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Momentum and crash sensitivity

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HIGHLIGHTS

- The paper proposes a risk-based explanation of the momentum anomaly on equity markets.
- Regressing the momentum strategy return on the return of a self-financing portfolio going long (short) in stocks with high (low) crash sensitivity in the USA from 1963 to 2012 reduces the momentum effect from a highly statistically significant 11.94% p.a. to an insignificant 1.84% p.a.
- We find additional supportive out-of sample evidence for our risk-based momentum explanation in a sample of 23 international equity markets.

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ABSTRACT

We suggest a risk-based explanation of the momentum anomaly. Controlling for the exposure to systematic crash risk reduces the momentum effect from a significant 11.94% p.a. to an insignificant 1.84% p.a. Similar results are obtained in a broad sample of international equity markets.

1. Introduction

The cross-sectional momentum effect is an omnipresent anom aly on financial markets. Jegadeesh and Titman (1993) find that a strategy of buying (selling) stocks that have performed well (poorly) over the past 12 months generates high risk-adjusted future returns on the US stock market. The momentum effect is not unique to the US stock market, but also can be found in other equity markets (Rouwenhorst, 1998; Griffin et al., 2003; Chui et al., 2010), country equity indices (Asness et al., 1997; Bhojraj and Swaminathan, 2006), currencies (Kho, 1996; LeBaron, 1999; Okunev and White, 2003; Menkhoff et al., 2012), commodities (Erb and Harvey, 2006; Gorton et al., 2013), and across asset classes (Asness et al., 2013).

Although momentum is widely documented on financial markets, there is still an active ongoing debate about its main drivers and determinants. While most studies advocate a behavioral explanation for the effect, i.e., momentum is driven by either overreaction or underreaction of investors, recent studies point out the riskiness of momentum strategies.[1] In particular, Barroso and Santa-Clara (2015) find that momentum strategies display large negative skewness and excess kurtosis, i.e., realizations of higher-order moments that are strongly disliked by investors (see, e.g., Kraus and Litzenberger, 1976; Fang and Lai, 1997). Similarly, Daniel

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[1] Explanation based on underreaction are provided, among others, by Chan et al. (1996), Barberis et al. (1998), Hong and Stein (1999), and Grinblatt and Han (2005). Overreaction of investors can explain to understand the momentum effect, among others, in DeLong et al. (1990), and Daniel et al. (1998).

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and Moskowitz (2016) show that momentum strategies can experience large, but infrequent crashes.[2]

Another recent strand of the literature shows that investors dislike (lower) tail sensitive assets (e.g., Kelly and Jiang, 2014; Chabi-Yo et al., forthcoming). Motivated by these recent results, we investigate whether momentum profits are driven by exposure of the momentum strategy to a systematic crash risk factor. Specifically, we regress the momentum portfolio long-short return (UMD) on the return of an investment strategy that buys stocks with high crash sensitivity and sells stocks with low crash sensitivity (CRASH) on the US stock market in the period from 1963 to 2012. The crash sensitivity of individual stocks is measured based on the lower tail dependence of their return time series with the market return time series (see Chabi-Yo et al., forthcoming). Our results indicate that the momentum strategy loads significantly positive on the crash sensitivity factor. While simultaneously controlling for the Fama and French (1993) factors, we show that including the crash sensitivity factor as an explanatory variable for the momentum return reduces its annualized alpha from a statistically significant 11.94% to an insignificant 1.84%.

As an out-of-sample check we also examine the relationship between the momentum return and the crash sensitivity factor on 23 international equity markets. We find that in 22 countries (i.e., in all countries except of Singapore) momentum loads positively on systematic crash sensitivity with corresponding statistical significance (at least on the 10% level) in 13 countries. Including the crash sensitivity factor as an explanatory variable in the regression setup lowers the alpha of momentum returns in 22 countries and enhances the adjusted R-square in 20 countries of our international sample.

Overall, our findings show that at least a substantial part of U.S. and international momentum profits represents a risk premium for the exposure of the strategy to systematic crash risk.

2. Main variables and data

We obtain annual data for US stock market momentum (as well as the Fama and French risk factors) from Kenneth French's webpage.[3] We display summary statistics for the annualized US momentum return in the period from 1963 to 2012 on the left side of the first row in Table 1. Consistent with the literature, we document that the momentum factor has a high positive annualized return (8.72%), but also shows significant negative skewness (−2.38) and excess kurtosis (12.91).

Annual data for the US crash sensitivity factor is obtained from Chabi-Yo et al. (forthcoming). Based on daily return data, the authors estimate an individual stock's lower tail dependence with the market using copula functions and refer to this measure as a stock's crash sensitivity. The crash sensitivity factor is then constructed as the equally-weighted average return of the quintile portfolio of stocks with the highest crash sensitivity minus the average return of the quintile portfolio of stocks with the lowest crash sensitivity. For a detailed explanation of the crash sensitivity estimation approach, we refer the reader to Chabi-Yo et al. (forthcoming). We display summary statistics for the annualized US crash sensitivity factor return in the period from 1963 to 2012 on the right side of the first row in Table 1.

Finally, we obtain momentum returns (as well as the Fama and French risk factors) and crash sensitivity factors for 23 international stock markets from Asness et al. (2017) and Weigert (2016). The construction of the international UMD and CRASH factors is very similar to those constructed for the USA and is detailed in the respective papers. We display summary statistics for the annualized momentum returns and crash sensitivity factors in Table 1 (rows 2 to 24). Consistent with the literature, we find that the UMD and CRASH factors are positive in every country in the sample and also statistically significantly different from zero in the majority of them. The sample period for each country starts with the availability of momentum return data in Asness et al. (2017) or crash sensitivity factor data in Weigert (2016), respectively. The sample period ends in 2012.

3. Empirical analysis

In our basic empirical setup, we regress the annual momentum return on the Fama and French (1993) or the Fama and French (2015) risk factors, respectively. We include the crash sensitivity risk factor as an additional explanatory variable to judge whether momentum is related to crash sensitivity. The exact regression setup is based on annual time-series data and can be specified as follows:

$$\begin{aligned} \mathrm{UMD}_t &= \alpha + \beta_1 \cdot \mathrm{MKT\text{-}RF}_t + \beta_2 \cdot \mathrm{SMB}_t + \beta_3 \cdot \mathrm{HML}_t \\ &\quad + \beta_4 \cdot \mathrm{RMW}_t + \beta_5 \cdot \mathrm{CMA}_t + \beta_6 \cdot \mathrm{CRASH}_t + \epsilon_t, \end{aligned}$$

where UMD_t denotes the momentum factor, $\mathrm{MKT\text{-}RF}_t$ denotes the excess market return, SMB_t denotes the Fama and French (1993) small-minus-big size factor, HML_t denotes the Fama and French (1993) high-minus-low book-to-market factor, RMW_t denotes the Fama and French (2015) robust-minus-weak profitability factor, CMA_t denotes the Fama and French (2015) conservative-minus-aggressive investment factor, and CRASH_t denotes the Chabi-Yo et al. (forthcoming) crash sensitivity factor. T-statistics of alphas and coefficient estimates are computed using Newey and West (1987) standard errors with 2 lags.

Table 2 displays the results of different specifications of this regression on the US stock market in the period from 1963 to 2012. In specification (1) we regress the momentum return on the Fama and French (1993) factors. We confirm that the momentum portfolio delivers a significantly positive annualized alpha which amounts to 11.9% with a t-statistic of 4.32. In specification (2), we extend the Fama and French (1993) three-factor model by the crash sensitivity factor. Our results indicate that the crash sensitivity factor strongly loads on the momentum portfolio with a coefficient estimate of 0.574 and a t-statistic of 5.73. The inclusion of the crash sensitivity factor in the regression model leads the momentum strategy's alpha to drop to 1.84% per annum. The alpha estimate is not statistically different from zero anymore (t-statistic of 0.52).

In specifications (3) and (4) we repeat the analysis, but use the Fama and French (2015) five-factor model as our baseline model.[4] As before, we find that the momentum strategy is highly profitable as long as we do not control for its exposure to systematic crash risk. Including the crash sensitivity factor in the regression model decreases the momentum strategy's alpha from a highly significant 13.2% to an insignificant 2.9% per annum.

To obtain additional robustness for our results, we also investigate the relationship between momentum and crash sensitivity on 23 international equity markets. To do so, we regress the country-specific momentum return on the country-specific Fama

[2] In 1932, the momentum strategy on the US equity market delivered a −91.54% return in just two months. In 2009, US equity momentum yielded a −73.42% return in a three-months period.

[3] To construct the momentum factor, six value-weighted portfolios are formed based on firm size and past returns (month $t-12$ up to $t-1$). The momentum factor is then computed as the average return on the two high past return portfolios minus the average return on the two low past return portfolios.

[4] Results are robust if we use a battery of alternative systematic risk factor models suggested in the literature (and also used in Chabi-Yo et al., forthcoming) or if we use value-instead of equally-weighted returns to construct the CRASH factor.

Table 1
Summary statistics.

Country	Sample	UMD					CRASH				
		Mean	Median	Std Dev	Skewness	Kurtosis	Mean	Median	Std Dev	Skewness	Kurtosis
USA	1963–2012	8.72%***	10.18%	18.60%	−2.38	12.91	16.62%***	15.82%	15.30%	+1.39	6.04
AUS	1963–2012	20.38%***	18.89%	20.06%	−0.23	5.71	13.58%***	13.30%	18.34%	−0.52	2.82
AUT	1963–2012	7.83%**	11.39%	25.67%	−1.38	11.89	1.01%	−0.08%	19.83%	+0.38	2.55
BEL	1987–2012	11.07%***	13.57%	19.51%	−1.07	9.81	6.05%*	4.03%	15.54%	+1.04	4.61
CAN	1985–2012	17.01%***	15.60%	23.97%	−0.82	7.42	9.24%**	11.82%	23.44%	−0.24	4.21
CHE	1985–2012	10.09%***	9.63%	17.09%	−0.57	7.96	7.39%*	5.94%	17.98%	−1.02	5.75
DEU	1987–2012	13.85%***	12.26%	24.57%	−0.28	8.37	8.89%**	11.45%	22.59%	−0.46	4.11
DNK	1987–2012	15.44%***	13.02%	22.46%	−0.81	5.44	1.31%	4.74%	20.48%	−0.60	3.47
ESP	1987–2012	7.86%**	10.22%	19.34%	−0.87	6.84	1.03%	−1.02%	24.44%	−0.18	3.49
FIN	1987–2012	13.26%***	10.48%	21.25%	−0.34	6.24	13.20%**	9.71%	21.55%	+0.35	4.08
FRA	1987–2012	8.40%***	9.60%	19.04%	−0.64	8.46	8.14%**	9.54%	16.67%	−0.41	4.29
GBR	1987–2012	13.70%***	14.14%	22.54%	−1.80	14.38	8.97%***	10.33%	14.81%	−0.26	4.07
GRC	1990–2012	9.46%*	12.70%	32.73%	−1.43	7.58	5.05%	4.46%	34.62%	+0.55	4.05
HKG	1987–2012	3.81%	5.26%	18.35%	−1.14	7.69	4.36%	29.61%	29.61%	−2.32	10.18
IRL	1989–2012	12.03%*	5.82%	40.88%	−1.25	10.80	3.49%	1.44%	17.78%	+0.12	3.48
ISR	1997–2012	12.09%**	17.11%	22.11%	−0.97	6.00	6.12%	4.90%	22.92%	−0.03	3.81
ITA	1987–2012	8.54%***	10.77%	18.45%	−0.31	5.60	8.48%**	10.09%	21.03%	+0.17	3.95
JPN	1987–2012	2.13%	0.60%	21.41%	−0.75	6.29	3.54%	1.02%	14.05%	+1.51	6.08
NLD	1987–2012	6.54%	5.25%	18.85%	−0.78	7.56	10.49%**	10.09%	18.39%	−0.51	4.49
NOR	1987–2012	6.02%**	11.75%	28.66%	−0.19	3.67	13.93%*	8.44%	30.80%	+0.77	4.08
NZL	1987–2012	13.69%***	14.23%	21.73%	−0.03	4.39	5.80%**	6.98%	20.27%	−0.42	3.35
PRT	1990–2012	11.24%**	10.72%	20.34%	−0.55	5.06	7.61%*	3.54%	21.41%	+0.51	3.24
SGP	1987–2012	3.94%	6.97%	20.53%	−3.07	22.21	7.39%**	9.51%	18.45%	−0.26	3.86
SWE	1987–2012	8.27%**	8.71%	25.58%	−0.46	5.89	9.58%**	10..91%	19.51%	−0.47	3.92

This table presents summary statistics for annual momentum returns (UMD) and the annual return of the crash sensitivity factor (CRASH) for the USA and 23 international stock markets. We obtain annual data for momentum returns in the USA from Kenneth French's webpage and data for international momentum returns from Asness et al. (2017). We obtain annual data for the crash sensitivity factor in the USA from Chabi-Yo et al. (forthcoming) and data for the international crash sensitivity factors from Weigert (2016). For each variable we display the mean, the median (50%-quantile), the standard deviation, the skewness, and the kurtosis. T-statistics for the mean returns are computed using Newey and West (1987) standard errors with 2 lags.

*** Indicate significance at the one percent level.

** Indicate significance at the five percent level.

* Indicate significance at the ten percent level.

Table 2
Momentum and crash sensitivity: US Evidence.

	(1) UMD	(2) UMD	(3) UMD	(4) UMD
MARKETRF	−0.213	−0.400**	−0.273	−0.419**
	−1.52)	(−2.54)	(−1.51)	(−2.20)
SMB	−0.102	−0.144	−0.109	−0.138
	(−0.65)	(−1.20)	(−0.75)	(−1.09)
HML	−0.289	0.055	−0.107	0.123
	(−1.64)	(0.27)	(−0.33)	(0.38)
RMW		−0.102	−0.062	
			(−0.40)	(−0.27)
CMA			−0.368	−0.148
			(−0.97)	(−0.39)
CRASH		0.574***		0.547***
		(5.73)		(4.81)
Alpha	0.119***	0.018	0.132***	0.029
	(4.32)	(0.52)	(5.95)	(0.91)
Observations	50	50	49	49
R^2	0.08	0.18	0.10	0.18

This table shows the results of time-series regressions of the following form:

$$\mathrm{UMD}_t = \alpha + \beta_1 \cdot \text{MKT-RF}_t + \beta_2 \cdot \mathrm{SMB}_t + \beta_3 \cdot \mathrm{HML}_t + \beta_4 \cdot \mathrm{RMW}_t + \beta_5 \cdot \mathrm{CMA}_t + \beta_6 \cdot \mathrm{CRASH}_t + \epsilon_t,$$

where UMD_t denotes the momentum factor, MKT-RF_t denotes the excess market return, SMB_t denotes the Fama and French (1993) small-minus-big size factor, HML_t denotes the Fama and French (1993) high-minus-low book-to-market factor, RMW_t denotes the Fama and French (2015) robust-minus-weak profitability factor, CMA_t denotes the Fama and French (2015) conservative-minus-aggressive investment factor, and CRASH_t denotes the Chabi-Yo et al. (forthcoming) crash sensitivity factor. The sample covers the US stock market and the sample period is from 1963 to 2012. T-statistics are in parentheses and are computed using Newey and West (1987) standard errors with 2 lags. ***, **, and * indicate significance at the one, five, and ten percent levels, respectively.

and French (1993) factors as well as the crash sensitivity factor for the respective country. Results are displayed in Table 3.

Column 1 displays the country, while column 2 (4) shows that alpha of the momentum return when controlling for the Fama and French (1993) factors the (Fama and French, 1993 factors and the CRASH factor). Column (3) shows the momentum strategy exposure to CRASH. Our results indicate that the crash sensitivity factor loads positively on momentum in 22 out of 23 countries; the coefficient estimate is statistically significant (at least on the 10% level) in 13 of these countries. The inclusion of the crash sensitivity factor as an explanatory variable in the regression setup lowers the momentum strategy's alpha in 22 countries with an average decrease of −3% per annum (Column 5). Moreover, we find that including crash sensitivity in the regression setup also raises the adjusted R-squared in 20 countries with an average increase of 0.11 (Column 6). Hence, we also find additional out-of sample support that the momentum effect is strongly related to a stock's crash sensitivity. The quantitative magnitude of the reduction is typically smaller than in the U.S.; however, it is still substantial particularly among many of the countries where the momentum strategy delivers significant Fama and French (1993) alphas to start with.

4. Conclusion

We find that controlling for the momentum strategy's crash sensitivity reduces its profitability markedly. Our results are in line with the idea that at least a substantial part of the profitability of the momentum effect is a compensation for systematic crash risk exposure. Hence, our results provide a risk-based explanation of the momentum anomaly. This finding does of course not preclude that alternative behavioral explanations also drive a part of the momentum strategy returns.

Table 3
Momentum and crash sensitivity: International evidence.

Country	3-Factor Alpha Alpha	CRASH	4-Factor Alpha with CRASH	Change in Alphas	Observations	Change in Adjusted R-squares
AUS	0.179**	0.331*	0.124*	−0.055	26	+0.064
	(2.74)	(1.82)	(1.78)			
AUT	0.092*	0.739**	0.049	−0.043	26	+0.307
	(1.75)	(2.82)	(1.07)			
BEL	0.176***	0.276	0.162***	−0.014	26	+0.031
	(6.12)	(0.97)	(4.49)			
CAN	0.141***	0.514**	0.073	−0.068	28	+0.202
	(3.89)	(2.53)	(1.15)			
CHE	0.095***	0.163	0.082**	−0.013	26	+0.028
	(3.02)	(0.64)	(2.03)			
DEU	0.134**	0.408*	0.094**	−0.040	26	+0.140
	(2.53)	(1.75)	(2.11)			
DNK	0.203***	0.090	0.202***	−0.001	26	−0.047
	(4.89)	(0.22)	(4.80)			
ESP	0.087	0.278	0.078	−0.009	26	+0.075
	(1.58)	(1.26)	(1.43)			
FIN	0.073	0.535***	0.036	−0.037	26	+0.183
	(1.35)	(3.48)	(0.90)			
FRA	0.126***	0.656***	0.091**	−0.035	26	+0.292
	(3.40)	(3.72)	(2.43)			
GBR	0.160***	0.540**	0.119*	−0.041	26	+0.067
	(3.92)	(2.03)	(2.00)			
GRC	0.113	0.398	0.110	−0.003	23	+0.032
	(1.30)	(0.85)	(1.23)			
HKG	0.034	0.087	0.029	−0.005	26	+0.021
	(0.95)	(1.23)	(0.90)			
IRL	0.194**	0.553*	0.152*	−0.042	24	+0.040
	(2.54)	(1.75)	(2.01)			
ISR	0.166***	0.228	0.137**	−0.029	16	+0.000
	(4.18)	(0.81)	(2.20)			
ITA	0.102***	0.509***	0.046*	−0.056	26	+0.344
	(2.94)	(4.42)	(1.79)			
JPN	0.083*	0.123	0.084*	+0.001	26	−0.043
	(1.86)	(0.57)	(1.97)			
NLD	0.089*	0.443***	0.028	−0.061	26	+0.146
	(1.93)	(3.18)	(0.65)			
NOR	0.140**	0.312*	0.112*	−0.028	26	+0.088
	(2.54)	(1.99)	(1.84)			
NZL	0.175***	0.651***	0.136***	−0.039	26	+0.372
	(4.73)	(3.02)	(3.86)			
PRT	0.082**	0.248	0.080*	−0.002	23	+0.009
	(2.14)	(1.29)	(1.78)			
SGP	0.005	−0.059	0.004	−0.001	26	−0.043
	(0.08)	(−0.26)	(0.07)			
SWE	0.013	0.662***	−0.052	−0.065	26	+0.132
	(0.28)	(3.77)	(−1.20)			
Average	0.116	0.378	0.086	−0.030	25.30	+0.110

This table presents results of the relationship between momentum (UMD) and crash sensitivity (CRASH) on 23 international equity markets. We regress the country-specific momentum return on the country-specific Fama and French (1993) factors as well as the crash sensitivity factor for the respective country. Column 1 displays the country, while column 2 (4) shows that alpha of the momentum return when controlling for the Fama and French (1993) factors (the Fama and French, 1993 factors and the CRASH factor). Column (3) shows the momentum strategy's exposure to CRASH. Column (5) displays the change in the momentum strategy's alphas when controlling for the CRASH factor. Column (6) denotes the number of annual returns in the respective regression. Column (7) reports the change in the adjusted R-squared when controlling for the CRASH factor in the regression. T-statistics are in parentheses and are computed using Newey and West (1987) standard errors with 2 lags.

*** Indicate significance at the one percent level.

** Indicate significance at the five percent level.

* Indicate significance at the ten percent level.

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