Tactical Allocation in Commodity Futures Markets: Combining Momentum and Term Structure Signals

GEORGIOS RALLIS*, JOËLLE MIFFRE**, ANA-MARIA FUERTES***

* Cass Business School, City University London

** EDHEC Business School, France.

Abstract

This paper examines the combined role of momentum and term structure signals for the design of profitable trading strategies in commodity futures markets. With significant annualized alphas of 10.14% and 12.66% respectively, the momentum and term structure strategies appear profitable when implemented individually. With an abnormal return of 21.02%, our double-sort strategy that exploits both momentum and term structure signals clearly outperforms the single-sort strategies. This double-sort strategy can additionally be utilized as a portfolio diversification tool. The abnormal performance of the combined portfolios cannot be explained by a lack of liquidity, data mining or transaction costs.

JEL classification: G13, G14

Keywords: Commodity futures, momentum, term structure, double-sort strategy.

1. Introduction

Commodity futures have become widespread investment vehicles among traditional and alternative asset managers. They are now commonly used for strategic and tactical asset allocations. The strategic appeal of commodity indices comes from their equity-like return, their inflation-hedging properties and their role for risk diversification (Greer, 1978; Bodie and Rosansky, 1980; Jensen *et al*., 2000; Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006; Chong and Miffre, 2010). Recent research has also established that commodity futures can be used to generate abnormal returns. For example, Erb and Harvey (2006) exploit the term-structure signals of 12 commodities and implement a simple long-short strategy that buys the 6 most backwardated commodities and shorts the 6 most contangoed commodities. In a similar vein, Erb and Harvey (2006) and Miffre and Rallis (2007) follow momentum signals and tactically allocate wealth towards the best performing commodities and away from the worst performing ones. These simple active strategies have been shown to be capable of generating attractive returns.[1]

This paper digs deeper into the tactical opportunities of commodity futures by introducing an active double-sort strategy that combines momentum and term structure signals. This novel strategy aims at consistently buying the backwardated winners whose prices are expected to appreciate, and shorting the contangoed losers whose prices are expected to depreciate. While doing this, we expand on the term structure-only (hereafter, TS-only) strategy of Erb and Harvey (2006) by assessing the sensitivity of the TS profits to the roll-return definition, the frequency of rebalancing of the long-short portfolios and the date of portfolio formation. We also provide an in-depth analysis of the risk, performance and trading costs of the single-sort (momentum-only and TS-only) and double-sort portfolios.

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[1] Other references on active management in commodity markets include Jensen *et al.* (2002), Wang and Yu (2004), Basu *et al.* (2006), Marshall *et al.* (2008).

Three contributions to the empirical literature on commodity futures markets are worth noting. First, we show that combining the momentum and term structure signals enhances the abnormal performance of either of the individual single-sort strategies. On a yearly basis, while the profitable momentum-only and TS-only strategies earn on average an abnormal return of 10.14% and 12.66%, respectively, the combined double-sort strategies, with an average annualized alpha of 21.02%, clearly provide the best signal on which to allocate wealth. A robustness analysis suggests that the superior profits of the double-sort strategies are not an artifact of lack of liquidity or data mining, and are robust to alternative specifications of the risk-return relationship. They are also robust to the high level of volatility experienced since January 2007. Second, the new commodity-based relative-strength portfolios emerge as excellent candidates for inclusion in well-diversified portfolios given the very low correlations between their returns and those of traditional asset classes. Hence, commodity futures may be tactically added to the asset mix of institutional investors not exclusively to earn abnormal returns but also to diversify the total risk of their global equity and/or fixed-income portfolios. Third, the proposed double-sort strategies are implemented on a small cross section of contracts that are cheap to trade, liquid and easy to sell short. Net of reasonable transaction costs, they still generate a yearly net alpha of 20.41% on average.

The article proceeds as follows. Section 2 presents the dataset. Sections 3 and 4 analyze the profits of the individual momentum strategies and term structure strategies, while Section 5 studies the performance of strategies that jointly exploit momentum and term structure signals. Section 6 provides robustness checks and Section 7 concludes.

2. Data

The dataset from *Datastream International* and *Bloomberg* spans the period January, 1 1979 to January, 31 2007. It consists of the daily closing prices on the nearby, second-nearby and distant contracts of 37 commodities: 13 agricultural futures (cocoa, coffee, corn, cotton, oats, orange juice, soybean meal, soybean oil, soybeans, sugar, wheat Kansas City, wheat CBOT, white wheat), 4 livestock futures (feeder cattle, frozen pork bellies, lean hogs, live cattle), 10 metal futures (aluminum, copper, gold, lead, nickel, palladium, platinum, silver, tin, zinc), 6 energy futures (Brent crude oil, crude oil, gas oil, heating oil, natural gas, unleaded gasoline), the futures on milk and lumber and two non overlapping diammonium phosphate contracts. To avoid survivorship bias, we include contracts that started trading after January 1979 or were delisted before January 2007. The total sample size ranges from a low of 22 contracts at the beginning of the sample period to a peak of 35 contracts from July 1997 onwards.

This study investigates the sensitivity of the TS profits to the date at which futures returns are measured. Two approaches are used to compile time series of futures returns. First, we assume that we hold the nearby contract up to the month prior to maturity. At the end of that month (EOM hereafter), we roll our position over to the second nearest-to-maturity contract and hold that contract up to one month prior to maturity. The procedure is then rolled forward to the next set of nearest and second-nearest contracts when a new sequence of futures prices is compiled. Second, we repeat this approach but, this time, the roll date is set to the 15th of the maturity month (15M hereafter) if the contract is traded on that day or to the 15th of the month prior to maturity otherwise. In both cases, futures returns are computed as the percentage change of the closing prices. Note that the rolling procedure used ensures that problems related to lack of liquidity are kept to a minimum since the nearest or second-nearest contracts are always used in the returns calculation.

Investors earn a total return on a fully-collateralized position in futures markets equal to the sum of the collateral return (e.g. Treasury-bill rate earned on the notional amount of the futures contract) and the futures return (i.e. percentage change in the futures price).[2]

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[2] In line with the asset pricing literature, the futures return is often called ‘excess return’ as the collateral return is taken out of the total return to calculate the futures return.

We assume therefore that investors hold unlevered positions in futures markets. Our long and short active strategies examined in isolation are fully collateralized. By construction, our combined long-short active strategies are therefore 50% collateralized.[3] The leverage is kept constant over time and the strategies are marked to market daily. Our combined long-short strategies could become fully collateralized if half of the trading capital was invested in the strategies and the rest held as collateral. The advantages of assuming fully-collateralized positions are twofold. First, the collateral can be used to pay for any margin calls and thus there should not be any liquidation of the futures positions before the end of the holding period because of a margin call. As liquid assets are available if and when needed, the unlevered positions have the merit of bearing little to no liquidity risk. Second, the single and double-sort strategies will generate a total return that includes not only the futures returns reported below (in Sections 3 to 6), but also the return earned on the collateral in excess of any margin call. This article only reports the excess return of the active strategies and thus under-estimates the total performance of the active portfolios by an amount equal to the collateral return (minus any margin call).

3. Single-Sort Strategies Based on Momentum

3.1. Methodology

A growing literature establishes that momentum strategies generate significant abnormal returns in equity markets (Jegadeesh and Titman, 1993, 2001; Chan *et al*., 1996).[4] In a recent paper, Miffre and Rallis (2007) extend this finding to futures markets. This paper

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[3] In line with Gorton and Rouwenhorst (2006), and Gorton, Hayashi and Rouwenhorst (2008), the returns of the combined long-short strategies have been computed by subtracting the returns of the shorts from the returns of the longs. In futures markets this implies a gross exposure that is double that of our trading capital.

[4] The profitability of momentum strategies has been shown to be related to different factors such as behavioral biases, industry effect, trading volume, the business cycle, liquidity risk, trading costs, the cross-sectional variation in unconditional expected returns, and time-varying unsystematic risk (Barberis *et al.*, 1998; Conrad and Kaul, 1998; Daniel *et al.*, 1998; Hong and Stein, 1999; Moskowitz and Grinblatt, 1999; Lee and Swaminathan, 2000; Chordia and Shivakumar, 2002; Korajczyk and Sadka, 2004; Lesmond *et al.,*. 2004; Sadka, 2006; Li *et al.*, 2008).

follows the same approach and, accordingly, at the end of each month futures contracts are sorted into quintiles based on their average return over the previous *R* months (ranking period). The futures contracts in each quintile are equally weighted. The performance of both the top (winner) and bottom (loser) quintiles is monitored over the subsequent *H* months (holding period). The resulting *R-H* momentum strategy buys the winner portfolio, shorts the loser portfolio and holds the long-short position for *H* months.

Following Moskowitz and Grinblatt (1999), Jegadeesh and Titman (2001) and Miffre and Rallis (2007) *inter alia*, the relative-strength portfolios are overlapping. For instance, with the 6-3 momentum strategy, the winner portfolio in, say, December is constructed by equally-weighting the top 3 quintile portfolios that were formed at the end of September (using March to August returns), October (using April-September returns) and November (using May-October returns). Hence, its December return is equal to the average return of those 3 overlapping portfolios. Likewise for the loser portfolio but with reference to the bottom 3 quintile portfolios. The return of the momentum strategy is then defined as the difference in the December returns of the winner and loser portfolios. Therefore an *R-H* momentum strategy implies forming portfolios at two distinct levels: at the end of each month individual commodity futures contracts are sorted into a winner (top quintile) portfolio and a loser (bottom quintile) portfolio based on the returns over the previous *R* months; then, effectively, at any point in time (month *t*) an equally-weighted portfolio is held (shorted) that combines the *H* overlapping winner (loser) portfolios formed at the end of months *t*-1, *t*-2,…, *t*-H. This procedure is rolled forward monthly.

To conserve space, the analysis is focused on the 13 permutations of ranking and holding periods that proved to be profitable on a risk-adjusted basis at the 5% level or better in Miffre and Rallis (2007). As a result, we consider 4 strategies with 1-month ranking period (1-1, 1-3, 1-6, 1-12), 4 strategies with 3-month ranking period (3-1, 3-3, 3-

6, 3-12), 3 strategies with 6-month ranking period (6-1, 6-3, 6-6) and 2 strategies with 12-month ranking period (12-1, 12-3). In our notation, say, 1-6 refers to a momentum strategy based on past 1-month returns (ranking period) and held for 6 months.[5]

The following multifactor model is then used to gauge the risk-adjusted returns:

$$R_{Pt} = \alpha + \beta_B \left(R_{Bt} - R_{ft}\right) + \beta_M \left(R_{Mt} - R_{ft}\right) + \beta_C \left(R_{Ct} - R_{ft}\right) + \varepsilon_{Pt} \qquad (1)$$

where R_{Pt} is the return of the long (L), short (S), or long-short (L-S) portfolio, R_{Bt}, R_{Mt} and R_{Ct} are, respectively, the returns on the Lehman Aggregate US total return bond index, the S&P500 composite index and the S&P GSCI (Standard & Poor's Goldman Sachs Commodity Index), R_{ft} is the risk-free rate (proxied by 3-month US T-Bills) and ε_{Pt} is an error term. Insignificance of α suggests that the returns from the active strategies are just a compensation for risk which is consistent with rational pricing in an efficient market.[6]

3.2. Performance evaluation and risk management

Table 1 reports summary statistics for the 13 winners (Panel A), 13 losers (Panel B) and 13 momentum portfolios (Panel C) outlined above.[7] Table 2 sets out the parameter estimates and significance tests for equation (1). Despite differences in the samples employed, the evidence confirms the main findings in Miffre and Rallis (2007), namely, that trend-following is a reliable source of returns in commodity futures markets.

[Insert Tables 1 and 2 around here]

Table 1, Panel C suggests that the return spread between winners and losers is positive and significant at better than the 5% level for 11 strategies. Accordingly, active

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[5] The unreported momentum strategies 6-12, 12-6 and 12-12 did not deliver significantly positive returns for the current sample (-1% to 2% a year) either.

[6] One could adopt any of the alternative multifactor models in the literature with, for instance, additional systematic risk factors such as co-skewness and co-kurtosis or nonlinear specifications (see Fuertes *et al.*, 2009). However, what is crucial when it comes to contrasting the performance of single-sort and double-sort strategies is that the same risk-adjustment be employed throughout.

[7] The Ljung-Box test unambiguously suggests that the monthly returns summarized in Table 1 are not autocorrelated despite arising from an overlapping-portfolio strategy. This is because (as explained in Section 3.1) the December return of, say, a 6-3 strategy is obtained as the *average* of the 3 winner

portfolio managers who consistently tilt their asset allocation towards the best performing commodity futures and away from the worst performing ones could earn an average return of 10.53% a year. Over the same period a long-only passive portfolio that equally-weights the 37 commodities only earns 3.40% a year, while the S&P GSCI earns 3.62%. As expected, the winner portfolios in Table 1, Panel A generate a positive and significant average return across strategies of 8.75% a year. In contrast, the losers in Table 1, Panel B generate a negative (albeit insignificant) average return at -1.46%. Hence, over the 1979-2007 period, the profitability of momentum strategies appears driven by the winners.[8]

The 13 momentum strategies clearly bear more risk than a long-only passive benchmark that equally-weights the 37 commodities. For example, Panel C indicates that the annualized volatility, downside risk and 99% Cornish-Fisher Value-at-Risk of the active long-short portfolios (20.17%, 12.59% and 15.27% on average) far exceed those of the benchmark (10.92%, 7.60% and 9.46%, respectively). Because of high levels of kurtosis in the return distribution of the winners in Panel A (8.9950 on average), the returns distribution of the average momentum portfolio is also more leptokurtic (at 6.0011) than that of the benchmark (4.6578). It follows that the additional reward earned on these momentum strategies relative to the passive benchmark may be a trivial compensation for the incremental risks that active investors bear.

To account for risk, we first standardize the returns with respect to both the total and downside risk and, accordingly, examine the reward-to-risk ratios and Sortino ratios of the portfolios. The results in Panel C of Table 1 suggest that the momentum returns more than compensate for the total risk of the trend-following strategy: the reward-to-risk ratios of the active long-short portfolios (0.5162 on average) systematically exceed that of the

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(loser) portfolios in December corresponding to the top (bottom) quintile portfolios constructed at the end of September, October and November. This averaging washes out the autocorrelation.

[8] Similarly, the maximum 12-month rolling returns of the winner portfolios in Table 1, Panel A (at 76.65% across strategies) are always much higher than the absolute value of the minimum 12-month rolling returns of the loser portfolios in Table 1, Panel B (at 43.33% on average).

passive benchmark (0.3112). Similarly, the returns of the relative-strength portfolios are sufficient to reward downside risk: the Sortino ratio of the benchmark (0.4473) is consistently below that of the 13 active strategies at 0.8302 on average.

We also adjust for risk with the multifactor model (1).[9] The results in Table 2 suggest that, in line with Miffre and Rallis (2007), the returns of virtually all long/short portfolios follow the ups and downs of the S&P GSCI (with a confidence level of at least 95%) whereas they appear essentially neutral to the risks present in the bond and equity markets. For 10 out of 13 strategies, the abnormal returns are positive and strongly significant at the 5% or 1% level, with an average α at 10.14% a year.[10] Thus the momentum returns are not merely a compensation for exposure to these risks. It turns out that the momentum profitability is essentially dictated by the abnormal performance of the winner portfolios – the α of the winners is significantly positive whereas that of the losers is negative but typically insignificant. The average outperformance of the long winner portfolios (6.02%) compares favorably to that of the short losers (-3.14%). This result is of interest since it challenges the somewhat common belief in the momentum literature that trend-following profits are mainly driven by short positions in losers (see, for example, Moskowitz and Grinblatt, 1999, Hong *et al.*, 2000).

3.3. Transaction costs

A potential flaw of the evidence presented thus far is that the active profits could be eroded by transaction costs or merely arise as a compensation for market frictions and thin trading (see Lesmond *et al.*, 2004). However, in the present context, there are natural

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[9] The residuals of each equation were subjected to the Breusch-Godfrey LM autocorrelation test and Engle LM heteroskedasticity test (both for a maximum lag order of 12). There is no evidence of autocorrelation but some marginal instances of heteroskedasticity. Hence, the significance *t*-ratios are based on either the usual OLS standard errors or heteroskedasticity-robust (White) ones, as appropriate.

[10] The sensitivities of the long-short portfolios to the S&P-GSCI are positive and mainly significant. The S&P-GSCI earned a positive mean return of 3.62% over the period 1979-2007. As a result, the alphas of the momentum portfolios, once annualized by multiplying them by 12, are, with the exception of the 1-1 strategy, less than the annualized arithmetic means reported in Table 1.

arguments against these explanations. For example, commodity futures markets have been shown to be subject to rather small trading costs ranging from 0.0004% to 0.033% (Locke and Venkatesh, 1997) which is well below the conservative 0.5% estimate of Jegadeesh and Titman (1993) or the more plausible 2.3% estimate of Lesmond *et al.* (2004) for equity momentum portfolios. Besides, although equity markets are subject to short-selling restrictions, short positions can be taken in commodity futures as straightforwardly as long positions. A third key point is that, in the active strategy, the nearest or next nearest contracts were used which are typically the most liquid ones and thus the cheapest to trade. Last but not least, only 37 commodity futures are used in the analysis which means that our strategies are far less trading intensive than the ones typically carried out in equity markets.

These points notwithstanding, it is key to assess the impact of trading costs on the momentum profits. Three elements influence the buying and selling of a commodity contract and hence, the strategies' turnover. These are: *a*) the rolling of contracts as maturity approaches, *b*) the change in the constituents of the active portfolios at the time of portfolio construction and *c*) monthly rebalancing to equal weights.[11] In order to quantify actual trading costs, we calculate the turnover of our portfolios by counting the number of contracts that are bought or sold in a given month.[12]

The results are reported in the last two rows of Table 1, Panel C. A turnover statistic of 1 indicates that we buy and sell the portfolio once. On average, the active strategies have a turnover of 9.05, while the constituents of the passive portfolio change hands less often (6.34 times a year). We take as estimate of transaction costs the conservative 0.033% of Locke and Venkatesh (1997) and report estimates of the net momentum

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[11] The monthly rebalancing to equal weights is minimal compared to the other two transaction costs and is not considered in this study. Likewise, we limit our analysis of trading costs to the measurement of round-trip transaction costs and ignore price impact and commissions.

[12] We avoid double counting, e.g. if the active strategy recommends in a given month retaining the contract in the following period and the contract does not roll on that month, trading costs are not incurred since there is no need to close the initial position and re-open a new one.

returns. Clearly transaction costs have an impact on momentum profits but not to the extent that they would wipe the positive momentum returns out. On average, the momentum strategy earns a net return of 9.62% or a net alpha of 8.76%. The best outcome net of round-trip transaction costs comes from the 1-1, 3-1 and 12-1 momentum strategies that earn net returns of 16.99%, 15.31% and 14.82% a year, respectively. We now turn our attention to the class of TS-only strategies.

4. Single-Sort Strategies Based on Term-Structure

4.1. Methodology

Keynes (1930) and Cootner (1960) put forward the idea that commodity futures prices depend on the net positions of hedgers. The general message is that producers and consumers of the underlying commodity transfer the risk of price fluctuations to speculators, who are willing to undertake this risk in the hope of a large positive return. If the supply by short hedgers exceeds the demand by long hedgers (namely, hedgers are net short), the futures price today has to be a downward-biased estimate of the futures price at maturity. This is to induce speculators to take long positions in commodity futures markets. The increase in the futures price as maturity approaches is referred to as normal backwardation. Conversely, if hedgers are net long, the futures price today has to exceed the futures price at maturity to persuade speculators to take short positions in commodity futures markets. The decrease in the futures price as maturity approaches is traditionally referred to as contango. Thus, normal backwardation and contango arise as a result of the inequality between the long and short positions of hedgers, which require the intervention of speculators to restore equilibrium (Bessembinder, 1992). This is why it is generally accepted that futures markets provide insurance to hedgers by ensuring the transfer of price risk to speculators. The insurance that net hedgers are willing to pay equals the premium earned by speculators for this risk bearing.

If commodity futures returns directly relate to the propensity of hedgers to be net long or net short, it becomes natural to design an active strategy that buys backwardated contracts and shorts contangoed contracts. The price gap between different-maturity contracts, called roll-return (R_t) or implied yield, can be used as a signal of whether a market is in backwardation or contango. It is defined as:

$$R_t = \left[\ln\left(P_{t,n}\right) - \ln\left(P_{t,d}\right)\right] \times \frac{365}{N_{t,d} - N_{t,n}} \tag{2}$$

where $P_{t,n}$ is the time t price of the nearest-to-maturity contract, $P_{t,d}$ is the price of the distant contract, $N_{t,n}$ is the number of days between time t and the maturity of the nearby contract and $N_{t,d}$ is the number of days between time t and the maturity of the distant contract. A positive R_t indicates that the price of the nearby contract exceeds that of the distant contract, namely, that the term structure of commodity futures prices is downward-sloping and so that the market is in backwardation. Conversely, a negative R_t signals an upward-sloping price curve and a contangoed market. Thus motivated, Erb and Harvey (2006) and Gorton and Rouwenhorst (2006) introduce a new dynamic asset allocation strategy that seeks to exploit the term structure of commodity futures prices by taking long positions in backwardated contracts and short positions in contangoed ones.

The first strategy we consider, TS_1, is similar to Erb and Harvey's (2006) and Gorton and Rouwenhorst's (2006). It buys each month the 20% of commodities with the highest roll-returns, shorts the 20% of commodities with the lowest roll-returns and holds the long-short positions for a month. The contracts in each quintile are equally-weighted.

Several TS-only strategies are deployed in an attempt to shed light on different issues that may impact their profitability. First, we assess how the choice of the *distant contract* influences profits. To do this, we use as proxy of the distant contract d in our calculation of the roll-return in (2) either the second nearest contract (this is the former TS_1 strategy) or the contract with the maturity that is the furthest away (this strategy is called TS_2).

Hence, we are implicitly testing whether the front end of the term structure conveys a better signal on which to base tactical trading than the whole curve.

Second, we investigate the link between the term structure profits and the *frequency* of the long-short portfolio rebalancing in a given month. Hence, instead of always assessing the constituents of the long-short portfolio once a month and holding the positions for the following month (TS_1), we allow for more frequent rebalancing. In particular, four short-term strategies are considered such that the portfolio formation takes place every $N=int(M/i)$ days, where M is the number of trading days in a given month, $int(.)$ is the rounding down integer operator and i = 2, 4, 7 or 10 depending on the active strategy. The hypothesis implicitly tested here is whether more frequent rebalancings give better term structure signals and hence, better performance. The analysis is conducted on a transaction cost-adjusted basis; namely, after accounting for the additional costs incurred while dynamically trading the portfolios i times a month as opposed to just once (TS_1). The strategies are called $TS_{3,i}$ for i = 2, 4, 7 or 10 rebalancings per month.

Finally, we assess the impact that the choice of the portfolio construction date has on the term structure returns. Accordingly, the roll-returns are measured and the portfolios formed either at the end of the month (EOM) or on the 15th of the month (15M).

4.2. Performance evaluation, risk management and transaction costs

Summary performance measures for the term-structure strategies TS_1, TS_2, $TS_{3,i}$ (i = 2, 4, 7, 10) are set out in Table 3. The top and bottom panels focus, respectively, on EOM and 15M returns. For 7 out of the 12 strategies, the term-structure long-short portfolios yield positive returns which are economically and statistically significant with a confidence level above 95%. Across those 7 strategies one could earn an average return of 12.28% a year by consistently buying the most backwardated contracts and selling the most contangoed ones. Over the same sample period a long-only equally-weighted portfolio of the 37 commodities earns 3.40% (EOM) or 5.07% (15M) a year. Table 3 also reports the net performance of the strategies where the calculations for the transaction costs are based on the same methodology as the one employed in Table 1. As with momentum in Table 1, transaction costs do not wipe out the term structure profits but decrease them by a marginal 0.91% return a year on average. As expected, the damaging impact of transaction costs is most felt for the strategies that trade more often.

[Insert Table 3 around here]

Uniformly across the 7 profitable term structure strategies, the most-backwardated portfolios always yield positive average returns which are significant both economically and statistically ranging from a high of 12.26% (TS_1, 15M) to a low of 8.08% ($TS_{3,i=7}$, EOM). Conversely, the average return from the most-contangoed portfolios is always insignificant, ranging from a low of -5.60% (TS_1, EOM) to a high of 0.13% ($TS_{3,i=10}$, EOM) per annum. Hence, the profits of the term structure signals are mainly driven by long positions in backwardated contracts.

A closer look at the term structure strategies provides interesting insights. First, the most profitable strategy is TS_1 with significant average profits of 14.10% a year, both with the EOM and 15M portfolios. The fact that TS_1 performs relatively (and in absolute terms) better than TS_2 suggests that the front-end of the term structure conveys a better signal for tactical trading than the whole curve. A comparison across $TS_{3,i}$ with i=2, 4, 7 and 10 indicates that the more frequent the rebalancing, the lower the returns. This result is reinforced by the fact that larger transaction costs are incurred with more regular rebalancing which exacerbates the difference in net returns between TS_1 and $TS_{3,i}$.

Second, analyzing the performance of the 15M approach can be seen as a robustness check on EOM because there is no fundamental reason to believe that the term structure profits should differ between EOM and 15M, namely, the portfolio formation date should not matter a priori. This is confirmed by statistical tests (detailed in Appendix A3) suggesting that, for 4 out of the 6 term structure strategies considered, the EOM and 15M returns are indistinguishable. Only in 2 cases, $TS_{3,i=7}$ and $TS_{3,i=10}$, do the EOM returns differ from the 15M returns but this could be a spurious result, that is, due to sampling variability. Moreover, the performance measures presented in Table 3 and Table 4 clearly suggest that investors should favor TS_1 (over $TS_{3,i=7}$ and $TS_{3,i=10}$), a strategy for which the EOM and 15M approaches are undoubtedly equivalent. Overall these findings lead us to conclude that the date of portfolio formation is, effectively, immaterial for term structure investors.[13]

Third, and as in Table 1, the active strategies on average bear substantially more risk than the passive benchmark. For example, the annualized volatility, downside volatility and 99% Cornish-Fisher VaR of the benchmark are roughly half of those of the active strategies. The returns distribution of the most profitable strategy, TS_1, is also substantially more leptokurtic than that of the EOM or 15M benchmark. Moreover, the 7 profitable active strategies present lower maximum drawdowns, higher maximum run-ups, lower minimum and higher maximum 12-month rolling returns than the benchmark.

The reward-to-risk and Sortino ratios of all 7 profitable active strategies exceed those of the passive EOM or 15M benchmark.[14] Hence, the high average returns of the term structure strategies appear to more than compensate investors for the increase in volatility and downside risk that they bear relative to the passive benchmark.

The multifactor model estimates are reported in Table 4. For virtually all of the 7 profitable term structure strategies identified in Table 3, the returns of the long-short portfolios follow the ups and downs of the S&P GSCI but are unrelated to the S&P500

[13] Nevertheless, a closer look at the performance measures for the $TS_{3,i=7}$ and $TS_{3,i=10}$ strategies might suggest that any possible outperformance of the EOM approach is driven by the negative returns of the EOM short contangoed portfolios. One possible explanation for this relates to the timing of the hedges placed by long hedgers and to the impact that these hedges may have on the price depreciation that contango implies. Possibly at EOM many more hedgers hold long positions than at 15M, while at 15M they have closed their positions. As a result the price decline implied by contango has to be stronger at EOM to entice more speculators to take short positions. Unfortunately, because the CFTC data on net hedging are not available at the relevant frequency over the time period and for the cross-section covered in our study, we cannot test this hypothesis directly.

and the Lehman Brothers indices. Clearly, the 7 profitable term structure strategies generate positive and significant alphas that average out at 12.66% a year. It turns out that TS_1 and $TS_{3,i=2}$ with annualized alphas above 14%, are the most profitable strategies on a risk-adjusted basis. In line with the evidence of Table 3, the alphas of the long-short portfolios tend to be driven by the outperformance of the long portfolios rather than by the underperformance of the short portfolios. For the 7 profitable TS strategies, the backwardated portfolios yield a significant (positive) alpha at better than the 5% level whereas only in 2 instances the contangoed portfolios yield a significant (negative) alpha.

[Insert Table 4 around here]

The evidence hitherto presented sums up as follows. First, individual momentum and term-structure signals exploited separately are capable of conveying information to the market that is of value to active traders. On average, the trend-following strategies and the term-structure strategies that are profitable at the 5% level earn, respectively, an annualized alpha of 10.14% and 12.66%. Second, with net returns above 13.5% a year, three momentum strategies (1-1, 3-1 and 12-1) and one term structure strategy (TS_1) stand out as conveying the best signals for tactical allocation. We propose next a double-sort approach that jointly exploits the two signals.

5. Double-Sort Strategies Combining Momentum and Term Structure

The commodity-based strategies discussed thus far were based on either momentum or term structure signals *individually* exploited. Since there remains the possibility that *jointly* using both types of signals is more fruitful, this section designs a double-sort strategy (Section 5.1), analyzes its performance (Section 5.2) and investigates the ability of the combined portfolio to serve as a tool for risk diversification (Section 5.3).

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[14] The results for the reward-to-risk ratios are consistent with Erb and Harvey (2006).

5.1. Methodology

Term structure trading strategies in commodity futures select, by definition, the most backwardated and contangoed contracts. Even though momentum strategies are not designed per se to overtly shortlist the commodities with the steepest term structures, it has been shown that, their long portfolios tend to contain backwardated contracts, while their short portfolios are heavily tilted towards contangoed commodities (see Miffre and Rallis, 2007). Hence, at first sight, one would be tempted to conclude that the momentum and term structure signals are rather similar. To shed further light on this issue, we calculate the Pearson correlation measure (and significance *t*-statistics) between the momentum and term structure returns. Table 5 sets out the results. The correlations are positive, as expected, but low enough to suggest that the two signals are not fully overlapping. The correlation can be as weak as 10.92% between the TS_1 (15M) and momentum (R=1, H=1) returns or as strong as 56.96% between the TS_2 (EOM) and momentum (R=3, H=12) returns. The mean correlation is 31.26%.

[Insert Table 5 around here]

These low correlations motivate the design of a third class of active strategies in commodity futures that combine both signals through a *double-sort* approach as follows. First, we compute the roll-returns at the end of each month and their 1/3 breakpoints to split the cross section of futures contracts into 3 portfolios, labeled *Low*, *Med* and *High*. We then sort the commodities in the *High* portfolio into 2 sub-portfolios (*High-Winner* and *High-Loser*) based on the mean return of the commodities over the past R months. In effect, the *High-Winner* and *High-Loser* portfolios contain 50% of the cross-section that was selected with the first term-structure sort or 50%×33.3% of the initial cross-section that was available at the end of a given month. Intuitively, *High-Winner* is thus made of the commodities that have both the highest roll-returns at the time of portfolio construction and the best past performance. Similarly, we sort the commodities in the

Low portfolio into 2 sub-portfolios (*Low-Winner* and *Low-Loser*) based on their mean return over the past *R* months. *Low-Loser* contains therefore commodities that have both the lowest roll-returns at the time of portfolio construction and the worst past performance. The combined strategy buys the *High-Winner* portfolio, shorts the *Low-Loser* portfolio and holds this position for one month.

The choices of one-month holding period (H=1) and monthly rebalancing were dictated by the fact that, as illustrated in Tables 1-4, the momentum strategies with H=1 and the TS_1 strategy stand out as the most profitable.[15] Following the evidence of Tables 1 and 2, the ranking periods (R) are set to 1, 3 and 12 months. The resulting strategies are called TS_1-$Mom_{1\text{-}1}$, TS_1-$Mom_{3\text{-}1}$ and TS_1-$Mom_{12\text{-}1}$. This choice of momentum and term structure signals is also naturally supported by the fact that their correlation turned out to be relatively low in Table 5. Alternatively, the two signals can be combined in reverse order, sorting first on momentum (1/3 breakpoints) and subsequently on roll-returns (1/2 breakpoint). The resulting strategies are called $Mom_{1\text{-}1}$-TS_1, $Mom_{3\text{-}1}$-TS_1 and $Mom_{12\text{-}1}$-TS_1.

5.2. Performance evaluation, risk management and transaction costs

Figure 1 plots the future value of $1 invested in TS_1-$Mom_{1\text{-}1}$, $Mom_{1\text{-}1}$, TS_1 and the passive benchmark. Figure 2 plots the corresponding return distribution. Both figures bear out the outstanding performance and very high risk of the active double- or single-sort strategies relative to the passive benchmark. Figure 1 suggests, in particular, that the superior performance of TS_1-$Mom_{1\text{-}1}$ seems to be driven by the relatively high returns generated both on $Mom_{1\text{-}1}$ until 1998 and on TS_1 from 1999 onwards.

[Insert Figures 1 and 2 around here]

Table 6 presents in Panel A summary statistics for the 6 double-sort strategies. Consistently across all of them, the annualized average return is highly significant both in economic and statistical terms (t-ratios above 3.65). On average, tactically allocating wealth towards the *High-Winner* (or *Winner-High*) portfolios and away from the *Low-Loser* (or *Loser-Low*) ones yields a return of 21.32% a year. Over the same period the passive benchmark returns 3.40% only and the S&P GSCI returns 3.62%. The average return of 21.32% also compares favorably to that for the 11 momentum-only and the 7 TS-only strategies (identified as profitable with a 95% confidence level or higher in Tables 1 and 3) at 10.53% and 12.28%, respectively.

[Insert Table 6 around here]

Out of the 6 combined strategies, the most profitable one is TS_1-$Mom_{1\text{-}1}$ with an average return of 23.55% a year, while TS_1-$Mom_{12\text{-}1}$ lies at the other end of the spectrum returning 18.81%. Worth noting is that the percentage of months with positive returns for the active double-sort strategies averages 60.1% (against 55.4% for the long-only passive portfolio), and that the double-sort strategies can capture up to 145.81% return on a run-up period of 4 months (TS_1-$Mom_{1\text{-}1}$) against 31.16% return on a run-up period of 9 months for the passive benchmark. Moreover, the maximum 12-month rolling return for the active double-sort strategies (at 143.27% on average) and the maximum monthly return (at 37.89% on average) are much higher than those of the benchmark (35.07% and 9.44%, respectively). The skewness of the combined portfolios tends to be positive (at 0.2151 on average) and significant at the 5% level, so it compares favorably to that of the benchmark (negative at -0.5087 and significant at the 5% level) and to those, often negative, reported in Tables 1 and 3 for the single-sort strategies.

Relative to the individual baseline strategies (c.f. Tables 1 and 3), the superior performance of the double-sort rebalancing approach appears driven by the fact that the long (short) portfolios perform better (worse) in the combined strategies than in the

[15] Given the superior performance of TS_1 (versus TS_2) shown in Tables 3 and 4, the roll-returns are measured relative to the 2nd nearest contract. Since the TS_1 performance for the EOM and 15M portfolio formation is undistinguishable, without loss of generality, we focus on the former hereafter.

individual ones. Across the profitable strategies identified, the long portfolios earn an average return of 14.05% in the double-sort strategy versus 9.15% in the momentum-only strategy and 9.63% in the TS-only strategy. Similarly, with an average loss at -7.26%, the short portfolios in the double-sort strategy tend to lose more than when either one of the two signals is considered in isolation (-1.38% for momentum-only and -2.23% for TS-only).[16] Hence, combining the two signals improves the gains of the long portfolios and exacerbates the losses of the short portfolios.

The transaction costs incurred with the double-sort strategy are of similar magnitude to those for the single-sort momentum strategy. It follows that the additional returns of the combined strategy cannot be a compensation for the additional costs of implementing the trades. In effect, the yearly net returns ranging from 18.25% (TS_1-$Mom_{12\text{-}1}$) to 22.88% (TS_1-$Mom_{1\text{-}1}$) are clearly significant in economic terms.

As the returns distribution plot (Figure 2) illustrates, the risk of the best active double-sort strategy is substantially higher than that of the long-only passive portfolio. On average, the annualized standard deviation and downside risk of the 6 double-sort strategies are 27.19% and 15.82%, respectively, while those of the passive benchmark are much smaller at 10.92% and 7.60%. The 99% Cornish-Fisher Value-at-Risk is also much higher for the combined strategies (22.77% on average) than for the long-only equally-weighted benchmark at 9.46%. However, the higher risk of the double-sort strategies is more than rewarded by the market. This is born out by reward-to-risk ratios and Sortino ratios that are consistently higher for the double-sort strategies (0.7846 and 1.3537 on average) than for the passive benchmark (0.3112 and 0.4473, respectively). On this

[16] The same conclusion holds if, instead of averaging across all the profitable strategies identified, we just focus on the momentum (1-1, 3-1 and 12-1) and the TS_1 strategies combined in the double-sort approach: the long portfolios earn an average return of 12.69% in the three momentum-only strategies and 8.49% in the TS_1-only strategy whereas the short portfolios lose 3.61% in the momentum-only strategies on average and 5.6% in the TS_1-only strategy.

simple risk-adjusted basis, the most profitable strategies are TS_1-$Mom_{1\text{-}1}$ (with a Sortino ratio of 1.5607) and $Mom_{12\text{-}1}$-TS_1 (with a reward-risk ratio of 0.8582).

We now turn our attention to the inferences from the multifactor model (Table 6, Panel B). Consistent with the individual trading strategies in Tables 2 and 4, the relative-strength long-short portfolios formed on the combined signals are exposed to commodity risks but are neutral to the risks present in the bond and equity markets. The average abnormal return of the 6 combined strategies equals 21.02% a year with a high of 23.66% for TS_1-$Mom_{1\text{-}1}$ and a low of 18.65% for $Mom_{3\text{-}1}$-TS_1 (all t-ratios are above 3.6). The alphas of the combined strategies are higher than those of the corresponding individual strategies. In contrast with the momentum-only strategies (c.f. Table 2) and the TS-only strategies (c.f. Table 4), both the positive alpha of the long *High-Winner* and *Winner-High* portfolios and the negative alpha of the short *Low-Loser* and *Loser-Low* portfolios are now statistically significant. This suggests that elements from both the long and short portfolios drive the profitability of the double-sort strategies.

5.3. Risk diversification

Investors have traditionally utilized commodity futures to manage risk. The risk diversification role of the double-sort strategies proposed in the paper is illustrated in Table 7 through the Pearson correlation coefficient (and significance t-statistics) between their returns and those of traditional asset classes.

[Insert Table 7 around here]

The average correlation between the active double-sort portfolio returns and the excess returns of the S&P500 index is -6.26%, ranging from -8.60% ($Mom_{12\text{-}1}$-TS_1) to -2.85% ($Mom_{1\text{-}1}$-TS_1), albeit statistically insignificant throughout. The correlations between the double-sort portfolio returns and the excess returns on the Lehman Brothers Aggregate US total bond index, the yields on 10-year T-bonds and the 3-month T-bill rate are also insignificant both economically and statistically with absolute averages, respectively, at 4.05%, 3.00% and 3.68%. These findings add to the earlier evidence (c.f. Table 6) that the returns of the double-sort strategies are largely immune to the swings in the equity and bond markets. Moreover, the active double-sort portfolio returns and those of a FX index (US$ vis-à-vis main currencies) have zero correlation at a 95% confidence level. Therefore, by tactically including commodity futures in their asset mix, institutional investors can simultaneously achieve two distinct goals: *i*) earning abnormal returns, and *ii*) reducing the total risk of their global equity and/or fixed-income portfolios.

In contrast, the active double-sort portfolio returns and the S&P GSCI excess returns are significantly correlated. This is consistent with our earlier findings of significantly positive sensitivities of the double-sort portfolio returns to the S&P GSCI excess returns (c.f. Table 6). A plausible rationale for this result is the relatively high weighting of S&P GSCI towards energy derivatives (Erb and Harvey, 2006) and the long positions of the active portfolios in typically-backwardated energy markets.

6. Robustness Analysis

In this section, we investigate whether the superior profits of the double-sort portfolios are a compensation for liquidity risk (Section 6.1), arise from data mining (Section 6.2), withstand alternative specifications of the risk-return trade-off (Sections 6.3 and 6.4) and are robust to an extended sample that takes into account the credit crunch (Section 6.5).

6.1. Liquidity risk

The possibility remains that the superior performance of the double-sort strategies is a compensation for a lack of liquidity in some of the portfolio constituents. This is assessed as follows. At the end of each month, the double-sort strategy TS_1-$Mom_{1\text{-}1}$ is deployed on the 80% of commodities with the highest volume (*HV*) in that month. The resulting portfolio is referred to as HV-TS_1-$Mom_{1\text{-}1}$. Likewise, a low-volume portfolio (LV-TS_1-$Mom_{1\text{-}1}$) is constructed with the 80% of the smallest volume commodities over the previous month. Two measures of volume are used: *a*) \$VOL defined as *number of contracts traded* × *number of units of underlying asset in one contract* × *price of the contract*, and *b*) %ΔVOL defined as the percentage change in the number of contracts traded (Wang and Yu, 2004). To make the results more robust, we consider different cut-off points for the volume, term structure and momentum signals resulting in a total of 12 high volume and 12 low volume strategies. For instance, the first strategy reported in Table 8, denoted Vol=0.8 / TS_1=0.33 / $Mom_{1\text{-}1}$=0.5, selects, first, the 80% of commodities with the highest (lowest) volume; the 33.3%×50% filtering rule is then applied for the term structure and momentum signals as discussed in Section 5.

[Insert Table 8 around here]

If the success of the proposed combined strategies in Section 5 is partly an artifact of liquidity risk, then the *HV* portfolios in Table 8 should underperform the corresponding double-sort portfolios in Table 6. At first sight, this is the case: the *HV* triple-sort portfolios based on HV=0.8 / TS_1=0.33 / $Mom_{1\text{-}1}$=0.5 earn 19.81% and 16.67% depending on the proxy for volume used, while the double-sort strategy based on TS_1=0.33 / $Mom_{1\text{-}1}$=0.5 in Table 6 earns 23.55%. However, the assertion that the profits of the double-sort strategies are in part an illusion induced by lack of liquidity may be too hasty. The returns of the *LV* portfolios in Table 8 (right-hand side) are indeed not higher than those of the corresponding *HV* portfolios (left-hand side). This is borne out by paired two-sample Student's *t*-statistics (Table 8; col. 8) which unambiguously suggest insignificant differences in returns. The latter is reinforced by the relatively high and significant correlations between the *HV* and *LV* strategies. Hence, it seems fair to conclude that liquidity risk does not have a significant impact on performance in this context.

At first sight, it might seem puzzling that the mean returns of the HV- TS_1-$Mom_{1\text{-}1}$ and LV-TS_1-$Mom_{1\text{-}1}$ portfolios (19.81% and 17.63%; Table 8) are lower than the unconditional mean return of the TS_1-$Mom_{1\text{-}1}$ double-sort portfolio (23.55%; Table 6).

One may be tempted to expect that the two sub-portfolios have mean returns that roughly average out to the mean return of $TS_1\text{-}Mom_{1\text{-}1}$ (23.55%). Clearly this is not the case. One possible explanation for this puzzle relates to the diversification return of Erb and Harvey (2006).[17] The latter comes from frequently rebalancing a portfolio of commodity futures to equal weights and equals $\frac{1}{2}\left(1-\frac{1}{K}\right)\overline{\sigma}^2\left(1-\overline{\rho}\right)$ (Erb and Harvey, 2006, p.86), where K is the number of assets in the portfolio, $\overline{\sigma}^2$ is the average variance of the constituents and $\overline{\rho}$ is their average correlation. Clearly, the diversification return rises with K and $\overline{\sigma}^2$ and falls with $\overline{\rho}$. This could explain why the double-sort portfolio, which contains a larger number of securities, can earn more than either one of the liquidity-based portfolios. Differences in average risks and correlations between the constituents of the three portfolios could also account for the observed difference in mean returns.

6.2. Are the profits of the double-sort strategies due to data snooping?

An important problem when evaluating a large set of trading rules is data mining or snooping. The *mining* occurs when a set of data is used more than once for inference or model selection. To deal with this problem we implement White's (2000) Reality Check for data snooping (RC) and the test for Superior Predictive Ability (SPA) developed by Hansen (2005). Both tests are built on the same framework: m alternative decision rules (point forecasts or trading rules) are compared to a benchmark, where performance is defined in terms of expected loss. The question of interest is whether any alternative trading rule is better than the benchmark. The complexity of this exercise arises from the need to control for the full set of alternatives. The latter leads to a composite null hypothesis and a t-statistic whose (asymptotic) distribution is non-standard and requires

[17] Erb and Harvey (2006) define the diversification return as the difference between the compound return of a fixed-weight portfolio and the weighted average of the compound returns of the individual constituents of the portfolio.

bootstrapping. Compared to RC, the SPA test is based on a studentized test statistic and a sample dependent distribution under the null hypothesis, both of which make it more powerful and less sensitive to the inclusion of poor and irrelevant alternatives.

The paper considers k=1,2,...,m (m=55) active trading rules: 13 momentum-only strategies (Section 3), 12 TS-only strategies (Section 4), 6 combined double-sort strategies (Section 5) and 24 volume-based strategies (Section 4.1) alongside the passive long-only benchmark rule represented by k=0. Let $r_{k,t}$ denote the month t returns of trading rule k. The returns are mapped into a "loss" by means of a linear function, on one hand, and two nonlinear (exponential) functions with different degrees of curvature, on the other. The former is $L_{k,t}=max(r_t)-r_{k,t}$, where $max(r_t)$ is the highest return in the full set of strategies k=0,1,...,m. The two nonlinear functions are $L_{k,t}=1/exp(\lambda r_{k,t})$ for λ=1 and 2. The qualitative ranking of the strategies according to these loss functions essentially corresponds to the ranking based on their alpha measures. Thus the sample performance of trading rule k=1,...,m relative to the benchmark is given by $d_{k,t}\equiv L_{0,t}-L_{k,t}$ over t=1,...,T months. Strategy k is better than the benchmark if and only if E[$d_{k,t}$]>0 where E[.] denotes expected value. The null hypothesis is that the best of the m active strategies does not outperform the benchmark, i.e. H_0: E[$d_{k,t}$]≤0, k=1,…,m.[18] Table 9 reports the results.

[Insert Table 9 around here]

With all three loss functions, the t-statistic p-values (for the null hypothesis that the 'best' trading rule does not outperform the passive benchmark) and the consistent SPA and RC statistic p-values (for the above H_0 that takes into account the full set of m=55 of trading rules) unanimously suggest rejection of the hypotheses at conventional significance levels, thus confirming that TS_1-$Mom_{1\text{-}1}$ is a relatively successful trading rule.

[18] The implementation is based on the stationary bootstrap of Politis and Romano (1994) based on B=10,000 pseudo time-series {$d_{k,t}$*} for each k, which are resamples of $d_{k,t}$ constructed by combining blocks with random lengths. The block-length is geometrically distributed according to $q\in$[0,1) so the expected block-length is 1/q. Two typical values are used, q={0.2, 0.5}, to robustify the results.

6.3. Performance evaluation using an augmented static model

The earlier multifactor regression model is now augmented with 3 additional systematic risk factors: *a*) the returns of the US$ effective (vis-à-vis main currencies) exchange rate index, *b*) unexpected inflation (UI), and *c*) unexpected change in US industrial production (UIP). The unexpected component at month *t* is measured as the difference between the economic variable at *t* and its most recent 12-month moving average.[19]

The coefficient estimates and significance *t*-ratios, set out in Appendix A1, are in line with our previous findings. First, for all three classes of strategies, the long-short portfolio returns are for the most part uncorrelated with the risk factors. Second, there are abnormal profits to be made from these active portfolio strategies; on average across those that appear profitable at better than the 5% level, the α is 10.22% per annum for the momentum-only signals, 10.09% for the TS-only signals and a more than two times larger 21.18% for the combined double-sort signals.

6.4. Conditional performance evaluation

Another possible criticism is that the returns from the active strategies are a compensation for *time-varying* risks (Chordia and Shivakumar, 2002). To account for the latter we estimate a conditional model that allows for the measures of risk and abnormal performance in (1) to vary over time as a function of a vector of pre-specified zero-mean information variables (Christopherson *et al.*, 1998).[20]

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[19] The correlations between the six risk factors range from -1.3% between UIP and S&P500 to 24% between LB and S&P500. So multicollinearity is not deemed to be an issue.

[20] The information variables used (as proxies for the business cycle) include the 1-month lagged term spread and default spread. Term spread is the difference between the redemption yield on US 30-year Treasury benchmark bonds and the US 3-month T-bill rate. Default spread is measured as the yield difference between Moody's Baa and Aaa-rated corporate bonds. As in Kat and Miffre (2008), two sets of additional mean-zero conditioning variables are considered. Accordingly, each alpha varies over time conditionally on the (lagged) return of the strategy under review. Likewise, the betas are allowed to change as a function of the previous month's realization of the systematic risk factor.

The results, reported in Appendix A2, indicate the presence of time variation in the risk and performance measures of the multifactor model (1). In particular, at the 5% level, the hypothesis of constant parameters is rejected for 12 out of 13 momentum-only strategies, for 8 out of 12 TS-only strategies and for 5 out of 6 double-sort strategies. In principle, these results suggest that restricting the measures of risk and abnormal performance to be constant as in model (1), instead of conditioning them on past information, might lead to poor conclusions on risk-adjusted performance. However, after allowing for time dependence in the regression parameters of model (1), the average alpha of the active strategies is of similar magnitude as previously reported. A total of 19 out of 31 strategies have positive and significant α at the 5% level in Appendix A2 versus 23 in Tables 2, 4 and 6. Most importantly the risk-adjusted abnormal returns of the combined double-sort strategies remain highly significant. Clearly, the superior performance uncovered is not merely a compensation for time-varying risks.

6.5. Performance over an extended dataset

In this section we test the robustness of the results to the unprecedented high levels of volatility experienced since January 2007 and to the slowdown in the real economy driven by the credit crunch.[21] Bearing this in mind, we extend the dataset until the end of November 2008 and report in Table 10 the performance of two single-sort strategies ($Mom_{1\text{-}1}$ and TS_1), one double-sort strategy (TS_1-$Mom_{1\text{-}1}$) and the long-only equally-weighted benchmark. The performance of the single and double-sort strategies is as good over the extended sample as it was over the previous period (January 1979-January 2007) which suggests the main results presented in the paper are not sample-specific. In particular, the annualized mean returns of $Mom_{1\text{-}1}$, TS_1, TS_1-$Mom_{1\text{-}1}$, the benchmark and the S&P-GSCI equal 18.31%, 14.65%, 23.15%, 2.42% and 2.70%, respectively.

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[21] This robustness check was added to the first version of the paper following a referee's suggestion which we gratefully acknowledge.

[Insert Table 10 around here]

Once again, the higher returns are not solely a compensation for the risks taken as borne out by the significantly positive (at the 1% level) alphas of the long-short portfolios. Most noteworthy, over the sample February 2007-November 2008, $Mom_{1\text{-}1}$, TS_1 and TS_1-$Mom_{1\text{-}1}$ present positive reward-to-risk ratios of 1.23, 1.23 and 0.86, while the reward-to-risk ratios of the benchmark and the S&P-GSCI are negative at, respectively, -0.50 and -0.31.

7. Conclusions

This article provides a thorough analysis of the risk and performance of three types of active strategies in commodity futures markets. Following the momentum signal of Jegadeesh and Titman (1993) and Miffre and Rallis (2007), the first class of strategies simply buys commodities with the best past performance (winners) and shorts commodities with the worst past performance (losers). Following the term structure signaling approach of Erb and Harvey (2006) and Gorton and Rouwenhorst (2006), the second type of strategies tactically allocates wealth towards backwardated commodities (with the highest roll-returns) and away from contangoed commodities (with the lowest roll-returns). Given the low return correlations between the above two types of trading rules, we propose a novel class of strategies that combines the momentum and term structure signals in order to consistently buy commodities with the best past performance (winners) *and* the highest roll-returns, and consistently short commodities with the worst past performance (losers) *and* the lowest roll-returns. According to this double-sort approach, active portfolio managers buy the commodities whose prices are expected to appreciate the most over the following month and sell the commodities whose prices are expected to depreciate the most.

Three main conclusions emerge from the analysis. First, while the individual momentum and term structure strategies perform well, the combined signals are more informative for tactically allocating wealth. On a yearly basis, the profitable momentum-only (TS-only) strategies earn an average return of 10.53% (12.28%) or an alpha of 10.14% (12.66%). With an average return of 21.32% and an alpha of 21.02%, the combined (double-sort) strategies are clearly superior. Over the same period, a passive long-only portfolio of commodity futures earned 3.40%, while the S&P GSCI index earned 3.62%. A robustness analysis suggests that the abnormal returns uncovered are not an artifact of liquidity risk, data snooping, additional non-investable macroeconomic risk factors or time-variation in risks. They are also robust to the market turbulence experienced since January 2007.

Second, the returns of these novel double-sort strategies are weakly correlated with the returns of traditional asset classes, making them attractive candidates for inclusion in well-diversified portfolios. This suggests that institutional investors may tactically add commodity futures to their asset mix not solely to earn abnormal returns but also to reduce the overall risk of their global equity and/or fixed-income portfolios.

Third, because the strategies are carried out on a small cross-section of 37 commodity futures contracts that are easy to sell short and often liquid, the dynamic double-sort investment approach proposed presents the additional appeal of being feasible and cheap to implement. Net of plausible transaction costs, the double-sort strategies still generate a yearly return of 20.71% or a yearly net alpha of 20.41% on average.

The risk management analysis highlights the fact that the long-short double-sort portfolios are substantially more risky than the long-only equally-weighted benchmark. In order to reduce downside risk, asset managers could implement the double-sort trading rules jointly with a stop-loss strategy. Accordingly, investors would opt for a double-sort portfolio when its return is above a given acceptable target return, and risk-free Treasury-bill futures contracts otherwise. A detailed analysis of the risk and performance of such a strategy constitutes an interesting avenue for future research.

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Table 1. Momentum Strategies: Summary Statistics

	R=1				R=3				R=6			R=12		Benchmark
	H=1	H=3	H=6	H=12	H=1	H=3	H=6	H=12	H=1	H=3	H=6	H=1	H=3	
Panel A: Long (Winner) Portfolios														
Annualized arithmetic mean	**0.1239**	**0.0982**	**0.0762**	**0.0580**	**0.1496**	**0.1017**	**0.0752**	**0.0596**	**0.0860**	0.0684	**0.0706**	**0.1072**	0.0634	0.0340
	(3.04)	(2.97)	(2.59)	(2.22)	(3.42)	(2.63)	(2.28)	(2.01)	(2.07)	(1.77)	(2.04)	(2.62)	(1.68)	(1.65)
Annualized geometric mean	0.1061	0.0860	0.0659	0.0497	0.1303	0.0838	0.0613	0.0487	0.0635	0.0484	0.0554	0.0875	0.0448	0.0283
Annualized volatility	0.2158	0.1747	0.1542	0.1361	0.2309	0.2031	0.1730	0.1540	0.2184	0.2024	0.1805	0.2127	0.1953	0.1092
Annualized downside volatility (0%)	0.1224	0.1115	0.1025	0.0916	0.1359	0.1269	0.1164	0.1015	0.1400	0.1336	0.1182	0.1343	0.1298	0.0760
Reward/risk ratio	0.5741	0.5624	0.4939	0.4260	0.6479	0.5006	0.4347	0.3874	0.3938	0.3379	0.3912	0.5038	0.3246	0.3112
Sortino ratio (0%)	1.0118	0.8812	0.7435	0.6329	1.1011	0.8010	0.6459	0.5878	0.6141	0.5120	0.5974	0.7977	0.4886	0.4473
Skewness	**0.6963**	**-0.4185**	**-0.7691**	**-0.6082**	0.2397	**-0.1412**	**-0.9770**	**-0.4153**	-0.2065	**-0.4726**	**-0.4432**	-0.1640	**-0.4277**	**-0.5087**
Kurtosis	**7.1451**	**8.4413**	**8.6200**	**6.5364**	**8.9946**	**10.4714**	**12.0432**	**8.5724**	**8.5031**	**9.4365**	**8.8693**	**10.3702**	**8.9317**	**4.6578**
99% VaR (Cornish-Fisher)	0.1612	0.1996	0.1753	0.1390	0.2272	0.2129	0.2138	0.1588	0.2142	0.2117	0.1876	0.2470	0.2219	0.0946
% of positive months	0.5268	0.5749	0.5650	0.5415	0.5749	0.5482	0.5502	0.5511	0.5076	0.5076	0.5399	0.5569	0.5201	0.5536
Maximum drawdown	-0.4622	-0.5449	-0.5296	-0.5628	-0.6003	-0.5955	-0.5633	-0.6151	-0.5091	-0.6267	-0.6000	-0.6985	-0.7206	-0.5215
Max 12M rolling return	0.9943	0.5437	0.5859	0.4716	0.7904	0.7338	0.7119	0.6330	0.9343	0.8597	0.8711	0.9019	0.9330	0.3507
Min 12M rolling return	-0.4293	-0.3906	-0.3816	-0.3833	-0.4374	-0.4564	-0.4410	-0.3792	-0.3767	-0.3816	-0.3428	-0.6330	-0.4461	-0.3297
Portfolio turnover (p.a.)	10.6802	10.6802	10.6797	10.6797	9.0895	9.0895	9.0895	9.0895	8.5870	8.5870	8.5870	8.2331	8.2331	6.3438
Panel B: Short (Loser) Portfolios														
Annualized arithmetic mean	-0.0530	-0.0048	0.0050	-0.0039	-0.0093	0.0037	0.0066	-0.0007	-0.0265	-0.0171	-0.0231	-0.0461	-0.0212	0.0340
	(-1.46)	(-0.18)	(0.19)	(-0.16)	(-0.27)	(0.12)	(0.23)	(-0.03)	(-0.75)	(-0.53)	(-0.74)	(-1.33)	(-0.64)	(1.65)
Annualized geometric mean	-0.0692	-0.0149	-0.0043	-0.0117	-0.0254	-0.0099	-0.0044	-0.0101	-0.0427	-0.0308	-0.0355	-0.0605	-0.0353	0.0283
Annualized volatility	0.1924	0.1434	0.1359	0.1252	0.1825	0.1671	0.1485	0.1371	0.1860	0.1694	0.1618	0.1799	0.1719	0.1092
Annualized downside volatility (0%)	0.1420	0.1010	0.0971	0.0930	0.1232	0.1095	0.1025	0.0984	0.1295	0.1165	0.1137	0.1318	0.1214	0.0760
Reward/risk ratio	-0.2755	-0.0335	0.0367	-0.0308	-0.0512	0.0223	0.0442	-0.0054	-0.1422	-0.1008	-0.1429	-0.2563	-0.1232	0.3112
Sortino ratio (0%)	-0.3734	-0.0476	0.0513	-0.0415	-0.0758	0.0340	0.0640	-0.0075	-0.2043	-0.1466	-0.2033	-0.3500	-0.1745	0.4473
Skewness	**0.3138**	0.1464	-0.1381	**-0.3410**	**0.6341**	**0.8100**	0.1398	-0.0526	**0.4766**	**0.5282**	**0.4640**	0.2016	**0.3508**	**-0.5087**
Kurtosis	**5.8259**	**4.0713**	**3.8899**	**3.9527**	**6.0693**	**6.6526**	**4.5905**	**4.3780**	**5.4499**	**5.6114**	**5.8770**	**4.3868**	**4.8411**	**4.6578**
99% VaR (Cornish-Fisher)	0.1573	0.0906	0.0958	0.0959	0.1159	0.1099	0.1072	0.0952	0.1310	0.1135	0.1107	0.1163	0.1064	0.0946
% of positive months	0.4583	0.4820	0.5196	0.5292	0.4910	0.4970	0.4954	0.5263	0.4804	0.4802	0.4724	0.4431	0.4737	0.5536
Maximum drawdown	-0.9325	-0.6887	-0.6456	-0.6553	-0.7904	-0.7414	-0.7175	-0.6822	-0.8379	-0.7617	-0.7904	-0.8791	-0.7812	-0.5215
Max 12M rolling return	0.6314	0.3487	0.3511	0.2994	0.6410	0.4555	0.3461	0.3563	0.4433	0.4709	0.4144	0.4480	0.4070	0.3507
Min 12M rolling return	-0.4694	-0.3137	-0.3663	-0.3774	-0.4322	-0.4240	-0.4081	-0.4049	-0.4885	-0.4621	-0.4690	-0.5367	-0.4802	-0.3297
Portfolio turnover (p.a.)	10.5459	10.5459	10.5432	10.5432	8.6457	8.6457	8.6457	8.6457	7.6420	7.6420	7.6420	7.1694	7.1694	6.3438
Panel C: Long-Short (Momentum) Portfolios														
Annualized arithmetic mean	**0.1769**	**0.1030**	**0.0711**	**0.0618**	**0.1589**	**0.0980**	**0.0686**	**0.0604**	**0.1125**	0.0855	**0.0937**	**0.1533**	0.0846	0.0340
	(3.48)	(3.24)	(3.22)	(3.75)	(3.06)	(2.27)	(2.15)	(2.39)	(2.32)	(1.94)	(2.42)	(3.04)	(1.87)	(1.65)
Annualized geometric mean	0.1511	0.0927	0.0664	0.0597	0.1290	0.0744	0.0559	0.0531	0.0833	0.0606	0.0759	0.1262	0.0586	0.0283
Annualized volatility	0.2691	0.1676	0.1160	0.0857	0.2741	0.2272	0.1674	0.1309	0.2545	0.2301	0.2020	0.2623	0.2349	0.1092
Annualized downside volatility (0%)	0.1565	0.1038	0.0727	0.0526	0.1642	0.1484	0.1096	0.0845	0.1602	0.1493	0.1283	0.1567	0.1503	0.0760
Reward/risk ratio	0.6572	0.6147	0.6134	0.7210	0.5797	0.4311	0.4100	0.4614	0.4420	0.3714	0.4642	0.5842	0.3601	0.3112
Sortino ratio (0%)	1.1304	0.9920	0.9789	1.1759	0.9680	0.6599	0.6262	0.7150	0.7021	0.5723	0.7305	0.9783	0.5630	0.4473
Skewness	**0.4158**	-0.1414	-0.1641	-0.2604	**0.3032**	-0.0867	**-0.2926**	-0.2159	0.1183	-0.0026	0.0125	**0.2765**	0.0583	-0.5087
Kurtosis	**5.6403**	**6.1104**	**7.7597**	**5.9013**	**5.6361**	**7.3088**	**7.9284**	**6.5852**	**5.0558**	**5.3710**	**5.2940**	**4.7840**	**4.6387**	4.6578
99% VaR (Cornish-Fisher)	0.2161	0.1482	0.1019	0.0819	0.2011	0.1822	0.1356	0.1045	0.1797	0.1545	0.1354	0.1818	0.1624	0.0946
% of positive months	0.5714	0.5958	0.5982	0.6031	0.5569	0.5843	0.5502	0.5387	0.5680	0.5502	0.5337	0.5723	0.5449	0.5536
Max runup (consecutive)	0.783389	0.47194	0.4216	0.2456	0.9138	0.8990	0.5543	0.3805	1.0101	0.8344	0.5509	0.8997	0.5793	0.3116
Runup length (months)	2	4	4	11	4	4	4	11	4	4	3	4	4	9
Maximum drawdown	-0.6235	-0.4046	-0.2098	-0.1901	-0.6708	-0.4941	-0.4995	-0.3203	-0.6767	-0.6680	-0.4159	-0.5887	-0.5387	-0.5215
Drawdown length (months)	96	24	19	18	28	90	52	18	97	52	49	53	18	0.78
Valley to recovery (months)	19	40	31	28	65	53	76	36	116	118	63	43	36	129
Max 12M rolling return	1.0857	0.5632	0.4917	0.4358	0.9174	0.9745	0.8805	0.7898	1.0519	1.0610	1.0700	1.2360	1.1251	0.3507
Min 12M rolling return	-0.5027	-0.3102	-0.1963	-0.1439	-0.5038	-0.3688	-0.3569	-0.2859	-0.4289	-0.3560	-0.3320	-0.4928	-0.4570	-0.3297
Portfolio turnover (p.a.)	10.6130	10.6130	10.6115	10.6115	8.8676	8.8676	8.8676	8.8676	8.1145	8.1145	8.1145	7.7013	7.7013	6.3438
Net return	0.1699	0.0960	0.0641	0.0548	0.1531	0.0921	0.0628	0.0545	0.1071	0.0801	0.0884	0.1482	0.0795	0.0319

The table reports summary statistics for the monthly returns of the long, short and long-short momentum portfolios. *R* is the ranking period in month and *H* the holding period. Benchmark refers to a long-only passive portfolio that equally-weights all 37 commodities. Significance *t*-ratios for the average return per annum are reported in parentheses; significance at the 5% level or better is denoted in bold.

Table 2. Momentum Strategies: Risk-Adjusted Performance

	R=1				R=3				R=6			R=12	
	H=1	H=3	H=6	H=12	H=1	H=3	H=6	H=12	H=1	H=3	H=6	H=1	H=3
Panel A: Long (Winner) Portfolios													
Annualized α	**0.1032**	**0.0744**	**0.0513**	**0.0382**	**0.1206**	**0.0720**	0.0490	0.0383	0.0551	0.0407	0.0472	**0.0823**	0.0357
	(2.85)	(2.95)	(2.31)	(2.19)	(3.29)	(2.25)	(1.87)	(1.81)	(1.58)	(1.27)	(1.71)	(2.49)	(1.24)
β_B	-0.1352	-0.1549	-0.1448	-0.1481	-0.0382	-0.1436	-0.1268	-0.1049	-0.0937	-0.1203	-0.1334	-0.1120	-0.0127
	(-0.77)	(-1.28)	(-1.41)	(-1.75)	(-0.22)	(-0.95)	(-1.03)	(-0.92)	(-0.56)	(-0.81)	(-1.07)	(-0.70)	(-0.09)
β_M	0.0462	**0.1116**	**0.1568**	**0.1228**	0.0829	**0.1747**	**0.1691**	**0.1115**	**0.1574**	**0.1612**	**0.1324**	0.1001	**0.1113**
	(0.61)	(2.22)	(3.12)	(3.59)	(1.14)	(2.43)	(2.66)	(2.35)	(2.07)	(2.28)	(2.19)	(1.54)	(1.97)
β_C	**0.6133**	**0.6400**	**0.5937**	**0.5697**	**0.7322**	**0.6951**	**0.6406**	**0.6283**	**0.7216**	**0.6919**	**0.6477**	**0.7253**	**0.7239**
	(7.05)	(15.71)	(13.68)	(20.32)	(12.39)	(9.94)	(10.69)	(12.81)	(9.64)	(9.99)	(10.62)	(13.65)	(15.70)
$\bar{R}^2$	0.2501	0.4312	0.4910	0.5691	0.3147	0.3828	0.4474	0.5341	0.3528	0.3759	0.4123	0.3660	0.4355
Panel B: Short (Loser) Portfolios													
Annualized α	**-0.0741**	-0.0227	-0.0136	-0.0189	-0.0258	-0.0140	-0.0096	-0.0112	-0.0502	-0.0347	-0.0401	-0.0611	-0.0322
	(-2.38)	(-1.03)	(-0.69)	(-1.04)	(-0.81)	(-0.50)	(-0.40)	(-0.51)	(-1.57)	(-1.21)	(-1.47)	(-1.90)	(-1.05)
β_B	-0.1596	-0.1867	**-0.1906**	**-0.1972**	-0.2307	-0.1860	-0.1920	**-0.2672**	-0.0621	-0.1254	-0.1528	-0.1993	-0.2645
	(-1.09)	(-1.82)	(-2.02)	(-2.24)	(-1.51)	(-1.38)	(-1.68)	(-2.42)	(-0.41)	(-0.92)	(-1.15)	(-1.28)	(-1.71)
β_M	**0.1406**	**0.1496**	**0.1301**	**0.1298**	**0.1816**	**0.1463**	**0.1317**	**0.1362**	**0.1878**	**0.1171**	**0.1440**	**0.1746**	**0.1764**
	(2.04)	(3.60)	(3.32)	(3.64)	(2.87)	(2.61)	(2.79)	(3.16)	(2.97)	(2.07)	(2.69)	(2.77)	(2.93)
β_C	**0.5161**	**0.4487**	**0.4888**	**0.4592**	**0.3997**	**0.4369**	**0.4537**	**0.4285**	**0.4555**	**0.4588**	**0.4484**	**0.3892**	**0.3773**
	(7.42)	(10.50)	(15.37)	(15.75)	(7.77)	(9.60)	(11.75)	(12.18)	(8.86)	(9.91)	(10.22)	(7.53)	(7.67)
$\bar{R}^2$	0.2339	0.3326	0.4307	0.4489	0.1699	0.2291	0.3076	0.3326	0.2069	0.2350	0.2537	0.1627	0.1715
Panel C: Long-Short (Momentum) Portfolios													
Annualized α	**0.1772**	**0.0972**	**0.0648**	**0.0570**	**0.1464**	**0.0861**	0.0587	**0.0495**	**0.1053**	0.0753	**0.0873**	**0.1434**	0.0679
	(3.44)	(2.99)	(2.83)	(3.49)	(2.82)	(1.99)	(1.84)	(2.00)	(2.17)	(1.71)	(2.24)	(2.87)	(1.52)
β_B	0.0243	0.0319	0.0458	0.0491	0.1925	0.0424	0.0651	0.1622	-0.0316	0.0051	0.0194	0.0873	0.2518
	(0.10)	(0.22)	(0.41)	(0.62)	(0.80)	(0.22)	(0.43)	(1.30)	(-0.14)	(0.02)	(0.10)	(0.36)	(1.12)
β_M	-0.0943	-0.0380	0.0267	-0.0070	-0.0987	0.0283	0.0375	-0.0247	-0.0304	0.0441	-0.0116	-0.0745	-0.0651
	(-0.92)	(-0.56)	(0.57)	(-0.22)	(-0.87)	(0.32)	(0.59)	(-0.51)	(-0.32)	(0.51)	(-0.15)	(-0.76)	(-0.74)
β_C	0.0972	**0.1913**	**0.1049**	**0.1106**	**0.3325**	**0.2582**	**0.1869**	**0.1998**	**0.2661**	**0.2331**	**0.1994**	**0.3362**	**0.3466**
	(1.17)	(2.68)	(2.29)	(4.20)	(2.65)	(2.50)	(3.63)	(5.04)	(3.41)	(3.28)	(3.18)	(4.18)	(4.85)
$\bar{R}^2$	-0.0025	0.0329	0.0193	0.0441	0.0403	0.0326	0.0324	0.0688	0.0259	0.0242	0.0215	0.0440	0.0633

The table reports coefficient estimates from (1). α measures abnormal performance, β_B, β_M and β_C measure the sensitivities of returns to the excess returns on Lehman Aggregate US total return bond index, the S&P500 composite index and the S&P GSCI, respectively. Significance *t*-ratios are in parentheses. *R* is the ranking period in month and *H* the holding period. The last row of each panel reports the adjusted goodness of fit statistic. Significance at the 5% level or better is denoted in bold.

Table 3. Term Structure Strategies: Summary Statistics

	TS_1			TS_2			$TS_{3,i=2}$			$TS_{3,i=4}$			$TS_{3,i=7}$			$TS_{3,i=10}$			Benchmark
	L	*S*	*L-S*	*L*	*S*	*L-S*	*L*	*S*	*L-S*	*L*	*S*	*L-S*	*L*	*S*	*L-S*	*L*	*S*	*L-S*	
Panel A: End-of-Month Returns																			
Annualized arithmetic mean	**0.0849**	-0.0560	**0.1410**	0.0360	-0.0416	0.0776	**0.0886**	-0.0465	**0.1388**	**0.0945**	-0.0339	**0.1339**	**0.0808**	-0.0070	**0.0946**	**0.0916**	0.0013	**0.0982**	0.0340
	(2.39)	(-1.63)	(3.13)	(1.05)	(-1.22)	(1.73)	(2.48)	(-1.42)	(3.08)	(2.72)	(-1.02)	(3.04)	(2.33)	(-0.21)	(2.12)	(2.60)	(0.04)	(2.16)	(1.65)
Annualized geometric mean	0.0697	-0.0699	0.1173	0.0200	-0.0562	0.0501	0.0733	-0.0598	0.1163	0.0808	-0.0483	0.1125	0.0662	-0.0223	0.0688	0.0770	-0.0142	0.0719	0.0283
Annualized volatility	0.1877	0.1822	0.2384	0.1812	0.1804	0.2379	0.1894	0.1736	0.2381	0.1839	0.1756	0.2328	0.1835	0.1761	0.2366	0.1868	0.1770	0.2402	0.1092
Annualized downside volatility (0%)	0.1170	0.1317	0.1580	0.1166	0.1283	0.1593	0.1136	0.1283	0.1462	0.1082	0.1299	0.1436	0.1097	0.1257	0.1526	0.1127	0.1245	0.1532	0.0760
Reward/risk ratio	0.4525	-0.3074	0.5913	0.1986	-0.2306	0.3261	0.4678	-0.2678	0.5829	0.5140	-0.1929	0.5751	0.4402	-0.0398	0.3998	0.4904	0.0074	0.4089	0.3112
Sortino ratio (0%)	0.7260	-0.4254	0.8920	0.3086	-0.3243	0.4867	0.7799	-0.3624	0.9493	0.8733	-0.2608	0.9325	0.7365	-0.0558	0.6196	0.8126	0.0106	0.6412	0.4473
Skewness	0.2174	**1.0354**	**-0.6958**	**0.4327**	**0.4725**	-0.1810	**0.3380**	**0.3643**	0.0012	**0.4399**	0.0078	0.0996	**0.4895**	0.0848	0.0399	**0.3357**	0.0787	0.1120	**-0.5087**
Kurtosis	**4.3603**	**10.4533**	**8.0891**	**4.2135**	**4.4392**	**4.5240**	**3.9897**	**5.7901**	**4.7753**	**4.3885**	**3.6289**	**3.9793**	**4.7754**	**4.0431**	**3.8868**	**4.7839**	**3.5449**	**3.8470**	**4.6578**
99% VaR (Cornish-Fisher)	0.1341	0.1540	0.2662	0.1166	0.1166	0.1932	0.1242	0.1340	0.1891	0.1200	0.1254	0.1670	0.1218	0.1277	0.1715	0.1328	0.1226	0.1695	0.0946
% of positive months	0.5595	0.4821	0.5774	0.5149	0.4583	0.5506	0.5327	0.4792	0.5804	0.5417	0.4762	0.5685	0.5327	0.5060	0.5387	0.5476	0.5000	0.5476	0.5536
Max runup (consecutive)			0.9145			0.5665			0.8172			0.8638			0.7473			0.8839	0.3116
Runup length (months)			13			10			5			10			10			10	9
Maximum drawdown	-0.4973	-0.8936	-0.5753	-0.6544	-0.8923	-0.4740	-0.4793	-0.8491	-0.5398	-0.4918	-0.8384	-0.5852	-0.5528	-0.7610	-0.7304	-0.5872	-0.7725	-0.7573	-0.5215
Drawdown length (months)			36			73			12			92			117			117	78
Valley to recovery (months)			84			15			146			65			94			95	129
Max 12M rolling return	0.7333	0.6767	0.8959	0.6304	0.4338	0.9807	0.8278	0.8729	1.4684	0.7282	0.7414	1.0763	0.7342	0.7505	0.9694	0.7233	0.8592	1.1156	0.3507
Min 12M rolling return	-0.4214	-0.5132	-0.4749	-0.4264	-0.5049	-0.3662	-0.3227	-0.4898	-0.5398	-0.3147	-0.5266	-0.4614	-0.3923	-0.5000	-0.4760	-0.4158	-0.5179	-0.4804	-0.3297
Portfolio turnover (p.a.)	8.7938	7.9433	8.3686	8.1743	6.9075	7.5409	11.7950	10.9269	11.3609	15.3782	14.7334	15.0558	19.1505	19.0273	19.0889	22.0784	22.8856	22.4820	6.3438
Net return			0.1354			0.0726			0.1313			0.1239			0.0820			0.0834	0.0319
Panel B: 15th-of-Month Returns																			
Annualized arithmetic mean	**0.1226**	-0.0147	**0.1410**	0.0580	-0.0026	0.0602	**0.1108**	0.0007	**0.1120**	**0.0972**	0.0226	0.0767	**0.0827**	0.0617	0.0263	**0.0922**	0.0551	0.0412	**0.0507**
	(3.71)	(-0.44)	(3.36)	(1.80)	(-0.08)	(1.40)	(3.28)	(0.02)	(2.61)	(2.91)	(0.69)	(1.79)	(2.35)	(1.90)	(0.58)	(2.70)	(1.71)	(0.95)	(2.43)
Annualized geometric mean	0.1130	-0.0303	0.1223	0.0446	-0.0184	0.0352	0.0993	-0.0146	0.0895	0.0849	0.0078	0.0522	0.0674	0.0482	-0.0027	0.0788	0.0414	0.0152	0.0455
Annualized volatility	0.1748	0.1784	0.2220	0.1709	0.1779	0.2274	0.1785	0.1762	0.2266	0.1768	0.1731	0.2265	0.1866	0.1721	0.2400	0.1808	0.1706	0.2289	0.1105
Annualized downside volatility (0%)	0.1052	0.1254	0.1408	0.1061	0.1267	0.1488	0.1066	0.1202	0.1484	0.1062	0.1143	0.1497	0.1174	0.1061	0.1664	0.1103	0.1119	0.1543	0.0741
Reward/risk ratio	0.7015	-0.0825	0.6351	0.3395	-0.0145	0.2646	0.6206	0.0041	0.4942	0.5494	0.1308	0.3386	0.4431	0.3586	0.1094	0.5099	0.3232	0.1799	0.4588
Sortino ratio (0%)	1.1658	-0.1173	1.0010	0.5472	-0.0204	0.4044	1.0392	0.0061	0.7547	0.9151	0.1981	0.5122	0.7047	0.5820	0.1578	0.8362	0.4927	0.2670	0.6842
Skewness	0.0325	0.1271	-0.3655	**0.6334**	-0.1171	0.2578	0.1638	0.2388	**-0.3511**	0.2082	**0.2790**	-0.1009	0.1049	**0.4518**	-0.0452	0.2339	-0.0378	0.1007	**-0.4990**
Kurtosis	**4.2516**	**8.1323**	**7.3440**	**7.7391**	**5.4984**	**4.4107**	**3.9160**	**5.9905**	**4.7186**	**3.7999**	**4.5979**	3.4036	**4.0192**	**4.0863**	3.3857	**4.0364**	**4.2293**	**3.5411**	**5.1919**
99% VaR (Cornish-Fisher)	0.1314	0.1776	0.2295	0.1399	0.1543	0.1608	0.1245	0.1446	0.1931	0.1200	0.1236	0.1633	0.1342	0.1082	0.1701	0.1244	0.1305	0.1573	0.0997
% of positive months	0.5833	0.4762	0.5923	0.5179	0.5089	0.5387	0.5714	0.4970	0.5565	0.5446	0.5119	0.5417	0.5595	0.5327	0.4970	0.5804	0.5387	0.5089	0.5714
Max runup (consecutive)			0.8203			0.7861			0.7545			0.5002			0.6091			0.5101	0.3373
Runup length (months)			5			10			5			10			11			3	9
Maximum drawdown	-0.3416	-0.7988	-0.6226	-0.4578	-0.7898	-0.5369	-0.3736	-0.7479	-0.5735	-0.3705	-0.5889	-0.5998	-0.4531	-0.5128	-0.7623	-0.3999	-0.5029	-0.6678	-0.3893
Drawdown length (months)			80			100			87			89			89			89	73
Valley to recovery (months)			82			80			93			122			170			166	50
Max 12M rolling return	0.7696	0.7443	1.1367	0.7427	0.4323	0.8793	0.7675	0.7249	1.0141	0.6171	0.6390	0.8055	0.6412	0.8368	0.7476	0.6010	0.6347	0.6896	0.4328
Min 12M rolling return	-0.3416	-0.4415	-0.5266	-0.3290	-0.4490	-0.4301	-0.3489	-0.4382	-0.4642	-0.3322	-0.4177	-0.4230	-0.3446	-0.3922	-0.5174	-0.2844	-0.3989	-0.4243	-0.2995
Portfolio turnover (p.a.)	8.8770	8.1175	8.4972	8.0808	6.7630	7.4219	11.9117	11.3077	11.6097	15.5363	15.2869	15.4116	19.4744	19.8775	19.6760	22.3437	23.8502	23.0969	6.3395
Net return			0.1354			0.0553			0.1043			0.0665			0.0133			0.0259	0.0486

TS_1 and $TS_{3,i}$ use the front-end of the term structure to measure roll-returns, while TS_2 uses the whole term structure, i is the number of rebalancing instances in a month. *L*, *S* and *L-S* stand for long, short and long-short, respectively. Benchmark refers to a long-only passive portfolio that equally-weights all 37 commodities. Significance *t*-ratios for the average return per annum in parentheses. Significance at the 5% level or better is denoted in bold.

Table 4. Term Structure Strategies: Risk-Adjusted Performance

	TS_1			TS_2			$TS_{3,i=2}$			$TS_{3,i=4}$			$TS_{3,i=7}$			$TS_{3,i=10}$		
	L	*S*	*L-S*	*L*	*S*	*L-S*	*L*	*S*	*L-S*	*L*	*S*	*L-S*	*L*	*S*	*L-S*	*L*	*S*	*L-S*
Panel A: End-of-Month Returns																		
Annualized α	**0.0662**	**-0.0746**	**0.1408**	0.0173	-0.0493	0.0666	**0.0728**	**-0.0669**	**0.1437**	**0.0767**	-0.0542	**0.1368**	**0.0617**	-0.0297	**0.0985**	**0.0715**	-0.0188	**0.0985**
	(2.31)	(-2.34)	(3.13)	(0.62)	(-1.48)	(1.51)	(2.57)	(-2.22)	(3.21)	(2.82)	(-1.78)	(3.12)	(2.27)	(-0.97)	(2.22)	(2.57)	(-0.61)	(2.19)
β_B	-0.1780	-0.0427	-0.1352	-0.2532	-0.3099	0.0567	**-0.2939**	0.0133	-0.3171	-0.1553	-0.0083	-0.1578	-0.0882	0.0482	-0.1434	-0.0969	-0.0071	-0.0933
	(-1.29)	(-0.28)	(-0.62)	(-1.88)	(-1.94)	(0.27)	(-2.00)	(0.09)	(-1.48)	(-1.11)	(-0.06)	(-0.75)	(-0.67)	(0.33)	(-0.67)	(-0.72)	(-0.05)	(-0.43)
β_M	0.0101	0.0997	-0.0895	0.0856	**0.1620**	-0.0764	0.0065	0.1127	-0.1019	-0.0355	0.1097	-0.1431	-0.0423	**0.1370**	**-0.1792**	-0.0282	**0.1314**	-0.1606
	(0.18)	(1.57)	(-1.00)	(1.54)	(2.45)	(-0.87)	(0.12)	(1.88)	(-1.15)	(-0.66)	(1.82)	(-1.65)	(-0.85)	(2.25)	(-2.03)	(-0.51)	(2.13)	(-1.80)
β_C	**0.6383**	**0.4126**	**0.2257**	**0.5948**	**0.2336**	**0.3612**	**0.6496**	**0.4034**	**0.2419**	**0.6570**	**0.4215**	**0.2296**	0.6500	0.4054	**0.2385**	0.6649	0.3869	**0.2762**
	(13.79)	(8.01)	(3.10)	(13.14)	(4.35)	(5.09)	(11.87)	(8.28)	(3.35)	(12.19)	(8.61)	(3.25)	(11.63)	(8.21)	(3.33)	(14.82)	(7.71)	(3.81)
$\bar{R}^2$	0.3615	0.1613	0.0243	0.3450	0.0686	0.0654	0.3744	0.1733	0.0368	0.3996	0.1838	0.0332	0.3901	0.1754	0.0385	0.3940	0.1565	0.0436
Panel B: 15th-of-Month Returns																		
Annualized α	**0.1035**	-0.0427	**0.1497**	0.0356	-0.0173	0.0523	**0.0925**	-0.0240	**0.1183**	**0.0816**	0.0035	0.0806	**0.0647**	0.0464	0.0234	**0.0730**	0.0358	0.0420
	(4.00)	(-1.48)	(3.54)	(1.43)	(-0.54)	(1.24)	(3.49)	(-0.81)	(2.77)	(2.98)	(0.12)	(1.89)	(2.33)	(1.52)	(0.52)	(2.74)	(1.20)	(0.98)
β_B	-0.1657	0.0823	-0.2242	-0.0862	-0.1773	0.0967	-0.1899	0.0252	-0.2169	-0.2182	-0.0913	-0.1290	-0.2046	-0.1350	-0.0752	-0.1983	-0.0735	-0.1387
	(-1.33)	(0.59)	(-1.10)	(-0.72)	(-1.15)	(0.48)	(-1.49)	(0.18)	(-1.06)	(-1.47)	(-0.64)	(-0.63)	(-1.49)	(-0.92)	(-0.35)	(-1.50)	(-0.51)	(-0.67)
β_M	0.0213	**0.1416**	-0.1233	0.0419	**0.1850**	-0.1391	0.0112	**0.1626**	-0.1484	-0.0105	**0.1415**	-0.1557	0.0032	**0.1245**	-0.1156	0.0369	**0.1579**	-0.1242
	(0.41)	(2.47)	(-1.47)	(0.85)	(2.89)	(-1.66)	(0.21)	(2.75)	(-1.75)	(-0.20)	(2.39)	(-1.84)	(0.06)	(2.06)	(-1.30)	(0.67)	(2.67)	(-1.46)
β_C	**0.6252**	**0.5229**	0.0947	**0.6289**	**0.2967**	**0.3288**	**0.6341**	**0.4480**	**0.1860**	**0.6083**	**0.4095**	**0.1972**	**0.6484**	**0.3607**	**0.2897**	**0.6329**	**0.3805**	**0.2490**
	(14.97)	(11.21)	(1.39)	(15.69)	(5.71)	(4.84)	(14.81)	(9.32)	(2.70)	(9.79)	(8.49)	(2.86)	(12.16)	(7.34)	(4.00)	(11.66)	(7.93)	(3.59)
$\bar{R}^2$	0.4008	0.2819	0.0097	0.4230	0.1050	0.0637	0.3960	0.2180	0.0276	0.3729	0.1851	0.0278	0.3790	0.1439	0.0426	0.3856	0.1694	0.0372

The table reports coefficient estimates for equation (1). α measures abnormal performance, β_B, β_M and β_C measure the sensitivities of returns to the excess returns on Lehman Aggregate US total return bond index, the S&P500 composite index and the S&P GSCI, respectively. Significance *t*-ratios are in parentheses. The last row of each panel reports the adjusted goodness of fit statistic. TS_1 and $TS_{3,i}$ use the front-end of the term structure to measure roll-returns, while TS_2 uses the whole term structure, i is the number of rebalancing instances in a month. *L*, *S* and *L-S* stand for long, short and long-short, respectively. Bold denotes significance at the 5% level or better.

Table 5. Correlations between Momentum and Term Structure Returns

	R = 1				R = 3				R = 6			R = 12		Average
	H = 1	H = 3	H = 6	H = 12	H = 1	H = 3	H = 6	H = 12	H = 1	H = 3	H = 6	H = 1	H = 3	
Panel A: End-of-Month Returns														
TS_1	0.1628	0.1893	0.2912	0.3108	0.2279	0.3270	0.3437	0.3527	0.2967	0.3083	0.2940	0.2654	0.2992	*0.2822*
	(3.02)	(3.51)	(5.52)	(5.88)	(4.26)	(6.28)	(6.62)	(6.75)	(5.64)	(5.86)	(5.54)	(4.95)	(5.62)	
TS_2	0.2926	0.3411	0.3766	0.5270	0.3989	0.4395	0.4433	0.5696	0.4480	0.4355	0.4448	0.5112	0.5335	*0.4432*
	(5.59)	(6.61)	(7.37)	(11.14)	(7.93)	(8.89)	(8.94)	(12.42)	(9.09)	(8.75)	(8.94)	(10.69)	(11.30)	
$TS_{3,i=2}$	0.1914	0.1806	0.2755	0.3178	0.2309	0.2815	0.3402	0.3645	0.3082	0.3148	0.3208	0.3208	0.3252	*0.2901*
	(3.62)	(3.35)	(5.20)	(6.02)	(4.32)	(5.33)	(6.54)	(7.01)	(5.88)	(6.00)	(6.10)	(6.09)	(6.16)	
$TS_{3,i=4}$	0.1916	0.1509	0.2625	0.3227	0.1899	0.2469	0.3196	0.3735	0.2927	0.3035	0.3319	0.3367	0.3327	*0.2812*
	(3.57)	(2.78)	(4.93)	(6.13)	(3.52)	(4.63)	(6.10)	(7.21)	(5.55)	(5.76)	(6.33)	(6.43)	(6.32)	
$TS_{3,i=7}$	0.1958	0.1662	0.2249	0.3232	0.2075	0.2365	0.2888	0.3838	0.2840	0.2776	0.3064	0.3472	0.3418	*0.2757*
	(3.65)	(3.07)	(4.19)	(6.14)	(3.86)	(4.42)	(5.45)	(7.45)	(5.37)	(5.22)	(5.79)	(6.65)	(6.52)	
$TS_{3,i=10}$	0.2142	0.1876	0.2650	0.3760	0.2397	0.2851	0.3447	0.4395	0.3243	0.3328	0.3736	0.3966	0.3947	*0.3211*
	(4.01)	(3.48)	(4.99)	(7.29)	(4.50)	(5.40)	(6.64)	(8.77)	(6.22)	(6.38)	(7.25)	(7.76)	(7.70)	
Average	*0.2081*	*0.2026*	*0.2826*	*0.3629*	*0.2491*	*0.3027*	*0.3467*	*0.4139*	*0.3256*	*0.3288*	*0.3452*	*0.3630*	*0.3712*	*0.3156*
Minimum	*0.1628*	*0.1509*	*0.2249*	*0.3108*	*0.1899*	*0.2365*	*0.2888*	*0.3527*	*0.2840*	*0.2776*	*0.2940*	*0.2654*	*0.2992*	*0.1509*
Maximum	*0.2926*	*0.3411*	*0.3766*	*0.5270*	*0.3989*	*0.4395*	*0.4433*	*0.5696*	*0.4480*	*0.4355*	*0.4448*	*0.5112*	*0.5335*	*0.5696*
Panel B: 15th-of-Month Returns														
TS_1	0.1092	0.1362	0.2091	0.2344	0.1767	0.2468	0.2060	0.2828	0.2140	0.1815	0.1772	0.2159	0.2222	*0.2009*
	(2.01)	(2.50)	(3.88)	(4.33)	(3.27)	(4.63)	(3.81)	(5.28)	(3.97)	(3.34)	(3.24)	(3.97)	(4.08)	
TS_2	0.2306	0.3498	0.3655	0.4741	0.4090	0.4531	0.4059	0.5385	0.4420	0.3977	0.3990	0.4911	0.5065	*0.4202*
	(4.33)	(6.80)	(7.12)	(9.68)	(8.17)	(9.23)	(8.03)	(11.45)	(8.94)	(7.84)	(7.83)	(10.13)	(10.52)	
$TS_{3,i=2}$	0.1857	0.1715	0.2451	0.3023	0.2170	0.2968	0.3072	0.3627	0.2590	0.2780	0.2821	0.2874	0.2987	*0.2687*
	(3.45)	(3.17)	(4.59)	(5.70)	(4.05)	(5.65)	(5.84)	(6.97)	(4.86)	(5.23)	(5.29)	(5.39)	(5.61)	
$TS_{3,i=4}$	0.1839	0.1865	0.2607	0.3246	0.2415	0.3122	0.3404	0.4043	0.2860	0.3222	0.3337	0.3251	0.3483	*0.2976*
	(3.42)	(3.46)	(4.90)	(6.17)	(4.53)	(5.97)	(6.55)	(7.92)	(5.41)	(6.15)	(6.37)	(6.18)	(6.66)	
$TS_{3,i=7}$	0.2242	0.2789	0.3377	0.4027	0.3203	0.3705	0.4027	0.4624	0.3458	0.3740	0.3793	0.3907	0.4097	*0.3614*
	(4.20)	(5.29)	(6.51)	(7.91)	(6.16)	(7.25)	(7.96)	(9.34)	(6.68)	(7.29)	(7.38)	(7.63)	(8.05)	
$TS_{3,i=10}$	0.1850	0.2027	0.2739	0.3402	0.2572	0.3248	0.3418	0.4105	0.3039	0.3352	0.3367	0.3472	0.3586	*0.3091*
	(3.44)	(3.77)	(5.17)	(6.50)	(4.85)	(6.24)	(6.58)	(8.07)	(5.79)	(6.43)	(6.44)	(6.65)	(6.88)	
Average	*0.1864*	*0.2209*	*0.2820*	*0.3464*	*0.2703*	*0.3340*	*0.3340*	*0.4102*	*0.3084*	*0.3148*	*0.3180*	*0.3429*	*0.3573*	*0.3097*
Minimum	*0.1092*	*0.1362*	*0.2091*	*0.2344*	*0.1767*	*0.2468*	*0.2060*	*0.2828*	*0.2140*	*0.1815*	*0.1772*	*0.2159*	*0.2222*	*0.1092*
Maximum	*0.2306*	*0.3498*	*0.3655*	*0.4741*	*0.4090*	*0.4531*	*0.4059*	*0.5385*	*0.4420*	*0.3977*	*0.3990*	*0.4911*	*0.5065*	*0.5385*

The table reports Pearson correlations for the monthly returns of the momentum and term structure (*TS*) portfolios. *R* and *H* are ranking and holding periods for the momentum strategy. TS_1 and $TS_{3,i}$ use the front-end of the term structure to measure roll-returns, while TS_2 uses the whole term structure, *i* is the number of rebalancing instances in a month. Significance *t*-statistics are in parentheses.

Table 6. Double-Sort Strategies: Summary Statistics and Risk-Adjusted Performance

	TS_1 - $Mom_{1\text{-}1}$			TS_1 - $Mom_{3\text{-}1}$			TS_1 - $Mom_{12\text{-}1}$			$Mom_{1\text{-}1}$ - TS_1			$Mom_{3\text{-}1}$ - TS_1			$Mom_{12\text{-}1}$ - TS_1			Benchmark
	L	*S*	*L-S*	*L*	*S*	*L-S*	*L*	*S*	*L-S*	*L*	*S*	*L-S*	*L*	*S*	*L-S*	*L*	*S*	*L-S*	
Panel A: Summary Statistics																			
Annualized arithmetic mean	**0.1771**	-0.0584	**0.2355**	**0.1445**	-0.0683	**0.2128**	**0.1214**	-0.0667	**0.1881**	**0.1556**	**-0.0795**	**0.2351**	**0.1252**	-0.0675	**0.1927**	**0.1194**	**-0.0954**	**0.2147**	0.0340
	(4.28)	(-1.61)	(4.51)	(3.37)	(-1.95)	(4.02)	(2.93)	(-1.84)	(3.65)	(3.46)	(-2.39)	(4.42)	(3.03)	(-1.91)	(3.67)	(2.97)	(-2.60)	(4.47)	(1.65)
Annualized geometric mean	0.1654	-0.0742	0.2180	0.1264	-0.0818	0.1893	0.1024	-0.0811	0.1632	0.1358	-0.0912	0.2156	0.1065	-0.0813	0.1654	0.1016	-0.1076	0.1999	0.0283
Annualized volatility	0.2189	0.1920	0.2761	0.2260	0.1850	0.2792	0.2158	0.1886	0.2680	0.2379	0.1759	0.2813	0.2181	0.1867	0.2766	0.2091	0.1909	0.2502	0.1092
Annualized downside volatility (0%)	0.1167	0.1432	0.1509	0.1298	0.1342	0.1614	0.1342	0.1371	0.1637	0.1370	0.1405	0.1558	0.1305	0.1349	0.1691	0.1324	0.1419	0.1486	0.0760
Reward/risk ratio	0.8092	-0.3043	0.8533	0.6397	-0.3691	0.7624	0.5626	-0.3537	0.7016	0.6543	-0.4520	0.8357	0.5738	-0.3616	0.6965	0.5708	-0.5001	0.8582	0.3112
Sortino ratio (0%)	1.5180	-0.4081	1.5607	1.1136	-0.5090	1.3187	0.9045	-0.4865	1.1491	1.1361	-0.5656	1.5093	0.9591	-0.5005	1.1391	0.9014	-0.6725	1.4456	0.4473
Skewness	**0.9442**	**0.3620**	**0.6577**	**0.6990**	**1.0767**	**0.4274**	-0.1251	**0.6264**	-0.0719	**0.5533**	-0.2445	**0.4833**	**0.2681**	**1.0686**	-0.1462	-0.2520	**0.8240**	-0.0598	**-0.5087**
Kurtosis	**10.6378**	**6.1464**	**7.8509**	**11.8247**	**10.7970**	**8.1027**	**8.2358**	**6.5063**	**5.1076**	**8.4725**	**3.6442**	**5.6203**	**6.9029**	**10.2905**	**6.4818**	**8.5172**	**7.0350**	**4.6317**	**4.6578**
99% VaR (Cornish-Fisher)	0.1963	0.1530	0.2257	0.2429	0.1573	0.2544	0.2280	0.1389	0.2230	0.2132	0.1341	0.2036	0.1909	0.1530	0.2601	0.2296	0.1334	0.1994	0.0946
% of positive months	0.5863	0.4554	0.6012	0.5629	0.4311	0.6198	0.5600	0.4277	0.5785	0.5744	0.4435	0.6042	0.5389	0.4401	0.5838	0.5631	0.4092	0.6185	0.5536
Max runup (consecutive)			1.4581			1.3803			1.1047			1.1122			0.9570			0.8522	0.3116
Runup length (months)			4			4			14			4			4			8	9
Maximum drawdown	-0.5190	-0.9363	-0.4470	-0.5293	-0.9228	-0.5948	-0.5056	-0.9250	-0.6381	-0.5483	-0.9528	-0.4889	-0.5736	-0.9294	-0.6618	-0.4868	-0.9592	-0.5262	-0.5215
Drawdown length (months)			25			29			37			29			32			19	78
Valley to recovery (months)			10			25			26			15			46			35	129
Max 12M rolling return	1.0089	0.5670	1.7197	1.1410	0.6792	1.3021	1.0236	0.4761	1.4135	0.9990	0.6490	1.4738	0.8690	0.5759	1.2795	0.9141	0.5485	1.4077	0.3507
Min 12M rolling return	-0.4008	-0.4604	-0.3927	-0.3936	-0.5109	-0.5365	-0.4172	-0.6089	-0.4368	-0.4972	-0.4826	-0.4737	-0.4467	-0.5225	-0.5565	-0.5153	-0.6343	-0.3945	-0.3297
Portfolio turnover (p.a.)	10.3774	10.0244	10.2009	9.4291	8.6275	9.0283	9.0252	7.7614	8.3933	10.5075	10.2579	10.3827	9.5150	8.7719	9.1434	8.9005	7.6882	8.2944	6.3438
Net return			0.2288			0.2069			0.1825			0.2282			0.1866			0.2093	0.0319
Panel B: Risk-Adjusted Performance																			
Annualized α	**0.1550**	**-0.0816**	**0.2366**	**0.1193**	**-0.0848**	**0.2041**	**0.1018**	**-0.0867**	**0.1886**	**0.1295**	**-0.0997**	**0.2292**	**0.1020**	**-0.0845**	**0.1865**	**0.0946**	**-0.1218**	**0.2163**	
	(4.25)	(-2.40)	(4.48)	(3.34)	(-2.51)	(3.96)	(3.09)	(-2.53)	(3.73)	(3.25)	(-3.30)	(4.29)	(2.91)	(-2.50)	(3.60)	(2.98)	(-3.60)	(4.56)	
β_B	-0.1918	0.0098	-0.2015	-0.1173	-0.1275	0.0103	-0.2864	-0.0304	-0.2560	-0.0616	-0.0861	0.0245	-0.1189	-0.1193	0.0004	-0.0901	0.0789	-0.1690	
	(-1.01)	(0.06)	(-0.68)	(-0.69)	(-0.79)	(0.04)	(-1.79)	(-0.18)	(-1.04)	(-0.32)	(-0.59)	(0.10)	(-0.71)	(-0.74)	(0.00)	(-0.58)	(0.48)	(-0.73)	
β_M	0.0697	**0.1785**	-0.1089	0.0551	**0.2023**	-0.1472	0.0871	**0.1837**	-0.0966	0.0876	**0.1507**	-0.0631	0.0525	**0.1838**	-0.1313	0.0742	**0.2094**	-0.1352	
	(0.98)	(2.65)	(-1.04)	(0.78)	(3.02)	(-1.44)	(1.35)	(2.73)	(-0.97)	(1.11)	(2.51)	(-0.59)	(0.75)	(2.74)	(-1.28)	(1.19)	(3.15)	(-1.45)	
β_C	**0.6624**	**0.3949**	**0.2675**	**0.7267**	**0.2888**	**0.4379**	**0.7523**	**0.3674**	**0.3849**	**0.6519**	**0.4245**	**0.2274**	**0.6724**	**0.3217**	**0.3507**	**0.7424**	**0.4164**	**0.3260**	
	(8.30)	(7.22)	(2.35)	(12.64)	(5.31)	(5.27)	(14.19)	(6.67)	(4.73)	(10.14)	(8.71)	(2.64)	(11.88)	(5.90)	(4.20)	(14.54)	(7.64)	(4.27)	
$\bar{R}^2$	0.2870	0.1467	0.0272	0.3227	0.0962	0.0738	0.3867	0.1332	0.0638	0.2331	0.1938	0.0125	0.2961	0.1083	0.0460	0.3944	0.1722	0.0539	

Panel A reports summary statistics for the monthly returns of the 6 double-sort strategies and Panel B reports coefficient estimates from (1). α measures abnormal performance, β_B, β_M and β_C measure the sensitivities of returns to the excess returns on Lehman Brothers Aggregate US total return bond index, the S&P500 composite index and the S&P GSCI, respectively. The last row reports the adjusted goodness of fit statistic. TS_1 uses the front-end of the term structure to measure roll-returns, $Mom_{R\text{-}H}$ refers to a momentum strategy with R-month ranking period and H-month holding period, *L*, *S* and *L-S* stand for long, short and long-short, respectively. Benchmark refers to a long-only strategy that equally-weights all 37 commodities. *t*-ratios are in parentheses and significance at the 5 % level or better is denoted in bold.

Table 7. Return Correlations of Combined Strategies and Traditional Asset Classes

	LB	S&P500	GSCI	FX	T-bond	T-bill
TS_1 - $Mom_{1\text{-}1}$	-0.0613	-0.0650	**0.1709**	-0.0408	0.0719	0.0695
	(-1.12)	(-1.19)	(3.17)	(-0.75)	(1.32)	(1.27)
TS_1 - $Mom_{3\text{-}1}$	-0.0200	-0.0695	**0.2759**	-0.0698	0.0023	0.0058
	(-0.37)	(-1.27)	(5.23)	(-1.28)	(0.04)	(0.11)
TS_1 - $Mom_{12\text{-}1}$	-0.0744	-0.0627	**0.2548**	0.0071	0.0044	0.0312
	(-1.34)	(-1.13)	(4.74)	(0.13)	(0.08)	(0.56)
$Mom_{1\text{-}1}$ - TS_1	-0.0049	-0.0285	**0.1423**	-0.0720	0.0844	0.0562
	(-0.09)	(-0.52)	(2.63)	(-1.32)	(1.55)	(1.03)
$Mom_{3\text{-}1}$ - TS_1	-0.0196	-0.0637	**0.2228**	**-0.1091**	-0.0142	-0.0286
	(-0.36)	(-1.16)	(4.16)	(-2.00)	(-0.26)	(-0.52)
$Mom_{12\text{-}1}$ - TS_1	-0.0630	-0.0860	**0.2305**	0.0044	0.0029	0.0294
	(-1.13)	(-1.55)	(4.26)	(0.08)	(0.05)	(0.53)
Absolute average	*0.0405*	*0.0626*	*0.2162*	*0.0505*	*0.0300*	*0.0368*

The table reports Pearson correlations and significance t-statistics (normally distributed) in parentheses. TS_1 uses the front-end of the term structure to measure roll-returns, $Mom_{R\text{-}H}$ is a momentum strategy with R-month ranking and H-month holding periods. LB, S&P500 and S&P GSCI represent, respectively, the excess returns on the Lehman Brothers Aggregate US total bond index, the S&P500 index and the Goldman Sachs Commodity Index. FX are the returns of the US$ effective (vis-à-vis main currencies) exchange rate index. T-bond and T-Bill are the US 10-year Treasury bond yields and the US 3-month Treasury Bill rate, respectively. Bold denotes significant at the 5 % level or better. The last row reports the average of the correlations in absolute value.

Table 8. Triple-Sort Strategy Based on Volume, Term Structure and Momentum

	High volume (*HV*)			Low volume (*LV*)			Tests	
	Annualized arithm. mean	Annualized volatility	Reward/risk ratio	Annualized arithm. mean	Annualized volatility	Reward/risk ratio	Mean difference	Pearson correlation
Panel A: Triple-sort strategy based on $ Volume								
Vol=0.8 / TS_1=0.33 / $Mom_{1\text{-}1}$=0.5	**0.1981**	0.2806	0.7058	**0.1763**	0.2798	0.6300	0.5597	**0.7295**
								(19.49)
Vol=0.8 / TS_1=0.5 / $Mom_{1\text{-}1}$=0.5	**0.1629**	0.2241	0.7269	**0.1428**	0.2056	0.6943	0.6968	**0.7496**
								(20.70)
Vol=0.8 / $Mom_{1\text{-}1}$=0.5 / TS_1=0.5	**0.1584**	0.2220	0.7137	**0.1555**	0.2072	0.7507	0.1003	**0.7492**
								(20.67)
Vol=0.8 / $Mom_{1\text{-}1}$=0.33 / TS_1=0.5	**0.2024**	0.2978	0.6798	**0.2210**	0.2681	0.8243	-0.5115	**0.7747**
								(23.39)
Vol=0.5 / TS_1=0.5 / $Mom_{1\text{-}1}$=0.5	**0.2285**	0.2882	0.7928	**0.1424**	0.2763	0.5153	1.2916	**0.2198**
								(4.12)
Vol=0.5 / $Mom_{1\text{-}1}$=0.5 / TS_1=0.5	**0.2162**	0.2895	0.7468	**0.1354**	0.2823	0.4798	1.1326	**0.1285**
Average	*0.1937*			*0.1594*				(2.37)
Panel B: Triple-sort strategy based on percentage change in volume								
Vol=0.8 / TS_1=0.33 / $Mom_{1\text{-}1}$=0.5	**0.1667**	0.2971	0.5613	**0.2215**	0.2801	0.7909	-1.4527	**0.7624**
								(21.56)
Vol=0.8 / TS_1=0.5 / $Mom_{1\text{-}1}$=0.5	**0.1563**	0.2334	0.6700	**0.1815**	0.2269	0.7997	-0.8506	**0.7703**
								(22.05)
Vol=0.8 / $Mom_{1\text{-}1}$=0.5 / TS_1=0.5	**0.1682**	0.2226	0.7557	**0.1697**	0.2151	0.7890	-0.0534	**0.7678**
								(21.87)
Vol=0.8 / $Mom_{1\text{-}1}$=0.33 / TS_1=0.5	**0.1912**	0.2962	0.6453	**0.2031**	0.2924	0.6945	-0.3385	**0.8003**
								(23.35)
Vol=0.5 / TS_1=0.5 / $Mom_{1\text{-}1}$=0.5	**0.2061**	0.2920	0.7059	**0.1553**	0.2661	0.5835	0.7639	**0.2071**
								(3.86)
Vol=0.5 / $Mom_{1\text{-}1}$=0.5 / TS_1=0.5	**0.1712**	0.2980	0.5744	**0.1174**	0.2566	0.4578	0.8054	**0.1981**
Average	*0.1786*			*0.1654*				(3.69)

The table reports summary statistics for the monthly returns of a triple-sort long-short strategy based on volume (Vol), term structure (TS_1) and momentum ($Mom_{1\text{-}1}$). The numbers reported in column 1 indicate the percentages of the available cross-section that are used to implement the triple-sort strategy. The last two columns report, respectively, a paired two-sample Student's t-statistic to determine whether the HV and LV returns are statistically different, and the return correlation measure with significance t-statistic in parenthesis. Bold denotes significant at the 5 % level or better.

Table 9. Tests for Superior Performance

Loss function	Best performing: Strategy	Loss	t-statistic	Most significant: Strategy	Loss	t-statistic	Consistent p-values: SPA test	RC test
Panel A: Long-only EOM benchmark, bootstrap dependence *q* =0.2								
linear	TS_1-$Mom_{1\text{-}1}$	0.6064	3.7007 (0.0002)	TS_1-$Mom_{1\text{-}1}$	0.6064	3.7007 (0.0002)	0.0020	0.0037
exp (λ =1)	TS_1-$Mom_{1\text{-}1}$	0.9836	3.2277 (0.0006)	TS_1-$Mom_{1\text{-}1}$	0.9836	3.2277 (0.0006)	0.0103	0.0146
exp (λ =2)	TS_1-$Mom_{1\text{-}1}$	0.9734	2.7382 (0.0024)	TS_1-$Mom_{1\text{-}1}$	0.9734	2.7382 (0.0024)	0.0400	0.0591
Panel B: Long-only 15M benchmark, bootstrap dependence *q* =0.2								
linear	TS_1-$Mom_{1\text{-}1}$	0.6064	3.4726 (0.0004)	TS_1-$Mom_{1\text{-}1}$	0.6064	3.4726 (0.0004)	0.0044	0.0067
exp (λ =1)	TS_1-$Mom_{1\text{-}1}$	0.9836	2.9942 (0.0011)	TS_1-$Mom_{1\text{-}1}$	0.9836	2.9942 (0.0011)	0.0190	0.0286
exp (λ =2)	TS_1-$Mom_{1\text{-}1}$	0.9734	2.5003 (0.0053)	TS_1-$Mom_{1\text{-}1}$	0.9734	2.5003 (0.0053)	0.0758	0.0995
Panel C: Long-only EOM benchmark, bootstrap dependence *q* =0.5								
linear	TS_1-$Mom_{1\text{-}1}$	0.6084	3.7517 (0.0000)	TS_1-$Mom_{1\text{-}1}$	0.6084	3.7517 (0.0000)	0.0027	0.0028
exp (λ =1)	TS_1-$Mom_{1\text{-}1}$	0.9836	3.2810 (0.0004)	TS_1-$Mom_{1\text{-}1}$	0.9836	3.2810 (0.0004)	0.0117	0.0142
exp (λ =2)	TS_1-$Mom_{1\text{-}1}$	0.9734	2.7908 (0.0019)	TS_1-$Mom_{1\text{-}1}$	0.9734	2.7908 (0.0019)	0.0401	0.0547
Panel D: Long-only 15M benchmark, bootstrap dependence *q* =0.5								
linear	TS_1-$Mom_{1\text{-}1}$	0.6084	3.5064 (0.0002)	TS_1-$Mom_{1\text{-}1}$	0.6084	3.5064 (0.0002)	0.0063	0.0067
exp (λ =1)	TS_1-$Mom_{1\text{-}1}$	0.9836	3.0292 (0.0008)	TS_1-$Mom_{1\text{-}1}$	0.9836	3.0292 (0.0008)	0.0225	0.0278
exp (λ =2)	TS_1-$Mom_{1\text{-}1}$	0.9734	2.5346 (0.0044)	TS_1-$Mom_{1\text{-}1}$	0.9734	2.5346 (0.0044)	0.0797	0.0992

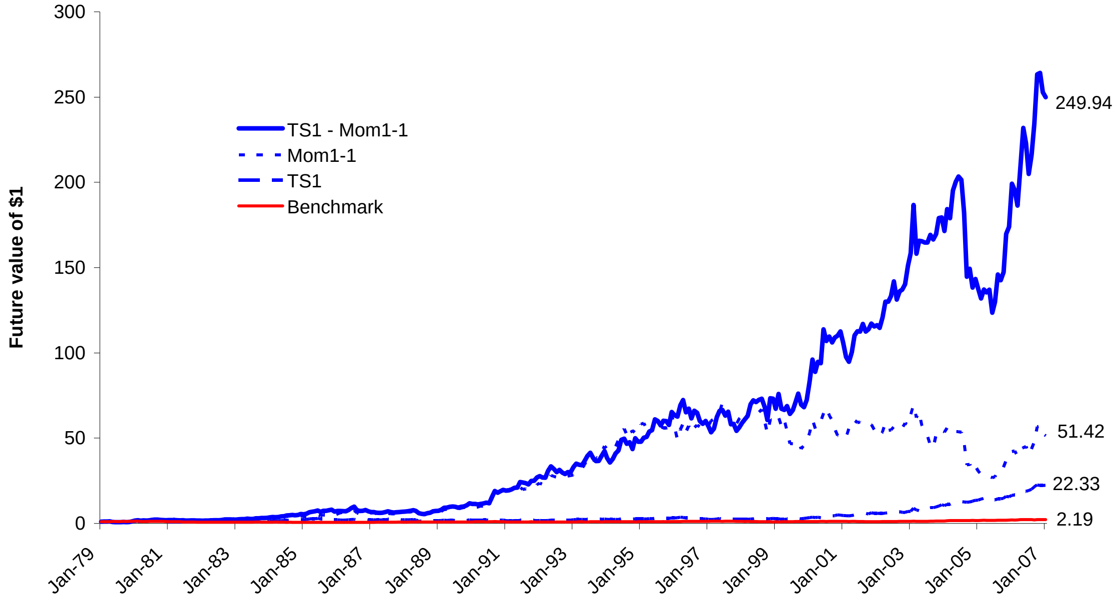
q is the parameter of the geometric distribution that governs the random block-length in the bootstrap samples. *t*-statistic refers to the comparison of a particular trading rule's performance and the passive benchmark; a significantly positive value indicates that the former outperforms the latter. Best performing is the trading rule with the smallest (largest) average loss (returns). Most significant is the trading rule with the largest *t*-statistic. The *p*-values reported in parentheses are for pairwise comparisons that ignore the full 'universe' of *m*=55 trading rules so they suffer from data mining whereas the consistent *p*-values reported in the final two columns for the SPA and RC tests summarize the evidence against the composite null hypothesis H_0: the benchmark is not inferior to any of the alternative strategies.

Table 10. Performance over an Extended Sample: January 1979 – November 2008

	Mom 1-1			*TS 1*			*TS 1 - Mom 1-1*			Benchmark
	L	*S*	*L-S*	*L*	*S*	*L-S*	*L*	*S*	*L-S*	
Annualized arithmetic mean	**0.1155**	-0.0676	**0.1831**	**0.0784**	**-0.0681**	**0.1465**	**0.1638**	-0.0677	**0.2315**	0.0242
	(2.87)	(-1.90)	(3.75)	(2.23)	(-2.00)	(3.38)	(4.06)	(-1.89)	(4.61)	(1.09)
Annualized volatility	0.2197	0.1948	0.2664	0.1922	0.1859	0.2366	0.2206	0.1962	0.2745	0.1217
Reward/risk ratio	0.5255	-0.3471	0.6872	0.4078	-0.3662	0.6190	0.7425	-0.3452	0.8434	0.1992
Annualized α	**0.1026**	**-0.0804**	**0.1830**	**0.0658**	**-0.0815**	**0.1472**	**0.1508**	**-0.0832**	**0.2340**	
	(2.96)	(-2.58)	(3.72)	(2.40)	(-2.66)	(3.41)	(4.45)	(-2.53)	(4.67)	
β_B	-0.1338	-0.1535	0.0197	-0.1668	-0.0347	-0.1322	-0.1916	-0.0042	-0.1873	
	(-0.79)	(-1.00)	(0.08)	(-1.24)	(-0.23)	(-0.62)	(-1.15)	(-0.03)	(-0.76)	
β_M	0.0134	**0.1304**	-0.1170	-0.0036	0.0960	-0.0997	0.0341	0.1688	-0.1347	
	(0.20)	(2.13)	(-1.21)	(-0.07)	(1.60)	(-1.18)	(0.51)	(2.62)	(-1.37)	
β_C	**0.5921**	**0.4844**	0.1077	**0.6325**	**0.4278**	**0.2047**	**0.6326**	**0.4003**	**0.2323**	
	(11.45)	(10.41)	(1.47)	(15.49)	(9.38)	(3.18)	(12.53)	(8.18)	(3.11)	

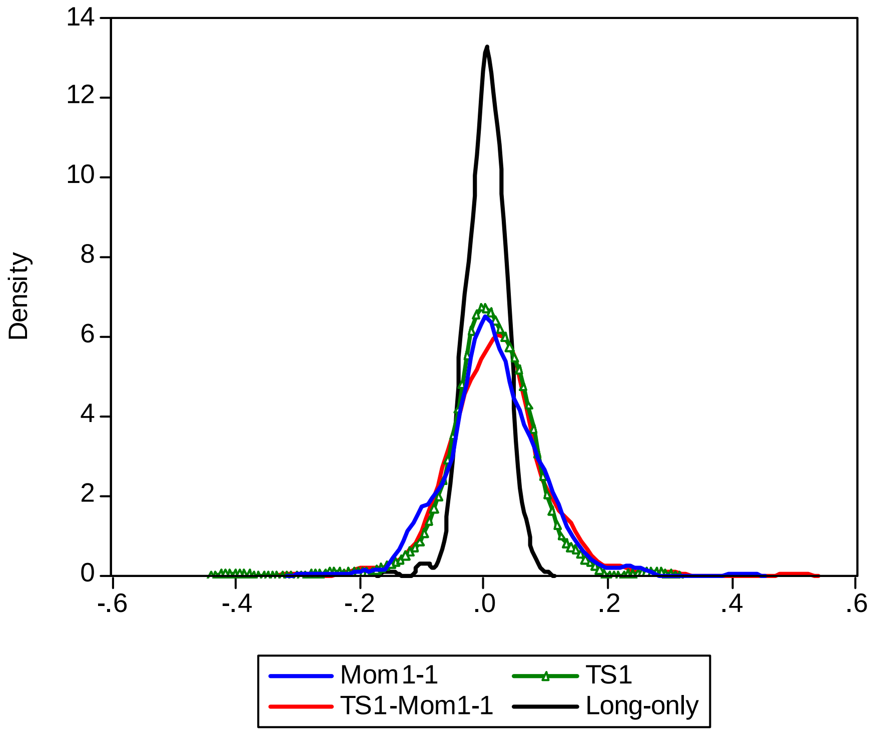
The table reports summary statistics for the monthly returns of two single-sort and one double-sort strategies over an extended sample spanning the period January 1979-November 2008. α measures abnormal performance, β_B, β_M and β_C measure the sensitivities of returns to the excess returns on Lehman Brothers Aggregate US total return bond index, the S&P500 composite index and the S&P GSCI, respectively. Mom_{1-1} refers to a momentum strategy with 1-month ranking period and 1-month holding period, TS_1 uses the front-end of the term structure to measure roll-returns, *L*, *S* and *L-S* stand for long, short and long-short, respectively. Benchmark refers to a long-only strategy that equally-weights all 37 commodities. *t*-ratios are in parentheses and significance at the 5% level or better is denoted in bold.

Figure 1. Future Value of $1



TS1 is the term structure strategy that measures roll-returns from the front-end of the term structure. Mom1-1 refers to a momentum strategy with 1-month ranking and holding periods. TS1-Mom1-1 combines the two signals in a double-sort strategy. Benchmark refers to a long-only portfolio that equally weights all 37 commodities.

Figure 2. Returns Distribution



TS1 is the term structure strategy that measures roll-returns from the front-end of the term structure, Mom1-1 refers to a momentum strategy with 1-month ranking and holding periods, TS1-Mom1-1 combines the two signals in a double-sort strategy. Long-only refers to a long-only portfolio that equally weights all 37 commodities.

APPENDICES

Table A1. Risk-Adjustment Performance from 6-Factor Model

Panel A: Momentum-Only Strategies

	R=1				*R*=3				*R*=6			*R*=12	
	H=1	*H*=3	*H*=6	*H*=12	*H*=1	*H*=3	*H*=6	*H*=12	*H*=1	*H*=3	*H*=6	*H*=1	*H*=3
α	**0.1798**	**0.0983**	**0.0651**	**0.0573**	**0.1483**	**0.0864**	0.0595	**0.0497**	**0.1059**	0.0759	**0.0873**	**0.1438**	0.0057
	(3.50)	(3.04)	(2.94)	(3.51)	(2.88)	(2.00)	(1.87)	(2.01)	(2.18)	(1.72)	(2.24)	(2.87)	(1.54)
β_B	-0.0101	0.0089	0.0355	0.0482	0.1524	0.0121	0.0530	0.1609	-0.0555	-0.0081	0.0209	0.0691	0.2414
	(-0.04)	(0.06)	(0.33)	(0.60)	(0.61)	(0.06)	(0.35)	(1.28)	(-0.24)	(-0.04)	(0.11)	(0.28)	(1.07)
β_M	-0.1151	-0.0462	0.0190	-0.0122	-0.1124	0.0219	0.0274	-0.0324	-0.0396	0.0354	-0.0216	-0.0873	-0.0799
	(-1.02)	(-0.70)	(0.43)	(-0.38)	(-1.09)	(0.25)	(0.43)	(-0.67)	(-0.41)	(0.40)	(-0.28)	(-0.88)	(-0.91)
β_C	0.0925	**0.1855**	**0.0995**	**0.1103**	**0.3215**	**0.2435**	**0.1833**	**0.1985**	**0.2557**	**0.2277**	**0.1990**	**0.3264**	**0.3427**
	(0.74)	(2.62)	(2.73)	(4.10)	(3.79)	(3.43)	(3.48)	(4.90)	(3.20)	(3.12)	(3.10)	(3.95)	(4.69)
β_{FX}	-0.3396	-0.2127	-0.0598	0.0046	-0.3656	-0.2181	-0.0664	0.0274	-0.1784	-0.0707	0.0463	-0.0905	-0.0311
	(-1.38)	(-1.40)	(-0.58)	(0.06)	(-1.52)	(-1.09)	(-0.45)	(0.24)	(-0.79)	(-0.35)	(0.26)	(-0.39)	(-0.15)
β_{UI}	0.8312	0.2748	-0.1251	-0.0459	0.4108	-0.3109	-0.0487	-0.2022	-0.1074	-0.1457	-0.2045	-0.3735	-0.1988
	(0.91)	(0.44)	(-0.32)	(-0.16)	(0.46)	(-0.41)	(-0.09)	(-0.48)	(-0.13)	(-0.19)	(-0.30)	(-0.43)	(-0.26)
β_{UIP}	-0.3730	-0.0933	-0.1447	**-0.1384**	-0.1463	-0.0281	-0.2141	**-0.2141**	-0.1177	-0.1716	-0.2807	-0.2633	**-0.3695**
	(-1.55)	(-0.71)	(-1.59)	(-2.06)	(-0.69)	(-0.16)	(-1.62)	(-2.11)	(-0.59)	(-0.94)	(-1.75)	(-1.27)	(-2.02)
$\bar{R}^2$	0.0060	0.0325	0.0191	0.0481	0.0404	0.0276	0.0318	0.0746	0.0198	0.0182	0.0226	0.0410	0.0670

Panel B: TS-Only Strategies

	EOM returns							15M Returns					
	TS_1	TS_2	$TS_{3,j=2}$	$TS_{3,j=4}$	$TS_{3,j=7}$	$TS_{3,j=10}$	Benchmark	TS_1	TS_2	$TS_{3,j=2}$	$TS_{3,j=4}$	$TS_{3,j=7}$	$TS_{3,j=10}$
α	**0.1414**	0.0661	**0.1447**	**0.1376**	**0.0995**	**0.0994**	0.0171	**0.1495**	0.0522	**0.1190**	0.0807	0.0239	0.0420
	(3.14)	(1.50)	(3.25)	(3.16)	(2.25)	(2.22)	(1.25)	(3.55)	(1.24)	(2.79)	(1.89)	(0.53)	(0.98)
β_B	-0.1329	0.0809	-0.3149	-0.1447	-0.1288	-0.0772	**-0.1884**	-0.1868	0.1319	-0.1937	-0.0969	-0.0548	-0.1131
	(-0.61)	(0.38)	(-1.46)	(-0.69)	(-0.60)	(-0.36)	(-2.83)	(-0.91)	(0.65)	(-0.94)	(-0.47)	(-0.25)	(-0.54)
β_M	-0.0994	-0.0750	-0.1183	-0.1579	**-0.1917**	-0.1724	**0.1199**	-0.1265	-0.1408	-0.1551	-0.1581	-0.1246	-0.1303
	(-1.11)	(-0.85)	(-1.33)	(-1.82)	(-2.17)	(-1.93)	(4.38)	(-1.51)	(-1.68)	(-1.82)	(-1.86)	(-1.39)	(-1.52)
β_C	**0.2282**	**0.3714**	**0.2459**	**0.2387**	**0.2508**	**0.2891**	**0.4420**	0.1145	**0.3485**	**0.2031**	**0.2160**	**0.3029**	**0.2623**
	(3.07)	(5.10)	(3.35)	(3.33)	(3.44)	(3.91)	(19.50)	(1.65)	(5.02)	(2.88)	(3.07)	(4.10)	(3.71)
β_{FX}	0.0346	0.1996	0.0371	0.1171	0.0909	0.1020	**-0.1443**	0.2800	0.2434	0.1307	0.2155	0.1470	0.2083
	(0.16)	(0.97)	(0.18)	(0.58)	(0.44)	(0.49)	(-2.25)	(1.42)	(1.24)	(0.66)	(1.08)	(0.70)	(1.04)
β_{UI}	0.1564	0.1074	0.3014	0.4091	0.6870	0.6861	0.0424	0.5695	0.6563	0.8440	0.6815	0.5543	0.3537
	(0.20)	(0.14)	(0.39)	(0.54)	(0.89)	(0.88)	(0.18)	(0.77)	(0.89)	(1.13)	(0.91)	(0.71)	(0.47)
β_{UIP}	-0.2916	-0.0916	**-0.4757**	**-0.4832**	**-0.4145**	**-0.4067**	-0.0669	-0.2811	-0.2191	-0.2904	-0.2225	-0.3520	-0.3059
	(-1.57)	(-0.50)	(-2.60)	(-2.70)	(-2.28)	(-2.21)	(-1.18)	(-1.62)	(-1.27)	(-1.65)	(-1.27)	(-1.91)	(-1.73)
$\bar{R}^2$	0.0229	0.0604	0.0479	0.0470	0.0470	0.0512	0.5677	0.0160	0.0658	0.0310	0.0290	0.0469	0.0410

Panel C: Combined Momentum and Term Structure Strategies

	TS_1 - $Mom_{1\text{-}1}$	TS_1 - $Mom_{3\text{-}1}$	TS_1 - $Mom_{12\text{-}1}$	$Mom_{1\text{-}1}$ - TS_1	$Mom_{3\text{-}1}$ - TS_1	$Mom_{12\text{-}1}$ - TS_1
α	**0.2383**	**0.2057**	**0.1893**	**0.2321**	**0.1886**	**0.2169**
	(4.58)	(3.98)	(3.74)	(4.38)	(3.65)	(4.58)
β_B	-0.2145	-0.0071	-0.2395	0.0023	-0.0544	-0.1595
	(-0.85)	(-0.03)	(-0.97)	(0.01)	(-0.22)	(-0.69)
β_M	-0.1248	-0.1603	-0.1074	-0.0884	-0.1569	-0.1475
	(-1.20)	(-1.56)	(-1.08)	(-0.84)	(-1.52)	(-1.58)
β_C	**0.2688**	**0.4377**	**0.3947**	**0.2310**	**0.3305**	**0.3316**
	(3.13)	(5.15)	(4.74)	(2.64)	(3.89)	(4.24)
β_{FX}	-0.1382	-0.1846	0.1251	-0.2593	-0.4120	0.0870
	(-0.57)	(-0.77)	(0.54)	(-1.05)	(-1.72)	(0.40)
β_{UI}	0.6207	0.6023	0.2067	1.2080	-0.0256	0.0527
	(0.68)	(0.67)	(0.24)	(1.31)	(-0.03)	(0.06)
β_{UIP}	-0.3631	-0.2432	-0.3682	**-0.5596**	-0.3993	-0.3792
	(-1.69)	(-1.14)	(-1.77)	(-2.56)	(-1.88)	(-1.94)
$\bar{R}^2$	0.0287	0.0718	0.0652	0.0300	0.0554	0.0568

The coefficient estimates and significance *t*-statistics (in parenthesis) are for multifactor model (1) augmented with three additional risk factors, FX, UI and UIP. FX are the returns of the US$ effective (vis-à-vis main currencies) exchange rate index, UI and UIP stand for unexpected inflation and unexpected change in industrial production, respectively. α is annualized. EOM are end-of-month returns and 15M are 15^{th}-of-month returns.

Table A2. Conditional Risk-Adjusted Performance

	α	*t*- statistic	p_1	p_2	p_3
Panel A: Momentum-Only Strategies					
$Mom_{1\text{-}1}$	**0.1657**	3.5333	0.3140	0.0000	0.0000
$Mom_{1\text{-}3}$	**0.0915**	3.1236	0.0777	0.0000	0.0000
$Mom_{1\text{-}6}$	**0.0619**	2.9704	0.1153	0.0071	0.0118
$Mom_{1\text{-}12}$	**0.0548**	3.4013	0.1100	0.0003	0.0003
$Mom_{3\text{-}1}$	**0.1408**	2.9240	0.0804	0.0000	0.0000
$Mom_{3\text{-}3}$	0.0795	1.9434	0.1137	0.0179	0.0088
$Mom_{3\text{-}6}$	0.0587	1.8776	0.0259	0.0005	0.0002
$Mom_{3\text{-}12}$	**0.0533**	2.1431	0.1101	0.0343	0.0231
$Mom_{6\text{-}1}$	0.0888	1.8588	0.0367	0.0015	0.0007
$Mom_{6\text{-}3}$	0.0673	1.5476	0.0483	0.0017	0.0013
$Mom_{6\text{-}6}$	**0.0853**	2.1970	0.0194	0.0218	0.0059
$Mom_{12\text{-}1}$	**0.1288**	2.6145	0.0300	0.0007	0.0002
$Mom_{12\text{-}3}$	0.0685	1.5219	0.2648	0.0505	0.0527
Average	*0.0977*				
Panel B: TS-Only Strategies					
TS_1 (EOM)	**0.1450**	3.1711	0.4250	0.1386	0.1587
TS_2 (EOM)	0.0569	1.2827	0.2741	0.0292	0.0401
$TS_{3,i=2}$ (EOM)	**0.1346**	2.9690	0.1628	0.1133	0.1352
$TS_{3,i=4}$ (EOM)	**0.1239**	2.8115	0.2337	0.0201	0.0308
$TS_{3,i=7}$ (EOM)	0.0847	1.9020	0.2271	0.0085	0.0168
$TS_{3,i=10}$ (EOM)	0.0841	1.8609	0.2949	0.0136	0.0278
TS_1 (15M)	**0.1385**	3.2118	0.8468	0.1673	0.2944
TS_2 (15M)	0.0314	0.7458	0.1988	0.0064	0.0072
$TS_{3,i=2}$ (15M)	**0.1086**	2.4999	0.3368	0.1072	0.1683
$TS_{3,i=4}$ (15M)	0.0748	1.7397	0.3329	0.0197	0.0361
$TS_{3,i=7}$ (15M)	0.0287	0.6442	0.1853	0.0009	0.0015
$TS_{3,i=10}$ (15M)	0.0407	0.9501	0.1938	0.0019	0.0035
Average	*0.1301*				
Panel C: Combined Momentum and Term Structure Strategies					
TS_1 - $Mom_{1\text{-}1}$	**0.2348**	4.9103	0.6343	0.0000	0.0000
TS_1 - $Mom_{3\text{-}1}$	**0.2133**	4.2339	0.0767	0.0000	0.0001
TS_1 - $Mom_{12\text{-}1}$	**0.2019**	4.0643	0.0156	0.0002	0.0001
$Mom_{1\text{-}1}$ - TS_1	**0.2319**	4.8324	0.4506	0.0000	0.0000
$Mom_{3\text{-}1}$ - TS_1	**0.1867**	3.5762	0.1410	0.0550	0.0590
$Mom_{12\text{-}1}$ - TS_1	**0.2155**	4.5484	0.0464	0.0079	0.0057
Average	*0.2140*				

α measures annualized conditional abnormal performance and *t*-statistic is the corresponding significance test statistic. Bold denotes significant at the 5% level or better. p_1 is the *p*-value for the composite hypothesis of constant abnormal performance, p_2 is the *p*-value for the composite hypothesis of constant measures of risk (the so-called *betas*), and p_3 is the *p*-value for the composite hypothesis of constant abnormal performance and risk. The reported average is for the conditional alphas that are significant at the 5% level or better.

Table A3. EOM versus 15M portfolio returns

	TS_1	TS_2	$TS_{3,i=2}$	$TS_{3,i=4}$	$TS_{3,i=7}$	$TS_{3,i=10}$
Panel A: Correlation between EOM returns and 15M returns						
Pearson $\rho_{EOM,15M}$	0.704	0.820	0.838	0.826	0.777	0.825
t -statistic	**18.133**	**26.148**	**28.079**	**26.731**	**22.558**	**26.719**
p-value	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Panel B: Normality analysis for spread						
skewness	**-0.762**	**-0.369**	0.0187	**0.8083**	**0.9917**	**0.9658**
p-value	*0.0000*	*0.0058*	*0.8887*	*0.0000*	*0.0000*	*0.0000*
kurtosis-3	**5.215**	**3.284**	**1.2517**	**3.0637**	**7.9509**	**6.0383**
p-value	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Jarque-Bera test	**413.29**	**212.39**	**21.954**	**167.99**	**932.09**	**562.69**
p-value	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Panel C: Paired difference tests						
t -statistic	-0.0013	0.6572	1.0701	**2.2295**	**2.2713**	**2.1687**
p-value	*0.9990*	*0.5115*	*0.2853*	*0.0264*	*0.0238*	*0.0308*
Wilcoxon rank statistic	0.5177	0.6810	1.3853	1.8135	**2.5969**	**2.0902**
p-value	*0.6050*	*0.4959*	*0.1660*	*0.0698*	*0.0094*	*0.0366*

Panel A reports the Pearson correlations between the EOM and 15M returns of the Long-Short portfolios, and significance *t*-statistic. Panel B reports for the EOM-15M return spread the skewness, excess kurtosis and Jarque-Bera statistics and significance *p*-values. Panel C reports the paired difference *t*-test and Wilcoxon signed ranked test for the null hypothesis that, respectively, the mean and median spread is zero. Bold denotes significance at the 5% or 1% level.