When the Long is Long and the Short is Short

Lifang Li*

Abstract

Through exploring the role and information content of return outliers, I show that extreme returns are part of the information diffusion process in the corporate bond market. Credit downgrades are imbued into prices instantly and lead to strong negative returns, while upgrades take months to be fully absorbed and eventually create positive outliers. Consistent with bad news traveling faster than good news, positive outliers identify "good" winners that are bonds yielding sustained price trends on which momentum capitalizes. In contrast, bonds yielding negative outliers are "bad" losers as their price trends are short-lived. Using outliers as instruments, I compare the informational efficiency of the long and short legs of the momentum strategy and provide an explanation of why the momentum effect for corporate bonds originates from the winner portfolio.

Keywords: momentum; outliers; informational efficiency; asymmetric responses; corporate bonds.

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*School of Economics and Finance, Xi'an Jiaotong University, Email: lifangli@mail.xjtu.edu.cn

Introduction

According to the theoretical framework of Hong and Stein (1999) (henceforth HS), momentum profitability stems from the continuation of the price trends originating from gradual diffusion of information.[1] In particular, the speed at which information is incorporated into prices is inversely related to momentum profitability. Consistently, using TRACE data, Li and Galvani (2021) find that the momentum effect is weaker for informationally more efficient corporate bond groups.[2]

This study further examines the informational efficiency of the winner and loser portfolios forming the corporate bond momentum strategy. I find that information diffuses at different rates in the two portfolios, due to their designed polarity in attracting news valued asymmetrically by the market. Specifically, I find that the winner portfolio is associated with slow diffusion of positive information shocks, while the loser portfolio reflects a much faster market reaction to negative news. According to HS, these findings imply that corporate bond momentum capitalizes on the return continuation of past winners more than that of past losers as indeed documented in previous studies (e.g., Li and Galvani, 2018; Jostova et al., 2013). In contrast, the literature finds that momentum in equities mainly relies on gains from the short leg of the strategy (e.g., Hong et al., 2000; Stambaugh et al., 2012), due to a slower market reaction to bad than good news (e.g., Frank and Sanati, 2018). The insight provided by this study is that momentum gains are driven by the component of the strategy that profits the most from gradual information diffusion, thus confirming the information-based explanation of the momentum effect proposed by HS.

The asymmetric market reaction to good and bad news for bonds roots in the nature of debt instruments. As formalized in the classical Merton model (Merton, 1974), the value of a stock and a corporate bond are linked to a long position in a call and a short

[1] Other familiar theoretical explanation of the momentum effect (e.g., Barberis et al., 1998; Daniel et al., 1998) also pose that some information shock initiates the price trends from which momentum strategies profit.

[2] Empirical evidence for the information-based explanation of the momentum effect for equities can be found in Hong et al. (2000), Savor (2012), Jiang and Zhu (2017), etc.

position in a put option on the value of the firm, respectively.[3] Therefore, unlike equities, the impact of good news on the price of the bond is limited due to the payoff of debt being bounded. In contrast, bad news increases the likelihood of the put being exercised and thus depreciates the bondholder's portfolio, due to a rise in default risk. Hence, bad news is more relevant to bond investors than positive information. Given their limited attention, fundamental bond investors should, therefore, react more promptly to negative than positive information shocks, causing bad news to be imbued into prices at a faster pace.

From a behavioral perspective, irrational retail bond investors still have the potential to overreact to good news thus speeding up the transmission of positive information.[4] However, this counterbalancing effect of retail investors' trading activities is weakened by the fact that the corporate bond market is dominated by institutions. Further, the resulted mispricing can be hard to correct given short-selling impediments for corporate bonds (e.g., Miller, 1977; Hendershott et al., 2018).

Consistently, the literature presents empirical evidence showing that bond prices are more sensitive to news regarding losses (e.g., Easton et al., 2009; De Franco et al., 2009) while trading activities are low when bond prices rise (e.g., Hong and Sraer, 2013), suggesting slow diffusion of good news.

In the framework of HS, the construction of the long and short legs of the momentum strategy should each reflect the gradual diffusion of extremely good and bad news. In particular, the momentum strategy selects as winners those bonds in the cross-section with the best past returns, which originate from the price appreciations linked to good news. Similarly, the loser portfolio includes bonds with the worst past returns that are

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

[4]Frank and Sanati (2018) document that retail investors tend to overreact to positive news and underreact to negative news, consistent with small investors rarely selling short (e.g., Barber and Odean, 2008) and having a much more severe informational disadvantage around bad than good news (e.g., Park et al., 2014).

likely caused by the diffusion of bad news. Whether the winning and losing positions extend to the holding period of the strategy depends on the persistence of their respective price trends, and thus on the diffusion speed of good and bad news. Specifically, the price trends of losers should be less sustained than those of winners, if information travels faster for bad than good news. Put differently, the loser portfolio should be more efficient than the winner portfolio in transmitting information, resulting in less mispricing and a weaker contribution to momentum profitability. In this paper, I explore these implications by examining the link between extreme returns (i.e., outliers) and the arrival of favorable and unfavorable information shocks, as well as their impacts on the momentum effect.[5]

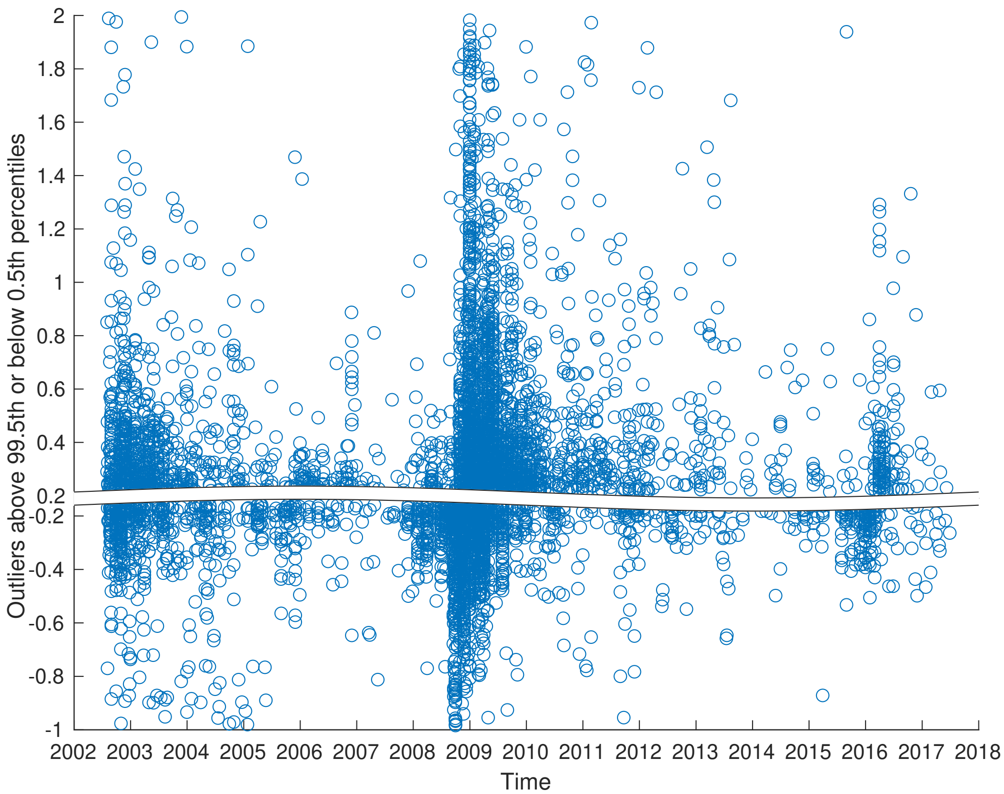
Return outliers are pervasive in the corporate bond market. Figure 1 depicts the monthly corporate bond returns above the 99.5th or below the 0.5th percentiles of the distribution over the 2002-2017 period, where returns are calculated from transaction-based prices recorded on the TRACE.[6] The figure shows clustering of outliers during market fluctuations, an unlikely pattern should outliers be pure statistical noise.

This study provides a direct link between extreme returns and bond rating downgrades and upgrades, suggesting that outliers can be informative. Regression results indicate that bond returns respond negatively to downgrades, with the impact being significantly stronger for returns classified as outliers. The implication is that the market often responds aggressively to bad news conveyed by a downgrade. The market also responds very promptly to downgrades, as the negative effect on both outliers and regular returns is only contemporaneous and does not extend to the following months. Upgrades, on the other hand, increase bond returns but at a slower pace than downgrades. In particular, for non-investment-grade bonds, I find that upgrades increase returns by only 30 bps in the current month, while the effect accumulates to more than a 4% increase in returns

[5]Relying on return outliers to gauge information shocks is not new in the finance literature. For instance, Barber and Odean (2008) interpret the extreme quantiles of the equity return distribution as proxies of investors' attention to news. Similarly, Frank and Sanati (2018) evaluate the asymmetric equity market response to good and bad news using returns deviating from normalized average returns.

[6]In Figure 1, returns are capped at 200% to highlight crisis clusters.

Figure 1: Bond Return Outliers Using the [99.5th 0.5th] Percentile Thresholds



The figure plots monthly corporate bond returns that are above the 99.5th or 0.5th percentiles of the return distribution, over the time period of August 2002-June 2017. In the figure, returns are capped at 200%.

over two months, which yields positive outliers. Therefore, these results confirm that extreme bond returns convey information, with negative outliers signaling a prompter price reaction to information shocks than positive extreme returns.

Having established the link between outliers and information, I can examine the relative informational efficiency of the two legs of the momentum strategy using outliers as instruments. The momentum strategy, by its very design, showcases the effect of outliers, as a bond yielding a positive (negative) extreme return during the strategy's formation period is extremely likely to be included in the winner (loser) portfolio. Therefore, outliers are expected to contribute substantially to the composition of the momentum portfolio and thus to its holding-period returns, especially when past returns are evaluated over short periods.

The conjecture that returns on the long leg of the momentum strategy are supported by longer price trends than those of the short leg yields testable predictions. Specifically, I predict that (a) removing bonds yielding positive outliers, which mainly affect the composition of the winner portfolio, should weaken the return continuation induced by the slow diffusion of good news, and thus decrease momentum gains through lowering returns for winners; (b) dropping negative outliers should increase the payoffs of shorting losers by excluding from the short leg bonds with price trends that are unlikely to extend over the holding period, due to quickly-absorbed negative information shocks. A complementary prediction (c) is that the asymmetric effect of positive and negative outliers on momentum profitability is not detectable when treating outliers has no impact on the composition of the momentum portfolio.

To evaluate these predictions, I remove either top or bottom outliers only from the formation period (FP) to test predictions (a) and (b), and only in the holding period (HP) to test prediction (c). The resulting changes in momentum profitability are evaluated against returns on the same strategies with no treatment of outliers. Treating outliers separately for the FP and HP is motivated by the observation that the composition of the long-short portfolio does not adjust for the arrival of news during the holding period.

The findings strongly confirm all three predictions. In particular, I find that the formation period treatment significantly decreases momentum gains when positive outliers are trimmed, while momentum profitability is greatly boosted when negative outliers are removed. This asymmetric effect disappears when the same procedures are conducted only in the holding period.

Summarizing, this paper's findings support the conjecture that the long leg of the momentum strategy is informationally less efficient than the short leg, due to the slower diffusion of good than bad news. Hence, the momentum effect for corporate bonds is mainly driven by the diffusion of good news in the winner portfolio. The analysis thus sheds some light on how information diffusion drives momentum returns and contributes to the understanding of the causes of the momentum effect in the corporate bond market.

This study also offers recommendations for both corporate bond momentum researchers and investors. As outliers potentially reflect the diffusion of extreme information shocks, researchers should be prudent when classifying certain abnormal prices or returns as pricing errors and eliminating them from the sample. Investors profiting from trading on the momentum effect can also draw insights from this study's results. The results show that the implementation of the momentum strategy in the corporate bond market should focus on capitalizing on the slow diffusion of positive news. In particular, I show that excluding from the momentum portfolio bonds yielding negative outliers during the formation period increases momentum profitability.

1 Data and Methodology

1.1 Return Calculation and All-sample Summary Statistics

The empirical analysis of this study relies on data from TRACE Enhanced, matched with Mergent FISD, for the period spanning from July 2002 to June 2017. TRACE provides the highest data quality for corporate bonds commencing from July 2002, as the reported prices are supported by actual transactions rather than being dependent on dealers' quotes or matrix pricing. Only publicly traded bonds are included in the sample.[7] Following the cleaning procedure described in Dick-Nielsen (2014), I reduce data reporting errors by removing all transactions that are marked as a cancellation, correction, and reversals, as well as their matched original trades.

I select in the sample only corporation-issued bonds that are not part of unit deals and are US-dollar denominated and pay a fixed-coupon, including zero-coupon bonds. Bonds with warrants and special contingencies (i.e., preferred shares, puttable, convertible, exchangeable, asset-backed, etc.) are also excluded. The final sample contains 956,518

[7] Hence, all transactions that are labeled as 144A are omitted from the sample.

monthly transaction-based price observations for 17,846 bonds issued by 2,563 firms. In the final sample, information on credit rating is available for about 99% of the bond-month observations.

Li and Galvani (2021) argue that calculating monthly returns using the last-available price of the month is suitable for the examination of the momentum effect in the corporate bond market, as this method highlights the effect of information transmission. Following their approach, I obtain the monthly prices for each bond in the sample by extracting the last available trade-size-weighted daily price in each month, where the weights for the calculation of daily prices are backed by intra-day transactions. If no trade is available in a given month for a bond, both the returns of the previous and following months are marked as missing.

The monthly return $r_{i,t+1}$ of bond i over the holding period from month t to $t+1$ is defined as follows:

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

where, $P_{i,t+1}$ is the price of bond i in month $t+1$, $C_{i,t+1}$ is the amount of coupon payment yielded by the bond between time t and $t+1$ (if any), which is calculated as the ratio of the annual coupon rate of bond i to its coupon frequency. The accrued interest $AI_{i,t+1}$ is defined as follows:

$$AI_{i,t+1} = C_{i,t+1}\left(\frac{d_{t+1}}{D_{t+1}}\right),$$

where d_{t+1} is the number of days between time $t+1$ and the last coupon payment date, and D_{t+1} is the number of days between the two consecutive coupon payment dates leading to, and following, the price $P_{i,t+1}$.[8] Summary statistics of bond returns, by year, are tabulated in Panel A of Table 1.

[8] Bond information required for the calculation of accrued interests, such as the coupon rate and frequency, the day-count convention, and the first coupon-payment date, is obtained from Mergent FISD.

Table 1: Summary Statistics

The table reports summary statistics by year for the monthly returns calculated in the TRACE sample. Panel A tabulates the total number of return observations, then average, standard deviation, median, maximum, and minimum of bond returns for each year. The first four columns of Panel B report the number and mean of return outliers in each year, partitioned into positive and negative outliers. The cut-offs for the identification of outliers are 99.5th and 0.5th percentiles of the return distribution. The last two columns of Panel B report for each year the percentage of outliers that were followed by a return of the opposite sign, at the bond level. Panel C reports the analogous statistics when outliers are identified by the 99th and 1st percentiles. The time period covered is from August 2002 to June 2017.

Panel A: Whole sample

Year	N	mean(%)	std	median(%)	maximum(%)	minimum(%)
2002	21768	1.971	0.301	1.058	4047.735	-97.608
2003	59246	1.254	0.108	0.635	926.175	-95.134
2004	63244	0.871	0.337	0.454	5267.932	-97.784
2005	62067	0.311	0.374	0.239	9275.542	-98.041
2006	61431	0.668	0.027	0.457	138.698	-64.665
2007	58528	0.312	0.025	0.412	96.734	-81.218
2008	56455	-0.088	0.16	0.187	1056.838	-98.417
2009	60286	3.194	0.499	1.246	11560.26	-95.44
2010	63976	1.022	0.096	0.549	1774.379	-71.657
2011	64361	0.783	0.054	0.46	741.199	-95.426
2012	65887	0.868	0.078	0.438	1627.895	-55.027
2013	67365	0.085	0.028	0.14	168.186	-65.776
2014	68618	0.571	0.021	0.305	238.463	-49.792
2015	71664	0.026	0.026	0.07	193.874	-87.129
2016	74258	0.56	0.034	0.247	133.188	-50.552
2017	37364	0.674	0.016	0.413	59.476	-46.611

Panel B: Outliers higher than 99.5th or lower than 0.5th percentiles

	Positive Outliers			Negative Outliers		
Year	N	mean(%)	Reversal (%)	N	mean(%)	Reversal (%)
2002	388	59.121	40.98	322	-27.121	65.84
2003	417	55.691	33.09	167	-30.086	79.04
2004	114	221.203	43.86	97	-35.901	57.73
2005	47	250.325	27.66	128	-25.47	50.78
2006	90	32.611	34.44	31	-24.328	58.06
2007	17	35.784	11.76	44	-26.491	47.73
2008	882	64.721	17.35	2378	-30.16	51.18
2009	2130	54.219	28.64	1167	-26.667	66.15
2010	243	61.477	30.04	68	-27.162	66.18
2011	124	65.345	17.74	62	-29.109	62.9
2012	58	102.73	20.69	43	-25.651	74.42
2013	48	53.477	35.42	29	-27.479	37.93
2014	19	52.209	26.32	22	-22.275	36.36
2015	21	43.153	33.33	110	-23.89	36.36
2016	179	36.336	22.91	104	-23.173	57.69
2017	6	38.012	33.33	11	-28.952	54.55

Panel C: Outliers higher than 99th or lower than 1st percentiles

	Positive Outliers			Negative Outliers		
Year	N	mean(%)	Reversal (%)	N	mean(%)	Reversal (%)
2002	804	37.219	38.56	629	-19.945	68.2
2003	859	35.694	33.88	492	-18.234	79.27
2004	224	120.826	46.43	220	-22.684	64.55
2005	119	109.399	31.93	423	-16.24	50.12
2006	255	22.258	54.12	95	-16.087	65.26
2007	50	22.901	24	216	-15.179	45.37
2008	1791	40.499	17.53	4174	-22.609	50.31
2009	3976	36.98	28.22	2005	-20.815	62.59
2010	502	38.397	36.45	184	-17.757	65.76
2011	234	42.394	29.06	273	-16.142	71.43

Year	N	Positive Outliers mean(%)	Reversal (%)	N	Negative Outliers mean(%)	Reversal (%)
2012	177	44.901	26.55	85	-19.139	70.59
2013	96	35.438	31.25	112	-15.996	58.04
2014	42	32.87	26.19	56	-16.494	33.93
2015	52	26.736	51.92	314	-16.227	35.35
2016	367	26.335	22.07	264	-16.736	61.36
2017	17	23.415	47.06	23	-19.942	52.17

1.2 Identification of Return Outliers

Similar to stock returns, corporate bond returns are also positively skewed as evident in Panel A of Table 1. Hence, the selection of thresholds for identifying and treating outliers needs to take into consideration this tail asymmetry to avoid arbitrarily transforming the return distribution and altering the statistical impact (e.g., Abarbanell and Lehavy, 2003). From this perspective, percentage thresholds for identification of outliers, although being sample-specific, would not alter the tail asymmetry of the distribution and thus are preferred than absolute cutoffs (e.g., +/-30% or +/-10%). Therefore, in this study, I use a set of commonly accepted percentiles in equity studies as thresholds to identify outliers, i.e., 99th and 1st percentiles of the return distribution (e.g., Leone et al., 2019), which correspond to 13.82% and -10.13% returns, respectively. Given the large size of the sample, I also apply the 99.5th and 0.05th percentile thresholds to avoid excluding too many observations while identifying returns that are sufficiently deviated from the sample mean to be considered out-sized. The 99.5th percentile threshold is also applied in Jostova et al. (2013) for the elimination of positive return outliers when studying the momentum effect in corporate bonds. The authors, however, do not propose a threshold for negative outliers. In the sample of this study, the cut-offs at the 99.5th and 0.5th percentiles correspond to returns of 21.51% and about -16%, respectively.[9]

Panel B of Table 1 reports summary statistics by year for the outliers identified in the sample using cut-offs of 99.5th and 0.5th percentiles of the return distribution. Figure 1 in the Introduction plots the distribution of outliers identified using the same thresholds and

[9] To compare, the 99.5th percentile threshold cuts the return sample at 30% in Jostova et al. (2013), which has a longer sample ranging from 1973 to 2011.

visually illustrates that positive outliers are more numerous and tend to be larger than negative ones. The number of outliers, both positive and negative, reaches its highest levels in 2008 and 2009. The analogous statistics for outliers identified at the 99th and 1st percentiles are in Panel C of the same table. Note that positive and negative outliers cluster over the crisis period, regardless of the cut-off points.

Panels B and C also list the percentage of outliers for which the following monthly return is of the opposite sign, at the bond level. These corrections are markedly more prevalent for negative than positive outliers for all years in the sample. Returns below the 0.5th and 1st percentiles of the return distribution are followed by a positive return in about 56% and 58% of the instances, respectively, on average over the years in the sample. The corresponding percentages for returns larger than the 99.5th and 99th percentiles are about 28.6% and 34%, respectively. This simple statistical illustration suggests that negative outliers are more likely to reverse within a short time period than positive ones, a possible outcome of bad news traveling faster than good news in the corporate bond market. Further, in the appendix, I show that extremely low prices are associated with both positive and negative return outliers much more often than extremely high prices. As extremely high prices are more likely to reflect pricing errors than low prices given the bounded payoff of corporate bonds, this finding also suggests that outliers may not be the result of reporting errors thus could contain information.

1.3 Momentum Strategies

Momentum strategies in this study are designed as in Jegadeesh and Titman (1993). The momentum portfolio is characterized by a formation and a holding period, separated by a formation month to avoid the bid-ask bounce. In each formation month t, for a formation period of j months, I sort bonds into deciles, on the basis of their historical cumulative returns over the months spanning from $t-j-1$ to $t-1$.[10] An equally-weighted portfolio of the bonds in the highest (lowest) decile identifies the long (short) leg of the momentum portfolio. Bonds included in the winner-minus-loser portfolio are held for the entire duration of the holding period.[11]

The holding period monthly return is defined, following Jegadeesh and Titman (1993), as the cross-sectional average of the monthly returns of the overlapping winner-minus-loser portfolios. The number of overlapping portfolios depends on the length of the holding period. I consider two representative (and familiar) short and long-term momentum strategies with symmetric formation and holding periods of three and six months, respectively.

1.4 Hypotheses

In this section, I develop two hypotheses to test the conjecture that the level of informational efficiency differs between the long and short legs of the momentum strategy. The first hypothesis proposes that outliers can be used as instruments to evaluate information diffusion speed.

Hypothesis 1. Return outliers reflect the asymmetric diffusion of extremely positive and negative information shocks.

Given the low liquidity of corporate bonds, the spreading of extreme news potentially carries large price impacts and thus could be associated with the extreme price movements creating return outliers. I thus conjecture that outliers could be driven by the spreading of extremely significant news. Further, as bonds payoffs are capped, bond investors are expected to be more sensitive to negative than positive information. There-

[10]Bonds for which one or more monthly returns are unavailable during the formation period are not considered for the winner-minus-loser portfolio, as it is standard in the momentum literature.

[11]An alternative is to exclude from the momentum portfolio bonds that expire earlier than the end of the holding period to condition on bond maturity (e.g., Khang and King, 2004; Li and Galvani, 2021). This limitation is not implemented in this study, to make momentum strategies as similar as possible to those implemented in studies of equity momentum.

fore, good news should be imbued into corporate bond prices slower than bad news, a feature that distinguishes the informational efficiency of the equity and corporate bond markets (e.g., Frank and Sanati, 2018; Easton et al., 2009). Hence, one should expect that the time elapsing between an information shock and a price response resulting in a return outlier is shorter for bad than good news.

Li and Galvani (2021) document that corporate bond momentum originates from the slow diffusion of information. Upon the confirmation of the link between outliers and information (Hypothesis 1), outliers can then be employed to contrast informational efficiencies between the winner and loser portfolios. Due to the design of the momentum strategy, yielding a positive (negative) outlier during the ranking period increases the probability that a bond is included in the winner (loser) portfolio. If top outliers convey information and identify price trends likely to continue in the holding period, removing them from the ranking period should decrease momentum profitability, by weakening the winner portfolio return. Conversely, removing negative outliers should increase momentum gains by decreasing the short leg's return, consistent with negative news being quickly imbued into prices, and thus not originating sustained price trends. Finally, if outliers are treated during the holding period when the diffusion of good and bad news does not affect the composition of the winner and loser portfolios, the contributions of positive and negative outliers to momentum profitability should be indistinguishable. These observations yield the second set of testable hypotheses.

Hypothesis 2. Removing positive (negative) outliers from the formation period of the momentum strategy should mostly decrease the holding period returns on the winner (loser) portfolio, resulting in a decrease (an increase) in momentum profitability. This asymmetric effect should not be present when outliers of opposite signs are trimmed from the holding period.

2 Outlier and Information

Although outliers in the corporate bond literature are often treated as noise or the result of pricing errors (e.g., Bessembinder et al., 2006; Gebhardt et al., 2005; Jostova et al., 2013), in this section, I explore the possibility that outliers are part of the information diffusion process with positive (negative) ones being associated with the arrival of good (bad) news, as outlined in Hypothesis 1 in Section 1.4.

To test this hypothesis, I identify the arrival of information shocks with bond-level rating upgrades and downgrades, and evaluate their relationship with the incidence of outliers. I do not interpret downgrades and upgrades respectively as bad and good news per se, as how a rating announcement is perceived by the market depends on investors' expectations (e.g., Frank and Sanati, 2018). Hence, I consider rating changes as identifiers of periods in which information arrives on the market, and leave the price response to the arrival of news to separate good from bad news.

The news of downgrades and upgrades should change corporate bond returns, possibly yield return outliers. Hence, I evaluate a bond-month level panel regression (Model 2) to explain bond monthly raw returns with downgrade (DNG) and upgrade (UPG) indicators, and their respective interactions with a dichotomous variable equaling one if the bond in that month yields an outlier and zero otherwise, which capture the outlier status. Formally, for bond b in month t, I have the following linear equation:

$$\begin{aligned} R_{bt} = \alpha_0 + \sum_{i=0}^{I} \{ & \beta_1^i outlier_{bt} * lag^i(DNG_{bt}) + \beta_2^i lag^i(DNG_{bt}) + \gamma_1^i outlier_{bt} * lag^i(UPG_{bt}) \\ & + \gamma_2^i lag^i(UPG_{bt}) \} + \sum_j \alpha_j Z_{bt}^j + \sum_b \theta_b bond_b + \sum_t \phi_t monthly_t + \epsilon_{bt} \\ & \qquad I = 0, 1, 2 \end{aligned} \tag{2}$$

The addition of the interaction terms is to distinguish the effects of information on normal returns and returns that are characterized as outliers.[12] The bond-level control variables summarized by Z^j in Model 2 include monthly trading volume, the credit rating at the end of the month, and an indicator for issuer' public-firm status. I also control for the bond level and the month level fixed effects.[13] Standard errors are two-way clustered along the firm and monthly dimensions. To determine whether there are delayed effects of information diffusion on returns, I modify the benchmark model by adding the first and second lags of the downgrade and upgrade dummies and their interactions with the outlier indicator. To ensure that the level of outlier returns does not drive the statistical inference, I also evaluate Model 2 for winsorized returns.

Table 2 tabulates the estimated coefficients on key variables in Model 2 with raw or winsorized returns as the dependent variable, where outliers are identified using the (99.5th, 0.5th) and (99th, 1st) percentiles of the return distribution, respectively. Regression results are obtained for the whole bond sample, and for high-grade (IG) and low-grade (NIG) bonds, independently.[14] Panel A reports results for the benchmark regressions when only the contemporaneous effect of information shocks on returns is evaluated. The results show that downgrades cause bond returns to decrease significantly by the magnitude ranging from 0.75% (winsorized) to 1.5% (raw) on average, for the whole bond sample. These changes are sizeable, as the sample mean of raw returns is 0.8% with a standard deviation of 19.5% (untabulated). The effect of downgrades on bond returns is more severe for low-grade than high-grade bonds, ranging from -1% (winsorized) to -2% (raw) for NIG bonds and from -0.5% (winsorized) to -0.8% (raw) for IG bonds, respectively, which can be explained by a sharper response to negative information of low-grade bonds, due to higher default risk. The mostly significant estimates on the interaction term

[12]The outlier variable itself is excluded from the regression as I am only interested in the interaction terms, and also the causality does not hold as it is the return size causing the outlier status not the other way around.

[13]Bond characteristics such as the coupon rate and time to maturity are excluded from the regression as they create collinearity with bond fixed effects.

[14]Credit group assignations are determined by the most conservative rating from S&P, Moody's, Fitch, and Duff and Phelps.

Table 2: The Role of Outliers in Transmitting Information

Panel A reports regression results for Model 2 in which bond-month raw or winsorized returns (both in percentage terms) are explained by indicators of credit rating upgrade (UPG) and downgrade (DNG), together with their interactions with a dichotomous variable ”outlier” that equals one if the bond in that month yields an outlier and zero otherwise. The two sets of cutoffs used to identify outliers for the interaction terms and winsorizing the dependent variable of bond returns are the (99.5th, 0.5th) and (99th, 1st) percentiles of the return distribution, respectively. For each set of outlier thresholds and for raw and winsorized return regressions, subsample results in non-investment-grade bonds (NIG) and investment-grade bonds (IG) are reported following the whole bond sample results (Whole). Each regression also includes the bond monthly trading volume, the credit rating at the end of the month, and an indicator for issuer’s public-firm status as control variables. Bond-level and monthly-level fixed effects are also controlled for. Coefficients on the constant and all control variables are omitted. Standard errors are two-way clustered at the firm and monthly levels. Panel B reports key variable coefficients of the same regressions when the regression additionally includes the first lag of the DNG and UPG indicators and their respective interactions with the outlier variable. Panel C reports the corresponding results when both the first and second lags of DNG and UPG, and their interactions with the outlier indicator are included in the regressions. Significance levels at 1%, 5%, and 10% are indicated by ***, **, and *, respectively. The time period covered is from August 2002 to June 2017.

	Raw (99.5th, 0.5th)			Winsorized (99.5th, 0.5th)			Raw (99th, 1st)			Winsorized (99th, 1st)		
	Whole	NIG	IG	Whole	NIG	IG	Whole	NIG	IG	Whole	NIG	IG
Panel A: Benchmark model with no lags												
1.outlier#1.dng	-9.194	-8.712	-8.015	-4.853**	-3.115**	-5.097*	-7.217**	-6.784**	-6.404*	-3.175***	-2.015***	-3.495**
	(5.657)	(5.296)	(5.775)	(2.031)	(1.409)	(2.880)	(3.604)	(3.378)	(3.728)	(1.035)	(0.699)	(1.437)
dng	-1.525***	-2.044***	-0.802***	-1.030***	-1.348***	-0.748***	-1.264***	-1.730***	-0.619***	-0.753***	-1.030***	-0.547***
	(0.320)	(0.560)	(0.197)	(0.190)	(0.294)	(0.189)	(0.286)	(0.509)	(0.171)	(0.141)	(0.243)	(0.144)
1.outlier#1.upg	-11.68	-15.67	5.392	-5.973	-7.352	2.819	-6.230	-9.633	1.638	-1.590	-2.493	0.299
	(11.67)	(12.11)	(9.301)	(5.579)	(5.503)	(6.444)	(8.542)	(9.572)	(3.438)	(2.961)	(3.331)	(2.141)
upg	0.0330	-0.335	0.155***	0.218***	0.256**	0.163***	0.0232	-0.354	0.157***	0.227***	0.303***	0.168***
	(0.0963)	(0.267)	(0.0441)	(0.0587)	(0.120)	(0.0410)	(0.0924)	(0.241)	(0.0431)	(0.0558)	(0.104)	(0.0390)
N	949646	167275	782371	949646	167275	782371	949646	167275	782371	949646	167275	782371
R-sq	0.043	0.050	0.062	0.193	0.245	0.220	0.043	0.050	0.062	0.200	0.245	0.228
adj. R-sq	0.025	0.026	0.043	0.177	0.226	0.203	0.025	0.026	0.043	0.185	0.226	0.212
r2_within	0.00270	0.00220	0.00179	0.0187	0.0188	0.00756	0.00265	0.00208	0.00198	0.0169	0.0181	0.00741
r2_a_within	0.00270	0.00216	0.00178	0.0187	0.0187	0.00755	0.00265	0.00204	0.00197	0.0169	0.0181	0.00740
N_clustervars	2	2	2	2	2	2	2	2	2	2	2	2
N_clust	179	179	179	179	179	179	179	179	179	179	179	179
rmse	15.38	33.11	7.169	3.102	4.834	2.471	15.38	33.11	7.168	2.684	3.915	2.251
Panel B: Model with one lag of downgrades and upgrades												

	Raw (99.5th, 0.5th)			Winsorized (99.5th, 0.5th)			Raw (99th, 1st)			Winsorized (99th, 1st)		
	Whole	NIG	IG	Whole	NIG	IG	Whole	NIG	IG	Whole	NIG	IG
1.outlier#1.dng	-14.90***	-18.05***	-8.318	-5.624***	-4.422***	-5.141*	-10.45***	-12.16***	-6.987**	-3.562***	-2.427***	-3.823***
	(5.060)	(5.995)	(5.518)	(1.698)	(1.227)	(2.707)	(3.318)	(4.137)	(3.513)	(0.925)	(0.646)	(1.350)
dng	-1.323***	-1.502***	-0.783***	-1.018***	-1.306***	-0.742***	-1.073***	-1.241***	-0.578***	-0.744***	-1.035***	-0.527***
	(0.249)	(0.405)	(0.201)	(0.193)	(0.286)	(0.191)	(0.218)	(0.371)	(0.169)	(0.143)	(0.233)	(0.145)
1.outlier#1L.dng	18.81**	25.92**	5.253	2.573	3.590*	1.861	11.58**	16.25**	4.733	1.313	1.257	2.054
	(7.372)	(10.06)	(8.144)	(2.225)	(2.116)	(4.496)	(4.554)	(6.813)	(5.154)	(1.288)	(1.045)	(2.383)
L.dng	-0.206	-0.543**	0.238	0.195	0.139	0.337*	-0.278	-0.583**	0.105	0.170	0.189	0.218*
	(0.187)	(0.261)	(0.194)	(0.155)	(0.193)	(0.199)	(0.176)	(0.277)	(0.135)	(0.104)	(0.155)	(0.122)
1.outlier#1.upg	-11.37	-15.61	7.061	-6.193	-7.639	3.660	-5.813	-9.528	3.198	-1.648	-2.766	1.362
	(11.56)	(11.30)	(9.551)	(5.903)	(5.226)	(6.423)	(8.869)	(9.320)	(3.811)	(3.076)	(3.228)	(2.356)
upg	0.0890	-0.130	0.155***	0.236***	0.314***	0.164***	0.0743	-0.160	0.153***	0.241***	0.354***	0.165***
	(0.0797)	(0.222)	(0.0444)	(0.0578)	(0.115)	(0.0458)	(0.0777)	(0.220)	(0.0443)	(0.0563)	(0.105)	(0.0381)
1.outlier#1L.upg	5.174	10.79***	-13.87**	4.062	5.951**	-6.514	2.258	6.093***	-6.928*	1.722	3.280**	-3.124
	(9.457)	(2.265)	(6.967)	(4.504)	(2.776)	(4.440)	(5.437)	(1.830)	(4.104)	(2.117)	(1.619)	(2.329)
L.upg	-0.106	-0.530**	0.0883*	0.0112	-0.218*	0.0798*	-0.114	-0.545**	0.0944**	0.0138	-0.207**	0.0832**
	(0.0783)	(0.251)	(0.0450)	(0.0537)	(0.111)	(0.0438)	(0.0830)	(0.259)	(0.0407)	(0.0470)	(0.0915)	(0.0381)
N	897786	160641	737145	897786	160641	737145	897786	160641	737145	897786	160641	737145
R-sq	0.045	0.055	0.061	0.197	0.254	0.226	0.044	0.053	0.062	0.205	0.252	0.236
adj. R-sq	0.026	0.030	0.041	0.182	0.234	0.210	0.025	0.028	0.042	0.189	0.233	0.219
r2_within	0.00616	0.00731	0.00206	0.0209	0.0238	0.00832	0.00494	0.00530	0.00251	0.0186	0.0205	0.00926
r2_a_within	0.00615	0.00724	0.00204	0.0209	0.0237	0.00830	0.00493	0.00523	0.00249	0.0186	0.0204	0.00925
N_clustervars	2	2	2	2	2	2	2	2	2	2	2	2
N_clust	178	178	178	178	178	178	178	178	178	178	178	178
rmse	14.57	30.60	7.242	3.059	4.761	2.417	14.57	30.63	7.240	2.649	3.869	2.205
Panel C: Model with two lags of downgrades and upgrades												
1.outlier#1.dng	-17.38***	-21.18***	-9.001	-5.877***	-4.551***	-5.313*	-11.80***	-13.73***	-7.607**	-3.695***	-2.422***	-4.091***
	(4.899)	(6.123)	(5.975)	(1.621)	(1.326)	(2.834)	(3.225)	(4.232)	(3.748)	(0.919)	(0.670)	(1.435)
dng	-1.234***	-1.345***	-0.764***	-1.000***	-1.290***	-0.739***	-0.993***	-1.105***	-0.550***	-0.734***	-1.040***	-0.519***
	(0.239)	(0.388)	(0.203)	(0.193)	(0.291)	(0.194)	(0.202)	(0.351)	(0.168)	(0.142)	(0.233)	(0.145)
1.outlier#1L.dng	16.18**	23.16**	3.534	2.205	3.347*	1.018	10.09**	14.72**	3.571	1.128	1.258	1.516
	(6.958)	(9.191)	(7.426)	(2.035)	(1.887)	(4.238)	(4.336)	(6.432)	(4.880)	(1.173)	(0.948)	(2.310)
L.dng	-0.102	-0.295	0.239	0.201	0.176	0.327*	-0.172	-0.364	0.119	0.170*	0.192	0.216*
	(0.165)	(0.252)	(0.185)	(0.152)	(0.189)	(0.190)	(0.153)	(0.269)	(0.127)	(0.100)	(0.148)	(0.118)

	Raw (99.5th, 0.5th)			Winsorized (99.5th, 0.5th)			Raw (99th, 1st)			Winsorized (99th, 1st)		
	Whole	NIG	IG	Whole	NIG	IG	Whole	NIG	IG	Whole	NIG	IG
1.outlier#1L2.dng	11.41*	13.91*	4.970	1.388	1.259	2.119	7.329*	8.121	4.805	0.883	0.249	2.240
	(6.177)	(7.811)	(8.311)	(1.827)	(1.752)	(4.815)	(3.855)	(5.128)	(5.324)	(1.094)	(0.921)	(2.610)
L2.dng	-0.0522	-0.420	0.303*	0.207*	0.0252	0.320*	-0.123	-0.394*	0.178	0.179**	0.107	0.200**
	(0.163)	(0.273)	(0.172)	(0.110)	(0.188)	(0.164)	(0.149)	(0.225)	(0.110)	(0.0703)	(0.128)	(0.0933)
1.outlier#1.upg	-11.66	-15.68	9.246	-5.985	-7.296	5.282	-5.756	-9.440	4.275	-1.491	-2.637	2.032
	(11.96)	(11.41)	(10.80)	(6.094)	(5.235)	(7.359)	(9.200)	(9.418)	(4.095)	(3.306)	(3.200)	(2.457)
upg	0.111	-0.0941	0.165***	0.250***	0.327***	0.175***	0.0933	-0.134	0.162***	0.252***	0.366***	0.174***
	(0.0718)	(0.192)	(0.0429)	(0.0628)	(0.114)	(0.0416)	(0.0699)	(0.194)	(0.0412)	(0.0563)	(0.104)	(0.0364)
1.outlier#1L.upg	4.075	9.110**	-12.66*	3.571	5.322*	-5.616	1.609	5.117**	-6.913*	1.362	2.907*	-3.248
	(9.675)	(3.539)	(7.308)	(4.622)	(3.187)	(4.913)	(5.704)	(2.180)	(4.082)	(2.244)	(1.727)	(2.172)
L.upg	-0.0847	-0.488**	0.0890**	0.0183	-0.200*	0.0813*	-0.0901	-0.495**	0.0968**	0.0235	-0.184**	0.0866**
	(0.0681)	(0.238)	(0.0436)	(0.0536)	(0.115)	(0.0425)	(0.0716)	(0.237)	(0.0391)	(0.0462)	(0.0905)	(0.0373)
1.outlier#1L2.upg	23.04***	20.67***	-3.191	9.791**	9.325***	-5.375	13.82**	12.32***	-0.277	4.520*	4.411**	-0.802
	(6.394)	(4.783)	(8.467)	(3.970)	(2.216)	(4.894)	(5.378)	(3.865)	(3.839)	(2.642)	(1.782)	(2.281)
L2.upg	-0.108*	-0.524***	0.0667*	-0.00818	-0.228**	0.0585*	-0.127*	-0.534***	0.0638*	-0.0275	-0.236***	0.0495
	(0.0625)	(0.184)	(0.0361)	(0.0550)	(0.0952)	(0.0333)	(0.0715)	(0.191)	(0.0359)	(0.0412)	(0.0813)	(0.0329)
N	857645	155338	702307	857645	155338	702307	857645	155338	702307	857645	155338	702307
R-sq	0.047	0.057	0.061	0.203	0.260	0.232	0.045	0.054	0.062	0.210	0.258	0.241
adj. R-sq	0.027	0.032	0.041	0.186	0.241	0.215	0.026	0.029	0.041	0.194	0.238	0.225
r2_within	0.00729	0.00864	0.00225	0.0225	0.0258	0.00921	0.00568	0.00599	0.00292	0.0197	0.0215	0.0110
r2_a_within	0.00727	0.00855	0.00222	0.0225	0.0257	0.00919	0.00566	0.00589	0.00290	0.0197	0.0214	0.0109
N_clustervars	2	2	2	2	2	2	2	2	2	2	2	2
N_clust	177	177	177	177	177	177	177	177	177	177	177	177
rmse	14.81	30.95	7.358	3.026	4.716	2.376	14.83	31.00	7.355	2.622	3.838	2.169

of outliers with downgrades indicate that downgrades are likely to generate return outliers, possibly more often than being associated with regular returns. The implication is that the market often responds aggressively to bad news conveyed by a downgrade, thus causing negative outliers to be informative.

The upgrade of credit rating, in general, is received as good news and causes winsorized returns to increase by above 2% on average in the whole bond sample and for NIG bonds. The positive impact on IG bond returns is lower at around 0.16%, in both raw and winsorized terms. The announcement of good news, however, never causes instant price reaction to the extent of generating outliers, suggesting that good news may take longer to be fully absorbed. This possibility is confirmed by results reported in Panels B and C, when one or two lags of the indicators of downgrades and upgrades are included in the regression, together with their interactions with the current month's outlier indicator.

I find that the contemporaneous effects of both downgrades and upgrades as revealed in Panel A remain robust after including their lagged terms. However, Panels B and C illustrate the dynamic effects of credit changes on returns. Focusing on downgrades first, results in both panels show that the news of downgrades that would cause a sharp decline in returns and yield outliers in the same month has the tendency to make prices bounce back in the following months, but only for NIG bonds. For instance, when outliers are identified by the (1st, 99th) percentile thresholds, I find that the announcement of downgrades decreases the same-month NIG bond raw returns by about 12% (Panel B) and 13.7% (Panel C), but the effect is reversed to an increase of about 16% and 14.7% over the following month, creating outliers below 1st or above 99th percentiles of the return distribution. This finding suggests that investors trading high-yield bonds react fast to bad news and often overreact to extreme downgrades, which then leads to subsequent price corrections. Meanwhile, IG bonds react to negative news as fast as NIG bonds, but to a much weaker extent. The results also suggest that there is not much overreaction to bad news from investors trading IG bonds, as the lagged downgrade terms (with and without interacting with the outlier dummy) are rarely significantly positive, indicating no subsequent price correction. Overall, the results for downgrades are consistent with negative news being imbued into bond prices over the same month of the announcement, yielding negative outliers, for both high- and low-grade bonds.

Consistent with an asymmetric market reaction to good and bad news, the announcement of upgrades increases returns slightly by less than 0.4% in the same month across bond samples, a price movement that does not create outliers. Consistent with good news diffusing slowly, an upgrade continues to impact returns positively in the following months. However, the price trends following an upgrade are opposite for IG and NIG bonds. For IG bonds, the positive impact diminishes over time from about 0.16% when the news is announced to about 0.08% in the following month and eventually to about 0.06% two months later. This diminishing trend is not associated with the generation of outliers. The impact of upgrades on NIG bonds instead intensifies over time and gradually results in extremely positive returns. In particular, depending on the outlier thresholds, the announcement of upgrades results in 3% (winsorized) to 11% (raw) return increases in the next month, causing large positive outliers. This effect almost doubles over the following two months, increasing extreme returns by about 4.4% (winsorized) to 20.7% (raw). Notably, the effect of upgrades on normal returns tends to reverse for NIG bonds as time goes by, suggesting an overreaction to good news from investors trading high-yield bonds. Overall, the results for upgrades highlight a slow diffusion of good news in corporate bond prices for both IG and NIG bonds, with extremely positive information eventually resulting in positive outliers only for NIG bonds.

Summarizing, results in Table 2 imply that, for both IG and NIG bonds, information is promptly incorporated into prices when it is associated with extreme price depreciation (i.e., is extremely bad news). There is, instead, and for NIG bonds only, a delay between the arrival of an information shock that causes a strong price appreciation (i.e., extremely good news) and the eventual price increase. Therefore, the findings in this section strongly confirm Hypothesis 1, with the relationship being most prominent in bonds with high default risk. The tepid reaction of IG bonds to good news, along with their strong reaction to bad news, suggests an explanation for the finding that the momentum effect in IG bonds is hard to detect, as both good and bad news is unlikely to create sustainable trends that make the strategy profitable. The results also confirm the literature's conclusion that NIG bonds are more sensitive to firm-level information than IG bonds.[15]

3 Outlier and Momentum

The results presented insofar support the view that outliers convey information and that positive news spreads slower than negative news, as stipulated in Hypothesis 1. I, therefore, employ outlier treatments to evaluate the effect of positive and negative information shocks in determining momentum profitability.

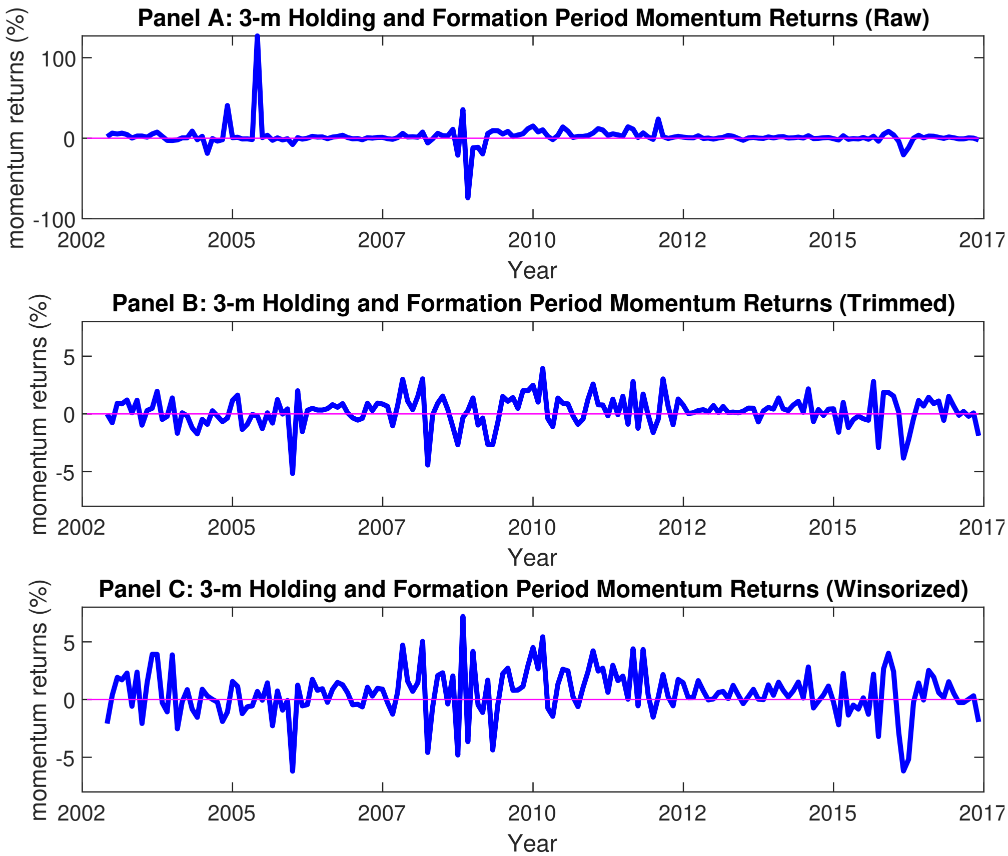
3.1 Do Outlier Treatments Matter?

Jostova et al. (2013) document that the momentum effect in corporate bonds is concentrated in the NIG bond sample and confirm the finding in Gebhardt et al. (2005) that momentum instead is absent for high-grade bonds.[16] Using two common outlier treatments, Figure 2 contrasts, for NIG bonds, the series of monthly returns on the standard momentum portfolio with three-month formation and holding periods for untreated bond returns (Panel A), when outliers are trimmed from the sample (Panel B), and when the return sample is winsorized (Panel C). The figure visually highlights the impact of outlier treatments on the momentum effect. As shown in Panel A, when bond returns are

[15] For instance, bond returns' response to same-issuer stock price changes (e.g., Blume et al., 1991; Kwan, 1996; Bittlingmayer and Moser, 2014) and earning announcements (e.g., Easton et al., 2009; Ronen and Zhou, 2013; Defond and Zhang, 2014) is concentrated exclusively in high-yield bonds.

[16] Li and Galvani (2021) argue that the concentration of the momentum effect in low-grade bonds is due to slow information diffusion caused by severe information asymmetry in the NIG bond sample. Conversely, lower levels of asymmetric information for high-grade bonds (e.g., Han and Zhou, 2013) reduce the ability of informed trading to originate momentum trends.

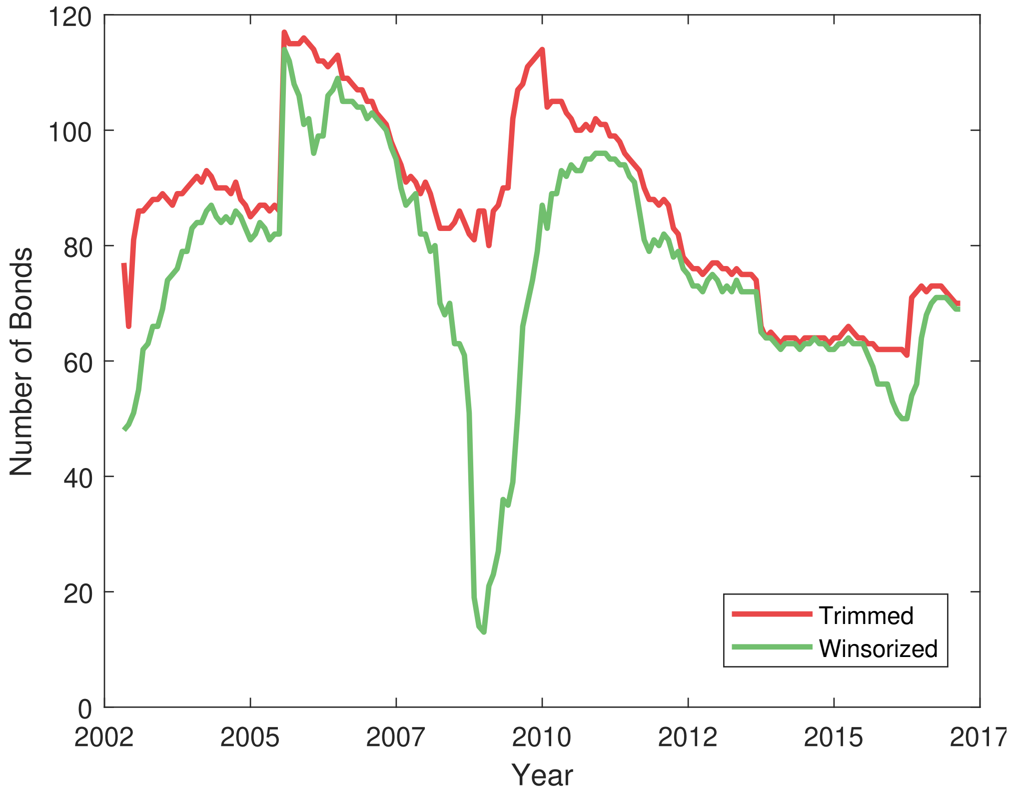
Figure 2: The 3-3 Momentum Returns in NIG bonds (P10-P1)



The figure plots the series of monthly returns on the decile-based momentum strategy with six-month formation and holding periods in non-investment-grade bonds, for the period from August 2002 to June 2017. Panel A plots the return series calculated leaving outliers untreated, while Panels B and C respectively plot the corresponding series for trimming and winsorizing outliers at the 99th and 1st percentiles of the return distribution.

untreated, the resulting momentum returns fluctuate violently around the year 2005 and during the financial crisis. These fluctuations markedly diminish when extreme returns are removed (Panel B) or winsorized (Panel C). The scale of the momentum returns in panels B and C further indicates that how we treat outliers matters to momentum profitability.

Figure 3: Number of Bonds in Winners



The figure plots the number of bonds that are included in the decile-based winner portfolio of the 3-month momentum strategy for the non-investment-grade bond subsample, when outliers are either removed or winsorized at the 99th and 1st percentiles of the return distribution.

3.1.1 Portfolio Compositions

Figure 2 demonstrates the effect of outlier trimming and winsorization on momentum returns, as these are the most commonly applied outlier treatments in the literature. Specific to the study of momentum in corporate bonds, both methods have been employed to treat extreme returns.[17] I argue that experimenting with the effect of outlier removal is particularly suited to this study's evaluation of the information diffusion in the winner and loser portfolios. The reason is that, due to the design of the momentum strategy, trimming outliers may lead to dramatically different momentum returns through changes in the portfolio composition. As momentum strategies include only bonds for which returns are available throughout the formation period (e.g., Jegadeesh and Titman, 1993), trimming outliers drops from the momentum portfolio any bond yielding extreme returns during the formation period, thus removing the associated information shocks yielding those extreme returns. This effect is not explicit for winsorization as bonds associated with outliers would not be dropped from the sample.[18]

Contrasting the size of momentum portfolios when outliers are removed or winsorized specifically highlights the effect of outlier removal on portfolio composition. Figure 3 plots the number of bonds in the NIG subsample that are selected, in each formation month, into the winner portfolio of the momentum strategy with formation and holding periods of three months, when outliers are trimmed or winsorized.[19] The figure shows that trimming outliers reduces the number of bonds included in the winner portfolio, especially during the financial crisis, the period over which outliers largely concentrate.[20] This reduction in portfolio size implies that the price trends generated by the information shocks causing outliers cannot contribute to momentum profitability. Experimenting with outlier trimming thus allows evaluating how winner and loser portfolio returns respond to artificially altered information flows. However, trimming outliers can only affect the portfolio composition during the formation period, as once the portfolio is formed, it is held throughout the holding period. Therefore, outlier removal during the holding period imposes no impact on the portfolio composition, and thus does not reveal the role of information diffusion in determining momentum profitability. In the next section, I will differentiate the treatment of outliers during the formation and holding periods to test Hypothesis 2.

[17] For instance, Jostova et al. (2013) filter the monthly return distribution by removing all returns above 30%. Gebhardt et al. (2005) removes adjacent return outliers that go opposite directions (above 95% and below -45%) and ascribe them to reporting errors. Li and Galvani (2021) winsorize returns using the 99.5th and 0.5th percentile cutoffs.

[18] However, winsorizing returns can still affect portfolio composition, relative to the use of untreated returns, by potentially selecting different bonds into the long and short legs of the strategy.

[19] The analogous plots for the loser side are omitted, as the figures are very much alike.

[20] The number of bonds included in the portfolio when outliers are winsorized is the same as when outliers are left untreated. Therefore, only one of the two series is included in the plot.

3.2 Asymmetric Outlier Treatments

Given the link between outliers and information, to evaluate how the diffusion of extremely good and bad news affects momentum profitability, I trim positive and negative outliers independently during the formation period of the momentum strategy. The asymmetric outlier treatments would artificially alter the flows of good and bad news for winners and losers, and result in asymmetric momentum return changes. In contrast, trimming either positive or negative outliers that fall during the holding period should not result in the expected asymmetric changes in momentum profitability.

Tables 3 and 4 report monthly average momentum returns as well as returns on the long and short legs of two representative strategies for the formation-period-only and holding-period-only outlier treatments, respectively. The two representative strategies are a short-term strategy with three-month formation and holding periods and a long-term strategy with six-month formation and holding periods. Thresholds for identifying outliers are the (99.5th 0.5th) and (99th 1st) percentiles of the return distribution. Untabulated results show that the momentum effect is missing for IG bonds regardless of outlier treatments, I thus perform the formation-period or holding-period outlier trimming only for the whole bond sample and the NIG bond subsample.

Table 3 reports the average returns of the short- and long-term momentum strategies and their components when outliers are treated in the formation period, for the whole bond sample in Panel A and NIG bonds in Panel B, respectively. Rows 2-4 in both panels display the results when top and/or bottom outliers are trimmed using the thresholds of the (99.5th, 0.5th) percentiles of the whole bond sample return distribution. Results for the thresholds at (99th, 1st) percentiles are reported in rows 5-7 of both panels. To provide a term of comparison, the first row in both panels lists the benchmark results when outliers are left untreated.

The results indicate that trimming positive and negative outliers separately during the formation period generally yields opposite impacts on momentum profitability. For

Table 3: Formation-Period Treatments of Outliers and Momentum Returns

The table contrasts the performance of the short- ($S(3,3)$) and long-term ($S(6,6)$) momentum strategies in raw returns and when top and/or bottom outliers are trimmed during the strategies' formation period, for the whole bond sample in Panel A and the non-investment-grade bond sample in Panel B. The average monthly returns and t-statistics on the two strategies and their long and short legs when outliers are retained in the samples are listed at the first row of each panel, followed by corresponding estimates for the formation-period treatments of outliers using thresholds of (99.5th, 0.5th) and (99th, 1st) percentiles of the return distribution. For each set of thresholds, outliers on both tails of the distribution, or only on the left tail (bottom) or right tail (top) of the distribution are trimmed separately. The last six rows in both panels report estimated α and t-statistics in the model $MR_t^{treated} - MR_t^{untreated} = \alpha + \epsilon_t$, in which the dependent variable is the spread between each time series supporting the average returns obtained in rows 2-7 and the benchmark portfolio return time series when outliers are left untreated. The estimates are obtained when at least one of the two time series yields significant average momentum returns. The t-statistics significant at the 0.05% level are highlighted in bold. The time period covered is from August 2002 to June 2017.

	S(3,3)			S(6,6)		
	Winner-Loser	Winner	Loser	Winner-Loser	Winner	Loser
Panel A: Whole Sample						
Raw	0.729	1.972	1.243	0.491	1.787	1.296
	(1.941)	**(4.946)**	**(3.257)**	(1.215)	**(4.508)**	**(3.076)**
Thresholds at the (99.5th, 0.5th) percentiles						
Trim top and bottom	0.284	1.008	0.724	0.171	0.787	0.616
	(1.438)	**(4.784)**	**(3.458)**	(0.864)	**(4.494)**	**(2.875)**
Trim top	-0.193	1.007	1.2	-0.378	0.794	1.171
	(-0.559)	**(4.797)**	**(3.179)**	(-1.068)	**(4.538)**	**(2.918)**
Trim bottom	1.031	1.747	0.715	0.693	1.311	0.618
	(3.346)	**(4.874)**	**(3.435)**	**(2.932)**	**(5.324)**	**(2.881)**
Thresholds at the (99th, 1st) percentiles						
Trim top and bottom	0.222	0.848	0.626	0.176	0.691	0.515
	(1.29)	**(4.342)**	**(3.611)**	(1.032)	**(4.052)**	**(2.934)**
Trim top	-0.341	0.843	1.183	-0.356	0.697	1.053
	(-0.997)	**(4.371)**	**(3.196)**	(-1.161)	**(4.105)**	**(3.041)**
Trim bottom	1.051	1.667	0.616	0.626	1.14	0.514
	(3.301)	**(4.628)**	**(3.582)**	**(3.385)**	**(5.701)**	**(2.921)**
Difference with raw						
(99.5th, 0.5th)	-0.445	-0.964	-0.519			
	(-1.343)	**(-2.211)**	**(-2.121)**			
Below 99.5th	-0.922	-0.965	-0.043			
	(-2.243)	**(-2.22)**	(-1.691)			
Above 0.5th	0.302	-0.225	-0.528	0.202	-0.476	-0.678
	(1.705)	(-1.95)	**(-2.117)**	(1.019)	**(-2.616)**	**(-2.332)**
(99th, 1st)	-0.507	-1.124	-0.617			
	(-1.524)	**(-2.411)**	**(-2.181)**			
Below 99th	-1.07	-1.129	-0.06			
	(-2.459)	**(-2.433)**	(-1.884)			

	S(3,3)			S(6,6)		
	Winner-Loser	Winner	Loser	Winner-Loser	Winner	Loser
Above 1st	0.322	-0.305	-0.627	0.135	-0.647	-0.782
	(1.471)	**(-2.867)**	**(-2.182)**	(0.549)	**(-2.458)**	**(-2.306)**
Panel B: Non-investment-grade Subsample						
Raw	2.11	4.706	2.597	1.226	3.777	2.551
	(2.15)	**(5.111)**	**(3.222)**	(1.529)	**(5.39)**	**(3.151)**
Thresholds at the (99.5th, 0.5th) percentiles						
Trim top and bottom	1.228	2.403	1.175	0.933	1.732	0.799
	(1.512)	**(2.989)**	**(3)**	(1.527)	**(2.966)**	**(2.166)**
Trim top	-0.224	2.333	2.557	-0.717	1.696	2.414
	(-0.212)	**(2.923)**	**(3.193)**	(-0.884)	**(2.927)**	**(2.972)**
Trim bottom	3.402	4.517	1.115	2.328	3.126	0.798
	(3.977)	**(5.071)**	**(2.9)**	**(3.552)**	**(4.86)**	**(2.169)**
Thresholds at the (99th, 1st) percentiles						
Trim top and bottom	0.96	1.853	0.892	0.693	1.346	0.653
	(1.267)	**(2.403)**	**(3.133)**	(1.194)	**(2.308)**	**(2.366)**
Trim top	-0.782	1.793	2.575	-0.805	1.372	2.176
	(-0.749)	**(2.402)**	**(3.176)**	(-1.033)	**(2.398)**	**(2.877)**
Trim bottom	3.442	4.283	0.842	2.309	2.944	0.635
	(4.076)	**(4.848)**	**(3.023)**	**(3.68)**	**(4.555)**	**(2.302)**
Difference with raw						
(99.5th, 0.5th)	-0.882	-2.303	-1.422			
	(-1.863)	**(-3.635)**	**(-2.772)**			
Below 99.5th	-2.334	-2.373	-0.04			
	(-3.622)	**(-3.538)**	(-0.754)			
Above 0.5th	1.292	-0.189	-1.482	1.102	-0.651	-1.753
	(2.262)	(-0.842)	**(-2.866)**	**(2.174)**	**(-2.209)**	**(-3.263)**
(99th, 1st)	-1.15	-2.853	-1.705			
	(-1.957)	**(-4.228)**	**(-2.712)**			
Below 99th	-2.892	-2.913	-0.022			
	(-4.388)	**(-4.304)**	(-0.599)			
Above 1st	1.332	-0.423	-1.755	1.083	-0.833	-1.916
	(1.666)	(-0.938)	**(-2.764)**	(1.836)	**(-2.495)**	**(-3.015)**

both sets of outlier thresholds, when both the top and bottom outliers are trimmed, no momentum effect is found for the short- and long-term strategies in both samples. In contrast, keeping outliers in the sample brings about (weakly) significant 72.9 bps and 2.11% average returns on the short-term strategy in the whole bond sample and for low-grade bonds, respectively. When either top or bottom outliers are trimmed, however, I find that the effect of two-way trimming is driven entirely by the removal of top outliers. Specifically, removing only positive outliers yields the weakest average momentum returns with negative point estimates that are statistically insignificant, while the opposite procedure (i.e., dropping negative extreme returns) results in the strongest momentum profits, regardless of the thresholds, for both the short- and long-term strategies in both samples. In particular, trimming negative outliers offers average returns of more than 60 bps and 2.3% on the long-term strategy using both sets of thresholds, and about 1% and 3.4% profits for the short-term strategy, in the whole bond sample and NIG bond subsample, respectively.

To evaluate the significance of the impact of outlier trimming on momentum profitability, I calculate the spread between the time series of momentum returns obtained with and without outlier treatments, and perform the following regression:

$$MR_t^{treated} - MR_t^{untreated} = \alpha + \epsilon_t \qquad t = 1, 2, \ldots, 179 \tag{3}$$

where $MR_t^{treated}$ $MR_t^{untreated}$ are the monthly holding period momentum returns in month t for the samples when positive and/or negative outliers are trimmed and for the untreated samples, respectively. A significant α indicates that the two time series are statistically different, and thus that trimming outliers significantly affects momentum profitability.[21]

The last six rows in both panels of Table 3 report the estimated values of α. I obtain these estimates only for the cases in which at least one of the two time series yields significant average momentum returns. In both panels, the results indicate that trimming positive outliers in the formation period generates significantly lower momentum returns on average than when outliers are retained in the sample. Importantly, the differences are entirely due to the decreased returns on the winner portfolios, as trimming positive outliers yields statistically indistinguishable average returns for the short leg. This finding

[21]Standard errors are adjusted using the Newey-West HAC estimation.

is consistent with positive outliers being associated with the slow diffusion of extremely good news in winners. Removing bonds yielding positive outliers in the formation period throws away "good" winners and hinders the identification of the momentum effect even for the low-grade bonds.

In contrast, trimming negative outliers results in higher momentum returns on average than when outliers are left untreated. For the short-term strategy, the difference of 0.3% is weakly significant for the outlier threshold of 0.5th percentile in the whole bond sample. The effect is further highlighted in the NIG bond subsample, as trimming negative outliers significantly increases momentum returns by 1.3% at the 0.5th percentile, and also weakly differentiates the two series at the 1st percentile. Consistent with hypothesis 2, the significant difference in momentum returns due to trimming negative outliers is delivered mainly through the loser portfolios. Specifically, returns on winners are indistinguishable before and after the negative outlier treatment for the short-term strategy of NIG bonds, using both thresholds.[22] For the long-term strategy, trimming negative outliers yields significantly higher momentum gains only for NIG bonds, applying both thresholds. In this case, although trimming negative outliers significantly decreases returns on both the winner and loser portfolios, the effect on the short legs, at -1.75% and -1.9% respectively for the two thresholds, more than doubles that on the long legs at -0.65% and -0.83%. As much lower returns on losers overweight the slight fall in returns on winners, the net effect thus boosts momentum profitability after the removal of negative outliers. Overall, the findings suggest that negative outliers are linked to the fast speed of extremely bad news getting imbued into bond prices, and trimming negative outliers should mostly eliminate "bad" losers and help improve momentum profitability.

Summarizing, results in Table 3 indicate that the informational efficiency of the two legs of the momentum strategy is unbalanced, with winners supported by prolonged

[22] In the whole bond sample, a weakly significant return decrease, at -0.225%, is realized on the winner portfolio of the short-term strategy when outliers are trimmed below the 0.5th percentile, which however is smaller than the effect of -0.528% on the loser portfolio, resulting in the weakly significant average momentum change of 0.3%.

price trends due to slow diffusion of good news, while the loser portfolio is more efficient with shorter trends caused by faster diffusion of bad news. Therefore, in the corporate bond market, the momentum effect is originated mainly from the winner portfolio (e.g., Jostova et al., 2013; Li and Galvani, 2018).

As the price trends caused by the diffusion of good news in winners and bad news in losers are identified during the formation period, trimming outliers of opposite signs during the holding period should not render the same asymmetric effect on momentum profitability as the formation period treatments. To illustrate, Table 4 replicates all the evaluations presented in Table 3 except that the outlier treatments this time are conducted in the holding period.

Results in Panels A and B of Table 4 indicate that trimming positive outliers yields significant momentum returns of slightly over 60 bps in the whole bond sample and about 1.3% for NIG bonds, for both the short- and long-term strategies, regardless of the thresholds. In contrast, trimming negative outliers offers no momentum profit in any case. Therefore, trimming positive and negative outliers separately during the holding period also results in an asymmetric effect on momentum returns. However, this asymmetric effect is not strong enough both economically and statistically to uphold the predicted momentum patterns due to asymmetric diffusion of good and bad news. In particular, results reported in the last six rows of both panels suggest that trimming either top or bottom outliers yields lower point estimates of momentum returns relative to the benchmark, for the short-term strategy in any case. Moreover, for both the short- and long-term strategies, the significant momentum returns offered by trimming positive outliers during the holding period are not strong enough to create significant deviations from the benchmark momentum returns when outliers are not trimmed. Therefore, results in Table 4 confirm that, unlike the formation-period treatments, trimming outliers during the holding period fails to reveal the role of gradual information diffusion in originating the momentum effect.

Table 4: Holding-Period Treatments of Outliers and Momentum Returns

The table contrasts the performance of the short- ($S(3,3)$) and long-term ($S(6,6)$) momentum strategies when top and/or bottom outliers are trimmed during the holding period of the strategies with respect to when outliers are left untreated (Raw), for the whole bond sample in Panel A and the non-investment-grade bond sample in Panel B. The average monthly returns and t-statistics on the two strategies and their long and short legs when outliers are retained in the samples are listed at the first row of each panel, followed by corresponding estimates for the holding-period treatments of outliers using thresholds of (99.5th, 0.5th) and (99th, 1st) percentiles of the return distribution. For each set of thresholds, outliers on both tails of the distribution, or only on the left tail (bottom) or right tail (top) of the distribution are trimmed separately. The last six rows in both panels report estimated α and t-statistics in the model $MR_t^{treated} - MR_t^{untreated} = \alpha + \epsilon_t$, in which the dependent variable is the spread between each time series supporting the average returns obtained in rows 2-7 and the benchmark portfolio return time series with outliers untreated. The estimates are obtained when at least one of the two time series yields significant average momentum returns. The t-statistics significant at the 0.05% level are highlighted in bold. The time period covered is from August 2002 to June 2017.

	S(3,3)			S(6,6)		
	Winner-Loser	Winner	Loser	Winner-Loser	Winner	Loser
Panel A: Whole Sample						
Raw	0.729	1.972	1.243	0.491	1.787	1.296
	(1.941)	**(4.946)**	**(3.257)**	(1.215)	**(4.508)**	**(3.076)**
Thresholds at the (99.5th, 0.5th) percentiles						
Trim top and bottom	0.233	1.02	0.787	0.149	0.931	0.782
	(1.916)	**(7.118)**	**(5.244)**	(1.068)	**(6.583)**	**(5.12)**
Trim top	0.605	0.74	0.135	0.65	0.72	0.07
	(3.13)	**(4.41)**	(0.53)	**(2.963)**	**(4.703)**	(0.258)
Trim bottom	0.283	2.265	1.982	-0.091	2.002	2.094
	(0.653)	**(5.747)**	**(4.51)**	(-0.199)	**(5.091)**	**(4.437)**
Thresholds at the (99th, 1st) percentiles						
Trim top and bottom	0.173	0.933	0.759	0.106	0.868	0.762
	(1.725)	**(7.823)**	**(6.36)**	(0.932)	**(7.012)**	**(6.603)**
Trim top	0.633	0.505	-0.128	0.736	0.53	-0.206
	(3.178)	**(3.262)**	(-0.486)	**(3.271)**	**(3.719)**	(-0.737)
Trim bottom	0.163	2.424	2.261	-0.262	2.135	2.397
	(0.354)	**(6.107)**	**(4.764)**	(-0.538)	**(5.428)**	**(4.74)**
Difference with raw (Whole Sample)						
(99.5th, 0.5th)	-0.496	-0.952	-0.456			
	(-1.382)	**(-3.041)**	(-1.481)			
Below 99.5th	-0.124	-1.232	-1.108	0.159	-1.067	-1.226
	(-0.226)	**(-2.848)**	(-1.565)	(0.317)	**(-3.211)**	(-1.626)
Above 0.5th	-0.446	0.293	0.739			
	(-1.12)	**(2.01)**	(1.339)			
(99th, 1st)	-0.556	-1.039	-0.484			
	(-1.536)	**(-3.094)**	(-1.394)			

	S(3,3)			S(6,6)		
	Winner-Loser	Winner	Loser	Winner-Loser	Winner	Loser
Below 99th	-0.096	-1.467	-1.371	0.245	-1.257	-1.502
	(-0.161)	**(-2.835)**	(-1.645)	(0.438)	**(-3.652)**	(-1.664)
Above 1st	-0.566	0.452	1.018			
	(-1.126)	**(2.227)**	(1.425)			
Panel B: Non-investment-grade Subsample						
Raw	2.11	4.706	2.597	1.226	3.777	2.551
	(2.15)	**(5.111)**	**(3.222)**	(1.529)	**(5.39)**	**(3.151)**
Thresholds at the (99.5th, 0.5th) percentiles						
Trim top and bottom	0.559	1.643	1.084	0.501	1.567	1.066
	(3.582)	**(8.343)**	**(5.385)**	**(3.011)**	**(8.088)**	**(5.552)**
Trim top	1.247	0.978	-0.269	1.34	1.001	-0.339
	(4.159)	**(4.008)**	(-0.68)	**(4.372)**	**(4.438)**	(-0.85)
Trim bottom	1.303	5.413	4.109	0.235	4.366	4.131
	(1.247)	**(5.906)**	**(4.583)**	(0.265)	**(6.254)**	**(4.699)**
Thresholds at the (99th, 1st) percentiles						
Trim top and bottom	0.413	1.429	1.016	0.379	1.388	1.009
	(3.702)	**(9.809)**	**(7.274)**	**(3.054)**	**(9.093)**	**(7.802)**
Trim top	1.284	0.419	-0.865	1.421	0.529	-0.892
	(4.268)	(1.915)	**(-2.169)**	**(4.625)**	**(2.549)**	**(-2.22)**
Trim bottom	1.118	5.819	4.7	-0.014	4.707	4.72
	(1.049)	**(6.318)**	**(5.037)**	(-0.015)	**(6.71)**	**(5.109)**
Difference with raw (NIG bonds)						
(99.5th, 0.5th)	-1.551	-3.063	-1.513	-0.725	-2.21	-1.485
	(-1.632)	**(-3.62)**	**(-2.224)**	(-0.958)	**(-3.556)**	**(-2.049)**
Below 99.5th	-0.863	-3.728	-2.866	0.114	-2.776	-2.89
	(-0.868)	**(-4.421)**	**(-2.318)**	(0.142)	**(-4.481)**	**(-2.946)**
Above 0.5th	-0.807	0.707	1.512			
	(-1.255)	**(3.247)**	(1.726)			
(99th, 1st)	-1.697	-3.277	-1.581	-0.847	-2.389	-1.542
	(-1.755)	**(-3.789)**	**(-2.198)**	(-1.086)	**(-3.746)**	**(-2.016)**
Below 99th	-0.826	-4.287	-3.462	0.195	-3.248	-3.443
	(-0.809)	**(-4.982)**	**(-2.535)**	(0.204)	**(-5.111)**	**(-3.067)**
Above 1st	-0.992	1.113	2.103			
	(-1.323)	**(3.688)**	(1.869)			

The difference between trimming outliers during either the formation or holding period can be visualized in Figure 4 for NIG bonds. Panels A and B of the figure depict the cumulative returns, over a one-year horizon, of holding the winner (Panel A) and loser (Panel B) portfolios of the short-term (3-month) strategy when either the top or bottom outliers falling in the formation period are trimmed. Panels C and D plot the analogous returns when only the outliers falling in the holding period are removed. For comparison, the figure also plots the corresponding cumulative returns in the untreated sample for the short-term strategy. Outliers in the figure are above or below the 99.5th and 0.5th percentiles of the return distribution.[23]

Panels A and B show that trimming positive outliers from the formation period strongly decreases the returns of holding the winner portfolio while leaving the returns on the loser portfolio mostly unchanged. As the momentum strategy is long in winners and short in losers, the combined effect is to decrease momentum gains. This result is consistent with positive outliers being particularly effective in identifying ”good” winners, that is, winners that are likely to experience return continuation.

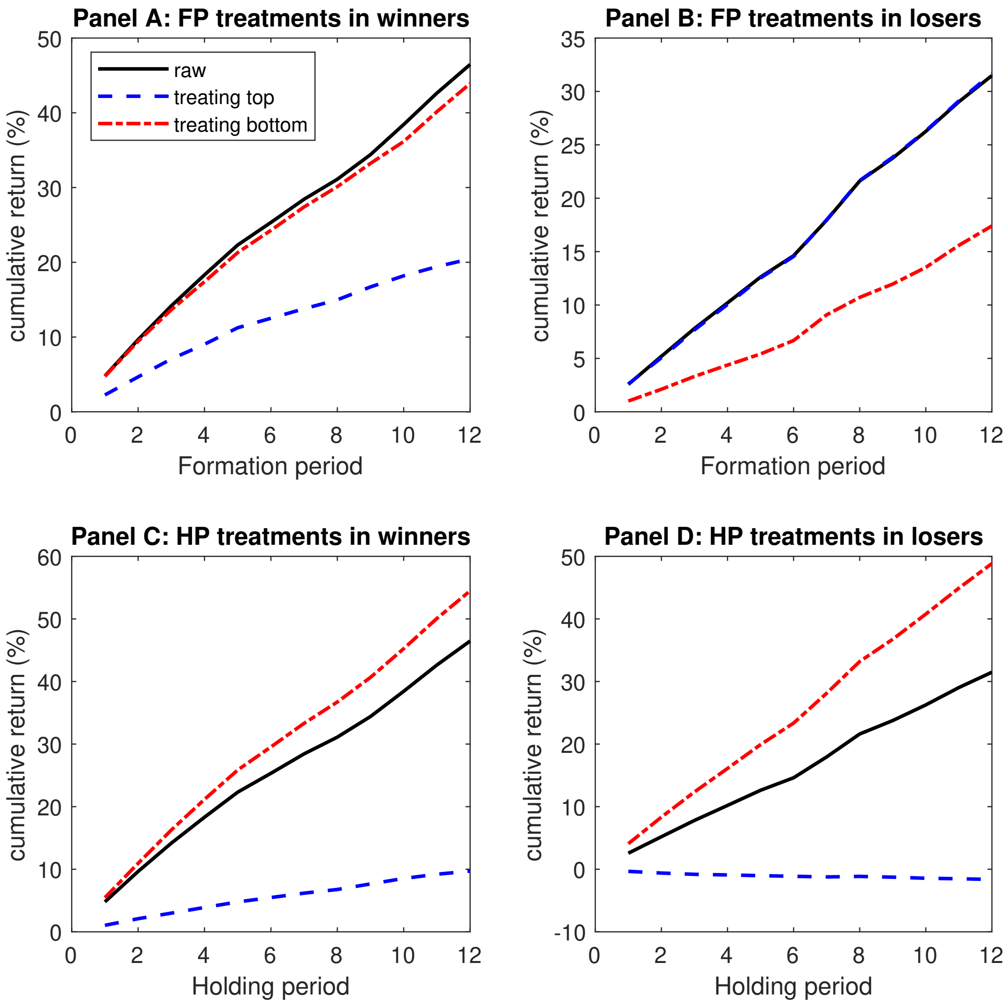
In contrast, removing negative outliers from the formation period strongly decreases the returns on the short leg of the momentum portfolio, which increases momentum profitability, while leaving the returns on the long leg almost unaltered. The implication is that negative outliers tend to identify ”bad” losers, that is, bonds that are unlikely to display return continuation over the holding period.

In Panels C and D, however, treating positive (negative) outliers in the holding period decreases (increases) the returns of both the winner and loser portfolios. The effect is more marked for positive than negative outliers, which is consistent with the average larger magnitudes of extremely positive returns, as shown in Table 1.

In conclusion, I present empirical evidence in support of Hypothesis 2. I show that the long leg of the momentum portfolio is informationally less efficient than the short leg, yielding more sustained trends that can be revealed through the treatment of top and bottom outliers in the portfolio formation period. This finding echos the summary statistics displayed in Table 1, where the share of outliers that are followed by a return of the opposite sign is higher for negative than positive outliers, in all the years of the

[23]The plot for the (99th, 1st) percentile thresholds is omitted as it resembles Figure 4 very closely.

Figure 4: Asymmetric Treatments [99.5th 0.5th]



The figure plots the cumulative returns on the winner and loser portfolios of the short-term P10-P1 momentum strategy in the NIG bond subsample, with and without trimming outliers of opposite signs that fall in the formation period (Panels A and B) or holding period (Panels C and D) from one month to one year. The thresholds for identifying outliers are the 99.5th and 0.5th percentiles of the return distribution.

sample. These findings are determined by the bounded payoff of bonds on the upside, which makes it likely that investors respond more promptly to negative than positive news, thus downward price trends are sustained for shorter periods than upward trends.

4 Recommendations

The corporate bond literature often treats return outliers as occurring due to chance (e.g., measurement error) that would add noise to the statistical assessment of the phenomenon of interest. Outlier trimming reflects this view and has been applied in several studies. For instance, Jostova et al. (2013) filter the monthly return distribution by removing all returns above 30%. Bessembinder et al. (2006) eliminate trades where bond returns are above 10% or below -10%.

This study's results show that one cannot discard the conjecture that a large share of extreme returns is informative for corporate bonds. If outliers are the result of news spreading, they yield insights on the corporate bond price generating processes. From the perspective of momentum studies, outliers contribute to identifying bonds that are likely to show the return continuation on which momentum capitalizes. Thus the information conveyed by these violent price movements should be retained in the sample. However, given that extreme returns are close to the ends of the finite-sample distribution, their relevance should be reduced to increase the statistical accuracy of the inference on momentum profitability. A possible approach is to winsorize the return distribution. Implicitly, winsorization assumes that outliers are not driven by chance, but rather they are the outcome of strongly volatile prices. Winsorization weakens the magnitude of the signal provided by an outlier but retains its potential association with the information shock. In terms of statistical inference, capping extreme returns yields more efficient estimates of portfolio and bond-level average returns, given the relatively short span of bonds' life.

Besides the direct effect on portfolio composition, outlier trimming raises concerns of sample selection bias, as bonds excluded from the momentum portfolio due to outlier removal might have common traits that are not revealed by returns alone.[24] None of these concerns arises when returns are winsorized.

[24]For example, in most years of this study's sample, the majority of outliers are not supported by institution-sized trades, and they represent departures from low price levels.

Offering recommendations on outlier treatments in general studies of corporate bonds is beyond the scope of this paper, as I focus only on evaluating the momentum effect. Nevertheless, researchers need to take into consideration the possibility that return outliers are part of the information diffusion process while deciding the appropriate data cleaning approach.

From the perspective of momentum investing, findings in this paper also offer practical suggestions. I show that positive outliers falling in the formation period identify bonds likely to display return continuation. Thus, to maximize momentum returns, bonds yielding positive outliers during the formation period should not be excluded from the construction of the momentum portfolio. In contrast, a tendency to reverse for negative outliers makes their removal from the ranking period beneficial to momentum profitability. In practice, bonds yielding negative outliers over the formation period are not good candidates for the loser portfolio.

5 Conclusions

This study examines the relative informational efficiency of the long and short legs of the momentum strategy through exploring the link between outliers and momentum profitability. The findings highlight that return outliers are crucial in determining the profitability of the momentum strategy. I show that including bonds with positive outliers when constructing the strategy tends to increase momentum gains, whereas bonds with negative outliers in the portfolio tend to weaken the momentum effect. By analyzing the diffusion process of credit downgrades and upgrades in corporate bond prices, I confirm the conjecture that the market reacts more promptly to negative information shocks than positive ones, which then results in the winner portfolio being supported by more sustained trends than the loser portfolio. Hence, this study provides an explanation for the interesting finding in the literature that the momentum effect in the corporate bond market is mainly contributed by the winner side (e.g., Jostova et al., 2013; Li and Galvani, 2018), in contrast to the role of the short leg in driving the equity momentum.

One implication of this study is that trimming extreme returns has some undesirable features when evaluating the momentum effect, among which the potential of reducing the pool of bonds that might experience the price trend continuation from which the momentum strategy profits. In periods with high concentrations of outliers, this effect is mirrored by a sharp decline in the number of bonds included in the long and short legs of the strategy. Hence, trimming outliers depletes the pool of bonds from which the momentum portfolio is drawn, at the time when risk diversification is needed the most. As a potential substitute, I propose that return winsorization may be better than outlier trimming, especially when leaving out the information content conveyed by extreme returns may be detrimental to the research question under consideration. Finally, from the perspective of profit-maximizing momentum investors, this study suggests that removing bonds yielding negative outliers occurring before portfolio formation could be beneficial.

References

Abarbanell, J. and R. Lehavy (2003). Biased forecasts or biased earnings? the role of reported earnings in explaining apparent bias and over/underreaction in analysts' earnings forecasts. *Journal of Accounting and Economics 36*(1-3), 105–146.

Barber, B. M. and T. Odean (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The review of financial studies 21*(2), 785–818.

Barberis, N., A. Shleifer, and R. Vishny (1998). A Model of Investor Sentiment. *Journal of Financial Economics 49*(3), 307–343.

Bessembinder, H., W. Maxwell, and K. Venkataraman (2006). Market transparency, liquidity externalities, and institutional trading costs in corporate bonds. *Journal of Financial Economics 82*(2), 251–288.

Bittlingmayer, G. and S. M. Moser (2014). What does the corporate bond market know? *Financial Review 49*(1), 1–19.

Blume, M. E., D. B. Keim, and S. A. Patel (1991). Returns and volatility of low-grade bonds 1977–1989. *Journal of Finance 46*(1), 49–74.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam (1998). Investor psychology and security market under-and overreactions. *The Journal of Finance 53*(6), 1839–1885.

De Franco, G., F. P. Vasvari, and R. Wittenberg-Moerman (2009). The informational role of bond analysts. *Journal of Accounting Research 47*(5), 1201–1248.

Defond, M. L. and J. Zhang (2014). The timeliness of the bond market reaction to bad earnings news. *Contemporary Accounting Research 31*(3), 911–936.

Dick-Nielsen, J. (2014). How to clean enhanced trace data. *Available at SSRN: https://ssrn.com/abstract=2337908 or http://dx.doi.org/10.2139/ssrn.2337908*.

Easton, P. D., S. J. Monahan, and F. P. Vasvari (2009). Initial evidence on the role of accounting earnings in the bond market. *Journal of Accounting Research 47*(3), 721–766.

Frank, M. Z. and A. Sanati (2018). How does the stock market absorb shocks? *Journal of Financial Economics 129*(1), 136–153.

Gebhardt, W. R., S. Hvidkjaer, and B. Swaminathan (2005). Stock and bond market interaction: Does momentum spill over? *Journal of Financial Economics 75*(3), 651–690.

Han, S. and X. Zhou (2013). Informed bond trading, corporate yield spreads, and corporate default prediction. *Management Science 60*(3), 675–694.

Hendershott, T., R. Kozhan, and V. Raman (2018). Short selling and price discovery in corporate bonds. *Journal of Financial and Quantitative Analysis*, 1–80.

Hong, H., T. Lim, and J. C. Stein (2000). Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *The Journal of Finance 55*(1), 265–295.

Hong, H. and D. Sraer (2013). Quiet bubbles. *Journal of Financial Economics 110*(3), 596–606.

Hong, H. and J. C. Stein (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of Finance 54*(6), 2143–2184.

Jegadeesh, N. and S. Titman (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance 48*(1), 65–91.

Jiang, G. J. and K. X. Zhu (2017). Information shocks and short-term market underreaction. *Journal of financial economics 124*(1), 43–64.

Jostova, G., S. Nikolova, A. Philipov, and C. W. Stahel (2013). Momentum in corporate bond returns. *Review of Financial Studies 26*(7), 1649–1693.

Khang, K. and T.-H. D. King (2004). Return reversals in the bond market: evidence and causes. *Journal of banking & finance 28*(3), 569–593.

Kwan, S. H. (1996). Firm-specific information and the correlation between individual stocks and bonds. *Journal of Financial Economics 40*(1), 63–80.

Leone, A. J., M. Minutti-Meza, and C. E. Wasley (2019). Influential observations and inference in accounting research. *The Accounting Review 94*(6), 337–364.

Li, L. and V. Galvani (2018). Market states, sentiment, and momentum in the corporate bond market. *Journal of Banking & Finance 89*, 249–265.

Li, L. and V. Galvani (2021). Informed trading and momentum in the corporate bond market. *Review of Finance 25*(6), 1773–1816.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of finance 29*(2), 449–470.

Miller, E. M. (1977). Risk, uncertainty, and divergence of opinion. *The Journal of finance 32*(4), 1151–1168.

Park, T.-J., Y. Lee, et al. (2014). Informed trading before positive vs. negative earnings surprises. *Journal of Banking & Finance 49*, 228–241.

Ronen, T. and X. Zhou (2013). Trade and information in the corporate bond market. *Journal of Financial Markets 16*(1), 61–103.

Savor, P. G. (2012). Stock returns after major price shocks: The impact of information. *Journal of financial Economics 106*(3), 635–659.

Stambaugh, R. F., J. Yu, and Y. Yuan (2012). The short of it: Investor sentiment and anomalies. *Journal of Financial Economics 104*(2), 288–302.

Appendix: The Association between Price and Return Outliers

Given the bounded payoff of debt, prices that are too large raise concerns of reporting errors. It is harder to make the analogous argument for low prices, as one cannot exclude that extremely low valuations are the response to very high levels of risk. Hence, an alternative conjecture to the claim that outliers are informative is that return outliers are generated by extreme prices that are reporting errors, high prices more so than low prices.

Empirically, the vast majority of return outliers do not stem from extremely large prices. Table A.1 shows that almost all of the return outliers are not associated with prices falling above the 99.5th price percentile (i.e., 141% of par), regardless of whether the extreme price level occurs at the end of the previous month or in the same month of the return outlier.[25] When they do, the return outlier is positive for a current month price outlier but negative for a previous month price outlier. In contrast, extremely low prices (i.e., 25% of par at the 0.5th percentile) are associated with a larger share of return outliers both in the same month and the next month. To summarize, if price reporting errors are the cause of extremely large prices, then these reporting errors generate only a few outliers, and only in the initial years of TRACE.[26]

Panel B of Figure A.1 illustrates the effect of eliminating prices above the 99.5th percentile of the price distribution on the concentration of return outliers. Comparing this panel to the corresponding plot in the untreated sample, in Figure 1, reveals that removing extremely high prices does not seem to affect the magnitude and frequency of return outliers.

Panel A of Figure A.1 shows that filtering extremely low prices below the 0.5th percentile of the price distributions weakens somewhat the magnitude and frequency of out-

[25] Results for the thresholds of 99th and 1st percentiles are very similar, thus are omitted.

[26] The discrepancy between the reported numbers in columns 2 and 6 of panels A and B are due to the fact that some prices are counted only once in the current (previous) month group due to missing data in their next (previous) month.

Table A.1: Return and Price Outliers

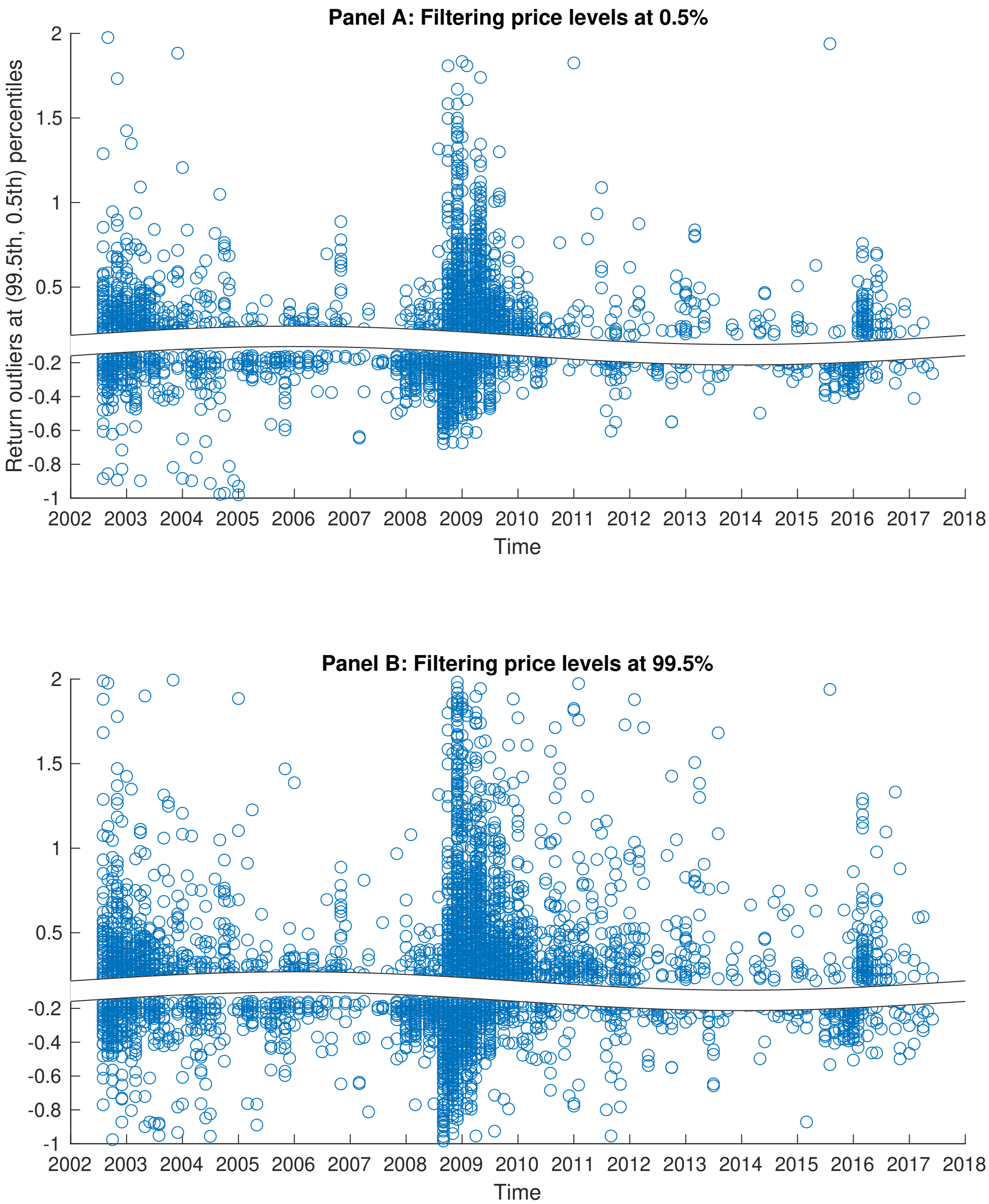
In Panel A, the first column of results reports the number of prices falling above the 99.5th percentile of the price distribution. The following three columns report the total number of return outliers for which the same-month price is above the 99.5th price percentile, also broken up in positive and negative outliers, where return outliers are identified using the 99.5th and 0.5th percentiles of the return distribution. The next four columns report corresponding statistics for prices falling below the 0.5th percentile of the price distribution. Panel B reports the analogous statistics but for return outliers for which the previous month's price falls above the 99.5th or below the 0.5th price percentiles, respectively.

	Price Outlier at 99.5th				Price Outlier at 0.5th			
Year	N. Obs	Return Outlier	Positive	Negative	N. Obs	Return Outlier	Positive	Negative
Panel A: Number of return outliers associated with a same-month price outlier								
2002	10	5	5	0	258	126	68	58
2003	69	8	8	0	309	114	71	43
2004	64	11	11	0	120	58	28	30
2005	130	0	0	0	117	42	23	19
2006	10	0	0	0	71	23	18	5
2007	7	0	0	0	24	10	7	3
2008	8	2	2	0	685	516	55	461
2009	10	1	1	0	1473	714	444	270
2010	105	1	1	0	811	180	150	30
2011	272	1	1	0	563	112	98	14
2012	1252	0	0	0	99	42	32	10
2013	552	2	2	0	48	31	20	11
2014	576	0	0	0	22	10	7	3
2015	661	0	0	0	40	25	9	16
2016	756	1	1	0	58	26	13	13
2017	247	0	0	0	18	9	4	5
Panel B: Number of return outliers associated with a previous-month price outlier								
2002	14	9	0	9	260	139	114	25
2003	64	6	0	6	333	129	107	22
2004	60	15	0	15	122	59	43	16
2005	135	2	0	2	104	31	25	6
2006	14	0	0	0	78	28	24	4
2007	1	0	0	0	22	9	7	2
2008	8	0	0	0	535	376	229	147
2009	10	1	0	1	1554	782	643	139
2010	102	0	0	0	822	183	159	24
2011	220	1	0	1	557	107	101	6
2012	1181	1	0	1	136	42	38	4
2013	640	1	0	1	48	31	21	10
2014	518	0	0	0	21	9	7	2
2015	706	0	0	0	32	17	9	8
2016	746	0	0	0	61	31	23	8
2017	221	0	0	0	18	8	4	4

liers. However, filtering low prices still does not disperse the return outliers' clusters.

As noted in Hong and Sraer (2013) when bond prices are low, information is likely to have a strong impact on bond prices, due to the upper bound in debt payoff. That return outliers are linked to low bond prices, not high prices, suggests that they might convey information, a possibility that finds corroboration in this study.

Figure A.1: Return Outliers after Filtering Prices



The figure plots return outliers above 99.5th and below 0.5th percentiles of the return distribution, when trimming prices below the 0.5th percentile of the price distribution (Panel A), or above the 99.5th percentile of the price distribution (Panel B). Returns are capped at 200% of par.