Corporate Bond Momentum Revisited

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Abstract

I show that corporate bond momentum is profitable despite recent concerns regarding its sensitivity to data uncertainty. Trimming formation-period positive (negative) outliers systematically weakens (strengthens) momentum profitability for both investment-grade and non-investment-grade bonds. This asymmetry reveals stronger return continuation in winner portfolios than in loser portfolios, consistent with informational heterogeneity within momentum portfolios. Importantly, negative outliers are more likely to reverse, contributing to short-lived price trends in loser portfolios. The robust profits from trimming negative outliers coincide with mitigated momentum crashes that are not explained by bear-market optionality. Instead, the asymmetric effect persists across market states and data choices.

Keywords: corporate bond momentum; return outliers; asymmetric information diffusion; trend reversals; momentum crashes.

JEL: G01, G10

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1 Introduction

The momentum effect, first identified for US stocks (Jegadeesh and Titman, 1993), exists in different stock markets (Chui, Titman, and Wei, 2010) and other asset classes (Asness, Moskowitz, and Pedersen, 2013).[1] It is also documented exclusively in non-investment-grade (NIG) corporate bonds (Gebhardt, Hvidkjaer, and Swaminathan, 2005; Jostova, Nikolova, Philipov, and Stahel, 2013). However, recent studies challenge the profitability of momentum trading in the corporate bond market, highlighting substantial data uncertainty in constructing monthly bond return samples (Jostova, Nikolova, and Philipov, 2024; Dickerson, Robotti, and Rossetti, 2024).[2] In particular, as the strategy favors bonds with extreme past returns by design, momentum profitability is shown to be highly sensitive to outlier treatment (Galvani and Li, 2023). Inappropriate outlier filtering that introduces look-ahead bias could inflate momentum returns (Dickerson et al., 2024; Dickerson, Robotti, and Rossetti, 2026), while leaving outliers untreated renders momentum largely undetectable (Dick-Nielsen, Feldhütter, Pedersen, and Stolborg, 2024).[3]

However, despite such data uncertainty, this study shows that corporate bond momentum is not an artifact of outlier treatment. Instead, focusing on outlier treatment during the formation period reveals robust momentum patterns for both non-investment-grade and investment-grade

[1]Exceptions are documented in Chui et al. (2010) and Jegadeesh and Titman (2023), which find that momentum is missing in the stock markets of several Asian countries (e.g., China, Japan, and Korea).

[2]This uncertainty arises from the complex nature of corporate bond data (e.g., infrequent trading and potential reporting errors), and is particularly severe in the TRACE (Trade Reporting and Compliance Engine) dataset. However, similar challenges also exist in other data sources, including the Lehman Brothers Fixed Income Database, which is a mix of dealers' quotes and matrix pricing covering the period of 1973 to 1997, and the ICE Data Pricing & Reference Data, which utilizes sophisticated algorithms to generate rules-evaluated prices and returns for an institutional round lot position. Notably, the momentum debate concerns only NIG bonds, as the literature consistently finds insignificant momentum in investment-grade bonds (e.g., Gebhardt et al., 2005; Jostova et al., 2013, 2024; Dickerson et al., 2024).

[3]Dick-Nielsen et al. (2024) confirm the results documented in Jostova et al. (2013) using the same right-tail outlier trimming approach, but find that the momentum effect is missing in the ICE quote data and the TRACE raw data excluding only verified erroneous outliers.

(IG) bonds. I show that momentum profitability is systematically strengthened by trimming formation-period negative outliers, whereas removing positive outliers in the formation period exerts a weakening effect. This asymmetry represents a widespread feature of corporate bond momentum and is consistent with informational heterogeneity between the long and short legs under the gradual information diffusion framework (Hong and Stein, 1999). Therefore, this study provides an economic rationale that helps reconcile conflicting empirical evidence and also sheds light on the source of the momentum effect in the corporate bond market.

The payoff structure of corporate bonds is nonlinear and bounded on the upside (Merton, 1974; Hong and Sraer, 2013), implying that good news exhibits limited price impact. In contrast, bad news is inherently more relevant given the sensitivity of corporate bond investors to default risk. Consistently, the literature presents empirical evidence showing that corporate bond prices react faster and stronger to bad news than to good news (e.g., Bartov, Faurel, and Mohanram, 2023). The stronger price reaction to bad news is coincident with elevated trading activity (Easton, Monahan, and Vasvari, 2009) and possible investor overreaction (Defond and Zhang, 2014).[4] These asymmetric market reactions to good and bad news may carry significant implications for momentum profitability.

It is well documented that return continuation in momentum portfolios stems from market underreaction to information (e.g., Jegadeesh and Titman, 1993; Chan, Jegadeesh, and Lakonishok, 1996; Savor, 2012). The underreaction occurs possibly due to investor conservatism (Barberis, Shleifer, and Vishny, 1998), or limited rationality (Hong and Stein, 1999), or limited attention (Da, Gurun, and Warachka, 2014).[5] As corporate bond investors are more likely to

[4]Defond and Zhang (2014) find that the strong price reaction to bad earnings news is partially reversed in the post-announcement period.

[5]One exception is Daniel, Hirshleifer, and Subrahmanyam (1998), which links momentum to investors' overconfidence and overreaction to private information.

underreact to good news than to bad news, I conjecture that return continuation in loser portfolios is less sustainable than that in winner portfolios. To the extent that return outliers signal price reactions to large information shocks, the more bonds associated with negative outliers are selected as losers, the less profitable the strategy should be.[6] In contrast, winner bonds associated with positive outliers should support momentum profitability. Given the prevalence of outliers in momentum portfolios, independently treating positive and negative outliers may generate systematically different momentum patterns, driven by changes in the relative informational efficiency of the long and short legs.

This study treats outliers prior to portfolio formation to avoid look-ahead bias. Moreover, treating outliers in the formation period directly alters the composition of momentum portfolios by changing the likelihood that treated bonds are classified as winners or losers.[7] This composition effect is particularly salient under outlier trimming, as bonds with missing returns in the formation period are precluded from portfolio construction (Jegadeesh and Titman, 1993). The resulting portfolios are expected to exhibit return continuation patterns that may showcase variations in the underlying informational efficiency.

Using TRACE data, I find that trimming negative outliers in the formation period yields significantly positive momentum excess returns and market-risk-adjusted alphas for NIG bonds under different outlier thresholds. The excess returns are significantly higher than those obtained in the raw data, driven entirely by decreased returns on the short leg. These findings are consistent with negative outliers identifying losers with short-lived price trends that may reverse during the

[6] Return outliers are commonly used to proxy for information shocks in the equity literature (e.g., Barber and Odean, 2008; Jiang and Zhu, 2017; Frank and Sanati, 2018). In Section A of the Internet Appendix, I confirm that corporate bond outliers are also informative, with their incidence predicted by credit rating upgrades and downgrades.

[7] Given that the momentum strategy is a buy-and-hold position, treating outliers that fall during the holding period does not have this composition effect.

holding period. Removing those ”bad” losers significantly improves momentum profitability.

In contrast, momentum excess returns after trimming positive outliers in the formation period are negative and significantly lower than benchmark returns in the raw data. The changes are due to reduced winner portfolio returns, consistent with positive outliers identifying ”good” winners with sustained return continuation, whose removal dampens momentum profitability.

Importantly, these asymmetric momentum patterns are also observed for IG bonds when outliers are identified at the 90th and 10th percentiles. However, unlike NIG bonds, momentum profits in IG bonds following negative outlier trimming are entirely due to market risk exposure, as risk-adjusted alphas are insignificant. This result is consistent with IG bonds being more sensitive to market-level than firm-level information (e.g., Li, 2022).

For both IG and NIG bonds, the asymmetric momentum patterns become more pronounced as outlier thresholds become less stringent. The contributions of the long and short legs to this asymmetry are also more clearly disentangled in samples that exclude bonds with extreme returns to filter out data noise.[8] While estimated momentum gains after trimming negative outliers vary materially due to data uncertainty, ranging between 0.45% and 2.36% per month for NIG bonds at the 0.5th percentile threshold, the contrasting patterns remain robust across data sources and sample specifications. These estimated profits are also sizable relative to the sample mean (median) monthly return of 1.54% (0.61%) for NIG bonds. These findings indicate that the asymmetric effect of trimming formation-period positive and negative outliers is systematic and represents a widespread feature of corporate bond momentum. Additional tests show that the asymmetric effect is weaker in convertible bonds, consistent with their equity-like payoff structure. In contrast, the same asymmetric effect becomes absent when outliers are treated

[8]Results are reported in Section D of the Internet Appendix.

during the holding period.

Taken together, the robust momentum patterns revealed by formation-period outlier treatment indicate that the momentum effect exists in the corporate bond market. Moreover, the finding that these patterns also extend to bonds with less extreme returns suggests a systematic asymmetry between winner and loser portfolios, with the former likely to include bonds with stronger return continuation than the latter. From an information diffusion perspective, the results are consistent with informational heterogeneity within momentum portfolios, potentially reflecting asymmetric market reactions to good and bad news.

Further analysis confirms that loser portfolios exhibit short-lived price trends, with bonds experiencing formation-period negative outliers being particularly prone to sharp reversals during the holding period. These reversals could contribute to momentum crash risk. Importantly, I show that trimming negative outliers in the formation period effectively eliminates momentum crashes. However, this result is inconsistent with the bear market optionality theory proposed by Daniel and Moskowitz (2016), which attributes equity momentum crashes to loser portfolios' sensitivity to sharp market rebounds following bear markets. In the corporate bond market, negative outlier reversals are not state-dependent, as trimming negative outliers bolsters momentum profits across both normal and bear market states. Moreover, the effect persists in bear markets regardless of subsequent market performance, suggesting that trimming negative outliers can serve as a hedge against bear market risk.

In summary, this study reconciles recent findings that corporate bond momentum is weak and sensitive to data filtering choices. I show that its sensitivity to formation-period outlier treatment is economically meaningful and potentially reflects informational heterogeneity within momentum portfolios. In particular, weak momentum originates from loser portfolios exhibiting short-lived, readily reversible price trends. The reversals are most evident among losers with negative outliers. Trimming these outliers during the formation period thus strengthens return continuation in loser portfolios and restores robust momentum profits for both IG and NIG bonds. These findings further motivate a momentum strategy that is implementable in real time.

This paper is not the first to examine the impact of treating positive or negative outliers on corporate bond momentum. Prior work treats outliers that are likely data errors and generally does not distinguish their roles in the formation and holding periods. In this case, treating positive outliers delivers significant momentum gains for NIG bonds (Jostova et al., 2013; Dick-Nielsen et al., 2024; Jostova et al., 2024), rendering the asymmetric momentum patterns documented in Galvani and Li (2023) for NIG bonds less compelling.[9] One exception is Dickerson et al. (2024), who highlight the forward-looking bias from treating holding period outliers and show that treating negative outliers in the formation period yields significant momentum returns for NIG bonds also in the error-free ICE data, lending credibility to findings based on TRACE data.

This study advances the literature by providing an economic rationale for the interaction between outliers and momentum in corporate bonds, suggesting that momentum profitability is not an artifact of outlier treatment. Further, this paper documents unconditional momentum profitability in IG bonds for the first time, challenging the broad consensus that momentum is unprofitable for IG bonds.

More broadly, this paper contributes to the growing literature on the credibility of empirical findings in the corporate bond market. Relative to equity studies, corporate bond research is constrained by the lack of a high-quality, error-free dataset. Prior studies document

[9] The documented momentum profits from treating positive outliers in these studies largely stem from outliers falling in the holding period, as trimming positive outliers in the formation period diminishes momentum returns.

replication concerns related to data errors (Dick-Nielsen et al., 2024), microstructure noise and ex-post data filtering (Dickerson et al., 2024, 2026), and uncertainty induced by multiple data choices (Jostova et al., 2024). This study highlights an additional concern regarding the handling of return outliers. I show that extreme returns in TRACE contain informative signals about the underlying return-generating process, despite potential reporting errors. Therefore, their treatment should be subject to scrutiny and guided by economic considerations to avoid distorting inference.

This study also contributes to the vast literature explaining the origin of the momentum effect. It has been demonstrated both theoretically and empirically that momentum originates from underreaction to information. Consistently, momentum profitability is shown to vary substantially in response to changing levels of informational efficiency in targeted assets, whether they are stocks of different characteristics (Hong, Lim, and Stein, 2000; Zhang, 2006), during different sentiment periods (Antoniou, Doukas, and Subrahmanyam, 2013), or corporate bonds characterized by different investor behaviors (Li and Galvani, 2021). This study further uncovers asymmetric momentum patterns consistent with informational heterogeneity within corporate bond momentum portfolios. These patterns are readily detectable through formation-period outlier treatment, highlighting the role of outliers in shaping momentum profitability. The findings thus justify an outlier-based strategy for momentum investing, which benefits from excluding bonds with extreme negative returns during portfolio construction.

2 Informational Heterogeneity within Momentum Portfolios

The contributions of the winner and loser portfolios to momentum profitability can be uneven. Indeed, the literature documents that momentum in stocks mainly originates from the loser side, reflecting the slower adjustment of stock prices to bad news than to good news due to market frictions such as managerial bad news hoarding (Hong et al., 2000) or short-sale constraints (Stambaugh, Yu, and Yuan, 2012). The two forces are not mutually exclusive, as the latter lowers the cost of managers' opportunistic reporting behaviors (e.g., Fang, Huang, and Karpoff, 2016).

With strong contractual incentives (e.g., promotion and bonuses), managers tend to withhold bad news (Kothari, Shu, and Wysocki, 2009), which eventually causes stock price crashes when the accumulated bad news can no longer be concealed from investors (Hutton, Marcus, and Tehranian, 2009).[10] Short-sale constraints can further hinder the incorporation of bad news in stock prices, increasing price crash risk (Hong and Stein, 2003).[11] Therefore, the stock market exhibits difficulty in processing bad news. In contrast, managers are often eager to push good news out (e.g., Kothari et al., 2009), and given retail investors' asymmetric trading patterns, stock prices tend to respond more promptly to good news (Frank and Sanati, 2018).

Market frictions may also restrict the informational efficiency of corporate bond loser portfolios, as shorting them is about as costly as shorting stocks (e.g., Asquith, Au, Covert, and Pathak, 2013). However, corporate bond momentum seems to rely largely on return continuation in winner portfolios (e.g., Li and Galvani, 2018). This discrepancy has received little attention and remains poorly understood in the literature. To fill this gap, this paper proposes an alternative explanation grounded in the nature of debt instruments and validates it through outlier treatment.

As formalized in the classical Merton (1974) model, the payoff of a debt instrument is

[10] Managers do not always hoard bad news. They may choose to voluntarily disclose bad news to increase stock-based compensation (Aboody and Kasznik, 2000) or to reduce the cost of litigation and maintain reputation (Skinner, 1994). Additionally, ex-ante conditional accounting conservatism could also counter managers' incentives to hide bad news (Kim and Zhang, 2016).

[11] Consistently, Deng, Gao, and Kim (2020) find that lifting short-sale constraints helps to reduce stock price crash risk partly through constraining managers' bad news hoarding behavior.

concave and bounded on the upside, while the equity payoff is linear in the underlying asset value.[12] Given the capped upside payoffs, corporate bonds are intrinsically less sensitive to good news than to bad news that raises default risk. As a result, bond investors prioritize following and trading on bad news (Addoum, Meursault, and Murfin, 2024; Wei and Zhou, 2016), and also demand more negative information from security analysts than stock investors (De Franco, Vasvari, and Wittenberg-Moerman, 2009). Further, the corporate bond market is dominated by institutional investors (Bessembinder, Kahle, Maxwell, and Xu, 2008) who have informational advantages over retail investors, especially around bad news (Park, Lee, et al., 2014). Consistently, the literature presents empirical evidence supporting stronger and timelier responses of corporate bonds to bad news than to good news, in terms of both prices and trading volume (e.g., Easton et al., 2009; Defond and Zhang, 2014). These asymmetric responses may be exacerbated by investor overreaction bias (Bordalo, Gennaioli, and Shleifer, 2018), given that corporate bond return reversals are observed only following sell herding of institutional investors (Cai, Han, Li, and Li, 2019).[13]

Theoretically, the efficient diffusion of bad news in corporate bonds can be disrupted by market frictions. Empirically, however, the introduction of TRACE has alleviated bad news hoarding behaviors (Rickmann, 2022) and reduced stock price crash risk through information spillover (Guan, Kim, Liu, and Xin, 2023). Short-sale constraints are also less binding for corporate bonds. The bounded upside payoff leaves limited room for corporate bonds to be overpriced, which eases price pressure and discourages speculative short selling (Hong and Sraer,

[12] A corporate bond is equivalent to holding a risk-free bond and shorting a put option on the value of the firm, whereas a stock corresponds to shorting the risk-free asset coupled with a long call option on the firm's value.

[13] From a behavioral perspective, default outcomes (tail events) are much more diagnostic for bad news than for good news in the sense of Tversky and Kahneman (1983). Hence, bond investors with diagnostic expectations (Bordalo et al., 2018) may overreact to bad news and underreact to good news.

2013). Indeed, borrowing demand for corporate bonds is largely driven by dealers' market-making activities (Goyal, Nozawa, and Qiu, 2024), while short-sale constraints exhibit weaker predictive power for future returns in corporate bonds than in stocks (Huang, Qin, and Wang, 2024). Hence, although market frictions cause stocks to underreact to bad news, their distorting effect on price discovery is notably weaker in corporate bonds and insufficient to alter the fundamental information diffusion process.

The asymmetric diffusion of good and bad news in corporate bonds predicts informational heterogeneity within momentum portfolios. According to the theoretical framework of Hong and Stein (1999), slower information diffusion entails stronger return continuation. As bad news travels faster than good news for corporate bonds, return continuation in loser portfolios should be less persistent than in winner portfolios. The implication is that the more bonds experiencing large negative information shocks are selected into the short leg, the less profitable the strategy should be. In contrast, bonds experiencing good news in the long leg should support momentum profitability. The resulting informational heterogeneity between the long and short legs helps explain their unbalanced contributions to corporate bond momentum documented in the literature.

By design, momentum strategies favor bonds with extreme past returns. To the extent that outliers signal price reactions to large information shocks, outlier-bearing winners and losers should also exhibit asymmetric return continuation. Treating outliers thus may systematically alter momentum profitability by reshaping the relative informational efficiency of the long and short legs. The remainder of this study provides empirical evidence supporting this potential link.

3 Data and Methodology

This section describes the data cleaning procedure and summary statistics, followed by the construction of momentum strategies. This study uses TRACE Enhanced data matched with Mergent FISD for the period spanning July 2002 to December 2021. Following the literature (e.g., Dickerson et al., 2024), the sample includes only publicly-traded fixed-rate bonds that are issued by US-based corporations and denominated in US dollars. Bonds with warrants and special contingencies (i.e., preferred shares, puttable, asset-backed, agency-backed, equity-linked, part of unit deals, etc.) are excluded except for convertible and exchangeable bonds, the two types that I classify as convertible bonds.[14] Bonds with less than one year to maturity are removed. Following the cleaning procedure described in Dick-Nielsen (2014), I remove all transactions that are marked as cancellations, corrections, and reversals, as well as their matched original trades.

3.1 Return Calculation and Sample Summary Statistics

This study employs the last available daily price in each month as the monthly price, with daily prices calculated following Bessembinder et al. (2008) as trade-size-weighted averages of intraday prices.[15] The monthly return $r_{i,t+1}$ of bond i over the holding period of month t to $t+1$ is defined in equation (1):

$$r_{i,t+1} = \frac{(P_{i,t+1} + AI_{i,t+1} + C_{i,t+1}) - (P_{i,t} + AI_{i,t})}{P_{i,t} + AI_{i,t}} \tag{1}$$

[14] I use both the convertible flag and the "CCOV" bond type to identify convertible bonds in FISD, as the two criteria do not perfectly overlap. The remaining bond types selected are CDEB, CMTN, and CMTZ, the three types included in the WRDS Bond Return Database. Following the literature, callable bonds and defaulted bonds are not excluded.

[15] Results based on alternative month-end price approaches are reported in Section E.2 of the Internet Appendix.

where, $P_{i,t+1}$ is the price of bond i in month $t+1$, $AI_{i,t+1}$ is the accrued interest associated with $P_{i,t+1}$, and $C_{i,t+1}$ is the coupon payment (if any) between time t and $t+1$. If no trade is available in a given month for a bond, both current- and next-month returns are marked as missing. For default-month returns, I follow the approach in Dick-Nielsen et al. (2024) and exclude accrued interest from the return calculation.[16] The average default return, defined as the average of non-missing default-month and preceding-month returns, is -26.1% in my sample.

As identifying erroneous outliers in TRACE is challenging, I adopt a conservative approach and retain all extreme returns in the sample.[17] The final dataset comprises 1,487,293 monthly return observations for 34,576 bonds issued by 4,855 firms, with credit rating information available for approximately 95% of observations.[18] Summary statistics of return distributions by bond type and credit quality are reported in Panel A of Table 1.

3.2 Statistical Properties of Return Outliers

As shown in Panel A of Table 1, corporate bond returns are positively skewed. To account for this tail asymmetry, I choose percentile thresholds of (99.5, 0.5) and (90, 10) to identify outliers.[19] Panel A further indicates that convertible bonds exhibit much greater return dispersion than straight bonds. Given this disparity, separate outlier thresholds are considered for straight and convertible bonds, with respective cutoffs highlighted in bold in Panel A. Figure 1 depicts

[16]Including accrued interest does not alter the main findings in this paper (results available upon request).

[17]The proportion of return outliers due to reporting errors is likely small. For instance, Dick-Nielsen et al. (2024) manually examine 5,000 extreme returns and remove only 292 detected errors. In Section E.1 of the Internet Appendix, I reproduce the main findings after excluding bonds with extreme returns above 2000%, aligning more closely with Dick-Nielsen et al. (2024), whose cleaned sample has a maximum return of 1,552.82% (see their data at: https://www.stolborg.com/data). The results are still robust.

[18]Credit group assignments follow the most conservative rating from S&P, Moody's, Fitch, and Duff and Phelps.

[19]The 99.5th percentile threshold is applied in Jostova et al. (2013) to eliminate positive outliers.

Table 1: Summary Statistics

The table reports summary statistics for monthly returns, categorized by bond type and credit quality. Panel A summarizes the entire sample and subsamples of straight bonds, convertible bonds, and their respective investment-grade (IG) and non-investment-grade (NIG) groups. The reported statistics include total observations, mean, standard deviation, median, max/min values, and percentile distributions. Panel B reports the count (N) and average (mean) of positive and negative outliers in each subsample, along with the share of outliers followed by returns of the opposite sign in the next month (Share_Rev). Outliers are identified using separate thresholds for straight and convertible bonds. Thresholds for straight bond outliers are the 99.5th and 0.5th percentiles of the straight all-bond return distribution in columns two to seven and the 90th and 10th percentiles in columns eight to thirteen. Analogous percentiles of the convertible all-bond return distribution are used as outlier thresholds for convertible bonds. The corresponding threshold returns are highlighted in bold in Panel A.

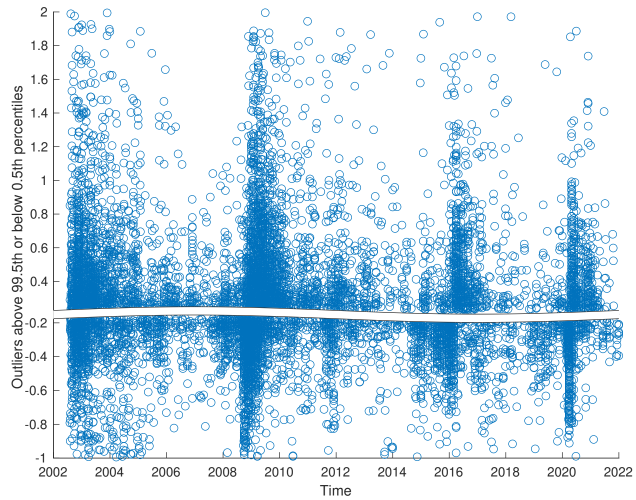
Panel A: Return Distributions

							Percentiles							
Sample	N	mean(%)	std(%)	median (%)	max(%)	min(%)	99.5th	99th	90th	75th	25th	10th	1th	0.5th
All	1487293	1.02	57.4	0.36	38595.7	-99.38	24.68	15.62	3.52	1.53	-0.4	-2.04	-11.8	-18.51
Straight	1433786	0.96	47.84	0.35	23441.2	-99.38	**22.99**	14.23	**3.37**	1.49	-0.38	**-1.93**	-10.8	**-17.31**
S-IG	1055776	0.59	30.9	0.29	10455.9	-99.38	11.42	8.63	2.89	1.29	-0.35	-1.68	-6.95	-9.76
S-NIG	337568	1.54	63.23	0.61	23441.2	-99	46.6	29.92	4.84	2.06	-0.48	-2.77	-22.21	-32.27
Convertible	53507	2.72	173.9	0.63	38595.7	-98.91	**51.5**	34.78	**9.15**	3.78	-1.85	**-6.37**	-25.91	**-35.14**
C-IG	6478	1.68	77.49	0.44	6222.5	-98.59	21.7	16.47	5.72	2.32	-1.03	-3.87	-13.55	-16.79
C-NIG	18345	5.12	292.81	0.75	38595.7	-98.27	65.81	41.79	9.55	4.09	-1.82	-6.36	-26.96	-35.54

Panel B: Return Outliers and Reversals

	Outliers identified at (99.5th, 0.5th) percentiles						Outliers identified at (90th, 10th) percentiles					
	Positive outliers			Negative outliers			Positive outliers			Negative outliers		
Sample	N	mean(%)	Share_Rev(%)	N	mean(%)	Share_Rev(%)	N	mean(%)	Share_Rev(%)	N	mean(%)	Share_Rev(%)
All	7437	114.93	31.8	7437	-32.038	56.3	148730	12.17	39.76	148730	-6.106	60.6
Straight	7169	105.58	31.7	7169	-31.238	56.5	143379	11.35	39.77	143379	-5.797	60.9
S-IG	946	161.13	44.7	1560	-26.159	71.4	82452	7.573	44.21	91576	-4.442	62.3
S-NIG	4925	78.915	31.8	4817	-32.366	53.8	51502	14.14	35.55	44693	-8.144	60.9
Convertible	268	365.04	35.8	268	-53.444	51.5	5351	34.3	39.51	5351	-14.392	52.7
C-IG	3	2126.2	33.3	4	-66.886	75	295	35.78	44.07	332	-11.397	56
C-NIG	127	592.94	33.1	94	-56.241	46.8	1947	54.53	37.49	1834	-14.88	52

Figure 1: Return Outliers Using the (99.5 0.5) Percentile Thresholds



The figure plots straight bond monthly returns, truncated at 200%, that are above the 99.5th or below the 0.5th percentile of the return distribution over the period of August 2002 to December 2021.

outliers for straight bonds identified using the (99.5, 0.5) percentile thresholds.[20] It shows that outliers are widespread and cluster during periods of market turmoil when trade frictions intensify.

Panel B of Table 1 reports summary statistics for positive and negative outliers, along with the share of outliers followed by a return reversal in the subsequent month. Notably, the reversal rate of negative outliers is markedly higher than that of positive outliers across all (sub)samples and under both threshold definitions, consistent with bad news traveling faster than good news in corporate bonds. Specifically, for straight bonds, returns below the 0.5th (10th) percentile are followed by a positive return in about 57% (61%) of cases, whereas only 32% (40%) of returns above the 99.5th (90th) percentile reverse trend in the next month. This asymmetry holds for both IG and NIG bonds, with IG bond outliers more likely to reverse trend, regardless of the sign. The reversal discrepancy between positive and negative outliers is narrower for convertible bonds, suggesting that they respond to good and bad news less asymmetrically than straight bonds.

Further analysis in Section A of the Internet Appendix indicates that outliers are

[20]Returns are truncated at 200% to highlight crisis clusters.

informative and respond more strongly to rating downgrades than to upgrades. Lagged downgrades also predict large return reversals, suggesting possible overreaction to bad news.

3.3 Momentum Strategies

Momentum strategies in this study are designed as in Jegadeesh and Titman (1993), with formation and holding periods separated by a formation month to mitigate the impact of bid-ask bounce. In each formation month t, for a j month formation period, bonds are sorted into deciles based on their cumulative returns over months $t - j$ to $t - 1$.[21] An equal-weighted (EW) portfolio of bonds in the highest (lowest) decile forms the long (short) leg of the momentum portfolio, which is held for a holding period of k months. The momentum return in month $t + 1$ is defined as the cross-sectional average of the month $t + 1$ returns of the k overlapping momentum portfolios formed in the previous k months. This study considers representative short- and long-term momentum strategies with symmetric formation and holding periods of three and six months, respectively.

3.3.1 Equal-weighted versus Value-weighted Portfolios

The literature has increasingly adopted the approach of value-weighted (VW) portfolios, using weights based on either amount outstanding or market capitalization (e.g., Dickerson et al., 2024). This study argues that missing bond returns in the holding period can distort the return calculation for VW portfolios more than for EW portfolios. The EW portfolio's monthly holding-period return is calculated as the cross-sectional average of non-missing bond returns.

[21] Bonds with missing returns during the formation period are excluded from the decile portfolios, consistent with standard practice in the literature.

This approach is equivalent to replacing each missing bond return with the average of non-missing returns. Instead, the VW portfolio's monthly return is the weighted average of all bond returns in the cross-section, with missing returns retaining their value-based weights. In this case, missing returns are treated as zero, which naturally has a greater distorting effect on the average return than the average itself. This issue is particularly relevant for TRACE, which suffers from significant missing data due to the infrequent trading of corporate bonds. Given this disadvantage of the value-weighted approach, this study's analysis relies on equal-weighted portfolios, with supporting results based on VW portfolios relegated to Section C of the Internet Appendix.

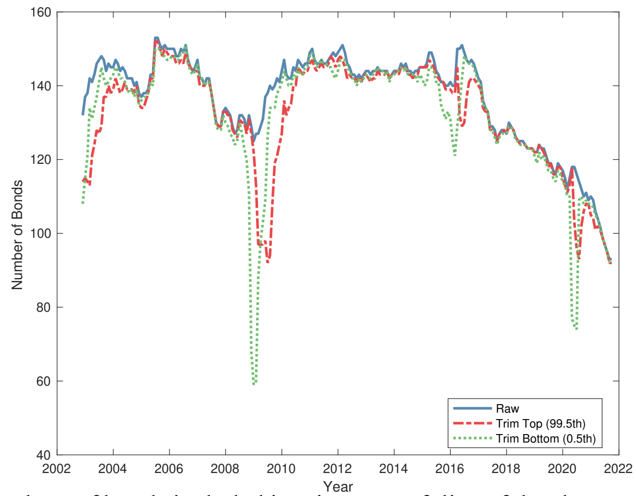
4 Outliers and Momentum

Due to the nature of corporate bond data and the design of momentum strategies, outliers can be prevalent in momentum portfolios, making momentum profitability highly sensitive to outlier treatment. This section discusses two interconnected channels through which outlier treatment may influence momentum returns. It distinguishes between outliers occurring before and after portfolio construction, as treating outliers during the holding period entails look-ahead bias and is not implementable in real time (Dickerson et al., 2024). In contrast, formation-period outlier treatment, apart from being implementable ex-ante, fundamentally shapes momentum profitability by altering portfolio composition and the associated return continuation.

4.1 The Portfolio Composition Effect

Momentum portfolios are formed by sorting bonds on their cumulative returns over the formation period, which are sensitive to return outliers. Hence, treating outliers in the formation

Figure 2: Number of Bonds as Winners



The figure plots the numbers of bonds included in winner portfolios of the short-term momentum strategy for straight non-investment-grade bonds, when 1) outliers are not treated (Raw), or 2) outliers above the 99.5th percentile of the return distribution are removed during the formation period (Trim Top), or 3) outliers below the 0.5th percentile are removed during the formation period (Trim Bottom).

period directly affects portfolio composition, particularly during volatile periods when outliers are concentrated. This effect is most evident under outlier trimming, which, following standard practice, excludes affected bonds from portfolio construction. Figure 2 shows that trimming either positive or negative outliers in the formation period decreases the number of bonds included in the short-term NIG bond momentum portfolios.[22] In contrast, outlier treatment in the holding period has no such composition effect, as momentum portfolios are held fixed once formed.[23]

4.2 The Information Diffusion Mechanism

Outlier treatment during the formation period may reshape momentum profitability if the changed portfolios, due to the composition effect, also exhibit variation in return continuation. As documented in the literature, return continuation in momentum portfolios could originate from

[22] The analogous plot for the loser side is omitted, as the two figures are very much alike.

[23] The composition effect is also briefly discussed in Galvani and Li (2023), which does not distinguish between formation- and holding-period outliers.

Figure 3: Short-term Momentum Returns in Straight NIG Bonds

The figure plots the series of monthly returns on the short-term momentum strategy for straight NIG bonds. Panel A plots the return series calculated leaving outliers untreated, Panel B corresponds to trimming both positive and negative outliers during the formation period (FP), and Panel C (D) presents the series when only positive (negative) outliers are trimmed during the formation period. The three gray shaded areas highlight momentum crashes associated with the benchmark return series in Panel A. Outliers are identified with the (99.5, 0.5) percentile thresholds of the straight all-bond return distribution.

gradual information diffusion (Hong and Stein, 1999), with stronger momentum observed among less efficient bonds (Li and Galvani, 2021). Consequently, given asymmetric diffusion of good and bad news in the corporate bond market, trimming positive and negative outliers independently in the formation period may lead to asymmetric variations in momentum profitability.

Figure 3 visually illustrates how formation-period outlier treatment affects momentum returns in NIG bonds. It contrasts the monthly momentum return series of the short-term strategy in the untreated sample (Panel A), when both positive and negative outliers are trimmed (Panel B), and when only positive (Panel C) or negative (Panel D) outliers are removed. Panel A indicates that the return series in the raw data is characterized by three sharp crashes (shaded in gray), rendering the strategy unprofitable on average. The crashes are largely mitigated in Panel

B (visible from the vertical axis scale), when momentum portfolios are restructured by formation-period outlier trimming. Importantly, the return series in Panels C and D exhibit fluctuations in opposite directions and on different scales. While removing positive outliers has little impact on momentum crashes, trimming negative outliers generates strong positive returns and virtually eliminates all three crashes. This contrasting effect implies that separately trimming positive and negative outliers during the formation period may generate momentum portfolios with systematically different return continuation patterns. Under the gradual information diffusion framework, these patterns could be linked to the asymmetric diffusion of good and bad news in the corporate bond market.

5 Asymmetric Momentum Patterns

This section formally evaluates the performance of momentum strategies when positive and negative outliers are trimmed separately in the formation period. Table 2 reports portfolio excess returns and market-risk-adjusted alphas for the short-term (Panel A) and long-term (Panel B) EW momentum strategies. Excess return differences from Model (2) are reported to quantify the spread between portfolio return series obtained with and without outlier treatment:

$$PR_t^{treated} - PR_t^{untreated} = \beta i_t + \epsilon_t \qquad t = 1, 2, \ldots, 233 \tag{2}$$

where $PR^{treated}$ is the treated monthly portfolio return series, $PR^{untreated}$ is the corresponding benchmark series obtained in the raw data, and i_t is a vector of ones. Outliers are identified using both the (99.5, 0.5) and (90, 10) percentile thresholds. The (90, 10) cutoffs mitigate the influence of the most extreme and error-prone observations and help ensure that the results are not driven by spurious outliers. As the percentile thresholds are sample-specific, results associated with a set of absolute cutoffs at +/-30% are also included for comparison.[24] Standard errors are adjusted using the Newey-West HAC estimation with three lags (e.g., Dickerson et al., 2024).

The results reveal an asymmetric effect of trimming positive and negative outliers in the formation period.[25] On the one hand, trimming negative outliers brings about highly significant momentum excess returns and risk-adjusted alphas for both strategies across all thresholds, in the straight all-bond and the NIG bond samples. The improved momentum profits are statistically distinguishable from the benchmark returns in the raw data, with positive spreads driven entirely by decreased returns on loser portfolios, as return changes on winner portfolios are small and mostly negative. These findings are consistent with negative outliers reflecting the quick diffusion of bad news. Trimming these outliers would potentially eliminate ”bad” losers with short-lived price trends, thus enhancing the performance of loser portfolios and boosting momentum profitability.

Surprisingly, when outliers below the 10th percentile are removed, even IG bonds achieve positive momentum excess returns significant at the 10% level for both strategies. Their spreads over the benchmark returns are also significant. This finding is novel to the literature, as it has been uniformly documented that IG bonds do not support unconditional momentum profits (e.g., Gebhardt et al., 2005; Dickerson et al., 2024; Jostova et al., 2024).[26] Importantly, momentum gains in IG bonds are entirely due to exposure to market risk, as their risk-adjusted alphas are

[24] The 30% cutoff is the 99.5th percentile threshold in Jostova et al. (2013). In this study's sample, the +/-30% cutoffs correspond to the 99.67th and 0.18th percentiles of the straight all-bond return distribution.

[25] The asymmetric effect also extends to less extreme decile portfolios (see Section B of the Internet Appendix).

[26] However, momentum strategies can be profitable for IG bonds conditionally. For instance, Li and Galvani (2018) document significant momentum returns for IG bonds following UP markets and low sentiment.

Table 2: Formation-Period Outlier Treatment and Momentum

The table contrasts the performance of momentum strategies in the raw data with that after trimming outliers in the formation period. Panel A tabulates results for the short-term ($S(3,3)$) EW strategy in the straight all-bond sample, and the non-investment-grade and investment-grade bond subsamples. Corresponding results for the long-term ($S(6,6)$) strategy are reported in Panel B. Each panel reports average monthly excess returns of the long-short momentum portfolios in the raw data and under three sets of outlier treatments. Outliers are identified at the (99.5, 0.5) and (90, 10) percentiles of the straight all-bond return distribution, and by the absolute cutoffs at +/-30%. Each panel also reports the estimated β from the model $PR_t^{treated} - PR_t^{untreated} = \beta i_t + \epsilon_t$, which evaluates the spread between the monthly portfolio return series associated with each outlier treatment and the benchmark return series when outliers are left untreated. The last block in each panel reports estimated alphas from the bond market CAPM. T-statistics significant at the 5% level are highlighted in bold. For IG bonds, three estimates significant at the 10% level are highlighted in bold italics. Standard errors are adjusted using the Newey-West HAC estimation with three lags.

	Whole			Non-investment-grade bonds			Investment-grade bonds		
	W-L	Winner	Loser	W-L	Winner	Loser	W-L	Winner	Loser
Panel A: Equal-weighted $S(3,3)$ Momentum Excess Returns									
Raw ER	0.448	2.184	1.735	-0.208	3.26	3.468	-0.21	0.609	0.818
	(0.965)	**(5.829)**	**(3.255)**	(-0.183)	**(5.580)**	**(2.648)**	(-1.104)	**(4.262)**	**(3.407)**
Trim 0.5	1.412	2.089	0.676	2.363	3.187	0.823	-0.056	0.608	0.663
	(5.160)	**(5.738)**	**(3.123)**	**(5.656)**	**(5.601)**	**(2.244)**	(-0.413)	**(4.274)**	**(3.546)**
Trim 10	1.964	2.352	0.387	3.69	4.127	0.436	*0.206*	0.611	0.404
	(4.276)	**(4.828)**	**(3.964)**	**(4.268)**	**(4.453)**	**(3.191)**	**(1.843)**	**(4.502)**	**(3.924)**
Trim -30%	1.237	2.129	0.891	1.963	3.194	1.23	-0.087	0.608	0.694
	(4.610)	**(5.753)**	**(3.213)**	**(4.514)**	**(5.585)**	**(2.519)**	(-0.623)	**(4.263)**	**(3.536)**
Trim 99.5	-0.403	1.044	1.446	-1.353	1.339	2.691	-0.228	0.588	0.815
	(-0.939)	**(4.979)**	**(3.096)**	(-1.442)	**(4.475)**	**(2.589)**	(-1.202)	**(4.271)**	**(3.407)**
Trim 90	-0.951	0.497	1.447	-2.375	0.533	2.907	*-0.32*	0.451	0.77
	(-1.972)	**(5.128)**	**(2.804)**	**(-2.051)**	**(4.347)**	**(2.407)**	**(-1.843)**	**(4.690)**	**(3.527)**
Trim 30%	-0.463	1.145	1.607	-1.786	1.476	3.261	-0.225	0.594	0.818
	(-0.983)	**(5.172)**	**(3.119)**	(-1.495)	**(4.623)**	**(2.496)**	(-1.179)	**(4.257)**	**(3.407)**
Excess return differences with raw									
Trim 0.5	0.964	-0.095	-1.059	2.572	-0.073	-2.644	0.154	-0.001	-0.155
	(2.384)	**(-3.804)**	**(-2.597)**	**(2.246)**	(-1.642)	**(-2.328)**	(1.417)	(-0.506)	(-1.432)
Trim 10	1.517	0.169	-1.348	3.898	0.867	-3.031	0.417	0.002	-0.414
	(2.570)	(0.893)	**(-2.730)**	**(2.248)**	(1.273)	**(-2.428)**	**(2.414)**	(0.158)	**(-2.377)**
Trim -30%	0.79	-0.055	-0.845	2.171	-0.066	-2.238	0.123	-0.001	-0.124
	(2.162)	**(-3.519)**	**(-2.290)**	**(2.006)**	**(-2.167)**	**(-2.060)**	(1.152)	(-1.403)	(-1.161)
Trim 99.5	-0.85	-1.14	-0.289	-1.144	-1.921	-0.776	-0.018	-0.021	-0.003
	(-3.611)	**(-4.722)**	**(-2.025)**	**(-2.238)**	**(-4.981)**	(-1.567)	(-1.831)	(-1.748)	(-0.918)
Trim 90	-1.399	-1.687	-0.288	-2.166	-2.727	-0.561	-0.11	-0.158	-0.048
	(-4.415)	**(-5.144)**	**(-2.350)**	**(-4.269)**	**(-5.220)**	(-1.821)	(-1.673)	**(-2.416)**	(-1.298)
Trim 30%	-0.911	-1.039	-0.128	-1.578	-1.784	-0.206	-0.015	-0.015	-0.001
	(-4.345)	**(-4.560)**	**(-4.392)**	**(-4.439)**	**(-4.981)**	**(-2.869)**	**(-2.218)**	(-1.941)	(-0.322)
Alphas from the bond market risk factor CAPM									
Raw Alpha	0.462	1.483	1.021	-0.055	2.465	2.519	-0.113	0.15	0.262
	(0.994)	**(6.294)**	**(2.314)**	(-0.046)	**(5.162)**	(1.941)	(-0.697)	**(2.013)**	**(2.037)**
Trim 0.5	1.281	1.397	0.115	2.32	2.419	0.098	-0.018	0.15	0.167
	(5.352)	**(6.308)**	(0.937)	**(5.943)**	**(5.213)**	(0.316)	(-0.134)	**(2.025)**	(1.785)
Trim 10	1.424	1.557	0.132	3.365	3.509	0.143	0.02	0.173	0.151
	(5.119)	**(5.898)**	**(1.981)**	**(3.388)**	**(3.379)**	(1.040)	(0.189)	**(2.207)**	**(2.246)**
Trim -30%	1.193	1.431	0.237	2.086	2.408	0.321	-0.023	0.149	0.172
	(4.897)	**(6.299)**	(1.670)	**(5.254)**	**(5.206)**	(0.848)	(-0.175)	**(2.005)**	(1.823)
Trim 99.5	-0.246	0.544	0.788	-1.069	0.807	1.875	-0.124	0.14	0.263
	(-0.579)	**(3.438)**	**(1.977)**	(-1.012)	**(2.759)**	(1.671)	(-0.770)	(1.920)	**(2.031)**
Trim 90	-0.652	0.176	0.827	-1.889	0.205	2.093	-0.122	0.133	0.255
	(-1.357)	**(2.448)**	(1.729)	(-1.499)	(1.531)	(1.616)	(-0.876)	(1.917)	**(2.161)**
Trim 30%	-0.282	0.631	0.913	-1.423	0.901	2.323	-0.122	0.142	0.263
	(-0.624)	**(3.798)**	**(2.134)**	(-1.177)	**(3.060)**	(1.820)	(-0.759)	(1.933)	**(2.037)**

	Whole			Non-investment-grade bonds			Investment-grade bonds		
	W-L	Winner	Loser	W-L	Winner	Loser	W-L	Winner	Loser
	Panel B: Equal-weighted $S(6,6)$ Momentum Excess Returns								
Raw ER	0.062	1.84	1.778	-0.525	2.506	3.03	-0.178	0.549	0.726
	(0.164)	**(5.626)**	**(3.666)**	(-0.560)	**(5.687)**	**(2.944)**	(-1.308)	**(4.329)**	**(3.970)**
Trim 0.5	0.858	1.501	0.642	1.547	2.149	0.601	-0.133	0.542	0.674
	(4.185)	**(5.807)**	**(2.975)**	**(4.533)**	**(5.455)**	(1.588)	(-1.005)	**(4.293)**	**(3.898)**
Trim 10	1.292	1.625	0.332	2.343	2.747	0.403	*0.169*	0.465	0.295
	(3.985)	**(4.768)**	**(4.112)**	**(4.372)**	**(4.787)**	**(3.493)**	**(1.928)**	**(4.293)**	**(4.192)**
Trim -30%	0.73	1.612	0.881	1.296	2.345	1.048	-0.15	0.547	0.697
	(3.320)	**(6.079)**	**(3.129)**	**(2.927)**	**(5.601)**	**(2.026)**	(-1.179)	**(4.318)**	**(4.031)**
Trim 99.5	-0.638	0.733	1.369	-1.474	0.87	2.344	-0.182	0.528	0.708
	(-1.633)	**(4.333)**	**(3.105)**	(-1.689)	**(4.032)**	**(2.443)**	(-1.348)	**(4.246)**	**(3.974)**
Trim 90	-0.704	0.417	1.12	-1.709	0.491	2.199	-0.147	0.393	0.539
	(-1.711)	**(4.406)**	**(2.537)**	(-1.539)	**(4.244)**	(1.895)	(-1.264)	**(4.411)**	**(3.836)**
Trim 30%	-0.622	0.801	1.423	-1.505	0.965	2.469	-0.182	0.535	0.716
	(-1.559)	**(4.428)**	**(3.169)**	(-1.705)	**(4.182)**	**(2.535)**	(-1.352)	**(4.262)**	**(3.976)**
	Excess return differences with raw								
Trim 0.5	0.796	-0.339	-1.135	2.073	-0.356	-2.429	0.045	-0.007	-0.052
	(2.647)	**(-3.537)**	**(-3.299)**	**(2.601)**	**(-3.367)**	**(-2.997)**	(1.385)	**(-2.576)**	(-1.561)
Trim 10	1.23	-0.216	-1.446	2.868	0.241	-2.627	0.347	-0.084	-0.431
	(2.500)	(-1.662)	**(-3.181)**	**(2.785)**	(0.822)	**(-2.712)**	**(2.914)**	**(-2.226)**	**(-3.058)**
Trim -30%	0.669	-0.228	-0.897	1.822	-0.161	-1.982	0.027	-0.002	-0.029
	(2.766)	**(-2.280)**	**(-3.295)**	**(2.652)**	**(-3.317)**	**(-2.852)**	(1.597)	(-1.774)	(-1.702)
Trim 99.5	-0.699	-1.108	-0.408	-0.949	-1.635	-0.686	-0.004	-0.022	-0.018
	(-3.276)	**(-4.629)**	**(-4.004)**	**(-3.635)**	**(-5.132)**	**(-4.432)**	(-0.539)	**(-2.495)**	(-1.691)
Trim 90	-0.766	-1.424	-0.658	-1.183	-2.015	-0.831	0.031	-0.156	-0.187
	(-2.933)	**(-4.889)**	**(-4.066)**	**(-2.304)**	**(-5.168)**	(-1.759)	(0.510)	**(-2.356)**	**(-3.044)**
Trim 30%	-0.684	-1.039	-0.355	-0.98	-1.541	-0.561	-0.004	-0.015	-0.01
	(-3.218)	**(-4.469)**	**(-3.811)**	**(-3.868)**	**(-5.045)**	**(-4.722)**	(-0.747)	**(-2.704)**	(-1.411)
	Alphas from the bond market risk factor CAPM								
Raw Alpha	0.226	1.276	1.049	-0.025	2.007	2.031	-0.114	0.162	0.276
	(0.620)	**(6.196)**	**(2.989)**	(-0.025)	**(5.055)**	**(1.973)**	(-0.837)	**(2.064)**	**(3.003)**
Trim 0.5	0.894	1.004	0.109	1.859	1.673	-0.187	-0.09	0.156	0.245
	(4.584)	**(5.780)**	(0.918)	**(5.540)**	**(4.731)**	(-0.540)	(-0.653)	**(1.990)**	**(2.763)**
Trim 10	0.887	1.037	0.149	2.012	2.159	0.146	0.007	0.139	0.131
	(4.394)	**(5.840)**	**(2.471)**	**(4.608)**	**(4.798)**	(1.173)	(0.059)	(1.804)	**(2.348)**
Trim -30%	0.885	1.118	0.232	1.787	1.856	0.068	-0.106	0.16	0.265
	(4.478)	**(5.983)**	(1.698)	**(4.518)**	**(4.986)**	(0.162)	(-0.776)	**(2.041)**	**(2.980)**
Trim 99.5	-0.357	0.334	0.69	-0.95	0.475	1.424	-0.118	0.147	0.265
	(-1.104)	**(2.885)**	**(2.150)**	(-1.048)	**(2.449)**	(1.466)	(-0.865)	(1.911)	**(2.893)**
Trim 90	-0.431	0.152	0.582	-1.339	0.218	1.556	-0.044	0.142	0.185
	(-1.150)	**(2.271)**	(1.525)	(-1.006)	(1.919)	(1.134)	(-0.350)	**(1.978)**	**(2.329)**
Trim 30%	-0.333	0.398	0.73	-0.961	0.564	1.524	-0.119	0.15	0.268
	(-1.010)	**(3.093)**	**(2.251)**	(-1.056)	**(2.680)**	(1.557)	(-0.873)	(1.942)	**(2.928)**

insignificant. This result is in stark contrast to the significant alphas reported for NIG bonds, and can be explained by the evidence that IG bonds are more sensitive to market-level information while NIG bonds are more sensitive to firm-level information (e.g., Kwan, 1996; Li, 2022).

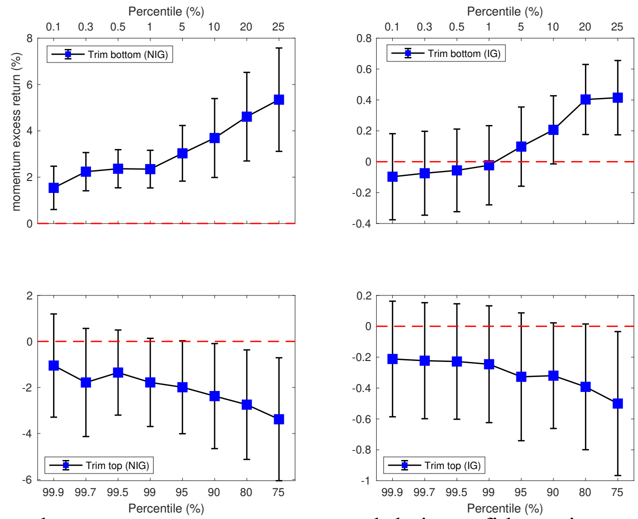
On the other hand, trimming positive outliers in the formation period yields negative and mostly insignificant momentum excess returns and alphas. This effect is driven by significantly lowered returns on winner portfolios in all cases. These findings are consistent with positive outliers being associated with the slow diffusion of good news and identifying winners with persistent price trends. Throwing away these ”good” winners further hinders the identification of the momentum effect, which is nonexistent in the raw data in the first place.

Across the three sets of thresholds, the asymmetric effect is the most pronounced under the least stringent (90, 10) percentile thresholds. In fact, relaxing the thresholds amplifies the asymmetric effect for both NIG and IG bonds, as clearly illustrated in Figure 4 for the short-term strategy. Section D of the Internet Appendix further examines the effects of trimming positive and negative outliers in samples that exclude bonds with extreme returns, defined using the +/-30% or +/-20% cutoffs, to mitigate data noise. The results indicate that the asymmetric effect remains robust, with the contributions of the long and short legs becoming more clearly disentangled. Taken together, the evidence reveals that the asymmetric effect is not driven by a few potentially erroneous tail observations. Instead, the asymmetry is systematic and represents a widespread feature of corporate bond momentum.

Table 3 reports the minimum and average winner portfolio sizes for the strategies employed in Table 2. The (90, 10) percentile thresholds are less desirable for NIG bonds, as they overly reduce portfolio size and thus undermine risk diversification. Whereas for IG bonds, the +/-30% and (99.5 0.5) percentile thresholds on average identify too few outliers to meaningfully alter momentum profitability. Instead, the (90, 10) thresholds strike a balance between identifying asymmetric momentum patterns and preserving sufficient portfolio breadth for IG bonds.

In summary, this section documents systematically asymmetric momentum patterns for both IG and NIG bonds when positive and negative outliers are trimmed separately in the formation period. The results are consistent with winner portfolios exhibiting stronger return

Figure 4: The Effect of Changing Thresholds



The figure plots estimated momentum excess returns and their confidence intervals when top or bottom outliers are trimmed in the formation period of the short-term (3,3) strategy for NIG bonds (left panels) and IG bonds (right panels), respectively. Thresholds for identifying outliers are the (99.9, 0.1), (99.7, 0.3), (99.5, 0.5), (99, 1), (95, 5), (90, 10), (80, 20), and (75, 25) percentiles of the straight all-bond return distribution. Standard errors are Newey-West adjusted with three lags.

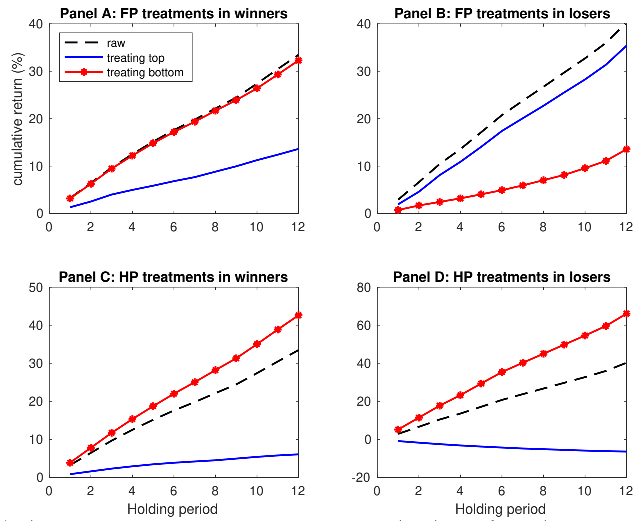
Table 3: Winner Portfolio Sizes

The table tabulates the minimum/average numbers of bonds included in the overlapping winner portfolios constructed with and without outlier trimming, for the short-term (3m) and long-term (6m) strategies in the straight all-bond sample, and the NIG/IG bond subsamples. Outlier treatments include trimming from the formation period positive or negative outliers using the (99.5, 0.5) and (90, 10) percentile thresholds, as well as the absolute cutoffs of +/-30%.

	Whole3m		NIG3m		IG3m		Whole6m		NIG6m		IG6m	
	min	avg	min	avg	min	avg	min	avg	min	avg	min	avg
Raw	413	560	93	137	285	415	376	513	93	127	255	380
Trim 30%	396	556	92	134	280	414	335	506	86	123	247	379
Trim 99.5	371	554	92	132	267	414	304	503	71	121	232	378
Trim90	69	428	13	91	53	334	32	333	2	65	30	266
Trim-30%	371	557	90	135	275	415	336	508	84	124	250	379
Trim0.5	300	553	59	132	240	413	265	502	50	120	214	377
Trim10	38	424	3	94	35	325	25	316	1	67	23	248

continuation than loser portfolios, possibly due to the slower diffusion of good news relative to bad news in the corporate bond market. This explanation provides a rationale for why corporate bond momentum stems from the long leg, as the short leg is more prone to trend reversals. The latter erodes the profitability of the momentum strategy and contributes to the lack of a discernible momentum effect in the raw data.

Figure 5: FP and HP Outlier Treatments



The figure plots cumulative excess returns over a one-year horizon for winner and loser portfolios of the short-term strategy in NIG bonds, with and without outlier trimming in the formation (FP) or holding (HP) period. Outlier thresholds are the (99.5, 0.5) percentiles of the straight all-bond return distribution.

5.1 Comparison with Holding-Period Outlier Treatment

Unlike formation-period outlier treatment, trimming outliers during the holding period does not affect momentum portfolio composition. Accordingly, such treatment should not generate the same asymmetric momentum patterns observed from trimming formation-period outliers. Indeed, Panel A of Table 4 shows that trimming negative outliers in the holding period yields negative and insignificant momentum returns for the short-term strategy across all three samples.[27] While trimming positive outliers produces significant momentum gains in the all-bond and NIG bond samples, these returns remain indistinguishable from the benchmark returns.[28]

Figure 5 contrasts the effects of outlier treatment during the formation (FP) and holding (HP) periods of the short-term strategy in NIG bonds. Panels A and B illustrate that trimming positive (negative) outliers in the formation period predominantly weakens (strengthens) the

[27] For the remaining analysis, outliers in the all-bond and NIG bond samples are identified by the (99.5, 0.5) percentile thresholds, while the (90, 10) percentile thresholds are used for IG bonds.

[28] The 0.652% excess return in the all-bond sample, obtained by trimming holding-period positive outliers, is very close to the 0.71% raw return reported in Jostova et al. (2013), which is based on an earlier sample spanning 1991–2011.

Table 4: Robustness Tests

The table tabulates portfolio excess returns and their benchmark spreads for the short-term strategy with and without outlier treatments, in the straight/convertible all-bond sample (Whole), and the corresponding NIG and IG bond subsamples. Panel A reports results for straight bonds with top and bottom outliers separately trimmed in the holding period (HP). Panel B presents convertible bond results when outliers are trimmed in the formation period (FP). Panel C evaluates the effect of formation-period outlier trimming on straight bond momentum after removing the three largest crash periods identified in the benchmark momentum return series. Each crash period includes the crash month plus two months preceding and two months following the crash. The crash months are February 2003, February 2009, and March 2016 in the all-bond sample and for NIG bonds, and January 2009, April 2009, and July 2010 for IG bonds. Outlier thresholds in the all-bond and NIG bond samples are the (99.5, 0.5) percentiles of the straight/convertible all-bond return distribution, and the (90, 10) percentile thresholds are used for IG bonds. Benchmark spreads are estimated from the model $PR_t^{treated} - PR_t^{untreated} = \beta i_t + \epsilon_t$. T-statistics significant at the 5% level are highlighted in bold. Standard errors are adjusted using the Newey-West HAC estimation with three lags.

	Whole			NIG bonds			IG bonds		
	W-L	Winner	Loser	W-L	Winner	Loser	W-L	Winner	Loser
Panel A: Holding period treatments in straight bonds									
Raw ER	0.448	2.184	1.735	-0.208	3.26	3.468	-0.21	0.609	0.818
	(0.965)	**(5.829)**	**(3.255)**	(-0.183)	**(5.580)**	**(2.648)**	(-1.104)	**(4.262)**	**(3.407)**
Trim HP top	0.652	0.696	0.042	1.623	0.77	-0.854	0.129	-0.212	-0.342
	(3.522)	**(3.969)**	(0.164)	**(5.347)**	**(2.897)**	(-1.871)	(1.222)	(-1.665)	(-1.925)
Trim HP bottom	-0.115	2.501	2.614	-1.964	3.952	5.915	-0.301	1.429	1.729
	(-0.188)	**(6.717)**	**(3.913)**	(-1.263)	**(6.786)**	**(3.474)**	(-1.216)	**(11.135)**	**(5.528)**
Excess return differences with raw									
Trim HP top	0.205	-1.488	-1.693	1.832	-2.49	-4.321	0.339	-0.821	-1.16
	(0.414)	**(-5.666)**	**(-3.225)**	(1.461)	**(-5.888)**	**(-3.194)**	(1.586)	**(-7.901)**	**(-4.209)**
Trim HP bottom	-0.562	0.317	0.879	-1.756	0.692	2.447	-0.091	0.82	0.911
	(-2.634)	**(5.040)**	**(3.473)**	**(-3.285)**	**(5.568)**	**(4.078)**	(-0.735)	**(7.244)**	**(4.509)**
Panel B: Formation period treatments in convertible bonds									
Raw ER	3.005	4.416	1.411	4.561	6.318	1.756	0.166	1.333	1.165
	(2.645)	**(3.823)**	**(2.875)**	**(2.490)**	**(3.488)**	**(2.411)**	(0.501)	**(4.075)**	**(3.996)**
Trim FP top	1.688	2.899	1.21	1.936	3.535	1.599	-0.426	0.801	1.226
	(2.200)	**(3.608)**	**(2.634)**	**(2.061)**	**(3.758)**	**(2.270)**	(-1.321)	**(2.607)**	**(4.149)**
Trim FP bottom	3.364	4.418	1.053	5.227	6.246	1.018	1.174	1.673	0.498
	(2.993)	**(3.792)**	**(2.575)**	**(2.888)**	**(3.420)**	(1.761)	**(2.709)**	**(3.707)**	**(2.497)**
Excess return differences with raw									
Trim FP top	-1.317	-1.518	-0.201	-2.626	-2.783	-0.157	-0.592	-0.531	0.061
	(-1.953)	**(-2.282)**	**(-2.053)**	**(-2.004)**	**(-2.151)**	(-1.241)	**(-2.194)**	**(-2.089)**	(0.813)
Trim FP bottom	0.359	0.002	-0.357	0.666	-0.072	-0.738	0.989	0.336	-0.653
	(1.760)	(0.044)	(-1.790)	(1.909)	(-1.014)	**(-2.191)**	**(2.714)**	(1.198)	**(-2.058)**
Panel C: Removing three crash periods									
Raw ER	1.182	2.017	0.834	1.635	2.877	1.241	0.081	0.534	0.452
	(4.467)	**(5.500)**	**(3.371)**	**(4.164)**	**(5.080)**	**(2.691)**	(0.774)	**(3.895)**	**(3.036)**
Trim FP top	0.236	0.947	0.71	0.137	1.144	1.007	-0.052	0.397	0.448
	(1.209)	**(4.394)**	**(2.996)**	(0.497)	**(3.814)**	**(2.310)**	(-0.554)	**(4.081)**	**(3.206)**
Trim FP bottom	1.447	1.937	0.489	2.257	2.786	0.528	0.232	0.536	0.304
	(4.886)	**(5.415)**	**(2.505)**	**(5.403)**	**(5.060)**	(1.619)	**(2.266)**	**(4.126)**	**(3.480)**
Excess return differences with raw									
Trim FP top	-0.946	-1.07	-0.124	-1.499	-1.733	-0.234	-0.133	-0.137	-0.004
	(-4.173)	**(-4.356)**	**(-4.521)**	**(-4.235)**	**(-4.601)**	**(-3.985)**	**(-2.572)**	**(-2.453)**	(-0.257)
Trim FP bottom	0.266	-0.079	-0.345	0.622	-0.091	-0.712	0.151	0.002	-0.148
	(3.017)	**(-3.514)**	**(-3.753)**	**(3.295)**	**(-2.377)**	**(-3.567)**	(1.721)	(0.184)	(-1.593)

performance of winner (loser) portfolios. This asymmetry is consistent with positive (negative) outliers being particularly effective in identifying ”good” winners (”bad” losers) that are more (less) likely to experience return continuation. In contrast, Panels C and D show that trimming positive (negative) outliers in the holding period simultaneously decreases (increases) returns on both winner and loser portfolios, with the effect of trimming positive outliers being stronger, possibly due to the positive skewness of the return distribution.

The effect of trimming positive outliers in Panel D highlights a strong presence of extremely positive returns in loser portfolios during the holding period, implying sharp trend reversals in the short leg.[29] Consistently, in the raw data, about 10% and 18% of losers yield positive outliers during the holding period of the short-term and long-term NIG bond strategies, respectively.[30] These shares decline to 4% and 6% after negative outliers are trimmed in the formation period. These findings confirm that price trends in loser portfolios are short-lived, with bonds experiencing extreme formation-period price declines being particularly prone to strong subsequent reversals, making them ”bad” losers for momentum strategies.

This section reveals the fundamentally different roles of formation- and holding-period outliers, with economically meaningful momentum patterns arising exclusively from trimming positive and negative outliers in the formation period.

5.2 Robustness Analysis Using Convertible Bonds

This section employs the convertible bond subsample as an out-of-sample validation of the main findings, leveraging the security's hybrid nature of both debt and equity.[31] Panel B of Table 4 shows that the momentum effect is strong and robust for convertible bonds, delivering

[29]This finding explains why trimming positive outliers in the holding period yields significant momentum gains.

[30]The corresponding shares of winners yielding negative outliers in the holding period are 4% and 7%, respectively. These numbers decrease slightly to 3% and 5% after trimming positive outliers in the formation period.

[31]See Batten, Khaw, and Young (2014) for a detailed survey on the pricing of convertible bonds.

significant gains in both the all-bond and NIG bond samples, with and without outlier treatment.[32] The asymmetric effect of trimming positive and negative outliers in the formation period is weaker in both samples, yielding largely insignificant return spreads over the benchmark.[33] This finding is consistent with convertible bonds responding to good and bad news less asymmetrically than straight bonds, due to their equity-like payoff structure.

5.3 The Effect of Data Uncertainty

Jostova et al. (2024) identify substantial uncertainty in momentum estimation arising from a taxonomy of data choices involved in constructing monthly bond return samples from TRACE. To account for such data uncertainty, this section summarizes findings based on alternative treatments of two key data choices, i.e., the handling of erroneous outliers and the choice of month-end prices.[34] The analysis is also conducted using the alternative WRDS bond return sample, which adopts several different but similarly reasonable data choices. To save space, details are reported in Section E of the Internet Appendix.

The results indicate that the asymmetric momentum patterns documented in this study remain robust across samples constructed using alternative data approaches.[35] However, estimated momentum gains from trimming negative outliers in the formation period vary considerably in different samples, highlighting the effect of data uncertainty. This variation is

[32] The winner and loser portfolios of IG bonds contain at most four bonds even without outlier treatment. The scarcity of convertible IG bonds renders the corresponding estimates unreliable.

[33] The exception occurs for NIG bonds when positive outliers are trimmed, which significantly reduces momentum returns by about 2.6%, driven entirely by the long leg.

[34] Jostova et al. (2024) show that uncertainty in momentum estimation largely arises from return-related data filters, including different treatments of return outliers, extreme return reversals, and alternative definitions of month-end returns and prices.

[35] The only exception is when the raw data sample is truncated at 30%, following one of the right-tail return filters adopted in Jostova et al. (2024). In this case, momentum is present in NIG bonds with and without trimming positive or negative outliers in the formation period. However, significant momentum gains for IG bonds are achieved only after trimming negative outliers. Therefore, the effect of trimming negative outliers remains the most robust.

particularly pronounced for NIG bonds, with momentum excess returns estimated for the short-term strategy spanning from 0.45% to 2.36% per month when negative outliers below the 0.5th percentile are trimmed.[36] Notably, the lowest estimate at 0.45% is still sizable, given that the mean (median) monthly return in the raw data is just 1.54% (0.61%) for NIG bonds. In contrast, estimated momentum gains for IG bonds are more stable, ranging from 0.21% to 0.32% following the trimming of negative outliers below the 10th percentile. In comparison, the sample mean and median monthly returns for IG bonds are 0.59% and 0.29%, respectively.

Overall, the findings based on alternative data choices align with Jostova et al. (2024), confirming that data uncertainty affects the magnitude of realized momentum returns, especially for NIG bonds. Nonetheless, this uncertainty does not alter the main conclusion that corporate bond momentum is shaped by asymmetric return continuation between winner and loser portfolios, a finding revealed by formation-period outlier treatment.

6 Negative Outliers and Momentum Crashes

Figure 3 in Section 4.2 visualizes how trimming negative outliers in the formation period prevents momentum crashes. Daniel and Moskowitz (2016) document that stock momentum crashes resemble the payoffs of writing a call option on bear market states, which incur substantial losses following sudden market upswings. Hence, it is warranted to examine whether corporate bond momentum strategies exhibit similar bear market optionality. The implication is that removing negative outliers in the formation period likely eliminates this optionality, which mitigates the risk of momentum crashes and enhances momentum profitability.

[36] The lowest estimate is obtained in the sample in which absolute bond returns are truncated at 30%.

Panel D in Table 4 examines whether negative outlier reversals are confined to momentum crash periods. The results indicate that the asymmetric effect of trimming positive and negative outliers still holds when periods of the three largest crashes are removed from the evaluation.[37] In particular, trimming negative outliers yields highly significant momentum profits that are distinguishable from the benchmark returns (spread significant at 10% for IG bonds). Hence, the effect of trimming negative outliers extends beyond mitigating momentum crashes.

6.1 The Bear Market Optionality

As trimming negative outliers in the formation period effectively eliminates momentum crashes, it remains relevant to verify whether the effect can be explained by the theory of bear market optionality. Table 5 presents conditional CAPM regression results based on Model 3 in Daniel and Moskowitz (2016), for the short-term strategy with and without outlier trimming in the formation period. In contrast to the results documented for stocks, corporate bond momentum in the raw data demonstrates *no* bear market optionality. Specifically, the $\hat{\beta}_{BU}$ estimates are insignificant for both IG and NIG bonds, with the IG bond coefficient exhibiting the wrong sign.

Results reported in the last three columns of Table 5 further indicate that the effect of trimming negative outliers persists across different market states. In normal markets, the treatment yields a significant alpha of 3.2% per month for NIG bonds and a significantly positive market exposure, $\hat{\beta}_0$, for IG bonds, consistent with IG (NIG) bonds being more sensitive to market-level (firm-level) information. In bear markets, the treatment still achieves 1.1% profits for NIG bonds after adjusting for market risk. Importantly, the significantly negative $\hat{\beta}_B$ and insignificant but positive $\hat{\beta}_{BU}$ for NIG bonds suggest that negative outlier reversals are strong and

[37] The three crashes for NIG bonds are highlighted in gray in Figure 3.

Table 5: The Bear Market Optionality

The table presents estimated coefficients and t-statistics from Model (3) in Daniel and Moskowitz (2016), when portfolio excess return series is explained by a conditional CAPM,

$$ER_{P,t} = \alpha_0 + \alpha_B I_{B,t-1} + (\beta_0 + I_{B,t-1}(\beta_B + \beta_{BU} I_{U,t}))ER_{M,t} + \epsilon_t$$

where $I_{B,t-1}$ is the one-month lagged bear market indicator that equals one if the past two-year cumulative bond market return is below the sample average, and $I_{U,t}$ is the UP-market indicator that equals one if the bond market excess return $ER_{M,t}$ is positive. The regression is performed on portfolio return series of the short-term momentum strategy, with and without the positive or negative outlier trimming in the formation period, for straight NIG bonds in Panel A and IG bonds in Panel B. The coefficients $\hat{\alpha}_0$ and $\hat{\alpha}_B$ are reported in raw terms. Outlier thresholds for NIG bonds are the (99.5, 0.5) percentiles of the straight all-bond return distribution, and the (90, 10) percentile thresholds are used for IG bonds. The t-statistics significant at the 5% level are highlighted in bold. Standard errors are adjusted using the Newey-West HAC estimation with three lags.

	No treatment			Trim top in FP			Trim bottom in FP		
	MOM	Winner	Loser	MOM	Winner	Loser	MOM	Winner	Loser
Panel A: Optionality in bear markets for the NIG $S(3,1)$ strategy									
α_0	0.009	0.042	0.033	-0.002	0.015	0.016	0.032	0.039	0.006
	(0.525)	**(4.384)**	**(2.016)**	(-0.269)	**(2.020)**	**(2.501)**	**(4.434)**	**(4.676)**	(1.572)
α_B	-0.002	-0.034	-0.033	0.005	-0.01	-0.017	-0.021	-0.03	-0.01
	(-0.116)	**(-2.954)**	(-1.769)	(0.569)	(-1.309)	(-1.555)	**(-2.377)**	**(-2.802)**	(-1.611)
β_0	-1.643	1.669	3.317	-1.364	0.925	2.294	0.212	1.688	1.482
	(-1.450)	**(2.951)**	**(2.859)**	**(-3.133)**	(1.328)	**(4.209)**	(0.654)	**(3.362)**	**(4.343)**
β_B	0.983	-0.5	-1.493	0.73	0.269	-0.471	-1.105	-0.662	0.432
	(0.847)	(-0.802)	(-1.246)	(1.471)	(0.369)	(-0.749)	**(-2.538)**	(-1.030)	(0.838)
β_{BU}	-0.113	0.836	0.982	-1.069	-0.241	0.861	1.201	0.915	-0.253
	(-0.118)	(0.807)	(0.743)	(-1.042)	(-0.600)	(0.660)	(1.533)	(0.811)	(-0.310)
Panel B: Optionality in bear markets for the IG $S(3,1)$ strategy									
α_0	-0.007	0	0.007	-0.005	-0.001	0.004	-0.005	0	0.004
	(-2.147)	(0.042)	**(2.442)**	**(-2.329)**	(-0.610)	**(2.806)**	(-1.584)	(-0.152)	(1.557)
α_B	0.003	-0.001	-0.004	0	0.002	0.001	0.001	0	-0.002
	(0.604)	(-0.382)	(-1.108)	(-0.046)	(1.083)	(0.159)	(0.273)	(-0.033)	(-0.740)
β_0	0.139	1.143	1.01	0.088	0.875	0.793	0.54	1.154	0.62
	(0.480)	**(13.076)**	**(4.337)**	(0.452)	**(7.804)**	**(7.638)**	**(2.056)**	**(12.453)**	**(2.739)**
β_B	-0.797	-0.192	0.596	-1.038	-0.164	0.865	-0.504	-0.228	0.266
	(-1.632)	(-0.999)	(1.652)	**(-2.509)**	(-0.879)	**(3.086)**	(-1.475)	(-1.100)	(1.154)
β_{BU}	0.249	0.141	-0.075	0.166	-0.053	-0.186	0.634	0.091	-0.51
	(0.384)	(0.471)	(-0.181)	(0.294)	(-0.208)	(-0.517)	(1.712)	(0.280)	**(-6.642)**

robust in bear markets, regardless of subsequent market performance. Hence, trimming negative outliers enables momentum portfolios to better hedge against downside risk. This hedging function is weaker for IG bonds, consistent with their lower sensitivity to bad news.

Taken together, the evidence rejects bear market optionality as an explanation for the trend reversal in loser portfolios. Given the results in Table 5, a more detailed analysis of the state-dependent momentum effect in corporate bonds after trimming positive and negative outliers in the formation period is highly relevant. However, this topic is beyond the scope of this paper, and future research in this direction is warranted.

7 Recommendations

Recent corporate bond literature emphasizes the sensitivity of empirical studies to data choices (e.g., Jostova et al., 2024; Dick-Nielsen et al., 2024; Dickerson et al., 2024, 2026), including the handling of return outliers. Beyond the issue of data uncertainty, this paper further highlights that routine outlier treatment may discard economically meaningful information embedded in large price movements.[38] Therefore, the treatment of outliers in corporate bond studies should be applied with caution and, preferably, supported by economic reasoning.

Specific to the study of corporate bond momentum, this paper shows that treating outliers in the formation period is justified by their interaction with return continuation in the winner and loser portfolios. Separately trimming positive and negative outliers thus reshapes the performance of traditional momentum strategies in opposite directions, contributing a novel perspective to the literature. In contrast, treating outliers in the holding period is not recommended as it suffers from look-ahead bias and likely distorts the evaluation of momentum profitability.

From a practical perspective, the findings of this study suggest that bonds with extreme negative returns are poor candidates for loser portfolios, and removing them from the ranking period can be beneficial to momentum profitability. However, this approach has the undesirable feature of reducing the pool of bonds from which momentum portfolios are drawn. In periods of high outlier concentrations, this effect is mirrored by a sharp decline in portfolio size at a time when risk diversification is needed the most. Therefore, investors need to balance the trade-off between constructing profitable momentum strategies and maintaining well-diversified portfolios.

[38] Although a majority of TRACE outliers are based on authentic transaction data, there are still unreliable data points caused by reporting errors. Therefore, the work of Dick-Nielsen et al. (2024) and Dickerson et al. (2026), among others, to establish a standard corporate bond dataset remains essential to the field.

8 Conclusions

This study re-evaluates the relationship between outliers and momentum in corporate bonds. I show that the momentum effect exists in the corporate bond market and that the sensitivity of momentum profitability to outlier treatment during the formation period is economically meaningful. In particular, separately trimming formation-period positive and negative outliers reveals robust and asymmetric momentum patterns for both IG and NIG bonds. These momentum patterns are systematic, extending to bonds with less extreme returns, and are thus consistent with stronger return continuation in winner portfolios and trend reversals in loser portfolios. Nevertheless, this asymmetry in return continuation is most detectable among outlier-bearing winner and loser bonds, given the prevalence of outliers in momentum portfolios and the stronger tendency of negative outliers to exhibit subsequent reversals. Accordingly, the findings of this study motivate a modified momentum strategy based on outlier-filtered signals.

This study interprets the results from an information diffusion perspective, suggesting that the documented asymmetric momentum patterns are consistent with intra-portfolio informational heterogeneity stemming from the nonlinear payoff structure of corporate bonds. However, the findings also warrant consideration of alternative explanations. Specific to the effect of trimming negative outliers, the associated frequent reversals may also reflect compensation for liquidity provision (Grossman and Miller, 1988), which could confound an interpretation based on information overreaction. Further distinguishing among these alternative mechanisms is beyond the scope of this study and remains a promising avenue for future research.

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Internet Appendix to ”Corporate Bond Momentum Revisited”

This Internet Appendix presents additional results that are not included in the main text.

A Explaining the Incidence of Outliers

Due to infrequent trading, corporate bond price reactions to significant news can be strong enough to yield extreme returns. Furthermore, informed institutional investors typically execute sizable orders to minimize transaction costs. These trades may exert a material price impact, thereby increasing the likelihood of outliers. Therefore, this appendix examines whether information shocks can predict the incidence of outliers in the straight bond samples.

I gauge information shocks using bond credit rating changes, including upgrades and downgrades, and test whether rating changes can increase the incidence of outliers in Model A.1:

$$log(Pr(outlier_{bt} = 1|x_{bt})) = \beta_0 + \beta_1 info_{bt} + \sum_j \alpha_j Z^j_{bt} + \sum_b \theta_b bond_b + \sum_t \phi_t month_t + \epsilon_{bt} \quad \text{(A.1)}$$

where the log probability of the return on bond b in month t being an outlier is explained by the variable $info_{bt}$, which equals 1 when there is a rating downgrade or upgrade on bond b in month t, and 0 otherwise. The control variables summarized by Z^j include monthly trading volume (volume) and credit rating (CR). Bond and year-month fixed effects are controlled for. Model A.1 is estimated using the Poisson pseudo-maximum likelihood (PPML) method (Correia et al., 2020) with firm and year-month two-way clustered standard errors.[1] Panel A of Table A.1 reports the exponentiated coefficients for the $info$ variable. The results indicate that credit rating changes significantly increase the likelihood of outliers across different thresholds, for both IG and NIG bonds.

Model A.2 differentiates the information signals of upgrades (UPG) and downgrades

[1] Zou (2004) shows that Poisson regression with modified variance can effectively model binary rare event data (e.g., outliers) by overcoming the underestimation problem associated with logistic regression (King and Zeng, 2001).

(DNG) and evaluates their predictive powers on the incidences of positive and negative outliers:

$$\begin{aligned} log(Pr(PNoutlier_{bt} = 1|x_{bt})) &= \beta_0 + \beta_1 DNG_{bt} + \beta_2 UPG_{bt} + \beta_3 lag(DNG)_{bt} \\ &+ \beta_4 lag(UPG)_{bt} + \sum_j \alpha_j Z^j_{bt} + \sum_b \theta_b bond_b + \sum_t \phi_t month_t + \epsilon_{bt} \end{aligned} \quad \text{(A.2)}$$

where the dependent variable is the log probability of yielding a positive (or negative) outlier $PNoutlier_{bt}$ for bond b in month t. One-month lagged information signals are included to capture their relative diffusion speeds. I rely on the regression results to infer whether the market perceives upgrades and downgrades as good or bad news. Exponentiated coefficients for regressions of positive and negative outliers are reported in Panels B and C of Table A.1, respectively. Control variable estimates are omitted for brevity.

The results indicate that same-month downgrades significantly increase the likelihood of negative outliers for both NIG and IG bonds, regardless of outlier thresholds. Downgrades also decrease the incidence of less extreme positive outliers for NIG bonds. Lagged downgrades predict more positive outliers for NIG bonds but more negative outliers for IG bonds at the (99.5, 0.5) percentiles. When outliers are identified at the (90, 10) percentiles, lagged downgrades predict more positive outliers for both IG and NIG bonds.[2] These findings suggest that investors interpret downgrade shocks as bad news and react promptly, leading to sharp price depreciation. The depreciation is reversed shortly due to corrections to overreaction. The observed reversals are stronger for NIG bonds, consistent with IG bonds being less sensitive to news related to default risk.

In contrast, same-month upgrades only significantly increase (decrease) the incidence of

[2] They also predict more negative outliers, but the effect is weaker across samples.

positive (negative) outliers at the (90, 10) percentiles, while lagged upgrades are associated with significantly fewer positive outliers for NIG bonds. The subdued reactions of outliers to upgrades align with the notion that positive information is less relevant to corporate bond investors. The findings in this section are consistent with May (2010), which documents that corporate bond prices react more strongly to downgrades than to upgrades.

B Outlier Treatment and Decile Portfolio Returns

This study finds that trimming positive and negative outliers separately in the formation period imposes asymmetric impacts on the winner and loser portfolios. Specifically, trimming positive outliers mainly reduces returns on the winner portfolio by strengthening its information efficiency. In contrast, trimming negative outliers substantially lowers returns on the loser portfolio by weakening its tendency to reverse trends during the holding period. These patterns are consistent with winner portfolios reflecting the slow diffusion of good news in corporate bonds and loser portfolios affected by bond investors overreacting to bad news. However, this asymmetry may not be confined to the portfolios with the best and worst past performance. Instead, it may also characterize less extreme decile portfolios. Table A.2 presents the effects of separately trimming positive and negative outliers during the formation period on the excess returns of each decile portfolio. Compared with the benchmark returns in the raw data, trimming positive outliers decreases returns on the higher-ranked portfolios more distinctly than on the lower-ranked ones, while trimming negative outliers disproportionately reduces returns on the lower-ranked portfolios.

Focusing on results for NIG bonds, for instance, trimming outliers above the 99.5th percentile decreases excess returns on the P9 portfolio by 31 bps (=1.099-0.788) but only by 4.9 bps (=0.899-0.85) on the P2 portfolio. Therefore, the treatment reduces the return spread between the two portfolios to -6.2 (=0.788-0.85) bps, down from 20 (=1.099-0.899) bps in the raw data. In contrast, trimming outliers below the 0.5th percentile reduces excess returns for the P2 portfolio by 31.4 (=0.899-0.585) bps compared with a mere 8.5 (=1.099-1.014) bps return decrease on the P9 portfolio, increasing their return spread to 43 (=1.014-0.585) bps. Therefore, the results in Table A.2 provide additional evidence in support of the asymmetric information diffusion mechanism proposed in this study.

C Value-Weighted Momentum Portfolios

As discussed in the main text, value-weighted (VW) portfolios have the disadvantage of distorting the calculation of holding-period returns due to missing data. Therefore, results for value-weighted portfolios are presented in this section as a robustness check on the main findings. Table A.3 reports momentum results from separately trimming positive and negative outliers during the formation period of the short-term value-weighted strategy, using market capitalization as portfolio weights. Following Dickerson et al. (2024), when the amount outstanding is missing, it is replaced with the face value at issuance.

The results suggest that the asymmetric effect of trimming positive and negative outliers persists for value-weighted portfolios, with negative outlier trimming offering significant momentum excess returns for both IG and NIG bonds. However, the momentum gains in NIG bonds (and also in the all-bond sample) are not statistically distinguishable from the benchmark returns in the raw data, possibly due to return distortions introduced by the value-weighting approach. After adjusting for market risk, trimming negative outliers yields significant alphas for NIG bonds but not for IG bonds, consistent with their different sensitivities to firm-level information.

D Samples Excluding Bonds with Extreme Returns

This section examines whether the documented asymmetric momentum patterns are confined to a small subset of bonds with extreme returns in the tails of the return distribution. The findings in the main text indicate that the asymmetric momentum patterns strengthen under less stringent outlier thresholds. Therefore, trimming less extreme returns in the formation period is expected to yield similar asymmetric momentum patterns. The underlying argument is that if the mechanism driving the asymmetric patterns is rooted in the fundamental characteristics of corporate bonds, then the asymmetry should be a widespread feature of corporate bond momentum. Table A.4 reports the effects of trimming positive and negative formation-period outliers across different samples that exclude bonds with extreme returns defined using the +/-30% and +/-20% cutoffs.

The results indicate that the asymmetric effect of trimming positive and negative outliers in the formation period persists across samples consisting of less extreme returns.[3] In particular, trimming negative outliers yields momentum excess returns ranging from 0.3% to 0.87% per month for NIG bonds and from 0.17% to 0.2% per month for IG bonds. These profits are sizable, given that the median monthly returns in the raw data are just 0.61% and 0.29% for NIG and IG bonds, respectively. Once again, adjusting for market risk yields insignificant alphas for IG bonds

[3] Positive and negative outliers in Table A.4 are identified using the 95th and 5th percentile thresholds to balance momentum portfolio sizes for IG and NIG bonds. Results are robust using alternative thresholds.

in all specifications.

Notably, when bonds with extreme returns are excluded, the effects of trimming positive and negative outliers become more clearly disentangled. In most cases, trimming positive outliers only significantly reduces returns on winner portfolios, whereas trimming negative outliers exclusively lowers returns significantly on loser portfolios. The results also support stronger trend reversals in loser portfolios in samples with more extreme returns. Specifically, trimming negative outliers reduces loser portfolio returns to a greater extent in samples that exclude bonds with extreme returns defined by the +/-30% cutoffs than in samples using the +/-20% cutoffs.

In summary, the results provide further evidence supporting the findings in the main text that the asymmetric effect of trimming positive and negative outliers in the formation period is systematic and may reflect asymmetric information diffusion in corporate bonds.

E The Effect of Data Uncertainty

This section reports detailed analyses in three subsections on how data uncertainty influences the conclusions of this paper. Specifically, the effect of trimming positive and negative outliers in the formation period of the short-term strategy is reexamined under alternative treatments of two key data choices: the handling of erroneous outliers and the choice of month-end prices. The analysis is also conducted using the alternative WRDS bond return sample, which adopts several different but similarly reasonable data choices.

E.1 Removing Erroneous Outliers

Since most outliers in TRACE reflect actual trading activity, they generally should not be excluded, except for those caused by reporting errors, which are not directly identifiable in TRACE. Dick-Nielsen et al. (2024) manually verify 5000 extreme returns and eliminate 292 detected errors. After dropping these 292 errors, the maximum return in their sample is 1552.82%.[4] In light of this result, I assume that all returns above 20 are erroneous and remove their associated bonds from the analysis. The distribution of these erroneous returns is displayed in Panel B of Figure A.1, while Panel A presents the distribution of less extreme returns populating the range between 200% and 2000%. The number of extreme returns in Panels A and B is 306 and 48, respectively. In Panel B, the maximum return value is 385.96, observed for a convertible bond on May 26, 2004. Additionally, there are 21 returns within the range of 20 to 50, 18 returns between 50 and 100, another six returns above 100 and below 150, one return in the range of 150 to 200, and one return between 200 and 250. These 48 values are associated with 46 bonds. Excluding those 46 bonds results in 1,383 monthly returns in total being dropped from the sample.

Results reported in Table A.5 indicate that removing bonds with erroneous returns improves the performance of the momentum strategy in the raw data, offering significant momentum excess returns in the straight all-bond sample and weakly significant (at 10%) gains for NIG bonds. Notably, for both IG and NIG bonds, the asymmetric effect of trimming positive and negative outliers in the formation period remains robust in this new sample. Trimming positive outliers yields negative momentum estimates in all cases, with return spreads over the benchmark being negative and mostly significant. In contrast, trimming outliers below the 0.5th

[4] Their data can be downloaded at: https://www.stolborg.com/data.

and 10th percentiles respectively produces about 1.1% and 1.5% momentum excess returns per month in the straight all-bond sample. The effect is even stronger for NIG bonds, offering excess returns of about 2% and 3.4% per month, respectively. Trimming outliers below the 10th percentile also yields significant momentum gains for IG bonds, at 0.3% per month. These momentum profits following trimming negative outliers are significantly distinguishable from the benchmark returns. Adjusting for bond market risk, trimming negative outliers still yields significant alphas in the all-bond sample and for NIG bonds. However, risk-adjusted alphas in IG bonds are insignificant, consistent with them being less sensitive to firm-level information than NIG bonds. Overall, the results confirm that the asymmetric momentum patterns documented in this study are not driven by extreme outliers exceeding 2000%, a threshold used to identify erroneous returns.

E.1.1 Removing Outliers as Defined in Jostova et al. (2024)

Jostova et al. (2024) examine the impact of data uncertainty on momentum profitability related to the handling of return outliers. The authors identify outliers using one-sided (right-tail) or two-sided (both-tail) thresholds with absolute magnitudes greater than or equal to 30% (i.e., 30%, 60%, 90%, and 100%), whereas a threshold of +/-30% corresponds to the most stringent outlier cutoff employed in this study.[5] As a result, outliers identified in Jostova et al. (2024) are substantially more extreme and therefore more likely to reflect entry or measurement errors. In this sense, the two studies differ both in their definition of outliers and in their interpretation of the role of outliers.

Jostova et al. (2024) treat extreme outliers as data entry errors and view outlier treatment

[5]This study mainly focuses on results associated with the two less restrictive thresholds of (99.5, 0.5) and (90, 10) percentiles.

as one of many data choices researchers must make when constructing monthly return samples from TRACE. In this case, outliers are treated in the full sample prior to data analysis, which introduces uncertainty at the sample construction stage, given that multiple reasonable alternatives exist for handling outliers. Indeed, the authors show that trimming outliers at different thresholds yields mostly significant momentum returns of varying magnitudes for NIG bonds, with trimming returns above 30% delivering the largest momentum gains. However, momentum in IG bonds remains muted across all alternative treatments.

As one alternative, this study adopts a conservative approach of retaining all extreme outliers in the raw data, which yields insignificant momentum returns for both IG and NIG straight bonds. Building on this result, I examine the relationship between outliers and momentum by focusing on the effects of formation-period outlier treatments. In this case, outlier treatment is incorporated into the data analysis under the assumption that outliers reflect valid price movements driven by salient information shocks in the corporate bond market. Trimming outliers during the formation period can therefore systematically affect momentum profitability by altering the strategy's informational efficiency. This mechanism predicts that momentum patterns associated with formation-period outlier treatments should apply to both IG and NIG bonds. Consistently, this study documents similar asymmetric momentum patterns for IG and NIG bonds following the trimming of positive and negative outliers. In particular, the significant momentum profits observed in IG bonds after trimming negative outliers stand in direct contrast to the insignificant results documented by Jostova et al. (2024), underscoring the distinct roles of outlier treatments in the two studies.

However, data uncertainty may still confound the conclusions of this paper. Indeed, some extreme outliers in this study's sample are likely to be erroneous and could be handled differently.

To account for this data uncertainty, this section follows the approach in Jostova et al. (2024) to identify extreme returns in the right tail or in both tails of the return distribution as data entry errors, using thresholds of 30% and -30%. It then examines whether removing those extreme outliers from the full sample meaningfully alters the asymmetric effect documented in the main analysis. Results are reported in Tables A.6 and A.7.

Consistent with Jostova et al. (2024), removing either one-sided or two-sided returns at the +/-30% threshold delivers significant but markedly different benchmark momentum profits for NIG bonds, respectively about 0.5% and 1.3% per month, highlighting the role of data uncertainty. In both cases, benchmark momentum returns for IG bonds are small and insignificant.

Focusing on formation-period outlier trimming, Table A.6 shows that in samples where returns above 30% or below -30% are dropped, trimming positive and negative outliers in the formation period continues to produce asymmetric momentum patterns for both IG and NIG bonds. However, momentum profits following negative outlier trimming are much weaker than in cases that retain the +/-30% tail returns. Specifically, momentum excess returns are about 0.45% for NIG bonds when outliers below the 0.5th percentile are trimmed, and 0.28% for IG bonds when trimming outliers at the 10th percentile.

Table A.7 indicates that, in samples where only returns above 30% are removed, trimming positive outliers produces even higher momentum excess returns and alphas than trimming negative outliers in the all-bond sample and among NIG bonds, although none of these profits exceed the benchmark returns. Despite the breakdown of asymmetric momentum patterns, the effect of trimming negative outliers remains more robust, producing significant momentum gains for both IG and NIG bonds, at about 0.26% and 0.62%, respectively. In contrast, momentum in

IG bonds fails to materialize when trimming positive outliers or under the benchmark strategy. Therefore, the prediction from the information diffusion mechanism still holds broadly, particularly for IG bonds.

E.2 Alternative Month-end Price Approaches

As discussed in Jostova et al. (2024), the infrequent trading of corporate bonds poses a challenge for calculating monthly returns in TRACE, which is another source of data uncertainty. As prices are often unavailable on the last trading day of the month, using this standard approach to identify month-end prices results in a sample with too many missing returns. As a result, several alternative approaches have been adopted in the literature, each with its drawbacks. The last-available-price (or end-of-month-price) approach used in this study offers a larger sample while also disrupting the information flow in momentum portfolios to a lesser extent (Li and Galvani, 2021). However, as argued by Jostova et al. (2024), the last available prices do not capture information released after the final trade in the month, and are therefore less accurate. Thus, it is necessary to validate the findings in this study using alternative month-end prices. This section presents results for the last-trading-day prices and the last-5-trading-day prices, respectively. The latter approach is commonly accepted in the literature as an attempt to balance sample size and information accuracy by restricting month-end prices to be within the last five trading days of the month.

Table A.8 reports momentum results following trimming positive and negative outliers in the formation period of the short-term strategy, when bond monthly returns are calculated with last-5-trading-day prices. Trimming positive outliers leads to negative momentum excess returns that are mostly insignificant, while trimming negative outliers produces momentum gains that are highly significant in the all-bond sample and for NIG bonds and weakly significant for IG bonds. Their spreads over the benchmark returns are also significant, except for IG bonds following the trimming of negative outliers. Adjusting for market risk yields significant alphas only when negative outliers are trimmed in the all-bond sample and for NIG bonds.

Table A.9 reports results based on the last-trading-day-price approach. Similarly, trimming positive outliers produces negative momentum estimates, whereas trimming negative outliers yields significant momentum excess returns and alphas in the all-bond sample and for NIG bonds, but only significant excess returns for IG bonds. However, benchmark spreads are mostly insignificant following negative outlier trimming.

Overall, the findings in this section are consistent with the analysis based on last-available prices, confirming robust asymmetric momentum patterns following trimming positive and negative outliers in the formation period. Nevertheless, data uncertainty stemming from alternative approaches to defining month-end prices materially affects momentum return estimates. In particular, under the last-available-price approach, estimated monthly momentum excess returns are 2.36% and 0.21% following negative outlier trimming at the 0.5th percentile for NIG bonds and at the 10th percentile for IG bonds, respectively. These estimates change to 1.33% and 0.22% under the last-5-day price approach, and to 0.81% and 0.29% when bond returns are computed using last-trading-day prices. While momentum profits for IG bonds are relatively stable across the three approaches, momentum returns for NIG bonds increase substantially with sample size. The superior performance of negative outlier treatment under the last-available-price approach supports the argument in Li and Galvani (2021) that information flow in momentum portfolios is less disrupted when using last-available prices.[6]

E.3 Results in the WRDS Bond Return Data

The WRDS Bond Return Database offers ready-to-use monthly returns calculated based on TRACE transaction data. The dataset has become an important data source for corporate bond empirical studies. The WRDS return data includes three bond types extracted from FISD, i.e., ”CDEB”, ”CMTN”, and ”CMTZ”, and drops all the other bond types, including ”CCOV” bonds. However, the sample does not filter on the ”convertible” flag provided by FISD, which also identifies convertible bonds. Since the convertible bond samples under the two approaches do not perfectly overlap, some convertible bonds remain in the WRDS bond return sample. Additionally, WRDS backfills missing monthly end-of-month prices using the most recent price from previous months, which differs from the approach adopted in this study. It also calculates coupon payments and accrued interests based on the last day of each month, which is often not the actual trading date. With these differences in mind, I extract from the WRDS data a subsample consisting only of bonds that overlap with the straight bond sample used in the main analysis to facilitate comparison.

Tables A.10 to A.12 report results for trimming positive and negative outliers in the formation period of the short-term strategy based on the three alternative returns (RET_EOM, RET_L5M, and RET_LDM) in the WRDS subsample. Overall, the asymmetric momentum patterns remain robust for both IG and NIG bonds. Following negative-outlier trimming, risk-adjusted alphas are again significant for NIG bonds but not for IG bonds. Across the three

[6] The reduced momentum gains for NIG bonds under the other two approaches are not driven by the use of the same outlier thresholds as in the main analysis. Applying approach-specific percentile thresholds only marginally improves the estimates.

return calculation approaches, using RET_EOM yields the highest momentum profits for NIG bonds, at about 0.75% after trimming negative outliers below the 0.5th percentile, but the lowest for IG bonds, at around 0.28% when using the 10th percentile threshold.

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Table A.1: The Impact of Information on the Incidence of Outliers

The table displays regression results for predicting the incidence of outliers in the full straight bond sample (Whole), and in the non-investment-grade (NIG) and investment-grade (IG) subsamples. Panel A reports results for Model A.1 where the log probability of a bond-month return being an outlier is explained by an information indicator equal to 1 if the bond experiences a rating change in the same month, and 0 otherwise. Panel B presents regression results for Model A.2, which distinguishes the effects of upgrade (UPG) and downgrade (DNG) signals and their respective one-month lags (L.UPG and L.DNG) on the log probability of yielding positive outliers. Corresponding results for predicting the incidence of negative outliers are tabulated in Panel C. Outlier thresholds are the (99.5, 0.5) and (90, 10) percentiles of the straight all-bond return distribution. Each regression includes the bond-level monthly trading volume (volume) and the month-end credit rating (CR) as control variables. Bond and year-month fixed effects are also controlled for. Control variable estimates are omitted for brevity. Reported coefficients are in exponential form. Standard errors reported in parentheses are two-way clustered at the firm and year-month dimensions. Significance levels at the 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

	Outliers identified at (99.5, 0.5) percentiles			Outliers identified at (90, 10) percentiles		
	Whole	NIG	IG	Whole	NIG	IG
	Panel A: not distinguishing positive and negative outliers					
info	1.426***	1.498***	1.240*	1.155***	1.137***	1.173***
	(0.088)	(0.098)	(0.147)	(0.021)	(0.020)	(0.028)
N	303472	134364	81661	1262702	325874	929096
r2_p	0.393	0.340	0.415	0.196	0.166	0.215
Bond & month FE	YES	YES	YES	YES	YES	YES
	Panel B: information impact on positive outliers					
DNG	0.969	1.038	0.789	0.834***	0.821***	0.944
	(0.108)	(0.119)	(0.128)	(0.037)	(0.036)	(0.051)
UPG	1.337	1.213	1.230	1.214***	1.149**	1.246***
	(0.257)	(0.257)	(0.921)	(0.051)	(0.063)	(0.069)
L.DNG	1.325***	1.444***	1.186	1.122***	1.118***	1.201***
	(0.125)	(0.142)	(0.319)	(0.047)	(0.039)	(0.070)
L.UPG	0.521***	0.455***	1.352	0.931	0.777***	1.077
	(0.103)	(0.104)	(0.588)	(0.046)	(0.042)	(0.060)
N	171379	89101	25127	1108443	300957	793584
r2_p	0.359	0.327	0.346	0.231	0.199	0.270
Bond & month FE	YES	YES	YES	YES	YES	YES
	Panel C: information impact on negative outliers					
DNG	2.152***	2.235***	1.743**	1.593***	1.609***	1.504***
	(0.218)	(0.221)	(0.460)	(0.070)	(0.073)	(0.079)
UPG	0.718	0.729	0.527	0.836***	0.759***	0.892**
	(0.154)	(0.175)	(0.237)	(0.033)	(0.044)	(0.046)
L.DNG	1.292***	1.151	2.105***	1.106***	1.056*	1.114**
	(0.119)	(0.105)	(0.592)	(0.037)	(0.031)	(0.059)
L.UPG	1.131	0.960	1.676	0.939*	0.936	0.958
	(0.258)	(0.207)	(1.025)	(0.035)	(0.042)	(0.048)
N	229694	104584	39043	1175198	301670	863275
r2_p	0.426	0.375	0.453	0.235	0.213	0.277
Bond & month FE	YES	YES	YES	YES	YES	YES

Table A.2: Formation-Period Treatments and Decile Portfolio Returns

The table tabulates monthly excess returns on the equal-weighted (EW) decile portfolios supporting the short-term ($S(3,3)$) strategy. Results for the straight all-bond sample are reported in Panel A, Panels B and C present results for non-investment-grade and investment-grade bonds, respectively. The first two rows in each panel report excess returns calculated without outlier treatment, followed by results calculated when negative or positive outliers are trimmed in the formation period. Outliers are identified at the (99.5, 0.5) and (90, 10) percentiles of the straight all-bond return distribution. T-statistics significant at the 5% level are highlighted in bold. Standard errors are adjusted using the Newey-West HAC estimation with three lags.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
Panel A: Excess returns in the straight all-bond sample											
Raw ER	1.735	0.559	0.577	0.444	0.482	0.463	0.518	0.531	0.659	2.184	0.448
	(3.255)	**(3.785)**	**(3.721)**	**(4.761)**	**(4.708)**	**(5.518)**	**(5.483)**	**(5.116)**	**(4.917)**	**(5.829)**	(0.965)
Trim 0.5	0.676	0.484	0.588	0.428	0.429	0.451	0.508	0.523	0.63	2.089	1.412
	(3.123)	**(4.039)**	**(3.261)**	**(4.842)**	**(5.229)**	**(5.501)**	**(5.491)**	**(5.097)**	**(4.925)**	**(5.738)**	**(5.160)**
Trim 10	0.387	0.305	0.385	0.329	0.382	0.415	0.466	0.518	0.593	2.352	1.964
	(3.964)	**(5.019)**	**(4.910)**	**(5.755)**	**(6.016)**	**(5.923)**	**(5.661)**	**(5.470)**	**(4.924)**	**(4.828)**	**(4.276)**
Trim 99.5	1.446	0.541	0.575	0.438	0.473	0.454	0.486	0.518	0.576	1.044	-0.403
	(3.096)	**(3.811)**	**(3.633)**	**(4.762)**	**(4.661)**	**(5.545)**	**(5.516)**	**(5.183)**	**(4.900)**	**(4.979)**	(-0.939)
Trim 90	1.447	0.576	0.474	0.408	0.382	0.362	0.382	0.428	0.42	0.497	-0.951
	(2.804)	**(3.642)**	**(4.155)**	**(4.714)**	**(4.964)**	**(5.340)**	**(5.623)**	**(5.606)**	**(5.330)**	**(5.128)**	**(-1.972)**
Panel B: Excess returns in the NIG bond subsample											
Raw ER	3.468	0.899	0.823	0.679	0.671	0.728	0.74	0.883	1.099	3.26	-0.208
	(2.648)	**(2.525)**	**(3.195)**	**(3.783)**	**(3.913)**	**(4.531)**	**(4.390)**	**(4.554)**	**(4.485)**	**(5.580)**	(-0.183)
Trim 0.5	0.823	0.585	0.608	0.604	0.609	0.675	0.696	0.822	1.014	3.187	2.363
	(2.244)	**(2.569)**	**(3.485)**	**(3.929)**	**(4.080)**	**(4.528)**	**(4.359)**	**(4.616)**	**(4.378)**	**(5.601)**	**(5.656)**
Trim 10	0.436	0.418	0.492	0.523	0.537	0.589	0.606	0.695	1.101	4.127	3.69
	(3.191)	**(3.980)**	**(4.882)**	**(5.307)**	**(5.059)**	**(4.820)**	**(4.664)**	**(4.424)**	**(3.920)**	**(4.453)**	**(4.268)**
Trim 99.5	2.691	0.85	0.777	0.637	0.624	0.645	0.669	0.702	0.788	1.339	-1.353
	(2.589)	**(2.508)**	**(3.196)**	**(3.739)**	**(3.928)**	**(4.355)**	**(4.367)**	**(4.392)**	**(4.392)**	**(4.475)**	(-1.442)
Trim 90	2.907	0.826	0.734	0.71	0.695	0.572	0.54	0.529	0.509	0.533	-2.375
	(2.407)	**(2.513)**	**(2.671)**	**(2.946)**	**(3.218)**	**(3.756)**	**(4.374)**	**(4.365)**	**(4.487)**	**(4.347)**	**(-2.051)**
Panel C: Excess returns in the IG bond subsample											
Raw ER	0.818	0.435	0.618	0.415	0.398	0.432	0.431	0.478	0.479	0.609	-0.21
	(3.407)	**(4.206)**	**(3.073)**	**(4.955)**	**(5.286)**	**(5.384)**	**(5.262)**	**(4.827)**	**(4.224)**	**(4.262)**	(-1.104)
Trim 0.5	0.663	0.482	0.56	0.408	0.393	0.432	0.43	0.479	0.479	0.608	-0.056
	(3.546)	**(3.917)**	**(3.556)**	**(5.027)**	**(5.317)**	**(5.431)**	**(5.258)**	**(4.827)**	**(4.235)**	**(4.274)**	(-0.413)
Trim 10	0.404	0.299	0.336	0.369	0.34	0.381	0.397	0.456	0.479	0.611	0.206
	(3.924)	**(5.010)**	**(4.433)**	**(5.128)**	**(5.860)**	**(5.487)**	**(5.308)**	**(5.025)**	**(4.459)**	**(4.502)**	(1.843)
Trim 99.5	0.815	0.436	0.631	0.414	0.396	0.431	0.43	0.476	0.475	0.588	-0.228
	(3.407)	**(4.219)**	**(2.950)**	**(4.978)**	**(5.284)**	**(5.382)**	**(5.276)**	**(4.834)**	**(4.245)**	**(4.271)**	(-1.202)
Trim 90	0.77	0.477	0.383	0.425	0.362	0.352	0.356	0.412	0.403	0.451	-0.32
	(3.527)	**(4.046)**	**(4.324)**	**(4.357)**	**(5.374)**	**(5.465)**	**(5.624)**	**(5.242)**	**(4.964)**	**(4.690)**	(-1.843)

Table A.3: The Asymmetric Effect Using Value-weighted Portfolios

The table contrasts the short-term value-weighted (VW) momentum strategy's performance in the raw data with that after trimming outliers in the formation period, for the straight all bonds, non-investment-grade bonds, and investment-grade bonds, respectively. The weights for the VW portfolios are calculated using the market capitalization of each bond. Panel A reports average monthly momentum excess returns and returns on the long/short legs using the raw data, followed by estimates based on two sets of outlier treatments. The two sets of outlier thresholds are the (99.5, 0.5) and (90, 10) percentiles of the straight all-bond return distribution. Panel B presents estimated β from the model $PR_t^{treated} - PR_t^{untreated} = \beta + \epsilon_t$, which evaluates the spread of the monthly portfolio return series associated with each outlier treatment over the benchmark return series when outliers are left untreated. Panel C reports alpha estimates obtained from the bond market CAPM. T-statistics significant at the 5% level are highlighted in bold. Standard errors are adjusted using the Newey-West HAC estimation with three lags.

	Whole			Non-investment-grade bonds			Investment-grade bonds		
	W-L	Winner	Loser	W-L	Winner	Loser	W-L	Winner	Loser
	Panel A: Value-weighted $S(3,3)$ momentum excess returns								
Raw ER	0.096	0.813	0.716	0.116	1.19	1.073	-0.017	0.554	0.569
	(0.472)	**(4.482)**	**(2.712)**	(0.313)	**(4.109)**	**(2.120)**	(-0.139)	**(3.827)**	**(3.256)**
Trim 0.5	0.245	0.792	0.547	0.511	1.143	0.632	0.021	0.553	0.531
	(1.613)	**(4.459)**	**(2.778)**	**(2.349)**	**(4.015)**	**(2.002)**	(0.183)	**(3.827)**	**(3.236)**
Trim 10	0.486	0.79	0.303	1.03	1.428	0.397	0.255	0.563	0.307
	(3.788)	**(4.759)**	**(3.789)**	**(2.870)**	**(3.361)**	**(3.098)**	**(2.511)**	**(4.096)**	**(3.765)**
Trim 99.5	-0.01	0.673	0.682	-0.143	0.853	0.996	-0.028	0.541	0.568
	(-0.050)	**(4.348)**	**(2.684)**	(-0.390)	**(3.867)**	**(2.074)**	(-0.234)	**(3.822)**	**(3.268)**
Trim 90	-0.26	0.457	0.716	-0.64	0.477	1.116	-0.146	0.418	0.563
	(-1.153)	**(4.701)**	**(2.673)**	(-1.408)	**(4.150)**	**(2.168)**	(-1.211)	**(4.198)**	**(3.344)**
	Panel B: Excess return differences with raw								
Trim 0.5	0.149	-0.021	-0.17	0.395	-0.046	-0.441	0.038	-0.001	-0.038
	(1.493)	**(-2.902)**	(-1.629)	(1.745)	(-1.879)	(-1.860)	(1.500)	(-0.549)	(-1.545)
Trim 10	0.39	-0.024	-0.413	0.914	0.238	-0.676	0.272	0.009	-0.263
	(1.892)	(-0.864)	(-1.943)	(1.558)	(0.783)	(-1.568)	**(2.482)**	(0.532)	**(-2.314)**
Trim 99.5	-0.106	-0.14	-0.034	-0.259	-0.336	-0.077	-0.012	-0.013	-0.001
	(-2.449)	**(-2.920)**	**(-2.087)**	**(-2.647)**	**(-3.018)**	(-1.564)	(-1.778)	(-1.530)	(-0.342)
Trim 90	-0.356	-0.357	-0.001	-0.756	-0.713	0.043	-0.129	-0.136	-0.007
	(-2.909)	**(-3.065)**	(-0.016)	**(-3.161)**	**(-3.377)**	(0.415)	**(-2.258)**	**(-2.145)**	(-0.410)
	Panel C: Alphas from the bond market risk factor CAPM								
Raw Alpha	0.247	0.297	0.049	0.52	0.59	0.069	0.029	0.086	0.056
	(1.458)	**(3.186)**	(0.401)	(1.766)	**(2.550)**	(0.205)	(0.225)	(1.107)	(0.600)
Trim 0.5	0.294	0.281	-0.014	0.652	0.564	-0.089	0.041	0.085	0.043
	(1.941)	**(3.060)**	(-0.135)	**(3.278)**	**(2.422)**	(-0.384)	(0.312)	(1.093)	(0.480)
Trim 10	0.242	0.3	0.057	0.81	0.926	0.115	0.056	0.121	0.064
	(2.421)	**(3.654)**	(1.296)	**(2.027)**	**(2.045)**	(0.913)	(0.539)	(1.409)	(1.431)
Trim 99.5	0.157	0.189	0.031	0.301	0.335	0.032	0.021	0.079	0.057
	(0.984)	**(2.398)**	(0.256)	(1.071)	(1.655)	(0.100)	(0.163)	(1.036)	(0.625)
Trim 90	0.064	0.124	0.059	0.011	0.147	0.135	0.016	0.087	0.07
	(0.411)	**(2.091)**	(0.510)	(0.036)	(1.307)	(0.412)	(0.133)	(1.283)	(0.787)

Table A.4: Excluding Bonds with Extreme Returns

The table reports results for trimming positive and negative outliers in the formation period of the short-term equal-weighted (EW) momentum strategy in samples excluding bonds with one-sided or both-sided tail returns under the +/-30% and +/-20% cutoffs. Positive and negative outliers are identified using the 95th and 5th percentiles of the all-bond return distribution in each sample. Panel A reports average monthly momentum excess returns and returns on the long/short legs for the straight all bonds, non-investment-grade bonds, and investment-grade bonds. Panel B presents estimated β from the model $PR_t^{treated} - PR_t^{untreated} = \beta + \epsilon_t$, which evaluates the spread of the monthly portfolio return series associated with each outlier treatment over the benchmark return series when outliers are left untreated. Panel C reports alpha estimates obtained from the bond market CAPM. T-statistics significant at the 5% level are highlighted in bold. Standard errors are adjusted using the Newey-West HAC estimation with three lags.

	Trim positive outliers at 95th percentile									Trim negative outliers at 5th percentile								
	Whole			Non-investment-grade bonds			Investment-grade bonds			Whole			Non-investment-grade bonds			Investment-grade bonds		
	W-L	Winner	Loser	W-L	Winner	Loser	W-L	Winner	Loser	W-L	Winner	Loser	W-L	Winner	Loser	W-L	Winner	Loser
Panel A: Equal-weighted $S(3,3)$ momentum excess returns																		
|R| within 30%	-0.173	0.548	0.72	-0.437	0.614	1.05	-0.094	0.498	0.591	0.291	0.703	0.411	0.383	0.968	0.584	0.19	0.574	0.383
	(-1.653)	**(5.485)**	**(4.868)**	**(-3.109)**	**(5.565)**	**(5.031)**	(-1.046)	**(4.751)**	**(4.469)**	**(3.431)**	**(5.519)**	**(4.743)**	**(4.991)**	**(6.140)**	**(4.806)**	**(2.211)**	**(4.477)**	**(4.561)**
below 30%	-0.173	0.544	0.716	-0.392	0.611	1.002	-0.094	0.494	0.587	0.311	0.72	0.407	0.431	1.007	0.575	0.194	0.575	0.38
	(-1.561)	**(5.316)**	**(4.570)**	**(-2.733)**	**(5.217)**	**(4.611)**	(-0.976)	**(4.656)**	**(4.192)**	**(3.503)**	**(5.398)**	**(4.521)**	**(4.887)**	**(5.755)**	**(4.624)**	**(2.242)**	**(4.416)**	**(4.338)**
above -30%	-0.217	0.553	0.77	-0.536	0.622	1.157	-0.095	0.504	0.598	0.463	0.874	0.41	0.867	1.449	0.581	0.195	0.581	0.385
	(-1.646)	**(5.336)**	**(4.339)**	**(-2.456)**	**(5.369)**	**(4.050)**	(-0.986)	**(4.688)**	**(4.297)**	**(4.037)**	**(5.615)**	**(4.492)**	**(4.052)**	**(5.283)**	**(4.444)**	**(2.245)**	**(4.452)**	**(4.382)**
|R| within 20%	-0.129	0.537	0.666	-0.358	0.594	0.95	-0.083	0.483	0.565	0.249	0.651	0.401	0.292	0.87	0.577	0.172	0.547	0.373
	(-1.446)	**(6.056)**	**(5.284)**	**(-3.297)**	**(6.210)**	**(5.668)**	(-1.030)	**(5.063)**	**(4.885)**	**(3.175)**	**(5.790)**	**(5.332)**	**(4.619)**	**(7.010)**	**(5.420)**	**(2.044)**	**(4.582)**	**(5.087)**
below 20%	-0.132	0.534	0.665	-0.357	0.594	0.95	-0.081	0.482	0.562	0.265	0.667	0.401	0.31	0.883	0.572	0.185	0.558	0.372
	(-1.393)	**(5.648)**	**(4.896)**	**(-3.041)**	**(5.583)**	**(5.184)**	(-0.963)	**(4.845)**	**(4.551)**	**(3.231)**	**(5.518)**	**(5.048)**	**(4.420)**	**(6.180)**	**(5.083)**	**(2.194)**	**(4.531)**	**(4.820)**
above -20%	-0.176	0.553	0.728	-0.531	0.618	1.149	-0.096	0.497	0.591	0.363	0.78	0.416	0.659	1.253	0.593	0.174	0.562	0.387
	(-1.683)	**(5.849)**	**(5.059)**	**(-2.911)**	**(6.103)**	**(4.851)**	(-1.082)	**(4.899)**	**(4.666)**	**(3.683)**	**(5.838)**	**(5.089)**	**(3.764)**	**(5.604)**	**(5.303)**	**(2.028)**	**(4.504)**	**(4.777)**
Panel B: Excess return differences with raw																		
|R| within 30%	-0.142	-0.163	-0.021	-0.341	-0.353	-0.012	-0.063	-0.076	-0.013	0.322	-0.007	-0.33	0.48	0.002	-0.478	0.221	0	-0.221
	(-3.091)	**(-3.315)**	**(-2.678)**	**(-4.648)**	**(-5.437)**	(-0.477)	(-1.775)	(-1.915)	(-1.592)	**(3.864)**	(-1.062)	**(-3.921)**	**(4.277)**	(0.062)	**(-4.611)**	**(3.205)**	(0.045)	**(-3.178)**
below 30%	-0.166	-0.181	-0.015	-0.37	-0.383	-0.013	-0.07	-0.077	-0.007	0.319	-0.005	-0.323	0.453	0.013	-0.441	0.217	0.003	-0.215
	(-3.321)	**(-3.286)**	(-1.419)	**(-4.811)**	**(-5.019)**	(-0.507)	(-1.918)	(-1.845)	(-0.759)	**(3.515)**	(-0.643)	**(-3.559)**	**(3.565)**	(0.502)	**(-3.723)**	**(2.954)**	(0.434)	**(-2.892)**
above -30%	-0.343	-0.398	-0.055	-0.772	-0.866	-0.094	-0.064	-0.081	-0.017	0.337	-0.077	-0.414	0.631	-0.04	-0.671	0.226	-0.004	-0.23
	(-3.527)	**(-3.682)**	**(-3.041)**	**(-3.734)**	**(-4.171)**	(-1.442)	(-1.651)	(-1.886)	(-1.572)	**(2.961)**	**(-2.576)**	**(-3.490)**	**(3.301)**	(-1.189)	**(-3.467)**	**(2.979)**	(-0.500)	**(-2.939)**
|R| within 20%	-0.109	-0.113	-0.004	-0.282	-0.282	0.001	-0.063	-0.067	-0.004	0.269	0	-0.269	0.367	-0.005	-0.372	0.192	-0.003	-0.195
	(-2.828)	**(-2.927)**	(-0.561)	**(-5.536)**	**(-6.153)**	(0.038)	(-1.733)	(-1.781)	(-0.700)	**(4.282)**	(-0.009)	**(-4.146)**	**(4.855)**	(-0.494)	**(-5.072)**	**(3.578)**	(-0.489)	**(-3.501)**
below 20%	-0.122	-0.13	-0.008	-0.3	-0.285	0.015	-0.069	-0.077	-0.009	0.275	0.003	-0.272	0.367	0.003	-0.364	0.197	-0.002	-0.199
	(-2.926)	**(-2.961)**	(-1.036)	**(-4.887)**	**(-5.300)**	(0.506)	(-1.922)	**(-1.996)**	(-1.379)	**(3.873)**	(0.628)	**(-3.763)**	**(4.306)**	(0.320)	**(-4.330)**	**(3.256)**	(-0.319)	**(-3.190)**
above -20%	-0.267	-0.286	-0.02	-0.694	-0.685	0.009	-0.068	-0.072	-0.004	0.273	-0.059	-0.332	0.496	-0.05	-0.546	0.202	-0.007	-0.208
	(-3.275)	**(-3.269)**	(-1.112)	**(-3.558)**	**(-3.711)**	(0.108)	(-1.755)	(-1.853)	(-0.714)	**(3.632)**	(-1.923)	**(-4.263)**	**(4.108)**	(-1.271)	**(-4.609)**	**(3.483)**	(-1.262)	**(-3.448)**
Panel C: Alphas from the bond market risk factor CAPM																		
|R| within 30%	-0.09	0.218	0.306	-0.276	0.314	0.588	-0.035	0.16	0.195	0.161	0.301	0.14	0.294	0.591	0.296	0.05	0.168	0.117
	(-0.983)	**(3.402)**	**(4.788)**	**(-2.657)**	**(3.161)**	**(4.387)**	(-0.419)	**(2.156)**	**(3.457)**	(1.946)	**(4.355)**	**(2.877)**	**(3.923)**	**(4.833)**	**(2.718)**	(0.555)	**(2.068)**	**(2.736)**
below 30%	-0.076	0.203	0.278	-0.232	0.289	0.52	-0.017	0.15	0.166	0.176	0.3	0.124	0.313	0.59	0.276	0.057	0.159	0.101
	(-0.767)	**(2.978)**	**(4.290)**	**(-2.150)**	**(2.576)**	**(3.508)**	(-0.180)	(1.939)	**(3.151)**	**(2.013)**	**(4.078)**	**(2.456)**	**(3.701)**	**(4.109)**	**(2.474)**	(0.618)	(1.963)	**(2.299)**
above -30%	-0.093	0.212	0.303	-0.276	0.314	0.589	-0.026	0.156	0.182	0.311	0.44	0.127	0.714	0.991	0.277	0.06	0.166	0.106
	(-0.902)	**(3.336)**	**(4.177)**	(-1.914)	**(3.015)**	**(3.499)**	(-0.297)	**(2.102)**	**(3.082)**	**(3.031)**	**(4.872)**	**(2.484)**	**(3.917)**	**(4.667)**	**(2.363)**	(0.650)	**(2.048)**	**(2.448)**
|R| within 20%	-0.068	0.25	0.317	-0.244	0.334	0.578	-0.046	0.186	0.231	0.127	0.299	0.171	0.222	0.549	0.326	0.034	0.186	0.15
	(-0.837)	**(4.378)**	**(5.104)**	**(-2.675)**	**(3.941)**	**(5.210)**	(-0.608)	**(2.658)**	**(4.065)**	(1.620)	**(4.549)**	**(4.003)**	**(3.061)**	**(5.637)**	**(3.558)**	(0.390)	**(2.221)**	**(3.713)**
below 20%	-0.061	0.224	0.284	-0.229	0.306	0.534	-0.034	0.165	0.198	0.13	0.284	0.153	0.218	0.517	0.297	0.041	0.173	0.131
	(-0.684)	**(3.499)**	**(4.562)**	**(-2.382)**	**(3.085)**	**(4.263)**	(-0.410)	**(2.249)**	**(3.771)**	(1.663)	**(4.097)**	**(3.423)**	**(2.934)**	**(4.314)**	**(2.947)**	(0.483)	**(2.153)**	**(3.111)**
above -20%	-0.088	0.245	0.333	-0.335	0.347	0.681	-0.041	0.178	0.218	0.232	0.397	0.165	0.541	0.877	0.336	0.04	0.179	0.137
	(-1.019)	**(4.268)**	**(5.157)**	**(-2.900)**	**(4.092)**	**(5.404)**	(-0.510)	**(2.457)**	**(3.734)**	**(2.511)**	**(5.058)**	**(3.677)**	**(3.569)**	**(5.068)**	**(3.470)**	(0.444)	**(2.150)**	**(3.277)**

Table A.5: The Asymmetric Effect without Erroneous Outliers above 20

The table contrasts the short-term equal-weighted (EW) momentum strategy's performance in the raw data with that after trimming outliers in the formation period, for the straight all bonds, non-investment-grade bonds, and investment-grade bonds, respectively. The raw data sample excludes bonds with erroneous returns above 20. Panel A reports average monthly momentum excess returns and returns on the long/short legs using the raw data, followed by estimates based on two sets of outlier treatments. The two sets of outlier thresholds are the (99.5, 0.5) and (90, 10) percentiles of the straight all-bond return distribution. Panel B presents estimated β from the model $PR_t^{treated} - PR_t^{untreated} = \beta + \epsilon_t$, which evaluates the spread of the monthly portfolio return series associated with each outlier treatment over the benchmark return series when outliers are left untreated. Panel C reports alpha estimates obtained from the bond market CAPM. T-statistics significant at the 5% level are highlighted in bold. Standard errors are adjusted using the Newey-West HAC estimation with three lags.

	Whole			Non-investment-grade bonds			Investment-grade bonds		
	W-L	Winner	Loser	W-L	Winner	Loser	W-L	Winner	Loser
Panel A: Equal-weighted $S(3,3)$ momentum excess returns									
Raw ER	0.596	1.813	1.216	0.848	2.928	2.079	-0.025	0.61	0.633
	(2.047)	**(6.178)**	**(3.410)**	(1.665)	**(5.365)**	**(3.128)**	(-0.214)	**(4.269)**	**(3.591)**
Trim 0.5	1.072	1.709	0.635	2.058	2.857	0.798	0.032	0.609	0.576
	(5.049)	**(6.198)**	**(3.015)**	**(5.297)**	**(5.314)**	**(2.200)**	(0.307)	**(4.282)**	**(3.668)**
Trim 10	1.487	1.808	0.32	3.394	3.829	0.434	0.296	0.611	0.314
	(5.951)	**(6.275)**	**(4.004)**	**(3.994)**	**(4.193)**	**(3.177)**	**(3.094)**	**(4.502)**	**(4.249)**
Trim 99.5	-0.177	0.862	1.038	-0.592	1.112	1.703	-0.041	0.587	0.628
	(-0.700)	**(5.057)**	**(3.176)**	(-1.280)	**(4.342)**	**(2.801)**	(-0.355)	**(4.273)**	**(3.604)**
Trim 90	-0.477	0.492	0.968	-1.152	0.533	1.684	-0.179	0.445	0.622
	(-1.691)	**(5.125)**	**(2.992)**	**(-2.217)**	**(4.342)**	**(2.850)**	(-1.514)	**(4.681)**	**(3.779)**
Panel B: Excess return differences with raw									
Trim 0.5	0.476	-0.105	-0.581	1.21	-0.071	-1.28	0.056	-0.001	-0.057
	(2.734)	**(-3.840)**	**(-3.123)**	**(3.194)**	(-1.604)	**(-3.411)**	(1.764)	(-0.315)	(-1.777)
Trim 10	0.891	-0.005	-0.896	2.546	0.901	-1.645	0.32	0.001	-0.319
	(2.779)	(-0.069)	**(-2.891)**	**(2.449)**	(1.357)	**(-2.833)**	**(2.752)**	(0.109)	**(-2.645)**
Trim 99.5	-0.773	-0.951	-0.178	-1.44	-1.816	-0.376	-0.016	-0.022	-0.006
	(-5.201)	**(-5.733)**	**(-4.023)**	**(-4.346)**	**(-4.961)**	**(-3.526)**	(-1.565)	(-1.769)	(-1.443)
Trim 90	-1.073	-1.321	-0.248	-2	-2.395	-0.395	-0.154	-0.165	-0.011
	(-4.902)	**(-5.483)**	**(-3.869)**	**(-4.327)**	**(-4.978)**	**(-2.379)**	**(-2.671)**	**(-2.475)**	(-0.561)
Panel C: Alphas from the bond market risk factor CAPM									
Raw Alpha	0.725	1.213	0.486	1.124	2.144	1.019	0.032	0.151	0.117
	(3.008)	**(6.143)**	**(2.610)**	**(2.602)**	**(5.040)**	**(2.044)**	(0.276)	**(2.019)**	(1.602)
Trim 0.5	1.046	1.126	0.079	2.044	2.098	0.054	0.046	0.151	0.104
	(5.117)	**(6.115)**	(0.682)	**(5.794)**	**(4.985)**	(0.184)	(0.404)	**(2.036)**	(1.547)
Trim 10	1.15	1.226	0.075	3.059	3.202	0.141	0.097	0.173	0.075
	(5.853)	**(6.338)**	(1.363)	**(3.137)**	**(3.136)**	(1.027)	(1.039)	**(2.206)**	(1.791)
Trim 99.5	0.031	0.372	0.339	-0.106	0.578	0.683	0.023	0.141	0.117
	(0.166)	**(3.344)**	**(2.028)**	(-0.310)	**(2.326)**	(1.535)	(0.196)	(1.925)	(1.600)
Trim 90	-0.115	0.171	0.286	-0.462	0.205	0.667	-0.013	0.128	0.14
	(-0.657)	**(2.388)**	(1.906)	(-1.310)	(1.528)	(1.668)	(-0.120)	(1.832)	**(1.996)**

Table A.6: The Asymmetric Effect with Absolute Bond Returns below 30%

The table contrasts the short-term equal-weighted (EW) momentum strategy's performance in the raw data with that after trimming outliers in the formation period, for the straight all bonds, non-investment-grade bonds, and investment-grade bonds, respectively. The raw data sample excludes bond returns (not the entire bonds) above 30% or below -30%. Panel A reports average monthly momentum excess returns and returns on the long/short legs using the raw data, followed by estimates based on two sets of outlier treatments. The two sets of outlier thresholds are the (99.5, 0.5) and (90, 10) percentiles of the straight all-bond return distribution. Panel B presents estimated β from the model $PR_t^{treated} - PR_t^{untreated} = \beta + \epsilon_t$, which evaluates the spread of the monthly portfolio return series associated with each outlier treatment over the benchmark return series when outliers are left untreated. Panel C reports alpha estimates obtained from the bond market CAPM. T-statistics significant at the 5% level are highlighted in bold. Standard errors are adjusted using the Newey-West HAC estimation with three lags.

	Whole			Non-investment-grade bonds			Investment-grade bonds		
	W-L	Winner	Loser	W-L	Winner	Loser	W-L	Winner	Loser
Panel A: Equal-weighted $S(3,3)$ momentum excess returns									
Raw ER	0.224	0.832	0.607	0.525	1.124	0.598	0.007	0.583	0.575
	(1.723)	**(5.458)**	**(3.280)**	**(3.349)**	**(5.280)**	**(2.107)**	(0.067)	**(4.338)**	**(3.941)**
Trim 0.5	0.248	0.829	0.58	0.448	1.129	0.68	0.037	0.582	0.544
	(2.109)	**(5.441)**	**(3.560)**	**(3.517)**	**(5.277)**	**(2.715)**	(0.391)	**(4.329)**	**(4.016)**
Trim 10	0.502	0.825	0.322	0.724	1.181	0.455	0.277	0.589	0.311
	(4.711)	**(5.639)**	**(4.231)**	**(5.554)**	**(5.512)**	**(3.588)**	**(3.027)**	**(4.565)**	**(4.413)**
Trim 99.5	0.113	0.712	0.599	0.324	0.921	0.597	-0.009	0.564	0.572
	(0.897)	**(5.178)**	**(3.266)**	**(2.016)**	**(5.115)**	**(2.120)**	(-0.088)	**(4.335)**	**(3.955)**
Trim 90	-0.088	0.487	0.574	-0.013	0.525	0.537	-0.114	0.447	0.56
	(-0.649)	**(5.387)**	**(3.226)**	(-0.062)	**(4.861)**	**(1.973)**	(-1.178)	**(4.857)**	**(3.992)**
Panel B: Excess return differences with raw									
Trim 0.5	0.024	-0.003	-0.027	-0.077	0.004	0.081	0.03	-0.001	-0.031
	(0.667)	(-1.398)	(-0.741)	(-1.008)	(0.685)	(1.069)	(1.386)	(-0.976)	(-1.454)
Trim 10	0.278	-0.006	-0.285	0.199	0.056	-0.143	0.271	0.006	-0.265
	(2.201)	(-0.436)	**(-2.181)**	(1.043)	(1.256)	(-0.733)	**(3.000)**	(0.562)	**(-2.849)**
Trim 99.5	-0.111	-0.119	-0.008	-0.202	-0.203	-0.001	-0.015	-0.018	-0.003
	(-4.551)	**(-4.514)**	**(-2.050)**	**(-4.515)**	**(-4.279)**	(-0.128)	(-1.929)	(-1.951)	(-1.143)
Trim 90	-0.312	-0.345	-0.033	-0.538	-0.599	-0.062	-0.121	-0.136	-0.015
	(-3.859)	**(-3.897)**	(-1.791)	**(-4.673)**	**(-4.567)**	(-1.360)	**(-2.295)**	**(-2.330)**	(-1.266)
Panel C: Alphas from the bond market risk factor CAPM									
Raw Alpha	0.249	0.399	0.15	0.583	0.698	0.115	0.01	0.155	0.144
	(1.962)	**(4.607)**	(1.516)	**(4.034)**	**(3.996)**	(0.501)	(0.105)	**(2.048)**	**(2.361)**
Trim 0.5	0.25	0.396	0.144	0.51	0.699	0.188	0.019	0.153	0.134
	(2.093)	**(4.579)**	(1.673)	**(4.147)**	**(4.029)**	(0.956)	(0.192)	**(2.022)**	**(2.339)**
Trim 10	0.31	0.4	0.089	0.575	0.756	0.18	0.092	0.177	0.085
	(3.380)	**(4.912)**	(1.788)	**(4.761)**	**(4.534)**	(1.471)	(0.980)	**(2.168)**	**(2.195)**
Trim 99.5	0.151	0.296	0.145	0.401	0.524	0.121	0.002	0.147	0.144
	(1.222)	**(3.918)**	(1.473)	**(2.730)**	**(3.533)**	(0.536)	(0.022)	(1.938)	**(2.371)**
Trim 90	0.051	0.185	0.134	0.147	0.236	0.088	0.001	0.145	0.143
	(0.423)	**(3.013)**	(1.404)	(0.803)	**(2.287)**	(0.396)	(0.009)	**(2.136)**	**(2.398)**

Table A.7: The Asymmetric Effect with Bond Returns below 30%

The table contrasts the short-term equal-weighted (EW) momentum strategy's performance in the raw data with that after trimming outliers in the formation period, for the straight all bonds, non-investment-grade bonds, and investment-grade bonds, respectively. The raw data sample excludes bond returns (not the entire bonds) above 30%. Panel A reports average monthly momentum excess returns and returns on the long/short legs using the raw data, followed by estimates based on two sets of outlier treatments. The two sets of outlier thresholds are the (99.5, 0.5) and (90, 10) percentiles of the straight all-bond return distribution. Panel B presents estimated β from the model $PR_t^{treated} - PR_t^{untreated} = \beta + \epsilon_t$, which evaluates the spread of the monthly portfolio return series associated with each outlier treatment over the benchmark return series when outliers are left untreated. Panel C reports alpha estimates obtained from the bond market CAPM. T-statistics significant at the 5% level are highlighted in bold. Standard errors are adjusted using the Newey-West HAC estimation with three lags.

	Whole			Non-investment-grade bonds			Investment-grade bonds		
	W-L	Winner	Loser	W-L	Winner	Loser	W-L	Winner	Loser
				Panel A: Equal-weighted $S(3,3)$ momentum excess returns					
Raw ER	0.497	0.715	0.217	1.294	0.863	-0.432	0.042	0.559	0.515
	(2.818)	**(4.292)**	(0.858)	**(4.679)**	**(3.419)**	(-0.982)	(0.394)	**(4.026)**	**(3.083)**
Trim 0.5	0.301	0.715	0.413	0.62	0.865	0.245	0.059	0.559	0.498
	(2.187)	**(4.278)**	(1.958)	**(3.626)**	**(3.397)**	(0.710)	(0.581)	**(4.018)**	**(3.169)**
Trim 10	0.428	0.738	0.309	0.55	0.966	0.416	0.262	0.566	0.303
	(3.846)	**(4.697)**	**(3.860)**	**(3.767)**	**(3.875)**	**(3.035)**	**(2.847)**	**(4.265)**	**(4.104)**
Trim 99.5	0.396	0.632	0.236	1.063	0.734	-0.33	0.031	0.545	0.513
	(2.233)	**(4.225)**	(0.943)	**(3.820)**	**(3.405)**	(-0.776)	(0.285)	**(4.086)**	**(3.102)**
Trim 90	0.227	0.462	0.235	0.796	0.485	-0.312	-0.075	0.434	0.509
	(1.140)	**(4.891)**	(0.980)	**(2.339)**	**(4.054)**	(-0.756)	(-0.691)	**(4.609)**	**(3.260)**
				Panel B: Excess return differences with raw					
Trim 0.5	-0.196	0	0.196	-0.674	0.003	0.677	0.017	0	-0.017
	(-2.339)	(-0.195)	**(2.358)**	**(-3.840)**	(0.282)	**(3.945)**	(0.782)	(-0.212)	(-0.808)
Trim 10	-0.069	0.023	0.092	-0.744	0.103	0.847	0.219	0.007	-0.212
	(-0.362)	(1.295)	(0.461)	**(-2.248)**	**(2.058)**	**(2.454)**	**(2.138)**	(0.635)	(-1.962)
Trim 99.5	-0.101	-0.083	0.019	-0.231	-0.129	0.102	-0.011	-0.013	-0.002
	(-3.878)	**(-3.025)**	**(2.053)**	**(-3.982)**	**(-2.514)**	**(2.373)**	(-1.286)	(-1.259)	(-0.704)
Trim 90	-0.271	-0.253	0.018	-0.498	-0.378	0.12	-0.118	-0.125	-0.007
	(-3.111)	**(-2.609)**	(0.486)	**(-3.498)**	**(-2.428)**	(1.277)	**(-2.276)**	**(-2.039)**	(-0.402)
				Panel C: Alphas from the bond market risk factor CAPM					
Raw Alpha	0.547	0.242	-0.306	1.356	0.361	-0.996	0.089	0.112	0.022
	(2.914)	**(2.158)**	(-1.564)	**(4.768)**	(1.420)	**(-2.226)**	(0.707)	(1.578)	(0.283)
Trim 0.5	0.341	0.24	-0.101	0.719	0.356	-0.364	0.081	0.11	0.028
	(2.161)	**(2.139)**	(-0.678)	**(4.024)**	(1.402)	(-1.122)	(0.659)	(1.563)	(0.370)
Trim 10	0.21	0.278	0.066	0.331	0.461	0.129	0.07	0.137	0.065
	(2.197)	**(2.802)**	(1.188)	**(2.253)**	(1.946)	(0.925)	(0.791)	(1.820)	(1.550)
Trim 99.5	0.463	0.181	-0.284	1.162	0.266	-0.897	0.088	0.113	0.024
	(2.409)	(1.792)	(-1.472)	**(4.073)**	(1.181)	**(-2.128)**	(0.680)	(1.545)	(0.306)
Trim 90	0.401	0.147	-0.256	1.043	0.168	-0.875	0.077	0.122	0.043
	(2.001)	**(2.032)**	(-1.388)	**(3.152)**	(1.272)	**(-2.188)**	(0.662)	(1.749)	(0.630)

Table A.8: The Asymmetric Effect under the Last-5-day Approach

The table contrasts the short-term equal-weighted (EW) momentum strategy's performance in the straight bond raw data with that after trimming outliers in the formation period, when bond monthly returns are calculated using the last daily prices within the last 5 trading days of each month. Trading days are determined based on the Treasury bond trading calendar, following the WRDS Bond Return Database. Panel A reports average monthly momentum excess returns and returns on the long/short legs using the raw data, followed by estimates based on two sets of outlier treatments. The two sets of outlier thresholds use the same cutoffs as those applied in the main analysis. Panel B presents estimated β from the model $PR_t^{treated} - PR_t^{untreated} = \beta + \epsilon_t$, which evaluates the spread of the monthly portfolio return series associated with each outlier treatment over the benchmark return series when outliers are left untreated. Panel C reports alpha estimates obtained from the bond market CAPM. T-statistics significant at the 5% level are highlighted in bold. Standard errors are adjusted using the Newey-West HAC estimation with three lags.

	Whole			Non-investment-grade bonds			Investment-grade bonds		
	W-L	Winner	Loser	W-L	Winner	Loser	W-L	Winner	Loser
Panel A: Equal-weighted $S(3,3)$ momentum excess returns									
Raw ER	0.112	1.344	1.231	0.194	2.141	1.946	-0.177	0.591	0.767
	(0.331)	**(5.222)**	**(2.969)**	(0.421)	**(4.588)**	**(2.860)**	(-0.770)	**(4.021)**	**(2.843)**
Trim 0.5	0.713	1.278	0.564	1.334	2.043	0.708	0.041	0.592	0.55
	(3.645)	**(5.168)**	**(2.435)**	**(4.376)**	**(4.543)**	(1.790)	(0.354)	**(4.044)**	**(3.289)**
Trim 10	0.98	1.338	0.357	1.809	2.22	0.41	0.221	0.596	0.374
	(4.564)	**(5.352)**	**(3.830)**	**(4.204)**	**(4.417)**	**(2.979)**	(1.872)	**(4.355)**	**(3.645)**
Trim 99.5	-0.287	0.793	1.079	-0.56	1.025	1.584	-0.198	0.572	0.769
	(-0.889)	**(4.440)**	**(2.759)**	(-1.245)	**(3.695)**	**(2.566)**	(-0.847)	**(4.048)**	**(2.819)**
Trim 90	-0.508	0.484	0.991	-1.23	0.538	1.767	-0.321	0.437	0.758
	(-1.626)	**(4.939)**	**(2.783)**	**(-2.147)**	**(4.151)**	**(2.724)**	(-1.387)	**(4.529)**	**(2.819)**
Panel B: Excess return differences with raw									
Trim 0.5	0.601	-0.065	-0.666	1.139	-0.098	-1.237	0.218	0.001	-0.217
	(2.470)	**(-3.198)**	**(-2.646)**	**(2.969)**	**(-2.104)**	**(-3.126)**	(1.267)	(0.379)	(-1.259)
Trim 10	0.868	-0.006	-0.874	1.615	0.079	-1.536	0.398	0.005	-0.393
	(2.262)	(-0.079)	**(-2.383)**	**(2.510)**	(0.458)	**(-2.549)**	(1.746)	(0.264)	(-1.732)
Trim 99.5	-0.399	-0.551	-0.152	-0.754	-1.116	-0.362	-0.021	-0.02	0.002
	(-3.788)	**(-4.597)**	**(-3.092)**	**(-3.092)**	**(-4.051)**	**(-2.337)**	(-1.966)	(-1.504)	(0.227)
Trim 90	-0.62	-0.86	-0.24	-1.424	-1.603	-0.179	-0.144	-0.154	-0.01
	(-3.328)	**(-4.338)**	**(-2.553)**	**(-3.318)**	**(-4.090)**	(-0.811)	**(-2.598)**	**(-2.237)**	(-0.340)
Panel C: Alphas from the bond market risk factor CAPM									
Raw Alpha	0.321	0.742	0.42	0.544	1.347	0.802	-0.095	0.109	0.203
	(1.214)	**(4.491)**	(1.829)	(1.467)	**(3.708)**	(1.663)	(-0.490)	(1.446)	(1.231)
Trim 0.5	0.753	0.695	-0.059	1.44	1.295	-0.146	0.057	0.112	0.054
	(3.793)	**(4.314)**	(-0.433)	**(4.952)**	**(3.579)**	(-0.480)	(0.435)	(1.477)	(0.593)
Trim 10	0.679	0.784	0.104	1.348	1.457	0.107	0.013	0.146	0.131
	(3.836)	**(4.652)**	(1.607)	**(3.959)**	**(3.744)**	(0.756)	(0.112)	(1.724)	(1.725)
Trim 99.5	-0.024	0.272	0.295	-0.053	0.438	0.49	-0.107	0.102	0.209
	(-0.100)	**(2.339)**	(1.372)	(-0.159)	(1.652)	(1.139)	(-0.547)	(1.361)	(1.237)
Trim 90	-0.114	0.146	0.26	-0.461	0.176	0.636	-0.133	0.106	0.238
	(-0.541)	**(2.015)**	(1.399)	(-1.198)	(1.396)	(1.505)	(-0.714)	(1.503)	(1.386)

Table A.9: The Asymmetric Effect under the Last-trading-day Approach

The table contrasts the short-term equal-weighted (EW) momentum strategy's performance in the straight bond raw data with that after trimming outliers in the formation period, when bond monthly returns are calculated using prices on the last trading day of each month. Trading days are determined based on the Treasury bond trading calendar, following the WRDS Bond Return Database. When the last observed prices in a month fall after the last trading day, they are used as month-end prices. Panel A reports average monthly momentum excess returns and returns on the long/short legs using the raw data, followed by estimates based on two sets of outlier treatments. The two sets of outlier thresholds use the same cutoffs as those applied in the main analysis. Panel B presents estimated β from the model $PR_t^{treated} - PR_t^{untreated} = \beta + \epsilon_t$, which evaluates the spread of the monthly portfolio return series associated with each outlier treatment over the benchmark return series when outliers are left untreated. Panel C reports alpha estimates obtained from the bond market CAPM. T-statistics significant at the 5% level are highlighted in bold. Standard errors are adjusted using the Newey-West HAC estimation with three lags.

	Whole			Non-investment-grade bonds			Investment-grade bonds		
	W-L	Winner	Loser	W-L	Winner	Loser	W-L	Winner	Loser
	Panel A: Equal-weighted $S(3,3)$ momentum excess returns								
Raw ER	0.127	0.959	0.831	0.102	1.478	1.375	0.036	0.597	0.56
	(0.462)	**(4.576)**	**(2.341)**	(0.197)	**(3.566)**	**(2.059)**	(0.263)	**(4.240)**	**(2.882)**
Trim 0.5	0.448	0.92	0.471	0.809	1.43	0.621	0.088	0.596	0.507
	(2.448)	**(4.573)**	(1.944)	**(2.813)**	**(3.388)**	(1.398)	(0.672)	**(4.246)**	**(2.814)**
Trim 10	0.637	0.935	0.296	0.904	1.436	0.446	0.292	0.583	0.29
	(4.111)	**(4.717)**	**(3.719)**	**(3.367)**	**(3.897)**	**(2.963)**	**(2.956)**	**(4.320)**	**(3.719)**
Trim 99.5	-0.033	0.715	0.747	-0.304	0.868	1.17	0.016	0.576	0.559
	(-0.118)	**(4.311)**	**(2.170)**	(-0.570)	**(3.055)**	(1.760)	(0.114)	**(4.233)**	**(2.916)**
Trim 90	-0.238	0.454	0.691	-0.998	0.426	1.432	-0.126	0.413	0.537
	(-0.932)	**(4.599)**	**(2.307)**	(-1.624)	**(2.903)**	**(2.117)**	(-0.935)	**(4.222)**	**(2.933)**
	Panel B: Excess return differences with raw								
Trim 0.5	0.321	-0.038	-0.359	0.706	-0.048	-0.754	0.052	-0.001	-0.052
	(2.075)	**(-2.083)**	**(-2.207)**	(1.689)	(-0.905)	(-1.751)	(1.737)	(-0.152)	(-1.690)
Trim 10	0.51	-0.024	-0.535	0.573	-0.009	-0.593	0.256	-0.014	-0.27
	(1.669)	(-0.274)	(-1.758)	(1.110)	(-0.081)	(-1.054)	**(2.009)**	(-0.795)	**(-2.051)**
Trim 99.5	-0.16	-0.244	-0.084	-0.406	-0.611	-0.204	-0.02	-0.021	0
	(-2.430)	**(-3.206)**	**(-3.228)**	(-1.653)	**(-2.720)**	**(-2.381)**	**(-2.047)**	(-1.542)	(-0.023)
Trim 90	-0.365	-0.505	-0.14	-1.14	-1.085	0.057	-0.162	-0.184	-0.022
	(-2.746)	**(-3.368)**	(-1.723)	**(-2.412)**	**(-3.204)**	(0.231)	**(-2.911)**	**(-2.989)**	(-0.823)
	Panel C: Alphas from the bond market risk factor CAPM								
Raw Alpha	0.357	0.407	0.049	0.273	0.714	0.44	0.124	0.132	0.008
	(1.505)	**(2.805)**	(0.233)	(0.598)	**(2.109)**	(0.803)	(0.746)	(1.480)	(0.060)
Trim 0.5	0.57	0.386	-0.185	0.996	0.686	-0.311	0.143	0.135	-0.009
	(2.884)	**(2.714)**	(-1.195)	**(3.458)**	**(2.038)**	(-0.893)	(0.852)	(1.509)	(-0.074)
Trim 10	0.372	0.42	0.046	0.678	0.741	0.074	0.093	0.145	0.051
	(2.628)	**(3.076)**	(1.095)	**(2.716)**	**(2.479)**	(0.616)	(0.833)	(1.597)	(1.084)
Trim 99.5	0.235	0.219	-0.017	-0.011	0.242	0.252	0.109	0.125	0.014
	(1.038)	(1.877)	(-0.083)	(-0.024)	(0.931)	(0.467)	(0.665)	(1.409)	(0.113)
Trim 90	0.086	0.107	0.02	-0.333	0.044	0.366	0.048	0.071	0.022
	(0.396)	(1.322)	(0.109)	(-0.746)	(0.319)	(0.762)	(0.310)	(0.940)	(0.180)

Table A.10: The Asymmetric Effect in the WRDS Bond Return (RET_EOM) Data

The table contrasts the short-term equal-weighted (EW) momentum strategy's performance in the WRDS Bond Return raw data with that after trimming outliers in the formation period, for the straight all bonds, non-investment-grade bonds, and investment-grade bonds, respectively. Bond returns (RET_EOM) are calculated using the end-of-month prices. Panel A reports average monthly momentum excess returns and returns on the long/short legs using the raw data, followed by estimates based on two sets of outlier treatments. The two sets of outlier thresholds are the (99.5, 0.5) and (90, 10) percentiles of the all-bond return distribution. Panel B presents estimated β from the model $PR_t^{treated} - PR_t^{untreated} = \beta + \epsilon_t$, which evaluates the spread of the monthly portfolio return series associated with each outlier treatment over the benchmark return series when outliers are left untreated. Panel C reports alpha estimates obtained from the bond-market CAPM. T-statistics significant at the 5% level are highlighted in bold. Standard errors are adjusted using the Newey-West HAC estimation with three lags.

	Whole			Non-investment-grade bonds			Investment-grade bonds		
	W-L	Winner	Loser	W-L	Winner	Loser	W-L	Winner	Loser
				Panel A: Equal-weighted $S(3,3)$ momentum excess returns					
Raw ER	-0.097	1.821	1.918	-0.063	1.608	1.67	-0.612	0.766	1.377
	(-0.183)	**(4.211)**	**(3.786)**	(-0.152)	**(4.445)**	**(2.715)**	(-1.936)	**(4.213)**	**(3.120)**
Trim 0.5	0.76	1.77	1.009	0.748	1.469	0.72	-0.273	0.741	1.013
	(1.936)	**(4.183)**	**(4.192)**	**(3.251)**	**(4.314)**	**(2.045)**	(-1.743)	**(4.354)**	**(3.609)**
Trim 10	1.383	1.952	0.568	0.91	1.46	0.549	0.275	0.702	0.425
	(2.730)	**(3.748)**	**(6.743)**	**(3.170)**	**(4.325)**	**(3.184)**	**(2.088)**	**(3.997)**	**(5.426)**
Trim 99.5	-0.871	0.851	1.721	-0.604	0.91	1.514	-0.716	0.649	1.363
	(-1.980)	**(5.590)**	**(3.408)**	(-1.368)	**(3.745)**	**(2.575)**	(-1.888)	**(4.426)**	**(2.981)**
Trim 90	-1.384	0.54	1.923	-0.874	0.738	1.61	-1.04	0.478	1.517
	(-2.184)	**(6.275)**	**(2.923)**	(-1.786)	**(4.823)**	**(2.806)**	(-1.829)	**(4.766)**	**(2.520)**
				Panel B: Excess return differences with raw					
Trim 0.5	0.857	-0.051	-0.909	0.811	-0.139	-0.95	0.339	-0.024	-0.364
	(2.635)	**(-3.318)**	**(-2.767)**	**(2.641)**	(-1.939)	**(-2.929)**	(1.641)	(-1.043)	(-1.713)
Trim 10	1.481	0.131	-1.35	0.973	-0.148	-1.121	0.888	-0.064	-0.951
	(2.773)	(1.035)	**(-2.794)**	(1.898)	(-1.171)	**(-1.992)**	**(2.209)**	(-1.045)	**(-2.337)**
Trim 99.5	-0.773	-0.97	-0.197	-0.541	-0.698	-0.157	-0.104	-0.117	-0.013
	(-2.022)	**(-2.557)**	(-1.478)	**(-2.976)**	**(-3.765)**	**(-2.126)**	(-1.270)	(-1.647)	(-0.313)
Trim 90	-1.286	-1.282	0.005	-0.81	-0.87	-0.06	-0.428	-0.288	0.14
	(-2.775)	**(-3.213)**	(0.020)	**(-2.916)**	**(-3.440)**	(-0.349)	(-1.547)	**(-2.308)**	(0.689)
				Panel C: Alphas from the bond market risk factor CAPM					
Raw Alpha	0.115	1.341	1.225	0.343	0.988	0.644	-0.414	0.314	0.727
	(0.266)	**(3.841)**	**(4.029)**	(1.007)	**(3.146)**	(1.377)	**(-2.094)**	**(3.504)**	**(3.251)**
Trim 0.5	0.788	1.299	0.51	0.866	0.887	0.02	-0.166	0.308	0.473
	(2.246)	**(3.783)**	**(4.558)**	**(3.859)**	**(2.858)**	(0.066)	(-1.488)	**(3.515)**	**(3.622)**
Trim 10	1.029	1.424	0.395	0.573	0.895	0.32	0.055	0.285	0.229
	(2.479)	**(3.465)**	**(5.358)**	**(2.003)**	**(2.717)**	(1.818)	(0.586)	**(3.072)**	**(4.765)**
Trim 99.5	-0.557	0.483	1.039	-0.119	0.42	0.538	-0.451	0.249	0.699
	(-1.909)	**(5.313)**	**(3.636)**	(-0.364)	(1.689)	(1.219)	**(-2.055)**	**(3.080)**	**(3.049)**
Trim 90	-0.91	0.283	1.192	-0.233	0.448	0.68	-0.634	0.199	0.831
	(-2.318)	**(4.276)**	**(3.103)**	(-0.658)	**(3.157)**	(1.614)	**(-2.001)**	**(2.482)**	**(2.626)**

Table A.11: The Asymmetric Effect in the WRDS Bond Return (RET_L5M) Data

The table contrasts the short-term equal-weighted (EW) momentum strategy's performance in the WRDS Bond Return raw data with that after trimming outliers in the formation period, for the straight all bonds, non-investment-grade bonds, and investment-grade bonds, respectively. Bond returns (RET_L5M) are calculated using the last-5-trading-day prices. Panel A reports average monthly momentum excess returns and returns on the long/short legs using the raw data, followed by estimates based on two sets of outlier treatments. The two sets of outlier thresholds use the same cutoffs as those applied in the RET_EOM sample. Panel B presents estimated β from the model $PR_t^{treated} - PR_t^{untreated} = \beta + \epsilon_t$, which evaluates the spread of the monthly portfolio return series associated with each outlier treatment over the benchmark return series when outliers are left untreated. Panel C reports alpha estimates obtained from the bond-market CAPM. T-statistics significant at the 5% level are highlighted in bold. Standard errors are adjusted using the Newey-West HAC estimation with three lags.

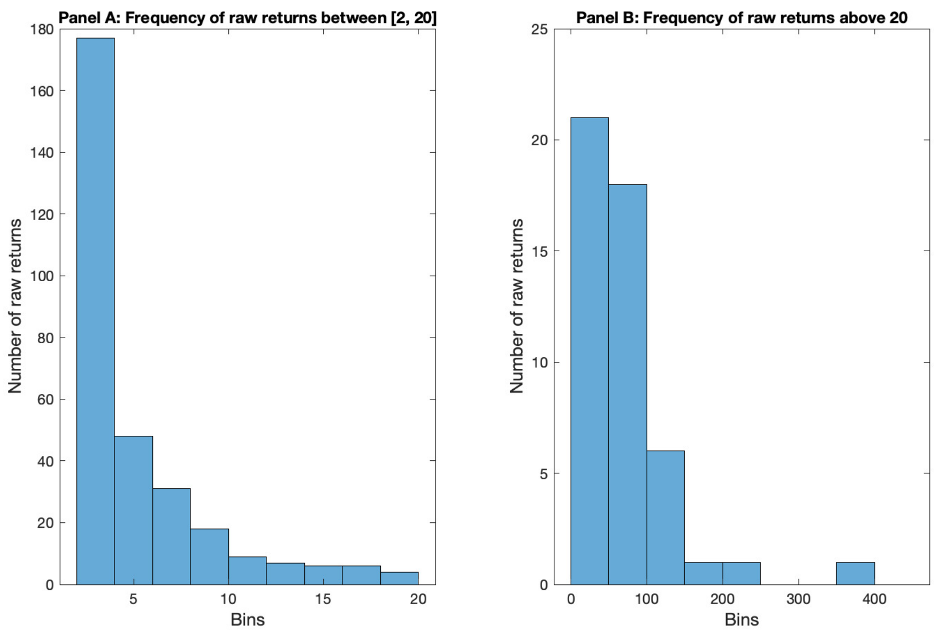
	Whole			Non-investment-grade bonds			Investment-grade bonds		
	W-L	Winner	Loser	W-L	Winner	Loser	W-L	Winner	Loser
	Panel A: Equal-weighted $S(3,3)$ momentum excess returns								
Raw ER	-0.022	0.904	0.925	0.169	1.222	1.052	-0.211	0.61	0.821
	(-0.077)	**(4.427)**	**(2.590)**	(0.434)	**(3.485)**	(1.756)	(-0.909)	**(4.226)**	**(3.024)**
Trim 0.5	0.321	0.868	0.546	0.542	1.131	0.589	0.027	0.608	0.58
	(2.074)	**(4.427)**	**(2.606)**	**(2.595)**	**(3.448)**	(1.506)	(0.242)	**(4.217)**	**(3.667)**
Trim 10	0.531	0.838	0.306	0.67	1.085	0.413	0.321	0.617	0.295
	(3.913)	**(4.799)**	**(4.316)**	**(2.981)**	**(3.478)**	**(3.188)**	**(3.214)**	**(4.565)**	**(4.372)**
Trim 99.5	-0.183	0.688	0.87	-0.126	0.768	0.894	-0.239	0.584	0.822
	(-0.638)	**(4.188)**	**(2.515)**	(-0.304)	**(3.080)**	(1.569)	(-0.999)	**(4.247)**	**(2.981)**
Trim 90	-0.368	0.46	0.827	-0.527	0.502	1.027	-0.384	0.43	0.813
	(-1.336)	**(4.924)**	**(2.606)**	(-1.039)	**(3.905)**	(1.774)	(-1.562)	**(4.664)**	**(2.889)**
	Panel B: Excess return differences with raw								
Trim 0.5	0.343	-0.036	-0.38	0.372	-0.091	-0.463	0.238	-0.002	-0.241
	(1.812)	**(-2.273)**	(-1.920)	(1.428)	(-1.586)	(-1.696)	(1.356)	(-0.864)	(-1.354)
Trim 10	0.553	-0.066	-0.619	0.501	-0.138	-0.638	0.532	0.007	-0.525
	(1.879)	(-1.608)	**(-1.994)**	(1.046)	(-1.700)	(-1.227)	**(2.379)**	(0.364)	**(-2.347)**
Trim 99.5	-0.16	-0.216	-0.056	-0.296	-0.454	-0.158	-0.028	-0.026	0.001
	(-2.919)	**(-3.342)**	**(-2.126)**	**(-2.043)**	**(-2.855)**	**(-2.281)**	(-1.911)	(-1.664)	(0.126)
Trim 90	-0.346	-0.444	-0.098	-0.696	-0.721	-0.025	-0.173	-0.18	-0.008
	(-2.767)	**(-3.138)**	**(-2.015)**	**(-2.598)**	**(-2.727)**	(-0.201)	**(-2.713)**	**(-2.488)**	(-0.236)
	Panel C: Alphas from the bond market risk factor CAPM								
Raw Alpha	0.166	0.339	0.172	0.529	0.495	-0.034	-0.147	0.125	0.272
	(0.744)	**(2.841)**	(0.925)	(1.638)	(1.708)	(-0.074)	(-0.781)	(1.617)	(1.649)
Trim 0.5	0.352	0.321	-0.033	0.691	0.457	-0.235	0.018	0.124	0.104
	(2.232)	**(2.714)**	(-0.278)	**(3.398)**	(1.584)	(-0.724)	(0.163)	(1.577)	(1.428)
Trim 10	0.248	0.327	0.079	0.311	0.439	0.127	0.084	0.164	0.079
	(2.418)	**(3.311)**	(1.947)	(1.528)	(1.632)	(0.999)	(0.847)	(1.811)	**(2.334)**
Trim 99.5	0.045	0.184	0.138	0.369	0.201	-0.169	-0.164	0.115	0.278
	(0.209)	(1.735)	(0.744)	(1.176)	(0.779)	(-0.393)	(-0.848)	(1.465)	(1.630)
Trim 90	-0.015	0.135	0.149	0.203	0.164	-0.041	-0.185	0.109	0.293
	(-0.076)	(1.853)	(0.898)	(0.579)	(1.294)	(-0.102)	(-0.957)	(1.396)	(1.626)

Table A.12: The Asymmetric Effect in the WRDS Bond Return (RET_LDM) Data

The table contrasts the short-term equal-weighted (EW) momentum strategy's performance in the WRDS Bond Return raw data with that after trimming outliers in the formation period, for the straight all bonds, non-investment-grade bonds, and investment-grade bonds, respectively. Bond returns (RET_LDM) are calculated using the last-trading-day prices. Panel A reports average monthly momentum excess returns and returns on the long/short legs using the raw data, followed by estimates based on two sets of outlier treatments. The two sets of outlier thresholds use the same cutoffs as those applied in the RET_EOM sample. Panel B presents estimated β from the model $PR_t^{treated} - PR_t^{untreated} = \beta + \epsilon_t$, which evaluates the spread of the monthly portfolio return series associated with each outlier treatment over the benchmark return series when outliers are left untreated. Panel C reports alpha estimates obtained from the bond-market CAPM. T-statistics significant at the 5% level are highlighted in bold. Standard errors are adjusted using the Newey-West HAC estimation with three lags.

	Whole			Non-investment-grade bonds			Investment-grade bonds		
	W-L	Winner	Loser	W-L	Winner	Loser	W-L	Winner	Loser
Panel A: Equal-weighted $S(3,3)$ momentum excess returns									
Raw ER	0.115	0.81	0.693	0.225	1.141	0.915	0.012	0.631	0.618
	(0.481)	**(4.342)**	**(2.192)**	(0.497)	**(3.189)**	(1.488)	(0.088)	**(4.595)**	**(3.267)**
Trim 0.5	0.31	0.777	0.466	0.546	1.001	0.464	0.091	0.632	0.54
	(1.951)	**(4.354)**	**(2.112)**	**(2.235)**	**(2.933)**	(1.120)	(0.741)	**(4.614)**	**(3.239)**
Trim 10	0.453	0.752	0.298	0.637	1.135	0.482	0.312	0.61	0.296
	(3.501)	**(4.717)**	**(4.161)**	**(2.695)**	**(3.635)**	**(2.790)**	**(3.126)**	**(4.702)**	**(4.129)**
Trim 99.5	0.001	0.655	0.653	-0.063	0.739	0.778	-0.021	0.596	0.616
	(0.004)	**(4.241)**	**(2.119)**	(-0.136)	**(2.816)**	(1.299)	(-0.148)	**(4.522)**	**(3.288)**
Trim 90	-0.118	0.447	0.564	-0.446	0.42	0.688	-0.179	0.421	0.6
	(-0.556)	**(4.797)**	**(2.223)**	(-0.875)	**(2.709)**	(1.142)	(-1.297)	**(4.558)**	**(3.338)**
Panel B: Excess return differences with raw									
Trim 0.5	0.194	-0.033	-0.227	0.325	-0.155	-0.451	0.079	0	-0.078
	(1.523)	**(-2.015)**	(-1.686)	(0.900)	(-1.562)	(-1.306)	**(2.118)**	(0.095)	**(-2.088)**
Trim 10	0.338	-0.057	-0.395	0.436	-0.034	-0.455	0.3	-0.022	-0.322
	(1.324)	(-1.460)	(-1.431)	(0.845)	(-0.261)	(-0.812)	**(2.333)**	(-0.991)	**(-2.397)**
Trim 99.5	-0.114	-0.155	-0.041	-0.284	-0.418	-0.137	-0.033	-0.035	-0.002
	(-2.460)	**(-2.867)**	**(-2.119)**	(-1.786)	**(-2.517)**	(-1.665)	**(-2.411)**	**(-2.115)**	(-0.298)
Trim 90	-0.233	-0.363	-0.13	-0.632	-0.672	-0.237	-0.192	-0.21	-0.019
	(-2.151)	**(-2.893)**	(-1.325)	**(-2.130)**	**(-2.497)**	(-0.854)	**(-3.099)**	**(-3.186)**	(-0.657)
Panel C: Alphas from the bond market risk factor CAPM									
Raw Alpha	0.317	0.274	-0.044	0.445	0.379	-0.066	0.079	0.171	0.091
	(1.516)	**(2.230)**	(-0.234)	(1.166)	(1.311)	(-0.129)	(0.547)	(1.762)	(0.783)
Trim 0.5	0.391	0.258	-0.134	0.574	0.288	-0.292	0.116	0.175	0.058
	(2.290)	**(2.170)**	(-0.977)	**(2.317)**	(0.981)	(-0.794)	(0.820)	(1.781)	(0.595)
Trim 10	0.193	0.273	0.079	0.37	0.473	0.092	0.1	0.185	0.084
	(1.783)	**(2.612)**	**(2.165)**	(1.695)	(1.799)	(0.746)	(0.926)	(1.832)	**(2.208)**
Trim 99.5	0.237	0.17	-0.068	0.307	0.159	-0.179	0.054	0.149	0.094
	(1.158)	(1.583)	(-0.373)	(0.824)	(0.622)	(-0.368)	(0.378)	(1.591)	(0.816)
Trim 90	0.142	0.118	-0.025	0.129	0.065	-0.243	-0.01	0.097	0.106
	(0.747)	(1.423)	(-0.154)	(0.306)	(0.442)	(-0.485)	(-0.067)	(1.123)	(0.952)

Figure A.1: Frequency of Monthly Returns Greater than 200%



The figure plots the distribution of corporate bond monthly returns greater than 200%. Panel A plots the frequency between 200% and 2,000%, with a bin width of 2. Panel B plots the frequency above 2,000%, with a bin width of 50.