Media Coverage and Corporate Bond Momentum

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July 14, 2024

Abstract

This paper shows that media information induces momentum in corporate bonds. Using a comprehensive media coverage dataset from RavenPack News Analytics, we find that bonds with high media coverage exhibit stronger momentum than those with low media coverage. This media-based momentum concentrates on non-investment-grade (NIG) bonds. Media tone enhances the effect of news coverage, and informed trading of bonds with high media coverage leads to stronger momentum in the short run. Momentum reverses in the long run with bonds of higher media coverage experiencing more pronounced reversals. Our results provide a novel explanation for the momentum in NIG bonds.

JEL classification: D03 G12

Keywords: business media, momentum, corporate bonds, informed trading, overreaction

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1. Introduction

Jegadeesh and Titman (1993) first document the evidence of momentum in the stock market. Stocks that performed better in the past three to twelve months continue to outperform in the next three to twelve months. Since this seminal work, voluminous papers have studied momentum from different perspectives in various asset markets (Asness, Moskowitz, and Pedersen, 2013; Erb and Harvey, 2006) for different asset classes (e.g., foreign currencies, commodities, options, and bonds), over different time horizons (Chabot, Ghysels, and Jagannathan, 2009; Fama and French, 2008), and in countries with different cultural and institutional background (Rouwenhorst, 1998; Chui, Titman, and Wei, 2010; Asness, Moskowitz, and Pedersen, 2013). Substantial evidence shows that momentum is pervasive, and its effect is robust across different time periods and markets. The significance and persistence of this effect prompt Fama and French (2008) to proclaim that "The premier anomaly is momentum".

The literature on momentum focuses on stocks, with much less attention paid to the corporate bond market, which has a comparable size in capitalization and is the primary source of financing for public firms. Only a few papers have studied corporate bond momentum, and the evidence is mixed. Gebhardt, Hvidkjaer, and Swaminathan (2005b) find no momentum for investment-grade corporate bonds[1] but instead discover a momentum spillover from stocks to bonds. Jostova, Nikolova, Philipov, and Stahel (2013) find significant momentum for high-yield corporate bonds but not for investment-grade bonds. Exploiting the different trading behaviors of investors on same-issuer bonds, Li and Galvani (2021) find informed trading drives of the momentum for corporate bonds. Using bond yields instead of returns, Guo, Lin, Wu, and Zhou (2022) uncover a form of price momentum, dubbed "trend momentum", for both speculative- and investment-grade bonds.

[1] See also Khang and King (2004).

Despites the enormous amount of research efforts, the central issue of the underlying causes of momentum is still far from being resolved. While there are numerous attempts to provide rational explanations for the momentum effect, the size of the momentum profits appears too large to reconcile with risk-based theories. The failure prompts researchers to resort to behavioral explanations. The two mainstream behavioral explanations are underreactions of security prices to information and investor overreactions to news. The theory of underreaction suggests that investors underreact to information, which causes a slow diffusion of information into security prices and induces momentum (see Barberis, Shleifer, and Vishny, 1998; Hong and Stein, 1999; Fama and French, 2012). On the other hand, Daniel, Hirshleifer, and Subrahmanyam (1998) propose a model in which investors' overconfidence and biased self-attribution generate delayed overreaction to information and result in momentum. Subsequent to the study of Daniel et al. (1998), a number of papers suggest that investor overreaction is a momentum driver (Cooper, Gutierrez, and Hameed, 2004; Chui, Titman, and Wei, 2010; Solomon, Soltes, and Sosyura, 2014; Adebambo and Yan, 2016; Chui, Subrahmanyam, and Titman, 2022). Prior investigation on the sources of momentum focuses on stock momentum. The issues related to bond momentum are considerably underexplored. Our paper attempts to fill this void by entertaining media coverage as a potential driver of momentum in the corporate bond market.

The literature suggests that media plays an important role in collecting, processing, and interpreting information, which has profound effects on trading and asset pricing in financial markets (Tetlock, 2007; Engelberg and Parsons, 2011). Hong and Stein (2007) suggest that media shapes the behavior of investors in the stock market. Using a comprehensive data set of articles from U.S. national and local newspapers, Hillert, Jacobs, and Muller (2014) find that firms heavily covered by the media exhibit stronger momentum in the stock market. This finding suggests that media coverage is an important driver of stock momentum. However, to this date, surprisingly, there has been no study of whether media coverage and the tone of the message may drive momentum in the corporate bond market.

This paper explores the role of media coverage in driving corporate bond momentum using the media coverage and tone data from RavenPack over the period of 2000-2020. Motivated by Hong, Lim, and Stein (2000), we construct a residual media coverage measure as a key return predictor from a cross-sectional regression that controls characteristic variables affecting the likelihood of a firm being covered by media. The momentum strategies are conducted similarly as Jegadeesh and Titman (1993), with the media coverage (tone) being accumulated (averaged) during the portfolio formation period. Using this setting, we investigate corporate bond momentum over different investment horizons.

The results are striking: there exists a pronounced media-driven momentum in the corporate bond market. Figure 1 shows that the momentum profit has a monotonically positive correlation with the residual media coverage variable over the short-term horizon. The momentum effect then weakens and turns into a negative territory 20 months later. Bonds with high media coverage exhibit the sharpest reversal. Consistent with this pattern, portfolio analysis shows that in the short run, the momentum is statistically significant for bonds with high media coverage but insignificant for bonds with low media coverage. The difference in momentum returns between the high and low coverage portfolios referred to as the media-based momentum, is significant up to a 12-month horizon. This momentum effect cannot be explained by risk factors, and is robust to using different regression specifications to calculate the residual media coverage. A breakdown of the whole bond sample by rating shows that the media-based momentum is much stronger for non-investment-grade (NIG) bonds.

[Insert Figure 1 here]

To explore the source of the media-based momentum, we conduct a battery of tests to evaluate investor overreaction to media news as a plausible cause for the media-based momentum. First, we check whether the momentum dynamics driven by media coverage exhibit a predictability pattern consistent with investor overreaction to news. The model of Daniel et al. (1998) predicts that the momentum effect will reverse in the long run as investors adjust their beliefs when public information arrives and drives the price back toward fundamentals. To test this hypothesis, we examine the momentum returns of holding portfolios over two different horizons from t+1 to t+12 and t+13 to t+24. The results show that both the full sample and the subsample of NIG bonds exhibit significant media-based momentum in the short term but a reversal in the long term. This momentum pattern is consistent with the prediction of the overreaction model of Daniel et al. (1998).

Second, if investor overreaction drives the media-based momentum, media tone, which energizes investors' emotions, should also play a significant role in this process. To investigate this possibility, we add media tone as another predictor in portfolio sorts. If winners (losers) have a positive (negative) media tone during the portfolio formation period, investors would be even more overconfident, leading to stronger and more persistent momentum. Consistent with this inference, we find that bonds with positive media tone have more pronounced momentum.

Moreover, for an informed but overconfident investor, if the subsequent public information confirms his private information, the self-attribution bias hypothesis predicts that it will trigger further overreaction. To test this hypothesis, we follow Li and Galvani (2021) to classify bonds into top and non-top groups using the volume of institution-sized trades as a proxy for informed trading. Compared to the private information possessed by informed investors, media coverage can be interpreted as an information signal that appears in public sources (see Hilbert et al., 2014). Gao et al. (2020) find that the effect of media coverage on bond prices is stronger when information asymmetry is high, and Han and Zhou (2013) show that information asymmetry is higher for NIG bonds. Together, this suggests that media coverage can reinforce the momentum triggered by informed trading in the short term, and this effect will be stronger for NIG bonds. Moreover, informed trading accompanied by media coverage can cause a stronger reversal in the long term if there is an overreaction to information. Our results confirm this prediction and suggest that media coverage is an important driver of momentum. Overall, substantial evidence indicates that media coverage generates bond momentum.

This paper contributes to the literature on momentum in financial markets. There are relatively few studies of bond momentum, and this issue is considerably underexplored. Given that the corporate bond market is a major financing source for public firms, it is important to understand the pricing mechanism and efficiency in this market. Corporate bonds differ from stocks in many ways, such as investor clientele, security characteristics, payoff structure, liquidity, and the information environment. Investigating this large asset class provides important out-of-sample evidence unavailable in tests based on stocks alone and, therefore, sheds light on the determinants of the momentum effect. This paper contributes to the literature by providing evidence that business media is an important driver for bond momentum. Bond momentum behaves differently from stock momentum, and the sources of the momentum in the corporate bond market also differ.

Importantly, we provide a novel explanation for a salient feature in the corporate bond market that the momentum concentrates in NIG bonds (see Jostova et al., 2013). We show that media coverage disseminates information that catches investor attention and drives bond momentum. As information asymmetry is higher for NIG bonds (see Han and Zhou, 2013), the effect of media coverage is stronger for this group of bonds. This explains why momentum in the corporate bond market is much stronger for NIG bonds. Li and Galvani (2021) find that bond momentum is linked to price adjustment in response to bond informed trading and suggest that different speeds of information diffusion explain the bond momentum pattern. Unlike their study, the driver for the NIG bond momentum we uncover in this paper is the media coverage, which is a public source of information, rather than the private information conveyed by informed trading. Our results suggest that media coverage is another important source of NIG bond momentum. Moreover, due to our focus on a different type of information effect, we identify overreaction to media news as a primary explanation for the media-based momentum.

The remainder of this paper is organized as follows. Section 2 discusses data and variable construction. Section 3 presents empirical results and conducts robustness tests. Section 4 explores the mechanism behind the media effect on bond momentum, and Section 5 provides additional tests. Finally, Section 6 summarizes the findings and concludes the paper.

2. Data and variables

We obtain bond issue, issuer, and transaction data from the Fixed Investment Securities (FISD), the enhanced Trading Reporting and Compliance Engine (TRACE), and the National Association of Insurance Commissioners (NAIC). Media information is collected from RavenPack, and firm characteristics data, such as firm size, book-to-market, turnover, and analyst coverage, are from the Center for Research in Security Prices (CRSP), Compustat, and I/B/E/S.

2.1 *Corporate bond data*

FISD provides issuance information for all fixed-income securities with a CUSIP, including issue- and issuer-specific information, such as issue date, coupon rate, maturity, issue amount, and credit ratings. Following Jostova et al. (2013), we eliminate non-US dollar-denominated bonds, bonds with unusual coupons (e.g., step-up, increasing-rate, pay-in-kind, and split-coupons), bonds backed by mortgages or other assets, and bonds that are part of unit deals. We also eliminate bonds with a call or put option. For bond ratings, we use Moody's ratings primarily, and if unavailable, use Standard and Poor's (S&P) ratings when possible.

Bond transaction data are collected from two databases: TRACE and NAIC. The enhanced TRACE database provides transaction data of publicly traded corporate bonds since July 2002. The NAIC database contains transaction data of publicly traded corporate bonds by life and property and casualty insurance companies and health maintenance organizations (HMOs) from January 1994 to December 2009. For transactions before July 2002, NAIC is the only data source, and after July 2002, we have both TRACE and NAIC data. If transactions of the same bond are covered in both datasets, we keep only those reported by TRACE.[2] Including the NAIC data increases the time span of our data sample and improves the test efficiency. We clean the TRACE data following the Dick-Nielsen (2014) procedure and remove transactions that are marked as cancellations, corrections, and reversals. In addition, we eliminate bond transactions labeled as when-issued, locked-in, or with special sales conditions. We also remove transaction records with a trading volume of less than $10,000. Private bonds or bonds issued by private firms are excluded from our main analysis due to the lack of financial statement information for private firms.

We obtain firm characteristics data, such as firm size, book-to-market, and turnover, from the Center for Research in Security Prices (CRSP) and Compustat. Analyst coverage data are collected from I/B/E/S. The monthly corporate bond return at month t is computed as:

[2] Both TRACE and NAIC provide daily transaction data.

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

where P_t is the price, AI_t is the accrued interest, and C_t is the coupon payment, if any, in month *t*. We use the last daily price of each month to calculate the bond's monthly returns, and the price of each day's last trading is used to proxy for the daily price. If there is no trading in month *t* or month *t-1*, the monthly return of time *t* is set as missing.

2.2 Media coverage and media tone

Media coverage and tone are the key variables for our empirical tests, which are collected from RavenPack News Analytics-Dow Jones Edition. The Dow Jones Edition of RavenPack analyzes relevant information from Dow Jones Newswires, regional editions of the Wall Street Journal, Barron's, and MarketWatch. It has published the world's business and financial news since January 1, 2000, which is also the starting day of our sample period. Following Bushman, Williams, and Wittenberg-Moerman (2017), we limit the news type to full articles (a news article composed of both a headline and one or more paragraphs of mostly textual material) to ensure the news contains practical information about the entities. We further restrict our sample data to a relevance score of 80 and above.

According to the user guide of RavenPack, the relevance score indicates how strongly the entity is related to the underlying news story. Values above 75 are considered significantly relevant.[3] We count the number of articles about a firm and take ln(1+number of articles) to proxy for its media coverage. All bonds issued by the same firm share the common media coverage and tone information. To measure media tone, we use CSS (composite sentiment score) provided by RavenPack. CSS ranges between 0 and 100, representing a given story's news sentiment by combining various textual analysis techniques. Since we care more about the

[3] Limiting data with relevance score of 90 and above or 100 produces similar results.

direction than the magnitude of sentiment, media tone is calculated as (CSS-50)/50, which ranges from -1 to 1. Media tone > 0 means the news is positive, media tone < 0 means the news is negative, and media tone = 0 means the news is neutral.

[Insert Table 1 here]

Table 1 examines the determinants of media coverage using the Fama-MacBeth regression. Consistent with the literature, firm characteristics significantly affect media coverage. We obtain the residual media coverage from regression IV (the last column in the table) that includes all characteristics. A similar approach is used in previous studies to remove the effect of firm characteristics. For example, Hong, Lim, and Stein (2000) use firm size and NASDAQ membership as explanatory variables to calculate residual analyst coverage. Hillert, Jacobs, and Müller (2014) employ firm size, analyst coverage, NASDAQ membership, and S&P 500 dummy to calculate residual media coverage. Specifically, we run the following regression:

$$\begin{aligned}&\text{Raw media coverage/Raw media tone}_{i,t} \\ &\quad = \alpha + \beta_1 \cdot \text{firm\_size}_{i,t} + \beta_2 \cdot \text{analyst\_coverage}_{i,t} + \beta_3 \cdot \text{NASDAQ}_{i,t} + \varepsilon_{i,t}\end{aligned} \tag{2}$$

where Raw media coverage is ln(1+no. news), firm_size is ln(1+market capitalization), analyst_coverage is ln(1+no. earnings estimates), NASDAQ is 1 (0) if the issuer is (not) a NASDAQ membership. Residual media coverage is the unexplained part of the regression, which is $\hat{\alpha} + \hat{\varepsilon}_{i,t}$. Residual media tone is calculated similarly.

We finally merge corporate bond data with the media coverage data. The sample period ranges from January 2000 to December 2020. There are 144,284 bond-month observations, with 2,631 bonds issued by 979 firms. Panel A of Table 2 provides the descriptive statistics of the sample. Panel B reports the time-series averages of the monthly mean of firm and bond characteristics for portfolios sorted by raw and residual media coverage. Each month, bonds are sorted into terciles based on cumulative raw/residual media coverage over the past 6 months. The distributions of firm size, analyst coverage, and NASDAQ dummy show that firm characteristic differences across the raw media coverage portfolios decrease with residual media coverage. For example, the firm size difference between high and low portfolios is 2.68 for raw coverage and 1.93 for residual coverage, and the t-value also decreases from 71.08 to 46.85. Figure 2 provides a more intuitive picture of the firm characteristic differences between high and low media coverage groups. As shown, firm characteristic differences are narrower for the groups formed by the residual media coverage than by the raw media coverage. Thus, using residual media coverage as a news measure can mitigate the noisy effect of firm characteristics on media coverage.

[Insert Figure 2 here]

Both raw and residual media coverages are negatively related to bond ratings, age, and coupon, while positively related to bond maturity and issue size. This suggests that the media tends to pay more attention to bonds with better ratings, lower coupon rates, longer maturity, larger issue size, and being more recently issued.

[Insert Table 2 here]

3. Empirical results

3.1 Baseline results

We use average monthly returns to identify losers and winners and construct momentum portfolios. Following the literature, we set the formation and holding period to six months and skip one month in between. Each month, we first sort all bonds into terciles based on the cumulative residual media coverage in the formation period, yielding low, medium, and high coverage portfolios. Within each coverage tercile, bonds are further sorted into three groups based on average monthly returns in the past 6 months, with winners (losers) ranking above the

70th percentile (below the 30th percentile). Finally, we construct a momentum portfolio by longing the winners and shorting the losers. Momentum return (or profit) is the return spread between winners and losers. Panel A of Table 3 shows the results of portfolio sorts, where J/K=6/6 indicates the formation period J and holding period K, which are set to 6 months. Coverage portfolios 1, 2, and 3 represent the lowest, medium, and highest coverage portfolios. Return spread 3-1 is the return difference between the highest and lowest coverage portfolios.

[Insert Table 3 here]

Panel A of Table 3 shows that the momentum profits monotonically increase with the residual media coverage. The high coverage portfolio has the highest and most significant momentum return of 0.18 (t=2.26). The medium coverage portfolio has the second highest momentum return of 0.13, which is significant at the 10% level (t=1.76), whereas the low coverage portfolio has an insignificant momentum return. The momentum return difference between high- and low-coverage portfolios, defined as media-based momentum in the remainder of the paper, is 0.28 and highly significant (t=3.59). Moreover, for losers and winners, the return differences between high- and low-coverage portfolios are -0.18 (t=-3.41) and 0.10 (t=1.84), respectively, indicating that winners (losers) with more media coverage tend to have higher (lower) future returns (momentum) than winners (losers) with less coverage. A possible reason is that bonds with higher coverage catch more investors' attention. The past performances of winners and losers are more likely in the market spotlight. As a result, more investors chase winners while abandoning losers, yielding dispersed future returns.

Panel B of Table 3 shows that media-based momentum is robust to controlling for risk factors. We regress media-based momentum returns on bond risk factors. MKT, SMB, and HML are the Fama-French three factors retrieved from Ken French's website. The default spread (DEF) is the difference in monthly returns between long-term investment-grade and government bonds. The long-term investment-grade bond returns are based on a value-weighted portfolio that includes all investment-grade bonds in our sample with at least ten years to maturity. The term spread (TERM) is the difference between the monthly return of the long-term government bond and the one-month T-bill rate, both from the Federal Reserve Board. Following Jostova et al. (2013), we set $\Delta TERM_t = (TERM_t - TERM_{t-1})$, $\Delta DEF_t = (DEF_t - DEF_{t-1})$, $mTERM_t = \Delta TERM_t / (1+TERM_{t-1})$, $mDEF_t = \Delta DEF_t / (1+DEF_{t-1})$.

Using the GMM with Newey-West adjusted standard errors, we estimate alphas using the following factor model:

$$\text{media based momentum}_t = \alpha + \boldsymbol{\beta}' \cdot \mathbf{F}_t + \varepsilon_t \quad (3)$$

where media-based momentum is the return difference between high- and low-coverage portfolios. F_t contains risk factors in seven different factor models described in the legend of Table 3. Panel B shows that alphas in different models are all significant at least at the 5% level. The value ranges from 0.277 to 0.294, close to the results in Panel A. Momentum returns associated with media coverage cannot be explained by conventional risk factors.

Panel C of Table 3 shows the media-based momentum returns when the portfolio holding period (K) is set to 4, 8, and 12 months, respectively. For brevity, only alphas relative to factor model (7) are reported here and in the remainder of this paper. As shown, media-based momentum persists up to a 12-month horizon. Though the magnitude of media-based momentum alphas declines from 0.32 to 0.20 when the portfolio is held for 4 to 12 months, it remains quite significant at K=12 (t=3.06). The contributing power of low- and high-coverage groups to media-based momentum varies across different holding periods. In the short term, high media coverage is the primary source of media-based momentum. The media-based momentum over a

4-month holding horizon is 0.32 (t=4.01). The momentum return for the high coverage portfolio is 0.23 (t=2.79), which accounts for 72% of the media-based momentum return. In the mid-term, both high coverage momentum and low coverage reversal contribute to the media-based momentum. For example, for the 12-month holding horizon, the high coverage momentum is 0.09 (t=1.46), and the low coverage reversal is -0.10 (t=-2.10). They contribute almost equally to the return (0.20) of the media-based momentum. Alphas of high-low coverage portfolios show a similar pattern of significance.

3.2 Robustness checks

We next examine whether our results are robust to different methods of calculating residual media coverage. In our base model, we use firm size, analyst coverage, and NASDAQ dummy as independent variables to calculate residual media coverage. To see if results are sensitive to different regression models, we use the unadjusted media coverage as the benchmark and modify the regression model specification in (2) by including different independent variables.

Panel A of Table 4 reports the results. Alphas are again estimated by the GMM with Newey-West adjusted standard errors. The initial media-based momentum is the raw momentum difference between high- and low-coverage portfolios. When we use the unadjusted (raw) media coverage, alphas are significant at the 10% level. This is consistent with the literature that raw media coverage contains noise that can weaken the information signal. To see the role of different variables in refining the signal, we remove one or two explanatory variables at a time from the base regression in (2). When adjusting the raw media coverage by firm size and analyst coverage, alphas become more significant, with t-values increasing to 2.14 and 2.24 separately. The results reveal the benefit of reducing noise and increasing the precision of the media coverage signal by adjusting for the characteristic effect. When controlling for the effects of both firm size and analyst coverage, alpha (0.27) of high-low momentum portfolio returns remains significant at the 5% level.

[Insert Table 4 here]

The literature has shown that bond characteristics can affect bond returns (see Gebhardt et al., 2005a). In panel B, we investigate whether bond characteristics, such as maturity, age, rating, and issue size, may absorb some of the media coverage effects on bond momentum. To start with, we calculate the bond characteristic-adjusted return. Each month, we split the bonds into deciles based on one bond characteristic. The characteristic-adjusted return is computed as the individual bond return minus the average return of the characteristic decile portfolio to which the bond belongs. Momentum portfolios are constructed similarly to Table 3, except they are based on the characteristic-adjusted return.

As is shown in panel B of Table 4, though momentum returns vary somewhat when the return is adjusted by different characteristics, the patterns of the media coverage effect on bond momentum are in line with the baseline results. The media-based momentum appears to be robust to the bond characteristic adjustment.

3.3 Regression tests

The preceding portfolio analysis shows that momentum returns monotonically relate to residual media coverage, and the high coverage portfolio is the driver of media-based bond momentum. To substantiate this finding, we next perform regression analysis with better controls for characteristics and other effects. Table 5 reports the results of pooled regressions. The dependent variable is the forward returns from months t+1 to t+6. The explanatory variables include $r_{t-6,\,t-1}$, which is the past six-month return from month t-6 to t-1. Res_coverage $\times$ $r_{t-6,\,t-1}$ is the interaction term of past cumulative residual media coverage and past monthly return during the formation period. The coefficient of this interaction variable is of primary interest as it represents the effect of media coverage on bond momentum. Control variables include bond and firm characteristics.

[Insert Table 5 here]

The results show that the coefficient of $r_{t-6,\,t-1}$ is significantly positive across all regression specifications, confirming that the average monthly returns of bonds during the past 6 months positively correlate with the future 6-month returns. In regression models II to VI, we add the interaction variable $\text{Res\_coverage} \times r_{t-6,\,t-1}$ as an explanatory variable and control for the effects of bond characteristics, firm characteristics, and Fama-French 48 industries, respectively. Results consistently show that the coefficient of $\text{Res}_{\text{coverage}} \times r_{t-6,\,t-1}$ is significantly positive, suggesting that media coverage has a strong positive effect on bond momentum.

The literature suggests momentum spillover from stocks to corporate bonds (see, for example, Gebhardt, Hvidkjaer, and Swaminathan, 2005b; Daniel, Patrick, and Jeroen, 2017). To capture this effect, we include the momentum strength of the issuer's stock among the firm characteristics in regression models III to VI. Following the method of Hillert et al. (2014), $\text{Momentum Strength}^{\text{Stock}}$ is obtained using the monthly return of the issuer's stock. It is calculated as the exponential of the absolute difference between the stock's formation period log return and the median formation period log return of all stocks in the sample, subtracted by 1. Consistent with the literature, the coefficient of $\text{Momentum Strength}^{\text{Stock}}$ is significantly positive across the board. More importantly, the results continue to show a significant media coverage effect on bond momentum even after controlling for the momentum spillover effect from stocks to bonds.

In models III and VI, we take bond ratings into consideration. NIG is a dummy variable, which has a value of 1 if the bond is rated below BBB- and 0, otherwise. The results show that

NIG bonds have both a stronger momentum effect and a media-based momentum effect. For example, in regression V, the coefficient of $r_{t-6,\,t-1} \times NIG$ is 13.888 and significant at the 1% level (t=13.26), suggesting that the momentum effect is much stronger for NIG bonds. In model VI, $\mathrm{Res}_{\mathrm{coverage}} \times r_{t-6,\,t-1} \times NIG$ is added to capture the media-based momentum effect for NIG bonds. The significantly positive coefficient (2.506) of $\mathrm{Res}_{\mathrm{coverage}} \times r_{t-6,\,t-1} \times NIG$ at the 1% level confirms that the positive effect of media coverage on bond momentum is more pronounced for NIG bonds.

4. Economic mechanism

In this section, we conduct more tests to explore the channels through which media coverage may drive bond momentum. We show that the media coverage effect we uncover is more in line with the prediction by the theory of overconfidence, self-attribution, and security market overreaction proposed by Daniel, Hirshleifer, and Subrahmanyam (1998).

4.1 Long-term reversal

Tests on long-term reversals will help distinguish between overreaction and underreaction-explanations of momentum. If overreaction is the main driver of media-based momentum, then bonds that have high media coverage should experience a higher momentum peak in the short term and a reversal in the long term. This is because high coverage attracts more investor attention and enhances investors' overreaction in the short term, which in turn will exert more downward pressure on the return in the long term when more public information about firm fundamentals is released, and momentum gives way to reversion toward the new fundamental value. We thus follow the literature of information reaction and analyze momentum profits for up to 24 months after portfolio formation. In each month, the momentum strategies are constructed in the same way as in Table 3. The formation period is set to 6 months, and the portfolios are held for two different horizons from month t+1 to t+12, and from t+13 to t+24.

[Insert Table 6 here]

Panel A of Table 6 shows that the media-based momentum exists for the full sample when the holding period is from month t+1 to t+12. However, when we divide the sample into IG and NIG groups, we again find that only NIG bonds exhibit significant media-based momentum.[4]

Panel B of Table 6 shows the results in the long term from month t+13 to t+24. The momentum return is negative for the full sample as well as IG and NIG subsamples, with the high coverage portfolio showing a stronger reversal. These results for NIG bonds support the view of investor overreaction. As investors overreact to media news, prices are pushed beyond fundamental values, which induces short-term momentum. But in the long term, momentum turns to reversal when more public information arrives, investors adjust their expectations, and prices pull back toward fundamentals.

4.2 Tone-enhanced media-based momentum

If overreaction drives media-based momentum, media tone should reinforce this effect. If winners (losers) receive a positive (negative) media tone during the formation period, investors will be even more overconfident about their judgment and abilities. Therefore, media tone can enhance the effect of media-based momentum.

[Insert Table 7 here]

To investigate this possibility, we add media tone as an additional sorting variable. Each month, we sort sample bonds into 3x3 portfolios based on media coverage and returns in the past 6 months in the same way as baseline analysis. A difference is that when computing momentum returns, we take the media tone into consideration. In particular, we calculate two momentum

[4] In contrast, IG bonds exhibit return reversal rather than momentum, which is consistent with the finding in Gebhardt et al. (2005). However, the magnitude is much smaller.

returns to investigate the effects of media tone. The first momentum return is taken from the return of winners with a positive tone *minus* the return of losers with a negative tone, which we refer to as PWNL momentum. The second momentum return is the return of winners with a negative tone *minus* the return of losers with a positive tone, which we refer to as NWPL momentum.

Panel A of Table 7 reports the results for J/K=6/6. The results show that the high-coverage portfolio has significant PWNL momentum (0.40, t=2.45) but insignificant NWPL momentum (0.04, t=0.28). The results are similar for the media-based momentum: the 3-1 return for PWNL momentum is 0.41 (t=2.06) while it is 0.02 (t=0.12) for NWPL momentum, which is economically insignificant. Compared with the baseline results in Table 3, both the high coverage momentum and media-based momentum are much higher when there is a positive media tone (or a PWNL momentum).

Panel B of Table 7 reports the effect of media tone in the short- and mid-term run, while panel C displays the results in the long-term run. Comparing PWNL and NWPL, we can find that the media-based momentum of PWNL is significant and persistent in the short- and mid-term run and turns to a reversal in the long run. However, the effect of media coverage on momentum is always insignificant for NWPL, either in the short- and mid-term or in the long-term. Compared with the baseline results, where the media tone effect is ignored, PWNL shows a higher momentum in the short- and mid-term run and turns to a deeper reversal in the long-term. For example, in Panel C of Table 3, the media-based momentum reaches 0.32 (t=4.01) at K=4. With the enhancement of media tone, the media-based momentum of PWNL is 0.48 (t=2.64) during the same holding period, which is much higher than the baseline result in Table 3. Panel B of Table 7 indicates that when the portfolio is held from t+13 to t+24, the baseline 3-1 return spread has a reversal of -0.41 (t=-4.91) for the full sample. In contrast, Panel C of Table 7 shows that PWNL has a much larger reversal of -0.71 (t=-3.39) for the full sample under the same holding condition. The results strongly suggest that media tone enhances the media-based momentum effect.

4.3 Overconfidence and self-attribution bias

Daniel et al. (1998) show that an informed but overconfident investor will overreact to his private signal. If subsequent public information confirms this signal, it will trigger further overreaction due to self-attribution bias and result in price momentum. Li and Galvani (2021) suggest that informed trading lies at the core of the momentum effect for corporate bonds. By splitting the firm-level bond cross-section into top (non-top) bonds characterized by higher (lower) volumes of institution-sized trades, they find that top bonds exhibit more informed trading and transmit information faster than non-top bonds. Also, fast news spreading generates short-lived momentum in top bonds, whereas momentum in non-top bonds is drawn out (long-lived) due to slow information diffusion. Built on these results, we use informed trading to proxy for private signals in the corporate bond market and consider media coverage as public information. For bonds with informed trading, high media coverage that confirms the private signal can reinforce momentum triggered by informed trading. In the long run, bonds with informed trading and high media coverage should have a deeper reversal than those without informed trading to compensate for the overreaction effects.

To see if this is the case, we perform bivariate portfolio sorts. We identify firm-level top (non-top) bonds following the method of Li and Galvani (2021). In each month and for each firm, the bond with the highest monthly trading volume of institution-sized trade is identified as the top bond of the firm. Other bonds issued by the same firm are classified as non-top bonds.

Institutional trades are trades with a par value ≥ \$500,000. When constructing the top bond momentum strategy, we identify bonds that have been top bonds over the past 6 months. Top bonds are then sorted into terciles by the cumulative residual media coverage during the formation period. Finally, bonds are further sorted into losers, medium, and winners within each coverage group based on past six-month returns. The momentum portfolio for non-top bonds is constructed analogously.

[Insert Table 8 here]

The results are reported in Table 8. Panel A compares the momentum effects of top and non-top bonds when J/K=6/6. The two groups reveal totally different results: media-based momentum for Top bonds is 0.54 and significant at 1% level (t=4.42), which is even higher than the result in the baseline framework. In contrast, Non-top bonds show an insignificant media-based momentum of 0.05 (t=0.64).

As we are interested in the momentum trends of top/non-top bonds in the short- and long-term, we split the momentum returns into two parts: holding the portfolios from t+1 to t+K (K=4, 8, and 12, Panel B) and from t+13 to t+K (K=16, 20, and 24, Panel C). The results confirm our hypothesis that media coverage reinforces the effect of informed trading. Panel B of Table 8 shows that top bonds have more significant and persistent high coverage and media-based momentum in the short and mid-term run than non-top bonds. One reason is that top bonds contain more informed trading. High media coverage disseminates public information, confirming investors' private information, leading to higher and further momentum. However, in the long run, as investors adjust their beliefs, higher momentum induced by high media coverage should turn to a more sharp reversal by behavioral theory. Results in panel C show that this is indeed the case. While both top and non-top bonds have a reversal in the long run, the magnitude and significance of reversal for top bonds are greater than for non-top bonds. For example, when the portfolio is held from t+13 to t+16, the high coverage portfolio of top bonds gets a reversal return of -0.29 (t=-2.81), stronger than the return reversal of non-top bonds (-0.26, t=-3.28). Return spread 3-1 for top bonds is -0.27 (t=-2.28), which is also lower (stronger reversal) than that of non-top bonds (-0.21,t=-2.55). This evidence suggests that a greater reversal of top bonds in the long term is accompanied by investor overreaction and biased self-attribution in the short term.

5. Additional tests

5.1 Bond rating and media-based momentum

Prior research shows that ratings play an important role in asset pricing anomalies, which include momentum (Avramov et al., 2013). Also, Jostova et al. (2013) find that momentum concentrates in NIG bonds. In light of the literature, we examine the effects of ratings on short-term momentum. Unlike Section 4.1, which focuses on the issue of momentum versus reversal, in this section, we focus on the short-term momentum with six-month holdings to provide a more precise comparison with the findings in the literature. In each month, bonds with ratings are sorted into 2 groups: bonds rated at or above BBB- are classified as Investment Grade (IG), while those rated below BBB- are classified as Non-Investment Grade (NIG). Within each rating group, we first sort all bonds into terciles based on the cumulative residual media coverage during the past six months. Then, within each coverage tercile portfolio, bonds are further sorted into three groups based on average monthly returns in the past six months, with winners (losers) ranking above the 70th percentile (below the 30th percentile). The holding period is set to six months.

Panel A in Table 9 shows the average monthly return for IG and NIG bonds are 0.60% and

1.62%, respectively. Bonds with high credit risk have high returns. The average monthly residual media coverage is 2.98 for IG bonds and 2.16 for NIG bonds. Panel B of Table 9 shows that IG bonds have no significant momentum for each media coverage portfolio, and the media-based momentum is also insignificant. In sharp contrast, for NIG bonds, high coverage portfolio has a significant momentum return of 0.57 (t=2.33). Importantly, the media-based momentum is significant, with an average monthly momentum return of 0.73%. The results show that media-based momentum is more pronounced for NIG bonds.

[Insert Table 9 here]

Gebhardt et al. (2005) find no evidence of momentum in investment-grade bonds. Jostova et al. (2013) are the first to document the existence of persistent momentum in the high-yield bond (NIG) segment of the corporate bond market. They find that the NIG momentum cannot be explained by interest rate risk, credit risk, systematic or bond-specific risk, microstructure noise, trading frictions, and bond market opaqueness. However, the reason why momentum only exists in NIG bonds is unclear in their paper. Our finding of the media-based momentum concentrating on NIG bonds and little evidence in IG bonds provides an explanation for the findings in the momentum literature in the corporate bond market (Gebhardt et al., 2005; Jostova et al., 2013). It has been documented that information asymmetry is higher for NIG bonds (see Han and Zhou, 2013). The literature also suggests that the effect of media coverage is stronger for firms with high information asymmetry (see Gao et al., 2020). Li and Galvani (2021) find that the information-based momentum is stronger for NIG bonds with high information asymmetry. Taken together, our finding that the media-based momentum is stronger for NIG bonds provides a novel explanation for the pattern of momentum in the corporate bond market. Our results suggest that media coverage disseminates information that reduces information asymmetry and drives the momentum in the corporate bond market, and this information effect is stronger for NIG bonds which have higher information asymmetry, leading to more pronounced momentum for these bonds. Our results compliment the finding of Li and Galvani (2021), which suggest that information trading generates momentum in NIG bonds. While our study and theirs both emphasize the importance of information in propelling momentum, we discover that media coverage is a novel source of information driving the momentum in NIG bonds.

We further investigate the economic channels of media-based momentum for NIG bonds. In Table 10, only NIG bonds are included in the sample for the channel analysis. The pooled OLS regression results in Panel A show that both raw momentum and media-based momentum are significant for NIG bonds, as the coefficients of $r_{t-6,t-1}$ and Res_coverage×$r_{t-6,t-1}$ stay positive at the 1% significance level across all regressions. Panel B shows the regression results after controlling for different channels (Δ). For brevity, we only report the parameter estimates for the variables of primary interest (i.e., past returns, media coverage, and interactions with channel measures). As indicated, the coefficients of interaction terms associated with both the information asymmetry channel and liquidity channel are all positive and significant at the 1% level, suggesting that the media-based momentum effect is stronger for bonds with greater information asymmetry and higher liquidity. The results are consistent with our conclusion that overconfident investors tend to overreact to information signals (Daniel et al., 1998). Risker (NIG) bonds tend to have higher information asymmetry. High media coverage provides more information to reduce information asymmetry and hence generates higher momentum. Solomon, Soltes, and Sosyura (2014) find that investors' overreaction is more pronounced when securities catch more public attention. NIG bonds with higher liquidity attract more attention from investors as they have high trading activity. The literature has also suggested the effect of media coverage is greater for bonds issued by firms with higher information asymmetry. Together, these factors explain the effect of media coverage on momentum can work through the information and liquidity channels.

[Insert Table 10 here]

5.2 Subsample analysis: market states, media effect, and momentum

The literature suggests that momentum returns in the equity and corporate bond market are state-dependent (Cooper, Gutierrez, and Hameed, 2004; Li and Galvani, 2018). Li and Galvani (2018) find that momentum gains exclusively follow the market upturn, whereas down markets herald momentum losses. The predictive power of the market state can be attributed to its influence on investors' overconfidence, which originates the momentum effect. In this section, we investigate the effect of media coverage on momentum in different states.

Similar to Li and Galvani (2018), we define a month as being in the Up (Down) market state if the average monthly market return over t-12 to t-1 is above or equal to (below) the average market return over the period of January 2000 to t-1. The earliest month in this analysis is January 2001, which is 12 months away from the starting month of our sample period. Among the entire 240 months, there are 74 Up and 166 Down months. For each month, we construct a momentum strategy based on the residual media coverage and past returns using the same method as in our baseline analysis. The holding period is set to six months.

[Insert Table 11 here]

The results are consistent with our prediction. Panel A of Table 11 shows that the high coverage momentum for the Up market is 0.55 and significant at the 1% level (t=4.02). By contrast, for the Down market, the momentum is insignificant. The media-based momentum exhibits a similar pattern: The Up market has a significant return of 0.46 (t=3.11), while the

Down market has only a barely significant return of 0.16 (t=1.68). The results suggest that the effect of media coverage on momentum is more pronounced in the Up market.

Panel B of Table 11 shows that in the Up market, both the high coverage and media-based momentum are more persistent. For example, in the Up market, the high coverage portfolio still has significant momentum of 0.53 (t=4.73) at K=12.

5.3 Firm-level analysis

The number of bonds issued by firms exhibits a large cross-sectional dispersion. Bonds issued by the same company are exposed to the same fundamentals, information flows, and firm-specific risk and tend to co-move with each other. This raises a potential concern that our empirical results could be mechanically influenced by multiple bonds issued by the same firm. To address this concern, we redo our tests based on a sample constructed at the firm level. Each month, we only keep one bond, which is the largest issue size for each issuer. We keep the most newly issued if there are multiple bonds with the same issue size. Using this firm sample, we construct momentum strategies in the same way as in our baseline analysis.

[Insert Table 12 here]

Table 12 shows that the effect of media coverage on momentum continues to hold at the firm level. There are several differences between the results at the bond level and firm level. First, at the firm level, the media-based momentum is dominated by the positive media-based return of winners, but at the bond level, it's driven by both the positive media-based return of winners and the negative media-based return of losers. For example, at the firm level, the media-based return is 0.39 (t=4.99) for winners and -0.00 (t=-0.04) for losers. The media-based momentum is 0.39 (t=3.28).

In comparison, at the bond level in Table 3, the media-based momentum is 0.28. The media-based returns for winners and losers are 0.10 (t=1.84) and -0.18 (t=-3.41), respectively. Both have a sizable contribution to the media-based momentum. Second, the high-coverage momentum is more persistent at the firm level. The momentum return for the high-coverage portfolio is still significant at the firm level (0.21, t=2.44) when K=12, while it is insignificant at the bond level over the same holding period. Such differences could be caused by the sample we choose, that is, at the firm-level, only the bond with the largest issue size is kept. As bonds with larger issue size are more liquid and more in the spotlight of the market, investors' overreaction would be stronger. Therefore, the media-based momentum effect could be more pronounced and persistent at the firm level. Notwithstanding this difference, the results show that the momentum effect is robust to the data across firm and bond levels.

5.4 Uncertainty and media-based momentum

Economic uncertainty can influence market mispricing by affecting investors' behaviors. For example, Hillert et al. (2014) find that investor overconfidence is positively related to the degree of uncertainty about a given stock. They find that the overreaction-driven momentum and reversal effects are particularly pronounced for stocks with higher uncertainty as they are hard to value. Birru and Young (2022) suggest that under higher uncertainty, investors' valuations are more subjective, which leads to relatively larger future corrections of sentiment-induced mispricing. Andrei, Friedman, and Ozel (2023) develop a multi-firm equilibrium model, which predicts that increased uncertainty attracts more investor attention to firm-level information and amplifies stock price reactions to earnings announcements. These findings lead to the possibility that the effect of media coverage on bond momentum varies with the degree of uncertainty. If media coverage positively affects bond momentum and investors' overreaction is the underlying driver, the media-based momentum in the corporate bond market should be more pronounced when there is higher uncertainty.

To test if the above hypothesis holds, we employ proxies for uncertainty at the aggregate and firm levels, similar to Birru and Young (2022). At the aggregate level, we use the Chicago Board of Exchange (CBOE) risk-neutral expected stock market volatility measure over the next 30 days for the S&P 500 (VIX). To measure firm-level uncertainty, we use two indicators. The first one is IVOL, which is calculated using the volatility of daily return residuals of the issuer's stock relative to the Fama and French (1993) three-factor model in the past six months. The second one is Turnover, the natural log of the average daily turnover of issuers' stock over the past six months. Daily turnover is calculated as share volume/shares outstanding. Following the method of Anderson and Dyl (2005) for stocks listed on NASDAQ, daily turnover after 01/01/1997 is calculated as 0.62*share volume/shares outstanding. In each month t, we first double-sort bonds into 3×3 groups on past cumulative media coverage and bond return, as in Table 3. Then, we sort bonds independently into terciles at the time-series level on VIX, and at the cross-sectional level on IVOL or Turnover. Low/high is the group of bonds with uncertainty ranking in the bottom/top tercile.

[Insert Table 13 here]

The results in Table 13 support our hypothesis. In Panel A of Table 13, when both formation and holding periods are set to 6 months, the media-based momentum is positively correlated with the uncertainty level, and the results are robust to the use of a multi-factor model. For example, when VIX is used to proxy for uncertainty at the aggregate level, the media-based momentum is 0.59 and significant at the 1% level (t=3.59) when uncertainty is high. The return spread decreases to 0.20 and is only significant at the 10% level (t=1.83) when the level of uncertainty is medium, and finally becomes insignificant under low uncertainty. For IVOL and Turnover, the results are comparable and exhibit a similar pattern over different holding horizons (see Panel B).

5.5 Attention and media-based momentum

Attention is a scarce cognitive resource (Kahneman, 1973). The inevitability of limited attention in relation to the vast amount of information available makes attention an important factor in agents' learning and decision-making processes (Hou, Peng, and Xiong, 2009). The literature, however, has produced conflicting evidence on the role of investors' attention on asset pricing. For example, Da, Engelberg, and Gao (2011) argue that attention can cause investors' overreaction, which predicts short-term price increases and long-term reversal. On the other hand, Andrei, Friedman, and Ozel (2023) argue that attention leads to information acquisition, which produces more acute price reactions to earnings announcements. Some researchers have suggested that media coverage is closely related to investors' attention. For example, Barber and Odean (2008) contend that news is a primary mechanism for catching investors' attention, while Yuan (2015) suggests that the Dow index and front-page articles can be a good proxy for market-wide attention. Given that the majority of investors in the corporate bond market are institutional investors, and inattention is less of a problem for institutional investors than for individuals (Barber and Odean, 2008), the role of attention in media-based bond momentum remains unclear.

To shed light on the role of investor attention, we add attention as another sorting dimension to test its effect on media-based momentum. Following Barber and Odean (2008), we use two proxies for attention: abnormal trading volume and abnormal returns. In each month t, abnormal trading volume is calculated as the ratio of the bond's average monthly trading volume during the formation period to its average monthly trading volume over the previous year (i.e., 12 months). Abnormal bond return is calculated analogously. We first double-sort bonds into 3×3 groups on past cumulative media coverage and bond returns, and within each group, we further independently sort bonds into terciles on abnormal trading volume (bond return). Low and High is the group of bonds with abnormal trading volume or abnormal bond return ranking below the lower tercile and above the upper tercile, and Medium is the group of bonds ranking between low and high cutoffs.

Panel A of Table 14 shows that media coverage is moderately positively correlated with investor attention. The correlation between media coverage and attention is 0.001 when abnormal trading volume is the proxy and 0.011 when abnormal bond return is the proxy. In Panel B, the low attention group has a significant media-based momentum of 0.35 (t=3.15) when the abnormal trading volume is used as the proxy for attention and 0.71 (t=3.55) when the abnormal bond return is used. In contrast, the media-based momentum is insignificant for both medium and high-attention groups, regardless of whether abnormal trading volume or abnormal bond return is used as the proxy for attention.

Panel C shows that when the holding period is set to different lengths, both the magnitude and significance of media-based momentum are highest for low-attention and lowest for high-attention groups. The results show that the effect of media coverage is stronger for bonds with lower investor attention. One possible reason is that the information effect of media news is greater for investors with limited attention.

[Insert Table 14 here]

5.6 Media types and momentum

RavenPack classifies news articles into three types: news flash, full article, and press release. The news flash refers to news articles composed of a headline and no body text. The full article refers to news articles composed of both a headline and one or more paragraphs of mostly textual material. The press release refers to corporate announcements originated by an entity and distributed via a news provider.

Different media types can affect capital markets differently in a non-mutually exclusive way. First, some news only disseminates firm-generated information broadly, whereas others can create new information for market participants (Drake, Guest, and Twedt, 2014). Second, the source of information matters. Empirical evidence suggests that investors consider business press articles a more credible source of information than analyst reports or firm disclosures (Drake et al., 2014; Kothari, Li, and Short, 2009). In our preceding analysis, media coverage is calculated using only full articles. Twedt (2016) uses news flash to isolate the information dissemination role of newswire from that of information creation of full articles. Similarly, in this paper, we consider full articles as a media type generated from the business press, creating new information instead of merely disseminating information. Both news flash and press releases are media types that only disseminate information without creating much new information. To see if different media types produce different momentum effects, we use the number of news flashes or press releases to calculate the residual media coverage.

[Insert Table 15 here]

Panel A of Table 15 shows that the average bond-month residual media coverage for news flash and press releases are 4.49 and 4.70, respectively, both higher than 2.71 for full articles. Panel B shows that media-based momentum is significant for news flash up to K=12 and turns into reversal when K=24. However, the media-based momentum for press releases is barely significant even at K=4 (0.16, t=1.82) and becomes insignificant at K=6. For high-coverage momentum, though it is significant up to K=6 for both news flash and press release, the magnitude for news flash is higher than for press release. However, the momentum profit for news flash and press releases is much lower and less persistent than in the baseline results using the full article. This is not surprising since full article news often contains new information and originates from business press instead of firms. Though news flash creates little new information, it reflects business media's choosing, filtering, and concentration process. In contrast, the press release is solely the broadcasting channel for news originated by firms. This explains why full articles have the strongest media coverage effect while press releases have the weakest media coverage effect.

6. Conclusion

Momentum has been a long-lasting anomaly in the stock market, and the sources of momentum are still unclear. Past studies focus on the stock momentum, while the literature on bond momentum is relatively small. Our paper fills this gap by studying momentum in the corporate bond market from the media perspective.

Our results show that the momentum for bonds with high media coverage is significant, whereas it is insignificant for bonds with low coverage. This pattern holds more strongly for NIG bonds. The momentum effect we uncover is robust for controlling risk factors and different residual media coverage calculations.

We find that investor overreaction to information is a plausible explanation for bond momentum. The bond price behavior in our sample is consistent with the prediction of the overreaction model of Daniel, Hirshleifer, and Subrahmanyam (1998). We conduct tests for different investment horizons, the effect of media tone, and splitting bond trades into informed and uninformed groups. The results suggest that overreaction to information is a plausible reason for the media-based momentum in the corporate bond market.

Finally, we provide an explanation for the concentration of momentum in NIG bonds documented in the literature (see Jostova et al., 2013). The literature suggests that the effect of media coverage on bond prices is greater for bonds with high information asymmetry (see Gao et al., 2020) and information asymmetry is higher for NIG bonds (see Han and Zhou, 2013). Taken together, these findings imply that the effect of media coverage on momentum will be stronger for NIG bonds. Consistent with this inference, we find that the effect of media coverage is greater for lower-grade bonds, and the media-based momentum concentrates on NIG bonds. Thus, the concentration of momentum in NIG bonds is explained by the concentration of the media coverage effect on the momentum in these bonds.

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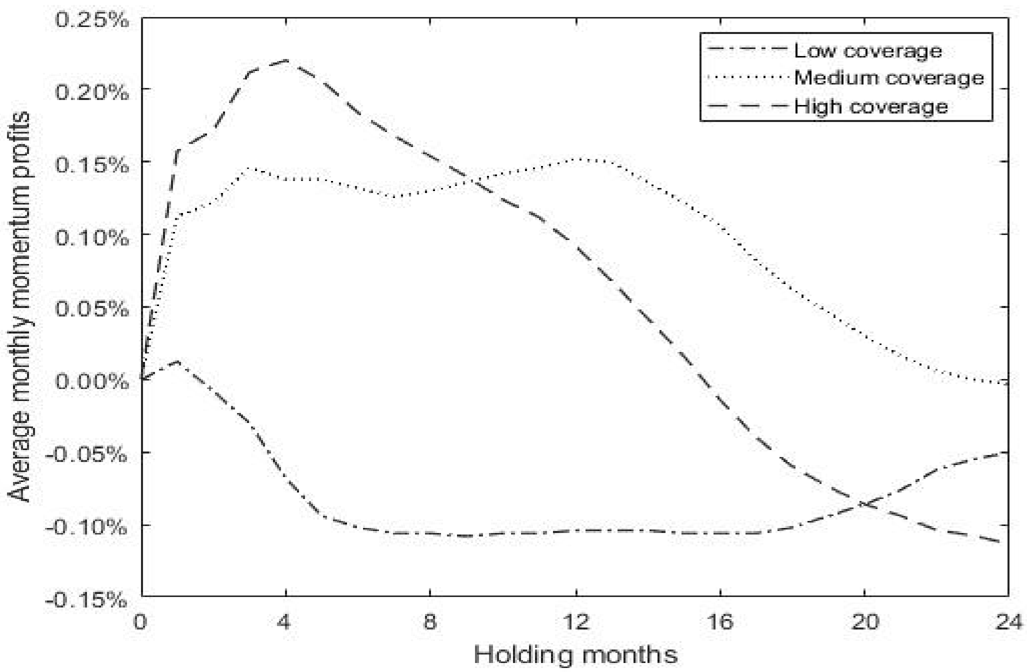

Figure 1. Buy-and-hold momentum profits for bonds with different residual media coverage. This figure shows the average monthly buy-and-hold returns for a winner-minus-loser long-short strategy for bonds with different residual media coverage levels. Residual media coverage is calculated using month-to-month rolling OLS regression with ln(1+no.articles) as the dependent variable and firm size, analyst coverage, and NASDAQ dummy as independent variables. In each month t, residual media coverage portfolios are formed based on the cumulative residual media coverage during the past 6 months. Bonds without any media coverage during the formation period are excluded. Within each coverage portfolio, bonds are further sorted into 3 groups based on average monthly returns during the past 6 months, with winners (losers) ranking above the 70th quintile (below the 30th quintile). The portfolios are held from t+1 to t+24 months, respectively.

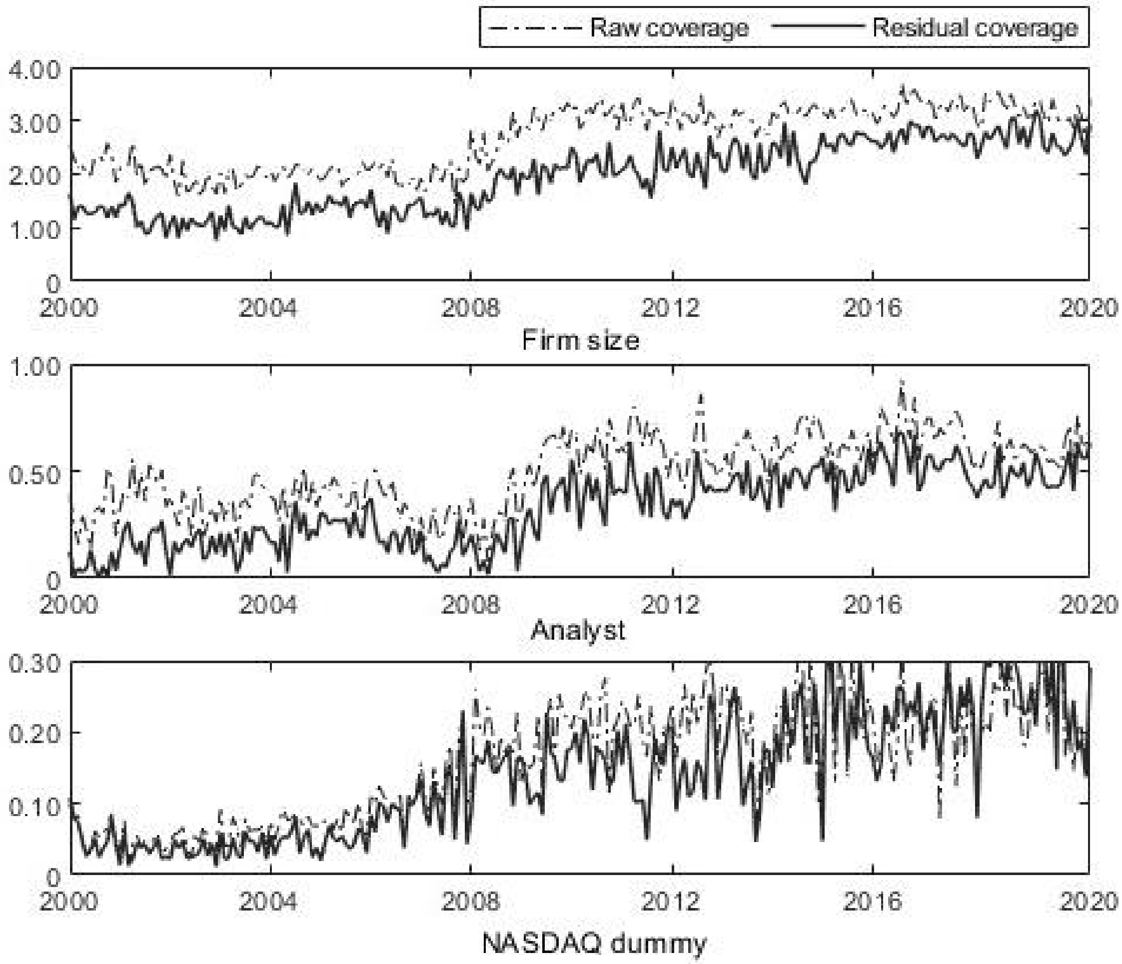

Figure 2. Monthly distribution of firm characteristic differences by raw and residual media coverage. This figure displays the firm characteristic differences between high and low media coverage groups based on raw and residual media coverage. Firm size is defined as ln(1+market capitalization), and market capitalization is in millions of dollars. Analyst coverage is calculated as ln(1+no. Earnings estimates). NASDAQ dummy is a dummy variable that equals 1 (0) if the firm is (not) listed on NASDAQ. Each month, we first calculate the average firm characteristics for low- and high-media coverage groups. Then, the absolute values of differences between high- and low-coverage groups are taken as the observations in this figure.

Table 1. Determinants of media coverage

This table reports the Fama-Macbeth (1973) regression results to explain media coverage. The sample period is 2000.01-2020.12. The dependent variable is media coverage, defined as ln(1+no. news). Firm size is defined as ln(1+market capitalization), and market capitalization is in millions of dollars. Analyst coverage is calculated as ln(1+no. Earnings estimates). NASDAQ dummy is a dummy variable that equals 1 (0) if the firm is (not) listed on NASDAQ. The *t*-statistics are in parentheses and are adjusted using Newey and West (1987) with a lag of five months. The signs *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Size (I)	Analyst (II)	NASDAQ (III)	Baseline (IV)
Firm size	0.174***			0.195***
	(57.82)			(34.17)
Analyst coverage		0.441***		0.070***
		(65.92)		(10.00)
NASDAQ dummy			-0.244***	0.072***
			(-25.09)	(11.51)
Constant	0.281***	0.583***	1.576***	-0.073***
	(12.27)	(22.87)	(86.89)	(-2.66)
Observations	252	252	252	252
Adjusted R^2	0.252	0.159	0.032	0.251

Table 2. Summary Statistics

The table reports summary statistics of the sample. All the data are monthly data. Panel A shows the descriptive statistics of the main variables. Raw media coverage is the total number of articles about a firm in each month. Raw media tone is calculated as (CSS-50)/50, and CSS (composite sentiment score) is extracted from RavenPack. Residual media coverage/tone is calculated using the formula (2) method. The rating ranges from 1 for AAA bonds to 22 for D bonds. Maturity is the natural logarithm of 1 plus the years to maturity. Issue size is in billion dollars and takes the natural logarithm. Age is the natural logarithm of 1 plus the number of years that have elapsed since the year of the company's IPO. Coupon is the bond annual coupon rate. Panel B displays the summary statistics by raw/residual media coverage. In each month, bonds are sorted into tercile based on cumulative raw/residual media coverage during the past 6 months. The signs *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Descriptive statistics

	Mean	Median	Min	Max	Std	P25	P75
Raw Media Coverage	44.51	10.00	1.00	990.00	99.71	4.00	34.00
Raw Media Tone	0.00	0.00	-0.92	1.00	0.05	-0.02	0.02
Residual Media Coverage	0.50	0.28	-2.33	4.62	1.23	-0.38	1.21
Residual Media Tone	-0.03	-0.02	-0.93	0.97	0.06	-0.05	0.00
Monthly Return (%)	0.72	0.39	-14.22	25.93	4.20	-0.49	1.65
Rating	8.10	7.00	1.00	22.00	3.97	5.00	10.00
Maturity	2.57	2.40	0.69	4.62	0.68	2.08	3.43
Issue size	5.90	5.70	-6.91	8.52	1.08	5.30	6.62
Age	1.83	1.90	0.15	3.42	0.81	1.20	2.44
Coupon	6.00	6.63	0.13	18.00	2.09	4.63	7.38
Firm Size	9.89	9.90	1.74	14.35	1.66	8.83	11.11
Analyst	2.80	2.89	1.10	3.93	0.49	2.56	3.14
NASDAQ dummy	0.11	0.00	0.00	1.00	0.31	0.00	0.00

Panel B. Summary statistics by raw/residual media coverage

Media	Firm size	Analyst	NASDAQ	Rating	Maturity	Issue size	Age	Coupon
Tercile sorts based on raw media coverage								
Low	8.67	2.55	0.18	9.46	15.00	5.43	1.83	6.05
Medium	9.72	2.82	0.11	8.15	15.54	5.82	1.84	6.01
High	11.23	3.03	0.05	7.01	16.20	6.45	1.81	5.95
High-Low	2.68***	0.50***	-0.16***	-2.47***	1.56***	1.07***	-0.01***	-0.09***
(t-stat)	(71.08)	(45.71)	(-29.73)	(-26.15)	(10.08)	(67.26)	(-3.68)	(-4.32)
Tercile sorts based on residual media coverage								
Low	9.14	2.67	0.16	8.68	15.86	5.48	1.89	6.13
Medium	9.70	2.78	0.13	8.29	16.25	5.72	1.89	6.07
High	10.90	2.96	0.04	7.36	16.59	6.39	1.83	6.05
High-Low	1.93***	0.32***	-0.14***	-1.39***	0.88***	0.97***	-0.06***	-0.10***
(t-stat)	(46.85)	(28.20)	(-24.78)	(-17.01)	(6.21)	(54.72)	(-5.86)	(-4.36)

Table 3. Residual media coverage and momentum returns

This table presents the effects of residual media coverage on momentum returns. In panel A, both the formation and holding periods are set to 6 months and skip one month in between. Residual media coverage portfolios are formed based on the cumulative residual media coverage during the past 6 months. Bonds without any media coverage during the formation period are excluded. Within each coverage portfolio, bonds are further sorted into 3 portfolios based on average monthly returns during the past 6 months, with winners (losers) ranking above the 70^{th} quintile (below the 30^{th} quintile). Coverage portfolios 1, 2, and 3 represent the lowest, medium, and highest coverage portfolios, respectively. Return spread 3-1 is the return difference between high and low coverage groups. Column Loser and Winner display the average monthly returns for losers and winners during the holding period. Column W-L displays the return difference between winners and losers. Panel B shows the estimated alphas (with Newey-West adjusted t-statistics in parentheses) using GMM with different factor models. The dependent variable is media-based momentum return, or the momentum return difference between high and low coverage groups. Factors included in the models are:

(1) mTERM
(2) mDEF
(3) mDEF, mTERM
(4) MKT,SMB,HML
(5) MKT,SMB,HML,MOM
(6) MKT, SMB, HML, mDEF, mTERM
(7) MKT, SMB, HML, ΔDEF, ΔTERM

where MKT, SMB, HML are FF3 factors of Fama and French (1993); the default spread (DEF) is the difference between the monthly returns of long-term investment-grade bonds and long-term government bonds; the term spread (TERM) is the difference between the monthly return of the long-term government bond and the one-month T-bill rate; $\Delta TERM_t=(TERM_t-TERM_{t-1})$, $\Delta DEFt=(DEF_t-DEF_{t-1})$, $mTERM_t=\Delta TERM_t/(1+TERM_{t-1})$, $mDEF_t=\Delta DEF_t/(1+DEF_{t-1})$, which are calculated following Jostova et al. (2013). In panel C, the holding periods are set to 4, 8, and 12 months respectively. Alpha is the intercept of media-based momentum regressed by factors included in model (7). The *t*-statistics are in parentheses. The signs *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Baseline results (J/K=6/6)

	Loser (L)	Winner (W)	W-L	t-stat
Coverage portfolio 1	0.89	0.79	-0.10	(-1.65)
Coverage portfolio 2	0.86	1.00	0.13*	(1.76)
Coverage portfolio 3	0.72	0.89	0.18**	(2.26)
Return spread 3-1	-0.18***	0.10*	0.28***	
t-stat	(-3.41)	(1.84)	(3.59)	

Panel B. Alphas of multi-factor models for media-based momentum (J/K=6/6)

Factor models	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Alpha	0.280**	0.294**	0.294**	0.284**	0.277**	0.294**	0.281**
t-stat	(2.30)	(2.36)	(2.36)	(2.26)	(2.20)	(2.29)	(2.25)

Panel C. Different holding period (J=6)

	K=4	K=8	K=12
Coverage portfolio 1	-0.09	-0.10*	-0.10**
	(-1.34)	(-1.88)	(-2.10)
Coverage portfolio 3	0.23***	0.14*	0.09
	(2.79)	(1.96)	(1.46)
Return spread 3-1	0.32***	0.24***	0.20***
	(4.01)	(3.48)	(3.06)
Alpha	0.33**	0.27*	0.23*
	(2.78)	(2.23)	(1.92)

Table 4. Robustness checks

This table shows the robustness checks for media-based momentum. For brevity, only the multi-factor model (7) in Table 3 is used to calculate Alpha. In panel A, residual media coverage is calculated using methods different from the baseline in formula (2). Different explanatory variables are included in the regression model to get residual media coverage. In Panel B, each month, characteristic-adjusted returns are computed by subtracting from individual monthly bond returns the average monthly return of the characteristic decile to which the bond belongs. Then, portfolios are constructed in the same way as Table 3. The *t*-statistics are in parentheses. The signs *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Different empirical designs of residual media coverage

	Raw coverage	Size	Analyst	Size+Analyst
Coverage portfolio 1	0.02	-0.12*	-0.08	-0.08
	(0.21)	(-1.88)	(-1.15)	(-1.29)
Coverage portfolio 3	0.42***	0.21**	0.21**	0.22***
	(5.17)	(2.60)	(2.59)	(2.75)
Return spread 3-1	0.41***	0.34***	0.29***	0.30***
	(4.93)	(4.17)	(3.61)	(3.85)
Alpha	0.25*	0.29**	0.32**	0.27**
	(1.65)	(2.14)	(2.24)	(1.98)

Panel B. Momentum profits based on characteristic-adjusted returns

	Maturity-adjusted	Age-adjusted	Rating-adjusted	Issue size-adjusted
Coverage portfolio 1	-0.04	-0.02	0.00	-0.01
	(-0.67)	(-0.42)	(0.08)	(-0.23)
Coverage portfolio 3	0.23***	0.24***	0.21***	0.23***
	(3.08)	(3.14)	(3.54)	(3.03)
Return spread 3-1	0.27***	0.26***	0.20***	0.24***
	(3.71)	(3.59)	(3.00)	(3.24)
Alpha	0.27***	0.26**	0.21**	0.24*
	(2.23)	(2.13)	(2.04)	(1.95)

Table 5. Media coverage and bond momentum

The table reports the pooled OLS regression results. The dependent variable is the forward average monthly return of each bond from t+1 to t+6. Independent variable $r_{t-6,t-1}$ is the average monthly return from t-6 to t-1. NIG is a dummy variable, which indicates 1 if the bond is rated below BBB- and 0 if not. Momentum strength^{Stock} is obtained using the monthly return of issuer's stock. It is calculated as exp(absolute difference between stock's formation period log return and the median formation period log return of all stocks in the sample)-1. The *t*-statistics are in parentheses. The signs *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Variable / Models	I	II	III	IV	V	VI
$r_{t-6,t-1}$	3.253***	1.177***	9.070***	8.885***	2.352***	4.049***
	(9.14)	(3.01)	(15.29)	(14.58)	(3.01)	(5.11)
Res_coverage × $r_{t-6,t-1}$		0.849***	0.664***	0.413***	0.428***	-0.330***
		(12.66)	(7.60)	(3.94)	(4.10)	(-2.70)
Age			0.122***	0.073***	0.086***	0.091***
			(4.71)	(2.66)	(3.16)	(3.34)
Rating			0.044***	0.022***	-0.000	-0.001
			(12.40)	(4.58)	(-0.06)	(-0.20)
Res_tone			0.776***	0.739***	0.767***	0.729***
			(3.79)	(3.62)	(3.77)	(3.60)
Maturity			0.006***	0.008***	0.010***	0.010***
			(6.59)	(8.40)	(9.82)	(9.77)
Momentum strength^{Stock}			0.001***	0.001***	0.001***	0.001***
			(4.87)	(4.91)	(4.91)	(4.74)
Book to market				0.124***	0.161***	0.202***
				(4.30)	(5.59)	(6.98)
Firm size				-0.038***	-0.050***	-0.039***
				(-3.12)	(-4.11)	(-3.23)
Analyst				-0.125***	-0.095***	-0.135***
				(-3.97)	(-3.03)	(-4.28)
$r_{t-6,t-1}$ × *NIG*					13.888***	8.644***
					(13.26)	(7.61)
Res_coverage × $r_{t-6,t-1}$ × *NIG*						2.506***
						(11.74)
R^2	0.011	0.013	0.034	0.056	0.063	0.069
Industry dummy	YES	YES	YES	YES	YES	YES
Month fixed effect	YES	YES	YES	YES	YES	YES

Table 6. Short-term momentum and long-term reversal

This table displays the momentum returns for the full sample, NIG bonds, and IG bonds over different holding periods. In each month t, the momentum strategies are constructed similarly to Table 3. The portfolios are held from month t+1 to t+12 (panel A), and from t+13 to t+24 (panel B). The *t*-statistics are in parentheses. The signs *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Momentum effect in t+1 to t+12 (J=6)

	Full sample			NIG bonds			IG bonds		
Media coverage	Loser (L)	Winner (W)	W-L	Loser (L)	Winner (W)	W-L	Loser (L)	Winner (W)	W-L
Coverage portfolio 1	0.90	0.79	-0.10**	1.21	1.07	-0.08	0.70	0.76	0.06
			(-2.10)			(-0.62)			(1.59)
Coverage portfolio 3	0.80	0.90	0.09	1.55	1.88	0.38*	0.62	0.57	-0.05
			(1.46)			(1.92)			(-1.24)
Return spread 3-1	-0.09**	0.10**	0.17***	0.31*	0.90***	0.46**	-0.08**	-0.19***	-0.12***
t-stat	(-2.28)	(2.23)	(4.34)	(1.69)	(4.67)	(1.98)	(-2.09)	(-5.88)	(-2.71)

Panel B. Momentum effect in t+13 to t+24 (J=6)

	Full sample			NIG bonds			IG bonds		
Media coverage	Loser (L)	Winner (W)	W-L	Loser (L)	Winner (W)	W-L	Loser (L)	Winner (W)	W-L
Coverage portfolio 1	1.10	1.03	-0.07	1.14	1.10	-0.04	0.90	0.86	-0.04
			(-1.11)			(-0.29)			(-0.59)
Coverage portfolio 3	1.39	0.91	-0.48***	2.75	2.01	-0.73***	1.13	0.63	-0.50***
			(-5.74)			(-2.92)			(-7.01)
Return spread 3-1	0.29***	-0.12**	-0.41***	1.57***	0.92***	-0.67**	0.23***	-0.24***	-0.46***
t-stat	(4.46)	(-2.33)	(-4.91)	(5.52)	(5.21)	(-2.16)	(3.69)	(-5.36)	(-6.35)

Table 7. Tone-enhanced momentum returns

This table presents the results of tone-enhanced momentum returns. Media tone is calculated by (CSS-50)/50, which ranges from -1 to 1. Media tone>0 means the news has a positive tone; media tone<0 means the news has a negative tone; media tone=0 means the news is neutral. PWNL is the return of winners with a positive tone minus the return of losers with a negative tone. NWPL is the return of winners with a negative tone minus the return of losers with a positive tone. The *t*-statistics are in parentheses. The signs *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Tone-enhanced momentum returns (J/K=6/6)

	PWNL				NWPL			
Media coverage	Loser (L)	Winner (W)	W-L	Alpha	Loser (L)	Winner (W)	W-L	Alpha
Coverage portfolio 1	0.89	0.96	-0.00	-0.03	0.96	0.87	-0.03	-0.06
			(-0.04)	(-0.18)			(-0.25)	(-0.37)
Coverage portfolio 2	0.89	1.07	0.12	0.15	1.07	1.06	0.12	0.11
			(0.86)	(0.74)			(0.86)	(0.61)
Coverage portfolio 3	0.76	1.26	0.40**	0.48**	0.88	0.83	0.04	-0.00
			(2.45)	(2.25)			(0.28)	(-0.02)
Return spread 3-1	-0.13**	0.33*	0.41**	0.52*	-0.06	-0.04	0.02	0.02
t-stat	(-2.24)	(1.74)	(2.06)	(1.92)	(-0.46)	(-0.69)	(0.12)	(0.10)

Panel B. Holding in the short- and mid-term: from t+1 to t+K (J=6)

	PWNL			NWPL		
Holding months	K=4	K=8	K=12	K=4	K=8	K=12
Coverage portfolio 1	0.01	0.02	0.08	-0.04	0.07	0.08
	(0.07)	(0.18)	(0.79)	(-0.26)	(0.62)	(0.74)
Coverage portfolio 3	0.44***	0.32**	0.36***	0.23	0.07	0.04
	(2.89)	(2.51)	(3.20)	(1.62)	(0.51)	(0.31)
Return spread 3-1	0.48***	0.30*	0.33**	0.27	0.00	-0.04
	(2.64)	(1.94)	(2.23)	(1.44)	(0.03)	(-0.22)
Alpha	0.57**	0.37	0.40*	0.26	-0.01	-0.05
	(2.29)	(1.54)	(1.74)	(1.28)	(-0.05)	(-0.24)

Panel C. Holding in the long-term: from t+13 to t+K (J=6)

	PWNL			NWPL		
Holding months	K=16	K=20	K=24	K=16	K=20	K=24
Coverage portfolio 1	0.17	0.22	0.20	0.30**	0.26**	0.19*
	(0.85)	(1.17)	(1.07)	(2.61)	(2.41)	(1.80)
Coverage portfolio 3	-0.24*	-0.42***	-0.51***	0.19	0.16	0.13
	(-1.96)	(-3.93)	(-5.11)	(1.09)	(1.06)	(0.83)
Return spread 3-1	-0.41*	-0.64***	-0.71***	-0.11	-0.09	-0.06
	(-1.74)	(-2.97)	(-3.39)	(-0.52)	(-0.49)	(-0.29)
Alpha	-0.36	-0.61*	-0.75**	-0.22	-0.08	-0.07
	(-1.11)	(-1.89)	(-2.57)	(-0.81)	(-0.32)	(-0.30)

Table 8. Informed trading and momentum

This table shows the momentum returns considering the factor of informed trading. In month *t*, and for each issuer *i*, the three bonds with the highest total volumes of institutional trades (if any) are identified as the firm *i*'s top-three bonds in month t. Henceforth, the top three bonds are called, for brevity, the top bonds. The remaining bonds issued by firm *i* in month t are the non-top bonds of firm i. Note that firms are not required to have three top bonds, or any top bond, in order to have a non-top bond. Institutional trades are trades with a par value >= $500,000. To form a top bond momentum strategy in the formation month t, we identify bonds that have been continuously top bonds over the formation period. Then, the top bonds are sorted into terciles based on cumulative residual media coverage during the formation period. Within each coverage group, bonds are further sorted into losers, medium, and winners based on past monthly returns. The momentum portfolio for non-top bonds is constructed analogously. Panel A shows the momentum returns when J/K=6/6. In panel B, tested holding periods are from month t+1 to t+K, and K is set to 4, 8, and 12, respectively. In panel C, tested holding periods are from month t+13 to t+K, and K is set to 16, 20, and 24, respectively. The *t*-statistics are in parentheses. The signs *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Informed trading and momentum (J/K=6/6)

	Non-top bonds				Top bonds			
Media coverage	Loser	Winner	W-L	Alpha	Loser	Winner	W-L	Alpha
Coverage portfolio 1	0.72	0.75	0.04	0.02	0.85	0.78	-0.07	-0.06
			(0.64)	(0.17)			(-0.96)	(-0.57)
Coverage portfolio 2	0.74	0.81	0.08	0.03	0.89	0.93	0.03	0.01
			(1.03)	(0.20)			(0.37)	(0.07)
Coverage portfolio 3	0.62	0.72	0.09	0.08	0.83	1.30	0.47***	0.44**
			(1.06)	(0.51)			(4.14)	(2.09)
Return spread 3-1	-0.09	-0.04	0.05	0.06	-0.02	0.52***	0.54***	0.50**
t-stat	(-1.30)	(-0.93)	(0.64)	(0.50)	(-0.27)	(5.31)	(4.42)	(2.29)

Panel B. Holding in the short- and mid-term run: from t+1 to t+K (J=6)

	Non-top bonds			Top bonds		
Holding months	K=4	K=8	K=12	K=4	K=8	K=12
Coverage portfolio 1	0.05	0.07	0.07	-0.09	-0.09	-0.03
	(0.88)	(1.04)	(1.33)	(-1.07)	(-1.40)	(-0.58)
Coverage portfolio 3	0.15	0.03	-0.03	0.55***	0.44***	0.43***
	(1.62)	(0.32)	(-0.43)	(4.30)	(3.80)	(4.24)
Return spread 3-1	0.10	-0.04	-0.10	0.64***	0.53***	0.47***
	(1.08)	(-0.48)	(-1.37)	(4.89)	(4.28)	(4.12)
Alpha	0.12	-0.05	-0.12	0.62***	0.50**	0.43**
	(0.95)	(-0.40)	(-1.02)	(2.90)	(2.26)	(2.13)

Panel C. Holding in the long term: from t+13 to t+K (J=6)

	Non-top bonds			Top bonds		
Holding months	K=16	K=20	K=24	K=16	K=20	K=24
Coverage portfolio 1	-0.05	0.01	-0.01	-0.02	-0.02	-0.06
	(-1.00)	(0.20)	(-0.20)	(-0.37)	(-0.35)	(-1.09)
Coverage portfolio 3	-0.26***	-0.09	-0.01	-0.29***	-0.21**	-0.11
	(-3.28)	(-1.31)	(-0.22)	(-2.81)	(-2.05)	(-1.06)
Return spread 3-1	-0.21**	-0.10	-0.01	-0.27**	-0.19	-0.05
	(-2.55)	(-1.39)	(-0.07)	(-2.28)	(-1.59)	(-0.43)
Alpha	-0.25*	-0.19	-0.08	-0.40***	-0.30*	-0.19
	(-1.70)	(-1.47)	(-0.66)	(-2.66)	(-1.86)	(-1.17)

Table 9. Residual media coverage and momentum returns by bond rating

This table shows the momentum returns considering bond rating. Both the formation and holding periods are set to 6 months. Panel A displays the summary statistics by rating. Bonds rated above BBB are classified as Investment Grade (IG), while bonds rated below BBB are classified as Non-Investment Grade (NIG). Panel B displays the momentum returns for different rating groups. In each month, IG and NIG bonds are sorted into terciles based on the cumulative residual media coverage during the past 6 months. Momentum returns are calculated following the method of Jegadeesh and Titman (1993). Alpha is the intercept of multi-factor models using return spread 3-1 or media-based momentum return as the dependent variable. For brevity, only model (7) in Table 3 is used as the basic multi-factor model for all the following results. The *t*-statistics are in parentheses. The signs *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Summary description by bond rating

	Distribution		Monthly Return			Residual Coverage		
Rating	N	Percent(%)	Mean	Median	Std	Mean	Median	Std
IG	72,682	50.37	0.60	0.40	3.06	2.98	2.77	1.48
NIG	18,767	13.01	1.62	0.81	7.19	2.16	1.95	1.07
Not Rated	52,835	36.62	0.67	0.35	4.18	2.40	2.20	1.21

Panel B. Momentum returns for different rating groups (J/K=6/6)

	IG bonds				NIG bonds			
Media coverage	Loser (L)	Winner (W)	W-L	Alpha	Loser (L)	Winner (W)	W-L	Alpha
Coverage portfolio 1	0.73	0.72	-0.01	-0.01	1.28	1.09	-0.14	-0.13
			(-0.21)	(-0.17)			(-1.02)	(-0.70)
Coverage portfolio 2	0.65	0.68	0.03	0.05	1.12	1.00	-0.11	-0.08
			(0.58)	(0.72)			(-0.42)	(-0.20)
Coverage portfolio 3	0.59	0.60	0.02	-0.01	1.31	1.75	0.57^{**}	0.61^{*}
			(0.40)	(-0.08)			(2.33)	(1.68)
Return spread 3-1	-0.15^{***}	-0.12^{***}	0.03	0.01	-0.04	0.81^{***}	0.73^{**}	0.76^{*}
t-stat	(-2.80)	(-2.71)	(0.50)	(0.07)	(-0.17)	(3.58)	(2.48)	(1.78)

Panel C. Different holding periods (J=6)

	IG bonds			NIG bonds		
Holding months	K=4	K=8	K=12	K=4	K=8	K=12
Coverage portfolio 1	0.02	0.03	0.06	-0.22	-0.07	-0.08
	(0.31)	(0.69)	(1.59)	(-1.27)	(-0.56)	(-0.62)
Coverage portfolio 3	0.03	-0.01	-0.05	0.68^{**}	0.38^{*}	0.38^{*}
	(0.46)	(-0.32)	(-1.24)	(2.28)	(1.72)	(1.92)
Return spread 3-1	0.01	-0.04	-0.12^{***}	0.92^{***}	0.44^{*}	0.46^{**}
	(0.15)	(-0.86)	(-2.71)	(2.70)	(1.70)	(1.98)
Alpha	0.01	-0.05	-0.13^{*}	0.93^{*}	0.47	0.48
	(0.07)	(-0.63)	(-1.94)	(1.77)	(1.27)	(1.41)

Table 10. Media-based momentum for NIG bonds

The table reports the media coverage effect on momentum for NIG bonds. The sample only include bonds with rating below BBB-. Panel A reports the pooled OLS regression results. The dependent variable is the forward average monthly return of each bond from t+1 to t+6. Independent variable $r_{t-6,t-1}$ is the average monthly return from t-6 to t-1. Res_coverage is the cumulative residual media coverage of each bond during month t-6 to t-1. Panel B displays the economic channels (Δ) of media-based momentum for NIG bonds.Volume is the natural log of monthly trading volume of each bond. Dispersion is the analyst dispersion extracted from I/B/E/S. Following Gao et al. (2020), stock liquidity is taken from Amihud (2002). The illiquidity is measured by the daily absolute stock returns divided by trading volume. We multiply it by -1 to convert it to a measure of liquidity. Monthly liquidity is the average of daily liquidity. Daily bond liquidity=$10^8 \times$ ((maximum price-minimum price)/average price)/total volume, and monthly bond liquidity is the average of daily liquidity. The t-statistics are in parentheses. The signs *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Pooled regression for NIG bonds

Variable / Models	I	II	III	IV
$r_{t-6,t-1}$	0.196***	0.118***	0.111***	0.094***
	(15.41)	(7.54)	(6.47)	(5.13)
Res_coverage		0.023	0.036**	0.037*
		(1.36)	(1.99)	(1.73)
Res_coverage$\times r_{t-6,t-1}$		2.348***	2.618***	3.747***
		(8.79)	(9.55)	(9.33)
Age			-0.221*	-0.121
			(-1.67)	(-0.85)
Rating			-0.019	-0.003
			(-0.89)	(-0.10)
Res_tone			1.663**	1.316*
			(2.28)	(1.71)
Maturity				0.008*
				(1.77)
Momentum strength^{Stock}				0.000
				(0.16)
Book to market				0.767***
				(6.80)
Firm size				0.006
				(0.07)
Analyst				-0.441***
				(-3.21)
Industry dummy	Yes	Yes	Yes	Yes
Month fixed effect	Yes	Yes	Yes	Yes
R^2	0.139	0.167	0.194	0.216

Panel B. Economic channels

Variable / Models	Information asymmetry		Liquidity	
	Volume	Dispersion	Bond liquidity	Stock liquidity
$r_{t-6,t-1}$	0.092***	0.103***	0.102***	0.105***
	(3.49)	(5.50)	(5.62)	(5.12)
Res_coverage	0.066**	0.032	-0.008	0.032
	(2.55)	(1.21)	(-0.44)	(1.43)
$Res\_coverage \times r_{t-6,t-1}$	1.137*	2.088***	5.634***	4.116***
	(1.79)	(3.85)	(14.63)	(9.55)
$Res\_coverage \times r_{t-6,t-1} \times \Delta$	1.089***	5.540***	1.631***	8.559***
	(5.51)	(4.96)	(8.02)	(4.32)
Control variables	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes
Month fixed effect	Yes	Yes	Yes	Yes
R^2	0.246	0.247	0.269	0.226

Table 11. Subsample analysis: Up and down markets

This table shows the media-based momentum under different market states. Following the method of Li and Galvani (2018), we define month t as being in the Up (Down) market state if the average monthly return of the equally weighted market portfolio in our sample over t-12 to t-1 is above or equal (below) the return constructed in the same way over January 2000 to t-1. In panel A, both the formation and holding periods are set to 6 months. In panel B, the holding period is set to 4, 8, 12 months, respectively. The *t*-statistics are in parentheses. The signs *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Market state and momentum returns (J/K=6/6)

	Up				Down			
Media coverage	Loser (L)	Winner (W)	W-L	Alpha	Loser (L)	Winner (W)	W-L	Alpha
Coverage portfolio 1	0.83	0.70	0.08	0.05	0.89	0.97	-0.13*	-0.13
			(0.73)	(0.35)			(-1.72)	(-1.05)
Coverage portfolio 3	0.74	0.77	0.55***	0.49**	0.62	1.17	0.02	0.03
			(4.02)	(2.14)			(0.23)	(0.17)
Return spread 3-1	-0.27***	0.20	0.46***	0.46*	-0.08	0.07	0.16*	0.16
t-stat	(-3.64)	(1.63)	(3.11)	(1.67)	(-1.28)	(1.15)	(1.68)	(1.17)

Panel B. Different holding periods (J=6)

	Up			Down		
Holding months	K=4	K=8	K=12	K=4	K=8	K=12
Coverage portfolio 1	0.06	0.15	0.20**	-0.13	-0.16**	-0.21***
	(0.55)	(1.47)	(2.37)	(-1.49)	(-2.37)	(-3.38)
Coverage portfolio 3	0.62***	0.51***	0.53***	0.07	-0.01	-0.09
	(4.18)	(3.92)	(4.73)	(0.67)	(-0.17)	(-1.14)
Return spread 3-1	0.56***	0.36**	0.33***	0.20**	0.14*	0.12
	(3.95)	(2.58)	(2.68)	(2.06)	(1.79)	(1.57)
Alpha	0.50**	0.37	0.33	0.22	0.14	0.11
	(2.18)	(1.52)	(1.50)	(1.59)	(1.12)	(0.88)

Table 12. Firm-level analysis

This table presents the effects of residual media coverage on momentum returns at the firm level. Each month and each issuer, we only keep one bond with the largest issuing size. If multiple bonds have the same issuing size, we keep the most newly issued ones. The momentum strategies are constructed in the same way as the baseline. The *t*-statistics are in parentheses. The signs *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Baseline results (J/K=6/6)

Media coverage	Loser (L)	Winner (W)	W-L	alpha
Coverage portfolio 1	0.88	0.80	-0.08	-0.09
			(-0.98)	(-0.80)
Coverage portfolio 3	0.88	1.19	0.31***	0.31*
			(3.16)	(1.83)
Return spread 3-1	-0.00	0.39***	0.39***	0.40**
t-stat	(-0.04)	(4.99)	(3.28)	(2.12)

Panel B. Residual media coverage and momentum returns: different holding period

Holding months	K=4	K=8	K=12
Coverage portfolio 1	-0.13	-0.06	-0.09
	(-1.42)	(-0.79)	(-1.37)
Coverage portfolio 3	0.26**	0.29***	0.21**
	(2.31)	(3.16)	(2.44)
Return spread 3-1	0.39***	0.35***	0.29***
	(2.95)	(3.18)	(2.94)
Alpha	0.40**	0.30*	0.28
	(2.19)	(1.65)	(1.54)

Table 13. Uncertainty and media-based momentum

This table explores the role of uncertainty for media-based momentum. VIX is the CBOE volatility index, which is used as the proxy for the aggregate uncertainty of the market. IVOL and Turnover are used as the proxy for firm-level uncertainty. IVOL is calculated using the volatility of daily return residuals of the issuers' stock with respect to Fama and French (1993) 3-factor model in the past six months. Turnover is the natural log of the average daily turnover of issuers' stock over the past six months. Daily turnover is calculated as share volume/shares outstanding. Following the method of Anderson and Dyl (2005), for stocks listed on NASDAQ, daily turnover after 01/01/1997 is calculated as 0.62*share volume/shares outstanding. Each month, we first double-sort bonds into 3×3 groups based on past cumulative media coverage and bond return in the same way as Table 3. Then, we further independently sort bonds into terciles based on the proxy of uncertainty. Low/high is the group of bonds with uncertainty ranking below/above 1/3. The *t*-statistics are in parentheses. The signs *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Investors' attention and media-based momentum (J/K=6/6)

	By VIX			By IVOL			By Turnover		
Uncertainty groups	Low	Medium	High	Low	Medium	High	Low	Medium	High
Coverage portfolio 1	-0.13	-0.08	-0.03	-0.00	0.12	-0.16*	-0.00	-0.03	-0.12
	(-1.55)	(-0.87)	(-0.33)	(-0.01)	(1.11)	(-1.73)	(-0.03)	(-0.42)	(-1.26)
Coverage portfolio 3	-0.11	0.12	0.57***	-3.76***	0.23*	0.28***	-3.05***	-0.05	0.31***
	(-1.53)	(1.09)	(3.69)	(-4.23)	(1.81)	(3.03)	(-3.15)	(-0.53)	(3.36)
Return spread 3-1	0.01	0.20*	0.59***	-3.93***	0.10	0.44***	-3.16**	0.01	0.43***
	(0.14)	(1.83)	(3.59)	(-3.55)	(0.69)	(3.77)	(-2.68)	(0.11)	(3.90)
Alpha	0.03	0.23	0.56**	-4.31***	0.12	0.43***	-3.34***	0.02	0.43***
	(0.19)	(1.36)	(2.05)	(-3.78)	(0.57)	(2.81)	(-3.60)	(0.12)	(2.65)

Panel B. Different holding periods (J=6)

	K=4			K=8			K=12		
Uncertainty groups	Low	Medium	High	Low	Medium	High	Low	Medium	High
					By VIX				
Return spread 3-1	0.05	0.25**	0.64***	-0.00	0.05	0.68***	0.03	-0.10	0.73***
	(0.47)	(2.08)	(3.38)	(-0.02)	(0.44)	(4.27)	(0.38)	(-1.08)	(5.46)
Alpha	0.08	0.29*	0.62**	0.02	0.07	0.64**	0.05	-0.09	0.69***
	(0.67)	(1.82)	(2.31)	(0.14)	(0.41)	(2.43)	(0.42)	(-0.58)	(3.34)
					By IVOL				
Return spread 3-1	-1.85	-0.00	0.44***	-3.56***	0.19	0.36***	-2.73**	0.09	0.31***
	(-1.37)	(-0.01)	(3.44)	(-3.34)	(1.33)	(3.60)	(-2.56)	(0.83)	(3.69)
Alpha	-2.52**	-0.01	0.46***	-3.70**	0.21	0.34***	-2.53*	0.06	0.30**
	(-2.93)	(-0.03)	(2.69)	(-2.97)	(1.04)	(2.65)	(-1.80)	(0.44)	(2.56)
					By Turnover				
Return spread 3-1	-1.00	-0.02	0.47***	-2.61**	0.05	0.37***	-1.90	0.10	0.32***
	(-0.70)	(-0.17)	(3.89)	(-2.35)	(0.51)	(3.73)	(-1.70)	(1.13)	(3.50)
Alpha	-1.95**	-0.02	0.49***	-2.62**	0.06	0.36**	-1.36	0.09	0.32**
	(-2.59)	(-0.13)	(2.89)	(-2.76)	(0.37)	(2.50)	(-1.09)	(0.62)	(2.33)

Table 14. Investors' attention and media-based momentum

This table presents the results of investors' attention and media-based momentum. In each month t, abnormal trading volume (bond return) is calculated as the ratio of the bond's average monthly trading volume (bond return) during the formation period to its average monthly trading volume (bond return) over the previous year (i.e., 12 months). In panel A, the last column is the correlation between abnormal trading volume/bond return with media coverage, and media coverage is the sum of residual media coverage of each bond during the past six months. In panel B, we first double-sort bonds into 3×3 groups based on past cumulative media coverage and bond return, as in Table 3. Then, we further independently sort bonds into terciles based on abnormal trading volume (bond return). Low/high is the group of bonds with abnormal trading volume or abnormal bond return ranking below/above 1/3; medium is the group of bonds ranking between low and high. Both the formation and holding period are set to 6 months. In panel C, the holding period is set to 4, 8, and 12 months, respectively. The *t*-statistics are in parentheses. The signs *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Summary description

	Mean	Median	Std	Min	Max	Correlation
Abnormal trading volume	0.97	1.00	0.48	0.02	2.16	0.001
Abnormal bond return	1.01	1.00	3.65	-24.45	27.50	0.011

Panel B. Investors' attention and media-based momentum (J/K=6/6)

	By abnormal trading volume			By abnormal bond return		
Attention groups	Low	Medium	High	Low	Medium	High
Coverage portfolio 1	-0.09	-0.07	-0.08	-0.08	-0.07	0.00
	(-0.97)	(-0.74)	(-0.98)	(-0.56)	(-0.62)	(0.02)
Coverage portfolio 3	0.28***	0.12	0.09	0.68***	0.20	0.04
	(2.98)	(1.10)	(1.04)	(4.08)	(1.39)	(0.29)
Return spread 3-1	0.35***	0.19	0.16	0.71***	0.14	0.11
	(3.15)	(1.49)	(1.74)	(3.55)	(0.99)	(0.68)
Alpha	0.35**	0.19	0.16	0.63**	0.13	0.16
	(2.39)	(1.08)	(1.26)	(2.44)	(0.69)	(0.65)

Panel C. Different holding periods (J=6)

	K=4			K=8			K=12		
Attention	Low	Mediu	High	Low	Medium	High	Low	Mediu	High
				By abnormal trading volume					
Return spread	0.43**	0.25*	0.21*	0.25***	0.18	0.15*	0.17*	0.14	0.13
	(3.35)	(1.94)	(2.05	(2.61)	(1.59)	(1.75)	(1.87)	(1.37)	(1.55
Alpha	0.43**	0.27	0.23*	0.25**	0.18	0.14	0.16	0.14	0.13
	(2.57)	(1.62)	(1.94	(2.05)	(1.02)	(1.00)	(1.37)	(0.85)	(0.89
				By abnormal bond return					
Return spread	0.53**	0.39**	0.23	0.71***	0.01	0.01	0.71**	0.02	0.00
	(2.23)	(2.45)	(1.14	(3.68)	(0.11)	(0.04)	(3.78)	(0.15)	(0.00
Alpha	0.43	0.38	0.31	0.65**	-0.01	0.02	0.65**	-0.00	0.01
	(1.60)	(1.93)	(1.06	(2.58)	(-0.03)	(0.10)	(2.41)	(-0.00)	(0.06

Table 15. Different media types and momentum

This table displays the media effect on bond momentum under different media types. According to the user guide of RavenPack, News flash refers to a news article composed of a headline and no body text. A press release refers to a corporate announcement originated by an entity and distributed via a news provider. In panel A, we focus on the sum of media coverage of individual bonds during the formation period, which is set to 6 months. Raw coverage is ln(1+no. articles). Residual coverage is calculated based on formula (2). In panel B, media coverage is calculated using only News flash and Press releases. The momentum strategy is constructed in the same way as the baseline. The signs *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Summary statistics of raw and residual media coverage (J=6)

	Mean	Median	Min	Max	Std	Sum
			Raw coverage			
News flash	14.23	13.37	0.69	35.60	7.10	1,497,199.70
Press release	11.25	9.78	0.69	33.18	6.45	1,175,109.60
			Residual coverage			
News flash	4.49	3.41	-6.78	26.01	5.40	401,917.19
Press release	4.70	3.10	-4.19	24.28	5.16	417,728.35

Panel B. Momentum effect under different media types (J=6)

	News flash				Press release			
Holding months	K=4	K=6	K=12	K=24	K=4	K=6	K=12	K=24
Coverage portfolio 1	-0.05	-0.09	-0.05	-0.03	0.01	0.02	0.03	-0.03
	(-0.76)	(-1.42)	(-0.96)	(-0.75)	(0.16)	(0.24)	(0.65)	(-0.79)
Coverage portfolio 3	0.20**	0.16**	0.11	-0.11**	0.17**	0.13*	0.04	-0.10**
	(2.38)	(1.98)	(1.62)	(-2.35)	(2.06)	(1.67)	(0.74)	(-2.02)
Return spread 3-1	0.26***	0.25***	0.15**	-0.09*	0.16*	0.11	0.01	-0.07
	(3.11)	(3.17)	(2.34)	(-1.84)	(1.82)	(1.35)	(0.14)	(-1.48)