Alternative reversal variable

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Abstract

In constructing the reversal variable, we tend to ignore the strong momentum in individual stock returns. A simple subtract the average of past 12-month return from previous month return allows us to alleviate the momentum return. Consequently, the reversals are significantly stronger. We also find that states of market have significant impact on reversal profit indirectly through momentum effect. In down market, when momentum effect appears weak, the profit of reversal strategy is significantly higher than in up market, when momentum effect is strong.

Asset pricing models; short-term reversal; momentum; anomalies, market states.
JEL classification: G12.

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1 Introduction

Financial literature proposes two investment strategies based on past returns. Specifically, one is based on firm's return of twelve months prior to the current month, called momentum strategy (Jegadeesh and Titman (1993)). The other is based on firm's previous month return, called short-term reversal strategy (Jegadeesh (1990)). For the momentum, it becomes conventional to construct it by taking past stock return from t-13 (or t-12) to t-2 as the criteria to classify the stock. The most recent month (t-1) is skipped in order to purge the negative effect of return reversal. Now, considering a simple situation that a stock, which is associated with both high prior month (t-1) and high past 12-month return (t-13 to t-2), how do we do? knowing that this stock will belong to the short side of reversal strategy, while belong to the long side of momentum strategy. If we implement Jegadeesh (1990) reversal strategy (put this stock in the short side), the profit of short-term reversal profit is likely negatively affected by this stock, who exhibits a strong momentum. In this paper, we begin by asking a simple question: does it exist a simple way to alleviate the momentum in individual stock return to construct the short-term reversal variable or forming the short-term reversal strategy.

In fact, it could be analytically shown by using the framework of Lo and MacKinlay (1990) that Jegadeesh (1990) reversal strategy could be decomposed into two components. The first is the difference between realized of previous month return and the average of stock return from t-13 to t-2 (hereafer R_{1-12}). The second, which involves buying the stocks that have outperformed the market portfolio and selling the stocks that have underperformed the market portfolio, is equivalent to momentum strategy. This decomposition not only implies that the profit of Jegadeesh (1990) reversal strategy is negative affected by stock return momentum, but also suggests that using R_{1-12} instead of previous month return (hereafter R_1) to implement the reversal strategy would give higher profit since this variable allows us to isolate the short-term reversal from the momentum in stock return.

Consistent with this decomposition, we find that reversal strategy based on R_{1-12} earns significantly higher risk-adjusted return than those of conventional reversal strategy, which is based on previous raw return. On average, the short-term reversal strategy based on R_{1-12} provides 25 bps improvement from that of standard reversal strategy. This improvement is unaffected by adjustment for common risk factors. The evidences obtained from the direct comparison based on Fama and MacBeth (1973) cross-sectional regressions corroborate with these findings.

Prior literature reports that states of market affect significantly the profitability of momentum strategy (e.g. Grundy and Martin (2001) and Cooper et al. (2004)). Recently, Hsu and Chen (2019) show that the variation of momentum profit across market states exits under style investing [2]. The above decomposition also suggests that the time-varying effect of momentum

[2] In particular, they show that that the relation between momentum return and return comovement driven by style investing is significantly stronger in 'optimist' market state.

profit could have impact on the profit of reversal strategy. In other words, the states of market would have indirect impact on the profit of reversal strategy via the influence it has on the momentum. Consistent with this assertion, we find that Jegadeesh (1990) reversal profit generated following 'up' market is about one third of the one realized following 'down' market. Similarly, we find that the profit of R_{1-12} based reversal strategy following increase market is significantly lower than following decline market. Importantly, we observe that, following market decline, when momentum effect is weak or does not exist, the profits of these strategies are not significantly different. However, following market increase, when momentum effect is strong, R_{1-12} based reversal strategy's return is considerably higher than conventional reversal strategy's one. The finding suggests that R_{1-12} helps to reduce the strong momentum effect of stock price during 'up' market.

We check the robustness of our findings by conducting the out-of-sample tests. In particular, we replicate these above results for European stock market. In overall, the results obtained in E.U market corroborate with U.S evidences.

We deem that our study contributes to the existing literature in the following ways. First of all, we show that Jegadeesh (1990) reversal effect is negatively affected by the momentum in stock return and propose a simple way to alleviate this problem. The idea is simple but certainly has important implication for the theoretical and practical purpose, given the number of studies, which employ the previous month return to control the reversal effect, and significantly improved reversal profit it offers. Secondly, our results also have important implications for several explanations that have been proposed in the literature to explain the short-term reversal. We show that market states also have a significant impact on short-term reversal profits, but in the inverse direction to what occurs for momentum profit. In particular, we find that the reversal profits are significantly higher in 'down' market than in 'up' market. The time-varying reversal profit across market states could be either due to the negative effect to the time-varying momentum profit and liquidity provision, which should be more pressing in the 'down' market. Our results are therefore complementary to the findings in Da et al. (2014), Avramov et al. (2006) and Hameed et al. (2010) and suggest that momentum could have significant impact on the strength of reversal. These evidences provide a different perspective of reversal profits, which could contribute further to the understanding of short-term reversal - an important phenomenon in stock price that is difficult to reconcile with risk-based model of expected return.

The rest of the paper is organized as follows. In Section 2, we decompose the conventional reversal strategy to the strategy based on R_{1-12} and the momentum strategy. In Section 3, we describe the data using in this paper. Section 4 presents our main findings on the performances of alternative reversal strategies. We verify the consistency of results by examining EU equity markets. In this section, we also investigate the influence of market states on reversal profits. We provide our concluding remarks in Section 5.

2 Analytical analysis

We follow Lo and MacKinlay (1990) and consider Jegadeesh (1990) reversal strategy that assigns a portfolio weight to stock 'i' at time 't' of

$$W_{i,t} = -\frac{1}{N}(R_{i,t-1}) - R_{M,t-1} \tag{1}$$

Where $R_{M,t-1} = \sum_{i=1}^{N} \mathrm{R}_{i,t-1}$ and N is the number of securities in the market.

The weight of Jegadeesh (1990)'s strategy implies buying the previous month loser securities and selling short the previous month winner securities. The profit for this strategy at time 't', P_t, is given by:

$$P_t = \sum_{i=1}^{N} W_{i,t} R_{i,t} \quad \text{or} \quad P_t = -\frac{1}{N}\sum_{i=1}^{N}(R_{i,t-1} - R_{M,t-1})R_{i,t} \tag{2}$$

To show the effect of momentum, we add and subtract $E12_{i,t-1}$, which is measured as $1/12\sum_{k=2}^{13} \mathrm{R}_{t-k}$, to equation (2)

$$P_t = -\frac{1}{N}\sum_{i=1}^{N}(R_{i,t-1} - E12_{i,t-1} - R_{M,t-1} + E12_{i,t-1})R_{i,t} \tag{3}$$

or we can rewrite equation (3) as:

$$P_t = -\frac{1}{N}\sum_{i=1}^{N}(R_{i,t-1} - E12_{i,t-1})R_{i,t} - \frac{1}{N}\sum_{i=1}^{N}(E12_{i,t-1} - R_{M,t-1})R_{i,t} \tag{4}$$

The decomposition from equation (4) tells that profit of conventional reversal strategy P_t is likely negatively affected by the momentum return (the second component) and using the difference between previous month return and its 12-month average return (R_{1-12}) to create the reversal strategy would probably provide higher profit than the one generated from strategy based on previous return.[3]. In Graph 1, we plot the returns on reversal and momentum strategies. As could be seen in the Graph, the correlation between them is negative. In other words, reversal return tend to be higher in the period of momentum crash.

3 Data

The data includes NYSE, AMEX, and NASDAQ common stock monthly returns from July 1963 to December 2016. We exclude stocks belonging to 5 percent smallest market capitalization to alleviate the potential micro-structure problem associated to these small stocks[4].The market return is the value-weighted index of all listed firms in CRSP and the risk-free rate is the one-month Treasury bill rate, both obtained from Ken French's data library[5].

[3]The analysis is similar to that of Hameed and Mian (2014). However, they employ this for motivation of the intra-industry reversal. The main idea is that neutralizing the momentum effect will enhance the short-term reversal profit.

[4]Note that none of paper's result is affected by whether we exclude these stocks.

[5]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/datalibrary. html

4 Results

4.1 Reversal strategies

We begin our analysis by computing the principle variable, R_{1-12}, as suggested by equation 4, which, is measured as the difference of previous return and the average of 12-month return from t-2 to t-13. However, we change a little bit to adapt for the empirical regularities. In fact, Novy-Marx (2012) shows that momentum return based on firm's performance twelve to seven months prior to the current month are stronger than the one based on firm's performance six to two months prior. To put more weight on the firm's performance twelve to seven months we compute R_{1-12} as $\sum_{k=2}^{13} \frac{k}{12}(\mathrm{R}_{t-1}\text{- } E12_{t-1})$[6]

In Panel A of the Table 1, we report the equal-weighted raw and risk-adjusted monthly returns for the recent loser, recent winner and the conventional reversal strategy. Consistent with Jegadeesh (1990)'s findings, we find a significant profit of 1.26% (t-statistic = 6.96) per month. The risk-adjusted profits are still large[7]. The CAPM and three-factor alphas are 1.12% (t-statistic = 6.46) and 1.05% (t-statistic = 5.72) per month respectively. The

[6]Our main results remained unchanged when we compute R_{1-12} as suggested by equation (4), which is computed as $R_{1-12} = \sum_{k=2}^{13} \frac{1}{12}(\mathrm{R}_{t-1} \text{ - } E12_{t-k})$. Note that Goyal and Wahal (2015), in their investigation of 37 other major stock markets, points out that there is no such 'echo' in return and that Novy-Marx (2012)'s findings are likely driven by the effect of short-term reversals from month t-2, indeed. Though their studies entertain different hypothesis, but this weighting scheme is consistent with both.

[7]The risk-adjusted profits are measured by regressing the monthly reversal profits on alternatively excess return of the market portfolio Sharpe (1964) and Fama and French (1993) three factors, which add the size factor (SMB) and the value factor (HML) to the excess return of the market portfolio.

R_{1-12} based reversal profits are reported in the Panel B. The profit is 1.51% (t-value = 9.15) per month, which is higher than that generated by the standard reversal strategy. The CAPM and three-factor alphas are 1.38% (t = 7.98) and 1.43% (t = 7.56) respectively. The additional profit of 0.25% per month is highly significant (t-statistic = 3.53) and is unaffected by adjustment for common risk factors.

*** Insert Table 1 about here ***

We also employ the Fama and MacBeth (1973) style cross-sectional regression to compare these strategies simultaneously [8]. From Table 2, we see that the return from the R_{1-12} based reversal strategy is 1.12% (t-statistic = 7.30) per month versus the conventional strategy's 0.45% (t-statistic = 1.92) per month. Dominance of R_{1-12} based reversal strategy becomes appearance when we look at the Fama and French risk-adjusted return. The risk-adjusted return for R_{1-12} based reversal strategy is 1.20% (t-statistic = 8.76), while those for Jegadeesh's one become insignificant 0.18% (t-statistic = 0.73).

Overall, the results provide supports to our arguments that using R_{1-12},

[8] In particular, we estimate the following cross-sectional regressions,

$$R_t = a_0 + j_{l,t} RL_{1,t-1} + j_{h,t} RH_{1,t-1} + l_t RL_{1-12,t-1} + h_t RH_{1-12,t-1} + \epsilon_t \qquad (5)$$

Where R_t is month 't' stock return. The independent variables are dummies that indicate whether the stock is held, either long or short in month 't' as part of one of the two strategies. In particular, $RL_{1,t-1}$ equals one if stock's previous month performance is in the bottom 20% and is zeros otherwise. $RW_{1,t-1}$ equals one if stock's previous month performance is in the top 20% and is zeros otherwise. $RL_{1-12,t-1}$ and $RH_{1-12,t-1}$ are defined similarly but stocks are ranked by R_{1-12} measure.

which allows us to purge the strong momentum of individual stock return from the reversal, will improve the reversal profit.

*** Insert Table 2 about here ***

4.2 Market states and reversals

To test the relation between market state and short-term reversal, we employ Cooper et al. (2004)'s approach. In particular, we first define the market state as 'up' ('down'), if the cumulative return of CRSP value weighted return, including dividends, over the formation period of momentum strategy (in our case is 12 months) is positive (negative). We also consider the alternative definition of market state. In particular, we define the market state as a 'up' ('down') if the cumulative CRSP value-weighted return in the past 24 months is positive (negative) (e.g Daniel and Moskowitz (2016). To test whether reversal profits in each market state are equal to zero, we regress the time series of average monthly reversal profits on two dummy variables for 'up' and 'down' market, with no intercept. To test if mean profit in 'down' (or low state) market are different from profits in 'up' (or high state) market, we regress average monthly reversal profits on 'down' market dummy, with a constant. This approach helps to preserve the full-time series of returns and allow us to estimate t-statistic that robust to auto-correlation and heteroscedasticity using Newey and West (1987) standard errors.

Since the results obtained from both definitions of market state are similar, we are focus only on the results for market states that are defined based on the cumulative return of 12 previous months. As can be seen in Panel A of Table 3 of the Table, from 1964 to 2016.12, following 'down' market, the raw, the CAPM and FF3 risk-adjusted reversal profits are 2.34% (t-statistic = 5.61), 2.28% (t-statistic = 5.49) and 2.34% (t-statistic = 5.61) respectively[9]. However, the reversal profits in the 'up' market are much lower. They are approximately one third of the ones realized in the 'down' market. Following the period of market increase, the raw, CAPM and Fama and French risk-adjusted profits are 0.86% (t-statistic = 5.15), 0.61% (t-statistic = 3.73), and 0.66% (t-statistic = 3.92) per month respectively. The t-statistic for testing the equality of the profits across 'up' and 'down' market are reported in the last row of Panel A. These t-statistics suggest that the reversal (adjusted) profits are statistically distinguish between two states.

We also examine if the R_{1-12} based reversal strategy return varies with market states. The results are also reported in Table 3 (the left column). We see that following 'down' market, the raw profit, CAPM and Fama and French risk-adjusted profits are 2.30% (t-statistic = 5.86), 2.28% (t-statistic = 5.93), and 2.40% (t-statistic = 5.72). Compare to the conventional reversal profit in the 'down' market, they are approximately the same. This result should not be surprise because the objective of R_{1-12} is to reduce the effect of momentum.

[9]To form the CAPM and Fama-French risk-adjusted profits, we first regress the time-series of raw reversal profits on the correspondent factors and a constant in order to obtain the estimated factor loadings. Then, the risk-adjusted returns are measured as the reversal return net of what is attributable to exposure to the market factor and Fama and French three factors.

In the 'down' market, when the momentum effect appears weak, the profit generated from R_{1-12} should be not (or less) significantly different to the one generated from raw return. Following 'up' market, the R_{1-12} based reversal strategy's (adjusted) returns are still statistically significant. Following 'up' market, compare to the conventional reversal profits, the R_{1-12} based reversal strategy's profit are higher. We see that the additional profits (for both raw and adjusted ones) are consistent with those reported in Table 1 and Table 2, about 30bps per month. However, R_{1-12} based reversal strategies profits obtained in the 'down' market is significantly higher than those in 'up' market. The results could be explained by liquidity provision. Because, in the 'down' market, it is also the period of liquidity dry-up, explaining higher reversal returns (see Campbell et al. (1993), Avramov et al. (2006)). However, this result could also be consistent with investor's overeaction. For example, Heyman et al. (2019) argue that the investor tend to overreact in the 'down' market, leading to recent 'winner' stocks are more likely to revert [10]. They show that besides liquidity, overreaction is an important factor that drives price reversals, especially during times of high volatility.

*** Insert Table 3 about here ***

[10] They measure the investor's overreaction by Google Search Volume Index

4.3 Robustness checks

4.3.1 E.U stock markets

We also investigate the implication of R_{1-12} on expected return in the EU data. This non-US examination delivers a useful out-of-sample test on the implication of R_{1-12} on expected returns. The obtained results confirm that the higher performance of R_{1-12} based strategy relative to conventional reversal strategy presents not only in U.S. equity market but also in other equity markets in European areas[11]. Also, we see that R_{1-12} based reversal strategy profits are significantly different conditioning on market states. The t-statistic for testing the equality of reversal profit across market states are highly significant.

4.3.2 Intra-industry reversals and Residual return reversals

Hameed and Mian (2014) find that compare to conventional reversal strategy, intra-industry reversals are stronger in magnitude and robust to market micro-structure biases. We find that R_{1-12} performance goes beyond the industry control.

We also compare the R_{1-12} based reversal strategy to residual return reversals strategy proposed by Blitz et al. (2013) and find that R_{1-12} strategy generates higher return than the residual return based strategy. In addition, one problem with residual return is that it does not cover the whole sample of

[11] The results are reported in Appendix A

population of stocks, much of small stocks are set to missing in the process of residual return estimation. Consequently, when controlling for residual return in the cross-sectional regressions, the coefficient of lag return remains highly significant. This imply that lag one month return owns the information that does not belong to lagged residual return. In contrast, the coefficient of lag return become small and insignificant after controlling for R_{1-12} [12].

5 Conclusion

It becomes conventional to implement the momentum strategy by taking the past return from 't-12' (or 13) to 't-2', skipping 't-1' as the criteria to classify the stock in order to purge the negative effect of return reversal. However, in implementing the reversal strategy, we tend to ignore the strong momentum in individual stock return. A simple subtract the past 12-month average return from the recent return allows us to alleviate the return momentum. Consequently, the reversals are significantly stronger. The additional profit of implementing the reversal strategy based on R_{1-12} is statistically and economically significant. For example, on average the short-term reversal strategy based on R_{1-12} yields returns that are higher than those of a conventional short-term reversal strategy about 25 bps per month. This improvement is unaffected by adjustment for common risk factors. The additional profit will be more impressive, about 45 bps per month, if we

[12]These results is reported in Appendix B

implement this strategy within industry.

Our results also contribute to the study of reversal anomaly by showing that market states have significantly impact on the profit of reversal strategy through momentum effect. We find that conditioning on the states of market has a significant impact on the profit of reversal strategies. In particular, following the 'down' market, when momentum effect appears weak, the profit of reversal strategy is significantly higher than following 'up' market, when momentum effect is strong.

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Table 1: Portfolio returns

	Raw returns	Risk-adjusted Returns	
		CAMP	FF3
Panel A: Conventional reversal strategy			
Loser	1.871	0.786	0.564
	(5.70)	(4.19)	(4.20)
Winner	0.609	-0.332	-0.485
	(2.13)	(-2.11)	(-4.62)
Loser -Winner	1.262	1.118	1.050
	(6.96)	(6.46)	(5.72)
Panel B: R_{1-12} based reversal strategy			
Low	1.984	0.912	0.691
	(6.32)	(5.12)	(6.01)
High	0.476	-0.463	-0.660
	(1.68)	(-2.98)	(-6.55)
Low - High	1.508	1.376	1.351
	(9.94)	(9.15)	(8.96)
Diff	0.246	0.257	0.301
	(3.53)	(4.04)	(4.47)

Note: Stocks are sorted alternatively by previous month return and by R_{1-12}. Loser (winner) are the equally-weighted return of 20% of stocks with lowest (highest) previous month return. Low (High), are the equally weighted return of 20% of stocks that have lowest (highest) R_{1-12}, where $R_{1-12} = \sum_{k=2}^{13} \frac{k}{12}(\mathrm{R}_{t-1} - E12_{t-k})$. *'Loser – Winner'* is the spread between loser and winner portfolio's return, while *'Low – High'* is the spread between low and high R_{1-12} portfolio's return. *Diff* is the difference between *'Low- High'* and *'Loser – Winner'* portfolio returns. Risk-adjusted returns are estimated by the capital asset pricing model (CAPM) and Fama and French (1993) three-factor model (FF3). These factors are available at French's website. The reported t-statistic (in parentheses) are Newest West (1987) corrected. The sample period is from 1964.07 to 2016.12.

Table 2: Pairwise comparison

	Raw returns	Risk-adjusted Returns	
		CAPM	FF3
RL_{1-12}	0.442	0.383	0.380
	(5.35)	(4.75)	(4.91)
RH_{1-12}	-0.679	-0.702	-0.818
	(-6.47)	(-7.24)	(-9.03)
RL_{1-12}-RH_{1-12}	1.121	1.086	1.198
	(7.31)	(7.63)	(8.76)
RL_1	0.134	-0.023	-0.050
	(0.95)	(-0.18)	(-0.38)
RW_1	-0.314	-0.349	-0.217
	(-2.25)	(-2.69)	(-1.72)
RL_1- RW_1	0.448	0.326	0.167
	(1.92)	(1.53)	(0.73)

Note: Each month between 1964.07 to 2016.12, a cross-sectional regression of the following form is estimated
$R_t = a_0 + j_{l,t}RL_{1,t-1} + j_{h,t}RH_{1,t-1} + l_tRL_{1-12,t-1} + h_tRH_{1-12,t-1} + \epsilon_t$
Where RL_1 (RL_{1-12}) equals one if stock i's previous month return (R_{1-12}) is in the bottom 20% and is zeros otherwise. RH_1 (RH_{1-12}) equals one if stock i's previous month return (R_{1-12}) is in the top 20% and is zeros otherwise. The raw returns in the table are the time series average of these coefficients. Risk-adjusted return are the estimated intercepts from the time-series regressions of these averages on the contemporaneous market factor (CAPM) and Fama-French three factors (FF3). The reported t-statistic (in parentheses) are Newest West (1987) corrected.

Table 3: Market states and reversal profits

		R_{1-12} based reversal strategy			Conventional reversal strategy		
Panel A: Market states are defined based on 12-month cumulative market return							
	nobs	raw	CAPM	FF3	raw	CAPM	FF3
Down	172	2.338	2.282	2.347	2.332	2.226	2.342
		(5.87)	(5.94)	(5.61)	(5.02)	(5.03)	(5.21)
Up	457	1.195	1.000	1.009	0.859	0.606	0.657
		(8.63)	(7.27)	(7.54)	(5.15)	(3.73)	(3.92)
Down $\neq$ *Up*		(2.67)	(3.15)	(2.91)	(2.94)	(3.51)	(3.39)
Panel B: Market states are defined based on 24-month cumulative market return							
Down	144	2.291	2.025	2.121	2.335	2.014	2.151
		(5.42)	(5.27)	(4.89)	(4.83)	(4.81)	(4.64)
Up	474	1.268	1.144	1.146	0.932	0.751	0.799
		(8.34)	(7.05)	(7.38)	(5.09)	(3.86)	(4.26)
Down $\neq$ *Up*		(2.24)	(2.22)	(1.91)	(2.66)	(2.77)	(2.49)

Note: The table present the conventional and R_{1-12} based reversal returns in 'up' and 'down' market. We also reported the risk-adjusted returns across market states, where CAPM and Fama and French adjusted returns are defined as the return net of what is attributable to exposure to the market factor and Fama and French (1993) three factors respectively. $Down \neq Up$ is the t-statistic of the test whether momentum profits in each state respectively equal to zeros. Panel A (Panel B) reports the results where market states are defined based on the cumulative return of the value weighted market index including dividends 12 (24) months priors to beginning of the holding period. The sample period is from 1964.07 to 2016.12.

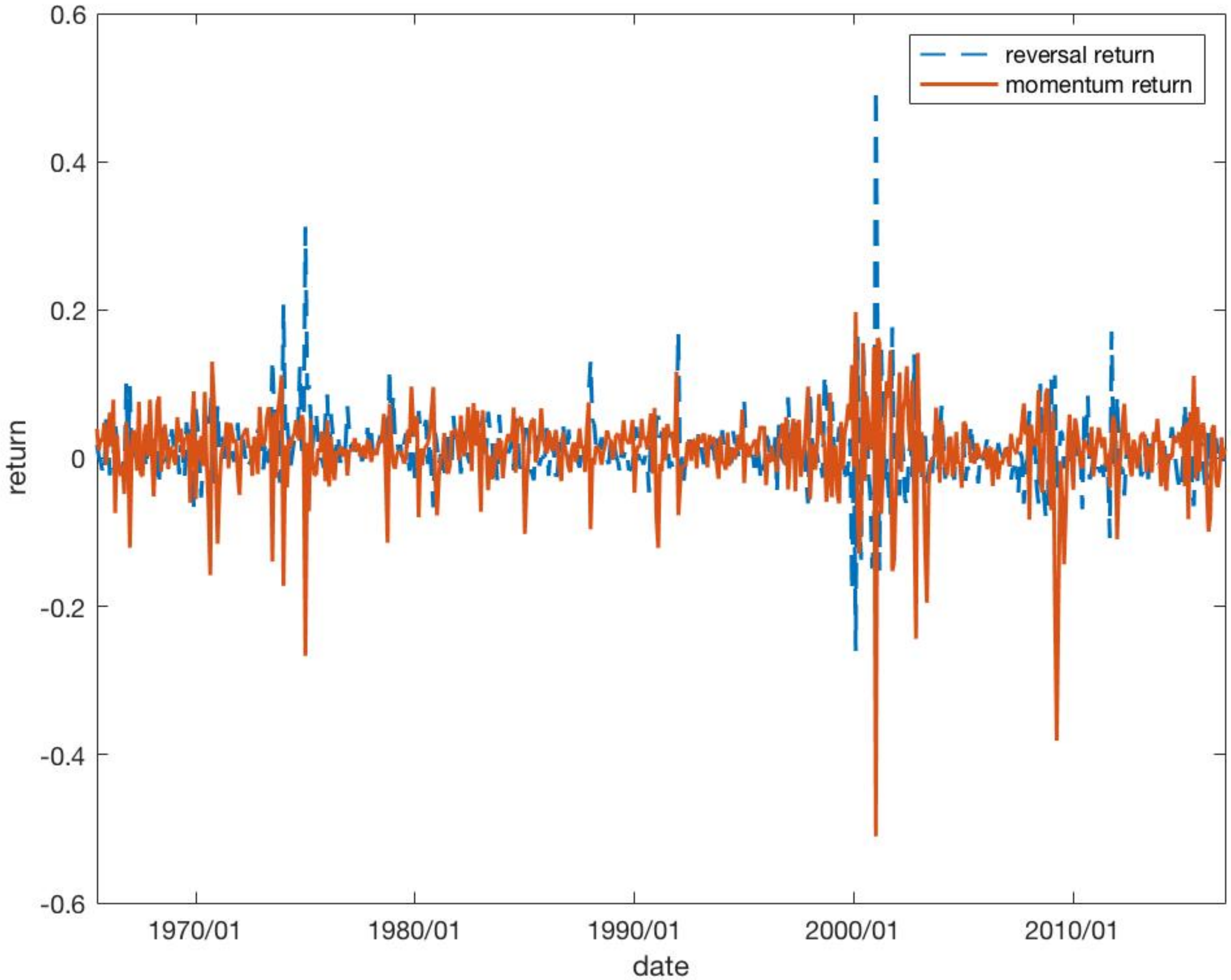

Figure 1: Time-series of returns from momentum and reversal strategy. This plot shows the returns on reversal and momentum strategies for the period from 1964.07 to 2012.06

A E.U stock markets

In this Appendix, we verify the robustness of our findings by conducting the out-of-sample tests. In particular, we replicate these above results for European stock market. In particular, we examine: (i) whether the reversal strategy based on R_{1-12} is significantly higher than that generated by conventional reversal strategy in European stock market; (ii) whether market states have significantly impact on European reversal strategy's profits. In Table 9, we presents summary statistic for the European countries included in our sample. Table 10 presents the results of the profit of reversal strategy formed following Fama and MacBeth (1973) style for E.U stock markets. Table 11, we examine our results about the relation between reversal profits and market states in EU stock market.

Table A.1: Summary statistics for E.U sample

Country	Firms	Weight
Austria	83	1,55
Belgium	132	4,78
Finland	91	2,64
France	658	29,36
Germany	639	28,52
Greece	188	1,29
Ireland	47	1,35
Italy	211	11,15
Netherlands	136	9,01
Portugal	72	1,10
Spain	129	9,24

Note: This table reports the average number of firms, average market equity (Size) and country's average percentage in term of total market equity for the countries included in the European sample. The data is from DataStream. The sample period is from 1990.01 to 2016.12.

Table A.2: Reversal profits: E.U evidences

	EU		GER		FR		ITALY		OTHERS	
	raw	adj	raw	adj	raw	adj	raw	adj	raw	adj
a_0	0.944	0.584	0.843	0.578	1.186	0.678	0.522	0.235	0.904	0.448
	(3.53)	(12.23)	(3.19)	(8.40)	(4.26)	(10.56)	(1.32)	(3.03)	(3.10)	(6.54)
RL_{1-12}	0.385	0.497	0.381	0.333	0.255	0.418	0.549	0.644	0.346	0.527
	(2.93)	(3.32)	(2.39)	(2.02)	(1.62)	(2.85)	(2.82)	(2.96)	(1.61)	(2.59)
RH_{1-12}	-1.161	-1.535	-1.383	-1.831	-1.153	-1.520	-0.711	-0.871	-1.158	-1.500
	(-7.11)	(-9.59)	(-5.65)	(-7.43)	(-5.28)	(-7.02)	(-3.15)	(-3.64)	(-5.88)	(-8.58)
RL_1	0.198	-0.132	0.051	-0.184	0.861	0.486	-0.325	-0.520	0.106	-0.281
	(1.04)	(-0.81)	(0.20)	(-0.76)	(3.70)	(2.26)	(-1.25)	(-1.92)	(0.47)	(-1.30)
RW_1	0.687	1.131	0.643	1.088	0.072	0.571	0.429	0.596	1.071	1.408
	(2.58)	(3.72)	(2.32)	(4.06)	(0.24)	(1.59)	(1.46)	(1.94)	(2.79)	(3.62)
RL_{1-12}- RH_{1-12}	1.546	2.032	1.764	2.165	1.408	1.938	1.259	1.515	1.504	2.027
	(6.56)	(9.42)	(6.04)	(7.40)	(5.00)	(7.49)	(3.60)	(3.91)	(4.15)	(6.23)
RL_1- RW_1	-0.489	-1.263	-0.592	-1.271	0.789	-0.085	-0.754	-1.117	-0.965	-1.689
	(-1.36)	(-3.44)	(-1.62)	(-3.41)	(1.94)	(-0.18)	(-1.58)	(-2.18)	(-1.81)	(-3.16)

Note: Each month between January 1990 to December 2016, a cross-sectional regression of the following form is estimated separately for European sample, Germany (GER), France (FR), ITALY, and Others which are group the remaining countries
$R_t = a_0 + j_{l,t}RL_{1,t-1}+ j_{h,t}RH_{1,t-1} + l_tRL_{1-12,t-1} + h_tRH_{1-12,t-1}+ \epsilon_t$
Where RL_1 (RL_{1-12}) equals one if stock i's previous month (R_{1-12}) return is in the bottom 20% and is zeros otherwise. RH_1 (RH_{1-12}) equals one if stock i's previous month (R_{1-12}) return is in the top 20% and is zeros otherwise. The raw returns in the table are the time series average of these coefficients. Risk-adjusted return are the intercepts from the time-series regressions of these averages on the contemporaneous market factor (CAPM) and Fama-French three factors (FF3). The reported t-statistic (in parentheses) are Newest West (1987) corrected.

Table A.3: Market state and reversal profits: E.U evidences

		R_{1-12} based reversal strategy			Conventional reversal strategy		
Panel A: Market states are defined based on 12-month cumulative market return							
	nobs	raw	CAPM	FF3	raw	CAPM	FF3
Down	119	1.765	1.640	1.810	1.485	0.933	1.556
		(5.71)	(5.06)	(5.66)	(3.67)	(2.35)	(4.05)
Up	205	0.856	0.711	0.764	0.111	-0.215	-0.033
		(3.97)	(3.29)	(3.49)	(0.35)	(-0.68)	(-0.10)
$Down \neq Up$		(2.31)	(2.60)	(2.30)	(2.74)	(3.28)	(2.31)
Panel B: Market states are defined based on 24-month cumulative market return							
Down	107	1.682	1.507	1.664	1.581	0.981	1.552
		(5.44)	(4.43)	(5.09)	(4.22)	(2.61)	(4.31)
Up	217	0.947	0.828	0.894	0.140	-0.175	0.057
		(4.52)	(3.96)	(4.10)	(0.41)	(-0.53)	(0.16)
$Down \neq Up$		(1.96)	(1.95)	(1.70)	(2.82)	(2.93)	(2.29)

Note: The table present the conventional and R_{1-12} based reversal returns in 'up' and 'down' market for EU stock markets. We also reported the risk-adjusted returns across market states, where CAPM and Fama and French adjusted returns are defined as the return net of what is attributable to exposure to the market factor and Fama and French (1993) three factors respectively. $Down \neq Up$ is the t-statistic of the test whether momentum profits in each state respectively equal to zeros. Panel A (Panel B) reports the results where market states are defined based on the cumulative return of the value weighted market index including dividends 12 (24) months priors to beginning of the holding period. The sample period is from 1990.01 to 2016.12

B Intra-industry reversals and Residual return reversals

Hameed and Mian (2014) argue that implement the reversal strategy within industry will isolate the short-term reversal from an across-industry momentum (Moskowitz and Grinblatt (1999)). They find that compare to the conventional reversal, the intra-industry reversal is stronger in magnitude and robust to market micro-structure biases. We show that R_{1-12} effect goes beyond the industry control. The R_{1-12} based reversal strategy within-industry provides significantly higher return than the one generated by Hameed and Mian (2014) within-industry reversal strategy (see Table B.1)

Recently, Blitz et al. (2013) reports that reversal strategy based on residual return, which is obtained from Fama and French (1993) three-factor regression, provides higher profit compare to the conventional strategy does. They argue that the conventional reversal strategy is negatively affected by the Fama and French (1993) three factors, making the profit lower. Therefore, forming the reversal strategy based on the return, which nets of Fama and French three-factor exposures, will improve the profit. In fact, the method proposed by Blitz et al. (2013) is also related to the idea of neutralizing the momentum effect. In particular, we find that applying Blitz et al. (2013)'s method for R_{1-12} does not improve significantly the R_{1-12} based reversal return (see Table B.2). Moreover, we find that R_{1-12} strategy generates higher return than the residual return based strategy (Table B.3). An additional problem

Table B.1: Intra-industry reversals

	returns	Risk-adjusted Returns	
		CAMP	FF3
Intra-industry reversal return	1.591	1.470	1.396
	(9.86)	(9.45)	(8.72)
Intra-industry R_{1-12} based reversal return	1.709	1.600	1.568
	(12.09)	(11.49)	(11.31)
Intra-industry vs conventional reversal return	0.328	0.352	0.347
	(5.04)	(5.48)	(4.91)
Intra-industry R_{1-12} based reversal return vs	0.447	0.482	0.519
conventional reversal return	(4.68)	(5.39)	(5.28)
Intra-industry R_{1-12} based reversal return vs	0.118	0.130	0.172
Intra-industry reversal return	(2.02)	(2.41)	(3.14)

Note: To form the (R_{1-12} based) reversal strategy within industries, we first sort stocks into industry groups based on Fama-French 10 industry classification and then rank stocks based on previous month returns (R_{1-12}) to form the equally-weighted lowest 20% and highest 20% portfolios within each industry. The lowest minus highest portfolio return in each industry is average across all industries to obtain intra-industry (R_{1-12} based) reversal return. The Table reports the conventional reversal, intra-industry reversal return and intra-industry R_{1-12} based reversal returns. Risk-adjusted returns are estimated by CAPM and Fama and French three-factor models. The reported t-statistic (in parentheses) are Newest West (1987) corrected. The sample period is from 1964.07 to 2016.12.

with residual return is that it does not cover the whole sample of population of stocks, much of small stocks are set to missing in the process of residual return estimation. Consequently, when controlling for residual return in the cross-sectional regressions, the coefficient of lag return remains highly significant. This imply that lag one month return owns the information that does not belong to lagged residual return. In contrast, the coefficient of lag return become small and insignificant after controlling for R_{1-12} (Table B.4).

Table B.2: Residual return reversal strategies

	Raw returns	Risk-adjusted Returns	
		CAMP	FF3
R_{1-12} based reversal return	1.508	1.376	1.351
	(9.94)	(9.15)	(8.96)
Residual reversal return using R_{1-12}	1.655	1.617	1.573
	(14.62)	(14.22)	(14.19)
Diff	0.151	0.243	0.218
	(1.65)	(2.70)	(2.31)

Note: Stocks are sorted by residual terms obtained from the regression of R_{1-12} on Fama and French three factors. Lower (higher) are the equally-weighted return of 20% of stocks with lowest (highest) previous month residual. The profit of residual reversal strategy using R_{1-12} is the spread between the 1st and 5th quintile portfolio return. The Table reports the profit of R_{1-12} based reversal strategy and the (Blitz et al., 2013) reversal strategy using R_{1-12}. The reported t-statistic (in parentheses) are Newest West (1987) corrected. The sample period is from 1964.07 to 2016.12.

Table B.3: Pairwise comparisons

	Raw returns	Risk-adjusted Returns	
		CAPM	FF3
RL_{1-12}	0.396	0.219	0.211
	(3.13)	(1.88)	(1.94)
RH_{1-12}	-0.715	-0.777	-0.777
	(-5.61)	(-6.70)	(-7.23)
RL_{1-12} -RH_{1-12}	1.111	0.996	0.989
	(7.02)	(6.32)	(6.32)
RRL	0.427	0.480	0.414
	(4.56)	(5.52)	(5.21)
RRH	-0.383	-0.321	-0.349
	(-3.89)	(-3.58)	(-4.51)
RRL - RRH	0.810	0.801	0.763
	(7.32)	(7.34)	(6.92)

Note: Table reports the estimated coefficients of the following regression
$R_t = a_0 + b_{l,t}RRL_{t-1} + b_{h,t}RRH_{t-1} + l_tRL_{1-12,t-1} + h_tRH_{1-12,t-1} + \epsilon_t$
Where RRL equals one if stock i's previous month residual return, which is residual term obtained from the Fama and French three-factor regression scaled by the standard deviation of return over the estimated period, is in the bottom 20% and is zeros otherwise. RRH equals one if stock i's previous month residual is in the top 20% and is zeros otherwise. RL_{1-12}) and RH_{1-12} indicate the bottom 20% and the top 20% stocks based on R_{1-12} respectively. The results reported for the raw returns in the table are the time series average of these coefficients. Risk-adjusted return are the intercepts from the time-series regressions of these averages on the contemporaneous market factor (CAPM) and Fama-French three factors (FF3). The reported t-statistic (in parentheses) are Newest West (1987) corrected. The sample period is from 1964.07 to 2016.12.

Table B.4: Cross-sectional regressions

	LRet	*RR*	R_{1-12}	*Beta*	*ME*	*BM*
1.	-0.052			0.000	-0.090	0.218
	(-11.84)			(0.11)	(-2.35)	(4.25)
2.	-0.038	-0.002		0.045	-0.091	0.224
	(-5.89)	(-3.87)		(0.301)	(-2.44)	(4.45)
3.	-0.002		-0.007	-0.040	-0.093	0.208
	(-0.11)		(-3.28)	(-0.28)	(-2.51)	(4.07)

Note: Each month 't' we regress the cross-section of stock return on several explanatory variables. The Table reports the time-series average of these coefficients along with their Newey and West (1987) adjusted t-statistic in parentheses. The control variables are residual return (RR), which is the residual term from the Fama and French three-factor regression scaled by the standard deviation of return over the estimated period; lagged one-month return (LRet); the log of market capitalization (ME); book-to-market ratio (BM). R_{1-12} is measured as $\sum_{k=2}^{13} \frac{k}{12}(\mathrm{R}_{t-1}$ - $E12_{t-k})$. The sample period is from 1964.07 to 2016.12.