Expected Skewness and Momentum

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Abstract

Motivated by the time-series insights of Daniel and Moskowitz (2016), we investigate the link between expected skewness and momentum in the cross-section. The alpha of skewness-enhanced (-weakened) momentum is about twice (half) as large as the traditional alpha. These findings are driven by the short leg. Portfolio sorts, Fama-MacBeth regressions, and the market reaction to earnings announcements suggest that expected skewness is an important determinant of momentum. Due to the simplicity of the approach, its economic magnitude, its existence among large stocks, and the success of risk management, the results are difficult to reconcile with the efficient market hypothesis.

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

JEL Classification Codes: G12, G14

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1 Introduction

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 cross-sectional momentum profits, in particular with respect to past loser stocks. The impact of skewness is economically large, statistically highly significant, holds among large firms, in international markets, and after controlling for a large set of firm characteristics previously linked to momentum profitability (e.g., past returns, idiosyncratic volatility, continuously arriving information, credit ratings).

Analyzing the relation between skewness and momentum constitutes a promising endeavour for several reasons. First, recent models show that skewness is an important determinant of equilibrium asset returns (Barberis and Huang, 2008; Bordalo et al., 2013; Brunnermeier et al., 2007; Mitton and Vorkink, 2007), which is corroborated by empirical evidence (Bali et al., 2011; Boyer et al., 2010; Conrad et al., 2013). Second, Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) uncover that the time-series of momentum returns is negatively skewed, which suggests that the momentum effect partly represents a skewness premium. Exploring this relation in the cross-section (as opposed to the time-series) is thus a natural choice. Third, among academics and practitioners alike, there is a controversial debate about the firm-level determinants of momentum (Bandarchuk and Hilscher, 2013; Asness et al., 2014), which is the "the center-stage anomaly of recent years" (Fama and French (2008, p. 1674)).

We hypothesize that parts of the momentum performance derive from different levels of skewness in the short and the long leg. More precisely, positive skewness carries a negative return premium (Bali et al., 2011; Boyer et al., 2010), and the time-series of loser returns is more positively skewed than the time-series of winner returns (Daniel and Moskowitz, 2016). If these insights also translate to the cross-section, then the resulting winner-loser momentum portfolio will yield a positive return premium. Based on this thought, momentum should be particularly pronounced if losers (winners) have a strong (weak) positive skew. Conversely, high (low) positive skewness on the winner (loser) leg is expected to reduce the profitability of momentum.

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. It is calculated as the maximum daily return during the preceding month. From the investor perspective, this approach has the additional advantage of being highly salient and easy to interpret, which makes it an intuitively appealing proxy for perceived (as opposed to expected) skewness as well.

We benchmark our findings against the traditional quintile-based momentum approach, which, after dropping small and illiquid stocks, delivers an average value-weighted monthly return of 0.81% (t = 4.28) over the period from January 1927 to December 2011. In contrast, a long-short momentum strategy with little skewness (henceforth: weakened momentum), which consists of winner (loser) stocks with ex ante positive (negative) skewness yields only 0.47% (t = 2.05). At the same time, one can double value-weighted momentum returns 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.

As both momentum formation period returns and the measure proposed in Bali et al. (2011) have predictive power for stock returns, a combination of both approaches as sketched above can naturally be expected to perform well. However, at least two aspects are surprising.

First, the magnitude of the combined effect is large. For instance, the 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 patterns can be identified in all size groups. Figure 1 further illustrates the economic meaningfulness. In the case of a traditional long/short momentum strategy, $1 invested at the beginning of January 1927 grows to $29,706 at the end of December 2011. In contrast, enhanced (weakened) momentum delivers $9,685,302 ($1,012). The economic and statistical magnitude of enhanced momentum appears to be roughly comparable to the largest return phenomena considered in Green et al. (2014) (100 anomalies) as well as Jacobs (2015) (100 partly different anomalies) or to the composite mispricing measure proposed in Stambaugh et al. (2015). With a value-weighted alpha of more than 1.50% per month, skewness-enhanced momentum also poses challenge for the five-factor model recently proposed in Fama and French (2015, 2016a, 2016b).

Insert Figure 1 here

Second, and similarly as in Daniel and Moskowitz (2016), our findings are driven by the short leg. More specifically, past loser stocks with positive expected skewness (contained in the enhanced momentum portfolio) yield large negative alphas and also heavily underperform past loser stocks with negative expected skewness (in the weakened momentum portfolio). In contrast, negatively skewed winner stocks (enhanced momentum) yield similar returns as positively skewed winners (weakened momentum).[1] This asymmetry between the long and the short leg points to limits to arbitrage in the sense of short-selling constraints. Many investors are not allowed to or not capable of taking short positions (see Stambaugh et al. (2012), Stambaugh et al. (2015) and the references therein). Similarly, there can be implicit barriers due to agency conflicts, relative performance measurement, and other aspects which may lead investors to refrain from shorting (e.g., Almazan et al. (2004), Engelberg et al. (2015b)).

A partly related explanation for the importance of the short leg may be the potentially asymmetric role of skewness for tail risk. Indeed, enhanced momentum has moderately higher tail risk than traditional momentum. Tail risk aversion in the sense of Bates (2008) or of Kelly and Jiang (2014) may thus partly explain our results. However, even after taking tail risk into account, returns to enhanced momentum are still very large. Moreover, and as illustrated in Figure 1, the risk management procedures suggested by Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) help to further increase the performance. In sum, if our findings represent a premium for cross-sectional skewness risk, then this premium is surprisingly large.[2]

The role of the short leg could also be related to the empirical pattern recently documented in An et al. (2016). The authors argue that reference-dependent preferences cause skewness-related anomalies to be concentrated among stocks where investors have lost money. However,

[1] In other words, implementing a traditional momentum strategy among stocks in the top quintile of the Bali et al. (2011) measure yields large long/short returns that are only slightly lower than the estimates for enhanced momentum as defined above.

[2] On a somewhat related note, Daniel and Moskowitz (2016, p. 45) argue that the time-series effects they document “may be loosely consistent with several behavioral findings, where in extreme situations individuals tend to be fearful and appear to focus on losses, largely ignoring probabilities.”

our findings hold after controlling for capital gain overhang and a broad range of other variables.

Finally, our findings may be driven by expectational errors. More specifically, investors may be overly optimistic about the prospects of past loser firms with positive expected skewness. In this case, investors should be negatively surprised upon the arrival of hard information. As discussed in detail in Engelberg et al. (2015a), investors would then be forced to update their biased beliefs, which may result in predictable earnings announcement returns. We find strong support for this conjecture. Enhanced momentum generates an abnormal three-day event-time return of more than 80 bp, which is disproportionately driven by the poor performance of the short leg. In sum, biased beliefs about future cash flows appear to be a driver of our results.

Our findings contribute to two strands of the literature. First, they add to the literature on the determinants of the momentum effect. Fama and MacBeth (1973) regressions with up to 20 firm-level controls (including past returns and idiosyncratic volatility) indicate that skewness is an important predictor of momentum profits. Further tests indicate that, taken in their entirety, our findings do not seem to neatly fit within any of the leading theories of momentum. Our findings thus suggest the need for the development of theoretical explanations that are consistent with the 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, Bali et al. (2011), Boyer et al. (2010), 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 analysis is based on daily and monthly return data for common stocks (CRSP share code equal to 10 or 11) traded on NYSE, Amex, or Nasdaq. The sample period covers 1927 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 as well as firms in the lowest NYSE decile. Doing so results in eliminating close to 50% of the firm months. To further mitigate concerns related to market microstructure, we compute both equally and value-weighted returns.

Balance sheet information, short interest, earnings dates and credit ratings are obtained from Compustat, and analyst-based information is gathered from $I/B/E/S$. Stock market and accounting data for 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. Our baseline analysis employs the approach proposed by Bali et al. (2011) and used in Bali et al. (2016) to explain the low beta anomaly:

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

Simply using the maximum daily return over the preceding month as a proxy for expected skewness offers a number of advantages. First, from an empirical point of view, the measure is intuitively appealing and easy-to-compute. Second, it nicely relates to the model of Barberis and Huang (2008), in which skewness is modelled by a small chance for an extreme return.

Third, and as Table 1 shows, the measure indeed forecasts future skewness better than past idiosyncratic skewness, which in fact has no predictive power. The approach of Bali et al. (2011) also yields better results than the alternative measure of Boyer et al. (2010).

Insert Table 1 here

Fourth, the connection between the maximum daily returns and the skewness of the underlying distribution can also be shown mathematically. For any random variable X with finite first three moments, Markov's inequality asserts for any $w > 0$:

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

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 (low) maximum returns are an indicator for high (low) positive skewness.

Fifth, investors may not necessarily base their trading decisions on the most powerful proxy for expected skewness, but instead rely on perceived skewness. Also in this regard, and in contrast to more complex skewness measures, the maximum daily return in the previous month is an intuitively appealing proxy. More specifically, it is a salient and natural indicator for positive skewness and thus likely to attract the attention of investors. Hence, it nicely corresponds to the model of Bordalo et al. (2012), in which skewness preference is related to salience.

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. The approach employs past skewness in combination with a set of firm characteristics (such as past idiosyncratic volatility, turnover, or industry classification, denoted as $X_{i,t-60}$ below) to predict future skewness. To assess idiosyncratic moments, we run rolling regressions of daily excess returns over the previous 60 months on the Fama and French (1993) factors. For firm i in month t, idiosyncratic volatility ($iv_{i,t}$) is the standard deviation and idiosyncratic skewness ($is_{i,t}$) is the standardized third momentum of the residuals. As Boyer et al. (2010), we then perform the following regression for each month t:

$$is_{i,t} = \alpha_t + \beta_t \cdot iv_{i,t-60} + \gamma_t \cdot is_{i,t-60} + \delta_t' \cdot X_{i,t-60} + \eta_{i,t} \tag{3}$$

In the second step, expected skewness is computed as:

$$SKEW_{i,t+60}^{\text{REG}} = \alpha_t + \beta_t \cdot iv_{i,t} + \gamma_t \cdot is_{i,t} + \delta_t' \cdot X_{i,t} \tag{4}$$

2.2 Baseline results

We start by conducting dependent 5x5 sorts. In each month, we first sort stocks into quintiles based on expected skewness and then form quintiles based on past cumulative returns. Winner (loser) stocks are in formation period quintile 5 (1). The construction of the baseline momentum portfolios follows Daniel and Moskowitz (2016). More precisely, 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. The baseline results are displayed in Table 2. Regular momentum, which consists of winners and losers in the third skewness quintile, serves as a benchmark. It delivers an equally (value-) weighted raw return of 0.93% (0.81%) per month.

Insert Table 2 here

If momentum profits are driven by different levels of skewness and associated return premiums of winners and 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 skewness and 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 of Table 2. 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 (Fama and French (1993)) alpha is 0.00% (0.12%) per month. Additionally controlling for long-term and short-term reversal yields an intercept of 0.33%, which is significant at the 10% level only. As Panel B shows, value-weighted returns are only slightly larger.

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. The monthly equally weighted raw return of enhanced momentum amounts to 1.90%, which is about twice the return of standard momentum. Accounting for the Fama and French (1993) factors yields a highly significant intercept of 2.55% per month. The intercept of the aforementioned five factor model is 2.58%. As before, the results are not altered by value-weighting portfolio returns. Raw returns amount to 1.65% per month. Alphas range from 2.14% to 2.36%.

To isolate the incremental effect of the double sorts, we compute the difference between enhanced momentum and weakened momentum. This momentum-neutral 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 conclusion, the evidence indicates that the momentum anomaly is strongly linked to expected skewness.

Panel C and D of Table 2 report equally and value-weighted raw returns separately for winners and losers in each skewness quintile. While there is no clear pattern for winners, loser returns decline monotonically, indicating that the effect is driven by the short leg.

To further explore this issue, we compute risk-adjusted returns. For brevity, we only document the (weaker) findings for value-weighted returns. Table 3 again verifies that the profitability of both the enhanced and the weakened momentum strategies is attributable to the short legs. In sum, skewness has an asymmetric impact on losers and winners.

Insert Table 3 here

2.3 How risky is skewness-enhanced momentum?

As already shown, traditionally employed risk factors (including short-term and long-term reversal) cannot explain the performance difference between weakened and enhanced momentum.

As alternative measures for risk, Table 4 shows average total volatility, average skewness, the 1% percentile of monthly returns, and the minimum monthly return. For illustration purposes, Table 4 also shows several return measures.

Insert Table 4 here

To measure the risk-return trade-off, we compute the Sharpe ratio, the Sortino ratio and the Omega ratio. 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

$$\Omega = \frac{\displaystyle\int_0^\infty (1 - F(x))dx}{\displaystyle\int_{-\infty}^0 F(x)dx} \tag{5}$$

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.

Enhanced (weakened) momentum returns displays a monthly volatility of 8.2% (7.3%). However, volatility fails to explain the performance difference as the Sharpe ratio of enhanced (weakened) momentum amounts to 0.70 (0.22), which is substantially greater (less) than the Sharpe ratio of traditional momentum (0.45).

Both enhanced momentum and regular momentum are negatively skewed, with a skewness of -1.87 and -0.99, respectively. The skewness of weakened momentum is exactly zero, which indicates that the Bali et al. (2011) measure works well. However, the Sortino ratios indicate that, on a risk-adjusted basis, enhanced momentum (0.73) clearly outperforms regular momentum (0.53) and weakened momentum (0.30).

Similar insights are gained from the Omega ratio. The Omega ratio of the market portfolio (1.59) should not be surpassed by any portfolio, because the ratio incorporates *any* risk. Indeed, the regular (weakened) momentum strategy obtains a value of only 1.46 (1.21). However, the Omega ratio of the enhanced momentum strategy is 1.83. In sum, enhanced momentum returns appear too large, even after accounting for skewness, to mainly represent a compensation for known forms of risk.

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. Relative to these estimates, our results seem large. In addition, the tail risk of enhanced momentum is moderate. The 1% percentile of monthly returns is -23.67%. For comparison, the 1% percentile of monthly returns of regular (weak) momentum is -16.33% (-16.63%), the 1% percentile of the market is -15.03%.

In the following, we explore whether the apparent imbalance between risk and return of enhanced momentum can be further magnified. Barroso and Santa-Clara (2015) show 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 in their study.

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 $\hat{\sigma}^2_{\text{Enhanced Momentum}_t}$ of enhanced momentum in month t according to the following formula (assuming one month has on average 21 trading days):

$$\hat{\sigma}^2_{\text{Enhanced Momentum}_t} = \frac{21}{126} \cdot \sum_{i=1}^{126} r^2_{\text{Enhanced Momentum}_{d_t - i}} \tag{6}$$

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%.[3] We denote the

[3]Note that the actual volatility of monthly returns will be higher because of the small autocorrelation of daily returns (Barroso and Santa-Clara, 2015). We pick the target level of 13% to match the realized volatility of risk managed enhanced momentum with the market volatility over the entire sample period. The resulting annualized

resulting returns of the risk-managed enhanced momentum as $r_{\text{Enhanced Momentum*}_t}$:

$$r_{\text{Enhanced Momentum*}_t} = \frac{\sigma_{\text{target}}}{\hat{\sigma_t}} \cdot r_{\text{Enhanced Momentum}_t} \tag{7}$$

Daniel and Moskowitz (2016) propose an alternative approach. 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 4 shows that the risk-management approaches are successful. In particular, the 1% percentile of returns amounts to about -13.8% for both risk-managed enhanced momentum strategies. In other words, the tail risk is now smaller than for weakened momentum, regular momentum or for the market. As a consequence, all performance measures increase substantially. For instance, the Sortino ratio of both risk-managed strategies is almost three times larger than the Sortino ratio of the market and about five times larger than the Sortino ratio of weakened momentum. In sum, it is difficult to explain the high enhanced momentum returns with known forms of risk.

2.4 Are findings attributable to differences in firm-characteristics?

Table 1 in the online appendix compares firm characteristics for stocks entering either the long or short leg of either the weakened or the enhanced momentum strategy. In total, we consider 18 variables which have previously been related to momentum profitability. Those variables are shortly described in the following, and explained in the appendix A in more in-depth. As uncovered by Bandarchuk and Hilscher (2013), idiosyncratic volatility and momentum strength are two key sources of momentum profits. In addition, we include age, analyst forecast dispersion, analyst coverage and cash flow volatility as proxies of information uncertainty (Zhang, 2006). Further, we rely on turnover (Lee and Swaminathan, 2000) and profitability (Novy-Marx, 2013). To control for the effects of liquidity, we include the bid-ask spread calculated based on the algo-

volatility is about 20%. In unreported robustness checks we have verified that inferences do not change if we use other levels of target volatility.

rithm of Corwin and Schultz (2012). We further add the continuous information variable proposed in Da et al. (2014), the 52-week high price (George and Hwang, 2004), and implied price risk (Chuang and Ho, 2014). To account for the disposition effect and the findings of An et al. (2016), 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. Finally, we use short interest.

Firms with high skewness, i.e., enhanced losers and weakened winners, tend to be firms with higher idiosyncratic volatility and higher bid-ask spreads, two characteristics that are often related to limits to arbitrage. Further, they are on average smaller[4] and younger firms with higher cash flow volatility, higher analyst forecast dispersion, and a lower credit rating. Collectively, this indicates that those stocks are hard to value. To test whether differences between enhanced and weakened momentum are attributable to these distinctions in firm characteristics, we conduct a number of Fama and MacBeth (1973) regressions of momentum profits on the skewness measure and a set of controls. We follow the methodology of Bandarchuk and Hilscher (2013) and define the dependent variable, momentum profits $r_{mom,t}$ of firm i, as follows:

$$r_{i,mom,t} = (r_{i,t} - r_{median,t}) \cdot sign\,(r_{i,t-12 \text{ to } t-2} - r_{median,t-12 \text{ to } t-2}) \tag{8}$$

where $r_{median,t}$ denotes the median profit of all stocks at month t. Thus, stocks with above median returns are considered to be winners. Stocks with below median returns are losers, and their returns are multiplied by -1. Because of the conjectured impact of skewness on winners and losers, we procede similarly with the expected skewness measure:

$$SKEW_{i,t+1} = SKEW_{i,t+1} \cdot sign\,(r_{i,t-12 \text{ to } t-2} - r_{median,t-12 \text{ to } t-2}) \tag{9}$$

The controls correspond to most characteristics outlined above plus the return in the skipped month, the return consistency variable of Grinblatt and Moskowitz (2004) and dummies for the 49 Fama/French industries (see Table 5). Not all firm characteristics are available for the whole sample period. We therefore run two sets of robustness checks which differ in the number of

[4]However, recall that economically less important small and illiquid stocks (about 50% of the CRSP common stock universe) are excluded from the analysis.

controls used as well as in the starting date (1927 or 1981).

We standardize all explanatory variables by months to make their impacts comparable, and multiply the resulting coefficients by 100. To mitigate the impact of outliers, we logarithmize idiosyncratic volatility, the 52-week high price, age, turnover and the bid-ask spread. Using the raw variables instead does not change inferences. The results of five regression specifications, all of which cover the entire sample period, are displayed in Table 5.

Insert Table 5 here

One standard deviation increase (decrease) of the skewness of winners (losers) reduces momentum profits by about 0.33%. The corresponding t-statistic is greater than six. Importantly, skewness clearly matters over and above idiosyncratic volatility.[5]

Next, we add credit rating, analyst coverage, analyst forecast dispersion, cash flow volatility, and profitability. Due to data availability, we restrict the analysis to the time period from January 1981 to December 2011. As before, we conduct the analysis in five specifications. Table 6 shows that the inclusion of the new control variables does not affect the role of the skewness measure. Again, one standard deviation increase (decrease) of the skewness of winners (losers) reduces momentum profits by about 0.34%.

Insert Table 6 here

2.5 Further robustness checks

2.5.1 Alternative sorting method

We run the baseline analysis (see Table 2) using reverse double sorts and independent sorts in specifications (1) and (2) of Table 7. The results are similar to the baseline findings.

Insert Table 7 here

[5]We follow previous work on momentum and idiosyncratic volatility (e.g., Arena and Haggard (2008), Bandarchuk and Hilscher (2013)) by estimating volatility on a rolling basis over the previous 12 months. The online appendix shows that inferences with respect to the impact of skewness do not change if we alternatively measure idiosyncratic volatility in the previous month or over the previous 36 months.

2.5.2 Portfolio tests to control for volatility and past returns

To corroborate the insights from the Fama and MacBeth (1973) regression in Table 5, we implement portfolio-level tests to control for the impact of idiosyncratic volatility and past returns. 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., the relative magnitude of past returns. This orthogonalization allows us to isolate the additional impact of skewness that matters over and above volatility and past returns. We conduct the aforementioned exercise of double sorting stocks into portfolios. We focus on value-weighted portfolio returns, as an unreported analysis yields stronger findings for equally-weighted returns. Specification (3) in Table 7 again confirms the insights from the baseline analysis. Most notably, enhanced momentum yields, after eliminating the role of idiosyncratic volatility (past returns), alphas between 1.44% and 1.61% (1.94% and 2.34%).

2.5.3 Alternative skewness measure

The final specification in Table 7 reports results obtained from conducting the analysis based on the expected skewness measure proposed in Boyer et al. (2010). Due to limited data availability, we focus on the subperiod from January 1961 onwards. Inferences do not change. For instance, the three factor alpha of enhanced (weakened) momentum amounts to 1.61% (0.32%).[6]

2.5.4 Subperiod analysis and different holding periods

Insert Table 8 here

In Panel A of Table 8, we repeat the analysis for three different subperiods (1961-2011, 1961-1991, 1991-2011). Again, inferences remain stable. Notably, in the most recent subperiod, returns for the weakened momentum strategy are essentially zero. In contrast, the enhanced momentum strategy 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), McLean and Pontiff (2016)). Indeed, profits of

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

regular momentum have been relatively small since 1991.

We also analyze longer holding periods. As Panel B of Table 8 shows, skewness significantly predicts momentum profits over holding periods of three, twelve and even up to 36 months.

2.5.5 Implementation costs

We use four different proxies for implementation costs. First, following Fama and French (2008), we divide the universe of stocks into three groups based on their market capitalization. (Only) for this particular analysis, 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. Table 9 demonstrate that the baseline findings exist in all size groups. 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.

Insert Table 9 here

We also use turnover, bid-ask spreads, as well as short interest on the loser side as additional proxies for implementation costs. For short interest, we first conduct conditional double-sorts of skewness and momentum and then sort losers based on short interest. For the other two variables, 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 the dependent double sorts on skewness and momentum for each part separately. Table 10 displays the results, which again are in line with the baseline findings.

Insert Table 10 here

3 Further insights

3.1 International evidence

We focus on MSCI developed markets to ascertain a high level of data quality (to measure expected skewness based on daily data), comprehensive data availability (for the control variables), and in order to be consistent with previous work on momentum (e.g., Asness et al. (2013)). 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, which are displayed in Table 11.

Insert Table 11 here

We rely on the Bali et al. (2011) skewness measure as well as on Fama and MacBeth (1973) regressions. 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 include implied price risk, 52-week high, continuous information, return consistency, and age.[7] Table 11 displays the results. Skewness significantly influences momentum profits in at least 75% of the countries in all three specifications. Results indicate 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. In addition, Table 5 of the online appendix shows 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 cross-sectional momentum profitability.

3.2 Biased investor beliefs

Engelberg et al. (2015a) propose an elegant way to distinguish among competing explanations for return predictability. In the rational expectations framework, future firm-level news is random so that the market reaction can not be predicted. In contrast, in the biased beliefs framework, investors may be overly optimistic (pessimistic) about certain groups of firms. The arrival of news would then force them to rapidly update their biased beliefs, resulting in abnormal returns over a short event window during which expected returns are close to zero. To explore this conjecture, we study the market reaction to firm-level earnings announcements. Abnormal announcement return are defined as the difference between the actual buy-and-hold

[7]For data availability reasons, we omit variables whose construction requires turnover. However, untabulated analyses indicate that the results obtained with the inclusion of these variables are similar.

return over the event days t=-1 to t=1 and the expected Fama and French (1993) three-factor buy-and-hold return. Table 12 shows strong support for a behavioral story.

Insert Table 12 here

Enhanced winner stocks on average generate a three-day abnormal return of 39 bp, which, however, is not very different from the abnormal return of regular winner stocks (25 bp). In stark contrast, enhanced loser stocks generate an abnormal return of -46 bp (t-stat -3.54) whereas regular loser stocks yield an abnormal return of essentially zero. In other words, investors appear to overstate the future prospects of past loser firms with positive skewness, and are negatively surprised by the arrival of hard facts. In sum, enhanced momentum is about two to three times stronger during news days than during regular days, suggesting that biased investor beliefs are an important driver of our findings.

3.3 Consistency with models of momentum

The predictable market reaction to firm-level news or the fact that enhanced momentum is particularly strong among high turnover stocks point towards a behavioral explanation. However, taken in their entirety, the findings do not seem to strongly support a specific prominent behavioral theory of momentum.

For instance, momentum in Daniel et al. (1998) arises due to two central biases, self-attribution 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, the model implies a reversal of momentum. However, as already shown in Panel B of Table 8, the impact of skewness on momentum does not revert in the long-run. This 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 (losers) which thus tend to deliver superior (inferior) performance in the next months. The fact that the profits of enhanced and weakened momentum are mainly driven by the short leg of the portfolios 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 and fast information diffusion. In contrast, and as Table 9 shows, enhanced (weakened) momentum delivers a three factor alpha of 1.87% (0.24%) among large (and thus highly visible) firms. To provide an additional test, we follow Hong et al. (2000) and sort on residual analyst coverage, which is by construction orthogonal to firm size. As shown in Table 7 of the online appendix, the three factor alpha of enhanced (weakened) momentum amounts to 1.90% (0.38)% per month for firms with high residual analyst coverage.

Barberis et al. (1998) conjecture that investors overreact to a series of good or bad news due to the representativeness heuristic. 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 4 of the 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 model intuition 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. However, the triple sorts shown in Table 7 of the online appendix indicate that enhanced momentum substantially outperforms weakened momentum, irrespective of the level of unrealized capital gains.

Finally, Avramov et al. (2007) argue that momentum is strong among low credit rating firms, but "nonexistent among high-grade firms" (p. 2503). Table 6 in the online appendix shows that this explanation is not applicable to our results. For instance, conditioning on high-grade firms, enhanced (weakened) momentum delivers a three factor alpha of 1.43% (-0.06%).

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

4 Conclusion

We document a strong and robust relation between expected skewness and cross-sectional momentum, in particular with respect to past loser stocks. 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. These findings hold among large stocks, stocks with low transaction costs, in different subperiods, and in an international setting. The risk-management methodologies of Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) can be employed to further improve the performance of skewness-enhanced momentum. Further tests indicate that limits to arbitrage and biased investor beliefs may be partial drivers of our findings. Nevertheless, and similar to Daniel and Moskowitz (2016), we cannot fully explain these findings with commonly-received theories of momentum.

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:

$$r_{i,t} - r_t^f = a + b_1 \text{MKTRF}_t + b_2 \text{SMB}_t + b_3 \text{HML}_t + \epsilon_{i,t} \tag{10}$$

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.

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

Unrealized Capital Gains: We define Unrealized Capital Gains as Grinblatt and Han

(2005):

$$\frac{P_{t-2} - R_{t-1}}{P_{t-2}} \tag{11}$$

with

$$R_{t-1} = \sum_{j=1}^{60} \left(V_{t-j} \prod_{i=1}^{j-1} (1 - V_{t-j+i}) \right) P_{t-j} \tag{12}$$

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

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

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.

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 as in 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:

$$r_{i,t} - r_t^f = a + b_1 \text{MKTRF}_t + b_2 \text{SMB}_t + b_3 \text{HML}_t + \epsilon_{i,t} \tag{14}$$

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.

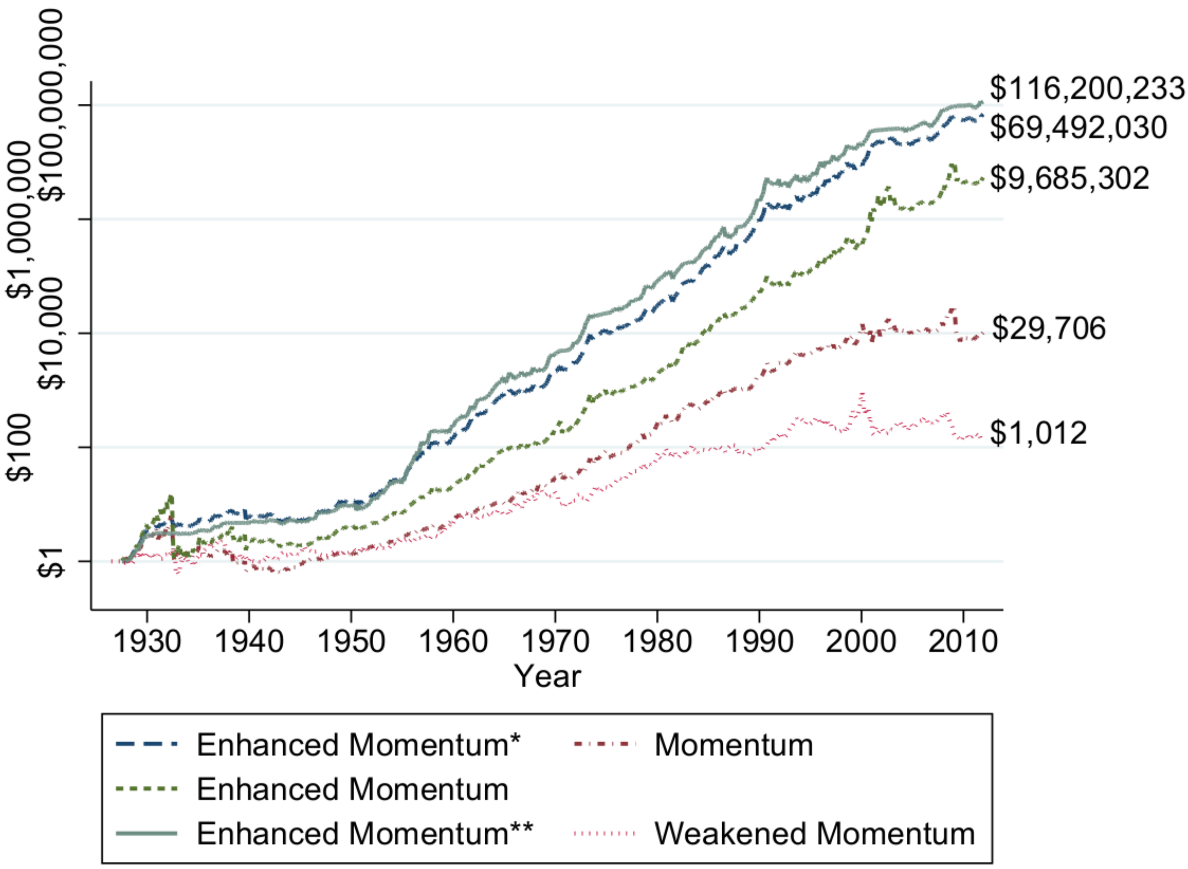
Short Interest: Monthly short interest is defined as the number of uncovered shares sold short (as obtained from Compustat) divided by the total number of shares outstanding.

Analyst Coverage: Analyst coverage is defined as the number of analysts providing 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 (2006), 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.

Figure 1: Cumulative Gains of Enhanced Momentum Strategies



This figure shows cumulative gains of two risk-managed enhanced momentum strategies (explained in detail in section 2.3), *Enhanced Momentum*, *Weakened Momentum* and *Momentum*. The risk-managed enhanced momentum strategies are derived from enhanced momentum as in Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) 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 the 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 (highest) quintile with respect to past cumulative returns in the short (long) leg. *Momentum* consists of winners (losers) in the third skewness quintile.

Table 1: Predictive Power of Skewness Measures

This table tests the predictive power of three skewness prediction variables. Panel A shows results for MAX, which is proposed in Bali et al. (2011) and which denotes the maximum daily return over the previous month. Panel A also shows the predictive power of past idiosyncratic skewness, which is computed from residuals obtained from regressing daily excess returns on the Fama and French (1993) model over the previous month. Panel B shows results for MAX, and for the skewness measure $SKEW^{\text{REG}}$ computed as in Boyer et al. (2010). Panel B also shows the predictive power of past idiosyncratic skewness, which is computed from residuals obtained from regressing daily excess returns on the Fama and French (1993) model over the previous month. In both panels, stocks are sorted into five equally sized portfolios based on the respective variable in month $t-1$. Columns (1) to (3) report the time-series mean, median as well as volatility of value-weighted portfolio returns in percent in month t. Column (4) shows the time-series skewness of the respective value-weighted portfolio return in month t. The sample period covers January 1926 to December 2011 for MAX and past idiosyncratic skewness, as well as January 1961 to December 2011 for $SKEW^{\text{REG}}$.

	(1)	(2)	(3)	(4)
	Mean Return	Median Return	Volatility	Skewness
Panel A: Portfolio Characteristics over the Period 1926 - 2011				
MAX Quintile 1	0.92	1.15	4.28	-0.53
MAX Quintile 5	0.61	1.09	6.69	0.53
Past Skewness Quintile 1	0.85	0.90	5.21	-0.02
Past Skewness Quintile 5	0.87	1.33	5.80	-0.40
Panel B: Portfolio Characteristics over the Period 1961 - 2011				
MAX Quintile 1	0.94	1.08	3.70	-0.47
MAX Quintile 5	0.59	1.06	7.41	0.39
Past Skewness Quintile 1	0.87	0.79	4.51	-0.40
Past Skewness Quintile 5	0.90	1.36	5.18	-0.50
$SKEW^{\text{REG}}$ Quintile 1	0.92	1.03	4.47	-0.50
$SKEW^{\text{REG}}$ Quintile 5	0.86	0.90	5.70	-0.32

Table 2: Expected Skewness and Momentum: Baseline Results

This table reports monthly portfolio returns (in percent) obtained from 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) excess portfolio returns of losers and winners in each skewness quintile. The sample period covers January 1927 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-adjusted Returns					
Factor Model	Raw	1F	3F	5F	
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	1F	3F	4F	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 Risk-adjusted Returns					
Factor Model	Raw	1F	3F	5F	
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	1F	3F	4F	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: Equally Weighted Excess Returns					
Skewness Quintile	1	2	3	4	5
Loser	0.78	0.76	0.46	0.27	-0.62
Winner	1.29	1.31	1.38	1.27	0.99
Panel D: Value-weighted Excess Returns					
Skewness Quintile	1	2	3	4	5
Loser	0.53	0.42	0.31	0.00	-0.67
Winner	0.98	1.09	1.13	1.14	1.00

Table 3: Raw and Risk-adjusted Returns of Winners and Losers

This table reports in Panel A value-weighted excess returns 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. Excess 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) 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 1927 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-adjusted Returns of Losers and Winners				
Specification / Factor Model	Raw	1F	3F	5F
(1): Enhanced Loser	-0.67*	-1.61***	-1.74***	-1.83***
t-stat	(-1.95)	(-9.29)	(-10.70)	(-9.66)
(2): Enhanced Winner	0.98***	0.53***	0.56***	0.53***
t-stat	(5.63)	(6.78)	(7.07)	(5.97)
(3): Weakened Loser	0.53***	0.02	-0.01	-0.07
t-stat	(2.84)	(0.22)	(-0.14)	(-0.70)
(4): Weakened Winner	1.00***	0.23	0.30*	0.45**
t-stat	(3.41)	(1.40)	(1.88)	(2.36)
(5): Regular Loser	0.31	-0.47***	-0.56***	-0.70***
t-stat	(1.31)	(-3.92)	(-5.00)	(-5.78)
(6): Regular Winner	1.13***	0.50***	0.54***	0.54***
t-stat	(5.18)	(4.79)	(5.04)	(4.65)
Panel B: Differences				
(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 4: Return, Risk and Performance Measures

This table reports return, risk, and performance measures for value-weighted returns of *Enhanced Momentum*, of the risk-managed enhanced momentum derived from Barroso and Santa-Clara (2015) (denoted as *Enhanced Momentum**), of the risk-managed enhanced momentum based on the procedure of Daniel and Moskowitz (2016) (denoted as *Enhanced Momentum***) , of *Weakened Momentum*, of *Regular Momentum* and the *Market*. *Enhanced*, *Regular* and *Weakened Momentum* are constructed as in Table 2. 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 with factors for long-term and short-term reversal) and monthly Fama and French (2015) alphas. As risk measures, the table shows time-series volatility (in percent), the realized skewness of the portfolio returns, the 1% percentile of monthly portfolio returns, as well as the minimum monthly return. As performance measures, the table reports the Sharpe ratio, the Sortino ratio and the Omega ratio. The Sharpe ratio is computed as the annualized monthly portfolio excess returns over annualized volatility of monthly portfolio returns. The Sortino ratio denotes annualized monthly portfolio excess return divided by downside volatility of monthly portfolio returns. The Omega ratio is computed as the discretized version of $\frac{\int_0^\infty (1-F(x))dx}{\int_{-\infty}^0 F(x)dx}$ from Shadwick and Keating (2002), where $F(x)$ denotes the cumulative distribution function of returns. The sample period covers January 1927 to December 2011, except for the computation of the Fama and French (2015) α, for which the range is July 1963 to December 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 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***	-
3-Factor α	1.97***	1.86***	2.31***	0.31	1.10***	-
5-Factor α	2.09***	1.95***	2.36***	0.52**	1.24***	-
Fama and French (2015) α	2.03***	2.13***	1.90***	0.81**	1.25***	-
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
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

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

This table presents results of Fama and MacBeth (1973) regressions. The methodology follows Bandarchuk and Hilscher (2013) and is explained in detail in the text. We regress momentum profits on the Bali et al. (2011) skewness measure and one month lagged control variables that have previously 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 August 1931 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.

	Momentum Returns				
Variable / Model	(1)	(2)	(3)	(4)	(5)
$SKEW^{\mathrm{MAX}}$	-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 presents results of Fama and MacBeth (1973) regressions. The methodology follows Bandarchuk and Hilscher (2013) and is explained in detail in the text. We regress momentum profits on the Bali et al. (2011) skewness measure and one month lagged control variables that have previously been associated with the profitability of momentum. Relative to table 5, the set of control variables is augmented by analyst forecast dispersion, analyst coverage, cash flow volatility, 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.

	Momentum Returns				
Variable / Model	(1)	(2)	(3)	(4)	(5)
$SKEW^{\mathrm{MAX}}$	-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
			(-1.20)	(-1.03)	(-1.45)
Turnover			-0.1436***	-0.1711***	-0.1526***
			(-2.64)	(-3.32)	(-2.87)
Bid/Ask Spread			-0.0738	-0.0410	-0.0600
			(-1.58)	(-0.96)	(-1.38)
Beta Market			0.0662	0.0820	0.0283
			(0.89)	(1.23)	(0.41)
Beta Size			-0.0053	-0.0168	0.0100
			(-0.09)	(-0.30)	(0.17)
Beta Book-to-Market			-0.0394	-0.0407	-0.0229
			(-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
			(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 the baseline specification (see Table 2). In (1) we conduct reverse dependent double sorts, 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 the Bali et al. (2011) skewness measure. 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 (2), we sort stocks independently into quintiles based on cumulative past return and our measure of skewness. In (3) and (4), we orthogonalize skewness with respect to one month lagged idiosyncratic volatility and momentum strength of past returns, respectively. Momentum strength is defined as in Bandarchuk and Hilscher (2013). In specifications (1) to (4), the sample period covers January 1927 to December 2011. Finally, in (5), we document results for an alternative skewness measure computed as in Boyer et al. (2010). For data availability reasons, the sample period covers January 1961 to December 2011. *Enhanced Momentum* is a long-short portfolio which buys past winners in the lowest expected 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	1F	3F	5F
1) Reverse Doublesort				
Enhanced Momentum	1.70***	2.09***	2.26***	2.30***
t-stat	(7.22)	(10.95)	(11.73)	(10.33)
Weakened Momentum	0.28	0.25	0.38*	0.56**
t-stat	(1.15)	(1.04)	(1.66)	(2.10)
2) Independent Doublesorts				
Enhanced Momentum	1.46***	1.88***	2.03***	2.04***
t-stat	(6.71)	(10.82)	(12.28)	(10.36)
Weakened Momentum	0.42*	0.15	0.21	0.47**
t-stat	(1.95)	(0.69)	(1.05)	(2.20)
3) Controlling for Volatility				
Enhanced Momentum	1.29***	1.44***	1.55***	1.61***
t-stat	(5.67)	(6.10)	(7.20)	(7.18)
Weakened Momentum	-0.03	0.26	0.49***	0.64***
t-stat	(-0.11)	(1.40)	(2.68)	(2.91)
4) Controlling for Past Returns				
Enhanced Momentum	1.85***	1.94***	2.19***	2.34***
t-stat	(6.46)	(6.89)	(7.82)	(8.05)
Weakened Momentum	0.15	0.07	0.20	0.35**
t-stat	(0.82)	(0.38)	(1.15)	(1.99)
5) Measure from Boyer since 1961				
Enhanced Momentum	1.12***	1.28***	1.61***	1.79***
t-stat	(4.02)	(4.83)	(5.88)	(6.22)
Weakened Momentum	0.34	0.33	0.32	0.40
t-stat	(1.42)	(1.33)	(1.32)	(1.59)

Table 8: Calendar-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 2. Displayed are average monthly value-weighted returns over the time periods 1961 - 2011, 1961 - 1991 and 1991 - 2011. 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. The methodology in Panel B follows Bandarchuk and Hilscher (2013) and is explained in detail in section 2.4. We regress cumulative momentum profits on the Bali et al. (2011) skewness measure and the control variables of Table 5. The sample period ranges from August 1931 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 via Time-series Regressions

Robustness Specification	RAW	1F	3F	5F
1) Since 1961				
Enhanced Momentum	1.87***	2.23***	2.22***	2.34***
t-stat	(5.51)	(7.55)	(8.54)	(8.83)
Weakened Momentum	0.40	0.09	0.44	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 Results via Fama and MacBeth (1973) Regressions

Variable / Holding Period	1 - 3	1 - 12	12 - 36	1 - 36
$SKEW^{\mathrm{MAX}}$	-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): Firm size

This table displays further robustness checks of the baseline specification (see Table 2). 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 stocks are stocks that fall within the 20% NYSE percentile regarding their market capitalization. Small stocks refers to stocks with a market capitalization between the 20% and the 50% NYSE percentile. Big stocks are stocks with above NYSE median market capitalization. *Enhanced*, *Regular* and *Weakened Momentum* portfolios are constructed as in Table 2. 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 1927 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.

Robustness Specification	RAW	1F	3F	5F
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)

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

This table displays further robustness checks of the baseline specification (see Table 2). 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 short interest for losers. *Enhanced* and *Weakened Momentum* portfolios are constructed as in Table 2. 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. Turnover, bid-ask spreads and short interest are lagged by one month. The sample period covers January 1927 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 5% level and *** indicate significance at the 1% level.

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

Table 11: International Evidence: Fama/MacBeth Regressions

This table presents results of Fama and MacBeth (1973) regressions in international stock markets. The methodology follows Bandarchuk and Hilscher (2013) and is explained in detail in section 2.4. We regress momentum profits on the skewness measure of Bali et al. (2011) and various control variables that have been associated with the profitability of momentum. For brevity, only the coefficient and corresponding t-statistic for expected skewness are reported. *Basic Controls* entail beta, beta book-to-market, beta size, idiosyncratic volatility, momentum strength and the one-month lagged return. *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. The *Group of 7* comprises Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States. *Pooled* entails entails all countries considered in this analysis. 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). Age is defined as the number of months since the firms first appearance in Datastream. All variables are standardized by months and the coefficients 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.

	Momentum Returns						
Country	Coefficient	T-Stat	Coefficient	T-Stat	Coefficient	T-Stat	Sample Period
Specification	1		2		3		
Australia	-0.28***	(-2.84)	-0.26***	(-2.68)	-0.23**	(-2.10)	1981 - 2013
Austria	-0.35***	(-2.60)	-0.38**	(-2.58)	-0.13	(-0.64)	1988 - 2013
Belgium	-0.64***	(-5.36)	-0.59***	(-4.56)	-0.58***	(-4.04)	1988 - 2013
Canada	-0.25**	(-2.25)	-0.29***	(-2.60)	-0.40***	(-3.24)	1984 - 2013
Denmark	-0.39***	(-2.85)	-0.42***	(-3.08)	-0.28**	(-2.10)	1987 - 2013
France	-0.27***	(-2.86)	-0.34***	(-3.67)	-0.31***	(-3.30)	1981 - 2013
Germany	-0.57***	(-6.60)	-0.57***	(-6.39)	-0.51***	(-7.10)	1981 - 2013
Italy	-0.32**	(-2.57)	-0.51***	(-3.96)	-0.35***	(-3.01)	1987 - 2013
Japan	-0.15**	(-2.19)	-0.14*	(-1.84)	-0.19***	(-2.86)	1981 - 2013
Netherlands	-0.61***	(-4.98)	-0.79***	(-6.49)	-0.75***	(-5.56)	1981 - 2013
Norway	-0.22	(-1.48)	-0.225	(-1.33)	-0.30	(-1.54)	1988 - 2013
Portugal	-0.45***	(-3.09)	-0.30*	(-1.91)	-0.26	(-1.45)	1988 - 2013
Singapore	0.01	(0.10)	0.07	(0.07)	-0.07	(-0.63)	1988 - 2013
Sweden	-0.61***	(-3.43)	-0.51***	(-2.86)	-0.74***	(-4.22)	1988 - 2013
Switzerland	-0.58***	(-6.72)	-0.58***	(-5.51)	-0.47***	(-4.76)	1988 - 2013
United Kingdom	-0.13	(-1.58)	-0.15**	(-1.98)	-0.15**	(-2.14)	1981 - 2013
Group of 7	-0.18***	(-3.40)	-0.22***	(-4.00)	-0.22***	(-4.13)	1981 - 2013
Pooled	-0.18***	(-3.66)	-0.22***	(-4.23)	-0.22***	(-4.26)	1981 - 2013
Industry Controls	yes		yes		yes		
Basic Controls	no		yes		yes		
All Controls	no		no		yes		

Table 12: Market Reaction to Earnings Announcements

This table displays abnormal returns around earnings announcements (event day t=0). *Enhanced*, *Regular* and *Weakened Momentum* portfolios are defined as in Table 2. Abnormal returns are expressed in % and computed as the difference between the buy-and-hold return over the event days t=-1 to t=1 and the expected buy-and-hold return given by a Fama and French (1993) factor model. Expected factor loadings are estimated from daily returns and rolling regressions over the previous twelve months (skipping the most recent month). To mitigate the impact of outliers, abnormal returns are winsorized at the 0.5% and the 99.5% levels. The sample period covers July 1971 to December 2011. Standard errors are double-clustered by firm and month. * indicates significance at the 10% level, ** indicate significance at the 5% level and *** indicate significance at the 1% level.

Panel A: Regular momentum			
	Regular Winner	Regular loser	Difference
Abnormal return	0.251***	-0.0204	0.271**
t-stat	(3.10)	(-0.27)	(2.57)
N	13,879	14,072	27,951
Panel B: Enhanced momentum			
	Enhanced winner	Enhanced loser	Difference
Abnormal return	0.394***	-0.459***	0.853***
t-stat	(7.27)	(-3.54)	(5.94)
N	13,297	11,615	24,912
Panel C: Weakened momentum			
	Weakened winner	Weakender loser	Difference
Abnormal return	-0.0973	0.105**	-0.202
t-stat	(-0.80)	(1.99)	(-1.52)
N	11,314	14,053	25,367

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