Momentum? What Momentum?

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Abstract

Risk-adjusted momentum returns are usually estimated by constructing momentum portfolios and then running a full-sample regression of their returns on a set of factors (portfolio-level risk adjustment). This approach implicitly assumes constant factor exposure of the momentum portfolio. However, momentum portfolios are characterized by strong turnover and time-varying factor exposure. We propose to estimate the risk exposure at the stock-level. The risk-adjusted return of the momentum portfolio in month t then is the actual return minus the weighted average of the expected returns of the component stocks (stock-level risk adjustment). Based on evidence from the universe of CRSP stocks, from sub-periods and size-based sub-samples, from volatility-scaled momentum strategies (Barroso and Santa-Clara 2015) and from an international sample covering 22 developed countries we conclude that the momentum effect may be much weaker than previously thought.

Keywords: Momentum, Risk adjustment, Time-series regression
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"If a reasonable change in the method of estimating abnormal returns causes an anomaly to disappear, the anomaly is on shaky footing, and it is reasonable to suggest that it is an illusion."

(Eugene Fama, 1998)

1 Introduction

The efficient markets hypothesis states that markets are weak form efficient if information in past return histories is fully reflected in prices (Fama 1970). This definition is in sharp contrast to the return continuation and reversal effects that have been documented over short-term (up to one month, Jegadeesh 1990; Lehmann 1990; Lo and MacKinlay 1990), medium-term (three to twelve months, Jegadeesh and Titman 1993), and long-term periods (up to 60 months, Bondt and Thaler 1985). Whereas there are risk-based explanations for long-term return anomalies (Fama 1998), the literature so far has not offered a convincing explanation for medium-term return continuation ("momentum"). The momentum effect is by now not only one of the most well-documented but also one of the most robust asset pricing anomalies. Subsequent to the work of Jegadeesh and Titman (1993), it has been documented across various markets and asset classes.[1]

The existing literature offers both behavioral and rational explanations for momentum.[2] Our paper rather takes a methodological approach. Standard asset pricing models like the Fama and French 3-factor (FF3) model (Fama and French 1993, 1996) or the Fama and French 5-factor (FF5) model (Fama and French 2015) fail to explain momentum profits.[3] The usual tests proceed by estimating full-sample factor sensitivities of momentum strategies at the portfolio level. We argue in this paper that factor sensitivities should be estimated at the stock level using rolling windows.

[1]Jegadeesh and Titman (2001) show that momentum persists out-of-sample. It has also been documented for international equity markets (Rouwenhorst 1998; Griffin et al. 2003; Chui et al. 2010; Fama and French 2012; Asness et al. 2013), stock market indices (Chan et al. 2000; Asness et al. 2013), industries (Moskowitz and Grinblatt 1999), currencies (Okunev and White 2003; Menkhoff et al. 2012), and commodity futures (Miffre and Rallis 2007; Asness et al. 2013). Momentum is pervasive for all size groups (Fama and French 2008; Israel and Moskowitz 2013). Only recently, momentum appears to be less significant (Jegadeesh and Titman 2011).

[2]For instance, Chan et al. (1996), Barberis et al. (1998), Hong and Stein (1999), and Hong et al. (2000) consider market underreaction as a source of momentum profits. Korajczyk and Sadka (2004) and Lesmond et al. (2004) show that momentum strategies require frequent trading in illiquid assets and that abnormal returns are lower after transaction costs. For a survey of explanations for the momentum effect see Jegadeesh and Titman (2011).

[3]Since momentum cannot be explained by existing factors, it is included as a separate factor into asset pricing models like the Carhart 4-factor model (Carhart 1997) or the Fama and French 6-factor model (Fama and French 2018).

We show that, when factor sensitivities are estimated at the stock level, momentum disappears in our sample of NYSE, Nasdaq and AMEX stocks covering 1963-2018. The magnitude and statistical significance of momentum returns thus depends on the method used to estimate abnormal returns.

We test the same 16 trading strategies as in Jegadeesh and Titman (1993). Each month, we sort stocks based on their prior *J-month* returns into decile portfolios. We construct zero net investment portfolios by investing into the winner stocks (decile 10) and shorting the loser stocks (decile 1). We hold the winner-minus-loser portfolios for the next *K-months* (K portfolios are held simultaneously). Formation and holding period span one, two, three, or four quarters, i.e. $J, K \in \{3, 6, 9, 12\}$. We start by showing results for non-adjusted returns. Before risk adjustment, 15 out of 16 tested strategies deliver returns that are positive and statistically different from zero. Thereafter, we adjust risk at the portfolio level using the Fama and French (2015) 5-factor model. Portfolio-level risk adjustment has little effect on mean returns and all 16 strategies deliver significant returns after portfolio-level risk adjustment. We proceed by adjusting risk at the stock level. The proposed stock-level risk adjustment captures on average 94% of the momentum returns that remain after portfolio-level risk adjustment. None of the 16 tested momentum strategies delivers returns that are significantly different from zero.

As an example, consider a strategy that ranks stocks into deciles based on their prior *6-month* returns and holds stocks for the next *6-months.* In the full sample this strategy delivers a non-adjusted return of 0.75% (t-ratio: 4.53) per month, a portfolio-level adjusted return of 0.77% (t-ratio: 4.64), and a stock-level risk adjusted return of 0.11% (t-ratio: 0.53). When we consider sub-periods we find that the *6-month/6-month* strategy only earns significant abnormal returns after stock-level risk adjustment in the first half of the sample (1963-1989) but not thereafter. However, even in the first half of the sample period, momentum returns are roughly 45% smaller if risk is adjusted at the stock level. When we take transaction costs into account the momentum return becomes insignificant even for the first half of our sample period. When we split the sample into size groups we find no significant momentum returns for any size category (micro caps, small and large stocks) when risk is adjusted at the stock level. We further implement the volatility-scaled momentum strategy proposed by Barroso and Santa-Clara (2015). While this strategy delivers high and significant momentum returns without risk adjustment and with portfolio-level risk adjustment, it does not deliver returns significantly different from zero after stock-level risk adjustment. Finally, we compile an international sample covering 22 developed countries. Without risk adjustment (with portfolio-level risk-adjustment) we find a significant momentum effect in 18 (17) countries. With stock-level risk-adjustment this number drops to 3.

It is important to know *why* stock-level risk adjustment reduces momentum profits significantly (or even eliminates them) while portfolio-level risk adjustment does not. Portfolio-level risk adjustment assumes constant factor exposures of the strategy under investigation. However, the factor exposures of momentum portfolios vary over time, and they do so in a systematic way. Momentum portfolios are characterized by huge turnover as stocks leave and other stocks enter the portfolio every month. Which stocks enter the long and short leg of the momentum portfolio depends on previous factor realizations. Consider the market factor as an example. When the excess return on the market is positive, high beta stocks perform well and low beta stocks perform poorly. Consequently, after a period of positive market excess returns the momentum portfolio will have high beta stocks in its long leg and low-beta stocks in its short leg, resulting in a high beta of the long-short portfolio. After a period of negative market excess returns the reverse will be true, resulting in a negative market beta of the long-short portfolio. Portfolio-level risk adjustment essentially estimates an average market beta of the momentum portfolio, and the average beta may well be (and in fact is) close to zero. Stock-level risk adjustment, on the other hand, captures the time-variation in the market exposure of the strategy. A similar argument can be made for the other factors of the FF5 model.

To provide empirical evidence on the dynamics of the factor exposure of momentum portfolios we use a regression approach similar to the one in Grundy and Martin (2001). The winner-minus-loser portfolio of a strategy that ranks stocks based on prior *6-month* returns and then holds stocks for *6-months* loads positively (negatively) on the FF5 factors when the past six months factor return was at least one standard deviation above (below) its mean during the formation period. The factor exposure of the momentum portfolio thus changes over time in a way that is related to past factor realizations, as suggested above. Consequently, full-sample portfolio-level betas do not accurately describe the risk exposure of momentum portfolios. We conclude that factor sensitivities and risk-adjusted returns of momentum portfolios should be estimated at the stock level.

Our paper is related to several previous papers on the momentum effect. The observation that the factor exposure of momentum portfolios is time varying has, among others, been made by

Grundy and Martin (2001), Wang and Wu (2011) and Daniel and Moskowitz (2016). The latter paper relates the time-varying factor exposure to the occurrence of momentum crashes. Barroso and Santa-Clara (2015) provide evidence that the risk of momentum strategies is predictable. Building on this insight they propose a scaled momentum strategy that delivers even higher abnormal returns then the conventional strategy. Grundy and Martin (2001) hedge momentum portfolio returns against dynamic factor exposure. They analyze factor exposure for both the winner and loser portfolio and show that a bet on momentum in stock returns involves a bet on momentum in the factor realizations. Hedging the factor exposure increases the profitability of the momentum strategy and reduces its variability. However, the hedging strategy propsed by Grundy and Martin (2001) is not implementable for investors since it assumes that future factor realizations are known at the time of portfolio formation. The only previous paper we are aware of that advocates a procedure similar to our stock-level risk adjustment is Wang and Wu (2011). They use the Fama and French (1993) 3-factor model and show that stock-level adjustment reduces momentum profits by 40%. Korajczyk and Sadka (2004) and Lesmond et al. (2004) adjust the momentum strategy for transaction costs, as we do in some of our analysis.

Our paper contributes to the literature in several important ways. First, we bring together the evidence presented in Grundy and Martin (2001) and Wang and Wu (2011). We extend the analysis of Wang and Wu (2011) by including evidence on the dynamic factor exposure of momentum portfolios. This step of the analysis relates formation period factor realizations and holding period factor exposure as is done in Grundy and Martin (2001). It explains *why* there are significant differences between portfolio-level and stock-level adjusted momentum portfolio returns and *why* stock-level risk adjustment is more appropriate for momentum portfolios. Second, we show that stock-level risk adjustment largely reduces or even eliminates the returns of a volatility-scaled momentum strategy as proposed by Barroso and Santa-Clara 2015. Third, we provide additional evidence from a large international sample. Finally, we employ a plethora of robustness checks in which, among other things, we complement previous research on momentum and size (Fama and French 2008; Israel and Moskowitz 2013).

The paper proceeds as follows. We present data and trading strategies in Section 2. In this section we also explain the differences between risk adjustment at the stock and portfolio level in detail. Results are presenbted in Section 3 and various robustness checks in Section 4. Section 5 concludes.

2 Data and Methodology

2.1 Data

We use data from two sources. First, we obtain stock price data from the Center for Research in Security Prices (CRSP). We restrict the sample to ordinary common shares (share code 10 or 11) traded on the NYSE, AMEX, or NASDAQ (exchange code 1, 2, or 3). We do not consider stocks with share prices below 3 dollars. Excluding shares with low prices alleviates microstructure-related concerns. Second, we download data on the Fama and French (2015) five factors from the data library of Ken French. Our sample spans the period from July 1963 until December 2018. There are 1,926 firms in the sample in the first year (1963) and there are 3,541 firms in the sample in the last year (2018). In total, the sample includes 22,376 distinct stocks.

We obtain both stock and factor data from the daily returns files. Using daily data allows us to replicate the analysis of Jegadeesh and Titman (1993) as closely as possible. For instance, Jegadeesh and Titman (1993) skip one week between formation and investment period. Skipping one week is not possible when using the monthly returns file. In Section 2.2, we further elaborate on this issue. By using daily data, we can also implement several robustness checks, e.g. we implement the volatility-scaled momentum strategies proposed by Barroso and Santa-Clara (2015). We calculate monthly returns by compounding the daily returns.

2.2 Methodology

We test the same *J-month/K-month* trading strategies as in Jegadeesh and Titman (1993). Each month, we sort stocks into ten portfolios based on their prior *J-month* returns. We then construct zero-cost portfolios by investing into the ten percent winner stocks and shorting the ten percent loser stocks. We hold the winner-minus-loser portfolios for the next *K-months*. Hence, we hold K portfolios simultaneously, i.e. one portfolio formed in the current month and one portfolio formed in each of the last K-J months (the portfolio formed K months ago is liquidated). All K portfolios receive the same weight. Formation and holding periods span one, two, three, or four quarters, i.e. $J,\ K \in \{3, 6, 9, 12\}$. We follow Jegadeesh and Titman (1993) and skip a week between formation and holding period. This avoids the short-term reversal documented in Lehmann (1990) and Lo and MacKinlay (1990). Other studies skip the first month between holding and formation period. We argue that in the context of the *J-month/K-month* strategies it is more appropriate to skip only one week. First month return is positive (after subtracting first week return) whereas returns start to become negative with the twelfth month, i.e. for periods with $K{=}12$ a positive return would be substituted with a negative return.[4]

We report results for stocks being equally-weighted within each decile portfolio. Weighting returns equally gives more weight to micro stocks (firms with market capitalization below the 20^{th} NYSE percentile), which comprise approximately 50% of the stocks in our sample. The majority of the empirical momentum literature uses equal-weighted returns as well (e.g. Jegadeesh and Titman 1993; Chan et al. 1996; Fama and French 1996; Rouwenhorst 1998; Hong et al. 2000; Jegadeesh and Titman 2001; Grundy and Martin 2001). We are aware of only a few papers that solely focus on value-weighted returns (e.g. Moskowitz and Grinblatt 1999; Daniel and Moskowitz 2016). We report results for micro, small, and big stocks in Section 4.3 and results for value-weighted returns within decile portfolios in the Internet Appendix. For every momentum strategy, we present non-adjusted, portfolio-level adjusted, and stock-level adjusted returns.

2.2.1 Portfolio-Level Risk Adjustment

We summarize the risk adjustment as it is usually done in the literature. To emphasize differences between adjustments at the portfolio level and at the stock level, we divide the process of risk adjustment into four steps (calculation of single portfolio returns, overlap portfolio returns, betas, and risk adjusted returns). We outline the steps as precisely as possible.

First, we calculate single portfolio returns. Each month, we form a winner and a loser portfolio for each length of the formation period (3, 6, 9, and 12 months), i.e. we form a total of eight portfolios every month. For these portfolios and the portfolios formed in the previous $K-1$

[4] For strategies that do not hold K overlapping portfolios but only one portfolio at once, e.g. the 11/1/1 strategies used in Carhart (1997) and Fama and French (2008, 2012, 2015), it is most appropriate to skip the entire month since the second month return is higher than the first month return.

months, we estimate returns by

$$r^{J,\,t-\kappa}_{p,\,\theta,\,t} = \frac{1}{N^{J,\,t-\kappa}_{p,\,\theta,\,t}} \sum_{i=1}^{N^{J,\,t-\kappa}_{p,\,\theta,\,t}} r^{J,\,t-\kappa}_{i,\,\theta,\,t}, \tag{1}$$

where $r^{J,\,t-\kappa}_{p,\,\theta,\,t}$ and $r^{J,\,t-\kappa}_{i,\,\theta,\,t}$ are the monthly returns of portfolio p and stock i at time t. The Greek letter θ denotes the type of portfolios and stocks, i.e. $\theta \in \{Winner,\, Loser\}$. Further, J is the length of the formation period and $t-\kappa$ is the point in time of portfolio formation.[5] For instance, $r^{6,\,t-1}_{p,\,Loser,\,t}$ is the return of the loser portfolio, which is based on a *6-month* formation period and formed at time $t-1$, at time t. $N^{J,\,t-\kappa}_{p,\,\theta,\,t}$ is the number of stocks in the respective portfolio.

Second, we estimate returns for the K overlapping portfolios by calculating the mean return of the portfolio formed in the current month and of the portfolios formed in the last $K-1$ months, i.e.

$$r^{J,\,K}_{\theta,\,t} = \frac{1}{K} \sum_{\kappa=0}^{K-1} r^{J,\,t-\kappa}_{p,\,\theta,\,t}, \tag{2}$$

where $r^{J,\,K}_{\theta,\,t}$ denotes the return of K overlapping portfolios of type θ that have been formed based on past *J-month* return. For instance, $r^{6,\,6}_{Loser,\,t}$ is the return of six overlapping loser portfolios, which are formed based on past six months return, in month t.

Third, we use these returns to estimate factor sensitivities and to calculate risk-adjusted returns. For each strategy's winner and loser portfolio, we run full-sample regressions of the excess return on the the market (MKTRF), size (SMB), book-to-market (HML), operating profitability (RMW), and investment factors (CMA). The regression model is

$$r^{J,\,K}_{\theta,\,t} - r_{f,t} = \alpha^{J,\,K}_{\theta} + \sum_{j} \beta^{J,\,K}_{\theta,\,j} f_{j,\,t} + \epsilon^{J,\,K}_{\theta}, \tag{3}$$

where $r_{f,t}$ is the risk-free rate at time t, $\beta^{J,\,K}_{\theta,\,j}$ are the factor sensitivities for the *J-month/K-month* strategies' winner and loser portfolios, and $f_{j,\,t}$ are the factor realizations at time t ($j \in \{MKTRF, SMB, HML, RMW, CMA\}$). Estimating factor sensitivities at the portfolio level using full-sample time-series regressions is widely implemented in the literature (e.g. see Jegadeesh and Titman 1993, Equation 9; Fama and French 1996, Equation 2; or Fama and French (2015),

[5] The large number of sub- and superscripts is necessary to cleanly distinguish between portfolios as we hold a total of 240 portfolios at the same time.

Equation 3).

Fourth, we use the estimated factor sensitivities to adjust returns, i.e.

$$ar_{\theta,t}^{J,K} = r_{\theta,t}^{J,K} - r_{f,t} - \sum_j \beta_{\theta,j}^{J,K} f_{j,t}, \tag{4}$$

where $ar_{\theta,t}^{J,K}$ denotes the risk-adjusted returns of the *J-month/K-month* strategies' winner and loser portfolios at time t. In the following, we refer to this type of risk adjustment as portfolio-level risk adjustment.

2.2.2 Stock-Level Risk Adjustment

In this part, we focus solely on the technicalities of stock-level risk adjustment. We defer any discussion on which risk adjustment is more appropriate to the latter parts. To adjust returns at the stock-level, we invert the order of portfolio-level risk adjustment presented in the previous section in Equations 1, 2, 3 and 4.

First, we run rolling-window time-series regressions at the stock level to estimate factor sensitivities, i.e.

$$r_{i,t} - r_{f,t} = \alpha_{i,t} + \sum_j \beta_{i,j,t} f_{j,t} + \epsilon_{i,t}, \tag{5}$$

where $r_{i,t}$ is the return of stock i, $r_{f,t}$ is the risk-free rate, $\beta_{i,j,t}$ are the stock-specific factor sensitivities, and $f_{j,t}$ are the factor realizations (all at time t). As in Section 2.2.1, we use an FF5 model, i.e. $j \in \{MKTRF, SMB, HML, RMW, CMA\}$. We estimate factor sensitivities over windows of 36 months. Hence, they are time-varying. Choosing a window length of 36 months is a reasonable trade-off between changes in risk exposure and short-term noise. Other studies, e.g. Grundy and Martin (2001) and Wang and Wu (2011), use this window length as well.[6] We require a minimum of 18 monthly returns for the regressions so that we obtain the first beta estimates in January 1965.

Second, we calculate risk-adjusted returns as in Equation 4 for every stock in the sample, i.e.

$$ar_{i,t} = r_{i,t} - r_{f,t} - \sum_j \beta_{i,j,t-1} f_{j,t}, \tag{6}$$

[6] In Section 4.2, we use betas that are calculated over horizons of 24 and 60 months. The results are similar.

where $ar_{i,t}$ is the risk-adjusted return of stock i at time t. We use beta estimates obtained from $t-36$ to $t-1$ to adjust returns at time t.

Third, we use the risk-adjusted stock returns to calculate risk-adjusted portfolio returns. Single portfolio returns are calculated analogously to Equation 1, i.e.

$$ar_{p,\theta,t}^{J,t-\kappa} = \frac{1}{N_{p,\theta,t}^{J,t-\kappa}} \sum_{i=1}^{N_{p,\theta,t}^{J,t-\kappa}} ar_{i,\theta,t}^{J,t-\kappa}, \tag{7}$$

where $ar_{p,\theta,t}^{J,t-\kappa}$ and $ar_{i,\theta,t}^{J,t-\kappa}$ are the abnormal returns of portfolio p and stock i, which are of type θ, sorted at time $t-\kappa$, and based on past *J-month* return, at time t.

Fourth, we calculate risk-adjusted returns for the overlap portfolios to obtain our estimate of the strategies' stock-level risk-adjusted returns, i.e.

$$ar_{\theta,t}^{J,K} = \frac{1}{K} \sum_{\kappa=0}^{K-1} ar_{p,\theta,t}^{J,t-\kappa}, \tag{8}$$

where, just as in Equation 4, $ar_{\theta,t}^{J,K}$ denotes the risk-adjusted returns of the *J-month/K-month* strategies' winner and loser portfolios at time t. In the following, we refer to this type of risk adjustment as stock-level risk adjustment.

3 Main Results

3.1 Full Sample Results

3.1.1 Total Return (No Risk Adjustment)

We show returns for all 16 momentum strategies in Table 1. The presented returns are monthly mean returns and not adjusted for risk. We calculate t-values using Newey and West (1987) standard errors with *K-1* lags. Unless indicated otherwise, all subsequent tables show t-ratios that are calculated using Newey and West (1987) standard errors as well. Readers who are familiar with the evidence in Jegadeesh and Titman (1993) can safely skip this subsection without missing out on new evidence.

All winner and loser portfolios show on average positive returns. The winner portfolios outperform the loser portfolios irrespective of formation and investment period. Hence, mean returns of all winner-minus-loser portfolios are positive as well. One strategy (*12-month/12-month*) leads to returns that are not significantly different from zero. Two strategies (*9-month/12-month* and *12-month/9-month*) generate returns that are significantly different from zero at the 5% level. All remaining strategies result in returns that are significant at the 1% level.

The *6-month/6-month* strategy generates a monthly mean return of 0.75% that is significantly different from zero at the 1% significance level (t-value: 4.53). The return is also economically meaningful. The strategy's one-year cumulative return equals 9.40%. Over the same sample period, the market generated on average a monthly (yearly) return of 0.53% (6.55%). The largest momentum returns are generated by the *9-month/3-month* strategy (0.85%) followed by the *9-month/6-month* and *12-month/3-month* strategies (both 0.79%).

[Insert Table 1 about here]

3.1.2 Portfolio-Level Risk Adjustment

The results presented in Table 1 provide evidence in favor of momentum in non-adjusted returns. We now turn to the question whether winners outperform losers after risk adjustment. We adjust returns at the portfolio level (as described in Section 2.2.1). Please note that risk adjustment does not affect the sorting of stocks, i.e. we still sort stocks into decile portfolios based on non-adjusted returns.

We show results in Table 2. The returns of both winner and loser portfolios are lower after portfolio-level risk adjustment. Whereas they are positive on average in Table 1, they are almost all negative for loser portfolios. The winner portfolios still generate on average positive returns. The aggregate effect of risk adjustment on winner-minus-loser portfolios' returns is small. All winner-minus-loser portfolios show returns that are significantly different from zero. The *12-month/12-month* strategy's returns are significant at the 5% level and all other strategies' returns are significant at the 1% level.

The *6-month/6-month* strategy generates a non-adjusted return of 0.75% (t-ratio: 4.53; Table 1) and a portfolio-level risk-adjusted return of 0.77% (t-ratio: 4.64). Returns after risk adjustment are thus even larger. They also remain economically meaningful, e.g. a monthly return of 0.77%

is equivalent to a yearly return of 9.64%. The largest momentum returns are generated by the *9-month/3-month* (0.89%), *12-month/3-month* (0.87%), and *9-month/6-month* (0.85%) strategies.

[Insert Table 2 about here]

3.1.3 Stock-Level Risk Adjustment

The evidence presented in Tables 1 and 2 is fully consistent with previous literature. Momentum returns are large and significant before and after (portfolio-level) risk adjustment. If momentum returns are robust, they should also show up when we make a reasonable change in the method of estimating abnormal returns.

We show results for stock-level risk adjustment in Table 3. We notice that returns of all winner and loser portfolios are positive. However, the winner portfolios' returns are smaller than in Tables 1 and 2. The loser portfolios' returns are almost as large as (and for some strategies even larger than) the winner portfolios' returns. Thereby, stock-level risk adjustment reduces winner-minus-loser portfolios' returns substantially. It explains approximately 94% of returns that are left unexplained by portfolio-level risk adjustment in Table 2.[7] No strategy shows returns with t-statistics above one and almost a third of the strategies even delivers negative returns on average.

The *6-month/6-month* strategy generates a non-adjusted return of 0.75% (t-ratio: 4.53; Table 1) and a portfolio-level risk-adjusted return of 0.77% (t-ratio: 4.64; Table 2). Adjusting risk at the stock-level reduces mean return to only 0.11% per month. The return is not different from zero at any reasonable significance level (t-ratio: 0.53). In addition, the strategy's return lacks economic significance. It results on average in a yearly return of only 1.33%. Only one strategy generates higher stock-level risk-adjusted returns than the *6-month/6-month* strategy. The *9-month/3-month* strategy generates on average a return of 0.15% (t-ratio: 0.69). The *3-month/3-month*, *6-month/12-month*, *9-month/12-month*, *12-month/9-month*, and *12-month/12-month* strategies show on average negative returns. We interpret these findings as evidence against momentum.

[Insert Table 3 about here]

[7]This number is obtained by comparing alphas in Table 2 with alphas in Table 3. If stock-level risk adjustment results in negative returns for the winner-minus-loser portfolio, the reduction is considered to equal one.

The effect of stock-level risk adjustment on the profitability of momentum strategies is substantial. Consider an investment of one dollar into the winner portfolio that is financed by selling short the loser portfolio. Assume that stocks are ranked over a period of six months and that portfolios are held for six months (*6-month/6-month* strategy). Further, assume that any gains of the strategy are reinvested. A zero-cost investment at the beginning of the period results in an amount of 65.50 dollar in 2018 (without any risk adjustment). Portfolio-level risk adjustment leads to an amount of 76.80 dollar. Stock-level risk adjustment results in a final amount of only 1.07 dollar. The cumulative return of the winner-minus-loser portfolios is displayed in Figure 1.[8]

[Insert Figure 1 about here]

3.2 Explanations

In asset pricing tests factor sensitivities are often calculated at the portfolio level to obtain more accurate estimates of the true underlying betas (e.g. see Fama and MacBeth 1973). However, stock-level risk adjustment (almost) fully captures returns of momentum strategies whereas portfolio-level risk adjustment does not. In this chapter, we discuss two related characteristics of momentum portfolios that jointly explain *why* there are such large differences between the two methods. We first consider the turnover of momentum portfolios and then focus on their time-varying factor exposure. Finally, we provide empirical evidence that our theoretical considerations accurately describe the risk exposure of momentum portfolios.

3.2.1 Turnover

Estimation of betas at the portfolio-level only leads to accurate results if portfolio composition is stable.[9] This assumption is rarely stated in literature and we argue that it is violated in this context. Our momentum portfolios show a very high turnover as we use monthly performance sorts

[8]Figure 1 shows the momentum crash from March until May 2009. As also described in Daniel and Moskowitz (2016), the large losses of the strategy are caused by the market recovering after the financial crisis. At the end of the recession, the winner (loser) portfolio consisted of stocks with low (high) market beta. Markets recovered sharply from March until May 2009. The high-beta stocks in the loser portfolio performed exceptionally well during these months. For instance, in April 2009 the loser portfolio had a (non-adjusted) return of 33.48% but the winner portfolio only generated a return of 5.47%.

[9]At the very least, it is required that the factor exposures of the stocks that constitute the portfolio are similar. We show in the next chapter that this assumption is violated as well.

to construct the *J-month/K-month* strategies. We hold K overlapping portfolios, i.e. every month we liquidate the portfolio formed K-J months ago and invest into a new portfolio. By contrast, the FF5 factor returns are constructed by sorting stocks into portfolios only once a year, and they are sorted on variables (such as firm size) which are much more persistent than returns (Fama and French 2015).

The *6-month/6-month* strategy sorts stocks into deciles based on past *6-month* performance. Whenever a winner (loser) portfolio is liquidated and replaced by new one, on average 86.21% (85.10%) of stocks in the portfolio are turned over. Since six portfolios are hold simultaneously, the actual monthly turnover of the six overlapping portfolios amounts to 14.37% and 14.18% on aggregate for winner and loser portfolios, respectively. These turnover ratios are extremely high compared to those of standard risk factors. For instance, portfolios formed based on market capitalization using NYSE breakpoints in June of each year show on average an *annual* turnover of only 5.22%. Hence, the composition of winner and loser portfolios is highly variable over time.

Further, most stocks in our sample with a valid ranking based on past six months performance show up in winner and loser portfolios. In particular 77.64% (81.03%) of stocks are sorted at least once into winner (loser) portfolios. This poses challenges on the estimation of betas at the portfolio level.

3.2.2 Cyclical Factor Exposure

Varying portfolio composition is not a problem if at least the factor exposures of stocks that enter/exit the portfolios are similar. This is not the case for momentum portfolios. Factor exposures of stocks that enter the winner and loser portfolios are pro-cyclical with respect to lagged factor realization.

For instance, consider the following insight of Grundy and Martin (2001) and Daniel and Moskowitz (2016). Assume that returns are generated by a simple one-factor model (CAPM). If the market premium is positive (negative) during the formation period, the winner portfolios will on average consist of high (low) beta stocks and the loser portfolio will consist of low (high) beta stocks. The winner-minus-loser portfolios will have positive (negative) beta. Hence, winner-minus-loser portfolios' factor exposure is time-varying and dependent on past factor realizations. Further, assume that momentum portfolios load equally often positively or negatively on the market factor.[10] Using portfolio returns to calculate factor sensitivities, it might spuriously seem that momentum portfolios have no significant risk exposure when they indeed are exposed to risk.

This observation can be carried over to multi-factor models. If returns are generated by a FF5 model, winner-minus-loser portfolios will on average load positively (negatively) on risk factors when factor realizations are positive (negative) during the formation period (all else equal).

3.2.3 Empirical Tests

In the previous section, we made the assertion that risk of momentum portfolios depends on past factor realizations and that risk adjustment at the portfolio level fails to detect fluctuations in betas. We distinguish in the following between an unconditional model and conditional model to analyze risk exposure. The unconditional model estimates factor sensitivities as in Equation 3 at the portfolio level over the full sample. The conditional model relates factor sensitivities to formation period factor realizations.

We focus for simplicity on the *6-month/6-month* strategy and rewrite the unconditional regression model presented in Equation 3, i.e.

$$r_{\theta,t}^{6,6} - r_{f,t} = \alpha_{\theta}^{6,6} + \sum_{j} \beta_{\theta,j}^{6,6} f_{j,t} + \epsilon_{\theta}^{6,6}, \tag{9}$$

where $r_{\theta,t}^{6,6}$ is the return of the *6-month/6-month* strategy's winner and loser portfolios and $r_{f,t}$ is the return of the risk-free rate (both at time t). The $\beta_{\theta,j}^{6,6}$ are factor sensitivities and $f_{j,t}$ are factor realizations at time t. In following representations, we drop the superscripts (e.g. we refer to the returns of the *6-month/6-month* strategy by $r_{\theta,t}$).

We show results in Table 4 Panel A. Winner and loser portfolios have market betas of 0.978 and 1.031. Both estimates are close to one. This is not surprising since we know that a large fraction of all stocks enter at least once winner and loser portfolios (see Section 3.2.1). As outlined in Section 3.2.2, it indeed seems that the winner-minus-loser portfolio has no significant exposure to the market factor with a beta of -0.053. The coefficient is not different from zero (t-ratio: -0.71). The only significant factor for the winner-minus-loser portfolio is the book-to-market factor (-0.464, t-ratio: -2.39). Even though this factor is significant, the magnitude of the estimated beta is low.

[10]The market premium was negative in approximately 40.36% of months from June 1963 until December 2018.

The winner-minus-loser portfolio loads positively on the other factors but none of the betas shows significance. The alpha equals 0.008 (compare Table 2: 0.0077) and is significant at the 1% level. According to this model, the *6-month/6-month* strategy has little to no risk exposure.

Momentum strategies lead frequently to large losses. These losses particularly tend to occur after market declines (Daniel and Moskowitz 2016). Hence, we know that momentum strategies are exposed to systematic risk and the unconditional model seems to be ill-suited. We use a conditional model as in Grundy and Martin (2001) to show that betas depend on past factor realizations, i.e.

$$r_{\theta,t} - r_{f,t} = \alpha_\theta + \sum_j \sum_\delta \beta^\delta_{\theta,j} D^\delta_{j,t} f_{j,t} + \epsilon_\theta, \tag{10}$$

where down, flat, and up interaction terms for every risk factor are used. Dummy variables $D^\delta_{j,t}$ ($\delta \in \{down, flat, up\}$) for the down (up) interaction terms are equal to one if the cumulative return for the respective factor over the last six months, i.e. during the formation period, is at least one standard deviation below (above) its monthly mean return:[11]

$$D^\delta_{j,t} = \begin{cases} 1, & if \sum_{\tau=t-6}^{t-1} r_{j,\tau} \text{ is of type } \delta; \\ 0, & \text{otherwise.} \end{cases} \tag{11}$$

As in the previous regression model, $r_{\theta,t}$ is the return of the *6-month/6-month* strategy's winner and loser portfolios and $r_{f,t}$ is the return of the risk-free rate (both at time t). $\beta^\delta_{\theta,j}$ are factor sensitivities dependent on past factor realizations.

We show results in Table 4 Panel B. The upside beta is larger than the downside beta for all factors. The spread in factor exposures following positive and negative realizations during the formation period is mostly larger than the betas estimated in Panel A. For instance, the downside beta of the winner-minus-loser portfolio for the market factor is -0.244 (t-ratio: -2.98) whereas the upside beta is 0.174 (t-ratio: 2.38). Hence, the momentum portfolio loads positively (negatively) on the market when six month cumulative return is at least one standard deviation above (below) average during the formation period. The conditional model better captures the variation in the risk exposure of momentum portfolios. The alpha is lower (0.004) but still significant at the 5%

[11] Both the standard deviation and mean are calculated over a rolling window of 36 months. All regressions use the full-sample.

level. The assumption that risk exposure of portfolios is stable over time, which would allow to adjust risk by using portfolio returns, seems to be violated for momentum portfolios.[12]

[Insert Table 4 about here]

The conditional model provides evidence that factor exposure of momentum portfolios varies over time but it still does not fully capture momentum returns as stock-level risk adjustment does. In Figure 2, we depict portfolio-level beta (black line) and average stock-level beta (grey line) for the market factor at each point in time. We also show six month cumulative return of the market factor (demeaned and scaled by standard deviation; red line).

The portfolio-level beta (-0.053) is by construction constant throughout the sample period. The average stock-level beta has a similar mean (-0.017) but varies throughout the sample period depending on the market factor's past return. The correlation between average stock-level beta and past cumulative return is approximately 0.65. Whenever cumulative return is below its mean return, e.g. during the financial crisis in 2007-2009, the winner-minus-loser portfolio tends to have negative beta (e.g. -1.16 in April 2009). Vice versa, whenever cumulative market return is above its mean, e.g. during the recovery of markets in 2010, the winner-minus-loser portfolio tends to have positive beta (e.g. 1.21 in February 2010). The relation of the average stock-level betas of the other factors with the factors' past cumulative return is even stronger. Hence, the example given in Section 3.2.2 seems to accurately describe the risk exposure of momentum portfolios. We conclude that it is reasonable to adjust risk of momentum portfolios at the stock level.

[Insert Figure 2 about here]

4 Extensions

Evidence so far suggests that momentum returns are lower and less significant than documented in the literature. The following sections are concerned with the robustness of the findings. Unless indicated otherwise, the *6-month/6-month* strategy is used to test for robustness. Formation and

[12]Some t-ratios, e.g. of $\beta^{Down}_{Winner,\,MKTRF}$ and $\beta^{Down}_{Loser,\,MKTRF}$, may appear quite high. Grundy and Martin (2001) report t-ratios of similar magnitude.

holding periods of six months are a reasonable trade-off between the minimum (3 months) and maximum lengths (12 months). This strategy is used fairly often in the literature, e.g. it is used by Jegadeesh and Titman (1993) for further analyses as well.

4.1 Sub-Periods and Models

Whereas the previous analyses used the full sample, in this part, we extend the analysis by looking in detail at various sub-periods. We show results for the complete period (1963-2018), the period used in Jegadeesh and Titman (1993) (1965-1989), and three other periods (1963-1979, 1980-1999, and 2000-2018). Further, we test different factor pricing models.

We show results in Table 5. Panel A presents returns when risk is adjusted by a CAPM. Before focusing at the risk-adjusted returns, it is worthwhile to have a look at the non-adjusted momentum returns during the sub-periods (row 1 in Panel A). For the complete period, estimated momentum returns are on average 0.75% per month (compare Table 1). In the period originally used in Jegadeesh and Titman (1993), mean return is 1.11%.[13] Likewise, we find momentum returns of 0.94% and 1.30% for the periods from 1963-1979 and from 1980-1999. Only in the last period, i.e. from 2000-2018, we find negative returns on average. Except for the last period, all momentum returns are significantly different from zero well above the 1% level. Returns are larger after portfolio-level risk adjustment using a CAPM. This holds for all sub-periods. For instance, momentum returns are 0.78% per month for the whole sample. When returns are adjusted at the stock-level, at least part of the momentum returns that are left unexplained by portfolio-level risk adjustment is captured. Momentum returns are lower by approximately 15% for the complete period (0.66% per month). However, they remain highly significant.

In Panel B, we add more factors and use an FF3 model. Portfolio-level risk adjustment leads to even higher momentum returns than in Panel A. Mean returns over the full sample are 0.91%. In addition, every sub-period shows higher returns as well. However, if risk is adjusted at the stock-level, the FF3 model captures approximately 57% of the returns. The momentum return of 0.39% per month is significantly different from zero at the 5% only. We make the same observation for the period from 1963-1979. For the period from 1965-1989 and 1980-1999, momentum returns are still significant at the 1% level.

[13]This estimate is almost identical to the estimate Jegadeesh and Titman (1993) report in Table 1 (1.10%).

Panel C presents results for an FF5 model. As already shown in Table 3, stock-level risk-adjusted returns are only 0.11% per month and not significant (t-ratio: 0.53) for the full sample. In every sub-period, momentum returns are reduced. Stock-level risk adjustment performs better in later periods. Momentum returns are not significant for the 1980-1999 and 2000-2018 periods. They remain significant at the 1% and 5% level for the period used in Jegadeesh and Titman (1993) and the period from 1963-1979 but they are lower by approximately 45% and 38%. Focusing on the mean return of 0.64% in the Jegadeesh and Titman (1993) period, we note two things. First, in hindsight, with more advanced factor models at hand, the reported t-statistic of 2.57 misses *in sample* the required historical adjusted cut-off of Harvey et al. (2015).[14] Second, it is not clear whether momentum returns (particularly in early periods) could have been profitably exploited.

For that reason, we consider an FF5 model with transaction costs in Panel D. We proxy transaction costs by using the CRSP closing spread. Whenever a position is entered or exited the stock-specific half spread is used. If the spread data is missing we use the median spread. Since momentum relies on trading in illiquid assets that likely have higher spreads than the median stock in our sample (Lesmond et al. 2004), our estimate of transaction costs is still conservative. If we take transaction costs into account, the momentum strategy leads in no sub-period to positive returns (before risk-adjustment). For instance, the mean return over the full sample is only -0.18%. After stock-level risk adjustment, we even find negative returns of approximately -0.80% per month that are significantly different from zero at the 1% level.

We summarize our evidence during sub-periods and across models as follows. Risk-adjusted momentum returns are lower when risk is adjusted at the stock-level. This holds for the CAPM, an FF3 model, and an FF5 model. Sub-periods might show significant returns after stock-level risk adjustment, but it is not clear whether investors could have made use of these opportunities.

[Insert Table 5 about here]

[14] Harvey et al. (2015) use the Holm-Bonferroni adjustment (Holm 1979) to deduce critical t-values to control for multiple testing problems with respect to other risk factors tested in the literature.

4.2 Short- and Long-term Betas

In our main analysis, we rely on betas estimated over the last 36 months. We now start to relax this assumption. Table 6 shows results for betas estimated over the last 24 months (Panel A) and over the last 60 (Panel B) months. The presented evidence still is at odds with the momentum effect and confirms the previous findings.

Panel A shows that average momentum returns after stock-level risk adjustment are lower when betas are estimated over shorter windows.[15] The momentum effect is virtually non-existent for all strategies. For instance, the *6-month/6-month* strategy delivers a monthly risk-adjusted return of only 0.04%. The strategy's mean return not only misses any statistical significance (t-ratio: 0.19) but also economic significance. Implementing the strategy would result on average in a cumulative return of only approximately 0.5% per year. Four strategies (*6-month/3-month*, *6-month/12-month*, *9-month/12-month*, and *12-month/9-month*) even deliver on average negative returns.

Conversely, Panel B shows that average momentum returns are larger and more significant when betas are estimated over longer intervals. As in Panel A, no strategy delivers returns that are different from zero at conventional significance levels. For instance, the *6-month/6-month* strategy generates a return of 0.24% per month. The return is not significantly different from zero (t-ratio: 1.33). One strategy (*12-month/12-month*) generates negative returns on average.

[Insert Table 6 about here]

4.3 Size Sub-Samples

All previous analyses used equal-weighted returns. Hence, micro stocks that comprise approximately 50% of our sample but only make up a small fraction of total market capitalization are over-weighted. These stocks might drive our results. We address this concern by sorting stocks each month into different size classes. Micro stocks are firms with market capitalization below the 20^{th} NYSE percentile, small stocks are firms with market capitalization above the 20^{th} and below the 50^{th} NYSE percentiles, and big stocks are firms with market capitalization above the 50^{th}

[15] Please note that risk adjustment at time t is based on beta estimates calculated from $t-24$ until $t-1$.

NYSE percentile. We sort stocks into ten portfolios based on prior *6-month* returns and construct zero-cost portfolios for each size class separately.

We display results in Table 7. The first column shows non-adjusted, portfolio-level adjusted, and stock-level adjusted returns for all stocks and summarizes previous findings. The third, fifth, and seventh columns show returns for micro, small, and big stocks. The non-adjusted returns of the winner-minus-loser portfolios are 0.72%, 0.97%, and 0.72% for micro, small, and big stocks. They are different from zero at the 1% significance level. Adjusting returns for risk at the portfolio level does not alter results much (0.67%, 1.08%, and 0.81%) and returns are still significant at the 1% level. The finding that momentum is pervasive for all size groups when accounting for risk at the portfolio level is consistent with previous evidence (Fama and French 2008; Israel and Moskowitz 2013). Stock-level risk adjustment renders returns insignificant for all size classes. The monthly average returns of winner-minus-loser portfolios are 0.10%, 0.24%, and 0.16% for micro, small, and big stocks and not significantly different from zero at conventional significance levels. The reduction in returns is of similar magnitude for all size classes. Hence, we conclude that our finding is not driven by micro stocks.

[Insert Table 7 about here]

4.4 Risk-Managed Momentum

Barroso and Santa-Clara (2015) use a risk-managed momentum strategy and show that the Sharpe ratio of the strategy almost doubles compared to a conventional momentum strategy. We follow Barroso and Santa-Clara (2015) and construct the same risk-managed strategy. We first calculate daily returns of the *6-month/6-month* strategy. We then compute the strategy's mean squared daily return over the last six months, i.e. over the last 126 trading days. Thereafter, we multiply the mean by 21 to obtain our forecast of monthly variance, i.e.

$$\hat{\sigma}^2_{WML,t} = 21 \sum_{j=0}^{125} r^2_{WML,d_{t-1}-j}/126, \tag{12}$$

where $\hat{\sigma}^2_{WML,t}$ is the variance forecast for the next month and $r_{WML,d_{t-1}}$ is the daily return of the *6-month/6-month* strategy on day $t-1$. We then estimate the returns of the risk-managed momentum strategy by

$$r_{WML^*,t} = \frac{\sigma_{target}}{\hat{\sigma}_t} r_{WML,t}, \tag{13}$$

where $r_{WML,t}$ and $r_{WML^*,t}$ are the monthly returns of the conventional and risk-managed momentum strategies. As Barroso and Santa-Clara (2015) do, we choose a target volatility σ_{target} that corresponds to an annualized volatility of 12%. The scaling parameter $\frac{\sigma_{target}}{\hat{\sigma}_t}$ determines the aggressiveness with which the strategy is implemented.

We show results in Table 8. The risk-managed momentum strategy produces on average a raw return of 1.38% per month. This return is statistically different from zero well above the 1% level (t-ratio: 6.55) and considerably larger than the conventional strategy's return (0.75%, compare Table 1). Portfolio-level risk adjustment increases the return to 1.43% per month and the strategy's return remains significant (t-ratio: 6.73). Stock-level risk adjustment captures a large fraction of the returns after portfolio-level risk adjustment. The monthly mean return of 0.44% is not significantly different from zero (t-ratio:1.57) and shows the effectiveness of our risk adjustment.

[Insert Table 8 about here]

4.5 International Evidence

We obtain international stock return data for 22 developed countries from Thomson Reuters Datastream. The data provided by Thomson Reuters contains more data errors than the data provided by CRSP.[16] Hence, we apply a number of data filters and largely follow Hong et al. (2003) and Chui et al. (2010) to screen out erroneous observations. Our final sample contains 20 countries and spans the period from 1990-2018. We provide a detailed summary of our sample construction in Appendix B.

We show results in Table 9. Without any risk-adjustment, we find significant momentum returns in all countries except for Japan and the US (column 2 and 3).[17] Momentum returns are statistically different from zero at the 5% level in two countries (Greece and Hong Kong). They are significant

[16] For instance, we find daily returns larger than 1,000% for almost every country in our sample.

[17] The finding that there is no momentum in Japan is consistent with existing literature (Griffin et al. 2003; Chui et al. 2010). Momentum returns in the US marginally miss significance at the 10% level. We attribute this to the sample period (1990-2018). As described in Section 4.1, average momentum returns have been negative in the US for the period from 2000 until 2018.

at the 1% level for all other countries. We find the highest momentum returns in Canada (1.55%), Australia (1.18%), and Denmark (0.97%).

Portfolio-level risk adjustment explains (if any) only a small fraction of momentum returns (column 4 and 5). All countries (except for Sweden) that showed significant momentum returns before risk adjustment also show significant momentum returns after portfolio-level risk adjustment. By contrast, stock-level risk adjustment captures a large fraction of momentum returns that are left unexplained by portfolio-level risk adjustment (column 6 and 7). Momentum returns are lower in all countries except for Sweden. For instance, Canada shows large and significant momentum returns before risk adjustment (1.55%; t-ratio: 4.98) and after portfolio-level risk adjustment (1.25%; t-ratio: 4.03) but not after stock-level risk adjustment (0.23%; t-ratio: 0.36).

We want to highlight that we still find momentum returns that are statistically different from zero after stock-level risk adjustment at the 10% level in one country (Norway), at the 5% level in one country (Denmark), and at the 1% level in two countries (Belgium and Switzerland). However, the countries with the largest stock markets, measured by the number of firms in our samples (i.e. Australia, Japan, France, Germany, UK, and Canada), do not show any significant momentum returns. A couple of countries (i.e. Hong Kong, Japan, Finland, Greece, UK, and US) show even negative momentum returns after stock-level risk adjustment.

Further, we want to highlight that when testing for significant momentum returns in a large sample of different countries t-statistics should be adjusted to account for multiple testing problems (e.g. Bonferroni adjustment). Comparing the t-ratios in Table 9 with the usual cut-offs rather overstates the significance of the momentum anomaly. Hence, we regard the momentum returns' low significance after stock-level risk adjustment as strong evidence against the momentum effect.

[Insert Table 9 about here]

5 Conclusion

There are good reasons to estimate betas by using portfolio returns. For instance, both measurement errors and changes in the betas might occur. However, neither the composition nor the risk exposure of momentum portfolios are stable enough to justify the use of the portfolio's return history to calculate factor sensitivities. In fact, momentum portfolios are characterized by extremely time-varying risk exposure. Hence, it is not appropriate to use portfolio-level risk adjustment in the context of momentum portfolios. To obtain betas for momentum portfolios, we claim that factor sensitivities should be calculated for individual stocks and that these factor sensitivities should be used to estimate the true risk exposure of momentum portfolios.

We show that a Fama and French 5-factor model explains a large fraction of momentum returns if factor sensitivities are calculated for individual stocks. Our findings are robust. For every sub-period in our sample, a Fama and French 5-factor model that is applied at the stock level captures a large part of the momentum anomaly. Regardless of whether we calculate betas for individual stocks over rolling windows of 24, 36, or 60 months, all 16 *J-month/K-month* strategies deliver returns that are not significantly different from zero at reasonable significance levels. Our findings are not driven by small capitalization stocks and our findings hold for micro, small, and big stocks. If we exploit any predictability in the momentum strategies' crash risk, we still do not find significant momentum returns. Even out-of-sample, i.e. in a large sample of developed countries, an international version of the Fama and French 5 factor model explains a large fraction of momentum returns.

We show that the momentum effect is less of a challenge to the efficient markets hypothesis than previously thought of. When analyzing long-term return anomalies, Fama (1998) pointed out that if "[i.] *a reasonable change in the method of estimating abnormal returns* [ii.] *causes an anomaly to disappear,* [iii.] *the anomaly is on shaky footing, and it is reasonable to suggest that it is an illusion"*. We are convinced that i.) our suggested change in the method of estimating abnormal returns is reasonable. Further, we show that ii.) momentum returns are lower and less significant than previously assumed. Further research is necessary to claim that iii.) the momentum effect is an illusion.

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A Appendix - Figures and Tables

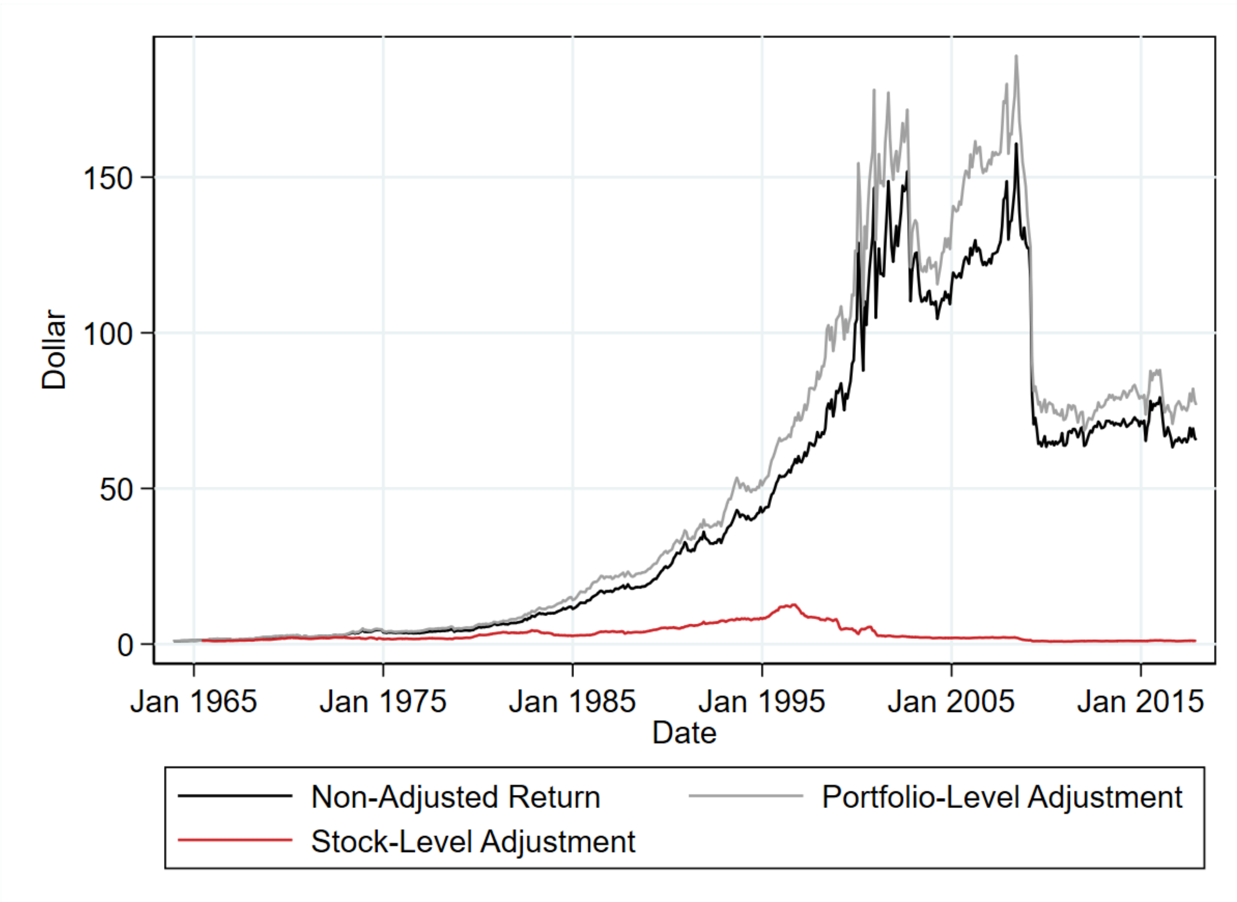

Figure 1: Momentum Profitability

This figure shows the cumulative return of the equal-weighted 6-*month*/6-*month* strategy. Stocks are ranked into ten portfolios based on their prior *6-month* performance. The winner (loser) portfolios consist of the ten percent best (worst) performing stocks of the formation period. Winner-minus-loser portfolios are held for the next *6-months*. One week is skipped between formation and holding period. Each month, six portfolios are held simultaneously. The black, grey, and red lines show non-adjusted, portfolio-level adjusted, and stock-level adjusted cumulative return. An FF5 model is used to adjust returns.

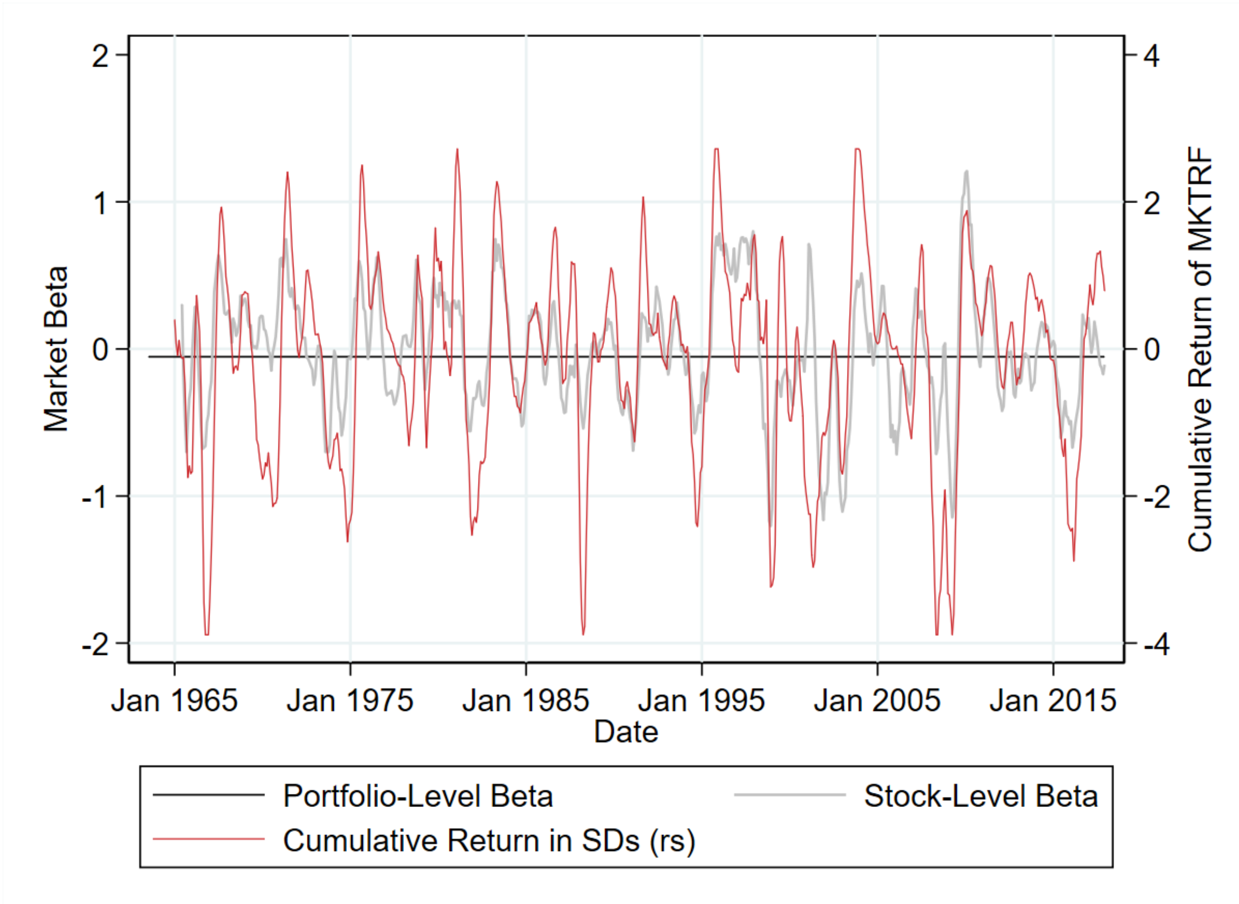

Figure 2: Market Factor Exposure

This figure shows beta estimates of the equal-weighted 6-*month*/6-*month* strategy for the market factor. The full-sample portfolio-level beta of the winner-minus-loser portfolio is depicted by the black line. The average stock-level beta of all stocks in the winner-minus-loser portfolio is depicted by the grey line. The factor's cumulative returns over the last six months (demeaned and scaled by standard deviation) is depicted by the red lines.

Table 1: Returns of Momentum Strategies

This table shows the monthly mean returns of the equal-weighted *J-month/K-month* strategies of Jegadeesh and Titman (1993). Stocks are ranked into ten portfolios based on their prior *J-month* performance. The winner (loser) portfolios consist of the ten percent best (worst) performing stocks of the formation period. Winner-minus-loser portfolios are held for the next *K-months*. One week is skipped between formation and holding period. Each month, K portfolios are held simultaneously. The *J-month* formation and the *K-month* holding periods are indicated in the first column and row, respectively. T-ratios are calculated using Newey and West (1987) standard errors.

	K =							
J =	3	t-ratio	6	t-ratio	9	t-ratio	12	t-ratio
3 Sell	0.0078	2.82	0.0081	2.92	0.0087	3.17	0.0091	3.43
3 Buy	0.0127	5.02	0.0135	5.22	0.0139	5.32	0.0137	5.29
3 Buy-Sell	0.0049	3.30	0.0054	4.19	0.0052	4.31	0.0046	3.99
6 Sell	0.0070	2.44	0.0077	2.67	0.0081	2.87	0.0093	3.37
6 Buy	0.0146	5.76	0.0152	5.77	0.0150	5.60	0.0141	5.36
6 Buy-Sell	0.0076	4.28	0.0075	4.53	0.0069	4.31	0.0048	3.22
9 Sell	0.0070	2.37	0.0076	2.58	0.0087	3.01	0.0101	3.57
9 Buy	0.0155	5.99	0.0155	5.70	0.0146	5.37	0.0136	5.10
9 Buy-Sell	0.0085	4.61	0.0079	4.47	0.0060	3.37	0.0036	2.18
12 Sell	0.0069	2.37	0.0086	2.87	0.0098	3.34	0.0112	3.91
12 Buy	0.0148	5.67	0.0146	5.37	0.0138	5.07	0.0130	4.85
12 Buy-Sell	0.0079	4.21	0.0061	3.25	0.0040	2.17	0.0018	1.06

Table 2: Portfolio-Level Risk Adjustment

This table shows the monthly mean returns of the equal-weighted *J-month/K-month* strategies of Jegadeesh and Titman (1993). Stocks are ranked into ten portfolios based on their prior *J-month* performance. The winner (loser) portfolios consist of the ten percent best (worst) performing stocks of the formation period. Winner-minus-loser portfolios are held for the next *K-months*. One week is skipped between formation and holding period. Each month, *K* portfolios are held simultaneously. The *J-month* formation and the *K-month* holding periods are indicated in the first column and row, respectively. Factor sensitivities for the FF5 model are calculated at the **portfolio level** using the full sample. T-ratios are calculated using Newey and West (1987) standard errors.

	K =							
J =	3	t-ratio	6	t-ratio	9	t-ratio	12	t-ratio
3 Sell	-0.0012	-1.13	-0.0014	-1.42	-0.0010	-0.98	-0.0007	-0.69
3 Buy	0.0037	4.72	0.0042	6.41	0.0044	7.11	0.0043	7.15
3 Buy-Sell	0.0049	3.38	0.0056	4.34	0.0054	4.35	0.0049	4.21
6 Sell	-0.0020	-1.67	-0.0017	-1.49	-0.0014	-1.29	-0.0006	-0.51
6 Buy	0.0056	6.64	0.0060	7.41	0.0057	7.13	0.0049	6.62
6 Buy-Sell	0.0076	4.43	0.0077	4.64	0.0071	4.42	0.0055	3.64
9 Sell	-0.0023	-1.82	-0.0020	-1.68	-0.0012	-0.94	-0.0001	-0.06
9 Buy	0.0066	7.41	0.0064	7.42	0.0056	6.55	0.0047	6.03
9 Buy-Sell	0.0089	4.92	0.0085	4.76	0.0068	3.86	0.0047	2.93
12 Sell	-0.0025	-1.98	-0.0014	-1.09	-0.0004	-0.31	0.0007	0.59
12 Buy	0.0062	6.89	0.0059	6.70	0.0051	5.97	0.0042	5.52
12 Buy-Sell	0.0087	4.77	0.0073	3.96	0.0054	3.03	0.0035	2.12

Table 3: Stock-Level Risk Adjustment

This table shows the monthly mean returns of the equal-weighted *J-month/K-month* strategies of Jegadeesh and Titman (1993). Stocks are ranked into ten portfolios based on their prior *J-month* performance. The winner (loser) portfolios consist of the ten percent best (worst) performing stocks of the formation period. Winner-minus-loser portfolios are held for the next *K-months*. One week is skipped between formation and holding period. Each month, *K* portfolios are held simultaneously. The *J-month* formation and the *K-month* holding periods are indicated in the first column and row, respectively. Factor sensitivities for the FF5 model are calculated at the **stock level** over the last 36 months. T-ratios are calculated using Newey and West (1987) standard errors.

	K =							
J =	3	t-ratio	6	t-ratio	9	t-ratio	12	t-ratio
3 Sell	0.0025	2.15	0.0022	1.79	0.0023	1.91	0.0025	2.07
3 Buy	0.0024	2.18	0.0027	3.08	0.0030	3.84	0.0027	3.87
3 Buy-Sell	-0.0001	-0.05	0.0005	0.31	0.0006	0.41	0.0002	0.14
6 Sell	0.0026	1.92	0.0026	1.88	0.0028	2.00	0.0032	2.27
6 Buy	0.0034	2.97	0.0038	3.68	0.0034	3.59	0.0030	3.68
6 Buy-Sell	0.0008	0.38	0.0011	0.53	0.0006	0.28	-0.0001	-0.06
9 Sell	0.0028	2.01	0.0029	1.94	0.0031	2.07	0.0036	2.36
9 Buy	0.0044	3.76	0.0038	3.54	0.0034	3.43	0.0030	3.40
9 Buy-Sell	0.0015	0.69	0.0009	0.40	0.0003	0.13	-0.0005	-0.26
12 Sell	0.0030	2.12	0.0033	2.22	0.0037	2.42	0.0039	2.58
12 Buy	0.0034	3.05	0.0034	3.28	0.0031	3.10	0.0031	3.36
12 Buy-Sell	0.0005	0.21	0.0001	0.04	-0.0007	-0.31	-0.0008	-0.39

Table 4: Dynamic Factor Exposure

This table shows conditional and unconditional factor exposure of winner-minus-loser, winner, and loser portfolio of the equal-weighted 6-*month*/6-*month* strategy. Panel A shows results for the full-sample unconditional betas that are used for adjusting returns in Table 2. Panel B shows results for betas conditioned on past factor realizations. Portfolio excess return is regressed on down, flat, and up interaction terms with the FF5 factors. Dummy variables for the down (up) interaction term are equal to one if the cumulative return for each factor over the last six months was at least one standard deviation below (above) its mean. Both standard deviation and mean are calculated over the last 36 months. T-ratios are calculated using Newey and West (1987) standard errors.

	Winner-Loser		Winner		Loser	
Parameter	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Panel A: Unconditional Model						
β_{MKTRF}	-0.053	-0.71	0.978	34.30	1.031	19.11
β_{SMB}	0.030	0.21	0.900	15.27	0.870	9.22
β_{HML}	-0.464	-2.39	-0.254	-3.34	0.210	1.61
β_{RMW}	0.176	0.69	-0.235	-2.42	-0.411	-2.42
β_{CMA}	0.417	1.46	0.016	0.15	-0.401	-2.08
$Intercept$	0.008	3.31	0.006	6.18	-0.002	-1.04
Panel B: Conditional Model						
β^{Down}_{MKTRF}	-0.244	-2.98	0.902	24.83	1.146	18.01
β^{Flat}_{MKTRF}	0.295	3.31	1.125	24.98	0.830	14.62
β^{Up}_{MKTRF}	0.174	2.38	1.051	34.12	0.877	13.32
β^{Down}_{SMB}	-0.566	-3.81	0.653	9.44	1.219	11.43
β^{Flat}_{SMB}	-0.206	-1.11	0.858	9.94	1.064	8.93
β^{Up}_{SMB}	0.447	4.19	1.047	13.43	0.600	10.23
β^{Down}_{HML}	-0.657	-3.56	-0.237	-3.07	0.420	3.12
β^{Flat}_{HML}	-0.491	-1.94	-0.290	-2.48	0.201	1.32
β^{Up}_{HML}	0.086	0.82	-0.080	-1.30	-0.166	-2.39
β^{Down}_{RMW}	-0.271	-1.09	-0.426	-3.48	-0.155	-0.98
β^{Flat}_{RMW}	0.558	3.19	-0.158	-1.48	-0.716	-6.70
β^{Up}_{RMW}	0.553	3.86	-0.062	-0.96	-0.615	-5.92
β^{Down}_{CMA}	-0.060	-0.30	-0.205	-2.09	-0.145	-0.94
β^{Flat}_{CMA}	0.044	0.18	-0.128	-1.32	-0.172	-0.99
β^{Up}_{CMA}	0.224	0.93	-0.062	-0.58	-0.286	-1.76
$Intercept$	0.004	2.26	0.005	5.64	0.001	0.53

Table 5: Momentum Returns across Models and during Subperiods

This table shows the monthly mean return of the equal-weighted 6-*month*/6-*month* strategy. Stocks are ranked into ten portfolios based on their prior *6-month* performance. The winner (loser) portfolios consist of the ten percent best (worst) performing stocks of the formation period. One week is skipped between formation and holding period. Each month, six portfolios are held simultaneously. Results are shown for non-adjusted, portfolio-level adjusted, and stock-level adjusted returns for the complete, Jegadeesh and Titman (1993), 1963-1979, 1980-1999, and 2000-2018 periods. A CAPM, FF3, and FF5 model are used to adjust returns (Panel A, B, and C). Panel D also considers a version of the FF5 model that takes into account transaction costs by including costs induced by the bid-ask spreads. T-ratios are calculated using Newey and West (1987) standard errors.

	All	t-ratio	JT Period	t-ratio	1963-1979	t-ratio	1980-1999	t-ratio	2000-2018	t-ratio
Panel A: CAPM										
Non-adjusted	0.0075	4.53	0.0111	5.77	0.0094	3.43	0.0130	7.48	-0.0004	-0.11
Portfolio-level	0.0078	4.77	0.0113	5.94	0.0095	3.57	0.0136	7.60	-0.0001	-0.03
Stock-level	0.0066	4.02	0.0103	5.24	0.0084	3.17	0.0134	6.98	-0.0024	-0.80
Panel B: FF3 Model										
Non-adjusted	0.0075	4.53	0.0111	5.77	0.0094	3.43	0.0130	7.48	-0.0004	-0.11
Portfolio-level	0.0091	5.51	0.0129	6.81	0.0110	4.03	0.0148	9.03	0.0011	0.32
Stock-level	0.0039	2.19	0.0079	3.66	0.0068	2.47	0.0082	3.86	-0.0031	-0.82
Panel C: FF5 Model										
Non-adjusted	0.0075	4.53	0.0111	5.77	0.0094	3.43	0.0130	7.48	-0.0004	-0.11
Portfolio-level	0.0077	4.64	0.0116	5.97	0.0102	3.56	0.0132	8.10	-0.0008	-0.22
Stock-level	0.0011	0.53	0.0064	2.57	0.0063	2.13	0.0030	0.89	-0.0052	-1.30
Panel D: FF5 Model and Transaction Costs										
Non-adjusted	-0.0018	-1.11	-0.0009	-0.41	-0.0021	-0.67	-0.0003	-0.14	-0.0033	-0.98
Portfolio-level	-0.0016	-1.00	-0.0003	-0.15	-0.0012	-0.39	-0.0001	-0.03	-0.0037	-1.09
Stock-level	-0.0080	-3.87	-0.0056	-2.18	-0.0054	-1.65	-0.0099	-3.15	-0.0080	-1.97

Table 6: Short-/Long-Term Beta Months

This table shows the monthly mean returns of the equal-weighted *J-month/K-month* strategies of Jegadeesh and Titman (1993). Stocks are ranked into ten portfolios based on their prior *J-month* performance. The winner (loser) portfolios consist of the ten percent best (worst) performing stocks of the formation period. Winner-minus-loser portfolios are held for the next *K-months*. One week is skipped between formation and holding period. Each month, K portfolios are held simultaneously. The *J-month* formation and the *K-month* holding periods are indicated in the first column and row. Factor sensitivities for the FF5 model are calculated at the **stock level** over the last **24 (60) months** in Panel A (B). T-ratios are calculated using Newey and West (1987) standard errors.

	K =							
J =	3	t-ratio	6	t-ratio	9	t-ratio	12	t-ratio
Panel A: Betas Calculated over 24 Months								
3 Sell	0.0021	1.67	0.0022	1.68	0.0023	1.75	0.0024	1.89
3 Buy	0.0024	1.86	0.0024	2.40	0.0028	3.31	0.0026	3.35
3 Buy-Sell	0.0002	0.11	0.0002	0.08	0.0006	0.33	0.0002	0.12
6 Sell	0.0027	1.86	0.0028	1.86	0.0029	1.94	0.0031	2.13
6 Buy	0.0027	2.13	0.0032	2.95	0.0030	2.98	0.0029	3.32
6 Buy-Sell	-0.0000	-0.01	0.0004	0.19	0.0001	0.07	-0.0002	-0.09
9 Sell	0.0029	1.96	0.0029	1.90	0.0030	1.96	0.0032	2.11
9 Buy	0.0038	3.12	0.0034	3.05	0.0033	3.11	0.0031	3.36
9 Buy-Sell	0.0010	0.41	0.0005	0.20	0.0002	0.10	-0.0001	-0.03
12 Sell	0.0028	1.98	0.0031	2.03	0.0032	2.10	0.0031	2.05
12 Buy	0.0030	2.59	0.0032	3.05	0.0032	3.12	0.0035	3.56
12 Buy-Sell	0.0002	0.07	0.0002	0.07	-0.0001	-0.02	0.0004	0.19
Panel B: Betas Calculated over 60 Months								
3 Sell	0.0021	1.96	0.0016	1.41	0.0016	1.44	0.0018	1.66
3 Buy	0.0025	2.61	0.0029	3.94	0.0033	4.93	0.0029	4.65
3 Buy-Sell	0.0004	0.23	0.0013	0.89	0.0017	1.25	0.0011	0.93
6 Sell	0.0019	1.56	0.0018	1.38	0.0018	1.43	0.0023	1.91
6 Buy	0.0038	3.70	0.0042	4.59	0.0039	4.56	0.0032	4.19
6 Buy-Sell	0.0019	0.98	0.0024	1.33	0.0021	1.20	0.0009	0.58
9 Sell	0.0020	1.54	0.0018	1.35	0.0022	1.61	0.0028	2.10
9 Buy	0.0049	4.63	0.0044	4.55	0.0039	4.24	0.0031	3.61
9 Buy-Sell	0.0029	1.45	0.0026	1.32	0.0017	0.91	0.0003	0.17
12 Sell	0.0019	1.46	0.0023	1.74	0.0029	2.06	0.0034	2.48
12 Buy	0.0040	3.80	0.0038	4.06	0.0033	3.59	0.0029	3.19
12 Buy-Sell	0.0021	1.03	0.0015	0.75	0.0005	0.23	-0.0005	-0.26

Table 7: Size-dependent Returns of Momentum Strategies

This table shows the monthly mean return of the equal-weighted 6-*month*/6-*month* strategy. Stocks are ranked into ten portfolios based on their prior *6-month* performance. The winner (loser) portfolios consist of the ten percent best (worst) performing stocks of the formation period. One week is skipped between formation and holding period. Each month, six portfolios are held simultaneously. Stocks are sorted and portfolios are formed for micro (firms with market capitalization below the 20^{th} NYSE percentile), small (above 20^{th} and below 50^{th} NYSE percentile), and big stocks (above 50^{th} NYSE percentile) separately. Results are shown for non-adjusted, portfolio-level adjusted, and stock-level adjusted returns. An FF5 model is used to adjust returns. T-ratios are calculated using Newey and West (1987) standard errors.

	All	t-ratio	Micro	t-ratio	Small	t-ratio	Big	t-ratio
Non-adjusted Return								
6-6 Sell	0.0077	2.67	0.0088	2.96	0.0055	1.80	0.0065	2.42
6-6 Buy	0.0152	5.77	0.0160	5.79	0.0153	5.40	0.0137	5.52
6-6 Buy-Sell	0.0075	4.53	0.0072	4.82	0.0097	4.79	0.0072	3.69
Portfolio-level Adjusted Return								
6-6 Sell	-0.0017	-1.49	-0.0013	-1.08	-0.0043	-3.17	-0.0018	-1.46
6-6 Buy	0.0060	7.41	0.0054	6.17	0.0064	6.38	0.0063	6.36
6-6 Buy-Sell	0.0077	4.64	0.0067	4.44	0.0108	5.34	0.0081	4.23
Stock-level Adjusted Return								
6-6 Sell	0.0026	1.88	0.0037	2.41	-0.0000	-0.01	0.0008	0.66
6-6 Buy	0.0038	3.68	0.0047	4.30	0.0024	1.77	0.0024	1.93
6-6 Buy-Sell	0.0011	0.53	0.0010	0.48	0.0024	0.92	0.0016	0.78

Table 8: Volatility-Managed Momentum

This table shows the monthly mean return of the equal-weighted and volatility-scaled 6-*month*/6-*month* strategy. Stocks are ranked into ten portfolios based on their prior *6-month* performance. The winner (loser) portfolios consist of the ten percent best (worst) performing stocks of the formation period. One week is skipped between formation and holding period. Each month, six portfolios are held simultaneously. Momentum returns are risk-managed in the fashion of Barroso and Santa-Clara (2015), i.e. variance is forecasted by $\hat{\sigma}^2_{WML,t} = 21\sum_{j=0}^{125} r^2_{WML,d_{t-1}-j}/126$ and forecasted variance is used to scale returns $r_{WML^*,t} = \frac{\sigma_{target}}{\hat{\sigma}_t} r_{WML,t}$. As Barroso and Santa-Clara (2015) do, we choose a target that corresponds to an annualized volatility of 12%. Results are shown for non-adjusted, portfolio-level adjusted, and stock-level adjusted returns. An FF5 model is used to adjust returns. T-ratios are calculated using Newey and West (1987) standard errors.

	Non-adjusted	t-ratio	Portfolio-level	t-ratio	Stock-level	t-ratio
6 Sell	0.0086	2.28	-0.0050	-3.51	0.0014	0.78
6 Buy	0.0223	5.96	0.0093	8.44	0.0058	4.26
6 Buy-Sell	0.0138	6.55	0.0143	6.73	0.0044	1.57

Table 9: International Evidence

This table shows the monthly mean returns of the equal-weighted 6-*month*/6-*month* strategy for a sample of 21 developed countries. In the fashion of Chui et al. (2010), stocks are ranked into three portfolios based on their prior *6-month* performance. The winner (loser) portfolios consist of the 33% percent best (worst) performing stocks of the formation period. One week is skipped between formation and holding period. Each month, six portfolios are held simultaneously. Results are shown for non-adjusted, portfolio-level adjusted, and stock-level adjusted returns. An international version of the FF5 model is used to adjust returns. Risk adjustment at the stock level uses Dimson betas with a lead and lag of one month to control for infrequent trading. T-ratios are calculated using Newey and West (1987) standard errors.

	Firms	Non-Adjusted	t-ratio	Portfolio-Level	t-ratio	Stock-Level	t-ratio
Asia & Pacific							
Australia	1,750	0.0118	5.32	0.0101	4.73	0.0031	0.68
Hong Kong	565	0.0070	2.44	0.0055	2.03	-0.0026	-0.49
Japan	4,712	-0.0007	-0.42	0.0001	0.03	-0.0061	-2.51
New Zealand	188	0.0075	4.00	0.0089	5.33	0.0032	0.98
Singapore	310	0.0087	2.70	0.0067	2.12	0.0017	0.24
Europe							
Austria	226	0.0070	3.20	0.0074	3.55	0.0033	1.05
Belgium	356	0.0072	3.84	0.0071	4.22	0.0055	2.72
Denmark	354	0.0097	5.72	0.0100	6.58	0.0062	2.41
Finland	255	0.0070	3.65	0.0043	2.26	-0.0003	-0.10
France	2,220	0.0062	3.75	0.0049	3.27	0.0035	1.35
Germany	2,030	0.0083	4.82	0.0054	3.56	0.0045	1.51
Greece	418	0.0054	2.09	0.0050	1.95	-0.0011	-0.23
Italy	608	0.0079	4.26	0.0071	4.16	0.0040	1.32
Netherlands	341	0.0070	3.61	0.0051	2.77	0.0045	1.54
Norway	513	0.0067	2.99	0.0061	2.90	0.0057	1.80
Portugal	199	0.0063	2.61	0.0053	2.24	0.0014	0.27
Sweden	951	0.0088	3.44	0.0033	1.39	0.0037	0.98
Switzerland	423	0.0076	3.63	0.0078	4.25	0.0067	3.00
UK	3,106	0.0065	3.56	0.0061	3.50	-0.0002	-0.06
North America							
Canada	5,147	0.0155	4.98	0.0125	4.03	0.0023	0.36
US	14,855	0.0031	1.64	0.0008	0.44	-0.0026	-0.77

B Appendix - Sample Construction (International Stock Returns)

International stock return data for 22 developed countries is downloaded from Thomson Reuters Datastream. To be included in our sample, as in Hong et al. (2003) and Chui et al. (2010), a stock must be listed on the major exchange(s) in the respective country. We include cross-listed stocks only in their home market.

We follow Hong et al. (2003) and Chui et al. (2010) and screen out a number of observations. First, we replace returns that are larger (smaller) than 100% (-95%) with the cut-off values. Second, in each month, we drop firms with market capitalization below the fifth percentile in the respective country. Third, we require at least 8 monthly observations for each firm. Fourth, we require at least 30 stocks for each country to be included in our analysis. Last, we drop countries with momentum portfolios that have a return history of less than five years. In addition to the filters of Hong et al. (2003) and Chui et al. (2010), we exclude stocks priced below 1 USD and stocks priced below 1 unit of the local currency.

In our sample remain 20 developed countries (not including the US), i.e. Australia (1,750 firms), Hong Kong (565), Japan (4,712), New Zealand (188), Singapore (310), Austria (226), Belgium (356), Denmark (354), Finland (255), France (2,220), Germany (2,030), Greece (418), Italy (608), Netherlands (341), Norway (513), Portugal (199), Sweden (951), Switzerland (423), UK (3,106), and Canada (5,147). Spain (43) and Ireland (74) drop out of our sample.

Moreover, we follow Chui et al. (2010) and apply a modified momentum strategy. The winner (loser) portfolios consist no longer of the ten percent best (worst) performing stocks over the formation period but of the 33% best (worst) performing stocks. This ensures that the momentum portfolios contain a sufficient number of stocks. The results are almost unchanged if we use decile sorts for the countries with the largest stock markets (i.e. Australia, Japan, France, Germany, UK, and Canada). We use the FF5 data for developed countries provided on Ken French's website to adjust returns and we use Dimson betas with a lead and lag of one month to control for infrequent trading.