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AVOIDING MOMENTUM CRASHES: DYNAMIC MOMENTUM AND CONTRARIAN TRADING

Abstract:

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JEL Classification: G12, G14, G15

Avoiding Momentum Crashes: Dynamic Momentum and Contrarian Trading

Victoria Dobrynskaya[1][2]

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High momentum returns cannot be explained by risk factors, but they are negatively skewed and subject to occasional severe crashes. I explore the timing of momentum crashes and show that momentum strategies tend to crash in 1-3 months after the local stock market plunge. Next, I propose a simple dynamic trading strategy which coincides with the standard momentum strategy in calm times, but switches to the opposite contrarian strategy after a market crash and keeps the contrarian position for three months, after which it reverts back to the momentum position. The dynamic momentum strategy turns all major momentum crashes into gains and yields an average return, which is about 1.5 times as high as the standard momentum return. The dynamic momentum returns are positively skewed and not exposed to risk factors, have high Sharpe ratio and alpha, persist in different time periods and geographical markets around the globe.

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1. INTRODUCTION

The profitability of momentum strategies - buying past winners and shorting past losers - which has been documented for different geographical markets (e.g. Jegadeesh and Titman, 1993; Rouwenhorst, 1998; Fama and French, 2012), time periods (Chabot et al., 2014a and 2014b) and asset classes (Menkhoff et al., 2012; Asness et al., 2013), was considered a market anomaly[3] until their risks were studied under the microscope. Apparently, the momentum returns are exposed to significant crash risk, are negatively skewed and leptokurtic (Daniel and Moskowitz, 2016; Daniel et al., 2016). Although the momentum crashes are rather rare, they are severe, with the greatest monthly historical losses up to 90%.

Such crash risk, measured by idiosyncratic or conditional skewness, can justify the momentum premium and explain this seemingly 'low-risk anomaly', as the theoretical models by Krauz and Litzenberger (1976), Harvey and Siddique (2000) and, more recently, Schneider et al. (2016) predict. This risk is particularly important to momentum style investors because the momentum returns are positively correlated across asset classes and geographical markets (Asness et al., 2013). The momentum returns are also asymmetrically exposed to the upside and downside market risks (Dobrynskaya, 2015), and require a compensation according to the Downside Risk CAPM (Ang et al., 2006).

This paper delivers the good news: the momentum crashes are partly forecastable and, hence, can be avoided. There is growing evidence in this respect. Chabot et al. (2014b) examine almost 1.5 centuries of data and find that momentum crashes were more likely to happen following high momentum returns, when interest rates were relatively low (in 1867–1907), or when momentum had recently outperformed the stock market (in 1927-2012). Daniel and Moskowitz (2016) show that the momentum crashes happen when the market rebounds after severe market crashes. Avramov et al. (2016) provide evidence that momentum profits are large (weak) following periods of high market liquidity (illiquidity). Daniel et al. (2016) estimate a hidden Markov model with calm and turbulent states and show that this model forecasts large momentum losses, which happen in turbulent states, better than alternative forecasting models suggested by the literature.

This evidence taken together suggests that the performance of momentum strategies is lagging behind the market performance. Such behavior seems to be a consequence of momentum portfolio formation procedure. For example, following a market loss, low-beta stocks turn out to be past winners and high-beta stocks – past losers. Hence, the winner-minus-loser momentum portfolio has a

[3] Starting from Jegadeesh and Titman (1993), many authors consistently report negative market betas of winner-minus-loser momentum strategies. The exposure to other risk factors is also insignificant (Fama and French, 2016).

negative beta in such periods by construction (Dobrynskaya, 2015; Daniel and Moskowitz, 2016). When the market rebounds with a positive return, the negative-beta portfolio loses.

In this paper, I thoroughly explore the timing of momentum crashes by looking at downside betas with respect to lagged market returns. I find that momentum strategies around the world tend to crash in one to three months after a severe local market loss. Because it is common in momentum trading to sort stocks according to their past performance, skipping the most recent month, and to rebalance such portfolios quarterly (Grinblatt and Titman, 1989, 1993)[4], the most severe momentum crashes theoretically should happen in the three-month window with a one-month lag after a market crash. The empirical evidence in this paper is in line with this prediction.

Based on this result, I propose a simple trading strategy which coincides with the standard momentum strategy in calm times, but switches to the opposite contrarian strategy in one month after a significant market loss. The contrarian position is then kept for three months[5], and it is switched back to the momentum position if no other market crash occurs. Such dynamic trading strategy is essentially a mixture of momentum and contrarian positions, which are changed depending on the observable market performance. The strategy turns the momentum crashes into gains and yields an average return, which is about 1.5 times as high as the standard momentum return. Most importantly, the dynamic momentum returns are positively skewed and co-skewed with the market, and they are not exposed to standard risk factors. The dynamic momentum alpha is always positive and highly statistically significant. Holding the contrarian position is necessary in only 15 percent of the months, but it allows avoiding all major momentum crashes in the sample period of 1927-2015.

The same strategy performs universally well in different geographical locations: globally, in North-American, European and Asian developed markets, in Latin-American and Eastern-European developing markets, even in Japan, where the standard momentum returns are insignificant. However, the local markets are not perfectly correlated with each other, and local market crashes often happen at different times. Therefore, regional dynamic momentum strategies do not always switch to the contrarian positions simultaneously. Hence, their superior performance in all regions cannot be a consequence of common components in momentum returns around the globe, but it is rather a consequence of common momentum portfolio formation procedures.

The dynamic strategy proposed in this paper also has a robust superior performance in three different 30-year sub-periods as well as in the recent 15 years, when the profitability of the standard

[4] An indirect evidence of the popularity of quarterly rebalancing of momentum portfolios is the finding in Jegadeesh and Titman (1993) that quarterly holding period yields the highest average returns among alternative holding periods examined in the paper.

[5] Other periods of holding the contrarian position are also profitable, although the three-month period is found to be optimal in the sample.

momentum strategy was questioned (Chordia et al., 2014; Bhattacharya et al., 2015). The strategy performance is also robust to out-of-sample tests.

This paper contributes to the growing literature on risk-managed momentum trading. A number of recent papers have proposed modified momentum strategies which minimize the crash risk of momentum and yield higher average returns and Sharpe ratios. Grundi and Martin (2001) were among the first to note the time-varying nature of momentum market beta and suggest hedging the momentum crashes, which tend to happen contemporaneously with market rises, by going long in the market. However, Daniel and Moskowitz (2016) argue that such strategy is not implementable in practice because it uses forward-looking betas, and show that using real-time betas does not improve the strategy performance. Instead, they make use of the forecastability of momentum returns and volatility and propose a dynamic momentum strategy levered up or down over time so that the strategy's conditional volatility is proportional to its conditional Sharpe ratio. Barroso and Santa-Clara (2015) propose an alternative momentum strategy with constant volatility by scaling the long-short momentum portfolio by its past realized volatility. The both Daniel and Moskowitz's (2016) and Barroso and Santa-Clara's (2015) volatility-adjusted momentum strategies have higher Sharpe ratios due to somewhat higher average returns and significantly lower volatility. The both strategies have lower crash risk indeed, although the returns remain to be negatively skewed.

A more complicated strategy is proposed by Jacobs et al. (2016). The authors suggest investing in a sub-sample of past winners with the lowest skewness and selling short a sub-sample of past losers with the highest skewness, thus loading more on the skewness risk factor ('skewness-enhanced' momentum). Such momentum strategy yields an even higher average return as a compensation for the greater crash risk. However, the crash risk can be managed by volatility scaling *a la* Barroso and Santa-Clara (2015) or Daniel and Moskowitz (2016) to maximize the Sharpe ratio.

Another solution to avoid the momentum crashes is a stop-loss strategy by Han et al. (2016). The authors simply close the positions in individual stocks in their momentum portfolio if the stock losses reach 15% trigger. Their strategy also has higher average returns, lower variance and higher skewness, than the original momentum strategy.

An important disadvantage of the above strategies is the requirement of an inflow or an outflow of funds when the strategies are scaled up or down, respectively, or when selective positions are closed. For example, consider the stop-loss strategy. Because most of momentum losses arise in the short portfolio of past losers, as Han et al. (2016) point out themselves, closing the short positions (i.e. buying stocks) at the stop-loss trigger would often require extra funds because it is not necessarily matched by a simultaneous closing of a long position. However, raising extra capital on a daily or hourly basis is problematic in practice.

Compared to the above strategies, the dynamic momentum strategy proposed in this paper is easier to implement because it requires neither additional estimations, besides what is needed for the standard momentum trading, nor extra inflows or outflows of funds. Moreover, it has an attractive risk-return profile, whereas the returns to most of the risk-managed momentum strategies remain negatively skewed. The dynamic momentum strategy does require some extra transaction costs, which are incurred when the long and short positions are reversed, but since the changes in the positions are required in only 4-7% of the months, the extra transaction costs cannot eliminate the gain in the risk-adjusted return. This strategy is particularly attractive to small investors, which do not have price impact on the market and can easily go “against the crowd”.

The rest of the paper is organized as follows. Section 2 described the data. In sections 3 and 4, I explore the timing of momentum crashes and propose and test alternative dynamic momentum strategies for the US. In section 5, the dynamic momentum strategy is applied to other geographical markets around the globe. I test the risk exposure of the dynamic momentum strategy in section 6. Section 7 is devoted to out-of-sample tests and other robustness checks, and section 8 concludes.

2. DATA

I consider equity momentum strategies in different geographical markets around the globe. The momentum portfolios represent the winner minus loser long-short portfolios where the winner and loser portfolios are sorted in a similar fashion: all stocks in the respective region are sorted by their previous-year returns skipping the most recent month, the stocks are assigned to n portfolios (n equals 3 or 10 depending on the data set), the two extreme portfolios are used to construct the long-short portfolio, which is held for one month. The portfolios are rebalanced this way monthly.

The main analysis in the paper is performed for the Fama-French US equal-weighted and value-weighted portfolios, for which the longest time series of data is available: from Jan 1927 until July 2015. These portfolios represent the most extreme momentum portfolios because the stocks are sorted into 10 portfolios in the cross-section, and the winner and loser portfolios are formed from the top and bottom deciles.

In addition to the ‘extreme’ US portfolios, I consider 13 ‘less extreme’ regional momentum portfolios, whose returns are taken from three sources: K. French’s data library, T. Moskowitz’s and MSCI websites.

The Fama-French (FF) portfolios include global (23 developed markets), European (16 developed markets), North-American (USA and Canada), US, Japanese and Asian-Pacific (4 developed markets) portfolios. The data cover the period from November 1990 until March 2016.

These portfolios are 'less extreme' because the winner and loser portfolios each contain 30 percent of stocks in the respective region. For example, comparing the US portfolio from this group to the 'extreme' US portfolio formed from deciles, we observe lower average returns and lower exposure to the momentum factor here, despite an almost perfect return correlation of 0.93.

The Moskowitz's momentum portfolios are constructed by Asness, Moskowitz and Pedersen (AMP, 2013) and include global, Continental European, UK, US and Japanese portfolios. The data are available for the period from January 1972 until July 2011. These portfolios are constructed from the top and bottom 33 percent of stocks from their sample of liquid companies with high market capitalization. Therefore, they are not perfectly correlated with the FF portfolios for the same region. For example, the AMP and FF US (Japanese) portfolios have a correlation of 0.87 (0.92) in the overlapping period. I use the FF and AMP portfolios for the same regions in order to check the robustness of the results.

The third group includes two MSCI long-only momentum portfolios for emerging markets: the general emerging markets portfolios (23 emerging markets, June 1991 - March 2016) and Latin-American portfolio (5 emerging markets, June 1995 – March 2016). These portfolios are constructed from the large and medium capitalization companies to ensure sufficient liquidity.

To construct the dynamic momentum portfolios in each region (i.e. to determine the time of switching to the contrarian position and back), I use the returns on the *local* market indices, which represent value-weighted portfolios of stocks in the respective regions. The local market indices are obtained from the same data sources as the respective momentum portfolio returns.

I use the following risk factors in the analysis of risk exposure of the dynamic momentum strategy: Time Series Momentum (TS MOM) from Moskowitz et al. (2012), Momentum (MOM), Market, Small-Minus-Big (SMB) and High-Minus-Low (HML) from Fama and French (1993) and Carhart (1997), the traded liquidity factor (PS LIQ) from Pastor and Stambaugh (2003), Quality-Minus-Junk (QMJ) from Asness et al. (2017), Betting-Against-Beta (BAB) from Frazzini and Pedersen (2014), S&P 100 Volatility Index^{SM} (VXO) from CBOE, Robust-Minus-Weak (RMW) and Conservative-Minus-Aggressive (CMA) from Fama and French (2015), AMP Value and Momentum (AMP VAL and AMP MOM) from Asness et al. (2013). All factors are constructed for the US. TS MOM, QMJ, BAB, AMP VAL and AMP MOM factor return data are from the AQR data library[6]. Market, MOM, SMB, HML, RMW and CMA factor return data are from the K. French's data library. PS LIQ factor data are from L. Pastor's website.

[6] https://www.aqr.com/library/data-sets

3. EXPLORING THE TIMING OF MOMENTUM CRASHES

Momentum returns are negatively skewed and tend to crash occasionally. In this section, I explore the timing of momentum crashes and whether the crashes are forecastable and could be avoided. The analysis is performed for the US equal-weighted and value-weighted momentum portfolios, for which almost 90 years of monthly data are available.

First of all, I look at the contemporaneous and lagged correlations of momentum and market returns and contemporaneous and lagged market betas. The first two columns of table 1 show that the momentum returns are negatively correlated with the contemporaneous market returns and, hence, serve as a hedge against the market risk. This is a well-known “low-risk anomaly” documented in numerous previous studies. But the correlation pattern is inverse U-shaped if we consider lagged market returns, and the maximum correlations are observed after 2-4 months. So, the momentum returns do react to the market returns, but with a significant delay of 2-4 months. Further lagged correlations and betas are insignificant. The value-weighted momentum portfolio reacts relatively faster than the equal-weighted portfolio. But even the maximum correlations and market betas with 3-month lags are rather low (although statistically significant): 0.11 and 0.17, respectively.

When the regular market beta is separated into the downside and upside betas, which are conditional on the market returns being negative or positive, respectively, we observe interesting patterns. The negative contemporaneous market beta, which is a weighted average of the upside and downside betas, is entirely due to the upside component: the momentum portfolios tend to perform very badly when the market returns are positive. When the market returns are particularly high, i.e. exceed the mean market return by 1.5 standard deviations, the momentum returns are particularly low. This is evidenced by the extreme upside betas of -1.05 and -1.1 which are even higher by the absolute values than the upside betas. The contemporaneous upside betas uncover that the momentum returns tend to crash in months of market jumps and continue to perform similarly in the following month.

However, the contemporaneous downside betas of momentum returns are close to zero, even positive. Hence, we cannot claim that the momentum returns go against the market all the time. There is a strong asymmetry in the contemporaneous upside and downside risks, as pointed out in Dobrynskaya (2015): the momentum strategy hedges the upside risk, but it does not hedge the downside risk. Moreover, once we consider lagged downside betas, which are conditional on the lagged market returns being negative, we see that the downside risk increases significantly after 2-4 months. So, the high lagged correlations and regular betas are entirely due to the downside component: the momentum portfolios tend to perform badly in 2-4 months *after* low market returns. The lagged extreme downside betas, which are conditional on the lagged market return being below its mean by 1.5 standard deviations, are even higher.

Such lagging behavior of momentum returns is illustrated on Figure 1. I pick the relatively calm middle period of the sample to see the patterns more clearly. The significant momentum losses are observed after downward trends in the market returns, market by arrows. Some momentum losses coincide with market gains, but not all.

How do the above findings square up? The upside betas show that momentum crashes happen when the market jumps, and the downside betas show that momentum crashes happen after market crashes. Apparently, these periods often coincide: the market jumps tend to happen after significant market crashes. Because the momentum strategy reacts to market crashes with delay, the momentum crashes are often (but not always) observed when the market already rebounds. Daniel and Moskowitz (2016) point this out earlier, but in this paper I identify the window for the momentum crashes. The momentum crashes happen not in the following month after a market crash, but usually in 1-3 months. Such timing is probably related to the common practice in momentum trading to sort stocks by their previous performance skipping the most recent month due to the short-term reversal effect and to rebalance the portfolios on a quarterly basis (Grinblatt and Titman, 1989, 1993).

Moreover, if we control for the lagged downside risk, the contemporaneous upside risk becomes insignificant. Hence, momentum crashes do not happen when a market jump does not follow a market plunge. The contemporaneous negative upside betas are, in fact, no more than a reflection of the high lagged downside betas.

To explore the timing of momentum crashes further, I consider the following one-month switching strategies: a strategy invests into the standard winner-minus-loser (WML) portfolio in normal times, but switches to the opposite loser-minus-winner (LMW) portfolio for one month in n months after a significant market plunge (1.5 standard deviations below the mean) or a significant market jump (1.5 standard deviations above the mean). Table 2 reports the returns and risks of such strategies with alternative lags n of 1-6 months. Because our aim is to identify the timing of the most significant momentum crashes, we are looking for a strategy which switches to contrarian 'in time', benefits from the momentum crashes and, hence, yields the highest average return.

First, consider the switching strategies which follow market plunges. As with market correlations and betas, we observe an inverse U-shaped pattern of returns. The highest returns are observed for strategies which switch to LMW in 2-4 months after a market plunge. The annualized returns to these strategies are about 1.5 times as high as the standard momentum returns. For

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example, in case of the equal-weighted returns, the switching strategies yield 14-16% per annum whereas the WML portfolio yields 10% per annum. The value-weighted returns are even higher.

Not only do the switching strategies have higher returns, but also lower risks. The Sharpe ratios increase up to 0.2, skewness increases from significantly negative values to close to zero or even positive values. The market betas become close to zero. Therefore, switching to a contrarian position 2-4 months after a market plunge and keeping the momentum position in other periods generates an attractive risk-return profile without significant crashes.

Since the returns to the three alternative switching strategies are similar, the momentum crashes are distributed evenly in the window of 2-4 months following a market plunge. In some cases, there is a sequence of momentum drawdowns in these three months. In other cases, we observe single significant momentum losses in particular months in the window. Because there is no "rule" for momentum crashes[7], and we can only identify the window for the most common momentum losses, it makes sense to keep the contrarian position during this window in order to benefit from most of momentum losses. This strategy is studied further in the subsequent sections.

Now consider the switching strategies which follow market jumps (the right panel of table 2). Strategies, which switch to LMW in the next two months after a market jump yield higher returns than the standard momentum strategy, but the difference is only 1-2 percentage points. These strategies also have negative skewness and market betas as the WML strategy. Therefore, the momentum losses which follow market jumps are insignificant.

The momentum losses which are *contemporaneous* to market jumps are significant, and a strategy which switches to the contrarian position in the months of market jumps would yield 18% and 21.65% in cases of equal and value weights, respectively (column t). This strategy would also have very high Sharpe ratio and positive skewness. But, unfortunately, this strategy is unattainable because the market jumps are only observed at the end of the month whereas the strategy should be formed at the beginning. This strategy can only be implemented if we can forecast market jumps in advance. Luckily, preceding market losses help us forecast momentum crashes in advance, and switching to the contrarian position after significant market losses allows us obtain a similarly attractive risk-return outcome.

4. DYNAMIC MOMENTUM STRATEGY

Following the previous analysis, in this section I propose a dynamic momentum strategy which invests into the WML portfolio in calm times, but switches to the LMW portfolio in one month after

[7] Indeed, there are cases when momentum strategies do not crash at all after a significant market loss. There are also some cases of momentum losses without preceding market losses.

a significant market plunge[8] and keeps the contrarian position for three months, after which it reverts to the momentum position if no market plunge occurs again. The long-short portfolio is rebalanced every month as the standard momentum portfolio and, hence, the transactions costs are similar. The winner and loser stocks are defined similarly looking at past returns only. This dynamic strategy can easily be implemented because the momentum and contrarian positions are changed only after a market plunge is observed. The contrarian position is kept for three months because most of the momentum crashes happen in this window[9].

The returns and risks of the equal-weighted and value-weighted US dynamic momentum strategies together with the US momentum and market returns are reported in table 3. Whereas the average market return in 1927-2015 was 11% per annum, the dynamic momentum strategy return would have been 17-18%. It is about 1.5 as high as the standard momentum return. It is also a little higher than the returns to the one-month switching strategies in table 2. Therefore, keeping the contrarian position for several months allows us to avoid more momentum losses, which may happen in a row. Most importantly, this strategy avoids all of the most significant momentum crashes, as illustrated on figure 2. This may seem a coincidence, but robustness checks for other markets and different sub-periods in section 5 allow us to conclude that this is rather a rule.

The dynamic momentum strategy cannot be improved further by switching to the contrarian position after a market jump. Even though the analysis in table 2 suggests that some of the momentum losses happen 1-2 months after a market rise and switching at this time can improve the portfolio returns, apparently these losses are already avoided due to the switching after the market plunges. Indeed, a strategy which switches to the contrarian position in the month following a market jump *in addition* to switching for three months in one month after a market plunge yields lower average returns by 1-2 percentage points than the dynamic strategy which only switches after the market losses.

The dynamic momentum strategy has a similar standard deviation as the standard momentum strategy; therefore, the higher Sharpe ratios are entirely due to the higher average returns. Despite the similar volatility of returns, the most valuable characteristic of the dynamic momentum is the positive skewness of the return distributions. The most significant momentum losses become the

[8] Here, I define a significant market plunge as a loss greater than 1.5 standard deviations below the mean market return. Such trigger level of the market loss is chosen arbitrary to ensure that, on one hand, all significant losses are included, but on the other hand, the strategy does not switch to the contrarian position too often to save the transaction costs. I did not optimize this parameter on purpose to avoid the data mining issues. However, I consider other levels of trigger losses in the robustness sections 7.1 and 7.2, and I show that all significant loss triggers 'work'.

[9] Of course, other specifications of the dynamic momentum strategy with other switching periods and lengths of the contrarian position are possible. The one-month switching strategies analyzed in the previous section also belong to this class of strategies. Generally, all these strategies which switch to the contrarian position within 6 months after a market plunge yield higher returns at lower risk than the standard momentum strategy.

most significant gains due to the contrarian positions in these times. The greatest losses (minimum observed monthly returns) are reduced from 89.7% (77.02%) to 30.29% (24.96%) for the equal-weighted (value-weighted) returns. But note that the contrarian positions are kept in only 14% of the months, and keeping the contrarian position all the time would generate negative returns. Also note that not all of the momentum losses are avoided. Sometimes the momentum strategies generate low returns without preceding market losses.

The dynamic momentum strategy has a positive contemporaneous market beta of about 0.5. Therefore, as pointed out earlier, the negative betas and upside betas of the momentum returns are due to the lagged reactions of momentum to preceding market losses (high lagged downside betas). Even though the negative market betas of momentum returns seem to be attractive characteristics, they come at the expense of significant momentum crashes in times when the overall market grows. The dynamic momentum strategy correlates positively (but not highly) with the market, has low crash risk (positive skewness) and higher than the market returns. It seems to be a very attractive trading strategy and represents a puzzling asset-pricing anomaly which cannot be explained by the standard risk factors.

To get more insight into the riskiness of momentum and dynamic momentum strategies, I consider their long and short legs separately. Columns 1 and 3 of table 4 report the returns and risks of the long and short positions in the WML portfolio. The high average return of the momentum strategy is due to the long position, whereas the negative skewness, high volatility and negative market beta are predominantly due to the short position. Therefore, it is the short position in past losers, which adds the riskiness to the momentum portfolio and reduces its profitability, but it is required to create a zero-cost strategy and to hedge the market risk.

Columns 2 and 4 report the characteristics of dynamic winner (DW) and dynamic loser (DL) portfolios, which follow the same trading rule as the dynamic momentum portfolio: they coincide with the underlying winner and loser portfolios, respectively, and switch to the opposite position (short for winners and long for losers) for three months following a market crash. Apparently, all of the crash risk of the loser portfolio is eliminated due to the long position in this time window. However, there is no improvement in the negative skewness of the winner portfolio. Therefore, the loser portfolio is the main contributor to the momentum crashes, and the improvement in the dynamic momentum returns is due to taking the long position in past losers in times when the market rebounds after a crash. This corresponds to the findings of Baltzer et al. (2014), who document the excessive selling of loser stocks by institutions during market downturns, which leads to upward jumps in losers' prices when the market rebounds.

5. GLOBAL AND REGIONAL DYNAMIC MOMENTUM

The dynamic momentum strategy discussed in the previous section may seem to be a result of data mining for the US. Therefore, I test the profitability of the same strategy for other geographical markets and other specifications of past winner and past loser portfolios as a robustness check. Specifically, I consider the Fama-French global, European, North-American, Japanese and Asian-Pacific long-short momentum portfolios, the Asness-Moskowitz-Pedersen global, Continental-European, UK and Japanese long-short momentum portfolios, and MSCI emerging-markets and Latin-American long-only momentum portfolios. I also consider the Fama-French and the Asness-Moskowitz-Pedersen momentum portfolios for the US which are formed from the top and bottom 30% (or 33%) of stocks sorted by the previous returns. Compared to the US momentum portfolios in the previous section, these portfolios are more diversified and are less exposed to the momentum factor.

The data for these portfolios are available for shorter periods, and this is another dimension of the robustness test. Moreover, I use the local market return for each momentum portfolio, and even though I apply the same dynamic momentum strategy everywhere, the switching to the contrarian position often happens at different times after the local market loss (i.e. the local market return is 1.5 standard deviations below the local market mean return) because different geographical markets are not perfectly correlated[10].

Table 5 reports the average returns and risks of the standard momentum and the dynamic momentum strategies in each market. In all cases, the dynamic momentum returns are about 1.5 times as high as the momentum returns. The highest momentum and dynamic momentum returns are observed in the European and the Asian-Pacific regions (up to 15% per annum). The long-only strategies in emerging markets and Latin America provide a similar level of returns. The North-American, UK and Japanese returns are somewhat lower. But even in Japan, where the momentum average return is less than 2% per annum and statistically insignificant, the dynamic momentum yields a statistically significant return of 5-7%.

The average returns to the US momentum and dynamic momentum portfolios are lower than in table 3, and this is no surprise given that the portfolios in table 5 contain greater proportions of winner and loser stocks and, hence, are less exposed to the momentum factor. The dynamic momentum returns are always higher than the standard momentum returns, although the difference is lower than in the case of the more extreme momentum portfolios analyzed previously.

[10] The online appendix shows that correlations of momentum and dynamic momentum returns across regions are far from perfect.

The risk profile of the dynamic momentum strategy returns is similar in all geographical markets. The returns have roughly the same standard deviations as those of the momentum returns, higher Sharpe ratios due to higher average returns, positive skewness and positive but low local market betas. Switching to the contrarian position for three months after the significant local market losses helps to turn most major momentum losses into gains, leading to positive skewness of returns. Indeed, the maximum observed monthly loss is significantly reduced in all cases (although not all losses are avoided).

Such an attractive risk-return profile of the dynamic momentum strategies is obtained when the contrarian position is kept in only 14-17% of months. Therefore, the standard momentum strategy yields significant positive returns most of the time with rare occasional crashes which usually happen 2-4 months after a significant local market crash. The structure of momentum returns is similar around the globe and seems to be a consequence of the past-looking momentum portfolio formation procedure.

6. EXPOSURE OF THE DYNAMIC MOMENTUM RETURNS TO RISK FACTORS

I test the exposure of the dynamic momentum returns to various risk factors, which were proposed in the literature to explain equity returns and which are listed in the data section 2. The sample period is restricted to January 1968 – July 2015 because data on some of the factors are unavailable for earlier years.

Table 6 reports the estimates of alternative time-series regressions where the US value-weighted dynamic momentum returns are regressed on one or several factor returns. Each column corresponds to a particular multifactor specification. For instance, column 4 is the Carhart (1997) four-factor model, and column (8) is the Fama and French (2015) five-factor model.

All factor betas are close to zero and statistically insignificant. The only exception is the QMJ factor, to which the dynamic momentum portfolio has a negative exposure. The regression adjusted R^2 do not exceed 0.1. The regression alphas, on the contrary, are positive and highly significant in all specifications. The annualized alphas vary between 12 and 19 percent, whereas the average dynamic momentum return is about 18 percent in this time period. Hence, the considered risk factors cannot explain the high returns to the proposed dynamic momentum strategy in full. Given that the returns to this strategy are also positively skewed and co-skewed with the market, this strategy questions the market efficiency and represents at attractive simple trading rule for a momentum investor.

7. ROBUSTNESS

7.1. ALTERNATIVE TRIGGERS FOR SWITCHING

In this section, I test the robustness of the US dynamic momentum strategy to the trigger market loss of 1.5 standard deviations below the mean for switching to the contrarian position. I consider alternative arbitrary triggers of 1, 2 and 2.5 standard deviations below the mean. Table 7 reports the characteristics of these alternative dynamic momentum portfolios as well as the underlying WML portfolio.

Increasing the trigger level of the loss obviously leads to lower frequency of switching to the contrarian position and lower average duration of the contrarian position because the switching happens only after more significant market losses. Because the greater momentum crashes tend to happen after more significant market losses, higher trigger levels are more efficient. Indeed, the strategies with triggers of 2 and 2.5 standard deviations yield higher average returns (21.74 and 19.26 percent, respectively) than the basic dynamic momentum strategy (18.39 percent). These strategies also have higher Sharpe ratios and market coskewness and lower market betas, which is attractive from the asset-pricing perspective. However, the higher average returns and Sharpe ratios come at the expense of lower (although still positive) skewness and greater occasional losses, which have not been eliminated due to less frequent switching.

Considering lower triggers for switching (1 standard deviation and lower) is inefficient because the contrarian position is kept too often, even after rather small market losses. Since the contrarian position is generally unprofitable in calm times, the average return to such dynamic momentum strategy (13.43 percent) is even lower than the standard momentum return (14.63 percent). On top of that, the extra transaction costs due to frequent switching are higher.

This analysis confirms the robustness of the superior performance of the dynamic momentum strategy with alternative loss trigger levels of 1.5 standard deviations and above. However, it is important to find a balance between less frequent switching, on one hand, and avoiding the major momentum crashes, on the other hand. The trigger levels between 1.5 and 2 standard deviations seem to be the optimal from this perspective.

7.2. OUT OF SAMPLE TESTING

In the previous analysis, the whole long sample mean return and standard deviation were used to identify market crashes and switch the positions. However, since they are not observable in real time, I test the robustness of the dynamic momentum strategy out of sample, when only historical information is available. I consider two methods how we can identify market crashes in real time.

In the first method, I use a five-year rolling window prior to the decision date. The mean market return and its standard deviation are calculated in this five-year window, and if the current market return is below the time-varying mean less 1,5 time-varying standard deviations, we consider this to be a market crash and switch the position in one month. Since this method uses only recent historical information, it can be suitable for an investor with short memory or time-varying preferences, when the investor cares more about smaller market crashes in relatively calm times than in turbulent times. However, this method requires switching to the contrarian position too often in calm times and too rarely in turbulent times.

The second method uses all historical information since the start of the sample up to the decision date to calculate the mean market return and the standard deviation and to identify market crashes. As time goes, this method becomes closer to the full-sample method used in the remainder of the paper.

Table 8 reports the characteristics of dynamic momentum strategies, which use the two methods to identify market crashes and switch the positions. We see that the dynamic strategies always have superior performance compared to the underlying momentum strategy. Thus, the results are robust in the out-of-sample test. The five-year rolling window method is, indeed, less profitable due to switching to the contrarian position too often in calm times when switching is, in fact, unnecessary. Moreover, this method generates higher transaction costs and, therefore, the net returns would be even lower. The "whole history" method is more attractive in terms of the risk-return profile.

Another possible method to design the dynamic momentum strategy is to set an ad hoc cut-off level for the market loss. Figure 3 plots the dynamic momentum returns for alternative ad hoc loss levels of 6-30 percent per month. Losses above 30 percent were not observed in the sample of 1927-2015, whereas losses below 6 percent require holding the contrarian position almost all the time and, hence, lead to close to zero or negative average returns.

We observe an inverse U-shaped relationship between the cut-off market loss level and the corresponding dynamic momentum return. The optimal ad hoc loss levels which lead to higher dynamic momentum returns are 8-20 percent. Losses below 8 percent require switching to the contrarian position too often, which is unnecessary. Losses above 20 percent, on the contrary, switch too infrequently and, hence, miss some of important momentum crashes. This optimal window includes the cut-off levels, which were used in the main analysis (the mean market return less 1.5 standard deviations) as well as more severe losses, used in the robustness section 7.1.

7.3. DYNAMIC MOMENTUM RETURNS IN SUB-PERIODS

As another robustness test, I analyze the US momentum and dynamic momentum portfolio returns in 30-year sub-periods and the most recent 15 years. The results are reported in table 9. The dynamic momentum returns are higher than the momentum returns in all sub-periods. The dynamic momentum strategies always have positive return skewness and market betas.

The improvement in average returns is particularly significant in the first sub-period 1927-1956 which is the most turbulent period with frequent and significant market and momentum losses and the highest proportion of contrarian months (20%). The major momentum crashes of about 90% per month are turned into gains due to the dynamic momentum trading. The improvement in return skewness from -4.25 (-2.78) to +3.6 (+2.38) for the equal-weighted (value-weighted) portfolio is dramatic.

The middle sub-period 1957-86 is, on the contrary, characterized by low volatility, stable market performance and no significant momentum crashes, as illustrated on figure 2. The returns to the dynamic and standard momentum strategies are roughly the same in this period because the percentage of contrarian months is low (9%). When there are (almost) no significant market crashes, there is (almost) no need to switch from the momentum to the contrarian position because the momentum strategies do not crash either. The standard momentum strategy yields high and low-risk returns in calm times.

The recent period 1987-2015 is more turbulent again with several global financial crises in the 2000s. Therefore, switching to the contrarian position is required more often, in 13% of months. As a result, the dynamic momentum strategy has a much better risk-return profile again. For instance, whereas the equal-weighted standard momentum average return is 8.73% with skewness of -2.97, the dynamic momentum average return is 16.88% with skewness of +2.06. The Sharpe ratio is increased from 35% to 69%. It is really hard to obtain such a high Sharpe ratio in the US stock market. The low market beta of 0.22 also suggests that the 16.88% average return looks like a free lunch.

In the recent 15 years of the 21st century, the profitability of momentum strategies has been questioned. The bottom panel of table 9 shows that the average momentum returns are low and statistically insignificant indeed. Bhattacharya et al. (2015) claim that the insignificant momentum return in this period is due to uncovering the momentum anomaly and greater market efficiency. However, the dynamic momentum returns are much higher than the momentum returns and even than the dynamic momentum returns in the previous calmer sub-periods. In fact, the performance of momentum and dynamic momentum strategies in the recent 15 years is similar to their performance in the turbulent period 1927-1956. In the both periods, the low average momentum returns are due to several significant momentum losses, which happened after significant market losses. The dynamic momentum strategy turns these losses into gains and yields high positively skewed return of about 20 percent per annum.

Therefore, the momentum anomaly has not disappeared in the recent years, it follows the same dynamics as it did in the previous century, but the losses following the global financial crises made it seem unprofitable in this short time window. However, the superior performance of the dynamic momentum strategy is robust in all sub-periods, regardless of uncovering the momentum anomaly and seemingly greater market efficiency.

8. CONCLUSION

The paper thoroughly explores the timing of momentum crashes and identifies a three-month window after a significant local market crash when a momentum crash is most likely to occur. This lagging behavior of momentum returns is a consequence of sorting momentum portfolios by past performance.

Because momentum crashes can usually be forecasted in advance, they can be avoided. I design a novel dynamic trading strategy which coincides with the momentum strategy in calm times, but reverts to the opposite contrarian strategy in one month after a market loss of 1.5-2 standard deviations. Then the contrarian position is kept for three months, after which it switches back to the momentum position if no other market crash occurs. Such dynamic strategy turns major momentum crashes into gains and yields higher average returns than the underlying momentum strategy. Most importantly, the dynamic momentum returns are positively skewed, have lower kurtosis and higher Sharpe ratios, have positive but generally insignificant market betas and are not exposed to standard risk factors.

Because the switching to the contrarian position happens in one month after a market crash when the market already rebounds, the market liquidity is rather high and the volatility is rather low at this time. Therefore, the switching does not require significant extra transaction costs. Moreover, taking the opposite position to the crowd is generally easier to implement with low price impact. Hence, the dynamic momentum strategy seems attractive from different perspectives and can be considered a 'low-risk anomaly' which questions the market efficiency.

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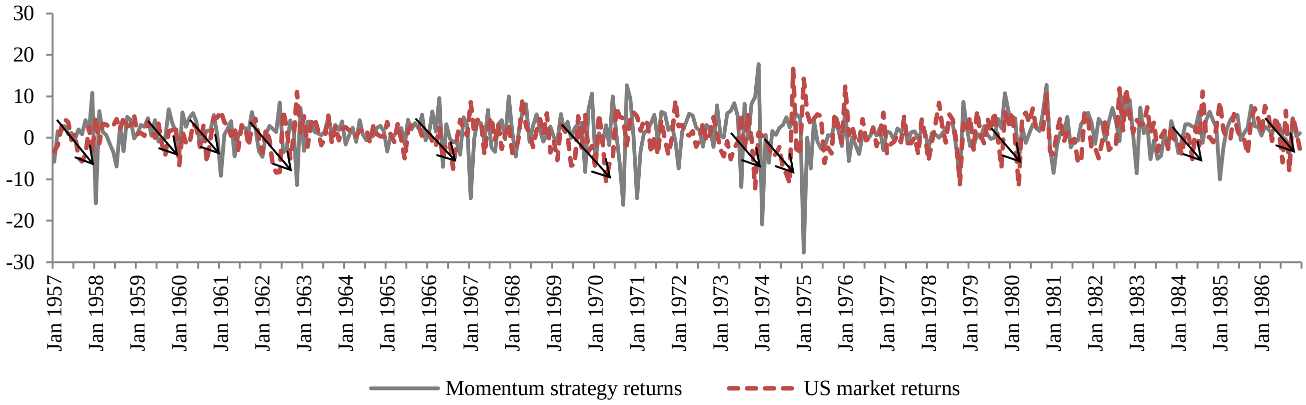
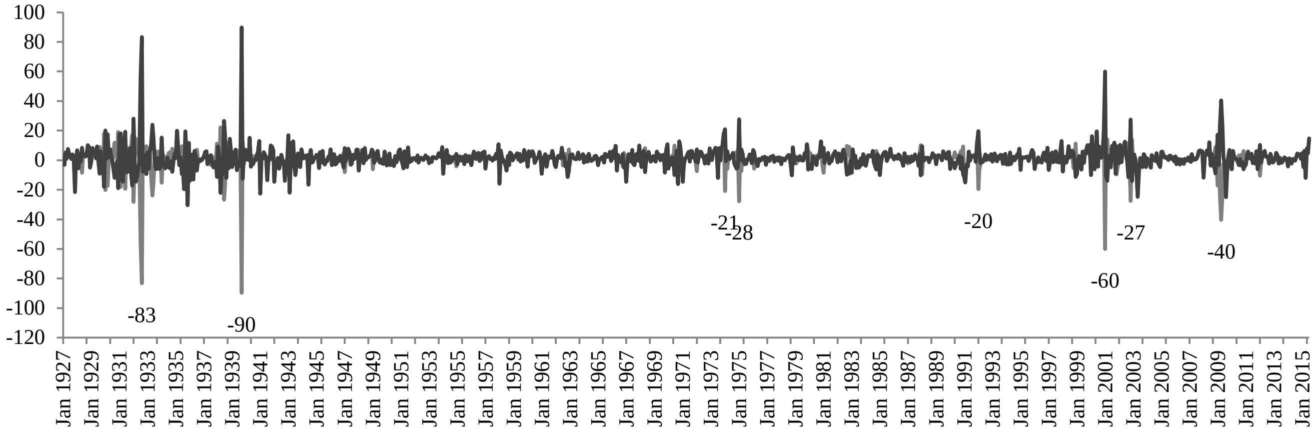
Figure 1. Predicting momentum losses by market losses



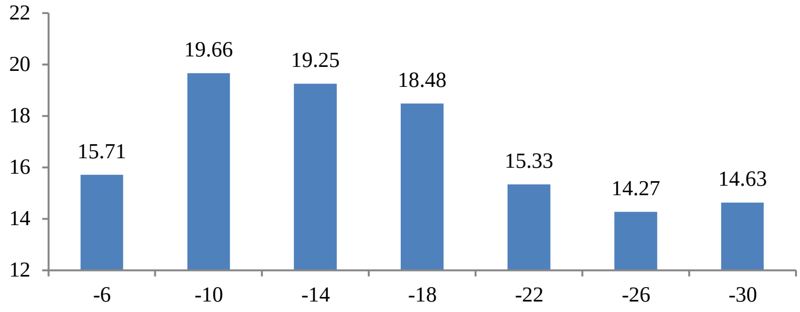
The figure illustrates the lagging behind nature of momentum returns. The US market return serves as the indicator. Sample period: January 1967- December 1986.

Figure 2. Returns to momentum and dynamic momentum strategies



The figure shows monthly returns to the US Fama-French equal-weighted momentum (light line) and dynamic momentum (dark line) strategies. The figure also indicates the most significant momentum crashes (in percent). Sample period: January 1927 – July 2015.

Figure 3. Dynamic momentum average returns for alternative triggers for switching the positions



The diagram plots the dynamic momentum strategy average returns (in percent pa, on the vertical axis) for alternative ad hoc cut-off levels for market losses (6-30 percent pm, on the horizontal axis), after which the momentum position is switched to the contrarian position. Sample period: Jan 1927 – July 2015.

Table 1. Contemporaneous and lagged correlations of momentum and market returns

	Corr (WML, Mkt)	Market beta	Downside beta	Extreme downside beta	Upside beta	Extreme upside beta
			Equal-weighted			
t,t	-0.30	-0.42	0.10	-0.13	-0.88	-1.05
t,t-1	-0.15	-0.22	0.00	-0.05	-0.41	-0.43
t,t-2	0.01	0.02	0.24	0.27	-0.17	-0.19
t,t-3	0.11	0.16	0.42	0.45	-0.06	-0.02
t,t-4	0.11	0.16	0.45	0.52	-0.09	0.02
t,t-5	0.03	0.05	0.12	0.19	-0.01	0.06
t,t-6	0.03	0.04	0.15	0.16	-0.05	0.08
			Value-weighted			
t,t	-0.37	-0.53	-0.10	-0.37	-0.90	-1.10
t,t-1	-0.13	-0.19	0.03	0.01	-0.37	-0.42
t,t-2	0.10	0.14	0.34	0.36	-0.04	-0.07
t,t-3	0.11	0.17	0.35	0.38	0.01	0.03
t,t-4	0.06	0.08	0.35	0.41	-0.15	-0.04
t,t-5	0.04	0.06	0.08	0.14	0.05	0.15
t,t-6	0.02	0.02	0.08	0.11	-0.03	0.12

The table reports contemporaneous and lagged market correlations, betas, downside and upside betas for the US Fama-French equal-weighted and value-weighted winner-minus-loser momentum portfolios. The downside (upside) betas are market betas conditional on the contemporaneous or lagged market return being negative (positive). The extreme downside (upside) betas are market betas conditional on the contemporaneous or lagged market return being 1.5 standard deviations below (above) the mean market return. Sample period: Jan 1927 – July 2015.

Table 2. Returns and risks of 1-month switching strategies

		Switching to contrarian following a market plunge in						Switching to contrarian following a market jump in						
	WML	**t-1**	**t-2**	**t-3**	**t-4**	**t-5**	**t-6**	**t**	**t-1**	**t-2**	**t-3**	**t-4**	**t-5**	**t-6**
Equal-weighted														
Average return	10.04	6.84	14.29	14.03	15.68	11.98	12.66	18.00	11.79	12.32	9.53	9.88	8.70	7.88
Sharpe ratio	0.38	0.24	0.55	0.52	0.59	0.45	0.48	0.69	0.45	0.45	0.35	0.38	0.31	0.28
Skewness	-4.27	-4.07	-2.27	-0.86	-0.95	-1.55	-0.91	2.23	-1.81	-1.28	-4.15	-4.15	-4.24	-4.22
Market beta	-0.42	-0.34	-0.14	0.09	0.09	-0.01	-0.09	0.14	-0.15	-0.27	-0.36	-0.41	-0.40	-0.41
Value-weighted														
Average return	14.63	12.31	19.11	16.93	18.20	14.92	15.74	21.65	15.77	15.04	13.23	14.78	11.92	12.00
Sharpe ratio	0.54	0.45	0.69	0.62	0.66	0.55	0.59	0.80	0.59	0.55	0.48	0.55	0.45	0.45
Skewness	-2.37	-2.10	-0.43	0.64	0.39	-0.13	-1.21	1.46	-0.54	-1.95	-2.32	-2.22	-2.34	-2.33
Market beta	-0.53	-0.37	-0.09	0.04	0.03	-0.06	-0.11	0.04	-0.27	-0.40	-0.44	-0.49	-0.51	-0.49

The table reports the characteristics of the underlying US winner-minus-loser momentum strategy and alternative one-month switching strategies, where the momentum position is switched to the opposite contrarian position for one month following a market plunge (1.5 standard deviations below the mean) or a market jump (1.5 standard deviations above the mean). The strategies differ according to when the contrarian position is taken. In column 't-1' the contrarian position is taken in the following month, in column 't-2' the contrarian position is taken in a month, and so on. The average return is reported in percent per annum. The Sharpe ratio is annualized. Sample period: Jan 1927 – July 2015.

Table 3. Returns and risks of the US dynamic momentum strategies

	Equal-weighted		Value-weighted		Market
	WML	DM	WML	DM	
Average return	10.04	17.44	14.63	18.39	11.18
	[3.67]	[6.34]	[5.28]	[6.42]	[5.40]
Standard deviation	26.66	26.34	27.14	26.95	18.68
Sharpe ratio	0.38	0.66	0.54	0.68	0.60
Skewness	-4.27	3.38	-2.37	1.82	0.16
Coskewness	-2.44	1.76	-2.34	1.90	0.00
	[-2.51]	[1.76]	[-3.61]	[2.54]	na
Market beta	-0.42	0.44	-0.53	0.51	1.00
	[-3.07]	[3.40]	[-3.69]	[3.88]	na
Minimum monthly return	-89.70	-30.29	-77.02	-24.96	-29.10
Percent of contrarian months		14%		14%	
Correlation with WML		-0.19		-0.09	
Correlation with the market		0.31		0.36	

The table reports annualized average returns and standard deviations of returns (in percent) of the US momentum (WML) and dynamic momentum (DM) strategies, their annualized Sharpe ratios and minimum observed monthly returns, return skewness, coskewness with the market (estimated as the coefficient of the squared market return) and market betas. Newey-West t-statistics are reported in brackets. The dynamic momentum strategy switched to the contrarian position for three months in one month after a market crash of more than 1.5 standard deviations below the mean and coincides with the standard momentum strategy in other times. The bottom rows show the dynamic momentum return correlation with the standard momentum and market returns and the percent of months when the contrarian position is kept. Sample period: Jan 1927 – July 2015.

Table 4. Returns and risks of the short and long legs of momentum portfolios

	Short leg		Long leg		Long-short	
	Loser	**DL**	**Winner**	**DW**	**WML**	**DM**
Average return	-3.63	4.30	18.26	14.10	14.63	18.39
	[-0.99]	[1.10]	[7.10]	[5.16]	[5.28]	[6.42]
Standard deviation	33.94	33.94	22.55	22.80	27.14	26.95
Sharpe ratio	-0.11	0.13	0.81	0.62	0.54	0.68
Skewness	-1.78	1.92	-0.50	-0.64	-2.37	1.82
Coskewness	-1.43	3.67	-0.91	-1.78	-2.34	1.90
	[-3.75]	[2.91]	[-3.11]	[-2.37]	[-3.61]	[2.54]
Market beta	-1.56	0.14	1.02	0.38	-0.53	0.51
	[-18.67]	[0.53]	[15.66]	[2.63]	[-3.69]	[3.88]
Minimum monthly return	-93.98	-42.26	-28.52	-28.88	-77.02	-24.96

The table reports the characteristics of the short (DL) and long (DW) positions in the US value-weighted momentum and dynamic momentum strategies. The average return and the standard deviation are reported in percent per annum. The Sharpe ratio is annualized. The market beta and coskewness are estimated with respect to the US market return. Newey-West t-statistics are reported in brackets. Sample period: Jan 1927 – July 2015.

Table 5. Momentum and dynamic momentum strategies around the glo

Panel A: Fama-French global and regional momentum portfolios (Nov 1990 -										
	Global		**European**		**North-American**		**US**		**Japanese**	
	WML	**DM**	**WML**	**DM**	**WML**	**DM**	**WML**	**DM**	**WML**	**DM**
Average return	7.54	11.25	11.22	14.89	7.15	10.63	6.71	8.84	1.50	7.05
	[2.81]	[4.26]	[4.06]	[5.51]	[2.14]	[3.22]	[1.97]	[2.61]	[0.49]	[2.32]
Standard deviation	13.54	13.32	13.92	13.63	16.83	16.67	17.28	17.22	15.39	15.29
Sharpe ratio	0.55	0.83	0.80	1.11	0.42	0.62	0.38	0.52	0.10	0.45
Skewness	-0.97	0.92	-1.27	0.81	-0.15	1.38	-1.59	1.50	-0.39	0.37
Market beta	-0.21	0.18	-0.25	0.07	-0.16	0.28	-0.29	0.22	-0.14	0.07
	[-2.05]	[1.90]	[-2.75]	[0.73]	[-1.37]	[2.74]	[-2.33]	[2.03]	[-1.77]	[1.02]
Minimum monthly return	-23.89	-11.80	-25.96	-13.91	-24.83	-12.20	-34.58	-16.50	-19.81	-14.23
Percent of contrarian months		15%		17%		16%		18%		14%
Panel B: Asness-Moskowitz-Pedersen global and regional momentum portfolios (Jan 1972-Jul 2011)										
	Global		**Continental-European**		**UK**		**US**		**Japanese**	
	WML	**DM**	**WML**	**DM**	**WML**	**DM**	**WML**	**DM**	**WML**	**DM**
Average return	5.45	7.82	8.12	8.50	6.02	8.99	5.44	6.57	1.72	4.89
	[2.94]	[4.26]	[3.38]	[3.54]	[2.38]	[3.58]	[2.08]	[2.52]	[0.57]	[1.62]
Standard deviation	11.66	11.54	14.73	14.72	0.19	15.81	16.41	16.37	18.57	18.52
Sharpe ratio	0.45	0.69	0.55	0.59	0.38	0.55	0.35	0.42	0.10	0.28
Skewness	-0.33	1.01	-0.29	0.40	-0.38	0.30	-0.07	0.57	-0.24	-0.09
Market beta	-0.07	0.13	-0.11	0.11	-0.06	0.04	-0.05	0.22	0.01	0.17
	[-1.17]	[2.45]	[-1.67]	[2.05]	[-1.37]	[0.92]	[-0.65]	[3.03]	[0.10]	[2.97]
Minimum monthly return	-19.05	-14.49	-22.65	-12.01	-20.96	-19.58	-22.03	-16.72	-22.88	-19.87
Percent of contrarian months		15%		17%		14%		16%		14%

The table reports annualized average returns and standard deviations of returns (in percent) of global and regional momentum (WML strategies, their monthly Sharpe ratios and minimum observed monthly returns, return skewness and market betas. Newey-West t-stat reports the percent of months when the contrarian position is kept in each region. The sample period is reported in panels A-C and de are value-weighted.

Table 6. Exposure of the dynamic momentum returns to risk factors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Annualized alpha	**0.15**	**0.14**	**0.17**	**0.13**	**0.12**	**0.17**	**0.19**	**0.19**	**0.14**
	[2.89]	**[2.53]**	**[4.70]**	**[2.67]**	**[2.47]**	**[2.68]**	**[2.85]**	**[4.45]**	**[2.67]**
MOM	0.36			0.38	0.38	0.48	0.23		
	[1.11]			[1.26]	[1.26]	[1.74]	[0.67]		
TS MOM		0.15							
		[0.84]							
Market			0.14	0.21	0.21	0.13	-0.01	0.11	0.23
			[0.99]	[1.88]	[1.87]	[1.24]	[-0.10]	[0.89]	[1.74]
SMB			0.14	0.15	0.16	0.02	-0.04	0.08	
			[0.76]	[1.00]	[1.03]	[0.13]	[-0.20]	[0.46]	
HML			-0.19	-0.06	-0.07	-0.01	-0.26	-0.10	
			[-0.84]	[-0.28]	[-0.32]	[-0.02]	[-1.01]	[-0.30]	
PS LIQ					0.21	0.22	0.19		
					[1.84]	[1.93]	[1.26]		
QMJ						-0.41	-0.52		
						[-1.83]	[-2.09]		
BAB						-0.26	-0.17		
						[-1.73]	[-1.04]		
d(VXO)							-0.10		
							[-1.07]		
RMW								-0.24	
								[-0.88]	
CMA								-0.20	
								[-0.47]	
AMP VAL									-0.02
									[-0.09]
AMP MOM									0.41
									[1.28]
R^2 adj	0.05	0.002	0.02	0.07	0.08	0.10	0.07	0.02	0.09
Sample period	Jan 1968 - Jul 2015	Jan 1985 - Jul 2015	Jan 1968 - Jul 2015	Jan 1968 - Jul 2015	Jan1968-Jul2015	Jan1968-Jul2015	Jul1986-Jul2015	Jan1968-Jul2015	Feb 1972 - Jul 2015

The table reports the US dynamic momentum betas to alternative risk factors estimated in alternative time-series regressions. TS MOM is Time Series Momentum from Moskowitz et al. (2012), MOM (momentum), Market, SMB (Small-Minus-Big) and HML (High-Minus-Low) are from Fama and French (1993) and Carhart (1997), PS LIQ is the traded liquidity factor from Pastor and Stambaugh (2003), QMJ is Quality-Minus-Junk factor from Asness et al. (2017), BAB is Betting-Against-Beta factor from Frazzini and Pedersen (2014), VXO is the market volatility factor from CBOE, RMW (Robust-Minus-Weak) and CMA (Conservative-Minus-Aggressive) are from Fama and French (2015), AMP VAL and AMP MOM are value and momentum factors from Asness et al. (2013). All factors are constructed for the US. Newey-West t-statistics are reported in brackets. The sample periods are restricted by data availability.

Table 7. Alternative triggers for switching to the contrarian position

	1 SD	1.5 SD	2 SD	2.5 SD	WML
Average return	13.43	18.39	21.74	19.26	14.63
	[4.98]	[6.42]	[7.94]	[6.24]	[5.28]
Standard deviation	27.19	26.95	26.74	26.90	27.14
Sharpe ratio	0.49	0.68	0.81	0.72	0.54
Skewness	1.90	1.82	1.66	0.94	-2.37
Coskewness	1.98	1.90	2.54	2.71	-2.34
	[2.80]	[2.54]	[3.49]	[2.80]	[-3.61]
Market beta	0.56	0.51	0.35	0.15	-0.53
	[4.43]	[3.88]	[2.37]	[0.93]	[-3.69]
Minimum monthly return	-24.96	-24.96	-39.39	-45.79	-77.02
Percent of switches	12%	7%	4%	2%	
Percent of contrarian months	28%	14%	8%	4%	
Average duration of contrarian position (months)	4.52	4.25	3.70	3.33	

The table reports the characteristics of alternative dynamic momentum strategies, which differ according to the severity of the preceding market crash (from 1 up to 2.5 standard deviations). For example, in the first column the strategy switches to the contrarian position after a market crash of more than 1 standard deviation below the mean. The average return and the standard deviation are reported in percent per annum. The Sharpe ratio is annualized. The market beta and coskewness are estimated with respect to the US market return. Newey-West t-statistics are reported in brackets. The table also reports the percent of months, in which the position is switched (from winner-minus-loser to loser-minus-winner and back), the percent of months, in which the contrarian position is kept, and the average duration of the contrarian position. The last column reports the characteristics of the basic US value-weighted momentum strategy (WML) for comparison. Sample period: Jan 1927 – July 2015.

Table 8. Out-of-sample tests: Other alternative triggers for switching to the contrarian position

	5-year mean and SD	**Whole history mean and SD**
Average return	18.28	22.51
Standard deviation	26.44	26.17
Sharpe ratio	0.69	0.86
Skewness	2.28	2.24
Coskewness	3.30	3.14
Market beta	0.33	0.36
Minimum monthly return	-24.85	-24.85
Percent of switches	10%	4%
Percent of contrarian months	20%	8%
Average duration of contrarian position (months)	4.08	3.64

The table reports the characteristics of alternative dynamic momentum strategies, which differ according to how the cut-off level for switching to the contrarian position is determined. In column 1, a market crash is determined by the previous 5-year market performance (a rolling window). If the market return in a given month is less than the 5-year mean minus 1.5 5-year standard deviations, this triggers switching to the contrarian position in one month.

In column 2, the market mean and the standard deviation are determined by the whole history of observations up to the current month (extending window). If the market return in a given month is less than the whole-history mean minus 1.5 whole-history standard deviations, this triggers switching to the contrarian position in one month.

The average returns and the standard deviations are reported in percent per annum. The Sharpe ratio is annualized. The market beta and coskewness are estimated with respect to the US market return. The table also reports the percent of months, in which the position is switched (from winner-minus-loser to loser-minus-winner and back), the percent of months, in which the contrarian position is kept, and the average duration of the contrarian position. Sample period: Jan 1932 – July 2015.

Table 9. US momentum and dynamic momentum strategies in sub-periods

	Equal-weighted		Value-weighted	
	WML	DM	WML	DM
	Jan 1927 - Dec 1956			
Average return	5.84	19.15**	11.94*	20.54**
Standard deviation	35.34	34.95	33.40	33.03
Sharpe ratio	0.17	0.55	0.35	0.62
Skewness	-4.25	3.60	-2.78	2.38
Market beta	-0.63	0.67	-0.74	0.77
Minimum monthly return	-89.70	-30.29	-77.02	-24.96
Percent of contrarian months		20%		20%
	Jan 1957 - Dec 1986			
Average return	15.50**	16.27**	18.27**	17.64**
Standard deviation	16.38	16.31	18.52	18.57
Sharpe ratio	0.94	1.00	0.97	0.94
Skewness	-1.36	0.14	-0.84	-0.42
Market beta	-0.08	0.06	-0.10	0.05
Minimum monthly return	-27.69	-16.18	-19.70	-18.79
Percent of contrarian months		9%		9%
	Jan 1987 - Jul 2015			
Average return	8.73	16.88**	13.62**	16.87**
Standard deviation	24.70	24.34	27.48	27.33
Sharpe ratio	0.35	0.69	0.48	0.62
Skewness	-2.97	2.06	-1.50	1.12
Market beta	-0.23	0.22	-0.41	0.29
Minimum monthly return	-59.99	-25.01	-45.79	-24.85
Percent of contrarian months		13%		13%
	Jan 1999 - Jul 2015			
Average return	4.62	21.81**	8.25	17.48*
Standard deviation	29.62	28.97	33.25	32.95
Sharpe ratio	0.17	0.76	0.24	0.52
Skewness	-2.79	2.14	-1.34	1.13
Market beta	-0.48	0.33	-0.73	0.52
Minimum monthly return	-59.99	-25.01	-45.79	-24.85
Percent of contrarian months		16%		16%

The table reports the characteristics of the US momentum (WML) and dynamic momentum (DM) strategies in sub-periods. The average return and the standard deviation are reported in percent per annum. The Sharpe ratio is annualized. The table also reports the percent of months, in which the contrarian position is kept. * denotes statistical significant at 5% level, ** denotes statistical significance at 1% level.

Online appendix for
Avoiding Momentum Crashes:
Dynamic Momentum and Contrarian Trading

by Victoria Dobrynskaya

Table A1 reports correlation matrices for the regional momentum and dynamic momentum returns. The momentum portfolio correlations in the top panel range from 0.3 to 0.95. Obviously, the highest correlations are observed for the alternative US momentum portfolios. The global, North-American and European momentum strategies are also highly correlated (correlations above 0.8). However, the Asian-Pacific and Japanese momentum portfolios are not highly correlated with each other and with the rest of the world. The average correlation across all momentum portfolios is 0.65.

The bottom panel of table A1 reports the same correlations for the regional dynamic momentum strategies. All correlations are significantly lower compared to the corresponding momentum correlations. The average correlation is now 0.47 in the range from -0.11 to 0.89. The lower dynamic momentum correlations confirm that the strategies often switch not simultaneously. Hence, we cannot claim that the higher profitability of the dynamic momentum strategies around the globe is simply due to the common components in the standard momentum returns.

Table A1. Correlation matrices for regional momentum and dynamic momentum returns

	FF Global	FF Europe	FF North America	FF Japan	FF Asian-Pacific	AMP Global	AMP Contin. Europe	AMP UK	AMP Japan	FF 10% US	FF 30% US	AMP 33% US
Momentum return correlations												
FF Global	1											
FF Europe	0.88	1										
FF North America	0.95	0.76	1									
FF Japan	0.62	0.42	0.48	1								
FF Asian-Pacific	0.55	0.45	0.50	0.32	1							
AMP Global	0.94	0.84	0.88	0.62	0.49	1						
AMP Continental Europe	0.81	0.90	0.72	0.38	0.41	0.85	1					
AMP UK	0.67	0.69	0.60	0.32	0.42	0.80	0.64	1				
AMP Japan	0.64	0.44	0.52	0.92	0.30	0.70	0.42	0.40	1			
FF 10% US	0.85	0.73	0.86	0.43	0.48	0.78	0.67	0.54	0.45	1		
FF 30% US	0.92	0.77	0.95	0.46	0.50	0.84	0.70	0.60	0.48	0.93	1	
AMP 33% US	0.88	0.70	0.94	0.44	0.46	0.89	0.69	0.61	0.49	0.80	0.87	1
Dynamic momentum return correlations												
FF Global	1											
FF Europe	0.60	1										
FF North America	0.86	0.41	1									
FF Japan	0.41	0.19	0.35	1								
FF Asian-Pacific	0.44	0.30	0.38	0.21	1							
AMP Global	0.48	0.69	0.49	0.27	0.30	1						
AMP Continental Europe	0.64	0.70	0.50	0.29	0.32	0.67	1					
AMP UK	-0.11	0.22	-0.10	-0.06	-0.01	0.39	0.09	1				
AMP Japan	0.37	0.13	0.30	0.79	0.21	0.29	0.34	0.04	1			
FF 10% US	0.78	0.44	0.83	0.31	0.36	0.48	0.47	-0.11	0.19	1		
FF 30% US	0.77	0.45	0.84	0.32	0.37	0.46	0.47	-0.09	0.22	0.82	1	
AMP 33% US	0.75	0.29	0.89	0.35	0.33	0.48	0.41	-0.03	0.32	0.74	0.75	1

The table reports the correlation matrix of global and regional value-weighted Fama-French (FF) and Asness-Moskowitz-Pedersen (AMP) momentum and dynamic momentum portfolios for the common sample period of June 1995-July 2011. The three portfolios for the US differ in the percent of stocks included in the winner and loser portfolios.