completely out of sample.

2.3. Portfolio analysis

We sort bonds into quintile portfolios by their expected returns estimated from Eq. (3), and form the equal-weighted portfolios that are rebalanced monthly. These portfolios are dubbed *trend portfolios* as they are constructed using yield 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 of the yield trend factor, similar in spirit to the construction of the momentum factor. Essentially, the yield trend factor portfolio longs bonds with the highest expected returns and shorts bonds with the lowest expected returns. This procedure for constructing the yield trend factor resembles that of Jegadeesh and Titman (1993), Gebhardt et al. (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 past horizon, we sort bonds on their expected returns estimated by multiple yield trend signals over various horizons. While focusing on quintile portfolio sorts, we also construct decile portfolios that are quite common in equity studies.

In a sense, the traditional momentum factor can be viewed as a degenerated case of our yield trend factor, under the constraint that there is only one 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 overly restrictive 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 et al., 2020). Hence, limiting the use of return signals to a restricted time horizon likely leads to an underestimation of the predictability of bond premia. As an extension of the momentum model, by accommodating differences in the timing of receiving and processing information or heterogeneous information diffusion, we form a yield trend factor that captures information for the short-, intermediate- and long-term predictive components in bond returns. Our methodology is therefore more capable of capturing relevant information signals over different investment horizons to determine whether return predictability indeed exists in the corporate bond market.

[5] It can be shown that these regressions are based on long-horizon yields with overlapping (monthly) observations. As a result, we need to take great care when computing the standard errors of the coefficients. Nevertheless, since our primary interest is on the parameter estimates of the regressions that will be used in the forecast, the statistical properties of these coefficients are not a concern.

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 enhanced 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, ratings, 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 U.S. dollar-denominated bonds with regular coupons and obtain the data up to June 2002.

The NAIC and TRACE databases contain corporate bond transaction data. The NAIC data set mainly covers transactions of insurance companies and we download the NAIC data from January 1994 to June 2002. We supplement the TRACE data with the NAIC data as TRACE coverage begins in July 2002. We follow the procedure of Bessembinder et al. (2008) to filter out canceled, corrected and commission trades. We also use the trade size-weighted average of intraday prices over the day as the closing price. 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 construct a long-span data sample to perform more efficient tests. 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 LBFI or NAIC. 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:

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

where P_t is the bond price, AI_t is accrued interest, and C_t is the coupon payment, if any, in month t.[6] We exclude bonds with a maturity of less than one year,[7] bonds with embedded options, and bonds with 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. We first screen data by deleting the observations with prices more than 1,000% or less than 5% of the face value to control for the impact of extreme prices. We use the last available price in a given month as the closing price of that month. Following previous studies, two consecutive month-end prices are required in order to compute the return in the second month.[8] For the bond returns since July 2002, we use the Wharton Research Data Services (WRDS) Bond Return database, which uses TRACE Enhanced as the primary data source for computing bond returns, and when TRACE Enhanced is not available, TRACE Standard is used. The variable name in WRDS is *ret_eom*, which is the monthly return calculated based on *price_eom* (last price at which a bond was traded in a given month) and accrued interest. We keep straight bonds only and download the data up to September 2019. The whole sample period runs from January 1973 to September 2019.[9]

Table 1 reports the summary statistics of the data. Panel A reports the data by rating, maturity, and source. We combine AAA and AA rated bonds together since there are only a limited number of observations of AAA-rated bonds, particularly during the financial crisis period. In terms of ratings, A-rated bonds account for the largest proportion of data observations. As for the distribution by maturity, bonds with maturities of less than or equal to three years account 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 in-depth analysis of bond premia across different ratings.

Panel B of Table 1 reports the summary statistics of bond 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 risk-free 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 et al. (2007), which are updated to the current time 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 risk-free 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 return is close to zero. However, its standard deviation is close to 1, suggesting that the long–short portfolio returns can be high.

[6] Note that when there is a coupon payment in month t, AI is dropped.

[7] The filter that excludes bonds with a maturity of less than one year has long been adopted in the corporate bond literature. See, for example, Warga (1991) and Eom et al. (2004). Bai et al. (2019) explain that the rule of removing bonds that have less than one year to maturity is applied to all major corporate bond indices. If a bond has less than one year to maturity, it will be delisted from major bond indices and as a result index-tracking investors will change their holding positions.

[8] For robustness, we also linearly interpolate the prices between months if there are no price observations in two consecutive months, which result in a larger sample and the empirical results are qualitative similar.

[9] In the Internet appendix, we provide results when we use the WRDS Bond Return database only. The results are stronger than those using the whole sample period except for junk bonds.

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 2019. The cut-off values for maturities are three and seven years. Panel B reports the summary statistics of returns, including gross returns and cash flow matched excess returns.

Panel A. Sample distribution

Rating	Maturity			Data source				Total
	Short	Medium	Long	DTSM	NAIC	TRACE	LBFI	
AAA	16,794	10,095	9081	2595	8534	9120	15,721	35,970
AA+	8967	3715	4037	2854	531	8299	5035	16,719
AA	16,812	11,598	11,906	2622	1889	11,930	23,875	40,316
AA−	31,213	14,673	6472	1873	5306	24,582	20,597	52,358
A+	41,586	25,621	16,499	2143	7327	37,016	37,220	83,706
A	57,671	40,842	31,663	8927	10,397	54,631	56,221	130,176
A−	32,896	28,424	24,741	8815	6338	35,136	35,772	86,061
BBB+	25,492	22,644	24,904	11,694	4265	32,853	24,228	73,040
BBB	24,335	23,368	23,884	7994	3554	32,253	27,786	71,587
BBB−	16,710	16,222	16,770	4828	3716	21,712	19,446	49,702
BB+	7368	6329	6823	2662	1451	9956	6451	20,520
BB	3715	4670	3172	1360	880	5653	3664	11,557
BB−	3541	3056	2750	883	560	4558	3346	9347
B+	2918	3318	3559	2442	238	3689	3426	9795
B	2435	1846	1603	195	367	3897	1425	5884
B−	1452	1203	2067	452	185	3358	727	4722
CCC+	766	809	2806	1687	56	2569	69	4381
CCC	680	580	935	137	88	1562	408	2195
CCC−	383	181	88	0	41	605	6	652
CC	381	218	119	3	103	327	285	718
C	105	63	127	0	2	207	86	295
D	2953	1966	1495	0	0	225	6189	6414
Total	299,173	221,441	195,501	64,166	55,828	304,138	291,983	716,115

Panel B. Summary statistics of returns

Rating	Gross return				Cash flow matched excess return			
	Mean (%)	Std. (%)	Skewness	Kurtosis	Mean (%)	S.D. (%)	Skewness	Kurtosis
All	0.71	1.66	0.42	9.03	0.12	1.22	−0.04	14.85
AAA + AA	0.63	1.56	0.81	10.79	0.06	0.88	−0.38	14.02
A	0.67	1.67	0.19	9.60	0.07	1.10	−0.97	22.82
BBB	0.74	1.84	−0.26	9.49	0.13	1.51	−0.19	11.68
Junk	0.96	2.53	0.32	13.89	0.35	2.73	−0.06	19.62

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 estimated from Eq. (3) for all bonds, where portfolios are held over a one-month holding horizon. Low (L) represents the portfolio of bonds with the lowest expected returns, and High (H) denotes the portfolio of bonds with the highest expected returns. The results clearly show that the bonds with high expected returns forecasted by yield trend signals have high returns ex post. The return differences between the High and Low (H–L) portfolios are all highly significant. For example, for the sample including all bonds (the first row), the H–L (yield trend factor) monthly return is 0.96% (or 11.52% per annum), which is significant at the 1% level (t-stat. = 14.09).

To see the yield trend effects for differently rated bonds, we report the results of portfolio sorts by rating category. The results show that yield trend signals have high predictive power for cross-sectional bond returns across all ratings. The monthly H–L return differences range from 0.80% for AAA/AA-rated bonds to 1.26% 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/AA-rated bonds is 0.46%, which is significant at the 5% level. In summary, the above results consistently show that bond returns are predictable for all rated bonds, not just for junk bonds as documented by Jostova et al. (2013). This finding confirms that past bond yields (prices) at various horizons contain important information for future bond returns. Restricting the past price information to a fixed horizon in predicting future bond returns will result in an underestimation of return predictability in the corporate bond market.

Why is there return predictability even for the investment-grade bonds? To provide some insight as to the possible source of return predictability for these bonds, we first analyze the temporal pattern of cross-sectional variations in returns using AAA/AA-rated bonds, which are of the highest quality, as an example. In Fig. 1, we plot the time series of the 20th and 80th percentiles of AAA/AA-rated bond returns each month. The results show that the cross-sectional variations are large even within the AAA/AA category, with an average standard deviation of 1.56%. Thus, the ex post quintile spread portfolio can have an average return of

Table 2

Returns of trend 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. We apply OLS method to estimate the coefficients. The moving average coefficients are then used to forecast a bond's return. We then sort all bonds into quintile portfolios (Panel A) or decile portfolios (Panel B) based on their expected returns. 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 2019.

Panel A. Quintile portfolios

Rating	Low	2	3	4	High	H–L	*t*-stats
All	0.37	0.53	0.62	0.78	1.33	0.96	14.09
AAA + AA	0.31	0.49	0.58	0.69	1.11	0.80	10.95
A	0.28	0.51	0.62	0.74	1.22	0.94	13.53
BBB	0.29	0.52	0.68	0.88	1.49	1.20	11.81
Junk	0.52	0.68	0.88	1.06	1.78	1.26	6.80

Panel B. Decile portfolios

Rating	Low	2	3	4	5	6	7	8	9	High	H–L	*t*-stats
All	0.31	0.42	0.50	0.56	0.59	0.65	0.73	0.84	1.05	1.61	1.30	13.95
AAA + AA	0.23	0.39	0.46	0.51	0.56	0.60	0.63	0.74	0.86	1.37	1.14	11.91
A	0.17	0.40	0.48	0.53	0.59	0.64	0.70	0.78	0.98	1.47	1.30	15.72
BBB	0.18	0.41	0.44	0.59	0.62	0.75	0.81	0.95	1.19	1.79	1.81	13.13
Junk	0.40	0.58	0.60	0.73	0.85	0.91	1.04	1.08	1.34	2.27	1.87	6.71

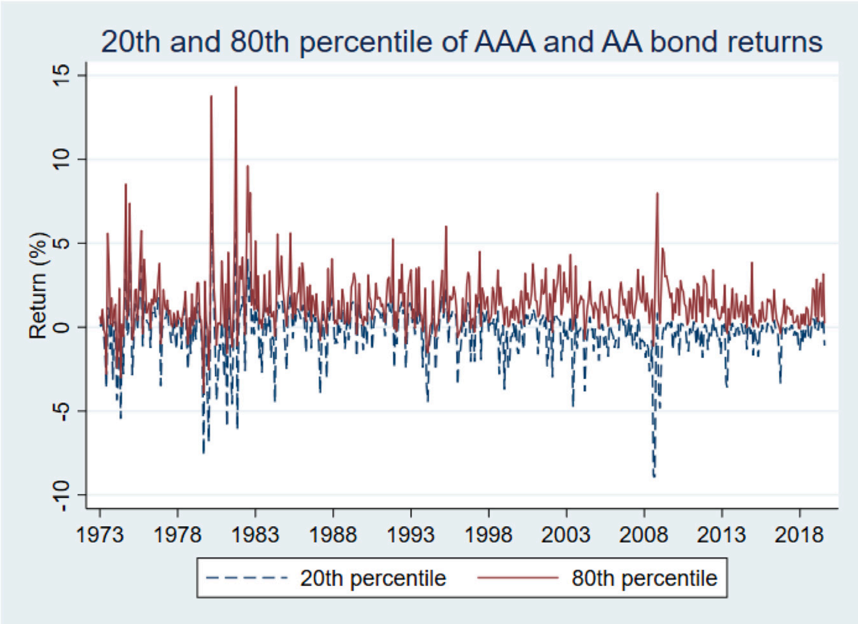

Fig. 1. 20th and 80th percentile of AAA/AA-rated bond returns. In this figure, we plot the time series of the 20th and 80th percentile of AAA and AA bond returns in each month.

as much as 3.77%. Of course, this analytical return spread is not achievable in real markets with frictions. As shown, our efficient forecasting approach can only generate the H–L portfolio return of 0.80%. The point we want to emphasize here is that it is plausible to derive profits from the return dynamics even for high quality AAA/AA-rated bonds using an efficient signal extraction method like ours as there exist significant temporal and cross-sectional variations in these bonds.[10]

The yield 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 et al., 2007, 2013). However, unlike previous findings of momentum concentrated in speculative-grade stocks (Avramov et al., 2007) and bonds (Jostova et al., 2013), 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 10.81%, and investment-grade bonds account for the remaining 89.19%. There is no evidence

[10] In Section 4.6, we provide an economic explanation for the trend premium.

that the Low portfolio contains more junk bonds than other portfolios. Thus, the yield trend premium we find is unlikely to be derived primarily from shorting the worst-rated bonds.

In sharp contrast to earlier studies (e.g., Jostova et al., 2013) that find predictability/momentum exists only in speculative-grade bonds, we find that the yield trend premium is everywhere in the corporate bond market, not just limited to speculative-grade bonds. In addition, the profits of our trading strategies do not derive predominantly from short positions. Indeed, as Table 2 shows, both High and Low yield trend portfolios have positive returns. Our trading 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 for both high-grade bonds and low-grade bonds.

Several recent studies find weak evidence of abnormal returns in the corporate bond market (see Chordia et al., 2017; Choi and Kim, 2018; Bai et al., 2019). 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. 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. For comparative purposes, we report the results of decile portfolio sorts in Panel B of Table 2. As indicated, decile portfolios sorted on MA signals generate much larger bond return spreads than do these studies. Bai et al. (2019) 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. The 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 yield trend anomaly we find hence poses an even bigger challenge to rational asset pricing theories in the corporate bond market.

In Fig. 2, we plot the time series of returns for the yield trend factor (H–L) over the entire sample period. It shows that the yield trend premium is quite stable over time. Moreover, the premia exhibit similar patterns across bonds of different ratings. These results again show that the yield trend premium is pervasive, not just limited to a particular rating class of corporate bonds. Further, unlike the negative returns of stock momentum strategies during the financial crisis documented by a number of studies (e.g., Daniel et al., 2019; Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016), our trading strategy generates positive returns in this period, exhibiting a more robust return predictability. The bond market appears to behave differently from the stock market, which experienced a momentum crash during the subprime crisis.[11]

In Fig. 3, we plot the mean of expected coefficients in Eq. (4), which are the weights we use in forming expected returns. As can be seen from the figure, there exist both positive and negative coefficients of past yield signals. These results are in line with the hypotheses of extrapolated beliefs and sticky expectations, which can be revealed over various time horizons. In particular, the coefficients of the MA signal at the one-month lag are overwhelmingly positive, which implies that bonds with a higher level of yield (lower price trend) in month t have a higher expected return in month $t+1$. This result supports the extrapolated beliefs hypothesis. At the same time, many coefficients of middle-term MA signals are negative. These results indicate that the expected returns of bonds with a higher level of historical yield (lower price trend) during one period are lower in month $t+1$. This finding is consistent with the sticky expectation hypothesis.

To assess the improvement by using the multiple MA signals jointly, we forecast the returns using a single MA signal and compare the results with those reported in Table 2. Table 3 shows the return spreads of quintile portfolios sorted by expected returns forecasted by a single MA signal. When the expected returns are predicted by $MA_{t-1,1}$, the return spread is 0.79%, which is significant at the 1% level (t-stats. = 8.08). The return spreads decrease as we use a longer-term MA signal. However, even the largest return spread still underperforms those based on all seven MA signals jointly, suggesting that not all predictive information is contained in a single MA signal.

The improvement by using the MA signals jointly over one single MA signal is of economic significance. Compared with the results in Tables 2 and 3, we find that, for all bonds, the difference in H–L return spreads using all seven MA signals and the best performed single MA signal ($MA_{t-1,1}$) is 0.17% per month or 2.04% per annum. The improvement for lower-grade bonds is even stronger. For example, the improvement for BBB-rated bonds is 0.48% per month or 5.76% per annum. The improvement for junk bonds is 0.21% per month or 2.52% per annum. Moreover, the results indicate that portfolios sorted by the past six- or twelve-month signal alone as in previous studies do not generate the highest predictability in corporate bond returns. This finding suggests that the bond momentum effect is much stronger than previously estimated.

Panel A of Table 4 reports summary statistics and extreme values of the yield trend factor portfolios of bonds (H–L). For comparison, we also report the results of the momentum factor portfolio of stocks (MOM). The yield trend factor portfolios of bonds have lower standard deviations and much higher Sharpe ratios than MOM. They also have positive skewness and high kurtosis. These findings are similar to the behavior of the stock trend factor documented by Han et al. (2016). The minimum returns of the yield trend factor portfolios decrease with ratings. However, they are still much greater than that of MOM. For example, the minimum value of MOM during the sample period is −34.58%, whereas it is only −13.43% for the yield trend factor portfolio consisting of junk bonds. The yield trend factor portfolios also have a smaller number of extreme negative observations. There is only one observation below three standard deviations for the whole bond sample. The yield trend factor portfolio of junk bonds has six observations below two standard deviations and one observations below three standard deviations. By contrast, the numbers of observations below two and three standard deviations are ten and three, respectively, for MOM.

In Panel B of Table 4, we report the correlations between the yield trend factor and other risk factors. 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.

[11] The mean H–L portfolio returns during the financial crisis (December 2007 to June 2009) are 2.94%, 1.84%, 2.55%, 3.97%, and 6.55% for all bonds and AAA/AA, A, BBB, and junk bonds, respectively.

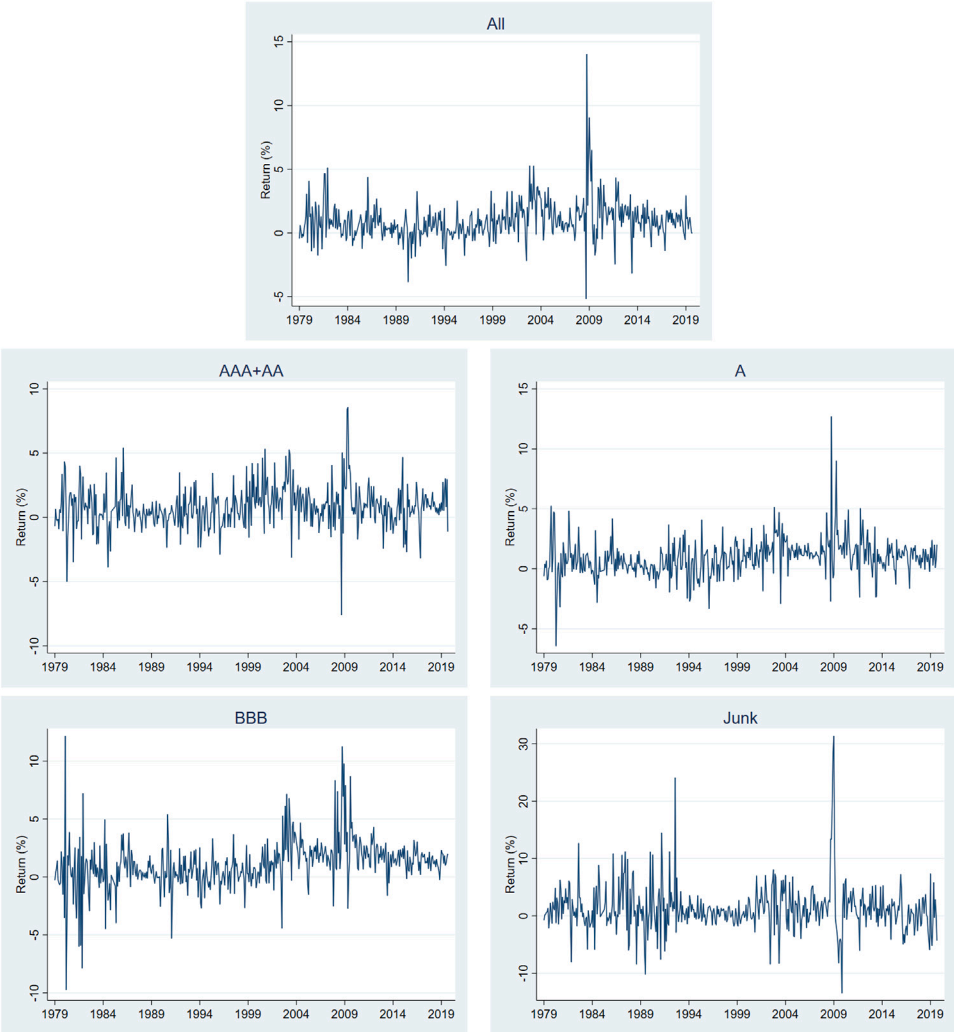

Fig. 2. Portfolio returns. In this figure, we plot the returns of yield trend factor portfolios.

Table 3

Return spreads of portfolios based on a single MA yield signal: 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 a single MA signal. The MA signals include the bond's moving average yields of lag lengths 1, 3, 6, 12, 24, 36, or 48 months. We use OLS method to estimate the coefficient on the MA signal. The moving average coefficients are then used to forecast a bond's return. We then sort all bonds into quintile portfolios based on their expected returns. 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 2019.

Rating	$MA_{t-1,1}$		$MA_{t-1,3}$		$MA_{t-1,6}$		$MA_{t-1,12}$		$MA_{t-1,24}$		$MA_{t-1,36}$		$MA_{t-1,48}$	
	H–L	t-stats	H–L	t-stats	H–L	t-stats	H–L	t-stats	H–L	t-stats	H–L	t-stats	H–L	t-stats
All	0.79	8.08	0.46	4.90	0.39	4.25	0.30	3.35	0.30	3.33	0.21	2.34	0.17	2.00
AAA + AA	0.63	7.17	0.46	5.44	0.42	5.07	0.38	4.61	0.35	4.19	0.33	3.99	0.33	4.08
A	0.70	6.97	0.49	5.15	0.40	4.56	0.31	3.75	0.28	3.59	0.27	3.52	0.26	3.53
BBB	0.72	5.96	0.55	4.78	0.31	2.87	0.42	3.84	0.42	4.66	0.39	4.92	0.37	4.85
Junk	1.05	4.14	0.88	3.35	0.84	3.24	0.63	2.49	0.38	1.65	0.47	2.13	0.39	1.80

We also calculate the value-weighted returns of yield trend portfolios. Unreported results (omitted for brevity) show that the mean value-weighted H–L return of all bonds is 0.88% with a t-stat. of 10.94 if quintile portfolios are constructed. These results are close to those reported in Table 2. The results of the value-weighted returns of yield trend portfolios of different ratings are also similar. Thus, the trend premium of bonds is robust to the choice of portfolio weights.

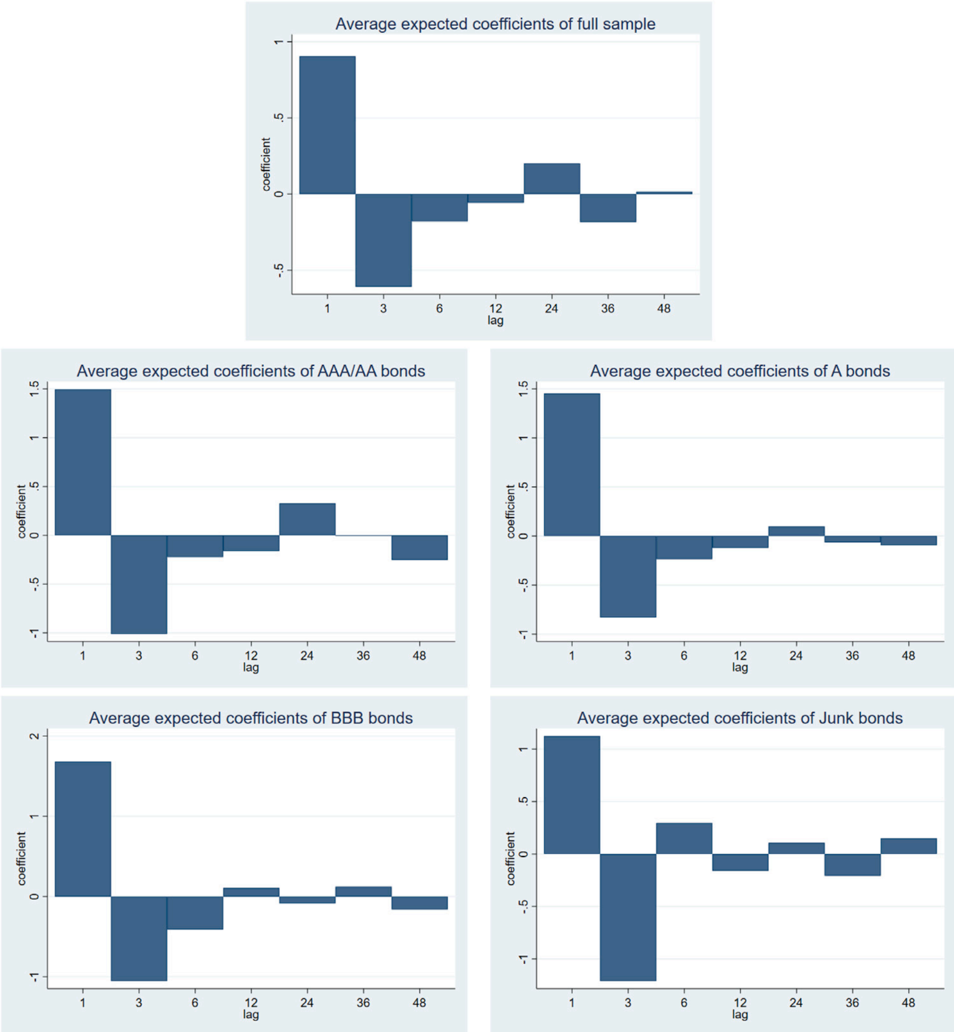

Fig. 3. Expected coefficients of the trend signal. In this figure, we plot the average of expected coefficients of the trend signal in Eq. (4).

Table 4
Trend factor portfolios: Summary statistics and correlations. Panel A reports the summary statistics of the trend factor portfolio returns (H–L). Panel B reports their correlations with conventional risk factors. The sample period is from January 1973 to September 2019.

Panel A. Summary statistics and extreme values							
	Std. (%)	Sharpe ratio	Skewness	Kurtosis	Min. (%)	$n(< -2Std.)$	$n(< -3Std.)$
All	1.50	0.64	1.93	17.04	−5.15	3	1
AAA + AA	1.60	0.50	0.28	6.80	−7.58	4	2
A	1.53	0.61	1.09	12.49	−6.42	3	1
BBB	2.23	0.54	1.96	19.49	−7.86	5	1
Junk	4.09	0.31	2.05	15.48	−13.43	6	1
MOM	4.45	0.13	−1.35	13.80	−34.58	10	3

Panel B. Correlation						
	MKT	SMB	HML	MOM	$\Delta TERM$	ΔDEF
All	0.05	0.07	−0.07	−0.07	0.02	0.12
AAA + AA	0.12	0.01	−0.06	−0.02	−0.02	−0.08
A	0.06	0.01	−0.01	−0.08	0.04	0.01
BBB	−0.05	−0.00	−0.05	−0.09	0.06	0.04
Junk	−0.07	0.07	−0.10	0.03	0.03	0.12

4.2. Alphas of bond trend portfolios

We next examine whether the 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 yield trend portfolios. We consider eight different sets of explanatory variables for $\mathbf{F_t}$: (1) $mTERM$, $mDEF$; (2) MKT, SMB, HML; (3) MKT, SMB, HML, MOM; (4) MKT, SMB, HML, RMW, CMA; (5) $mTERM$, $mDEF$, MKT, SMB, HML, MOM; (6) $\Delta TERM$, ΔDEF, MKT, SMB, HML, MOM; (7) MKT^{Bond}, DRF, CRF, LRF; and (8) $rTERM$, $rDEF$, MKT, SMB, HML, MOM.

MKT, SMB, HML, RMW, and CMA are the returns of the market, size, book-to-market, profitability and investment factors in Fama and French (1993, 2015). MOM is the Carhart (1997) momentum factor. $\Delta TERM_t = (TERM_t - TERM_{t-1})$ and $\Delta DEF_t = (DEF_t - DEF_{t-1})$, $mTERM_t = \Delta TERM_t/(1 + TERM_{t-1})$, $mDEF_t = \Delta DEF_t/(1 + DEF_{t-1})$, $rTERM_t = rSBTSY10_t - r_{f,t}$, and $rDEF_t = rSBC3B_t - rSBTSY10_t$. $TERM_t$ is the difference between the long-term government bond yield and the Treasury bill rate, DEF_t is the difference between BAA and AAA corporate bond yields. The data for these risk factors come from the Amit Goyal's and Kenneth French's websites. $rSBTSY10$ is the return on long-term government bonds based on the FTSE US ten-year on-the-run Treasury index from Bloomberg (ticker: SBTSY10). $rSBC3B$ is the return on BBB-rated corporate bonds based on the FTSE US broad BBB credit index from Bloomberg (ticker: SBC3B). Similar variables are used by Jostova et al. (2013) to examine the effects of systematic risk factors on bond momentum portfolio returns. MKT^{Bond}, DRF, CRF, and LRF are the corporate bond market factors – market risk, downside risk, credit risk, and liquidity risk – identified by Bai et al. (2019), which are downloaded from Jennie Bai's website.[12] We calculate the Gibbons et al. (1989) (GRS) statistics to test the null hypothesis that all intercepts are zero.

Panel A of Table 5 reports the alphas of time series regressions for the whole sample. The results show that the risk-adjusted returns of Low portfolios are all negative, whereas those of High portfolios are all positive. The α_ps of H–L portfolios are all positive and highly significant. The results suggest that returns of trend factor portfolios (H–L) cannot be explained by standard risk factors. 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 the alphas.

Panels B, C, and D of Table 5 report regression results by bond rating for models (6), (7), and (8), respectively. The H–L portfolios alphas are again all highly significant across ratings. A substantial proportion of the trend portfolio return cannot be explained by standard risk factors. The alphas of H–L portfolios tend to increase as the rating decreases. Overall, the results show that yield trend portfolio returns cannot be explained by systematic risk factors and that the unexplained excess returns tend to be larger for lower-grade bonds.

4.3. Economic gains of trend factor portfolios

An important issue is how much economic gain can be achieved by incorporating yield trend factor portfolios into 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 yield 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 yield trend factor portfolios (θ^*). The difference between these two Sharpe ratios indicates the incremental gain from adding yield trend portfolios.

Panel A of Table 6 reports the maximum Sharpe ratios.[13] 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 0.20 and 0.28, respectively. The values increase dramatically to more than 0.70 when yield trend factor portfolios are included. The monthly θ^* of combining yield trend factor portfolios with MKT, SMB, HML, and MOM is 0.82 or 2.84 ($0.82 \times \sqrt{12}$) per annum. This is a highly economically significant Sharpe ratio. Incorporating bond trend factor portfolios increases the monthly Sharpe ratio by more than 0.50 for most cases (1.73 per annum). The results show substantial economic gains from adding the yield trend factor in investment portfolios. For comparative purposes, we also compute 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 0.04. These results suggest that the economic gains contributed by yield trend factor portfolios are not derived from the benefit of including the indices of the corporate bond market in 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 previous studies (e.g., Grundy and Martin, 2001; Barroso and Santa-Clara, 2015), we

[12] $rTERM$ and $rDEF$ start from February 1980, while the common risk factors of Bai et al. (2019) start from July 2004.

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

Table 5
Alphas of trend portfolios: Quintile portfolios. This table reports alphas from eight factor models: (1) $mTERM$, $mDEF$; (2) MKT, SMB, HML; (3) MKT, SMB, HML, MOM; (4) MKT, SMB, HML, RMW, CMA; (5) $mTERM$, $mDEF$, MKT, SMB, HML, MOM; (6) $\Delta TERM$, ΔDEF, MKT, SMB, HML, MOM; (7) MKT^{Bond}, DRF, CRF, LRF; and (8) $rTERM$, $rDEF$, MKT, SMB, HML, MOM. Variables are as defined in the paragraph following the model in equation (6) in the text. GRS is the test statistics of Gibbons et al. (1989) with null hypothesis that all the alphas are zero. The sample periods run from January 1973 to September 2019 for models (1) to (6), July 2004 to September 2019 for model (7), and February 1980 to September 2019 for model (8).

Model/Rating	Low	2	3	4	High	H–L	*t*-stats	Adj. R^2 (%)	GRS
Panel A. Alpha: All bonds									
1	−0.05	0.11	0.20	0.36	0.92	0.97	14.19	0.41	42.35***
2	−0.12	0.08	0.18	0.34	0.84	0.96	13.78	0.18	39.44***
3	−0.09	0.08	0.17	0.32	0.90	0.98	13.90	0.63	42.01***
4	−0.11	0.08	0.17	0.32	0.84	0.95	13.22	0.51	36.72***
5	−0.11	0.04	0.14	0.29	0.87	0.98	13.94	1.18	41.96***
6	−0.10	0.05	0.14	0.30	0.88	0.98	13.97	2.48	42.07***
7	−0.44	−0.17	−0.02	0.19	0.73	1.17	8.67	7.18	16.70***
8	−0.24	−0.10	−0.02	0.13	0.72	0.96	13.27	1.85	38.31***
Panel B. Alpha by rating under model (6)									
AAA + AA	−0.14	0.03	0.11	0.21	0.64	0.78	10.42	1.00	23.31***
A	−0.16	0.04	0.13	0.26	0.78	0.94	13.11	1.26	39.51***
BBB	−0.19	0.02	0.18	0.39	1.10	1.29	12.32	1.49	34.54***
Junk	−0.04	0.17	0.38	0.57	1.32	1.36	7.17	3.11	16.83***
Panel C. Alpha by rating under model (7)									
AAA + AA	−0.14	−0.03	0.04	0.07	0.39	0.53	5.24	39.80	5.87***
A	−0.47	−0.18	−0.04	0.12	0.68	1.15	10.39	18.04	24.96***
BBB	−0.70	−0.31	−0.00	0.30	1.17	1.87	13.72	3.15	41.51***
Junk	−0.72	−0.35	0.15	0.47	0.71	1.43	3.89	2.14	5.00***
Panel D. Alpha by rating under model (8)									
AAA + AA	−0.24	−0.09	−0.02	0.05	0.48	0.72	9.61	5.41	19.99***
A	−0.30	−0.10	−0.02	0.09	0.62	0.92	12.72	1.62	38.15***
BBB	−0.38	−0.14	0.02	0.22	0.95	1.33	12.35	1.34	32.45***
Junk	−0.26	−0.02	0.18	0.39	1.17	1.42	7.18	1.52	14.35***

***Denotes significance at the 1% level.

calculate the break-even transaction costs (BETCs) of H–L returns. It suffices to consider the most comprehensive factor model with factors $\Delta TERM, \Delta DEF$, MKT, SMB, HML, MOM, or model (6) in Table 5.[14] 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 yield trend factor portfolio insignificantly different from zero at the 5% level.

Panel B of Table 6 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 50% across all rating categories. They are almost equally distributed between High and Low portfolios, suggesting that the turnover of the yield trend factor portfolio is not dominated by either the long or short leg. The right side of Panel B reports the BETCs results. For the full sample including all bonds, it takes a transaction cost of 2.02% to completely offset the H–L returns, and 1.74% to make H–L returns statistically insignificant at the 5% level. For H–L risk-adjusted returns, it takes transaction costs of 2.06% and 1.77%, respectively. For the results by rating, BETCs grow higher as bond ratings decrease, consistent with the pattern of yield trend returns reported earlier.

The BETC 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 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. Moreover, the estimates of BETCs suggest that the yield trend premium is higher than the transaction cost of corporate bonds. Edwards et al. (2007) and Bao et al. (2011) report an average round-trip transaction cost of about 48 bps and 89 bps per dollar trading for a median-sized corporate bond trade, respectively.[15] We also follow Dick-Nielsen et al. (2012) to compute the imputed round-trip costs (IRC) using TRACE data only. The IRCs of H–L portfolios for All, AAA/AA, A, BBB, and junk bonds are 0.55%, 0.44%, 0.49%, 0.58%, and 0.79%, respectively. Asquith et al. (2013) report that the cost of borrowing corporate bonds is between 10 and 20 bps, which is comparable to the cost of borrowing stocks. Thus, while it may be harder to short corporate bonds, in practice it is feasible to short bonds at reasonable costs. The yield trend trading strategy is still profitable even after accounting for the cost of shorting corporate bonds. Thus, the yield trend premium survives transaction costs easily.

[14] We do not use model (7) since the factor data only start from July 2004.
[15] The measure used in Bao et al. (2011) captures the broader impact of illiquidity above and beyond the effect of the bid–ask spread.

Table 6

Economic significance. This table reports the economic significance of the trend factor portfolios. Panel A reports the change of maximum Sharpe ratio by using the trend factor portfolios (H–L) of different ratings jointly with stock market factor portfolios. 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 (6) in Table 5. 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. The sample period is from January 1973 to September 2019.

Panel A. Change of maximum Sharpe ratio

Stock factor portfolio	θ_p	θ^*	Diff.	Δ
MKT	0.15	0.75	0.60	0.55
$MKT+SMB+HML$	0.20	0.77	0.58	0.56
$MKT+SMB+HML+MOM$	0.28	0.82	0.54	0.59

Panel B. Turnover ratio and BETCs

Rating	Turnover ratio (%)			BETCs (%)			
				Zero return		Insignificance	
	Low	High	H–L	Raw	Adjusted	Raw	Adjusted
All	24.20	23.34	47.54	2.02	2.06	1.74	1.77
AAA + AA	23.39	23.85	47.24	1.69	1.65	1.39	1.34
A	24.83	24.74	49.57	1.90	1.90	1.62	1.61
BBB	25.94	26.90	52.84	2.27	2.44	1.89	2.05
Junk	24.67	23.57	48.23	2.61	2.82	1.86	2.05

Table 7

Bivariate portfolio analysis. This table reports the returns of portfolios sorted by the bond's expected return and characteristic. We first sort bonds by their characteristics into tercile groups, and then in each tercile, we further sort the bonds to construct quintile trend portfolios. We then average the resulting 3 × 5 trend portfolios across the terciles 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 size, age, time to maturity, coupon rate, moving average yields of last six months ($MA_{t-1,6}$), moving average yields of last four years ($MA_{t-1,48}$), moving average returns of last six months ($MA^{ret}_{t-1,6}$), moving average returns of last four years ($MA^{ret}_{t-1,48}$), imputed-round-trip cost (IRC), and the Amihud illiquidity measure. H–L is the difference between High and Low portfolios in the one-month holding horizon. Portfolios are equally-weighted and rebalanced each month. The t-statistics measure the significance of H–L returns.

Rating	Bond size		Age		Maturity		Coupon		$MA_{t-1,6}$		$MA_{t-1,48}$		$MA^{ret}_{t-1,6}$		$MA^{ret}_{t-1,48}$		IRC		Amihud	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
	H–L	t-stats	H–L	t-stats	H–L	t-stats	H–L	t-stats	H–L	t-stats	H–L	t-stats	H–L	t-stats	H–L	t-stats	H–L	t-stats	H–L	t-stats
	Small		Young		Short		Low		Small		Small		Small		Small		Small		Small	
All	1.16	12.02	0.70	10.14	0.67	11.06	0.67	9.22	0.47	9.77	0.51	9.79	1.15	11.65	1.00	10.34	1.01	10.47	0.68	5.21
AAA + AA	0.97	9.57	0.54	7.46	0.62	8.36	0.73	7.99	0.45	8.16	0.53	8.52	1.00	11.03	0.89	9.53	0.72	5.87	0.33	3.54
A	1.21	13.14	0.71	9.28	0.64	11.38	0.70	9.76	0.54	10.21	0.55	9.04	1.14	14.16	0.96	12.07	1.11	10.46	0.59	5.06
BBB	1.53	12.16	0.89	9.31	0.91	10.25	0.94	8.08	0.57	9.44	0.76	9.30	1.35	10.01	1.15	8.80	1.82	12.68	0.96	6.03
Junk	2.05	5.89	1.00	5.01	0.67	3.21	1.37	6.77	0.69	6.61	0.75	6.23	1.55	4.62	1.49	4.74	1.39	4.73	0.83	2.31
	Medium		Medium		Medium		Medium		Medium		Medium		Medium		Medium		Medium		Medium	
All	0.92	12.02	0.89	11.37	0.80	11.49	1.01	12.67	0.86	14.76	0.91	13.34	0.61	13.21	0.76	13.48	1.11	10.78	0.98	7.58
AAA + AA	0.84	10.40	0.72	7.52	0.58	9.90	0.69	8.82	0.60	10.41	0.64	10.27	0.52	9.51	0.60	10.63	0.58	6.59	0.48	5.11
A	0.81	11.04	0.78	11.32	0.80	13.32	0.82	11.19	0.71	12.81	0.82	11.68	0.60	11.34	0.74	12.11	1.05	8.98	0.89	6.92
BBB	1.13	11.82	1.23	10.97	1.10	11.75	1.32	11.77	1.04	14.23	1.16	10.43	0.85	10.61	0.93	12.19	1.85	12.60	1.75	12.85
Junk	0.78	3.91	1.23	4.83	0.81	3.37	1.60	5.59	1.25	7.52	1.35	6.43	0.79	4.89	1.17	5.74	1.47	4.15	1.12	4.01
	Large		Old		Long		High		High		High		High		High		High		High	
All	0.67	9.53	1.26	13.59	1.35	13.48	1.19	12.00	1.29	11.67	1.28	11.82	0.90	12.70	0.98	15.00	1.89	9.57	2.24	13.19
AAA + AA	0.63	8.34	1.13	11.97	1.29	13.11	1.10	12.75	1.18	12.21	1.18	13.53	0.84	10.31	0.93	10.43	1.27	8.97	1.63	10.54
A	0.67	9.47	1.29	15.52	1.39	18.10	1.26	15.77	1.32	15.69	1.30	14.87	0.93	14.99	1.04	14.62	1.79	14.03	2.36	19.13
BBB	0.77	8.40	1.46	11.83	1.60	11.32	1.33	12.54	1.56	11.40	1.55	12.25	1.03	11.46	1.31	14.48	2.70	15.57	3.42	19.08
Junk	0.71	4.16	1.54	4.95	1.88	6.00	0.79	2.63	1.72	4.55	1.78	4.84	1.31	4.88	0.84	3.84	1.64	3.49	2.04	4.46
	Average		Average		Average		Average		Average		Average		Average		Average		Average		Average	
All	0.92	13.36	0.95	14.32	0.94	14.79	0.95	14.49	0.87	15.16	0.90	14.80	0.89	15.52	0.91	15.24	1.34	11.38	1.30	10.32
AAA + AA	0.81	11.83	0.80	11.64	0.83	14.50	0.84	12.86	0.74	14.44	0.79	14.93	0.79	13.45	0.80	12.84	0.86	9.01	0.81	8.35
A	0.90	13.59	0.93	14.27	0.94	17.73	0.93	14.31	0.86	16.92	0.89	14.75	0.89	16.97	0.91	15.45	1.32	13.27	1.28	11.63
BBB	1.14	13.79	1.19	13.46	1.20	13.35	1.19	13.43	1.06	15.08	1.15	13.92	1.08	13.66	1.13	14.99	2.12	16.71	2.04	15.42
Junk	1.18	7.08	1.25	7.18	1.12	6.44	1.26	6.88	1.22	8.17	1.29	7.81	1.22	7.44	1.17	6.66	1.50	4.92	1.33	4.55

Overall, our results show that the profit of the yield trend trading strategy is of economic significance and much larger than the typical trading costs of bonds. Asset pricing theories grappling with an aggregate equity Sharpe ratio of 0.30 face a much greater challenge when considering a combination with a bond trend portfolio, which has a Sharpe ratio about three times larger. This finding provides a stimulus for developing new theories to understand the economic forces behind it.

4.4. Bivariate portfolio analysis

In this subsection, we conduct robustness checks using bivariate portfolio sorts, in which we control for cross-sectional pricing effects of bond characteristics and historical returns.

4.4.1. Bivariate portfolio analysis using MAs and other bond characteristics

Previous studies document that bond returns are affected by bond characteristics. This raises a concern that yield 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 terciles on a bond characteristic and then further sort bonds in each tercile into five trend portfolios to yield 3×5 portfolios. Finally, for each quintile trend portfolio, we average across terciles of bond characteristic portfolios to obtain trend portfolio returns. The resulting trend portfolios all have a similar distribution of bond characteristics. We consider six bond characteristics: bond issue size, age, time to maturity, coupon rate, average past yield from month $t-6$ to $t-1$ ($MA_{t-1,6}$), and average past yield from month $t-48$ to $t-1$ ($MA_{t-1,48}$).

Table 7 reports the results of controlling for the effects of bond characteristics. It appears that the yield trend premium is stronger in small bonds, old bonds, and bonds with longer time to maturity, higher coupon rates, and higher past yields. Although the trend premium varies with bond characteristics, results continue to show highly significant H–L portfolio returns across the board. The yield trend premium persists even after controlling for bond characteristics, and the effect strengthens as the bond rating decreases. For example, controlling for the effect of bond issue size, the H–L portfolio return is 0.81% for AAA/AA-rated bonds and 1.18% for junk bonds. The results of controlling for age, coupon, and past yields 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 7, confirming that the predictive power of yield trend signals for cross-sectional bond returns is not driven by the yield level in the past month. The results suggest that yield trend signals contain important information beyond that in the bond yields over the past one- or six-month horizons.

4.4.2. Bivariate portfolios analysis using MAs of historical bond returns

To firmly establish the robustness of cross-sectional return predictability to the effects of conventional bond momentum or reversion, we perform bivariate portfolio sorts by directly controlling for these effects. We first sort bonds into terciles (Loser, Medium, and Winner) based on their returns over the past six months ($MA^{ret}_{t-1,6}$) or 48 months ($MA^{ret}_{t-1,48}$). Then, for each of these tercile portfolios, we further sort bonds into quintiles based on their expected returns forecast by MA signals. The intersection of momentum (reversion) and expected return sorts results in 15 (3×5) portfolios. We calculate the return of each trend portfolio by averaging across all three momentum (reversion) portfolios. The resulting trend portfolios have an effective control for the conventional bond momentum (reversion) effect.

Columns (13) to (16) of Table 7 continue to show a significant bond trend premium even after controlling for the effects of short- and long-term historical returns. The H–L portfolio returns are all highly significant for the whole sample as well as for each rating category. For example, when we control for the effect of bond returns in the past six months, the spread of the H–L portfolio returns is 0.89%, which is significant at the 1% level for the full sample that includes all bonds. The results of controlling for bond returns in the past 48 months are similar. Moreover, the H–L portfolio returns increase as bond ratings decrease. The mean returns of the H–L portfolios of junk bonds are 1.22% and 1.17%, respectively, after controlling for bond returns in the past six and 48 months. These results suggest that the yield trend premium is not driven by conventional bond momentum or reversion.

4.4.3. Bivariate portfolios analysis using bond illiquidity measures

A number of studies link the cross-section of bond returns to bond illiquidity (e.g., Chen et al., 2007; Bao et al., 2011; Feldhütter, 2012; Dick-Nielsen et al., 2012; Dick-Nielsen and Rossi, 2018). To see whether the yield trend premium may simply reflect different levels of bond illiquidity, we investigate the robustness of the predictive power of MA signals to controlling for bond illiquidity. We use the Amihud illiquidity (Amihud, 2002) measure and the imputed round-trip cost (IRC, Feldhütter, 2012) as proxies for a bond's illiquidity. Since high-frequency data are required to calculate these two measures, we only use the TRACE data in this analysis. The sample period runs from July 2002 to September 2019 with 270,736 observations.

Columns (17) to (20) of Table 7 report the results of bivariate portfolio analysis using the illiquidity measures as control variables. We first sort all bonds into terciles based on one illiquidity measure and then further sort the bonds in each tercile into five yield trend portfolios to generate 3×5 portfolios. For each quintile trend portfolio, we average across the tercile of illiquidity portfolios to obtain yield trend portfolios. These yield trend portfolios have similar levels of bond illiquidity. The results show the trend premium is higher for less liquid bonds. For example, the H–L return spread of all bonds is 1.01% for the Low IRC group and 1.89% for the High IRC group. Using the Amihud measure, the H–L return spreads of all bonds for the Low and High groups are 0.68% and 2.24%, respectively. The results continue to show strong yield trend premia even after controlling for bond illiquidity. The overall H–L return spread is 1.34% if we control for IRC, and is 1.30% if we control for the Amihud illiquidity measure, both significant at the 1% level. The results of different ratings are also overwhelmingly significant. These return spreads are close to those reported in the third subperiod of the left column of Table 10. Thus, the yield trend premium cannot be explained by bond illiquidity.

4.5. 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 the 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 $B_{j,kt}, k = 1, \dots, m$ are the bond characteristic variables. We consider six regression models with different controls: (1) no bond-specific variable; (2) bond size, age, time to maturity, and coupon rate; (3) bond size, age, time to maturity, coupon rate, moving average yield of last six months ($MA_{t-1,6}$), and moving average yield of last four years ($MA_{t-1,48}$); (4) bond size, age, time to maturity, coupon rate, $MA_{t-1,6}$, $MA_{t-1,48}$, moving average returns of last six months ($MA^{ret}_{t-1,6}$), and moving average returns of last four years ($MA^{ret}_{t-1,48}$); (5) bond size, age, time to maturity, coupon rate, $MA_{t-1,6}$, $MA_{t-1,48}$, $MA^{ret}_{t-1,6}$, $MA^{ret}_{t-1,48}$, IRC, and Amihud illiquidity; and (6) bond size, age, time to maturity, coupon rate, $MA_{t-1,6}$, $MA_{t-1,48}$, $MA^{ret}_{t-1,6}$, $MA^{ret}_{t-1,48}$, IRC, Amihud illiquidity, and four bond factor betas of Bai et al. (2019).[16]

Table 8 reports the results of the Fama–MacBeth cross-sectional 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. The results show a significantly positive z_1 across the board, again suggesting that the MA signals have predictive power for future corporate bond returns cross-sectionally. The predictive power of MA signals is robust to controlling for all bond characteristics (e.g., z_1 remains highly significant in model (6) that includes all control variables).

Bond characteristic variables do help to explain returns cross-sectionally. When no bond characteristic variable is included (model (1)), the adjusted R-squared value is only 7.15% for the sample that includes all bonds. It gradually increases as we add more characteristic variables and eventually reaches 27.99% when all characteristic variables are included. In addition, the results (omitted for brevity) show that past bond returns ($MA^{ret}_{t-1,6}$) can predict the bond returns in the next month cross-sectionally. More importantly, the inclusion of the characteristic variables in the cross-sectional regression has little impact on the significance of z_1, which remains highly significant even after controlling for these effects.

4.6. What drives the predictability?

The preceding results show sizable return spreads between the portfolios with high and low expected returns conveyed by MA signals. The yield trend premium remains significant even after controlling for bond ratings and characteristics. To the extent that the cash flows of bonds within the same rating category do not differ much from each other, the significant return spread is attributable to changes in corporate discount rates (or the expected rate of returns) driven by bond fundamentals. If so, there should be a negative relation between the yield trend signal and future changes in bond fundamentals. More specifically, a higher level of expected returns for one bond will signal a deterioration in its future fundamentals, resulting in a higher discount rate ex ante.

To investigate whether the MA signals contain information about future changes in bond fundamentals, we run the following ordered probit model:

$$\Delta Rate^*_{j,t+n} = \alpha + z_1 E_t[r_{j,t+1}] + \sum_{k=1}^{m} c_k Control_{j,kt} + \varepsilon_{j,t+1}. \tag{8}$$

The dependent variable $\Delta Rate^*_{j,t+n}$, changes in the true (latent) default risk for bond j between month t and month $t+n$, are unobserved. Instead, we observe changes in the nominal rating, $\Delta Rate_{j,t+n}$, given by the credit rating agency. The rating changes because the fundamentals of the bond issuer change, which affects its default risk. We set $\Delta Rate_{j,t+n}$ equal to -1 if bond j experiences a downgrade, 0 if its rating is unchanged, and 1 if it receives an upgrade. The relationship between $\Delta Rate_{j,t+n}$ and $\Delta Rate^*_{j,t+n}$ in a probit setting is:

$$\Delta Rate_{j,t+n} = -1 \text{ if } \Delta Rate^*_{j,t+n} \le \mu_1,$$
$$\Delta Rate_{j,t+n} = 0 \text{ if } \mu_1 < \Delta Rate^*_{j,t+n} \le \mu_2,$$
$$\Delta Rate_{j,t+n} = 1 \text{ if } \Delta Rate^*_{j,t+n} > \mu_2.$$

The control variables in the probit regression include bond size, age, and coupon rate. In addition, we control for year and rating fixed effects in the panel regression.[17]

[16] For each bond, we regress its excess returns on MKT^{Bond}, DRF, CRF, and LRF to estimate $\beta_{i,MKT}$, $\beta_{i,DRF}$, $\beta_{i,CRF}$, and $\beta_{i,LRF}$ using the full sample data.

[17] Since the ordered probit regression is nonlinear and the probit maximum likelihood estimator is not consistent in the presence of heteroskedasticity (see Greene, 2012), we cannot use the robust standard errors by clustering. To address this concern, we assume that bond ratings affect variances and estimate parameters under this form of heteroskedasticity. The difference between this approach and the robust standard error clustered by rating is that it changes the likelihood function and as a result, parameter estimates may change. We also run the regression assuming homoskedasticity. The results are similar with stronger statistics.

Table 8

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 future (month $t+1$) return of bond j forecast by MA signals in month t, and $B_{j,kt}, k = 1, \ldots, m$ are bond characteristic variables. The regression is a Fama–MacBeth cross-sectional regression. We consider six models that use different bond characteristics in the regression: (1) no bond-specific variable; (2) bond size, age, time to maturity, and coupon rate; (3) bond size, age, time to maturity, coupon rate, moving average yield of last six months ($MA_{t-1,6}$), and moving average yield of last four years ($MA_{t-1,48}$); (4) bond size, age, time to maturity, coupon rate, $MA_{t-1,6}$, $MA_{t-1,48}$, moving average returns of last six months ($MA^{ret}_{t-1,6}$), and moving average returns of last four years ($MA^{ret}_{t-1,48}$); (5) bond size, age, time to maturity, coupon rate, $MA_{t-1,6}$, $MA_{t-1,48}$, $MA^{ret}_{t-1,6}$, $MA^{ret}_{t-1,48}$, IRC, and Amihud illiquidity; (6) bond size, age, time to maturity, coupon rate, $MA_{t-1,6}$, $MA_{t-1,48}$, $MA^{ret}_{t-1,6}$, $MA^{ret}_{t-1,48}$, IRC, Amihud illiquidity, and four bond factor betas of Bai et al. (2019). For brevity, we only report the estimates of the coefficient of expected returns z_1. The sample periods run from January 1973 to September 2019 for models (1) to (4), July 2002 to September 2019 for model (5), and July 2004 to September 2019 for model (6).

		All	AAA + AA	A	BBB	Junk
	z_1	0.54	0.61	0.69	0.66	0.36
Model 1	t-stat.	10.12	9.59	8.59	9.58	5.14
	avg. R^2 (%)	7.15	13.04	11.85	12.02	9.71
	z_1	0.57	0.68	0.77	0.70	0.39
Model 2	t-stat.	10.84	13.14	13.35	11.60	5.03
	avg. R^2 (%)	16.77	33.55	27.67	27.39	20.06
	z_1	0.59	0.82	0.86	0.82	0.42
Model 3	t-stat.	7.83	13.10	17.48	13.08	3.58
	avg. R^2 (%)	22.40	38.92	32.37	32.68	31.54
	z_1	0.54	0.76	0.79	0.73	0.38
Model 4	t-stat.	7.52	12.27	15.64	12.48	3.75
	avg. R^2 (%)	26.44	44.09	36.40	36.81	38.41
	z_1	0.88	0.87	1.13	0.96	0.72
Model 5	t-stat.	11.40	12.83	18.57	24.67	8.19
	avg. R^2 (%)	22.08	44.09	33.32	28.07	35.40
	z_1	0.87	0.86	1.08	0.92	0.76
Model 6	t-stat.	10.69	14.28	17.80	24.37	8.27
	avg. R^2 (%)	27.99	53.91	39.69	33.82	44.34

Table 9 reports the results based on the full sample and each rating category. For brevity, we focus on the estimate of z_1. Panel A shows the results for the rating change in the next month ($n = 1$), while Panel B reports the results for the rating change in the next three months ($n = 3$). The results lend support to our hypothesis. The z_1 coefficients are overwhelmingly negative, indicating that bonds with higher expected returns are more likely to be downgraded in the next one to three months. The results strongly suggest that MA signals contain important fundamental information for future bond rating changes. Thus, an important source of the MA predictive power lies in the ability of corporate bond yield information to predict future changes in fundamentals.

5. Additional tests

5.1. Subperiod analysis

Previous studies in the equity market show that the momentum effect varies over time. This brings up the issue of whether cross-sectional bond return predictability or the yield trend premium varies over different subperiods. To address this issue, we examine the yield trend premium for different sample 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 the NAIC started reporting bond transactions and the other is July 2002 when TRACE was established.

Column (1) of Table 10 reports the H–L portfolio returns for the three subperiods. The results show that the initiation of TRACE coverage is associated with higher cross-sectional bond return predictability. As shown, the returns of H–L portfolios are much higher in the third subperiod compared with those in the first subperiod except for junk bonds. For the full sample including all bonds, the H–L return in the first subperiod is only 0.63% with a t-value of 7.02, whereas it is 1.42% with a t-value of 11.48 in the third subperiod. It seems that the yield trend premium is higher when the bond trading data become more transparent. The increase in predictability is the largest for BBB bonds. On the other hand, the results are weaker for junk bonds during the TRACE period, which could be due to a relatively small number of monthly observations.

Previous studies also show that return predictability changes with macroeconomic conditions. Returns tend to be more predictable in a bad economy than in a good economy (Rapach et al., 2010). There is also substantial evidence that macroeconomic fundamentals are the driving force for time variations in risk premia and return predictability (Lin et al., 2018). To see whether macroeconomic conditions play a role in the trend premium, we next examine the relation between cross-sectional bond return predictability and macroeconomic conditions.

Table 9

Ordered probit regressions of rating changes. This table reports the ordered probit regressions of rating changes on the expected returns predicted by MA signals and other bond-specific variables,

$$\Delta Rate^{*}_{j,t+n} = \alpha + z_1 E_t[r_{j,t+1}] + \sum_{k=1}^{m} c_k Control_{j,kt} + \varepsilon_{j,t+1}.$$

The dependent variable $\Delta Rate^{*}_{j,t+n}$, changes in the true (latent) default risk for bond j between month t and month $t+n$, are unobserved. Instead, we observe changes in the nominal rating, $\Delta Rate_{j,t+n}$, given by the credit rating agency. We set $\Delta Rate_{j,t+n}$ equal to -1 if bond j experiences a downgrade, 0 if its rating is unchanged, and 1 if it experiences an upgrade. The relationship between $\Delta Rate_{j,t+n}$ and $\Delta Rate^{*}_{j,t+n}$ is the following,

$\Delta Rate_{j,t+n} = -1$ if $\Delta Rate^{*}_{j,t+n} \le \mu_1$,
$\Delta Rate_{j,t+n} = 0$ if $\mu_1 < \Delta Rate^{*}_{j,t+n} \le \mu_2$,
$\Delta Rate_{j,t+n} = 1$ if $\Delta Rate^{*}_{j,t+n} > \mu_2$.

The control variables include bond size, age and coupon rate. We also control for year fixed effect and rating fixed effect in the panel regressions. We assume bond rating affects the variance in the ordered probit model. Panels A and B report the results using the rating change in the following month ($n = 1$) and the next three months ($n = 3$) , respectively. The sample period is from January 1973 to September 2019.

	All	AAA + AA	A	BBB	Junk
Panel A: Rating changes in the next month					
z_1	−0.036	−0.007	−0.018	−0.037	−0.015
	(−10.12)	(−2.34)	(−6.35)	(−9.74)	(−5.98)
Controls	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Rate Fixed Effects	Yes	Yes	Yes	Yes	Yes
# of obs.	644,832	123,334	273,119	178,564	69,815
Pseudo R^2 (%)	3.22	7.58	2.52	1.74	3.35
Panel B: Rating changes in the next three months					
z_1	−0.032	−0.000	−0.023	−0.045	−0.009
	(−10.68)	(−0.12)	(−10.70)	(−11.97)	(−4.80)
Controls	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Rate Fixed Effects	Yes	Yes	Yes	Yes	Yes
# of obs.	644,832	123,334	273,119	178,564	69,815
Pseudo R^2 (%)	4.39	11.33	4.34	2.30	3.51

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 indices of non-farm payroll employment, industrial production, real personal income, and real manufacturing and trade sales. Columns (3) to (6) of Table 10 report the results for the periods associated with different macroeconomic conditions. For the sample including all bonds, the H–L return spreads for the high-recession probability and low-growth periods are 1.21% and 1.19%, respectively. These numbers are substantially higher than those for the low-recession probability and high-growth periods (0.82% and 0.74%, 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).

5.2. Robustness tests

In this subsection, we run several additional tests for robustness. First, we extract information from all seven MA *return* signals. A bond's expected return now is a linear combination of its own MA return signals. Panel A of Table 11 shows that the trend premium of return signals is smaller than the trend premium of yield signals: the H–L portfolio return using all bonds decreases from 0.96% to 0.74%. This underperformance also occurs for the results by rating. Thus, the MA signals are weaker when they are constructed by bond returns. Nevertheless, all the H–L return spreads sorted by MA return signals are still significant at the 1% level.

As previous studies suggest that both yields and yield spreads are predictors for expected bond returns (see, e.g., Gebhardt et al., 2005a; Lin et al., 2014), we also extract information from seven MA *yield spread* signals. We first obtain the equivalent risk-free bond yield by constructing a synthetic Treasury bond with the same coupon and maturity as the underlying corporate bond, and then subtract this risk-free bond yield from the corporate bond yield to get the cash flow matched yield spread. We then forecast an individual bond's expected return using the information from MA yield spread signals. Panel B shows that the average return of the H–L portfolio sorted by MA yield spread signals using all bonds is 0.92% per month, which is close to the result in Table 2. The results show that our results are robust to the use of cash flow matched yield spread signals.

Table 10

Trend portfolio returns for different subperiods. This table reports the returns of portfolios sorted by bonds' expected returns for different subperiods. We use a two-step procedure to forecast 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) 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. SRP and real GDP growth rate are from Federal Reserve at St. Louis. 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 2019.

Rating	Bond data periods		SRP		GDP growth rate	
	(1)	(2)	(3)	(4)	(5)	(6)
	H–L	t-stats	H–L	t-stats	H–L	t-stats
	Jan. 1973–Dec. 1993		Low		Low	
All	0.63	7.02	0.82	9.37	1.19	7.99
AAA + AA	0.50	4.47	0.66	6.62	0.99	6.59
A	0.49	4.61	0.79	8.27	1.17	8.39
BBB	0.54	2.68	0.85	7.71	1.65	7.33
Junk	1.46	4.50	1.32	4.84	1.49	3.86
	Jan. 1994–Jul. 2002		Medium		Medium	
All	0.61	5.72	0.87	9.04	0.95	8.93
AAA + AA	0.87	5.86	0.71	6.59	0.86	8.20
A	0.71	5.44	0.90	8.87	1.09	10.73
BBB	0.40	3.09	1.22	10.29	1.30	9.05
Junk	0.69	3.59	0.68	2.88	1.01	3.71
	Aug. 2002–Sep. 2019		High		High	
All	1.42	11.48	1.21	7.67	0.74	8.61
AAA + AA	1.02	8.53	1.03	6.40	0.54	4.66
A	1.44	13.09	1.14	7.39	0.56	5.03
BBB	2.16	17.10	1.54	6.00	0.62	4.79
Junk	1.38	4.28	1.78	4.22	1.29	4.42

Next, we test whether the yield trend premium is robust to the use of cash flow matched excess returns.[18] Panel C of Table 11 reports the results. The yield trend premium is robust to using the cash flow matched excess return to calculate the trading profit. The average H–L portfolio return using all bonds is 0.91%, significant at the 1% level. 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 cannot explain the yield trend premium of corporate bonds.

Corporate bonds generally trade much less frequently than stocks. 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 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 11 reports the results of this alternative specification. Although the yield trend premium becomes somewhat weaker after we control for the forward looking bias, they remain highly significant. Thus, our finding of a significant yield trend premium is robust to controlling for infrequent trading.

5.3. A machine learning approach

In this subsection, we use the comprehensive set of all 48 MA yield signals as predictors to forecast bond expected returns in the first step. To mitigate the potential over-fitting problem arising from a large number of predictors, we apply the elastic-net (e-Net) method of Zou and Hastie (2005), a widely used machine learning approach, to circumvent over-fitting by shrinkage of predictors.

To begin with, and note there are 48 predictors now, we can change equation (2) to the following matrix form:

$$r_{j,t} = \mathbf{x_{jt-1}}'\beta_t + \varepsilon_{j,t}, \tag{9}$$

where $\mathbf{x_{jt-1}} = (1, MA_{jt-1,1}, \ldots, MA_{jt-1,48})'$ is a 49×1 vector of predictors and $\beta_\mathbf{t} = (\beta_{0,t}, \ldots, \beta_{48,t})'$ is a 49×1 vector of parameters.

Due to the large number of correlated regressors used in the predictive regression, the conventional ordinary least squares (OLS) approach is prone to inaccurate parameter estimation, causing poor out-of-sample prediction. The recent advance in the machine learning methodology suggests that using penalization techniques can mitigate this estimation problem. A least absolute shrinkage and selection operator ("LASSO") employs an ℓ_1 penalty by allowing continuous shrinkage to zero, while a ridge regression imposes an ℓ_2 penalty to preclude shrinkage to zero. Zou and Hastie (2005) propose an elastic-net approach to include both ℓ_1 and ℓ_2 penalties. This elastic-net approach mitigates a problem in the LASSO regression that tends to arbitrarily select a single predictor

[18] 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.

Table 11
Robustness test. 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. In Panel A (B), the MA signals include the bond's moving average returns (yield spreads) of lag lengths 1, 3, 6, 12, 24, 36, and 48 months. Panel C uses the cash flow matched excess returns. Panel D reports the results by replacing missing observations with zero returns. We apply OLS method to estimate the coefficients. The moving average coefficients are then used to forecast a bond's return. We then sort all bonds into quintile portfolios (Low, 2, 3, 4, and High) based on their expected returns. 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 2019.

Rating	Low	2	3	4	High	H–L	t-stats
Panel A. 7 MA return signals							
All	0.48	0.63	0.62	0.66	1.23	0.74	10.24
AAA + AA	0.45	0.58	0.59	0.60	0.96	0.51	6.85
A	0.44	0.61	0.61	0.63	1.08	0.64	8.12
BBB	0.34	0.66	0.66	0.80	1.38	1.04	10.35
Junk	0.60	0.85	0.76	1.04	1.76	1.17	5.88
Panel B. 7 MA yield spread signals							
All	0.38	0.52	0.65	0.79	1.30	0.92	14.25
AAA + AA	0.29	0.49	0.61	0.71	1.07	0.77	12.14
A	0.30	0.53	0.62	0.73	1.19	0.90	14.66
BBB	0.29	0.54	0.68	0.91	1.44	1.15	12.62
Junk	0.58	0.57	0.95	1.03	1.79	1.21	6.41
Panel C. Cash flow matched excess returns							
All	−0.21	−0.08	0.01	0.16	0.70	0.91	12.83
AAA + AA	−0.24	−0.09	0.00	0.07	0.49	0.74	11.47
A	−0.29	−0.09	0.01	0.10	0.61	0.90	14.32
BBB	−0.30	−0.10	0.04	0.22	0.85	1.15	10.51
Junk	−0.08	0.05	0.24	0.43	1.20	1.28	6.73
Panel D. Replace missing observations with zero returns							
All	0.35	0.51	0.60	0.75	1.23	0.89	14.16
AAA + AA	0.30	0.46	0.55	0.66	1.01	0.71	10.83
A	0.27	0.49	0.59	0.71	1.14	0.87	13.14
BBB	0.29	0.51	0.66	0.85	1.39	1.10	11.42
Junk	0.50	0.70	0.84	1.01	1.69	1.18	6.68

from a set of correlated predictors and becomes less informative in a setting with many correlated predictors. The e-Net has become a widely used method to reduce the dimension of variables in finance research (e.g., Rapach et al., 2013; Kozak et al., 2020 and the references therein). Following previous studies, we employ the e-Net method to estimate the coefficients of bond yield signals:

$$\hat{\beta} = \underset{\beta}{\operatorname{argmin}}(\|r - \mathbf{x}'\beta\|^2 + \lambda\|\beta\| + (1-\lambda)\|\beta\|^2), \tag{10}$$

where λ is the regularization parameter corresponding to the LASSO norm (ℓ_1 penalty term), and $1-\lambda$ is the weight placed on the ridge norm (ℓ_2 penalty term). The number of folds used in cross-validating λ is set to be 5. Elastic-net regression is a linear model whereby excessively large parameters are discouraged.

We sort bonds into quintile portfolios by their expected returns, which are a linear combination of all 48 yield signals, and the weights are the moving average of the coefficients estimated by the e-Net method. Table 12 reports the equal-weighted portfolio returns. The average H–L portfolio return using all bonds is 0.89%, significant at the 1% level. Compared with Table 2, there is no improvement by using all 48 yield signals and the e-Net method. Further inspections by different ratings suggest that the baseline model that uses seven MA signals and the conventional multiple regression method is sufficient to extract information from corporate bond yields. Nevertheless, this exercise confirms the existence of strong return predictability in corporate bond markets.

5.4. *Yield trend premia 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 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 13 reports the results of yield trend portfolio returns for bonds issued by public firms. As shown, the results are slightly stronger than 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 1.07% with a t-value of 13.87, while it is 0.96% in Panel A of Table 2. The results by rating are similar. Thus, there is no evidence that yield trend premia are weaker for public firms. The results are also consistent with our findings for Table 10 that greater data transparency generates a stronger yield trend premium as public firms are more transparent.

Table 12

Returns of trend portfolios: Elastic-net method. 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, 2, 3, …, 46, 47, and 48 months. We apply elastic-net approach of Zou and Hastie (2005) to estimate the coefficients. The moving average coefficients are then used to forecast a bond's return. We then sort all bonds into quintile portfolios (Low, 2, 3, 4, and High) based on their expected returns. 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 2019.

Rating	Low	2	3	4	High	H–L	*t*-stats
All	0.40	0.55	0.64	0.76	1.29	0.89	12.37
AAA + AA	0.34	0.50	0.57	0.66	1.10	0.76	9.88
A	0.28	0.52	0.63	0.75	1.20	0.91	12.64
BBB	0.25	0.51	0.67	0.93	1.50	1.25	12.49
Junk	0.64	0.67	0.88	1.03	1.90	1.26	5.38

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 controlling 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 yield trend portfolios.[19] For each quintile trend portfolio, we then average returns across the three portfolios formed by stock market anomaly variables.

Panel B of Table 13 reports the results of bivariate portfolio sorts. For brevity, we only report the results for the full sample.[20] The results show the trend premium is higher for small firms, firms with low asset growth, and firms with high idiosyncratic volatility. Moreover, all H–L portfolio returns are significantly positive. The results continue to show significant yield trend premia across the board. Thus, stock market anomaly variables cannot explain the yield trend premium.

Finally, we run a cross-sectional regression of firm-level bond returns on their expected returns implied by MAs with and without stock market anomaly variables each month. For brevity, we focus on the coefficient of expected bond returns. Panel C of Table 13 reports the mean coefficients and *t*-statistics of MA return forecasts (expected returns) and the mean adjusted R-squared value. The results continue to show a significant relation between expected returns and their future returns, even after controlling for the effects of stock market anomaly variables. This evidence again strongly suggests that MA yield signals have predictive power for future bond returns over and beyond that of stock market anomaly variables.

6. Conclusion

In this paper, we investigate the cross-sectional predictability of returns in the corporate bond market by incorporating yield trend signals over multiple horizons, which contain much richer information for expected returns than prior studies that rely on only one lagged return signal over a fixed horizon. As a result, it is more informationally efficient and capable of detecting strong out-of-sample return predictability in the corporate bond market across all rating categories, which is new to the literature.

We uncover evidence that there is a significant yield trend premium, not only in speculative-grade bond returns, but also in investment-grade bond returns. Yield trend premia in all rating categories survive transaction costs and are of economic significance. Conventional risk factors, bond characteristics, and illiquidity cannot explain these premia. The trading strategy based on yield trend

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

[20] 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.

Table 13

Trend premia of public firms. This table reports trend premia of public firms. Panel A reports the returns of portfolios sorted by bonds' expected returns. Panel B reports the results of trend premia of all public firms controlling for stock market anomaly variables. 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 also 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. Panel C reports the results of 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. We report the mean coefficients of return forecast, their *t*-stats and the average adjusted R-squared of monthly cross-sectional regressions. The sample period is from January 1973 to September 2019.

Panel A. Univariate portfolio analysis

Rating	Low	2	3	4	High	H–L	*t*-stats
All	0.31	0.52	0.63	0.82	1.38	1.07	13.87
AAA + AA	0.27	0.48	0.61	0.75	1.06	0.79	10.88
A	0.25	0.49	0.61	0.76	1.33	1.07	14.95
BBB	0.21	0.48	0.67	0.90	1.51	1.29	13.93
Junk	0.34	0.55	0.87	1.09	1.79	1.38	6.33

Panel B. Bivariate portfolio analysis

Stock variable	Low		Medium		High		Average	
	H–L	*t*-stats	H–L	*t*-stats	H–L	*t*-stats	H–L	*t*-stats
Size	1.13	7.00	1.14	13.58	0.70	10.16	0.99	13.04
Accruals	0.98	6.77	0.79	8.00	0.94	8.33	0.90	10.36
Profitability	0.95	6.02	0.93	11.27	1.07	11.92	0.98	12.36
Earning surprise	0.96	6.44	0.94	13.39	0.99	9.04	0.96	12.12
Value	0.91	9.26	1.01	10.61	1.03	8.00	0.98	12.05
Asset growth	1.05	6.94	1.07	12.23	0.84	9.73	0.99	12.47
Net stock issuance	0.98	11.55	0.95	8.60	1.01	7.77	0.98	11.90
Idiosyncratic. Volatility	0.86	10.39	1.01	12.36	1.17	7.75	1.01	13.59

Panel C. Cross-sectional regression

Without controlling variables			With controlling variables		
Coefficient	*t*-stats	avg. R^2 (%)	Coefficient	*t*-stats	avg. R^2 (%)
1.03	8.68	10.74	1.27	12.39	28.44

signals earns higher returns in periods of slow economic growth and recession. The results are robust to different measures of bond returns and to controlling for bond characteristics. Overall, there is strong evidence that bond returns are predictable in the entire corporate bond universe.

We provide exploratory evidence for the economic sources of return predictability by yield trends. Our analysis suggests that the trend signals extracted from corporate bond yields contain important information for bond fundamentals that drive expected bond returns. We find that yield signals predict rating changes for corporate bonds: A higher yield trend signals higher default risk and expected returns. This finding suggests that a plausible source for the predictive power of the yield signal is its ability to predict changes in fundamentals that influence bond default risk.

It will be interesting to further explore the relation of bond market return predictability to stock market return predictability, as well as its relation to various stock anomalies. Moreover, presumably similar predictors and tools can be useful for exploring return predictability in other asset classes, such as the currencies and carry-trades, where interest rates play a similar role as bond yields. We leave these for future research.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.finmar.2021.100687.

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