Expected Skewness and Momentum

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Abstract

Motivated by the time-series insights of Daniel and Moskowitz (2014), we investigate the link between expected skewness and momentum in the cross-section. The three factor alpha of skewness-enhanced (-weakened) momentum strategies is about twice (half) as large as the traditional momentum alpha. In fact, skewness is among the most important cross-sectional determinants of momentum. Our findings do not neatly fit within a specific prominent theory of momentum. Due to the simplicity of the approach, its economic magnitude, and its existence among large stocks and in the recent past, the results appear difficult to reconcile with the efficient market hypothesis.

Keywords: Momentum, skewness, market efficiency, return predictability, behavioral finance

JEL Classification Codes: G12, G14

^{*}We wish to express our thanks to Byoung-Kyu Min, Lubos Pastor, Ralitsa Petkova, and to the seminar participants at the 18th Conference of the Swiss Society for Financial Market Research (SGF) and at the University of Mannheim for helpful comments and valuable suggestions. All remaining errors are our own. Send correspondence to: Tobias Regele, Finance Department, University of Mannheim, L5, 2, 68131 Mannheim, Germany. Phone: +49 621 1811539. E-mail: toregele@mail.uni-mannheim.de. Heiko Jacobs, Finance Department, University of Mannheim, L5, 2, 68131 Mannheim, Germany. E-mail: jacobs@bank.bwl.uni-mannheim.de. Phone: +49 621 1813453. Martin Weber, Finance Department, University of Mannheim, L5, 2, 68131 Mannheim, Germany. E-mail: weber@bank.bwl.uni-mannheim.de. Phone: +49 621 1811532.

1 Introduction

One of the most puzzling and robust anomalies in capital markets is the momentum effect, which denotes the continuation of medium term returns (Jegadeesh and Titman, 1993, 2001). In this paper, we comprehensively explore a new dimension in firm-level momentum profitability. More precisely, we document a strong relation between expected idiosyncratic skewness and momentum profits in the cross-section of stock returns.¹ The impact of skewness is economically large, statistically highly significant, holds among large firms, in the recent past, and after controlling for virtually all firm characteristics previously linked to momentum profitability (e.g. past returns, volatility, continuously arriving information, credit rating, the 52-week high or unrealized capital gains). In sum, skewness appears to be among the most important cross-sectional determinants of momentum profits.

Analyzing the relation of skewness and momentum constitutes a promising endeavour for at least the following three reasons. First, recent asset pricing models show that skewness is an important determinant of equilibrium asset returns (Barberis and Huang, 2008; Brunnermeier et al., 2007; Mitton and Vorkink, 2007; Bordalo et al., 2013), which is corroborated by empirical evidence (Boyer et al., 2010; Bali et al., 2011; Conrad et al., 2013). Thus, analyzing the interaction of skewness and known anomalies in capital markets constitutes an auspicious undertaking. Second, recent work has uncovered that the time-series of momentum returns is negatively skewed (Daniel and Moskowitz, 2014; Barroso and Santa-Clara, 2015), and we know that and momentum is pervasive (Asness et al., 2013). Therefore, as a matter of course, examining the connection between skewness and momentum in the cross-section is a natural and promising choice. Third, among academics and practitioners alike, there is an ongoing and controversial debate among the firm-level determinants of momentum (Bandarchuk and Hilscher, 2013; Asness et al., 2014).

We hypothesize that the outperformance of winners is partly driven by negative skewness, whereas the underperformance of losers in parts derives from their positive skew. If losers are on average more positively skewed than winners, then the resulting winners-losers momentum portfolio will be negatively skewed. Therefore, we conjecture that, in the cross-section, the average long-short momentum returns increase with the difference in the level of skewness of the long and short leg of the portfolio.

¹For the sake of readability, we will refer to expected idiosyncratic skewness as skewness in the following, unless otherwise stated.

As a proxy for expected skewness, our baseline analysis relies on the measure proposed by Bali et al. (2011) because of its simplicity, its economic persuasiveness and its ability to predict realized skewness. This measure is calculated as the maximum daily return during the preceding month. We benchmark our findings against the profitability of the traditional momentum approach based on past return quintiles, which, after dropping small and illiquid stocks, delivers an average value-weighted monthly excess return of 0.81% (t = 4.28) in the United States over the period from January 1927 to December 2011 (see section 2.2).

We start with a long-short momentum strategy with little skewness, which consists of winner (loser) stocks with ex ante particularly positive (negative) skewness. We find that the profitability of momentum is strongly diminished: monthly long-short returns estimates decrease to 0.47% (t = 2.05) for this skewness-weakened strategy (henceforth: weakened momentum). At the same time, one can in fact double the value-weighted returns delivered by the traditional momentum approach by focusing on negatively skewed winners and positively skewed losers. This skewness-enhanced strategy (henceforth: enhanced momentum) yields a raw long-short return of 1.65% (t = 6.26) per month over the same sample period.

Superior (inferior) returns of enhanced (weakened) momentum cannot be attributed to commonly-received risk factors.² On the contrary, return patterns are even more pronounced if we control for traditional measures of risk: the monthly Fama and French (1993) three factor alpha equals 0.21% (t = 1.50) for weakened momentum, 0.96% (t = 5.83) for traditional momentum, and 2.14% (t = 11.42) for enhanced momentum. These effects can be identified in all size groups. For instance, even for large stocks with a market capitalization above the NYSE median, the three factor alpha of an enhanced (weakened) momentum strategy is 1.87% (0.24%) with a t-statistic of 8.60 (1.14).

Moreover, our findings withstand a number of robustness checks. For example, they hold also in the recent past, in multivariate cross-sectional regressions or portfolio sorts, or in portfolios with particularly low implementation costs. Most importantly, our findings are robust to numerous controls such as idiosyncratic volatility or past returns.

To provide out-of-sample tests, we repeat the analysis in 16 international developed stock mar-

 $^{^2\}mathrm{Note}$ that traditional risk measures such as the correlation with market in the CAPM do not account for skewness.

kets. We focus on developed markets to ascertain a high level of data quality (e.g. to measure expected skewness), comprehensive data availability (e.g. for the control variables), and in order to be consistent with previous literature (e.g. Asness et al. (2013)). Using Fama and MacBeth (1973) regressions, we find that one standard deviation increase (decrease) of the skewness of winners (losers) diminishes momentum profits by on average 0.36% (across countries), irrespective of the inclusion of variables that have previously been argued to enhance momentum profits, such as volatility, past returns and momentum strength. This relation is statistically significant at the 5% level for 75% of the countries under consideration. Notably, the relation holds in the Group of 7, i.e., Canada, France, Germany, Italy, Japan and the United Kingdom.

Also in monetary terms, our results are strong and cast doubt on the notion of efficient financial markets by virtue of the simplicity of their construction. Inspired by Daniel and Moskowitz (2014), we invest \$1 at the beginning of January 1927 in each of the three long-short strategies and compare the terminal values at the end of December 2011. Figure 1 demonstrates that our findings are impressive from an economic point of view.

Insert Figure 1 here

The usual momentum strategy delivers a terminal value of \$29,706. This value is about 14-fold of the terminal value of a buy-and-hold strategy of the market portfolio which yields \$2,107. The enhanced momentum strategy delivers a terminal value of \$9,685,302, which is more than 325-fold the usual momentum strategy and almost 4,500-fold of the aforementioned buy-and-hold of the market portfolio. The weakened momentum accumulates a rather small amount of \$1,012 over the same sample period.³

While enhanced momentum has moderately higher tail risk than traditional momentum, its risk-adjusted return is still surprisingly large. Thus, it seems difficult to explain the abnormal returns with aversion against tail risk (Bates, 2008). For instance, the Omega ratio (Shadwick and Keating, 2002) which accounts for *all* moments of the return distribution shows that enhanced momentum clearly outperforms traditional momentum approaches.

By applying the risk management procedure recently suggested by Barroso and Santa-Clara (2015), the profitability increases further. Figure 1 demonstrates that risk management suc-

 $^{^{3}}$ The comparison with the market should be interpreted with care as momentum strategies in general require active trading whereas the market is a buy-and-hold investment. Nevertheless, turnover matters for both enhanced and weakened momentum to a similar extent, and the differences in terminal value across momentum strategies thus provide an illustration for the economic magnitude of our main findings.

ceeds in ameliorating the cumulative gains of the enhanced momentum strategy. These gains amount to more than \$69 million, which is about 7.2 times the gains of the plain version of enhanced momentum and more than 2,300-fold of the gains of the traditional momentum. Application of an alternative risk management method proposed by Daniel and Moskowitz (2014) yields similar results: the terminal value obtained by this risk-managed version of enhanced momentum is larger than \$116 million.

On average, the characteristics of stocks entering weakened and enhanced momentum portfolios are similar. However, differences in the average profitability of momentum strategies are mainly attributable to the short leg of the strategies. To some extent, this finding points to limits to arbitrage as many investors are not allowed to go short (Stambaugh et al., 2012). However, short interest for enhanced losers tends to be larger than short interest for weakened losers, which indicates that a subset of market participants without binding short-selling constraints might aim at actively exploiting the return patterns which we uncover.

To better understand the underlying drivers, we also analyze the long-term profitability of enhanced and weakened momentum strategies for up to 36 months after the formation period. On the one hand, we find that the impact of skewness on momentum profits does not revert in the long-run, but continues to persist, even after controlling for a large set of firm characteristics that have previously been related to momentum profits. On the other hand, we find that the interaction of skewness and momentum holds among large firms, firms with high residual analyst coverage, low institutional ownership, good credit rating and irrespective of their unrealized capital gains. Taken together, these findings appear to provide a challenge for popular theories of momentum, which are based on investor overreaction (Daniel et al., 1998), investor underreaction followed by overreaction (Barberis et al., 1998; Hong and Stein, 1999), agency issues in delegated fund management (Vayanos and Woolley, 2013), credit risk (Avramov et al., 2007) or the disposition effect (Grinblatt and Han, 2005).

Our findings contribute to two strands of the literature. First, we add to the momentum literature by highlighting that large parts of the momentum profitability are attributable to return premia received for skewness. In fact, Fama and MacBeth (1973) regressions with up to 20 firm-level controls indicate that skewness is among the strongest predictors of momentum profits. For instance, its role seems to be more important and to go clearly beyond the impact of idiosyncratic volatility (Bandarchuk and Hilscher, 2013), information uncertainty (Zhang, 2009),

continuously arriving information (Da et al., 2014), implied price risk (Chuang and Ho, 2014), or credit rating (Avramov et al., 2007). Increasing (decreasing) the skewness of winners (losers) by one standard deviation diminishes momentum profits by about 0.33%. With respect to models of momentum, our findings collectively suggest the need for the development of theoretical explanations that are consistent with the strong empirical patterns.

Second, we add to the rapidly growing strand of literature that highlights the pricing of expected idiosyncratic skewness. Barberis and Huang (2008), Brunnermeier et al. (2007) and Mitton and Vorkink (2007) show that pricing of idiosyncratic skewness is possible in equilibrium models when investors are not homogeneous or deviate from rational utility maximization. On the empirical side, Boyer et al. (2010), Bali et al. (2011) and Conrad et al. (2013) find that a portfolio that buys (sells) stocks with negative (positive) expected idiosyncratic skewness yields significant risk-adjusted excess returns. Several papers also link expected idiosyncratic skewness to seemingly unrelated financial phenomena such as the underperformance of IPOs (Green and Hwang, 2012), the distress risk puzzle (Conrad et al., 2014) or the pricing of options (Boyer and Vorkink, 2014). We contribute to this work by establishing a strong link between expected idiosyncratic skewness and the momentum puzzle.

2 Empirical Analysis

2.1 Data and Methodology

Our baseline analysis in the United States is based on daily and monthly return data for all common stocks (CRSP share code equal to 10 or 11) traded on NYSE, AMEX, or NASDAQ. The sample period covers 1926 to 2011. As it is common in the momentum literature (Jegadeesh and Titman, 2001), we exclude stocks with a beginning of holding period price below \$5. Further, we eliminate firms whose market capitalization falls within the lowest NYSE decile. Doing so results in eliminating close to 50% of the CRSP common stock universe. Thus, we ensure that our findings are not driven by economically less relevant small and illiquid stocks. To further mitigate concerns related to market microstructure, we provide both equally and value-weighted returns in our empirical analysis. The final sample consists of about 1.67 million firm-month observations. Furthermore, balance sheet information, short interest and credit ratings are obtained from Compustat, and analyst-based information is gathered from I/B/E/S.

Stock market and accounting data for 16 developed international markets is gathered from

Datastream and Worldscope, respectively. Details about the sample construction are provided in the online appendix.

Recall our claim that expected skewness should matter for returns of the momentum strategy in the cross-section. Assessing ex ante skewness is a difficult exercise since skewness is not persistent and past skewness alone badly predicts future skewness (Chen et al., 2001; Singleton and Wingender, 1986). Consequently, we need a model to forecast future skewness based on information that is available today. As outlined in the literature review, recent work has proposed several approaches (Bali et al., 2011; Boyer et al., 2010; Conrad et al., 2013).

Simply using the maximum daily return over the past month, as suggested by Bali et al. (2011), is arguably an intuitive and easy-to-compute measure for expected skewness:

$$SKEW_{i,t+1}^{\text{MAX}} = \max_{\{\tau \text{ in month t }\}} r_{i,\tau}$$
(1)

The connection between maximum daily returns and the skewness of the underlying distribution can also be mathematically shown. It is motivated by a direct application of Markov's inequality. For any random variable X with finite first three moments, Markov's inequality asserts for any w > 0:

$$P(|X - \mathbb{E}(X)| > w) \le \frac{\mathbb{E}\left(\left(|X - \mathbb{E}(X)|\right)^3\right)}{w^3} \Leftrightarrow P(|X - \mathbb{E}(X)| > w) \le \frac{|\gamma_3| \cdot \sigma^3}{w^3}$$
(2)

where γ_3 and σ denote the skewness and volatility of X. Thus, skewness provides an upper bound for extreme realizations of X. The occurrence of returns that strongly deviate from the respective means indicate high levels of absolute skewness. In other words, high maximum returns are an indicator for high positive skewness and low minimum returns indicate low skewness. Hence, we have a strong mathematical link between the measure and skewness, and it can be intuitively assessed by investors. In addition, as shown in Table 1 in the online appendix, this measure predicts future skewness more accurately than past skewness. Further, it has also been used to explain the Betting-against-Beta anomaly (Bali et al., 2014). Thus, the measure by Bali et al. (2011) constitutes our baseline proxy for the empirical analysis.

The more complex model of Boyer et al. (2010) has successfully been used in Green and Hwang (2012), and we will use it to ascertain our results.⁴ The idea is to estimate expected skewness

⁴The third cited model of expected skewness (Conrad et al., 2013) is based on information obtained from option markets. Implied expected skewness is derived from prices of options with different maturities. We do

from information contained in the cross-section of stock returns. More precisely, the approach employs past skewness in combination with a set of firm characteristics (such as past idiosyncratic volatility, turnover, or industry classification) to predict future skewness (see also Chen et al. (2001)). To assess idiosyncratic moments, we run regressions using daily data:

$$r_{i,t} - r_t^f = a + b_1 \text{MKTRF}_t + b_2 \text{SMB}_t + b_3 \text{HML}_t + \epsilon_{i,t}$$
(3)

where MKTRF, SMB and HML denote the Fama and French (1993) factors, and calculate idiosyncratic moments based on $\epsilon_{i,t}$. For the estimation of the residual returns $\epsilon_{i,t}$, we include daily return data from the previous 60 months in the regressions. Idiosyncratic volatility $iv_{i,t}$ and skewness $is_{i,t}$ of firm *i* in month *t* are then computed based on the residual daily returns. More precisely, idiosyncratic volatility is the standard deviation and idiosyncratic skewness the standardized third momentum of the residuals $\epsilon_{i,t}$. As Boyer et al. (2010), we then perform the following regression for each month *t*:

$$is_{i,t} = \alpha_t + \beta_t \cdot iv_{i,t-60} + \gamma_t \cdot is_{i,t-60} + \delta'_t \cdot X_{i,t-60} + \eta_{i,t}$$
(4)

and also the same set of firm characteristics. In the second step, we compute our measure of expected skewness as

$$SKEW_{i,t+60}^{\text{REG}} = \alpha_t + \beta_t \cdot iv_{i,t} + \gamma_t \cdot is_{i,t} + \delta'_t \cdot X_{i,t}$$
(5)

Results we present in Table 1 in the online appendix show that this measure forecasts future skewness better than past skewness. However, the measure of Bali et al. (2011) predicts skewness more accurately.

2.2 Baseline Results

We start by conducting dependent 5x5 sorts of our baseline skewness measure (the maximum daily return over the previous month) and formation period returns. In each month, we first sort all stocks into quintiles based on expected skewness and then form further quintiles based on their past cumulative returns. Winner (loser) stocks are stocks in formation period quintile 5 (1). Our construction of the baseline momentum portfolios follows Daniel and Moskowitz (2014). More precisely, we choose a formation period of twelve months, a holding period of one

not employ this procedure since data for option markets are only available for a rather short timespan, namely from 1996 onwards. Moreover, skewness is computed from risk-neutral probabilities that might actually strongly deviate from physical probabilities. As skewness is essentially driven by the likelihood of small probability events, risk-neutral skewness can be very different from actual skewness.

month and skip one month in between (during which skewness is measured).

Our baseline results on the link between the profitability of the momentum strategy and expected skewness are displayed in Table 1. Regular momentum, which consists of winners and losers in the third skewness quintile, serves as a benchmark for modified momentum strategies (see below). It delivers an equally (value-) weighted raw return of 0.93% (0.81%) per month.

Insert Table 1 here

If momentum profits are driven by the negative skewness of winners and positive skewness of losers, they will be diminished after controlling for skewness. To investigate this claim, we construct a portfolio by buying positively skewed winners and selling negatively skewed losers. Thus, the long leg consists of stocks that are in the top quintile with respect to both their skewness and the past cumulative return. Likewise, the short leg comprises negatively skewed losers, i.e., stocks in the bottom quintile with respect to both characteristics.

Equally weighted portfolio returns are presented in Panel A. Indeed, averaged over the period from 1927 to 2011, this skewness-weakened momentum delivers a raw return of only 0.21% per month, which is statistically indistinguishable from zero. Similarly, the CAPM intercept is 0.00% per month. The inclusion of the Fama and French (1993) factors does not influence the results as the intercept stays insignificant at 0.12%. If we additionally include factors for long-term and short-term reversal, the intercept slightly increases to 0.33%, which is significant only at the 10% level. As Panel B shows, the results are not substantially altered if we focus on value-weighted portfolios. Irrespective of the factor model or return weighting scheme employed, the long-short return is always considerably smaller than the return of a traditional momentum portfolio which does not condition on skewness.

We now focus on the oppositive strategy by constructing a portfolio with ex ante negatively skewed winners in the long leg and positively skewed losers in the short leg. If momentum profits are caused by the difference in skewness premia for winners and losers, the aforementioned double sorting will amplify the returns of the zero-cost portfolio.

Again, we first look at equally weighted returns presented in Panel A of Table 1. The monthly raw return of enhanced momentum amounts to 1.90%, which is about twice the return of standard momentum returns. Accounting for market risk and the Fama and French (1993) factors ascertains our results as the intercepts are 2.40% and 2.55% per month respectively. The intercept of the aforementioned five factor model is 2.58%. All intercepts are highly significant at any conventional significance level. As before, the results are not altered by value-weighting portfolio returns. Raw returns amount to 1.65% per month. On a risk-adjusted basis, the longshort portfolio yields a CAPM intercept of 2.14% and a Fama and French (1993) intercept of 2.31%. The inclusion of factors for long- and short-term reversal delivers an alpha of 2.36%.

To isolate the incremental effect of the double sorts, we consider the strategy enhanced momentum *minus* weakened momentum, which is by construction momentum-neutral. This strategy yields large and strongly significant returns for both equal and value-weighting, irrespective of risk-adjusting. For example, the Carhart (1997) intercept for value-weighted returns amounts to 1.72% and is significant at any conventional level.

In essence, we are able to double momentum profits by focusing on ex ante negatively skewed winners and strongly positively skewed losers. By the same token, the profitability of the momentum strategy is strongly diminished after cancelling the positive (negative) skewness return premiums of winners (losers). In conclusion, the evidence indicates that the momentum anomaly is strongly linked to skewness.

As a next step, we analyze whether the long or short legs of enhanced and weakened momentum equally cause our results. Panel C and D of Table 1 report equally and value-weighted raw returns of winners and losers in each skewness quintile. While there is no clear pattern for winners, loser returns decline monotonically, indicating that the effect is mainly driven by the short leg.

To further explore the differences in returns of both legs of enhanced and weakened momentum, we compute risk-adjusted returns. Moreover, we test whether loser and winner returns of the two modified momentum strategies differ significantly from traditional momentum. Since our findings are always weaker for value-weighted return, we document only these results, but unreported analysis confirms that the same applies to equally weighted returns. Table 2 below shows the main findings.

Insert Table 2 here

The profitability of both the enhanced and the weakened momentum strategies are attributable to their short legs. There is no significant difference between the returns of enhanced, weakened, and regular winners. However, weakened losers significantly surpass regular losers by 0.21% per month, which in turn strongly outperform enhanced losers by 0.98% on a monthly basis. The return difference between weakened and enhanced losers amounts to 1.20%.

One reason for the asymmetrical effect of skewness on winners and losers might be the following: both short-selling positively skewed losers and buying negatively skewed winners loads skewness risk on an investor's portfolio. However, the former potentially yields unbounded losses while the risk of loss is limited by the initial investment for the latter. The goal of the following section is thus to investigate whether the superior (inferior) returns of the enhanced (weakened) momentum are a compensation for additional (less) risk.

2.3 How risky is skewness-enhanced momentum?

As already shown, traditionally employed risk factors such as the Fama and French (1993) factors or factors for long- and short-term reversal indicate that the performance difference between weakened and enhanced momentum is not attributable to risk. We thus rely on various further approaches. Namely, we compute the average total volatility, the average skewness, the 1% percentile of monthly returns and the minimum monthly return over our sample period. To measure performance, we compute the well-known Sharpe ratio, the Sortino ratio and the Omega ratio for each portfolio. The Sortino ratio is calculated like the Sharpe ratio, but with downside volatility in the denominator, and thereby accounts for skewness. The Omega ratio (Shadwick and Keating, 2002) is defined as

$$\Omega = \frac{\int_0^\infty (1 - F(x))dx}{\int_{-\infty}^0 F(x)dx}$$
(6)

where F(x) denotes the cumulative distribution function of returns. Thus, the Omega ratio accounts for *all* moments and not only for volatility and skewness. In addition to the aforementioned risk and performance measures, we compute the median, the maximum return and the 1-Factor, 3-Factor and 5-Factor α and the Fama and French (2015) α of each portfolio. Table 3 displays the results.

Insert Table 3 here

For all factor models considered, the α s of any enhanced momentum portfolio are about twice as big as for regular and weakened momentum. Enhanced momentum returns display a monthly volatility of 8.1% while the volatility of weakened momentum amounts to 7.3%. Both modified momentum portfolios are more volatile than the regular momentum strategy with a volatility of 6.3%. However, volatility fails to explain the performance difference as the Sharpe ratios of enhanced (weakened) momentum amount to 0.70 (0.22) and are therefore substantially greater (less) than the Sharpe ratio of traditional momentum which equals 0.45.

As a next step, we look at the skewness of the portfolios under consideration. Both enhanced momentum and regular momentum are strongly negatively skewed, with a skewness of -1.87 and -0.99, respectively. The skewness of weakened momentum strategy is exactly zero, which indicates that our employed measure for expected skewness works reasonably well. The Sortino ratios of enhanced (weakened) momentum are 0.73 and 0.30, respectively. The Sortino ratio of the markets amounts to 0.53 which again suggests that enhanced momentum returns appear too large, even after accounting for skewness, to mainly represent a compensation for known forms of risk. Note that the Sortino ratios of regular momentum and the market portfolio are equal. Hence, after accounting for skewness, traditional momentum does not deliver superior performance in comparison with the market (see also Daniel and Moskowitz (2014)).

Finally, we compute the Omega ratio for each of the portfolios. The Omega ratio of the market portfolio should not be surpassed by any portfolio, because the Omega ratio takes account of *all* moments and therefore incorporates *any* risk. Indeed, the Omega ratio of the market portfolio amounts to 1.58 and exceeds the ratio of the regular momentum which amounts to 1.46. However, the Omega ratio of the enhanced momentum is 1.83 and thus considerably greater than the one of the market portfolio, while the Omega ratio of the weakened momentum amounts to 1.21. We conclude that the performance of enhanced momentum strategy cannot be convincingly explained by existing risk models.

If investors are particularly averse against large negative returns, they will require a return premium for tail risk (Bates, 2008). For instance, Kelly and Jiang (2014) show that crash risk commands a return premium of about 6% per year. However, in view of the performance documented above, our results seem too strong to be attributable to investors' aversion against crash risk. We also point out that the tail risk of enhanced momentum is moderate: The 1% percentile of monthly returns is -23.67% which is commensurable to the 1% percentile of monthly returns of regular momentum or the market which amount to -16.33% and -15.00%, respectively.

In the following, we explore whether the apparent imbalance between risk and return of the enhanced momentum can be further magnified. A recent paper by Barroso and Santa-Clara (2015) shows that the skewness risk of momentum can be significantly reduced by means of a fairly simple risk management procedure. Their idea is to scale the momentum strategy based on forecasted variance to keep the realized variance constant, i.e., to increase exposure when the forecasted variance is low and divest when it is high. Since momentum returns tend to be higher in calm market conditions, this procedure greatly improves the performance of momentum.

It seems natural to apply their methodology to enhanced momentum in an attempt to partly reduce the skewness risk. Following Barroso and Santa-Clara (2015), we compute a monthly variance forecast based on daily return data of enhanced momentum from the previous six months. Let $r_{\text{Enhanced Momentum}_{d_t}}$ denote the return of the last trading day in month t. We then compute the volatility forecast $\hat{\sigma}_{\text{Enhanced Momentum}_t}^2$ of enhanced momentum in month t according to the following formula (assuming one month has on average 21 trading days):

$$\hat{\sigma}_{\text{Enhanced Momentum}_t}^2 = \frac{21}{126} \cdot \sum_{i=1}^{126} r_{\text{Enhanced Momentum}_{d_t-i}}^2 \tag{7}$$

The next step is to scale the monthly returns of enhanced momentum, $r_{\text{Enhanced Momentum}t}$, to achieve a pre-specified variance σ_{target} . We then evaluate the performance of the risk managed enhanced momentum strategy for a pre-specified target volatility of 13%.⁵ We denote the resulting returns of the risk-managed enhanced momentum as $r_{\text{Enhanced Momentum}*_t}$:

$$r_{\text{Enhanced Momentum}*_t} = \frac{\sigma_{\text{target}}}{\hat{\sigma}_t} \cdot r_{\text{Enhanced Momentum}_t}$$
(8)

Daniel and Moskowitz (2014) also propose a methodology to reduce the inherent skewness risk of momentum. In contrast to the aforementioned risk-management procedure, their method separately estimates the expected return and volatility in a dynamic setting. The investment weights are then chosen based on these estimates to maximize the conditional Sharpe ratio of the resulting strategy. As before, we scale the strategy's volatility to the volatility of the market.

Table 3 shows that the risk-management approaches succeed in reducing the tail risk of enhanced momentum. In particular, the 1% of returns amounts to about -13.8% for both risk-managed enhanced momentum strategies, which is greater than -16.33% and -15.03% for the regular momentum and the market, respectively. As a consequence, all performance measures increase

⁵Note that the actual volatility of monthly returns will be higher because of small autocorrelation of daily returns (Barroso and Santa-Clara, 2015). We pick the target level of 13% because we want to match the realized volatility of our risk managed enhanced momentum with the one of the market over the entire sample period. In unreported robustness checks we have verified that inferences do not change if we use other levels of target volatility.

substantially for the risk-managed enhanced momentum strategies. For instance, the Sortino ratio of both risk-managed enhanced momentum strategies is almost three times the Sortino ratio of the market and about five times the Sortino ratio of weakened momentum.

As depicted in Figure 1 in the introduction, both forms of risk management appear to work well in the long run: Measured from 1927 to 2011, the terminal wealth of both strategies is more than seven times greater than the gains of the baseline form of enhanced momentum, more than 2,300 times the gains of regular momentum and more than 32,000-fold the gains of the market.

2.4 Are findings attributable to cross-sectional differences in firm-characteristics?

To identify possible sources of the large differences in momentum profits, we compare firm characteristics for stocks entering either the long or short leg of either the weakened or the enhanced momentum strategy. In total, we consider 19 variables which have previously been related to momentum profitability. Those variables are shortly described in the following, and explained in the appendix more in-depth.

Idiosyncratic volatility and momentum strength are two key sources of momentum profits as recently uncovered by Bandarchuk and Hilscher (2013). Thus, we include these two variables. In addition, we include age, analyst forecast dispersion, analyst coverage and cash flow volatility as proxies of information uncertainty (Zhang, 2009). Further, we insert turnover (Lee and Swaminathan, 2000) and profitability (Novy-Marx, 2013). To control for effects of liquidity, we include the bid-ask spread calculated based on the algorithm of Corwin and Schultz (2012). We further add the continuous information variable from Da et al. (2014), the 52-week high price (George and Hwang, 2004), the return consistency variable from Grinblatt and Moskowitz (2004) and implied price risk (Chuang and Ho, 2014). To account for the disposition effect, we include the unrealized capital gains measure from Grinblatt and Han (2005). We also control for the market factor, size, and the book-to-market ratio by including the respective Betas. We obtain those Betas from time series regressions using daily data from the previous twelve months. Finally, we include market capitalization and short interest.

Every month, we sort stocks into deciles according to each characteristic and compute the average decile for enhanced, weakened and regular momentum together with their long and short legs. Then, we compute the time-series average of the average deciles for each characteristic and each portfolio. Compared to using the raw characteristic (such as market capitalization in million USD), this procedure has the advantage of accounting for time-series variation in average values (such as the typical listed firm becoming larger in our sample period). Moreover, comparisons can be made easily and intuitively. The results are depicted in Table 4 below.

Insert Table 4 here

Apparently, firms with high skewness, i.e., enhanced losers and weakened winners, are on average harder to value and more difficult to arbitrage than firms with low skewness. These stocks tend to be firms with high idiosyncratic volatility and high bid-ask spreads, two characteristics that are often related to limits to arbitrage. Further, they are on average small and young firms with high cash flow volatility, high analyst forecast dispersion, and a rather bad credit rating which collectively indicates that those stocks are hard to value. However, recall that we excluded economically less important small and illiquid stocks (about 50% of the CRSP common stock universe).

Note that firms with high skewness are part of both the enhanced and the weakened momentum portfolio. Thus, simple differences in firm characteristics are unlikely to explain our findings. Nevertheless, high skewness firms enter the enhanced strategy in the short leg and the weakened strategy in the long leg. At the same time, our results are mainly driven by the short leg. These findings could point to limits to arbitrage that might stem from the fact that many institutional investors such as mutual funds are not allowed to go short (Almazan et al., 2004). Alternatively, those investors who are principally allowed to go short might choose not to do so because of noise trader risk (e.g. Shleifer and Vishny (1997)) or other potential risks and costs related to shorting (see e.g. Engelberg et al. (2014) or Stambaugh et al. (2014) for overviews).

However, short interest for enhanced losers is on average substantially larger than short interest for weakened losers. This implies that short-selling constraints or related limits to arbitrage do not seem to drive our findings. In contrast, these findings are suggestive of the idea that a subset of sophisticated investors who are capable of going short might try to exploit the low expected returns from losers with high expected skewness.

The last two columns of Table 4 show that, on average, similar firms enter the enhanced and weakened momentum strategy. Thus, it seems unlikely that the enormous performance difference is attributable to distinctions in firm characteristics. To address this issue more rigorously, we conduct a number of Fama and MacBeth (1973) regressions of momentum profits on our skewness measure and a set of controls. This approach allows us to ascertain the robustness of

the relation between skewness and momentum documented in the above analysis, and it also helps us to quantify the role of skewness relative to other firm-level variables. We follow the methodology of Bandarchuk and Hilscher (2013) and define the dependent variable, momentum profits $r_{mom,t}$ of firm *i*, as follows:

$$r_{i,mom,t} = (r_{i,t} - r_{median,t}) \cdot sign \left(r_{i,t-12 \text{ to } t-2} - r_{median,t-12 \text{ to } t-2} \right)$$
(9)

where $r_{median,t}$ denotes the median profit of all stocks at month t. Thus, stocks with above median returns are considered winners and stocks with below median returns are losers and hence their returns are multiplied by -1. Because of the conjectured impact of skewness on winners and losers, we proceed similarly with the expected skewness measures $SKEW_{i,t+1}^{MAX}$ and $SKEW_{i,t+1}^{REG}$:

$$SKEW_{i,t+1} = SKEW_{i,t+1} \cdot sign\left(r_{i,t-12 \text{ to } t-2} - r_{median,t-12 \text{ to } t-2}\right)$$
(10)

The controls we take into account correspond to most characteristics outlined in Table 4 plus the return in the skipped month and dummies for the 49 Fama/French industries (see Table 5). Not all firm characteristics are available for the whole sample period starting from 1926. We therefore run two sets of robustness checks which differ in the number of controls used as well as in the starting date (1926 or 1981).

We standardize all explanatory variables by months to make their impacts comparable. Further, we logarithmize idiosyncratic volatility, the 52-week high price, age, turnover and the bid-ask spread, since those variables are positively skewed. Using the raw variables instead does not change inferences. The results of the first regression, which covers the entire sample period, are displayed in Table 5. All resulting coefficients are multiplied by 100. In specification (1), we regress momentum profits on skewness and in specification (4), we include our first set of control variables (available from 1926 on). We repeat this exercise in specifications (2) and (5) and add dummies for 49 Fama/French industries. Specification (3) reports results for the set of control variables without including skewness.

Insert Table 5 here

Amongst all the variables employed, skewness has clearly the strongest impact on momentum profits, both, statistically and economically. One standard deviation increase (decrease) of the skewness of winners (losers) reduces momentum profits by about 0.34%. The coefficient obtained for the skewness variable barely changes after controlling for all the variables specified above

and stays significant at any conventional significance level with a T-statistic of greater than 6. Most of the variables that should affect momentum profits according to previous work do have the predicted impact, except return consistency (Grinblatt and Moskowitz, 2004), which is subsumed by the implied price risk proxy by Chuang and Ho (2014). Also, note that the economic and statistical significance of skewness on momentum returns is not affected by the inclusion of idiosyncratic volatility and past returns. Thus, skewness seems to matter over and above volatility and past returns for momentum returns.

Next, we add credit rating, analyst coverage, analyst forecast dispersion, and cash flow volatility to proxy for information uncertainty as suggested by Zhang (2009). Furthermore, we account for profitability. Due to data availability, we constrict our dataset to January 1981 to December 2011. Note that the cross-section is confined to larger firms as data for these variables are not available for all stocks. As before, we conduct the analysis in five specifications. Table 6 reports the results.

Insert Table 6 here

The inclusion of the new control variables does neither affect the statistical nor the economic significance of the skewness measure. Again, one standard deviation increase (decrease) of the skewness of winners (losers) reduces momentum profits by about 0.34%, which indicates that the magnitude of the impact of skewness on momentum is stable over time. In line with previous findings in the literature, credit rating and cash flow volatility significantly affect momentum profits positively. Interestingly, idiosyncratic volatility and momentum strength are insignificant in specification (5). Untabulated results show that both variables stay significant without the inclusion of the additional control variables in the same time period. In contrast, the impact of skewness is not deterred by the new controls. This indicates that the impact of skewness goes beyond and above the impact of volatility on the profitability of the momentum strategy, irrespective of the specific sample period taken into account.

2.5 Further robustness checks

We employ portfolio sorts and Fama and MacBeth (1973) regressions which both have their merits. The advantage of portfolio sorts is that they are not restricted to linear relations between the analyzed variables. However, they do not allow for multivariate robustness checks, which in turn is the advantage of regression-based approaches. Their disadvantage is the possibility of erroneous inference if the underlying relation is non-linear. We start with portfolio sorts and report the results in Table 7 below.

Insert Table 7 here

2.5.1 Alternative sorting method

To ascertain the robustness of our baseline results presented in Table 1, we repeat the analysis for reverse double sorts and independent sorts in specifications (1) and (2) of Table 7. For specification (1), we sort all stocks into quintiles with respect to their past cumulative return and obtain five portfolios. Within each of the five momentum portfolios, we sort stocks again into quintiles based on their prior month's maximum daily return. The weakened and enhanced momentum portfolios are constructed in the same spirit as before. For specification (2), we independently sort stocks into quintiles based on momentum and the skewness measure. In both cases, the results are very similar to our baseline results. The weakened momentum portfolio delivers small returns that are statistically often indistinguishable from zero. In contrast, the enhanced momentum portfolio yields large and strongly significant returns. Risk-adjustment does not strongly alter these results.

2.5.2 Portfolio tests to control for volatility and past returns

To corroborate the insights from our multivariate Fama and MacBeth (1973) regression in Table 5, we implement portfolio-level tests to control for the impact of idiosyncratic volatility and past returns.

More precisely, we follow Bandarchuk and Hilscher (2013) and conduct cross-sectional regressions of the skewness measure on 25 portfolios based on idiosyncratic volatility. We repeat this exercise for momentum strength, i.e., strength of past returns. The resulting regression residuals are then employed for the following analyses. This orthogonalization allows us to isolate the additional impact of skewness that matters over and above volatility and past returns. If skewness drives our results, they will not be shattered by the application of this procedure. We conduct the aforementioned exercise of double sorting stocks into portfolios. We focus on value-weighted portfolio returns, as an unreported analysis shows stronger findings for equally-weighted returns.

Specification (3) in Table 7 indicates that our results are indeed not significantly weakened by accounting for volatility. As in our baseline analysis, momentum profits vanish in the weakened momentum portfolio, which delivers an insignificant value-weighted raw return of -0.03% per month. Standard risk-adjustments produce partly statistically significant but economically rather small intercepts. Thus, even after idiosyncratic volatility is taken into consideration, cancelling the return premium of skewness diminishes the abnormal return of the momentum portfolio. In constrast, particularly amplified returns can again be obtained by holding the enhanced momentum portfolio, which yields a value-weighted return 1.29%, a CAPM intercept of 1.44% and and three factor and five factor intercept of 1.55% and 1.61%, respectively.

Similarly, in specification (4) in Table 7, we show that controlling for past returns does not alter our results. Raw monthly returns for enhanced (weakened) momentum amount to 1.85% (0.15%) and the respective five factor alphas are 2.34% and 0.35%. Consequently, our strong results can neither be explained by idiosyncratic volatility nor by past returns.

2.5.3 Alternative skewness measure

The final specification in Table 7 reports results obtained for conducting the analysis based on the measure of expected skewness by Boyer et al. (2010). Due to data availability, we focus on the subperiod from January 1961 onwards. The outcomes displayed confirm our previous findings. For instance, the three factor alpha of enhanced momentum amounts to 1.61% per month while the weakened momentum only delivers 0.32%.

As a further robustness check, we also repeat the multivariate Fama and MacBeth (1973) regression with the Boyer et al. (2010) measure. We obtain very similar results, which are documented in Table 2 of our online appendix.

2.5.4 Subperiod Analysis and Different Holding Periods

In Panel A of Table 8, we repeat the analysis for three different subperiods. In particular, we investigate the profitability of enhanced, weakened and regular momentum in the intervals 1961-2011, 1961-1991 and 1991-2011. Enhanced (weakened) momentum profits are in any time periods substantially larger (smaller) than regular momentum profits. For instance, from 1961 onwards, the weakened momentum portfolio yields an insignificant monthly return of 0.40%. In contrast, the return of the enhanced momentum portfolio amounts to a highly significant 1.87%. As before, risk-adjusting returns does not change the results. Looking at the most recent subperiod which starts in 1991, the results are in line with previously obtained findings. Returns for the weakened momentum are essentially zero, even after accounting for risk. The enhanced momentum delivers about 2% per month. This is noteworthy as it is often argued that both implementation costs and the profits generated by many long-short anomalies have decreased over time (e.g. Chordia et al. (2014), Hanson and Sunderan (2014), McLean and Pontiff (2015)).

In line with this conjecture, profits of regular momentum are small and insignificant since 1991, while profits of enhanced momentum are large and statistically highly significant.

Insert Table 8 here

We also analyze the impact of skewness on momentum profits for longer holding periods. As panel B of Table 8 shows, this impact is not transitory. Skewness predicts momentum profits over holding periods of three, twelve and even up to 36 months. This finding shows that our results are not restricted to a holding period of one month, but also apply to longer investment horizons.

2.5.5 Implementation Costs

To ascertain that our obtained results are not driven by illiquid stocks with high implementation costs, we conduct a set of triple-sorts. We use five proxies for implementation costs, namely size, institutional ownership, turnover, bid-ask spread and short interest on the loser side.

First, following Fama and French (2008), we divide the universe of stocks into three groups based on their market capitalization. Note that we take all firms into account for this particular analysis, i.e., we do not exclude penny stocks or small stocks. Micro stocks fall within the 20% NYSE percentile regarding their market capitalization. Small stocks have a market capitalization between the 20% and the 50% NYSE percentile and big stocks have above NYSE median market capitalization. We construct enhanced, weakened and regular momentum separately for each group as previously described by means of dependent double sorts on skewness and momentum.

In the second triple sorting exercise, we sort all stocks into two groups according to their percentage of institutional ownership. Stocks with above (below) median fraction of institutional ownership are denoted as high (low) institutional ownership. Table 9 displays the results of our triple sorting exercises.

Insert Table 9 here

Specifications (1) to (3) demonstrate that the previously documented amplification and diminution of returns of the momentum strategy by means of expected skewness works in all size groups. The effect is particularly pronounced amongst micro stocks. The return difference between the enhanced and weakened momentum amounts to more than 3.5% per month for these stocks. For small and big stocks, the enhanced momentum yields about twice the profits of traditional momentum. Notably, even for big stocks, the Fama and French (1993) alpha of enhanced momentum amounts to 1.87% per month compared to 0.97% and 0.24% for regular and weakened momentum, respectively.

Similarly, in specifications (4) and (5), the enhanced (weakened) momentum yields returns that are about double (half) the returns of the regular momentum, but the effect is moderately stronger for stocks with low institutional ownership. Now, we use turnover, bid-ask spreads and short interest on the loser side as additional variables in our triple-sorting exercises. For the former two, we divide the universe of stocks into two parts: high (low) turnover / bid-ask spreads are stocks with above (below) median turnover / bid-ask spreads. We then conduct our dependent double sorts on skewness and momentum for each part separately. Specifications (1) - (4) of Table 10 display the results. Evidently, returns of the enhanced momentum portfolios are in all cases substantially greater than the returns of the weakened momentum portfolio. For instance, the Fama/French three factor alpha of the enhanced momentum for high turnover stocks amounts to 2.85% compared to 0.42% for the weakened momentum.

Insert Table 10 here

As a last check, we perform triple-sorts based on skewness, momentum and short interest on the loser side. To this end, we first conduct conditional doublesorts of skewness and momentum and then sort losers based on short interest. As before, our findings are fortified in this exercise as demonstrated by the results shown in specifications (5) and (6) of Table 10. The enhanced momentum portfolio outperforms the regular momentum strongly, which in turn outperforms the weakened momentum, irrespective of the level of short interest on the loser side.

2.6 International Evidence

To conduct out-of-sample tests, we repeat the analysis in international stock markets. International stock market data has to be treated with care since the data quality is in general inferior compared to U.S. data (Ince and Porter, 2006). Because our skewness measure is based on maximum daily returns, a high level of data quality is essential for our analysis. Thus, we focus on developed markets (according to the MSCI classification), we require that at least 25 years of data are available and that the cross-section consists of at least 50 firms in any given month after all data screenings (see the online appendix). These requirements constrict our sample to 16 countries, namely Australia, Austria, Belgium, Canada, Denmark, France, Germany, Italy, Japan, Netherlands, Norway, Portugal, Singapore, Sweden, Switzerland and the United Kingdom. We use Fama and MacBeth (1973) regressions to examine the impact of skewness on momentum profits and conduct the same steps as in section 2.4. We use our skewness measure derived from Bali et al. (2011) for our international analysis. In the baseline specification, we regress momentum returns on skewness and industry controls. In a second test, we include Beta, Beta Book-to-Market, Beta Size, idiosyncratic volatility, momentum strength and the one-month lagged return. Finally, we augment our set of controls with Implied Price Risk (Chuang and Ho, 2014), 52-Week High (George and Hwang, 2004), Continuous Information (Da et al., 2014), Return Consistency (Grinblatt and Moskowitz, 2004) and Age.⁶ Table 11 displays the results. Skewness significantly influences momentum profits in at least 75% of the countries in all three specifications. Irrespective of the specification, our results show that one standard deviation increase (decrease) of the skewness of winners (losers) reduces momentum profits by on average 0.36% (across countries). Pooled across all 16 countries, skewness is again a highly significant predictor of momentum profits. In this setting, the economic impact of skewness on momentum amounts to about 0.20% per standard deviation change.

Insert Table 11 here

Notably, our results hold in the countries of the Group of 7, which are highly developed and industrialized countries for which the data quality is likely to be high. Besides the United States, the Group of 7 comprises Canada, France, Germany, Italy, Japan and the United Kingdom. Pooling across those countries yields results that closely resemble pooling across all 16 countries. In the Table 4 of the online appendix, we document that countries in which the impact of skewness is particularly strong display significantly larger momentum profits. This effect is again consistent with the view that skewness is a key determinant of momentum profits.

3 Consistency with Models of Momentum

Several models can accommodate medium-term momentum and long-term reversal by building either on investor underreaction followed by overreaction (Barberis et al., 1998; Hong and Stein, 1999) or by (continuing) investor overreaction (Daniel et al., 1998). Cross-sectional variation in the biases or frictions underlying the model setting allow for cross-sectional variation in the return patterns. For instance, if one assumes that many biases tend to be more pronounced for stocks which are hard to value, then stronger mispricings among stocks with high information

⁶We omit any variables that require turnover to be computed because of data availability. Turnover is for many countries only available for a short period of time and a small cross-section which would reduce the sample size and the power of our analysis substantially. However, untabulated analyses indicate that the results obtained with the inclusion of these variables are very similar.

uncertainy are in line with the implications of several mistaken-beliefs models (see e.g. Baker and Wurgler (2007) or Hirshleifer (2001) for discussions). As documented before, our results are particularly pronounced among small firms. Further, we show in specifications (1) - (4) of Table 12, that the impact of skewness on momentum is stronger for younger firms with high idiosyncratic volatility. Taken together, these findings point towards a behavioral explanation. However, we argue in the following that the striking findings seem hard to reconcile with a specific prominent existing behavioral theory of momentum.

Insert Table 12 here

For instance, momentum in Daniel et al. (1998) arises due to two central investor biases, selfattribution and overconfidence. Mistaken beliefs lead investors to overweight (underweight) public signals which confirm (contradict) their private information. Selective information processing causes them to attribute confirming information as evidence for their own skill, whereas disconfirming information is largely ignored. This mechanism increases overconfidence even more and prices continue to overreact. In the long run, and due to more valuable public information, the overreaction-driven mispricing is gradually corrected. Consequently, their model implies a reversal of momentum. To explore the long-run profitability of the strategies, we analyze average holding period portfolio returns for 36 months after the initial portfolio formation. We conduct Fama and MacBeth (1973) regressions with the previously used control variables to measure the impact of skewness on cumulative momentum profits. The results, that are tabulated in panel B of Table 8 document that the impact of skewness on momentum does not revert in the long-run. For instance, a one standard deviation increase (decrease) in skewness of the winners (losers) diminishes the three year holding period return of momentum by about 3.3%. This lack of long-run reversal is hard to bring in line with models of momentum that are based on investor overreaction.

Underreaction to news is suggested by Hong and Stein (1999) as an alternative explanation of momentum profits. Investors underreact to good (bad) news about winners (loser) and which tend to deliver superior (inferior) performance in the future as investors slowly process the good news. The fact that the profits of enhanced and weakened momentum portfolios are mainly driven by the short leg of the portfolio could potentially be reconciled with Hong et al. (2000) who argue that bad news travels slowly. However, momentum models based on investors underreaction predict that profits should be small for firms with a high degree of visibility. We have already shown in Table 9 that enhanced (weakened) momentum delivers a three factor alpha of 1.87% (0.24%) per month. To provide an additional test, we follow Hong et al. (2000) and construct residual analyst coverage by cross-sectionally regressing analyst coverage on firm size (both logarithmized) for every month. Doing so provides us with an additional measure of visibility, which is by construction orthogonal to firm size, and which we use to conduct tripple sorts. As displayed in rows (1) and (2) of Table 13, the three factor alpha of enhanced (weakened) momentum amounts to 1.90% (0.38)% per month for firms with high residual analyst coverage. Arguably, these findings are inconsistent with momentum theories based on underreaction.

Insert Table 13 here

Barberis et al. (1998) conjecture that due to the representativeness heuristic, investors overreact to a series of good or bad news. Thereby, recent winners (losers) are eventually over- (under-) valued in medium-run, which reverses in the long run. However, low (high) past cumulative returns in the formation period predict a high (low) maximum return in the following month, as shown in Table 3 of our online appendix. Thus, a series of bad news, reflected by low returns in the formation period, is interrupted by a high maximum return, before it ultimately leads to weak performance in the evaluation period. Similarly, a series of good news predicts a low maximum daily return in the following month before a high return follows. Consequently, it seems hard to reconcile the claim of Barberis et al. (1998) with our empirical evidence.

Another explanation of momentum is given by Grinblatt and Han (2005) who associate the anomaly with the disposition effect, i.e., the tendency to sell winners quickly and hold onto losers. In their model, momentum arises due to differences in unrealized capital gains. Winners (losers) tend to be stocks with large (small) aggregate unrealized capital, which have a higher (lower) expected return. Thus, momentum should not be profitable after controlling for unrealized capital gains. To test whether this conjecture explains our findings, we conduct tripple sorts with unrealized capital gains. Rows (3) and (4) of Table 13 show the enhanced momentum substantially outperforms weakened momentum, irrespective of the level of unrealized capital gains. Returns of the former are always large and highly significant, while the latter delivers small and mostly insignificant returns. We conclude that the disposition effect cannot explain the empirically observable pattern.

Avramov et al. (2007) argues that momentum is strong among companies with a bad credit rating, but "nonexistent among high-grade firms" (p. 2503). To test whether credit rating drives our results, we conduct tripple sorts. Specifications (5) and (6) of Table 12 show that this explanation is not applicable to the results documented in this paper. For instance, enhanced momentum delivers a highly significant monthly three factor alpha of 1.43%, while weakened momentum only yields -0.06%, for firm with a good credit rating. Thus, differences in credit rating cannot explain our results.

Finally, the recent friction-based model of Vayanos and Woolley (2013) proposes that momentum and reversal are driven by flows between investment funds and agency issues between fund managers and investors. However, as Table 9 shows, our findings are if anything slightly stronger among stocks with low institutional ownership, suggesting that fund flows are not a major driver of our findings.

In sum, the puzzling performance differences between skewness-enhanced momentum and skewnessweakened momentum do not neatly fit within a specific prominent theory of momentum. At the same time, the strong economic magnitude of our findings calls for the development of theoretical explanations.

4 Conclusion

We document a strong and robust relation between expected skewness, assessed by the gauges of Bali et al. (2011) and Boyer et al. (2010), and momentum. This relation is particularly strong for losers and withstands a battery of robustness checks. Making use of this finding, we construct a weakened momentum portfolio which has a zero-skew return distribution as well as an enhanced momentum portfolio which has a particularly pronounced skewness. Returns of the former are often statistically insignificant and economically small, whereas returns of the latter are surprisingly large and outshine the profitability of the usual momentum strategy by far. These findings are robust among large stocks and in the recent past and in international stock markets.

The risk-management methodologies of Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2014) can be employed to further improve the performance of skewness-enhanced momentum. The resulting raw and risk-adjusted returns are enormous and cast doubts on the notion of efficient markets, which is particularly puzzling in view of the simplicity of the construction of the strategies. Similar to Daniel and Moskowitz (2014), we cannot convincingly explain these findings with commonly-received theories of momentum in the literature.

Table 1: Expected Skewness and Momentum: Baseline Results

This table reports portfolio returns (in percent) that are computed based on dependent double sorts on expected skewness and past returns. Stocks are sorted into five equally sized portfolios based on the skewness measure of Bali et al. (2011). Within each quintile, we sort stocks again into quintiles according to their past cumulative returns. We use a formation period of twelve months, a holding period of one month, and skip one month in between, during which skewness is measured. Enhanced Momentum denotes the portfolio that consists of stocks in the highest (lowest) skewness quintile and in the lowest (highest) quintile with respect to past cumulative returns in the short (long) leg. Weakened Momentum comprises stocks in the lowest (highest) skewness quintile and in the lowest (highest) quintile with respect to past cumulative returns in the short (long) leg. Regular Momentum consists of winners and losers in the third skewness quintile. Panel A and B show equally and value-weighted risk-adjusted returns of Enhanced, Weakened and Regular Momentum. We denote risk-adjusting for the CAPM by 1F. 3F refers to the Fama and French (1993) model and 4F to the Carhart (1997) model. 5F (6F) is the former (latter) augmented with factors for long-term and short-term reversal. Panel C (D) shows equally weighted (value-weighted) raw portfolio returns of losers and winners in each skewness quintile. The sample period covers January 1926 to December 2011. We adjust t-statistics for serial correlation using Newey and West (1987) standard errors with a lag of six months. *indicates significance at the 10% level, ** indicate significance at the 5% level and *** indicate significance at the 1% level.

Panel A: Equally	Weighted	Risk-adju	sted Retur	rns	
Factor Model	Raw	$1\mathrm{F}$	3F	$5\mathrm{F}$	
Enhanced Momentum	1.90***	2.40***	2.55***	2.58***	
t-stat	(8.44)	(13.40)	(14.75)	(12.03)	
Weakened Momentum	0.21	0.00	0.12	0.33*	
t-stat	(1.19)	(-0.01)	(0.74)	(1.80)	
Regular Momentum	0.93^{***}	1.09***	1.24^{***}	1.38^{***}	
t-stat	(5.72)	(7.41)	(8.36)	(7.88)	
Factor Model	Raw	$1\mathrm{F}$	3F	$4\mathrm{F}$	6F
Enhanced-Weakened Momentum	1.69^{***}	2.40***	2.43***	2.10***	1.86***
t-stat	(5.43)	(9.48)	(10.67)	(9.42)	(6.97)
Panel B: Value-	weighted F	₹isk-adjust	ed Return	ns	
Factor Model	Raw	$1\mathrm{F}$	3F	$5\mathrm{F}$	
Enhanced Momentum	1.65***	2.14***	2.31***	2.36***	
t-stat	(6.26)	(10.15)	(11.42)	(9.74)	
Weakened Momentum	0.47^{**}	0.21	0.31	0.52**	
t-stat	(2.05)	(0.98)	(1.50)	(2.14)	
Regular Momentum	0.81^{***}	0.96^{***}	1.10^{***}	1.24^{***}	
t-stat	(4.28)	(5.13)	(5.83)	(6.04)	
Factor Model	Raw	$1\mathrm{F}$	3F	$4\mathrm{F}$	6F
Enhanced-Weakened Momentum	1.18***	1.93***	2.00***	1.72***	1.51***
t-stat	(3.21)	(6.16)	(7.21)	(5.90)	(4.64)
Panel C: Equ	ally Weig	hted Raw	Returns		
Skewness Quintile	1	2	3	4	5
Loser	1.07	1.06	0.75	0.56	-0.32
Winner	1.58	1.60	1.68	1.56	1.28
Panel D: Va	alue-weigh	ted Raw F	Returns		
Skewness Quintile	1	2	3	4	5
Loser	0.82	0.71	0.61	0.29	-0.37
Winner	1.28	1.38	1.42	1.43	1.30

Table 2: Raw and Risk-adjusted Returns of Winners and Losers

This table reports in panel A value-weighted raw and risk-adjusted returns of the long and short legs of *Enhanced*, *Weakened* and *Regular Momentum*. Specifications (1) and (2) display *Enhanced Losers* and *Winners*, respectively. *Enhanced Losers (Winners)* are stocks that are in the highest (lowest) skewness quintile and in the lowest (highest) quintile with respect to past cumulative returns. Returns for *Weakened Losers* and *Winners* are reported in specifications (3) and (4). *Weakened Losers (Winners)* comprise stocks that are in the lowest (highest) skewness quintile and in the lowest (highest) skewness quintile and in the lowest (highest) quintile with respect to past cumulative returns. *Regular Loser* and *Winner* returns of *Regular Momentum*, which comprises winners and losers in the third skewness quintile, are shown in specifications (5) and (6). Panel B reports differences of *Losers* and *Winners* of *Enhanced* and *Regular* and of *Regular* and *Weakened Momentum*. We denote risk-adjusting for the CAPM by 1F, 3F refers to the Fama and French (1993) model and 5F is the latter augmented with factors for long-term and short-term reversal. The sample period covers January 1926 to December 2011. We adjust t-statistics for serial correlation using Newey and West (1987) standard errors with a lag of six months. * indicates significance at the 10% level, ** indicate significance at the 5% level and *** indicate significance at the 1% level.

Panel A: Raw and Risk-a	djusted Re	eturns of L	osers and V	Winners
Specification / Factor Model	Raw	$1\mathrm{F}$	3F	$5\mathrm{F}$
(1): Enhanced Loser	-0.37	-1.32***	-1.45***	-1.53***
t-stat	(-1.10)	(-7.72)	(-9.06)	(-8.22)
(2): Enhanced Winner	1.28***	0.82***	0.86***	0.83***
t-stat	(7.42)	(10.72)	(10.92)	(9.36)
(3): Weakened Loser	0.82***	0.32***	0.28***	0.23**
t-stat	(4.44)	(3.23)	(3.00)	(2.45)
(4): Weakened Winner	1.30^{***}	0.53^{***}	0.59^{***}	0.75^{***}
t-stat	(4.42)	(3.14)	(3.64)	(3.84)
(5): Regular Loser	0.61^{**}	-0.17	-0.27**	-0.40***
t-stat	(2.56)	(-1.40)	(-2.35)	(-3.29)
(6): Regular Winner	1.42^{***}	0.79***	0.83***	0.84^{***}
t-stat	(6.53)	(7.37)	(7.45)	(6.78)
Par	nel B: Diff	erences		
(5) - (1)	0.98***	1.15***	1.18***	1.13***
t-stat	(4.92)	(5.98)	(6.89)	(6.28)
(5) - (3)	-0.21*	-0.49***	-0.55***	-0.63***
t-stat	(-1.79)	(-4.37)	(-4.92)	(-5.48)
(6) - (2)	0.14	-0.03	-0.02	0.01
t-stat	(1.17)	(-0.26)	(-0.22)	(0.07)
(6) - (4)	0.12	0.27^{*}	0.24^{*}	0.09
t-stat	(0.79)	(1.83)	(1.73)	(0.58)
(3) - (1)	1.20***	1.63***	1.73***	1.76***
t-stat	(5.14)	(8.32)	(9.52)	(8.37)
(4) - (2)	0.02	-0.30	-0.26	-0.09
t-stat	(0.08)	(-1.62)	(-1.52)	(-0.41)

Table 3: Return, Risk and Performance Measures

2011. * indicates significance at the 10% level, ** indicate significance at the 5% level and *** indicate significance at the 1% level. Significance of the median is assessed by a mentum*) derived from Barroso and Santa-Clara (2015), the risk-managed enhanced momentum (denoted as Enhanced Momentum**) based on the procedure of Daniel with factors for long-term and short-term reversal) and monthly Fama and French (2015) alphas. The displayed risk measures are time-series volatility (in percent) and returns. As performance measures, we report the Sharpe ratio, the Sortino ratio and the Omega ratio. The Sharpe ratio is computed as annualized monthly portfolio excess portfolio returns. The Omega ratio is computed as the dicretized version of $\frac{\int_{0}^{\infty}(1-F(x))dx}{\int_{0}^{\infty}F(x)dx}$ from Shadwick and Keating (2002), where F(x) denotes the cumulative distribution function of returns. The sample period covers January 1926 to December 2011, except for the computation of the 7-Factor α , for which the range is July 1963 to December This table reports return, risk and performance measures of the value-weighted Enhanced Momentum, the risk-managed Enhanced Momentum (denoted as Enhanced Moand Moskowitz (2014), Weakened Momentum, Regular Momentum and the Market. Enhanced, Regular and Weakened Momentum are constructed as in Table 1. As return measures, the table shows the monthly mean and median return (in percent), monthly 3-Factor alphas, monthly 5-Factor alphas ((Fama and French, 1993) model augmented skewness of portfolio returns. The minimum and maximum of monthly portfolio returns are also displayed. In addition, we document the 1% percentile of monthly portfolio returns over annualized volatility of monthly portfolio returns. The Sortino ratio denotes annualized monthly portfolio excess return divided by downside volatility of monthly Wilcoxon signed-rank test.

	Enhanced Momentum*	Enhanced Momentum ^{**}	Enhanced Momentum	Weakened Momentum	Regular Momentum	Market
1) Return Measures						
Mean	1.67^{***}	1.68^{***}	1.65^{***}	0.47^{**}	0.81^{***}	0.91^{***}
Median	1.97^{***}	1.40^{***}	2.00^{***}	0.49	1.01^{***}	1.30^{***}
1-Factor α	1.89^{***}	1.82^{***}	2.14^{***}	0.21	0.96^{***}	ı
3-Factor α	1.97^{***}	1.86^{***}	2.31^{***}	0.31	1.10^{***}	ı
5-Factor α	2.09^{***}	1.95^{***}	2.36^{***}	0.52^{**}	1.24^{***}	ı
Fama and French (2015) α	2.03^{***}	2.13^{***}	1.90^{***}	0.81^{**}	1.25^{***}	ı
2) Risk Measures						
Volatility	5.46	5.46	8.17	7.32	6.29	5.46
Skewness	-0.47	0.01	-1.87	0.00	-0.99	0.13
1% Percentile	-13.84	-13.83	-23.67	-16.63	-16.33	-15.03
Minimum	-31.73	-24.89	-72.36	-48.15	-44.74	-29.01
Maximum	23.17	32.67	31.67	47.31	36.69	38.37
3) Performance Measures						
Sharpe Ratio	1.06	1.07	0.70	0.22	0.45	0.39
Sortino Ratio	1.48	1.53	0.73	0.30	0.53	0.53
Omega Ratio	2.22	2.38	1.83	1.21	1.46	1.59

able 4: Firms Characteristics of Modified Momentum P	ortfolio
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first sorted into five equally sized portfolios based on their maximum daily return from the previous month (Bali et al., 2011), which constitutes our skewness measure. Within of twelve months and a holding period of one month and skip one month in between, during which skewness is measured. Enhanced, Regular and Weakened Losers, Winners Rating are available from January 1981 onwards. Cash Flow Volatility is available from July 1965 and data on Short Interest starts in January 1973. The Bid/Ask Spread is calculated based on the algorithm of Corwin and Schultz (2012). Beta, Beta Book-to-Market and Beta Size are computed from rolling regressions using daily data over the The 52-Week High variable is computed as suggested by George and Hwang (2004). Continuous Information is constructed as in Da et al. (2014). Return Consistency is measured as in Grinblatt and Moskowitz (2004). For each stock in the portfolio, we compute its decile for each characteristic every month. Then, we calculate the equally-weighted average for each portfolio and report the monthly average of the average portfolio deciles. Average deciles are reported for Enhanced, Regular and Weakened Momentum and the respective This table reports average monthly deciles of stock characteristics of portfolios that are computed based on dependent doublesorts for skewness and momentum. Stocks are each quintile, we calculate momentum portfolios, i.e., we sort stocks according to their past cumulative returns. To construct the momentum portfolios, we use a formation and Momentum are constructed as in Tables 1 and 2. The sample period covers January 1926 to December 2011. Analyst Forecast Dispersion, Analyst Coverage and Credit previous twelve months. Unrealized Capital Gains are constructed as in Grinblatt and Han (2005). Implied Price Risk is as in Chuang and Ho (2014). Losers and Winners.

Average Deciles									
	Enhanced Winner	Enhanced Loser	Enhanced Momentum	Weakened Loser	Weakened Winner	Weakened Momentum	Regular Winner	Regular Loser	Regular Momentum
Idiosyncratic Volatility	3.64	8.40	5.75	7.88	3.45	5.41	5.73	5.81	5.77
Momentum Strength	7.96	8.75	8.31	8.86	6.22	7.37	8.94	7.62	8.27
52-Week High	6.87	4.54	5.79	6.12	5.90	5.98	6.50	5.19	5.84
Continuous Information	3.02	8.62	5.47	3.99	7.15	5.75	3.32	7.80	5.58
Return Consistency	3.94	1.04	2.62	4.02	1.10	2.34	3.91	1.09	2.49
Unrealized Capital Gains	7.87	2.12	5.82	7.24	4.16	5.18	7.65	3.15	5.25
Implied Price Risk	7.51	3.18	5.77	7.62	3.04	4.78	7.49	3.01	5.20
Age	5.72	4.55	5.00	4.61	6.07	5.20	5.13	5.24	5.19
Turnover	4.67	6.99	5.65	7.41	4.65	5.77	6.34	5.83	6.08
Bid/Ask Spread	3.89	7.40	5.50	6.17	4.64	5.34	4.78	5.85	5.32
Beta Market	4.25	7.06	5.49	7.23	4.02	5.34	6.30	5.81	6.05
Beta Size	4.55	6.68	5.50	6.84	4.34	5.42	5.67	5.47	5.57
Beta Book-to-Market	5.5	5.04	5.48	5.05	5.51	5.33	5.40	5.44	5.42
Size	6.68	4.20	5.51	5.70	6.17	5.92	6.33	5.32	5.82
Analyst Forecast Dispersion	4.49	7.62	5.89	5.73	5.62	5.66	5.00	6.61	5.81
Analyst Coverage	5.57	5.39	5.46	5.05	5.85	5.46	5.66	5.67	5.67
Credit Rating	4.28	7.52	5.33	7.33	4.12	4.96	5.75	5.76	5.75
Profitability	5.45	5.53	5.50	5.87	5.26	5.50	5.96	5.65	5.81
Cash Flow Volatility	4.64	6.85	5.70	6.67	4.59	5.44	5.72	5.69	5.70
Short Interest	5.56	7.31	6.25	7.13	5.62	6.29	6.59	6.54	6.56

Table 5: Expected Skewness and Momentum: Fama/MacBeth Regressions

This table presents results of Fama and MacBeth (1973) regressions. Following Bandarchuk and Hilscher (2013) we regress momentum profits on our skewness measure from Bali et al. (2011) and various control variables that have been associated with the profitability of momentum. The Bid/Ask Spread is calculated based on the algorithm of Corwin and Schultz (2012). Beta, Beta Book-to-Market and Beta Size are computed from rolling regressions using daily data over the previous twelve months. Unrealized Capital Gains are constructed as in Grinblatt and Han (2005). Implied Price Risk is as in Chuang and Ho (2014). The 52-Week High variable is computed as suggested by George and Hwang (2004). Continuous Information is constructed as in Da et al. (2014). Return Consistency is measured as in Grinblatt and Moskowitz (2004). The sample period ranges from January 1926 to December 2011. All variables are standardized by months. All obtained coefficients are multiplied by 100. We adjust t-statistics for serial correlation using Newey and West (1987) standard errors with a lag of six months. * indicates significance at the 10% level, ** indicate significance at the 1% level.

	Mom	entum Retur	ns		
Variable / Model	(1)	(2)	(3)	(4)	(5)
SKEW ^{MAX}	-0.3324***	-0.3178***		-0.3471***	-0.3434***
	(-7.00)	(-6.79)		(-6.08)	(-6.11)
Idiosyncratic Volatility		· · · ·	0.0621^{*}	0.0791^{**}	0.0611*
			(1.84)	(2.56)	(1.90)
Momentum Strength			0.1564^{***}	0.1853^{***}	0.1637^{***}
_			(3.80)	(4.39)	(4.00)
52-Week High			-0.0876**	-0.0683**	-0.0858**
_			(-2.26)	(-1.99)	(-2.15)
Continuous Information			-0.1261***	-0.1012***	-0.1040***
			(-6.76)	(-6.24)	(-5.90)
Return Consistency			-0.0082	-0.0105	-0.0131
-			(-0.41)	(-0.57)	(-0.72)
Unrealized Capital Gains			0.1159***	0.1359***	0.1295***
			(4.16)	(4.81)	(4.79)
Implied Price Risk			0.2443***	0.2118***	0.2177***
-			(5.92)	(5.63)	(5.50)
Age			0.0213	0.0035	0.0306
			(0.22)	(0.04)	(0.39)
Turnover			0.0046	0.0186	0.0116
			(0.14)	(0.54)	(0.32)
Bid/Ask Spread			-0.0579**	-0.0412*	-0.0451**
			(-2.35)	(-1.86)	(-2.03)
Beta Market			0.0068	-0.0044	-0.0156
			(0.17)	(-0.12)	(-0.39)
Beta Size			-0.0028	-0.0049	-0.0092
			(-0.09)	(-0.16)	(-0.32)
Beta Book-to-Market			-0.0309	-0.0592*	-0.0366
			(-0.92)	(-1.85)	(-1.05)
Lag Return			0.1018***	0.0976***	0.1081***
			(3.03)	(2.79)	(3.09)
49 Fama/French Industries	no	yes	yes	no	yes

Table 6: Expected Skewness and Momentum: Fama/MacBeth Regressions

This table reports a robustness check of the results presented in Table 5. The dependent variable is momentum profits and the previously employed set of control variables from Table 5 is augmented by Analyst Forecast Dispersion, Analyst Coverage, Cash Flow Volatility as suggested by (Zhang, 2009), Credit Rating and Profitability. Due to data availability, the sample period ranges from January 1981 to December 2011. All variables are standardized by months. All obtained coefficients are multiplied by 100. We adjust t-statistics for serial correlation using Newey and West (1987) standard errors with a lag of six months. * indicates significance at the 10% level, ** indicate significance at the 5% level and *** indicate significance at the 1% level.

	Mome	entum Returr	ıs		
Variable / Model	(1)	(2)	(3)	(4)	(5)
SKEW ^{MAX}	-0.3852***	-0.3673***		-0.3420***	-0.3362***
	(-4.24)	(-4.21)		(-3.16)	(-3.17)
Idiosyncratic Volatility			0.0051	-0.0044	-0.0339
			(0.06)	(-0.06)	(-0.47)
Momentum Strength			0.0520	0.1202	0.1012
			(0.51)	(1.30)	(1.11)
52-Week High			-0.0989	-0.1033*	-0.0869
			(-1.47)	(-1.73)	(-1.40)
Continuous Information			-0.1270^{***}	-0.0874^{**}	-0.0925***
			(-3.45)	(-2.57)	(-2.70)
Return Consistency			0.0511	0.0080	0.0285
			(1.16)	(0.21)	(0.72)
Unrealized Capital Gains			0.1553^{***}	0.1725^{***}	0.1591^{***}
			(2.72)	(2.98)	(2.90)
Implied Price Risk			0.1654^{***}	0.1049**	0.1123**
			(3.10)	(2.09)	(2.37)
Age			-0.0606	-0.0543	-0.0702
E.			(-1.20)	(-1.03)	(-1.45)
Turnover			-0.1436^{+++}	-0.1711^{***}	-0.1526^{+++}
D: 1 / A -l- Come - 1			(-2.04)	(-3.32)	(-2.87)
Bid/Ask Spread			-0.0738	-0.0410	-0.0000
Data Markat			(-1.08)	(-0.90)	(-1.38)
Deta Market			(0.80)	(1.92)	(0.0285)
Boto Sizo			(0.89)	(1.23)	(0.41)
Deta Size			-0.0033	(0.30)	(0.17)
Beta Book-to-Market			(-0.09)	(-0.30)	(0.17)
Deta Dook-to-Market			(-0.53)	(-0.61)	(-0.32)
Lag Return			0 1304**	0.0934^{*}	0.1159**
			(2.40)	(1,70)	(2.02)
Credit Rating			0.0979^{***}	0.0972**	0.0881**
			(2.69)	(2.57)	(2.46)
Analyst Forecast Dispersion			0.0552	0.0665^{*}	0.0569
U I			(1.32)	(1.70)	(1.41)
Analyst Coverage			0.0706^{*}	0.0805^{+*}	0.0770*
			(1.72)	(2.11)	(1.91)
Cash Flow Volatility			0.2085^{***}	0.1757^{***}	0.2147^{***}
-			(3.21)	(2.70)	(3.26)
Profitability			-0.0496	-0.0070	-0.0531
			(-1.08)	(-0.18)	(-1.14)
49 Fama/French Industries	no	yes	yes	no	yes

Table 7: Expected Skewness and Momentum: Robustness Tests

This table displays several robustness checks of our baseline specification in Table 1. In (1) we conduct reverse dependent doublesorts, i.e., we first sort stocks into quintiles based on their past cumulative return. We then sort stocks within each quintiles into five quintiles based on our measure of skewness from Bali et al. (2011). As before, we use a formation of twelve months and a holding period of one month and skip one month in between, during which skewness is measured. In (1), (2) and (3), the sample period covers January 1926 to December 2011. In (2), we sort stocks independently into quintiles based on cumulative past return and our measure of skewness. In (3) and (4), we orthogonalize our skewness measure with respect to idiosyncratic volatility and momentum strength of past returns, respectively. Momentum strength is defined as in Bandarchuk and Hilscher (2013). Finally, in (5), we document results for our second skewness measure from Boyer et al. (2010) from 1961 onwards. We construct Enhanced and Weakened Momentum as follows: Enhanced Momentum is a long-short portfolio which buys past winners in the lowest skewness quintile and short sells losers in the highest skewness quintile. Similarly, Weakened Momentum is constructed by short selling losers in the lowest skewness quintile and buying winners in the highest skewness quintile. Average monthly value weighted returns are displayed for the resulting portfolios. Besides raw return, we report the corresponding risk-adjusted returns. We denote risk-adjusting for the CAPM by 1F, 3F refers to the (Fama and French, 1993) model and 5F is the latter augmented with factors for long-term and short-term reversal. We adjust t-statistics for serial correlation using Newey and West (1987) standard errors with a lag of six months. * indicates significance at the 10% level, ** indicate significance at the 5% level and *** indicate significance at the 1% level.

Robustness Specification	RAW	$1\mathrm{F}$	3F	$5\mathrm{F}$
1) Reverse Doublesort				
Enhanced Momentum t-stat Weakened Momentum t-stat 2) Independent Doublesorts	$\begin{array}{c} 1.70^{***} \\ (7.22) \\ 0.28 \\ (1.15) \end{array}$	$2.09^{***} \\ (10.95) \\ 0.25 \\ (1.04)$	$2.26^{***} \\ (11.73) \\ 0.38^{*} \\ (1.66)$	$\begin{array}{c} 2.30^{***} \\ (10.33) \\ 0.56^{**} \\ (2.10) \end{array}$
Enhanced Momentum t-stat Weakened Momentum t-stat 3) Controlling for Volatility	$\begin{array}{c} 1.46^{***} \\ (6.71) \\ 0.42^{*} \\ (1.95) \end{array}$	$\begin{array}{c} 1.88^{***} \\ (10.82) \\ 0.15 \\ (0.69) \end{array}$	$2.03^{***} \\ (12.28) \\ 0.21 \\ (1.05)$	$2.04^{***} \\ (10.36) \\ 0.47^{**} \\ (2.20)$
Enhanced Momentum t-stat Weakened Momentum t-stat 4) Controlling for Past Returns	$\begin{array}{c} 1.29^{***} \\ (5.67) \\ -0.03 \\ (-0.11) \end{array}$	$1.44^{***} \\ (6.10) \\ 0.26 \\ (1.40)$	$1.55^{***} \\ (7.20) \\ 0.49^{***} \\ (2.68)$	$\begin{array}{c} 1.61^{***} \\ (7.18) \\ 0.64^{***} \\ (2.91) \end{array}$
Enhanced Momentum t-stat Weakened Momentum t-stat 5) Measure from Boyer since 1961	$\begin{array}{c} 1.85^{***} \\ (6.46) \\ 0.15 \\ (0.82) \end{array}$	$\begin{array}{c} 1.94^{***} \\ (6.89) \\ 0.07 \\ (0.38) \end{array}$	$2.19^{***} \\ (7.82) \\ 0.20 \\ (1.15)$	$\begin{array}{c} 2.34^{***} \\ (8.05) \\ 0.35^{**} \\ (1.99) \end{array}$
Enhanced Momentum t-stat Weakened Momentum t-stat	$\begin{array}{c} 1.12^{***} \\ (4.02) \\ 0.34 \\ (1.42) \end{array}$	$\begin{array}{c} 1.28^{***} \\ (4.83) \\ 0.33 \\ (1.33) \end{array}$	$\begin{array}{c} 1.61^{***} \\ (5.88) \\ 0.32 \\ (1.32) \end{array}$	$\begin{array}{c} 1.79^{***} \\ (6.22) \\ 0.40 \\ (1.59) \end{array}$

Table 8: Calender-time and Event-time Analyses

This table presents results of time-series regressions in Panel A and Fama and MacBeth (1973) regressions in panel B. In panel A we compute Enhanced Momentum, Weakened Momentum and Regular Momentum as in Table 1. Average monthly value-weighted returns over the time periods 1961 - 2011, 1961 - 1991 and 1991 -2011 are displayed for the resulting portfolios. Besides raw return, we report the corresponding risk-adjusted returns. We denote risk-adjusting for the CAPM by 1F, 3F refers to the (Fama and French, 1993) model and 5F is the latter augmented with factors for long-term and short-term reversal. In panel B, we follow Bandarchuk and Hilscher (2013) and regress cumulative momentum profits on our skewness measure from Bali et al. (2011) and the control variables of Table 5 that have been associated with the profitability of momentum. We report regression results for cumulative returns over holding periods of 1 - 3, 1 - 12, 12 - 36 and 1 - 36 months. Cumulative returns are winsorized at the 99.9% and 0.1% level. The Bid/Ask Spread is calculated based on the algorithm of Corwin and Schultz (2012). Beta, Beta Book-to-Market and Beta Size are computed from rolling regressions using daily data over the previous twelve months. Unrealized Capital Gains are constructed as in Grinblatt and Han (2005). Implied Price Risk is as in Chuang and Ho (2014). The 52-Week High variable is computed as suggested by George and Hwang (2004). Continuous Information is constructed as in Da et al. (2014). Return Consistency is measured as in Grinblatt and Moskowitz (2004). The sample period ranges from January 1926 to December 2011. All variables are standardized by months. All obtained coefficients are multiplied by 100. We adjust t-statistics for serial correlation using Newey and West (1987) standard errors with a lag of six months. * indicates significance at the 10% level, ** indicate significance at the 5% level and *** indicate significance at the 1% level.

Panel A: Calendar-	time Results	s via Time-s	eries Regress	ions
Robustness Specification	RAW	$1\mathrm{F}$	3F	$5\mathrm{F}$
1) Since 1961				
Enhanced Momentum	1.87***	2.23***	2.22^{***}	2.34^{***}
t-stat Weakoned Momentum	(5.51)	(7.55)	(8.54)	(8.83) 0.66**
t-stat	(1.26)	(0.31)	(1 43)	(1.99)
Regular Momentum	0.78***	0.81***	1.03^{***}	1.23***
t-stat	(3.24)	(3.40)	(4.14)	(4.69)
2) Between 1961 and 1991	_			
Enhanced Momentum	1.88^{***}	2.08^{***}	2.21^{***}	2.31^{***}
t-stat	(6.28)	(7.50)	(8.79)	(8.97)
Weakened Momentum	0.49	0.31	0.58^{**}	0.91^{***}
t-stat	(1.60)	(1.04)	(2.16)	(3.23)
Regular Momentum	0.93^{***}	0.94^{***}	1.18***	1.58^{***}
t-stat	(3.80)	(3.78)	(5.21)	(6.72)
3) Since 1991	-			
Enhanced Momentum	1.85^{***}	2.51^{***}	2.41^{***}	2.39^{***}
t-stat	(2.64)	(4.65)	(5.20)	(5.29)
Weakened Momentum	[0.28]	-0.27	[0.02]	[0.07]
t-stat	(0.44)	(-0.48)	(0.04)	(0.11)
Regular Momentum	0.56	0.63	0.78*	0.77
t-stat	(1.22)	(1.39)	(1.65)	(1.58)
Panel B: Event-time Rest	ults via Fam	a and MacE	Beth (1973) R	egressions
Variable / Holding Period	1 - 3	1 - 12	12 - 36	1 - 36
SKEW ^{MAX}	-0.2610**	-0.9400**	-2.7889***	-3.2928***
t-stat	(-2.58)	(-2.55)	(-4.47)	(-3.83)
Controls	yes	yes	yes	yes

Table 9: Implementation Costs (1/2): Size and Institutional Ownership

This table displays further robustness checks of our baseline specification from Table 1. Specifications (1) to (3) report value-weighted returns of portfolios constructed by triple sorts using skewness, momentum and size. Following Fama and French (2008), we divide the universe of stocks in three groups: Micro are stocks that fall within the 20% NYSE percentile regarding their market capitalization. Small refers to stocks with a market capitalization between the 20% and the 50% NYSE percentile and Big are stocks with above NYSE median market capitalization. *Enhanced, Regular* and *Weakened Momentum* portfolios are constructed as in Table 1. We report raw and risk-adjusted returns. Risk-adjusting for the CAPM is denoted as 1F. 3F refers to the Fama and French (1993) model and 5F is the latter augmented with factors for long-term and short-term reversal. Specifications (4) and (5) display returns for triple sorts using skewness, momentum and institutional ownership. Stocks with above (below) median fraction of institutional ownership are denoted as high (low) institutional ownership. The sample period covers January 1926 to December 2011 for specifications (1) to (3) and January 1980 to December 2011 for specifications (4) and (5). We adjust t-statistics for serial correlation using Newey and West (1987) standard errors with a lag of six months. * indicates significance at the 10% level, ** indicate significance at the 5% level and *** indicate significance at the 1% level.

Robustness Specification	RAW	1F	3F	$5\mathrm{F}$
1) Micro				
Enhanced Momentum	2.78***	3.25***	3.70***	3.68^{***}
t-stat	(6.32)	(8.53)	(10.10)	(8.86)
Weakened Momentum	-0.99**	-0.89**	-0.64*	-0.47
t-stat	(-2.25)	(-2.51)	(-1.92)	(-1.07)
Regular Momentum	1.20***	1.36***	1.56^{***}	1.81***
t-stat	(5.04)	(6.64)	(7.90)	(8.06)
2) Small		. ,	. ,	. ,
Enhanced Momentum	2.10***	2.54***	2.68***	2.66***
t-stat	(8.40)	(11.97)	(12.46)	(12.00)
Weakened Momentum	-0.08	-0.18	-0.12	0.03
t-stat	(-0.33)	(-0.81)	(-0.54)	(0.13)
Regular Momentum	0.90^{***}	1.14^{***}	1.32^{***}	1.32^{***}
t-stat	(5.36)	(8.57)	(9.65)	(7.48)
3) Big				
Enhanced Momentum	1.12***	1.64***	1.87***	1.89***
t-stat	(3.99)	(7.50)	(8.60)	(7.38)
Weakened Momentum	0.39^{*}	0.14	0.24	0.46*
t-stat	(1.71)	(0.62)	(1.14)	(1.81)
Regular Momentum	0.62^{***}	0.81^{***}	0.97^{***}	1.02^{***}
t-stat	(3.52)	(5.25)	(6.39)	(5.56)
4) High Institutional Ownership				
Enhanced Momentum	1.85***	2.29***	2.18^{***}	2.22***
t-stat	(3.61)	(5.13)	(5.31)	(5.40)
Weakened Momentum	0.49^{*}	0.50^{**}	0.68^{***}	0.91^{***}
t-stat	(1.81)	(2.05)	(2.77)	(3.06)
Regular Momentum	0.75^{***}	0.97^{***}	1.13^{***}	1.20^{***}
t-stat	(3.87)	(5.71)	(6.52)	(5.68)
5) Low Institutional Ownership				
Enhanced Momentum	2.05***	2.54***	2.49***	2.55***
t-stat	(4.06)	(5.36)	(5.53)	(5.62)
Weakened Momentum	0.40	0.41^{*}	0.57^{**}	0.67^{**}
t-stat	(1.47)	(1.70)	(2.19)	(2.17)
Regular Momentum	0.86^{***}	1.10^{***}	1.25^{***}	1.26^{***}
t-stat	(4.55)	(6.87)	(7.47)	(6.33)

Table 10: Implementation Costs (2/2): Turnover, Bid-Ask Spreads and Short Interest

This table displays further robustness checks of our baseline specification from Table 1. Specifications (1) and (2) report value-weighted returns of portfolios constructed by triple sorts using skewness, momentum and turnover. Stocks with above (below) median turnover are denoted as high (low) turnover. Similarly, (3) and (4) report value-weighted returns of triple-sorted portfolios using skewness, momentum and bid-ask spreads. Finally, (5) and (6) show value-weighted returns of triple-sorted portfolios using skewness, momentum and bid-ask spreads. Finally, (5) and (6) show value-weighted returns of triple-sorted portfolios are constructed as in Table 1. We report raw and risk-adjusted returns. Risk-adjusting for the CAPM is denoted as 1F. 3F refers to the Fama and French (1993) model and 5F is the latter augmented with factors for long-term and short-term reversal. The sample period covers January 1926 to December 2011 for specifications (1) to (4) and January 1973 to December 2011 for specifications (5) and (6). We adjust t-statistics for serial correlation using Newey and West (1987) standard errors with a lag of six months. * indicates significance at the 10% level, ** indicate significance at the 1% level.

Robustness Specification	RAW	1F	3F	$5\mathrm{F}$
1) High Turnover				
Enhanced Momentum t-stat Weakened Momentum t-stat 2) Low Turnover	$2.28^{***} \\ (7.98) \\ 0.50^{*} \\ (1.90)$	$2.74^{***} \\ (10.62) \\ 0.27 \\ (1.03)$	$2.85^{***} \\ (10.92) \\ 0.42^{*} \\ (1.74)$	$2.90^{***} \\ (10.13) \\ 0.71^{***} \\ (2.89)$
Enhanced Momentum t-stat Weakened Momentum t-stat 3) High Bid-Ask Spread	$\begin{array}{c} 0.94^{***} \\ (3.34) \\ 0.24 \\ (1.13) \end{array}$	$1.24^{***} \\ (4.70) \\ 0.23 \\ (0.94)$	$1.49^{***} \\ (5.61) \\ 0.31 \\ (1.27)$	$1.41^{***} \\ (5.67) \\ 0.23 \\ (1.08)$
Enhanced Momentum t-stat Weakened Momentum t-stat 4) Low Bid-Ask Spread	$2.16^{***} \\ (6.58) \\ -0.32 \\ (-0.96)$	$2.59^{***} \\ (8.22) \\ -0.41 \\ (-1.17)$	$2.74^{***} \\ (8.84) \\ -0.29 \\ (-0.86)$	$\begin{array}{c} 3.10^{***} \\ (8.71) \\ -0.24 \\ (-0.69) \end{array}$
Enhanced Momentum t-stat Weakened Momentum t-stat 5) High Short Interest (Loser)	$\begin{array}{c} 0.62^{***} \\ (2.78) \\ 0.39^{*} \\ (1.81) \end{array}$	$\begin{array}{c} 0.93^{***} \\ (4.40) \\ 0.25 \\ (1.17) \end{array}$	$\begin{array}{c} 1.06^{***} \\ (5.13) \\ 0.29 \\ (1.40) \end{array}$	$\begin{array}{c} 1.05^{***} \\ (4.98) \\ 0.42^{*} \\ (1.92) \end{array}$
Enhanced Momentum t-stat Weakened Momentum t-stat 6) Low Short Interest (Loser)	$\begin{array}{c} 1.68^{***} \\ (6.19) \\ 0.49^{**} \\ (2.19) \end{array}$	$2.17^{***} \\ (10.01) \\ 0.24 \\ (1.15)$	$2.34^{***} \\ (11.22) \\ 0.34^{*} \\ (1.71)$	$2.39^{***} \\ (9.38) \\ 0.57^{**} \\ (2.43)$
Enhanced Momentum t-stat Weakened Momentum t-stat	$\begin{array}{c} 1.91^{***} \\ (4.77) \\ 0.28 \\ (0.63) \end{array}$	$2.14^{***} \\ (5.40) \\ -0.02 \\ (-0.06)$	$2.36^{***} \\ (5.98) \\ 0.33 \\ (0.78)$	$2.38^{***} \\ (6.02) \\ 0.49 \\ (1.12)$

Table 11: International Evidence: Fama/MacBeth Regressions

This table presents results of Fama and MacBeth (1973) regressions in international stock markets. Following Bandarchuk and Hilscher (2013) we regress momentum profits and Moskowitz (2004). Age is defined as the number of months since the firms first appearance in Datastream. All variables are standardized by months and the coefficients on our skewness measure from Bali et al. (2011) and various control variables that have been associated with the profitability of momentum. We report only the coefficient and All Controls are the Basic Controls augmented with Implied Price Risk, 52-Week High, Continuous Information, Return Consistency and Age. The Betas and Idiosyncratic Volatility are computed from rolling regressions using daily data over the previous twelve months. Implied Price Risk is as in Chuang and Ho (2014). The 52-Week High e-statistic of our skewness measure. Basic Controls entail Beta, Beta Book-to-Market, Beta Size, Idiosyncratic Volatility, Momentum Strength and the one-month lagged return. variable is computed as suggested by George and Hwang (2004). Continuous Information is constructed as in Da et al. (2014). Return Consistency is measured as in Grinblatt are multiplied by 100. We adjust t-statistics for serial correlation using Newey and West (1987) standard errors with a lag of five months. * indicates significance at the 10% level, ** indicate significance at the 5% level and *** indicate significance at the 1% level.

		Momentu	ım Returns				
Country	Coefficient	T-Stat	Coefficient	T-Stat	Coefficient	T-Stat	Sample Range
Australia	-0.2845^{***}	(-2.84)	-0.2571^{***}	(-2.68)	-0.2311^{**}	(-2.10)	1981 - 2013
Austria	-0.3514^{***}	(-2.60)	-0.3789^{**}	(-2.58)	-0.1309	(-0.64)	1988 - 2013
Belgium	-0.6412^{***}	(-5.36)	-0.5858^{***}	(-4.56)	-0.5763^{***}	(-4.04)	1988 - 2013
Canada	-0.2523^{**}	(-2.25)	-0.2879^{***}	(-2.60)	-0.4018^{***}	(-3.24)	1984 - 2013
Denmark	-0.3878***	(-2.85)	-0.4204^{***}	(-3.08)	-0.2824^{**}	(-2.10)	1987 - 2013
France	-0.2679^{***}	(-2.86)	-0.3437^{***}	(-3.67)	-0.3149^{***}	(-3.30)	1981 - 2013
Germany	-0.5717^{***}	(-6.60)	-0.5727^{***}	(-6.39)	-0.5123^{***}	(-7.10)	1981 - 2013
Italy	-0.3242^{**}	(-2.57)	-0.5134^{***}	(-3.96)	-0.3477^{***}	(-3.01)	1987 - 2013
Japan	-0.1472^{**}	(-2.19)	-0.1350^{*}	(-1.84)	-0.1923^{***}	(-2.86)	1981 - 2013
Netherlands	-0.6104^{***}	(-4.98)	-0.7875***	(-6.49)	-0.7467^{***}	(-5.56)	1981 - 2013
Norway	-0.2168	(-1.48)	-0.2185	(-1.33)	-0.2977	(-1.54)	1988 - 2013
Portugal	-0.4513^{***}	(-3.09)	-0.3011^{*}	(-1.91)	-0.2634	(-1.45)	1988 - 2013
Singapore	0.0105	(0.10)	0.0069	(0.07)	-0.0725	(-0.63)	1988 - 2013
Sweden	-0.6142^{***}	(-3.43)	-0.5134^{***}	(-2.86)	-0.7406^{***}	(-4.22)	1988 - 2013
Switzerland	-0.5809^{***}	(-6.72)	-0.5776^{***}	(-5.51)	-0.4681^{***}	(-4.76)	1988 - 2013
Uk	-0.1295	(-1.58)	-0.1515^{**}	(-1.98)	-0.1515^{**}	(-2.14)	1981 - 2013
Group of 7	-0.1788***	(-3.40)	-0.2239^{***}	(-4.00)	-0.2233^{***}	(-4.13)	1981 - 2013
Pooled	-0.1791^{***}	(-3.66)	-0.2225^{***}	(-4.23)	-0.2161^{***}	(-4.26)	1981 - 2013
Industry Controls Basic Controls All Controls	yes no no		yes yes no		yes yes yes		

Table 12: Robustness Tests: Volatility, Age and Credit Rating

This table displays further robustness checks of our baseline specification from Table 1. Specifications (1) and (2) report value-weighted returns of portfolios constructed by triple sorts using skewness, momentum and idiosyncratic volatility. Stocks with above (below) median idiosyncratic volatility are denoted as high (low) idiosyncratic volatility. Similarly, (3) and (4) report value-weighted returns of triple-sorted portfolios using skewness, momentum and age. Finally, (5) and (6) show value-weighted returns of triple-sorted portfolios using skewness, momentum and credit rating. *Enhanced* and *Weakened Momentum* portfolios are constructed as in Table 1. We report raw and risk-adjusted returns. Risk-adjusting for the CAPM is denoted as 1F. 3F refers to the Fama and French (1993) model and 5F is the latter augmented with factors for long-term and short-term reversal. The sample period covers January 1926 to December 2011 for specifications (1) to (4) and January 1985 to December 2011 for specifications (5) and (6). We adjust t-statistics for serial correlation using Newey and West (1987) standard errors with a lag of six months. * indicates significance at the 10% level, ** indicate significance at the 5% level and *** indicate significance at the 1% level.

Robustness Specification	RAW	$1\mathrm{F}$	3F	$5\mathrm{F}$
1) High Idiosyncratic Volatility				
 Enhanced Momentum t-stat Weakened Momentum t-stat 2) Low Idiosyncratic Volatility Enhanced Momentum t-stat 	$\begin{array}{c} 2.55^{***}\\ (8.67)\\ -0.05\\ (-0.17)\\ \end{array}$	$2.96^{***} \\ (11.29) \\ 0.05 \\ (0.17) \\ 1.24^{***} \\ (6.81) $	$3.16^{***} \\ (11.68) \\ 0.22 \\ (0.74) \\ 1.44^{***} \\ (8.03)$	$3.08^{***} \\ (10.47) \\ 0.35 \\ (1.15) \\ 1.40^{***} \\ (7.58)$
Weakened Momentum t-stat 3) Older Firms	$ \begin{array}{c} 0.08 \\ (0.48) \end{array} $	-0.08 (-0.49)	-0.00 (-0.02)	$\begin{pmatrix} 0.15 \\ (0.82) \end{pmatrix}$
Enhanced Momentum t-stat Weakened Momentum t-stat 4) Younger Firms	$\begin{array}{c} 1.01^{***} \\ (4.41) \\ 0.36 \\ (1.53) \end{array}$	$\begin{array}{c} 1.44^{***} \\ (7.22) \\ 0.08 \\ (0.32) \end{array}$	$\begin{array}{c} 1.60^{***} \\ (8.28) \\ 0.17 \\ (0.73) \end{array}$	$\begin{array}{c} 1.73^{***} \\ (8.55) \\ 0.46^{*} \\ (1.73) \end{array}$
Enhanced Momentum t-stat Weakened Momentum t-stat 5) Bad Credit Rating	$\begin{array}{c} 2.33^{***} \\ (7.89) \\ 0.50^{**} \\ (2.07) \end{array}$	$2.83^{***} \\ (11.34) \\ 0.28 \\ (1.22)$	$2.98^{***} \\ (12.48) \\ 0.42^{*} \\ (1.95)$	$\begin{array}{c} 3.03^{***} \\ (10.54) \\ 0.65^{***} \\ (2.61) \end{array}$
Enhanced Momentum t-stat Weakened Momentum t-stat 6) Good Credit Rating	$\begin{array}{c} 2.44^{***} \\ (3.20) \\ 0.98 \\ (1.58) \end{array}$	$2.94^{***} \\ (4.38) \\ 0.82 \\ (1.28)$	$2.85^{***} \\ (4.83) \\ 1.12^{*} \\ (1.92)$	$2.87^{***} \\ (4.85) \\ 1.13^{*} \\ (1.89)$
Enhanced Momentum t-stat Weakened Momentum t-stat	$\begin{array}{c} 0.96^{**} \\ (2.01) \\ 0.06 \\ (0.13) \end{array}$	$\begin{array}{c} 1.34^{***} \\ (3.42) \\ -0.21 \\ (-0.51) \end{array}$	$\begin{array}{c} 1.43^{***} \\ (3.71) \\ -0.06 \\ (-0.16) \end{array}$	$\begin{array}{c} 1.43^{***} \\ (3.76) \\ -0.06 \\ (-0.16) \end{array}$

Table 13: Robustness Tests: Residual Analyst Coverage and Unrealized Capital Gains

This table displays further robustness checks of our baseline specification from Table 1. Specifications (1) and (2) report value-weighted returns of portfolios constructed by triple sorts using skewness, momentum and residual analyst coverage. Residual analyst coverage is obtained from cross-sectional regressions of $\log(1 + \text{number of estimates for the firm's earnings next year)}$ on $\log(1 + \text{size})$. Stocks with above (below) median residual analyst coverage are denoted as high (low) residual analyst coverage. Similarly, (3) and (4) report value-weighted returns of triple-sorted portfolios using skewness, momentum and unrealized capital gains. *Enhanced* and *Weakened Momentum* portfolios are constructed as in Table 1. We report raw and risk-adjusted returns. Risk-adjusting for the CAPM is denoted as 1F. 3F refers to the Fama and French (1993) model and 5F is the latter augmented with factors for long-term and short-term reversal. The sample period covers January 1926 to December 2011 for specifications (1) and (2) and January 1981 to December 2011 for specifications (3) and (4). We adjust t-statistics for serial correlation using Newey and West (1987) standard errors with a lag of six months. * indicate significance at the 10% level, ** indicate significance at the 5% level and *** indicate significance at the 1% level.

Robustness Specification	RAW	1F	3F	$5\mathrm{F}$
1) High Residual Analyst Coverage				
Enhanced Momentum	1.47***	1.96***	1.90***	1.95***
t-stat	(2.65)	(3.97)	(4.21)	(4.26)
Weakened Momentum	0.29	-0.12	0.38	0.45
t-stat	(0.58)	(-0.26)	(0.89)	(1.06)
2) Low Residual Analyst Coverage				
Enhanced Momentum	1.99***	2.36***	2.25***	2.24^{***}
t-stat	(4.64)	(6.14)	(6.73)	(6.72)
Weakened Momentum	-0.27	-0.67	-0.10	-0.00
t-stat	(-0.59)	(-1.52)	(-0.24)	(-0.01)
3) High Unrealized Capital Gains				
Enhanced Momentum	0.78***	1.10***	1.10***	1.26***
t-stat	(3.43)	(4.89)	(4.87)	(5.26)
Weakened Momentum	0.39	0.16	0.34	0.47
t-stat	(1.36)	(0.56)	(1.11)	(1.49)
4) Low Unrealized Capital Gains				
Enhanced Momentum	1.33***	1.85***	2.05***	2.06***
t-stat	(4.29)	(6.58)	(7.47)	(7.40)
Weakened Momentum	0.39*	0.16	0.18	0.40^{*}
t-stat	(1.86)	(0.72)	(0.85)	(1.76)



Figure 1: Cumulative Gains of Enhanced Momentum Strategies

This figure shows cumulative gains of two risk-managed enhanced momentum strategies, *Enhanced Momentum*, *Weakened Momentum*, *Momentum* and the *Market*. The risk-managed enhanced momentum strategies are derived from enhanced momentum as in Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2014) and denoted as *Enhanced Momentum** and *Enhanced Momentum***. For each momentum portfolio, the strategy invests \$1 in the risk-free rate at the beginning of the sample period in January 1927 and complements it with the zero-investment long-short portfolio. For the portfolio construction, stocks are first sorted into five equally sized portfolios based on our skewness measure from Bali et al. (2011). Within each quintile, we sort stocks again into quintiles according to their past cumulative returns. We use a formation period of twelve months and a holding period of one month and skip one month in between, during which skewness is measured. *Enhanced Momentum* denotes the portfolio that consists of stocks in the highest (lowest) skewness quintile and in the lowest (highest) quintile with respect to past cumulative returns in the short (long) leg. *Weakened Momentum* comprises stocks in the lowest (highest) skewness quintile and in the lowest stocks in the high stort (long) leg. *Momentum* consists of winners (losers) in the third skewness quintile. Cumulative returns in the short (long) leg. *Momentum* consists of winners (losers) in the third skewness quintile. Cumulative gains of the market are calculated for a buy-and-hold strategy that invests \$1 in the market portfolio at the beginning of the sample period.

A Variable definitions

IDIOSYNCRATIC VOLATILITY: We estimate idiosyncratic volatility from regressions of returns on the Fama and French (1993) factors using daily data from the previous twelve months:

$$r_{i,t} - r_t^f = a + b_1 \text{MKTRF}_t + b_2 \text{SMB}_t + b_3 \text{HML}_t + \epsilon_{i,t}$$
(11)

We define idiosyncratic volatility as the standard deviation of the residuals $\epsilon_{i,t}$.

MOMENTUM STRENGTH: Following Bandarchuk and Hilscher (2013), we define momentum strength as exp(absolute value of the difference between the stock's log return during the formation period and the median of formation period log returns of all stocks) -1.

52-WEEK HIGH: The 52-Week High is defined as the ratio of current price to the highest price achieved within the past 52 weeks as in George and Hwang (2004).

CONTINUOUS INFORMATION: We define Continuous Information for (losers) winners as the (negative) difference between the percentage of negative and positve daily returns in the formation period as suggested by Da et al. (2014).

RETURN CONSISTENCY: Following Grinblatt and Moskowitz (2004), we define Return Consistency as a dummy that takes the value one if a winner's (loser's) monthly returns are positive (negative) for at least eight months of the formation period, which covers the past twelve months, and zero otherwise.

UNREALIZED CAPITAL GAINS: We define Unrealized Capital Gains as Grinblatt and Han (2005):

$$\frac{P_{t-2} - R_{t-1}}{P_{t-2}} \tag{12}$$

with

$$R_{t-1} = \sum_{j=1}^{60} \left(V_{t-j} \prod_{i=1}^{j-1} (1 - V_{t-j+i}) \right) P_{t-j}$$
(13)

where P_t denotes the share price at time t and V_t the trading volume at time t.

IMPLIED PRICE RISK: Following Chuang and Ho (2014), we define Implied Price Risk as

$$\Phi\left(\frac{\ln\left(\frac{P_{t-1}}{P_{t-13}}\right) - 12 \cdot \hat{\mu}}{\sqrt{12 \cdot \hat{\sigma}^2}}\right) \tag{14}$$

where $\hat{\mu}$ and $\hat{\sigma}^2$ denote the realized mean and variance of returns from the past 36 months and P_t denotes the share price at time t. $\Phi(.)$ refers to the cumulative distribution function of the standard normal distribution.

AGE: Age is defined as the number of month since the firm's first appearance in CRSP.

TURNOVER: Turnover is share volume divided by shares outstanding. We multiply turnover by 0.5 before 1.1.1997 and by 0.62 afterwards for NASDAQ stocks (see e.g. Anderson and Dyl (2005)).

BID/ASK SPREAD: We estimate the Bid/Ask Spread by employing the algorithm of Corwin and Schultz (2012).

BETA, BETA SIZE, BETA BOOK-TO-MARKET: We estimate Betas from regressions of returns on the Fama and French (1993) factors using daily data from the previous twelve months:

$$r_{i,t} - r_t^f = a + b_1 \text{MKTRF}_t + b_2 \text{SMB}_t + b_3 \text{HML}_t + \epsilon_{i,t}$$
(15)

We define Beta as b_1 , Beta Size as b_2 and Beta Book-to-Market as b_3 .

LAG RETURN: We define Lag Return as the return of month t - 1 to account for short-term reversal (Jegadeesh, 1990).

CREDIT RATING: We rely on the S&P domestic long term issuer credit rating (obtained from Compustat), which uses 22 ratings from AAA to D.

ANALYST FORECAST DISPERSION: Forecast dispersion is defined as the standard deviation of earnings per share forecasts scaled by the mean absolute EPS forecast. We only consider firms with at least two forecasts based on I/B/E/S summary files.

SHORT INTEREST: Monthly short interest is defined as the number of uncovered shares sold short (as obtained from Compustat) divided by the total number of shares outstanding.

ANALYST COVERAGE: Analyst coverage is defined as the number of analysts which provide fiscal year end estimates based on I/B/E/S summary files. If a firm has a missing value for the number of analysts, a value of 0 is assigned.

CASH FLOW VOLATILITY: As in Zhang (2009), cash flow volatility is defined as the standard deviation of cash flow from operations in the past 5 years (conditioning on at leat three non-missing observations). Cash flow from operations is computed as earnings before extraordinary items minus total accruals, scaled by total assets. Following the standard in the literature (e.g. Fama and French (1992)), values are updated once every year at the end of June.

PROFITABILITY: As in Novy-Marx (2013), profitability is measured as gross profits (revenues minus cost of goods sold) scaled by total assets. Following the standard in the literature (e.g. Fama and French (1992)), values are updated once every year at the end of June.

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