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Abstract

The momentum strategy as described in the seminal work of Jegadeesh and Titman (1993) leads to stream of studies on theoretical work of momentum effect and empirical analysis in different financial assets and markets of several countries. However, the characteristics displayed by the momentum strategy have often being argued that was associated with risk exposures to pricing factors and time-varying risk. Especially, the investment portfolio's performance endanger profound drawdown risk when the market rebounds after financial crisis. In this study, I proposed the time series residual momentum strategy to mitigate the magnitude of losses. If the stock positively (negatively) deviates from predicted intrinsic values during a short-term period, it is denoted as over-valuation (under-valuation). Through investigating the U.S. stock market, the empirical results show the proposed strategy can not only achieve significant improvement for the conventional momentum strategy, but also can substantially reduce the drastic losses from financial crises.

Key words: Momentum; Fama-French Factors; Asset Pricing; Financial Crisis
JEL classification: C3; G2

1. Introduction

As Isaac Newton said "What goes up must come down." Everything in earth should obey the law of gravity. Therefore, it is natural to assume the law of gravity can also be applied in financial market. However, academic studies have found out that stocks which perform better than the other stocks in recent past will continue for a certain period. The phenomenon is called "momentum" effect. Past studies also have confirmed that this effect has been observed not only in the stock market but also in commodity and currency markets. The profit cannot be explained away by saying that high-performance stocks are more risky, or by arguing that the trading cost would eat up all the profit, instead they are considered potential profitable.

This anomaly also drives a juggernaut through one of the tenets in financial theory, which is the efficient market hypothesis. In the weak-form efficient market hypothesis, the past price movements should provide no guide to future price changes. Investors should have no logical reasons to prefer the past winners to the past losers. Therefore, we are going to revisit the conventional momentum strategy in the U.S. stock market by using the residual analysis over a longer period from January 1930 to December 2010. Our proposed strategy can control the short-term behavior and intermediate continuation of a stock.

The intermediate-horizon return continuations are first reported by Jegadeesh and Titman (1993). They propose the momentum strategy, which buys the past winning stocks over the previous three to twelve months and sells the past losing stocks over the same period exhibits substantial profit. Although these results have been widely accepted, researchers are still in debate over the sources of the profit and the interpretation of the evidence. The momentum effect is not only remarkably persistent in stock market but also in commodity and currency markets. Okunev and White (2003) find momentum effect in currencies. Erb and Harvey (2006) find momentum effect in commodities. Moskowitz, Ooi and Pedersen (2012) find momentum effect in exchange traded futures contracts. Moreover, the momentum effect is worldwide. Rouwenhorst (1998) finds evidence of momentum effect in developed stock markets, and Rouwenhorst (1999) documents momentum effect in emerging markets.

Although the momentum strategy tends to work well on the winners and the losers over the past three-to-twelve months, the momentum effect disappears for longer periods in three or five year. Just as trees do not grow to the sky, share prices do not rise forever. Many investigators have argued the momentum strategies to display characteristics that are often associated with factors of price risk. Chordia and Shivakumar (2002) reveal the profits of momentum strategies to exhibit strong variation across the business cycle. In their study, they show the conventional momentum strategy earns 14.70% annualized return during expansions and loses 8.70% during recessions over the period from January 1930 to December 2009. Cooper, Gutierrez and Hameed (2004) further examine the variation of average returns to the U.S. equity momentum strategies. They find in “UP” states, which are defined by the lagged three-year return of the market, the historical mean of returns of a equally-weighted momentum strategy is 0.93% per month. In “DOWN” states, the historical mean of returns of a equally-weighted momentum strategy is -0.37% per month. It means those losers often experience strong gains after the market collapses. In such circumstances, implementation of the momentum strategy will result in persistent strings of negative returns. It leads to a momentum crash.

In this paper, we propose a more effective strategy, time series residual momentum, which ranks all eligible stocks based on their total returns and residual returns in the recent past months. The advantage of the time series momentum strategy is not only to reduce the time-varying exposures but also to eliminate the "value risk," which occurs when a stock is overvalued. Therefore, this time series residual momentum strategy performs better than the conventional momentum strategy and the the residual momentum strategy. Most important of all, it can avoid the huge loss of the conventional momentum strategy after 2000.

To sum, in past decades, financial academics and practitioners have recognized that the momentum strategy can generate significant profit and that the momentum effect exists in many financial markets. But, fewer people notice the collapse of the momentum is profound especially after the financial crisis. In this study, we adjust the conventional momentum strategy in the U.S. stock market by using the residual analysis over the period from January 1930 to December 2010. The modification we proposed can take care of the short-term behavior and the intermediate continuation of a stock. The empirical results show the modification can largely improve the conventional momentum strategy.

2. Momentum Crash

We first examine the conventional momentum strategy over a longer period in the U.S. stock market from January 1930 to December 2010. Most of time, the market appears to underreact to the public information and results in consistent price momentum. However, in extreme conditions, the past losers of the momentum strategy often comprise a very high premium. When the market conditions are going better, those past losers will experience strong gains. This leads to a "momentum crash." It is because the returns of the conventional momentum strategies are highly-skewed. Therefore, investors who implement the conventional momentum strategy will experience strings of negative returns, especially after the market collapses.

Data and Portfolio Formation

The data for the study is from CRSP monthly files. Our data consists of all domestic, primary stocks listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and Nasdaq (NASDAQ) stock markets during the period from January 1929 to December 2010. We utilize only the returns on common shares with a 10 or 11 CRSP share-code. Close-end funds, Real Estate Investment Trust (REITs), unit trusts, American Depository Receipts (ADRs), and foreign stocks are excluded from the analysis. We also exclude stocks with price below $1 during the formation periods to reduce the microstructure effect associated with low-price stocks.

Following most of the literature, we rank the stocks based on their past twelve-month returns excluding the most recent month. Then we assign these stocks into 10 equally weighted portfolios at the end day of each formation

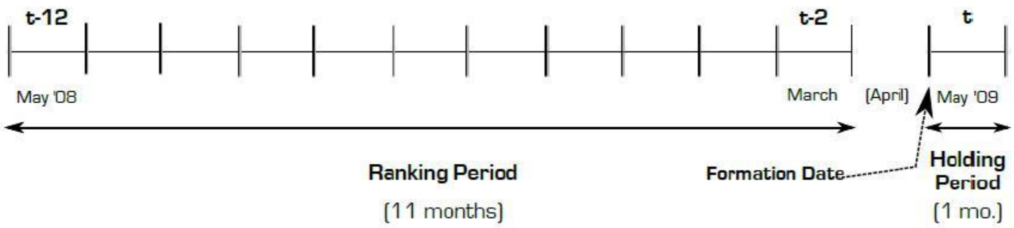

Fig. 1. Momentum Portfolio Formation

month. Each portfolio is held for one month following the formation month. The reason why we focus on their past twelve-month returns excluding the most recent month is that this momentum definition is currently most broadly used and readily available through the PR1YR factor of Carhart (1997). The momentum strategy is typically to disentangle the intermediate horizon momentum effect from the short reversal effect documented by Jegadeesh (1993) and Lehmann (1990).

Figure 1 illustrates time line of the portfolio formation process for the momentum returns in May 2009. The ranking period returns are the cumulative returns from the close of the last trading day in April 2008 to the close of the last trading day in March 2009. We sort all firms that meet the data requirements into 10-decile portfolios which are labeled P1 to P10 according to their cumulative returns over the ranking period. The 10% of firms with the highest ranking period returns go into portfolio P10, the "[W]inner"-decile portfolio, and those with the lowest ranking period returns go into portfolio P1, the "[L]oser"-decile portfolio. The return on a zero investment "Winner-Minus-Loser" (WML) portfolio is the difference of the return on the Winner and the return on the Loser portfolio in each period.

The monthly returns of the decile portfolios are based on the equally-weighted returns. Decile membership does not change in a month, except for the case of delisting. We also consider the overlapping portfolios approach, which is a strategy that holds a series of portfolios selected in the current month and the previous month. The market return we used is Dow Jones Industry Average (DJIA) index downloaded from Yahoo! Finance. [1] The risk-free rate and the cross-sectional Fama-French three factors are downloaded from the data library of Kenneth R. French. [2]

Momentum Portfolio Performance

Table 1 presents the moments of the momentum decile portfolios from January 1930 to December 2010. For all portfolios, Mean, Std, Skew and Kurt

[1] We use DJIA instead of S&P 500 because the first trading day of S&P 500 is Jan 3, 1950.

[2] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french

denote the full-period realized mean, stand deviation, skewness and kurtosis of the monthly returns to the portfolios. The average return of the winner portfolio is 1.63% per month and is 0.69% of the loser portfolio. A self-financing strategy that buys the top 10%, Winner, and sells the bottom 10%, Loser, produces profits of 0.94% per month. The result is consistent with the existing literature, which states that there is a strong momentum premium over the past 80-year period.

Table 1
Twelve-Month Momentum Portfolio Characteristics, January 1930-December 2010

Portfolio	Mean	Std	Skew	Kurt
P1 (Past Loser)	0.69%	0.1067	2.3866	17.9023
P2	0.82%	0.0819	1.6241	14.4532
P3	1.01%	0.0781	2.1760	20.5349
P4	1.06%	0.0719	1.5558	15.7259
P5	1.15%	0.0690	1.1678	13.2865
P6	1.20%	0.0663	0.9465	12.3870
P7	1.28%	0.0645	0.4184	7.8186
P8	1.41%	0.0676	0.6713	9.8730
P9	1.54%	0.0718	0.3366	6.9300
P10 (Past Winner)	1.63%	0.0870	1.0294	13.4764
WML	0.94%	0.0701	-2.7992	22.7026

The skewness of the past loser portfolio is 2.3866, and the skewness of the past winner portfolio is 1.0294. The skewness of the past loser portfolio is more than twice of the skewness of the past winner portfolio. One should note that the past loser portfolios are considerably positively-skewed than the past winner portfolios. Therefore, the skewness of WML portfolio is -2.7992, which is largely negative-skewed. Another thing we should note is that the kurtosis of WML portfolio is 22.7026, which is also considerably large than usual.

The skewness of returns on momentum portfolios is not surprising. For example, Wall Street calls a high momentum stock that suddenly collapses as a “torpedo.” A torpedoed stock is a stock hit by new negative information after a long period of positive information. As the stock price has continuously increased in the past, investors may expect that the company’s business is in good conditions. Hence, the upward trend in earnings will more likely continue. However, it remains possible that the trend of increasing earnings may suddenly reverse. When it occurs, the positive effect on the stock’s earnings may also be reversed, ex. some stocks in the technology sector, where new innovations make existing technologies obsolete. Those fast-growing companies

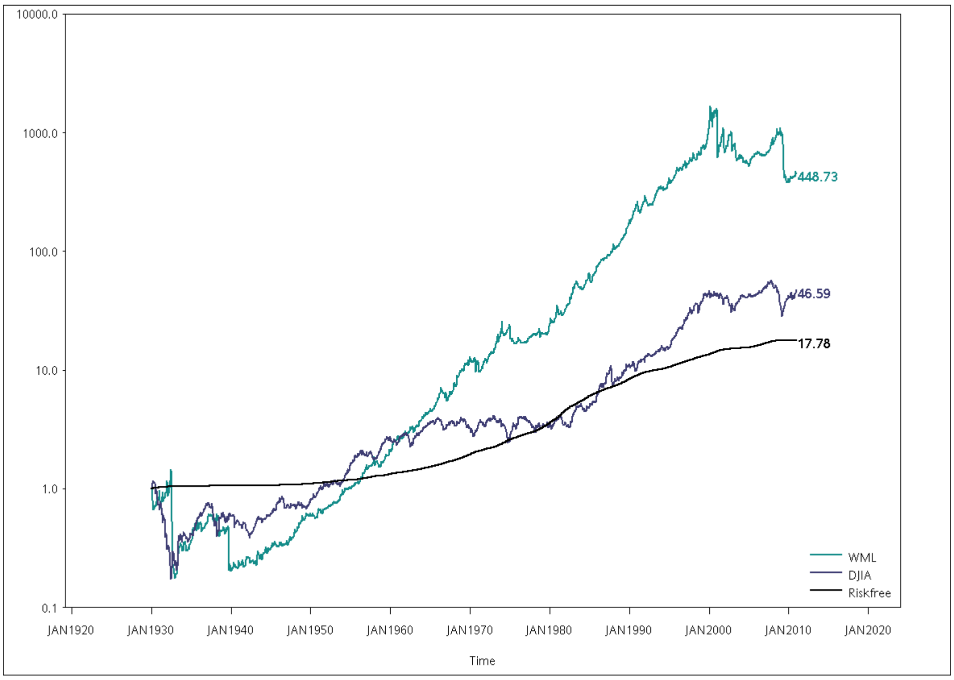

Fig. 2. Cumulative Monthly Returns of WML, DJIA and Risk-free, January 1930-December 2010

which depend on existing technologies might be affected. The growth of these firms suddenly stop.

Figure 2 presents the cumulative monthly returns[3] for investing \$1 initially in (1) the risk-free asset; (2) the DJIA index; and (3) the zero investment portfolio, WML portfolio, respectively, over the period from January 1930 to December 2010. On the right side of the plot, we present the final dollar values for each of the three portfolios. We can see the final value of WML is \$448.73, DJIA is \$46.59, and the risk-free asset is \$17.78. The momentum strategy does earn a significant return.

Momentum Crashes

Good things don't last long. The momentum strategy appears to loose their profitability in the recent years. Again, we plot the cumulative monthly returns for investments in the risk-free asset, the DJIA index, and the WML portfolio from January 2000 to December 2010 as shown in Figure 3. We can find the WML portfolio loses almost 70% at the end of 2010. In fact, it lost 1.46% per annum over the period from January 2000 to December 2010. The large losses of the WML portfolio occured in the first half of 2009,

[3] The cumulative return on an implementable strategy is an investment at time 0 and fully reinvested at each time point. During the period, there is no cash put in or taken out. $R(t, T)$ denotes the cumulative return between time t to T , $R(t, T) = \prod_{s=t+1}^{T}(1 + R_s)$.

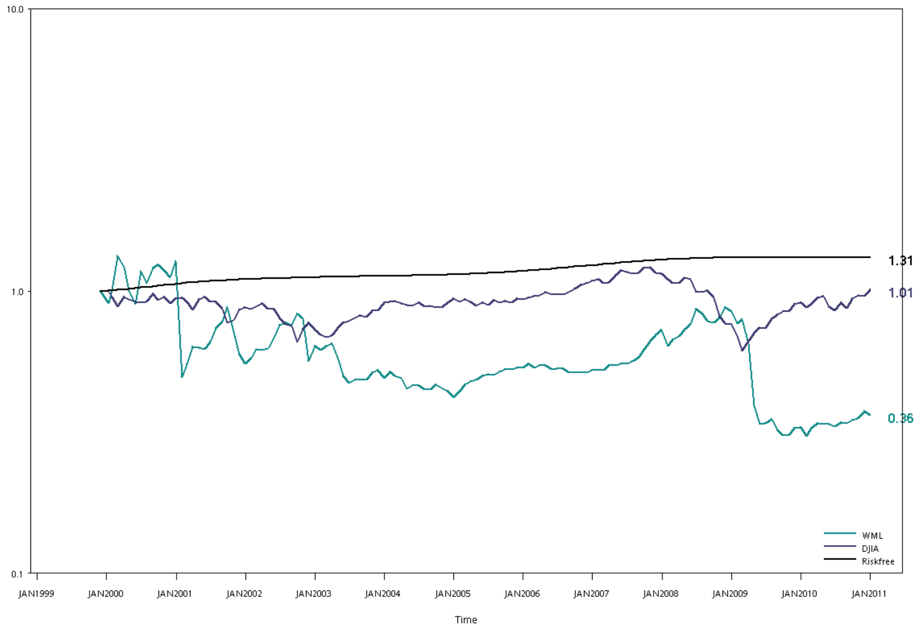

Fig. 3. Cumulative Monthly Returns of WML, DJIA and Riskfree, January 2000-December 2010

especially in March, April, and May. The losses were 18.22%, 39.52%, and 14.29% respectively. The rough under-performance appears when the market rebounds from the bottom. We argue that the large negative skewness of the WML portfolio can cause the momentum crash.

Table 2
Top 10 Worst-Month WML Portfolio Returns

Rank	Month	Past Loser	Past Winner	WML	DJIA
1	1932/07	77.76%	15.58%	-62.18%	25.79%
2	2001/01	78.79%	17.74%	-61.05%	0.92%
3	1932/08	100.08%	43.18%	-56.91%	35.76%
4	1939/09	81.67%	24.78%	-56.89%	11.72%
5	2009/04	48.12%	8.61 %	-39.52%	7.35%
6	2002/11	37.68%	8.26 %	-29.42%	5.94%
7	1932/01	29.66%	5.14 %	-24.53%	-1.73%
8	1975/01	44.12%	20.02%	-24.10%	14.19%
9	1938/06	38.84%	16.52%	-22.32%	24.26%
10	1974/01	24.72%	4.84 %	-19.88%	0.55%

Table 2 presents the top ten worst-month returns of the WML strategy over the periods from January 1930 to December 2010. The table also gives the contemporaneous monthly returns of DJIA. These returns often occur when the market has dramatic downturns, and during a month where the market gradually rises. For example, during the two-month period from July to August in 1932, the DJIA increased 61.55%, but the return of the WML portfolio decreased 119.09%. As we can also see from the Table 2, during the two-month period, returns of the Past Loser deciles are 77.76% and 100.08% outperform the returns of the Past Winner deciles which are 15.58% and 43.18% respectively. Thus, the strong momentum reversals can be characterized as a momentum crash. The momentum crash happens in the short side of the portfolio, the past losers portfolios, which are crashing up rather than down. We should also notice that these momentum crashes are also clustered as shown in Figure 4. The strong performance of the past losers occurs over the span of multiple months.

Robustness Check

For robustness check, we also plot the cumulative monthly WML portfolio returns over the period from January 1930 to December 2010 by considering different formation periods, i.e., we rank the stocks based on the past j-month return, where j=3, 6, and 9. The result is shown as Figure 5. We can see the cumulative monthly WML return based on the past 3-month return is $2.79. The cumulative monthly WML return basing on the past 6-month return is $7.11. And the cumulative monthly WML return basing on the past 9-month return is $17.11. The best performance of cumulative monthly WML return is based on past 12-month return, which reaches $448.73. Thus, we focus on the 12-month formation period as our momentum strategy analysis hereafter.

Table 3 presents the moments of the momentum decile portfolios from January 1930 to December 2010 based on the past 3-month return. The skewness of the past loser portfolios is 1.5887, and the skewness of the past winner portfolios is 0.3401. The skewness of WML portfolios is -2.8086, which is negative. The kurtosis of WML portfolios is 22.8985. Table 4 presents the moments of the momentum decile portfolios from January 1930 to December 2010 based on the past 6-month return. The skewness of the past loser portfolios is 2.0914, and the skewness of the past winner portfolios is 0.0396. The skewness of WML portfolios is -2.6249, which is negative. The kurtosis of WML portfolios is 19.7919. Table 5 presents the moments of the momentum decile portfolios from January 1930 to December 2010 based on the past 9-month return. The skewness of the past loser portfolios is 2.1495, and the skewness of the past winner portfolios is 0.8497. The skewness of WML portfolios is -3.1013, which is negative. The kurtosis of WML portfolios is 22.4271.

Further, we plot the cumulative monthly WML portfolio returns over the period from January 2000 to December 2010 by considering different formation periods as shown in Figure 6. We can see the cumulative monthly WML return

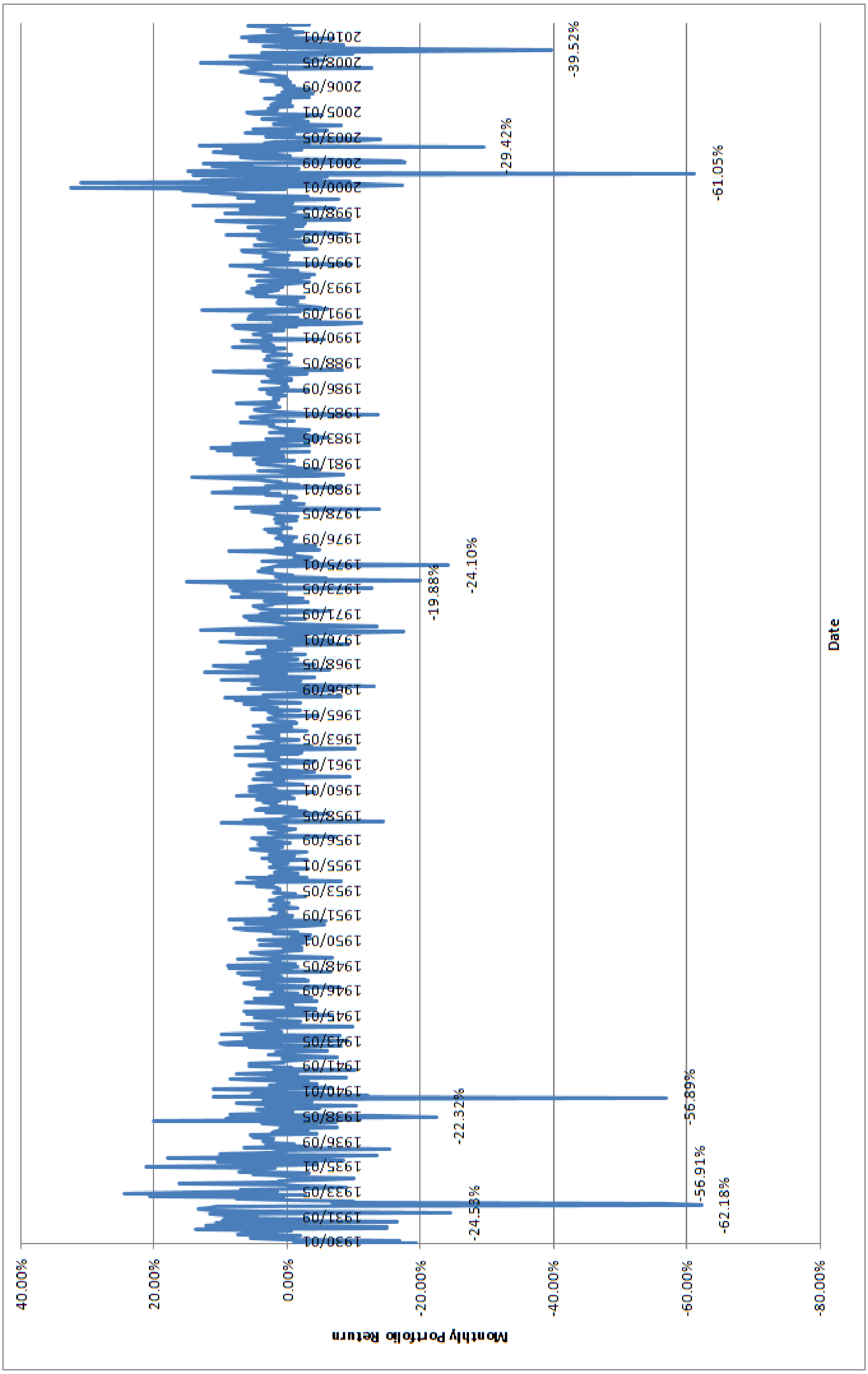

Fig. 4. Momentum Portfolio Performance, January 1930-December 2010

Table 3
Characteristics of 3-month Momentum Portfolios, January 1930-December 2010

Portfolio	Mean	Std	Skew	Kurt
P1 (Past Loser)	0.91%	0.1013	1.5887	10.4791
P2	1.09%	0.0871	1.8941	15.8793
P3	1.23%	0.0807	2.1182	19.4230
P4	1.19%	0.0719	1.2167	13.2133
P5	1.15%	0.0671	0.6108	8.6659
P6	1.17%	0.0664	0.7823	11.5043
P7	1.15%	0.0644	0.3849	7.1533
P8	1.16%	0.0664	0.3782	7.8832
P9	1.16%	0.0700	0.2545	6.3014
P10 (Past Winner)	1.24%	0.0805	0.3401	6.3945
WML	0.33%	0.0613	-2.8086	22.8985

Table 4
Characteristics of 6-month Momentum Portfolios, January 1930-December 2010

Portfolio	Mean	Std	Skew	Kurt
P1 (Past Loser)	0.95%	0.1073	2.0914	13.6075
P2	1.02%	0.0878	2.0454	16.3411
P3	1.06%	0.0794	1.7692	15.2567
P4	1.16%	0.0761	2.1912	20.9869
P5	1.16%	0.0692	1.3928	14.3128
P6	1.18%	0.0680	1.0820	13.3095
P7	1.17%	0.0641	0.3624	7.9755
P8	1.18%	0.0644	-0.1076	5.2800
P9	1.35%	0.0689	-0.0565	5.1462
P10 (Past Winner)	1.44%	0.0811	0.0396	4.4203
WML	0.49%	0.0691	-2.6249	19.7919

based on the past 3-month return is \$0.51. The cumulative monthly WML return based on the past 6-month return is \$0.47. And the cumulative monthly WML return based on the past 9-month returns is \$0.2. It shows that the momentum crash won't eliminate no matter how many months of the past j-month return we consider, where j=3, 6, 9, and 12.

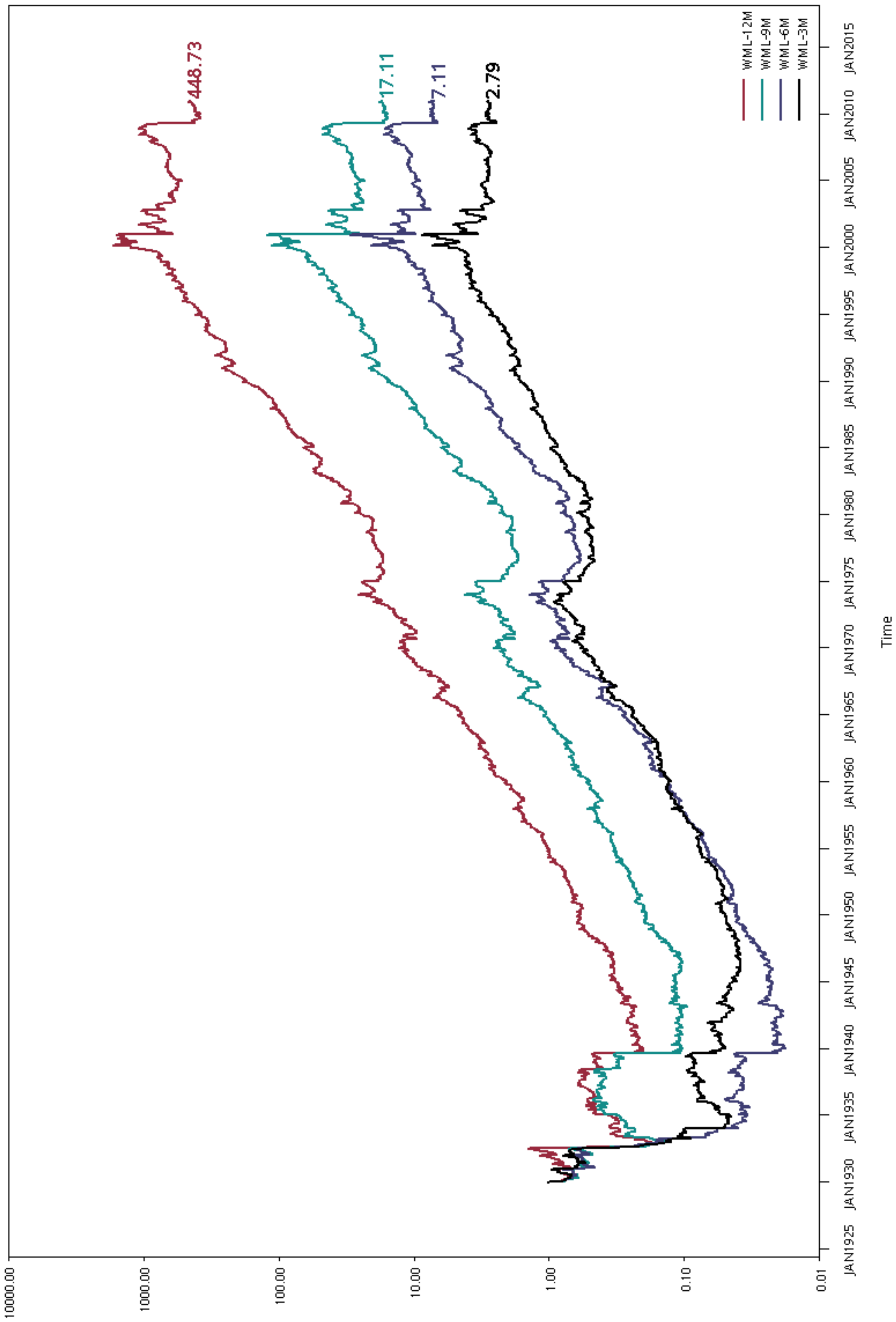

Fig. 5. j-Month Momentum Portfolios Performance, January 1930-December 2010

Table 5
Characteristics of 9-month Momentum Portfolios, January 1930-December 2010

Portfolio	Mean	Std	Skew	Kurt
P1 (Past Loser)	0.82%	0.1066	2.1495	15.7713
P2	0.97%	0.0870	2.2791	19.8423
P3	1.02%	0.0780	1.6489	15.1072
P4	1.07%	0.0713	1.2550	12.4999
P5	1.09%	0.0686	1.1951	12.7131
P6	1.19%	0.0665	1.0374	12.1164
P7	1.28%	0.0668	0.8437	10.9467
P8	1.28%	0.0673	0.4746	10.1607
P9	1.44%	0.0717	0.4868	8.7271
P10 (Past Winner)	1.48%	0.0852	0.8497	11.3598
WML	0.66%	0.0736	-3.1013	22.4271

3. Time Series Residual Momentum Strategy

Many investigators have argued that the characteristics displayed by the momentum strategy are often associated with factors of price risk. Chordia and Shivakumar (2002) show that the profits of momentum strategies to exhibit strong variation across the business cycle. They report that the conventional momentum strategy earns 14.70% annualized return during expansions and loses 8.70% during recessions over the period from January 1930 to December 2009.

In addition, Blitz, Huij and Martens (2011) also argue that the conventional momentum strategies exhibit the time-varying exposures to Fama-French three factors. To counter this drawback, they propose the "residual momentum strategy" to reduce the time-varying exposures by ranking all stocks based on its own residual returns instead of the total returns. Blitz, Huij and Martens (2011) show that the residual momentum strategy can earn profits that are about twice as large as the conventional momentum strategy with more consistency over time.

The literature on momentum strategies focus on the relative performance of securities in cross-sectional perspective. Moskowitz, Ooi and Pedersen (2012) propose the "time series momentum strategy" in equity index, currency, commodity, and bond futures. They only focus on a security's past returns. They found that the past twelve-month returns of a security to show strong positive influence on its future return with persistent effect for about one year, followed by partially-reversed role over longer horizons. This strategy can also deliver

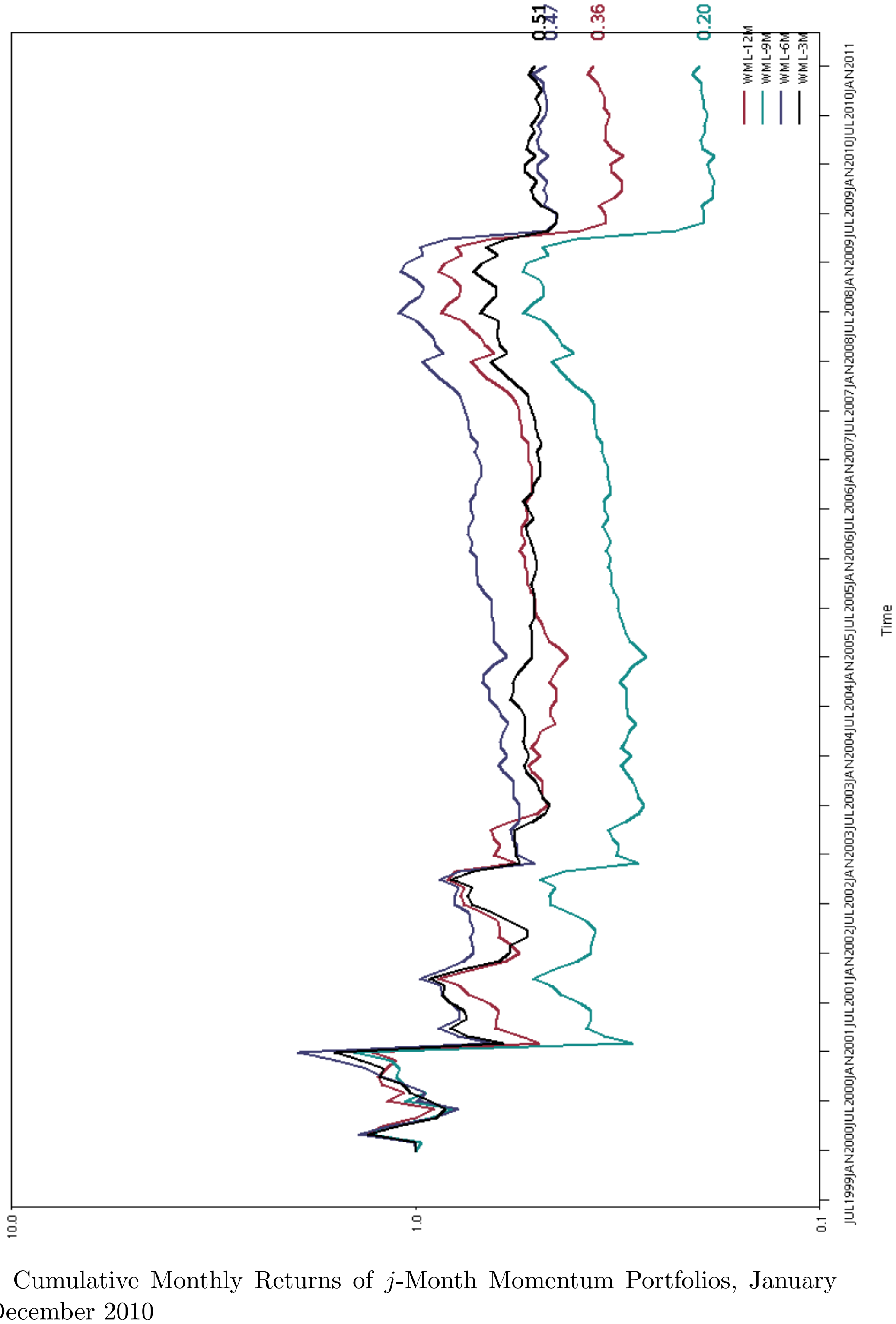

Fig. 6. Cumulative Monthly Returns of j-Month Momentum Portfolios, January 2000-December 2010

substantial abnormal returns with little exposure to the standard asset pricing factor to perform well during extreme market condition.

The advantage of cross-sectional residual momentum is to reduce the time-varying exposures. On the other hand, the advantage of the time series momentum is that the security's past returns provide strong positive predictability to its future returns. Hence, it is natural to combine the cross-sectional residual momentum strategy and time series momentum strategy into the "time series residual momentum strategy." Our empirical evidence shows the strategy can avoid the huge loss in recent years.

Cross-Sectional Residual Momentum

The residual momentum strategy proposed by Blitz, Huij and Martens (2011) is also known as a "cross-sectional" residual momentum strategy, since their approach focused on the cross-sectional relative performance in residual returns of securities. Their formula is shown as follows. In each month t, the residual returns are estimated by using Fama-French three factors model, that is,

$$r_t^i = \alpha^i + \beta_1^i \mathrm{MKT}_t + \beta_2^i \mathrm{SMB}_t + \beta_3^i \mathrm{HML}_t + \epsilon_t^i \tag{1}$$

where r_t^i is the excess return of stock i in month t. MKT_t, SMB_t, and HML_t are the excess returns of factor-mimicking portfolios for the market, size and, value in month t. $\alpha^i, \beta_1^i, \beta_2^i$ and β_3^i are parameters to be estimated. And ϵ_t^i is the residual return.

Only the stocks with complete return history of over 36-month rolling regression window were included. The purpose of using 36-month rolling windows is to ensure having a sufficient number of return observations to obtain accurate estimates for stock exposures to the market, size, and value. In order to obtain the residual return, the regression over 36-month rolling windows, was run, i.e., over the period from $t-36$ to $t-1$ to get the estimated parameters $\hat{\alpha}^i, \hat{\beta}_1^i, \hat{\beta}_2^i$ and $\hat{\beta}_3^i$ of each stock i. The estimated residual return of stock i in month t is

$$e_t^i = r_t^i - (\hat{\beta}_1^i \mathrm{MKT}_t + \hat{\beta}_2^i \mathrm{SMB}_t + \hat{\beta}_3^i \mathrm{HML}_t), \tag{2}$$

where the estimated $\hat{\alpha}^i$ is not included, since the intercept of regression served as a general control for the misspecification in the model for expected stock returns.

At each formation month t, they rank all eligible stocks into 10-decile portfolios according to the estimated residual returns from past twelve months, standardized by the standard deviation over the same period of time. The cumulative monthly returns of the residual momentum strategy and total return momentum strategy are plotted by Blitz, Huij and Martens (2011) in Figure 7.

As a result, the highest value of the residual momentum strategy over the period from January 1930 to December 2010 was about \$10,000, larger than those of total return momentum. This suggested that the performance of

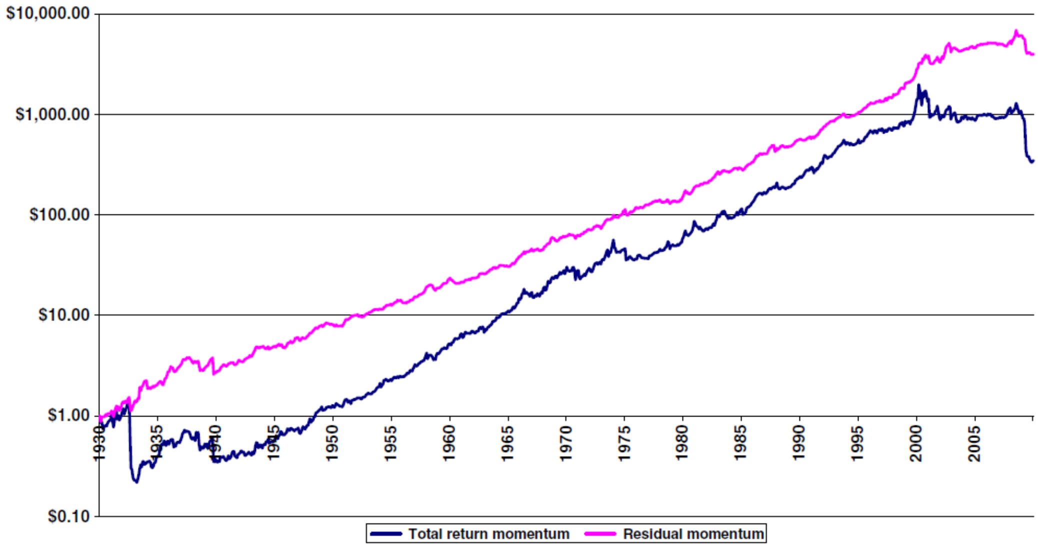

Fig. 7. Cumulative monthly returns plot by Blitz, Huij and Martens (2011), January 1930-December 2010

the residual momentum strategy is more consistent in compared to the conventional momentum strategy. In addition, this also exposed how poorly the conventional momentum strategy has performed during "The Great Depression" that started from 1929 and lasted until the late 1930s or early 1940s.

Time Series Momentum

The literature on momentum strategies focus on the relative performance of securities in cross-sectional perspective. Moskowitz, Ooi and Pedersen (2012) propose the "time series momentum strategy" in equity index, currency, commodity, and bond futures, with focus on past returns of a security. In their study, they first examine the time series predictability of future returns across different time horizons. In other words, they regress the excess return r_t in the month t on its lagged h months return, r_{t-h}. Both of the returns are scaled by their ex-ante volatilities, σ^2_{t-1} and σ^2_{t-h-1},

$$\frac{r_t}{\sigma^2_{t-1}} = \alpha + \beta_h \frac{r_{t-h}}{\sigma^2_{t-h-1}} + \epsilon_t, \tag{3}$$

where the ex-ante volatility is annualized as follows:

$$\sigma^2_t = 261 \sum_{i=0}^{\infty} (1-\delta)\delta^i (r_{t-1-i} - \bar{r_t})^2. \tag{4}$$

261 is the factor which scales the variance to be annual, $\bar{r_t}$ is the exponential weighted average return, and the weight $(1-\delta)\delta^i$ add up to 1. The parameter δ is chosen so that the center of mass of the weight is 60 days. The way to adjust futures returns by their ex-ante volatilities is similar to use the Generalized Least Squares instead of Ordinary Least Squares. They find a positive

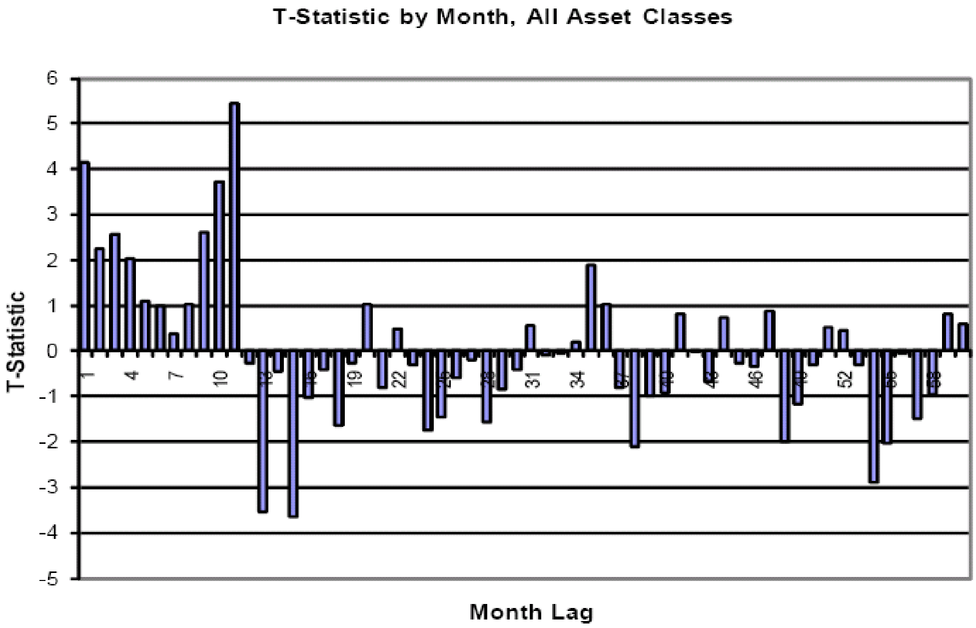

Fig. 8. Time Series Predictability by Moskowitz, Ooi and Pedersen (2010)

t-statistic for the first twelve months, indicating the significant continuation and trend in its return.

Figure 8 shows that t-statistics are positive in twelve months. This indicates the significant return continuation or trends. In their study, the most strong time series momentum effect are on the properties of the past twelve-month time series momentum and one month holding period. The time series momentum strategy is defined to take a long position if the past twelve-month cumulative excess return is positive and a short position if the past twelve-month cumulative excess return is negative. The position is scaled by the ex-ante annualized volatility that is 0.60%. Therefore, the return of the time series momentum strategy for security i from time t to $t+1$ is as follow:

$$\mathrm{sign}(r^i_{t-12,t})\frac{0.06\%}{\sigma^i_t}r^i_{t,t+1}, \tag{5}$$

where σ^i_t is defined as same as (4) and $r^i_{t,t+1}$ is the return of security i from time t to $t+1$.

Time Series Residual Momentum

Previous literatures have generally attributed the momentum effect to firm-specific returns, arguing that investors have either under-reacted or belatedly overreacted to the firm-specific returns. Recently, Lewellen (2002) studied the momentum effect in focusing on the role of industry, size, and **B/M** factors. Lewellen (2002) argued that it is impossible to explain the significant component of momentum through firm-specific returns with behavioral model. Instead, that the excess covariance, not underreaction, can explain the momentum effect in the portfolios.

It is well known that the momentum effect is a cross-sectional result and it is not the same as positive autocorrelation. As Lo and MacKinlay (1990) showed in 1990, the possibility of momentum effect been caused by the autocorrelation in returns, the lead-lag relation among stocks (cross-serial correlation) or the cross-sectional dispersion in unconditional means. Later, Lewellen (2002) has also proposed a simpler strategy based on Lo and Mackinlay's theory to consider holding assets in proportion to the market-adjust returns, shown as followed.

The proportion weight of asset i in month t is

$$w_t^i = \frac{1}{N}(r_{t-1}^i - r_{t-1}^m), \tag{6}$$

where r_{t-1}^i is the asset's return in month $t-1$, r_{t-1}^m is the corresponding return on the equally-weighted index, and N is the total number of stocks. Assuming that returns have unconditional mean $\mu \equiv E[r_t]$ and autocovariance matrix $\Omega \equiv E[(r_{t-1} - \mu)(r_t - \mu)']$. Therefore, the portfolio return in month t equals

$$\pi_t = \sum_i w_t^i r_t^i = \frac{1}{N}\sum_i (r_{t-1}^i - r_{t-1}^m) r_t^i, \tag{7}$$

and the expected profit is

$$\begin{aligned} E[\pi_t] &= \frac{1}{N}E[\sum_i (r_{t-1}^i r_t^i)] - \frac{1}{N}E[\sum_i (r_{t-1}^m r_t^i)] \\ &= \frac{1}{N}\sum_i (\rho_i + \mu_i^2) - (\rho_m + \mu_m^2), \end{aligned} \tag{8}$$

where ρ_i and ρ_m are the autocovariances of asset i and the equally-weighted index m. (8) shows that the profit of the portfolio depends on the magnitude of asset autocovariances relative to market's auto-covariance. (8) can also be written into a matrix notation. Let the average autocovariance equal $\mathrm{tr}(\Omega)/N$ and the autocovariance of the market portfolio equal $\mathbf{1}'\Omega\mathbf{1}/N^2$. $\mathrm{tr}(\cdot)$ denotes the sum of the diagonals and $\mathbf{1}'$ is a vector of ones. Therefore, (4.8) equals

$$\begin{aligned} E[\pi_t] &= \frac{1}{N}\mathrm{tr}(\Omega) - \frac{1}{N^2}\mathbf{1}'\Omega\mathbf{1} + \sigma_\mu^2 \\ &= \frac{N-1}{N^2}\mathrm{tr}(\Omega) - \frac{1}{N^2}[\mathbf{1}'\Omega\mathbf{1} - \mathrm{tr}(\Omega)] + \sigma_\mu^2, \end{aligned} \tag{9}$$

where σ_μ^2 is the cross-sectional variance of unconditional expected returns [collecting the μ_i^2 and μ_m^2 terms in (8)].

The decompositions of Lewellen (2002) suggest the profit of momentum

Table 6
Categories of Momentum Strategy

	Momentum	**Residual Momentum**
Cross Section	Jegadeesh and Titman (1993), ...	Blitz, Huij and Martens (2011)
Time Series	Moskowitz, Ooi and Pedersen (2012)	Our study

to rise in three ways as followed. First, stocks are positively autocorrelated, so firms currently with high returns are expected to have high returns in the future. Second, since the stock returns are negatively correlated to the lagged returns of other stocks, high future returns can be predicted by the other stocks' poor performances. Third, stocks simply have high unconditional expected returns relative to the other stocks. Overall, the empirical finding of Lewellen (2002) has concluded the lead-lag relations to play an important role among stocks.

One of the advantages in cross-sectional residual momentum is that it consists of the ability to reduce the time-varying exposure effect of the conventional momentum strategies. This time series momentum shows that the future returns of a stock can be forecast by its past returns. In addition, in the decomposition of Lewellen (2002), it is natural to combine the cross-sectional residual momentum strategy with time series momentum strategy into the "time series residual momentum strategy." Summary of the different categories in current momentum strategy is shown in Table 6.

Methodology

Without loss of generality, we assume that there are n securities with T_i to be the length of security i. To implement the time series residual momentum strategy, the first step is to estimate the time series residual returns of each security. In following with Blitz, Huij and Martens (2011), we ran the following regression through the same equation as equation (1) in month t, for each security i, where the residual returns e_t^i is obtained by equation (2).

We propose a measure of value risk, denoting $q_t^i(j)$ for security i based on its own past j-month time series residual return in the month t. The $q_t^i(j)$ is

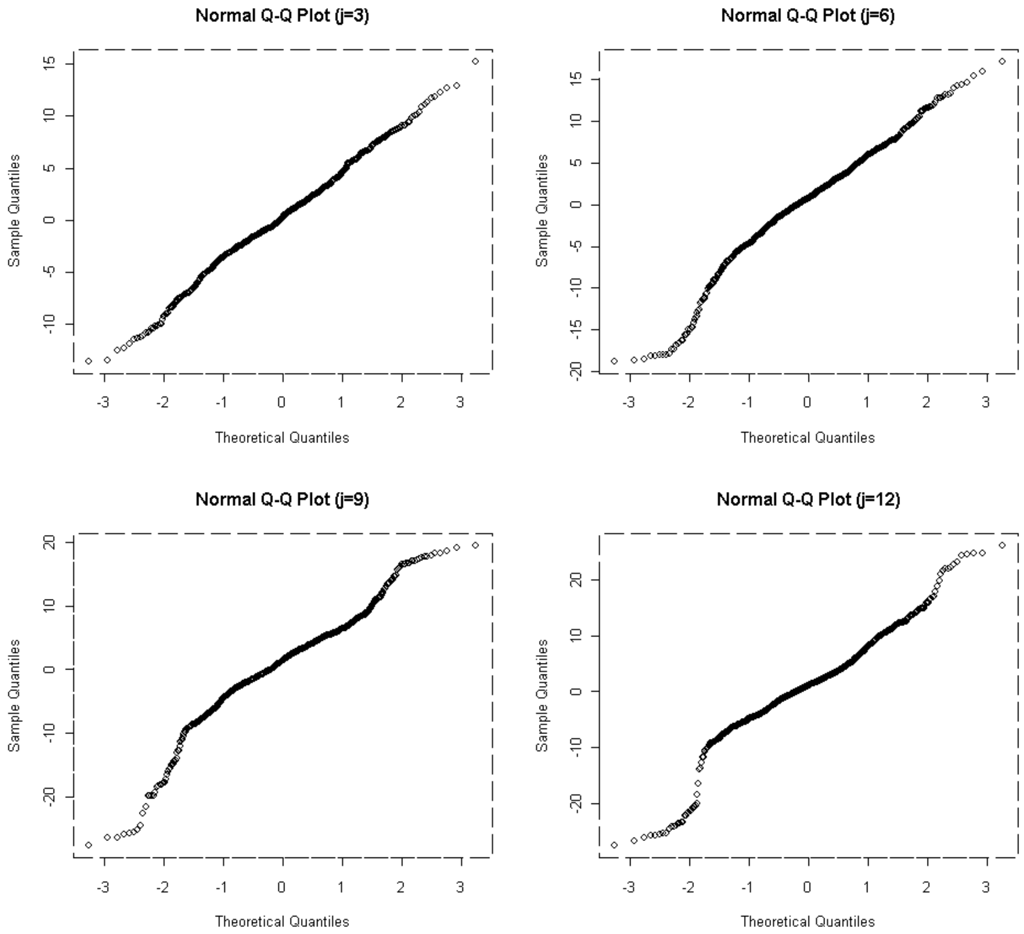

Fig. 9. Q-Q plot

defined as:

$$q_t^i(j) = \Phi(\frac{\sum_t^{t-j+1} e_t^i}{\sqrt{j \times \hat{\sigma}_t^2}}), \tag{10}$$

where $\hat{\sigma}_t^2$ is the variance of e_t^i over the same period, j is the strength of value risk over the past j months (j = 3, 6, 9 or 12), and Φ is the cumulative function of a standard Normal distribution.

$q_t^i(j)$ can be viewed as a proxy measure of the present value relative to its long-term equilibrium level. $q_t^i(j)$ is used to describe whether or not a stock's recent j-month return has been overvalued. Through this formula, we can form the portfolios based on independently sort all eligible stocks by their own past 12-month accumulative monthly return and j-month value-risk measure, $q_t^i(j)$ at each formation month t.

In argument regarding to whether or not $\frac{\sum_t^{t-j+1} e_t^i}{\sqrt{j \times \hat{\sigma}_t^2}}$ follows a Standard Normal distribution can be confirmed by a Q-Q plot of $\frac{\sum_t^{t-j+1} e_t^i}{\sqrt{j \times \hat{\sigma}_t^2}}$ for a stock with its permno number 10006, as shown in Figure 9. The Q-Q plot was constructed using different j-month, j=3, 6, 9 and 12. In j=3, the sample quantiles were approvimate to the Standard Normal distribution, confirming that it is not inappropriate to use Φ as the transformation.

In order to form the portfolios, the stocks were first assigned into one of 10 portfolios based on their cumulative returns over the previous twelve months. The top 10% of firms with the highest ranking period returns were filed into portfolio P10, the "[W]inner" decile portfolio. On the other hand, the bottom 10% of firms with the lowest ranking period returns were filed into portfolio P1, the "[L]oser" decile portfolio. Besides, the stocks are also independently assigned into one of the 3 portfolios with the categories of [U]nder, [M]iddle and [O]ver, based on the value-risk measures over the same period of time. In combination of the two separately arranged ranking methods, up to 30 value-risk momentum portfolios were obtained. "WU-LO" was defined as the monthly portfolio return of the "[W]inner that is [U]nder-valued minus the [L]oser that is [O]ver-valued." A return on a zero investment of a WU-LO portfolio is the difference between the return in the undervalued winner and overvalued loser portfolio in each time period. In this study, only monthly return over next one month was focused based on a equally-weighted average of the portfolio returns.

Empirical results

The results are shown in Table 7, where the standard deviations are in the parentheses. As seen from the table, when $j = 3$, the monthly average return of the WU-LO portfolio is 2.44% that is equal to 33.57% annual return. For $j = 6$, the monthly average return of the WU-LO portfolio is 1.67% that is equal to 22.06% annual return. For $j = 9$, the monthly average return of the WU-LO portfolio is 1.74% that is equal to 23.01% annual return. Overall, the returns of these three WU-LO portfolios outperformed the conventional momentum strategy. We further use one-tailed t-test to examine the difference between the returns of WU-LO portfolio and WML. For $j = 3$, the t-test statistic of WU-LO portfolio to WML is 3.4675 with p-value < 0.01. For $j = 6$, the t-test statistic of WU-LO portfolio to WML is 1.4003 with p-value < 0.1. For $j = 9$ and $j = 12$, the t-test statistics are not significant at 5% significant level.

Initially, our study focused on the consideration of short-termed contrarian and the continuation in intermediate momentum of each stock. As a result, the improvement in conventional momentum strategy with value risk was observed, mainly due to the undervaluing of a firm at its high momentum. At this circumstance, the stock price will tend to rise instead of fall in the following month. Thus, our strategy was aimed at controlling the short-term behavior of a stock and the persistent intermediate momentum.

Table 7 Characteristics of Time Series Momentum Srategy

j-Months IPR		P1 (Loser)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (Winners)	WU-LO
3	Under	0.98%	1.26%	1.39%	1.40%	1.42%	1.36%	1.52%	1.59%	1.65%	1.44%	
		(0.0909)	(0.0718)	(0.0661)	(0.0626)	(0.0615)	(0.0608)	(0.0628)	(0.0663)	(0.0699)	(0.0842)	2.44%
	Middle	0.41%	0.83%	0.91%	0.94%	1.11%	1.20%	1.25%	1.39%	1.49%	1.70%	
		(0.0772)	(0.0606)	(0.0524)	(0.0488)	(0.0471)	(0.0463)	(0.0462)	(0.0490)	(0.0545)	(0.0695)	
	Over	-1.00%	0.14%	0.45%	0.52%	0.81%	0.88%	1.04%	1.26%	1.42%	1.61%	(0.0601)
		(0.0807)	(0.0670)	(0.0618)	(0.0568)	(0.0558)	(0.0531)	(0.0543)	(0.0558)	(0.0608)	(0.0741)	
6	Under	0.70%	1.13%	1.31%	1.36%	1.40%	1.29%	1.40%	1.63%	1.63%	0.97%	
		(0.0879)	(0.0687)	(0.0633)	(0.0604)	(0.0608)	(0.0605)	(0.0629)	(0.0686)	(0.0744)	(0.0896)	1.67%
	Middle	0.16%	0.82%	0.94%	0.88%	1.09%	1.21%	1.29%	1.45%	1.60%	1.44%	
		(0.0788)	(0.0615)	(0.0523)	(0.0485)	(0.0472)	(0.0458)	(0.0463)	(0.0497)	(0.0553)	(0.0698)	
	Over	-0.70%	0.18%	0.47%	0.56%	0.90%	0.95%	1.08%	1.24%	1.38%	1.62%	(0.0713)
		(0.0881)	(0.0737)	(0.0688)	(0.0607)	(0.0575)	(0.0556)	(0.0554)	(0.0558)	(0.0596)	(0.0738)	
9	Under	0.64%	1.10%	1.26%	1.25%	1.34%	1.14%	1.38%	1.50%	1.50%	1.22%	
		(0.0861)	(0.0676)	(0.0625)	(0.0596)	(0.0612)	(0.0627)	(0.0665)	(0.0720)	(0.0834)	(0.1073)	1.74%
	Middle	-0.33%	0.65%	0.83%	0.97%	1.08%	1.25%	1.29%	1.56%	1.62%	0.97%	
		(0.0822)	(0.0618)	(0.0521)	(0.0493)	(0.0467)	(0.0459)	(0.0473)	(0.0501)	(0.0613)	(0.0800)	
	Over	-0.52%	0.42%	0.69%	0.64%	0.87%	0.94%	1.10%	1.25%	1.46%	1.45%	(0.1048)
		(0.1124)	(0.0805)	(0.0739)	(0.0628)	(0.0586)	(0.0559)	(0.0545)	(0.0563)	(0.0596)	(0.0718)	
12	Under	0.58%	1.03%	1.23%	1.20%	1.28%	1.20%	1.54%	1.52%	1.93%	0.25%	
		(0.0851)	(0.0656)	(0.0612)	(0.0589)	(0.0614)	(0.0655)	(0.0715)	(0.0879)	(0.1256)	(0.1388)	-0.15%
	Middle	-0.03%	0.74%	0.87%	1.04%	1.18%	1.30%	1.25%	1.33%	0.90%	-0.02%	
		(0.0924)	(0.0588)	(0.0511)	(0.0481)	(0.0469)	(0.0460)	(0.0523)	(0.0615)	(0.0888)	(0.1134)	
	Over	0.40%	0.67%	1.03%	0.89%	0.94%	1.12%	1.35%	1.39%	1.24%	1.40%	(0.1385)
		(0.1241)	(0.0902)	(0.0785)	(0.0663)	(0.0608)	(0.0572)	(0.0573)	(0.0594)	(0.0622)	(0.0755)	

Figure 10 plot the monthly portfolio return of the time series momentum strategy ($j = 3$) over the period from July 1967 to December 2010. As a result, the time series momentum strategy was shown to perform better than the conventional momentum strategy as shown in Figure 3.4. In addition, the WU-LO portfolio returns were observed to be more stable than the returns of conventional momentum portfolio, though we also recognized the imperfection of our strategy with incapability of avoiding a huge loss of -37.86% in April 2009. Further plotting on the cumulative monthly return of conventional momentum strategy and time series residual momentum strategy over the time period from July 1967 to December 2010 was also shown in Figure 11. As a result, the cumulative monthly return of WU-LO is $116,926.2; whereas the cumulative monthly return of WML was shown to be $69.09. In considering the performance after 2000, the cumulative monthly return was also plotted for conventional momentum strategy and time series residual momentum strategy over the time period from January 2000 to December 2010, as shown in Figure 12. The WML was shown to lose about 70% in December 2010 compared to its initial investment in January 2000. As for the value using our strategy, 217.10% was observed in December 2010 comparing to its initial investment in January 2000.

4. Conclusions and Future Researches

The momentum effect has been widely accepted in financial market. But, fewer people notice the collapse of the momentum is profound especially after financial crisis. There are "momentum crashes." Just as trees do not grow to the sky, likewise, share prices do not rise forever. The momentum crash is because that conventional momentum strategy exhibits substantial time-varying exposures to the market.

In this study, we revisit the conventional momentum strategy in the U.S. stock market by the residual analysis and the price-risk adjustment over a long period of time, from January 1930 to December 2010. Such time-varying exposures of the conventional momentum strategy can be reduced by the residual analysis and the price-risk adjustment. The idea was when a firm is undervalued (under-priced) at its high momentum; the stock price tends to rise instead of fall in the following month. Conversely, when a firm is overvalued (over-priced) at its low momentum, the stock price tends to fall instead of rise. The strategies that we proposed can control the short-term behavior of a stock and the intermediate continuation.

Overall, our empirical results showed that through these two strategies, significant improvement was observed in compared to the conventional momentum strategy, suggesting it to be a better way for portfolios management in future studies. Even more, this new concept of residual analysis can also be further applied to other financial markets as commodities and currencies.

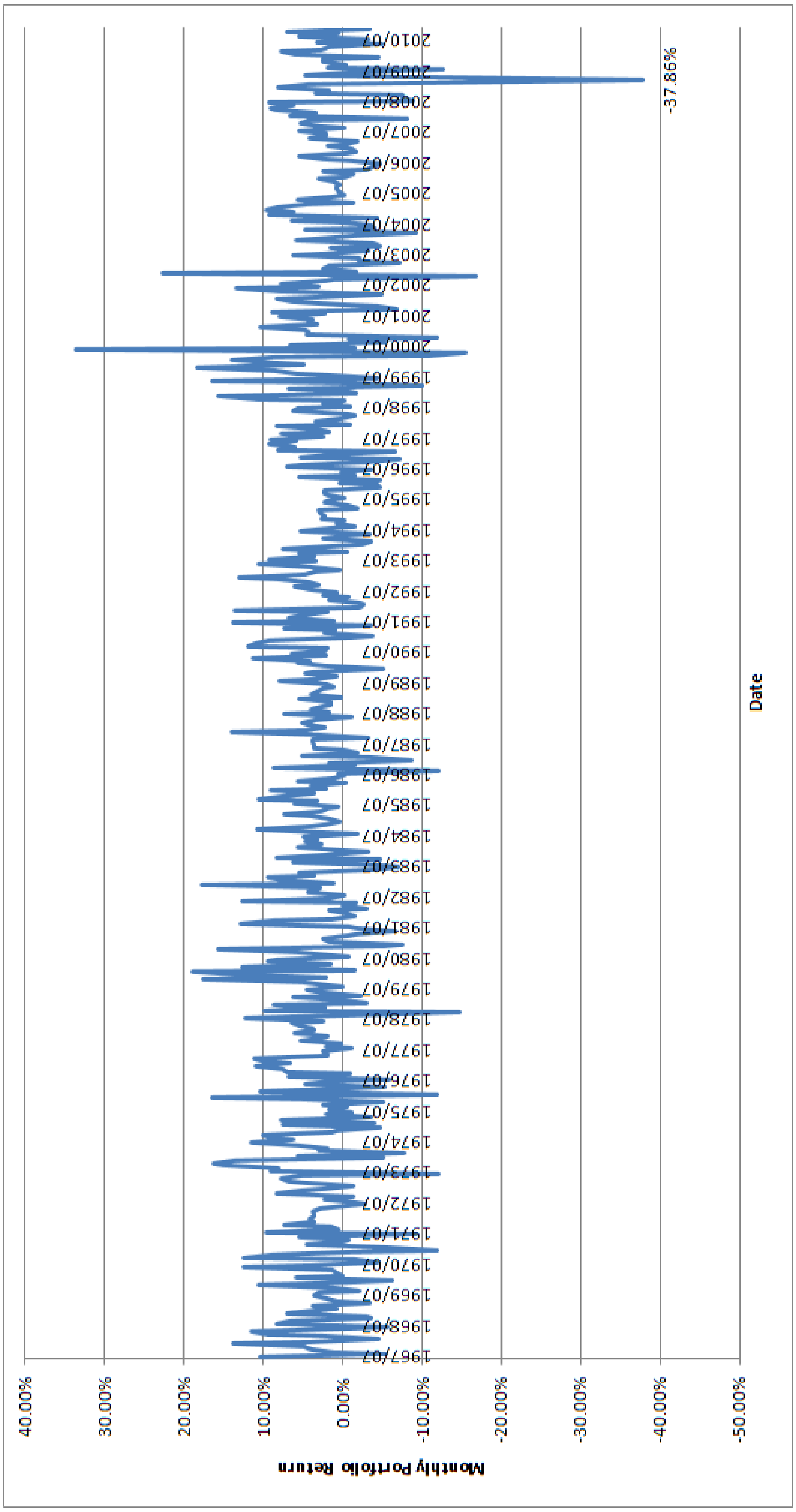

Fig. 10. Time Series Momentum Portfolio Performance, July 1967-December 2010

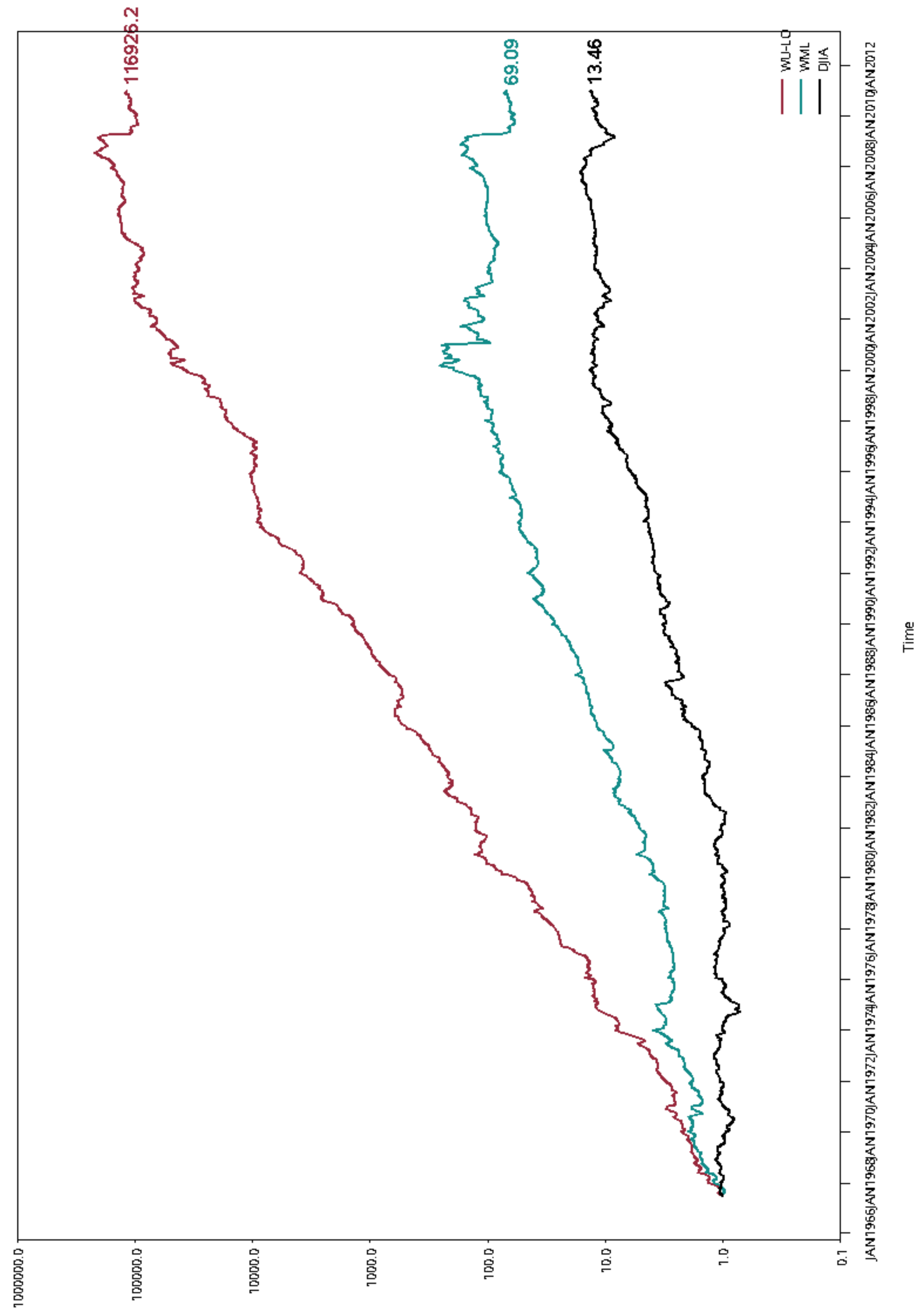

Fig. 11. Cumulative Monthly Returns of WML, WU-LO, July 1967-December 2010

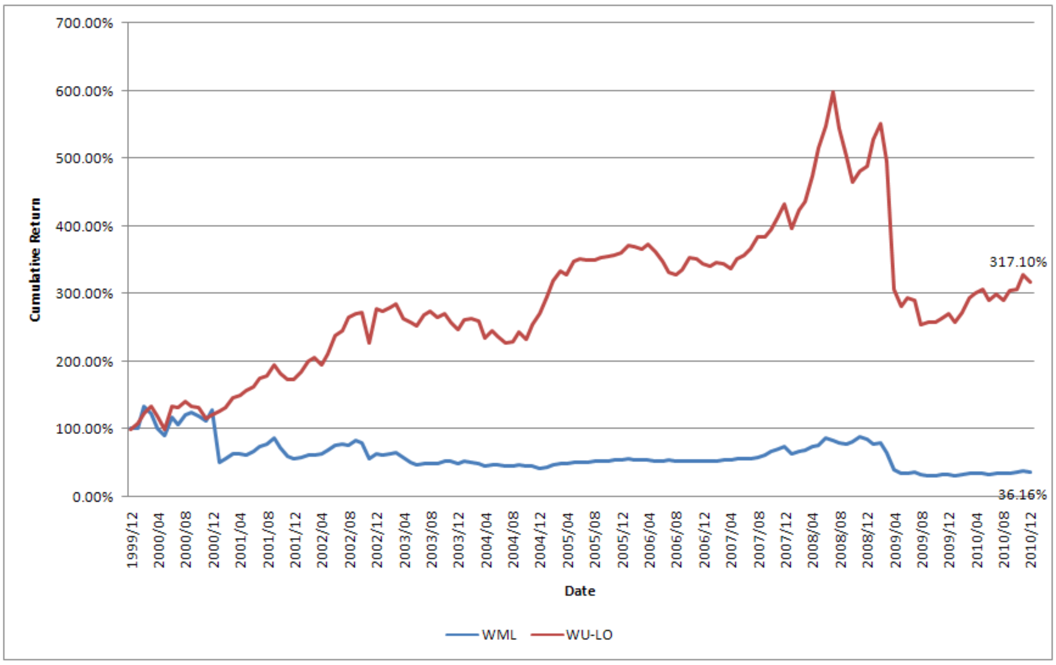

Fig. 12. Cumulative Monthly Returns of WML, WU-LO, January 2000-December 2010

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