December 4, 2011 Comments Welcome

Momentum Crashes

Kent Daniel and Tobias Moskowitz*

- Abstract -

Across numerous asset classes, momentum strategies have produced high returns, high Sharpe ratios, and strong positive alphas relative standard asset pricing models. However, the returns to momentum strategies are skewed: they experience infrequent but strong and persistent strings of negative returns. These momentum "crashes" are forecastable: they occur following market declines, when market volatility is high, and contemporaneous with market "rebounds." The data suggest that low *ex-ante* expected returns in crash periods result from a a conditionally high premium attached to the the option-like payoffs of the past-loser portfolios.

*Graduate School of Business, Columbia University and Booth School of Business, University of Chicago and NBER; emails: *kd2371@columbia.edu* and *Tobias.Moskowitz@chicagobooth.edu*. We thank Pierre Collin-Dufresne, Gur Huberman, Mike Johannes, Tano Santos, Paul Tetlock, Sheridan Titman, and participants of the NBER Asset Pricing Summer Institute, the Quantitative Trading & Asset Management Conference at Columbia, and seminars at Columbia, Rutgers, Yale and Kepos Capital and SAC for helpful comments and discussions.

1 Introduction

A momentum strategy is a bet that past returns will predict future returns. Consistent with this, a long-short momentum strategy is typically implemented by buying past winners and taking short positions in past losers.

Momentum appears pervasive: the academic finance literature has documented the efficacy of momentum strategies in numerous asset classes, from equities to bonds, from currencies to commodities to exchange-traded futures.[1] Momentum is strong: in US equities, where this investigation is focused, we see an average annualized return difference between the top and bottom momentum deciles of 16.5%/year, and an annualized Sharpe ratio of 0.82 (Post-WWII, through 2008).[2] This strategy's beta over this period was -0.125, and it's correlation with the Fama and French (1992) value factor was strongly negative.[3] Momentum is a strategy employed by numerous quantitative investors within multiple asset classes and even by mutual funds managers in general.[4]

However, the strong positive returns of momentum strategies are punctuated with strong reversals, or "crashes." Like the returns to the carry trade in currencies, momentum returns are negatively skewed, and the crashes can be pronounced and persistent.[5] In our 1927-2010 sample, the two worst months for the aforementioned momentum strategy are consecutive: July and August of 1932. Over this short period, the past-loser decile portfolio returned 236%, while the past-winner decile saw a gain of only 30%. In a more recent crash, over the three-month period from March-May of 2009, the past-loser decile rose by 156%, while the decile of past winners portfolio

[1] A fuller discussion of this literature is given in Section 2

[2] Section 3 gives a detailed description of the construction of these value-weighted momentum portfolios, and summary statistics on their performance.

[3] Not surprisingly, momentum returns are not priced by either the CAPM or the Fama and French (1993) three-factor model (see Fama and French (1996)). A Fama and French (1993) model augmented with a momentum factor, as proposed by Carhart (1997) is necessary to explain the momentum return. Also note that Asness, Moskowitz, and Pedersen (2008) argue that a three factor model (based on a market factor, and a value and momentum factor) is successful in pricing value and momentum anomalies in cross-sectional equities, country equities, commodities and currencies.

[4] Jegadeesh and Titman (1993) motivate their investigation of momentum with the observation that "...a majority of the mututal funds examined by Grinblatt and Titman (1989, 1993) show a tendency to buy stocks that have increased in price over the previous quarter."

[5] See Brunnermeier, Nagel, and Pedersen (2008), and others for evidence on the skewness of carry trade returns.

gained only 6.5%.

We investigate the predictability of these momentum crashes. At the start of each of the two crashes discussed above (July/August of 1932 and March-May of 2009), the broad US equity market was down significantly from earlier highs. Market volatility was high. Also, importantly, the market as a whole rebounded significantly in these momentum crash months.

This is consistent with the general behavior of momentum crashes: they tend to occur in times of market stress, specifically when the market has fallen and when *ex-ante* measures of volatility are high. They also occur when contemporaneous market returns are high. Note that our result here is consistent with that of Cooper, Gutierrez, and Hameed (2004), who find that the momentum premium falls to zero when the past three-year market returns has been negative.

These patterns are suggestive of the possibility that the changing beta of the momentum portfolio may partly be driving the momentum crashes. As documented by Grundy and Martin (2001, GM), the betas of momentum strategies can fall significantly as the market falls. Intuitively, this result is straightforward, if not often appreciated: when the market has fallen significantly over the momentum formation period – in our case from 12 months ago to 1 month ago – there is a good chance that the firms that fell in tandem with the market were and are high beta firms, and those that performed the best were low beta firms. Thus, following market declines the momentum portfolio is likely to be long low-beta stocks (the past winners), and short high-beta stocks (the past losers).

We verify empirically that there is dramatic time variation in the betas of momentum portfolios. Using beta estimates based on daily momentum decile returns we find that, following major market declines, betas for the past-loser decile rises above 3 , and falls below 0.5 for past winners.

However, GM further argue that performance of the momentum portfolio is dramatically improved — particularly in the pre-WWII era, by dynamically hedging the market and size risk in the portfolio. While we replicate their results with a similar methodology, overall our empirical results do not support GM's conclusion. The reason for this is that, when GM create their hedged momentum portfolio, they calculate their hedging coefficients based on forward-looking measured betas.[6] Therefore, their hedged portfolio returns are not an implementable strategy.

GM's procedure, while not technically valid, should not bias their estimated performance if their forward-looking betas are uncorrelated with future market returns. However we show that this correlation is present, is strong, and does bias GM's results.

The source of the bias is a striking correlation of the loser-portfolio beta with the return on the market. In a bear market, we show that the up- and down-market betas differ substantially for the momentum portfolio. Using Henriksson and Merton (1981) specification, we calculate up- and down-betas for the momentum portfolios.[7] We show that, in a bear market, momentum portfolio up-market beta is more than double its down-market beta (-1.47 *versus* -0.66), and that this difference is highly statistically significant ($t = 5.1$). Outside of bear markets, there is no statistically significant difference.

More detailed analysis shows that most of the up- *versus* down-beta asymmetry in bear market is driven by the decile of past-losers: for this portfolio the up- and down betas differ by 0.6, while for the past-winner decile the difference is -0.2.

Our examination of momentum crashes outside the US and other asset classes reveals similar patterns. In Section 5, we show that the same option-like behavior is present for cross-sectional equity momentum strategies in Europe, Japan, the UK, and for a global momentum strategy. In addition the optionality is a feature of commodity- and currency-momentum strategies.

There are several possible explanations for this option-like behavior. For the equity momentum strategies, one possibility is that the optionality arises because, for a firm with debt in its capital structure, a share of common stock is a call option on the underlying firm value (Merton 1990). Particularly in the distressed periods where this option-like behavior is manifested, the underlying firm values in the past loser

[6] At the time GM undertook their study, only monthly CRSP data was available in the pre-1972 sample period. They therefore used a five-month forward-looking regression to determine the hedging coefficients.

[7] Following Henriksson and Merton (1981), the up-beta is defined as the market-beta conditional on the contemporaneous market return being positive, and the down-beta is the market beta conditional on the contemporaneous market return being negative.

portfolio have generally suffered severe losses, and are therefore potentially much closer to a level where the option convexity would be strong. The past winners, in contrast, would not have sufferred the same losses, and would still be in-the-money.

This hypothesis, however, does not seem plausible for the commodity and currency strategies, which also exhibit strong option-like behavior. In the conclusion we briefly discuss another behaviorally motivated potential explanations for this phenomenon, but a fuller understanding is an area for future research.

The layout of the paper is as follows: In Section 2 we review the literature we build upon in our analysis. Section 3 describes the data and portfolio construction. Section 4 documents the empirical analysis for momentum strategies in US equities, and Section 5 performs similar analyses on momentum strategies in international equities and in other asset classes. Section 6 speculates about the sources of the premia we observe, discusses areas for future research, and concludes.

2 Literature Review

A momentum strategy involves constructing a long-short portfolio, which purchases assets with strong performance, and sells assets with poor recent performance.

The performance of momentum strategies in U.S. common stock returns is documented in Jegadeesh and Titman (1993, JT). JT examine portfolios formed by sorting on past returns. For a portfolio formation date of t, their portfolios are formed on the basis of returns from $t - \tau$ months up to $t - 1$ month.[8] JT examine strategies for τ between 3 to 12 months, and hold these portfolios between 3 and 12 months. Their data is from 1965-1989. For all horizons, the top-minus-bottom decile spread in portfolio returns is statistically strong. However, JT also note the poor performance of momentum strategies in pre-WWII US data.

Jegadeesh and Titman (2001) note the continuing efficacy of the momentum portfolios in common stock returns from the time of the publication of their original paper.

[8] The motivation for skipping the last month prior to portfolio formation is the presence of the short-term reversal effect as documented by Jegadeesh (1990).

2.1 Momentum in Other Asset Classes

Strong and persistent momentum effects are also present outside of the US equity market. Rouwenhorst (1998) finds evidence of momentum in equities in developed markets, and Rouwenhorst (1999) documents momentum in emerging markets. Asness, Liew, and Stevens (1997) demonstrates positive abnormal returns to a country timing strategy which buys a country index portfolio when that country has experienced strong recent performance, and sells the indices of countries with poor recent performance. Momentum is also present outside of equities: Okunev and White (2003) find momentum in currencies; Erb and Harvey (2006) in commodities; Moskowitz, Ooi, and Pedersen (2010) in exchange traded futures contracts; and Asness, Moskowitz, and Pedersen (2008) in bonds. Asness, Moskowitz, and Pedersen (2008) also integrate the evidence on within-country cross-sectional equity, country-equity, country-bond, currency, and commodity value and momentum strategies.

Among common stocks, there is evidence that momentum strategies perform well for industry strategies, and for strategies that are based on the firm specific component of returns (see Moskowitz and Grinblatt (1999), Grundy and Martin (2001).)

2.2 Sources of Momentum

The underlying mechanism responsible for momentum is as yet unknown. By virtue of the high Sharpe-ratios associated with the mometum effect, these return patterns are difficult to explain within the standard rational-expectations asset pricing framework. Following Hansen and Jagannathan (1991), In a frictionless framework the high Sharpe-ratio associated with zero-investment momentum portfolios implies high variability of marginal utility across states of nature. Moreover, the lack of correlation of momentum portfolio returns with standard proxy variables for macroeconomic risk (*e.g.,* consumption growth) sharpens the puzzle still further (see, *e.g.*, Daniel and Titman (2011))

A number of behavioral theories of price formation proport to yield momentum as an implication. Daniel, Hirshleifer and Subramanyam (1998, 2001) propose a model in which momentum arises as a result of the overconfidence of agents; Barberis, Shleifer, and Vishny (1998) argue that a combination of representativeness; Hong and Stein (1999) model two classes of agents who process information in different ways; Grinblatt and Han (2005) argue that agents are subject to a disposition effect, and as a result are averse to recognizing losses, and are too quick to sell past winners.[9] George and Hwang (2004) point to a related anomaly – the 52-week high – and argue that it is a result of anchoring on past prices.

2.3 Time Variation in Momentum Risk and Return

Grundy and Martin (2001) argue that, by their nature, momentum portfolios will have significant time-varying exposure to systematic factors. Because momentum strategies are bets on past winners, they will have positive loadings on factors which have had a positive realization over the formation period of the momentum strategy. For example, if the market went up over the last 12 months, a 12-month momentum strategy will be long high-beta stocks and short low-beta stocks, and will therefore have a high market beta.

However, GM further argue that the Fama and French (1993) market, value and size factors do not explain the returns to a momentum strategy. In fact, they show that hedging out a momentum strategy's dynamic exposure to size and value factors dramatically reduces the strategy's return volatility, increases the Sharpe ratio, and eliminates the momentum strategy's historically poor performance in January, and it's poor record in the pre-WWII period. However, as we discuss in Section 4.4, their hedged portfolio is constructed based on forward-looking betas, and is therefore not an implementable strategy. In this paper, we show that this results in a strong bias in estimated returns, and that a hedging strategy based on *ex-ante* betas does not exhibit the performance improvement noted in GM.

Cooper, Gutierrez, and Hameed (2004) examine the time variation of average returns to US equity momentum strategies. They define UP and DOWN market states based on the lagged three-year return of the market. They find that in UP states, the historical mean return to a EW momentum strategy has been *0.93%/month*. In contrast in DOWN states the mean return has been -*0.37%/month*. They find similar results, controlling for market, size & value based on the unconditional loadings of

[9] Frazzini (2006) examines the presence of the disposition effect on the part of mutual funds.

the momentum porfolios on these factors.[10]

Finally, the result that the betas of winner-minus-loser portfolios are nonlinearly related to contemporaneous market returns has also been documented elsewhere. In particular Rouwenhorst (1998), documents this feature for non-US momentum strategies.[11] However, Chan (1988) and DeBondt and Thaler (1987) earlier document this non-linearity for longer-term winner/loser portfolios is non-linearly to the market return, though DeBondt and Thaler do their analysis on the returns of longer-term winners and losers as opposed to the shorter-term winners and losers we examine here. Boguth, Carlson, Fisher, and Simutin (2010), building on the results of Jagannathan and Korajczyk (1986), note that the interpretation of the measures of abnormal performance (*i.e.*, the alphas) in Chan (1988), Grundy and Martin (2001) and Rouwenhorst (1998) are problematic.

3 Data and Portfolio Construction

Our pricipal data source is CRSP. Using CRSP data, we construct monthly and daily momentum decile portfolios. Both sets of portfolios are rebalanced only at the end of each month. The universe start with all firms listed on NYSE, AMEX or NASDAQ as of the formation date. We utilize only the returns of common shares (with CRSP share-code of 10 or 11). We require that the firm have a valid share price and a valid number of shares as of the formation date, and that there be a minimum of 8 valid monthly returns over the 11 month formation period. Following convention and CRSP availability, all prices are closing prices, and all returns are from close to close.

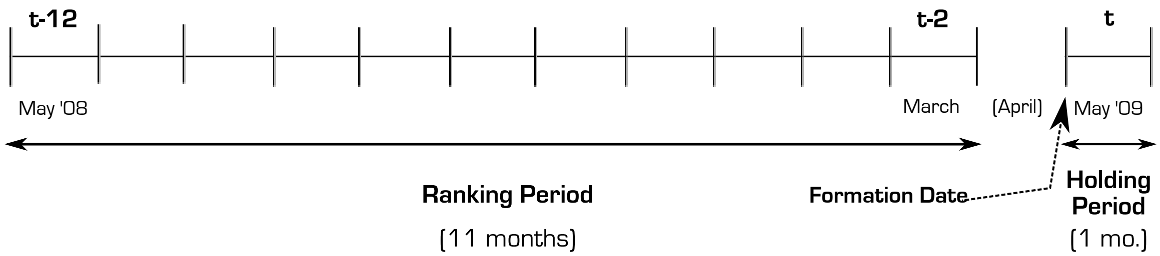
Figure 1 illustrates the portfolio formation process used in determining the momentum portfolios returns for the one month holding period of May 2009. To form the portfolios, we begin by calculating ranking period returns for all firms. The ranking period returns are the cumulative returns from close of the last trading day of April 2008 through the last trading day of March 2009. Note that, consistent with the literature, there is a one month gap between the end of the ranking period and the start of the holding period.

[10]Cooper, Gutierrez, and Hameed (2004) do not calculate conditional risk measures, *e.g.* using the instruments proposed by Grundy and Martin (2001).

[11]See, Table V, p. 279.

Figure 1: **Momentum Portfolio Formation**

This figure illustrates the formation of the momentum decile portfolios. As of close of the final trading day of each month, firms are ranked on their cumulative return from 12 months before to one month before the formation date.



All firms meeting the data requirements are placed into one of ten decile portfolios on the basis of their cumulative returns over the ranking period. However, the portfolio breakpoints are based on NYSE firms only. That is, the breakpoints are set so that there are an equal number of NYSE firms in each of the 10 portfolios.[12] The firms with the highest ranking period returns go into portfolio 10 – the "[W]inner" decile portfolio – and those with the lowest go into portfolio 1, the "[L]oser" decile. We also evaluate the returns for a zero investment Winner-Minus-Loser (WML) portfolio, which is the difference of the Winner and Loser portfolio each period.

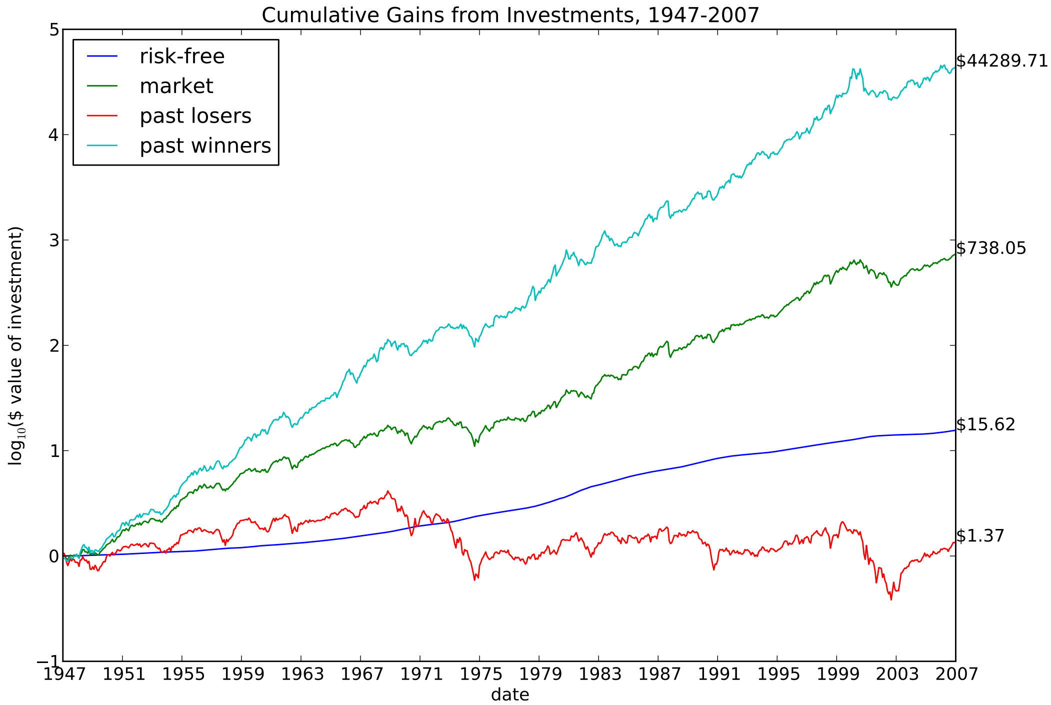
The holding period returns of the decile portfolios are the value-weighted returns of the firms in the portfolio over the one month holding period from the closing price last trading day in April through the last trading day of May. Given the monthly formation process, portfolio membership does not change within month, except in the case of delisting. This means that, except for dividends, cash payouts, and delistings, the portfolios are buy and hold portfolios.

The market return is the CRSP value weighted index. The risk free rate series is the one-month Treasury bill rate.[13]

[12] This typically results in having more firms in the extreme portfolios, as the average return variance for AMEX and NASDAQ firms is higher than for NYSE firms.

[13] The source of the 1-month Treasury-bill rate is Ibbotsen, and was obtained through Ken French's data library. I convert the monthly risk-free rate series to a daily series by converting the risk-free rate at the beginning of each month to a daily rate, and assuming that that daily rate is valid through the month.

Figure 2: **Momentum Components, 1947-2007**



4 US Equities – Empirical Results

4.1 Momentum Portfolio Performance

Figure 2 presents the cumulative monthly log returns for investments in (1) the risk-free asset; (2) the CRSP value-weighted index; (3) the bottom decile "past loser" portfolio; and (4) the top decile "past winner" portfolio. The y-axis of the plot gives the cumulative log return for each portfolio. On the right side of the plot, we present the final dollar values for each of the four portfolios.

Consistent with the existing literature, there is a strong momentum premium over this 50 year period. Table 1 presents return moments for the momentum decile portfolios over this period. The winner decile excess return averages 15.4%/year, and the loser portfolio averages -1.3%/year. In contrast the average excess market return is 7.5%. The Sharpe-Ratio of the WML portfolio is 0.83, and that of the market is 0.52. Over this period, the beta of the WML portfolio is slightly negative, -0.13, giving it an the WML portfolio an unconditional CAPM alpha of 17.6%/year (t=6.8). As one would expect given the high alpha, an *ex-post* optimal combination of the market and

Table 1: **Momentum Portfolio Characteristics, 1947-2007**

This table presents characteristics of the monthly momentum portfolio excess returns over the 50 year period from 1947:01-2006:12. The mean return, standard deviation, alpha are in percent, and annualized. The Sharpe-ratio is annualized. The α, $t(\alpha)$, and β are estimated from a full-period regression of each decile portfolio's excess return on the excess CRSP-value weighted index. For all portfolios except WML, SK denotes the full-period realized skewness of the monthly log returns (not excess) to the portfolios. For WML, SK is the realized skewness of $\log(1+r_{\text{WML}}+r_f)$.

	Momentum Decile Portfolios											
	1	2	3	4	5	6	7	8	9	10	WML	Mkt
μ	-1.3	4.0	5.5	6.4	6.2	7.2	7.8	10.0	10.9	15.4	16.7	7.5
σ	23.6	19.0	16.3	15.2	14.2	14.7	14.6	15.0	16.0	20.2	20.1	14.5
α	-11.3	-4.3	-1.8	-0.6	-0.5	0.2	0.8	2.9	3.3	6.4	17.7	0
$t(\alpha)$	(-6.3)	(-3.3)	(-1.6)	(-0.7)	(-0.6)	(0.2)	(1.1)	(3.7)	(3.8)	(4.7)	(6.8)	(0)
β	1.33	1.11	0.97	0.94	0.90	0.94	0.93	0.95	1.01	1.20	-0.13	1
SR	-0.06	0.21	0.34	0.42	0.44	0.49	0.53	0.67	0.68	0.76	0.83	0.52
sk	-0.17	-0.21	-0.15	-0.33	-0.66	-0.67	-0.75	-0.51	-0.79	-0.74	-1.68	-1.34

WML portfolios has a Sharpe ratio of 1.02, close to double that of the market. A pattern that we will explore further is the skeweness – note that the winner portfolios are considerably more negatively skewed than the loser portfolios, even over this relatively benign period.

4.2 Momentum Crashes

Since 1926, there have been a number of long periods over which momentum underperformed dramatically. Figures 3 and 4 show the cumulative daily returns to the same set of portfolios over the recent period from March 8, 2009 through December 31, 2010, and over a period starting in June, 1932, and continuing through WWII to December 31, 1945. Over both of these two periods, the loser portfolio strongly outperforms the winner portfolio.

Finally, Figure 5 plots the cumulative (monthly) log returns to the an investment in the WML portfolio.[14]

Table 3 presents the worst monthly returns to the WML strategy. In addition, this table gives the lagged two-year returns on the market, and the contemporaneous

[14] I describe the calculation of cumulative returns for long-short portfolios in Appendix A.1.

Figure 3: **2009-10 Momentum Performance**

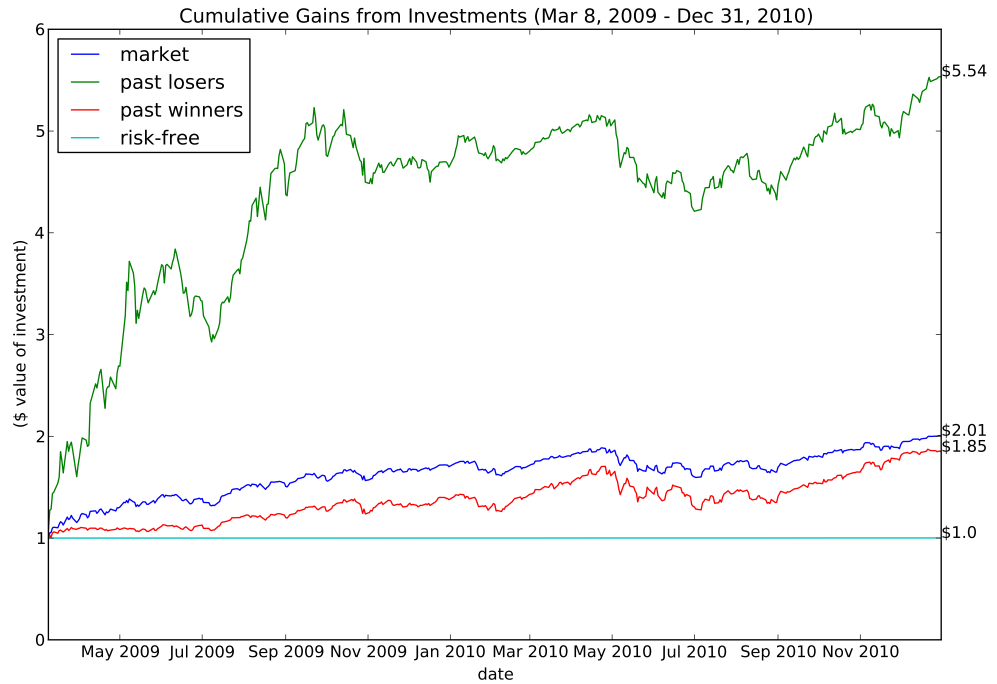


Figure 4: **Momentum in the Great Depression**

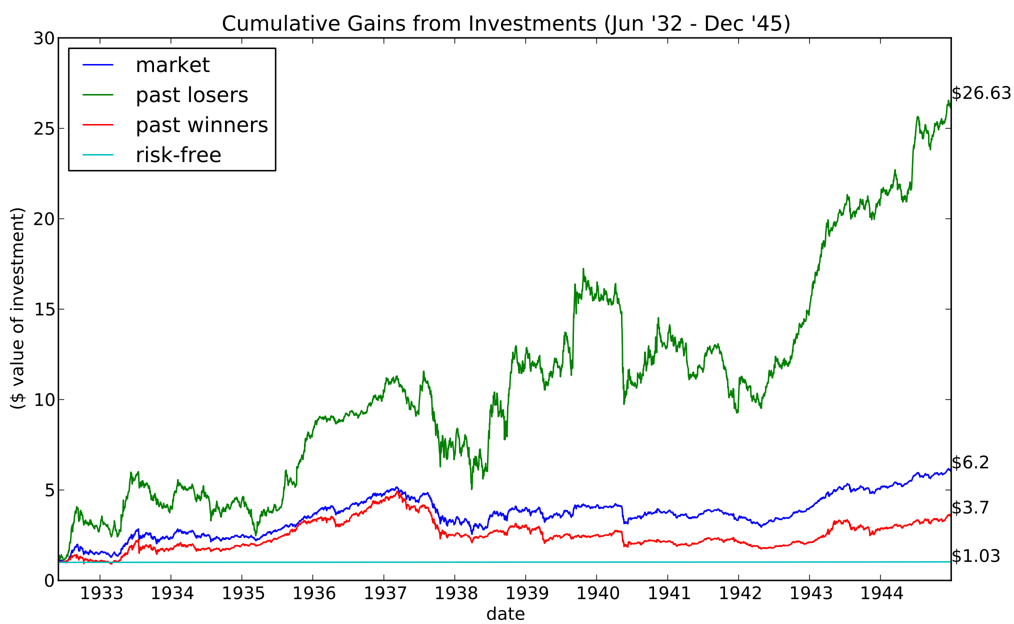
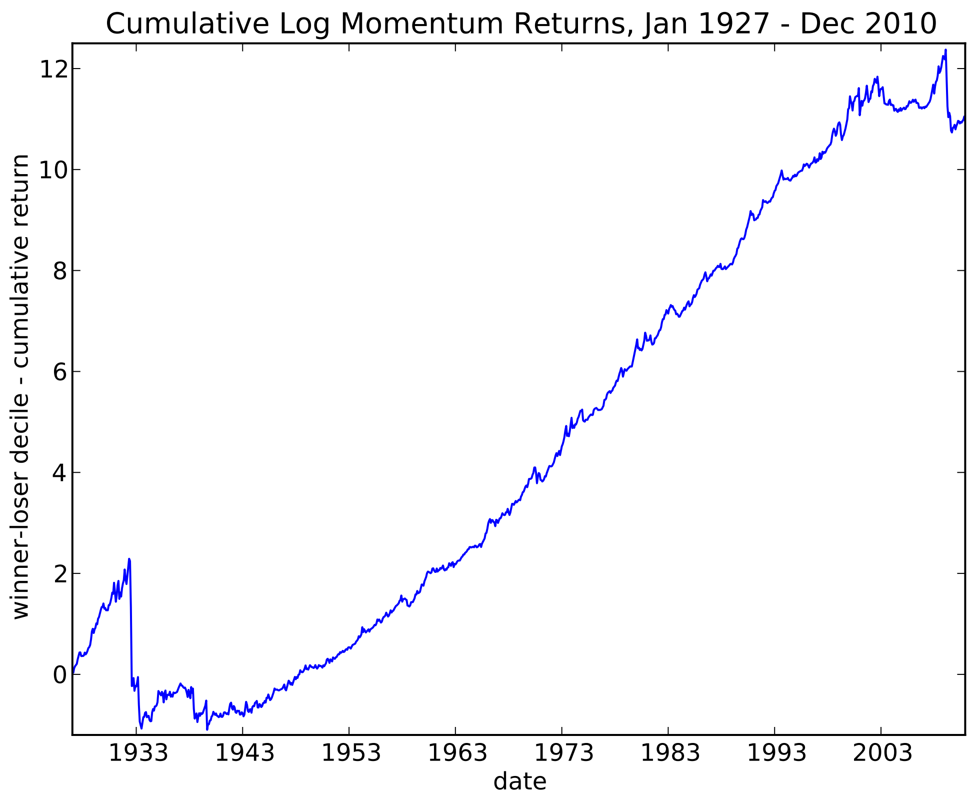


Figure 5: **Cumulative Momentum Returns**



monthly market return. There are several points of note this Table and in Figures 3-5 that we will examine more formally in the remainder of the paper:

1. While past winners have generally outperformed past loses, there are relatively long periods over which momentum experiences severe losses.

2. These "crash" periods occur after severe market downturns, and during months where the market rose, often in a dramatic fashion.[15]

3. The crashes do not occurs over the span of minutes or days. A crash is not a Poisson jump. The take place slowly, over the span of multiple months.

4. Related to this, the extreme losses are clustered: Note that the two worst are in July and August of 1932, following a market decline of roughly 90% from the 1929 peak. March and April of 2009 are ranked 7th and 3rd worst, and April

[15]For January 2001, the past 2 year market returns is positive, but as of the start of 2001, the CRSP value weighted index was below the high (set on March 24, 2000) by 17.5%.

Table 2: **Momentum Portfolio Characteristics, 1927-2010**

The calculations for this table are similar those in Table 1, except that the time period is 1927:01-2010:12. Also, $sk(m)$ is the skewness of the monthly log returns, and $sk(m)$ is the skewness of the daily log returns.

	Momentum Decile Portfolios											
	1	2	3	4	5	6	7	8	9	10	WML	Mkt
μ	0.2	4.7	4.9	6.6	6.7	7.5	8.4	9.9	10.8	14.6	14.4	7.4
σ	34.4	28.7	24.7	22.6	21.0	20.4	19.5	18.8	19.8	22.7	27.7	18.9
α	-11.2	-5.1	-3.7	-1.4	-0.9	-0.0	1.3	3.1	3.7	7.2	18.4	0
$t(\alpha)$	(-5.8)	(-3.5)	(-3.2)	(-1.5)	(-1.1)	(-0.1)	(1.9)	(4.4)	(4.4)	(5.4)	(6.5)	(0)
β	1.56	1.34	1.18	1.10	1.03	1.03	0.97	0.93	0.96	1.01	-0.54	1
SR	0.01	0.17	0.20	0.29	0.32	0.37	0.43	0.53	0.54	0.64	0.52	0.39
sk(m)	0.13	-0.05	-0.12	0.17	-0.05	-0.32	-0.65	-0.53	-0.81	-0.92	-6.32	-0.58
sk(d)	-0.21	0.16	0.15	0.37	-0.10	0.02	-0.49	-0.58	-0.72	-0.74	-1.47	-0.44

and May of 1933 are the 5th and 10th worst. And three of the worst are from 2009 – over a three-month period in which the market rose dramatically and volatility fell. One was in 2001, and all of the rest are from the 1930s. At some level it is not surprising that the most extreme returns occur in periods of high volatility. However, the extreme positive momentum returns, are not as large in magnitude, or as concentrated.[16]

5. Closer examination shows that crash performance is mostly attributable to short side. For example, in July and August of 1932, the market actually rose by 82%. Over these two month, the winner decile rose by 30%, but the loser decile was up by 236%. Similarly, over the three month period from March-May of 2009, the market was up by 29%, but the loser decile was up by 156%. Thus, to the extent that the strong momentum reversals we observe in the data can be characterized as a crash, they are a crash where the short side of the portfolio – the losers – are crashing up rather than down.

4.3 Risk of Momentum Returns

The data in Table 3, is suggestive that large changes in market beta may help to explain some of the large negative returns earned by momentum strategies.

[16]The highest monthly momentum return over the same period sample is 26.1%, in February 2000.

Table 3: **Worst Monthly Momentum Returns**
This table presents the 11 worst monthly returns to the WML portfoio over the 1927:01-2010:12 time period. Also tabulated are Mkt-2y, the 2-year market returns leading up to the portfolio formation date, and Mkt_t, the market return in the same month.

Rank	Month	WML_t	Mkt-2y	Mkt_t
1	1932-08	-0.7896	-0.6767	0.3660
2	1932-07	-0.6011	-0.7487	0.3375
3	2009-04	-0.4599	-0.4136	0.1106
4	1939-09	-0.4394	-0.2140	0.1596
5	1933-04	-0.4233	-0.5904	0.3837
6	2001-01	-0.4218	0.1139	0.0395
7	2009-03	-0.3962	-0.4539	0.0877
8	1938-06	-0.3314	-0.2744	0.2361
9	1931-06	-0.3009	-0.4775	0.1380
10	1933-05	-0.2839	-0.3714	0.2119
11	2009-08	-0.2484	-0.2719	0.0319

For example, as of the beginning of March 2009, the firms in the loser decile portfolio were, on average, down from their peak by 84%. These firms included the firms that were hit hardest in the finanical crisis: among them Citigroup, Bank of America, Ford, GM, and International Paper (which was levered). In contrast, the past-winner portfolio was composed of defensive or counter-cyclical firms like Autozone. The loser firms, in particular, were often extremely levered, and at risk of bankruptcy. In the sense of the Merton (1990) model, their common stock was effectively an out-of-the-money option on the underlying firm value. This suggests that there were potentially large differences in the market betas of the winner and loser portfolios.

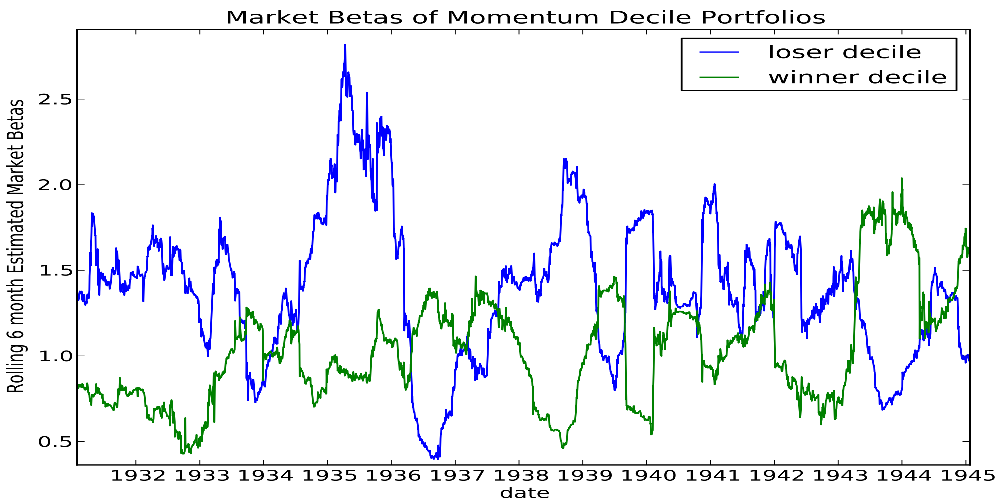
This is in fact the case. In Figure 6 we plot the market betas for the winner and loser momentum deciles, estimated using 126 day ($\approx$ 6 month) rolling regressions with daily data, and using 10 daily lags of the market return in estimating the market. Specifically, we estimated a daily regression specification of the form:

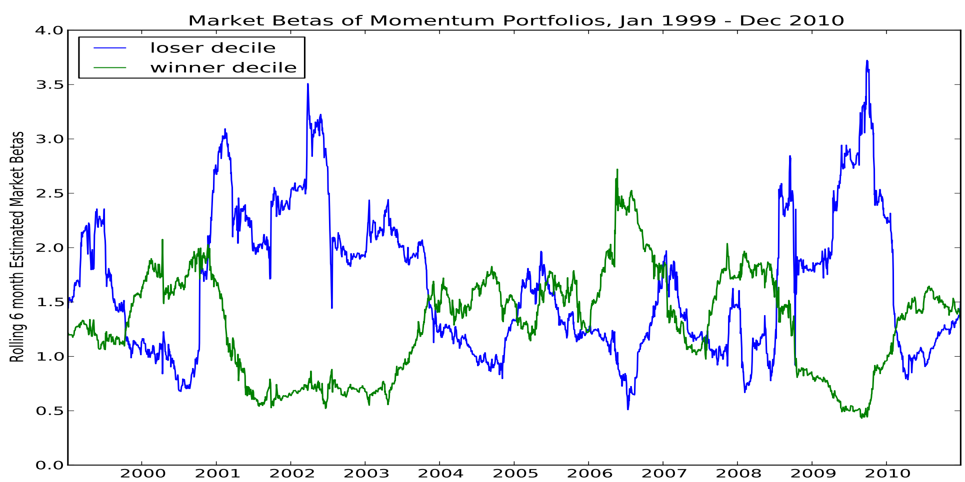
$$\tilde{r}^e_{i,t} = \beta_0 \tilde{r}^e_{m,t} + \beta_1 \tilde{r}^e_{m,t-1} + \cdots + \beta_{10} \tilde{r}^e_{m,t-10} + \tilde{\epsilon}_{i,t} \tag{1}$$

and then report the sum of the estimated coefficients $\hat{\beta}_0 + \hat{\beta}_1 + \cdots + \hat{\beta}_{10}$. Particularly for the past losers portfolios, and especially in the Pre-WW-II period, the lagged coefficients are strongly significant, suggesting that the prices of firms in these portfolios

Figure 6: **Market Betas of Winner and Loser Decile Portfolios**

These two plots present the estimated market betas over the periods 1931-1945, and 1999-2010. The betas are estimating by running a set of 128-day rolling regressions. Each regression uses 10 (daily) lagged market returns in the estimations of the beta as a way of accounting for the lead-lag effects in the data.





respond slowly to market-wide information.

4.4 Hedging the Market Risk in the Momentum Portfolio

Grundy and Martin (2001) investigate hedging the market and size risk in the momentum portfolio. They find that doing so dramatically increases the returns to a momentum portfolio. They find that a hedged momentum portfolio has a high average return and a high Sharpe-ratio in the pre-WWII period when the unhedged momentum portfolio suffers.

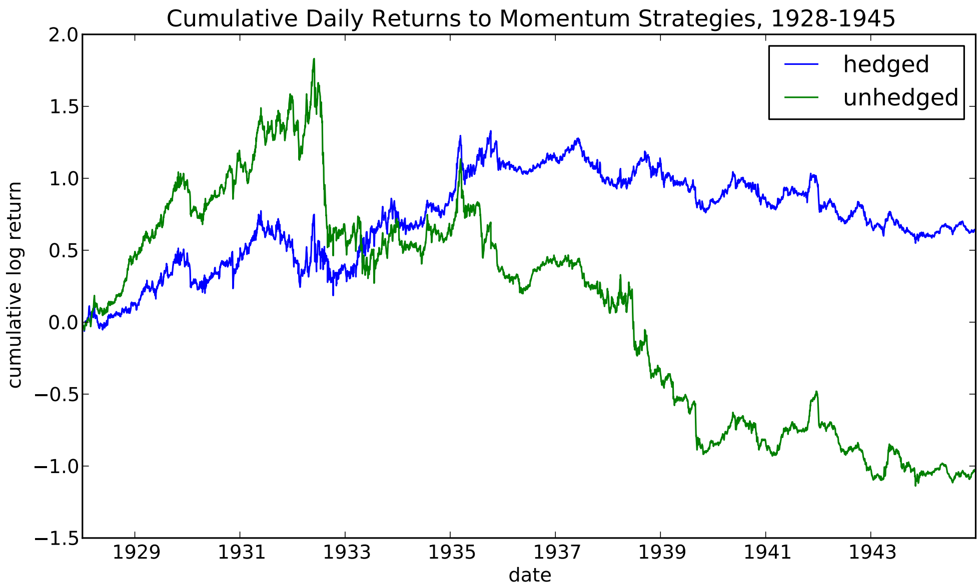
At the time that Grundy and Martin (2001) undertook their research, daily stock data was not available through CRSP in the pre-1962 period. Given the dynamic nature of momentum's risk-exposures, estimating the future hedge coefficients with *ex-ante* is problematic. As a result they investigate the efficacy of hedging primarily based on an *ex-post* estimate of the portfolio's market and size betas, estimated using monthly returns over the current month and the future five months.

However, to the extent that the future momentum-portfolio beta is correlated with the future return of the market, this procedure will result in a biased estimate of the returns of the hedged portfolio. In Section 4.5, we will show there is in fact a strong correlation of this type which in fact does result in a large upward bias in the estimated performance of the hedged portfolio.

We first estimate the performance of a WML portfolio which hedges out market risk using an *ex-post* estimate of market beta, following Grundy and Martin (2001).[17] We construct the *ex-post* hedged portfolio in a similar way, though using daily data. Specifically, the size of the market hedge is based on the future 42-day (2 month) realized market beta of the portfolio being hedged. Again, to calculate the beta we use 10 daily lags of the market return, as shown in equation (1). We do not hedge size exposure.

[17] Note that Grundy and Martin (2001) also hedge out size risk. We do not. This presumably also increases the performance of their hedged portfolio. It is well known that (1) the momentum portfolio has a strongly positive SMB beta; and (2) that both the size portfolio and the momentum portfolio underperform in January. with their four month beta estimation period, the estimated size beta will tend to be larger in January. Thus, the ex-post hedged portfolio should upward biased performance as well.

Figure 7: **Ex-post Hedged Momentum Portfolio Performance**



The ex-post hedged portfolio exhibits considerably improved performance, consistent with the results of Grundy and Martin (2001). Figure 7 plots the performance of the *ex-post* hedged WML portfolio over the period form 1928-1945, and that of the unhedged portfolio.

4.5 Option-like Behavior of the WML portfolio

We now show that the realized performance of the *ex-post* hedged portfolio is an upward biased estimate of the *ex-ante* performance of the portfolio. The source of the bias is that in down markets, the market beta of the WML portfolio is strongly *negatively* correlated with the contemporaneous realized performance of the portfolio. This means that the *ex-post* hedge will have a higher market beta when future market returns are high, and a lower beta when future market returns are liw.

The relationship between lagged and contemporaneous market returns and the WML portfolio beta are illustrated with a set of monthly time-series regressions, the results of which are presented in Table 4. The variables used in the regressions are:

1. $\tilde{R}_{\text{WML},t}$ is the WML return in month t.

Table 4: **Market Timing Regression Results**
This table presents the results of estimating four specifications of a monthly time-series regressions run over the period 1927:01 - 2010:12. In all cases the dependent variable is the return on the WML portfolio. The independent variables are described in the text.

		Estimated Coefficients *(t-statistics in parentheses)*			
Coeff.	Variable	(1)	(2)	(3)	(4)
$\hat{\alpha}_0$	1	0.015	0.017	0.017	0.017
		(6.5)	(7.1)	(7.2)	(7.8)
$\hat{\alpha}_B$	I_B		-0.020	0.006	
			(-3.7)	(0.8)	
$\hat{\beta}_0$	$\tilde{R}^e_{m,t}$	-0.534	0.033	0.033	0.031
		(-12.5)	(0.6)	(0.6)	(0.6)
$\hat{\beta}_B$	$\mathrm{I}_B \cdot \tilde{R}^e_{m,t}$		-1.157	-0.688	-0.736
			(-15.1)	(-5.8)	(-7.1)
$\hat{\beta}_{B,U}$	$\mathrm{I}_B \cdot \mathrm{I}_U \cdot \tilde{R}^e_{m,t}$			-0.814	-0.724
				(-5.1)	(-6.3)
R^2_{adj}		0.136	0.306	0.323	0.324

2. $\tilde{R}^e_{m,t}$ is the excess CRSP value-weighted index return in month t.

3. $\mathrm{I}_\mathbf{B}$ is an *ex-ante* **B***ear-market* Indicator. It is 1 if the cumulative CRSP VW index return in the 24 months leading up to the start of month t is *negative*, and is zero otherwise.

4. $\mathrm{I}_\mathbf{L}$, is an *ex-ante bul* **L***-market* Indicator. is a a is 1 if the cumulative CRSP VW index return in the 24 months leading up to the start of month t is *positive*, and is zero otherwise. *Note that* $I_L = (1 - I_B)$

5. $\tilde{\mathrm{I}}_\mathbf{U}$ is the contemporaneous – *i.e.,* not *ex-ante* **U***p-Month* indicator variable. It is 1 if the excess CRSP VW index return is positive in month t, and is zero otherwise.[18]

Regression (1) in Table 4 fits an unconditional market model to the WML portfolio:

$$\tilde{R}_{\text{WML},t} = \alpha_0 + \beta_0 \tilde{R}_{m,t} + \tilde{\epsilon}_t$$

Consistent with the results in the literature, the estimated market beta is somewhat

[18]Of the 1008 months in the 1927:01-2010:12 period, there are 186 bear market months. There are 603 Up-months, and 405 down-months.

negative, -0.534, and that the $\hat{\alpha}$ is both economically large (1.5%/month), and statistically significant.

Regression (2) in Table 4 fits a conditional CAPM with the bear market I_B indicator as a instrument:

$$\tilde{R}_{\text{WML},t} = (\alpha_0 + \alpha_B I_B) + (\beta_0 + \beta_B I_B)\tilde{R}_{m,t} + \tilde{\epsilon}_t.$$

This specification is an attempt to capture both expected return and market-beta differences in bear-markets. First, consistent with Grundy and Martin (2001), we see a striking change in the market beta of the WML portfolio in bear markets: it is -1.2 lower, with a t-statistc of -15 on the difference. The intercept is also lower: The point estimate for the alpha in bear markets – equal to $\hat{\alpha}_0 + \hat{\alpha}_B$ – is now -0.3%/month.

Regression (3) introduces an additional element to the regression which allows us to assesses the extent to which the up- and down-market betas of the WML portfolio differ. The specification is similar to that used by Henriksson and Merton (1981) to assess market timing ability of fund managers:

$$\tilde{R}_{\text{WML},t} = [\alpha_0 + \alpha_B \cdot I_B] + [\beta_0 + I_B(\beta_B + \tilde{I}_U \beta_{B,U})]\tilde{R}_{m,t} + \tilde{\epsilon}_t. \tag{2}$$

Now, if $\beta_{B,U}$ is different from zero, this suggests that the WML portfolio exhibits option-like behavior relative to the market. Specifically, a negative $\beta_{B,U}$ would mean that, in bear markets, the momentum portfolio is effectively short a call option on the market: in months when the contemporaneou market return is negative, the WML portfolio beta is -0.65. But when the market return is positive, the market beta of WML is considerably more negative – specifically, the point estimate is $\hat{\beta}_0 + \hat{\beta}_B + \hat{\beta}_{B,U} = \mathbf{-1.47}$.

The predominant source of this *optionality* turns out to be the loser portfolio. Table 5 presents the results of the regression specification in equation (2) for each of the ten momentum portfolio. The final row of the table (the $\hat{\beta}_{B,U}$ coefficient) shows the strong up-market betas for the loser portfolios in bear markets. For the loser decile, the down-market beta is 1.516 (= 1.253 + 0.263) and the up-market beta is 0.607 higher (2.12). Also, note the slightly negative up-market beta increment for the winner decile (= −0.207).

Table 5: **Momentum Portfolio Optionality in Bear Markets**
This table presents the results of a regressions of the excess returns of the 10 momentum portfolios and the Winner-Minus-Loser (WML) long-short portfolio on the CRSP value-weighted excess market returns, and a number of indicator variables. For each of these portfolios, the regression estimated here is:

$$\tilde{R}^e_{i,t} = [\alpha_0 + \alpha_B I_B] + [\beta_0 + I_B(\beta_B + \tilde{I}_U \beta_{B,U})]\tilde{R}_{m,t} + \tilde{\epsilon}_t$$

where R^e_m is the CRSP value-weighted excess market return, I_B is an *ex-ante* **B**ear-market indicator and I_U is a contemporaneous *UP*-market indicator, as defined in the text on page 17. The time period is 1927:01-2010:12.

Coef.	Momentum Decile Portfolios – Excess Monthly Returns *(t-statistics in parentheses)*										
Est.	1	2	3	4	5	6	7	8	9	10	WML
$\hat{\alpha}_0$	-0.011	-0.005	-0.003	-0.002	-0.000	-0.000	0.001	0.003	0.003	0.006	0.017
	(-6.6)	(-4.2)	(-3.0)	(-1.9)	(-0.4)	(-0.1)	(2.1)	(4.4)	(3.9)	(5.1)	(7.2)
$\hat{\alpha}_B$	-0.004	-0.002	-0.003	-0.006	-0.006	-0.003	-0.001	-0.002	0.005	0.002	0.006
	(-0.7)	(-0.6)	(-1.0)	(-2.3)	(-2.8)	(-1.4)	(-0.4)	(-1.1)	(2.2)	(0.7)	(0.8)
$\hat{\beta}_0$	1.253	1.058	0.940	0.928	0.898	0.951	0.956	0.995	1.084	1.285	0.033
	(33.3)	(38.5)	(42.7)	(50.7)	(55.5)	(68.7)	(64.9)	(67.4)	(64.0)	(50.5)	(0.6)
$\hat{\beta}_B$	0.263	0.331	0.341	0.145	0.144	0.077	0.036	-0.117	-0.113	-0.425	-0.688
	(3.1)	(5.4)	(6.9)	(3.5)	(4.0)	(2.5)	(1.1)	(-3.5)	(-3.0)	(-7.4)	(-5.8)
$\hat{\beta}_{B,U}$	0.607	0.406	0.236	0.349	0.220	0.128	-0.006	-0.009	-0.215	-0.207	-0.814
	(5.4)	(4.9)	(3.6)	(6.3)	(4.5)	(3.1)	(-0.1)	(-0.2)	(-4.2)	(-2.7)	(-5.1)

4.5.1 Asymmetry in the Optionality

It is interesting that the optionality associated with the loser portfolios that is apparent in the regressions in Table 5 is only present in bear markets. Table 6 presents the same set of regressions as in Table 5, only now instead of using the Bear-market indicator I_B, we a the bul**L** market indicator I_L. The key variables here are the estimated coefficients and t-statistics on $\beta_{L,U}$, presented in the last two rows of the Table. Unlike in Table 5, no significant asymmetry is present in the loser portfolio, the winner portfolio asymmetry is comparable to what is present in Table 5. Also the WML portfolio shows no statistically significant optionality, unlike what is seen in bear markets.

For the winner portfolios, we obtain the same slightly negative point estimate for the up-market beta increment. There is no apparent variation associated with the past market return.

Table 6: **Momentum Portfolio Optionality in Bull Markets**

This table presents the results of a regressions of the excess returns of the 10 momentum portfolios and the Winner-Minus-Loser (WML) long-short portfolio on the CRSP value-weighted excess market returns, and a number of indicator variables. For each of these portfolios, the regression estimated here is:

$$\tilde{R}^e_{i,t} = [\alpha_0 + \alpha_L I_L] + [\beta_0 + I_L(\beta_L + \tilde{I}_U \beta_{L,U})]\tilde{R}_{m,t} + \tilde{\epsilon}_t$$

where R^e_m is the CRSP value-weighted excess market return, I_L is an *ex-ante* bul*L*-market indicator and I_U is a contemporaneous *UP*-market indicator, as defined in the text on page 17. The time period is 1927:01-2010:12.

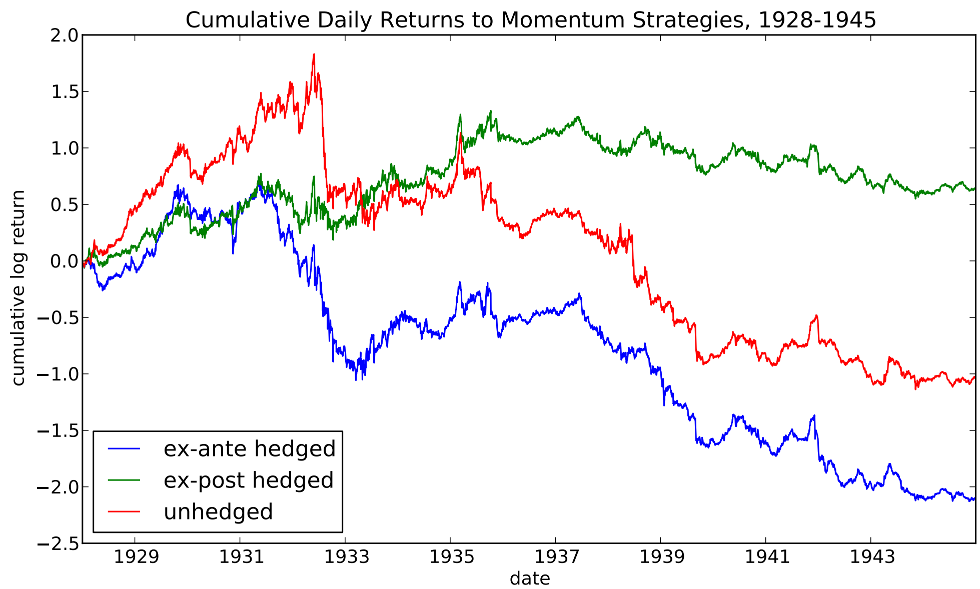
Coef.	Momentum Decile Portfolios – Excess Monthly Returns *(t-statistics in parentheses)*										
Est.	1	2	3	4	5	6	7	8	9	10	WML
$\hat{\alpha}_0$	0.005	0.006	0.002	0.004	0.001	0.002	0.000	-0.000	0.001	0.001	-0.006
	(1.5)	(2.3)	(0.8)	(2.5)	(0.3)	(1.4)	(0.1)	(-0.1)	(0.7)	(0.5)	(-1.2)
$\hat{\alpha}_L$	-0.017	-0.011	-0.005	-0.008	-0.002	-0.002	-0.001	0.002	0.003	0.008	0.023
	(-3.7)	(-3.4)	(-2.0)	(-3.6)	(-1.1)	(-1.2)	(-0.4)	(1.3)	(1.4)	(2.6)	(3.6)
$\hat{\beta}_0$	1.885	1.639	1.428	1.284	1.174	1.104	0.985	0.866	0.837	0.724	-1.161
	(47.9)	(57.1)	(62.7)	(67.5)	(69.2)	(76.4)	(64.7)	(57.0)	(48.2)	(27.7)	(-21.1)
$\hat{\beta}_L$	-0.642	-0.581	-0.508	-0.405	-0.313	-0.154	-0.079	0.104	0.267	0.653	1.302
	(-8.2)	(-10.2)	(-11.2)	(-10.7)	(-9.3)	(-5.4)	(-2.6)	(3.4)	(7.7)	(12.6)	(11.9)
$\hat{\beta}_{L,U}$	0.019	0.004	0.048	0.108	0.080	0.009	0.115	0.059	-0.055	-0.194	-0.216
	(0.2)	(0.0)	(0.7)	(1.9)	(1.5)	(0.2)	(2.5)	(1.3)	(-1.0)	(-2.4)	(-1.3)

4.6 *Ex-ante* Hedge of the market risk in the WML Portfolio

The results of the preceding section suggest that calculating hedge ratios based on future realized hedge ratios, as in Grundy and Martin (2001), is likely to produce strongly upward biased estimates of the performance of the hedged portfolio. As we have seen, the realized market beta of the momentum portfolio tends to be more negative when the realized return of the market is positive. Thus, the hedged portfolio – where the hedge is based on the future realized portfolio beta – will buy more of the market (as a hedge) in months where the market return is high.

Figure 8 adds the cumulative log return to the *ex-ante* hedged return to the plot from Figure 7. The strong bias in the ex-post hedge is clear here.

Figure 8: ***Ex-Ante* Hedged Portfolio Performance**



4.7 Market Stress and Momentum Returns

One very casual interpretation of the results presented in Section 4.5 is that there are option like payoffs associated with the past losers in bear markets, and the value of this option on the economy is not reflected in the prices of the past losers. This casual interpretation further suggests that the value of this option should be a function of the future variance of the market.

In this section we examine this hypothesis. Using daily market return data, we construct an *ex-ante* estimate of the market volatility over the next one month. In Table 7, we use this market variance estimate in combination with the bear-market indicator I_{B} previously employed to forecast future WML returns.

To summarize, we find that both estimated market variance and the bear market indicator independently forecast future momentum returns. The direction is as suggested by the results of the previous section: in periods of high market stress – bear markets with high volatility – momentum returns are low.

Table 7: **Momentum Returns and Estimated Market Variance**
This table presents estimated coefficients for the variations on the following regressions specification:

$$\tilde{r}_{\mathrm{WML},t} = \gamma_0 + \gamma_{Rm2y} \cdot \mathrm{I_B} + \gamma_{\sigma_m^2} \cdot \hat{\sigma}_m^2 + \gamma_{int} \cdot \mathrm{I_B} \cdot \hat{\sigma}_{m,t}^2 + \tilde{\epsilon}_t$$

Here, I_B is the bear market indicator described on page 17. σ_m^2 is an *ex-ante* estimator of market volatility over the next month. The regression is monthly, over the period 1927:01-2010:12.

	$\hat{\gamma}_0$	$\hat{\gamma}_\mathrm{B}$	$\hat{\gamma}_{\sigma_m^2}$	$\hat{\gamma}_{int}$
1	0.0168	-0.0260		
	(6.08)	(-4.05)		
2	0.0211		-0.3248	
	(7.02)		(-5.38)	
3	0.0219	-0.0129	-0.2686	
	(7.22)	(-1.79)	(-3.95)	
4	0.0168			-0.3825
	(6.46)			(-5.99)
5	0.0186	-0.0019	-0.0940	-0.2880
	(5.43)	(-0.21)	(-0.87)	(-2.07)

5 International Equities and Other Asset Classes

In the academic literature, momentum effects were first documented in individual equities in the United States. Subsequent research has demonstrated the existence of strong momentum effects both among common stocks in other investment regions, and in other asset classes.[19]

We investigate the extent to which the same momentum crash patterns we observe in US equities are also present in these other asset markets: first in international equity markets and then in other asset classes.

5.1 Data

The data we use for this analysis is similar to that used in Asness, Moskowitz, and Pedersen (2008). The international stock markets we analyze are the U.S., U.K.,

[19]The research on this topic is cited in Section 2.

Japan and Continental Europe. For other asset classes, we utilize data on government bonds, commodities, currencies, and country equity strategies.

5.1.1 International Stock Market Data

Our sample is constructed by starting with all stocks from the U.S., U.K., Japan and Continental Europe market. The source for the U.S. data is CRSP, as in the rest of our paper. For the other regions, we use the BARRA International universe. We select only common equity, with at least 12 months of past return history. We exclude REITS, financials, foreign shares, stocks with share prices less than $1 (US) at the beginning of the month. We require that there be a book value in the last 6 months, where the US book value data is from COMPUSTAY and outside the US book value data is from Worldscope.

In order to ensure that the momentum strategies we construct are tradeable with minimal transaction costs, within each market we select the set of common stocks with the highest market capitalization, where the cutoff is such we include the top 90% of total market cap of each market. This corresponds to roughly the largest 15-20% of names in each market.[20]

The samples for the U.S. and U.K. begin in January 1972. Continental Europe and Japan begin in February, 1974. For each market, the last month of our sample is July, 2011.

The market portfolios we use for each region are from MSCI: specifically the MSCI US, MSCI UK, MSCI Europe, MSCI Japan indices, and the MSCI global for the global strategy.

5.1.2 Data for Other Asset Classes

Again here, our data is similar to that used in Asness, Moskowitz, and Pedersen (2008). Specifically, for equity country selection, the universe of country index futures

[20]Because of the different time period. sample selection criteria and momentum definition, we generate results for the US strategy in this section which are slightly different from the longer sample results in the rest of the paper.

consists of the following 18 developed equity markets: Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, U.K., and U.S. Returns and price data as well as book values are obtained from MSCI. The sample begins in January, 1978, and ends in July, 2011. The minimum number of equity indices being 8 and all 18 indices represented after 1980.

For currencies, we get spot exchange rates from Datastream and LIBOR short rates from Bloomberg, covering the following 10 currencies: Australia, Canada, Germany (spliced with the Euro), Japan, New Zealand, Norway, Sweden, Switzerland, U.K., and U.S. The data cover the period January, 1979 to July, 2011, where the minimum number of currencies is 7 at any point in time and all 10 currencies are available after 1980.

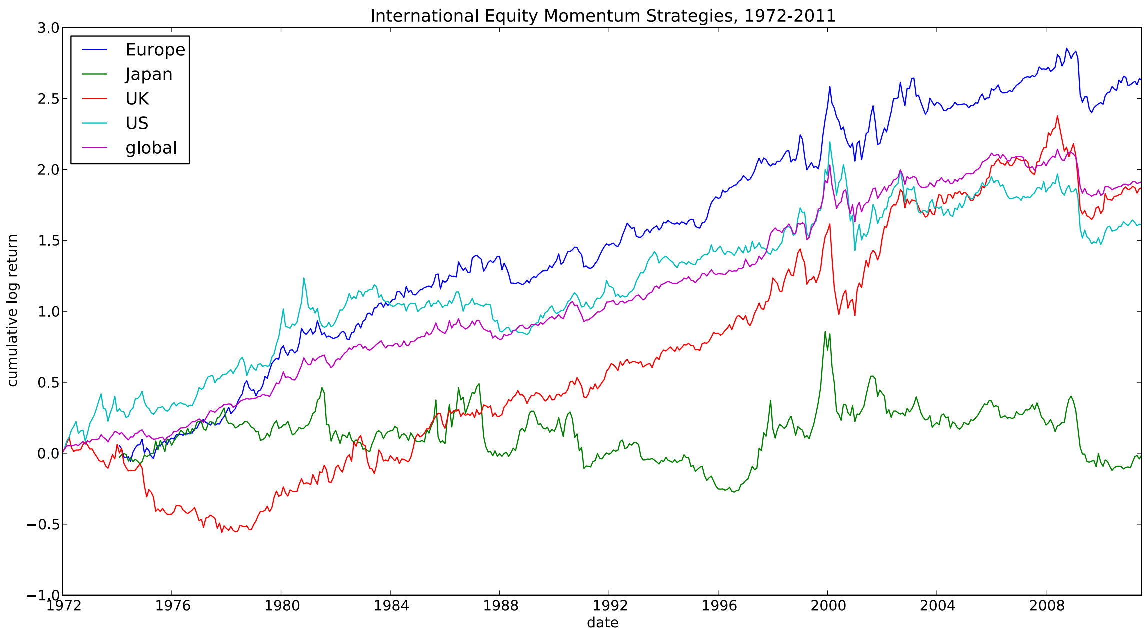
For country government bonds, we get data on bond index returns from Datastream. We obtain government bond data for the following 10 countries: Australia, Canada, Denmark, Germany, Japan, Norway, Sweden, Switzerland, U.K., and U.S. The sample of returns covers the period January, 1982 to July 2011, where the minimum number of country bond returns is 6 at any point in time and all 10 country bonds are available after 1990.

For commodities, we use 27 different commodity futures. Our data on Aluminum, Copper, Nickel, Zinc, Lead, Tin is from London Metal Exchange (LME), Brent Crude, Gas Oil is from Intercontinental Exchange (ICE), Live Cattle, Feeder Cattle, Lean Hogs is from Chicago Mercantile Exchange (CME), Corn, Soybeans, Soy Meal, Soy Oil, Wheat is from Chicago Board of Trade (CBOT), WTI Crude, RBOB Gasoline, Heating Oil, Natural Gas is from New York Mercantile Exchange (NYMEX), Gold, Silver is from New York Commodities Exchange (COMEX), Cotton, Coffee, Cocoa, Sugar is from New York Board of Trade (NYBOT), and Platinum from Tokyo Commodity Exchange (TOCOM). The commodities sample covers the period January, 1972 to July, 2011, with the minimum number of commodities being 10 at any point in time and all 27 commodities available after 1980.

As with our cross-sectional equity strategies, the definition of the market index is different for each asset class. It is the MSCI WORLD for country index futures, an equal-weighted average of all country bonds for bond markets, an equal-weighted average of all currencies for currency markets, and the GSCI for commodities.

5.2 Cross Section Equity Momentum outside the US

Figure 9: **Equity Market Momentum - Cumulative Returns**
This Figure presents the cumulative returns to momentum strategies in Continental Europe, Japan, the UK, the US. We also present the cumulative return to a Global strategy.



We begin by examining the time variation of momentum effects in international equity markets. We form zero-investment momentum portfolios in each region. Specifically, in each region, all stocks are sorted on the cumulative return from 12 months prior to the formation date to 1 month prior to the formation date (*i.e.*, they are 12-2 momentum portfolios), The momentum return we calculate is difference between the return to a value-weighted portfolio of the top one-third of names, and a value-weighted portfolio of the bottom one-third of names.

Figure 9 presents the cumulative returns to these momentum strategies. Several key features are evident from this plot. First, consistent with the results in other studies, over this time period there are strong momentum effect in each of the regions except Japan. Second, there is significant co-movement across the strategies, but they are not perfectly correlated.[21]. Over this time period, the pairwise correlations across the four markets range from 29% (UK/Japan) to 53% (US/Europe).

Panels A, B and C of Table 8 presents the results of regressions similar to those run in Section XX of this paper. Panel A shows presents the estimated coefficients and t-statistics from:

$$\tilde{R}_t^{mom} = (\alpha_0 + \alpha_B I_B) + (\beta_0 + \beta_B I_B)\tilde{R}_{m,t}^e + \tilde{\epsilon}_t. \tag{3}$$

As noted earlier, in each regression, the excess market portfolio returns used corresponds to the US dollar return of stock market within in which the momentum strategy is constructed, net of the treasury-bill rate.

Consistent with the results presented earlier, the market betas of the momentum strategy are dramatically lower in bear markets. Also, the abnormal return of the momentum strategies – significant in bull-markets, is lower in bear markets across in each region. However, while the directions are consistent the differences are not statistically significant over this shorter period.

Panel B investigates the optionality in the momentum strategy in bear markets. The regression here is:

$$\tilde{R}_t^{\text{mom}} = (\alpha_0 + \alpha_B I_B) + (\beta_0 + I_B[\beta_B + \tilde{I}_U \beta_{B,U}])\tilde{R}_{m,t}^e + \tilde{\epsilon}_t. \tag{4}$$

Consisitent with the long-period US results, there is statistically significant optionality in each region except the US. Again, because these are equity market strategies, this is consistent with a Merton (1974) theory. Common stocks that have lost significant value, particularly in bear market, are like out of the money call options on the firm, and consequently should exhibit option-like behavior.

Finally, in Panel C, we add an the realized market variance over the preceding 6 months, demeaned and lagged by a month:[22]

$$\tilde{R}_t^{\text{mom}} = [\alpha_0 + \alpha_B I_B + \alpha_V \hat{\sigma}_m^2] + [\beta_0 + \beta_B I_B + \beta_V \hat{\sigma}_m^2]\tilde{R}_{m,t}^e + \tilde{\epsilon}_t. \tag{5}$$

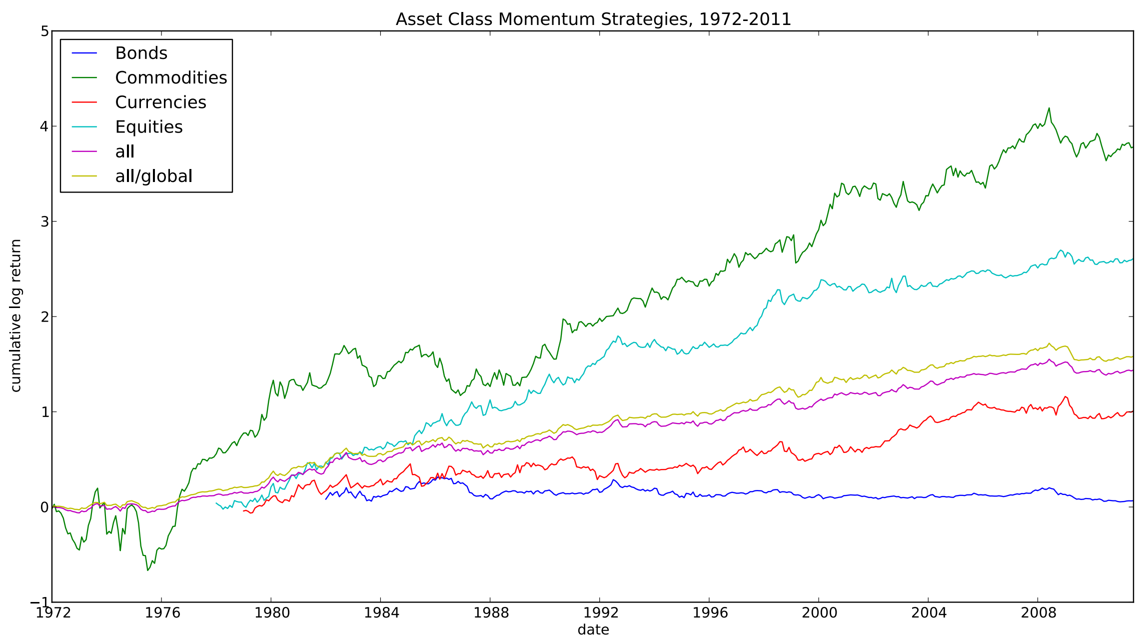
[21]See Asness, Moskowitz, and Pedersen (2008)

[22]This is consistent with the market variance measure used earlier in this paper, though in the rest of the paper we construct this measure with daily rather monthly data.

Two interesting results are apparent here. First, higher *ex-ante* market variance is generally associated with more negative momentum strategy betas. Second, higher variance is also associated with lower future returns to momentum. This last relation is statistically significant in all markets, and again is consistent with our earlier results for the US market over the longer period.

5.3 Momentum in Other Asset Classes

Figure 10: **Momentum in Other Asset Classes - Cumulative Returns**
This Figure presents the cumulative returns to momentum strategies in Continental Europe, Japan, the UK, the US. We also present the cumulative return to a Global strategy.



We now examine momentum effects in other asset classes. Again, we form zero-investment momentum portfolios in each asset class. As with the other momentum portfolios in this section, we first sort all assets within an asset class on the basis of their cumulative return from 12 months prior to the formation date to 1 month prior to the formation date (*i.e.,* they are 12-2 portfolios).[23] The momentum return we calculate is difference between the return to a equal-weighted portfolio of the top one-third of names, and a equal-weighted portfolio of the bottom one-third of names.

[23]The assets comprising each asset class are listed in Section 5.1.2.

Table 8: **Time Series Regressions for International Equity Markets**

This table below reports the estimated coefficients and t-statistics from regressions of the monthly returns to zero-investment equity momentum strategies in each region on the indicated set of RHS variables. In Panels A, B, and C we report the results of estimating equations (3), (4), and (5) respectively.

Vars.	Europe	Japan	UK	US	global
Panel A					
1	0.007	0.002	0.006	0.005	0.005
	(3.4)	(0.5)	(2.7)	(1.9)	(3.6)
I_B	-0.004	-0.001	-0.007	-0.001	-0.004
	(-0.8)	(-0.3)	(-1.3)	(-0.2)	(-1.3)
$\tilde{R}^e_m$	0.072	0.251	0.025	0.171	0.032
	(1.6)	(4.8)	(0.6)	(2.9)	(0.9)
$\mathrm{I}_B \cdot \tilde{R}^e_m$	-0.525	-0.531	-0.206	-0.613	-0.284
	(-6.9)	(-6.9)	(-3.2)	(-6.4)	(-4.6)
Panel B					
1	0.007	-0.001	0.006	0.003	0.005
	(3.0)	(-0.3)	(2.6)	(1.2)	(3.2)
I_B	0.012	0.013	0.004	0.005	0.005
	(1.8)	(1.8)	(0.6)	(0.5)	(1.0)
$\tilde{R}^e_m$	0.075	0.248	0.026	0.167	0.029
	(1.7)	(4.7)	(0.6)	(2.9)	(0.8)
$\mathrm{I}_B \cdot \tilde{R}^e_m$	-0.305	-0.284	0.016	-0.556	-0.092
	(-2.6)	(-2.0)	(0.1)	(-3.2)	(-0.9)
$\mathrm{I}_B\mathrm{I}_U\tilde{R}^e_m$	-0.443	-0.392	-0.329	-0.085	-0.338
	(-2.5)	(-2.1)	(-2.2)	(-0.3)	(-2.2)
Panel C					
1	0.010	0.005	0.009	0.008	0.007
	(4.2)	(1.4)	(3.5)	(3.2)	(4.7)
I_B	0.003	0.002	-0.001	0.007	0.002
	(0.5)	(0.4)	(-0.1)	(1.2)	(0.4)
σ^2_m	-0.143	-0.150	-0.141	-0.197	-0.116
	(-2.7)	(-2.3)	(-2.3)	(-3.3)	(-3.1)
$\tilde{R}^e_m$	0.109	0.242	0.069	0.216	0.052
	(2.4)	(4.4)	(1.6)	(3.6)	(1.4)
$\mathrm{I}_B \cdot \tilde{R}^e_m$	-0.372	-0.539	-0.092	-0.523	-0.201
	(-4.3)	(-6.8)	(-1.2)	(-5.0)	(-2.8)
$\sigma^2_m \cdot \tilde{R}^e_m$	-1.787	0.449	-2.390	-1.836	-1.011
	(-3.0)	(0.5)	(-2.9)	(-2.1)	(-1.9)

Figure 10 plots the cumulative log returns to each of the strategies. Every strategy except the bond strategy produces returns that are different from zero at conventional signficance levels. The annualized Sharpe ratios range are 0.35, 0.52 and 0.72 for the currency, commodity, and country-equity momentum strategy. Moreover, the correlations between the momentum strategies are quite low, ranging from 6.7% (currency/commodity) to 21.6% (commodity/equity).

The "all" strategy is an equal volatility weighted average portfolio across the four asset classes. The "all+stock" portfolio combines the four asset-class and the four international equity momentum strategies. Over this sample period, the Sharpe ratios of these strategies are 0.66 and 0.76 respectively.

Table 9 presents the results of time series regressions for the asset-class momentum strategies. Panels A, B, and C we report the results of estimating equations (3), (4), and (5) respectively. The excess market return we use here is, for each asset class, the equal-weighted average of the US dollar returns of the assets comprising that asset class, net of the treasury-bill rate.

The patterns revealed in Table 9 are similar to what we see in international equities. First, and not surprisingly, the set of $\mathrm{I}_B \cdot \tilde{R}^e_m$ coefficient and t-statistics in the last row of Panel A show that, in all asset classes, the momentum portfolio's market beta is significantly more negative in bear markets. The intuition that, following a bear market, the loser side of the momentum portfolio will have a high market beta is valid for other asset classes as well.

The I_B coefficients in the second row of Panel A provide evidence is weakly consistent with the earlier finding that market-risk adjusted momentum returns are lower following bear markets. The point estimates are all negative, except for Bonds, but only in the currency market is the I_B coefficient statistically significant.

The set of regressions in Panel B help to assess whether the optionality present in cross-sectional equity momentum strategies is also present here. The $\mathrm{I}_B\tilde{\mathrm{I}}_U\tilde{R}^e_m$ coefficient is negative for all asset classes, and is statistically significant for currencies and commodities, and for the combination portfolio. This result is intriguing. While a model such as Merton (1974) would argue that equities would exhibit option-like features, it is not clear that such a model would easily explain the optionality present

Table 9: **Time Series Regressions for other Asset Classes**

The table below reports the results of regressing the returns to zero-investment momentum strategies for each asset class on the indicated set of RHS variables. In Panels A, B, and C we report the results of estimating equations (3), (4), and (5) respectively.

Vars.	Bonds	Commodities	Currencies	Equities	all	all+stock
Panel A						
1	0.000	0.012	0.005	0.008	0.004	0.004
	(0.4)	(3.2)	(3.0)	(4.0)	(4.4)	(5.0)
I_B	0.000	-0.007	-0.009	-0.001	-0.002	-0.003
	(0.1)	(-1.1)	(-3.1)	(-0.4)	(-1.0)	(-1.3)
$\tilde{R}^e_m$	0.247	0.276	0.270	0.280	0.148	0.080
	(3.8)	(3.6)	(3.1)	(6.1)	(2.4)	(1.8)
$\mathrm{I}_B \cdot \tilde{R}^e_m$	-0.423	-0.709	-0.984	-0.642	-0.472	-0.365
	(-2.8)	(-4.3)	(-7.5)	(-8.6)	(-3.7)	(-4.4)
Panel B						
1	-0.002	0.009	0.003	0.005	0.002	0.003
	(-1.5)	(2.4)	(1.7)	(2.4)	(2.3)	(3.4)
I_B	0.005	0.017	0.008	0.010	0.008	0.007
	(1.5)	(1.8)	(2.0)	(2.1)	(2.7)	(2.3)
$\tilde{R}^e_m$	0.287	0.288	0.302	0.283	0.183	0.094
	(4.5)	(3.7)	(3.4)	(6.1)	(2.8)	(2.1)
$\mathrm{I}_B \cdot \tilde{R}^e_m$	-0.346	0.040	-0.498	-0.474	0.260	-0.024
	(-0.9)	(0.1)	(-1.8)	(-4.2)	(0.8)	(-0.2)
$\mathrm{I}_B \mathrm{I}_U \tilde{R}^e_m$	-0.211	-1.327	-0.889	-0.338	-1.138	-0.692
	(-0.4)	(-2.6)	(-2.4)	(-1.9)	(-2.7)	(-3.2)
Panel C						
1	0.001	0.013	0.006	0.008	0.004	0.005
	(1.2)	(3.2)	(2.8)	(3.8)	(4.4)	(5.5)
I_B	-0.000	-0.007	-0.009	-0.001	-0.001	0.000
	(-0.0)	(-1.0)	(-3.0)	(-0.2)	(-0.4)	(0.0)
σ^2_m	-0.029	-0.059	-0.013	-0.020	-0.025	-0.049
	(-1.4)	(-0.7)	(-0.4)	(-0.5)	(-1.2)	(-2.3)
$\tilde{R}^e_m$	0.290	0.250	0.267	0.300	0.188	0.109
	(3.7)	(2.7)	(2.9)	(6.2)	(2.7)	(2.3)
$\mathrm{I}_B \cdot \tilde{R}^e_m$	-0.448	-0.718	-0.987	-0.585	-0.360	-0.238
	(-2.9)	(-4.1)	(-7.3)	(-7.0)	(-2.6)	(-2.4)
$\sigma^2_m \cdot \tilde{R}^e_m$	-1.145	0.876	0.173	-0.957	-1.558	-1.363
	(-0.8)	(0.5)	(0.2)	(-1.4)	(-1.5)	(-1.9)

in currency and commodity markets.

The final panel of Table 9 estimates equation (5) for the other-asset-class momentum strategies. Here the signs in the relation between lagged volatility and momentum strategy returns are again negative in each of the four asset classes. However, over this sample period the results are statistically significant only for the "all+stock" portfolio that combines all momentum strategies.

6 Conclusions and Future Work

In "normal" environments, the market appears to underreact to public information, resulting in consistent price momentum. This effect is both statistically and economically strong. We see momentum manifested not only in equity markets, but across a wide range of asset classes.

However, in extreme market enviroments, the market prices of past losers embody a very high premium. When market conditions ameliorate, these losers experience strong gains, resulting in a "momentum crash." We find that, in bear market states, and in particular when market volatility is high, the down-market betas of the past-losers are low, but the up-market betas are very large. This optionality does not apper to generally be reflected in the prices of the past losers. Consequently, the expected returns of the past losers are very high, and the momentum effect is reversed.

The effects are loosely consistent with several behavioral findings.[24] In extreme situations, where individuals are fearful, they appear to focus on losses, and probabilities are largely ignored. Whether this behavioral phenomenon is fully consistent with the empirical results documented here is a subject for further research..

[24]See Sunstein and Zeckhauser (2008), Loewenstein, Weber, Hsee, and Welch (2001), and Loewenstein (2000)

Appendicies

A Detailed Description of Calculations

A.1 Cumulative Return Calculations

The cumulative return, on an (implementable) strategy is an investment at time 0, which is fully reinvested at each point – *i.e.*, where no cash is put in or taken out, That is the cumulative arithmetic returns between times t and T is denoted $R(t,T)$.

$$R(t,T) = \prod_{s=t+1}^{T} (1 + R_s) - 1,$$

where R_s denotes the arithmetic return in the period ending at time t, where $r_s = log(1 + R_s)$ denotes the log-return over period s,

$$r(t,T) = \sum_{s=t+1}^{T} r_s.$$

For long-short portfolios, the cumulative return is:

$$R(t,T) = \prod_{s=t+1}^{T} (1 + R_{L,s} - R_{S,s} + R_{f,t}) - 1,$$

where the terms $R_{L,s}$, $R_{S,s}$, and $R_{f,s}$ are, respectively, the return on the long side of the portfolio, the short side of the portfolio, and the risk-free rate. Thus, the strategy reflects the cumulative return, with an initial investment of V_t, which is managed in the following way:

1. Using the $\$V_0$ as margin, you purchase $\$V_0$ of the long side of the portfolio, and short $\$V_0$ worth of the short side of the portfolio. Note that this is consistent with Reg-T requirements. Over each period s, the margin posted earns interest at rate $R_{f,s}$.
2. At then end of each period, the value of the investments on the long and the short side of the portfolio are adjusted to reflect gains to both the long and short side of the portfolio. So, for example, at the end of the first period, the

> investments in both the long and short side of the portfolio are adjusted to set their value equal to the total value of the portfolio to $V_{t+1} = V_t \cdot (1 + R_L - R_S + R_f)$.

Note that, for monthly returns, this methodology assumes that there are no margin calls, etc, except at the end of each month. These calculated returns do not incorporate transaction costs.

References

Asness, Clifford S., John M. Liew, and Ross L. Stevens, 1997, Parallels between the cross-sectional predictability of stock and country returns, *Journal of Portfolio Management* 23, 79–87.

Asness, Clifford S., Toby Moskowitz, and Lasse Pedersen, 2008, Value and momentum everywhere, University of Chicago working paper.

Bandarchuk, Pavel, and Jens Hilscher, 2011, Sources of momentum profits: Evidence on the irrelevance of characteristics, Working Paper – Brandeis University, Department of Economics and International Businesss School.

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics* 49, 307–343.

Boguth, Oliver, Murray Carlson, Adalai Fisher, and Mikhail Simutin, 2010, Conditional risk and performance evaluation: Volatility timing, overconditioning, and new estimates of momentum alphas, *Journal of Financial Economics, forthcoming*.

Brunnermeier, Markus K., Stefan Nagel, and Lasse H. Pedersen, 2008, Carry trades and currency crashes, *NBER Macroeconomics Annual*.

Campbell, John Y., Jens Hilscher, and Jan Szilagyi, 2008, In search of distress risk, *The Journal of Finance* 63, 2899–2939.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Chan, K.C., 1988, On the contrarian investment strategy, *Journal of Business* 61, 147–163.

Cooper, Michael J., Roberto C. Gutierrez, and Allaudeen Hameed, 2004, Market states and momentum, *Journal of Finance* 59, 1345–1365.

Daniel, Kent D., David Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor psychology and security market under- and over-reactions, *Journal of Finance* 53, 1839–1886.

——— , 2001, Overconfidence, arbitrage, and equilibrium asset pricing, *Journal of Finance* 56, 921–965.

Daniel, Kent D., and Sheridan Titman, 2011, Testing factor-model explanations of market anomalies, Columbia Business School Working Paper.

DeBondt, Werner F. M., and Richard H. Thaler, 1987, Further evidence on investor overreaction and stock market seasonality, *Journal of Finance* 42, 557–581.

Erb, Claude B., and Campbell R. Harvey, 2006, The strategic and tactical value of commodity futures, *Financial Analysts Journal* 62, 69–97.

Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427–465.

———, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

———, 1996, Multifactor explanations of asset pricing anomalies, *Journal of Finance* 51, 55–84.

Frazzini, Andrea, 2006, The disposition effect and underreaction to news, *Journal of Finance* 61, 2017–2046.

George, Thomas J., and Chuan-Yang Hwang, 2004, The 52-week high and momentum investing, *The Journal of Finance* 59, 2145–2176.

Grinblatt, Mark, and Bing Han, 2005, Prospect theory, mental accounting and momentum, *Journal of Financial Economics* 78, 311–339.

Grinblatt, Mark, and Sheridan Titman, 1989, Mutual fund performance: an analysis of quarterly portfolio holdings, *Journal of Business* 62, 393–416.

———, 1993, Performance measurement without benchmarks: An examination of mutual fund returns, *Journal of Business* 66, 47–68.

Grundy, Bruce, and J. Spencer Martin, 2001, Understanding the nature of the risks and the source of the rewards to momentum investing, *Review of Financial Studies* 14, 29–78.

Hansen, Lars P., and Ravi Jagannathan, 1991, Implications of security market data for models of dynamic economies, *Journal of Political Economy* 99, 225–262.

Henriksson, Roy D., and Robert C. Merton, 1981, On market timing and investment performance. II. Statistical procedures for evaluating forecasting skills, *Journal of Business* 54, 513–533.

Hong, Harrison, and Jeremy C. Stein, 1999, A unified theory of underreaction, momentum trading and overreaction in asset markets, *Journal of Finance* 54, 2143–2184.

Jagannathan, Ravi, and Robert A. Korajczyk, 1986, Assessing the market timing performance of managed portfolio, *Journal of Business* 59, 217–235.

Jegadeesh, Narasimhan, 1990, Evidence of predictable behavior of security returns, *Journal of Finance* 45, 881–898.

———, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65–91.

——— , 2001, Profitability of momentum strategies: An evaluation of alternative explanations, *Journal of Finance* 56, 699–720.

Loewenstein, George, Elke U. Weber, Chris K. Hsee, and Ned Welch, 2001, Risk as Feelings, *Psychological bulletin* 127, 267–286.

Loewenstein, George F., 2000, Emotions in economic theory and economic behavior, *American Economic Review* 65, 426–432.

Merton, Robert C., 1974, On the pricing of corporate debt: The risk structure of interest rates, *The Journal of Finance* 29, 449–470.

——— , 1990, Capital market theory and the pricing of financial securities, in *Handbook of Monetary Economics* (North-Holland: Amsterdam).

Moskowitz, Tobias J., and Mark Grinblatt, 1999, Do industries explain momentum?, *The Journal of Finance* 54, 1249–1290.

Moskowitz, Tobias J., Yoa Hua Ooi, and Lasse H. Pedersen, 2010, Time series momentum, University of Chicago Working Paper.

Okunev, John, and Derek White, 2003, Do momentum-based strategies still work in foreign currency markets?, *Journal of Financial and Quantitative Analysis* 38, 425–447.

Rouwenhorst, K. Geert, 1998, International momentum strategies, *Journal of Finance* 53, 267–284.

——— , 1999, Local return factors and turnover in emerging stock markets, *Journal of Finance* 54, 1439–1464.

Sunstein, Cass R., and Richard Zeckhauser, 2008, Overreaction to fearsome risks, Harvard University Working Paper.