CFR Working Paper NO. 20-09

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First version: October 13, 2020
This version: October 23, 2020

Abstract

Risk-adjusted momentum returns are usually estimated by sorting stocks into a regularly rebalanced long-short portfolio based on their prior return and then running a full-sample regression of the portfolio 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 high 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 20 developed countries, we conclude that the momentum effect may be much weaker than previously thought.

Keywords: Momentum, Risk adjustment, Time-series regression
JEL Classifications: C58, G12

*We thank Andreas Hackethal, Alexander Hillert and seminar participants at Leibniz Center for Research SAFE in Frankfurt, the BVI event of the Centre for Financial Research and the Universities of Graz and Mannheim for valuable comments.

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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."

(Fama (1998, p. 303))

1 Introduction

Momentum is the tendency of past winner stocks to outperform past loser stocks over the next couple of months (Jegadeesh and Titman 1993). It is one of the most well-documented and well-researched asset pricing anomalies. Yet, a convincing explanation for the existence of profitable momentum strategies is missing.[1] We thus do not know *why* momentum strategies seemingly allow investors to earn abnormal returns. The existence of momentum returns also poses a challenge to the concept of weak-form market efficiency as defined by Fama (1970). This paper contributes to a better understanding of the nature of the apparent profitability of momentum strategies. We argue that the usual procedure to adjust momentum profits for risk is insufficient, and that the profitability of the momentum strategy largely disappears when an appropriate adjustment procedure is implemented.

Previous papers usually estimate risk-adjusted momentum returns by sorting stocks into a long-short portfolio based on their prior return. The portfolio is rebalanced monthly. The returns of the momentum portfolio are then regressed on a set of factors in a full-sample regression. This methodology, which we denote *portfolio-level risk adjustment*, implicitly assumes constant factor exposure of the momentum portfolio. However, momentum portfolios are characterized by high turnover which results in strongly time-varying factor exposure.[2] We propose to estimate factor sensitivities at the stock level using a rolling window approach. For each month t we estimate the factor exposure for the stocks in the winner and the loser portfolio using data up to month $(t-1)$.

[1] Existing literature offers both behavioral and rational explanations for the existence of momentum in stock returns. Papers advocating a behavioral explanation include those of Chan et al. (1996), Barberis et al. (1998), Hong and Stein (1999), and Hong et al. (2000). These papers all consider some form of market underreaction as a source of momentum profits. Papers proposing rational explanations can be distinguished into those that consider macroeconomic risk (e.g. Chordia and Shivakumar 2002 and Griffin et al. 2003) and those that consider market frictions (e.g. Korajczyk and Sadka 2004 and Lesmond et al. 2004). Jegadeesh and Titman (2011) provide a survey of explanations of the momentum effect.

[2] Because the standard portfolio-level risk adjustment does not explain momentum profits researchers have augmented existing factor models by a momentum factor, resulting in e.g. the Carhart 4-factor model (Carhart 1997) or the Fama and French 6-factor model (Fama and French 2018).

We then estimate the expected return in month t for each stock. The momentum profit in month t is then the actual return of the long-short portfolio minus the weighted average of the expected returns of the individual stocks. This procedure, which we denote *stock-level risk adjustment*, accounts for the turnover in the momentum portfolio because, in each month, the factor exposure of the momentum portfolio is based on the actual composition of the winner and loser portfolios.

We implement the procedure using a sample of NYSE, Nasdaq and AMEX stocks covering the period 1963-2018. When constructing momentum portfolios we closely follow the procedure proposed by 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*. As Jegadeesh and Titman (1993) do, we choose $J, K \in \{3, 6, 9, 12\}$, resulting in a total of 16 strategies. Without risk adjustment 15 of the 16 strategies deliver returns that are positive and significantly different from zero. We then account for risk using portfolio-level risk adjustment based on the Fama and French (2015) 5-factor model. The adjustment has little effect on the profitability of the momentum portfolios. Again, 15 of the 16 strategies deliver significant abnormal returns.[3] However, when we implement the stock-level risk adjustment procedure the profitability largely disappears. The adjustment on average captures 94% of the momentum returns that remain after portfolio-level risk adjustment. *None* of the 16 strategies delivers returns that are significantly different from zero. Thus, and in contrast to the prior literature, we find that the Fama and French (2015) 5-factor model explains the profitability of momentum strategies.

When we split the sample into size groups we find no significant momentum returns for any size category (micro, small and large cap stocks) when risk is adjusted at the stock level. When we consider sub-periods we find that the momentum strategy earns significant abnormal returns after stock-level risk adjustment in the first part of the sample period (1963-1979) but not thereafter. However, even during this sub-period momentum returns are roughly 44% smaller if risk is adjusted at the stock level rather than at the portfolio level, and the corresponding t-statistic is 2.13 and

[3] Hou et al. (2015) show that their q-factor model captures momentum through the profitability factor, which is highly correlated with the Carhart (1997) momentum factor. The fact that the q-factor model explains momentum returns when portfolio-level risk adjustment is applied does not invalidate our analysis. Portfolio-level risk adjustment, by counterfactually assuming constant factor exposures, results in inaccurate risk adjustment irrespective of the results that the procedure delivers.

is thus clearly below the adjusted critical value proposed by Harvey et al. (2015). When we take transaction costs into account momentum profits become negative even for the first part of our sample period.

Besides these sample splits 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 20 developed countries. Without risk adjustment [with portfolio-level risk-adjustment] we find a significant momentum effect (at the 5% level or better) in 19 [16] countries. With stock-level risk-adjustment this number drops to 3.

While we use the Fama and French (2015) 5-factor model in our main analysis we also implement other models. The CAPM is unable to explain momentum returns even with stock-level risk adjustment. The Fama and French (1993) 3-factor model significantly reduces, but does not eliminate momentum returns. In contrast, the Fama and French (2015) 5-factor model as well as the Hou et al. (2015) q-factor model and the Hou et al. (2020) q^5-model result in insignificant abnormal returns. Thus, the profitability and investment factors appear to be necessary to explain momentum returns.

We also examine *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, it is well known that the factor exposures of momentum portfolios vary over time in a systematic way (Grundy and Martin 2001; Wang and Wu 2011; Daniel and Moskowitz 2016; Kelly et al. 2020). 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 therefore recommend that factor sensitivities and risk-adjusted returns of momentum portfolios should be estimated at the stock level.

Our paper is related to several strands of the literature. First, it relates to the extensive literature that documents momentum in equity markets.[4] Jegadeesh and Titman (1993) are the first to provide evidence of momentum in US stock returns. Momentum is pervasive; it exists across size groups (Fama and French 2008; Israel and Moskowitz 2013) and across countries (Rouwenhorst 1998; Griffin et al. 2003; Chui et al. 2010; Fama and French 2012; Asness et al. 2013). Barroso and Santa-Clara (2015) provide evidence that the risk of momentum strategies is predictable. Building on this insight they propose a volatility-scaled momentum strategy that delivers even higher abnormal returns than the standard strategy. Our paper complements this literature by showing that the existence and magnitude of momentum returns crucially depend on the way in which returns are adjusted for risk. If we adjust returns for risk at the stock level, the momentum effect disappears for the universe of NYSE, Nasdaq, and AMEX stocks. We further show that, with stock-level risk adjustment, there is no momentum in micro, small, or large cap stocks. Moreover, 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). Finally, we provide

[4] Momentum has also been documented for currencies (Okunev and White 2003; Menkhoff et al. 2012), commodity futures (Miffre and Rallis 2007; Asness et al. 2013), equity indices (Chan et al. 2000; Asness et al. 2013) and industries (Moskowitz and Grinblatt 1999).

evidence that the FF5 factors can explain momentum returns also in an international sample covering 20 developed countries if risk is adjusted at the stock-level.

Second, our paper relates to previous research analyzing the factor exposure of momentum portfolios. Grundy and Martin (2001), Wang and Wu (2011), Daniel and Moskowitz (2016), and Kelly et al. (2020), among others, make the observation that the factor exposure of momentum portfolios is time varying. Grundy and Martin (2001) hedge momentum portfolio returns against dynamic factor exposure. They analyze factor exposure for both winner and loser portfolios 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 proposed by Grundy and Martin (2001) assumes that future factor realizations are known at the time of portfolio formation. Their strategy is thus not implementable. Wang and Wu (2011) propose a procedure, based on the Fama and French (1993) 3-factor model, that is similar to our stock-level risk adjustment and find that it reduces momentum profits by 40%. Daniel and Moskowitz (2016) relate time-varying factor exposure to the occurrence of momentum crashes. Kelly et al. (2020) use instrumental principal component analysis (IPCA, Kelly et al. (2019)) to estimate a conditional factor model that captures the time-varying factor loadings of momentum and reversal strategies. Our paper contributes to this literature in several important ways. The stock-level risk adjustment procedure we advocate is simpler than the IPCA procedure proposed by Kelly et al. (2020) and is routed in the traditional regression-based asset pricing test framework. We show that the Fama and French (2015) 5-factor explains momentum profits when we adjust for risk at the stock level while the Fama and French (1993) 3-factor model does not. We further relate formation period factor realizations and holding period factor exposures (as Grundy and Martin (2001) do) to explain *why* stock-level portfolio adjustment is necessary to capture the time-varying factor exposure of momentum strategies.

Our results have important implications. First, they document that the apparent profitability of momentum strategies is, to a large extent, a compensation for risk. These strategies may thus be delivering risk premiums rather than abnormal returns. Second, the intuition of the stock-level risk adjustment procedure carries over to other applications. All investment strategies that are characterized by high portfolio turnover are potentially affected by time-varying factor exposures. Consequently, both researchers and portfolio managers may want to consider stock-level risk adjustment when evaluating investment strategies.

The remainder of the paper is organized as follows. We present data and trading strategies in Section 2. In this section we also explain the differences between risk adjustment at the portfolio and stock level in detail. We present our main results in Section 3 and various robustness checks in Section 4. We conclude in Section 5.

2 Data and Methodology

2.1 Data

We use data from several sources. First, we obtain stock price data from the daily return files of the Center for Research in Security Prices (CRSP).[5] 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 daily data on the risk-free rate and the five Fama and French (2015) factors from the data library of Ken French. Data on the q factors (Hou et al. 2015; Hou et al. 2019, 2020) is obtained from the q-factors data library. Our sample covers the period from July 1963 to December 2018 and contains 22,376 distinct stocks. There are 1,926 stocks in the sample at the beginning of the sample period in 1963 and there are 3,541 stocks in the sample at the end of the sample period in 2018.

2.2 Methodology

We test the same *J-month/K-month* trading strategies as Jegadeesh and Titman (1993). For each month of the sample period we sort stocks into ten portfolios based on their prior *J-month* return. We follow the majority of the literature (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) and report results for equally-weighted decile portfolios.[6] Equal-weighting 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. We report separate results for micro,

[5] We calculate monthly returns by compounding the daily returns.

[6] We are aware of only a few papers that focus on value-weighted returns, e.g. Moskowitz and Grinblatt (1999) and Daniel and Moskowitz (2016).

small, and large cap stocks in Section 4.2 and results for value-weighted decile portfolio returns in the Internet Appendix (attached to this version of the paper as appendix C).

We next construct zero net investment portfolios by investing into the 10 % winner stocks (decile 10) and shorting the 10 % loser stocks (decile 1). We follow Jegadeesh and Titman (1993) and skip one week between formation and holding period to avoid the short-term reversal documented in Lehmann (1990) and Lo and MacKinlay (1990). We hold the winner-minus-loser portfolios for the next K months. Hence, we hold K portfolios simultaneously. The return of the momentum strategy in a month then is simply the equally-weighted average of the returns of the K long-short portfolios. We follow Jegadeesh and Titman (1993) and choose formation and holding periods of one, two, three, and four quarters, i.e. $J,\ K \in \{3,\ 6,\ 9,\ 12\}$. The intersection of formation and holding periods results in a total of 16 investment strategies.

No Risk Adjustment. The procedure described above delivers, for each combination of formation period J and holding period K, the time series of the returns of the respective $J,\ K$ momentum strategy. The strategy is a zero net investment strategy long in past winners and short in past losers. To test whether the strategy earns a mean return that is significantly different from zero we regress the returns on a constant and test the intercept against zero using Newey-West standard errors with $(K-1)$ lags.

Portfolio-Level Risk Adjustment. The risk adjustment procedure that is routinely applied in the literature[7] consists of a full sample regression of the return of the momentum strategy on a set of factors, i.e.

$$r_t^{J,K} - r_{f,t} = \alpha^{J,K} + \sum_j \beta_j^{J,K} f_{j,t} + \epsilon_t^{J,K}. \tag{1}$$

J, K denote the formation and holding period, respectively, of the strategy under investigation, t denotes time, j denotes the factors and $r_{f,t}$ is the risk-free rate. The slope coefficients $\beta_j^{J,K}$ deliver estimates of the factor exposure of the momentum strategy, implicitly assumed to be constant over the entire sample period. The intercept $\alpha^{J,K}$ is an estimate of the abnormal return of the J, K

[7]See e.g. Jegadeesh and Titman (1993), Equation 9; Fama and French (1996), Equation 2; or Fama and French (2015), Equation 3.

momentum strategy.

We refer to this procedure as *portfolio-level risk adjustment*. In our main analysis we use the Fama and French (2015) 5-factor model comprising the market (MKTRF), size (SMB), book-to-market (HML), operating profitability (RMW), and investment (CMA) factors. t-statistics are based on Newey-West standard errors with $(K-1)$ lags.

Stock-level Risk Adjustment. Consider a month τ. The momentum portfolio consists of K equally-weighted long-short portfolios. We identify all stocks that are included in any of these portfolios. For each stock we then estimate the time series regression

$$r_{i,t} - r_{f,t} = \alpha_{i,\tau} + \sum_j \beta_{i,j,\tau} f_{j,t} + \epsilon_{i,t}, \tag{2}$$

where $r_{i,t}$ is the return of stock i in month t, $r_{f,t}$ is the risk-free rate, $\beta_{i,j,\tau}$ are the stock-specific factor sensitivities, and $f_{j,t}$ are the factor realizations.

In our main analysis we use the Fama and French (2015) 5-factor model, and we estimate the time-series regressions using data for the 36 months prior to month τ.[8] Given that return data is available from July 1963 onward, we would obtain the first estimates for July 1966. However, at the beginning of the sample period we only require a minimum of 18 (rather than 36) monthly returns for the regressions, such that we obtain the first beta estimates for January 1965. Our results are insensitive to this choice.

We use the factor sensitivities $\beta_{i,j,\tau}$ obtained from equation 2 to obtain estimates of the expected return for stock i in month τ as

$$E(r_{i,\tau}) = r_{f,\tau} + \sum_j \beta_{i,j,\tau} f_{j,\tau}. \tag{3}$$

The abnormal return of stock i in month τ is

$$AR_{i,\tau} = r_{i,\tau} - E(r_{i,\tau}). \tag{4}$$

[8] A 36 months estimation period has also been used by Grundy and Martin (2001) and Wang and Wu (2011). It provides a reasonable solution to the trade-off between time-variation in the factor sensitivities and estimation error. In Section 4.4 we estimate factor sensitivities over horizons of 24 and 60 months. The results are similar to those of the main analysis.

We then aggregate the abnormal returns in two steps. First, we identify the stocks which are included in the long and short leg of each of the K winner-minus-loser portfolios. We obtain the abnormal return for each of the K portfolios as the equally-weighted average abnormal return of the stocks in the long leg minus the equally-weighted average abnormal return of the stocks in the short leg.[9] Second, we calculate an equally-weighted average of the abnormal returns of the K long-short portfolios.

The procedure described above delivers, for each month, an estimate of the abnormal return of the J, K momentum portfolio. To test whether the abnormal return is significantly different from zero, we regress the time series of returns on a constant and test the intercept against zero using Newey-West standard errors with $(K-1)$ lags. We refer to this procedure as *stock-level risk adjustment*.

The stock-level risk adjustment procedure is based on data that is available at the time of portfolio formation and is thus implementable. It accounts for the time-varying composition of the momentum portfolio because, in each month, factor exposures are based on the actual composition of the portfolio in that month. Finally, the procedure also accommodates changing factor exposure of individual stocks because stock-specific exposure is always estimated based on the most recent 36 months of data.

Decile-Portfolio Risk Adjustment. There is an alternative to the stock-level risk adjustment procedure that is somewhat simpler to implement (and, as will be shown later, delivers almost identical results). Consider, as before, a month τ in which we hold K equally-weighted long-short portfolios. We again identify all stocks that are included in any of these portfolios. We now calculate the return of each portfolio in the 36 months prior to month τ as the equally-weighted average of the returns of the stocks in the long leg minus the equally-weighted average of the returns of the stocks in the short leg.[10] We then estimate, for each of the K portfolios, the time series regression

[9] We report results for value-weighted portfolios in the internet appendix (appendix C in this version of the paper).

[10] Note that this procedure is very different from the portfolio-level risk adjustment described above. For the decile-portfolio risk adjustment, we calculate, for each month, 36 months of past returns based on the current composition of the K portfolios comprising the momentum strategy and regress them on the factors. The resulting factor sensitivities are used to estimate the expected returns of the K portfolios only for a single month. For the next month the factor sensitivities are re-estimated based on the portfolio compositions of that month. In contrast, the portfolio-level risk adjustment procedure estimates a single regression for the full sample period and ignores changes in the composition of the momentum portfolio.

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

where $r_{p,t}$ is the return of portfolio p in month t, $r_{f,t}$ is the risk-free rate, $\beta_{p,j,\tau}$ are the portfolio-specific factor sensitivities, and $f_{j,t}$ are the factor realizations. The factor sensitivities $\beta_{p,j,\tau}$ are used to obtain estimates of the expected return and the abnormal return for portfolio p in month τ as

$$E(r_{p,\tau}) = r_{f,\tau} + \sum_j \beta_{p,j,\tau} f_{j,\tau}, \tag{6}$$

$$AR_{p,\tau} = r_{p,\tau} - E(r_{p,\tau}). \tag{7}$$

This procedure delivers an estimate of the abnormal return for each of the K winner-minus-loser portfolios for each month τ. We aggregate the abnormal returns by calculating an equally-weighted average of the abnormal returns of the K portfolios. To test for significance, we regress the resulting time series of returns on a constant and test the intercept against zero using Newey-West standard errors with $(K-1)$ lags. We refer to this procedure as *decile-portfolio risk adjustment*.

3 Main Results

In this section we first describe our main results for the full sample covering 1963 to 2018. Results for sub-periods and for different size groups are reported in section 4. We then analyze in detail why the results obtained using the stock-level risk adjustment procedure differ from those obtained by the traditional portfolio-level risk adjustment.

3.1 Full Sample Results

Total Return (No Risk Adjustment). We first present results based on raw returns for all 16 momentum strategies under investigation. Table 1 shows the monthly mean returns of the long leg, the short leg and the long-short portfolio, together with t-statistics based on Newey and West (1987) standard errors with $(K-1)$ lags. The results shown in Table 1 are for equally-weighted portfolios. Those for value-weighted portfolios are shown in Table IA1 in the internet appendix (attached as appendix C) and are qualitatively similar. The results are fully in line with those of previous studies such as Jegadeesh and Titman (1993). The returns of the winner and loser portfolios are positive irrespective of the choice of the formation and holding period, but the winner portfolios always outperform the loser portfolios. Consequently, the long-short portfolio has a positive return in all 16 cases and is significant at the 5% [1%] level in 15 [13] cases. The returns are also economically large, ranging from 0.18% to 0.85% per month.

We consider the *6-month/6-month* strategy as an example. It generates a monthly mean return of 0.75%, significant at the 1% level (t-statistic 4.53). This return is equivalent to an annual return of 9.4% which is economically large and compares favorably with the average annual market return of 6.55% during the sample period.

[Insert Table 1 about here]

Portfolio-Level Risk Adjustment. The results presented in Table 1 provide evidence in favor of a momentum effect in non-adjusted returns. They do not answer the question whether a momentum strategy is profitable after risk adjustment. We therefore adjust returns at the portfolio level (as is described in Section 2.2 and as is common practice in the literature). It is worth noting that the risk adjustment does not affect the sorting of stocks, i.e. the composition of the decile portfolios and the momentum portfolio is the same as before.

The results are shown in Table 2 and are again fully consistent with previous findings.[11] Unsurprisingly, the returns of the winner and loser portfolios (i.e. the long and the short leg of the momentum strategy) are lower after risk adjustment. They are always positive for the winner portfolios but mostly negative for the loser portfolio. The return of the long-short strategy is hardly affected by the portfolio-level risk adjustment. It delivers a positive return in all 16 cases, significant at the 5% level in 15 cases. The returns range between 0.35% and 0.89% and are thus of the same order of magnitude as the non-adjusted returns shown in Table 1. The *6-month/6-month* strategy generates an adjusted return of 0.77% per month, even slightly larger than the non-adjusted return of 0.75% documented in Table 1 above.

[Insert Table 2 about here]

[11] The results for value weighted portfolios are again similar. They are shown in Table IA2.

Stock-Level Risk Adjustment. The evidence presented so far is fully consistent with the previous literature. The momentum strategy delivers returns that are large and significant before and after (portfolio-level) risk adjustment. However, we have argued above that risk-adjustment at the stock level is preferable because it takes the time-variation in the composition of the momentum portfolio and the resulting time variation of the factor loadings into account.

The results obtained with the stock-level risk adjustment procedure are shown in Table 3. They are dramatically different from those presented above. The abnormal returns of the long leg of the momentum strategy are much smaller than those shown in Table 2. On average they are about half as large. At the same time the abnormal returns of the short leg are much larger. They are positive in each single case and larger than the abnormal returns of the long leg in five cases. The abnormal return of the long-short strategy is close to zero. The individual values range from -0.08% to 0.15% and are insignificant without exception. In fact, the largest t-statistic is 0.69.[12]

The *6-month/6-month* strategy (which delivered highly significant unadjusted and portfolio-level adjusted returns of 0.75% and 0.77%, respectively) generates an abnormal return of 0.11% with a t-statistic of 0.53. This value corresponds to an annualized abnormal return of a mere 1.33%.

[Insert Table 3 about here]

Decile-Portfolio Risk Adjustment. In section 2 we have introduced the decile-portfolio level risk adjustment as an alternative to the stock-level risk adjustment. The results obtained with this procedure are shown in Table 4. They are very similar to those obtained with stock-level risk adjustment. In particular, the abnormal returns of the long-short portfolios range from -0.11% to 0.16% and are all insignificant, the largest t-value being 0.73. Because of the similarity of the results we focus on stock-level risk adjustment in the remainder of the paper.

[Insert Table 4 about here]

Our results with stock-level and decile portfolio-level risk adjustment imply that, for the full sample analyzed here, there is no evidence of a momentum effect. To illustrate the significance

[12]Results for value-weighted portfolios, shown in Table IA3, are similar, albeit slightly weaker (the *3-month/12-month* strategy earns an abnormal return of 0.48% with a t-statistic of 1.98, significant according to traditional standards but not according to the adjusted Harvey et al. (2015) critical values).

of this finding we perform the following exercise. In January 1965[13] we invest one US-$ into the winner portfolio and finance the investment by shorting the loser portfolio.We base our choice of winners and losers on the return during the past six months, and we hold each stock for six months (i.e. we implement a *6-month/6-month* strategy). Any intermediate gains from the strategy are reinvested. As shown in Figure 1 this investment strategy results in a terminal value at the end of 2018 of 57.15 US-$. The momentum crashes (Daniel and Moskowitz 2016) are clearly visible in the corresponding graph in Figure 1. If, rather than the raw return, we consider the abnormal return after portfolio-level risk adjustment, we obtain an even higher terminal value, at 65.25 US-$. In contrast, the terminal value after stock-level risk adjustment amounts to a mere 1.75 US-$, implying that the huge raw return of the momentum portfolio is a compensation for the risk of the strategy.

[Insert Figure 1 about here]

3.2 Explanations

The results presented thus far imply that portfolio-level and stock-level risk adjustment yield very different estimates of the abnormal returns of momentum strategies. These differences are driven by two (related) characteristics of momentum portfolios, the turnover in the portfolios and systematic time-variation in the factor exposures. In this section we discuss both characteristics in turn. We then estimate a conditional factor model as proposed by Grundy and Martin (2001) and show that, while the model captures some of the time variation in factor loadings, it fails to fully account for the dynamic risk exposure of the momentum strategy and does not explain its profitability.

As noted previously, portfolio-level risk adjustment is based on the implicit assumption that the factor exposure of the momentum portfolio is constant. This assumption may be violated if either the composition of the momentum portfolio changes over time, or if the systematic risk of the stocks comprising the portfolio changes. In the context of the momentum strategy, changing portfolio composition is of obvious importance because the momentum portfolio is updated every month. A J, K momentum strategy implies that every month one of the K long-short portfolios that are held simultaneously is liquidated and replaced by a new portfolios that contains the 10%

[13] We assume that the investment is made in January 1965 rather than in June 1963 (the start of our sample period) because the stock-level risk adjustment procedure requires a return history of at least 18 months.

winner and the 10% loser stocks of the previous J months. The stocks in the new winner-loser portfolio usually are different from those in the portfolio that is liquidated. We consider the *6-month/6-month* strategy as an example. When we compare the component stocks of the winner [loser] portfolio that is liquidated to those of the winner [loser] portfolio that is newly added, we find that on average 86.2% [85.1%] of the stocks are different. Because 6 long-short portfolios are held simultaneously, these figures imply that 14.4% [14.2%] of the stocks in the long [short] leg of the aggregate momentum portfolio are turned over *every month*.[14]

Additional evidence of the high turnover of the momentum portfolio is provided by the fact that 77.64% [81.03%] of the stocks in our sample are sorted into a winner (loser) portfolio at least once. These figures imply that many stocks appear in both the long and the short leg of the momentum portfolio at some point in time.

The changing portfolio composition would not affect the factor exposure of the momentum portfolio in a systematic way if the factor exposure of the stocks that leave the portfolio was similar to the exposure of the stocks that enter. However, this is not the case. Rather, as Grundy and Martin (2001) and Daniel and Moskowitz (2016) have shown, the factor exposure of the stocks entering the winner and loser portfolios varies in a systematic way with past factor realizations. To see this, assume that the CAPM holds. If the market excess return is positive during the formation period, high beta stocks [low beta stocks] will earn high [low] returns and, consequently, the winner [loser] portfolio will be populated by high [low] beta stocks, implying that the long-short portfolio has positive market exposure. By a similar argument, after a period of negative market excess returns,[15] the winner [loser] portfolio will be populated by low [high] beta stocks, implying that the long-short portfolio has negative market exposure. Thus, the market exposure of the momentum portfolio is systematically related to past realizations of the market factor. Portfolio-level risk adjustment will yield an estimate of the *average* market exposure of the momentum portfolio (which may well be close to zero) but is unable to capture its time variation.

The intuition described above is not confined to the market factor but carries over to other factors as well. If, for example, the return of the size factor is positive during the formation period,

[14]These turnover ratios are extremely high when compared to those of standard risk factors. For instance, size portfolios formed based on market capitalization using NYSE breakpoints in June of each year have, on average, an *annual* turnover ratio of only 5.22%.

[15]We note that the market excess return was negative in 40.4% of the months in our sample period, June 1963 to December 2018.

small [large] stocks earn high [low] returns. The winner [loser] portfolio will then comprise small [large] firms, implying that the long-short portfolio has positive exposure to the size factor. In general, the long-short portfolio will tend to load positively (negatively) on a factor when the factor realizations were positive (negative) during the formation period.

It is an empirical question how large the cyclical changes in the factor exposures are. To shed light on this issue we follow Grundy and Martin (2001) and compare an unconditional and a conditional factor model. The unconditional model is simply the 5-factor model that we used for the portfolio-level adjustment. We estimate the model for the aggregate momentum portfolio and separately for the long and the short leg. For ease of exposition we only show (in Panel A of Table 5) the results for the *6-month/6-month* strategy. While the market exposure of the winner and the loser portfolios are both close to one, the estimated exposure for the long-short portfolio is close to zero, at -0.053, and is insignificant. Similarly, the exposures to the size, profitability and investment factors are also insignificant. The only significant loading is the sensitivity to the book-to-market factor. It is negative, at -0.46, due to a negative [positive] exposure of the winner [loser] portfolio. According to these estimates, the momentum portfolio has very little exposure to systematic risk. It should thus come as no surprise that (as documented in Tables 1 and 2 above) the abnormal return after portfolio-level risk adjustment is not substantially different from the unadjusted return of the momentum strategy.

The conditional model we estimate follows Grundy and Martin (2001), i.e.

$$r_{\theta,t} - r_{f,t} = \alpha_\theta + \sum_j \sum_\delta \beta^\delta_{\theta,j} D^\delta_{j,t} f_{j,t} + \epsilon_{\theta,t}, \tag{8}$$

where θ denotes the portfolio under consideration (long, short or long-short), $f_{j,t}$ denotes the return of factor j in month t and $D^\delta_{j,t}$ is a set of dummy variables that indicate whether the return of factor j during the J-months formation period preceding month t is more than one standard deviation below its mean ("down"), more than one standard deviation above its mean ("up"), or within one standard deviation from its mean ("flat").[16] The states for each factor are denoted $\delta \in \{down, flat, up\}$. The slope coefficients $\beta^\delta_{\theta,j}$ then measure the exposure of portfolio θ to factor j in the down, up and flat state of the respective factor. The results are shown in Panel B of Table 5.

[16]We use rolling windows of 36 months to estimate the factor means and standard deviations. We obtain qualitatively similar results when we use the full sample instead.

Consistent with the argument laid out above the up-beta is larger than the down beta for all five factors. In each single case the down beta is negative while the up-beta is positive. The spreads between the up-beta and the down-beta are substantial and range from 0.284 for the investment factor to 1.01 for the size factor. Consider the market factor as an example. The unconditional model in Panel A estimates an insignificant exposure of −0.05 while the conditional model yields significant estimates of −0.24 (t-statistic 2.98) for the down state and 0.17 (t-statistic 3.34) for the up state. These results imply that, as argued above, the factor exposure of the momentum portfolio depends in a systematic way on past factor realizations, and that the variation of the exposure is substantial.

[Insert Table 5 about here]

The conditional model captures the time variation of factor exposures but it does not fully explain the apparent profitability of the momentum strategy. The intercept of the conditional model, while smaller than that of the unconditional model, is still significant. Its value of 0.004 (t-statistic 2.26) implies that the momentum portfolio delivers an abnormal return of 0.4% per month. To explain this finding we compare the factor exposure estimates obtained from the conditional model to those obtained from our stock-level risk adjustment procedure. Figure 2 shows (again for the *6-month/6-month* strategy) the market exposure estimated by the unconditional model (the solid horizontal line), the up and down betas estimated by the conditional model (the two dotted horizontal lines) and the time-varying market exposure obtained from the stock-level adjustment procedure. The figure further shows the past 6-months return of the CRSP value-weighted index measured in standard deviations. Note that, while we use the market factor as an example here, we obtain similar (and sometimes even stronger) results for the other factors.

The figure reveals that the variation in the market exposure of the momentum portfolio is much stronger than indicated by the conditional model. Its market beta frequently exceeds 0.5 and in some case even exceeds 1 and, on several occasions (following events such as the financial crisis), drops below −1. The figure further shows that the market exposure of the momentum strategy is indeed closely related to the market return during the 6-months formation period. In fact, the correlation between the market beta and the past market return is 0.65. From these findings we conclude that stock-level risk adjustment is indeed necessary to fully capture the dynamic risk exposure of the momentum portfolio.

[Insert Figure 2 about here]

4 Robustness Checks and Extensions

In this section we discuss various extensions of our main analysis and present the results of several robustness checks. Specifically, we test which of the factors of the Fama and French (2015) 5-factor model explain the momentum returns and whether the Hou et al. (2015) q-factor model and the q^5 model (Hou et al. 2019, 2020) yield similar results. We then present results for different size groups and sub-periods, and we account for transaction costs. We further demonstrate that the results are robust to the length of the period over which the factor exposure for the stock-level risk adjustment is estimated. Finally, we show that the stock-level adjustment procedure can explain the returns of the Barroso and Santa-Clara (2015) volatility-scaled momentum strategy, and that the adjustment procedure also works in a broad international sample. Unless denoted otherwise we present results for the *6-month/6-month* strategy.

4.1 Which Factors?

In the previous section we have shown that stock-level risk adjustment fully explains the profitability of momentum strategies when the Fama and French (2015) 5-factor model is used to adjust for risk. It is important to know which of the 5 factors capture the momentum effect. To shed light on this issue we repeat the stock-level risk adjustment procedure for various factor models. Specifically, we use the CAPM, the Fama and French (1993) 3-factor model, the 3-factor model augmented by either the investment or the profitability factor, and the Fama and French (2015) 5-factor model. We further implement the Hou et al. (2015) q-factor model and the q^5 model (Hou et al. 2019, 2020) to test whether they deliver results which are similar to those obtained with the Fama and French (2015) 5-factor model.

The results for the winner, the loser and the winner-minus-loser portfolios are shown in Table 6. Besides the results for the factor models listed above the Table also shows, in the first line, the returns of the momentum strategy without risk adjustment. They are identical with those in Table 1. The momentum strategy delivers a monthly raw return of 0.75%. Adjusting for market risk reduces the return only slightly, to 0.66%. Adding the size and the book-to-market factors reduces the return substantially, to 0.39%. However, the return is still significant with a *t*-statistic of 2.19. Thus, stock-level risk adjustment with the Fama and French (1993) factors does not fully explain the profitability of the momentum strategy. Adding the investment or the profitability factor reduces the return further, to 0.33% and 0.23%, respectively. These results imply that the profitability factor is particularly important to explain the profitability of the momentum strategy. Adding both factors simultaneously results in the Fama and French (2015) 5-factor model. The return of the momentum strategy is reduced to 0.11% with a *t*-statistic of 0.53, the result already shown in Table 3 above. The last two lines of Table 6 provide evidence that the q-factor model and the q^5 model (both of which include an investment and a profitability factor) are also able to explain the profitability of the momentum strategy. They deliver insignificant abnormal return estimates of 0.28% and 0.17%, respectively.

[Insert Table 6 about here]

4.2 Size Sub-Samples

The main results presented above were based on equally-weighted returns. Hence, micro caps that comprise approximately 50% of our sample but only account for a small percentage of the total market capitalization are over-weighted. Consequently, our results might be driven by micro caps. We address this concern by sorting stocks each month into three size classes. We define micro caps as firms with a market capitalization below the 20^{th} NYSE percentile, small caps as firms with market capitalization between the 20^{th} and the 50^{th} NYSE percentiles, and large caps as are firms with market capitalization above the 50^{th} NYSE percentile. We sort stocks into ten portfolios based on their prior *6-month* returns and construct long-short portfolios based on the past returns for each size class separately.

The results are presented in Table 7. The three panels of the Table show non-adjusted results, results after portfolio-level and results after stock-level risk adjustment. The first two columns repeat the results (returns and t-statistics) for the full sample already shown in Tables 1, 2 and 3 above. The subsequent columns show separate results for micro, small and large caps. The non-adjusted returns of the winner-minus-loser portfolios are 0.72%, 0.97%, and 0.72% for micro, small, and big stocks, respectively. They are different from zero at the 1% significance level. Adjusting returns for risk at the portfolio level does not materially change the results The returns are 0.67%, 1.08%, and 0.81% for micros, small and large caps, respectively, and 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). After stock-level risk adjustment the return is insignificant in all three size groups. It is *smallest* for the micros caps, at 0.1% per month with a t-statistic of 0.48. Returns for small and large caps are 0.24% and 0.16%, respectively, and are also insignificant. We therefore conclude that our main findings are not driven by micro caps.

[Insert Table 7 about here]

4.3 Sub-Periods and Transaction Costs

All results presented so far are based on data covering the entire sample period 1963-2018. In this subsection we present results for three sub-periods of approximately equal length, 1963-1979, 1980-1999 and 2000-2018. For each sub-sample, Table 8 shows the return of the *6-month/6-month* strategy, together with its t-statistic without risk adjustment, with portfolio-level and with stock-level risk adjustment. For ease of comparison the first two columns repeat the results for the full sample.

When the returns of the momentum portfolio are not adjusted for risk, or when they are adjusted at the portfolio level, there is a strong and highly significant momentum effect in the 1963-1979 and 1980-1999 sub-periods. In contrast, there is no significant momentum effect in the most recent sub-period.[17] Momentum returns after stock-level risk adjustment are always markedly lower. In the first sub-period they drop from 0.94% per month after portfolio-level risk adjustment to 0.63%

[17]It is well known that the momentum effect has become weaker since the turn of the century. Hanson and Sunderam (2014) argue that an increase in the amount of capital devoted to momentum-based strategies has resulted in reduced profitability of these strategies.

after stock-level risk adjustment. The t-statistic is 2.13, significant at the 5% level by traditional standards but below the adjusted 5% critical value according to Harvey et al. (2015). In the second sub-period 1980-1999 stock-level risk adjustment reduces the return of the momentum strategy from 1.3% per month to an insignificant 0.3%. In the most recent sub-period the momentum profits are negative. We thus conclude that the stock-level risk adjustment procedure explains the returns of the momentum strategy post-1980. Results for the 1963-1979 sub-period are more ambiguous and depend on the standards used to judge statistical significance.

[Insert Table 8 about here]

The results shown in Table 8 do not account for transaction costs. We calculate momentum profits after transaction costs as follows. We track the composition of the momentum portfolio over time. Whenever a stock enters the portfolio or exits from the portfolio we charge transaction costs. We use the CRSP closing half-spread at the respective point in time as an estimate of the transaction costs. If data on the closing spread is missing we use the median closing spread of all stocks in the CRSP universe. This procedure results in a conservative estimate of the magnitude of the transaction costs because stocks with missing spread data are likely to have above-average transaction costs.

The results are shown in Table 9. They reveal that the momentum strategy is unprofitable after transaction costs. The returns are negative irrespective of the sub-sample considered, and irrespective of whether and how one adjusts for risk. These results confirm earlier findings by Lesmond et al. (2004) and Korajczyk and Sadka (2004).

[Insert Table 9 about here]

4.4 Short- and Long-term Betas

In our main analysis we estimate factor sensitivities over the 36 months preceding portfolio formation for the stock-level risk adjustment procedure. Our results may be sensitive to that choice. We therefore re-estimate the results shown in Table 3 using the prior 24 months and 60 months to estimate the factor exposure.

Results based on a 24-months estimation window are shown in Panel A of Table 10. The results are very similar to those in Table 3. None of the 16 momentum strategies delivers a significant risk-adjusted return. The largest abnormal return estimate (for the *9-month/3-month* strategy) amounts to 0.10% per month, with a t-statistic of 0.69. The abnormal returns obtained with a 60-months estimation window, shown in Panel B of Table 10, are slightly larger than those obtained from the 24-months and 36-months estimation windows, but again are insignificant without exception. It is again the *9-month/3-month* strategy which delivers the highest abnormal return (0.29%), but even this estimate is insignificant, with a t-statistic of 1.45. We therefore conclude that our results are not sensitive to the length of the period used to estimate factor exposures.

[Insert Table 10 about here]

4.5 Volatility-Scaled Momentum

Barroso and Santa-Clara (2015) provide evidence that the risk of momentum strategies is predictable. Building on this insight they develop a volatility-scaled momentum strategy and show that it delivers a Sharpe ratio that is almost twice as high than that of the standard momentum strategy. They conclude (p.111) that "[r]isk-managed momentum is a much greater puzzle than the original version".

We replicate their approach to analyze whether stock-level risk adjustment can explain the return of a scaled momentum strategy. We first calculate the daily returns of the non-adjusted *6-month/6-month* strategy. We then compute the daily mean squared returns over the previous 126 trading days (approximately 6 months) and multiply the mean by 21 to obtain a forecast of the monthly variance, i.e.

$$\hat{\sigma}^2_{WML,t} = 21 \sum_{j=0}^{125} r^2_{WML,d_{t-1}-j}/126, \tag{9}$$

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

$$r_{WML^*,t} = \frac{\sigma_{target}}{\hat{\sigma}_t} r_{WML,t}, \tag{10}$$

where $r_{WML,t}$ and $r_{WML^*,t}$ are the monthly returns of the conventional and the volatility-scaled momentum strategies, respectively. Following Barroso and Santa-Clara (2015) 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.

The results are shown in Table 11. The risk-managed momentum strategy on average delivers a raw return of 1.38% per month, significantly different from zero at the 1% level (t-statistic 6.55) and considerably larger than the corresponding return of the non-scaled strategy (0.75% as shown in Table 1). The return of the scaled strategy after portfolio-level risk adjustment is even larger, at 1.43% per month. In contrast, the stock-level adjustment procedure captures a large fraction of the return of the scaled strategy. The monthly stock-level adjusted mean return is 0.44% and is not significantly different from zero (*t*-statistic 1.57). We therefore conclude that the stock-level adjustment procedure largely explains the return of a volatility-scaled momentum strategy.

[Insert Table 11 about here]

4.6 International Evidence

We have shown that the stock-level risk adjustment procedure does a good job at explaining the returns of momentum strategies in the US. We now analyze whether the procedure also works in international markets. We obtain stock return data for 22 developed countries from Thomson Reuters Datastream. We apply a number of data filters and largely follow Hong et al. (2003) and Chui et al. (2010) to screen out erroneous observations.[18] Our final sample contains 20 countries and spans the period from 1990-2018. We provide a detailed summary of the sample construction in Appendix B.

The number of listed firms is much smaller in most countries other than the US. Sorting stocks into decile portfolios according to their past return is, therefore, inappropriate. We follow Chui

[18]The data provided by Thomson Reuters contains more data errors than the data provided by CRSP. For instance, we find daily returns larger than 1,000% for almost every country in our sample.

et al. (2010) and sort stocks into terciles within each country. The 33% stocks with the highest [lowest] prior return constitute the winner [loser] portfolio.[19] We obtain data on the Fama and French (2015) factors for developed countries from Kenneth French's website. To account for infrequent trading we estimate factor sensitivities using Dimson (1979) betas with a lag and a lead of one month.

For each country we report the number of firms and the returns and t-statistics of unadjusted, portfolio-level adjusted and stock-level adjusted momentum portfolios in Table 12. Without risk adjustment we find a significant momentum effect in 19 of the 20 non-US countries. The exception is (in accordance with the prior literature, e.g. Griffin et al. 2003, Chui et al. 2010) Japan. The countries with the highest momentum returns are Canada (1.55%), Australia (1.18%) and Denmark (0.97%).

Portfolio-level risk adjustment changes the results only slightly. The adjusted returns are smaller than the unadjusted returns for the majority of the countries, but we still find a significant return (at the 5% level or better) in 16 out of 20 countries. The countries with the highest momentum returns are, as before, Canada (1.25%), Australia (1.01%) and Denmark (1.00%). In contrast, stock-level risk adjustment explains the profitability of the momentum strategy in most countries. The returns are lower after stock-level adjustment than after portfolio-level adjustment in all countries except Sweden, and they are negative in five countries (and significantly so in Japan). The adjusted returns are positive but insignificant in 12 countries. We find significant momentum profits after stock-level risk adjustment only in three of the smaller countries in the sample (Belgium, Denmark and Switzerland). Switzerland and Belgium are also the countries with the highest adjusted returns, at 0.67% and 0.62%, respectively.

These results allow the conclusion that stock-level risk adjustment is able to explain momentum profits not only in the US but also in a broad international sample.

[Insert Table 12 about here]

[19] Our results remain largely unchanged when we use decile sorts for the countries with a sufficiently large number of listed stocks (Australia, Canada, France, Germany, Japan and the United Kingdom).

5 Conclusion

Momentum portfolios are characterized by high turnover. As a consequence, the factor exposure of momentum portfolios varies over time, and it does so in a way that is systematically related to past factor realizations. The portfolios tend to load positively (negatively) on factors that performed well (poorly). The risk-adjusted return of momentum strategies is usually estimated by running a full sample regression of the portfolio returns on a set of factors. This procedure is based on the implicit assumption that the factor exposure of the momentum portfolio is constant. Essentially, the procedure adjusts for the *average* factor exposure, which may well be close to zero.

We propose to adjust for risk at the stock level rather than at the portfolio level. In each month we identify the stocks that are included in the long and short leg of the momentum portfolio and estimate their exposure to the Fama and French (2015) factors from the most recent 36 months of data. We use the regression results to construct estimates of the expected returns of the individual stocks and their abnormal returns in the month under consideration. The risk-adjusted momentum return then is simply the weighted average of the abnormal returns of the component stocks. This procedure, which we denote stock-level risk adjustment, accounts for the time-varying factor exposure of the momentum portfolio. When we apply it to a broad sample of US stocks covering 1963-2018 we find no significant momentum effect in the full sample or in sub-samples of large, small and micro caps. When we consider sub-periods, we find a significant momentum effect for 1963-1979 (albeit with a t-statistic that does not exceed the adjusted 5% critical value as proposed by Harvey et al. (2015)), but not thereafter. These results are robust to the choice of the formation and holding period, to the length of the period used to estimate factor exposures, and to the weighting scheme (equally-weighted versus value-weighted). We further find that the stock-level risk adjustment procedure explains the returns of a volatility-scaled momentum strategy (Barroso and Santa-Clara (2015)) as well as those of momentum portfolios in an international sample covering 20 developed countries.

Our results imply that the momentum effect may actually be much weaker than previously thought, and that the returns to momentum strategies may, to a large extent, be a compensation for risk. This insight has potentially important implications for portfolio managers pursuing momentum-based investment strategies. Our findings also suggest promising avenues for future research. The stock-level risk adjustment procedure could be applied to other anomalies as well. Those anomalies that require high portfolio turnover are, in our view, the most promising candidates.

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A Appendix - Figures and Tables

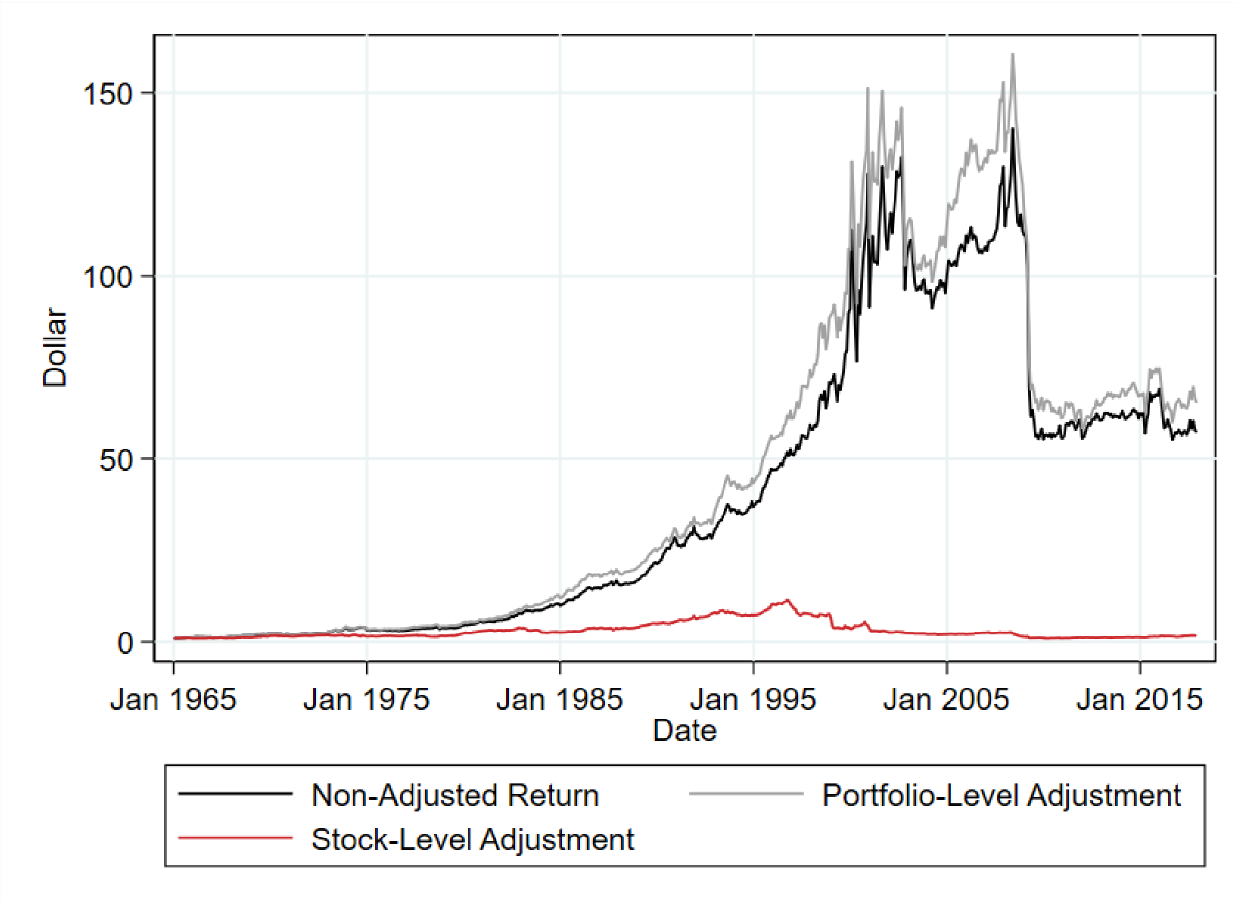

Figure 1: Momentum Profitability

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.

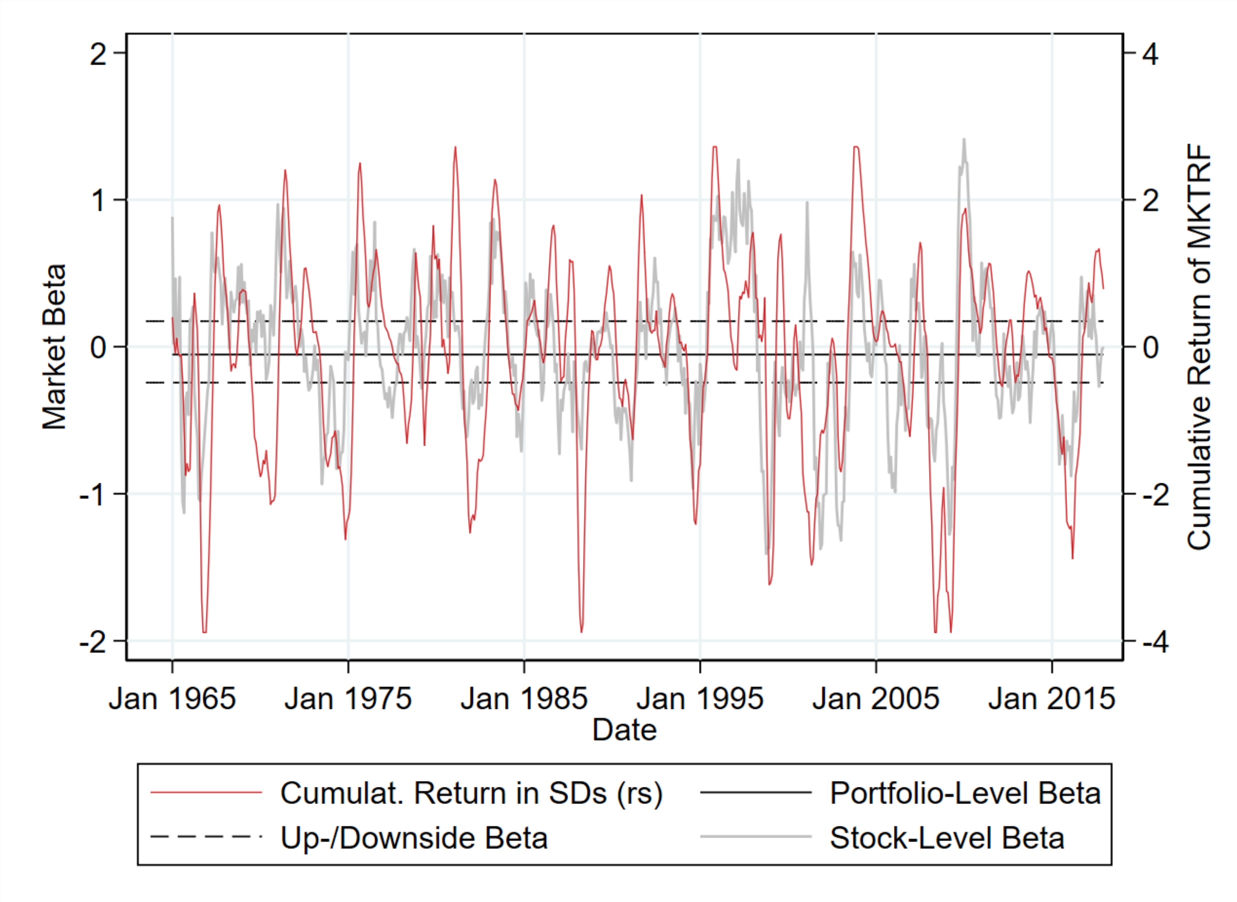

Figure 2: Market Factor Exposure

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. Upside and downside betas are depicted by the dashed lines. The average stock-level beta of all stocks in the winner-minus-loser portfolio is depicted by the grey line. The market factor's cumulative return over the last six months (demeaned and scaled by standard deviation) is depicted by the red line.

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 with $(K-1)$ lags.

	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 with $(K-1)$ lags.

	K =							
J =	3	t-ratio	6	t-ratio	9	t-ratio	12	t-ratio
3 Sell	-0.0012	-0.78	-0.0014	-0.94	-0.0010	-0.67	-0.0007	-0.48
3 Buy	0.0037	3.96	0.0042	5.55	0.0044	6.16	0.0043	6.23
3 Buy-Sell	0.0049	2.33	0.0056	2.90	0.0054	2.96	0.0049	2.98
6 Sell	-0.0020	-1.23	-0.0017	-1.04	-0.0014	-0.93	-0.0006	-0.38
6 Buy	0.0056	5.67	0.0060	6.18	0.0057	6.07	0.0049	5.58
6 Buy-Sell	0.0076	3.28	0.0077	3.31	0.0071	3.30	0.0055	2.81
9 Sell	-0.0023	-1.37	-0.0020	-1.25	-0.0012	-0.73	-0.0001	-0.05
9 Buy	0.0066	6.24	0.0064	6.21	0.0056	5.57	0.0047	5.01
9 Buy-Sell	0.0089	3.71	0.0085	3.61	0.0068	3.09	0.0047	2.41
12 Sell	-0.0025	-1.54	-0.0014	-0.85	-0.0004	-0.25	0.0007	0.49
12 Buy	0.0062	5.97	0.0059	5.76	0.0051	5.05	0.0042	4.54
12 Buy-Sell	0.0087	3.79	0.0073	3.20	0.0054	2.56	0.0035	1.85

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 with $(K-1)$ lags.

	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: Risk-Adjusted Momentum Returns using Decile Portfolio Adjustment

This table shows the monthly abnormal 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. We adjust risk by using the decile portfolios. Each month, we form K new winner and K new loser portfolios. We obtain the returns of the resulting K long-short portfolios for the previous 36 months and regress them on the Fama and French (2015) factors to obtain the factor loadings which we then use to estimate the expected and the abnormal return of the portfolios in the current month. The abnormal return of the momentum strategy then is the equally-weighted average of the abnormal returns of the K long-short portfolios held simultaneously during the month. 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 with $(K-1)$ lags.

	K =							
J =	3	t-ratio	6	t-ratio	9	t-ratio	12	t-ratio
3 Sell	0.0016	1.40	0.0015	1.25	0.0018	1.48	0.0020	1.71
3 Buy	0.0021	1.88	0.0022	2.54	0.0025	3.20	0.0023	3.13
3 Buy-Sell	0.0005	0.26	0.0008	0.45	0.0007	0.47	0.0003	0.18
6 Sell	0.0017	1.34	0.0020	1.47	0.0023	1.68	0.0028	2.06
6 Buy	0.0030	2.63	0.0033	3.15	0.0029	2.96	0.0025	2.92
6 Buy-Sell	0.0013	0.61	0.0013	0.62	0.0006	0.30	-0.0002	-0.12
9 Sell	0.0022	1.61	0.0024	1.66	0.0028	1.90	0.0033	2.29
9 Buy	0.0038	3.25	0.0032	2.94	0.0029	2.75	0.0025	2.69
9 Buy-Sell	0.0016	0.73	0.0008	0.38	0.0001	0.03	-0.0008	-0.41
12 Sell	0.0025	1.78	0.0029	2.00	0.0035	2.28	0.0037	2.51
12 Buy	0.0030	2.55	0.0028	2.61	0.0025	2.41	0.0026	2.67
12 Buy-Sell	0.0005	0.22	-0.0001	-0.05	-0.0010	-0.44	-0.0011	-0.55

Table 5: 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_{MKTRF}^{Down}	-0.244	-2.98	0.902	24.83	1.146	18.01
β_{MKTRF}^{Flat}	0.295	3.31	1.125	24.98	0.830	14.62
β_{MKTRF}^{Up}	0.174	2.38	1.051	34.12	0.877	13.32
β_{SMB}^{Down}	-0.566	-3.81	0.653	9.44	1.219	11.43
β_{SMB}^{Flat}	-0.206	-1.11	0.858	9.94	1.064	8.93
β_{SMB}^{Up}	0.447	4.19	1.047	13.43	0.600	10.23
β_{HML}^{Down}	-0.657	-3.56	-0.237	-3.07	0.420	3.12
β_{HML}^{Flat}	-0.491	-1.94	-0.290	-2.48	0.201	1.32
β_{HML}^{Up}	0.086	0.82	-0.080	-1.30	-0.166	-2.39
β_{RMW}^{Down}	-0.271	-1.09	-0.426	-3.48	-0.155	-0.98
β_{RMW}^{Flat}	0.558	3.19	-0.158	-1.48	-0.716	-6.70
β_{RMW}^{Up}	0.553	3.86	-0.062	-0.96	-0.615	-5.92
β_{CMA}^{Down}	-0.060	-0.30	-0.205	-2.09	-0.145	-0.94
β_{CMA}^{Flat}	0.044	0.18	-0.128	-1.32	-0.172	-0.99
β_{CMA}^{Up}	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 6: Return-Sorted Portfolios

This table shows monthly mean returns of ten equal-weighted portfolios sorted on prior *6-month* performance. The winner (loser) portfolios consist of the ten percent best (worst) performing stocks of the formation period. Portfolios are held for the next *6-months*. One week is skipped between formation and holding period. Each month, 6 portfolios are held simultaneously. We show excess returns, CAPM alphas, FF3 alphas, FF5 alphas, q-factor alphas and q^5 alphas. All returns are adjusted at the stock level. T-ratios are calculated using Newey and West (1987) standard errors.

	Loser	Winner	WML
Return	0.77	1.52	0.75
	(2.67)	(5.78)	(4.53)
CAPM Alpha	-0.09	0.57	0.66
	(-0.50)	(4.05)	(4.02)
FF3 Alpha	-0.03	0.37	0.39
	(-0.22)	(4.12)	(2.19)
FF3 + Inv. Alpha	0.02	0.35	0.33
	(0.18)	(3.83)	(1.74)
FF3 + Prf. Alpha	0.17	0.40	0.23
	(1.21)	(4.00)	(1.12)
FF5 Alpha	0.26	0.38	0.11
	(1.88)	(3.68)	(0.53)
q-factor Alpha	0.30	0.58	0.28
	(2.24)	(5.72)	(1.50)
q^5 Alpha	0.38	0.55	0.17
	(2.64)	(5.04)	(0.82)

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	-1.04	-0.0013	-0.82	-0.0043	-2.26	-0.0018	-0.97
6-6 Buy	0.0060	6.18	0.0054	5.99	0.0064	5.21	0.0063	4.72
6-6 Buy-Sell	0.0077	3.31	0.0067	3.62	0.0108	3.87	0.0081	2.80
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: Momentum Returns during Sub-Periods

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 1963-1979, 1980-1999, and 2000-2018 periods. T-ratios are calculated using Newey and West (1987) standard errors.

	All	t-ratio	1963-1979	t-ratio	1980-1999	t-ratio	2000-2018	t-ratio
Non-adjusted	0.0075	4.53	0.0094	3.43	0.0130	7.48	-0.0004	-0.11
Portfolio-level	0.0077	3.31	0.0113	3.03	0.0130	6.10	-0.0030	-0.80
Stock-level	0.0011	0.53	0.0063	2.13	0.0030	0.89	-0.0052	-1.30

Table 9: Momentum Returns during Sub-Periods after Transaction Costs

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, 1963-1979, 1980-1999, and 2000-2018 periods. We account for 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	1963-1979	t-ratio	1980-1999	t-ratio	2000-2018	t-ratio
Non-adjusted	-0.0018	-1.11	-0.0021	-0.67	-0.0003	-0.14	-0.0033	-0.98
Portfolio-level	-0.0016	-0.68	-0.0001	-0.02	-0.0002	-0.07	-0.0058	-1.51
Stock-level	-0.0080	-3.87	-0.0054	-1.65	-0.0099	-3.15	-0.0080	-1.97

Table 10: Short-/Long-Term Beta

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 11: 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 12: 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	4.90	0.0031	0.68
Hong Kong	565	0.0070	2.44	0.0055	1.88	-0.0026	-0.49
Japan	4,712	-0.0007	-0.42	0.0001	0.04	-0.0061	-2.51
New Zealand	188	0.0075	4.00	0.0089	5.10	0.0032	0.98
Singapore	310	0.0087	2.70	0.0067	2.17	0.0017	0.24
Europe							
Austria	226	0.0070	3.20	0.0074	3.77	0.0033	1.05
Belgium	356	0.0072	3.84	0.0071	4.71	0.0055	2.72
Denmark	354	0.0097	5.72	0.0100	7.00	0.0062	2.41
Finland	255	0.0070	3.65	0.0043	1.96	-0.0003	-0.10
France	2,220	0.0062	3.75	0.0049	2.82	0.0035	1.35
Germany	2,030	0.0083	4.82	0.0054	3.01	0.0045	1.51
Greece	418	0.0054	2.09	0.0050	1.80	-0.0011	-0.23
Italy	608	0.0079	4.26	0.0071	3.31	0.0040	1.32
Netherlands	341	0.0070	3.61	0.0051	2.65	0.0045	1.54
Norway	513	0.0067	2.99	0.0061	2.68	0.0057	1.80
Portugal	199	0.0063	2.61	0.0053	2.11	0.0014	0.27
Sweden	951	0.0088	3.44	0.0033	1.21	0.0037	0.98
Switzerland	423	0.0076	3.63	0.0078	3.79	0.0067	3.00
UK	3,106	0.0065	3.56	0.0061	3.53	-0.0002	-0.06
North America							
Canada	5,147	0.0155	4.98	0.0125	3.71	0.0023	0.36

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.

C Internet Appendix

This is the Internet Appendix to the paper "Momentum? What Momentum?" by Erik Theissen and Can Yilanci (2020). Tables IA1, IA2, and IA3 show **value-weighted** non-adjusted, portfolio-level adjusted, and stock-level adjusted returns. They correspond to Tables 1, 2, and 3 in the paper.

Table IA1: Returns of Momentum Strategies

This table shows the monthly mean returns of the **value-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 with $(K-1)$ lags.

	K =							
J =	3	t-ratio	6	t-ratio	9	t-ratio	12	t-ratio
3 Sell	0.0051	1.81	0.0054	1.93	0.0057	2.10	0.0058	2.20
3 Buy	0.0114	4.99	0.0119	4.97	0.0124	5.23	0.0122	5.15
3 Buy-Sell	0.0063	3.16	0.0064	3.65	0.0067	4.27	0.0064	4.58
6 Sell	0.0045	1.51	0.0045	1.48	0.0043	1.49	0.0054	1.93
6 Buy	0.0128	5.46	0.0139	5.61	0.0142	5.75	0.0133	5.48
6 Buy-Sell	0.0083	3.45	0.0094	4.16	0.0098	4.86	0.0079	4.35
9 Sell	0.0034	1.09	0.0031	1.03	0.0043	1.43	0.0056	1.98
9 Buy	0.0146	6.09	0.0149	5.87	0.0142	5.63	0.0130	5.22
9 Buy-Sell	0.0113	4.55	0.0117	5.00	0.0099	4.66	0.0074	4.03
12 Sell	0.0016	0.51	0.0035	1.11	0.0049	1.62	0.0062	2.17
12 Buy	0.0141	5.74	0.0140	5.47	0.0133	5.25	0.0124	4.95
12 Buy-Sell	0.0125	4.97	0.0105	4.43	0.0084	3.93	0.0062	3.19

Table IA2: Portfolio-Level Risk Adjustment

This table shows the monthly mean returns of the **value-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 with $(K-1)$ lags.

	K =							
J =	3	t-ratio	6	t-ratio	9	t-ratio	12	t-ratio
3 Sell	-0.0032	-1.82	-0.0032	-1.95	-0.0031	-1.96	-0.0033	-2.23
3 Buy	0.0039	3.15	0.0039	3.53	0.0045	4.72	0.0043	5.32
3 Buy-Sell	0.0071	2.71	0.0071	2.86	0.0076	3.36	0.0076	3.83
6 Sell	-0.0040	-1.97	-0.0044	-2.19	-0.0049	-2.67	-0.0042	-2.60
6 Buy	0.0051	3.54	0.0061	4.44	0.0065	5.39	0.0057	5.47
6 Buy-Sell	0.0091	2.90	0.0105	3.38	0.0113	4.17	0.0099	4.35
9 Sell	-0.0051	-2.47	-0.0058	-2.90	-0.0051	-2.84	-0.0041	-2.54
9 Buy	0.0070	4.80	0.0074	5.32	0.0068	5.40	0.0057	5.23
9 Buy-Sell	0.0121	3.85	0.0132	4.35	0.0119	4.48	0.0098	4.43
12 Sell	-0.0071	-3.40	-0.0059	-3.04	-0.0049	-2.91	-0.0040	-2.56
12 Buy	0.0069	4.89	0.0068	5.19	0.0061	5.25	0.0052	5.17
12 Buy-Sell	0.0140	4.57	0.0127	4.48	0.0110	4.62	0.0092	4.62

Table IA3: Stock-Level Risk Adjustment

This table shows the monthly mean returns of the **value-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 with $(K-1)$ lags.

	K =							
J =	3	t-ratio	6	t-ratio	9	t-ratio	12	t-ratio
3 Sell	0.0006	0.49	0.0009	0.64	0.0008	0.64	0.0006	0.52
3 Buy	0.0019	1.70	0.0022	2.20	0.0027	3.06	0.0027	3.38
3 Buy-Sell	0.0012	0.68	0.0013	0.72	0.0018	1.17	0.0020	1.40
6 Sell	0.0014	0.90	0.0011	0.67	0.0007	0.46	0.0008	0.54
6 Buy	0.0027	2.24	0.0038	3.08	0.0040	3.66	0.0039	3.80
6 Buy-Sell	0.0013	0.56	0.0027	1.18	0.0033	1.61	0.0031	1.62
9 Sell	0.0007	0.43	0.0002	0.11	0.0003	0.20	0.0005	0.35
9 Buy	0.0045	3.61	0.0046	3.56	0.0044	3.64	0.0040	3.47
9 Buy-Sell	0.0038	1.69	0.0044	1.92	0.0041	1.83	0.0035	1.66
12 Sell	-0.0005	-0.29	0.0003	0.17	0.0005	0.33	0.0005	0.30
12 Buy	0.0043	3.25	0.0045	3.43	0.0042	3.29	0.0040	3.27
12 Buy-Sell	0.0048	1.98	0.0042	1.76	0.0036	1.58	0.0035	1.63

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