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The asymmetric effects of industry specific volatility in momentum returns

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Abstract

In this paper, we look specifically at the effect of industry volatility on momentum returns, a phenomenon that has been overlooked in previous studies. We find that industry volatility has asymmetric effects on the winner and loser portfolios. The cross-sectional variation in the returns of high and low-volatility winners is driven primarily by industry volatility. It disappears after controlling for the effect of industry volatility on total firm volatility. However, for firms in the loser portfolios, the differential return between high and low volatile stocks remains even after adjusting for industry volatility. This implies that momentum returns are mainly induced by industry specific news at the winners' level and firm-specific factors at the losers' level. The results are robust even after controlling for different levels of liquidity.

KEYWORDS

industry, liquidity, London Stock Exchange, momentum, volatility

1 | INTRODUCTION

Momentum, documented by Jegadeesh and Titman (1993), is the phenomenon whereby securities that have out-performed their peers (winners) on average continue to outperform them, and securities that have under-performed their peers (losers) continue to underperform them. It is a well-established empirical fact going back to the Victorian age on UK data (see: Chabot, Ghysels, & Jagannathan, 2009), over two centuries on US equity data (see: Geczy & Samonov, 2016) and many years of out-of-sample testing in at least 40 other countries (see: Asness, Moskowitz, & Pedersen, 2013). Several studies attempt to explain the momentum effect in the literature review. Conrad and Kaul (1998) argue that momentum profits are a compensation for risk. Daniel et al. (1998) and Barberis et al. (1998) show, using behavioural models, that investors' biases lead to short-run momentum. Jegadeesh and Titman (2001) provide empirical evidence in support of the aforementioned behavioural studies. Grinblatt and Han (2005) attribute the profitability of momentum strategies to the disposition effect. More recently, Antoniou, Doukas, and Subrahmanyam (2013) Luo, Subrahmanyam, and Titman (2018) argue that momentum arises due to under-reaction to information. Although many potential explanations of the momentum phenomenon do not stand up to close scrutiny,[1] volatility seems to be an element that plays an important role.

Zhang (2006) finds that high-volatility stocks in the winner (loser) portfolios earn higher (lower) returns than lower volatility stocks, whereas Ang, Hodrick, Xing, and Zhang (2006) and Arena, Haggard, and Yan (2008) find that higher volatility stocks always underperform lower volatility stocks regardless of past performance. These studies employ total volatility or idiosyncratic volatility estimated from the residuals of conventional asset pricing models, implying that firm risk contributes partially to momentum returns. On the other hand, Daniel and Moskowitz (2016) show that, irrespective of the individual stock volatility, momentum payoffs are significantly lower when the overall market is highly volatile. Further evidence, from Wang and Xu (2015), shows that volatile markets predict low momentum returns. Their findings suggest that momentum payoffs are higher when markets are down and market volatility is low than in high, volatile up-markets. This implies that volatility at the market level dominates the return to the market in its effect on momentum payoffs. Although, low market volatility is associated with higher market returns and vice versa, Daniel and Moskowitz (2016) suggest that high market volatility is independent of bear market states. However, the evidence on market states and momentum suggests that momentum strategies are more profitable during up-markets than during down-markets. Cooper, Gutierrez, and Hameed (2004) find stronger momentum following up-markets.[2] An up-market is normally associated with low volatility and a down-market with high volatility.

Volatility, however, can be measured in many different ways. There is individual firm volatility that can be broken down into several components, such as that due to the market, the industry or the firm itself. Campbell, Lettau, Burton, and Xu (2001) show that the volatility of an individual stock is correlated to industry volatility as well as to market volatility. Importantly, the evidence from the literature shows that the relative importance of industry volatility has dominated that of the market one in recent years. For example, Ferreira and Gama (2005) find that the share of local industry volatility in total firm volatility dominates that of the world or the country volatility, concluding that local industry volatility leads the other volatility measures.[3] Lee (2019) finds that industry risk has a greater effect on corporate cash holdings than economy-wide and idiosyncratic risk. Likewise, there is evidence from the UK market that much of the volatility in the stock market could be attributed to sectors or subsectors and that the role of market risk has diminished as the driving force for overall firm volatility (See Black, Buckland, & Fraser, 2002; Morana & Sawkins, 2004). A possible explanation for this could be investing in sector mutual funds given their advantageous performance relative to the more diversified mutual funds.[4] These sector funds, however, have idiosyncratic risks that affect all stocks within that portfolio. This risk exposure gives rise to industry volatility in influencing stock volatility.

Thus, we have strong evidence that industry volatility plays an important role in explaining both firm volatility and market volatility. We also have strong evidence that momentum returns are sensitive to both firm volatility and market volatility. However, the effect of industry volatility on momentum returns has been overlooked. Some previous studies have looked at industry portfolio returns and their influence on momentum profits (see for example, Moskowitz & Grinblatt, 1999; Pan, Liano, & Huang, 2004; Swinkels, 2002), but no studies have looked at the effect of industry volatility on momentum profits. This study is a first attempt to fill this gap.

Therefore, in this paper we look specifically at the effect of industry volatility on momentum returns, a phenomenon that has been overlooked in previous studies. Our approach is based on the argument that the individual components of stock volatility have different effects on momentum returns. For example, the industry component of stock volatility need not have the same effect on momentum returns as the idiosyncratic volatility component. In fact, Gutierrez and Gutierrez Jr. and Prinsky (2007) and Blitz, Huij, and Martens (2011) find that momentum strategies yield different outcomes when based on idiosyncratic versus non-idiosyncratic returns. On the other hand, the industry lead–lag effect implies that firm reaction to common factors is not homogeneous. Scowcroft and Sefton (2005) find that while industry momentum drives momentum profits of large-cap stocks, firm-specific components influence momentum profits at the small-cap level. This complements the findings of Jegadeesh and Titman (1995) who show that while small stocks react with a delay to common factors, large firms react instantaneously to common factors. Furthermore, Hou (2007) emphasizes the role of industry in the lead–lag effect by providing evidence of intra-industry large firms dominating those from outside the industry in predicting returns of small firms. More recently, Hoberg and Phillips (2018) use text-based network industry classification (TNIC) and find that only idiosyncratic shocks transmit slowly and generate industry momentum. The evidence from the above studies recommends that idiosyncratic volatility could have a different effect on stock returns than total volatility.

To exploit these insights we orthogonalize firm volatility with respect to the volatility of its relevant industry to estimate an innovative measure of idiosyncratic volatility that we use to analyse momentum returns. In the major contribution of this paper, we find that industry volatility does have asymmetric effects on the winner and loser portfolios. The cross-sectional variation in the returns of high and low-volatility winners is driven primarily by industry volatility. It disappears when controlling for the effect of industry volatility on total firm volatility. However, for firms in the loser portfolios, the differential return between high and low volatile stocks remains even after adjusting for industry volatility. This effect holds after controlling for liquidity.[5] This implies that industry news induce momentum returns at the winners' level but not at the losers' level. We think that the reason for this is that poor performing or financially distressed firms are likely to be more sensitive to decisions made to overcome internal financial and organizational constraints than to market conditions. For example, Kruse (2002) finds that the relation between industry performance and the probability of asset sales is strong among well performing firms. However, among firms suffering from financial distress or negative earnings the growth of their industry is not related to the probability of asset sales, suggesting that these firms are forced to sell assets regardless of the price received.

The rest of the paper is structured as follows. Section 2 presents the data and methodology, Section 3 presents and discusses results and the final section concludes the paper.

TABLE 1 Summary statistics for liquidity samples

	Number of stocks 1987–2018			
	Maximum	**Minimum**	**Median**	**Average**
Sample A	857	561	658	677
Sample B	743	460	589	591
Sample C	439	41	253	251

Note: This table presents statistics for stocks within samples A, B and C. At each month t during the sample period. All stocks within FTSE All Share constitute sample A after eliminating stocks that are priced below 30 pence, or that do not have return observations a year before formation. Sample B contains sample A excluding stocks that are not traded at least once each month during the 6 months prior to the formation date. Sample C excludes stocks from sample B that are not traded at least once each week during the 6 months prior to the formation date.

2 | DATA AND METHODOLOGY

2.1 | Data

The data consists of all the stocks included in the FTSE All Share index between 1987 and 2018.[6] FTSE All Share Constituents are down-loaded from DataStream as of March 2001. Before that date, we used Financial Times constituent lists and matched constituent names with the Journal of the Institute of Actuaries and the "ShareDATA Services." To avoid survivorship bias we include both live and dead stocks. We also control for the IPO effect and exclude stocks that have no return observations over the year prior to the formation date. We examine momentum performance under three different levels of liquidity: sample A includes all constituents of FTSE All Share with an average of 677 stocks, Sample B with an average of 591 stocks excludes all stocks in Sample A that are not traded over any month during the 6 months prior to the formation date, and Sample C is limited to liquid stocks that traded each week during the 6 months prior to the formation date. Though there is not a substantial difference between the number of constituents of samples A and B, the number drops to an average of 251 stocks in Sample C, suggesting that almost two thirds of Sample B are not traded every week. Table 1 shows the maximum, minimum, median and average number of stocks for samples A, B and C. Thus, a monthly overlapping momentum strategy applied to the three liquidity samples involves a total of 583,835 firm-months. Figure 1 exhibits a graphical representation of the size of each sample over the sample period. Unsurprisingly, the number of weekly traded stocks (i.e., Sample C) is shown to increase after 1997 following the introduction of the SETS trading platform in London Stock Exchange.

The stocks are grouped into 35 industries following the UK FT classification. Asness, Porter, and Stevens (2000) argue that in order to avoid a bias of macro over micro factors, it is more appropriate to use a more detailed classification than the 20 industries of Moskowitz and Grinblatt (1999).They use 48 industries for the US, which is about equivalent to our classification, given that the number of shares in the US exceeds those in the UK by far. Table 2 displays the average number of constituents in each industry over the whole sample period and reports monthly average returns and the *SD*s for each sector.

2.2 | Methodology

To examine the relationship of momentum and liquidity we employ single sorted quintile portfolios conditioned on the past J-month returns. When we focus on volatility, we double sort, first in quintiles and then in three volatility based sub-portfolios within each quintile so as to guarantee a sufficient number of stocks. Momentum portfolios are constructed as in Jegadeesh and Titman (1993). All stocks that meet the inclusion criteria for samples A, B and C at the beginning of each month t are ranked based on their past *J-month* returns. The top past performers are assigned to the winner portfolio and the worst to the loser portfolio. The momentum portfolio is formed as an overlapping zero-cost set that longs winners and shorts losers for k months each time, with k positions open simultaneously, that is, in any month t, winner (loser) portfolios consist of the winning (losing) stocks at month t as well as the past $k - 1$ months. The return of

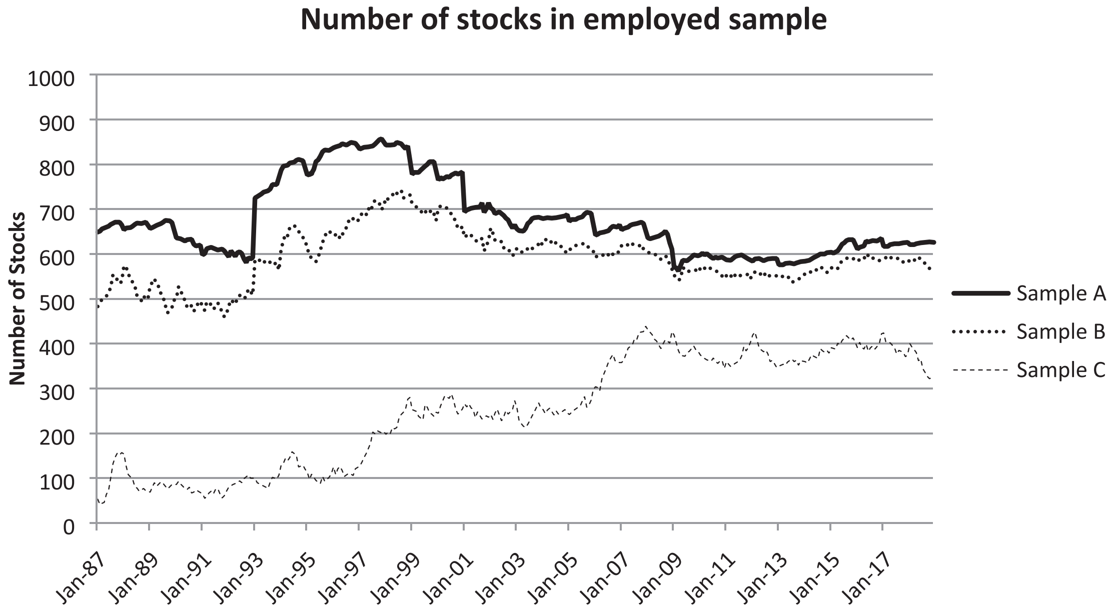

FIGURE 1 This figure depicts a chronological representation of the number of stocks over the sample period 1987–2018 for each of the samples A, B and C identified above. The stocks that meet the criteria are counted at the formation date of the portfolios

the momentum portfolio at month t is therefore the average return of k momentum portfolios formed between months $t - k + 1$ and t:

$$\underset{Momentum,t}{\overset{J\times K}{R}} = \sum_{f=t-k+1}^{f=t} \frac{R_{Winner,f} - R_{Loser,f}}{k}, \tag{1}$$

where $R_{Momentum,t}$ is the momentum profit at month t for k open positions; $R_{Winner,f}$ and $R_{Loser,f}$ are the equally weighted mean monthly returns at month t for the corresponding winner and loser portfolios formed in month f respectively.

This paper reports six strategies of *JxK* formations (where J takes the values 6, 9 and 12 and K takes the values 1 and 6).[7] We skip a month between portfolio formation and holding to control for potential microstructure effects and short-run reversals (Jegadeesh & Titman, 2001). Our results control for the lead–lag effect over short horizons.[8]

We test the explanatory power of stock return volatility before and after industry adjustment to capture the impact of industry volatility on cross-sectional returns. To allow for volatility to contain market wide components associated with industry volatility that is, for intercorrelation (see Ferreira & Gama, 2005), at first we do not adjust the returns to market risk to avoid indirectly controlling for industry effects. However, we test the robustness of our results by employing market risk as well as size and growth risk as in Fama and French (1993). Volatility is first measured by the *SD* (σ) of the weekly (Wednesday to Wednesday) stock returns. If the industry-adjusted volatility provides similar results to the unadjusted one, then the industry role is not significant relevant to variations in momentum returns. To estimate the adjusted volatility we employ three methods. Under the first, at each formation month, we regress the past 52 weekly individual stock returns on the relevant industry returns and then calculate the *SD* of the estimated residual that represents industry-adjusted returns volatility. Every month, the volatility of industry-adjusted returns is estimated for all stocks from the following equation[9]:

$$\mathrm{r_{it}} = \alpha_\mathrm{i} + \beta_\mathrm{i}\mathrm{R_{It}} + \varepsilon_\mathrm{it}, \tag{2}$$

where r_{it} is the weekly return of stock i at week t, R_{It} is the weekly return of the relevant industry I at week t and ε_{it} is the residual term for stock i at week t. Therefore, the industry-adjusted returns volatility will be the *SD* of ε_{it}.

Based on the findings in the literature that industry volatility is a more important component than the market volatility in the individual stock volatility and that companies within the same industry have are highly correlated,[10] we explore the role of industry volatility rather than industry returns. Our second adjustment method involves regressing the past 26 stock's *SD*s (each estimated from 52 weekly returns) on the industry's *SD* at each formation month. The industry-adjusted sigma is estimated from the residuals of the following equation:

$$\sigma_\mathrm{it} = \alpha_\mathrm{i} + \beta_\mathrm{i}\sigma_\mathrm{It} + \xi_\mathrm{it}, \tag{3}$$

where σ_{it} is the *SD* of stock i at week t, σ_{It} is the sigma of the industry I (to which stock i belongs) at week t, and ξ_{it}

TABLE 2 Summary statistics for FTSE all share sectors

Type of industry	Mean number of constituents	Mean monthly return	*SD*
Aerospace & defence	6.56	0.42%	3.10%
Automobiles & parts	7.21	0.29%	4.54%
Banks	9.12	0.28%	3.58%
Beverages	13.18	0.75%	2.66%
Construction & materials	36.09	0.39%	3.02%
Chemicals	13.82	0.55%	2.96%
General industries	16.97	0.44%	3.12%
Industrial engineering	31.62	0.60%	3.15%
Electronic & electric equipment	24.62	0.51%	3.69%
Electricity	5.79	0.58%	2.56%
Forestry & paper	8.71	0.44%	4.59%
Food & drug retailers	11.68	0.34%	2.79%
Food producers	17.47	0.43%	2.36%
General retailers	41.94	0.17%	2.85%
Health/care equipment & services	12.65	0.46%	2.69%
Leisure & household goods	12.91	0.26%	3.60%
TCH hardware & equipment	6.41	0.46%	5.36%
Non-life insurance	14.85	0.29%	3.04%
Equity investment institutions	135.32	0.52%	2.11%
Travel & leisure	33.12	0.50%	2.71%
Life insurance	7.91	0.52%	3.85%
Media	31.53	0.45%	2.93%
Mining	8.00	0.63%	4.35%
Oil & gas production	18.26	0.44%	3.08%
Personal goods	9.85	0.85%	3.30%
Pharmaceutical & biological	11.09	0.65%	3.02%
Real estate	39.53	0.17%	3.00%
Software & computer services	16.26	0.54%	3.67%
General finance	31.06	0.57%	3.12%
Support services	43.12	0.44%	2.49%
Industrial metals	5.62	0.26%	7.43%
Tobacco	2.06	0.76%	3.21%
Industrial transportation	15.18	0.31%	2.59%
Fixed line telecommunications	7.53	0.23%	3.52%
GS/WT/MUL utilities	7.82	0.35%	2.16%

Note: This table shows the mean number of FTSE ALL Share constituents in each sector in the UK Stock Market according to the Financial Times classification, the mean monthly rate of return and the *SD* of the relevant sector. At the beginning of each year, each company is assigned to its relevant sector and the number of companies in each sector is averaged among all years. Interim changes of sector type take effect at the turn of the year only. The monthly average returns and the *SD* from weekly returns are reported for each sector. The sample period is 1986–2019.

is the residual term at week t for stock i. To obtain a ranking tool, we estimate the *SD* of ξ_{it} and we call this estimate the industry-adjusted sigma.[11]

In the final method, in each formation month the 48 monthly individual stock returns are regressed on the Fama–French three-factor model prior to the formation date. This method represents a robustness test to capture the market wide effect of volatility from factors other than the industry effect. The adjusted volatility is the *SD* of the residuals from the FF3F model:

$$\mathrm{R_{it}} - \mathrm{r_f} = \alpha_i + \beta_{i1}(\mathrm{Rm_t} - \mathrm{r_f}) + \beta_{i2}\mathrm{SMB_t} + \beta_{i3}\mathrm{HML_t} + \gamma_{it}, \tag{4}$$

where R_{it} is the monthly return of stock i at month t, R_{mt} is the monthly return of the FTSE All Share index at month t, SMB_t is the small-minus-big factor at week t, HML_t is the high-minus-low factor at month t, and γ_{it} is the residual term for stock i at month t.[12]

3 | RESULTS

The first section presents the results on the persistence of momentum profits against liquidity. Next, we report the volatility of the loser and winner portfolios for all levels of liquidity prior to the formation date. Finally, the paper examines the impact and extent of each type of volatility on momentum returns and then tests for robustness of the results.

3.1 | Momentum profits and liquidity

This subsection examines momentum strategies and their performance with reference to liquidity using samples with different liquidity levels. Table 3 reports returns from three portfolios: winner (W), loser (L), and winner minus loser (W-L), for six *J*x*K* strategies (where $J = 6$, 9, or 12 months, and $K = 1$ or 6 months) and for the three different liquidity samples.[13] Overall, momentum strategies are profitable. Returns are significant at the 1% level for all six strategies across all three liquidity samples. This is evidence that liquidity does not account for the momentum effect. It is also interesting that in all strategies the loser portfolios have substantially larger returns (in absolute value) compared to those of winners and, as a result, generate the bulk of performance to the momentum portfolios. The contribution of the loser portfolio increases for all portfolios as the holding period increases because winners' returns fade faster than losers' returns. The percentage decrease of the winner performance between the 1 and 6 month holding periods across all liquidity samples is much higher than that of losers.

Sample C includes the largest, most liquid stocks in the UK market. Hence, the fact that they deliver momentum profits is indirect evidence that momentum is not due to

TABLE 3 Momentum returns relative to the liquidity of stocks

J×K	6×1	6×6	9×1	9×6	12×1	12×6
All stocks Sample A						
W	0.49*	0.28	0.50*	0.34	0.59**	0.27
L	−1.25***	−1.18***	−1.37***	−1.23***	−1.36***	−1.17***
W − L	**1.74*** **	**1.46*** **	**1.87*** **	**1.57*** **	**1.95*** **	**1.44*** **
Monthly traded stocks Sample B						
W	0.52*	0.30	0.53*	0.35	0.61**	0.29
L	−1.27***	−1.20***	−1.33***	−1.24***	−1.38***	−1.17**
W − L	**1.79*** **	**1.50*** **	**1.86*** **	**1.59*** **	**1.99*** **	**1.46*** **
Weekly traded Sample C						
W	0.48	0.21	0.56*	0.23	0.53*	0.15
L	−1.28**	−1.18**	−1.36***	−1.19**	−1.33**	−1.11**
W − L	**1.76*** **	**1.39*** **	**1.92*** **	**1.42*** **	**1.86*** **	**1.26*** **

Note: This table shows the profits (in percentages) of momentum strategies with formation periods of 6, 9, and 12 months and holding periods of 1 and 6 months skipping a month between the formation and the holding period for three liquidity samples described below. At each month within the sample period, all stocks within the FTSE All Share are ranked based on their previous *J*-month performance and held for *K* months. All stocks within FTSE All Share constitute Sample A after eliminating stocks that are priced below 30 pence, or that do not have return observations a year before formation. Sample B contains Sample A excluding stocks that are not traded at least once each month during the 6 months prior to the formation date. Sample C excludes stocks that are not traded at least once each week during the 6 months prior to the formation date from Sample B. Stocks in the top quintile are assigned to the winner portfolio (W), and those in the lowest quintile to the loser portfolio (L). A zero-cost portfolio is formed by buying W and selling L (W-L). The Newey–West heteroskedasticity and auto-correlation-consistent method is applied for adjustment of *SEs*. The sample period is 1986–2019.The subscripts ***, **, and * denote statistical significance at the 1, 5, and 10% significance level, respectively.

the small firm effect, which is consistent with previous UK evidence such as Ellis and Thomas (2004) and Badreddine, Galariotis, and Holmes (2012), who find significant momentum profits for FTSE350 and UK optioned stocks, respectively. In addition, given their size and trading characteristics, such firms are least affected by infrequent trading and thus it is less likely their momentum profits are attributed solely to non-synchronous trading (see Lo & Mackinlay, 1990b). Given that weekly traded stocks are more immune to market microstructure effects such as short position constraints than less liquid stocks, and that they do not suffer from severe thin trading, implies that the continuation of losers is primarily driven by market reaction which is in line with the Hong, Stein, and Lim (2000) proposal of bad news travelling slowly.

3.2 | Winners, losers and volatility

In the previous section, we showed that the loser stocks are the drivers of momentum returns and this applies also to the highly liquid stocks that generate significant momentum profits. Thus, the momentum phenomenon cannot be attributed solely to thinly traded stocks. Each month we estimate the volatility of the winner and loser as well as the difference in their average volatilities, to understand whether the higher contribution of losers to momentum profits could be attributed to volatility. This assesses the possibility that the difference in the degree of volatility between winners and losers could justify the variations in the magnitude of winner and loser portfolio returns. The Wilcoxon signed rank test is employed to test for the significance of the observed volatility values and the Newey–West test for the significance of their difference.

The volatility across all stocks in each of the winner and loser portfolio is averaged every month of the sample period resulting in 384 average observations for each of the winner and loser portfolios. The time series median of these averages is displayed in Table 4. Table 4 presents estimated median volatilities of winner and loser portfolios as well as their difference ($\sigma_{W-}\sigma_L$) measured by: the

TABLE 4 Volatility (measured by the *SD*) for all samples relative to liquidity

	Average number of observations	σ_{Winner}	σ_{Loser}	$\sigma_{Winner} - \sigma_{Loser}$
Sample A				
SD	135	4.23 (0.00)	4.91 (0.00)	−0.70 (0.00)
SD of ind. adjusted return	135	3.81 (0.00)	4.45 (0.00)	−0.41 (0.00)
SD of adjusted sigma	135	0.22 (0.03)	0.30 (0.00)	−0.08 (0.00)
SD of FF3F residuals	135	26.35 (0.00)	31.96 (0.00)	−4.64 (0.00)
Sample B				
SD	117.9	4.19 (0.00)	4.95 (0.13)	−0.69 (0.00)
SD of ind. adjusted return	117.9	3.76 (0.00)	4.49 (0.00)	−0.44 (0.00)
SD of adjusted sigma	117.9	0.21 (0.00)	0.30 (0.01)	−0.08 (0.00)
SD of FF3F residuals	117.9	26.11 (0.00)	30.91 (0.00)	−5.23 (0.00)
Sample C				
SD	49.9	4.17 (0.00)	5.51 (0.03)	−0.80 (0.00)
SD of ind. adjusted return	49.9	3.78 (0.00)	4.39 (0.00)	−0.32 (0.00)
SD of adjusted sigma	49.9	0.19 (0.49)	0.26 (0.00)	−0.07 (0.00)
SD of FF3F residuals	49.9	23.67 (0.00)	26.29 (0.21)	−3.75 (0.00)

Note: This table shows the volatility of the winner and loser portfolios in each of the three samples A, B and C described in previous tables. Stocks in the top quintile are assigned to the winner portfolio, and those in the lowest quintile to the loser portfolio. The zero net investment portfolio is the winner minus loser portfolio *(W-L)*. The volatility of the winner (loser) portfolio at month *t* is the equally weighted average of the volatilities of all stocks in the winner (loser) portfolio. The median of all volatilities across the sample period is estimated. Volatility of a stock at month *t* is measured using: *SD* of stock returns (52-weekly returns), *SD* of residuals from industry-adjusted returns (52 weekly individual stock returns regressed on the industry returns), *SD* of residuals from industry-adjusted sigmas (past 26 stock's *SD*s each estimated from 52 weekly returns regressed on the industry's *SD*), and *SD* of the residuals from Fama–French-adjusted returns (52 weekly individual stock returns regressed on the market, small-minus-big and high-minus-low returns), all using weekly returns from Wednesday to Wednesday. The number of stocks in a quintile is averaged throughout the 384 months period. The *p*-values of the Wilcoxon signed rank test, reported in parentheses, test the significance of the median for the winner and loser portfolios and the equality of *W-L* volatility to zero. The sample period is 1986–2019.

TABLE 5 Momentum returns and volatility: Total volatility versus industry-adjusted volatility

	SD of stock returns σ				Sigma of residuals from industry-adjusted returns $\sigma(\varepsilon_{ir})$				*SD* of residuals from industry-adjusted sigma $\sigma(\xi)$			
Sample A	**Panel A**				**Panel B**				**Panel C**			
	High σ	**Med σ**	**Low σ**	**High – Low**	**High σ(ε)**	**Med σ(ε)**	**Low σ (ε)**	**High – Low**	**High σ(ξ)**	**Med σ(ξ)**	**Low σ(ξ)**	**High – Low**
Winners	0.25	0.54**	0.68***	**−0.43****	0.30	0.48	0.70*	**−0.40*****	0.31	0.41	0.50*	**−0.19**
Quintile 2	0.08	0.46*	0.62***	**−0.54*****	0.20	0.38	0.58**	**−0.88*****	0.04	0.38	0.48**	**−0.44*****
Quintile 3	−0.14	0.34	0.42*	**−0.56*****	−0.10	0.28	0.44*	**−0.54*****	−0.23	0.25	0.35	**−0.58*****
Quintile 4	−0.40	0.09	0.26	**−0.66*****	−0.37	0.11	0.20	**−0.57*****	−0.44	−0.05	0.18	**−0.62*****
Losers	−2.43***	−0.94**	−0.35	**−2.08*****	−2.26***	−1.00**	−0.46	**−1.80*****	−2.48***	−1.09**	−0.47	**−2.01*****
W – L	**2.68*****	**1.47*****	**1.03*****	**1.65*****	**2.56*****	**1.48*****	**1.16*****	**1.40*****	**2.79*****	**1.50*****	**0.97*****	**1.82*****
Sample B	**Panel D**				**Panel E**				**Panel F**			
	High σ	**Med σ**	**Low σ**	**High – Low**	**High σ(ε)**	**Med σ(ε)**	**Low σ (ε)**	**High – Low**	**High σ(ξ)**	**Med σ(ξ)**	**Low σ(ξ)**	**High – low**
Winners	0.24	0.55**	0.75***	**−0.51*****	0.27	0.50*	0.77***	**−0.50*****	0.35	0.38	0.56**	**−0.21**
Quintile 2	0.04	0.46*	0.60***	**−0.56*****	0.16	0.36	0.58**	**−0.42*****	0.00	0.38	0.48**	**−0.48*****
Quintile 3	−0.16	0.33	0.47*	**−0.63*****	−0.12	0.27	0.50**	**−0.62*****	−0.18	0.22	0.35	**−0.53*****
Quintile 4	−0.47	0.06	0.23	**−0.70*****	−0.44	0.09	0.17	**−0.61*****	−0.54	−0.05	0.14	**−0.68*****
Losers	−2.45***	−0.97**	−0.38	**−2.07*****	−2.29***	−1.03**	−0.48	**−1.81*****	−2.49***	−1.08**	−0.57	**−1.92*****
W – L	**2.69*****	**1.52*****	**1.13*****	**1.56*****	**2.56*****	**1.53*****	**1.25*****	**1.31*****	**2.84*****	**1.46*****	**1.13*****	**1.71*****
Sample C	**Panel G**				**Panel H**				**Panel I**			
	High σ	**Med σ**	**Low σ**	**High – Low**	**High σ(ε)**	**Med σ(ε)**	**Low σ (ε)**	**High – Low**	**High σ(ξ)**	**Med σ(ξ)**	**Low σ(ξ)**	**High – low**
Winners	0.33	0.45	0.69***	**−0.36***	0.26	0.51	0.67***	**−0.41****	0.37	0.37	0.45	**−0.08**
Quintile 2	−0.10	0.50*	0.76***	**−0.85*****	0.08	0.37	0.70***	**−0.62*****	0.02	039	0.53*	**−0.51*****
Quintile 3	0.04	0.33	0.47**	**−0.43****	0.07	0.29	0.49*	**−0.42****	−0.02	0.20	0.35	**−0.37****
Quintile 4	−0.26	0.08	0.32	**−0.58****	−0.29	0.13	0.28	**−0.57*****	−0.43	0.12	0.18	**−0.61*****
Losers	−2.34***	−1.00**	−0.21	**−2.13*****	−2.18***	−1.09**	−0.29	**−1.89*****	−2.51***	−0.99**	−0.37	**−2.14*****
W – L	**2.67*****	**1.45*****	**0.90*****	**1.77*****	**2.44*****	**1.60*****	**0.96*****	**1.48*****	**2.88*****	**1.36*****	**0.82****	**2.06*****

Note: This table shows the impact of industry-adjusted volatility on the cross-section of momentum returns for three samples of different liquidity levels. Samples A, B and C are as described above. At each month within the sample period, stocks are ranked based on their previous 6 months performance and held for 1 month. Stocks in the top quintile are assigned to the winner portfolio, and those in the lowest quintile to the loser portfolio. Within each quintile stocks are equally sorted into three sub-portfolios on the basis of their volatility. Three measures of stock volatility are used: the *SD* σ of the stock's 52 past weekly returns prior to the formation date; the *SD* σ of the past 52 weekly observations of the residual term from the regression $r_{i,t} = \alpha_i + \beta_i R_{I,t} + \varepsilon_{i,t}$, where $r_{i,t}$ is stock *i*'s weekly return at time t, $R_{I,t}$ is the weekly return of the sector *I* of which stock *i* belongs to at time t and $\varepsilon_{i,t}$ is the residual term at time *t*; The *SD* of the residuals from regressing the last 26 *SD*s $\sigma_{i,t}$ against σ_{IT} of the relevant sector: $\sigma_{it} = \varphi_i + \beta_i \sigma_{It} + \xi_{it}$ where $\sigma_{i,t}$ and $\sigma_{I,t}$ are the *SD*s of stock *i* and its sector *I*, respectively, estimated as above, and $\xi_{j,t}$ is the residual term at week *t*. The monthly average returns of the sub-portfolios for all quintiles are presented in percentages when they are held a month after the formation date. The Newey–West *t*-statistics are reported in parentheses. The sample period is 1986–2019.The superscripts ***, **, and * denote statistical significance at the 1, 5, and 10% significance level, respectively.

SD of stock returns over the past 52 weeks (named *SD*); the *SD* of the residuals from regressing past 52 weekly individual stock returns on industry returns; the *SD* of residuals from regressing individual stock sigmas based on 52 weekly returns on the relevant industry sigmas (named industry-adjusted sigma) and, finally, the *SD* of the residuals from regressing past 48 monthly individual stock returns on the market, size and growth risks as in Fama and French (1993) (*SD* of FF3F residuals).

Given the Chi-square distribution of observations, we hypothesize the significance of the median portfolio volatility and report the *p*-values of the Wilcoxon signed rank test. The reported *p*-value, in panel A, indicates that the median portfolio volatility is significantly different from that of the hypo-thesized median volatility for most portfolios. The right-skewed distribution of the volatility observations reflects large positive deviations from the estimated median in comparison to smaller deviations to the left side of the median. Losers' volatility is consistently larger than that of winners across all samples. For instance, in Sample A the *SD* is 4.21% (4.91%) for the winner (loser) portfolio. The difference of the two portfolios is about the same in all three samples. In fact, the loser portfolio volatility exceeds that of the winners' in 76.5, 78.6 and 72.4% of the cases within samples A, B and C, respectively.

3.3 | Cross-sectional momentum returns and industry volatility

Previously, we have shown that losers contribute more to momentum returns irrespective of liquidity, and are more volatile than winners as shown above. Zhang (2006) argues that stocks with higher volatility underreact more to news than stocks with lower volatility. If so, past winners with higher volatility are expected to gain more than those with lower volatility, whereas past losers with higher volatility earn less than lower volatility loser portfolios. However, Ang et al. (2006) argue that stocks with higher volatility earn less than stocks with lower volatility irrespective of past performance. Arena et al. (2008) find that stocks with higher idiosyncratic volatility perform better (worse) than those of lower idiosyncratic volatility if they were past winners (losers). This section aims to clarify the ambiguity regarding the relation of stock volatility and momentum returns providing out-of-sample evidence and attempts to explain these variations using industry factors. In order to provide comparable results to Zhang (2006) and Ang et al. (2006), portfolios are held for a holding period of 1 month.[14]

Stocks are split into quintiles based on past performance, and then each quintile is divided into three sub-portfolios on the basis of total volatility or industry-adjusted volatility.[15] Table 5 reports the cross-section of momentum returns with respect to *SD* of stock returns, and the two industry-adjusted volatility measures. Using the *SD* of stock returns σ, the return differential between high and low-volatility stocks is significant and always negative, that is, high-volatility stocks earn lower returns across all quintiles. For instance, the results in panel A of Table 5, show that, the *High–Low* differences yield a monthly return of −0.43% (−2.08%) for winners (losers) and are statistically significant.

These findings extend to those using industry-adjusted volatility. Sorting stocks with respect to the *SD* of the residual term $\varepsilon_{i,t}$, that is, the idiosyncratic volatility not captured by industry returns (see Equation 2) yields a *High–Low* difference of −0.40% (−1.80%) for winners (losers) at the 1% level of significance (See Table 5, panel B). The results also show that adjustment to industry returns cannot explain the return differentials between winners and losers which confirm the findings of Nijman et al. (2004) who show that for Europe the country and industry factors are less pertinent to momentum, as they indicate that dispersion in future stock returns when conditioning on momentum deciles leaves an insignificant effect of industry past performance in favour of idiosyncratic factors. Next, we adjust volatility to industry risk as opposed to the previous methods of adjusting stock returns to industry returns. Wang and Xu (2015) provide evidence that market volatility has a negative effect on momentum returns when market overall volatility is measured over past 6 months and past 12 months even between large-cap stocks. We control for industry volatility effect by regressing the *SD* of individual stock returns on industry *SD* and sort stocks within each quintile (formed as previously) according to the estimated *SD* of ξ_{it} (see Equation 3). Table 5, Panel C, shows that the higher volatility stocks again underperform lower volatility ones and this is statistically significant in all but the winner portfolio. Thus, the differential return between winners disappears with respect to $\sigma(\xi_{it})$ meaning that industry risk explains the variations between high and low-volatility winners. The *High–Low* difference in the loser portfolio, on the other hand, is a significant −2.01% at the 1% level of significance.

To ensure that the results from testing the cross-sectional effect of volatility are not driven by illiquid stocks contaminating Sample A, we eliminate stocks that are not traded at least once a month during the formation period and then apply the double sorting criteria as above. We repeat the above steps and report the results in Panels D, E and F for the three volatility measures. The monthly traded stocks Sample, Sample B, contains on average 591 stocks in each formation period, which is approximately 13% less than those in Sample A. The results are essentially similar to those of Sample A. The return differential between high and low-volatility stocks is significantly negative regardless of past performance when sorting stocks relevant to their σ_i or $\sigma(\varepsilon_{i,t})$, the residual term from adjustment to industry returns. However, when we control for industry volatility $\sigma(\xi_{it})$, the differential return between high and low volatile winners disappears. Thus, the former result that industry volatility is the major driver of the cross-sectional variation in the winner portfolio return is confirmed after excluding illiquid stocks.

We further limit the potential illiquidity effect on volatility by restricting our sample to the weekly traded stocks during the formation period. This results in Sample C that contains 251 stocks on average. Despite the substantial drop in the number of weekly traded stocks from monthly traded stocks, Table 5, Panels G, H and I,

TABLE 6 Momentum returns and industry-adjusted volatility outside crisis

***SD* of residuals from industry-adjusted sigma σ(ξ) outside crisis**				
	Panel A: Sample A			
	High σ(γ)	**Medium σ(γ)**	**Low σ(γ)**	**High – Low**
Winners	0.49*	0.59**	0.69***	**−0.20**
Quintile 2	0.24	0.57**	0.66***	**−0.42*** **
Quintile 3	0.02	0.45*	0.53**	**−0.51*** **
Quintile 4	−0.17	0.20	0.36	**−0.53*** **
Losers	−2.04***	−0.72*	−0.23	**−1.81*** **
W – L	**2.53*** **	**1.31*** **	**0.92*** **	**1.61*** **
	Panel B: Sample B			
	High σ(γ)	**Medium σ(γ)**	**Low σ(γ)**	**High – Low**
Winners	0.55*	0.56**	0.76***	**−0.21**
Quintile 2	0.22	0.58**	0.67***	**−0.44*** **
Quintile 3	0.06	0.42*	0.54**	**−0.48*** **
Quintile 4	−0.26	0.22	0.33	**−0.59*** **
Losers	−2.03***	−0.71	−0.31	**−1.72*** **
W – L	**2.58*** **	**1.27*** **	**1.07*** **	**1.51*** **
	Panel C: Sample C			
	High σ(γ)	**Medium σ(γ)**	**Low σ(γ)**	**High – Low**
Winners	0.54	0.56*	0.65**	**−0.11**
Quintile 2	0.17	0.57**	0.70***	**−0.52*** **
Quintile 3	0.23	0.41	0.55**	**−0.31* **
Quintile 4	−0.18	0.38	0.35	**−0.53*** **
Losers	−2.12***	−0.62	−0.08	**−2.04*** **
W – L	**2.66*** **	**1.18*** **	**0.73** **	**1.93*** **

Note: This table shows the impact of stock volatility on the cross-section of momentum returns for three samples of different liquidity levels. Samples A, B and C are as described above. At each month within the sample period, stocks are ranked based on their previous 6 months performance and held for 1 month. Stocks in the top quintile are assigned to the Winner portfolio, and those in the lowest quintile to the Loser portfolio. Within each quintile stocks are equally sorted into three sub-portfolios on the basis of their volatility. The *SD* of the residuals from regressing the last 26 *SD*s $\sigma_{i,t}$ against σ_{IT} of the relevant sector: $\sigma_{it} = \varphi_i + \beta_i\sigma_{It} + \xi_{it}$ where $\sigma_{i,t}$ and $\sigma_{I,t}$ are the *SD*s of stock *i* and its sector *I*, respectively, estimated as above, and $\xi_{j,t}$ is the residual term at week *t*. The monthly average returns of the sub-portfolios for all quintiles are presented in percentages when they are held a month after the formation date. The Newey–West *t*-statistics are reported in parentheses. The sample period is 1986–2019 excluding the months with negative returns surrounding the Black Wednesday of 1992 Sterling crisis and the global financial crisis of 2008.The subscripts ***, **, and * denote statistical significance at the 1, 5, and 10% significance level, respectively.

confirms the results of the previous samples. A remarkable finding is that the *High–Low* losers return increases in Sample C. This shows that liquidity further exacerbates the volatility effect among losers. Particularly, liquidity allows low-volatility stocks to earn a higher return leading to a wider *High–Low* return. Controlling for industry volatility reveals similar results to the previous samples. Again, the *High–Low* differential return among winners disappears indicating that industry volatility effect is robust across all liquidity levels.[16] Our results support those of Scowcroft and Sefton (2005). However, we find that liquidity reinforces the impact of industry volatility on winners, but we do not find a similar effect on the losers' side. Hence, the results suggest that industry volatility has an asymmetric effect on the cross-sectional winner and loser returns.

The difference between winners and losers is greatest when volatility is high and declines monotonically with volatility. This is consistent for all samples and using all volatility measures. For instance, using the total volatility

TABLE 7 Momentum returns and Fama–French adjusted returns volatility

***SD* of residuals from FF3F adjusted returns σ(γ)**				
	Panel A: Sample A			
	High σ(γ)	**Medium σ(γ)**	**Low σ(γ)**	**High – Low**
Winners	0.36	0.49*	0.63***	**−0.27***
Quintile 2	0.14	0.43*	0.58**	**−0.44*****
Quintile 3	−0.22	0.39	0.45	**−0.67*****
Quintile 4	−0.36*	0.02	0.29	**−0.65*****
Losers	−2.47***	−0.86*	−0.40	**−2.07*****
W – L	**2.83*****	**1.35*****	**1.03*****	**1.80*****
	Panel B: Sample B			
	High σ(γ)	**Medium σ(γ)**	**Low σ(γ)**	**High – Low**
Winners	0.32	0.53*	0.69***	**−0.37****
Quintile 2	0.10	0.39	0.61***	**−0.51*****
Quintile 3	−0.18	0.38	0.45	**−0.63*****
Quintile 4	−0.47	0.04	0.25	**−0.72*****
Losers	−2.47***	−0.86**	−0.47	**−2.00*****
W – L	**2.79*****	**1.39*****	**1.16*****	**1.63*****
	Panel C: Sample C			
	High σ(γ)	**Medium σ(γ)**	**Low σ(γ)**	**High – Low**
Winners	0.32	0.49	0.64*	**−0.32***
Quintile 2	0.04	0.51*	0.59**	**−0.55*****
Quintile 3	−0.07	0.41	0.46*	**−0.53*****
Quintile 4	−0.40	0.22	0.28	**−0.68*****
Losers	−2.32***	−0.98*	−0.27	**−2.05*****
W – L	**2.64*****	**1.47*****	**0.91*****	**1.73*****

Note: This table shows the impact of stock volatility on the cross-section of momentum returns for three samples of different liquidity levels. Samples A, B and C are as described above. At each month within the sample period, stocks are ranked based on their previous 6 months performance and held for 1 month. Stocks in the top quintile are assigned to the Winner portfolio, and those in the lowest quintile to the Loser portfolio. Within each quintile stocks are equally sorted into three sub-portfolios on the basis of their volatility. Volatility is the *SD* σ of the past 48 monthly observations of the residual from the FF3F model: $r_{it} - r_f = \alpha + \beta_1(Rmt - r_f) + \beta_2 SMB_t + \beta_3 HML_t + \gamma_t$, where r_{it} is the weekly return of stock i at week t, R_{mt} is the weekly return of the FTSE All Share index at week t, SMB_t is the small-minus-big factor at week t, HML_t is the high-minus-low factor at week t, and γ_{it} is the residual term for stock i at week t; The monthly average returns of the sub-portfolios for all quintiles are presented in percentages when they are held a month after the formation date. The Newey–West *t*-statistics are reported in parentheses. The sample period is 1986–2019.The subscripts ***, **, and * denote statistical significance at the 1, 5, and 10% significance level, respectively.

measure, the return for momentum return in panel A generates 2.68, 1.47 and 1.03% monthly average returns for high, moderate and low-volatility portfolios respectively, rendering a differential return of 1.65% between high and low-volatility momentum strategies and is positive at the 1% level of significance.

3.4 | Robustness checks: Cross-sectional momentum returns excluding crisis periods

Previous studies have shown that momentum performance is closely related to market conditions. Cooper et al. (2004) show that momentum strategies do not deliver profits following bad market states. Galariotis et al. (2014) find that momentum returns are not related to market states in the UK. We test whether the role of volatility in explaining cross-sectional stock returns is influenced by periods of extreme down-markets. In particular, we re-examine if the industry-adjusted sigma can still explain the differential return among the winner portfolios by omitting crisis periods.[17] Table 6 reports the results. They confirm the previous findings in Table 5. Momentum profits are significant across all measures of volatility for all levels of liquidity. The differential return between high and low volatile portfolios is significant for all but the winner portfolio. Again, the *High–Low* differential return among winners disappears indicating that industry volatility effect is robust across all liquidity levels.

3.5 | Robustness checks: Cross-sectional momentum returns and volatility of FF3F residuals

To provide a consistent comparison with the literature, we use idiosyncratic volatility of the residuals from FF3F adjusted returns and report the results in Table 7. We rank stocks and construct portfolios as in the previous section. Sorting stocks with respect to the *SD* of the residual term from regressing individual stock returns on the Fama–French three-factor model as shown in Equation (4) does not eliminate the cross-sectional variation in momentum returns between high and low-volatility stocks. The results in panel A of Table 7 show that *High–Low* differences are statistically significant and yield a monthly return of −0.27% (−2.07%) for winners (losers) which is comparable to the findings of Ang et al. (2006) that *High–Low* winner portfolio generates a return of −0.48% (t-statistic: −2.01). Although the return differential between high and low winner portfolios is reduced, the results indicate that market, size and growth factors cannot eliminate the cross-sectional variation in returns. Our findings show that the results of Arena et al. (2008) are robust to sample-market and sample-period choice and contradict expectations that higher volatility implies higher under-reaction and hence larger returns in absolute value over the holding period. The results hold for all pre-defined liquidity samples when idiosyncratic volatility from FF3F adjusted returns are employed.

On the other hand, the cross-sectional differential return between losers and winners (*W-L*) is positive in all cases as would be expected, and has a direct monotonic relationship with volatility, confirming the findings from previous research. The return for (*W-L*) portfolio generates 2.83, 1.35 and 1.03% monthly average returns for high, moderate and low-volatility portfolios respectively, rendering a differential return of 1.80% between high and low-volatility momentum strategies (Table 7 panel A).

The monotonic relationship between momentum returns and volatility is present for the samples B and C (monthly traded stocks sample and weekly traded stocks sample), i.e., as volatility goes up so do momentum returns. For instance, panel C shows that using only weekly traded stocks, a momentum strategy with high-volatility stocks yields a monthly average return of 1.73% (significant at the 1% level) in excess of another strategy based on low-volatility stocks. The higher differential return between momentum strategies supports the evidence of Blitz et al. (2011) that residual components can extract higher profits from momentum strategies. This finding contributes to our understanding of the extant impact of volatility in cross-sectional momentum returns and the asymmetric effects of industry and liquidity in momentum returns.

4 | CONCLUSION

This paper uses UK data to examine the effect of industry volatility on the momentum phenomenon. Before accounting for the effect of industry volatility, our results show that momentum strategies are profitable for all levels of liquidity, implying that there are no patterns to confirm theoretical expectations that illiquid stocks experience substantially higher momentum payoffs. Overall, long positions in low-volatility winners and a short position in high-volatility losers deliver superior momentum returns. This profitability is driven by losers and the stronger contribution from the loser side is associated with a significant higher volatility for losers than for winners. The high volatility of the losers is shown to increase during the formation period. These results are irrespective of the liquidity samples used.

When we look at the impact of volatility on momentum returns before adjusting for the industry effect, our results are in line with those of Ang et al. (2006) in that low-volatility stocks earn higher returns than high-volatility stocks. These findings are also robust to varying levels of liquidity. However, adjusting volatility to account for the industry effect yields some interesting insights. The industry volatility effect is asymmetric with respect to winner and loser portfolios. For winner portfolios the differential returns between high and low-volatility stocks disappears, which is evidence that it is industry volatility that is driving the differential. Furthermore, higher levels of liquidity strengthen the impact of industry volatility. On the other hand, the variation in returns among high and low-volatility stocks within the loser portfolios tends to become larger after adjusting for industry and this differential is exacerbated by liquidity.[18] These results are robust with respect to other measures of idiosyncratic risk such as the single index model and the Fama and French (1993) three-factor model. The main conclusion of these findings is that industry volatility plays an important role in the cross-sectional returns of winners but not losers. Specifically, industry volatility, rather than industry returns, can explain the differential return among winners. It is also interesting to note that liquidity, which seems to have little or no influence on the momentum phenomenon before accounting for industry volatility, has an important effect after industry volatility is accounted for.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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ENDNOTES

[1] See Asness, Frazzini, Israel, and Moskowitz (2014).

[2] Galariotis, Holmes, Kallinterakis, and Ma (2014) and Phua, Chan, Faff, and Hudson (2010) provide further evidence on market states and momentum.

[3] Boamah, Loudon, and Watts (2017) show that while country risk dominated industry risk prior to the global financial crisis in all of the African markets, the importance of industry effects rose after 2009 and approximated the country effect for some markets.

[4] See for example O'Neal (2000) and Choi, Fedenia, Skiba, and Sokolyk (2017).

[5] We just observe that it is wider possibly because more frequently traded stocks react faster to decisions taken to overcome the financial and organizational constraints.

[6] Stock returns span from the period 1986 to 2019.

[7] We have tested holding periods K of 3, 9 and 12 months as well but did not report them here for brevity.

[8] See Lo and Mackinlay (1990a) for more on the lead–lag effect.

[9] We run 583,835 regressions for each of our model; that is, 1,751,505 regressions for the three employed models across the three liquidity samples.

[10] See Ferreira and Gama (2005) and Black et al. (2002) on country and industry volatility components and Nijman, Swinkels, and Verbeek (2004) on industry and country role on momentum returns.

[11] We start with Equation (2) and follow Ferreira and Gama (2005) to present volatility as Equation (3) $\sigma_{it} = \varphi_i + \beta_i \sigma_{It} + \xi_{it}$. The residual term ξ_{it} is essentially the stock volatility that is not captured by the industry volatility. In order to create a ranking tool of these residuals, we estimate their *SDs*. Our derivation of Equation (3) from Equation (2) follows the same principle as in Ferreira and Gama (2005).

[12] SMB and HML factors, as in Fama and French (1993), represent the average return on the three small portfolios minus the average return on the three big portfolios, and the average return on the two value portfolios minus the average return on the two growth portfolios, respectively. The SMB and HML portfolios factors are constructed using FTSE All Share constituents following Fama and French (1993).

[13] We use various JxK combinations to verify similarity of the momentum profits with previous studies in the literature. Momentum profits for holding periods of 3, 9 and 12 months, not reported here, are significant for all samples.

[14] We repeated our calculations using the 6-month holding period; results were qualitatively similar and are available from the authors on request.

[15] To obtain the industry-adjusted returns volatility, we regress each stock's return on its relevant industry return and estimate the *SD* of the residuals. We rank stocks within each quintile with respect to its estimated idiosyncratic volatility. We split each quintile into three sub-portfolios. We repeat this method on a monthly basis. This technique is applied for each volatility measure that is employed in this paper.

[16] Further testing not reported here shows that the impact of $\sigma(\xi_{it})$ is stronger among liquid stocks (sample 'C') in that it eliminates the cross-sectional variation in winners return for up to a 6 month holding period. This is interpreted as a stronger industry volatility effect among more liquid winners than less liquid winners.

[17] Following the suggestions of the referee, we distinguish two crises, the Black Wednesday of 1992 Sterling crisis and the global financial crisis of 2008.

[18] This effect on the loser portfolio could explain the results of Avramov, Cheng, and Hameed (2015), who show that momentum profits are large (weak) when the markets are highly liquid (illiquid).

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