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Outliers and Momentum in the Corporate Bond Market

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Abstract

How we filter outliers matters in empirical research. As a demonstration, we analyze how momentum returns respond to different outlier treatments in the corporate bond market TRACE database. We find that momentum profitability depends crucially on return outliers. Specifically, outlier trimming vanishes momentum returns, whereas winsorization yields a robust but conservative assessment of the momentum effect. Price filters show that momentum is generated by low-priced bonds and volume filters reveal that momentum profits during the 2007-2009 crisis were due to the activities of small investors. Lastly, finer partitions of the bond cross-section are shown to deliver superior momentum gains without sacrificing portfolio diversification over bonds and issuers.

Keywords: momentum; outliers; winsorization; corporate bonds; TRACE.

JEL: G01, G10

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Introduction

The events of the recent decades have brought into the focus of researchers the challenges of dealing with relatively short samples that include periods marked by extreme price movements (e.g., Baker et al. (2020)). Contributing to this discussion, this study highlights the effects of outlier treatments on portfolio profitability when the sample covers a relatively short period that includes a large cluster of outliers. Specifically, we evaluate the effect of outlier treatments on the profitability of the momentum strategy using corporate bond transaction-based prices as recorded in TRACE Enhanced.

The momentum strategy capitalizes on the return continuation of past best and worst performers. Extraordinary price shifts substantially contribute to the identification of the securities included in the momentum portfolio, especially when past returns are evaluated over short periods. Momentum returns, therefore, showcase the effect of outliers by reason of the very design of the momentum strategy.

The corporate bond literature disagrees on how to treat outliers, and various treatments are in use, including the removal of extreme returns or prices and winsorizing the return distribution. The approach used to identify outliers also varies. For instance, most recent studies follow Bai et al. (2019) and identify prices under $5 or above $1000 as outliers. However, the treatment of outliers differs, as some studies drop from the sample the bonds yielding price outliers (e.g., Bai et al., 2019; Huynh and Xia, 2021) while others drop only outlier observations (e.g., Goldberg and Nozawa, 2021). Other contributions also use different price cutoffs (e.g., Han and Zhou, 2013; Li, 2021). Some studies drop low volume transactions along with, or instead of, trimming price outliers, also with different cutoffs (e.g., Bao et al., 2018; Bai et al., 2019). Another group of studies excludes from the sample return outliers, rather than extreme prices (e.g., Jostova et al., 2013). There are also papers suggesting that also using the untreated sample is a viable option when prices and returns stem from actual transactions (e.g., Bessembinder et al., 2018). The relatively conservative approach of outlier winsorization is used in Li and Galvani (2018, 2021), who argue that dropping observations supported by actual transactions would disrupt the information flow revealed by prices.

Drawing from the literature, our study considers symmetric and asymmetric return outlier treatments, return outlier removal and winsorization, as well as filters based on price levels and trading volumes. Our results foster the discussion on the implications of outlier treatments for assessing portfolio profitability using a familiar database in finance research (i.e., TRACE) and a well-understood trading strategy, namely momentum.

Figure 1 depicts monthly corporate bond returns above the 99.5th or below the 0.5th percentiles of the return distribution over the 2002-2017 period.[1] The figure demonstrates how ignoring the outlier cluster associated with the 2007-2009 financial crisis may be problematic when performing statistical analysis on bond returns, due to the short lifespan of bonds, and especially for samples covering a relatively short time period, like the TRACE database.

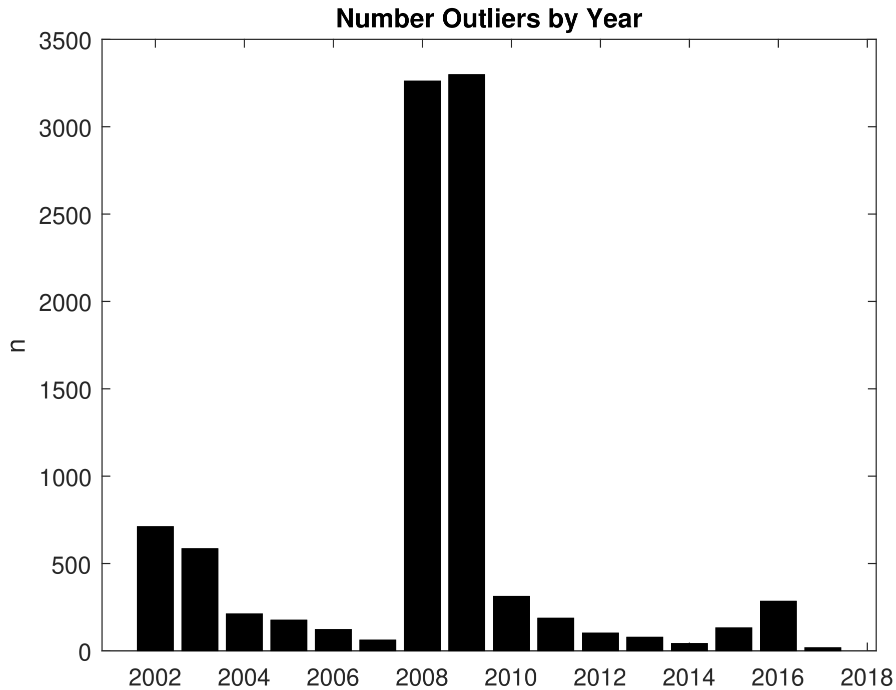
Outliers can occur due to chance (e.g., measurement error). If this is the case, outliers are just noises and hinder the statistical assessment of the phenomenon of interest, in this study, the momentum effect. Outlier trimming reflects this view and has been applied in several studies.[2] Identifying outliers using the 0.5th and 99.5th percentiles of the return distribution, we find that outlier trimming vanishes the significant momentum gains found in the raw return sample, regardless of whether the 2007-2009 crisis is included in the sample.[3] The implication is that the strategy's profitability is due to the bonds yielding the most extreme 1% of the return distribution. Additionally, we find that negative and positive outliers do not equally contribute to momentum profitability. Specifically,

[1]To foster comparability with the literature on corporate bond momentum, our analysis relies on the sample used in Li and Galvani (2021). This sample period ends in the pre-pandemic period. At the time of writing, TRACE Enhanced, which is updated at a very low frequency, does not cover most of the market turmoil caused by the pandemic and the invasion of Ukraine. The 2007-2009 crisis period is defined as the time interval from May 2007 to December 2009. In early June 2007, Bear Stearns halted redemptions in one of its funds exposed to low-rate mortgage-backed securities.

[2]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%.

[3]We also experiment with identifying outliers using absolute cut-offs drawn from the literature (e.g., +/-30%), and obtain the same result.

Figure 1: Bond Return Outliers per Year



The figure plots the number of monthly corporate bond returns that are above the 99.5th and below the 0.5th percentile of the return distribution, over the time period August 2002-June 2017. The thresholds identifying outliers correspond to returns of 21.51% and about -16%, respectively.

top outliers identify bonds yielding stronger momentum gains than bottom outliers.

As argued in Li and Galvani (2021), the information content conveyed by violent price movements should be retained in the sample. However, given that extreme returns are close to the ends of the finite-sample return distribution, in some instances, we might want to decrease their relevance to increase statistical accuracy. A possible approach is to winsorize the return distribution.

Winsorization is a well-established procedure that limits how extreme a return is allowed to be (e.g., Cowan and Sergeant, 2001; Cao et al., 2018).[4] With winsorization, extremely high and low returns are set equal to specified cut-offs, typically determined by sample-specific percentiles, in this study, the 0.5th and 99.5th percentiles of the return

[4]Winsorization is also applied in the WRDS Corporate Bond Returns Database, which calculates bond returns using TRACE and Mergent FISD, as in this study.

distribution. Implicitly, winsorization assumes that outliers are not driven by chance but rather are the outcome of violent fluctuations in 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.

Average momentum profits in the winsorized sample are lower than those found using untreated returns but show similar levels of significance. Further, winsorization appears to mitigate the impact of subsamples marked by a high concentration of outliers. Specifically, the results show that winsorizing the return distribution yields comparable momentum gains when the sample includes or excludes the 2007-2009 crisis period. Thus winsorizing returns is a conservative but robust approach to estimate momentum profitability.

As in previous studies, we find that the momentum effect is not profitable for investment-grade bonds (e.g., Gebhardt et al., 2005), while that there are significant momentum gains for low-grade bonds (e.g., Jostova et al., 2013). Our analysis adds that even in the NIG sample, outlier treatments have profound implications on the assessment of momentum profitability. For instance, in the untreated return sample, the short-term momentum strategy's return is a strong 2.11%, which, however, drops to 0.248% when trimming both positive and negative return outliers. When we exclude the 2007-2008 sample, the variation in NIG momentum returns over outlier treatments is even more dramatic.[5]

The distinctive effects of outlier trimming and winsorization on momentum profitability originate in their impact on 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 those bonds yielding extreme returns during the formation period. We show that, when out-

[5]We do not restrict this study's analysis to low-grade bonds as high-grade bonds still yield strong conditional momentum returns (e.g., Li and Galvani, 2018).

liers are eliminated, the number of bonds in either leg of the momentum portfolio drops drastically during the financial crisis, a period marked by a high incidence of outliers. This effect on portfolio composition is less of a concern when winsorizing returns, as outliers are substituted with appropriate return thresholds, and outlier-yielding bonds can still qualify for inclusion in the momentum portfolio. Besides considering outlier treatments, this study discusses the effect on momentum of filters on bond prices. In TRACE prices are reported as percentages of par value. Hence, prices that are either very small or very large raise concerns of errors in data. From this perspective, the removal of extreme prices from the sample could foster statistical accuracy, an approach already employed in the literature (e.g., Han and Zhou, 2013; Lin et al., 2017). We find that excluding 1% of the prices vanishes momentum gains. These results imply that extreme price levels are essential to the profitability of the momentum effect in the corporate bond market.

Previous studies have suggested that information shocks affect more low- than high-priced bondsHong and Sraer (2013). If momentum originates from gradual information diffusion, then the effect of prices on momentum should be concentrated on low-priced bonds. Consistently, we find that momentum gains disappear when low, not high, prices are removed. Specifically, momentum profitability is driven by prices lower than 25% of par value.

The literature has established a positive relationship between trade size and levels of informed trading in the corporate bond market (e.g., Han and Zhou, 2013). Cognizant of these results, we also experiment with a theory-driven price filtering approach. We remove from the sample prices that are supported only by small-sized transactions, i.e., prices supported by trading volumes that are unlikely to be linked to informed trading. We find that removing these prices vanishes momentum returns when the 2007-2009 crisis period is included in the sample but has little effect in "normal markets," that is, when the crisis is excluded from the sample. In particular, the results show that the momentum profits observed during the crisis period are attributable to the activities of small and presumably uninformed traders.

This study introduces our findings on the effect of outliers treatments using the standard decile-based momentum portfolios (e.g., Jostova et al., 2013). Following the equity momentum literature, this strategy identifies the winner and loser portfolios by sorting the cross-section into ten quantiles. However, in any given month, there are many more corporate bonds than equities on the market. In our sample, for example, there is an average of 5,344 bonds in the monthly cross-section. From this perspective, sorting past bond returns into deciles, while strongly diversifying against idiosyncratic risk, may result in portfolios of winners and losers that fail to identify really outstanding and egregious return showings. Decile-based momentum portfolios might thus not be the best choice to capitalize on the momentum effect for corporate bonds.

According to theoretical explanations of the momentum effect (e.g., Hong and Stein, 1999; Daniel et al., 1998; Barberis et al., 1998), stronger price trends during the formation period yield larger momentum returns. Building on this insight, we propose sorting bonds into more than ten quantiles when identifying past winners and losers. Momentum strategies based on increasingly finer partitions should yield higher momentum gains, as the selected bonds would have experienced, on average, more exceptional price trends. Consistent with the predictions of the theoretical models, we find that momentum profitability progressively increases when ranking the bond return cross-section into 20, 30, and then 50 quantiles, rather than deciles. An analysis of the winner and loser portfolios shows that using 50 quantiles strikes a balance between highlighting momentum gains and diversifying idiosyncratic risk at the bond and issuer levels.

The superior performance of the momentum strategy based on 50 quantiles over the familiar decile-based portfolio is confirmed in the untreated return sample and for all the outlier treatments considered in this study. For instance, when using winsorized returns, the profitability of the short and long-term momentum strategies about triples using 50 quantiles with respect to relying on deciles. Our results also show that using strategies based on 50 quantiles, which include a large share of investment-grade bonds, yields momentum gains that are close to those obtained for the pure low-grade bond momentum strategies. With respect to the low-grade bond strategy, the 50-quantile portfolio is better diversified on issuers and requires to engage in fewer (costly) sales of low-grade bonds.

While this study focuses on momentum strategies, we show that outlier treatments might have unintended consequences for portfolio design. In particular, when asset inclusion into a portfolio depends on data availability over a certain time period, removing outliers might strongly affect portfolio composition, with the effect raising particular concerns in samples that include clusters of outliers.

1 Data and Methodology

1.1 Return Calculation and All-sample Summary Statistics

Our empirical analysis relies on data from TRACE Enhanced, matched with Mergent's FISD, for the period spanning from July 2002 to June 2017. We include in our sample only publicly traded bonds.[6] Following the cleaning procedure described in Dick-Nielsen (2014), we reduce data reporting errors by removing all transactions that are marked as a cancellation, correction, and reversals, as well as their matched original trades.[7]

We select bonds that are US-dollar denominated and pay a fixed-coupon, including zero-coupon bonds. Further, we retain in the sample only bonds issued by corporations, and that are not part of unit deals. We exclude bonds with warrants and special contingencies (i.e., preferred shares, puttable, convertible, exchangeable, asset-backed, etc.). The final sample contains 956,518 monthly transaction-based price observations for 17,846 bonds issued by 2,563 firms. In the final sample, information on credit grade is available for about 99% of the bond-month observations.

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

[7] Eliminating all agency (e.g., dealer) transactions that may raise concerns of double-counting does not affect this paper's results.

Following Li and Galvani (2021), we obtain the month-end 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. An alternative approach to calculate bond returns is to rely only on the last price falling in the last five days of the month (e.g., Jostova et al., 2013). An appendix shows that this study's conclusions find support also when returns are calculated using the last-five-day approach.[8]

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 $P_{i,t+1}$.[9] Summary statistics of bond returns, by year, are tabulated in Panel A of Table 1.

[8]See Li and Galvani (2021) for a comparison of the return samples obtained using the last-available and last-five-day price filters.

[9]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 30% and -30%. 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 99.5th and 0.5th percentiles of the return distribution. 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 30% or lower than -30%

	Positive Outliers			Negative Outliers		
Year	N	mean(%)	Reversal (%)	N	mean(%)	Reversal (%)
2002	221	84.855	47.06	78	-46.223	70.51
2003	224	82.031	33.04	55	-49.932	78.18
2004	71	339.779	47.89	39	-58.575	61.54
2005	26	432.657	23.08	22	-51.493	77.27
2006	27	50.983	14.81	6	-43.239	50
2007	7	52.308	14.29	9	-51.233	55.56
2008	531	90.756	18.64	826	-46.486	56.3
2009	1255	74.451	27.49	328	-39.266	74.39
2010	144	86.449	27.08	21	-43.613	61.9
2011	85	83.791	15.29	15	-58.88	66.67
2012	42	132.694	19.05	7	-46.613	100
2013	32	67.379	31.25	6	-49.299	50
2014	12	67.954	25	3	-40.247	33.33
2015	10	62.223	20	20	-39.089	55
2016	84	49.396	23.81	17	-38.956	58.82
2017	3	50.669	33.33	5	-36.409	40

Panel C: 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

Year		Positive Outliers			Negative Outliers	
	N	mean(%)	Reversal (%)	N	mean(%)	Reversal (%)
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

1.2 Momentum Strategies

We design momentum strategies as described 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, we 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. We consider two representative (and familiar) short and long-term momentum strategies with symmetric formation and holding periods of three and six months, respectively. These are the decile-based short and long-term momentum portfolios considered in this study, which are collectively referred to as P10-P1 strategies.

[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)). This limitation is not implemented in this study, to make momentum strategies as similar as possible to those implemented in studies of equity momentum.

1.2.1 Momentum with Finer Partitions

Studies of the momentum effect in the equity market rely on ranking past cumulative returns of stocks into deciles to identify the winner and loser portfolios. Momentum in corporate bonds has typically also been evaluated using decile-based momentum strategies, or even coarser partitions of the bond cross-section (e.g., Jostova et al., 2013; Gebhardt et al., 2005). In our sample, the number of bonds classified as winners (P10) and losers (P1) of the decile-based momentum strategy is consistently large in all the months. For the short-term momentum strategy, there is a minimum (average) of 386 (485) bonds in each of the top and bottom deciles. For the long-term strategy, the corresponding minimum (average) is of 356 (439) bonds. To contrast, in their analysis of momentum in US equities Asness et al. (2013) find that the minimum (average) number of stocks in each decile is about 35 (70), per month. The difference in the numerosity of the winner (and loser) portfolios between corporate bonds and equities is due to the fact that there are many more outstanding corporate bonds than equities on the market in each month.

The theoretical explanations of the momentum effect (e.g., Hong and Stein, 1999; Daniel et al., 1998; Barberis et al., 1998) predict that stronger price trends during the formation period yield larger momentum returns. Building on this insight, we propose to sort bonds into more than ten quantiles to identify past winners and losers. Consistent with the predictions of the theoretical models, momentum strategies based on increasingly finer partitions should yield higher momentum gains, as the selected bonds would have experienced, on average, more exceptional price trends. A finer partition of the cross-section, however, necessarily results in fewer bonds in each leg of the momentum portfolio. Hence, the partition must also be sufficiently coarse to allow diversifying idiosyncratic risk.

We evaluate the monthly returns on momentum strategies based on 20, 30, and 50 quantiles. The resulting momentum portfolios differ from the P10-P1 portfolios only in the number of bins in which the bond cross-section is partitioned. In our sample, the balance between risk diversification and the identification of exceptional past returns appears to be better reached using 50 quantiles rather than 10, 20, or 30 quantiles. Specifically, results reported in the appendix show that 50 quantiles yield short- and long-term winner and loser portfolios that are well-diversified both over bonds and issuers. Therefore, in this study, we also examine the returns of momentum portfolios based on 50 quantiles, which are henceforth referred to as the P50-P1 strategies.[12]

As the P50-P1 momentum strategies capitalize on the return continuation of more extreme price trends than those implied by the decile-based (P10-P1) portfolio, the expectation is that momentum investing should be more profitable for the P50-P1 strategies than for the decile-based momentum portfolios, both in the short and long runs.

1.3 Identification of Return Outliers

There is no definite rule to identify return outliers. A standard statistical procedure is to assume that returns below the 0.5th and above the 99.5th percentiles of the return distribution are sufficiently deviated from the sample mean to be considered out-sized. The drawback of this approach is that the thresholds for which a return is classified as an outlier are necessarily sample-specific. An alternative is to refer to previous studies covering long time periods and use the thresholds implied by their distribution. Jostova et al. (2013) cover a sample ranging from 1973 to 2011, which is of an exceptional length for studies on corporate bonds. The authors propose the cut-off of 30%, which is about the 99.5th percentile of the return distribution in their sample, to identify a (positive) outlier. They do not propose a threshold for negative outliers. We experiment with the 30% cut-off, which, however, we also adapt to the left side of the return distribution, so that returns below -30% are considered negative outliers. To compare, in our sample, the cut-offs at the 99.5th and 0.5th percentiles correspond to returns of 21.51% and about -16%,

[12]In the appendix, we also replicate the core results of this paper for momentum strategies with 20 and 30 quantiles, namely the P20-P1 and P30-P1 momentum portfolios.

respectively.[13]

Panel B of Table 1 reports yearly summary statistics for the outliers of the 2002-2017 TRACE sample, where outliers are identified using the absolute cut-offs of +/-30%. We note that positive outliers are more numerous and tend to be larger than negative ones. Further, the number of outliers, both positive and negative, reaches its highest levels in 2008 and 2009. The analogous statistics using the 0.5th and 99.5th percentiles of the return distribution are in Panel C of the same table. Note that positive and negative outliers cluster over the crisis period also using the relative cut-offs.

Panels B and C 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 -30% and below the 0.5th percentile of the return distribution are followed by a positive return in about 62% and 56% of the instances, respectively, on average over the years in the sample. The analogous percentages for returns above 30% and larger than the 99.5th percentile are about 26% and 28%, respectively.

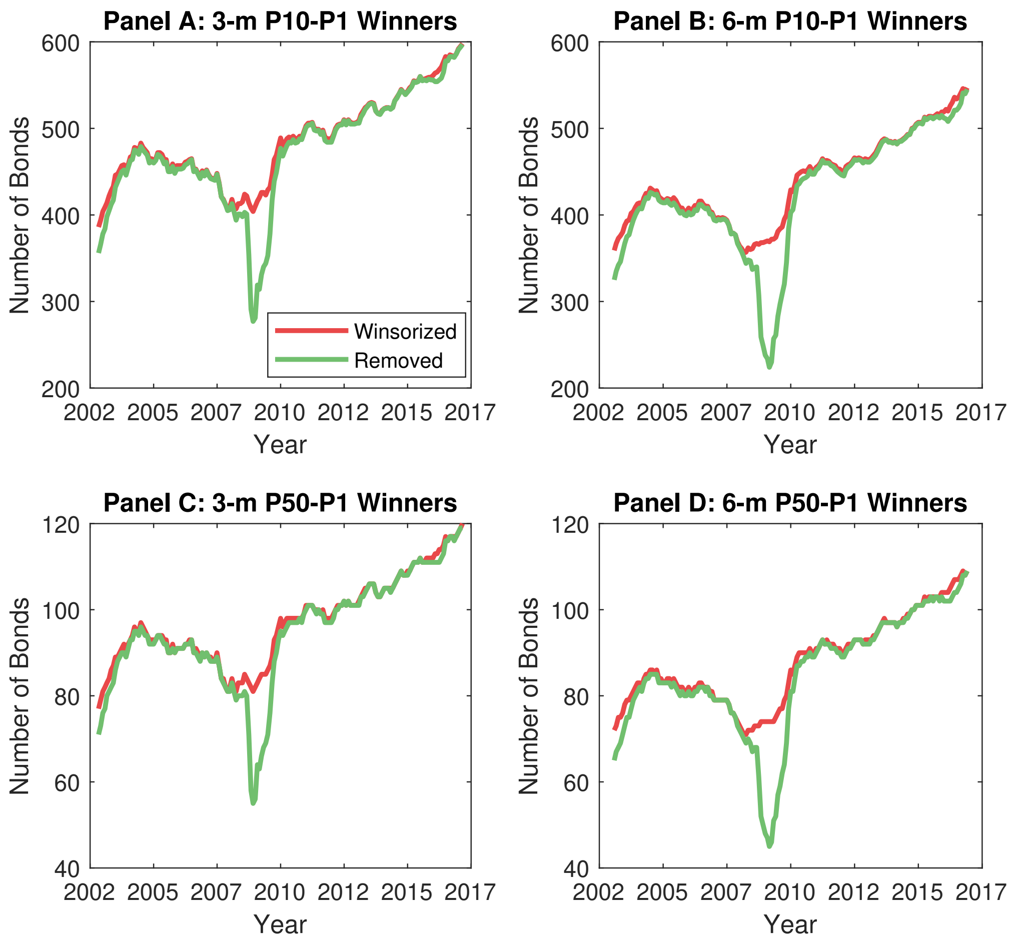
1.4 Portfolio Composition and Outlier Treatments

Outliers may occur due to chance (e.g., measurement error) and thus add just noise to the statistical assessment of the phenomenon of interest, in this study the momentum effect. However, outliers may also be realizations of fat-tail data generating processes, on the nature of which they yield insights. Outlier trimming and winsorization are two commonly used outlier treatments implicitly reflecting the former and latter views of extreme returns, respectively.

Removing a return outlier has important repercussions on the composition of momen-

[13] As 21.51% is lower than 30%, the percentile approach makes it more likely for a large return to be classified as an outlier than using the 30% cut-off. The same ordering applies for the negative cut-offs. In our sample, thresholds yielding cut-offs close to +/-30% are the 99.8th and the 0.2th percentiles, at about 38% and -27%, respectively.

Figure 2: Number of Bonds in Winners



The figure plots the number of bonds that are included in the winner portfolio of the momentum strategy, when outliers are either removed or winsorized. Panels A and B plot the two series for the decile-based winner portfolios (P10) of the short and long-term momentum strategies, respectively. Panels C and D plot the corresponding series for the P50 winner portfolios. Outliers are winsorized or removed using the 99.5th and 0.5th percentiles of the return distribution.

tum portfolios. This is due to the standard (in the literature) portfolio formation rule that a bond is excluded from the momentum portfolio when any of its formation period returns are missing. As a result, removing outliers may deplete the pool of bonds showing extreme price trends, the continuation of which the momentum strategy capitalizes on. This drawback does not affect winsorization, as the appropriate threshold substitutes an extreme return. Hence, a bond needs not to be dropped from the momentum portfolio, if any of its returns is classified as an outlier during the formation period.

We illustrate how the trimming of outliers affects portfolio composition in Figure 2, where we plot the number of bonds selected into the winner portfolios in each formation month for the decile and 50 quantile-based short and long-term strategies. The analogous plots for the loser side are omitted, as the figures are very much alike. Figure 2 shows that, during the crisis, trimming outliers results in an extraordinary dip in the number of bonds included in the long leg of the momentum strategy. This effect is clearly missing when returns are winsorized.

Finally, 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.[14] None of these concerns arises when returns are winsorized. We note that, while this study focuses on the momentum strategy, these considerations raise more general concerns on the practice of trimming outliers when designing portfolios for which securities selection depends on the availability of data over a certain time period.

2 Results for Return Outlier Treatments

Tables 2 and 3 report the average returns on the short and long-run momentum strategies, respectively, as well as the returns on their long and short legs, in the untreated sample and for different outliers treatments. In both tables, Panel A shows momentum returns when outliers are left untreated. Panels B, C and D tabulate returns on the same strategies for different outlier treatments. We consider both the P10-P1 and P50-P1 designs, which are based on sorting past returns into deciles and 50 quantiles, respectively.

The effect of outliers on the profitability of the momentum strategy should be particularly marked for the short-term P50-P1 portfolio, as exceptional returns are averaged over fewer observations. Long-term investment strategies and portfolios that include more securities place lower weights over individual observations, and thus their payoffs are less

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

Table 2: 3-month Formation and Holding Periods Momentum Returns

The table reports the average monthly returns and their t-statistics (in bold when significant at the 0.05% level) for the 3-month formation and holding period momentum strategy and its winner and loser portfolios, based on deciles and 50 quantiles, for the whole sample and for the subsample obtained excluding the financial crisis period, respectively. Panel A lists momentum returns when no outlier treatment is applied (untreated returns). Panel B displays returns based on two-sided and one-sided outlier winsorization using the percentile thresholds of 99.5% and 0.5% of the return distribution. Panels C and D report the corresponding results for the removal of outliers based on the percentile thresholds, and on the absolute cut-offs of +/-30%, respectively. The time period covered is from August 2002 to June 2017. The financial crisis period spans from May 2007 to December 2009.

	P10-P1	Winner=P10	Loser=P1	P50-P1	Winner=P50	Loser=P1
Panel A: Untreated returns						
with crisis	0.729	1.972	1.243	2.905	5.427	2.522
	(1.941)	**(4.946)**	**(3.257)**	**(2.235)**	**(3.974)**	**(3.971)**
without crisis	0.635	1.579	0.944	2.45	4.338	1.889
	(2.775)	**(6.387)**	**(5.614)**	**(2.563)**	**(4.477)**	**(5.176)**
Panel B: Winsorized returns						
Winsorize top 99.5th percentile and bottom 0.5th percentile						
with crisis	0.278	1.09	0.812	0.702	1.884	1.182
	(1.919)	**(6.464)**	**(4.227)**	**(3.245)**	**(7.732)**	**(4.538)**
without crisis	0.26	1.055	0.795	0.666	1.914	1.248
	(1.908)	**(7.201)**	**(5.488)**	**(3.055)**	**(8.577)**	**(5.624)**
Winsorize top 99.5th percentile						
with crisis	0.382	0.954	0.572	0.755	1.592	0.837
	(2.039)	**(5.486)**	**(2.262)**	**(2.677)**	**(6.051)**	**(2.364)**
without crisis	0.223	0.991	0.768	0.604	1.721	1.118
	(1.623)	**(6.828)**	**(5.18)**	**(2.636)**	**(7.697)**	**(4.727)**
Winsorize bottom 0.5th percentile						
with crisis	0.823	2.195	1.372	3.291	5.912	2.621
	(2.275)	**(5.341)**	**(3.978)**	**(2.5)**	**(4.317)**	**(3.962)**
without crisis	0.72	1.656	0.936	2.855	4.67	1.815
	(3.18)	**(6.652)**	**(5.86)**	**(3.012)**	**(4.76)**	**(5.69)**
Panel C: Removing outliers (percentile threshold)						
Removing top 99.5th percentile and bottom 0.5th percentile						
with crisis	0.093	0.832	0.739	0.164	1.149	0.985
	(0.83)	**(6.628)**	**(5.142)**	(1.015)	**(7.474)**	**(5.132)**
without crisis	0.115	0.841	0.726	0.192	1.228	1.036
	(1.009)	**(6.654)**	**(5.641)**	(1.138)	**(7.698)**	**(5.649)**
Removing top 99.5th percentile						
with crisis	0.51	0.66	0.15	0.842	0.794	-0.048
	(2.63)	**(4.458)**	(0.59)	**(3.089)**	**(4.054)**	(-0.137)
without crisis	0.135	0.778	0.644	0.337	1.055	0.718
	(1.106)	**(6.122)**	**(4.668)**	**(1.782)**	**(6.388)**	**(3.457)**
Removing bottom 0.5th percentile						
with crisis	0.937	1.992	1.055	4.057	5.775	1.718
	(2.945)	**(5.681)**	**(5.337)**	**(3.004)**	**(4.103)**	**(5.564)**
without crisis	0.788	1.609	0.821	3.213	4.501	1.288
	(3.545)	**(6.618)**	**(5.991)**	**(3.456)**	**(4.713)**	**(6.267)**
Panel D: Removing outliers (absolute threshold)						
Removing returns above 30% or below -30%						
with crisis	0.201	0.85	0.65	0.422	1.232	0.81
	(1.538)	**(5.858)**	**(3.647)**	**(2.169)**	**(6.359)**	**(3.276)**
without crisis	0.144	0.886	0.742	0.264	1.339	1.076
	(1.138)	**(6.641)**	**(5.258)**	(1.374)	**(7.363)**	**(5.099)**
Removing returns above 30%						
with crisis	0.454	0.763	0.309	0.733	1.025	0.292
	(2.403)	**(4.838)**	(1.234)	**(2.677)**	**(4.657)**	(0.83)
without crisis	0.146	0.85	0.703	0.303	1.228	0.925
	(1.13)	**(6.355)**	**(4.886)**	(1.446)	**(6.595)**	**(4.099)**
Removing returns below -30%						
with crisis	0.693	1.936	1.243	3.05	5.456	2.405

	P10-P1	Winner=P10	Loser=P1	P50-P1	Winner=P50	Loser=P1
	(1.963)	**(5.389)**	**(3.94)**	**(2.257)**	**(4.061)**	**(3.558)**
without crisis	0.694	1.604	0.91	2.727	4.447	1.72
	(3.048)	**(6.503)**	**(5.664)**	**(2.874)**	**(4.615)**	**(5.413)**

Table 3: 6-month Formation and Holding Periods Momentum Returns

The table reports the average monthly returns and their t-statistics (in bold when significant at the 0.05% level) for the 6-month formation and holding period momentum strategy and its winner and loser portfolios, based on deciles and 50 quantiles, for the whole sample and for the subsample obtained excluding the financial crisis period, respectively. Panel A lists momentum returns when no outlier treatment is applied (untreated returns). Panel B displays returns based on two-sided and one-sided outlier winsorization using the percentile thresholds of 99.5% and 0.5% of the return distribution. Panels C and D report the corresponding results for the removal of outliers based on the percentile thresholds, and on the absolute cut-offs of +/-30%, respectively. The time period covered is from August 2002 to June 2017. The financial crisis period spans from May 2007 to December 2009.

	P10-P1	Winner=P10	Loser=P1	P50-P1	Winner=P50	Loser=P1
Panel A: Untreated returns						
with crisis	0.491	1.787	1.296	2.14	4.772	2.632
	(1.215)	**(4.508)**	**(3.076)**	(1.712)	**(3.506)**	**(4.143)**
without crisis	0.551	1.447	0.896	1.802	3.728	1.926
	(2.688)	**(6.052)**	**(5.572)**	**(3.096)**	**(5.026)**	**(5.349)**
Panel B: Winsorized returns						
Winsorize top 99.5th percentile and bottom 0.5th percentile						
with crisis	0.178	0.978	0.8	0.438	1.674	1.236
	(1.029)	**(6.323)**	**(3.856)**	(1.813)	**(7.448)**	**(4.46)**
without crisis	0.24	0.994	0.755	0.538	1.816	1.279
	(1.617)	**(6.543)**	**(5.435)**	**(2.307)**	**(8.225)**	**(5.676)**
Winsorize top 99.5th percentile						
with crisis	0.241	0.828	0.586	0.435	1.359	0.923
	(1.074)	**(5.434)**	**(2.133)**	(1.51)	**(6.134)**	**(2.608)**
without crisis	0.173	0.922	0.749	0.388	1.627	1.239
	(1.184)	**(6.166)**	**(5.229)**	(1.631)	**(7.475)**	**(5.146)**
Winsorize bottom 0.5th percentile						
with crisis	0.602	2.014	1.412	2.78	5.294	2.514
	(1.504)	**(4.829)**	**(3.79)**	**(2.096)**	**(3.762)**	**(4.434)**
without crisis	0.678	1.534	0.856	2.439	4.14	1.701
	(2.932)	**(6.316)**	**(5.702)**	**(2.876)**	**(4.752)**	**(5.995)**
Panel C: Removing outliers (percentile threshold)						
Removing top 99.5th percentile and bottom 0.5th percentile						
with crisis	0.012	0.678	0.665	0.014	0.935	0.922
	(0.101)	**(5.548)**	**(4.713)**	(0.08)	**(6.176)**	**(4.832)**
without crisis	0.072	0.725	0.653	0.094	1.069	0.975
	(0.592)	**(5.614)**	**(5.419)**	(0.524)	**(6.787)**	**(5.223)**
Removing top 99.5th percentile						
with crisis	0.475	0.561	0.086	0.743	0.704	-0.04
	(2.205)	**(4.207)**	(0.324)	**(2.534)**	**(4.124)**	(-0.11)
without crisis	0.068	0.682	0.614	0.142	0.952	0.81
	(0.533)	**(5.221)**	**(4.719)**	(0.739)	**(5.857)**	**(3.928)**
Removing bottom 0.5th percentile						
with crisis	0.441	1.47	1.03	2.427	4.028	1.601
	(1.769)	**(6.126)**	**(5)**	**(2.627)**	**(4.315)**	**(5.115)**
without crisis	0.622	1.341	0.719	2.398	3.538	1.14
	(3.218)	**(6.563)**	**(5.555)**	**(3.452)**	**(4.98)**	**(5.58)**
Panel D: Removing outliers (absolute threshold)						
Removing returns above 30% or below -30%						
with crisis	0.136	0.711	0.575	0.255	1.009	0.754
	(0.85)	**(5.305)**	**(2.975)**	(1.1)	**(5.737)**	**(2.769)**
without crisis	0.094	0.782	0.688	0.13	1.198	1.068

	P10-P1	Winner=P10	Loser=P1	P50-P1	Winner=P50	Loser=P1
	(0.702)	**(5.817)**	**(5.13)**	(0.633)	**(6.834)**	**(5.049)**
Removing returns above 30%						
with crisis	0.392	0.649	0.257	0.595	0.862	0.268
	(1.818)	**(4.663)**	(0.957)	**(2.057)**	**(4.59)**	(0.741)
without crisis	0.097	0.758	0.662	0.173	1.128	0.954
	(0.718)	**(5.635)**	**(4.849)**	(0.824)	**(6.376)**	**(4.323)**
Removing returns below -30%						
with crisis	0.253	1.497	1.244	1.667	3.958	2.291
	(0.762)	**(5.991)**	**(3.535)**	(1.894)	**(4.632)**	**(3.51)**
without crisis	0.59	1.42	0.83	2.076	3.675	1.599
	(2.936)	**(6.042)**	**(5.434)**	**(3.565)**	**(4.955)**	**(4.998)**

likely to be driven by individual returns.

When outliers are left untreated (Panel A), there are significant momentum returns in the sample excluding the crisis, for all four strategies. When the crisis is included in the sample, only the short-run portfolios are profitable, and only weakly for the decile-based strategy. The short-term P50-P1 portfolio yields the highest monthly momentum returns among the four momentum portfolios, at 2.9% and 2.45%, when the crisis is included or excluded from the sample, respectively.

Panel B in Tables 2 and 3 reports the calculated average momentum returns after winsorizing outliers at the 0.5th and 99.5th percentiles of the bond return distribution. When both tails of the return distribution are winsorized, momentum returns in the sample excluding the crisis period are rather similar to those calculated in the sample including the crisis. This similarity holds for both the short and long-run momentum portfolios based on either 10 or 50 quantiles. The same consistency also applies to the long and short legs of the four strategies.[15] Hence, winsorization yields a consistent assessment of momentum profitability with respect to the inclusion of the outlier cluster in the sample. We note that winsorizing returns results in a more conservative assessment of momentum profitability with respect to that yielded by untreated returns.

Panel C in Tables 2 and 3 report the momentum returns for outlier trimming, using the same cut-offs employed for winsorization. Two-sided trimming yields no momentum in the short and long terms, for both the P10-P1 and P50-P1 strategies, regardless of

[15] A mild discrepancy is that the returns on the long-run P50-P1 strategy are respectively weakly and strongly significant in the samples with and without the crisis.

whether the crisis is included in the sample. Note that removing these extreme returns denies the momentum gains found in the untreated sample both for the P10-P1 and P50-P1 strategies. The implication is that the profitability of the momentum strategy is due to the bonds yielding the extreme 1% of the return distribution.

One-sided treatments of outliers, while seen in the literature, are problematic, as they artificially change the degree of asymmetry of the return distribution. As reported in Panels B and C of Tables 2 and 3, removing or winsorizing only positive outliers generally reduces momentum gains. In contrast, treating only negative outliers boosts momentum profitability, with respect to the untreated sample.[16]

Panel D in Tables 2 and 3 tabulates the momentum gains obtained after removing outliers employing the +/-30% absolute cut-offs. Both for two-sided and one-sided treatments, the results yield conclusions that are similar to the ones obtained using the relative thresholds. The only exception is for the short-term P50-P1 strategy, which yields strongly significant profits when outliers are identified using the +/-30% cut-offs (in Panel D), but offers insignificant returns when outliers are identified using the percentile cut-offs (in Panel C), in the sample including the crisis. As the absolute thresholds identify fewer outliers than the relative cut-offs, this exception is consistent with the absolute thresholds retaining more bonds with extreme returns in the momentum portfolio, the impact of which is stronger for the P50-P1 strategy than for the remaining three portfolios, as extreme returns are averaged over fewer observations.

As shown in Tables 2 and 3, in the untreated sample momentum strategies based on 50 quantiles yields stronger momentum returns than the analogous decile-based strategies, both in the long and short runs, and in samples including and excluding the crisis. Outlier

[16]Jostova et al. (2013) trim returns falling above the 99.5th percentile of the return distribution, which corresponds to about 30% in their 1973-2011 bond sample (which includes TRACE). Focusing on the period common to their and our studies, the average monthly returns on the six-month momentum strategy differ by less than a bps (at 0.924% and 0.916%, respectively), when we also trim returns at the 99.5th percentile. Their monthly momentum returns for the six-month strategy are available at https://business.gwu.edu/gergana-jostova, courtesy of Professor G. Jostova.

treatments do not alter this conclusion.[17]

Hindrances to short-selling (e.g., Miller (1977)) may provide a possible explanation for price trends that are more drawn out for bonds with positive than negative outliers. If outliers are deviations from fundamentals, then a positive outlier is corrected by potentially expensive short positions, whereas an extreme negative return is corrected by going long, typically a cheaper option in terms of trading costs.

We conclude this section with a few comments on the effect of removal of outlier reversals, that is, of pairs of consecutive outliers of opposite sign, for the same bond.[18] Possibly due to the small number of outlier reversals in the sample, we find that removing them yields momentum returns that are very close to those observed in the untreated sample, as shown by Table A.4 in the appendix.

3 Credit Risk

Many studies have documented that the momentum effect in the corporate bond market is profitable only for non-investment-grade (NIG) bonds (e.g., Jostova et al., 2013). Given the small size of the NIG bond sample and the relatively short period covered by TRACE, the effect of outliers may be particularly severe on momentum returns in the low-grade sample.[19] Further, outliers are more prevalent for NIG bonds than in the whole-bond sample.[20] Therefore, we explore whether the momentum strategy's profitability is driven by outliers when sorting bonds by credit rating.

Table 4 reports estimated monthly returns for momentum strategies in the investment-

[17]Further, for winsorized returns, relying on the 50 quantiles brings about significant long-term momentum gains, which are absent for the P10-P1 strategy.

[18]Gebhardt et al. (2005) removes outlier reversals and ascribe them to reporting errors.

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

[20]For instance, using the +/-30% cut-offs, the share of outliers in the all-bond return sample is 0.4%, while the corresponding percentage for the NIG bond sample is 1.9%. For the 99.5th and 0.5th cut-offs, the share of outliers in the whole sample is, by definition, 1%, and the corresponding percentage for the NIG sample is 3.8% (untabulated results).

Table 4: Momentum Returns by Credit Risk (decile portfolios)

The table reports average monthly returns and their t-statistics (in bold significant at the 0.05% level) for the P10-P1 momentum strategies of short and long-term horizons, and corresponding winner and loser portfolios, for the investment-grade and non-investment-grade bonds, respectively, in the untreated sample and for outlier treatments based on relative and absolute cut-offs. Panel A displays results for the whole sample, and Panel B reports results for the sample excluding the financial crisis. The time period covered is from August 2002 to June 2017. The financial crisis period spans from May 2007 to December 2009.

	Investment-grade subsample						Non-investment-grade subsample					
	S(3,3)			S(6,6)			S(3,3)			S(6,6)		
	P10-P1	Winner=P10	Loser=P1	P10-P1	Winner=P10	Loser=P1	P10-P1	Winner=P10	Loser=P1	P10-P1	Winner=P10	Loser=P1
Panel A: August 2002 to June 2017												
Untreated returns												
Estimate	-0.123	0.602	0.725	-0.134	0.552	0.686	2.118	4.716	2.598	1.242	3.802	2.559
t-stat	(-0.899)	**(3.992)**	**(3.504)**	(-0.718)	**(4.207)**	**(2.968)**	**(2.146)**	**(5.086)**	**(3.223)**	(1.549)	**(5.396)**	**(3.157)**
Winsorizing top 99.5th percentile and bottom 0.5th percentile												
Estimate	-0.081	0.603	0.684	-0.106	0.539	0.644	0.784	2.004	1.22	0.638	1.828	1.19
t-stat	(-0.759)	**(4.343)**	**(4.265)**	(-0.826)	**(4.214)**	**(3.856)**	**(3.885)**	**(7.881)**	**(4.375)**	**(2.763)**	**(7.928)**	**(4.094)**
Winsorizing top 99.5th percentile												
Estimate	-0.028	0.56	0.587	-0.046	0.51	0.556	0.924	1.707	0.783	0.772	1.474	0.702
t-stat	(-0.232)	**(3.906)**	**(3.12)**	(-0.277)	**(4.028)**	**(2.658)**	**(3.071)**	**(6.509)**	**(1.982)**	**(2.329)**	**(6.308)**	**(1.704)**
Winsorizing bottom 0.5th percentile												
Estimate	-0.144	0.661	0.805	-0.124	0.612	0.736	2.39	5.194	2.804	1.816	4.383	2.568
t-stat	(-1.177)	**(4.424)**	**(4.413)**	(-0.913)	**(4.447)**	**(4.014)**	**(2.59)**	**(5.511)**	**(3.855)**	**(2.071)**	**(5.359)**	**(3.935)**
Removing top 99.5th percentile and bottom 0.5th percentile												
Estimate	-0.04	0.602	0.642	-0.097	0.515	0.613	0.248	1.278	1.03	0.216	1.098	0.883
t-stat	(-0.42)	**(4.847)**	**(4.897)**	(-0.928)	**(4.238)**	**(4.781)**	(1.766)	**(7.754)**	**(5.106)**	(1.585)	**(7.004)**	**(5.019)**
Removing top 99.5th percentile												
Estimate	0.036	0.521	0.485	0.045	0.482	0.438	1.17	0.919	-0.251	1.133	0.826	-0.306
t-stat	(0.331)	**(3.824)**	**(2.821)**	(0.303)	**(3.861)**	**(2.345)**	**(3.971)**	**(4.507)**	(-0.635)	**(3.698)**	**(4.438)**	(-0.771)
Removing bottom 0.5th percentile												
Estimate	-0.083	0.701	0.784	-0.168	0.58	0.748	3.277	5.134	1.857	1.953	3.608	1.654
t-stat	(-0.752)	**(5.181)**	**(5.113)**	(-1.309)	**(4.542)**	**(4.985)**	**(3.723)**	**(5.689)**	**(5.054)**	**(2.84)**	**(5.628)**	**(4.408)**
Removing returns above 30% or below -30%												
Estimate	-0.043	0.585	0.629	-0.086	0.516	0.602	0.609	1.341	0.732	0.523	1.149	0.626
t-stat	(-0.416)	**(4.39)**	**(4.068)**	(-0.683)	**(4.104)**	**(3.717)**	**(3.291)**	**(6.569)**	**(2.763)**	**(2.254)**	**(6.127)**	**(2.166)**
Removing returns above 30%												
Estimate	-0.006	0.55	0.556	-0.01	0.503	0.513	1.024	1.135	0.111	0.975	0.997	0.021
t-stat	(-0.052)	**(3.906)**	**(3.061)**	(-0.062)	**(3.972)**	**(2.564)**	**(3.464)**	**(5.038)**	(0.279)	**(3.122)**	**(4.885)**	(0.052)
Removing returns below -30%												
Estimate	-0.114	0.643	0.757	-0.167	0.558	0.725	2.341	4.884	2.544	1.208	3.592	2.384
t-stat	(-0.962)	**(4.555)**	**(4.421)**	(-1.134)	**(4.339)**	**(4.004)**	**(2.301)**	**(5.467)**	**(3.431)**	(1.503)	**(5.439)**	**(3.191)**
Panel B: Subsample excluding May 2007 to December 2009												
Untreated returns												
Estimate	-0.017	0.582	0.598	-0.016	0.53	0.546	2.629	4.617	1.988	1.867	3.92	2.053

	Investment-grade subsample						Non-investment-grade subsample					
	S(3,3)			S(6,6)			S(3,3)			S(6,6)		
	P10-P1	Winner=P10	Loser=P1	P10-P1	Winner=P10	Loser=P1	P10-P1	Winner=P10	Loser=P1	P10-P1	Winner=P10	Loser=P1
t-stat	(-0.158)	**(4.426)**	**(4.844)**	(-0.14)	**(3.917)**	**(4.963)**	**(2.597)**	**(4.493)**	**(5.121)**	**(3.128)**	**(5.047)**	**(5.18)**
Winsorizing top 99.5th percentile and bottom 0.5th percentile												
Estimate	-0.011	0.568	0.579	-0.04	0.505	0.546	0.705	2.055	1.35	0.631	1.974	1.343
t-stat	(-0.103)	**(4.377)**	**(4.761)**	(-0.371)	**(3.808)**	**(4.997)**	**(3.572)**	**(8.96)**	**(5.985)**	**(3.2)**	**(9.012)**	**(6.249)**
Winsorizing top 99.5th percentile												
Estimate	-0.011	0.564	0.575	-0.045	0.502	0.547	0.674	1.853	1.179	0.567	1.786	1.22
t-stat	(-0.103)	**(4.339)**	**(4.708)**	(-0.414)	**(3.779)**	**(4.984)**	**(3.192)**	**(7.997)**	**(4.764)**	**(2.701)**	**(8.165)**	**(5.107)**
Winsorizing bottom 0.5th percentile												
Estimate	-0.017	0.586	0.603	-0.013	0.533	0.547	2.809	4.895	2.086	2.496	4.362	1.866
t-stat	(-0.163)	**(4.464)**	**(4.9)**	(-0.117)	**(3.944)**	**(4.984)**	**(2.762)**	**(4.74)**	**(5.706)**	**(2.758)**	**(4.77)**	**(6.07)**
Removing top 99.5th percentile and bottom 0.5th percentile												
Estimate	-0.013	0.564	0.578	-0.047	0.5	0.546	0.265	1.414	1.149	0.236	1.266	1.03
t-stat	(-0.129)	**(4.36)**	**(4.89)**	(-0.435)	**(3.759)**	**(5.138)**	(1.93)	**(8.568)**	**(6.528)**	(1.9)	**(8.156)**	**(6.966)**
Removing top 99.5th percentile												
Estimate	-0.011	0.555	0.566	-0.048	0.492	0.54	0.517	1.199	0.682	0.388	1.122	0.734
t-stat	(-0.102)	**(4.284)**	**(4.679)**	(-0.448)	**(3.701)**	**(5)**	**(3.187)**	**(6.923)**	**(3.25)**	**(2.668)**	**(6.884)**	**(3.984)**
Removing bottom 0.5th percentile												
Estimate	-0.017	0.59	0.607	-0.006	0.546	0.552	3.341	4.801	1.46	2.589	3.842	1.253
t-stat	(-0.163)	**(4.498)**	**(5.045)**	(-0.05)	**(3.964)**	**(5.102)**	**(3.349)**	**(4.702)**	**(7.217)**	**(3.487)**	**(5.067)**	**(7.278)**
Removing returns above 30% or below -30%												
Estimate	-0.012	0.564	0.575	-0.044	0.5	0.544	0.382	1.502	1.12	0.304	1.379	1.075
t-stat	(-0.109)	**(4.349)**	**(4.719)**	(-0.408)	**(3.768)**	**(4.974)**	**(2.317)**	**(7.858)**	**(5.323)**	**(1.996)**	**(7.772)**	**(5.78)**
Removing returns above 30%												
Estimate	-0.012	0.56	0.573	-0.047	0.497	0.544	0.439	1.368	0.929	0.407	1.304	0.897
t-stat	(-0.117)	**(4.315)**	**(4.69)**	(-0.436)	**(3.745)**	**(4.97)**	**(2.362)**	**(6.994)**	**(4.009)**	**(2.388)**	**(7.222)**	**(4.345)**
Removing returns below -30%												
Estimate	-0.016	0.585	0.601	-0.014	0.532	0.546	2.902	4.735	1.834	2.163	3.908	1.745
t-stat	(-0.155)	**(4.459)**	**(4.875)**	(-0.125)	**(3.93)**	**(4.968)**	**(2.879)**	**(4.627)**	**(5.506)**	**(3.688)**	**(5.02)**	**(5.153)**

grade and low-grade samples, for the short and long-term decile portfolios.[21] The results confirm the finding documented in the literature (e.g., Jostova et al. (2013) and Gebhardt et al. (2005)) that investment-grade bonds do not yield significant momentum gains.[22]

Momentum in NIG bonds is significant for most outlier treatments, regardless of whether the crisis period is included or excluded from the sample. Momentum gains turn only weakly significant, however, when removing outliers using the 0.5th and 99.5th percentiles of the return distribution, a treatment that excludes more outliers than using the +30% cut-offs. Using absolute thresholds to remove outliers yields momentum gains that are strongly significant. One-sided treatments confirm that trimming positive outliers yields momentum gains that are lower than those obtained by removing negative outliers. Hence, the momentum returns in the NIG sample also support the view that positive outliers are better than negative ones at identifying bonds that are likely to display return continuation. In contrast, as already suggested by outliers' summary statistics, negative outliers are more prone to identify bonds which may reverse during the holding period.

The NIG decile-based strategies yield average momentum gains that are comparable to those offered by the P50-P1 strategies, in the untreated sample (Panel A of Tables 2 and 3). This similarity is surprising given that, on average, P50-P1 portfolios include a large share of IG bonds, as shown in Table 5, and there is no evidence of momentum profitability for high-grade bonds. The high returns of the P50-P1 strategy do not come at the cost of higher exposure to idiosyncratic risk. As reported in the appendix (e.g., Table A.1), the P50-P1 strategies are slightly more well-diversified than the decile-based NIG-bond portfolios both in terms of the average number of bonds included in each leg of the momentum portfolio and the number of issuers there represented.

[21] The winner and loser decile portfolios include at least 44 bonds in the NIG bond sample. However, their analogs for the P50-P1 strategies each contain an average of fewer than 15 bonds, a level that is too low to rule out the possibility that the assessment of momentum profitability is driven by idiosyncratic risk. As such, the P50-P1 strategies are not discussed for the NIG sample.

[22] In untabulated results, we find that also the returns on the P50-P1 strategies in IG bonds fail to alter this conclusion.

Table 5: Shares of NIG and IG bonds in P50 and P1 Portfolios

The first column reports the average, over months, of the number of bonds included in the long and short legs of the 3 and 6-month P50-P1 strategy, in the untreated sample. Next, the table reports the minimum and average of the share of high and low-grade included in the winner and loser portfolios. The time period covered is from August 2002 to June 2017.

	N.bond	minimum		mean	
		NIG share	IG share	NIG share	IG share
3-m P50	97	4.59	0	63.03	30.89
3-m P1	97	2.54	0	43.13	52.21
6-m P50	88	2.88	0	68.40	27.03
6-m P1	88	2.11	0	45.46	50.24

Hence, this study suggests that relying on a finer partition of the cross-section to design momentum strategies yields profits comparable to those offered by NIG momentum portfolios, where both approaches yield portfolios with a sufficiently large number of bonds presume the diversification of bond and firm-level idiosyncratic risk. The advantage of the 50-quantile strategies is that, on average, it requires shorting fewer low-grade bonds.

4 Price Outliers and Momentum

In TRACE, prices are reported as percentage of par. From this perspective, prices that are either very small or very large raise concerns of errors in data. If price outliers are noise, removing them from the sample could increase statistical accuracy. The approach of removing extreme price levels from the sample has already been used in the literature. For instance, using TRACE data, Han and Zhou (2013) remove prices outside the range of \$10 to \$500, while Lin et al. (2017) rely on the \$50-\$150 range, for a longer sample of corporate bonds.

To evaluate the impact of filtering extreme price levels on momentum profitability, we eliminate prices falling below the 0.5th and above the 99.5th percentiles of the price distribution, where the corresponding price thresholds are about 25% and 141% of par value, respectively.[23]

Panels A and B of Table 6 report momentum returns after filtering price levels at the 0.5th and 99.5th percentiles of the price distribution, when the 2007-2009 crisis period is either included in or excluded from the sample, respectively. The first rows of the same panels report the corresponding momentum returns in the untreated sample for comparison.

The results show that excluding 1% of the prices vanishes momentum gains for all strategies, both when the crisis period is included in, or excluded from, the sample. These results imply that extreme price levels are essential to the profitability of the momentum effect, in the corporate bond market.[24]

As shown in Tables 2 and 3, trimming return outliers eliminates momentum gains, for all strategies, both when the crisis is included in or excluded from the sample. In our sample, the vast majority of outliers stems from the impact of price movements on very low price levels.[25] Hence, the absence of momentum profits observed when return outliers are trimmed suggests that the vanishing of momentum when trimming very high and very low prices may be the consequence of the exclusion of only very low prices. The results, reported in Panels A and B of Table 6, confirm that momentum gains disappear only when low prices are removed. In contrast, removing prices above the 99.5th percentile of the price distribution yields momentum returns that are virtually identical to those detected in the untreated sample. Hence, short and long-run momentum gains are driven by prices lower than 25% of par value.

Hong and Sraer (2013) argues that the payoff of debt becomes more responsive to

[23] In untabulated results, we find that the price-level filter leaves 98.8% of the returns in the sample. The maximum (minimum) bond return in the price-level filtered sample is 197.6% and -67.8%.

[24] We have also experimented with a less restrictive filter using the 0.05th and 99.95th percentiles, corresponding to price-level thresholds of about 0.16% and 157% of par value, which keeps 99.88% of the returns. The results for the two filters are very similar but for a significant return on the short-term decile-based strategy in the sample excluding the crisis, using the less restrictive price filter. The remaining strategies yield insignificant momentum gains for both price filters for the samples including and excluding the crisis (untabulated).

[25] When a bond yields an outlier, its initial price is on average (median) only 66% (60%) of the average price of the same bond, over time (untabulated).

information when prices are low rather than high. From this perspective, the finding that momentum gains are associated with low bond prices, but not with high bond prices, is not unexpected, as it is consistent with information originating the momentum effect, as theorized in Hong and Stein (1999).

Lastly, as we are on a safer ground arguing that extremely high prices may be errors than prices on the left tail, given the bounded payoff of debt, we cannot conclude that price reporting errors are the main source of momentum returns.

4.1 Volume Filters on Prices

Some bonds trade very infrequently and attract very low trading volume. It is therefore possible that momentum profitability does depend on illiquid bond-month combinations. To explore this possibility, we remove from the sample the monthly price of bonds with extremely low monthly trading volume, using the 0.5th percentile of the monthly volume distribution, namely $5,000.[26] In untabulated results, we find that removing prices supported by very low trading volume does not substantially alter the severity and frequency of outliers.[27]

Panels C and D of Table 6 report momentum returns after filtering prices supported by levels of trading volume below the 0.5th percentile, in the sample including and excluding the crisis. The results show that this low-volume price filter has virtually no impact on the momentum effect, which is expected, given its very moderate impact on the return and outlier samples.

A conservative estimate of the volume threshold to identify transactions of retail investors is $100,000 (e.g., Edwards et al. (2007)). Thus, we experiment with removing prices supported by a monthly volume lower than $100,000, a level corresponding to

[26] Prices are removed from the sample before calculating returns. If the price of a bond is trimmed in a given month, then the bond-level returns for the previous and following months are marked as missing.

[27] For instance, we find that the maximum (minimum) bond return in the price-volume filtered sample is 1,958% (-98%) when filtering prices at the 0.5th percentiles of the volume distribution. The filter retains 99.14% of the returns (untabulated).

Table 6: Filtering Prices by Level and Trading Volume

The table reports average monthly returns and t-statistics (in bold when significant at the 0.05% level) for the short and long-term P10-P1 and P50-P1 momentum strategies, and their winner and loser components, in the untreated sample, and when bond returns are calculated after filtering prices based on trading volume or level, respectively. To filter on price levels, monthly prices are removed, at the 0.5th and 99.5th percentiles of the price distribution, and only at the 0.5th percentile, in the last row. For volume-based price filtering, a price is removed from the sample if it is supported by a monthly trading volume below the 0.5th percentile of the monthly volume distribution, and if supported by a monthly volume lower than $100,000. Panel A displays results for the whole sample, and Panel B reports results for the sample excluding the crisis. The time period covered is from August 2002 to June 2017. The crisis period spans from May 2007 to December 2009.

		S(3,3)			S(6,6)			S(3,3)			S(6,6)	
	P10-P1	Winner=P10	Loser=P1	P10-P1	Winner=P10	Loser=P1	P50-P1	Winner=P50	Loser=P1	P50-P1	Winner=P50	Loser=P1
Panel A: Price-level Filters: August 2002 to June 2017												
Untreated Sample												
Estimate	0.729	1.972	1.243	0.491	1.787	1.296	2.905	5.427	2.522	2.14	4.772	2.632
t-stat	(1.941)	**(4.946)**	**(3.257)**	(1.215)	**(4.508)**	**(3.076)**	**(2.235)**	**(3.974)**	**(3.971)**	(1.712)	**(3.506)**	**(4.143)**
Filter price at (0.5%, 99.5%)												
Estimate	0.069	0.928	0.859	-0.056	0.784	0.84	0.019	1.342	1.323	-0.311	1.067	1.378
t-stat	(0.406)	**(5.31)**	**(3.52)**	(-0.251)	**(5.306)**	**(3.058)**	(0.082)	**(5.177)**	**(4.058)**	(-1.087)	**(5.281)**	**(3.878)**
Filter price at 0.5%												
Estimate	0.085	0.975	0.89	-0.051	0.792	0.842	0.137	1.574	1.436	-0.327	1.055	1.382
t-stat	(0.475)	**(5.366)**	**(3.616)**	(-0.226)	**(5.324)**	**(3.068)**	(0.391)	**(4.377)**	**(4.16)**	(-1.143)	**(5.255)**	**(3.893)**
Filter price at 99.5%												
Estimate	0.716	1.929	1.213	0.491	1.783	1.293	2.802	5.214	2.412	2.17	4.803	2.633
t-stat	(1.925)	**(4.864)**	**(3.19)**	(1.214)	**(4.495)**	**(3.068)**	**(2.204)**	**(3.881)**	**(3.852)**	(1.734)	**(3.523)**	**(4.141)**
Panel B: Price-level Filters: Subsample excluding May 2007 to December 2009												
Untreated Sample												
Estimate	0.635	1.579	0.944	0.551	1.447	0.896	2.45	4.338	1.889	1.802	3.728	1.926
t-stat	**(2.775)**	**(6.387)**	**(5.614)**	**(2.688)**	**(6.052)**	**(5.572)**	**(2.563)**	**(4.477)**	**(5.176)**	**(3.096)**	**(5.026)**	**(5.349)**
Filter price at (0.5%, 99.5%)												
Estimate	0.136	0.916	0.781	0.063	0.81	0.747	0.147	1.373	1.226	-0.106	1.162	1.268
t-stat	(1.017)	**(6.517)**	**(5.275)**	(0.446)	**(5.819)**	**(5.165)**	(0.694)	**(6.617)**	**(5.188)**	(-0.479)	**(6.42)**	**(5.083)**
Filter price at 0.5%												
Estimate	0.156	0.974	0.818	0.07	0.82	0.75	0.292	1.655	1.364	-0.124	1.149	1.273
t-stat	(1.034)	**(6.351)**	**(5.332)**	(0.492)	**(5.828)**	**(5.191)**	(0.754)	**(4.492)**	**(4.965)**	(-0.565)	**(6.418)**	**(5.116)**
Filter price at 99.5%												
Estimate	0.619	1.527	0.907	0.551	1.443	0.892	2.329	4.083	1.754	1.838	3.765	1.927
t-stat	**(2.815)**	**(6.317)**	**(5.574)**	**(2.669)**	**(6.01)**	**(5.54)**	**(2.58)**	**(4.408)**	**(5.178)**	**(3.133)**	**(5.036)**	**(5.337)**
Panel C: Volume Filters: August 2002 to June 2017												
Filter volume at 0.5%												
Estimate	0.727	1.975	1.248	0.487	1.785	1.298	2.874	5.416	2.542	2.112	4.765	2.653
t-stat	(1.915)	**(4.902)**	**(3.239)**	(1.187)	**(4.438)**	**(3.053)**	**(2.197)**	**(3.937)**	**(3.97)**	**(1.662)**	**(3.44)**	**(4.128)**
Filter volume below 100K												

	S(3,3)			S(6,6)			S(3,3)			S(6,6)		
	P10-P1	Winner=P10	Loser=P1	P10-P1	Winner=P10	Loser=P1	P50-P1	Winner=P50	Loser=P1	P50-P1	Winner=P50	Loser=P1
Estimate	0.507	1.704	1.196	0.19	1.478	1.287	1.748	4.186	2.437	0.792	3.464	2.672
t-stat	(1.486)	**(5.552)**	**(3.019)**	(0.509)	**(5.523)**	**(2.984)**	(1.726)	**(4.223)**	**(3.698)**	(1.021)	**(4.489)**	**(3.878)**
Panel D: Volume Filters: Subsample excluding May 2007 to December 2009												
Filter volume at 0.5%												
Estimate	0.632	1.578	0.946	0.542	1.438	0.896	2.402	4.3	1.897	1.749	3.695	1.946
t-stat	**(2.739)**	**(6.322)**	**(5.592)**	**(2.621)**	**(5.962)**	**(5.537)**	**(2.527)**	**(4.454)**	**(5.141)**	**(2.986)**	**(4.889)**	**(5.259)**
Filter volume below 100K												
Estimate	0.606	1.529	0.923	0.508	1.425	0.917	2.249	4.028	1.779	1.581	3.582	2.002
t-stat	**(2.366)**	**(5.558)**	**(5.343)**	**(2.221)**	**(5.269)**	**(5.321)**	**(2.047)**	**(3.591)**	**(4.809)**	**(2.277)**	**(4.065)**	**(5.202)**

about the 10th percentile of the distribution of monthly trading volumes. To provide an intuition for this exercise, in each month we exclude prices of bonds that are traded in corners of the market in which only retail investors operate.[28]

The results in Panels C and D of Table 6 show that trimming volumes below $100,000 does not affect the profitability of the momentum effect, with respect to using the untreated sample, but only when the crisis is excluded from the sample. When the crisis is included, momentum gains are absent for all the strategies considered. In particular, momentum gains disappear even for the short-term P50-P1 portfolio, which typically unearths strong momentum profits. The implication is that retail investors' trading activities significantly contributed to the momentum strategy's profitability during the crisis period.

5 Conclusions

This study examines how different treatments of return outliers affect the assessment of momentum profitability in the corporate bond TRACE sample. Our findings highlight that return outliers lie at the core of the profitability of the momentum strategy. One-sided outlier treatments indicate that positive outliers tend to increase momentum gains, whereas negative ones tend to weaken the momentum effect. A possible explanation of the preeminent role of positive outliers in determining the momentum effect is that the associated mispricing is harder to correct than that of low returns, due to impediments to short selling.

We document that trimming extreme returns has some undesirable features, among which the potential of reducing the pool of bonds that might experience the price trend

[28] This filter results in about 13.7% of bond returns being dropped from the sample. Removing all trades below $100,000 to increases statistical accuracy (e.g., Bessembinder et al., 2008) would drop more monthly returns. However, from the perspective of studying momentum, it is unclear why small investors' trades should be trimmed, as both informed and uninformed agents might contribute to the momentum profitability (e.g., Hong and Stein, 1999).

continuation on which the momentum strategy profits. In periods marked by a high concentration of outliers, this effect is mirrored by a sharp decrease 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. In contrast, winsorization raises fewer concerns than trimming as a method to deal with outliers.

Lastly, this study makes a strong case for using finer partitions than deciles for momentum strategies in corporate bonds. Finer partitions allow for a sharper juxtaposition of past winners and losers, which enhances momentum profitability. We find that using 50 quantiles strongly improves momentum profitability while maintaining risk diversification. Portfolios based on sorting the all-bond cross-section into 50 quantiles outperform the familiar decile-based momentum strategies in low-rating bonds, while including a sufficiently large number of bond/issuer combinations to presume the diversification of idiosyncratic risk. A distinctive cost advantage of the 50-quantile strategies is that it requires shorting fewer low-grade bonds than pure NIG-bond momentum strategies.

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Appendix

Diversification of Finer Partition Strategies

A consideration when deciding the fineness of the partition that defines a momentum strategy is that the winner and loser portfolios should include sufficiently many securities to diversify idiosyncratic risk. For bond momentum strategies, an additional concern is the number of issuers represented in the winner and loser portfolios, as same-issuer bonds are subject to the same firm-level shocks.

Concerns about poor diversification are fully unwarranted for decile-based bond strategies. As shown in Table A.1, the number of bonds classified as winners and losers of the decile-based momentum strategy is consistently large in all the months in the sample. For the short-term momentum strategy, there is a minimum (average) of 386 (485) bonds in each of the top and bottom deciles. For the long-term strategy, the corresponding minimum (average) is 356 (439) bonds. The winner and loser portfolios, on average, include bonds issued by more than two-hundred firms and account for a minimum of sixty issuers per month.

The diversification of strategies based on partitions finer than deciles is unlikely to be self-evident. We thus discuss the diversification afforded by the P50-P1 strategies by comparing them against the momentum portfolios that are used in the literature to analyze the momentum effect in the corporate bond and equity markets. For bonds, the yardsticks are the decile-based momentum strategy in low-grade bonds. For equities, we refer to the diversification assessment of the decile-based momentum strategy for US stocks presented in Asness et al. (2013).

Our results show that concerns of poor portfolio diversification are unwarranted also for strategies based on partitions of the cross-section finer than deciles. On average, there are 97 and 88 bonds in each of the winner (and loser) portfolios for the short and long-term

Table A.1: Number of Bond and Issuers in Momentum Portfolios

The table reports the average, minimum and maximum (over months) of the bonds included in the winner and loser portfolios, and of their issuers, for the momentum strategies with formation and holding periods of three and six months. The time period covered is from August 2002 to June 2017.

	mean		minimum		maximum	
	bondN	firmN	bondN	firmN	bondN	firmN
			Whole P10-P1			
3m-winners	485.1	244.9	386	87	598	341
3m-losers	485.2	246.6	386	65	598	346
6m-winners	439.1	213.4	356	71	547	307
6m-losers	439.2	216.6	356	62	547	310
			Whole P20-P1			
3m-winners	242.5	131.1	193	24	299	190
3m-losers	242.6	137.4	193	30	299	198
6m-winners	219.5	112.4	178	18	273	179
6m-losers	219.6	119.4	178	27	274	173
			Whole P30-P1			
3m-winners	161.7	90.1	129	16	199	136
3m-losers	161.7	96.3	129	16	199	138
6m-winners	146.4	78.0	119	14	182	128
6m-losers	146.4	83.5	119	16	182	123
			Whole P50-P1			
3m-winners	97.0	56.9	77	13	120	90
3m-losers	97.1	61.0	77	12	120	92
6m-winners	87.8	49.1	71	11	109	88
6m-losers	87.8	52.2	71	11	109	80
			NIG P10-P1			
3m-winners	86.4	44.1	61	7	117	81
3m-losers	86.5	50.3	62	11	117	79
6m-winners	78.5	38.6	57	4	108	76
6m-losers	78.6	45.3	57	9	108	70

P50-P1 strategies, respectively.[29] Further, for the P50-P1 strategy, the average number of issuers for the short-term winner and loser portfolios are 57 and 61. The corresponding averages for the long-term strategy are 49 and 52 issuers.

To compare against our first diversification benchmark, in the NIG-bond sample the decile-based winner and loser portfolios of the short- and long-term strategies include on average 86 and 79 bonds, respectively. The NIG-bonds included in the decile-based winner and loser portfolios are issued by an average of 44 and 50 firms for the short-term strategy and 39 and 45 firms for the long-term portfolio. Hence, the P50-P1 strategies are slightly more well-diversified than the decile-based NIG-bond portfolios both in terms of

[29]Using 20 and 30 quantiles yields portfolios that, by design, are more diversified than the P50-P1 strategies.

the average number of bonds included in each leg of the momentum portfolio and the number of issuers there represented.[30]

In their analysis of equity momentum in the US, Asness et al. (2013) find that the minimum (average) number of stocks in each decile is about 35 (70) per month. As shown in Table A.1, the P50-P1 strategy is more diversified than this benchmark equity momentum strategy in terms of the average and minimum number of bonds included in the winner and loser portfolios. The equity and bond momentum strategies are also comparably diversified in terms of the average number of firms represented in either leg of the momentum portfolio. However, a difference is that the minimum number of issuers for the P50-P1 portfolio is lower, resting at about a dozen issuers. Specifically, we find that in about 15% of the months, the P50-P1 strategy includes bonds issued by less than 35 issuers (untabulated). In these months, the winner and loser portfolios of the P50-P1 strategy are less diversified on firms than the equity momentum portfolio.[31]

Overall, our findings indicate that, with the potential exception of periods of extreme market turmoil, finer partitions deliver portfolio diversification levels that are superior or at least comparable to those offered by the benchmark momentum portfolios for equities.

We do not experiment with partitions finer than deciles in the NIG-bond sample, as they yield strategies that are unlikely to deliver acceptable levels of portfolios diversification.

Alternative Momentum Strategies

[30]Focusing on the minimum number of bonds included in the winner and loser portfolios fails to alter this conclusion.

[31]The months in which we find weaker diversification on issuers about coincide, being mostly concentrated over the months between the summer of 2008 and the winter of 2009 (untabulated results). An explanation of why exceptional bond returns were offered by fewer firms than average over the financial crisis is left for future investigation.

Table A.2: 3-month Formation and Holding Periods Momentum Returns (20 and 30 quantiles)

The table tabulates average monthly returns and their t-statistics (in bold when significant at the 0.05% level) for the 3-month formation and holding period momentum strategy and corresponding winner and loser portfolios by sorting bonds into 20 and 30 quantiles, for the whole sample and for the subsample obtained excluding the financial crisis period, respectively. Panel A reports momentum returns without any treatment of outliers. Panel B displays results based on two-sided and one-sided outlier winsorization with percentile thresholds at 99.5% and 0.5% of the return distribution. Panels C and D report the corresponding results for the removal of outliers based on the percentile thresholds at 99.5% and/or 0.5% and the absolute cut-offs of 30% and/or -30%, respectively. The time period covered is from August 2002 to June 2017. The financial crisis period spans from May 2007 to December 2009.

	P20-P1	Winner=P20	Loser=P1	P30-P1	Winner=P30	Loser=P1
Panel A: Untreated returns						
with crisis	1.337	3.022	1.685	1.885	3.903	2.019
	(2.178)	**(4.583)**	**(3.413)**	**(2.245)**	**(4.353)**	**(3.627)**
without crisis	1.13	2.388	1.258	1.616	3.101	1.485
	(2.794)	**(5.642)**	**(5.406)**	**(2.791)**	**(5.168)**	**(5.31)**
Panel B: Winsorized returns						
Winsorize top 99.5th percentile and bottom 0.5th percentile						
with crisis	0.423	1.387	0.964	0.52	1.576	1.056
	(2.315)	**(6.912)**	**(4.238)**	**(2.616)**	**(7.24)**	**(4.362)**
without crisis	0.383	1.363	0.98	0.486	1.573	1.087
	(2.184)	**(7.725)**	**(5.393)**	**(2.496)**	**(8.017)**	**(5.434)**
Winsorize top 99.5th percentile						
with crisis	0.529	1.19	0.661	0.616	1.346	0.73
	(2.263)	**(5.676)**	**(2.172)**	**(2.392)**	**(5.783)**	**(2.226)**
without crisis	0.334	1.261	0.927	0.429	1.435	1.006
	(1.88)	**(7.19)**	**(4.9)**	**(2.149)**	**(7.34)**	**(4.799)**
Winsorize bottom 0.5th percentile						
with crisis	1.51	3.344	1.834	2.144	4.286	2.143
	(2.474)	**(4.993)**	**(3.839)**	**(2.553)**	**(4.745)**	**(3.843)**
without crisis	1.285	2.515	1.231	1.845	3.291	1.446
	(3.211)	**(5.914)**	**(5.744)**	**(3.216)**	**(5.442)**	**(5.74)**
Panel C: Removing outliers (percentile threshold)						
Removing top 99.5th percentile and bottom 0.5th percentile						
with crisis	0.116	0.977	0.861	0.138	1.065	0.927
	(0.845)	**(7.11)**	**(5.092)**	(0.922)	**(7.367)**	**(5.106)**
without crisis	0.138	1.005	0.867	0.161	1.103	0.942
	(0.972)	**(7.173)**	**(5.512)**	(1.036)	**(7.409)**	**(5.515)**
Removing top 99.5th percentile						
with crisis	0.673	0.733	0.061	0.772	0.774	0.002
	(2.774)	**(4.34)**	(0.196)	**(2.928)**	**(4.245)**	(0.005)
without crisis	0.193	0.906	0.713	0.254	0.978	0.724
	(1.258)	**(6.409)**	**(4.145)**	(1.498)	**(6.454)**	**(3.849)**
Removing bottom 0.5th percentile						
with crisis	1.757	3.099	1.342	2.545	4.069	1.524
	(2.972)	**(4.917)**	**(5.335)**	**(2.973)**	**(4.517)**	**(5.426)**
without crisis	1.417	2.432	1.016	2.018	3.163	1.146
	(3.573)	**(5.835)**	**(5.939)**	**(3.534)**	**(5.344)**	**(6.073)**
Panel D: Removing outliers (absolute threshold)						
Removing returns above 30% or below -30%						
with crisis	0.303	1.015	0.712	0.361	1.111	0.75
	(1.852)	**(6.179)**	**(3.361)**	**(2.016)**	**(6.308)**	**(3.279)**
without crisis	0.187	1.075	0.888	0.222	1.191	0.968
	(1.172)	**(7.035)**	**(5.034)**	(1.269)	**(7.19)**	**(5)**
Removing returns above 30%						
with crisis	0.592	0.882	0.29	0.676	0.948	0.273
	(2.494)	**(4.822)**	(0.947)	**(2.617)**	**(4.774)**	(0.825)
without crisis	0.198	1.013	0.815	0.25	1.112	0.862
	(1.194)	**(6.594)**	**(4.479)**	(1.35)	**(6.661)**	**(4.284)**

	P20-P1	Winner=P20	Loser=P1	P30-P1	Winner=P30	Loser=P1
Removing returns below -30%						
with crisis	1.345	2.987	1.641	1.937	3.894	1.956
	(2.202)	**(4.795)**	**(3.775)**	**(2.241)**	**(4.473)**	**(3.689)**
without crisis	1.233	2.424	1.19	1.755	3.156	1.401
	(3.063)	**(5.76)**	**(5.505)**	**(3.035)**	**(5.285)**	**(5.493)**

Table A.3: 6-month Formation and Holding Periods Momentum Returns (20 and 30 quantiles)

The table tabulates average monthly returns and their unadjusted t-statistics (in bold when significant at the 0.05% level) for the 6-month formation and holding period momentum strategy and corresponding winner and loser portfolios by sorting bonds into 20 and 30 quantiles, for the whole sample and for the subsample obtained excluding the financial crisis period, respectively. Panel A reports momentum returns without any treatment of outliers. Panel B displays results based on two-sided and one-sided outlier winsorization with the percentile thresholds at 99.5% and 0.5% of the return distribution. Panels C and D report corresponding results for the removal of outliers based on the percentile thresholds at 99.5% and/or 0.5% and the absolute cut-offs of 30% and/or -30%, respectively. The time period covered is from August 2002 to June 2017. The financial crisis period spans from May 2007 to December 2009.

	P20-P1	Winner=P20	Loser=P1	P30-P1	Winner=P30	Loser=P1
Panel A: Untreated returns						
with crisis	0.957	2.719	1.762	1.374	3.46	2.087
	(1.437)	**(3.955)**	**(3.235)**	(1.576)	**(3.726)**	**(3.517)**
without crisis	0.935	2.157	1.222	1.261	2.739	1.478
	(2.811)	**(5.424)**	**(5.358)**	**(2.756)**	**(4.944)**	**(5.434)**
Panel B: Winsorized returns						
Winsorize top 99.5th percentile and bottom 0.5th percentile						
with crisis	0.262	1.227	0.965	0.33	1.4	1.07
	(1.267)	**(6.673)**	**(3.967)**	(1.473)	**(6.963)**	**(4.1)**
without crisis	0.327	1.283	0.957	0.391	1.483	1.092
	(1.739)	**(7.114)**	**(5.274)**	(1.89)	**(7.553)**	**(5.415)**
Winsorize top 99.5th percentile						
with crisis	0.323	1.011	0.688	0.368	1.143	0.775
	(1.221)	**(5.587)**	**(2.136)**	(1.314)	**(5.756)**	**(2.263)**
without crisis	0.223	1.17	0.947	0.274	1.344	1.07
	(1.197)	**(6.636)**	**(4.998)**	(1.319)	**(6.949)**	**(5.042)**
Winsorize bottom 0.5th percentile						
with crisis	1.123	3.004	1.881	1.654	3.809	2.155
	(1.728)	**(4.363)**	**(3.834)**	(1.894)	**(4.111)**	**(3.968)**
without crisis	1.141	2.279	1.138	1.59	2.937	1.347
	(2.961)	**(5.728)**	**(5.584)**	**(2.939)**	**(5.274)**	**(5.733)**
Panel C: Removing outliers (percentile threshold)						
Removing top 99.5th percentile and bottom 0.5th percentile						
with crisis	0.01	0.776	0.766	0.006	0.836	0.83
	(0.064)	**(5.779)**	**(4.553)**	(0.038)	**(5.9)**	**(4.6)**
without crisis	0.07	0.856	0.786	0.076	0.941	0.866
	(0.465)	**(6.086)**	**(5.068)**	(0.458)	**(6.38)**	**(5.065)**
Removing top 99.5th percentile						
with crisis	0.6	0.61	0.01	0.673	0.641	-0.032
	(2.294)	**(4.062)**	(0.032)	**(2.393)**	**(4.016)**	(-0.094)
without crisis	0.069	0.786	0.717	0.089	0.851	0.762
	(0.436)	**(5.476)**	**(4.227)**	(0.511)	**(5.611)**	**(4.098)**
Removing bottom 0.5th percentile						
with crisis	0.967	2.209	1.242	1.498	2.854	1.356
	(2.33)	**(5.381)**	**(4.901)**	**(2.574)**	**(4.851)**	**(4.954)**
without crisis	1.111	1.99	0.879	1.556	2.543	0.987
	(3.47)	**(6.053)**	**(5.228)**	**(3.481)**	**(5.554)**	**(5.305)**
Panel D: Removing outliers (absolute threshold)						

	P20-P1	Winner=P20	Loser=P1	P30-P1	Winner=P30	Loser=P1
Removing returns above 30% or below -30%						
with crisis	0.19	0.821	0.631	0.223	0.894	0.671
	(0.969)	**(5.418)**	**(2.723)**	(1.049)	**(5.531)**	**(2.688)**
without crisis	0.098	0.94	0.842	0.108	1.041	0.932
	(0.577)	**(6.225)**	**(4.827)**	(0.584)	**(6.481)**	**(4.854)**
Removing returns above 30%						
with crisis	0.493	0.729	0.236	0.554	0.779	0.225
	(1.894)	**(4.573)**	(0.734)	**(1.994)**	**(4.539)**	(0.652)
without crisis	0.108	0.902	0.794	0.123	0.99	0.867
	(0.632)	**(5.954)**	**(4.45)**	(0.658)	**(6.143)**	**(4.4)**
Removing returns below -30%						
with crisis	0.606	2.244	1.639	0.975	2.876	1.901
	(1.156)	**(5.338)**	**(3.318)**	(1.449)	**(4.855)**	**(3.303)**
without crisis	1.04	2.128	1.087	1.425	2.701	1.276
	(3.146)	**(5.404)**	**(5.128)**	**(3.119)**	**(4.892)**	**(5.124)**

Filtering out Return Reversal

Table A.4 illustrates the effect of removing return reversals. The results show that removing reversals yields momentum returns that are very close to those observed in the untreated sample.

Return Sample and the Last-five-day Price Filer

In this study, we calculate returns using the last-available price filter as in Li and Galvani (2021), rather than relying on the last price falling in the last five of the month, as in Jostova et al. (2013). A comparison between the two return samples obtained using these methodologies can be found in Li and Galvani (2021). For the purpose of this study, it suffices to note that using the last-five-day approach does not alter this paper's conclusions. Table A.5 clearly indicates that different outlier treatments paint a very different picture of momentum profitability also when returns are calculated using the last price falling in the last five days of the month, a conclusion we demonstrate using the NIG-bond sample.

We are not inclined to employ the last-five-day price filter in our study, as it has important implications for portfolio formation. Momentum strategies include only bonds for which returns are available throughout the formation period (e.g., Jegadeesh and Titman (1993)). Hence, when we drop from the month-*t* cross-section those bonds with the last price falling earlier than the last five days of the month, we automatically exclude those

Table A.4: Filtering Outlier Reversals

The table tabulates average monthly returns and their unadjusted t-statistics (in bold when significant at the 0.05% level) for the P10-P1 and P50-P1 momentum strategies of short and long-term horizons, and corresponding winner and loser portfolios, based on six different treatments of outliers, respectively. These treatments include removing all outliers that experienced (outlier) reversal in the next month, removing outlier reversals that are supported by institutional-sized trades, and remove those outlier reversals that are not supported by institutional-sized trades. The three treatments are applied to outliers identified based on the percentile thresholds at 99.5% and 0.5% and the absolute cut-offs of +/-30%, respectively. Panel A displays results for the whole sample, and Panel B reports results for the sample excluding the financial crisis. The time period covered is from August 2002 to June 2017. The financial crisis period spans from May 2007 to December 2009.

	S(3,3)			S(6,6)			S(3,3)			S(6,6)		
	P10-P1	Winner=P10	Loser=P1	P10-P1	Winner=P10	Loser=P1	P50-P1	Winner=P50	Loser=P1	P50-P1	Winner=P50	Loser=P1
Panel A: August 2002 to June 2017												
Removing outlier reversal based on +/-30%												
Estimate	0.67	1.817	1.147	0.22	1.44	1.22	2.983	5.064	2.082	1.497	3.817	2.32
t-stat	(1.898)	**(4.966)**	**(3.307)**	(0.654)	**(5.597)**	**(3.115)**	**(2.296)**	**(3.735)**	**(3.619)**	(1.824)	**(4.295)**	**(3.915)**
Removing outlier reversal with inst. trades based on +/-30%												
Estimate	0.767	1.914	1.147	0.338	1.554	1.216	3.114	5.277	2.162	1.677	4.041	2.364
t-stat	**(2.082)**	**(4.898)**	**(3.106)**	(0.965)	**(5.362)**	**(2.955)**	**(2.405)**	**(3.865)**	**(3.572)**	**(1.988)**	**(4.36)**	**(3.849)**
Removing outlier reversal without inst. trades based on +/-30%												
Estimate	0.634	1.872	1.238	0.352	1.657	1.305	2.727	5.237	2.51	1.958	4.537	2.579
t-stat	(1.77)	**(5.029)**	**(3.47)**	(0.928)	**(4.677)**	**(3.251)**	**(2.086)**	**(3.863)**	**(4.067)**	(1.591)	**(3.414)**	**(4.169)**
Removing outlier reversal based on 99.5th and 0.5th percentiles												
Estimate	0.635	1.763	1.127	0.17	1.344	1.173	2.928	4.997	2.069	1.468	3.655	2.187
t-stat	**(1.83)**	**(4.928)**	**(3.381)**	(0.535)	**(5.665)**	**(3.126)**	**(2.222)**	**(3.642)**	**(3.68)**	(1.798)	**(4.152)**	**(3.813)**
Removing outlier reversal with inst. trades based on 99.5th and 0.5th percentiles												
Estimate	0.751	1.878	1.127	0.308	1.486	1.178	3.071	5.21	2.139	1.682	3.944	2.261
t-stat	**(2.038)**	**(4.853)**	**(3.107)**	(0.902)	**(5.404)**	**(2.911)**	**(2.353)**	**(3.805)**	**(3.542)**	**(1.987)**	**(4.269)**	**(3.724)**
Removing outlier reversal without inst. trades based on 99.5th and 0.5th percentiles												
Estimate	0.617	1.847	1.231	0.333	1.629	1.297	2.659	5.171	2.512	1.928	4.502	2.574
t-stat	**(1.76)**	**(5.044)**	**(3.531)**	(0.894)	**(4.641)**	**(3.299)**	**(2.044)**	**(3.812)**	**(4.137)**	(1.551)	**(3.347)**	**(4.172)**
Panel B: Subsample excluding May 2007 to December 2009												
Removing outlier reversal based on +/-30%												
Estimate	0.659	1.525	0.866	0.498	1.357	0.859	2.574	4.141	1.567	1.733	3.5	1.767
t-stat	**(2.911)**	**(6.223)**	**(5.454)**	**(2.458)**	**(5.798)**	**(5.419)**	**(2.735)**	**(4.315)**	**(5.195)**	**(2.94)**	**(4.729)**	**(5.076)**
Removing outlier reversal with inst. trades based on +/-30%												
Estimate	0.662	1.543	0.882	0.513	1.372	0.859	2.605	4.22	1.616	1.79	3.557	1.768
t-stat	**(2.941)**	**(6.276)**	**(5.531)**	**(2.524)**	**(5.849)**	**(5.42)**	**(2.77)**	**(4.386)**	**(5.3)**	**(3.032)**	**(4.804)**	**(5.075)**
Removing outlier reversal without inst. trades based on +/-30%												
Estimate	0.628	1.556	0.928	0.523	1.417	0.894	2.402	4.243	1.841	1.715	3.627	1.912
t-stat	**(2.733)**	**(6.34)**	**(5.541)**	**(2.586)**	**(5.999)**	**(5.553)**	**(2.514)**	**(4.405)**	**(5.098)**	**(2.974)**	**(4.925)**	**(5.289)**
Removing outlier reversal based on 99.5th and 0.5th percentiles												
Estimate	0.631	1.491	0.861	0.434	1.277	0.844	2.483	4.036	1.553	1.632	3.34	1.707
t-stat	**(2.816)**	**(6.195)**	**(5.44)**	**(2.381)**	**(6.139)**	**(5.386)**	**(2.647)**	**(4.241)**	**(5.145)**	**(2.861)**	**(4.621)**	**(4.994)**

	S(3,3)			S(6,6)			S(3,3)			S(6,6)		
	P10-P1	Winner=P10	Loser=P1	P10-P1	Winner=P10	Loser=P1	P50-P1	Winner=P50	Loser=P1	P50-P1	Winner=P50	Loser=P1
Removing outlier reversal with inst. trades based on 99.5th and 0.5th percentiles												
Estimate	0.641	1.516	0.875	0.462	1.303	0.841	2.549	4.133	1.584	1.738	3.429	1.692
t-stat	**(2.876)**	**(6.268)**	**(5.509)**	**(2.512)**	**(6.208)**	**(5.365)**	**(2.731)**	**(4.347)**	**(5.206)**	**(3.055)**	**(4.76)**	**(4.948)**
Removing outlier reversal without inst. trades based on 99.5th and 0.5th percentiles												
Estimate	0.615	1.542	0.927	0.508	1.403	0.895	2.332	4.189	1.857	1.661	3.588	1.928
t-stat	**(2.684)**	**(6.306)**	**(5.544)**	**(2.526)**	**(5.976)**	**(5.564)**	**(2.442)**	**(4.355)**	**(5.131)**	**(2.877)**	**(4.872)**	**(5.312)**

bonds from any momentum portfolio with a formation period including month t. The effect results magnified for long formation periods. The percentage of bonds excluded in each given month is not small. Li and Galvani (2021) note that the last-five-day filter misses 25% of the monthly returns yielded by the last-available-price approach, on average, over the calendar months. The month of December misses about 32% of them, as only about 68% of last-available prices fall in the last five days of the month.

Bonds that are excluded from the cross-section by the last-five-day filter are more likely to trade infrequently, and thus their prices are likely to transmit information more slowly. Using the last-five-day price filter would therefore interact with information diffusion, where the gradual information of news causes corporate bond momentum, as shown in Li and Galvani (2021).

Table A.5: NIG Bond Momentum Returns Using the Last-5-day Approach

The table reports the average monthly returns and their t-statistics (in bold when significant at the 0.05% level) for the short- and long-term decile momentum strategies and their winner and loser portfolios, for the August 2002-June 2017 period and for the subsample obtained excluding the financial crisis. Bond returns are calculated using the last transaction falling within the last five trading days of the month. The financial crisis period spans from May 2007 to December 2009. Panel A lists momentum returns when no outlier treatment is applied (untreated returns). Panel B displays returns based on two-sided and one-sided outlier winsorization using the percentile thresholds of 99.5% and 0.5% of the return distribution. Panels C and D report the corresponding results for removing outliers based on the 99.5th and 0.5th percentile thresholds, and on the absolute cut-offs of +/-30%, respectively.

	Short-term Strategy S(3,3)			Long-term Strategy S(6,6)		
	P10-P1	Winner=P10	Loser=P1	P10-P1	Winner=P10	Loser=P1
			Panel A: Untreated returns			
2002-2017	0.49	2.761	2.272	-0.221	2.132	2.353
	(0.878)	**(5.345)**	**(2.848)**	(-0.309)	**(5.321)**	**(2.815)**
Excluding crisis	0.525	2.265	1.74	0.055	1.92	1.865
	(1.409)	**(7.255)**	**(4.228)**	(0.143)	**(6.59)**	**(4.434)**
			Panel B: Winsorized returns			
Winsorize top 99.5th percentile and bottom 0.5th percentile						
2002-2017	0.6	1.799	1.198	0.327	1.514	1.187
	(2.778)	**(6.954)**	**(4.027)**	(1.344)	**(6.287)**	**(3.862)**
Excluding crisis	0.383	1.705	1.322	0.262	1.598	1.336
	(1.909)	**(7.345)**	**(5.464)**	(1.219)	**(7.02)**	**(5.513)**
Winsorize top 99.5th percentile						
2002-2017	0.784	1.513	0.728	0.527	1.242	0.714
	(2.382)	**(5.62)**	(1.686)	(1.441)	**(5.144)**	(1.558)
Excluding crisis	0.453	1.585	1.131	0.273	1.482	1.208

	Short-term Strategy S(3,3)			Long-term Strategy S(6,6)		
	P10-P1	Winner=P10	Loser=P1	P10-P1	Winner=P10	Loser=P1
	(2.063)	**(6.729)**	**(4.221)**	(1.19)	**(6.496)**	**(4.448)**
Winsorize bottom 0.5th percentile						
Excluding crisis	0.59	2.442	1.851	0.163	2.094	1.931
	(1.649)	**(7.694)**	**(4.789)**	(0.439)	**(7.219)**	**(4.816)**
Panel C: Removing outliers (percentile threshold)						
Removing top 99.5th percentile and bottom 0.5th percentile						
2002-2017	0.248	1.234	0.986	0.18	1.084	0.904
	(1.573)	**(6.949)**	**(4.373)**	(1.121)	**(6.135)**	**(4.585)**
Excluding crisis	0.221	1.381	1.16	0.197	1.27	1.073
	(1.506)	**(7.829)**	**(5.949)**	(1.396)	**(7.368)**	**(6.373)**
Removing top 99.5th percentile						
2002-2017	1.163	0.94	-0.223	1.03	0.828	-0.202
	(3.611)	**(4.378)**	(-0.523)	**(3.008)**	**(4.106)**	(-0.455)
Whole excluding crisis	0.484	1.195	0.711	0.301	1.114	0.813
	(2.701)	**(6.353)**	**(3.016)**	(1.829)	**(6.016)**	**(3.95)**
Removing bottom 0.5th percentile						
2002-2017	1.256	2.962	1.706	0.285	1.981	1.696
	(3.204)	**(6.979)**	**(5.062)**	(0.717)	**(7.531)**	**(4.326)**
Excluding crisis	0.963	2.372	1.409	0.726	2.039	1.313
	(3.728)	**(8.267)**	**(6.558)**	**(3.104)**	**(7.944)**	**(6.61)**
Panel D: Removing outliers (absolute threshold)						
Removing returns above 30% or below -30%						
2002-2017	0.561	1.267	0.706	0.502	1.085	0.582
	(2.486)	**(5.895)**	**(2.363)**	(1.838)	**(5.366)**	(1.752)
Excluding crisis	0.269	1.397	1.128	0.21	1.31	1.099
	(1.511)	**(7.03)**	**(4.897)**	(1.209)	**(6.916)**	**(5.239)**
Removing returns above 30%						
2002-2017	0.964	1.114	0.15	0.852	0.961	0.109
	(3.008)	**(4.745)**	(0.347)	**(2.417)**	**(4.441)**	(0.237)
Excluding crisis	0.383	1.314	0.932	0.281	1.247	0.966
	(1.909)	**(6.406)**	**(3.66)**	(1.462)	**(6.41)**	**(4.13)**
Removing returns below -30%						
2002-2017	0.406	2.707	2.302	-0.397	1.853	2.249
	(0.655)	**(6.538)**	**(3.171)**	(-0.545)	**(6.462)**	**(2.899)**
Excluding crisis	0.722	2.257	1.535	0.348	1.915	1.567
	(2.408)	**(7.44)**	**(5.304)**	(1.219)	**(6.844)**	**(5.288)**

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