Trend Following: Equity *and* Bond Crisis Alpha

CARL HAMILL, SANDY RATTRAY and OTTO VAN HEMERT[1]

This version: August 30th, 2016

ABSTRACT

We study time-series momentum (trend-following) strategies in bonds, commodities, currencies and equity indices between 1960 and 2015. We find that momentum strategies performed consistently both before and after 1985, periods which were marked by strong bear and bull markets in bonds respectively. We document a number of important risk properties. First, that returns are positively skewed, which we argue is intuitive by drawing a parallel between momentum strategies and a long option straddle strategy. Second, performance was particularly strong in the worst equity and bond market environments, giving credence to the claim that trend-following can provide equity *and* bond crisis alpha. Putting restrictions on the strategy to prevent it being long equities or long bonds has the potential to further enhance the crisis alpha, but reduces the average return. Finally, we examine how performance has varied across momentum strategies based on returns with different lags and applied to different asset classes.

Keywords: trend following, momentum, crisis alpha, skewness

JEL codes: E32, E44, G11, G12, G14

[1] Hamill, Rattray and Van Hemert are at Man AHL. The authors would like to thank Nick Granger, Campbell Harvey, Anthony Ledford, Matthew Sargaison and Tim Wong for valuable comments. Please direct correspondence to: ovanhemert@ahl.com.

Introduction

Over the last few years we have seen futures trend following being used as a tool for institutional investors looking for "crisis alpha".[2] For investors this means a strategy that can be expected to deliver outperformance during (typically equity) market stress periods. In this paper we address three questions:

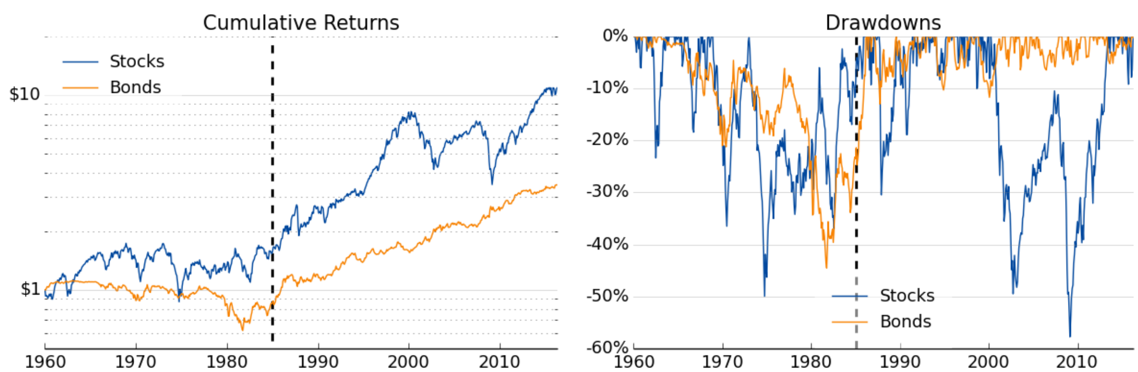
- *First,* should we expect futures trend following to be profitable in an environment where government bond yields rise?
- *Second,* are the protection characteristics of trend following confined to equities, or do they work in government bonds as well?
- *Third,* is it possible to improve the protection characteristics of a futures momentum strategy by removing the ability to be long equities or bonds?

Backdrop

Government bonds have experienced an extended bull market since 1985. This is illustrated in the left panel of Figure 1, where we plot the cumulative excess return of US 10-year Treasuries (yellow line) and the US S&P 500 index (blue line), relative to the US T-bill rate. This shows a near straight line up for bonds since 1985. The right panel of Figure 1 plots the drawdown level, which rarely exceeded 10% for bonds in the post-1985 period. A trend following strategy would have benefitted from the consistent upward trend after 1985 by holding a (predominantly) long bonds position.

Figure 1: stock and bond market cumulative excess returns and drawdowns since 1960

The figure shows in the left panel the cumulative returns of stocks (S&P 500 index) and bonds (US 10y Treasury), in excess of the US T-Bill rate. The right panel shows the drawdown relative to the highest cumulative return achieved to date for both stocks and bonds. The data period is January 1960 to December 2015 and the dashed, vertical line separates the pre- and post-1985 period.



The strong bond performance was driven by significant rates compression. US yields fell from almost 16% in the early 1980s, to below 2% as at March 2016. Many economists believe yields cannot fall much further, even though slightly negative yields are possible, as we have seen recently in several developed

[2] Kaminski (2011) defines crisis alpha as "profits which are gained by exploiting the persistent trends that occur across markets during times of crisis".

Electronic copy available at: http://ssrn.com/abstract=2831926

markets. So it is natural to ask if trend-following strategies can maintain performance in the absence of a bond market tailwind, and indeed if they can protect against stress in bond markets of the form seen in the 1960s, 70s and early 80s.

Outline

In this paper we seek to shed light on these questions by studying trend-following strategies from 1960 onwards. Importantly, this includes the pre-1985 period, which shows a starkly different picture compared to post-1985. Over the 1960-1985 period bonds experienced negative excess returns on average, while stock markets provided modest positive average excess returns and quite frequent drawdowns (Figure 1).

We start by discussing the data available to us in Section 1, followed by the definition of a straightforward momentum strategy in Section 2. Extending our analysis back to 1960 requires us to use monthly data and augment the available history of futures and forward returns with proxies based on cash returns, financed at the local short-term rate.

In Section 3, we show that strategies based on the past four months' returns (lag 1 to 4) experienced consistently strong performance, as do strategies based on returns of almost a full year ago (lag 9 to 11). However, strategies based on returns at the intermediate horizon (lag 5 to 8) underperformed consistently, over time and across asset classes. Next, we form a strategy that (within our framework) best explains the representative BTOP50 managed futures index (which we refer to as "*momCTA")* and find that this replicating strategy puts almost all weight on lags 1 to 4, thus largely ignoring the predictability of lags 9 to 11.

Next, we show that *momCTA* inherits two important risk characteristics that are particularly associated with momentum strategies based on recent returns. First, in Section 4, we show that *momCTA* has positively skewed returns, in particular when returns are evaluated over multiple months (we specifically consider 3 and 12-month evaluation windows). We argue this result is intuitive and related to the property of adding to winners and cutting losers, which is similar to the dynamic replication of a long option straddle position.

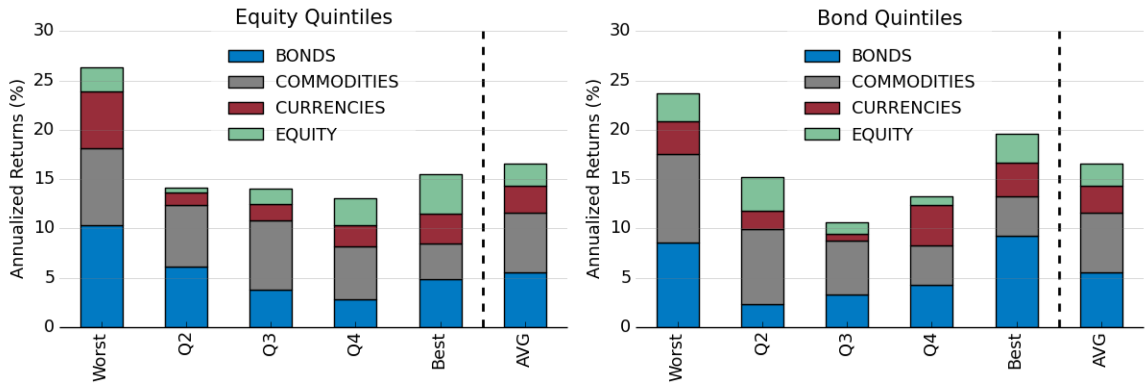
Then, in Section 5, we show that *momCTA* performed particularly well in the worst equity and bond market environments, giving credence to a claim that trend-following can provide equity *and* bond crisis alpha. This is illustrated in Figure 2, which shows the average annualized *momCTA* return for rolling 3-month windows for different equity (left panel) and bond (right panel) market return quintiles. Performance was not only strong in the worst, but also in the best equity and bond market environments, revealing a well-known "equity smile" and a lesser-known, but even more pronounced "bond smile".

We find that the equity and bond crisis alpha was further enhanced when restricting the equity and bond position to be non-positive. This comes at the cost of lower general performance and unfavorable cross-market effects, however. Indeed we find that a non-positive equity (bond) restriction worsened the performance during a bond (equity) market decline.

Finally, in Section 6, we provide concluding remarks.

Figure 2: *momCTA* performance, equity and bond quintiles, rolling 3m window

The figure shows the annualized average *momCTA* return for rolling 3-month windows, attributed to the four asset classes covered, under different general equity and bond market conditions. In the left panel the results are reported for equity market quintiles, with quintile 1 corresponding to the worst 3-month S&P 500 returns and quintile 5 to the best. The right-most bar corresponds to the average return across all periods. Similarly, the right panel shows results for different bond market (US Treasury) quintiles. Returns do not include interest income, i.e. can be considered excess returns, and are gross of transaction costs and fees. The measurement period is January 1960 to December 2015.



1. Data

Extending the sample period to start in 1960 comes with its challenges. Many other papers that have looked at trend-following strategies start later. Moskowitz, Ooi and Pedersen (2012), for example, evaluate trend following strategies from 1985 onwards "to ensure that a comprehensive set of instruments have data". We believe that starting in 1960 strikes the right balance for our research question. Starting earlier than 1960 is problematic for commodities, as one either has to omit the asset class before 1960, rely on imperfect and only intermittently available data, or rely on spot returns thus ignoring the roll yield component of return.[3] Starting in 1960 provides an opportunity to study the worst bond market drawdown the US experienced since at least 1900, as the 10-year yield rose from below 5% in 1960 to a peak of almost 16% in the early 1980s.

In Table 1, we provide an overview of the securities used in our analysis, and report the start date and some summary statistics. While we start the evaluation of momentum strategies in 1960, our data start as early as 1950 to allow for a so-called warm-up period for obtaining volatility and correlation risk estimates needed in the strategy construction. For securities with data starting after 1960 only, we maintain a warm-up period of one year so that they are included in the momentum strategy return one year after the reported data start date.

[3] Some white papers have accepted such simplifying assumptions for commodities (as well as other simplifying assumptions for the other asset classes) and studied trend following strategies over multiple centuries. Examples include Hurst, Ooi and Pedersen (2012), Lempérière et al (2014), and Greyserman (2012), who start their analysis in 1903, 1800 and 1300 respectively.

Table 1: Data

This table provides the start date for the securities used in this paper, as well as some descriptive statistics. The Euro (EUR/USD) is augmented with the Deutsche Mark prior to the January 1999 introduction of the Euro.

	Cash start date	Futures/forwards start date	Mean (annualized)	Standard deviation (annualized)	Skewness	Kurtosis
BONDS						
Australian 10yr Bond	Jan-77	Dec-84	0.21%	3.60%	-0.45	23.48
Canadian 10yr Bond	Jan-50	Feb-90	1.68%	6.31%	0.25	6.12
French 10yr Bond (OAT)	Jan-50	Jun-12	2.17%	5.68%	-0.29	5.50
German 10yr Bond (Bund)	Jan-50	Jun-83	3.08%	5.10%	-0.33	1.95
Italian 10yr Bond (BTP)	Jan-50	Sep-11	2.72%	10.14%	0.40	2.26
Japanese 10yr Bond (JGB)	Jan-72	Mar-83	3.16%	5.86%	0.13	6.39
UK 10yr Bond (Gilts)	Jan-50	Nov-82	1.85%	6.32%	0.25	3.00
US 2yr Treasury Note	Jan-50	Jul-05	0.83%	2.70%	0.71	12.16
US 5yr Treasury Note	Jan-50	Oct-91	1.52%	5.06%	0.24	6.12
US 10yr Treasury Note	Jan-50	May-82	1.87%	6.80%	0.43	3.86
US 30yr Treasury Bond	Jan-50	Sep-77	1.84%	9.80%	0.27	3.40
COMMODITIES - AGRICULTURALS						
Cocoa (CSCE)	N/A	Sep-59	3.76%	30.68%	0.65	1.40
Coffee (CSCE)	N/A	Aug-73	4.73%	37.20%	1.22	4.24
Corn	N/A	Jul-59	-2.06%	23.66%	1.20	6.57
Cotton	N/A	Jul-59	2.58%	23.29%	0.68	3.49
Lean Hogs	N/A	Sep-69	3.45%	26.00%	0.24	1.23
Live Cattle	N/A	Nov-64	4.76%	16.95%	-0.29	2.11
Soyabeans	N/A	Jul-59	5.58%	25.66%	1.56	10.81
Soyameal	N/A	Jul-59	9.79%	30.29%	1.94	13.86
Soyaoil	N/A	Mar-68	7.57%	31.38%	1.42	6.64
Sugar (CSCE)	N/A	Jan-61	0.55%	42.53%	1.10	2.99
Wheat	N/A	Jul-59	-1.59%	24.89%	0.72	3.29
COMMODITIES - ENERGIES						
Brent Crude Oil	N/A	Jun-88	13.05%	34.42%	0.47	3.13
Gas Oil	N/A	Apr-81	8.41%	31.73%	0.49	2.03
Heating Oil	N/A	Mar-79	7.97%	32.88%	0.70	3.22
Natural Gas	N/A	Apr-90	-5.70%	54.36%	1.82	10.71
RBOB Gasoline	N/A	Dec-84	16.42%	36.43%	0.43	2.52
WTI Crude Oil	N/A	Oct-83	7.29%	33.35%	0.25	2.04
COMMODITIES - METALS						
Aluminium (LME)	N/A	Jan-80	-2.10%	22.21%	1.00	4.23
Copper (COMEX)	N/A	Jul-59	10.06%	27.32%	0.36	3.41
Gold	N/A	Dec-74	1.43%	19.30%	0.39	3.27
Nickel	N/A	Jul-79	7.04%	34.74%	1.44	9.15
Palladium	N/A	Nov-05	11.62%	32.63%	-0.15	3.92
Platinum	N/A	Mar-68	4.31%	27.77%	0.36	4.46
Silver	N/A	Jan-72	4.58%	32.39%	0.65	4.85
Zinc	N/A	Jan-75	1.97%	24.65%	-0.02	1.33
CURRENCIES						
AUD/USD	Jan-73	Jan-75	2.02%	10.83%	-0.76	3.77
CAD/USD	Jan-73	Jan-77	0.48%	6.64%	-0.88	7.83
EUR/USD	Jan-73	Jan-75	1.25%	12.14%	0.37	2.51
JPY/USD	Jan-73	Nov-76	0.82%	14.69%	2.41	25.44
NZD/USD	Jan-73	Dec-88	2.63%	9.18%	-0.34	3.68
NOK/USD	Jan-73	Dec-88	1.08%	9.38%	-0.24	1.96
SEK/USD	Jan-73	Dec-88	0.71%	10.07%	-0.40	2.64
CHF/USD	Jan-73	Feb-75	2.78%	14.91%	1.57	12.22
GBP/USD	Jan-73	Feb-75	1.07%	10.18%	0.06	2.19
EQUITIES						
Australian SPI200 Index	Jan-50	Mar-83	7.08%	16.61%	-1.15	11.34
CAC 40	Jan-50	Nov-88	6.68%	18.87%	-0.10	1.17
Dax Index	Sep-59	Nov-90	3.75%	19.53%	-0.17	1.61
Dutch All Index	Dec-50	Oct-88	7.72%	17.82%	-0.42	2.10
FTSE	Jan-50	May-84	6.67%	18.22%	0.84	14.14
Ibex 35 Index	Jan-50	Jan-92	6.19%	18.79%	-0.09	2.06
Italy All Index	Jan-50	Dec-94	5.16%	23.10%	0.40	2.08
S&P 500 Index	Jan-50	Apr-82	6.99%	14.41%	-0.37	1.35
S&P Canada 60 Index	Jan-50	May-87	5.74%	15.22%	-0.67	2.39
Tokyo Stock Exchange Index	Jan-50	Jul-92	8.23%	18.89%	0.02	1.31

For commodities we have data on various agricultural futures contracts and some metals going back to the 1960s. The first oil futures contract, however, was only introduced in the early 1980s. For currencies we have data from 1973 onwards only. Before that, from 1944 to 1971, the rules of Bretton Woods provided a system of fixed exchange rates which led to limited exchange rate moves and an unsuitable investment environment. For the initial years we use spot exchange rates, corrected for the short-rate differential to make it comparable to futures returns. For equities and bonds we have monthly cash data going back well before 1960 from Global Financial Data for a number of countries. We deduct the local short rate from the return to make it comparable to the return of an unfunded instrument like a future. The equity and bond market data requires us to do our entire analysis based on monthly data.

As a general rule we use cash, and then futures or forwards data as soon as it is available. However, we make an exception for securities that are subject to market regulation that is so severe that the price hardly fluctuates, making those securities unsuitable for investment. Specifically, we filtered for securities for which the rolling 12-month volatility estimate at some point dropped to a level of 0.05 times the average 12-month volatility. Three securities were flagged. The first is silver, which we include only from 1972 onwards. Before that, silver prices did not fluctuate freely, as they were tied to the US monetary system until 1968 and in the years after that subject to Government intervention. The other two are the Japanese and Australian 10-year bonds which will only be included from 1972 and 1977 respectively, as before that price fluctuations were severely subdued due to a combination of capital controls, currency intervention, and other monetary policies.

2. A straightforward momentum strategy

As discussed in the previous section, extending the equity and bond data back to 1960 means we have to work with monthly rather than daily data. We consider the following general formula for the momentum signal of security *k*, observed at time *t-1*:

$$mom_{t-1}^{k} = \frac{w_1 R_{t-1}^{k} + w_2 R_{t-2}^{k} + \ldots}{\sigma_{t-1}^{k} \sqrt{w_1^2 + w_2^2 + \ldots}}, \qquad [1]$$

where:

- R_{t-i}^{k} is the monthly return of security *k* at lag *i*
- w_i is the weight given to lag *i*, which is assumed to be the same for all securities *k*
- σ_{t-1}^{k} is the standard deviation of monthly returns for security *k*, observed at time *t-1*[4]
- $\sqrt{w_1^2 + w_2^2 + \ldots}$ is to achieve a unit standard deviation (approximately) for the signal[5]

[4] We estimate the standard deviation of returns using exponentially decaying weights. We take the maximum of an estimate based on a half-life of 6 months and 0.5 times an estimate based on a half-life of 24 months, where the latter acts as a floor in case the volatility is temporarily very low.
[5] We also cap the signal value so that it is between -2 and 2, to prevent putting too much weight on outliers. We omit this step from the formula for ease of exposition.

In the next section we will consider different weights, *w*. The weights will typically be positive to capture momentum rather than reversal behavior and are required to sum to one.

The signal value indicates how many risk units one would want to hold in a security. To turn this into a dollar position, we need to divide by the volatility estimate a second time (so that all assets are trading the same amount of risk for a given strength signal). The strategy performance is then given by summing over the signal-volatility ratio times the next period return, while multiplying by a gearing factor to scale to a given risk target:

$$Performance_t = \sum_k Gearing_{t-1}^k \frac{mom_{t-1}^k}{\sigma_{t-1}^k} R_t^k \qquad [2]$$

The gearing factor is such that, on average, the resulting portfolio has an ex-ante annualized volatility estimate of 10%, and risk is spread equally over the four asset classes: bonds, commodities, currencies and equity. Within the equities, bonds and currencies, we allocate equal weights to the different constituent securities. Within commodities we give equal weight to the agriculture, metals and energies subsectors, and within these subsectors we give equal weight to the different constituent securities. For securities that only have data available at a later date, we redistribute the risk in the preceding period equally to the other securities in the same asset class.[6]

We use unfunded instruments for our security returns in this analysis (i.e. futures, forwards, or cash instruments financed at the local short rate). This means that the performance in Equation [2] should be interpreted as an excess return. If you wanted to know the total performance, you would add up the short rate, possibly with a haircut to reflect the fact that some margin needs to be posted and that the interest rate on the margin account may be below the short rate. Between 1960 and 2015, the US T-bill return and inflation rate averaged 4.8% and 3.9% respectively and, unsurprisingly, moved mostly in line with each other with a correlation of 0.72. An 18% haircut, which we think is not unreasonable, would equate the average interest income rate and inflation rate, and thus the excess returns reported can alternatively be considered as a reasonable proxy for the inflation-adjusted (real) return.

Finally, we ignore transaction costs and fees, which would impact the general profitability of momentum strategies, but less so the dynamics of momentum returns, which is the main focus of this paper. Assuming a two basis point transaction cost for outright trades leads to a reduction in the annualized return of 0.42% for the main strategy we will introduce (the *momCTA* strategy). This estimate is broadly in line with experience over current trading conditions for a medium-term trend strategy, while it is harder to make statements about earlier periods.

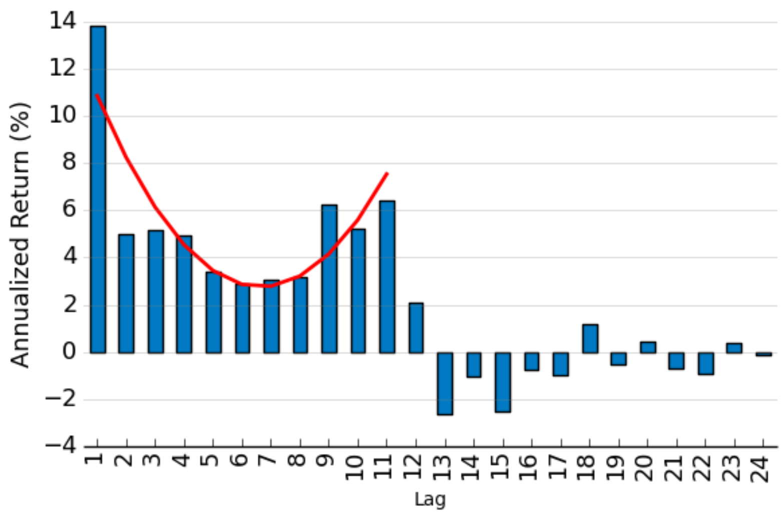
[6] The gearing process starts with the individual securities which are all scaled to 10% average ex-ante volatility using $mom*10\%/\sigma$. Then in each aggregation step (from individual securities to asset classes and then asset classes to the overall portfolio) we achieve a 10% average ex-ante portfolio volatility by multiplying with the weight given to a security or sector and then dividing by a factor $\sqrt{w'\Omega w}$, where w is a vector of relative weights (a vector of ones, except in the case of the commodities sector, as mentioned in the main text), and Ω is the correlation matrix between constituent strategy returns based on exponentially decaying weights with a 24-month half-life.

3. Performance

In Figure 3 we present the annualized excess return for trend strategies based on a single month's return, where we vary the lag from 1 (past month) to 24 (the return 24 months ago). Using the notation of Equation [1], the left-most bar is based on $w_1 = 1$ (other lags zero), the next bar is for $w_2 = 1$ (other lags zero), etc., all the way up to $w_{24} = 1$ (other lags zero) for the right-most bar.

Figure 3: Performance of single-month momentum strategies

The blue bars in the figure show the annualized return for momentum strategies based on the first 24 lags. The red line represents the quadratic fit on the first 11 lags. Returns do not include interest income, i.e. can be considered excess returns, and are gross of transaction costs and fees. The measurement period is January 1960 to December 2015.



It is noteworthy that returns for lags up to 11 months ago are predictive with a positive sign for the following month's return, as evidenced by the solidly positive performance.[7] In contrast, the return 12 months ago is much less predictive, with only a modestly positive performance. At first sight this may seem odd, as other papers on futures trend-following have claimed predictability up to 12-months out, and proposed a trading strategy based on 12-month momentum. In unreported results we find that the main reason that the return 12 months ago is not as predictive is due to using monthly rather than daily data, which effectively adds a half-month lag on average.[8] Also worth observing from Figure 3 is that the

[7] Also for stocks the predictive power does not seem confined to the first, say, 6 months. In fact, there is a lively academic debate on whether the first 6 lags are less predictive than the next 6 lags, see e.g. Novy-Marx (2012), Goyal and Wahal (2015).

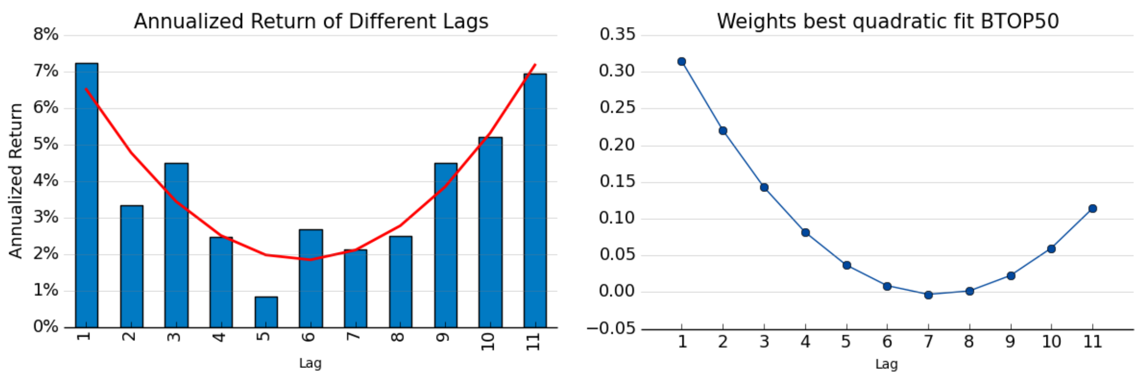
[8] To understand this, recall that the position of the lag 12 momentum strategy in, say January 2000 will be based on the return over January 1999. On January 1st 2000 this means the position is based on returns up to 12 months ago. However, by the time it is January 15th, 2000, the position is based on returns up to 12.5 months ago, and on January 31st, 2000, it is based on returns up to 13 months ago. Returns just over 12 months ago are predictive with the opposite sign, see for example Baltas and Kosowski (2013) who show in their Figure 1 that past weekly returns are predictive with a positive sign up to lag 52 and predictive with a negative sign for lags 53 and 54. We find (in unreported results) that using daily data for the post-1985 period for which this is mostly available, the lag 12 momentum strategy does perform strongly, as then the position on January 15th, 2000 would be based on returns

annualized returns for lags 1 through 11 display a pronounced U-shape, where the red line represents the quadratic fit.

Next we explore which weights in Equation [1] correspond best to the returns of the representative BTOP50 managed futures index, for which we have return data from January 1987.[9] We deduct the US T-bill rate from the index returns to give an excess return. In Figure 4 (left panel) we first plot the annualized return for single-month momentum strategies, as we did in Figure 3, but now using data from 1987 onwards and up to lag 11. Again we see that the quadratic fit is U-shaped and this time nearly symmetric. To prevent overfitting and to facilitate comparison with the U-shape found for the performance of different lags, we impose that the weights are a quadratic function of the lag and set weights at lag 12 and beyond to zero. Subject to these restrictions, the weights that lead to the highest correlation with the BTOP50 index return are plotted in Figure 4 (right panel). We will refer to the strategy based on these weights as the *momCTA* strategy.

Figure 4: Single-month momentum performance & weights BTOP50 replication (post 1987)

The left panel (blue bars) shows the annualized return of momentum strategies based on the first 11 lags. The quadratic fit is given by the red line. Returns do not include interest income, i.e. can be considered excess returns, and are gross of transaction costs and fees. In the right panel we show the weights to the first 11 lagged returns of the momentum strategy that has the highest correlation with the excess returns of the BTOP50 index, while imposing a quadratic functional form on the weights as a function of the lag. The measurement period is 1987-2015, which corresponds to the time period for which we have performance data for the BTOP50 index.



The monthly returns to *momCTA* and the excess returns of the BTOP50 index have a correlation coefficient of 0.62 over the 29-year history, which we consider reasonably high given that the *momCTA* strategy is defined on monthly data, while BTOP50 managers most likely use daily data for computing signal values and risk measures. What is noteworthy is that the optimal quadratic weights (right panel) are not nearly as symmetrically U-shaped as is the quadratic fit of single-month momentum performance (left panel). In fact, 76% of the optimal quadratic weights come from the first 4 lags. This indicates that trend-followers seem to have mostly focused on the predictability of recent lags and largely ignored the historically strong predictability of lags 9 to 11.

over the January 15th to February 15th, 1999 period, i.e. shifted forward by a half a month relative to the case of monthly returns.

[9] The BTOP50 Index seeks to replicate the overall composition of the managed futures industry. For more information see: http://www.barclayhedge.com/research/indices/btop/.

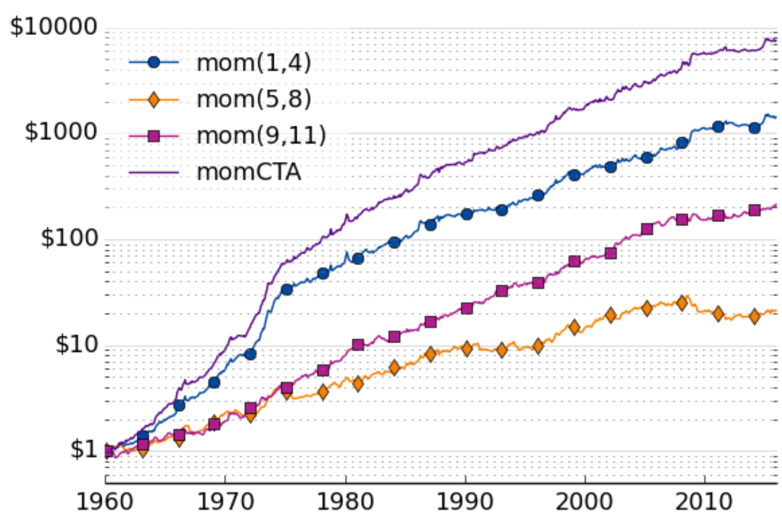
In Figure 5, we plot the cumulative returns for the following momentum strategies, which are all defined by Equation [1] and differ only in terms of the weights given to different lagged returns:

- ***mom(1,4)*** based on the past four months' returns ($w_1 = w_2 = w_3 = w_4 = 1/4$, other lags zero)
- ***mom(5,8)*** based on returns from 5 to 8 months ago ($w_5 = w_6 = w_7 = w_8 = 1/4$, other lags zero)
- ***mom(9,11)*** based on returns from 9 to 11 month ago ($w_9 = w_{10} = w_{11} = 1/3$, other lags zero)
- ***momCTA***, based on the past 11 month returns, weights given in Figure 4 (right panel)

We chose *mom(1,4)*, *mom(5,8)* and *mom(9,11)* such that they capture the different parts of the U-shape in performance illustrated in Figure 3 and Figure 4 (right panel). We use a log-scale and thus a constant performance over time would correspond to a straight line. The monthly returns of *momCTA* and *mom(1,4)* correlate 0.92, while the correlations between the other pairs are much lower, ranging between 0.20 and 0.40. The performance of *momCTA* and *mom(1,4)* around 1974 stands out, which can be largely attributed to bonds and commodities whose returns displayed very strong 1-month momentum. Besides that, the *momCTA* and *mom(1,4)* perform quite consistently over the 56 year period considered. The *mom(9,11)* strategy also performs consistently, and since the mid-1970s has performed about as well as mom(1,4), as can be seen by comparing the slope of the cumulative return curves. In contrast, the *mom(5,8)* strategy has consistently underperformed the other strategies.

Figure 5: Cumulative performance for different momentum strategies

The figure shows the cumulative return for different momentum strategies, run at 10% ex-ante volatility. Returns are compounded and plotted against a log-scale, so that a straight line corresponds to constant performance over time. Returns do not include interest income, i.e. can be considered excess returns, and are gross of transaction costs and fees. The measurement period is January 1960 to December 2015.



All strategies target an ex-ante annual volatility of 10% on average. For *momCTA* and *mom(1,4)* the realized value is slightly above target at 10.5% (in both cases), while for *mom(5,8)* and *mom(9,11)* it is slightly below target at 9.2% and 8.9% respectively. While the cumulative performance plotted in Figure 5 is affected by the realized volatility, the annualized Sharpe ratio reported in Table 2 is not. We report the Sharpe ratio both for the case where all securities are included and for the individual asset classes. In all cases, *mom(5,8)* clearly underperforms *momCTA*, *mom(1,4)* and *mom(9,11)*.

Table 2: Sharpe Ratio for different momentum strategies

The table reports the annualized Sharpe ratio, determined as the annualized (excess) return divided by the annualized volatility of returns, for different momentum strategies. Returns do not include interest income, i.e. can be considered excess returns, and are gross of transaction costs and fees. Different columns correspond to different sets of securities to which the strategy is applied. The measurement period is January 1960 to December 2015.

Strategy	**Securities included in analysis**				
	All	Bonds	Commodities	Currencies	Equities
momCTA	1.56	1.18	1.07	0.57	0.64
mom(1,4)	1.30	0.99	0.87	0.48	0.55
mom(5,8)	0.64	0.32	0.56	0.19	0.34
mom(9,11)	1.12	0.54	0.91	0.52	0.51

The strong performance for lags 1 to 4, which then tapers off from lag 5 to 8, seems consistent with the wisdom that price trends often arise from under-reactions to news. The uptick in performance for lags 9 to 11 is harder to explain with a pure under-reaction to news story and is likely partially related to an annual seasonality effect, and partially to a footprint left by the prevalence of 12-month windows in reporting and evaluating financial data. The less clear economic story for *mom(9,11)* may be one reason that *momCTA*, our proxy for the momentum strategy employed in live trading by trend-followers, is much closer to *mom(1,4)*. However, another possible explanation is that the risk characteristics of *mom(1,4)* are more favorable than those for *mom(9,11)*, as indeed we show in the subsequent sections.

4. Skewness

Investors do not necessarily limit their interest to the average return and the standard deviation of returns, the two most basic parameters of the return distribution. Rather they may also care about the asymmetry of the return distribution and may be particularly averse to occasional large negative returns. In other words, investors may dislike negatively skewed return distributions and be drawn to positively skewed return distributions.

We find that the monthly returns of *mom(1,4)* and the highly correlated *momCTA* strategy display considerable positive skewness. The positive skewness is further enhanced when using a 3- month evaluation window, which arguably is a more relevant horizon for an institutional investor. Using a 12-month evaluation window also yields similar results. Table 3 shows the outcome, both where all securities are included, and for individual asset classes. The *momCTA* and *mom(1,4)* strategies have considerably positively skewed returns for all asset classes, while the *mom(5,9)* and *mom(9,11)* strategies have a much lower (and often negative) skewness statistics.

We have confirmed the robustness of these findings in a number of ways. First, we have looked at the pre- and post-1985 time periods separately. Secondly, we have re-run the models omitting 2008, which is when most extreme positive returns occurred and so has a disproportionate impact on a higher-order moment like skewness. Finally, we have recalculated the statistics using the alternative Bowley and Pearson measures of skewness measures.[10] All three of these tests give a similar conclusion to the original experiment: that *momCTA* and *mom(1,4)* display considerable positive skewness for 3 and 12 month evaluation periods.

Table 3: Skewness for different momentum strategies

The table reports the annualized skewness of 3-month overlapping returns for different momentum strategies. Returns do not include interest income, i.e. can be considered excess returns, and are gross of transaction costs and fees. Different columns correspond to different sets of securities to which the strategy is applied. The measurement period is January 1960 to December 2015.

Skewness 3-month overlapping returns

Strategy	**Securities included in analysis**				
	All	Bonds	Commodities	Currencies	Equities
momCTA	1.04	0.71	1.21	1.40	0.96
mom(1,4)	1.13	0.53	1.08	1.59	0.81
mom(5,8)	-0.06	-0.41	0.01	0.51	-0.24
mom(9,11)	0.16	0.38	0.41	0.17	0.11

Skewness 12-month overlapping returns

Strategy	**Securities included in analysis**				
	All	Bonds	Commodities	Currencies	Equities
momCTA	1.48	0.08	0.97	1.86	0.89
mom(1,4)	1.80	0.24	0.95	2.38	0.88
mom(5,8)	-0.07	-0.70	-0.13	0.86	0.26
mom(9,11)	-0.07	0.23	-0.16	0.24	-0.05

The positive skewness at a multi-month evaluation window for *momCTA* and *mom(1,4)* seems intuitive given the close parallel between a momentum strategy and a long straddle strategy, where one frequently loses a limited amount of money when the underlying stays bound within a limited range, but sometimes makes big gains when the underlying moves a lot (up or down).[11,12] In fact the trading profile of a trend-follower involves adding to winning positions (riding winners) and reducing losing positions (cutting losers), much like the dynamic replication of an option straddle strategy. This involves holding an amount in the underlying equal to the delta of a straddle.[13] In Figure 6 we graphically illustrate this point by plotting the delta of a straddle, as a function of the distance to the strike price, expressed as a

[10] Bowley's measure of skewness is defined as: $B(75,25) = (Q_{75} + Q_{25} - 2Q_{50})/(Q_{75} - Q_{25})$, where Q_x is the x-th percentile of the return distribution and so Q_{50} is the median. We also confirmed robustness using $B(90,10)$ and $B(95,5)$. The Pearson skewness coefficient is determined as $Pearson = 3(\mu - Q_{50})/\sigma$, where μ and σ are the mean and standard deviation of returns respectively.

[11] A long straddle strategy involves holding both a long call and a long put option on the same underlying with the same strike price and maturity.

[12] Fung and Hsieh (2001) argue that trend following strategies are theoretically more related to lookback straddles, but find that empirically standard straddles explain trend-following returns as well as lookback straddles.

[13] The analogy does not hold for a trend-follower who takes a binary approach and either holds a fixed-size long or short position or a zero position, rather than gradually building up and down positions as the signal strength changes.

number of standard deviations.[14] Alongside we plot the position of a trend follower, as a function of past returns, also expressed as a number of standard deviations, and scaled and capped such that the most extreme positioning is achieved for +/-2 standard deviation moves.[15]

5. Crisis alpha

Next we evaluate the performance of the *momCTA* strategy during different equity and bond market environments. To this end we form quintiles based on rolling 3-month equity (S&P 500) and bond (10y Treasury) returns and report the average return of the *momCTA* strategy for each of the quintiles. As noted before, we argue that using 3 months for the evaluation window may be more appropriate as it may take an institutional investor at least a couple of months to reposition themselves and shift gears when faced with a changing market environment.

Figure 6: delta of straddle vs momentum response function

The figure shows the delta of a call (red line), put (green line), and the call plus put, or straddle (blue line), as a function of the distance from the strike price, expressed as a number of standard deviations. Plotted alongside, is the response function of a trend-follower as a function of past returns and expressed as a number of standard deviations also (purple dashed line).

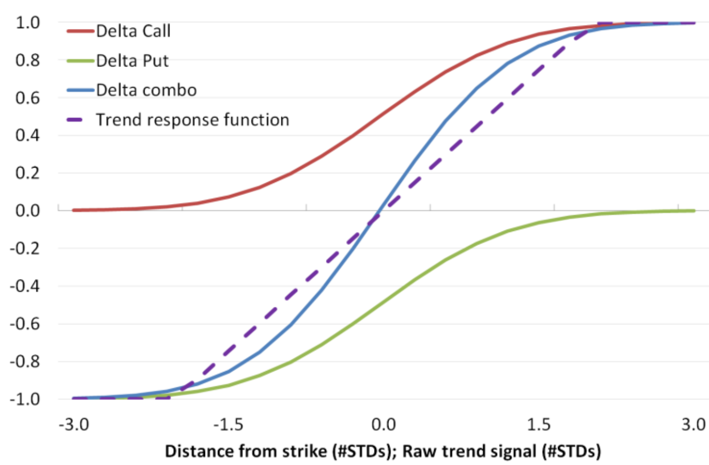


Figure 2 (presented in the introduction) shows the result for different equity (left panel) and bond (right panel) performance quintiles, and the right-most bar corresponds to the unconditional average return. We note that *momCTA* performs particularly well when general equity and bond markets are at their worst, giving credence to a claim that trend-following provides equity and bond crisis alpha.

[14] The delta of the straddle is given by $2N(d)-1$, where $N(.)$ is the cumulative normal distribution function and $d=\left[\ln(S/K)+\left(r+\sigma^2/2\right)\tau\right]/\left(\sigma\sqrt{\tau}\right)$, which for a small time to maturity, τ, is well approximated by the log return relative to the strike price, $\ln(S/K)$, scaled by $\sigma\sqrt{\tau}$, such that it is expressed as a number of standard deviation moves over the time to maturity period. For the illustration we set the annual risk free rate, $r=1\%$, annual volatility, $\sigma=15\%$, and time to maturity, $\tau=1/12$ years (1 month). We then vary moneyness, S/K, and plot the delta versus $\ln(S/K)/\sigma\sqrt{\tau}$.

[15] A more formal mathematical proof of how trend-following strategies naturally exhibit positively skewed strategy returns is given by Martin and Zou (2012).

Performance is also strong in the best equity and bond market environments, giving rise to a well-known "equity smile" and a lesser-known, but even more pronounced "bond smile". [16]

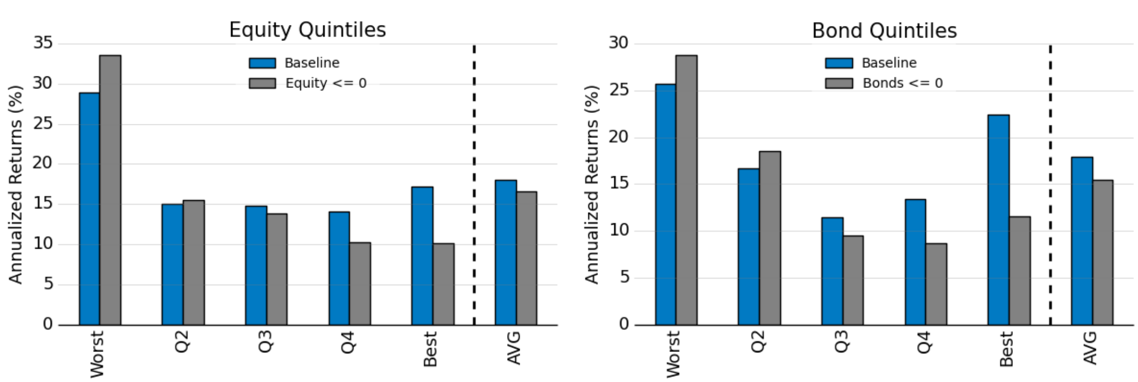
We decompose the strategy returns into the performance from the four different asset classes.[17] Interestingly, equities, bonds and currencies all show both an equity and bond smile. The performance of commodities displays more of a left skew, with performance particularly strong during the worst periods for equites and bonds.

We performed the following sensitivity checks: (i) using a 12-month rolling performance evaluation window (rather than 3 months) and (ii) starting the analysis in 1974, when we have data for currencies. In both cases we find that the *momCTA* strategy does well in both the worst equity and worst bond market environments. We also analyzed the *mom(1,4)*, *mom(5,8)* and *mom(9,11)* strategies and find that *mom(1,4)* stands out in terms of providing such crisis alpha, which is in line with the skewness results presented in the previous section. Further details, including figures, can be found in Appendix A.

Next, we explore how we might further enhance the crisis alpha characteristic of trend-following strategies. Specifically, we run versions of the *momCTA* strategy where positions in equities are capped at zero. This will ensure that the strategy is well positioned during periods of equity market decline (as it can never be long). Obviously, this will also ensure that during an equity bull market the strategy can only be flat or short (i.e. erroneously positioned in equities). We repeat this exercise for bonds. We scale the restricted returns to have (ex-post) the same volatility as the baseline (unrestricted) case, so as to facilitate a comparison between the two versions.

Figure 7: *momCTA* performance, equity and bond quintiles, rolling 3m window (restrictions)

The figure shows the annualized average momCTA return for rolling 3-month windows, with and without a restriction to hold no long positions in equities (left panel) or bonds (right panel). We scale the restricted returns to have (ex-post) the same volatility as the baseline case, so as to facilitate the comparison between the two versions. In the left panel the results are reported for equity market quintiles, with quintile 1 corresponding to the worst 3-month S&P 500 returns and quintile 5 to the best. The right-most bar corresponds to the average return across all periods. Similarly, the right panel shows results for different bond market (US Treasury) quintiles. Returns do not include interest income, i.e. can be considered excess returns, and are gross of transaction costs and fees. Different columns correspond to different sets of securities to which the strategy is applied. The measurement period is January 1960 to December 2015.



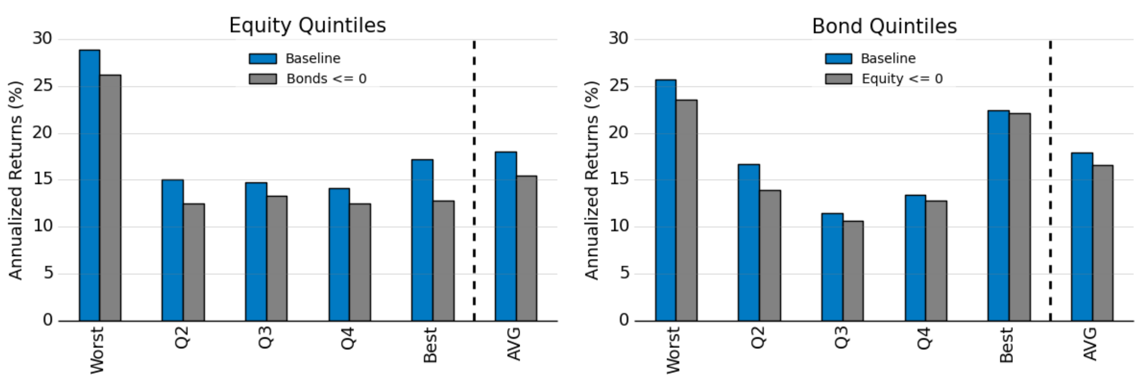
[16] A similar smile pattern is obtained when plotting the Sharpe Ratio instead of annualized returns.
[17] For currencies our data only starts in 1973; prior to that the risk is redistributed to the other sectors. We find that the percentage of observations for which currencies data is available is roughly equally spread among the different quintiles. As a robustness check we run our analysis from 1974 onwards, see Appendix A.

In Figure 7 we compare the performance for our baseline (unrestricted) case to that of using the no-long equity restriction for equity quintiles (left panel) and no-long bond restriction for bond quintiles (right panel). In both cases, the position capping further improves the already good performance in quintile 1, while reducing the performance in quintiles 3, 4 and 5. Also the average performance (averaged over all quintiles) goes down, which can be seen as the price one pays for the enhanced crisis alpha return profile.

For an investor who cares about both the equity and bond crisis alpha return profile, the situation is more nuanced, however, due to an unfavorable cross effect. As we show in Figure 8, a no-long bond restriction worsens the return in all equity quintiles (left panel), and similarly a no-long equity restriction worsens the return in all bond quintiles (right panel). In particular the worse performance in quintile 1 is an undesirable cross-effect and may at first sight be surprising, given that common fundamental factors would typically imply a positive equity-bond correlation (Baele, Bekaert and Inghelbrecht (2010)). However, at times of severe stock market uncertainty, the equity-bond correlation has empirically turned very negative, which is often ascribed to a flight-to-safety effect (Connolly, Stivers and Sun (2005)).

Figure 8: *momCTA* performance, equity and bond quintiles, rolling 3m window (cross-restrictions)

The figure shows the annualized average momCTA return for rolling 3-month windows, with and without a *cross*-restriction to hold no long positions in bonds (left panel) or equities (right panel). We scale the restricted returns to have (ex-post) the same volatility as the baseline case, so as to facilitate the comparison between the two versions. In the left panel the results are reported for equity market quintiles, with quintile 1 corresponding to the worst 3-month S&P 500 returns and quintile 5 to the best. The right-most bar corresponds to the average return across all periods. Similarly, the right panel shows results for different bond market (US Treasury) quintiles. Returns do not include interest income, i.e. can be considered excess returns, and are gross of transaction costs and fees. Different columns correspond to different sets of securities to which the strategy is applied. The measurement period is January 1960 to December 2015.



6. Concluding remarks

In this paper we have studied the performance of trend-following strategies since 1960, a time period that includes extended bull and bear markets for both equities and bonds. We have shown that a strategy that closely matches the BTOP50 performed consistently over the 56 years covered. It also has a number of compelling risk characteristics: positively skewed returns and strong performance in the worst equity and bond market environments, which we refer to as equity and bond market crisis alpha respectively.

Despite 56 years of supportive empirical evidence, it is natural to ask the question whether momentum strategies will continue to be profitable. In this respect it is worth noting that academic papers on the topic date back to at least Jegadeesh and Titman (1993) and performance has persisted for the 20+ years since then. While a meaningful amount of capital is dedicated to exploiting the momentum phenomenon, there is evidence that there are very large players that have a tendency to take the other side (knowingly or unknowingly), possibly ameliorating concerns that too much capital is chasing momentum profits. For example, Lou, Polk and Skouras (2016) present evidence that stock momentum is different from other trading strategies in that professional, institutional investors tend to "trade against the momentum characteristic".

As a final note, we should emphasize that the design of our momentum strategy was deliberately barebones, as any frills added would call into question whether the risk and return characteristics identified are general effects or specific to the chosen formulation. Many additional considerations do play an important role when running a live momentum strategy on futures, including fine-tuning the trading signal definition, portfolio construction, risk management, and execution.

References

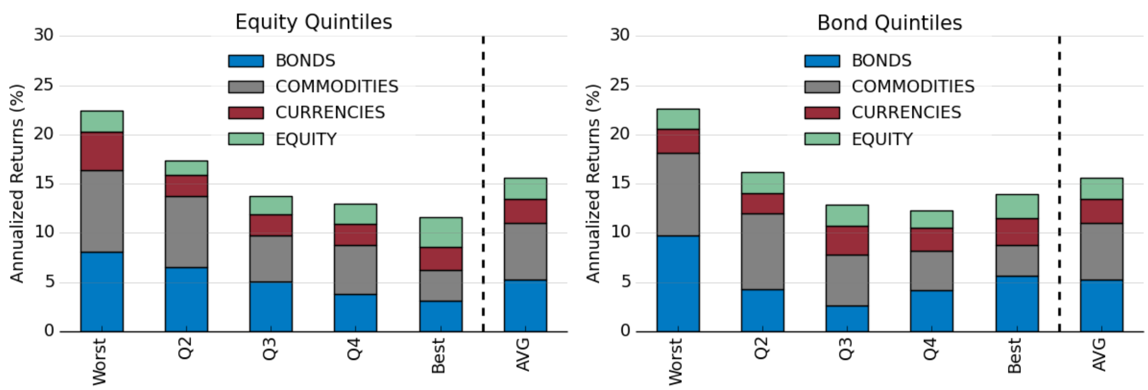
- Baele, L., G. Bekaert, and K. Inghelbrecht (2010), “The Determinants of Stock and Bond Return Comovements”, *Review of Financial Studies*, 23(6), 2374-2428.
- Baltas, N., and R. Kosowski (2013), “Momentum Strategies in Futures Markets and Trend-Following Funds”, working paper.
- Connolly, R., C. Stivers, and L. Sun (2015), “Stock Market Uncertainty and the Stock-Bond Return Relation”, *Journal of Financial and Quantitative Analysis*, 40(1), 161-194
- Fung, W., and D. Hsieh (2001), “The risk in hedge fund strategies: theory and evidence from trend followers”, *Review of Financial Studies*, 14(2), 313-341.
- Goyal, A., and S. Wahal (2015), “Is momentum an echo?”, *Journal of Financial and Quantitative*, 50(6), 1237-1267.
- Greyserman, A. (2012), “The Multi-Centennial View of Trend Following.” ISAM white paper.
- Hurst, B., Y. Ooi, L. Pedersen (2012), “A century of evidence on trend-following investing”, AQR white paper.
- Jegadeesh, N., and S. Titman’s (1993), “Returns to Buying Winners and Selling Losers: Implications for Stocks Market Efficiency”, *Journal of Finance*, 48(1), 65-91.
- Kaminski, K. (2011), “In Search of Crisis Alpha: A Short Guide to Investing in Managed Futures”, working paper.
- Lempérière, Y., C. Deremble, P. Seager, M. Potters, and J. Bouchaud (2014), “Two centuries of trend following”, CFM white paper.
- Lou, D., C. Polk, and S. Skouras (2016), “A Tug of War: Overnight Versus Intraday Expected Returns”, Working Paper.
- Martin, R. and D. Zou. (2012), “Momentum trading: ‘skews me”, *Risk*, 25(8), 52-57.
- Moskowitz, T., Y. Ooi, and L. Pedersen (2012), “Time series momentum”, *Journal of Financial Economics*, 104(2), 228–250.
- Novy-Marx, R. (2012), “Is momentum really momentum?”, *Journal of Financial Economics*, 103(3), 429–453.

Appendix A: Sensitivity analyses for equity and bond crisis alpha and smiles

We find that for rolling 12-month evaluation windows, the equity smile becomes a full-on left-skew with *momCTA* doing best in quintile 1 (worst equity markets) and worst in quintile 5. The bond smile flattens somewhat but the *momCTA* performance continues to be strong in quintile 1. See Figure A1.

Figure A1: *momCTA* performance, equity and bond quintiles, rolling 12m window

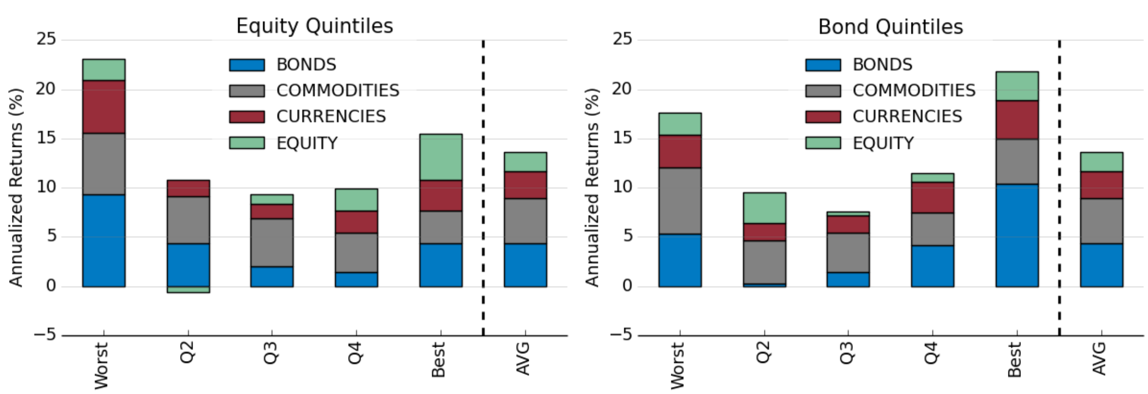
The figure shows the annualized average momCTA return for rolling 12-month windows, attributed to the four asset classes covered. In the left panel the results are reported for equity market quintiles, with quintile 1 corresponding to the worst 12-month S&P 500 returns and quintile 5 to the best. The right-most bar corresponds to the average return across all periods. Similarly, the right panel shows results for different bond market (US Treasury) quintiles. Returns do not include interest income, i.e. can be considered excess returns, and are gross of transaction costs and fees. Different columns correspond to different sets of securities to which the strategy is applied. The measurement period is January 1960 to December 2015.



When we start our analysis in 1974, post Bretton Woods, and when we have currency data, the bond and equity smiles still remain. See Figure A2.

Figure A2: *momCTA* performance, equity and bond quintiles, rolling 3m window, post-1974

The figure shows the annualized average momCTA return for rolling 3-month windows, post 1974, attributed to the four asset classes covered. In the left panel the results are reported for equity market quintiles, with quintile 1 corresponding to the worst 3-month S&P 500 returns and quintile 5 to the best. The right-most bar corresponds to the average return across all periods. Similarly, the right panel shows results for different bond market (US Treasury) quintiles. Returns do not include interest income, i.e. can be considered excess returns, and are gross of transaction costs and fees. Different columns correspond to different sets of securities to which the strategy is applied. The measurement period is January 1974 to December 2015.

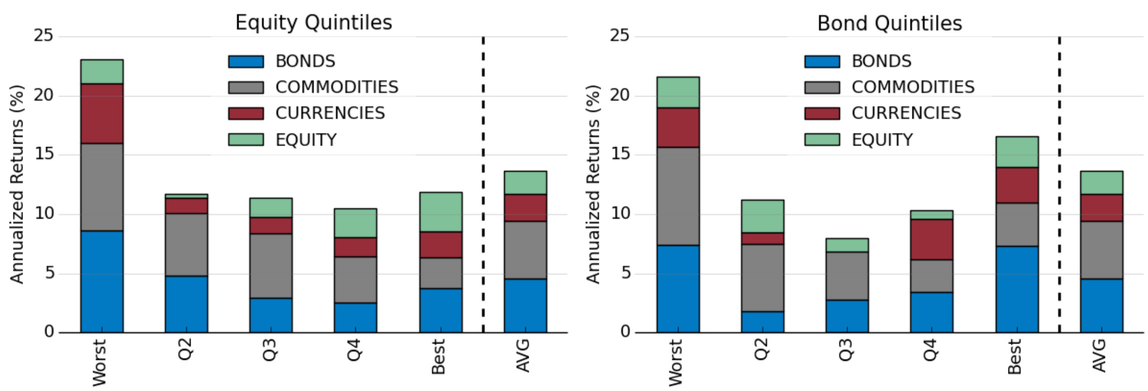


We find that equity and bond smiles are obtained for *mom(1,4)* but are less clear for *mom(5,8)* and *mom(9,11)*. See Figure A3.

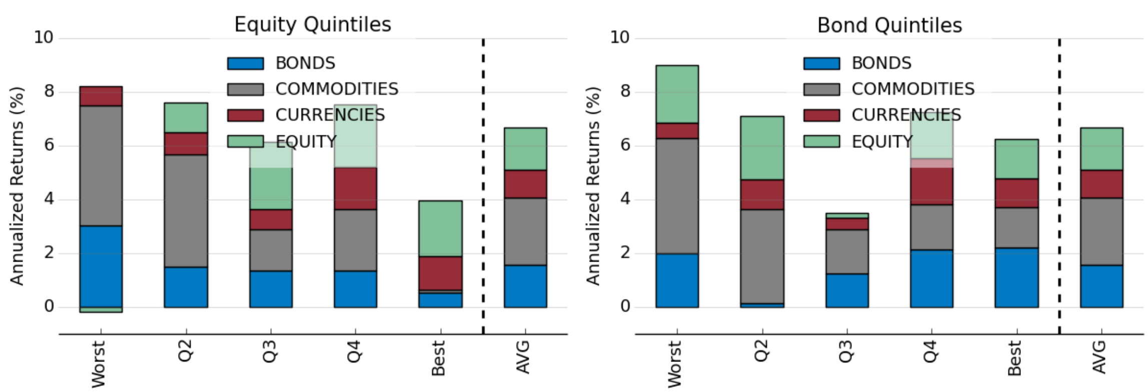
Figure A3: *mom(1,4)*, *mom(5,8)*, *mom(9,11)* performance, equity and bond quintiles, roll. 3m window

The figure shows the annualized average mom(1,4), mom(5,9) and mom(9,11) return for rolling 3-month windows, attributed to the four asset classes covered. In the left panel the results are reported for equity market quintiles, with quintile 1 corresponding to the worst 3-month S&P 500 returns and quintile 5 to the best. The right-most bar corresponds to the average return across all periods. Similarly, the right panel shows results for different bond market (US Treasury) quintiles. Returns do not include interest income, i.e. can be considered excess returns, and are gross of transaction costs and fees. Different columns correspond to different sets of securities to which the strategy is applied. The measurement period is January 1960 to December 2015.

mom(1,4)



mom(5,8)



mom(9,11)