International Review of Financial Analysis 31 (2014) 1–12

Contents lists available at ScienceDirect

International Review of Financial Analysis

Trend following, risk parity and momentum in commodity futures

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ARTICLE INFO

Article history:
Received 31 January 2013
Received in revised form 19 July 2013
Accepted 4 October 2013
Available online 22 October 2013

JEL classification:
G12
G13
G15
F65

Keywords:
Trend following
Momentum
Risk parity
Equally-weighted
Portfolios
Commodity futures

ABSTRACT

We show that combining momentum and trend following strategies for individual commodity futures can lead to portfolios which offer attractive risk adjusted returns which are superior to simple momentum strategies; when we expose these returns to a wide array of sources of systematic risk we find that robust alpha survives. Experimenting with risk parity portfolio weightings has limited impact on our results though in particular is beneficial to long–short strategies; the marginal impact of applying trend following methods far outweighs momentum and risk parity adjustments in terms of risk-adjusted returns and limiting downside risk. Overall this leads to an attractive strategy for investing in commodity futures and emphasises the importance of trend following as an investment strategy in the commodity futures context.

1. Introduction

The benefits of investing in commodities as an asset class both as a portfolio diversifier and as an inflation hedge have been increasingly of interest to academics and investors especially since the wide-ranging study by Gorton and Rouwenhorst (2006). However, investment in commodities is not straightforward and is generally accessed in financial markets by liquid futures' contracts traded on organised exchanges. In this paper we contribute to the growing evidence that applying a trend following investment strategy to a variety of asset classes leads to enhanced risk adjusted returns. In particular we show that combining momentum and trend following strategies for individual commodity futures can lead to portfolios which offer attractive risk adjusted returns; when we expose these returns to a wide array of sources of systematic risk we find that robust alpha survives. Experimenting with risk parity portfolio weightings has limited impact on our results though it is beneficial to long–short strategies; the marginal benefit of applying trend following methods far outweighs momentum and risk parity adjustments in terms of risk-adjusted returns and limiting downside risk.

Momentum strategies involve ranking assets based on their past return (often the previous twelve months) and then buying the winners and selling the losers. Momentum is one anomaly in the financial literature that has been demonstrated to offer enhanced future returns. Many studies since Jegadeesh and Titman (1993) have focussed on momentum at the individual stock level. More recently Asness, Moskowitz, and Pedersen (2013) find momentum effects within a wide variety of asset classes. In terms of commodity futures, Miffre and Rallis (2007) and Erb and Harvey (2006) were amongst the first to show that momentum strategies earn significant positive excess returns. The purpose of this paper is to show how a momentum strategy for commodity futures which also employs a trend following overlay can significantly enhance investment performance relative to both long only and long–short momentum strategies.

Trend following has been widely used in futures markets, particularly commodities, for many decades (see Ostgaard, 2008). Trading signals can be generated by a variety of methods such as moving average crossovers and breakouts with the aim of determining the trend in prices. Long positions are adopted when the trend is positive and short positions, or cash, are taken when the trend is negative. As trend following is generally rule-based it can aid investors since losses are mechanically cut short and winners left to run. This is frequently the reverse of investors' natural instincts. The return on cash (in this case the 3-month US Treasury Bill rate) is also an important factor either as collateral in futures or as the risk-off asset for long-only methods. Examples of the effectiveness of trend following for commodity futures, amongst others, are Szakmary, Shen, and Sharma

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http://dx.doi.org/10.1016/j.irfa.2013.10.001

(2010) and Hurst, Johnson, and Ooi (2010); Hurst, Ooi, and Pedersen (2010). As with momentum strategies, much of the research is focussed on equities with Wilcox and Crittenden (2005) and ap Gwilym, Clare, Seaton, and Thomas (2010) as examples. Recent attempts at explaining the success of trend following include Faber (2007) who uses trend following as a means of tactical asset allocation and demonstrates that it is possible to form a portfolio that has equity-level returns with bond-level volatility. Ilmanen (2011) offers a variety of explanations as to why trend following may have been successful historically, including investor under-reaction to news and herding behaviour.

A few studies have sought to combine the momentum and trend-following strategies in equities. Faber (2010) examines momentum and a form of trend following in equity sector investing in the United States. Antonacci (2012) analyses the returns from momentum trading of pairs of investments and then applies a quasi-trend following filter to ensure that the winners have exhibited positive returns. This is based on the argument that extreme (positive) past returns or volatility should be taken account of in identifying a risk factor to increase momentum profitability. Past positive performance of individual assets is a good signal for future returns. The risk-adjusted performance of these approaches appears to be a significant improvement on benchmark buy-and-hold portfolios. Bandarchuk and Hilscher (2013) present a similar strategy arguing that many of the characteristics that have been identified as being correlated with, or explanations for, the presence of enhanced momentum profits are just related to extreme past returns. Conditioning on this effect, they find no role for characteristics such as book to market (Sagi & Seasholes, 2007), forecast dispersion (Verardo, 2009) and credit rating (Avramov, Chordia, Jostova, & Philipov, 2007) in raising momentum profitability. In this paper we direct attention to the ability of a trend following rule to enhance momentum profitability in commodity futures.

Behavioural and rational asset pricing explanations for momentum and trend following have been offered in the literature. Hong and Stein (1999) is representative of behavioural approaches which could generate momentum or trend following behaviour whilst Sagi and Seasholes (2007) examines trend behaviour in single risky assets which could be applicable to the construction of a momentum portfolio.

Momentum studies for a range of markets typically weight equally all assets chosen in the winners (or losers) portfolio. Following Ilmanen (2011), we argue that this is not the ideal approach, especially in the case of commodity futures, and that investors would be better served by volatility weighting past returns. Failing to do this leads to the most volatile assets spending a disproportionate amount of time in the highest and lowest momentum portfolios. Finally, in this paper we also examine how risk parity weighting affects strategy performance.

Section 2 contains a description of our data whilst in Section 3 we examine the role of momentum and trend following investment strategies along with different portfolio formation techniques using both risk parity and equal weighting portfolio construction methods; Section 4 presents the empirical results for applying these methods to our commodities data whilst in Section 5 we control for both transactions' costs and explore sources of systematic risk which may be present in our analysis. Section 6 concludes.

2. Data and methods

The commodity futures data examined in this paper are the full set of 28 DJ-UBS commodity excess return indices. These returns series are inclusive of spot and roll gains but assume no returns on collateral put up.[1] We choose these assets since they are all easily and actively traded through commodity Exchange Traded Funds (ETF or CETF) on stock markets around the world. The Commodity Futures Trading Commission (CFTC) estimates the size of the overall commodity index market, consisting of trading in the individual commodity futures that we analyse and the overall liquidity-weighted indices such as the DJ-UBS CI, at over $200bn, worldwide.[2] The long-term time series of futures return indices that we analyse are created following common practice by rolling adjacent individual futures contracts between monthly returns observations. The rolling together of the underlying futures contracts to form an index return follows transparent, public and fixed rules. In the DJ-UBS case the adjacent futures contracts are rolled together proportionally over trading days 5 to 9 in the relevant month, increasing the weight of the new contract in the return index by 20% per day. This smoothing dilutes the impact of choosing any particular day of the month to roll a contract and hence leads to a more robust measure of underlying return on the contracts.[3] Alternative versions of this rolling method are employed by Gorton and Rouwenhorst (2006) and Asness et al. (2013) where they focus on higher frequency data but perform monthly rolls of contracts. A further issue is whether the fully publicised 'rolling' rules impact the futures' contract returns. Stoll and Whaley (2010, p 65) state categorically that their estimates show that 'Commodity index rolls have little futures price impact, and inflows and outflows from commodity index investment do not cause futures prices to change' Stoll and Whaley (2010), Basak and Palova (2013), Irwin (2013) and Hamilton and Wu (2013), amongst others, examine the relationship between commodity index trading and futures contract prices with a major question relating to the merits of the hypothesised impact of the 'financialisation of commodities', i.e. does the volume of investing in commodities via indices lead to destabilising behaviour for the underlying futures prices? The evidence from these papers is that they find no causal relationship.[4] We focus our empirical analysis on the investment properties of the returns to the individual DJ-UBS indices as an investable portfolio strategy.

The full data period runs from January 1991 to June 2011. The period of study is 1992–2011 with all observations being monthly data. The first year of data is used to calculate trend-following signals and momentum rankings. Throughout the paper all values are total returns (unless specified) and are in US dollars.

The 28 commodities are:

Aluminium	Heating oil	Soybean oil	Platinum
Coffee	Lean hogs	Sugar	Tin
Copper	Live cattle	Unleaded gas	Brent crude
Corn	Natural gas	Wheat	Feeder cattle
Cotton	Nickel	Zinc	Gas oil
Crude oil	Silver	Cocoa	Orange juice
Gold	Soybean	Lead	Soybean meal

A summary of the properties of the returns series is shown in Table 1. The spread of variability and return is notable with some commodities such as natural gas and coffee showing a volatility of returns substantially higher than others, along with severe drawdowns and often negative risk-adjusted returns. The Sharpe ratios are generally unattractive as individual asset investments. There is also clear evidence of non-normality in returns.

3. Investment strategies in commodity futures: portfolio weighting, momentum and trend following

We begin by reviewing two key aspects of portfolio formation for commodity futures, namely the justification for using trend following

[1] A full description of the construction of the indices can be found in Dow-Jones (2012) and at http://www.djindexes.com/commodity/.

[2] An example of a provider of commodity ETF's based on the indices analysed in this paper is ETF Securities, http://www.etfsecurities.com/institutional/uk/en-gb/products.aspx.

[3] An explanation of the practical issues involved in rolling returns can be found at http://www.followingthetrend.com/futures-charts/futures-data-adjustments/.

[4] These studies mostly focus on the impact of trading a commodity index constructed from a number of individual commodity return indices. We treat each commodity separately.

Table 1
Summary statistics. The data are DJ-UBS commodity excess return indices. These returns are inclusive of spot and roll gains but assume no returns on collateral put up. Data period: 1992–2011 with all observations being monthly data. All data are total returns and are in US dollars. A full description of the construction of the indices can be found in Dow–Jones (2012).

Commodity	Annualised excess return (%)	Annualised volatility (%)	Sharpe ratio	Max. monthly return (%)	Min. monthly return (%)	Maximum drawdown (%)	Skew
Aluminium	−0.76	19.00	−0.04	15.81	−16.94	65.07	0.11
Coffee	−2.50	39.90	−0.06	53.70	−31.19	90.13	1.02
Copper	8.75	26.27	0.33	31.35	−36.47	63.95	−0.03
Corn	−7.79	25.52	−0.31	22.19	−20.44	90.27	0.00
Cotton	−4.73	27.87	−0.17	24.55	−22.64	93.46	0.36
Crude oil	5.73	31.30	0.18	35.16	−31.93	76.09	−0.02
Gold	4.19	15.25	0.27	16.40	−18.46	54.05	0.25
Heating oil	5.32	30.80	0.17	33.86	−29.01	71.04	0.19
Lean hogs	−10.92	24.91	−0.44	21.60	−25.96	93.67	−0.08
Live cattle	−1.49	13.62	−0.11	9.87	−20.73	51.27	−0.64
Natural gas	−14.81	49.74	−0.30	50.19	−35.08	98.58	0.47
Nickel	5.89	34.88	0.17	37.66	−27.78	80.48	0.24
Silver	7.91	28.39	0.28	28.18	−23.63	52.14	0.09
Soybean	4.14	23.88	0.17	20.49	−22.08	51.06	−0.11
Soybean oil	0.24	25.44	0.01	26.46	−25.20	69.27	0.07
Sugar	4.28	32.41	0.13	31.06	−29.70	64.74	0.14
Unleaded gas	7.60	33.10	0.23	38.05	−38.94	71.05	−0.08
Wheat	−10.05	27.75	−0.36	37.74	−25.27	92.63	0.53
Zinc	−0.45	25.41	−0.02	27.39	−33.78	75.93	−0.07
Cocoa	−4.15	30.51	−0.14	34.56	−25.01	85.71	0.63
Lead	6.54	28.61	0.23	26.26	−27.52	73.04	0.02
Platinum	9.75	20.26	0.48	25.52	−31.33	62.22	−0.76
Tin	8.27	22.41	0.37	22.53	−22.13	54.21	0.43
Brent crude	10.97	28.91	0.38	33.95	−33.36	72.00	−0.15
Feeder cattle	2.42	13.42	0.18	11.76	−15.33	36.12	−0.20
Gas oil	7.20	29.92	0.24	29.46	−31.01	72.38	0.01
Orange juice	−8.32	29.52	−0.28	29.17	−22.60	91.82	0.36
Soybean meal	7.80	25.16	0.31	26.13	−20.39	44.92	0.31

and/or momentum strategies in selecting individual assets together with the method of weighting those assets in the portfolio.

3.1. Momentum and trend following strategies

A momentum strategy is a simple trading rule which involves taking a long investment position in rank-ordered, relatively good performing assets (winners) and a short position in those which perform relatively poorly (losers) over the same investment horizon. It is an explicit bet on the continuation of past relative performance into the future. Trend following, although closely related to momentum investing, is fundamentally different in that it does not order the past performance of the assets of interest, though it does rely on a continuation of, or persistence in, price behaviour based upon technical analysis. There is a tendency at times to use the terms 'momentum' and 'trend following' almost interchangeably, yet the former has a clear cross sectional element to it in that the formation of relative performance rankings is across the universe of stocks (or other securities) over a specific period of time, only to be continued in a time-series sense and eventually mean reverting after a successful 'winning' holding period. It should also be noted that momentum studies usually use monthly data whereas trend following rules are applied to all frequencies of data.

The underlying economic justification for trend following rules lies in behavioural finance tenets such as those relating to herding, disposition, confirmation effects, and representativeness biases (for example see Asness et al. (2013) or Ilmanen (2011)). At times information travels slowly, especially if assets are illiquid and/or if there is high information uncertainty; this leads to investor underreaction. If investors are reluctant to realise small losses then momentum is enhanced via the disposition effect. Indeed both of these phenomena relate to the difference between the current price and the purchase price: poorly anchored prices allow more leeway for sentiment-driven changes. And there is now growing academic evidence to suggest that these trend following strategies can produce attractive, risk-adjusted returns (including for commodities as shown by Szakmary et al. (2010), for example). However, such findings are not universal: for example, see Park and Irwin (2007) in their review of 9 studies using trading rules for commodity futures. Ilmanen (2011) suggests that the typical Sharpe ratio for a single asset using a trend following strategy lies between 0 and 0.5 but rises to between 0.5 and 1 when looking at a portfolio.

3.2. Risk parity vs equal portfolio weights

The first issue to deal with in forming portfolios of commodity futures is that of weights of individual assets. The vast differences in the volatility of returns to the commodities that we examine lead to the question of whether the portfolios formed based on a trend following or momentum strategy (or indeed any strategy, for that matter), are dominated by the volatility of the returns of individual commodities with the most extreme volatilities and drawdowns. In the data examined here, the commodities with the highest return volatility (>30% annual volatility) are natural gas, coffee, nickel, unleaded gas and sugar (see Table 1). In the simple equal-weighted 12-month momentum strategy portfolio, evaluated below, these commodities are over-represented when compared with average representation across the 28 commodities by 15%. The lowest volatility (<20% annual volatility) commodities feeder cattle, live cattle, gold, aluminium and platinum appear 12% less often than the average. The resolution to this problem of reduced diversity of portfolio holdings that has developed in both markets and in the literature is risk-parity weighting.[5] This employs volatility weights rather than equal, market value or rule-of-thumb weights (such as the 60/40 equity/bond weights traditionally employed). The idea behind this is to weight assets inversely by their contribution to portfolio risk; this has the effect of overweighting low risk assets and in practice leads to massively overweight bond components of equity/bond portfolios in recent years (see Montier, 2010) and ensuing superior performance due to the bull market in bonds.

In this paper we employ realised volatility measures for constructing the inverse volatility weights using a spread of windows of days over which volatility is computed. This type of measure has been shown by Andersen and Bollerslev (1998), amongst others, to provide an

[5] See Dalio (2004) for an early justification for risk-parity weighting and Asness, Frazzini, and Pedersen (2011) for a recent argument.

Table 2
Risk parity portfolios — monthly rebalancing. This table shows the annualised average returns in percentages from portfolios formed from the 28 commodity futures of the DJ-UBSCI for the period Jan 1992–Jun 2011. The risk-parity portfolios are formed using inverse relative volatility weights where relative volatility is calculated using between 10 and 120 days of return data prior to the portfolio formation date.

Winners	Equal weight	Volatility period (days)					
		10	20	30	60	90	120
Annualised excess return (%)	4.45	4.17	3.82	3.86	3.73	3.73	3.82
[Newey–West t-statistic]	[1.36]	[1.39]	[1.27]	[1.27]	[1.23]	[1.23]	[1.25]
Annualised volatility (%)	12.79	11.28	11.40	11.44	11.43	11.47	11.50
Sharpe ratio	0.35	0.37	0.33	0.34	0.33	0.32	0.33
Max. monthly return (%)	12.76	10.59	10.75	10.75	10.91	10.88	10.85
Min. monthly return (%)	−20.59	−18.72	−18.61	−18.31	−18.76	−18.80	−18.95
Maximum drawdown (%)	48.16	43.86	43.68	43.86	44.88	45.27	45.47
Skew	−0.69	−0.84	−0.78	−0.72	−0.81	−0.83	−0.84

Table 3
Average annualised returns over periods of interest.

	Equal weight	Volatility periods (days)						TF&MOM	
		10	20	30	60	90	120	EW	RP
Surprise Fed Rate Hike	−0.36	−0.36	−0.31	−0.31	−0.33	−0.36	−0.41	0.32	1.32
Tech Bubble	1.27	0.84	0.77	0.80	0.83	0.88	0.89	2.18	2.06
Tech Bust	0.32	0.03	0.06	0.08	0.05	0.06	0.08	1.03	1.53
Easy Credit	2.07	2.12	2.05	2.04	2.01	2.02	2.04	1.57	0.32
Credit Crunch	−1.43	−1.04	−1.08	−1.09	−1.20	−1.25	−1.24	1.01	3.27

The periods concerned are: Surprise Fed Rate Hike (94/2–94/3), Tech Bubble (99/1–2000/3), Tech Bust (2000/4–2004/3), Easy Credit (2002/8–2004/3), Credit Crash (2007/7–2009/3). TF&MOM is the return on the equally weighted and risk parity weighted versions of the 6-month trend following adjustment to the 12-month momentum strategy highlighted in Section 4.4.

unbiased and efficient measure of underlying volatility.[6] Given the monthly frequency of the returns data, we compute realised return volatility measures for between 10 and 120 days prior to the date of the measurement of returns. Portfolio weights are then constructed to be proportional to the inverse of observed volatility. This process is repeated at the end of each month. The risk parity portfolios have the characteristic of increasing the relative diversity of portfolio holding of individual commodity futures. The 60-day risk-parity momentum portfolio shows an over-representation of high versus low volatility commodities across the whole dataset of only 2% when compared with equal average representation.

The baseline portfolio returns against which we will evaluate all of the strategies in this paper are the equal weighted and risk parity long-only portfolios of all commodities whose characteristics are shown in Table 2. It can be seen that the average annual return in excess of the 3-month US Treasury Bill rate is 4.45% for the equally weighted portfolio. Average returns are somewhat lower for the basic risk parity portfolios, although both are significantly positive given the size of the Newey–West t-statistics employed throughout this paper. The trade-off of return against volatility is shown by the slightly lower volatility in risk parity portfolios. The Sharpe ratios for the equally weighted and risk parity portfolios are similar as indeed are the monthly maximum and minimum returns and maximum drawdown: there would seem to be little benefit in using risk parity as a portfolio construction technique for commodity futures.

Another metric for assessing the performance of the strategies examined in this paper is their returns in recent periods of market turbulence. This approach is proposed by Hurst, Johnson et al. (2010) in their assessment of risk parity portfolios. The periods we consider are the surprise increase in Fed interest rates (1994), the period of the Tech boom and separately bust (1999–2004), the period of easy credit and finally the credit crunch. Average returns of the baseline strategies are shown in Table 3 and show that the risk parity strategies have lower absolute average returns than the equally weighted strategy. The most pronounced differences between the two across the two most recent periods were when risk parity returns were somewhat lower during the period of easy credit and were a full 40 basis points more during the credit crunch. Below we monitor these measures along with more standard summary statistics.

4. Results

4.1. The returns from trend following in commodity futures

We consider a trend following rule that is popular with investors which is based on simple monthly moving averages of returns.[7] The buy signal occurs when the individual commodity future return moves above the average where we consider moving averages ranging from 6 to 12 months. The intuition behind the simple trend following approach is that whilst current market price is most certainly the most relevant data point, it is less certain whether the most appropriate comparison is a month or a year ago (Ilmanen, 2011). Taking a moving average therefore dilutes the significance of any particular observation. With each of the rules, if the rule 'says' invest we earn the return on the commodity future over the relevant holding period which we fix at one month; however when the return 'says' do not invest we earn the return on cash over the holding period of one month. The rules are therefore binary: we either earn the return on the risky asset or the return on cash. In this case this return is the Treasury bill interest rate which has zero excess return. Previous research including Annaert, Van Osselaer, and Verstraete (2009) for equities, for example, suggests better performance from the longer moving averages examined in this paper.

Table 4 presents our results for both long positions in panel A and long–short positions in panel B. The long positions return either the one month excess return or zero depending on the trend following signal. The long–short strategies allow for short positions for those periods when the trend following buy signal is negative. All strategies show a positive excess return which is significantly higher than those

[6] Some alternatives are canvassed by Baltas and Kosowski (2013).

[7] Ostgaard (2008) introduced a range of trend following rules for commodity futures.

Table 4
Trend following portfolios — monthly trading Jan 1992–Jun 2011.

	Moving average period (months)						
	6	7	8	9	10	11	12
Long-only							
Annualised excess return (%)	5.77	6.04	5.86	5.29	5.16	5.16	5.40
[Newey–West t-statistic]	[3.06]	[3.20]	[3.13]	[2.90]	[2.87]	[2.81]	[2.88]
Annualised volatility (%)	7.93	7.94	7.84	7.80	7.74	7.81	7.79
Sharpe ratio	0.73	0.76	0.75	0.68	0.67	0.66	0.69
Max. monthly return (%)	9.92	9.92	9.37	9.37	9.14	9.80	9.80
Min. monthly return (%)	−7.11	−7.06	−7.06	−7.06	−6.91	−6.91	−6.91
Maximum drawdown (%)	14.24	12.43	13.57	15.20	15.99	16.73	16.76
Skew	0.34	0.46	0.29	0.27	0.25	0.29	0.31
Long–short							
Annualised excess return (%)	6.35	6.87	6.52	5.38	5.09	5.11	5.60
[Newey–West t-statistic]	[2.66]	[2.84]	[2.77]	[2.38]	[2.27]	[2.39]	[2.63]
Annualised volatility (%)	10.19	10.29	10.04	10.03	10.12	10.07	10.00
Sharpe ratio	0.62	0.67	0.65	0.54	0.50	0.51	0.56
Max. monthly return (%)	20.59	20.59	20.59	20.59	20.59	20.59	20.59
Min. monthly return (%)	−9.25	−9.25	−9.25	−9.25	−9.46	−10.33	−10.33
Maximum drawdown (%)	17.35	17.46	16.24	18.80	20.97	18.84	17.98
Skew	1.27	1.28	1.29	1.28	1.11	1.11	1.10

for the passive positions shown in Table 2. Shorter length moving average signals provide a higher return than longer with the highest return for the 7-month moving average signal. These average excess returns are all significantly larger than zero. They are not, however, statistically significantly different from one another. The long only strategies provide the highest Sharpe ratio reflecting the generally rising market over the sample period and at around 0.7 are comfortably in the range suggested by Ilmanen (2011) of 0.5–1.0. Note that the annualised volatility without trend following in Table 2 at 12.79% for the equally weighted portfolio is roughly 50% more than the trend following equivalent (at around 7.94% in Table 4): this elevated return with much lower volatility (often a half to a third of a buy and hold equivalent) is a typical finding for a range of asset classes and historical periods (see ap Gwilym et al., 2010; Faber, 2007). Note also that the maximum drawdown for trend following portfolios is roughly one-third that of long only equal weighting or risk parity strategies: again this is a typical finding that may be particularly desirable to investors. In addition, long–short strategies do provide even higher average returns which are generally more positively skewed, though the Sharpe ratios are inferior to the long-only case (see Table 4). Further in the most recent period of market turbulence during the credit crisis, trend following provided average returns of 0.64% per annum for long only, compared to −1.43% with no trend following (Table 3).

4.2. The returns from momentum investing in commodity futures

The results from following a simple momentum investing strategy are shown in Table 5. The strategy we examine is based on the

Table 5
Momentum portfolios — monthly trading Jan 1992–Jun 2011.

	Momentum calculation period (months)						
	6	7	8	9	10	11	12
Winners							
Annualised excess return (%)	9.95	8.52	5.91	4.93	7.10	10.67	11.12
[Newey–West t-statistic]	[2.09]	[1.92]	[1.50]	[1.34]	[1.77]	[2.45]	[2.53]
Annualised volatility (%)	20.10	19.93	19.87	19.38	19.45	19.25	19.36
Sharpe ratio	0.50	0.43	0.30	0.25	0.37	0.55	0.57
Max. monthly return (%)	17.75	16.61	16.61	16.81	17.47	16.81	16.81
Min. monthly return (%)	−25.04	−27.72	−29.45	−26.52	−25.88	−25.88	−28.92
Maximum drawdown (%)	48.67	50.70	50.63	54.11	52.73	49.80	51.56
Skew	−0.14	−0.29	−0.44	−0.32	−0.26	−0.31	−0.56
Losers							
Annualised excess return (%)	0.16	1.13	1.65	0.58	−0.83	−2.49	−1.16
[Newey–West t-statistic]	[0.39]	[0.61]	[0.73]	[0.49]	[0.17]	[0.26]	[0.08]
Annualised volatility (%)	17.87	17.54	17.18	17.91	17.88	17.12	17.42
Sharpe ratio	0.01	0.06	0.10	0.03	−0.05	−0.15	−0.07
Max. monthly return (%)	20.05	22.40	22.42	26.60	28.22	23.56	23.56
Min. monthly return (%)	−19.83	−22.75	−21.78	−21.78	−20.64	−21.78	−21.14
Maximum drawdown (%)	62.29	58.57	54.24	50.98	57.35	69.55	60.68
Skew	0.21	0.42	0.47	0.79	1.03	0.61	0.62
Long winners–short losers							
Annualised excess return (%)	7.58	5.46	2.49	2.19	5.57	11.31	10.31
[Newey–West t-statistic]	[2.27]	[1.97]	[1.13]	[1.08]	[1.77]	[3.10]	[2.82]
Annualised volatility (%)	22.24	21.08	20.98	21.67	22.59	21.69	21.53
Sharpe ratio	0.34	0.26	0.12	0.10	0.25	0.52	0.48
Max. monthly return (%)	21.49	20.17	20.40	20.60	19.48	20.60	19.89
Min. monthly return (%)	−22.38	−26.50	−25.54	−31.07	−32.56	−26.66	−26.66
Maximum drawdown (%)	49.49	37.02	48.98	53.63	46.37	32.23	38.76
Skew	−0.07	−0.21	−0.13	−0.48	−0.61	−0.24	−0.27

Table 6
12-Month momentum subdivision — monthly trading Jan 1992–Jun 2011.

	Momentum calculation period (months)			
	1	2–6	7–12	12
Winners				
Annualised excess return (%)	8.08	9.24	7.57	11.12
Annualised volatility (%)	18.53	19.53	18.29	19.36
Sharpe ratio	0.44	0.47	0.41	0.57
Max. monthly return (%)	16.37	16.61	18.20	16.81
Min. monthly return (%)	−17.92	−24.55	−26.32	−28.92
Maximum drawdown (%)	48.88	49.58	63.56	51.56
Skew	−0.13	−0.28	−0.47	−0.56
Losers				
Annualised excess return (%)	0.93	1.62	−3.62	−1.16
Annualised volatility (%)	18.00	17.80	16.90	17.42
Sharpe ratio	0.05	0.09	−0.21	−0.07
Max. monthly return (%)	16.26	22.39	18.28	23.56
Min. monthly return (%)	−17.31	−21.43	−16.31	−21.14
Maximum drawdown (%)	66.47	62.15	71.33	60.68
Skew	0.07	0.36	0.32	0.62
Long winners–short losers				
Annualised excess return (%)	4.50	5.40	9.71	10.31
Annualised volatility (%)	22.55	21.64	19.91	21.53
Sharpe ratio	0.20	0.25	0.49	0.48
Max. monthly return (%)	17.23	23.60	15.36	19.89
Min. monthly return (%)	−22.08	−22.39	−20.26	−26.66
Maximum drawdown (%)	76.68	38.48	47.73	38.76
Skew	−0.28	−0.04	−0.11	−0.27

momentum in commodity returns over a range of prior periods ranging from 6 to 12 months. Portfolios are constructed for quartiles of highest (winner) and lowest (loser) commodity futures based on their cumulative return over the range of prior months. Returns are then computed for the month of the construction of the portfolios. Given the number of commodity futures that we examine, there are 7 returns in each of the winner and loser portfolios. The panels of summary statistics shown in Table 5 are for long positions in the winner and loser portfolios and long winner–short loser portfolios.

The long investments in winner portfolios show high and significant positive excess returns for momentum calculation periods at the short and long ends. This is greatest at the longer end; 12-month momentum provides an average annualised excess return of 11.12% which is significantly greater than for the medium length calculation periods. This is in excess of that achieved by any of the long trend following strategies discussed above but comes at the price of much higher volatility. The Sharpe ratio of the 12-month momentum strategy is 0.57 which is clearly lower than that of any of the trend-following strategies which is maximised at 0.76 for the 7-month trend-following portfolio. The performance of all momentum strategies are also negatively skewed and show much larger maximum drawdowns compared to all trend following strategies (in Table 4). Further (and not shown here) long-only momentum strategies all resulted in average losses over the credit crisis period. This highlights the point made by Daniel and Moskowitz (2011) and Daniel, Jagannathan, and Kim (2012) that momentum strategy returns are often skewed and are subject to momentum crashes where momentum portfolio returns fall abruptly following a downturn in the market overall. Part of the motivation for introducing a trend following element to a momentum strategy in commodity futures is to reduce the skewness in returns and the associated crash risk.

Novy-Marx (2012) has recently raised the question of the relative performance of momentum strategies based on different length periods of momentum. His results show limited returns from shorter length periods of up to 6 months compared with longer periods between 6 and 12 months. Table 6 shows a comparison of four momentum periods for our commodity futures data. These show that, contrasting with Novy-Marx, that returns and Sharpe ratios are higher for 12 month momentum returns than for short or medium length periods. Unlike evidence in Novy-Marx (2012), there is some evidence from column 2 of Table 6 that averaging over 2–6 months provides for a higher average return and Sharpe ratio than for the average of 7–12 months. However, these

Table 7
Risk parity 12-month momentum portfolios — monthly trading Jan 1992–Jun 2011.

	Volatility period (days)					
	10	20	30	60	90	120
Winners						
Annualised excess return (%)	11.23	10.41	11.61	11.05	10.67	10.31
[Newey–West t-statistic]	[2.42]	[2.25]	[2.54]	[2.60]	[2.52]	[2.46]
Annualised volatility (%)	18.72	18.93	19.03	18.82	19.02	19.11
Sharpe ratio	0.60	0.55	0.61	0.59	0.56	0.54
Max. monthly return (%)	16.81	16.81	16.81	16.93	16.93	16.93
Min. monthly return (%)	−26.40	−25.88	−25.88	−25.88	−25.88	−25.88
Maximum drawdown (%)	51.56	56.25	51.75	49.22	48.86	48.57
Skew	−0.45	−0.38	−0.36	−0.45	−0.43	−0.44
Losers						
Annualised excess return (%)	−2.12	−3.32	−2.47	−2.77	−3.33	−2.83
[Newey–West t-statistic]	[0.33]	[0.63]	[0.39]	[0.48]	[0.65]	[0.52]
Annualised volatility (%)	14.24	14.69	14.61	14.53	14.48	14.41
Sharpe ratio	−0.15	−0.23	−0.17	−0.19	−0.23	−0.20
Max. monthly return (%)	14.75	14.75	14.75	14.75	14.75	14.75
Min. monthly return (%)	−16.75	−17.99	−17.46	−17.46	−17.46	−17.46
Maximum drawdown (%)	63.65	71.48	65.72	65.11	67.30	64.70
Skew	0.24	0.10	0.12	0.13	0.21	0.20
Long winners–short losers						
Annualised excess return (%)	10.31	12.87	13.16	12.91	13.16	12.23
[Newey–West t-statistic]	[3.28]	[3.50]	[3.68]	[3.62]	[3.65]	[3.57]
Annualised volatility (%)	21.53	19.48	19.40	19.43	19.74	19.81
Sharpe ratio	0.48	0.66	0.68	0.66	0.67	0.62
Max. monthly return (%)	19.89	17.71	17.65	19.89	19.89	19.89
Min. monthly return (%)	−26.66	−15.72	−15.72	−15.72	−15.72	−15.21
Maximum drawdown (%)	38.76	39.55	31.72	30.30	28.43	28.14
Skew	−0.08	−0.01	−0.01	0.00	0.02	0.05

are both dominated by the 12 month period. The discontinuity in performance raises questions about the applicability of popular behavioural and rational explanations of the effectiveness of momentum strategies.

4.3. Risk parity trend following and momentum portfolios

The portfolio returns shown in Tables 4 and 5 for trend following and momentum portfolios separately are for the standard equally-weighted cases. Next, we evaluate the contribution that risk-parity weighting might make to these strategies. Table 7 provides results for the highest return, 12-month momentum strategy for a range of volatility measurement periods and is directly comparable to the last column in Table 5. As with the simple raw returns reported above in Table 2, the impact of risk-parity weighting is to increase the presence of lower volatility commodities in portfolios. Thus amongst winner portfolios, returns are slightly less volatile and have a somewhat lower maximum drawdown as well as being less negatively skewed than in the equally-weighted case. Average returns for winners are higher for some volatility periods. The performance of loser portfolios is much worse under risk-parity weighting although this is not significantly different from zero given the size of the t-statistics. Consequently, average returns and Sharpe ratios for winner-loser portfolios are much higher in this case. For a 30-day volatility measurement period, average returns are some 13.16% with a Sharpe ratio of 0.68 compared to, say, 10.31% and 0.48 for the long–short equally weighted portfolio in Table 5 (12 month momentum calculation period). Overall the results of adding the risk parity overlay to momentum investing have limited impact on the results but do lead to some overall improvement, especially with regard to maximum drawdowns.

What if we overlay trend following on the simple returns and apply risk-parity weighting? The results are shown in Table 8, where 7- and 12-month moving average-based strategies are reported, and may be compared with the equally weighted version in Table 4 which has no trend following. These show, as with the results for momentum strategies, that the biggest impact of risk-parity weighting is on loser portfolios and, consequently, on long winner–short loser portfolios. Average returns and Sharpe ratios are significantly higher for long–short portfolios for longer volatility calculation periods with the trend following overlay. These should also be compared with the risk-parity portfolios in Table 2 which do not adjust for trend following, where drawdowns are at least 3 times as big and Sharpe ratios are only half the size of Table 8. These results show that risk-parity weighting can have rather limited effects relative to equal weighting but that more predictable and substantial effects come from applying trend following.

Inker (2010) has raised a number of concerns with risk parity weighting in the context of strategies in equity and bond markets. These are mostly concerned with the use of leverage to extend the weight given to bonds in portfolios which we do not consider here. The remaining concern raised by Inker is that the attractiveness of previously low volatility return assets such as bonds might be overstated as they are subject to significant skewness risk. In our

Table 8
Risk parity trend following portfolios — monthly trading Jan 1992–Jun 2011.

	Volatility period (days)						
7-month moving average signal	10	20	30	60	90	120	180
Long-only							
Annualised excess return (%)	5.01	5.10	5.22	5.35	5.40	5.51	5.51
[Newey–West t-statistic]	[2.97]	[2.94]	[2.95]	[3.03]	[3.03]	[3.07]	[3.05]
Annualised volatility (%)	7.08	7.16	7.17	7.13	7.20	7.22	7.24
Sharpe ratio	0.71	0.71	0.73	0.75	0.75	0.76	0.76
Max. monthly return (%)	8.62	9.25	9.41	9.73	9.62	9.67	9.76
Min. monthly return (%)	−7.30	−6.98	−6.79	−6.73	−6.72	−6.74	−6.75
Maximum drawdown (%)	13.30	13.06	12.78	12.65	12.69	12.74	12.77
Skew	0.12	0.22	0.33	0.37	0.33	0.35	0.36
Long–short							
Annualised excess return (%)	5.29	5.84	6.03	6.41	6.52	6.64	6.52
[Newey–West t-statistic]	[2.64]	[2.81]	[2.85]	[2.92]	[2.93]	[2.94]	[2.86]
Annualised volatility (%)	8.91	8.95	8.94	8.96	9.00	9.04	9.10
Sharpe ratio	0.59	0.65	0.67	0.72	0.72	0.73	0.72
Max. monthly return (%)	18.72	18.61	18.31	18.76	18.80	18.95	19.06
Min. monthly return (%)	−7.35	−7.14	−6.85	−6.70	−6.78	−6.73	−6.84
Maximum drawdown (%)	15.31	14.45	14.03	12.23	12.01	12.69	12.96
Skew	1.46	1.43	1.39	1.55	1.51	1.55	1.56
12-month moving average signal							
Long-only							
Annualised excess return (%)	5.05	4.99	5.09	5.18	5.19	5.29	5.26
[Newey–West t-statistic]	[2.83]	[2.75]	[2.78]	[2.87]	[2.86]	[2.90]	[2.88]
Annualised volatility (%)	7.05	7.10	7.13	7.07	7.11	7.14	7.17
Sharpe ratio	0.72	0.70	0.71	0.73	0.73	0.74	0.73
Max. monthly return (%)	8.80	9.42	9.56	9.74	9.62	9.69	9.71
Min. monthly return (%)	−7.03	−6.68	−6.68	−6.44	−6.54	−6.53	−6.43
Maximum drawdown (%)	15.76	15.52	15.54	15.34	15.41	15.50	15.67
Skew	0.24	0.30	0.37	0.39	0.35	0.37	0.38
Long–short							
Annualised excess return (%)	5.37	5.60	5.77	6.08	6.09	6.20	6.02
[Newey–West t-statistic]	[2.77]	[2.81]	[2.88]	[3.03]	[3.01]	[3.05]	[2.98]
Annualised volatility (%)	8.81	8.85	8.89	8.87	8.89	8.92	8.96
Sharpe ratio	0.61	0.63	0.65	0.69	0.68	0.69	0.67
Max. monthly return (%)	18.72	18.61	18.31	18.76	18.80	18.95	19.06
Min. monthly return (%)	−8.09	−8.03	−8.13	−7.96	−7.72	−7.66	−7.73
Maximum drawdown (%)	15.79	15.84	16.15	14.65	14.69	14.18	14.03
Skew	1.38	1.37	1.27	1.43	1.42	1.46	1.48

Table 9
Trend following 60-day risk parity 12-month momentum portfolios — monthly Jan 1992–Jun 2011.

	Moving average period (months)						
	6	7	8	9	10	11	12
Winners							
Annualised excess return (%)	12.77	12.90	12.87	12.37	12.09	11.79	12.43
[Newey–West t-statistic]	[3.39]	[3.49]	[3.41]	[3.30]	[3.26]	[3.10]	[3.23]
Annualised volatility (%)	16.17	16.41	16.54	16.64	16.56	16.83	16.91
Sharpe ratio	0.79	0.79	0.78	0.74	0.73	0.70	0.73
Max. monthly return (%)	16.93	16.93	16.93	16.93	16.93	16.93	16.93
Min. monthly return (%)	−13.00	−13.00	−13.00	−13.00	−13.00	−14.26	−14.26
Maximum drawdown (%)	31.43	30.73	30.19	28.95	28.22	32.18	31.79
Skew	0.06	0.14	0.12	0.10	0.07	0.00	0.01
Losers							
Annualised excess return (%)	−3.07	−4.02	−3.46	−3.26	−3.07	−3.23	−3.40
[Newey–West t-statistic]	[0.72]	[1.04]	[0.80]	[0.71]	[0.64]	[0.69]	[0.74]
Annualised volatility (%)	12.93	12.97	13.22	13.50	13.62	13.65	13.78
Sharpe ratio	−0.24	−0.31	−0.26	−0.24	−0.23	−0.24	−0.25
Max. monthly return (%)	14.75	14.75	14.75	14.75	14.75	14.75	14.75
Min. monthly return (%)	−17.46	−17.46	−17.46	−17.46	−17.46	−17.46	−17.46
Maximum drawdown (%)	62.18	66.65	66.46	66.79	64.66	64.64	66.52
Skew	0.04	0.07	0.07	0.07	0.05	0.05	0.08
Long winners–short losers							
Annualised excess return (%)	14.70	15.94	15.28	14.48	13.92	13.88	14.69
[Newey–West t-statistic]	[3.84]	[4.07]	[3.98]	[3.91]	[3.86]	[3.86]	[4.04]
Annualised volatility (%)	19.33	19.53	19.33	19.54	19.56	19.53	19.65
Sharpe ratio	0.76	0.82	0.79	0.74	0.71	0.71	0.75
Max. monthly return (%)	19.59	19.59	19.59	19.89	19.89	19.89	19.89
Min. monthly return (%)	−14.84	−14.84	−14.84	−14.84	−14.84	−15.72	−15.72
Maximum drawdown (%)	31.87	32.01	31.44	31.00	30.07	30.17	30.83
Skew	−0.08	−0.10	−0.09	−0.06	−0.07	0.00	−0.02

commodity futures data we do not see any substantial skewness risk with lower volatility commodities and therefore do not anticipate the increased weight attached to these commodities in the risk parity portfolio increasing skewness risk at the portfolio level. Indeed the addition of the trend following component reduces skewness in returns as is noted above.

Table 10
Risk adjustment of returns: long only portfolios.

Simple average–long only			
	Average		Average
TF & MOM RP	1.126	TF RP	0.463
	[3.49]		[3.03]
TF & MOM EW	1.125	MOMRP	1.026
	[3.42]		[2.60]

Equity factors–long only	Alpha	MKT	SMB	HML	UMD	R2
TF & MOM RP	0.877	0.233	−0.0036	0.0823	0.158	0.0844
	[2.80]	[3.24]	[0.04]	[0.92]	[3.01]	
TF & MOM EW	0.873	0.218	−0.0018	0.0877	0.173	0.0797
	[2.83]	[3.05]	[0.02]	[0.99]	[3.19]	
TF RP	0.350	0.104	0.00732	0.0546	0.0562	0.0420
	[2.41]	[2.61]	[0.19]	[1.44]	[2.01]	
MOM VW	0.649	0.436	0.0075	0.136	0.146	0.0705
	[1.64]	[3.54]	[0.08]	[1.47]	[2.42]	

Hedge fund risk factors–long only	Alpha	SBD	SFX	SCOM	EMF	SSF	BMF	CSF	EMRF	R2
TF & MOM RP	1.14	−1.59	−0.539	8.89	−0.0974	0.0557	1.64	−1.28	0.200	0.0312
	[3.42]	[0.89]	[0.38]	[3.63]	[0.75]	[0.52]	[1.11]	[1.41]	[2.25]	
TF & MOM EW	1.16	−1.02	−0.985	8.04	−0.119	0.0731	1.42	−0.773	0.201	0.0302
	[3.39]	[0.60]	[0.71]	[3.81]	[0.90]	[0.69]	[0.90]	[0.73]	[2.29]	
TF RP	0.464	−0.564	−0.304	4.05	−0.0878	−0.0442	1.21	0.0222	0.142	0.0311
	[3.08]	[0.69]	[0.50]	[3.53]	[1.31]	[1.13]	[1.69]	[0.05]	[3.36]	
MOM RP	0.910	−1.19	−1.17	6.61	−0.0260	0.0938	−1.46	−5.31	0.257	0.0322
	[2.36]	[0.46]	[0.63]	[2.23]	[0.19]	[0.86]	[0.72]	[2.19]	[2.57]	

The risk factors are; the Fama–French four US equity market factors, MKT, SMB, HML and UMD and, secondly the eight hedge fund factors of Fung and Hsieh (2001): the PTFS Bond (SBD), Currency (SFX) and Commodity Trend (SCOM) lookback straddle returns; Equity Market Factor (EMF), Size Spread Factor (SSF), Bond Market Factor (BMF), Credit Spread Factor (CSF) and Emerging Market Risk Factor (EMRF). Portfolios are either equal-weight (EW) or risk-parity weighted (RP) for trend following (TF), momentum (MOM) or a combination of the two (TF & MOM).

Table 11
Risk adjustment: long–short portfolios.

Simple average–long–short

	Average		Average
TF & MOM RP	1.398	TF RP	0.565
	[4.07]		[2.92]
TF & MOM EW	1.272	MOMRP	1.172
	[3.41]		[3.62]

Equity factors–long–short

	Alpha	MKT	SMB	HML	UMD	R2
TF & MOM RP	1.238	−0.0064	−0.0014	0.042	0.263	0.0780
	[3.46]	[0.06]	[0.02]	[0.36]	[3.75]	
TF & MOM EW	1.11	−0.0948	0.0512	0.0998	0.296	0.116
	[2.90]	[0.85]	[0.52]	[0.70]	[4.20]	
TF RP	0.601	−0.122	−0.0307	−0.0299	0.0847	0.0644
	[2.65]	[1.25]	[1.04]	[0.46]	[3.05]	
MOM RP	0.930	0.142	0.0312	0.0866	0.225	0.0576
	[2.85]	[1.71]	[0.37]	[0.77]	[3.05]	

Hedge fund risk factors–long–short

	Alpha	SBD	SFX	SCOM	EMF	SSF	BMF	CSF	EMRF	R2
TF & MOM RP	1.49	−0.753	−0.310	7.10	−0.141	0.124	1.53	0.761	0.0246	0.0215
	[4.00]	[0.36]	[0.16]	[2.07]	[0.92]	[0.86]	[0.78]	[0.41]	[0.24]	
TF & MOM EW	1.44	−2.31	−1.35	7.17	−0.139	0.191	1.34	0.211	−0.0642	0.0296
	[3.64]	[1.13]	[0.66]	[2.24]	[0.91]	[1.25]	[0.64]	[1.36]	[0.58]	
TF RP	0.687	−0.367	0.0528	4.15	−0.146	−0.0546	2.31	2.57	0.0301	0.0226
	[3.33]	[0.33]	[0.06]	[2.43]	[2.03]	[1.25]	[1.92]	[1.84]	[0.70]	
MOM RP	1.15	0.563	−0.928	3.37	−0.0496	0.221	−2.15	−3.50	0.0233	0.0312
	[3.22]	[0.23]	[0.48]	[0.96]	[0.33]	[1.60]	[1.10]	[2.20]	[0.23]	

The risk factors are: the Fama–French four US equity market factors, MKT, SMB, HML and UMD and, secondly the eight hedge fund factors of Fung and Hsieh (2001): the PTFS Bond (SBD), Currency (SFX) and Commodity Trend (SCOM) lookback straddle returns; Equity Market Factor (EMF), Size Spread Factor (SSF), Bond Market Factor (BMF), Credit Spread Factor (CSF) and Emerging Market Risk Factor (EMRF). Portfolios are either equal-weight (EW) or risk-parity weighted (RP) for trend following (TF), momentum (MOM) or a combination of the two (TF & MOM).

4.4. The performance of combined trend following and momentum portfolios

Finally, we examine whether combining the two strategies could provide a set of portfolios which perform better than either of the two strategies alone. Interest in combined strategies has arisen in the context of designing strategies in a variety of markets outside of commodity futures, see Antonacci (2012), for example. Our results shown in Table 9 provide the summary evidence for a set of combined strategies; those of between 6 and 12-month trend following and 12-month momentum risk-parity portfolios based on a 60-day volatility calculation. For a commodity to now be in the winner portfolio it must be in the top quartile of assets based on the momentum calculation and also have a positive trend according to the trend following rule. Losers must be in the bottom quintile of the momentum rankings and have a negative trend. Considering winner portfolios, the average excess returns from these strategies exceed those from any of the winner strategies examined thus far. Compared with momentum-only returns in Table 5 with, say a 12 month momentum period, the 7 month moving average trend following return at 12.90% is over 1.85% higher with a standard error of 0.27%. As a result of the impact of the lower volatility of trend following strategies, these higher returns are achieved at lower levels of volatility than in the case of momentum-only strategies and so have a higher Sharpe ratio than any of the previous strategies. There is no evidence of any skewness in these returns and they are also subject to lower maximum drawdown than previous strategies. Loser portfolios provide a consistently small negative and more volatile set of returns which are also not skewed. Winner–loser portfolios thus provide the highest set of returns for all trend-following moving average calculation periods and generate the highest average excess return of 15.94% and a Sharpe ratio of 0.82. (Table 9)These results show that amongst all momentum strategies, the introduction of trend following leads to reduced variability and a positive impact on skewness. If the risk-parity results in Table 9 are compared with those from equally weighted portfolios with similar momentum and moving average parameters, it can be shown that risk parity leads to slightly higher average returns at a lower level of volatility.[8] This is consistent with the original promoters of risk-parity portfolios and the evaluations of broader asset classes such as Asness et al. (2013), for example. Finally, examining the periods of market turbulence, the final column of Table 3 shows that both equally weighted and risk parity returns from the combined 6-month trend following and 12-month momentum strategy provide positive returns over all of these periods and, in particular, the most recent credit crisis period where the winner–loser strategy delivered in excess of 3% pa.

In this section we have shown that whilst a momentum strategy can deliver high returns, this is associated with high negative skewness and maximum drawdown. This is true of equally and risk parity weighted versions of the strategy and for long-only winners portfolios and long–short, winners–losers strategies. Trend following in itself provides a more modest but significantly higher return than passive strategies but higher Sharpe ratios reflecting reduced volatility. The addition of trend following to a momentum strategy reduces the downside risk of the momentum approach without sacrificing returns. The reduced negative skewness is also reflected in reduced maximum drawdown. Whether the significant enhanced average returns from these strategies is compensation for exposure to important risk factors is our next concern.

5. Understanding the profitability of strategy returns

5.1. Risk adjusted returns

The properties of returns presented thus far refer to unconditional returns from trend following and momentum strategies. In this section we examine whether these excess returns are explained by widely

[8] These results are available from the authors.

Table 12
Transactions costs adjustment.

Average returns–long only	Gross	Net		Gross	Net		Gross	Net
TF & MOM RP	12.90	12.62	TF EW	6.04	5.91	TF RP	5.35	5.31
	[3.49]	[3.38]		[3.20]	[2.99]		[3.03]	[2.91]
TF & MOM EW	12.86	12.52	MOM EW	11.12	10.83	MOM RP	11.05	10.76
	[3.42]	[3.37]		[2.53]	[2.48]		[2.60]	[2.54]
Average returns–long–short	Gross	Net		Gross	Net		Gross	Net
TF & MOM RP	15.94	15.65	TF EW	6.87	6.75	TF RP	6.41	6.37
	[4.07]	[3.99]		[2.84]	[2.79]		[2.92]	[2.86]
TF & MOM EW	13.76	13.01	MOM EW	10.31	9.75	MOM RP	12.91	12.21
	[3.41]	[3.38]		[2.82]	[2.70]		[3.62]	[3.55]

Portfolios are either equal-weight (EW) or risk-parity weighted (RP) for trend following (TF), momentum (MOM) or a combination of the two (TF & MOM).

employed risk factors. For clarity, we examine the returns from particular strategies. These are equally and volatility-weighted versions of trend following based on a 7-month moving average window, momentum based on a 12-month prior period and the combination of these two strategies (Tables 9). In particular we examine estimates of alphas after regressing the returns from the strategies on two sets of risk factors which have been shown to explain substantial and significant amounts of the variation of returns in other markets; the Fama–French–Cahart four US equity market factors, MKT, SMB, HML and UMD and, secondly the eight hedge fund factors of Fung and Hsieh (2001): the PTFS Bond (SBD), Currency (SFX) and Commodity Trend (SCOM) lookback straddle returns; Equity Market Factor (EMF), Size Spread Factor (SSF), Bond Market Factor (BMF), Credit Spread Factor (CSF) and Emerging Market Risk Factor (EMRF). Whilst the Fama–French–Cahart factors have become a standard benchmark for many asset return models, the eight factors found by Fung and Hsieh to explain hedge fund returns well also provide a suitable benchmark against which to judge the levels of returns for the various strategies shown above.

The results of these estimates for the long-only strategies are shown in Table 10 where Newey–West t-statistics are shown in square brackets. Looking across all of the strategy returns and risk factors, there is little evidence that exposure to these factors is able to account for the returns from the strategies. Comparison of the estimated alphas from the two risk adjustment regressions with the raw alpha shows that the alphas remain large and significantly larger than zero. Most of the coefficients on the risk factors are small and insignificantly different from zero. Amongst the regressions for the long-only strategies the coefficients on the US equity market excess return and, perhaps unsurprisingly, the return to the Cahart momentum factor (UMD) are positive and individually significantly different to zero. The regressions for the Fama–French factors are jointly significant but explain no more than 8.4% of the variation in returns in any case. For the Fung and Hsieh hedge fund factors, the Commodity Trend lookback straddle return has a positive and significant effect on the four portfolio returns as does the Emerging Market return factor and marginally, the Credit Spread factor for the momentum portfolio return. These positive effects imply that the trend following and momentum strategies we examine are providing a hedge against the risks that these factors represent. These models explain somewhat less of the variation in returns than the Fama–French–Cahart model. The estimated alphas remain high and significantly different from zero. Amongst the long–short strategies, the estimation results in Table 11 show a lower level of significant exposure to the two sets of risk factors and a somewhat reduced fit. In both cases the estimated alphas are reduced less by the risk adjustment than in the long-only cases. The Fama–French momentum factor UMD is significantly priced in all of the first set of regressions, whilst the fit is generally below 10%. In the Fung–Hsieh hedge fund factors model, only the return from the Commodity trend lookback straddle is significant, although again the Credit Spread factor is significant in the case of the momentum-only strategy. The fit in terms of $R^2$of these models is around 2.5%.

The analysis of risk explanations for the trend following and momentum returns that we have found therefore suggests that whilst risk factors can provide a statistically significant contribution and explain some of the variation in returns, there remains a significant alpha which is at least two-thirds of the level of the raw excess returns and exceeds them in some cases.

5.2. Transaction costs

Realising the returns to the trend following and momentum strategies analysed in this paper in practice would require accommodating transaction costs, in this section we assess how the average returns presented above might be modified by allowing for transaction costs. In doing this we try to be realistic by allowing for a fixed brokerage

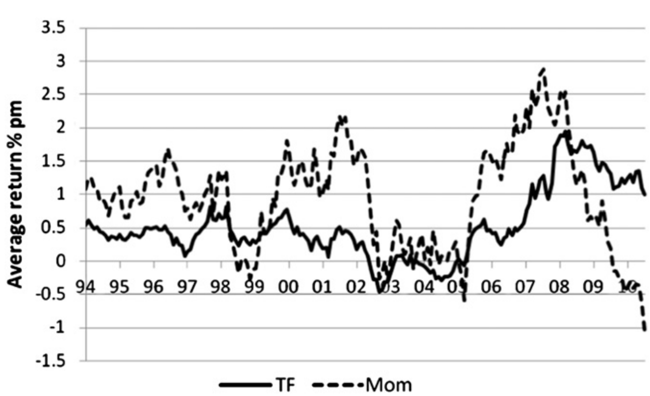

Fig. 1. Rolling average 36-month returns for commodity strategies: 6 month MA trend following and 12 month momentum.

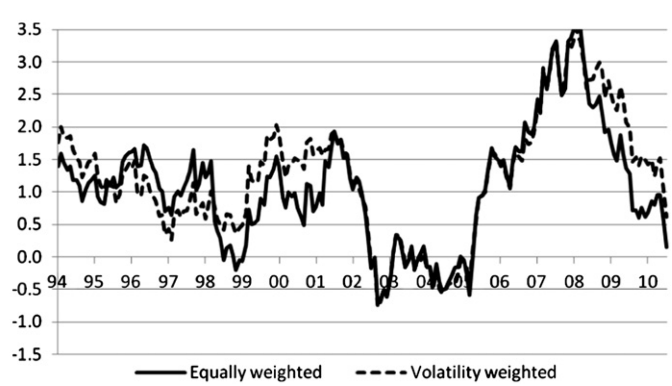

Fig. 2. Rolling average 36-month returns for commodity strategies: 6 month MA trend following and 12 month momentum combined strategy.

commission as well as applying a bid-ask spread. The sum of these costs is then subtracted from gross returns as a percentage of average contract value, assuming one round-turn trade every month. Following Szakmary et al. (2010) we set the fixed brokerage fee at $10 per contract and the bid-ask spread at one tick. Locke and Venkatesh (1997) and discussion with market participants suggest that this is a representative level for the bid-ask spread in commodity futures markets.[9] In our calculations, for the range of commodities, the fixed cost element amounts to between 6 and 0.5 basis points, whilst the one tick, bid-ask spread is between 5.2 and 0.7 basis points. Having applied these costs, the differences between gross returns and returns net of transaction costs for the selected strategy returns evaluated in Section 5.1 can be seen in Table 12. The differences in average returns are not large at no more than 0.5% and well within one standard error of the gross returns. The extent to which trading costs have reduced over time due to improvements in the efficiency of trading technologies would make the net returns we analyse underestimates of performance in more recent parts of the sample period. Assessment of time variation in returns should take this into account.

5.3. Time-variation in the returns to investment strategies

The analysis presented thus far focusses on average returns and performance in particular episodes. The stability over time of momentum and trend following returns is clearly of interest — especially to those with shorter investment horizons. In Figs. 1 and 2 we present average excess returns to a number of strategies calculated over rolling windows of 36 months. All of these returns show significant time variation. This is more apparent in the behaviour of momentum returns (Fig. 1) where the highest returns can be seen in the 2008–9 period having been lowest in the 2004–6 period. Trend following returns show lower time variation and remain at an enhanced level from 2009 to the end of the sample. It can be seen from the figures that the addition of trend following to the momentum strategies dominates the difference in returns (Fig. 2): it matters less whether the portfolios are equally or risk-weighted (compare the lines in Fig. 2). This is of importance for those investors with shorter investment horizons.[10] As noted above, it can be expected that the performance of returns net of transaction costs for all strategies could be enhanced by improvements in trading technologies in the later part of the sample period.

6. Conclusion

It is no surprise that momentum and trend following rules are popular with professional and retail investors alike. They offer enhanced returns over passive strategies and sometimes higher Sharpe ratios in various markets. In this paper we have shown that this is true for commodity futures. We have shown significant average excess returns for momentum strategies but these come at the price of substantial negative skewness and maximum drawdown. Our results demonstrate momentum crash risk as proposed by Daniel and Moskowitz (2011). We also show significant average excess returns for a variety of trend following strategies. These produce somewhat lower returns than momentum rules but with higher Sharpe ratios and without the large negative skewness. The addition of trend following to a momentum strategy is shown to provide both high returns and lower drawdowns and skewness. This is especially true of portfolios where weights are measured by inverse volatility rather than being equal, thus overcoming the large differences in volatility of different commodities. This finding adds to the literature which tries to explain momentum returns. In our results, the contribution to momentum performance of the characteristics offered in this literature are captured by trend following. We show that the enhanced average excess return to the strategies examined is not mainly compensation for exposure to well-known risk factors and remains once account is taken of transaction costs. Whether crash risk is a good explanation for momentum returns, this seems not to be the case for trend-following or the combined momentum and trend following strategies that we examine. In future work we intend to follow up on this idea.

[9] We apply these averages as the index data examined in this paper does not include actual contracts.

[10] The potential limits to arbitrage when strategy returns are time varying is surveyed by Duffie (2010). Time variation in simple momentum returns from foreign exchange momentum strategies is shown by Menkhoff, Sarno, Schmeling, and Schrimpf (2012), although they do not examine trend following returns.

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