JOURNAL OF MONEY, BANKING AND FINANCE
Vol. 7, No. 2, 2021, pp. 171-189

URL : www.esijournals.com

ESI PUBLICATIONS
Gurugaon, India

Momentum Returns and Volatility. Does Volatility Matter for Winner-Minus-Loser Strategy? Evidence from the Idiosyncratic Volatility and Conditional Volatility.

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ARTICLEINFO

Received: 30 September 2021
Revised: 26 October 2021
Accepted: 09 November 2021
Published: 30 December 2021

Abstract: This paper investigates the momentum return of U.S. equity spanning from January 1990 to December 2020 incorporating the use of idiosyncratic volatility proposed by Fu (2009), and conditional volatility by Moreira and Muir (2017). The results indicate that the presence of Idiosyncratic volatility does not help improve the momentum return. Using conditional volatility portfolio-sorted, risk-adjusted return improves as investors lower their return to reduce the risk related to the momentum return. We also investigate the source of momentum returns. The result indicates that the momentum return can be explained by economic variables. However, the size is small, and investors largely ignore the economic factors when forming the momentum portfolio.

Keywords: Momentum, Idiosyncratic Volatility, Factor Models

JEL Classification: G11, G12

INTRODUCTION

Jegadessh and Titman (1993) observe the behavior of U.S. equities and test a trading strategy by buying stocks that have performed well in the past and selling stocks that have performed poorly in the past. The long and short positions can generate a substantial profit over a certain period. The trading strategy shows that investors can use the historical information based on the stock prices to form a zero-trading strategy and be able to

To cite this article:

Phuvadon Wuthisatian (2021). Momentum Returns and Volatility. Does Matter for Winner-Minus-Loser Strategy? Evidence from the Idiosyncratic Volatility and Conditional Volatility. *Journal of Money, Banking and Finance*, Vol. 7, No. 2, 2021, pp. 171-189.

receive a positive return. The strategy is called "momentum strategy". Since then, the momentum trading strategy has been extensively observed in many asset types such as commodity, foreign exchange, international, and bond markets (Okunev and White, 2003; Chui, Titman, and Wei, 2010; Aness, Moskowitz, and Pedersen, 2013).

The momentum strategy, however, appears to have no clear explanation whether momentum return can be explained by the presence volatility. Barroso and Santa-Clara (2015) use time-varying to manage momentum portfolios and report a greater return, lower volatility, and higher Sharpe ratio than plain momentum strategy. Motivated by their findings, in this paper we investigate the use of volatility sorted portfolios to determine the risk-adjusted return of winner-minus-loser (WML) strategy.

Fu (2009) tests for the returns in equity markets based on idiosyncratic volatility and ranks portfolios based on the size of volatility. The result indicates that portfolio-sorted based on volatility can yield a greater return and lower the overall risk. Ang *et al.* (2009) test for the return using idiosyncratic volatility of U.S. stock markets and conclude that the return reversals occur, making the characteristic of returns to be consistent with that of momentum strategy. These findings contribute to the momentum-volatility sorted portfolios as we primarily focus on this paper.

We test the sample of daily U.S. firm level data from 1990 to 2020. The momentum return is constructed as winner portfolio minus loser portfolio or winner-minus-loser (WML). Winner portfolio is classified as the top ten percent of stock excess returns while loser portfolio is the bottom ten percent. The results are consistent with documented literatures. Then, we use the idiosyncratic volatility sorting using GJR-GARCH model suggested by Fu (2009). The results, however, do not show the improvement of the overall momentum returns.

We then test further to see whether conditional volatility proposed by Moreia and Muir (2017) can provide a better risk-adjusted performance for WML portfolio. We find that conditional volatility does help to improve risk-adjusted return for WML. However, the percentage of return is sacrificed in order to achieve a higher Sharpe ratio.

Explaining the source of momentum return, we incorporate the use of Fama-McBeth (1973) two-step regression with economic variables. However, the size of economic variables is small, closing to zero. This indicates that investors are not taking economic variables to form portfolio. Rather, they are interested in the historical return and sort portfolio based on the performance of stocks.

The paper is organized as follows. Section II provide related literatures. Data and methodology are presented in Section III. The empirical results are provided in Section IV. Lastly, Section V concludes the paper.

LITERATURE REVIEWS

Momentum Returns and Return Reversals

The momentum return has been substantially documented (Jegadeesh and Titman, 1993; Jegadeesh and Titman, 2001; Okunev and White, 2003; Menkhoff *et al.*, 2012; Barroso and Santa-Clara, 2015). Investors receive a positive return while using a zero-investment strategy[1], indicating that investors take relatively zero risk in their investment to generate positive return. Profits, however, can be reserved for a longer horizon of holding period. Moskowitz, Ooi, ad Pedersen (2012) indicate the return reversals in multiple instruments after one-year holding period. Their results empirically show that the momentum strategy can profit only in the short-run.

McLean (2010) report the momentum disappearance as the result of the return reversals. His finding suggests that reversals occur because of mispricing. The market adjusts the true value of stocks, turning winners to be losers and vice versa. Booth, Fung, and Leung (2016) report the similar result that momentum-reversal occurs due to the size of market capitalization causing the stock prices to move into opposite direction.

Momentum and Market Efficiency Hypothesis (MEH)

One argument of momentum strategy is whether the strategy follows the market efficient hypothesis (EMH). Malkiel and Fama (1970) propose the idea of market correction due to the arrival of new information. The market price, then, should reflect the new available of information. EMH, however, shows that anomalies occur marking it harder to conclude the market is efficient. De Bondt and Thaler (1985) observe the reaction of investors due to the arrival of new information. The finding shows that investors overreact to the new information, and the behavior of investors violates the EMH.

Jegadeesh and Titman (1993), Daniel, Hirschlerifer, and Subrahmanyam (1997), and Low and Tan (2016) find that anomalies are largely due to the investor's confidence and reactions to the information. Then, the attributions of momentum anomaly can explain the investment behavior, which reflects to the arrival of new information to interpret into the investments. In turn, investors tend to overreact to the new information and violate the MEH such that investor sell winner stocks and buy loser stocks. Investors, who are able to take a long position on winners and short position on losers, can generate a positive return. These results provide an important contribution to finance literature that there is a potential positive return using the momentum strategy.

Risk-Managed Momentum Return

Barroso and Santa-Clara (2015) propose the use of volatility-adjusted risk factor to manage the momentum portfolio. They argue that plain momentum strategy suffers greatly during the market crashes, making the strategy less attractive for investors to implement. Risk-management momentum strategy provides a greater return, increases the Sharpe ratio, reduces the kurtosis and left-skewness. Daniel and Moskowitz (2016) test for the momentum crashes under bull and bear market conditions using the dynamic momentum strategy. The strategy is based on the forecast of momentum's mean and variance to improve the momentum strategy. Their result suggests that momentum strategy can be managed, helping to double alpha and the Sharpe ratio. Additionally, they test for other asset classes and the result is pronounced.

Idiosyncratic Volatility and Equity Return

Fu (2009) explains in his empirical work that portfolio-managed volatility can provide a greater return. His work is based on the idiosyncratic volatility from risk-loading factors from three-factor model. Modification of GARCH to determine the size of idiosyncratic volatility is used to capture the leverage effect as well as the time-varying of volatility. His empirical presents that the idiosyncratic volatility factor helps to reduce the volatility in portfolio as well as provide a higher risk-adjusted return. Ang *et al.* (2009) also test for risk-managed return based on idiosyncratic volatility. Their result, consistent of Fu (2009), indicates that investors can proxy for the size of volatility and yield a greater return when taking the risk-factors into account.

Their results suggest that momentum return can be managed by controlling the size of volatility. Motivated by their findings, we test for the risk-managed momentum and hypothesize that if momentum return can be managed, then WML portfolio should show higher return, lower volatility, and increase Sharpe ratio.

DATA

The primary source of data is from Center for Research in Security Prices (CRSP) and Compustat. Daily U.S. equity data is obtained from January 1990 to December 2020. To be considered in the sample, stocks must be traded in NYSE, AMEX, or NASDAQ. As suggested by literature (Banz, 2981; Maillard, Roncalli, and Teiletche, 2010; Daniel and Moskowitz; 2016), we use CRSP sharecode of 10 and 11 to collect the common equity data. We also winzorize potential outliers in our sample by 1% for each tail. Hoberg and Phillips (2010) indicate the use of 1% winzorizing to eliminate and control for extreme values in the sample.

Table 1 presents the summary statistics of 48 industries based on SIC Code provided by Kenneth French's Website . Among all 48 industries, Automobiles and Trucks industry provide the greatest volatility with standard deviation of 16.57%. This is due to the change in the recent auto-manufacturing companies to shift to electric vehicles. Furthermore, Automobiles and Trucks industry suffered from the Covid-19 pandemic as the industry tend to move along with the economic cycle. Surprisingly, Trading industry provides the highest return with the mean return of 2.44% and standard deviation of 8.98%. Trading sector has become very popular among investors since many brokerage firms decided to have zero commission fees, making it more attractive for investors pushing the higher return for firms in this sector.

Table 1: Presents the summary statistics of 48 industries from January 1990 to December 2020. The data are from the Center for Research in Security Prices (CRSP) and Compustat. The data exclude stocks that are not traded in NYSE, AMEX, and Nasdaq. Each industry is classified based on SIC Code provided by Kenneth French Website. The sample is winzorized 1% for each tail to eliminate the extreme values

ID	*Name*	*Mean*	*Stdev*	*Median*	*Obs*
1	Agriculture	1.90%	7.79%	1.57%	3,418
2	Food Products	0.90%	6.11%	0.87%	15,858
3	Candy and Soda	0.58%	4.06%	0.59%	3,901
4	Beer and Liquor	0.93%	5.94%	0.91%	4,962
5	Tobacco Products	0.46%	6.47%	0.42%	1,751
6	Recreation	0.74%	8.19%	0.65%	10,051
7	Entertainment	1.09%	8.62%	0.98%	16,046
8	Printing and Publishing	1.42%	6.42%	1.45%	11,638
9	Consumer Goods	1.04%	6.75%	1.05%	17,077
10	Apparel	1.54%	7.21%	1.04%	11,391
11	Healthcare	0.87%	7.81%	0.75%	23,416
12	Medical Equipment	0.85%	7.51%	0.78%	36,148
13	Pharmaceutical Products	0.28%	8.80%	0.16%	61,141
14	Chemicals	1.03%	6.38%	0.98%	19,831
15	Rubber and Plastic Products	2.04%	7.52%	1.35%	7,713
16	Textiles	1.14%	7.16%	1.04%	4,927
17	Construction Materials	1.68%	6.32%	1.78%	18,243

contd. table 1

ID	*Name*	*Mean*	*Stdev*	*Median*	*Obs*
18	Construction	0.93%	7.60%	1.02%	13,827
19	Steel Works Etc	0.59%	6.51%	0.64%	14,788
20	Fabricated Products	1.70%	6.28%	1.62%	3,221
21	Machinery	1.34%	6.25%	1.20%	33,356
22	Electrical Equipment	1.64%	7.98%	1.53%	26,766
23	Automobiles and Trucks	-0.38%	16.57%	-0.24%	34,170
24	Aircraft	1.01%	6.77%	0.95%	15,138
25	Shipbuilding, Railroad Equipment	1.26%	6.37%	1.12%	4,838
26	Defense	-0.13%	5.79%	-0.11%	1,927
27	Precious Metals	0.17%	4.95%	0.12%	1,845
28	Non-Metallic and Industrial Metal Mining	0.29%	8.06%	0.27%	14,557
29	Coal	0.43%	8.73%	0.35%	8,548
30	Petroleum and Natural Gas	-0.88%	7.62%	-0.40%	2,663
31	Utilities	1.04%	7.96%	0.95%	215
32	Communication	0.20%	4.89%	0.24%	38,632
33	Personal Services	0.28%	8.73%	0.34%	43,193
34	Business Services	1.09%	7.78%	1.11%	12,427
35	Computers	0.75%	10.52%	0.84%	151,909
36	Electronic Equipment	1.13%	7.90%	1.21%	36,911
37	Measuring and Control Equipment	0.78%	7.41%	0.83%	64,347
38	Business Supplies	1.69%	8.22%	1.53%	21,215
39	Shipping Containers	0.73%	5.81%	0.84%	11,163
40	Transportation	0.65%	5.74%	0.54%	3,941
41	Wholesale	0.44%	6.68%	0.47%	32,662
42	Retail	0.84%	7.55%	0.73%	48,068
43	Restaurants, Hotels, Motels	0.87%	7.27%	0.85%	55,110
44	Banking	0.45%	6.93%	0.48%	23,851
45	Insurance	1.21%	7.92%	1.12%	124,213
46	Real Estate	1.15%	5.22%	0.13%	38,840
47	Trading	2.44%	7.67%	2.35%	11,028
48	Others	0.40%	8.98%	0.37%	316,637

Momentum Portfolio Construction

We construct the momentum portfolio based on cumulative excess returns as suggested by Jegadeesh and Titman (1993), and Barroso and Santa-Clara (2015). The cumulative returns are formed based on the past 12 months up until 1 month before the formation date (from t-12 to t-2). Asness (1997), Fama and French (1996), and Daniel and Moskowitz (2016) suggest the potential reversals that could happen at time t-1. To avoid the reversal issue, we form the returns from time t-12 to 1-2. We then divide the sample into ten portfolios.

Ten portfolios are characterized by the size of the return. The top 10% is classified as winner while the bottom 10% is loser. The difference between winner and loser or winner-minus-loser (WML) is the top 10% minus the bottom 10%. Table 2 reports the summary statistics of momentum portfolios.

Table 2: Presents the portfolio sorted of U.S. equity from January 1990 to December 2020. The data are from the Center for Research in Security Prices (CRSP) and Compustat. The data exclude stocks that are not traded in NYSE, AMEX, and Nasdaq. The CRSP share code 10 and 11 are used for common equities. Portfolio 1 presents the loser portfolio, which contains the return of bottom 10%. Portfolio 10 presents the winner portfolio, which contains the return of top 10%. Winner minus loser (WML) is zero investment strategy which is long portfolio 10 and short portfolio 1. The portfolio is formed based on the past 12 months up until 1 month before the formation date (t-12 to t-2). SR denotes for Sharpe Ratio

Portfolio	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*WML*
Mean	-6.34%	-5.44%	-3.84%	-1.22%	-1.20%	1.58%	3.89%	6.87%	7.38%	9.44%	15.78%
Stdev	12.30%	13.42%	8.73%	3.22%	3.40%	5.50%	6.66%	9.12%	14.90%	18.35%	19.67%
SR	-0.52	-0.41	-0.44	-0.38	-0.35	0.29	0.58	0.75	0.50	0.51	0.80

As expected, the loser portfolio (portfolio 1) shows a negative return while the winner portfolio (portfolio 10) has a positive return. WML portfolio shows the higher return, and Sharpe ratio than the winner portfolio. The result is consistent with documented literature that WML strategy provides greater return than investing in winner portfolio. The result stems from the fact that investors profit from both long and short positions from their investments with zero-investment cost.

We also divide the sample into sub-period. Table 3 reports the sub-period result. Panel A shows the summary statistics from 1990 to 2000, 2000 to 2010 represents in Panel B, and 2010 to 2020 in Panel C. Each sub-period shows the similar result that WML portfolio yields a greater return, Sharpe ratio, and helps reducing the skewness and kurtosis.

The size of WML is relatively larger overtime as reported in panel C that the WML can generate the return up to 17.56% while the Sharpe ratio is 0.89. The explanation of this phenomena is the Covid-19 aftermath. Goodell (2020), and Albulescu (2021) empirically report that the pandemic increased the volatility in the market, making the return in U.S. equity to be highly skewed. Then, the source of WML during the recent period is due to the market volatility as well as the expectation of investors towards the market.

Idiosyncratic Factor

Barroso and Santa-Clara (2015), and Daniel and Moskowitz (2016) argue that momentum return can be managed. Plain momentum strategy provides a

Table 3: Presents the portfolio sorted of U.S. equity. The data are from the Center for Research in Security Prices (CRSP) and Compustat. The data exclude stocks that are not traded in NYSE, AMEX, and Nasdaq. The CRSP share code 10 and 11 are used for common equities. Portfolio 1 presents the loser portfolio, which contains the return of bottom 10%. Portfolio 10 presents the winner portfolio, which contains the return of top 10%. Winner minus loser (WML) is zero investment strategy which is long portfolio 10 and short portfolio 1. Panel A reports from the period of 1990 to 2000, Panel B shows the preiod of 2000 to 2010, and Panel C indicates the period of 2010 to 2020. The portfolio is formed based on the past 12 months up until 1 month before the formation date (t-12 to t-2). SR denotes for Sharpe Ratio

Panel A: 1990 to 2000

Portfolio	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*WML*
Mean	-3.58%	-2.24%	-1.38%	-0.51%	-0.05%	1.25%	2.44%	3.57%	4.31%	5.87%	9.45%
Stdev	8.54%	7.65%	8.21%	5.44%	4.41%	5.32%	6.12%	7.18%	8.44%	9.85%	10.05%
SR	-0.42	-0.29	-0.17	-0.09	-0.01	0.23	0.40	0.50	0.51	0.60	0.94

Panel B: 2000 to 2010

Portfolio	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*WML*
Mean	-4.21%	-3.87%	-2.11%	-0.28%	0.87%	2.10%	3.44%	4.58%	5.67%	7.02%	11.23%
Stdev	10.85%	9.42%	8.48%	6.21%	5.28%	6.87%	7.49%	8.41%	9.58%	12.18%	13.15%
SR	-0.39	-0.41	-0.25	-0.05	0.16	0.31	0.46	0.54	0.59	0.58	0.85

Panel C: 2010 to 2020

Portfolio	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*WML*
Mean	-7.35%	-5.84%	-4.11%	-1.85%	-0.57%	1.23%	3.47%	5.82%	7.85%	10.21%	17.56%
Stdev	13.58%	14.21%	10.58%	6.58%	5.71%	7.98%	8.47%	11.84%	15.21%	19.44%	19.83%
SR	-0.54	-0.41	-0.39	-0.28	-0.10	0.15	0.41	0.49	0.52	0.53	0.89

worse outcome during crash periods. Managing the risk of momentum strategy provides a greater outcome. In this paper, we follow the use of idiosyncratic risk factor proposed by Fu (2009). Fu (2009) defines idiosyncratic risk as the error term to help explaining the stock movement. However, it is uncorrelated to the market risk. Portfolio-sorted based on idiosyncratic volatility can generate a significant return greater than the market return.

We estimate the idiosyncratic volatility using Fama-French (2016) five-factor model as follows:

$$R_{it} - r_t = \alpha_i + \beta_i MKT_t + s_i SMB_t + h_i HML_t + c_i CMA_i + r_i RMW_i + \varepsilon_{it}, \varepsilon_{it} \sim N(0, \sigma_{it}^2)$$

Where $R_{it} - r_t$ is the excess return of stock i, MKT_t is the value-weighted f portfolio over the one-month T-bill rate, SMB_t is the return of the smallest one-third of firms minus the return of the largest one-third firms, HML_t is the return of the highest one-third of book-to-market ratio firms minus the return of the lowest one-third of book-to-market ratio firms, CMA_i is the return of conservative firms minus the return of aggressive firms to measure the investment factor, and RMW_i is the return of robust firms minus the return of weak firms to measure the profitability factor. The idiosyncratic volatility is measured by the residual value, ε_{it}.

Merton (1987) and Ang *et al.* (2006) test for the idiosyncratic volatility using GARCH model. However, Fu (2009) argues that, to observe the idiosyncratic volatility, the time-varying estimation must be determined. He proposes the use of modified GARCH to capture both time-varying factor and leverage effect of U.S. equity. The model is estimated as follows:

$$\sigma_{it}^2 = w + \sum_{i=1}^{q}[a_i + \gamma_i I_{[\varepsilon_{t-1}<0]}]\varepsilon_{t-1}^2 + b_i \sigma_{t-1}^2$$

The equation describes GJR-GARCH (Glosten, Jagannathan, and Runkle, 1993). The p and q are defined as the number ranging from 1 < *p*, *q* < 3[3]. GJR-GARCH is supported by Hansen and Lunde (2005) that the model can capture the presence of leverage effect and the model itself is superior than the standard GARCH (*p*, *q*).

Momentum Portfolio - Conditional Volatility

Moreira and Muir (2017) show the empirical result of using conditional volatility to construct the portfolio return. The portfolios are constructed based on the volatility by scaling an excess return and inverse conditional volatility. The conditional volatility portfolio sorting can help to capture the potential increase in return and decrease risk exposure in portfolios. The portfolio is constructed as:

$$f_{t+1}^{\sigma} = \frac{c}{\widehat{\sigma_t^2(f)}} f_{t+1}$$

Where f_{t+1} is the one period buy-and hold portfolio excess return, f_{t+1}^{σ} is the one-period portfolio volatility, $\sigma_t^2(f)$ is the idiosyncratic volatility that is determined in the previous section, and c is a constant arbitrary number to measure the scaling conditional volatility.

To determine the proxy for portfolio conditional variance, $\sigma_t^2(f)$, we use an approximation of the previous monthly realized variance as the proxy for the conditional variance,

$$\sigma_t^2(f) = RV_t^2(f) = \sum_{d=1/22}^{1}(f_{t+d} - \frac{\Sigma_{d=1/22}^{1} f_{t+1}}{22})^2$$

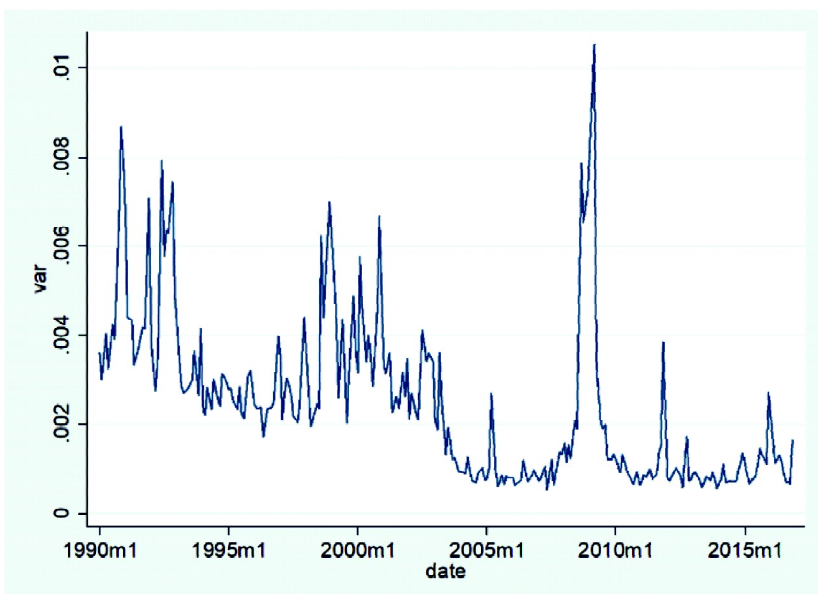
Where $RV_t^2(f)$ is the previous month realized variance with approximation of 22 trading days.

Then, we use five-factor model of Fama and French (2017) for time-series regression as:

$$f_{t+1}^{\sigma} = \alpha + \beta f_{t+1} + \epsilon_{t+1}$$

Figure 1 shows the conditional volatility of five-factor model. These factors show the similar trend and can capture the change in financial market during financial crises. Then, it can be concluded that these factors can be use as a proxy for portfolio conditional volatility.

Figure 1: Shows the idiosyncratic volatility of 5-factor model spanning period from January 1990 to December 2020 estimated from equation: $R_{it} - r_t = \alpha_i + \beta_i (MKT_t) + s_i SMB_t + h_i HML_t + c_i CMA_i + r_i RMW_i + \varepsilon_{it}$, $\varepsilon_{it} \sim N(0, \sigma_{it}^2)$" where MKT_t, SMB_t, HML_t, CMA_t, and RMW_i are factor loadings as proposed by Fama-French 5-factor model" . Then, the conditional volatility is estimated by the GJR-GARCH equation: $\sigma_{it}^2 = w + \Sigma_{i=1}^{q} [a_i + \gamma_i I_{[\varepsilon_{t-1}<0]}] \varepsilon_{t-1}^2 + b_i \sigma_{t-1}^2$



EMPIRICAL RESULTS

Momentum Return

We test for the presence of momentum return in individual industry to see whether the source of momentum return exists. WML portfolio is constructed by taking the difference between top 10% excess return and bottom 10% excess return. Table 4 reports the result. Dividing sample into 48 industries based on the SIC Code from Kenneth French Website, we find that momentum return is pronounced in all sectors.

The result also suggests that loser portfolio, in general, provides a negative return while winner portfolio shows a positive return. WML helps improving the return and Sharpe ratio. The result is consistent with documented literature indicating that momentum return can be found in all industries, and it helps managing the better performance of portfolio.

Table 4: Presents the portfolio sorted based on the excess return of U.S. equity from January 1990 to December 2020. The data are from the Center for Research in Security Prices (CRSP) and Compustat. The data exclude stocks that are not traded in NYSE, AMEX, and Nasdaq. The CRSP share code 10 and 11 are used for common equities. Each industry is classified based on SIC Code provided by Kenneth French Website. Winner minus loser (WML) is zero investment strategy which is long winner portfolio and short loser portfolio. SR denotes for Sharpe Ratio

ID	*Name*	*WML*	*Stdev*	*SR*
1	Agriculture	2.94%	15.08%	0.19
2	Food Products	4.61%	14.10%	0.33
3	Candy and Soda	7.02%	14.84%	0.47
4	Beer and Liquor	5.70%	15.13%	0.38
5	Tobacco Products	10.63%	15.97%	0.67
6	Recreation	2.45%	14.20%	0.17
7	Entertainment	2.24%	13.34%	0.17
8	Printing and Publishing	4.26%	14.05%	0.30
9	Consumer Goods	3.76%	13.99%	0.27
10	Apparel	4.15%	13.42%	0.31
11	Healthcare	2.30%	13.49%	0.17
12	Medical Equipment	2.96%	13.30%	0.22
13	Pharmaceutical Products	2.40%	13.19%	0.18
14	Chemicals	2.68%	14.45%	0.19
15	Rubber and Plastic Products	3.03%	14.14%	0.21
16	Textiles	3.99%	13.50%	0.30
17	Construction Materials	2.85%	13.98%	0.20
18	Construction	1.81%	14.13%	0.13
19	Steel Works Etc	1.56%	14.09%	0.11
20	Fabricated Products	4.08%	14.04%	0.29
21	Machinery	1.97%	13.85%	0.14
22	Electrical Equipment	1.00%	13.84%	0.07
23	Automobiles and Trucks	1.89%	11.18%	0.17
24	Aircraft	2.60%	14.73%	0.18
25	Shipbuilding, Railroad Equipment	3.22%	14.21%	0.23

contd. table 4

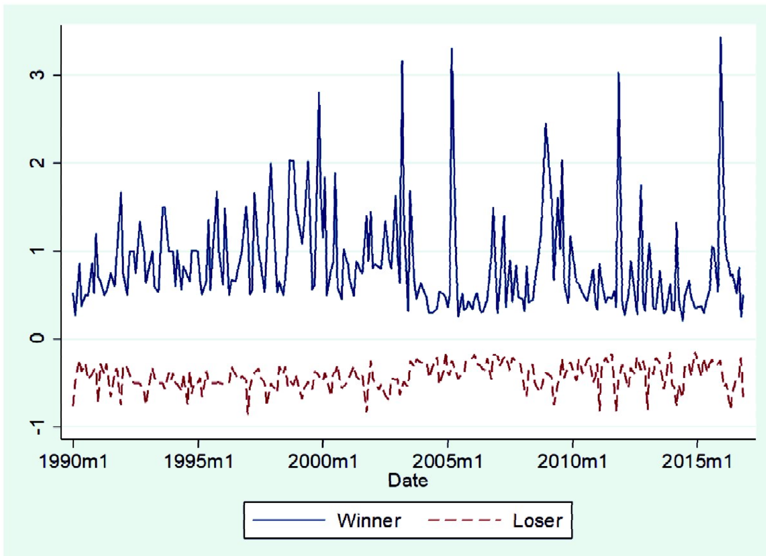
ID	*Name*	*WML*	*Stdev*	*SR*
26	Defense	0.91%	16.16%	0.06
27	Precious Metals	3.01%	13.28%	0.23
28	Non-Metallic and Industrial Metal Mining	4.85%	13.14%	0.37
29	Coal	2.18%	13.35%	0.16
30	Petroleum and Natural Gas	2.74%	14.93%	0.18
31	Utilities	1.00%	13.41%	0.07
32	Communication	8.85%	15.74%	0.56
33	Personal Services	2.21%	14.25%	0.16
34	Business Services	2.53%	14.07%	0.18
35	Computers	1.54%	13.58%	0.11
36	Electronic Equipment	1.32%	12.94%	0.10
37	Measuring and Control Equipment	2.58%	13.25%	0.19
38	Business Supplies	1.71%	13.51%	0.13
39	Shipping Containers	3.08%	14.96%	0.21
40	Transportation	3.76%	14.86%	0.25
41	Wholesale	3.46%	14.28%	0.24
42	Retail	2.09%	13.65%	0.15
43	Restaurants, Hotels, Motels	1.87%	13.35%	0.14
44	Banking	3.61%	14.02%	0.26
45	Insurance	5.74%	14.78%	0.39
46	Real Estate	3.88%	14.86%	0.26
47	Trading	4.35%	14.48%	0.30
48	Others	10.33%	15.75%	0.66

Using the sample for all the industries helps to improve the performance of WML portfolio as reported in table 2. Consistent with Jegadeesh and Titman (1997), Moskowitz and Grinblatt (1999), and Lesmond, Schill, and Zhoc (2004), momentum return stems from the difference between winner and loser stocks. Without the available of new information, investors can profit from the zero-investment strategy by longing winners and shorting losers based on the historical returns. Figure 2 shows the difference between winners and losers. As expected, the winners provide a positive return while losers show a negative return over the period.

Momentum Return and Idiosyncratic Volatility

This section analyzes the effect of idiosyncratic volatility to momentum return. Table 5 reports the regression result of five-factor model. Consistent with Ang *et al.* (2006) and Fu (2009), the negative coefficient of SMB indicates that small firms have not outperformed large firms. However, the size of SMB is getting close to zero, showing the minimal effect to the firm size.

Figure 2: Provides the difference in excess return of top 10% (winner) and bottom 10% (loser) from January 1990 to December 2020. The excess return is calculated as the difference between daily return minus daily market return. The solid line represents the winner return while dash line represents loser return



HML, CMA, and RMW also report the similar result reported by Fama and French (2017). The size of volatility (Vol) is comparable to what Fu (2009) reports.

Table 5: Presents the regression from equation: $R_{it} - r_t = \alpha_i + \beta_i\,(MKT_t) + s_i\,SMB_t + h_i\,HML_t + c_i\,CMA_i + r_i\,RMW_i + \varepsilon_{it}$, $\varepsilon_{it} \sim N(0, \sigma^2_{it})$ where MKT_t, SMB_t, HML_t, CMA_t, and RMW_i are factor loadings as proposed by Fama-French 5-factor model. The idiosyncratic volatility (Vol) is measured by GJR-GARCH equation: $\sigma^2_{it} = w + \Sigma^q_{i=1}[a_i + \gamma_i I_{[\varepsilon_{t-1}<0]}]\varepsilon^2_{t-1} + b_i\,\sigma^2_{t-1}$. The coefficients of factor loadings and conditional idiosyncratic volatility are reported with the spanning period from January 1990 to December 2020.

Variables	*Mean*	*Stdev.*
MKT	0.15%	1.41%
SMB	-0.04%	1.97%
HML	0.44%	2.63%
CMA	-0.28%	4.06%
RMW	0.57%	3.23%
Vol	12.87%	15.91%

Table 6 reports the momentum strategy based on idiosyncratic volatility. We argue that if momentum return can be managed, then the volatility can be used to control the WML return. Portfolio 1 reports the highest volatility portfolio while portfolio 10 is the least volatility portfolio. WML is the winner minus loser strategy or portfolio 1 minus portfolio 10. The result shows that the sorting based on idiosyncratic volatility, however, does not help to increase the momentum return. WML has the mean return of 11.79%, with the standard deviation of 15.41%. Meanwhile, the plain momentum strategy yields a better result as reported in table 2.

The result clearly shows that sorting-portfolio based on idiosyncratic volatility does not help to improve the performance of momentum return. In fact, it is used to control for the size of volatility. The plausible explanation of this result is that investors decide to forgo return to lower the size of risk in momentum portfolio.

Table 6: Presents the characteristics of momentum portfolios based on idiosyncratic volatility from 5-factor model from January 1990 to December 2020. Portfolio 1 represents the highest 10% of idiosyncratic volatility while Portfolio 10 represents the lowest 10% of idiosyncratic volatility. Vol represents the conditional volatility estimated by $R_{it} - r_t = \alpha_i + \beta_i (MKT_t) + s_i SMB_t + h_i HML_t + c_i CMA_i + r_i RMW_i + \varepsilon_{it}$, $\varepsilon_{it} \sim N(0, \sigma^2_{it})$ where MKT_t, SMB_t, HML_t, CMA_t, and RMW_i are factor loadings as proposed by Fama-French 5-factor model. The idiosyncratic volatility is measured by GJR-GARCH equation: $\sigma^2_{it} = w + \Sigma^q_{i=1}[a_i + \gamma_i I_{[\varepsilon_{t-1}<0]}]\varepsilon^2_{t-1} + b_i\ \sigma^2_{t-1}$. Winner minus loser (WML) is zero investment strategy which is long portfolio 10 and short portfolio 1. SR denotes for Sharpe Ratio.

Portfolio	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*WML*
Mean	15.68%	12.11%	10.58%	6.87%	7.18%	8.64%	7.33%	6.20%	5.44%	3.89%	11.79%
Vol	26.21%	23.58%	20.12%	18.74%	16.39%	15.44%	14.33%	12.68%	10.81%	6.87%	15.41%
SR	0.60	0.51	0.53	0.37	0.44	0.56	0.51	0.49	0.50	0.57	0.77

Risk-Managed Momentum

We now sort portfolio based on the conditional volatility to explain whether WML return can be increasing. Constructed the portfolio based on the conditional volatility proposed by Moreira and Muir (2017), the result is reported in table 7. Portfolio 1 indicates the highest conditional volatility while portfolio 10 shows the lowest conditional volatility. The result shows that the WML portfolio provides a better risk-adjusted return than the plain momentum strategy or idiosyncratic volatility portfolio-sorting as reported by Sharpe ratio of 0.94.

The higher Sharpe ratio is resulted from the use of conditional volatility portfolio sorting, which is helping to lower the size of standard deviation of WML to 14.75%. However, the mean return is decreasing to 13.90% compared to 15.78% of plain momentum strategy (table 2). The explanation of this phenomena is that investors sacrifice certain percentage of return as they try to lower the size of volatility in WML portfolio. If investors are risk-adverse, then they are willing to take lower return strategy to achieve a substantial risk-adjusted performance portfolio. Plain momentum offers a higher return, but it does come with a higher volatility, which makes risk-adverse investors form portfolio with the use of volatility.

Table 7: Provides the portfolios based on the size of excess return by using $f_{t+1}^{\sigma} = \frac{c}{\widehat{\sigma_t^2(f)}} f_{t+1}$ from January 1990 to December 2020. Portfolio 1 represents the highest 10% conditional volatility while Portfolio 5 represents the lowest 10% conditional volatility. Conditional Volatility is estimated by $\sigma_t^2(f) = RV_t^2(t) = \Sigma_{d=1/22}^{1}(f_{t+d} - \frac{\Sigma_{d=1/22}^{1} f_{t+d}}{22})^2$, where RV_t^2 (*f*) is the previous month realized variance with approximation of 22 trading days. Winner minus loser (WML) is zero investment strategy which is long portfolio 10 and short portfolio 1. SR denotes for Sharpe Ratio

Portfolio	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*WML*
Mean	3.57%	2.16%	-1.03%	4.44%	6.59%	7.12%	5.83%	8.81%	9.12%	10.33%	13.90%
Conditional Volatility	20.17%	18.67%	18.55%	11.67%	13.49%	14.12%	13.15%	11.48%	12.08%	11.41%	14.75%
SR	0.18	0.12	-0.06	0.38	0.49	0.50	0.44	0.77	0.75	0.91	0.94

Source of Momentum Return

Barroso and Santa-Clara (2015) test for the WML return of U.S. equity and explain that the variance or conditional volatility can be used to explain the momentum return. Daniel and Moskowitz (2016) also argue that using variance for the approximation of the managed-momentum portfolio, the return relatively increases as well as Sharpe Ratio while the risk is smaller.

We construct the portfolio based on two-step regression proposed by Fama-McBeth (1973) modified with Daniel and Moskowitz (2016) risk-managed return. The model is presented as following:

$$r_{WML,t+1} = \lambda_0 + \widehat{\beta_i}\lambda_t + \mu_i X_t + \theta_i Z_{i,t} + \alpha_{i,t+1}$$

Where $r_{WML,t+1}$ is the WML portfolio at time *t*+1, $\hat{\beta}_i$ is a vector of the coefficients of five-factor model and X_t is a vector of economic variables, and θ_i is the vector of control variable. We are using conditional volatility as a control variable as Moreira and Muir (2017) propose.

We determine the vector of risk-loading factors from the first-step regression. Then, we determine eh momentum portfolio of WML based on the second-step regression. The choice of economic variables are CPI, Bond

Yield, and T-Bill to control the change in excess return of U.S. equity (Bekaert and Wu, 2000; Chrisoffersen *et al.*, 2012; Menkhoff *et al.*, 2012).

Table 8 reports the result. As expected, the economic variables are statistically. However, the size of coefficient of these economic variables appears to be small, closing to zero. It indicates that economic variables may not be a good explanatory variable to explain the change in WML return. The plausible explanation is that WML, in fact, is not driven by economic variables, rather it is driven by the past historical return.

We also break down the main result to run the regression for each economic variable. The result does not change. This is to confirm that the performance of WML is not affected by the economic variables. Investors are looking at the historical return of stocks to form the portfolio. Economic variables, however, are not significantly important for investors since winners tend to perform relatively well in the future and losers, on the other hands, tend to perform worse in the future. Investors then ignore the economic variables.

We then can conclude that the potential explanatory factor for WML return is purely based on the past information. Investors disregard the use of other economic variables to adjust their portfolio formation.

Table 8: Reports the portfolio predictability from $r_{i,t+1} = \lambda_0 + \widehat{\beta}_i\lambda_t + \mu_i X_t + \theta_i Z_{i,t} + \alpha_{i,t+1}$, where $\hat{\beta}i$ is a vector of the coefficients estimated from the first step (MKTRF, SMB, HML, MOM), and *Xt* is a vector of economic variables, and θ_i is the vector of control variables (Idiosyncratic factor). Newey-West t-statistic is reported in parenthesis.

	1	*2*	*3*	*4*	*5*
Constant	0.00	0.00	0.00	0.00	0.00
	(-0.66)	(-0.08)	(-0.65)	(-0.24)	(-0.73)
MKT	0.32	0.226	0.375	0.234	0.369
	(-2.14)	(-1.99)	(-2.37)	(-2.01)	(-2.34)
SMB	-0.169	-0.039	-0.264	-0.034	-0.299
	(-2.43)	(-2.34)	(-2.25)	(-2.29)	(-2.55)
HML	0.045	0.149	0.008	0.065	0.031
	(-2.17)	(-2.94)	(-2.11)	(-2.28)	(-2.16)
CPI	0.011		0.008		
	(-2.35)		(-2.65)		
T-Bill	0.009			0.008	
	(-3.22)			(-3.55)	
Bond	0.049				0.058
	(-3.47)				(-3.94)
Vol	-0.046	-0.054	-0.041	-0.04	-0.071
	(-5.89)	(-7.29)	(-5.25)	(-5.29)	(-9.40)

CONCLUSIONS AND REMARKS

This paper provides a comprehensive study of momentum return of U.S. equity spanning from January 1990 to December 2020. Constructing portfolio based on the past returns, we find that the winners and losers provide positive and negative returns, respectively. Consistent with documented literatures, the winner-minus-loser portfolio or WML helps increase the return, reduce volatility, and improve Sharpe ratio. We also document that the momentum return can be found in all 48 industries, indicating that momentum return can be found in any asset types.

Using idiosyncratic volatility and conditional volatility portfolio sorting, the result shows that only conditional volatility can be used to improve the WML performance by increasing the size of Sharpe ratio. However, investors sacrifice certain percentage of return to achieve the higher risk-adjusted return. This result indicates that investors are well aware of information of past return, then they are willing to forgo some of their potential return to lower the size of volatility and higher Sharpe ratio.

We also test for the source of momentum return. We incorporate the use of two-step regression from Fama-McBeth (1973) along with economic variables. The result shows that economic variables can explain the source of momentum return. However, the size is relatively small, closing to zero. Then, it indicates that investors do not include economic variables to form WML portfolio, rather they use the historical return of stocks to determine the portfolio.

Our contribution towards this paper is to explain whether momentum return can be managed. We find, consistent with documented literatures, that momentum return can be managed and be able to make a higher risk-adjusted return. However, to explain the source of momentum return, economic variables seem to be not important factors for investors. We shed the light of the future research to incorporate variables to explain the source of momentum return.

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