Momentum Returns of U.S. Equities:
Diversification, Idiosyncratic Volatility, and Momentum Prediction of Industry Portfolios

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Abstract

This paper investigates the presence of momentum returns in U.S. equities using industry portfolio approach spanning from 1990 to 2017. Using winner-minus-loser strategy, taking a long on winners and taking a short on losers, can generate substantial returns over the time. Divining into 48 industries, the result suggests that the presence of momentum exists in all the 48 industries. Using idiosyncratic volatility measure proposed by Fu (2009), momentum return does not improve. Adding liquidity factor for double sorting also suggests the similar result. Testing for momentum predictability using Moreira and Muir (2017) inverse conditional volatility, momentum returns are affected by the size of liquidity and risk factors rather than economic variables.

Keywords: Momentum, Idiosyncratic Volatility, Factor Models

JEL Classification: G11, G12

1. Introduction

Momentum refers to a motion that an object has. The term can broadly use in fields such as in physics, in sports, or even in finance. The momentum in finance, by the definition, is an investment strategy to take two opposite positions; taking a long (buy) on stocks that have performed well in the past and taking a short (sell) on stocks that have performed poorly in the past. The strategy is called "Momentum Strategy" or "Winner minus Loser Strategy". Jegadeesh and Titman (1993) observe the behavior of U.S. equities and test for momentum strategy. Their result shows that momentum strategy can generate a positive return, creating an investment opportunity for investors to exploit such trading behavior since the strategy can create a positive return with zero-investment[1]. The momentum behavior has been extensively studied in

[1] Zero-investment refers to taking both long and short positions to generate a positive profit.

many asset types such as commodity, foreign exchange market, international stock market, and so on[2]. Most of the literatures point out the same idea that there is an existence of momentum returns in most of the asset types and momentum profits tend to appear in many periods of time.

Although the momentum strategy has been widely observed, there is no well-documented literature providing a clear-cut where the source of momentum profit is from. Most of the literature observe the sorted momentum portfolios based on the excess return regardless any risks involved in momentum profits. Profits generated from momentum within industries has been largely ignored. From this, we investigate the source of momentum profits whether it arises from within industries. From the literature standpoint, momentum strategy is based on the previous returns, which can be in any assets and markets. The combination of different industries may yield the profits from the strategy better than using stand-alone industry. If combining different industries provides a greater momentum profit, then there must be that some industries significantly perform as a better diversification benefit than the others.

The long-standing belief is that the higher risks will be compensated with higher returns. To receive the benefit of diversification purpose, investors should seek for stocks/assets that provide a negative correlation among them. Then, if they believe that momentum benefits are trading such risks for higher returns, they should be able to distract the diversification benefits of momentum strategy and, by sorting based on risks, they should be able to observe the same patterns of momentum behaviors. Motivated by this question, we explore the possibility of the source of momentum returns by using the size of volatility instead of using excess returns to sort the portfolios. Testing based on the size of volatility, we propose the use of both 3 factor and 5-factor to determine the volatility, and estimate the conditional volatility using GJR-GARCH model[3].

[2] For example, Okunev and White (2003) find the momentum in currencies, Chui, Titman, and Wei (2010) find individualism tend to extract more momentum profits than collectivism, Asness, Moskowitz, and Pedersen (2013) show that the momentum can be found in many asset classes.

[3] Engle and Ng (1993) test for ARCH and GARCH types and conclude that GJR is the best measure of new information of stock prices.

The objective of this paper is to provide a greater detail of momentum returns using excess returns, and conditional volatility. Sorting the momentum strategy based on conditional volatility has not been extensively observed or documented by literatures. The closely related paper is Ang et al. (2009), who test for the return reversals of the standard idiosyncratic volatility of U.S. stock data. Their finding provides an importance to the literature showing the presence of the reversals of stock returns. Motivated by their results, we test for all 48 industries[4] as well as individual industries of the U.S. equity data to see whether the returns can be higher using conditional volatility portfolio sorting.

The initial hypotheses towards the momentum strategy are (i) using all 48 industries we should be able to observe the pattern of the momentum strategy and the size of momentum profit must be high enough for investors to implement momentum strategy, (ii), diving into 48 industries, some industries may provide a better return than the others. Combing all 48 industries, the benefits of diversification should be pronounced, and (iii), sorting portfolios based on the conditional volatility, we should expect to see the size of momentum profit to be higher than that of traditional momentum portfolio sorting.

To investigate the momentum strategy, our primary focus is on the U.S. equities. Using daily U.S. firm level data from 1990 to 2017, we construct the momentum return based on winner minus loser (WML) strategy[5]. The portfolios are formed based on the size of the excess returns. The top 10% of stock excess returns is grouped up and named the winner portfolio. The bottom 10% of stock excess returns is classified as the loser portfolio[6]. To avoid potential outliers, we winzorize 1% of each tail to eliminate potential outliers. More details are discussed under data and methodology section. In general, we find that, consistent with documented literatures, the momentum return in U.S. equities is shown. Dividing the sample into 48

[4] We use SIC Code to divide into 48 industries from Kenneth French Website. The SIC Code is available at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html.
[5] Refer to short sell loser portfolio and long winner portfolio.
[6] Top and bottom 10% sorting is suggested by many literatures such as Daniel and Moskowitz (2016), Barroso and Santa-Clara (2014).

industries, as classified based on SIC code provided through Kenneth French Website[7], the momentum profit for individual industry is also pronounced.

We argue that the source of momentum benefits may come from diversification purpose. Then, we run pairwise correlation based on the excess returns of all 48 industries and pair the industries that have a strong negative correlation. Choosing the strong pairs of negative correlation, we find that, however, the momentum cannot attain the highest as we find based from all 48 industries. Opposite to what investors believe, high risks are compensated with higher returns, the potential source of momentum return is purely based on excess returns rather than the correlation among industries.

This finding provides an important question whether the momentum profit can be determined based on the idiosyncratic risk. Fu (2009) documents the returns in equity markets based on idiosyncratic risk and finds that ranking portfolios based on volatilities can yield a significant gain and substantially higher than market return. Motivated by his finding, we test for GJR-GARCH model[8] to determine the conditional idiosyncratic volatility and find that both 3 and 5-factor provide similar magnitude of conditional volatility for both mean and standard deviation. Then, we sort the portfolio into five quintile portfolios[9]. Sorting based on the idiosyncratic volatility, however, does not provide an ideal result as it does for sorting based on excess returns.

We then argue that using one-dimension portfolio sorting may not be appropriate since there is a need to control for factors such as volatilities and liquidity when sorting portfolios. Then, we sort portfolios based on excess returns followed by using illiquidity (Amihud, 2002) and idiosyncratic volatility for second sorting (double sorting). The double sorting can eliminate a surprisingly high momentum return since there is no control for such returns. We find that using double sorting can control for the momentum returns. The difference between high and low portfolio is pronounced supporting the momentum returns.

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[7] Kenneth French. U.S. Data library: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[8] We follow Hansen and Ng (1993) that GJR-GARCH type is most suit to measure the volatility in stock markets.
[9] Fu (2009) and Ang et al. (2009) construct the conditional volatility and divide into five quintile portfolios.

Once we determine the factors that affect the change in momentum returns, we turn our analysis based on volatility by scaling on the excess returns using the inverse of conditional variance as suggested by Moreira and Muir (2017) to capture the potential increase and decrease risk exposure of the portfolios. We test for multiple factors to control for the size of the returns such as Fama-French 3-factor (the excess market return, size factor, and value factor), and momentum factor (MOM). We also include liquidity factor as well as idiosyncratic volatility as we find that these factors can control for momentum returns. The result shows that, in fact, these factors are statistically significant to control for the returns when using by-factor regression.

The main results of the current paper are (i) we find that there is strong momentum return for all industries, but diversification benefit does not improve the momentum returns, (ii) using idiosyncratic risk to sort for loser and winner portfolio does not provide a better result than using excess return approach, and (iii) sorting portfolios based on the inverse conditional variance including multiple factors shows that the momentum returns are affected the most by the size of liquidity and the risk factors.

2. Literature Review

Jegadeesh and Titman (1993) observe a trading strategy in U.S. equities by buying stocks that have been performed well in the past and selling stocks that have been performed poorly in the past. They find that the trading strategy can yield a substantial positive return. The positive returns continue up to 6- to 12-month. However, in a longer time frame, the potential return reversals could occur making winner stocks to become losers and losers to be winners. Jegadeesh and Titman (2001) test for the continuation of momentum strategy using U.S. equity data spanning from 1990 to 1998. Their result show that the momentum returns can be found even using the recent data. They argue that presence of momentum exists, and investors can potentially benefit from momentum strategy. Their findings have received a lot of attention. The presence of momentum has been expanding into many asset classes such as commodity, foreign exchange, international stock market, and so on.

The presence of momentum strategy, however, is not supported by the market efficiency hypothesis (MEH) proposed by Malkiel and Fama (1970) that the market itself can be adjusted due to the arrival of new information and the market price should reflect to the new information. De Bondt and Thaler (1985) challenge the market efficiency hypothesis (MEH). They hypothesize that if new information plays an important role for investors, then investors will overreact, and such behavior can violate the MEH. Their finding provides an empirical evidence that investors do overreact to the new information resulting in selling winner stocks and buying loser stocks. Their result provides an important to finance literature is that there is a potential profit using momentum strategy in equity markets that investors can exploit from.

The momentum in currency market is documented by Okunev and White (2003). They test for the major currency exchange rates from 1975 to 2000. Adjusting for interest rate differential, they report that investors can extract positive returns using the momentum strategy in foreign exchange market. Menkhoff et al. (2012b) also test for the momentum returns using carry trade to form the portfolios. The portfolios are formed based on the excess returns. The top 10% currency excess returns are defined as winner portfolio while the bottom 10% excess returns are described as loser portfolio. The difference between winner and loser, winner minus loser (WML) strategy, generates approximately 10% per annum. Also, they report that the size of momentum returns is not affected by the business cycle, liquidity risk, carry trade risk, volatility risk, three-factor, or four-factor model, rather it can be explained by the country risk and transaction costs. Their findings support the presence of momentum returns in currency market and the momentum return is not affected by volatility risks contributed to the momentum returns puzzle regarding the sources of returns.

Chui, Titman, and Wei (2010) provide an empirical test for momentum returns based on a country's characteristic such individualism and collectivism. They argue that a specific behavior can contribute to the size of momentum return as individualisms tend to be risk-takers while collectivisms are risk adverse. Then, the size of momentum returns is higher in individualism countries such as U.S. than collectivism countries such as Japan. However, individualisms can potentially suffer from overconfidence behaviors by taking too much risk and resulting in return reversals. Their documented evidence does provide an explanation of financial behavior to the momentum returns.

Momentum strategy can generate substantial benefits for investors; however, the benefits tend to disappear at a longer horizon. Titman and Jegadeesh (2001) provde an empirical evidence based on the different horizon periods to use momentum strategy. They find that, in general, momentum profits tend to be higher during the first year of the strategy. The strategy, however, starts to decline until the profits become negative after 2 to 3 years of strategy period. This evidence has also been observed by Moskowitz, Ooi, and Pedersen (2012), which they test for 58 instruments and find a strong significance of stock return predictability based on the past performance for all the instruments. They also document that the excess returns of these instruments reverse over longer horizon suggesting momentum strategies disappear after a certain holding period.

The recent literature from Daniel and Moskowitz (2016), using the U.S. equity data, provides an empirical evidence sorting portfolios into 10 deciles based on the excess returns. They find that the momentum portfolio (winner minus loser portfolio) provides a higher return, Sharpe ratio, and positive skewness than stand-alone portfolio. Their finding gains a lot of attention in scholar work of the presence of momentum returns. They indicate that, extending from the previous work of Barroso and Santa-Clara (2015)[10], using time-varying to manage momentum portfolio can substantially provide a greater return, lower volatility, and higher Sharpe ratio than plain momentum strategy.

The presence of international asset in momentum returns is also observed. Rouwenhorst (1998) reports the findings of momentum in international assets, using 12 European countries during the period 1980 to 1995. His finding supports the momentum strategy presented by Jegadeesh and Titman (1993). Moreover, Chan, Hameed, and Tong (2000) provide an evidence of the profitability of momentum strategies using both U.S. and international equity. They document that the presence of international assets in momentum strategies

[10] Barroso and Santa-Clara (2015) provide an evidence that momentum can be managed using constant time-varying model to forecast the momentum returns.

can help achieving higher returns than using only one equity market. Naranjo and Porter (2007) point out that momentum would be more beneficial if international assets are included into portfolios, especially when adding emerging markets. Using firm level data across developed and emerging countries, their finding indicates that inclusion of emerging markets provides higher returns than using purely from developed markets.

In sum, momentum strategy can generate investment opportunities for investors to engage in such strategy. The strategy is not only limited in the U.S. equity market, but also in many various asset types such as commodity, foreign exchange, and international stock markets[11]. Then, investors would receive greatly benefit of momentum strategy if they combine these asset types together.

The paper is organized as follows. Section 3 provide data and methodology used to construct portfolios and determine the momentum returns. Then, we present the empirical results in section 4. Section 5 concludes the paper.

3. Data and Methodology

3.1. U.S. Equity Data

The primary sources of our data are from the Center for Research in Security Prices (CRSP) and Compustat. We obtain daily U.S. equities from January 1990 to December 2017. We exclude stocks that are not traded in NYSE, AMEX, and Nasdaq. Also, we use CRSP share code of 10 and 11 to collect common equity data[12]. To eliminate potential outliers, we winzorize the data for each tail at 1%. Winzorizing at 1% is supported by Hoberg and Phillips (2010) that 1% winzoring at each tail can be used to control for extreme values when forming portfolios. We define each industry based on SIC Code provided by Kenneth French's

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[11] Momentum strategy has been observed through many asset classes: FX, bond, commodities. See. Moskowitz and Grinblatt (1999), Menkhoff et al. (2012b), Rouwenhorst (1999), Okunev and White (2003), Asness, Moskowitz, and Pedersen (2013), Novy-Marx (2012).

[12] Banz (1981), Maillard et al. (2010), Daniel and Moskowitz (2016) suggest using share code 10 and 11 to get common stock data.

Website. We divide into 48 industries to provide a comprehensive industry level data based on Kenneth French's SIC Code.

Table 1 presents the summary statistics of 48 industries. Most of the industries, except for Automobile and Trucks, Defense, and Oil, experience a positive return. Trading industry generates the highest return (2.44%) than any other industries. Automobile and Trucks, surprisingly, depicts the greatest volatility among industries (approximately 60% of standard deviation). The plausible explanation is that Automobile and Trucks industry suffers from the recent financial crises than any other industries. Then, the negative return with high volatility are expected from the industry. The number of observations (Obs) is also reported at the last column. Other industry contains the highest number of observations, which is 316,637 observations, while Utility industry has the lowest number is 215 observations.

[Insert Table 1 Here]

3.2. Momentum Portfolio Construction – Excess Return

We construct the momentum portfolios based on the cumulative returns[13]. The cumulative returns are formed based on the past 12 months up until 1 month before the formation date (from t-12 to t-2)[14]. Using up to the last month (t-1) can potentially generate the return reversals. Momentum strategy, as suggested by Lehman (1990), can turn winners into losers, and vice versa. To avoid this issue, we calculate the cumulative returns from t-12 up to t-2.

We then calculate the excess return. The excess return is calculated using the end of the day return minus daily market return. Top 10% of stock excess returns is classified as the winner portfolios while bottom

[13] Barroso and Santa-Clara (2015), Jegadeesh and Titman, 1993) suggest the use of cumulative returns as portfolios are formed based on past performance to observe the momentum profits.
[14] Daniel and Moskowitz (2016), Asness (1997), Fama and French (1996) provide empirical evidences that the reversals could happen at the month t-1.

10% is the loser portfolio. Then, the winner minus loser (WML) is top 10% portfolio minus bottom 10% portfolio[15].

Figure 1 provides the difference excess returns between winner and loser portfolios. The winner, as expected, shows a positive excess return while loser depicts a negative return. This result is consistent with documented literature (Asness, 1997, Jegadeesh and Titman, 1993, Jegadeesh and Titman, 2001) that winner portfolio provides a positive return overtime while loser portfolio, on the other hand, generates a negative return.

[Insert Figure 1 Here]

calculate the excess return based on the monthly return using the average return for each month and sort portfolios based on the excess returns. The bottom 10% or portfolio 1 is lower portfolio and the top 10% or portfolio 10 is the winner portfolio. Table 2 presents the result. As expected, the return of loser portfolio (portfolio 1) is negative while winner portfolio (portfolio 10) is positive. The difference between return and standard deviation of winner and loser portfolios are pronounced, which loser portfolio (1) has a return of -7.98% with standard deviation of 12.30% compared to winner portfolio (10) with a return of 10.47% with standard deviation of 18.35%. The Sharpe ratio (SR) provides a consistent result that winner portfolio provides a substantial higher return per unit of risk than loser portfolio (-0.1608 for loser and 0.6515 for winner).

[Insert Table 2 Here]

Compared to value-weighted market return (MKT-Ret), the WML strategy, defined as taking a long position on winner portfolio (10) and taking a short position on loser portfolio (1), greatly outperforms the market return. The mean return of WML is 18.45% while the market benchmark generates only 6.2%. Sharpe ratio (SR) from WML (0.94) is also higher than market's Sharpe ratio (0.40). The return from

[15] Ranking based on 10 deciles. Top 10% until bottom 10%. See. Daniel and Moskowitz (2016), Menkhoff et al. (2012b).

momentum strategy helps increasing return, and higher Sharpe ratio than investing purely on the market benchmark[16].

3.3. Idiosyncratic Factors

We are now interested in the potential gains from momentum strategy based on the movement of idiosyncratic risk or risk factors to stock returns. Idiosyncratic risk, as defined by literatures, is the error term of the regression, which helps explain the change in the stock movement in which it is not correlated with the market risk. We test whether the idiosyncratic risk in stock returns can help predict the short-term return and improve the return from momentum strategy. We implement the strategy based on 3-factor model proposed by Fama and French[17]. Using these models, we expect to see the improvement of momentum strategy as well as the co-movement between the industries.

We specify using Fama-French model as proposed by Ang et al. (2009) as follows:

$$r_i = \alpha_i^L + \beta_i^L MKT^L + s_i^L SMB^L + h_i^L HML^L + \varepsilon_i^L$$

Where $r_i$is the daily excess U.S. dollar return of stock i, $MKT^L$is the value-weighted of local market portfolio over the one-month T-bill rate, $SMB^L$is the return of the smallest one-third of local firm minus the return of the largest one-third of local firm characterized by the market capitalization, and $HML^L$is the return of the highest one-third of book-to-market ratio minus the return of the lowest one-third of the lowest book-to-market ratio. The idiosyncratic volatility is measured by the standard deviation of the residual, ε_i^L, after the estimation from the regression model.

Fu (2009), however, points out that using the monthly stock returns with one-month lagged idiosyncratic volatility depicts a negative relation. He argues that, different from Ang et al. (2006) and Merton (1987),

[16] Menkhoff et al. (2012b) document their finding that the WML strategy increases the performance better than investing in risk-free rate, market benchmark, or bond yields.

[17] Fama and French (2017) propose the use of five-factor to test for international assets. I exclude the use of five-factor since Fu (2009) and Ang et al. (2009) use three-factor to capture the idiosyncratic volatility from the ARCH-GARCH type model.

that idiosyncratic volatilities are time-varying, and he proposes that using exponential GARCH is more appropriate. He finds a positive significant relation between the estimated conditional volatilities and expected returns. To observe the leverage effect in volatilities, we use GJR-GACRH model (Glosten, Jagannathan, and Runkle, 1993) including asymmetric terms that can capture an important phenomenon in the conditional variance of equities. The model is estimated as follows:

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

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

The equation above describes the GJR-GARCH (p,q) model, where p and q defined as the number ranging from $1 \leq p,q \leq 3$. The choice of p and q is based on Akaike Information Criteria (AIC). GJR-GARCH model is supported by Hansen and Lunde (2005) that the model can capture the leverage effect and more superior than using standard GARCH(p,q) model. They test for the IBM stock return with various conditional model and conclude that the standard GARCH is superior than using other types of conditional volatility model to predict the stock returns. The purpose of using this GJR-GARCH is to estimate the conditional variance, σ_{it}^2. The modification of the conditional variance as described in the equation is to capture the possible shocks that occur from the lagged period[18].

3.4. Portfolios sorted based on idiosyncratic volatility

Sorting based on volatility, as suggested by Fu (2009) and Moreira and Muir (2017), the size of return should be higher as the risk exposure is reduced, improving the return per unit risk. We construct portfolios based on the size of idiosyncratic volatility based on GJR-GARCH as showed in previous section. We define that Portfolio1 is firms with the highest 20% of idiosyncratic volatility and portfolio 5 is firms with the lowest 20% of volatility. The portfolio construction is based on only 5 quintile portfolios instead of 10

[18] Fu (2009) uses this modified EGARCH as to determine the leverage effect.

decile portfolios since many literatures (Fu, 2009, Menkhoff et al., 2012b, Ang et al., 2009) suggest the use of 5 quintile portfolios to be able to observe the movement of volatility in portfolio sorting.

4. Empirical Results

4.1. Momentum in individual industries

Previous section, we estimate the momentum of all 48 industries of U.S. equity. We find that there is a potential profit for investors to take a WML strategy in U.S. equities. In this section, however, we focus on the individual industries as divided by SIC Code to see whether the possible momentum return exists in individual industries. We follow the portfolio construction based on excess returns and rank from bottom 10% to top 10%. Table 3 presents 48 individual industries with 10 quintile portfolios. WML refers to the winner portfolio (portfolio10) minus loser portfolio (portfolio 1). SR is defined as the Sharpe ratio for each portfolio. The results suggest that, in general, the loser portfolio depicts a negative return in all the industries while winner portfolio shows a positive return. For a complete 10 decile portfolios, see the Appendix A1. For example[19], the Food Products industry indicates a negative return in loser portfolio (portfolio 1) of -1.19% with the Sharpe ratio of -0.0808 and the portfolio 10 or winner portfolio shows a positive return of 3.41% with the Sharpe ratio of 0.2680. Taking long position on winner and short on loser or WML strategy, we find that most of the industries provide a greater return such as Food Products with mean of 4.61% as well as an improvement in Sharpe ratio of 0.3267 under WML portfolio. We also document the similar results for other industries that WML portfolio substantially provides a better return. The Sharpe ratio, consistent with most of the industries, improves when WML strategy is estimated.

[Insert Table 3 Here]

4.2. Relation between industries

[19] Refer to the Appendix A1.

The objective of this research is to test whether source of profit from momentum strategy is from within and/or between the industries. If there is a diversification benefit, then momentum profits should be higher when using cross-industries asset combination than purely from within the industry. We test the correlation between 48 industries. We find, however, that, using excess returns to compute the correlation between industries, these 48 industries indicate both positive and negative correlation. This finding is opposite to the general intuitive of the recent work of Barberis et al. (2005), which they find the strong co-movement between industries.

The low to moderate co-movement between the industries during 1990 to 2017 may result from the disappearance in diversification benefits taken by investors. The diversification benefit is a traded off to a potential gain as suggested by Villalonga (2004) that diversification may destroy value of asset holdings.

4.3. Argument against the diversification of momentum return

This section, we analyze the possible sources of momentum returns from diversification strategy. Motivated by the fact that the momentum benefit is from taking a long position from winner and a short position from loser, we now are interested whether the combination between industries can generate a greater return than using only one specific industry. We test for pair industries that show a high negative correlation. The Appendix A2 shows the result. Using strong negative correlation between industries, we find that the result is consistent to the main results. Loser portfolio generates negative return while winner portfolio provides positive return. The WML portfolio can increase return and Sharpe ratio. Also, combining between industries can generate a substantial return than using only individual industry.

However, the diversification between industries is not be able to achieve a higher return than using all 48 industries as presented in table 2. This finding provides two important elements to momentum strategy. First, the momentum strategy return is purely from the excess return rather than the correlation among industries. Second, diversification benefit does not contribute to the gains in momentum sorted portfolios. This can be explained that why momentum strategy violates MEH as proposed by De Bondt and Thaler

(1985) that investors overreact to the price movement of winners and losers creating the mispricing in assets.

4.4. Idiosyncratic Factors

Table 4 shows the result from the regression based on 3-factor model. Consistent with Ang et al. (2009) that the mean of SMB is negative (-0.152%) indicating that small firms have not outperformed large firms based on recent spanning period of 1990 to 2017. The other risk loading factors are also consistent with documented literatures indicating that the market and HML are positive (0.111% and 0.349%, respectively)[20]. The size of conditional volatility is comparable to what Fu (2009) reports[21]. Our conditional volatility has a mean of 11.13% with standard deviation of 10.51%. Using the recent period from January 1990 to December 2017 can capture the presence of the conditional idiosyncratic volatility estimated by GJR-GARCH.

[Insert Table 4 Here]

Figure 4 provides the idiosyncratic volatility movement from January 1990 to December 2017. As the graph shows, the idiosyncratic volatility depicts the huge swing during the financial crisis, especially during the collapse of the Lehman Brothers in 2008. The swing in idiosyncratic volatility is possibly explained by the change in country specific risks as suggested by Brooks and Del Negro (2005) that country specific risks play as the role of changing in conditional volatility.

[Insert Figure 2 Here]

4.5. Portfolios sorted based on idiosyncratic volatility

We now turn our analysis of momentum strategy based on idiosyncratic volatility as determined in the previous section. Portfolios are constructed based on the level of conditional volatility as portfolio 1 is firms

[20] Ang et al. (2009) report the coefficients of 0.66%, -0.08%, and 0.15% for market risk, SMB, and HML.
[21] Fu (2009) reports the mean of conditional volatility of 12.67% with standard deviation of 10.91%.

with the highest 20% of idiosyncratic volatility and portfolio 5 is firms with the lowest 20% of volatility. We argue that using 5 portfolios would provide more meaningful results and is more consistent with other documented literatures (see. Fu, 2009, Menkhoff et al., 2012b, Ang et al., 2009).

Table 5 presents the results. Ranking based on idiosyncratic volatility, however, does not yield the ideal result as presented using excess returns. Portfolio 1, as expected, provides a highest conditional volatility of 27.08% while portfolio 5 has the lowest conditional volatility of 9.37%. The return is highest for the most volatile portfolio (portfolio 1) with the mean of 1.97% while portfolio 5 depicts an average mean return of 1.23%. It is worthwhile to note that portfolio 4 has a negative return which is -1.45%. The intuition of ranking portfolios based on idiosyncratic volatility is to determine whether the volatility can play in the momentum profit. The result, however, suggests that ranking based on the conditional volatility is not better off than using plain momentum strategy as presented in table 2. The plausible reason for investors to implement this strategy is that they want to lower their risks to compensate to their returns. The WML portfolio gives 3.20% return which is higher than investing into lowest idiosyncratic volatility portfolio. Shape ratio of WML portfolio is also higher than other portfolios (0.0727 for portfolio 1 and 0.1313 for portfolio 5, and 0.1915 for WML).

[Insert Table 5 Here]

4.6. Idiosyncratic Risk with Fama-French Five-Factor model

The presence of 5-factor model is also taken into our analysis. Fama and French (2016) test for the 5-factor model with international assets by adding profitability and investment factors to extend the 3-factor model. Their results show that adding these factors can help capture the average return patterns for both U.S. and international stocks; however, they point out the issue that the model does not fully capture the low average returns for small stocks which these stocks behave the same way as the low profitability stocks that invest aggressively.

The 5-factor model is estimated as follows:

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

Where $r_i$is the daily excess U.S. dollar return of stock i, $MKT^L$is the value-weighted of local market portfolio over the one-month T-bill rate, $SMB^L$is the return of the smallest one-third of local firm minus the return of the largest one-third of local firm characterized by the market capitalization, $HML^L$is the return of the highest one-third of book-to-market ratio minus the return of the lowest one-third of the lowest book-to-market ratio, CMA_i (conservative minus aggressive) is an investment factor and RMW_i (robust minus weak) is a profitability factor. The idiosyncratic volatility is measured by the standard deviation of the residual, ε_i^L, after the estimation from the regression model.

The estimation of conditional volatility is based on the GJR-GARCH model as proposed by the previous section. Table 6 indicates the results. The sizes of risk factor loadings are comparable to what we find with 3-factor model. SMB is negative confirming that the big firms have outperformed the small firms, however, the size is almost getting close to zero. CMA provides a negative mean of -0.28% indicating that firms during the recent period tend to invest more conservatively than aggressively. RMW has a mean of 0.57% providing that firms in the U.S. are more profitable in the sample period.

E(VOL) reports the conditional volatility from the GJR-GARCH estimation. The size is similar to that of 3-factor conditional volatility (mean of 12.87% with standard deviation of 15.91%). Then, using GJR-GARCH estimation with 5-factor provides a comparable estimation as we find in 3-factor model.

[Insert Table 6 Here]

Then, we sort portfolio based on the 5-factor conditional idiosyncratic risk. Table 7 reports our findings. we find that, consistent with sorting based on the 3-factor conditional volatility, the return based on WML portfolio does not yield the highest return as it does for sorting based on the excess return. In fact, ranking based on 5-factor conditional volatility provides a higher return with comparable risk (3.98% mean with 15.44% standard deviation compared with 3-factor WML mean of 3.2% and standard deviation of 16.71%). Ranking based on 5-factor conditional volatility provides better return as well as the higher Sharpe ratio of

0.2578 compared to 3-factor conditional volatility Sharpe ratio of 0.1915. The result, however, cannot achieve the highest returns as presented in table 2. Then, the source of momentum returns is nothing more than purely based on excess returns.

Sorting based on idiosyncratic volatility, however, does not provide a better return than using purely excess return to rank the momentum returns. Then, we confirm the evidence that the momentum returns are based on sorting based on the excess returns not from idiosyncratic risk.

[Insert Table 7 Here]

4.7. Double Sorting Portfolios **-** *liquidity and idiosyncratic volatility*

Previously, we analyze the size of returns based on either excess returns or idiosyncratic volatility. Now, we test for double sorting which is suggested by literatures (Fama and French, 1993, Bali and Hovakimian, 2009). Using double sorting benefits the analysis in two ways. Firstly, we can confirm whether liquidity or idiosyncratic volatility can be used as the proxy for the momentum portfolios. Second, double sorting eliminates the "too high and too low excess returns" and "too high and too low risky" stocks in portfolio construction.

The sorting begins with using excess returns of five portfolios and then we sort based on the size of liquidity and the idiosyncratic volatility. The reason of doing double sorting is that we want to see the possibility explanations that can be used to describe the change in momentum returns.

We follow Amihud (2002) to measure the stock illiquidity as the ratio of the daily stock return and the trading volume in dollars.

$$Stock\ illiquidity = \frac{|r_{i,t}|}{Vol_{i,t}}$$

Where $r_{i,t}$is the return of stock i and time t and $Vol_{i,t}$ is the trading volume in dollars of stock i and time t.

Table 8 presents the result. Double sorting based on liquidity and idiosyncratic volatility depicts that we can observe, partially, the momentum returns. The momentum return (5-1 or WML portfolio) after controlling for liquidity, as shown on panel A, provides approximately 15% return while sorting based on idiosyncratic volatility (E(Vol) in Panel B decreases the return to 11.29%. Both are statistically significant indicating that liquidity and idiosyncratic volatility can be seen as factors that control for momentum returns.

[Insert Table 8 Here]

4.8. Portfolio - Inverse Conditional Volatility

In the previous section, the portfolios are formed based on the size of idiosyncratic volatility. The result, however, shows that the volatility-based portfolios cannot help determining the improvement of the momentum returns. Then, we construct portfolios based on the volatility by scaling an excess return by the inverse of conditional variance as suggested by Moreira and Muir (2017) to capture the potential increase and decrease risk exposure of the portfolios. The portfolio is constructed as following:

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

Where ft+1 is the one period buy-and hold portfolio excess return, $f_{t+1}^{\sigma}$is the one-period portfolio volatility, $\sigma_t^2(f)$is the proxy for the conditional variance of the portfolio, and c is a constant arbitrary number to measure the scaling conditional volatility.

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

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

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

We use both daily and monthly data from Kenneth French's website on the excess market return (Mktrf), size factor (SMB), value factor (HML), momentum factor (MOM). Time-series regression presents as follows:

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

Figure 3 presents realized variance for each factor. As expected, these variables provide similar trend. Then, it is safe to conclude that these factors can be used to predict the portfolio conditional variance.

[Insert Figure 3 Here]

Table 9 reports regression results based on single factor, 3-factor, and 3-factor plus momentum. As expected, these factors are statistically significant as reported by p-value. Then, the portfolios can be formed based on these factors. Moreover, consistent with Moreira and Muir (2017), the alpha (constant) is positive in all the cases which reflect that investors benefit from such momentum strategy.

[Insert Table 9 Here]

Then, we sort the portfolios based on the excess returns. Top 20% represent the winner portfolio while bottom 20% is loser portfolio. The difference between winner and loser portfolio is categorized as WML portfolio as we mention in the previous section. Table 10 shows the result. Using inverse conditional volatility from three factors plus momentum factor to form portfolios, in fact, helps to reduce the size of standard deviation of each portfolio. The result, however, does not show any improvement in WML portfolio return. The size of return is less than sorting based purely on excess return. Using this strategy helps to reduce the risk involved in the momentum investment strategy while the Sharpe ratio is 0.536, which is less than the sorting based purely on excess return with the Sharpe ratio of 0.94 reported in table 2. We, however, can only argue that the size of return on WML portfolio is not affected by the traditional 3-factor and momentum factor.

[Insert Table 10 Here]

4.9. Portfolio Predictability

This section analyzes the predictability of the momentum portfolio returns. Barroso and Santa-Clara (2015) test for the predictability on portfolio sorted based on U.S. equities. They argue that realized variance can be used to predict the certain moment of stock return. Sorting portfolios based on realized variance, their result suggest that realized variance portfolio sorting can improve the return as well as Sharpe ratio. Motivated by the findings, Daniel and Moskowitz (2016) also test for the predictability for momentum portfolio using realized variance for multiple asset classes[22]. Their results suggest that momentum can be managed through realized variance and can yield a significant return to lower risk.

We follow the regression from Fama-MacBeth (1973). They suggest the use of two-step regression to determine the coefficients of risk-loading factors[23]. Once coefficients are determined, quintile regression can be formed using the initial coefficients. The model is presented as following:

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

Where $r_{WML,t+1}$is the WML portfolio at time t+1, $\hat{\beta} i$ is a vector of the coefficients estimated from the first step (MKTRF, SMB, HML, MOM), and Xt is a vector of economic variables, and θ_i is the vector of control variables (Idiosyncratic factor and liquidity factor).

We include CPI, bond yield, and T-bill as economic variables. These variables have been extensively studied and proven that they can present to the change in excess returns of equity markets, especially in the U.S.[24] equity. We first determine the vector of risk-loading factors coefficients from the first-step regression and determine the momentum portfolio of WML based on the second-step regression model. Table 11 presents the results. As expected, all the economic variables are statistically significant and able to explain the change in excess returns. We also present using only beta coefficients as well as one economic variable

[22] Daniel and Moskowitz (2016) test for momentum return using realized variance in many asset classes such as U.S. equities, International equities, Foreign Exchange (FX), bonds.
[23] We use MKTRF, SMB, HML, and MOM as risk-loading factors since these variables are mainly used in literatures. See. Ang et al. (2006), Ang et al. (2009), Fu (2009), Fama and French (2015).
[24] Bekaert and Wu (2000), Chrisoffersen et al. (2012), Menkhoff et al. (2012b) use these variables to test for the change in excess returns of U.S. equities.

for each model. It seems that the change in WML portfolio return is not affected by the economic variables as we believe. The size of economic variables appears to be small; although they are all economically significant. The plausible explanation is that the momentum returns in fact are not driven by the economic factors since the returns are based on the previous performance of the assets themselves rather than other external forces. Using each variable to run the regression model does not worsen the initial result. Then, using economic variables do not actually have any impact to the change in WML portfolio prediction since the main source of the return depends highly on the previous information from the risk-loading factors rather than other economic variables.

[Insert Table 11 Here]

5. Conclusion and Remarks

This paper provides a comprehensive study of momentum returns of U.S. and international assets from spanning period of January 1990 to December 2017. Using a traditional momentum portfolio construction based on excess returns, we find that, consistent with literatures, loser portfolios depict negative returns while winner portfolios show positive returns. Winner minus loser (WML) portfolio provide a better return and Sharpe ratio. Dividing into 48 industries and testing for momentum returns, the momentum returns are pronounced in all 48 industries.

A long-standing belief in finance that the diversification benefit comes from correlation among industries and can potentially explain the source of momentum return, we then test for pairs of industries that provide the highest negative correlations. We find, however, that these pairs of industries do not improve a return. Then, we investigate further using GJR-GARCH to observe the conditional idiosyncratic volatility based from 3 and 5-factor models. We sort portfolios based on the level of conditional idiosyncratic volatility. Our results show that sorting based on idiosyncratic volatility cannot help achieving the highest possible returns. In fact, using idiosyncratic volatility sorting only helps increasing Sharpe ratio, not overall portfolio return.

The arguments that the return on WML may be affected by other factors such as idiosyncratic factor and liquidity, we test for these factors. We conduct double sorting based on liquidity and idiosyncratic volatility and find that these factors actually can control the size of the momentum return and account for other factors that might affect the WML portfolio return such as economic variables. In addition, we examine the predictability of these momentum portfolio by applying the approach of inverse conditional volatility proposed by Moreira and Muir (2017). The result indicates that the traditional 3-factor and momentum factor are responsible for the predictability of momentum portfolio while economic variables are small and do not contribute much to the change in WML portfolio return.

Our findings confirm that the momentum return come purely from excess returns not from neither correlations nor idiosyncratic risks. This research, however, is in needs to investigate further for possible sources of momentum returns. The possibilities of returns can come in many ways such as economic variables or new sorting techniques.

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Table 1: Returns based on 48 Industries. The table presents the daily returns of 48 industries from January 1990 to December 2017. Each industry is classified based on SIC Code provided by Kenneth French Website. The excess return is calculated by end of the day return minus the market return (Value-weighted return). The returns are adjusted with SIC share code of 10 and 11.

ID	Name	Mean	Stdev	Obs
1	Agriculture	0.019	0.0779	3,418
2	Food Products	0.009	0.0611	15,858
3	Candy and Soda	0.0058	0.0406	3,901
4	Beer and Liquor	0.0093	0.0594	4,962
5	Tobacco Products	0.0046	0.0647	1,751
6	Recreation	0.0074	0.0819	10,051
7	Entertainment	0.0109	0.0862	16,046
8	Printing and Publishing	0.0142	0.0642	11,638
9	Consumer Goods	0.0104	0.0675	17,077
10	Apparel	0.0154	0.0721	11,391
11	Healthcare	0.0087	0.0781	23,416
12	Medical Equipment	0.0085	0.0751	36,148
13	Pharmaceutical Products	0.0028	0.088	61,141
14	Chemicals	0.0103	0.0638	19,831
15	Rubber and Plastic Products	0.0200	0.0752	7,713
16	Textiles	0.0114	0.0716	4,927
17	Construction Materials	0.0168	0.0632	18,243
18	Construction	0.0093	0.076	13,827
19	Steel Works Etc	0.0059	0.0651	14,788
20	Fabricated Products	0.0170	0.0628	3,221
21	Machinery	0.0134	0.0625	33,356
22	Electrical Equipment	0.0164	0.0798	26,766
23	Automobiles and Trucks	-0.0038	0.6165	34,170
24	Aircraft	0.0101	0.0677	15,138
25	Shipbuilding, Railroad Equipment	0.0126	0.0637	4,838
26	Defense	-0.0013	0.0579	1,927
27	Precious Metals	0.0017	0.0495	1,845
28	Non-Metallic and Industrial Metal Mining	0.0029	0.0806	14,557
29	Coal	0.0043	0.0873	8,548
30	Petroleum and Natural Gas	-0.0088	0.0762	2,663
31	Utilities	0.0104	0.0796	215
32	Communication	0.0020	0.0489	38,632
33	Personal Services	0.0028	0.0873	43,193
34	Business Services	0.0109	0.0778	12,427
35	Computers	0.0075	0.1052	151,909
36	Electronic Equipment	0.0113	0.079	36,911
37	Measuring and Control Equipment	0.0078	0.0741	64,347
38	Business Supplies	0.0169	0.0822	21,215

39	Shipping Containers	0.0073	0.0581	11,163
40	Transportation	0.0065	0.0574	3,941
41	Wholesale	0.0044	0.0668	32,662
42	Retail	0.0084	0.0755	48,068
43	Restaurants, Hotels, Motels	0.0087	0.0727	55,110
44	Banking	0.0045	0.0693	23,851
45	Insurance	0.0121	0.0792	124,213
46	Real Estate	0.0115	0.0522	38,840
47	Trading	0.0244	0.0767	11,028
48	Others	0.0040	0.0898	316,637

Table 2: Momentum Portfolios. The table presents the characteristics of U.S. momentum monthly excess returns from January 1990 to December 2017. The data are from the Center for Research in Security Prices (CRSP) and Compustat. The data exclude stocks that are not traded in NYSE, AMEX, and Nasdaq. The CRSP share code 10 and 11 are used for common equities. Delcie 1 portfolio is the loser portfolio, which contains the bottom 10% of the stocks with the worst losses. Decile 10 portfolio is the winner portfolio, which provides the top 10% of stocks with the largest gains. Winner minus loser (WML) is zero investment strategy which is long portfolio 10 and short portfolio 1. SR denotes for Sharpe Ratio. MKT-Ret is the value-weighted market return.

Portfolio	1	2	3	4	5	6	7	8	9	10	WML	MKT-Ret
Mean	-7.98%	-7.46%	-3.83%	-1.38%	-0.32%	1.39%	3.29%	5.70%	9.60%	10.47%	18.45%	6.25%
Stdev.	12.30%	13.42%	8.73%	3.22%	3.40%	5.50%	6.66%	9.12%	14.90%	18.35%	19.67%	15.82%
SR	-0.16	-0.56	-0.44	-0.43	-0.10	0.25	0.49	0.62	0.64	0.65	0.94	0.40

Table 3: Momentum Portfolios based on 48 Individual Industries. The table presents the summary statistics based on individual industries of WML portfolio. The characteristics of momentum decile portfolio excess returns from January 1990 to December 2017 of all 48 industries. The data are from the Center for Research in Security Prices (CRSP) and Compustat. The data exclude stocks that are not traded in NYSE, AMEX, and Nasdaq. The CRSP share code 10 and 11 are used for common equities. Each industry is divided based on SIC Code from Kenneth French Website. The table reports mean (WML) and standard deviation (Stdev) for all portfolio deciles. Winner minus loser (WML) is zero investment strategy which is long on winner portfolio or top 10% and short on loser portfolio or bottom 10%. SR denotes for Sharpe Ratio.

ID	Name	WML	Stdev	SR
1	Agriculture	0.0294	0.1508	0.1946
2	Food Products	0.0461	0.1410	0.3267
3	Candy and Soda	0.0702	0.1484	0.4728
4	Beer and Liquor	0.0570	0.1513	0.3770
5	Tobacco Products	0.1063	0.1597	0.6657
6	Recreation	0.0245	0.1420	0.1728
7	Entertainment	0.0224	0.1334	0.1681
8	Printing and Publishing	0.0426	0.1405	0.3030
9	Consumer Goods	0.0376	0.1399	0.2684
10	Apparel	0.0415	0.1342	0.3096
11	Healthcare	0.0230	0.1349	0.1704
12	Medical Equipment	0.0296	0.1330	0.2227
13	Pharmaceutical Products	0.0240	0.1319	0.1821
14	Chemicals	0.0268	0.1445	0.1858
15	Rubber and Plastic Products	0.0303	0.1414	0.2142
16	Textiles	0.0399	0.1350	0.2958
17	Construction Materials	0.0285	0.1398	0.2039
18	Construction	0.0181	0.1413	0.1278
19	Steel Works Etc	0.0156	0.1409	0.1108
20	Fabricated Products	0.0408	0.1404	0.2908
21	Machinery	0.0197	0.1385	0.1425
22	Electrical Equipment	0.0100	0.1384	0.0724
23	Automobiles and Trucks	0.0189	0.1118	0.1693
24	Aircraft	0.0260	0.1473	0.1766
25	Shipbuilding, Railroad Equipment	0.0322	0.1421	0.2263
26	Defense	0.0091	0.1616	0.0563
27	Precious Metals	0.0301	0.1328	0.2269
28	Non-Metallic and Industrial Metal Mining	0.0485	0.1314	0.3693
29	Coal	0.0218	0.1335	0.1634
30	Petroleum and Natural Gas	0.0274	0.1493	0.1838
31	Utilities	0.0100	0.1341	0.0742
32	Communication	0.0885	0.1574	0.5619
33	Personal Services	0.0221	0.1425	0.1554

34	Business Services	0.0253	0.1407	0.1797
35	Computers	0.0154	0.1358	0.1134
36	Electronic Equipment	0.0132	0.1294	0.1024
37	Measuring and Control Equipment	0.0258	0.1325	0.1945
38	Business Supplies	0.0171	0.1351	0.1265
39	Shipping Containers	0.0308	0.1496	0.2060
40	Transportation	0.0376	0.1486	0.2534
41	Wholesale	0.0346	0.1428	0.2425
42	Retail	0.0209	0.1365	0.1534
43	Restaurants, Hotels, Motels	0.0187	0.1335	0.1404
44	Banking	0.0361	0.1402	0.2577
45	Insurance	0.0574	0.1478	0.3884
46	Real Estate	0.0388	0.1486	0.2607
47	Trading	0.0435	0.1448	0.3005
48	Others	0.1033	0.1575	0.6559

Table 4: Fama-French 3-factor model and idiosyncratic volatility. The table presents the regression from equation: $R_{it} - r_t = \alpha_i + \beta_i MKT_t + s_i SMB_t + h_i HML_t + \varepsilon_{it}, \varepsilon_{it} \sim N(0, \sigma_{it}^2)$ where MKT_t, SMB_t, and HML_t are factor loadings as proposed by Fama-French 3-factor model. The idiosyncratic volatility is measured by GJR-GARCH equation: $\sigma_{it}^2 = w + \sum_{i=1}^{q} [a_i + \gamma_i I_{[\varepsilon_{t-1}<0]}]\varepsilon_{t-1}^2 + b_i \sigma_{t-1}^2$. The coefficient of factor loadings and conditional idiosyncratic volatility, E(VOL), are reported with the spanning period from January 1990 to December 2017.

	3-Factor	
Variables	Mean	Stdev.
MKT	0.111%	1.158%
SMB	-0.152%	1.908%
HML	0.346%	2.525%
E(VOL)	11.132%	10.514%

Table 5: Momentum Portfolio based on idiosyncratic volatility. The table presents the characteristics of momentum decile portfolio based on idiosyncratic volatility from January 1990 to December 2017. Portfolio 1 represents the highest 20% of idiosyncratic volatility while Portfolio 5 represents the lowest 20% of idiosyncratic volatility. E(VOL) represents the conditional volatility estimated by $R_{it} - r_t = \alpha_i + \beta_i MKT_t + s_i SMB_t + h_i HML_t + \varepsilon_{it}, \varepsilon_{it} \sim N(0, \sigma_{it}^2)$ where MKT_t, SMB_t, and HML_t are factor loadings as proposed by Fama-French 3-factor model. The idiosyncratic volatility is measured by GJR-GARCH equation: $\sigma_{it}^2 = w + \sum_{i=1}^{q} [\, a_i + \gamma_i I_{[\varepsilon_{t-1}<0]}]\varepsilon_{t-1}^2 + b_i \sigma_{t-1}^2$. Winner minus loser (WML) is zero investment strategy which is long portfolio 5 and short portfolio 1. SR denotes for Sharpe Ratio.

Portfolio	1	2	3	4	5	WML
Mean	0.0197	0.0173	0.0120	-0.0145	0.0123	0.0320
E(VOL)	0.2708	0.1713	0.1576	0.1173	0.0937	0.1671
SR	0.0727	0.1010	0.0761	-0.1236	0.1313	0.1915

Table 6: Fama-French 5-factor model and idiosyncratic volatility. The table presents the regression from equation: $R_{it} - r_t = \alpha_i + \beta_i(R_{mt} - r_t) + s_i SMB_t + h_i HML_t + c_i CMA_i + r_i RMW_i + \varepsilon_{it}, \varepsilon_{it} \sim N(0, \sigma_{it}^2)$ where MKT_t, SMB_t, HML_t, CMA_t, and RMW_i are factor loadings as proposed by Fama-French 5-factor model. The idiosyncratic volatility is measured by GJR-GARCH equation: $\sigma_{it}^2 = w + \sum_{i=1}^{q}[a_i + \gamma_i I_{[\varepsilon_{t-1}<0]}]\varepsilon_{t-1}^2 + b_i\sigma_{t-1}^2$. The coefficient of factor loadings and conditional idiosyncratic volatility, E(VOL), are reported with the spanning period from January 1990 to December 2017.

	5-Factor	
Variables	Mean	Stdev.
MKT	0.15%	1.41%
SMB	-0.04%	1.97%
HML	0.44%	2.63%
CMA	-0.28%	4.06%
RMW	0.57%	3.23%
E(VOL)	12.87%	15.91%

Table 7: Momentum Portfolio based on idiosyncratic volatility of 5-factor model. The table presents the characteristics of momentum decile portfolio based on idiosyncratic volatility from 5-factor model from January 1990 to December 2017. Portfolio 1 represents the highest 20% of idiosyncratic volatility while Portfolio 5 represents the lowest 20% of idiosyncratic volatility. E(VOL) represents the conditional volatility estimated by $R_{it} - r_t = \alpha_i + \beta_i(R_{mt} - r_t) + s_i SMB_t + h_i HML_t + c_i CMA_i + r_i RMW_i + \varepsilon_{it}, \varepsilon_{it} \sim N(0, \sigma_{it}^2)$ where MKT_t, SMB_t, HML_t, CMA_t, and RMW_i are factor loadings as proposed by Fama-French 5-factor model. The idiosyncratic volatility is measured by GJR-GARCH equation: $\sigma_{it}^2 = w + \sum_{i=1}^{q}[a_i + \gamma_i I_{[\varepsilon_{t-1}<0]}]\varepsilon_{t-1}^2 + b_i \sigma_{t-1}^2$. Winner minus loser (WML) is zero investment strategy which is long portfolio 5 and short portfolio 1. SR denotes for Sharpe Ratio.

Portfolio	1	2	3	4	5	WML
Mean	0.0287	0.0187	-0.0103	0.0097	0.0111	0.0398
E(VOL)	0.2621	0.1673	0.1447	0.1255	0.0973	0.1544
SR	0.1095	0.1118	-0.0712	0.0773	0.1141	0.2578

Table 8: Double Sorting. The table presents the double sorting of momentum portfolio based on Amihud's liquidity (LIQ) and idiosyncratic volatility factor (E(Vol)) from January 1990 to December 2017. Portfolio 1 represents the highest 20% portfolio return while Portfolio 5 represents the lowest 20% portfolio return. 5-1 or Winner minus loser (WML) is zero investment strategy which is long portfolio 5 and short portfolio 1. SR denotes for Sharpe Ratio.

	Excess Return					
Panel A	1	2	3	4	5	WML
LIQ	-6.50%	-2.60%	2.80%	4.80%	8.70%	15%

	Excess Return					
Panel B	1	2	3	4	5	WML
E(Vol)	-3.80%	-1.15%	3.46%	6.78%	7.49%	11.29%

Table 9: Time Series Regression on 3-factor plus momentum factor. The table presents that characteristics of 3-factor and momentum factor on the portfolio construction based on inverse conditional volatility. The dependent variable is one-period portfolio volatility determined by $f_{t+1}^{\sigma} = \frac{c}{\widehat{\sigma_t^2}(f)} f_{t+1}$, where $f_{t+1}$is one-period buy and hold portfolio excess return, c is constant arbitrary number to measure the scaling conditional volatility, and $\sigma_t^2(f)$ is monthly realized variance. The time series regression is $f_{t+1}^{\sigma} = \alpha + \beta f_{t+1} + \epsilon_{t+1}$.The parentheses are reported p-value.

Model	(1)	(2)	(3)	(4)	(6)	(5)
Constant	0.0031	0.0026	0.0035	0.0033	0.0019	0.0020
	(000)	(000)	(000)	(000)	(000)	(000)
MKTRF	0.0071				0.0077	0.0076
	(000)				(000)	(000)
SMB		0.0040			0.0054	0.0054
		(000)			(000)	(000)
HML			-0.0020		0.0021	0.0013
			(000)		(000)	(000)
MOM				-0.0019		-0.0016
				(000)		(000)

Table 10: Portfolio based on inverse conditional variance. The table provides the portfolios based on the size of excess return by using $f_{t+1}^{\sigma} = \frac{c}{\widehat{\sigma_t^2(f)}} f_{t+1}$ from January 1990 to December 2017. Portfolio 1 represents the highest 20% portfolio return while Portfolio 5 represents the lowest 20% portfolio return. Conditional Variance is estimated by $\sigma_t^2(f) = RV_t^2(f) = \sum_{d=1/22}^{1}(f_{t+d} - \frac{\sum_{d=1/22}^{1} f_{t+d}}{22})^2$, where $RV_t^2(f)$ is the previous month realized variance with approximation of 22 trading days. 5-1 or Winner minus loser (WML) is zero investment strategy which is long portfolio 5 and short portfolio 1. SR denotes for Sharpe Ratio.

Portfolio	1	2	3	4	5	WML
Mean	-1.86%	0.58%	2.14%	4.43%	6.78%	8.64%
Conditional Variance	18.76%	20.17%	18.55%	11.67%	13.49%	16.13%
SR	-0.099	0.029	0.115	0.380	0.503	0.536

Table 11: Portfolio Predictability. The table reports the portfolio predictability from $r_{i,t+1} = \lambda_0 + \widehat{\beta_\iota}\lambda_t + \mu_i X_t + \theta_i Z_{i,t} + \alpha_{i,t+1}$, where $\hat{\beta} i$ is a vector of the coefficients estimated from the first step (MKTRF, SMB, HML, MOM), and Xt is a vector of economic variables, and θ_i is the vector of control variables (Idiosyncratic factor and liquidity factor). LIQ is liquidity factor and E(VOL) is idiosyncratic volatility factor. Newey-West t-statistic is reported in parenthesis.

	1	2	3	4	5
Constant	0.000	0.000	0.000	0.000	0.000
	(0.66)	(-0.08)	(0.65)	(0.24)	(0.73)
MKTRF	0.320	0.226	0.375	0.234	0.369
	(2.14)	(1.99)	(2.37)	(2.01)	(2.34)
SMB	-0.169	-0.039	-0.264	-0.034	-0.299
	(-2.43)	(-2.34)	(-2.25)	(-2.29)	(-2.55)
HML	0.045	0.149	0.008	0.065	0.031
	(2.17)	(3.00)	(2.11)	(2.28)	(2.16)
MOM	0.316	0.232	0.438	0.229	0.427
	(2.54)	(2.26)	(2.84)	(2.13)	(2.76)
CPI	0.011		0.008		
	(2.35)		(2.65)		
T-Bill	0.009			0.008	
	(3.22)			(3.55)	
Bond	0.049				0.058
	(3.47)				(3.94)
LIQ	-0.072	-0.066	-0.074	-0.047	-0.071
	(-0.34)	(-0.34)	(-0.36)	(-0.23)	(-0.35)
E(VOL)	-0.046	-0.054	-0.041	-0.040	-0.071
	(-5.89)	(-7.29)	(-5.25)	(-5.29)	(-9.40)

Figure 1: Difference between winner and loser. The figure provides the difference in excess return of top 10% (winner) and bottom 10% (loser) from January 1990 to December 2017 of all 48 industries. The excess return is calculated as the difference between daily return minus daily market return. The solid line represents the winner return while dash line represents loser return.

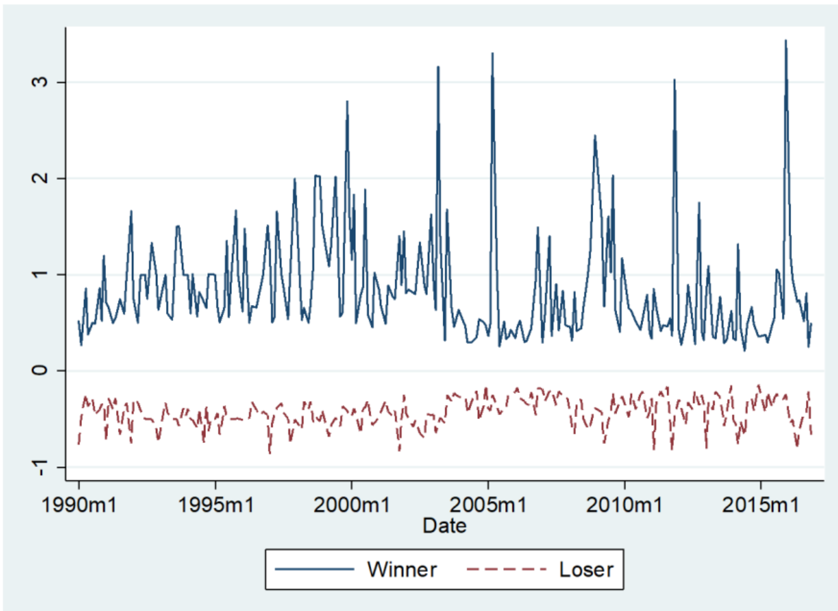


Figure 2: Idiosyncratic Volatility of 3-factor model. The figure shows the idiosyncratic volatility of 3-factor model spanning period from January 1990 to December 2017 estimated from equation: $R_{it} - r_t = \alpha_i + \beta_i(R_{mt} - r_t) + s_i SMB_t + h_i HML_t + \varepsilon_{it}$. Then, the conditional volatility is estimated by the GJR-GARCH equation: $\sigma_{it}^2 = w + \sum_{i=1}^{q}[\, a_i + \gamma_i I_{[\varepsilon_{t-1}<0]}]\varepsilon_{t-1}^2 + b_i\sigma_{t-1}^2$

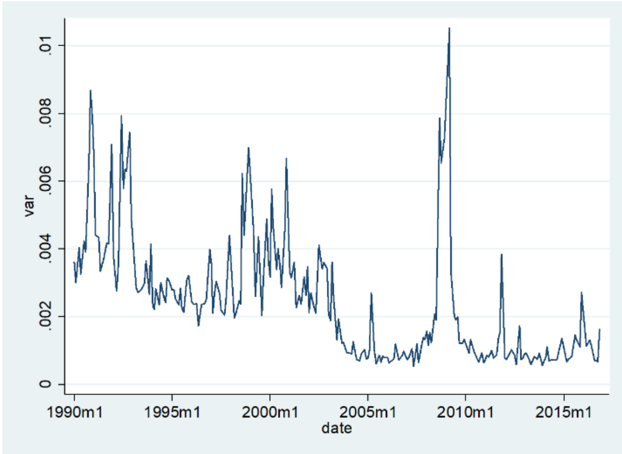
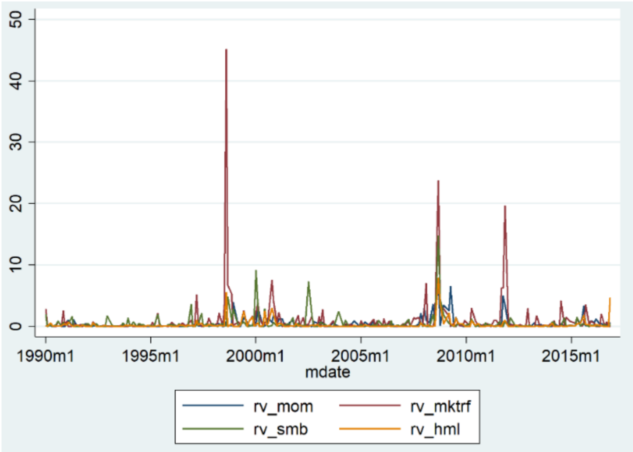


Figure 3: Realized Variance of 3-factor and momentum factor. The figure shows the size of realized variance of 3-factor and momentum factor spanning period from January 1990 to December 2017 estimated from equation: $\sigma_t^2(f) = RV_t^2(f) = \sum_{d=1/22}^{1}(f_{t+d} - \frac{\sum_{d=1/22}^{1} f_{t+d}}{22})^2$



Appendix A1: 48 Industries Portfolio Construction. The table presents the characteristics of momentum decile portfolio excess returns from January 1990 to December 2017 of all 48 industries. The data are from the Center for Research in Security Prices (CRSP) and Compustat. The data exclude stocks that are not traded in NYSE, AMEX, and Nasdaq. The CRSP share code 10 and 11 are used for common equities. Each industry is divided based on SIC Code from Kenneth French Website. Decile 1 portfolio is the loser portfolio, which contains the bottom 10% of the stocks with the worst losses. Decile 10 portfolio is the winner portfolio, which provides the top 10% of stocks with the largest gains. The table reports mean and standard deviation (Stdev) for all portfolio deciles. Winner minus loser (WML) is zero investment strategy which is long portfolio 10 and short portfolio 1. SR denotes for Sharpe Ratio.

Industry	Portfolio	1	2	3	4	5	6	7	8	9	10	WML
Agriculture	Mean	-0.01	-0.0137	-0.011	-0.003	-0.0038	0.0087	0.0248	0.0268	0.0168	0.0193	0.0294
	Stdev	0.1557	0.1182	0.1027	0.0961	0.0855	0.0682	0.1032	0.1014	0.1054	0.1412	0.1508
	SR	-0.0645	-0.116	-0.1068	-0.0311	-0.0449	0.1278	0.2406	0.2644	0.1593	0.1368	0.1946
Food Products	Mean	-0.0119	-0.0167	-0.0127	-0.0129	-0.0021	0.0061	0.0181	0.0288	0.03	0.0341	0.0461
	Stdev	0.1479	0.1251	0.1045	0.0912	0.074	0.0749	0.084	0.0967	0.1117	0.1274	0.141
	SR	-0.0808	-0.1333	-0.1212	-0.1415	-0.0278	0.0812	0.2153	0.298	0.2684	0.268	0.3267
Candy and Soda	Mean	-0.0206	-0.0219	-0.0222	-0.0107	0.0046	0.005	0.0174	0.0246	0.0302	0.0496	0.0702
	Stdev	0.1412	0.1056	0.0954	0.0772	0.08	0.0775	0.0842	0.0851	0.1077	0.1628	0.1484
	SR	-0.1456	-0.2069	-0.233	-0.1391	0.0572	0.0639	0.207	0.289	0.2803	0.3047	0.4728
Beer and Liquor	Mean	-0.0277	-0.0363	-0.0123	-0.0115	-0.0061	0.0123	0.0309	0.0335	0.0294	0.0293	0.057
	Stdev	0.1666	0.132	0.098	0.0926	0.08	0.0777	0.0876	0.0935	0.1075	0.1207	0.1513
	SR	-0.1663	-0.2752	-0.1258	-0.1246	-0.0767	0.1577	0.3529	0.3584	0.2737	0.243	0.377
Tobacco Products	Mean	-0.056	-0.0386	-0.0071	-0.0197	-0.0003	-0.0006	0.0204	0.0341	0.0601	0.0503	0.1063
	Stdev	0.1732	0.1132	0.0897	0.0776	0.0722	0.0804	0.0766	0.078	0.1194	0.1328	0.1597
	SR	-0.3233	-0.341	-0.0788	-0.2535	-0.0041	-0.0076	0.2657	0.4375	0.5037	0.3791	0.6657
Recreation	Mean	-0.008	-0.0056	-0.0139	-0.0095	-0.0038	0.0132	0.021	0.0216	0.0233	0.0166	0.0245
	Stdev	0.1411	0.1242	0.0983	0.0917	0.0773	0.0672	0.0847	0.1036	0.1124	0.1438	0.142
	SR	-0.0565	-0.0452	-0.1415	-0.1037	-0.0496	0.1959	0.2477	0.2083	0.2076	0.1152	0.1728
Entertainment	Mean	-0.004	-0.0082	-0.0167	-0.0069	-0.0107	0.0143	0.019	0.029	0.025	0.0184	0.0224
	Stdev	0.1316	0.1241	0.1103	0.0933	0.0801	0.0771	0.0955	0.1013	0.1175	0.1369	0.1334
	SR	-0.0303	-0.066	-0.1518	-0.0739	-0.1329	0.1855	0.1989	0.2865	0.2127	0.1347	0.1681
Printing and Publishing	Mean	-0.0135	-0.014	-0.0073	-0.006	0.001	0.0111	0.018	0.0212	0.0263	0.0291	0.0426

	Stdev	0.1468	0.1301	0.1062	0.0845	0.0763	0.0722	0.0839	0.0951	0.1094	0.1277	0.1405
	SR	-0.0916	-0.1077	-0.0686	-0.0712	0.0134	0.1535	0.2144	0.2224	0.2402	0.2279	0.303
Consumer Goods	Mean	-0.0109	-0.0143	-0.0076	-0.006	-0.0036	0.0076	0.0206	0.0285	0.0212	0.0266	0.0376
	Stdev	0.1398	0.1177	0.0987	0.0946	0.0883	0.0755	0.0898	0.0933	0.1053	0.1402	0.1399
	SR	-0.0782	-0.1217	-0.0768	-0.0632	-0.0403	0.1012	0.23	0.3052	0.2015	0.19	0.2684
Apparel	Mean	-0.0103	-0.0149	-0.0074	-0.0041	-0.0031	0.0097	0.0187	0.0233	0.0207	0.0312	0.0415
	Stdev	0.1417	0.1236	0.0982	0.0982	0.0765	0.0731	0.0812	0.095	0.118	0.1193	0.1342
	SR	-0.0727	-0.1208	-0.075	-0.0417	-0.0403	0.1321	0.2305	0.2458	0.1758	0.2619	0.3096
Healthcare	Mean	-0.0084	-0.002	-0.0115	-0.0057	-0.004	0.0071	0.0212	0.0221	0.0231	0.0145	0.023
	Stdev	0.1307	0.118	0.1087	0.0933	0.0856	0.0727	0.0906	0.0988	0.1056	0.1432	0.1349
	SR	-0.0646	-0.0169	-0.1053	-0.0609	-0.0463	0.098	0.2344	0.2232	0.2192	0.1016	0.1704
Medical Equipment	Mean	-0.0056	-0.0024	-0.0118	-0.0062	-0.0041	0.0117	0.0158	0.0195	0.0198	0.024	0.0296
	Stdev	0.1309	0.1108	0.1133	0.0953	0.0838	0.0813	0.1011	0.1017	0.1139	0.1372	0.133
	SR	-0.0428	-0.0219	-0.1039	-0.0647	-0.0485	0.1441	0.1559	0.1916	0.1743	0.175	0.2227
Pharmaceutical Products	Mean	-0.0051	-0.0014	-0.007	-0.0049	-0.0053	0.0106	0.0153	0.0143	0.014	0.0189	0.024
	Stdev	0.1221	0.1099	0.1117	0.0981	0.083	0.0861	0.0964	0.1027	0.1141	0.1514	0.1319
	SR	-0.0416	-0.0125	-0.0629	-0.0502	-0.0644	0.1228	0.1583	0.1393	0.1226	0.1251	0.1821
Chemicals	Mean	-0.0082	-0.0029	0.0015	-0.0036	-0.0014	0.0066	0.0117	0.0176	0.0214	0.0186	0.0268
	Stdev	0.1531	0.1208	0.1008	0.0891	0.0818	0.0769	0.0819	0.0962	0.1109	0.1272	0.1445
	SR	-0.0538	-0.0238	0.0147	-0.0406	-0.0169	0.0863	0.143	0.1833	0.1926	0.1462	0.1858
Rubber and Plastic Products	Mean	-0.0089	-0.0165	-0.0227	-0.0077	-0.0031	0.0121	0.0229	0.0334	0.0257	0.0214	0.0303
	Stdev	0.1493	0.1262	0.1092	0.0906	0.0757	0.0643	0.0801	0.0943	0.1033	0.1257	0.1414
	SR	-0.0594	-0.1311	-0.2082	-0.0855	-0.0405	0.1889	0.2856	0.3539	0.2489	0.1704	0.2142
Textiles	Mean	-0.0147	-0.0228	-0.0178	-0.0059	-0.0023	0.0143	0.0284	0.0305	0.0257	0.0252	0.0399
	Stdev	0.1377	0.1416	0.1097	0.0839	0.0739	0.0745	0.0834	0.0941	0.1059	0.1295	0.135
	SR	-0.107	-0.1613	-0.1621	-0.0699	-0.0308	0.1926	0.34	0.3236	0.243	0.1946	0.2958
Construction Materials	Mean	-0.0074	-0.0176	-0.0102	-0.0068	-0.0032	0.0091	0.0219	0.0269	0.0232	0.0211	0.0285
	Stdev	0.1453	0.1286	0.1044	0.0878	0.0782	0.0793	0.0802	0.0922	0.1115	0.1289	0.1398
	SR	-0.051	-0.1366	-0.0981	-0.0777	-0.0411	0.1144	0.2735	0.292	0.2083	0.1637	0.2039

Construction	Mean	-0.0052	0.0032	-0.0051	-0.0006	-0.0044	0.0092	0.0173	0.0124	0.0104	0.0128	0.0181
	Stdev	0.1454	0.1133	0.1082	0.0951	0.0825	0.0744	0.0887	0.1078	0.11	0.133	0.1413
	SR	-0.036	0.028	-0.0472	-0.0062	-0.0535	0.1231	0.1947	0.1152	0.0941	0.0964	0.1278
Steel Works Etc.	Mean	-0.0034	-0.0002	-0.0019	0.0003	-0.0031	0.0061	0.0166	0.0138	0.0086	0.0122	0.0156
	Stdev	0.1448	0.1272	0.1086	0.0934	0.0763	0.0883	0.0901	0.097	0.1041	0.1331	0.1409
	SR	-0.0236	-0.0012	-0.0175	0.0033	-0.0405	0.0694	0.1842	0.1424	0.0826	0.0916	0.1108
Fabricated Products	Mean	-0.0178	-0.0194	-0.0083	0.0115	-0.0102	0.0071	0.0236	0.0274	0.015	0.023	0.0408
	Stdev	0.1502	0.1346	0.0997	0.0948	0.0719	0.0669	0.0921	0.0839	0.1062	0.1207	0.1404
	SR	-0.1188	-0.1444	-0.0835	0.1213	-0.1413	0.1064	0.256	0.3261	0.1416	0.1904	0.2908
Machinery	Mean	-0.0015	-0.0049	0.0014	-0.0019	-0.0012	0.0073	0.0153	0.0166	0.0099	0.0182	0.0197
	Stdev	0.1426	0.1301	0.1066	0.0905	0.081	0.0757	0.0891	0.0979	0.1116	0.1304	0.1385
	SR	-0.0107	-0.0373	0.0128	-0.0212	-0.0152	0.096	0.1718	0.1698	0.0884	0.1397	0.1425
Electrical Equipment	Mean	-0.0048	0.0043	-0.0077	-0.0002	-0.0008	0.0104	0.0197	0.0159	0.0151	0.0052	0.01
	Stdev	0.1321	0.1222	0.1132	0.0962	0.0783	0.0809	0.0946	0.1017	0.1126	0.1511	0.1384
	SR	-0.0365	0.0348	-0.0682	-0.002	-0.0103	0.1283	0.2079	0.1561	0.1338	0.0344	0.0724
Automobiles and Trucks	Mean	-0.0032	-0.0144	-0.0184	-0.0163	-0.0107	0.0019	0.0087	0.0138	0.0086	0.0157	0.0189
	Stdev	0.107	0.1062	0.0936	0.0822	0.0765	0.0759	0.0848	0.0953	0.104	0.1213	0.1118
	SR	-0.03	-0.1358	-0.1969	-0.1979	-0.1405	0.0252	0.1027	0.1445	0.0823	0.1295	0.1693
Aircraft	Mean	-0.0017	-0.0106	0.0008	-0.0011	-0.0001	0.0107	0.0116	0.0171	0.0142	0.0243	0.026
	Stdev	0.1518	0.125	0.1047	0.089	0.0809	0.0819	0.0878	0.0919	0.1076	0.1382	0.1473
	SR	-0.011	-0.0845	0.0077	-0.0121	-0.0014	0.1311	0.1317	0.1856	0.1319	0.1761	0.1766
Shipbuilding, Railroad Equipment	Mean	-0.0066	-0.0085	-0.0035	-0.0005	-0.0076	0.011	0.0066	0.0215	0.0238	0.0255	0.0322
	Stdev	0.1453	0.1329	0.0971	0.0903	0.0743	0.0874	0.0773	0.0965	0.1143	0.1357	0.1421
	SR	-0.0456	-0.0637	-0.0356	-0.0056	-0.1016	0.1263	0.0855	0.2223	0.2077	0.1881	0.2263
Defense	Mean	-0.0063	-0.007	-0.0084	-0.0011	-0.0068	0.0058	0.0112	0.0138	0.0343	0.0028	0.0091
	Stdev	0.1653	0.1174	0.0957	0.0968	0.071	0.0841	0.0867	0.1003	0.1163	0.1543	0.1616
	SR	-0.0383	-0.0593	-0.0875	-0.0113	-0.0963	0.0687	0.1288	0.1374	0.2946	0.018	0.0563

Precious Metals Non-Metallic and Industrial Metal	Mean	-0.0008	-0.0228	0.0097	-0.0093	-0.0013	0.0092	0.0116	0.0195	0.0131	0.0293	0.0301
	Stdev	0.1251	0.1137	0.0918	0.106	0.0721	0.0935	0.0971	0.1112	0.0894	0.1483	0.1328
	SR	-0.0066	-0.2006	0.1054	-0.0877	-0.0183	0.0985	0.1194	0.1754	0.1463	0.1976	0.2269
Mining	Mean	-0.0121	-0.007	-0.0085	-0.004	-0.0089	0.0077	0.0168	0.0162	0.0149	0.0364	0.0485
	Stdev	0.1305	0.1168	0.1057	0.0947	0.0845	0.0788	0.0924	0.101	0.0988	0.1331	0.1314
	SR	-0.0926	-0.0595	-0.08	-0.0426	-0.1053	0.0983	0.1818	0.16	0.1509	0.2737	0.3693
Coal	Mean	-0.0022	-0.0039	-0.0112	-0.0034	-0.0031	0.0037	0.0084	0.0117	0.0154	0.0196	0.0218
	Stdev	0.136	0.1244	0.1098	0.0919	0.0857	0.0721	0.0869	0.1006	0.1162	0.1284	0.1335
	SR	-0.0161	-0.0314	-0.1016	-0.037	-0.0359	0.0519	0.0971	0.1167	0.1327	0.1529	0.1634
Petroleum and Natural Gas	Mean	-0.0197	0.001	-0.0026	-0.0086	-0.0016	0.0055	0.0117	0.0157	0.0152	0.0077	0.0274
	Stdev	0.1594	0.1163	0.0823	0.0942	0.0793	0.076	0.0754	0.0809	0.1077	0.1291	0.1493
	SR	-0.1237	0.0084	-0.0313	-0.0914	-0.0202	0.0728	0.1548	0.1945	0.1409	0.0598	0.1838
Utilities	Mean	-0.0004	0.0005	-0.004	0.0015	-0.0031	0.007	0.0173	0.0156	0.0124	0.0096	0.01
	Stdev	0.1344	0.1187	0.1088	0.0956	0.0848	0.0771	0.0884	0.102	0.1083	0.1336	0.1341
	SR	-0.0028	0.004	-0.0368	0.0157	-0.0366	0.0912	0.1961	0.1526	0.1146	0.0718	0.0742
Communication	Mean	-0.0384	-0.0279	-0.0138	-0.0033	0.0006	0.0101	0.0194	0.0255	0.037	0.0501	0.0885
	Stdev	0.1705	0.11	0.0922	0.0813	0.0738	0.073	0.0736	0.0838	0.1007	0.1313	0.1574
	SR	-0.2251	-0.254	-0.1496	-0.0406	0.0084	0.139	0.2638	0.3043	0.3674	0.3815	0.5619
Personal Services	Mean	-0.0107	-0.0058	-0.0094	-0.0038	-0.002	0.0088	0.0155	0.0196	0.0186	0.0114	0.0221
	Stdev	0.1365	0.1145	0.1062	0.0931	0.0887	0.0804	0.095	0.1053	0.119	0.1543	0.1425
	SR	-0.0784	-0.0511	-0.0889	-0.0407	-0.0221	0.1094	0.1636	0.1865	0.156	0.0742	0.1554
Business Services	Mean	-0.0054	-0.0032	-0.0136	-0.0113	-0.0035	0.0084	0.0178	0.0222	0.0233	0.0199	0.0253
	Stdev	0.1383	0.1146	0.1122	0.0993	0.0831	0.0806	0.0851	0.1004	0.1125	0.1455	0.1407
	SR	-0.0389	-0.0282	-0.1217	-0.1142	-0.0426	0.1046	0.2091	0.2211	0.2073	0.1369	0.1797
Computers	Mean	-0.0058	-0.003	-0.0085	-0.0047	-0.0041	0.0096	0.0169	0.0161	0.0176	0.0096	0.0154

	Stdev	0.1282	0.1166	0.1125	0.0995	0.0852	0.0844	0.0951	0.1074	0.1191	0.1508	0.1358
	SR	-0.0452	-0.026	-0.0757	-0.047	-0.0479	0.1142	0.1782	0.1499	0.1476	0.0636	0.1134
Electronic Equipment	Mean	-0.0035	-0.005	-0.0031	-0.001	-0.0017	0.0126	0.0166	0.0137	0.0181	0.0097	0.0132
	Stdev	0.1239	0.1071	0.1092	0.0984	0.0832	0.0807	0.0944	0.1015	0.1099	0.1403	0.1294
	SR	-0.0282	-0.0471	-0.0283	-0.0101	-0.0208	0.1564	0.1755	0.1353	0.1648	0.0695	0.1024
Measuring and Control Equipment	Mean	-0.0155	-0.0059	-0.0018	-0.0014	-0.0017	0.0063	0.0107	0.0101	0.0083	0.0102	0.0258
	Stdev	0.126	0.1135	0.1065	0.0981	0.0816	0.0836	0.0955	0.1038	0.109	0.1453	0.1325
	SR	-0.1231	-0.0518	-0.017	-0.0144	-0.0211	0.0755	0.1125	0.0974	0.0761	0.0705	0.1945
Business Supplies	Mean	-0.0007	-0.0045	-0.0068	-0.0059	-0.0044	0.0087	0.0211	0.0185	0.0199	0.0164	0.0171
	Stdev	0.1357	0.119	0.1132	0.0966	0.0753	0.0748	0.0861	0.1048	0.1185	0.1339	0.1351
	SR	-0.0054	-0.0374	-0.0598	-0.0614	-0.0579	0.117	0.2454	0.1766	0.1681	0.1221	0.1265
Shipping Containers	Mean	-0.0084	-0.012	-0.0006	-0.0004	0.0018	0.0073	0.014	0.0183	0.0159	0.0224	0.0308
	Stdev	0.1547	0.1233	0.0982	0.0899	0.0748	0.08	0.0845	0.0944	0.116	0.1395	0.1496
	SR	-0.0546	-0.097	-0.0057	-0.0045	0.0245	0.091	0.1653	0.1943	0.1368	0.1604	0.206
Transportation	Mean	-0.0077	-0.0149	-0.0097	-0.0138	0.0006	0.0136	0.0156	0.0297	0.023	0.0299	0.0376
	Stdev	0.1551	0.1179	0.093	0.094	0.0834	0.0679	0.0837	0.0908	0.1113	0.1354	0.1486
	SR	-0.0499	-0.126	-0.1046	-0.1466	0.0072	0.2	0.1867	0.3268	0.2067	0.2209	0.2534
Wholesale	Mean	-0.0063	-0.0078	-0.0076	-0.0068	-0.0022	0.0054	0.013	0.0205	0.0211	0.0284	0.0346
	Stdev	0.1458	0.1208	0.1028	0.0949	0.0828	0.0803	0.0898	0.0991	0.1105	0.1368	0.1428
	SR	-0.0429	-0.065	-0.0738	-0.0715	-0.0262	0.0673	0.1442	0.2072	0.1912	0.2074	0.2425
Retail	Mean	-0.0043	-0.0048	-0.013	-0.0044	-0.0069	0.0089	0.0211	0.0251	0.0208	0.0166	0.0209
	Stdev	0.135	0.1194	0.1115	0.0982	0.0785	0.077	0.0892	0.1023	0.1144	0.1394	0.1365
	SR	-0.0318	-0.0398	-0.1168	-0.0445	-0.0873	0.1151	0.2366	0.2452	0.1814	0.1194	0.1534
Restaurants, Hotels, Motels	Mean	-0.0001	-0.0097	-0.0043	-0.0037	-0.0047	0.0105	0.0186	0.0211	0.0183	0.0187	0.0187
	Stdev	0.1301	0.1208	0.1008	0.0897	0.0787	0.0777	0.0877	0.1066	0.1152	0.1402	0.1335
	SR	-0.0004	-0.0803	-0.0426	-0.0409	-0.0596	0.1345	0.2123	0.1975	0.1586	0.1332	0.1404
Banking	Mean	-0.013	-0.0051	-0.0128	-0.0078	-0.0039	0.0069	0.0206	0.0212	0.0259	0.0232	0.0361

	Stdev	0.1449	0.1214	0.1092	0.0952	0.0745	0.0807	0.0859	0.1035	0.1061	0.131	0.1402
	SR	-0.0896	-0.0418	-0.1173	-0.0823	-0.0521	0.0856	0.2399	0.2049	0.2441	0.1769	0.2577
Insurance	Mean	-0.0087	-0.0232	-0.0164	-0.009	-0.0026	0.0107	0.0243	0.0308	0.0339	0.0487	0.0574
	Stdev	0.1524	0.1167	0.096	0.0829	0.0728	0.0719	0.0786	0.0911	0.104	0.1386	0.1478
	SR	-0.0572	-0.199	-0.1711	-0.1082	-0.0359	0.1494	0.3085	0.3381	0.3259	0.3513	0.3884
Real Estate	Mean	-0.0051	-0.0161	-0.0104	-0.0043	-0.0027	0.0079	0.015	0.0236	0.0276	0.0337	0.0388
	Stdev	0.1611	0.1191	0.0975	0.0909	0.0752	0.0785	0.0793	0.0893	0.102	0.1237	0.1486
	SR	-0.0316	-0.1348	-0.1071	-0.0476	-0.0356	0.1007	0.1895	0.264	0.2708	0.272	0.2607
Trading	Mean	-0.0128	-0.0231	-0.0222	-0.0143	-0.0065	0.011	0.0246	0.0356	0.0304	0.0307	0.0435
	Stdev	0.1521	0.1215	0.0998	0.0929	0.0734	0.0706	0.0753	0.0909	0.1176	0.13	0.1448
	SR	-0.0843	-0.19	-0.2221	-0.1541	-0.0888	0.1559	0.3271	0.3911	0.2587	0.236	0.3005
Others	Mean	-0.0416	-0.0327	-0.021	-0.0111	-0.0039	0.0034	0.0153	0.0285	0.0458	0.0617	0.1033
	Stdev	0.1623	0.1037	0.0867	0.0795	0.0725	0.0736	0.0755	0.0853	0.0998	0.1479	0.1575
	SR	-0.2562	-0.3151	-0.2421	-0.1401	-0.0544	0.0463	0.2032	0.3345	0.4591	0.4174	0.6559

Appendix A2: Pair industries momentum return. The table presents the momentum returns based on the pair between industries with strong negative correlations. Portfolio 1 (loser) is defined as the bottom 10% of excess returns while portfolio 10 (winner) is top 10% of excess returns. WML is the winner minus loser or zero investment strategy taking a long position of winner and short position of loser. Correlation column presents the correlation between the industries.

Portfolio		1	2	3	4	5	6	7	8	9	10	WML	Correlation
Steel Work - Petroleum and Natural Gas	Mean	-0.0317	-0.0031	-0.0029	-0.0046	-0.0078	0.0168	0.0517	0.0304	0.0234	0.0329	0.0646	-0.1087
	Stdev	0.2895	0.1266	0.1057	0.0970	0.0790	0.0876	0.0878	0.0969	0.1050	0.1306	0.2365	
	SR	-0.1095	-0.0246	-0.0278	-0.0470	-0.0984	0.1920	0.5889	0.3141	0.2232	0.2522	0.2732	
Business Service - Retail	Mean	-0.0156	-0.0118	-0.0348	-0.0147	-0.0165	0.0282	0.0621	0.0697	0.0607	0.0493	0.0649	-0.0929
	Stdev	0.2743	0.2358	0.2235	0.2001	0.1587	0.1531	0.1785	0.2039	0.2251	0.2821	0.2769	
	SR	-0.0568	-0.0500	-0.1556	-0.0737	-0.1042	0.1841	0.3478	0.3416	0.2695	0.1749	0.2344	
Retial - Steel Work	Mean	-0.0027	-0.0027	-0.0249	-0.0164	-0.0052	0.0212	0.0546	0.0462	0.0512	0.0432	0.0460	-0.1024
	Stdev	0.2817	0.2417	0.2191	0.2001	0.1566	0.1684	0.1763	0.2009	0.2204	0.2737	0.2790	
	SR	-0.0097	-0.0112	-0.1135	-0.0819	-0.0330	0.1259	0.3098	0.2298	0.2323	0.1580	0.1648	
Fabricated Products - Personal Services	Mean	-0.0312	-0.0102	-0.0224	-0.0035	-0.0090	0.0261	0.0459	0.0559	0.0446	0.0263	0.0575	-0.0878
	Stdev	0.2758	0.2340	0.2133	0.1845	0.1709	0.1534	0.1862	0.2095	0.2355	0.3034	0.2850	
	SR	-0.1133	-0.0436	-0.1048	-0.0189	-0.0525	0.1703	0.2465	0.2667	0.1894	0.0867	0.2019	
Banking - Others	Mean	-0.0600	-0.0562	-0.0265	-0.0211	-0.0075	0.0308	0.0760	0.0892	0.0640	0.0792	0.1393	-0.0888
	Stdev	0.3249	0.2549	0.2065	0.1805	0.1459	0.1471	0.1570	0.1933	0.2098	0.2598	0.3032	
	SR	-0.1847	-0.2204	-0.1283	-0.1167	-0.0513	0.2096	0.4843	0.4612	0.3050	0.3051	0.4593	
Entertainment - Transportation	Mean	-0.0072	-0.0348	-0.0395	-0.0206	-0.0236	0.0396	0.0549	0.0817	0.0664	0.0631	0.0702	-0.0905
	Stdev	0.2708	0.2527	0.2194	0.1894	0.1593	0.1481	0.1924	0.2003	0.2373	0.2694	0.2703	
	SR	-0.0264	-0.1378	-0.1798	-0.1089	-0.1483	0.2671	0.2853	0.4081	0.2800	0.2342	0.2598	
Computer - Recreation	Mean	-0.0170	-0.0071	-0.0229	-0.0111	-0.0132	0.0296	0.0513	0.0463	0.0536	0.0294	0.0464	-0.0831
	Stdev	0.2567	0.2338	0.2247	0.1989	0.1698	0.1654	0.1902	0.2153	0.2382	0.3016	0.2717	
	SR	-0.0661	-0.0303	-0.1020	-0.0560	-0.0775	0.1792	0.2697	0.2151	0.2250	0.0975	0.1707	