Time-Varying Payoffs of Return-Adjusted Momentum Strategies

Weifeng Hung	J. Jimmy Yang
Corresponding author: Department of Finance, Feng Chia University, Taiwan. E-mail: wfhung@fcu.edu.tw. The paper is financially supported by the Ministry of Science and Technology in Taiwan (MOST 105-2410-H-035-013).	College of Business, Oregon State University, USA. Email: jimmy.yang@bus.oregonstate.edu .
Pai-Ta Shih	**Chin-Ho Chen**
Department of Finance, National Taiwan University, Taiwan. E-mail: ptshih@ntu.edu.tw .	Department of Finance, Feng Chia University, Taiwan. E-mail: chinho.rrriver.chen6@gmail.com

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Abstract

We compare the performance of return-adjusted momentum strategies. The total returns are adjusted by CAPM, Fama-French (1993) three-factor model, Fama-French (2017) five-factor model, Daniel, Grinblatt, Titman, and Wermers (1997) characteristics model, Haugen and Baker (1996) and Lewellen (2014) Fama-MacBeth regression model. The return-adjusted momentum strategies exhibit not only higher abnormal performance but also less extreme downside risk than the total return momentum. The evidence suggests that abnormal performance of time-esries factor-adjusted momentum strategies are similar across the factor models and outperform cross-sectional characteristic-adjusted and cross-sectional regression -adjusted momentum strategies. The results suggest that merely controlling for time-varying market risk exposure can significantly reduce the downside risks. Contributions of other risk factors related to size, book-to-market ratio, investment, and profitability to momentum downside risk are limited.

Keywords: Factor, Characteristic, Momentum

JEL classification: G11, G12

1. INTRODUCTION

Finding an efficient solution to large negative skewness risk of Jegadeesh and Titman (1993) momentum (JT momentum) is an essential and practical issue to global fund managers who incorporate momentum into their investment decisions. Grundy and Martin (2001) and Blitz, Huij and Martens (2011) document that momentum exhibits time-varying risk exposures and hence are likely to underperform in markets with strong reversals. Specifically, momentum loads positively (negatively) on risk factors when risk factors have positive (negative) premiums during the formation period of the strategy. Once the sign of risk premiums reverse over the holding period, the momentum suffers. For example, negative market returns in the 2008 financial crisis caused the momentum to be tilted towards the low-beta stocks of the market in early 2009. Once the market returns reverse in 2009, the momentum exhibits large losses due to its negative market exposures. Blitz, Huij, and Martens propose a solution to the time-varying risk exposures problem by suggesting a momentum strategy based on residual returns estimated using the Fama and French (1993) three-factor model. They indicate that residual momentum outperforms the total return momentum after adjusting risk. Further, residual momentum exhibits risk-adjusted profits that are about twice as large as those associated with total return momentum.

Daniel and Moskowitz (2013) point out that a momentum crash occurs followed by a market rebound. Momentum profits experience fat tail distribution and are known as negatively skewed with excess kurtosis. That is, momentum exhibits positive average returns but can also experience infrequent but significant negative returns. For example, in July and August of 1932, the momentum strategy suffers a significant crash and has a cumulative return of −70.24% for the two months. During the market decline, momentum tends to long buy low-beta stocks (the past winners) and short sell high beta stocks (the past losers). As the market reverse quickly, the momentum will crash because they have a conditionally large negative beta (Grundy and Martin, 2001). Momentum investors are not able to benefit from using time-varying betas to avoid the crashes in real time. They propose a simple optimal dynamic weighting strategy that can select the timing of the portions of capital invested in the momentum portfolio and they also show that this dynamic-weighting procedure can significantly double the Sharpe ratio of the static momentum. The idea of Daniel and Moskowitz (2013) dynamic weighting momentum is to reduce exposure to momentum during the volatile periods. Further, the dynamic weighting momentum also significantly outperforms the constant volatility momentum (Barroso and Santa-Clara 2014).

Haugen and Baker (1996), Hanna and Ready (2005), and Lewellen (2014) document that the past coefficients of Fama-MacBeth regression can forecast future stock returns. Expected returns are estimated by using a firm's current characteristics and the historical slopes of Fama-MacBeth regressions. They show that expected returns are positively associated with realized returns, particularly during the shorter horizons. Haugen and Baker (1996) and Hanna and Ready (2005) use 12-months rolling average of Fama-MacBeth slopes to estimate expected returns. However, Lewellen (2014) shows that forecasts based on long histories of 120-months work better and, are quietly strongly associated with future returns. Lewellen shows that for a single month, a stock with higher cross-sectional expected returns will earn relatively higher future stock return during the next month. Mainly, Lewellen (2014) shows that Fama-MacBeth expected returns exhibit persistence and stability. However, whether a stock with cumulative expected returns during prior 12 months also exhibits similar or stronger prediction to future stock return is still unsolved. This paper augments adjusted returns based on past slopes of Fama-MacBeth regression to construct momentum strategy. Using a stable and persistent adjusted returns rather than total return, we test whether Fama-MacBeth momentum can avoid the problems of time-varying risk exposures, big crashes over market rebound and long-run reversal facing total return momentum.

As suggested by Daniel and Titman (1997), stock characteristics provide better ex-ante forecasts of the cross-sectional patterns of future returns. In addition to risk factors, stock characteristics might also be a crucial determinant of stock returns. However, how stock characteristics affect momentum has seldom been studied empirically. We attempt to explore how vital characteristics influence the performance of momentum strategy. The adjusted returns are calculated by the difference between raw return and the return on the corresponding characteristic benchmark portfolio. Further, Daniel and Titman (1997) argue that characteristic matching model has more statistical power and is more straightforward than factor model in detecting abnormal performance.

Many studies show that momentum profits are higher for stocks with specific characteristics.[1] For example, momentum returns are higher for stocks with small market capitalization (Hong et al., 2000) and the high book-to-market ratio (Daniel and Titman 1999). Bandarchuk and Hilscher (2012) show that enhanced momentum profit is not due to characteristic per se, but is due to the interaction between characteristic and extreme past returns. After controlling for the influence of extreme past returns, the enhanced momentum profits coming from size, R^2, turnover, analyst

[1] Prior studies argue that firms with a high book-to-market ratio tend to have high future returns and poor past performances (e.g., Fama and French, 1992; 1996; Lakonishok et al., 1994; Kothari and Shanken, 1997). Others show that average stock return is cross-sectionally determined by firm size. Stocks with smaller market capitalization tend to subsequently earn higher returns ((e.g., Banz, 1981; Basu, 1977; Reinganum, 1981; Fama and French, 1992; Daniel and Titman, 1997).

coverage and forecast dispersion, market-to-book ratio and illiquidity disappear. That is, extreme past returns are an important source of variation in momentum profits. They also show that double sorting upon characteristics and past return is not informative in improving momentum profits when characteristics are highly correlated with extreme past returns. Since there are high correlations between characteristics, past returns, and volatility, it is hard to disentangle what explains variation in momentum profits.

In this paper, we comprehensively compare the performance of several types of return-adjusted momentum strategies. The total returns are adjusted by CAPM (FF1, thereafter), Fama-French (1993) three-factor model (FF3, thereafter), Fama-French (2017) five-factor model (FF5, thereafter), Daniel, Grinblatt, Titman, and Wermers (1997) characteristics adjusted model (DGTW, thereafter), Haugen and Baker (1996) and Lewellen (2014) Fama-MacBeth regression model (FMG, thereafter). We show that the average monthly momentum profits on return-adjusted portfolios are all higher than total return momentum. Further, momentum strategies based on factor adjusted returns exhibit higher returns than momentum strategies based on characteristic-adjusted and regression-adjusted returns. Factor-adjusted momentum strategies are more efficient to reduce the extreme loss and experience less drawdown in 2009 than JT momentum. Moreover, the DGTW and FMG momentum also suffer much lose during 2009 financial crisis.

We examine the momentum performance in the year 2009. Notably, we explore the periods from March 2009 to May 2009. The results in table 3 indicate that the market recovered in 2009 with returns of 9, 11, and 7% over the months March, April, and May, respectively, total return momentum's negative market beta caused a streak of substantial losses. The average losses of JT momentum for these three months are

-35.74%. However, the average losses are quite similar to three-factor adjusted momentum strategies FF1, FF3, and FF5 of -13.93%, -12.96%, and -13.96%, respectively. The average losses of DGTW and FMG momentum of -27.49% and -25.17% are higher than factor adjusted momentum, however, lower than JT momentum. Align with the prediction of market rebound, the loss of momentum strategies mainly due to significant rebound of losers.

Several studies show that momentum profits underperform in January (Grinblatt and Moskowitz, 2004; Jegadeesh and Titman 1993, 2001). Similarly, except to the time series factor adjusted momentums (FF1, FF3, and FF5), the cross-sectional characteristic-adjusted momentum (DGTW) and cross-sectional regression-adjusted momentum (FMG) also suffers in January. Consistent with the tax-losing hypothesis, the JT momentum is stronger in December. Also, the DGTW and FMG momentum earn higher profits at the end of the year. Many studies show that momentum profits underperform in January (Grinblatt and Moskowitz, 2004;Jegadeesh and Titman 1993, 2001). Similarly, except for the factor-adjusted momentums (FF1, FF3, and FF5), the characteristic-adjusted momentum (DGTW) and regression return adjusted momentum (FMG) also suffers in January. Consistent with the tax-losing hypothesis, the JT momentum is particularly stronger in December. Also, the DGTW and FMG momentum earn higher profits in the end of the year.

JT momentum underperforms during contractions as defined by the NBER (Chordia and Shivakumar, 2002). The vast market rebound often occurs in recession periods. The results indicate that the factor-adjusted momentum exhibits positive momentum pattern in recessionary periods. Moreover, the JT, DGTW and FMG momentum strategies are stronger in high sentiment months. However, for factor-adjusted momentum strategies perform indifferently for low and high sentiment months.

2. LITERATURE REVIEW

Since Jegadeesh and Titman (1993) firstly suggest a strategy that buys winner stocks (stocks with higher prior raw returns) and sells loser stocks (stocks with lower prior raw returns) can earn positive abnormal returns. The finding challenges the hypothesis that markets are semi-strong-form efficient.

Several studies propose the modified momentum strategy. Moskowitz and Grinblatt (1997) show that industry momentum dominates momentum in individual stocks. George and Hwang (2004) propose a strategy based on the ratio of current price to the prior 52-week high; they show that the 52-week high momentum can generate profits comparable to those of JT momentum. They also show that 52-week high strategy can explain most of JT momentum profits, and that profits of the strategy do not reverse in the long run. Novy-Marx (2012) shows that momentum profits are primarily driven by stock performance over 12 to 7 months before portfolio formation, not the recent past performance over 6 to 2 months, suggesting a contradiction to the traditional view of momentum, which rising stocks tend to keep rising, while falling stocks tend to keep falling.

Regarding the source of momentum profits, Chordia and Shivakumar (2002) document that the macroeconomic-related expected returns can explain the JT momentum in the US stock market. However, Griffin et al. (2003) show that there is no evidence that the profits of JT momentum are driven by macroeconomic risks in the international market. Lesmond, Schill, and Zhou (2004) show that positive profits of JT momentum cannot be obtained after considering transaction cost. They argue that the momentum profits mainly come from short-leg (i.e., selling losers), and the losers tend to have small market value, low liquidity, and high volatility. On the other hand, Korajczyk and Sadka (2004) and Hanna and Ready (2005) show that momentum strategy earns significant excess returns after adjusting transaction cost.

Gutierrez and Prinsky (2007) propose an abnormal momentum strategy that continues to be profitable after formation period, where abnormal return is determined by firm's idiosyncratic return, suggesting underrection to the firm-specific news. In a similar vein, Arena et al. (2008) show that momentum profits are pronounced for stocks with high idiosyncratic volatility, which suggests that because of limits of arbitrage, the momentum profits persist. They content that momentum profits result from underreaction to firm-specific information, for which idiosyncratic volatility can be viewed as a proxy for firm-specific information. However, McLean (2010) show that momentum is not related to idiosyncratic risk.

3. DATA AND PORTFOLIO FORMATION

3.1. Data

The data of the sample period is from July 1966 to December 2016. The Fama and French three factors plus UMD, RMW, and CMA factor are downloaded from the Kenneth French's website.[2] The penny stocks that their price is less than $1 are excluded. The relevant accounting data are drawn from COMPUSTAT. Only firms with ordinary common equity (security type 10 or 11 in CRSP) are included (i.e., ADRs, REITs, and unit of beneficial interest are excluded). To avoid selection/survival bias, firms are not included until they have been in COMPUSTAT for two years. Firms with a negative book value of common equity are deleted each year in which negative book equity is recorded. Market data are assumed to be known

[2] Please refer to the Kenneth French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/ data_library.html)

immediately; accounting data are assumed to be known four months after the end of the fiscal year (Lewellen 2014). All characteristics, except monthly returns, are Winsorized monthly at their 1st and 99th percentiles. We use market capitalization and book-to-market ratio as essential characteristics to explain expected returns.

3.2. Total Return Momentum

Following Fama and French in constructing momentum (WML) factor, for the end of each month *t*, we sort all stocks in NYSE to obtain ten-group breakpoints by their cumulative total returns during previous 12 months and skip one month between portfolio formation and holding period to avoid the effects of bid-ask bounce, price pressure, and any lagged reaction (i.e., the t−11 to t−2-month returns). We then use NYSE breakpoints to assign firms into deciles. The portfolio is held for one month, and portfolio returns are equally weighted. Stocks with the highest rank are assigned into Winner portfolio, and stocks with the lowest rank are assigned into Loser portfolio. The spread portfolio (WML) is Winner-minus-Loser portfolio.

3.3. Time-Series Factor-Adjusted Momentum

Similar to the procedure of Blitz, Huij, and Martens (2011) we calculate the firm-specific return of a given stock. For each stock *j* and month *t*, we estimate Eq. (1) over previous 36-month rolling windows:

$$R_{j,t} - R_{ft} = a_j + b_j MKT_t + s_j SMB_t + h_j HML_t + r_j RMW_t + c_j CMA_t + e_{jt}, \qquad (1)$$

where R_j is the return on stock *j* in month *t*, R_f is the one-month T-bill rate in month *t*, MKT_t, SMB_t, HML_t, RMW_t, CMA_t are the return on the CRSP weighted index in month *t*, the monthly return on the size, book-to-market, profitability, and investment factor in the calendar month *t*, respectively. We calculate one-factor (CAPM) adjusted (*MKT* as the independent variable), three-factor (Fama and French, 1993) adjusted (*MKT*, *SMB*, and *HML* as independent variables), and five-factor (Fama and French,

2015) adjusted (all explanatory variables in Eq. (1)) returns.

We calculate the firm-specific returns e_{jt} of the stock in month t based on the estimated parameters. That is, the residual return is estimated each month for all stocks. As suggest by Blitz, Huij, and Martens (2011), we do not include an intercept in residuals to avoid the potential long-run reversal effect. We then identify firm-specific return winners and losers over the 12-month formation period by cumulating the monthly residual returns of each stock over the 12 months. The parameters of (1) and the firm-specific return are updated each month. The strategy based on residual returns is called the factor-adjusted momentum.

3.4. Cross-sectional Characteristic-Adjusted Momentum

Following the procedure of Daniel, Grinblatt, Titman, and Wermers (1997, DGTW), we construct the two-way sorting benchmark portfolios. First, the universe of stocks is independently sorted into size and book-to-market quintiles. We compute a monthly value-weighted average return for each of the 25 (5 x 5) portfolios. Second, the monthly characteristic-adjusted return for each stock is the difference between the stock's monthly raw return and its corresponding benchmark portfolio return. The deciles momentum portfolio is constructed upon the characteristic-adjusted returns.

3.5. Cross-sectional Regression-Adjusted Momentum

Following Lewellen (2014), we use past 120-months rolling average Fama and MacBeth slope to estimate expected stock returns. Specifically, at the beginning of every month, we conduct Fama and MacBeth regressions of current returns on the prior size and book-to-market ratio with a 120-month rolling window. Then, we derive the coefficients as the rolling averages of Fama and MacBeth slopes. For each firm at month t, we multiply current firm characteristic by average Fama and MacBeth slopes as the predicted return of that firm. The difference between realized return and predicted return as the regression-adjusted returns. For each month *t*, we sort all stocks into deciles by their cumulative the regression-adjusted returns.

4. EMPIRICAL RESULTS

Table 1 provides the results of monthly profits on momentum portfolios. The monthly abnormal payoffs on JT momentum is significantly positive with 0.57% (*t*-statistic of 2.15). The average alphas of momentum profits on all types of return-adjusted portfolios are all significantly positive. For example, for time-series return-adjusted momentums, the FF1, FF3, and FF5 return-adjusted momentum earns 1.07%, 0.92%, and 0.83%. For cross-sectional return-adjusted momentum, the DGTW and FMG momentums obtain 0.80% and 0.87%, respectively. When we focus on long-, short-leg separately. The momentum profits of JT and cross-sectional return-adjusted momentum (i.e., DGTW and FMG) mainly come from long-position. However, for time-series return-adjusted momentum (such as FF1, FF3, and FF5), both long-leg and short-leg contributes to the momentum payoffs.

[Table 1 here]

Table 2 confirms the finding that payoffs on JT momentum are very similar to the payoffs on DGTW and FMG cross-sectional return-adjusted momentums. For example, Panel A indicates that the correlation between profits of JT momentum and DGTW (or FMG) is 0.938 (0.946), which is higher than the correlation between JT momentum and time-series return-adjusted momentum of FF1 (FF3) is 0.732 (0.710). Panel B suggests that the time-series return-adjusted momentums not only earn higher profits but experience lower tail and extreme risks. For instance, FF1, FF3, and FF5 models, they have relatively higher Sharpe ratio but relatively lower tail risks comparing to JT, DGTW and FMG momentums.

[Table 2 here]

Fig. 1 indicates that the return-adjusted momentum earns higher buy-and-hold returns than total return momentum. We assume that at the beginning of the holding period, the position is $1. At the end of holding period, the cumulative return of JT momentum is $0.65. However, the cumulative returns are $355.73, $131.52, $102.96, $6.86, and $7.73 for FF1, FF3, FF5, DGTW, and FMG return-adjusted momentum strategies, respectively.

[Figure 1 here]

Fig. 2 suggests that JT momentum suffers from highest drawdowns than return-adjusted strategies. For example, total return momentum suffers from a maximum drawdown magnitude of 98% negative during the 2009 financial crisis. Factor adjusted momentum also suffers its worst drawdown during this period but with a magnitude and length less than half as severe as for total return momentum. Characteristic-adjusted and regression-adjusted return suffer above 80% during this period.

[Figure 2 here]

We also explore the calendar month performance of momentum strategies. Many studies show that momentum profits exhibit the seasonal pattern. For instance, Grinblatt and Moskowitz (2004) and Jegadeesh and Titman (1993, 2001) find a January effect for the total return momentum strategy. More specifically, the average monthly returns are negative in January. The possible explanation for the fact is the tax-losing effect. Institutional investors attempt to realize loss by selling losers at the end of the year and rebalance the position by buying these losers back in January, thus, cause significant rebound of losers in January.

The calendar monthly performance is shown in Fig. 3. The figure suggests that JT momentum suffers in January. Similarly, except for the factor adjusted momentums (FF1, FF3, and FF5), the characteristic-adjusted momentum (DGTW) and regression return adjusted momentum (FMG) also suffers in January. Consistent with the tax-losing hypothesis, the JT momentum is notably stronger in December. Also, the DGTW and FMG momentum earn higher profits at the end of the year.

[Figure 3 here]

Daniel and Moskowitz (2013) point out that a momentum crash occurs followed by a market rebound. For example, in July and August of 1932, the momentum strategy suffers a significant crash and has a cumulative return of −70.24% for the two months. During the market decline, momentum tends to long buy low-beta stocks (the past winners) and short sell high beta stocks (the past losers). As the market reverse quickly, the momentum will crash because they have a conditionally large negative beta (Grundy and Martin, 2001). We examine the momentum performance in year 2009. Particularly, we explore the periods from March 2009 to May 2009. The results in Table 3 indicate that the market recovered in 2009 with returns of 9, 11, and 7% over the months March, April, and May, respectively, total return momentum's negative market beta caused a streak of large losses. The average losses of JT momentum for these three months are -35.74%. However, the average losses are quite similar to three-factor adjusted momentum strategies FF1, FF3, and FF5 of -13.93%, -12.96%, and -13.96%, respectively. The average losses of DGTW and FMG momentum of -27.49% and -25.17% are higher than factor adjusted momentum, however, lower than JT momentum. Align with the prediction of market rebound, the loss of momentum strategies mainly due to significant rebound of losers.

[Table 3 here]

Chordia and Shivakumar (2002) document that the momentum profits are captured by business-cycles macroeconomic variables, suggesting consistency with the risk explanation. They show that the total return momentum is significantly positive during expansionary periods and insignificantly negative during recessionary periods. In contrast, in addition to expansionary periods, Blitz et al. (2011) indicate that the residual momentum also earns significantly positive returns during recessionary periods because the systematic risk exposures of residual momentum have been controlled for.

Consistent with Blitz et al. (2011) and Chordia and Shivakumar (2002), Table 4 suggests that JT momentum underperforms during contractions as defined by the NBER. The huge market rebound often occurs in recession periods. JT momentum earns a high average performance during expansionary periods, about 0.6% per month. However, the performance is −1.20% per month during recessionary periods. The results also indicate that the factor-adjusted momentum exhibits positive momentum pattern in recessionary periods.

[Table 4 here]

From July 1966 to December 2014, we adopt Baker and Wurgler (2006) monthly sentiment index to measure investor sentiment. The six components of Baker and Wurgler (2006) sentiment index are the closed-end fund discount, the number and the first-day returns of IPOs, NYSE turnover, the equity share in total new issues, and the dividend premium. The Baker and Wurgler (2006) sentiment index are the residuals orthogonal to macroeconomic variables. Prior study document that momentum profits are particularly significant during optimistic periods. For example, Antoniou, Doukas, and Subrahmanyam (2010) find that the momentum effect is stronger when sentiment is high, and they suggest this result is consistent with the slow spread of bad news during high-sentiment periods.

The average returns separately for the high and low sentiment months are shown in Table 5. The JT, DGTW and FMG momentum strategies are stronger in high sentiment months. However, for factor-adjusted momentum strategies perform indifferently for low and high sentiment months.

[Table 5 here]

5. CONCLUDING REMARKS

Grundy and Martin (2001) and Blitz, Huij and Martens (2011) document that momentum exhibits time-varying risk exposures and hence are likely to underperform in markets with strong reversals. Specifically, momentum loads positively (negatively) on risk factors when risk factors have positive (negative) premiums during the formation period of the strategy. Once the sign of risk premiums reverse over the holding period, the momentum suffers. Daniel and Moskowitz (2013) point out that a momentum crash occurs followed by a market rebound. During the market decline, momentum tends to long buy low-beta stocks (the past winners) and short sell high beta stocks (the past losers). As the market reverse quickly, the momentum will crash because they have a conditionally large negative beta (Grundy and Martin, 2001). Momentum investors are not able to benefit from using time-varying betas to avoid the crashes in real time.

Haugen and Baker (1996), Hanna and Ready (2005), and Lewellen (2014) document that the past coefficients of Fama-MacBeth regression can forecast future stock returns. Expected returns are estimated by using a firm’s current characteristics and the historical slopes of Fama-MacBeth regressions. They show that expected returns are positively associated with realized returns, particularly during the shorter horizons.

Daniel and Titman (1997) argue that stock characteristics provide better ex-ante forecasts of the cross-sectional patterns of future returns. In addition to risk factors, stock characteristics might also be a crucial determinant of stock returns. However, how stock characteristics affect momentum has seldom been studied empirically. We attempt to explore how important characteristics influence the performance of momentum strategy. The adjusted returns are calculated by the difference between raw return and the return on the corresponding characteristic benchmark portfolio.

We examine the performance of momentum strategy based on firm-specific information. The firm-unique information is extracted from the following models: CAPM, Fama-French (1993) three-factor model, Fama-French (2017) five-factor model, Daniel, Grinblatt, Titman, and Wermers (1997) characteristics-adjusted model, Haugen and Baker (1996) and Lewellen (2014) Fama-MacBeth regression model. We show that the average monthly momentum profits on return-adjusted portfolios are all higher than total return momentum. Further, momentum strategies based on factor adjusted returns exhibit higher returns than momentum strategies based on characteristic-adjusted and regression-adjusted return. Factor-adjusted momentum strategies are more efficient to reduce the extreme loss and experience less drawdown in 2009 than JT momentum. Moreover, the DGTW and FMG momentum also suffer much lose during 2009 financial crisis.

Except for the factor adjusted momentums (FF1, FF3, and FF5), the characteristic benchmark return adjusted momentum (DGTW) and regression return adjusted momentum (FMG) also suffer in January. Consistent with the tax-losing hypothesis, the JT momentum is particularly stronger in December. Also, the DGTW and FMG momentum earn higher profits at the end of the year.

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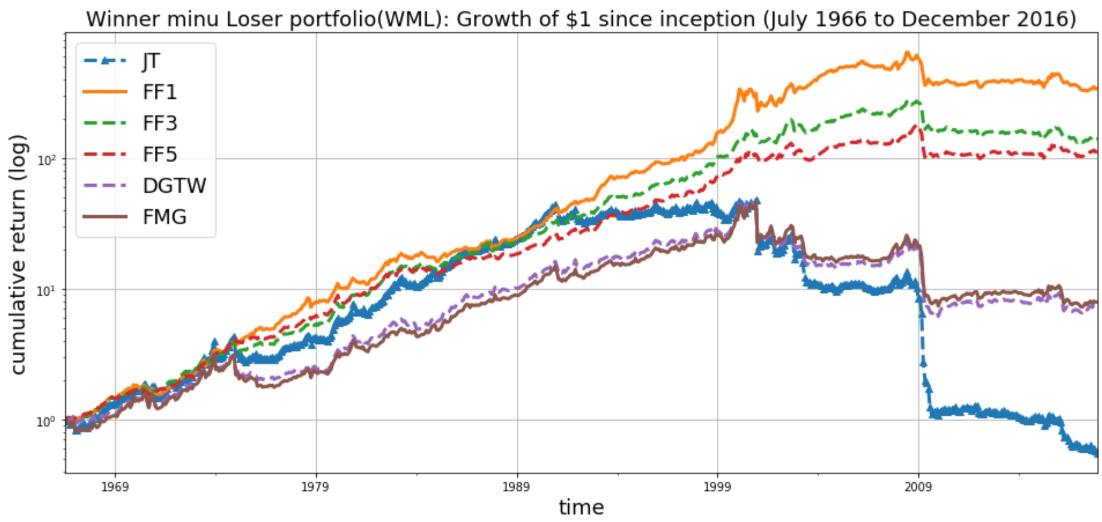

Fig. 1. Buy-and-hold performance of momentum

The figure shows the buy-and-hold stock performance for six momentum strategies. The descriptions of six momentums are shown in Table 1. The sample period is from July 1966 to December 2016.

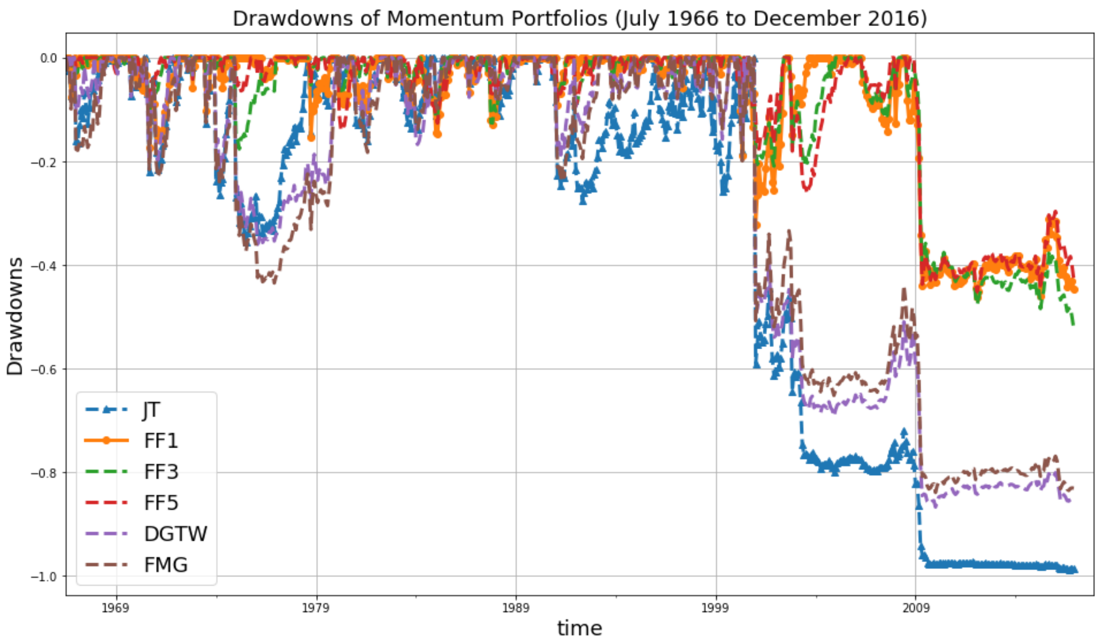

Fig. 2. Drawdowns of momentum

The figure shows the drawdown for six momentum strategies. The descriptions of six momentums are shown in Table 1. The sample period is from the July 1966 to December 2016. The drawdown at time t is defined as the ratio of buy-and-hold return at time t over the historical high buy-and-hold return up to time t, minus 1.

Fig. 3. Calendar month performance

The figure shows the calendar month for six momentum strategies. The descriptions of six momentums are shown in Table 1. The sample period is from July 1966 to December 2016.

Table 1. Monthly abnormal performance of return-adjusted momentums

This table shows the performance of return-adjusted momentums. The sample period is from July 1966 to December 2016. We exclude the stocks with price less than $1. The JT momentum is defined as a zero-cost portfolio that long-buy top winner portfolio and short-sell loser portfolio based on the cumulative prior 12-month raw return excluding the most recent month. The factor-adjusted momentum is a zero-cost portfolio that long-buy top winner portfolio and short-sell loser portfolio based on the cumulative prior 12-month factor-adjusted return excluding the most recent month standardized by the standard deviation of the residual returns over the same period. Three types of factor-adjusted returns are defined as follows. One-factor (CAPM) adjusted (only include *MKT* as independent variable in Eq. (1)), three-factor (Fama and French, 1993) adjusted (include *MKT*, *SMB*, and *HML* as independent variables as independent variable in Eq. (1)), and five-factor (Fama and French, 2015) adjusted (include all explanatory variables in Eq. (1)) returns. Characteristics-adjusted return is defined as the difference between the stock's monthly raw return and its corresponding characteristic benchmark portfolio return. The benchmark portfolio return is the value-weighted average return on independent double sorting 25 (5 x 5) size and book to market portfolios. Fama and MacBeth regression adjusted return is the difference between realized return and predicted return. The predicted return is the past 120 months rolling average Fama and MacBeth slope multiplies current firm characteristic. The monthly Fama and French (1993)'s alpha of each momentum portfolio is provided. t-statistics are in parentheses. The asterisks *, **, and *** indicate significance at the 10, 5, and 1 levels, respectively.

	Loser	Winner	Winner-Loser
JT	0.206	0.771***	0.565**
	(0.97)	(7.63)	(2.15)
FF1	-0.323***	0.741***	1.065***
	(-2.66)	(9.34)	(6.37)
FF3	-0.282***	0.634***	0.917***
	(-2.73)	(8.87)	(6.95)
FF5	-0.197*	0.632***	0.828***
	(-1.95)	(8.59)	(6.51)
DGTW	-0.076	0.722***	0.798***
	(-0.43)	(8.59)	(3.67)
FMG	-0.099	0.769***	0.868***
	(-0.54)	(8.26)	(3.75)

Table 2. Correlation coefficients among return-adjusted momentums

Panel A shows the correlation coefficients among return-adjusted momentums. The sample period is from July 1966 to December 2016. We exclude the stocks with price less than $1. Panel B presents the downside risks on the payoff of each momentum strategy, measures include Sharpe ratio (SR), 1% value at risk time-series monthly raw returns (VaR1%), and the minimum monthly raw return (Min).

Panel A: Correlation coefficients

	JT	FF1	FF3	FF5	DGTW	FMG
JT	1.000	0.732	0.710	0.623	0.938	0.946
FF1		1.000	0.818	0.734	0.754	0.769
FF3			1.000	0.912	0.711	0.699
FF5				1.000	0.620	0.597
DGTW					1.000	0.981
FMG						1.000

Panel B: Downside risks

	JT	FF1	FF3	FF5	DGTW	FMG
SR	0.029	0.259	0.265	0.262	0.089	0.091
VaR1%	-0.241	-0.117	-0.083	-0.077	-0.171	-0.177
Min	-0.591	-0.271	-0.234	-0.234	-0.491	-0.508

Table 3. Monthly raw returns during March 2009 to May 2009

The table shows the monthly raw return for six momentum strategies during March 2009 to May 2009. The descriptions of six momentums are shown in Table 1. The sample period is from the period of July 1966 to December 2016.

	JT	FF1	FF3	FF5	DGTW	FMG
Panel A: WML						
March 2009	-0.229	-0.072	-0.050	-0.056	-0.175	-0.174
April 2009	-0.565	-0.200	-0.225	-0.225	-0.378	-0.372
May 2009	-0.278	-0.145	-0.114	-0.138	-0.271	-0.210
Average	-0.357	-0.139	-0.130	-0.140	-0.275	-0.252
Panel B: Loser						
March 2009	0.299	0.164	0.154	0.159	0.244	0.254
April 2009	0.623	0.353	0.362	0.381	0.530	0.533
May 2009	0.301	0.185	0.150	0.173	0.313	0.254
Average	0.408	0.234	0.222	0.238	0.363	0.347
Panel C: Winner						
March 2009	0.070	0.092	0.104	0.103	0.069	0.081
April 2009	0.058	0.153	0.137	0.156	0.152	0.161
May 2009	0.023	0.040	0.036	0.035	0.042	0.044
Average	0.050	0.095	0.092	0.098	0.088	0.095

Table 4. Monthly raw returns over the NBER business cycle

This table shows the returns of six momentum strategies during economic expansions and recessions, as defined by the National Bureau of Economic Research (NBER). The descriptions of six momentums are shown in Table 1. The sample period is from the period of July 1966 to December 2016. t-statistics are in parentheses. The asterisks *, **, and *** indicate significance at the 10, 5, and 1 levels, respectively.

	Expansion	Recession
JT	0.006**	-0.012
	(2.28)	(-1.00)
FF1	0.012***	0.006
	(6.88)	(0.96)
FF3	0.009***	0.005
	(7.38)	(0.94)
FF5	0.008***	0.005
	(7.00)	(1.01)
DGTW	0.007***	-0.007
	(3.51)	(-0.76)
FMG	0.008***	-0.006
	(3.49)	(-0.64)

Table 5. Monthly raw returns under different investor sentiment

This table shows the returns of six momentum strategies over the different investor sentiment. A high-sentiment month is one in which the value of the BW sentiment index is above the median value for the sample period, and the low-sentiment months are those with below-median values. The descriptions of six momentums are shown in Table 1. The sample period is from the period of July 1966 to September 2015. t-statistics are in parentheses. The asterisks *, **, and *** indicate significance at the 10, 5, and 1 levels, respectively.

	Low sentiment	High sentiment
JT	-0.000	0.006*
	(-0.04)	(1.89)
FF1	0.013***	0.009***
	(5.51)	(3.69)
FF3	0.009***	0.009***
	(4.35)	(4.99)
FF5	0.009***	0.007***
	(4.46)	(4.38)
DGTW	0.003	0.007**
	(0.98)	(2.36)
FMG	0.003	0.008***
	(0.91)	(2.57)