CHAPTER 1

Seeking Crisis Alpha

INTRODUCTION

The idea of risk management is to provide some protection during adverse events. However, the cost of that protection must be balanced against the benefit. For example, in a strategy that uses costly long put options to eliminate the downside, the portfolio's return should not be greater than the risk-free rate. By contrast, we focus on the idea of crisis alpha, which uses dynamic methods that lower risk and also preserve excess returns. In this sense, they provide alpha when it is most needed—during crisis periods.[1]

Trend following is one technique that works especially well with a crisis-alpha strategy. Theoretically, trend-following strategies sell in market drawdowns (mimicking a dynamic replication of a long put option) and buy in rising markets (mimicking a dynamic replication of a long call option). This resembles a long straddle position and induces positive convexity. While it is possible to purchase the long straddle directly, that is expensive. Implementing a trend-following strategy is not expensive, but it is not as reliable as taking option-based insurance.

Much of our book focuses on these costs and benefits. We assess the after-cost performance of different strategies (including option-based strategies) in various risk-on events.

Our starting point is a deep dive into time-series momentum (trend-following) strategies in bonds, commodities, currencies, and equity indices between 1960 and 2015. Over the last few years, institutional investors have turned to futures trend-following strategies to provide "crisis alpha."[2] Our analysis shows that these 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, returns are positively skewed, which is consistent with the theoretical link 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.

Backdrop

Government bonds have experienced an extended bull market since 1985. This is illustrated in the left panel of Figure 1.1, where we plot the cumulative excess return of U.S. 10-year Treasuries and the S&P 500 index, relative to the U.S. T-bill rate. This shows a steady increase in cumulative bond returns since 1985. The right panel of Figure 1.1 plots the drawdown level, which rarely exceeded 10 percent for bonds in the post-1985 period. A trend-following strategy holding a (predominantly) long bonds position would have benefited from the consistent upward direction after 1985.

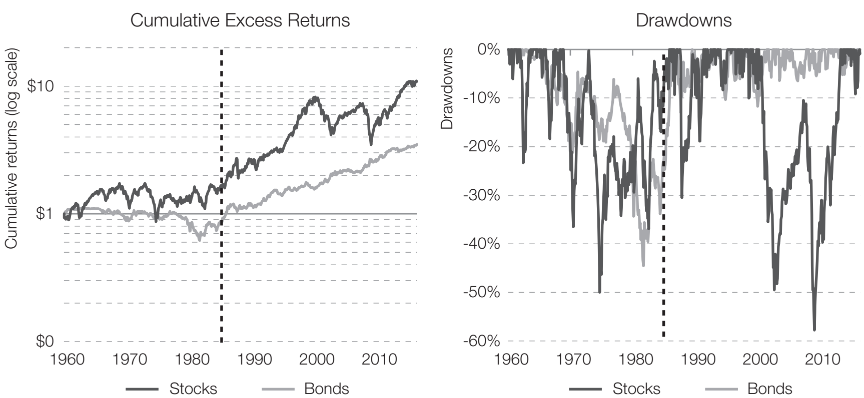

FIGURE 1.1 Cumulative excess returns and drawdowns in the stock and bond markets (1960–2015). The left panel shows the cumulative return of stocks (S&P 500 index) and bonds (U.S. 10-year Treasury), in excess of the U.S. T-Bill rate. The right panel shows the drawdown relative to the highest cumulative 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 interest-rate compression. U.S. yields fell from almost 16 percent in the early 1980s, to below 2 percent in March 2016. While in some countries yields have turned slightly negative, most economists believe yields cannot become very negative, and as such we are unlikely to see a similarly large yield compression in future decades. In light of this, it is natural to ask whether, in the absence of a bond market tailwind, trend-following strategies can maintain performance and protect against bond-market stress similar to that seen in the 1960s, 1970s, and early 1980s.

Outline

In this chapter we seek to shed light on three questions by studying trend-following strategies from 1960 onwards:

1. Should we expect futures trend following to be profitable in an environment where government bond yields rise?
2. Are the protective characteristics of trend following confined to equities, or do they work for government bonds as well?
3. Is it possible to improve the protection characteristics of a futures momentum strategy by removing the ability to be long equities?

Importantly, there is a stark difference between the pre-1985 period and the post-1985 period. Between 1960 and 1985, bonds experienced negative excess returns on average while stock markets provided modest positive average excess returns and quite frequent drawdowns (Figure 1.1).

In the first section, we discuss the available data to ground our understanding of the markets between 1960 and 1985. The second section defines a straightforward momentum strategy. 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 the next section, we show that strategies based on the past four months' returns (lag 1 to 4) experience consistently strong performance, as do strategies based on returns of almost a full year ago (lags 9 to 11). However, strategies based on returns at the intermediate horizon (lags 5 to 8) underperform consistently over time and across asset classes. Next, we form a momentum strategy that places weights on historical lagged returns, such that it best matches the representative BTOP50 managed futures index (we label our strategy *momCTA*) and find that this replicating strategy allocates almost all weight on lags 1 to 4, thus largely ignoring the predictability of lags 9 to 11.

In the two sections that follow, we show that *momCTA* inherits two important risk characteristics that are particularly associated with momentum strategies based on recent returns. In the section about skewness, 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 strategy's property of adding to winners and cutting losers, which is similar to the dynamic replication of a long option straddle position.

Then, in the section on crisis alpha, we show that *momCTA* performed particularly well in the worst equity and bond market environments, giving empirical support to a claim that trend-following can provide crisis alpha for both equities *and* bonds. Performance was strong in not only the worst but also the best equity and bond market environments, revealing a well-known equity market smile and a lesser-known, but even more pronounced bond market smile.

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

DATA

Many other papers that have looked at trend-following strategies start their analysis well after 1960. 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; however, using a sample period that starts in 1960 presents certain challenges. Starting earlier than 1960 is problematic for commodities because 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 United States experienced since at least 1900, as the 10-year yield rose from below 5 percent in 1960 to a peak of almost 16 percent in the early 1980s.

In Table 1.1, 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 the 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.

TABLE 1.1 **Data.** This table provides the start date for the securities used in this chapter, as well as some descriptive statistic for monthly security returns. 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 (annual)	Standard deviation (annual)	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 Note	Jan-50	Jul-05	0.83%	2.70%	0.71	12.16
US 5yr Note	Jan-50	Oct-91	1.52%	5.06%	0.24	6.12
US 10yr Note	Jan-50	May-82	1.87%	6.80%	0.43	3.86
US 30yr 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

(*Continued*)

TABLE 1.1 (*Continued*)

	Cash start date	Futures/ forwards start date	Mean (annual)	Standard deviation (annual)	Skewness	Kurtosis
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

TABLE 1.1 (*Continued*)

	Cash start date	Futures/ forwards start date	Mean (annual)	Standard deviation (annual)	Skewness	Kurtosis
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						
Australia SPI200	Jan-50	Mar-83	7.08%	16.61%	−1.15	11.34
France CAC 40	Jan-50	Nov-88	6.68%	18.87%	−0.10	1.17
Germany DAX	Sep-59	Nov-90	3.75%	19.53%	−0.17	1.61
Dutch All	Dec-50	Oct-88	7.72%	17.82%	−0.42	2.10
U.K. FTSE	Jan-50	May-84	6.67%	18.22%	0.84	14.14
Spain IBEX 35	Jan-50	Jan-92	6.19%	18.79%	−0.09	2.06
Italy All	Jan-50	Dec-94	5.16%	23.10%	0.40	2.08
U.S. S&P 500	Jan-50	Apr-82	6.99%	14.41%	−0.37	1.35
Canada S&P 60	Jan-50	May-87	5.74%	15.22%	−0.67	2.39
Japan TSE	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 that 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 analysis based on monthly data.[4]

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 identified by this filter. The first is silver, which we include only from 1972 onwards. Before that, silver prices did not fluctuate freely because they were tied to the U.S. monetary system until 1968; in the years immediately following 1968, they were subject to government intervention. The other two are the Japanese and Australian 10-year bonds, which will be included only from 1972 and 1977, respectively, because before that price fluctuations were severely subdued due to a combination of capital controls, currency intervention, and other monetary policies.

STRATEGY

After analyzing the data, we explore a basic 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 $t–1$:

$$mom_{t-1}^{k} = \frac{w_1 R_{t-1}^{k} + w_2 R_{t-2}^{k} + \dots}{\sigma_{t-1}^{k}\sqrt{w_1^2 + w_2^2 + \dots}} \tag{1.1}$$

where:

- R^k_{t-i} 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^k_{t-1} is the standard deviation of monthly returns for security k, observed at time t-1[5]
- $\sqrt{w_1^2 + w_2^2 + \ldots}$ is to achieve a unit standard deviation (approximately) for the signal[6]

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).[7] The strategy performance is found by summing over the performance for each traded market, which in turn is found by multiplying the signal–volatility ratio, the next period return, and a leverage or gearing factor to scale to a given risk target:

$$Performance_t = \sum_k Gearing^k_{t-1} \frac{mom^k_{t-1}}{\sigma^k_{t-1}} R^k_t \tag{1.2}$$

The gearing factor is such that, on average, the resulting portfolio has an ex-ante annualized volatility estimate of 10 percent, and risk is spread equally over the four asset classes: bonds, commodities, currencies, and equities. Within equities, bonds, and currencies, we allocate equal risk weights to the different constituent securities. Choosing equal weights is quite common in academic studies (albeit usually for dollar allocations), as it's in a way a model-free choice. Any other weighting scheme would require justification for exactly how and why you deviate from equal weighting. 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 have data available only at a later date, we redistribute the risk in the preceding period equally to the other securities in the same asset class.[8]

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 1.2 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 U.S. T-bill return and inflation rate averaged 4.8 percent and 3.9 percent, respectively, and, unsurprisingly, they moved mostly in line with one another, revealing a correlation of 0.72. An 18 percent haircut in the short rate, which we think is reasonable, would equate with the average interest income rate and inflation rate. Thus, the reported excess returns can alternatively be considered as a reasonable proxy for the inflation-adjusted (real) returns.

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 chapter. Assuming a two-basis-point transaction cost for outright trades leads to a reduction in the annualized return of 0.42 percentage points for the main strategy, which we will call the *momCTA* strategy. This estimate is broadly in line with experience over current trading conditions for a medium-term trend strategy, whereas it is harder to make statements about earlier periods.

PERFORMANCE

In Figure 1.2 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 1.1, the leftmost bar is based on $w_1 = 1$ (other lags zero), the next bar is for $w_2 = 1$ (other lags zero), and so on, all the way up to $w_{24} = 1$ (other lags zero) for the rightmost bar.

It is noteworthy that returns for lags up to 11 months ago are strongly predictive with a positive sign for the following month's return, as evidenced by the solidly positive performance.[9] In contrast, the one-month return 12 months ago is much less predictive, with only a modestly positive performance. At first sight this may seem odd. In fact, 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.[10] Also worth observing from Figure 1.3 is that the annualized returns for lags 1 through 11 display a U-shape, where the curved line represents the quadratic fit.

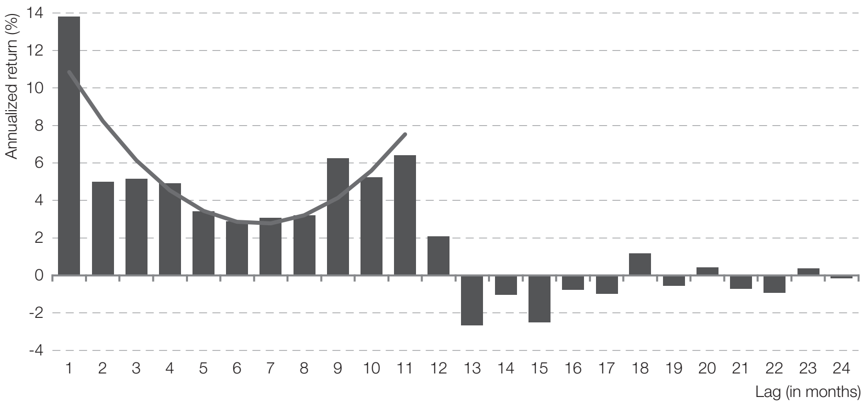

FIGURE 1.2 Performance of single-month momentum strategies. The bars show the annualized return for momentum strategies based on the first 24 lags. The curved line represents the quadratic fit on the first 11 lags. Returns do not include interest income, so they can be considered excess returns and are gross of transaction costs and fees. The measurement period is January 1960 to December 2015.

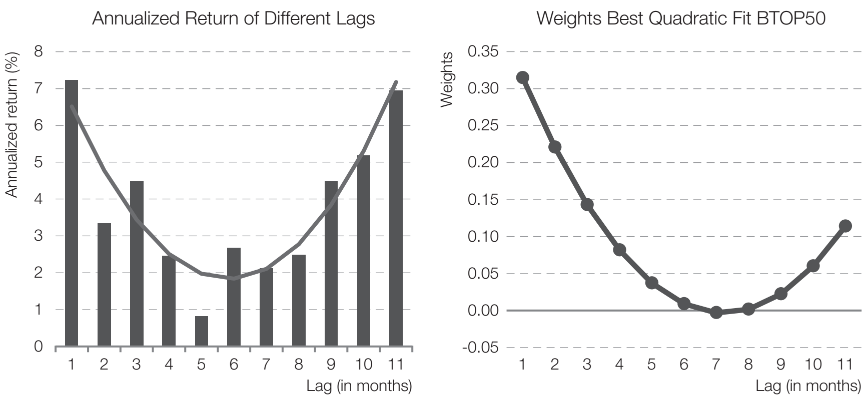

FIGURE 1.3 Single-month momentum performance and weights BTOP50 replication (post-1987). The bar graph in the left panel shows the annualized return of momentum strategies based on the first 11 monthly lags. The quadratic fit is given by the curved line. Returns do not include interest income, so they 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 monthly 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.

Next we explore which weights in Equation 1.1 correspond best to the returns of the representative BTOP50 managed futures index, for which we have return data from January 1987.[11] Our goal is to develop a close proxy for the BTOP50 so that we can examine performance in the period the BTOP50 was not available from 1960–1986. We deduct the U.S. T-bill rate from the index returns to give an excess return. In Figure 1.3 (left panel), we first plot the annualized return for single-month momentum strategies, as we did in Figure 1.2, but now we use the 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 1.3 (right panel). We will refer to the strategy based on these weights as the *momCTA* strategy.

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. We consider this to be 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 the quadratic fit of single-month momentum performance (left panel). In fact, 76 percent of the optimal quadratic weights come from the first four 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.

In Figure 1.4, we plot the cumulative returns for the following momentum strategies, which are all defined by Equation 1.1 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 months ago ($w_9 = w_{10} = w_{11} = 1/3$ ther lags zero)
- ***momCTA***, based on the past 11 months' returns, weights given in Figure 1.3 (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 Figures 1.2 and 1.3 (right panel). To be clear, our goal here is to deliberately examine non-overlapping historical returns to see how far back they are predictive. We use a log-scale, so a constant performance over time would correspond to a straight line. The monthly returns of *momCTA* and *mom(1,4)* have a correlation of 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 as particularly strong. This can be largely attributed to bonds and commodities whose returns displayed very strong one-month momentum. Besides that, the *momCTA* and *mom(1,4)* perform stronger quite consistently over the 56-year period considered. Comparing the slope of the cumulative return curves of the *mom(9,11)* and *mom(1,4)*, it's clear that the *mom(9,11)* strategy also performs consistently and, since the mid-1970s, has performed about as well as *mom(1,4)*. In contrast, the *mom(5,8)* strategy has consistently underperformed the other strategies.

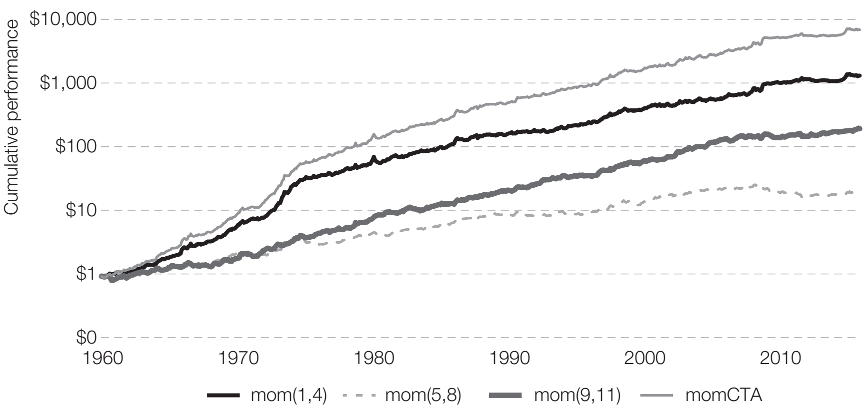

FIGURE 1.4 **Cumulative performance for different momentum strategies.** All strategies are run at 10 percent ex-ante volatility. Returns are compounded and plotted against a log-scale, so that a straight line corresponds to constant performance over time. This is also reflected on the y-axis, which follows a log scale. Returns do not include interest income, so they 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 percent on average. For *momCTA* and *mom(1,4)* the realized value is slightly above target at 10.5 percent (in both cases), while for *mom(5,8)* and *mom(9,11)* it is slightly below target at 9.2 percent and 8.9 percent respectively. While the cumulative performance plotted in Figure 1.4 is affected by the realized volatility, the annualized Sharpe ratio reported in Table 1.2 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 1.2 **Sharpe ratio for different momentum strategies.** This 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 lags 5 to 8, seems consistent with the wisdom that price trends often arise from an initial underreaction to news followed by a gradual response in the month immediately after the story breaks. The uptick in performance for lags 9 to 11 is harder to explain with a pure underreaction to a news story; news released nine or more months in the past is likely to have been digested by the market, even if there is an initial underreaction. It 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 news-based economic interpretation is more difficult to apply to *mom(9,11)*, which 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 we show in the subsequent sections.

SKEWNESS

The two most basic parameters of the return distribution are average return and standard deviation of returns, but investors do not necessarily limit their interest to these. 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 three-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 1.3 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(5,8)* and *mom(9,11)* strategies have much lower (and often negative) skewness statistics. This suggests that much of the positive convexity is being driven by faster momentum speeds. That is, the segments from lags 5 through 11 are not substantially contributing to positive skewness.

TABLE 1.3 **Skewness for different momentum strategies.** The annualized skewness of three-month overlapping returns for different momentum strategies are reported. Returns do not include interest income, so they 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 three-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

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. Second, we have rerun the models omitting 2008, which is when most extreme positive returns occurred, giving that year 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.[12] 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.

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.[13] With a long straddle strategy, one frequently loses a limited amount of money when the underlying asset price stays bound within a limited range, but sometimes one makes big gains when the underlying asset makes big moves up or down.[14] In fact, the trading profile of a trend follower involves adding to winning positions (called *riding winners*) and reducing losing positions (called *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.[15] In Figure 1.5, we illustrate this point by plotting the delta of a straddle as a function of the distance to the strike price, expressed as a number of standard deviations.[16] On the same graph, we plot the position

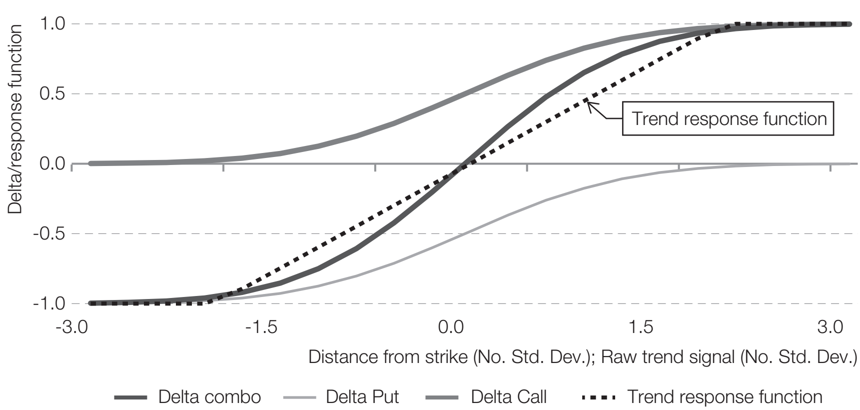

FIGURE 1.5 Delta of straddle versus momentum response function. Figure 1.5 shows the delta of a call, put, and the straddle (i.e., call plus put) as a function of the distance from the strike price, expressed as a number of standard deviations. Plotted alongside this is the response function of a trend follower as a function of past returns and also expressed as a number of standard deviations.

of a trend follower, as a function of his or her 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.[17]

CRISIS ALPHA

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

Figure 1.6 shows the result for different equity (left panel) and bond (right panel) performance quintiles; the rightmost bar corresponds to the unconditional average return. We note that *momCTA* performs particularly

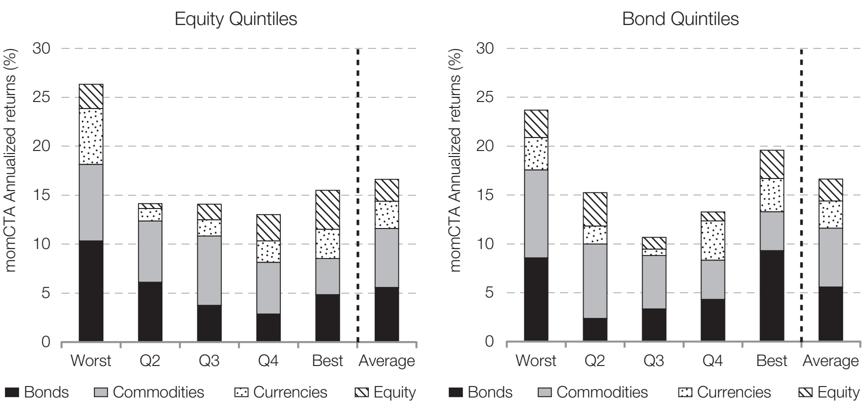

FIGURE 1.6 ***momCTA* performance, equity and bond quintiles, rolling three-month window.** The figure shows the annualized average *momCTA* return for rolling three-month windows, attributed to the four asset classes covered, under different general equity and bond market conditions. In the left panel, the results are reported for equity market quintiles, with quintile 1 corresponding to the worst three-month S&P 500 returns and quintile 5 to the best. The rightmost bar corresponds to the average return across all periods. Similarly, the right panel shows results for different bond market (U.S. Treasury) quintiles. Returns do not include interest income (i.e., they can be considered excess returns) and are gross of transaction costs and fees. The sample period is January 1960 to December 2015.

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. 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."[18]

We also decompose the strategy returns into the performance from the four different asset classes: bonds, commodities, currencies, and equities.[19] 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 equities 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. *Mom(1,4)* stands out by providing such crisis alpha, which is in line with the skewness results presented in the previous section. Further details, including figures illustrating *mom(1,4)*, *mom(5,8)*, and *mom(9,11)*, can be found in the chapter appendix.

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 1.7 shows the annualized average *momCTA* return for rolling three-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 three-month S&P 500 returns and quintile 5 to the best. The rightmost bar corresponds to the average return across all periods. Similarly, the right panel shows results for different bond market (U.S. Treasury) quintiles. Returns do not include interest income (i.e., they can be considered

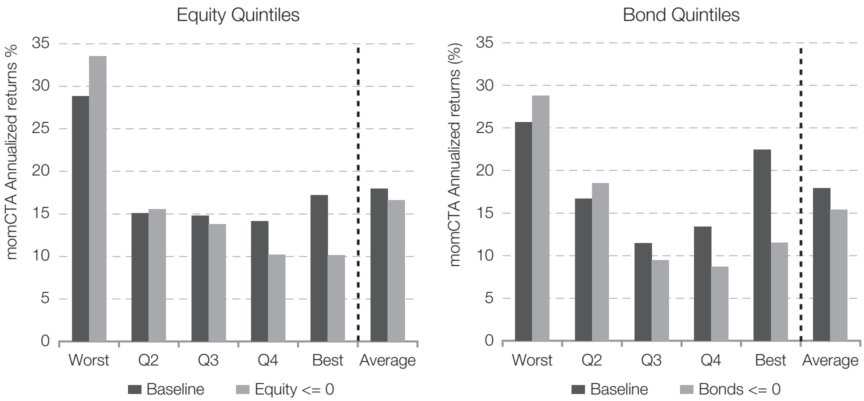

FIGURE 1.7 ***momCTA* performance, equity and bond quintiles, rolling three-month window (restrictions).** In Figure 1.7, we compare the performance for our baseline (unrestricted) case to that of using the no-long-equity restriction for equity quintiles (left panel) and no-long-bond restriction for bond quintiles (right panel). Quintile 1 corresponding to the worst three-month returns and quintile 5 to the best. The rightmost bar corresponds to the average return across all periods. Returns do not include interest income (i.e., they can be considered excess returns) and are gross of transaction costs and fees. The sample period is January 1960 to December 2015.

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 sample period is January 1960 to December 2015.

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 1.8, 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 worst 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).

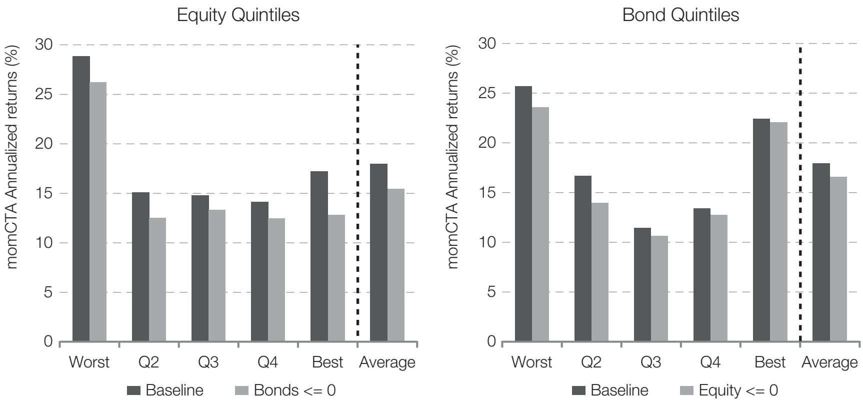

FIGURE 1.8 momCTA performance, equity and bond quintiles, rolling three-month window (cross-restrictions). Figure 1.8 shows the annualized average *momCTA* return for rolling three-month windows, with and without a cross-restriction to hold no long positions in bonds (left panel) or equities (right panel). 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 three-month S&P 500 returns and quintile 5 to the best. The rightmost bar corresponds to the average return across all periods. Similarly, the right panel shows results for different bond market (U.S. 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 sample period is January 1960 to December 2015.

CONCLUDING REMARKS

In this chapter, we have introduced a key component of strategic risk management: identification of active strategies that serve to cushion portfolios in times of stress. Trend-following strategies theoretically have such a property in that they resemble the dynamic replication of long straddles—but without the cost of initiating such an option position. In this sense, we refer to this particular strategy as generating crisis alpha.

While the track record of live trend-following strategies has been impressive, that record only begins in the late 1980s. An obvious question is whether the recent experience has been special. Indeed, during this time period, interest rates have declined from very high levels to historically low levels. As such, we evaluate these strategies between 1960 and 2015, a time period that includes extended bull and bear markets for both equities and bonds. The strategy that we construct closely matches the BTOP50 (over the period the BTOP50 is available) and the strategy has performed consistently over the full 56-year period. 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 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 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 addressing 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."

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 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.

While time-series momentum strategies tend to do well, on average, in periods of poor equity and bond performance, there are key questions that remain unanswered, in particular:

1. Are the strategies providing consistent performance when we drill down to specific drawdown episodes (this chapter only reported averages)?
2. How do these strategies perform in recessions (periods that are especially sensitive to investors because of losses in income from human capital)?
3. How do trend-following methods compare to alternative protective strategies such as buying put options or investing in gold?

These questions are addressed in the next chapter.

APPENDIX 1A: 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 (the 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 1A.1.

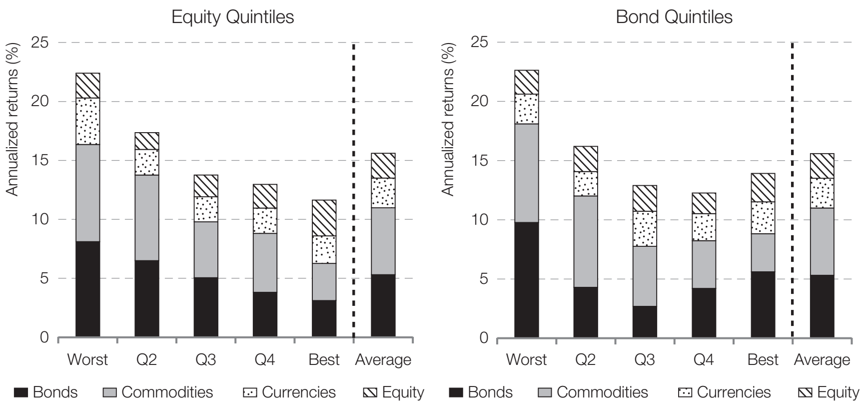

FIGURE 1A.1 ***momCTA* performance, equity and bond quintiles, rolling 12-month window.** The figure shows the annualized average *momCTA* return for rolling 12-month windows, attributed to the four asset classes covered. In the left panel the results are reported for equity market quintiles, with quintile 1 corresponding to the worst 12-month S&P 500 returns and quintile 5 to the best. The rightmost bar corresponds to the average return across all periods. Similarly, the right panel shows results for quintiles from a different bond market (U.S. Treasury). 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 1A.2.

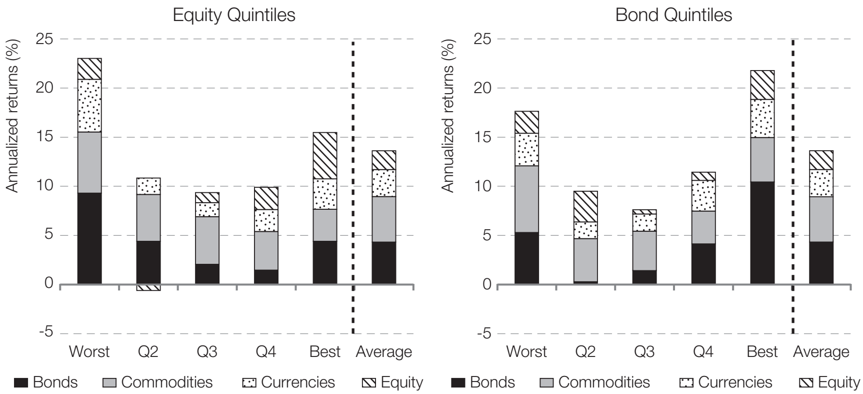

FIGURE 1A.2 ***momCTA* performance, equity and bond quintiles, rolling three-month window, post-1974.** The figure shows the annualized average *momCTA* return for rolling three-month windows, post-1974, attributed to the four asset classes covered. In the left panel the results are reported for equity market quintiles, with quintile 1 corresponding to the worst three-month S&P 500 returns and quintile 5 to the best. The rightmost bar corresponds to the average return across all periods. Similarly, the right panel shows results for different bond market (U.S. 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)* that use more distant past returns. See Figure 1A.3.

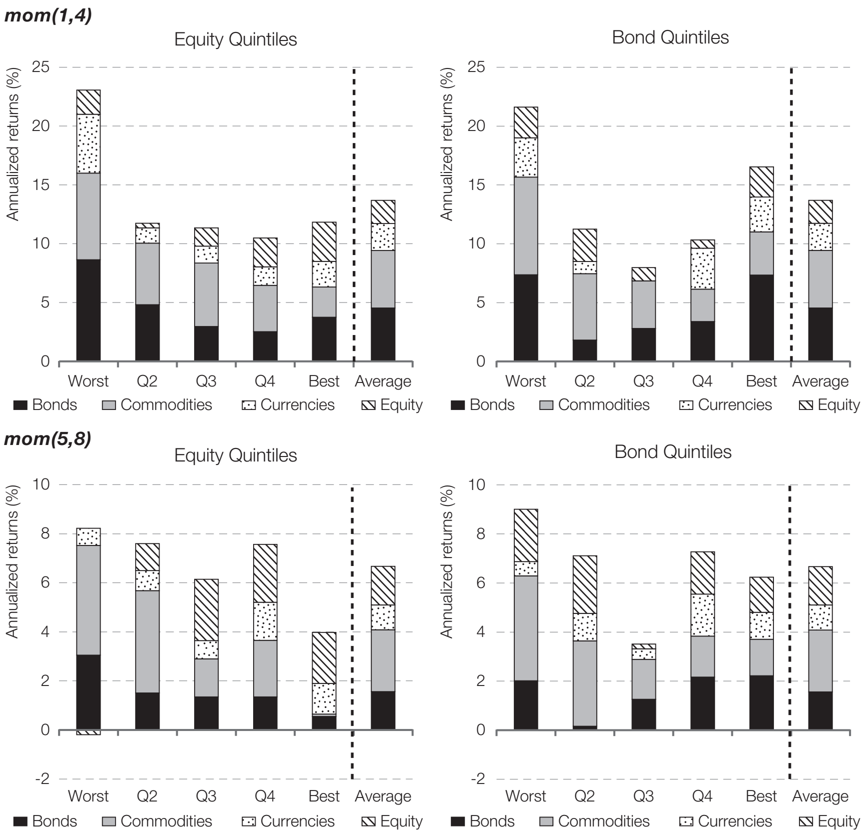

FIGURE 1A.3 ***mom(1,4)*, *mom(5,8)*, *mom(9,11)* performance, equity and bond quintiles, rolling three-month window.** Figure 1A.3 shows the annualized average *mom(1,4)*, *mom(5,9)*, and *mom(9,11)* return for rolling three-month windows, attributed to the four asset classes covered. In the left panel the results are reported for equity market quintiles, with quintile 1 corresponding to the worst three-month S&P 500 returns and quintile 5 to the best. The rightmost bar corresponds to the average return across all periods. Similarly, the right panel shows results for different bond market (U.S. 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.

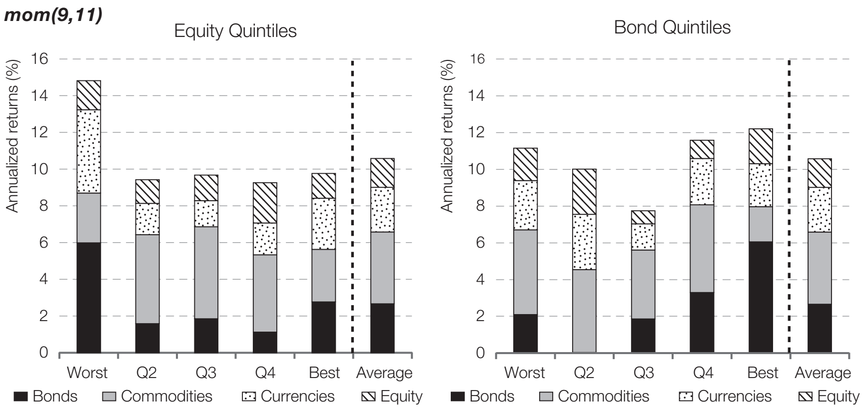

FIGURE 1A.3 (*Continued*)

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