On Commodity Trading Strategies: Momentum, Term Structure, Maturity, Indexation

by

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Getting to "Ithaca" (the end result) is always important, but it is the journey to get there that counts the most.

As you set out for Ithaca
hope your road is a long one,
full of adventure, full of discovery…
……..
Ithaca gave you the marvellous journey.
Without her you wouldn't have set out.
She has nothing left to give you now.
And if you find her poor, Ithaca won't have fooled you.
Wise as you will have become, so full of experience,
you'll have understood by then what these Ithakas mean.
K.Kavafis

Declaration

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Abstract

The thesis investigates the presence of idiosyncratic characteristics in commodity futures markets that lead to profitable trading strategies, effectively testing the efficiency of commodity markets. First, short-term continuation and long-term reversal in commodity futures prices are examined. While contrarian strategies do not work, 13 profitable momentum strategies have been identified that generate 9.38% average return a year. On average the momentum strategies buy backwardated contracts and sell contangoed contracts. Testing the direct implication of this behavior, the strategy of buying the most backwardated and selling the most contangoed commodities is examined. With significant annualized alphas of 10.14% and 12.66% respectively the momentum and term structure strategies appear profitable when implemented individually. The thesis continues by investigating the combined role of momentum and term structure signals. 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. The thesis continues by examining the role of momentum, term structure and time to maturity/expiry factors in the design of enhanced commodity indices. In a long-only framework the momentum parameterized Standard & Poor's Goldman Sachs Commodity Index (S&P- GSCI former GSCI) and Dow-Jones UBS Commodity Index (DJ-UBSCI former DJ-AIGCI) yield 0.46 and 0.9 times higher returns than the traditional S&P-GSCI and DJ-UBSCI respectively. The term structure parameterized S&P-GSCI and DJ-UBSCI exhibit 0.63 and 0.68 times higher returns respectively. The combined parameterized indices increase the outperformance by 0.65 and 1.02 times and the longer maturity indices yield on average 1.37 and 1.97 times higher returns than the traditional indices respectively. These findings can be exploited for diversification purposes in a long-only commodity world or deployed as a framework to facilitate choosing among commodity indices.

Keywords: Commodity futures, Momentum, Term Structure, Backwardation, Contango, Diversification, Commodity indices

1. Introduction

1. 1. Renewed Interest of Commodity Markets

Modern commodity futures have been traded in the US markets for more than a century. In a more informal form they have been traded since antiquity. However, they are still a relatively unknown asset class. Commodity markets have witnessed swings similar to a ‘rollercoaster ride’ over the past 5 years. Commodity supply and demand mismatch fueled by the growth of consumption of raw material in developing countries prompted concerns that the world is heading towards a new phase of commodity scarcity and helped built enormous tensions. A recent dramatic drop in commodity prices following the slowdown of the global economy temporarily released these tensions. Research interest in commodity markets has recently been resurrected fueled by institutional investors. Investors with economic views on inflation find commodities as a valuable hedge. Their interest in commodity markets has increased significantly. According to IFSL research (2008) the notional value outstanding of banks’ OTC commodity derivatives contracts reached the record $9.0 trillion in 2007. The majority was energy related.

The sharp increase in oil prices during the last years is encouraging the development of alternative energy sources such as nuclear, bio-fuels as well as renewable energies such as wind and hydro power. This is consequently increasing the strategic importance of many forgotten commodities such as uranium, platinum, sugar, corn and even water. New more complicated products have attracted interest such as weather derivatives, gas and power derivatives and emissions based products. [1]

This research strives to satisfy the increasing interest in commodities, to address the misconceptions around the asset class and to shed light on the diversifying role commodities can play in an investor’s portfolio. This chapter provides an overview of the fundamentals of commodity pricing, of the case for strategic asset allocation in

[1] There have been prior to the current oil shocks (‘73-’74, ’79-’80, ’90), but they were short lived and linked to geopolitical events such wars and embargos. These supply shocks have not resulted in a general surge in derivatives commodities such as the current one fueled by the demand of emerging market economies.

commodities, of any early research into tactical trading and any similarities of commodities to the equity market. It concludes with an overview and the layout of the thesis.

1. 2. Fundamentals of Commodity Pricing

This section presents the four theories that have been put forward to explain the pricing of commodity futures: the asset pricing perspective, the theory of insurance, the hedging pressure hypothesis and the theory of storage. None of these theories give us a final answer as to what the fair price of a commodity futures contract is but they are all part of the evolution of thoughts and, as such, they help us determining the fundamentals of commodity futures prices. These theories to some extend overlap but for the sake of clarity we will present them in turn.

1. 2. 1. The asset pricing perspective

Models examining the existence of a risk premium in commodity markets have been developed within the context of the capital asset pricing model (CAPM). Dusak (1973) finds no statistically significant beta coefficients explaining commodity futures returns when measuring risk premiums and systematic risks in commodity markets. Additionally, Black (1976) argues that commodity futures are not capital assets, resemble more to "sports bets" and as a result commodity futures are not included in the "market portfolio". A CAPM commodity based version has been developed by Grauer and Litzenberger (1979). They conclude that the pricing of a commodity futures contract depends on the expected price of the commodity futures contract, the covariance of its price with the general price level (inflation) and the covariance of the real price of the asset with the marginal utility of income. Bodie and Rosansky (1980) find betas that are not significantly different from zero, when examining 23 commodities excluding energy futures. Baxter et al. (1985) confirm the finding even when using a weighting scheme between the S&P 500 and DJ-UBSCI to calculate the systematic factor. The asset pricing models fail to describe the pricing of commodity futures. The inherent problem with using the CAPM when investing in commodities, as noted by Greer (1997), may be that commodities are not capital assets but instead consumable, transformable and often perishable assets with unique attributes.

1. 2. 2. The theory of insurance

Keynes (1930) and Hicks (1939) have introduced the theory of normal backwardation in which they argue that the futures price of a commodity should always be less than the expected future spot price of the same commodity. As maturity approaches, the futures price converges to the expected future spot price making the excess returns of this commodity positive. This positive premium is considered as the insurance premium commodity producers are willing to offer to commodity investors to go long commodity futures. This way commodity producers are hedging part or their commodity exposure with all the benefits that it entails to them. In a world of risk-averse commodity hedgers and investors backwardated term structures are the norm. However, it is challenging to prove the existence of normal backwardation, since it is unobservable. The expected futures spot price is something illusive. The actual term structure versus the expected spot price is unobservable. The empirical implementations of the theory of normal backwardation examine the a posteriori excess returns in commodity futures markets to provide evidence of the theory. However, the insurance premium is locked at the time of the trade and received on expiry. So only ceteris paribus, the observed excess returns could be associated to the insurance premium. Dependent on the period analyzed and the changes in commodity future expected spot prices, even though normal backwardation could hold, the actual average risk premium observed ex-post could be as well negative. Out of the 29 commodity futures that Kolb (1992) examines only 9 exhibit statistically significant positive excess returns, when 4 have statistically significant negative excess returns and the rest show insignificant excess returns. He concludes that “normal backwardation is not normal”, since normal backwardation suggests that all commodity futures should have positive excess returns. Similar findings on the individual commodity performance supporting the prior conclusions are presented by Bodie and Rosansky (1980), Fama and French (1987) and Gorton and Rouwenhorst (2006). However the presence of a portfolio insurance premium is not excluded. Most long-only investors in commodity futures invest through commodity indices and both Bodie and Rosansky (1980) and Gorton and Rouwenhorst (2006) report statistically significant returns for commodity portfolios and indices. Insurance is given on a portfolio/index level according to the weightings of that portfolio/index. Because of that we cannot conclude that the theory of insurance does not hold if some commodities exhibit negative excess returns.

1. 2. 3. The hedging pressure hypothesis

The hedging pressure hypothesis proposed first by Cootner (1960) goes a step further suggesting that hedging pressure can be present by both commodity producers and consumers. It is the demand and supply of this insurance risk premium that defines whether a commodity market is in backwardation or contango. The theory of normal backwardation assumes that hedgers have a long exposure in the underlying commodity and that they want to insure that exposure from price fluctuations by hedging, selling commodity futures. The hedging pressure theory suggests that hedgers can either have positive or negative exposure in the underlying commodity markets and will take an opposite position in the commodity futures markets to mitigate risk. The level of this pressure from the hedgers will define the term structure of commodity futures markets and the positive or negative excess returns of the markets. Risk premia exist in both markets. Bessembinder (1992) provides evidence that net hedging indeed influence the average returns of 16 futures. When hedgers are net short, commodities on average exhibit positive excess returns and when hedgers are net long, commodities exhibit on average negative excess returns. De Roon et al. (2000) find similar results when examining 29 futures markets. Anson (2002) analyzes the example of Exxon, one of the largest oil producers, that has by default a positive exposure to oil. It can reduce its exposure to oil price fluctuations by hedging in the oil futures market. This way Exxon will have a less volatile cash flow stream, will predict and budget costs better, will be able to plan better future investments. Hedging reduces the overall cost of capital and decreases the risk premium investors will demand to hold Exxon. Alternatively, a consumer of aluminum, such as Boeing, one of the top manufacturers of airplanes, has by default negative exposure to aluminum prices. For the same reasons, it can hedge by purchasing aluminum futures. Exxon and Boeing are willing to pay for this insurance premium. Exxon sells oil futures at an expected loss and Boeing buys aluminum futures at an expected loss.

1. 2. 4. The theory of storage

The theory of storage has been described by Kaldor (1939) and Working (1948). Inventories of commodities play an important role in determining commodity futures prices. In line with this theory, the pricing of commodity futures incorporates storage costs, the interest rate and the convenience yield. The latter derives from the benefit of holding inventories that in turn lowers the probability of a disruption in production. It can be seen as a risk premium linked to inventory levels. It is an embedded option to time the consumption of the inventory of the commodity. There is a negative relationship between convenience yield and level of inventories. The convenience yield is high when inventories are low and the convenience yield is low when inventories are high. The convenience yield depends on the storage costs as well. Commodities with higher storage costs could have lower inventories and as a result high convenience yields. Lower storage costs could have the opposite effect. Gorton et al. (2008) link the risk premium to inventory levels. The basis as a proxy for the convenience yield exhibits a negative, non-linear relationship with the level of inventories. Furthermore prior returns inertia seems to be correlated with the level of inventories. They identify a risk premium in commodity futures markets that relates to the level of storage, with commodities with low inventory (that are presumably in backwardation) outperforming commodities with high inventory (that are presumably in contango) by 8.06% a year over the period December 1969 to December 2006 (t-statistic of 3.19).

1. 3. Commodities for strategic asset allocation

This section presents idiosyncratic characteristics of commodities that make them excellent candidates for inclusion in well-diversified portfolios of investors. Commodities are an interesting asset class on a standalone basis, from a portfolio perspective and as a hedge against inflation and event risk. Many influential studies have focused on commodities the last years shedding light on the interesting properties of the asset class.

1. 3. 1. Distributional properties

A study by Bodie and Rosansky (1980) has been one of the pioneering studies in the field of commodities showing that an equally-weighted portfolio of commodities can produce statistically significant returns comparable to equity indices. Jensen et al. (2000) show that including commodities (in particular the S&P-GSCI) in a portfolio consisting of equities, bonds, T-Bill and real estate generates greater returns than when not including commodities. Gorton and Rouwenhorst (2006) point out the profitability of commodity investing. They create an equally-weighted index of 34 commodity futures for the period July 1959 to March 2004 and measure this index against properties of traditional benchmark indices. Since 1959, commodity futures have outperformed equities and bonds and have exhibited similar Sharpe ratios as equities. The return distribution of commodity returns exhibits positive skewness in direct contrast with the negative skewness of equities.

Erb and Harvey (2006) point out that an equally-weighted portfolio of commodity futures may have equity-like return but refute the explanation that Gorton and Rouwenhorst (2006) provide that the equity like return is due to a risk premium that is embedded in the price of the individual commodities. Erb and Harvey (2006) show that out of the 36 individual commodity futures that Gorton and Rouwenhorst studied, 18 had seemingly positive mean returns, 18 had seemingly negative mean returns with only one of these 36 means that is significant at the 5% level. As the average excess return of individual commodity futures is zero, it is hard to argue that a portfolio of commodity futures could earn a positive risk premium. In fact, Erb and Harvey (2006) claim that it is not the performance of the individual commodity futures that determines the performance of an equally-weighted portfolio of commodities. Rather it is the frequent rebalancing of the portfolio constituents to equal-weights, as well as the return on the collateral, that are the key drivers of the portfolio performance in Bodie and Rosansky (1980) and in Gorton and Rouwenhorst (2006). Erb and Harvey (2006) argue that there is nothing on the historical record to give investors comfort that future spot and roll returns will be substantially positive. However, they point out that commodity indices, which are in fact strategies on commodities, have exhibited equity-like returns because of the frequent rebalancing that is embedded in the strategy itself. Gorton and Rouwenhorst (2006) provide evidence that due to short term momentum in commodity futures returns, the rebalancing of the equally weighted commodity index does play a role in delivering higher returns. But they point out that the highest role is being played by the diversification benefits between the different commodities.

Kat and Oomen (2006), examining commodities on a univariate basis, find lower returns in commodities than equities. With the exception of energy, commodities do not seem to generate a consistently positive risk premium. Examining the statistical parameters of the distribution of commodity returns they point out that volatility and kurtosis are comparable to that of US large cap equities but contrary to popular perception there is little skewness to be found. Returns and volatility vary across different phases of the business cycle.

1. 3. 2. Diversification properties

Bodie and Rosansky (1980) in a comprehensive analysis of the performance of 23 commodity futures from 1950 to 1976, find that investors can reduce the risk of their combined portfolio by 30% without a lossing returns, if 60% is allocated to equities and 40% to commodities. Jensen et al. (2000) provide evidence that the allocation of their diversified portfolio consisting of equities, bonds, T-Bills, real estate and commodities varies depending on the monetary policy. During periods of expansive monetary policy the allocation in commodities is small, while in periods of restrictive monetary policy the allocation to commodities comprises a significant portion of the portfolio. This argues in favor of the diversification properties of commodities.

Gorton and Rouwenhorst (2006) in their study of an equally-weighted index of 34 commodity futures for the period July 1959 to March 2004, provide evidence that commodities exhibit negative correlations against equities and bonds. This, in conjunction with the different signs of skewness in the distribution of returns of commodities and equities, make commodities act as an excellent diversifier of risk and a natural hedge against event risks in equities. Equities are particularly exposed to event risk. The more allocation investors hold in equities, the more they are sensitive to event risks, the more they should hold commodities as a hedge against that risk. Geopolitical events that are generally unexpected like wars, oil supplies disruption and political uncertainty can cause sharp increases to energy prices. On the other hand natural causes related to weather or other natural disasters, droughts and floods can reduce the supply of agricultural products and cause sharp increases to the prices of these commodities. All these events are unexpected; they have no correlation with each other. This way the commodity market can provide a huge diversification benefit if investors hold a broad portfolio of commodities.

Erb and Harvey (2006) also show that diversification into commodities would have improved the performance of equity portfolios. Kat and Oomen (2006) provide evidence that correlations of commodities with other asset classes depend on the business cycle. Kat and Oomen (2006), examining commodities on a multivariate approach, find that correlations between commodity groups are insignificant but within the groups very strong. The diversifying properties of commodities are confirmed by the insignificant correlation to equities and bonds.

1. 3. 3. Inflation hedging properties

Gorton and Rouwenhorst (2006) provide evidence that commodities as an asset class demonstrate positive correlation to inflationary periods, in direct contrast to a negative correlation for both stocks and bonds. They show that the correlation of commodities with changes in inflation and unexpected inflation is even higher. Kat and Oomen (2006) confirm the positive correlation to unexpected inflation. Erb and Harvey (2006) adopt a more criticizing view against the hedging properties of commodities. Although they confirm that changes in the annual rate of inflation help explain 43% of the variability of the excess returns for the S&P-GSCI with a statistically significant positive beta, they argue that individual commodity futures have experienced varying exposure to unexpected inflation. They point out that composition of the commodity portfolio is the determining factor of its inflation hedging ability. The equally weighted portfolio has a positive but insignificant inflationary beta.

1. 4. Momentum and Contrarian Presence in Equity Markets

Inefficiencies have been thoroughly investigated in many markets prior to the commodity one bringing into light tactical trading opportunities. Early signs of momentum and contrarian strategies have been present in the equity markets giving food for thought of their existence in other markets, the commodity one included. Efficient markets should reflect all available information (Fama, 1998). The notion that markets have a tendency to overreact and underreact opposes the market efficiency hypothesis and provides the theoretical framework to support momentum and contrarian strategies.

Momentum strategies rely on the principle that asset prices that have increased in the near past will continue to increase in the near future and asset prices that have decreased in the near past will continue to decrease in the near future. On a longer term horizon contrarian trading strategies have been developed to capture the mean reversion of asset prices. Many studies have been conducted regarding the profitability of momentum and contrarian trading strategies in equity markets. The majority of them show that markets are not truly efficient and that momentum strategies can yield abnormal returns contrary to classic asset pricing models. Empirical research shows evidence of momentum over short horizons (3–12 months) and reversals over long horizons (3–5 years).

Jegadeesh (1990), Chan et al. (1996, 2000), Rouwenhorst (1998), Grundy and Martin (2001) and Lewellen (2002) empirically prove that holding a long position in equities with the strongest relative performance and selling equities with the poorest relative performance generates positive abnormal returns over a formation and holding period ranging from three to twelve months. Jegadeesh and Titman (1993, 2001, 2002) show that equities with higher returns over a 3 to 12 months horizon continue to outperform equities with lower past returns. Moskowitz and Grinblatt (1999) show that momentum exists across industries. Conrad and Kaul (1998), Lee and Swaminathan (2000), and Hong et al. (2000) provide evidence supporting momentum strategies.

On the other side, DeBondt and Thaler (1985, 1987), Chan (1988), Richards (1997) provide evidence that the contrarian strategy of holding a long position in equities with the poorest relative performance and selling equities with the strongest relative performance generates positive abnormal returns over a formation and holding period ranging from three to five years. Jegadeesh (1990) also confirms the presence of negative serial correlation in equity returns over a longer time period.

Even in shorter term horizons momentum and reversal characteristics do exist. Jegadeesh (1990), Martell and Trevino (1990), Jegadeesh and Titman (1995), Antoniou et al. (2003) and Wang and Yu (2004) provide evidence that reversals also exist over shorter horizons of 1 week to 3 months.

Outside the US, Rouwenhorst (1998) have examined international momentum strategies in 12 European countries. The momentum effect is present in all the countries but one where it is positive but statistically insignificant. Liu et al. (1999) find similar positive results in the UK. Chui et al. (2000) provide evidence that momentum is present in the Asian markets with the exception of Korea and Japan. Contrarian strategies have been confirmed in markets outside the US as well (Rouwenhorst, 1998; Chan et al., 2000; Dissanaike, 1997; De Bondt et al.,1999).

Fama and French (1996) have stated that although their three-factor asset pricing model can explain the returns of the long horizon reversal portfolios it definitely cannot explain the momentum effect. The intercepts of their model are larger than those of the single-factor CAPM model. Grundy and Martin (2001) argue that expected returns from the Fama and French three-factor model, even in a conditional form with time-varying risks and expected returns, cannot explain momentum returns. Providing support to these results, Jegadeesh and Titman (2001) believe that cognitive biases of investors may be related to momentum effects (Daniel et al., 1998; Barberis et al., 1998).

Around earnings announcements investors tend to underreact to information (the “earnings momentum” by Chan et al., 1996). Jegadeesh and Titman point out the concentration of momentum profits among stocks with high trading volume (Lee and Swaminathan, 2000) and low analyst coverage (Hong and Stein, 1999; Hong et al., 2000). Following the behaviorists, “inertia” in abnormal returns (momentum) is generated by characteristics of investor behavior: expectations extrapolation and selective (conditioning) information, the “gradual diffusion of information hypothesis” of Hong and Stein (1999) and Hong et al. (2000), conservatism in updating expectations (Barberis et al., 1998) and biased self attribution (Daniel et al.,1998).

On the other hand, the efficient market supporters oppose the profitable exploitation of momentum and contrarian strategies in equity markets. This is due to high turnover and high transaction costs (Moskowitz and Grinblatt, 1999; Grundy and Martin, 2001; Korajczyk and Sadka, 2004; Lesmond et al., 2004) low liquidity and large bid-ask spreads, the nonsychronous trading effect, the neglected and small firm effect or the low price effect (Lesmond et al., 2004) or market restrictions in short selling, time-varying risk effects (De Bondt and Thaler, 1985 and 1987; Chan, 1988; Ball and Kothari, 1995), distressed firm effects, trading volume, and the extent of analyst coverage (Lee and Swaminathan, 2000; Hong et al., 2000).

1. 5. Inefficiency in Commodity Markets

Arbitrage opportunities do exist in markets that are usually efficient. The presence of these opportunities suggests that the prices of some assets are temporarily out of line. The arbitrage mechanism as well as active trading are responsible for adjusting prices and driving markets back to efficiency.

In commodity futures markets there are no restrictions in short selling. Short selling in the underlying assets markets is expensive, difficult, and at times only possible to the owner of the asset. Liquidity in commodity futures markets is far greater partly due to the smaller amount of capital required for participation (initial margin) and the lower transaction costs.[2] When trading front contracts close to maturity liquidity is typically not a problem. In commodity futures markets the underlying assets have lower risk of ceasing to exist and each contract is identical to every other in a specific market. Consequently, in the futures markets in general and in the commodity futures markets in particular, the arbitrage mechanism is stronger and profitable arbitrage opportunities should not exist or at least they should be of lower magnitude and frequency.

If the momentum and reversal patterns of returns in the equity markets are caused by under or overreaction of investors or are due to frictions in the markets, it is not unreasonable to anticipate similar patterns in other risky assets returns like the commodity futures markets. There has been evidence of autocorrelation in futures price changes in previous studies. Stevenson and Bear (1970) find that futures price moves are not independent of all past moves. They provide evidence that corn and soybean futures price changes are positively autocorrelated when testing for random walks in these two commodity futures prices. Dusak (1973) shows patterns in wheat, corn and soybean futures returns suggesting they are not normally distributed. Cargill and Rausser (1975) provide evidence that the commodity market behavior cannot be explained accurately by a random walk model. Petzel (1980) shows that corn futures prices are positively autocorrelated. Helms et al. (1984) find the same results in soy

[2] Round-trip transaction costs (the full bid–ask spread) range from 0.0004% to 0.033% of notional value, which are much less than those often cited for equities (Locke and Venkatesh, 1997). Large traders can negotiate much lower commissions. A more detailed analysis is following in section 3.3.3.

contracts. Taylor (1985, 1986) examines agricultural and financial commodities and finds positive autocorrelation. Martell and Trevino (1990) search on the intraday data of commodity futures prices and find autocorrelation. Lukac et al. (1988, 1989) test different technical trading systems and generate positive returns from commodity futures showing that trading models can give better predictions on future commodity prices than random walk.

Ma et al. (1989, 1990) and Park et al. (1997) follow with studies expanding research into futures in general, not only commodities. These studies confirm that futures prices exhibit autocorrelation like in commodity futures markets. Wang and Yu (2004) provide evidence of weekly return reversals in futures markets, the performance of which are positively correlated with changes of volume and negatively correlated with changes of open interest. Evidence of inefficiencies in the futures markets are supported by studies on Commodity Trading Advisors (CTAs). CTAs are funds using trend following and momentum signals in futures markets, which include the commodity market. Brorsen and Townsend (2002) show that CTAs exhibit performance persistence. Bhardwaj et al. (2008) after correcting their database of CTAs from biases provide evidence of their poor after fees performance to investors. However, they point out that managers generate outperformance from trading futures but most of it is being stripped off by the fees that they charge. Akey (2005) makes a case in favor of active investing in commodities providing evidence that non-financial futures CTAs have significantly outperformed traditional commodity indices. The outperformance is even higher when natural resources hedge funds are added to the commodity traders' portfolio. The performance of CTAs can be indicative of inefficiencies in the futures markets; however CTAs invest only a small proportion of their assets in commodity futures markets. Akey (2005) estimated that that proportion was 10%.

More recently, Gorton and Rouwenhorst (2006) point out that the futures basis seems to carry important information about the risk premium of commodities. They have shown that a portfolio that buys high basis commodities (in backwardation) and sells low basis commodities (in contango) has historically produced a statistically significant 10% per annum outperforming the equally-weighted portfolio of commodities. Gordon et al. (2008) continue showing that momentum and term structure strategies stem in part from the selection of commodities when inventories are low.

Erb and Harvey (2006) present evidence that term structure and momentum based strategies of commodity futures yield very favorable returns. They show that a momentum strategy on the S&P-GSCI (former GSCI) taking advantage of the inertia in its returns produces better results that the S&P-GSCI itself. In addition a portfolio of buying prior winners and selling prior losers in the commodity futures markets doubles the reward to risk ratio against the S&P-GSCI. But even term structure signals help time investing in the S&P-GSCI. The strategy of going long the S&P-GSCI when backwardated and short when contangoed outperforms the traditional long-only approach and buying contracts with the highest and selling the ones with the lowest roll-returns provide equally good results.

Vrugt et al. (2004) present active commodity market timing strategies that outperform commodity indices. They provide evidence that commodities are affected by measures of the business cycle, the monetary environment and market sentiment. Using the CFTC Commitment of Traders Report Shen et al. (2004) produce strong evidence that commercial traders are contrarians, while non-commercial traders use trend-following strategies. Basu et al. (2006) show that the information contained in the Commitment of Traders report could have helped a long-only portfolio manager to successfully time the recent commodity bullish market. All these are early studies providing evidence that inefficiencies exist in the commodity markets.

1. 6. How to Gain Exposure in Commodities

Once investors feel comfortable with an asset class, the question becomes what to buy and how to buy it. There are a number of ways to invest in commodities. For most investors investing directly in the ownership of the assets does not make sense. Buying and controlling a warehouse full of crude oil or soybeans is a logistical nightmare. Buying futures contracts based on the underlying commodities is not an attractive option either. It requires a large investment to achieve diversification across a broad spectrum of commodities. And if the investment focus is long-term, the investor bares the risk of continuous rebalancing of his portfolio of commodity futures. This roll-return or return from rebalancing is one of the least understood but most important aspects of commodity investing.

Some investors looking for commodity exposure invest in equities related to commodities like commodity producers rather than the commodities themselves. It makes sense to transfer the direct investment and storage to the specialist company and hold a piece in that company. But often the exposure to equity markets that comes with owning shares of a commodity-related company outweighs the exposure to the commodity market itself. Investing in Exxon, for example, could be viewed as a way to invest in crude oil. But apart from being a proxy for the price of oil, Exxon is a business. The price of crude oil is not the sole determinant of the share price. After all, different companies have different management practices, different investment philosophy, different quality of staff, different corporate culture and different strength and weaknesses across areas and functions. Gorton and Rouwenhorst (2006) point out that investing in commodity related companies is not necessarily the best way to gain exposure in commodities. They find that the mean return of a portfolio of commodity futures is higher that the mean returns of a portfolio of companies heavily involved in the extraction, production, storage or transportation of commodities. While equities and commodity futures exhibit close to zero correlation (at 0.05 but insignificant at the 5% level against the S&P 500), commodity producers on the other hand, have positive correlation with equities (0.57 against the S&P 500) and at the same time positive but lower correlation with commodity futures (at 0.40 against the equally-weighted commodity futures portfolio in the study). Jin and Jorion (2006) provide evidence supporting the imperfect correlation of commodities with commodity producers. They point out that one of the reasons is the hedging of the production. The average oil firm hedges 33 percent of its next year's production and the average gas firm hedges 41 percent. This hedging activity although helps protect the stability of cash flows for the company, it decreases the natural exposure to commodity price fluctuations in a commodity producer. This reduces the possible gains from a sudden spike in commodity prices.

Investing in natural resources hedge funds and commodity trading advisors (CTAs) is another way of gaining exposure to commodity markets. It is worth noting however that the former invest in equities related to commodities with all the incremental exposures discussed above and the latter invest by only a small proportion in commodity futures. Akey (2005) have estimated that approximately 90% of the assets in CTAs as of August 2004 were linked to financial market futures, with just 4% in the energy sector, 4% in the metals sector, and 2% in other commodity sectors.

In an attempt to mitigate some of the problems mentioned above, investors interested in getting exposure to commodity markets can consider investments linked to commodity indices. There are well-known commodity indices (e.g., Standard & Poor's Goldman Sachs Commodity Index, Dow-Jones UBS Commodity Index) that are tracked by professional fund managers, index trackers, exchange traded funds, mutual funds and commodity pool funds accessible to individual investors. In turn, the managers invest in swaps, structured notes, index futures contracts, and sometimes the underlying futures contracts themselves, to achieve index-like returns. Typically in the past, such management expertise has been available only to institutional investors and high net-worth individuals, but this has started to change over the last years.

The previous sections have provided evidence that commodity futures have idiosyncratic characteristics that if properly exploited can generate abnormal returns. Our research focuses in these idiosyncratic characteristics of commodities providing more information on tactical asset allocation options investors can follow to gain exposure to commodity markets.

1. 7. Overview of the Thesis

It has been widely accepted that momentum and contrarian characteristics in equity markets do exist, but the degree of their profitable exploitation is questioned. In the first chapter we examine whether these characteristics persist in commodity futures markets, markets that are known for their high levels of liquidity, low transaction costs, lack of short-selling restrictions and deep volume in the underlying asset. A finding that momentum strategies are profitable in these markets would stand in contrast to the efficient market hypothesis and would contradict numerous studies suggesting that transaction costs, low liquidity and small price effect, nonsychronous trading effect, neglected and small firm effect, market restrictions and not the behavior of investors are responsible for the momentum characteristics that assets present.

To assess the above controversy, we test whether profitable momentum and contrarian strategies do exist in the futures market of commodities, the market that can be characterized as the nearest to efficiency market with low transaction costs, high trading frequency and high liquidity. Out of the 56 momentum and contrarian strategies developed over different horizons, 13 momentum strategies over horizons that range from 1 to 12 months are found highly profitable, delivering an average outperformance of 12.04% against the equally-weighted basket of commodity futures considered in the study.

The correlation with the traditional asset classes stay low making the long-short momentum-based portfolios excellent candidates for inclusion in well-diversified portfolios. A thorough analysis of the returns of the active portfolios reveals links between the previous price action and the term structure of the commodity curve. Momentum strategies buy on average backwardated commodities and sell on average commodities in contango. This implicitly suggests that a term structure strategy that buys the most backwardated and sells the most contangoed commodities is likely to be profitable and could explain part (if not all) of the momentum effect. Furthermore, it implicitly suggests that if only part of the momentum effect is explained, then a strategy that captures both signals could exhibit even higher levels of profitability.

In the second chapter we expand our momentum research to a broader commodity universe and update it to include a period of volatility and sharp moves. Following the observations of the previous chapter, we test whether the term structure of the commodity curve has explanatory power on commodity returns. We create term structure strategies that tactically allocate wealth towards backwardated commodities (with the highest roll-returns) and away from contangoed commodities (with the lowest roll-returns). When implemented individually momentum and term structure strategies yield significant annualized alphas of 10.14% and 12.66% respectively against the equally-weighted basket of commodities. Going a step further, momentum and term structure signals have been combined in the design of trading strategies in commodity futures markets. This double-sort strategy yields an annualized alpha of 21.02% and its performance cannot be explained by lack of liquidity or transaction costs.

In the third chapter we are investigating possible areas of development and usage of our previous research in the long-only commodity world. We examine the performance of the two traditional commodity indices, Standard & Poor's Goldman Sachs Commodity Index (S&P- GSCI former GSCI) and Dow-Jones UBS Commodity Index (DJ-UBSCI former DJ-AIGCI), and different versions thereof enhanced by momentum, term structure or time to maturity/expiry signals. The more weight is being allocated to the constituents that exhibit higher prior returns and the less weight to the ones woth lower prior returns, the higher the outperformance of these indices compared to the traditional ones. The more weight is being allocated to the constituents that exhibit higher backwardation and the less weight to the ones in contango, the higher the outperformance of these indices compared to the traditional ones. When index weights are being adjusted according to the momentum and term structure signals combined, the risk-adjusted performance of these traditional indices is improving significantly. The last enhancement is a maturity-type enhancement that consists in holding longer term maturities instead of the shorter term ones of the traditional indices. Being consistently in the back end of the commodity curve helps avoid the higher volatility of the front of the curve and the potential losses from rebalancing (roll-return); as such, it could act as a better proxy for long-term commodity returns.

The enhanced indices provide a highly profitable option of diversification to investors. They can be used to gain similar exposure to commodity markets as the traditional ones and at the same time earn excess return. This study can also be deployed as a framework to facilitate choosing among commodity indices. Different trading parameters, rolling procedures and technical specifications can have a significant impact on the risk-adjusted returns of long-only commodity indices.

1. 8. Layout of the Thesis

The thesis proceeds as follows. Section 2 introduces the first empirical chapter of the thesis titled "Momentum Strategies in Commodity Futures Markets" where momentum trading strategies are investigated. Section 3 presents the second empirical chapter titled "Tactical Allocation in Commodity Futures Markets: Combining Momentum and Term Structure Signals" where momentum strategies have been updated and trading strategies based on the term structure and combined signals are being investigated. Section 4 introduces the third empirical chapter titled "Traditional and Enhanced Commodity Indices: Momentum, Term Structure and Maturity Signals" where enhanced indices based respectively on momentum, term structure, a combination of these two signals and the time-to-maturity of the contracts are being analyzed. Finally section 5 concludes.

2. Momentum Strategies in Commodity Futures Markets

2. 1. Introduction

Commodity futures are excellent portfolio diversifiers and, for some, an effective hedge against inflation (Bodie and Rosansky, 1980; Bodie, 1983). They also offer leverage and are not subject to short-selling restrictions. Besides, the nearby contracts are typically very liquid and cheap to trade. For all these reasons, commodity futures are good candidates for strategic asset allocation and have been proved to be useful tools for alpha generation (Jensen et al., 2002; Vrugt et al., 2004; Wang and Yu, 2004; Erb and Harvey, 2006).

This chapter examines the profitability of 56 momentum and contrarian strategies in commodity futures markets. The momentum strategies buy the commodity futures that outperformed in the recent past, sell the commodity futures that under-performed and hold the relative-strength portfolios for up to 12 months. The contrarian strategies do the opposite. They buy the commodity futures that underperformed in the distant past, sell the commodity futures that outperformed and hold the long-short portfolios for periods ranging from 2 to 5 years. To put this differently, this chapter investigates whether the short-term price continuation and the long-term mean reversion identified in equity markets by Jegadeesh and Titman (1993, 2001) and De Bondt and Thaler (1985) are present in commodity futures markets. The chapter also builds on the research of Erb and Harvey (2006) who show that a momentum strategy with a 12-month ranking period and a 1-month holding period is profitable in commodity futures markets.

While contrarian strategies do not work, the article identifies 13 profitable momentum strategies in commodity futures markets. Tactically allocating wealth towards the best performing commodities and away from the worst performing ones generates an average return[3] of 9.38% a year. Over the same period, a long-only

[3] The term “return” is used loosely to refer to the performance of the momentum and contrarian strategies. It is noted that the term is improper in futures markets as, aside from the initial margins, no

equally-weighted portfolio of commodity futures lost 2.64%. In line with the analysis of Erb and Harvey (2006), this result suggests that active investment strategies have historically been profitable in commodity futures markets.

While they are not merely a compensation for risk, the momentum returns are found to be related to the propensity of commodity futures markets to be in backwardation or in contango. The results indeed suggest that the momentum strategies buy backwardated contracts and sell contangoed contracts. Therefore our analysis indicates that one can link the momentum profits in commodity futures markets to an economic rationale related to Keynes (1930) and Hicks (1939) theory of normal backwardation. Interestingly, the momentum returns are also found to have low correlations with the returns of traditional asset classes, making the commodity-based relative-strength strategies good candidates for inclusion in well-diversified portfolios.

There are strong rationales for implementing momentum strategies in commodity futures markets rather than in equity markets: Our commodity-based long-short strategies have lower transaction costs,[4] trade liquid contracts with nearby maturities, are not subject to the short-selling restrictions that are often imposed in equity markets and focus on 31 commodity futures only (as opposed to hundreds or thousands of stocks). It is therefore unlikely that the abnormal returns we identify will be eroded by the costs of implementing the momentum strategy or will be a compensation for a lack of liquidity (as in Lesmond et al., 2004).

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cash payment is made at the time the position is opened. It follows that a definition of returns that implicitly assumes that investors purchase the futures contract at the settlement price is, by definition, inaccurate. Note however that a definition that considers the initial margin as an investment is also incorrect since the initial margin is just a good faith deposit (and not an investment) and is redeemed to the trader (along with accrued interests and marking-to-market profits or losses) at the time he/she enters a reversing trade. Based on this and in line with, among others, Dusak (1973) and Bessembinder (1992), the chapter measures futures returns as the change in the logarithms of settlement prices. Had futures returns been measured relative to the margins and on a fully-collateralized basis, the momentum profits would have been further enhanced. Our definition of return is free of collateral and therefore more conservative.

[4] Transaction costs in futures markets (measured as bid-ask spread) range from 0.0004% to 0.033% (Locke and Venkatesh, 1997), which is much less than the 0.5% estimate of Jegadeesh and Titman (1993) or the 2.3% estimate of Lesmond et al. (2004) for the equity market. A more detailed analysis is following in section 3.3.3.

On a less positive note, institutional investors who implement momentum strategies in commodity futures markets have to post initial margins, monitor margin accounts on a daily basis, roll-over contracts before maturity and pay margin calls. As they are not born by equity asset managers, such costs have to be weighed against the benefits of implementing momentum strategies in commodity futures markets. The margin calls and roll-over risk, however, should not be overstated: As the momentum strategies buy backwardated contracts and sell contangoed contracts, little to no cash will be required for margin calls and the roll-over trades will be more often than not profitable.

This chapter proceeds as follows. Section 2.2 introduces the dataset. Section 2.3 outlines the methodology used to construct momentum and contrarian portfolios. It also presents the risk models that are employed to measure the abnormal returns of the strategies. Section 2.4 discusses the results from the momentum strategies. In particular, it highlights the relationship between momentum profits, backwardation and contango and the diversification properties of the momentum portfolios. Section 2.5 focuses on the contrarian strategies. Finally section 2.6 concludes.

2. 2. Data

The data, obtained from Datastream International, comprises settlement prices on 31 US commodity futures contracts. We consider 13 agricultural futures (cocoa, coffee C, corn, cotton #2, milk, oats, orange juice, soybean meal, soybean oil, soybeans, sugar #11, wheat, white wheat), 4 livestock futures (feeder cattle, frozen pork bellies, lean hogs, live cattle), 6 metal futures (aluminum, copper, gold 100 oz, palladium, platinum, silver 1000 oz), 5 oil and gas futures (heating oil, light crude oil, natural gas, regular gas, unleaded gas) and the futures on diammonium phosphate, lumber and western plywood.

Table 2.1. Commodity Characteristics

Commodity	Ann.Mean	Ann.Volatility	Exchange	Start Date
aluminium	0,0313	0,1441	NYMEX	30/6/1999
cocoa	-0,1021	0,2903	NYBOT	31/1/1979
coffee	-0,0468	0,3835	NYBOT	31/1/1979
copper	0,0241	0,3153	CMX-NYMEX	31/1/1979
corn	-0,0800	0,2177	CBT	31/1/1979
cotton nb 2	-0,0225	0,2455	NYBOT	31/1/1979
diammonium	-0,0077	0,1464	CBT	31/10/1991
feeder cattle	0,0141	0,1465	CME	31/1/1979
frozen pork bellies	-0,0964	0,3909	CME	31/1/1979
gold 100 oz	-0,0361	0,1872	CMX-NYMEX	31/1/1979
heating oil	0,1398	0,3497	NYMEX	31/1/1979
lean hogs	0,0045	0,2642	CME	31/1/1979
lght crude oil	0,1115	0,3298	NYMEX	31/3/1983
live cattle	0,0523	0,1628	CME	31/1/1979
lumber	-0,0441	0,3151	CME	31/1/1995
milk	-0,0678	0,2226	CME	29/3/1996
natural gas	0,0175	0,5022	NYMEX	30/4/1990
oats	-0,0960	0,3001	CBT	31/1/1979
orange juice	-0,0519	0,2840	NYBOT	31/1/1979
palladium	0,0019	0,3629	NYMEX	31/1/1979
platinum	0,0012	0,2675	NYMEX	31/1/1979
regular gas	-0,0568	0,3515	NYMEX	30/10/1981
silver	-0,1347	0,2608	CBT	29/5/1981
soybean meal	0,0073	0,2411	CBT	31/1/1979
soybean oil	-0,0553	0,2561	CBT	31/1/1979
soybeans	-0,0501	0,2239	CBT	31/1/1979
sugar	-0,1421	0,4834	NYBOT	31/1/1979
unleaded gas	0,1872	0,3640	NYMEX	31/12/1984
western plywood	-0,0466	0,1965	CBT	31/1/1979
wheat	-0,0849	0,2161	CBT	31/1/1979
white wheat	-0,0323	0,2453	MGE	28/2/1991

Ann.Mean: Annualized arithmetic mean/return
Ann.Volatility: Annualized standard deviation (volatility)

The dataset spans the period January, 31 1979 to September, 30 2004. Our starting dataset consists of all the available commodity futures in the database. We mitigate problems of low liquidity and high transaction costs by filtering out futures with average trading volume below 1,000 contracts over the period January, 31 1979 to September, 30 2004.[5] To avoid survivorship bias, we include contracts that started trading after January 1979 or were delisted before September 2004. All contracts used in this chapter and their performance and descriptive characteristics are presented in Table 2.1. It entails the start date of inclusion for each contract and the exchange it is traded. The total sample size ranges from a low of 22 contracts at the beginning of the period to a peak of 27 contracts over the periods March 1996-July 1997 and July 1999-September 2004.[6] On the performance side, unleaded gas has the highest return, in direct contrast to silver that has the lowest, and natural gas is the most volatile commodity compared to aluminium that exhibits the lowest volatility.

The chapter tests the sensitivity of the results to the technique employed to compute futures returns. Two approaches are used to compile time series of futures prices and, consequently, time series of futures returns. In both cases, futures returns are computed as the change in the logarithms of the settlement prices.

First, we collect the futures prices on all nearest and second nearest contracts. We hold the first nearby contract up to one month before maturity. At the end of that month, we roll our position over to the second nearest 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 returns is compiled. Second, we re-iterate this approach but, this time, we switch to the most distant (in place of the nearby) contract and use weekly[7] (in place of monthly) settlement prices. To be more specific, we collect weekly settlement prices on all maturity contracts. We hold the first contract up to two weeks before maturity. At this

[5] The omitted contracts are for ammonia, boneless beef, broiler chickens, butter, cheddar cheese, cotton seed, fresh pork bellies, nonfat dry milk, potatoes, oriented strand board and white shrimp. It is noted that excluding these contracts introduces a look-ahead bias.

[6] We use the Ljung-Box Q statistics to test for 1st and 12th order serial correlation in futures returns. The results, available on request, indicate presence of serial correlation in more than half of the series at the 10% level. This crude test suggests that today's returns depend on past values and is an indication that long-short strategies might be profitable in commodity futures markets.

[7] We download Wednesday prices to ensure that the results are not driven by week-end effect.

time, we roll our long position to the contract whose maturity is the furthest away and hold it up to two weeks before it matures. The process is repeated throughout the dataset to generate a sequence of investable distant maturity futures returns.

This sensitivity analysis is interesting for two reasons. First, it enables us to test whether the profits of the trading rule depend on the choice of the roll-over date (as highlighted, among others, in Ma et al., 1992). Second, if the momentum profits are related to backwardation and contango, trading contracts whose maturity is the furthest away might generate superior profits. This potential benefit, however, has to be weighed against the liquidity risk that is involved in trading maturing contracts and contracts with far distant maturities. It could indeed be the case that, due to a lack of liquidity, the choice of i) a later roll-over date and ii) distant maturity contracts has a damaging impact on momentum profits. This point notwithstanding, the sensitivity of the results to the roll-over date is an empirical question that deserves attention as it is of interest to institutional investors.

At the roll-over date, one could adjust the price level *ex-post* to eliminate the price gap between the futures contract that is closed out and the futures contract that is entered into. We favor a correction-free approach instead. The reasons for using unadjusted price series are twofold. First, as real transaction prices are used in practice, momentum and contrarian strategies have to be implemented on unadjusted price series if they are to be meaningful to institutional investors. Second, if, as we argue, the momentum strategy buys backwardated contracts and sells contangoed contracts, part of the momentum profits will come from the profits generated on the roll-over trades. As a result, adjusting the price levels on the roll-over date might eliminate part of the momentum profits that institutional investors seek to earn.

2. 3. Methodology

This chapter analyzes any combination of ranking periods of 1, 3, 6, 12, 24, 36 and 60 months and holding periods of 1, 3, 6, 12, 18, 24, 36 and 60 months. These permutations result in 32 short-term momentum strategies with four ranking periods

(1, 3, 6 and 12 months) and eight holding periods (1, 3, 6, 12, 18, 24, 36 and 60 months) and in 24 long-term contrarian strategies with three ranking periods (24, 36 and 60 months) and eight holding periods (1, 3, 6, 12, 18, 24, 36 and 60 months).

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 decision to form quintiles was based on the fact that our cross section is too small to accommodate deciles as is common in the literature on equity momentum. By adding more futures to the quintile portfolios, our approach enhances risk diversification at the cost of lowering the dispersion of returns between the best and worst performing futures and thus the profitability of the strategies. The futures contracts in each quintile are equally-weighted.[8] The performance of both the top and bottom quintiles is monitored over the subsequent *H* months (holding period) over which no rebalancing takes place. We call the resulting strategy the *R-H* momentum or contrarian strategy.

We follow the approach of Moskowitz and Grinblatt (1999) and Jegadeesh and Titman (2001) and form overlapping winner and loser portfolios. Taking, as an example, the 6-3 momentum strategy, the winner portfolio in, say, December is formed by equally weighting the top quintile portfolios of the previous 3 months, formed at the end of September, October and November. The same applies to the loser portfolio. Its return is equal to the average return in December of the bottom quintiles that were formed at the end of September, October and November.[9] The return of the momentum (contrarian) strategy is then simply defined as the difference in the December returns of the winner (loser) and loser (winner) portfolios. The procedure is rolled over to the next month, where another set of winner, loser, momentum and contrarian portfolios is formed.

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[8] A strategy that assumes equal-weighting might prove difficult to implement in illiquid markets. To mitigate problems related to lack of liquidity, we filter out futures with average trading volume below 1,000 contracts. Another approach would have been to adopt a weighting scheme that assigns higher weights to the contracts with higher open interests. In the light of recent evidence suggesting that trading activity enhances short-term contrarian profits in futures markets (Wang and Yu, 2004), a weighting scheme based on open interests might yield interesting results.

[9] As the November winner and loser contribute towards only a third of the December momentum profits, it is reasonable to assume that the momentum profits are not driven by bid-ask bounce. As a result and following Moskowitz and Grinblatt (1999), we decided not to skip a month between the ranking and holding periods.

The following multifactor model is then used to measure the profitability of the strategy after accounting for risk

$$R_{Pt} = \alpha + \beta_B\left(R_{Bt} - R_{ft}\right) + \beta_M\left(R_{Mt} - R_{ft}\right) + \beta_C\left(R_{Ct} - R_{ft}\right) + \varepsilon_{Pt} \tag{2.1}$$

R_{Pt} is the excess return (without the return from the collateral) of the winner, loser, or momentum portfolio, R_{Bt}, R_{Mt} and R_{Ct} are the returns on Datastream government bond index, the S&P500 composite index and S&P-GSCI (former GSCI) respectively, R_{ft} is the risk-free rate and ε_{Pt} is an error term.

As the possibility remains that the momentum profits are a compensation for time-varying risks (Chordia and Shivakumar, 2002), we estimate a conditional model that allows for the measures of risk and abnormal performance (β_B, β_M, β_C and α) in (2.1) to vary over time as a function of Z_{t-1}, a vector of pre-specified mean-zero information variables (Christopherson et al., 1998)

$$\begin{aligned} R_{Pt} = \alpha_0 + \alpha_1 Z_{t-1} + & \\ & \beta_{B0}\left(R_{Bt} - R_{ft}\right) + \beta_{B1}\left(R_{Bt} - R_{ft}\right)Z_{t-1} + \\ & \beta_{M0}\left(R_{Mt} - R_{ft}\right) + \beta_{M1}\left(R_{Mt} - R_{ft}\right)Z_{t-1} + \\ & \beta_{C0}\left(R_{Ct} - R_{ft}\right) + \beta_{C1}\left(R_{Ct} - R_{ft}\right)Z_{t-1} + \varepsilon_{Pt} \end{aligned} \tag{2.2}$$

Z_{t-1} includes proxies for the business cycle such as the first lag in (i) the dividend yield on the S&P500 composite index, (ii) the term structure of interest rates and (iii) default spread.[10] The first lag on the momentum returns is also used as a predictor of the abnormal performance of the momentum strategy one period ahead.

Insignificant estimates of α in (2.1) and α_0 in (2.2) indicate that the momentum returns are merely a compensation for risk and are therefore consistent with rational pricing in an efficient market.

[10] The term structure is measured as the difference between the yield on US Treasury bonds with at least 10 years to maturity and the US three-month Treasury-bill rate. Default spread is measured as the yield difference between Moody's Baa and Aaa-rated corporate bonds.

2. 4. Momentum Strategies

This section presents the results of our commodity-based relative-strength strategies. We focus on the profits that the strategies generate (Section 2.4.1), the risk factors that may drive the performance (Section 2.4.2), the constituents of the long-short portfolios and how they relate to the propensity of commodity markets to be in backwardation or contango (Section 2.4.3) and the ability of momentum portfolios to act as portfolio diversifiers and inflation hedge (Section 2.4.4).

2. 4. 1. Momentum profits

Table 2.2 displays summary statistics of returns of short-term momentum strategies, where the rows represent the ranking periods and the columns the holding periods. It is clear from Table 2.2 that the winner portfolios typically outperform the loser portfolios over holding periods that range from 1 to 12 months. With only 3 exceptions out of 16 strategies (for the 6-12, 12-6 and 12-12 momentum strategies), the difference in returns between the winner and the loser portfolios is positive and significant at the 10% level. Across the 13 strategies that are profitable, one could earn an average return of 9.38% a year by consistently buying the best performing commodity futures and selling the worst performing ones. Over the same period, a long-only portfolio that equally weights the 31 commodities we considered lost 2.64% a year. The results in Table 2.2 are in line with Jegadeesh and Titman (1993, 2001) who identify short-term price continuation in equity markets. They are also consistent with Erb and Harvey (2006) who observe that a 12-1 momentum strategy is profitable in commodity futures markets.

Across the 13 strategies that are profitable at the 10% level, the loser portfolios always yield negative and significant average return that range from a low of -10.83% (for the 6-1 strategy) to a high of -5.16% (for the 3-12 strategy). The evidence from the 13 winner portfolios is less strong both in economic and statistical terms. The winner portfolios offer average returns that can, at times, be negative and range from a low of -1.75% (for the 1-12 strategy) to a high of 7.26% (for the 3-1 strategy). As in Hong et al. (2000), the price continuation in commodity futures markets is therefore mainly driven by the losers.

Table 2.2. Summary statistics of returns of momentum strategies

	Holding Period of 1 Month			Holding Period of 3 Months			Holding Period of 6 Months			Holding Period of 12 Months		
	Winners	Losers	Momentum	Winners	Losers	Momentum	Winners	Losers	Momentum	Winners	Losers	Momentum
Panel A: Ranking Period of 1 Month												
Mean	0.0239	-0.0847	0.1087	0.0126	-0.0688	0.0814	0.0088	-0.0677	0.0765	-0.0175	-0.0702	0.0527
	(0.60)	(-2.16)	(2.13)	(0.39)	(-2.32)	(2.58)	(0.30)	(-2.41)	(3.35)	(-0.67)	(-2.74)	(3.20)
Standard deviation	0.2016	0.1987	0.2584	0.1631	0.1496	0.1593	0.1454	0.1406	0.1145	0.1290	0.1274	0.0820
Reward-to-risk ratio	0.1187	-0.4265	0.4205	0.0772	-0.4598	0.5108	0.0608	-0.4811	0.6681	-0.1353	-0.5509	0.6435
Panel B: Ranking Period of 3 Months												
Mean	0.0726	-0.0655	0.1380	0.0398	-0.0648	0.1046	0.0121	-0.0643	0.0764	0.0031	-0.0516	0.0547
	(1.83)	(-1.78)	(2.79)	(1.08)	(-1.95)	(2.47)	(0.37)	(-2.15)	(2.34)	(0.11)	(-1.88)	(2.23)
Standard deviation	0.2000	0.1853	0.2494	0.1853	0.1665	0.2130	0.1619	0.1493	0.1635	0.1341	0.1359	0.1214
Reward-to-risk ratio	0.3629	-0.3532	0.5535	0.2146	-0.3890	0.4911	0.0747	-0.4308	0.4674	0.0228	-0.3799	0.4503
Panel C: Ranking Period of 6 Months												
Mean	0.0104	-0.1083	0.1188	-0.0001	-0.0869	0.0868	0.0033	-0.0872	0.0905	-0.0323	-0.0528	0.0205
	(0.25)	(-2.72)	(2.37)	(0.00)	(-2.40)	(1.93)	(0.10)	(-2.57)	(2.30)	(-1.08)	(-1.76)	(0.65)
Standard deviation	0.2060	0.1996	0.2515	0.1886	0.1810	0.2252	0.1667	0.1689	0.1961	0.1480	0.1474	0.1555
Reward-to-risk ratio	0.0506	-0.5427	0.4722	-0.0007	-0.4803	0.3854	0.0196	-0.5165	0.4614	-0.2183	-0.3582	0.1318
Panel D: Ranking Period of 12 Months												
Mean	0.0407	-0.1053	0.1460	0.0085	-0.0758	0.0843	-0.0306	-0.0402	0.0096	-0.0397	-0.0097	-0.0300
	(1.01)	(-2.73)	(2.84)	(0.25)	(-2.10)	(1.86)	(-0.94)	(-1.19)	(0.23)	(-1.27)	(-0.31)	(-0.82)
Standard deviation	0.1993	0.1916	0.2557	0.1693	0.1786	0.2236	0.1610	0.1662	0.2072	0.1518	0.1520	0.1788
Reward-to-risk ratio	0.2041	-0.5495	0.5709	0.0499	-0.4246	0.3768	-0.1899	-0.2417	0.0463	-0.2613	-0.0635	-0.1679

The mean and standard deviation are annualized. The reward-to-risk ratio is measured as the ratio of the annualized mean to the annualized standard deviation. *t*-ratios for the significance of the mean are in parentheses. Our definition of returns assumes that we hold contracts up to one month before maturity, at which date the position is rolled over to the second nearest contract and held up to one month prior to maturity. Futures prices are collected at a monthly frequency.

The reward-to-risk ratio should not be used in isolation to compare the different strategies for two main reasons: a) as a variance-based measure it is valid only for spherically symmetric distributions, and b) it only allows for linear comparisons, assuming linear relationship of risk and return. For a more accurate comparison, the full risk profile of the strategies, the risk aversion curve of investors, the elasticity of demand for risky assets, as well as, possible portfolio combinations of the riskier but more profitable strategies with the risk-free rate, should be analyzed. A more detailed risk profile of the strategies is provided in the next chapters. All others are possible extensions for future research.

As the possibility remains that the momentum strategies pay off as a compensation for risk, Table 2.2 also reports the annualized standard deviations and the reward-to-risk ratios of the strategies. As expected, the most profitable strategies rank among the most risky. For example, the 12-1 momentum strategy offers the highest average return (14.60%) and, with a standard deviation of 25.57%, it is also the second most volatile. On the other hand, the 1-12 momentum strategy has the lowest level of risk (8.20%) and, subsequently, the lowest average return (5.27%).

Over the period March 1979 - September 2004, a portfolio that equally weights the 31 commodity futures considered in this chapter had a negative reward-to-risk ratio equal to -0.2442. Over the same period, the S&P500 composite index had an expected Sharpe ratio of 0.3101. Simultaneously, the 13 profitable momentum strategies in Table 2.2 had reward-to-risk ratios ranging from 0.3768 (for the 12-3 strategy) to 0.6681 (for the 1-6 strategy), with an average at 0.4978. This indicates that commodity-based relative-strength strategies perform better on a risk-adjusted basis than passive long-only strategies in equity and commodity futures markets.

One may question whether the momentum profits identified over the period March 1979 - September 2004 in Table 2.2 will be sustained in the future. The recent interest of institutional investors in commodity futures is a factor that could impact future momentum profits. In numerous studies, institutional investors, through block trades, have been linked to price continuation. Gemmill (1996) has documented that price continuation in equities is following block purchases and price reversal is following block sales, but the relationship between total price impact and block size is significant only in the case of block purchases. Although the past is not necessarily a reliable guide to the future, we compare the momentum risk-adjusted returns in the later period (June 1998 – September 2004) to those earned in earlier periods (March 1979 – July 1985, August 1985 – December 1991, January 1992 – May 1998) and use this information to test whether the momentum profits have increased or decreased recently due to a rising interest of institutional investors in commodity futures. If momentum profits have shrunk over time, it is likely that future profits will also be compressed. The reward-to-risk ratios of the 16 momentum strategies are reported in Table 2.3 over four consecutive periods of equal duration. 10 out of 16 strategies generated their best risk-adjusted return in the later period. Over the same period, only one strategy (the 1-1 strategy) yielded its worst performance. As the recent interest of institutional investors has not shrunk the momentum profits, one can expect the profits of the long-short strategies to be sustainable in the near future too. It is also noted from Tables 2.2 and 2.3 that with relatively few exceptions (for the 3-6 and 6-3 strategies over the period January 1992 – May 1998 and the 1-1 strategy over the period June 1998 – September 2004), the 13 strategies that are profitable over the long run in Table 2.2 generate positive risk-adjusted returns in each of the four sub-periods.

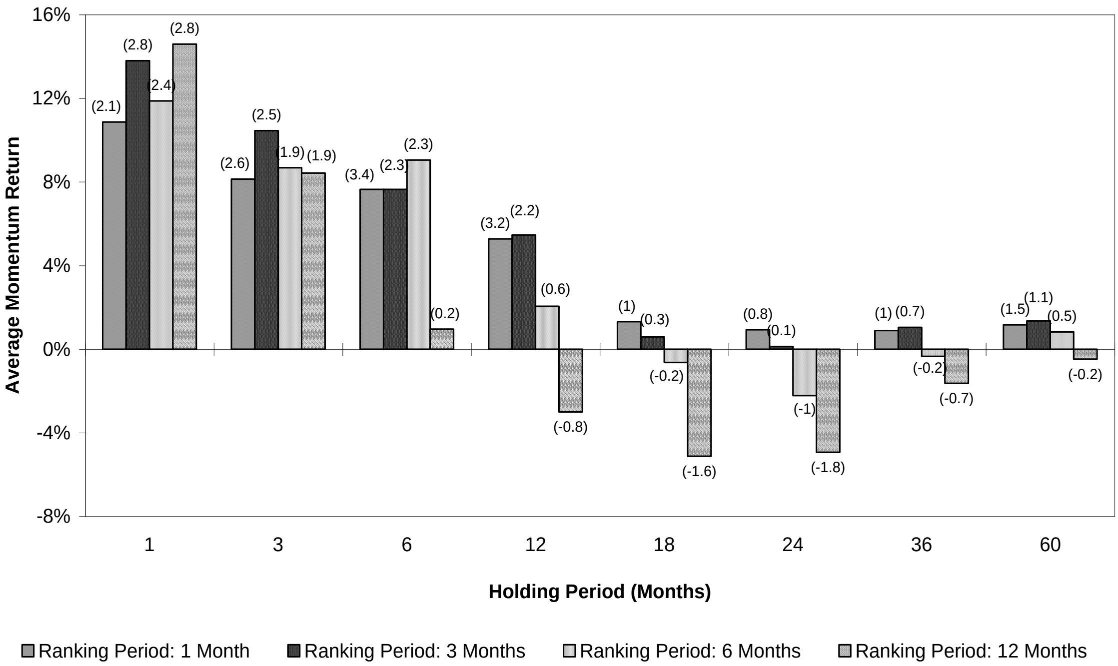
Table 2.3. Reward-to-risk ratios of momentum portfolios over time

	Mar 1979 - Jul 1985	Aug 1985 - Dec 1991	Jan 1992 - May 1998	Jun 1998 - Sep 2004	Mar 1979 - Sep 2004
Panel A: Ranking Period of 1 Month					
H = 1	0.6123	0.8360	0.6873	-0.4485	0.4205
H = 3	0.2803	0.5945	0.7646	0.5078	0.5108
H = 6	0.5463	0.6783	0.4763	0.9990	0.6681
H = 12	0.3338	0.8223	0.6393	0.7815	0.6435
Panel B: Ranking Period of 3 Months					
H = 1	0.5584	0.4094	0.7001	0.6047	0.5535
H = 3	0.6082	0.2333	0.3841	0.7166	0.4911
H = 6	0.4819	0.4064	-0.0404	0.9075	0.4674
H = 12	0.4067	0.3351	0.3117	0.7030	0.4503
Panel C: Ranking Period of 6 Months					
H = 1	0.7690	0.2625	0.0827	0.6772	0.4722
H = 3	0.4614	0.2922	-0.0175	0.7103	0.3854
H = 6	0.5157	0.3553	0.2027	0.7261	0.4614
H = 12	0.0363	0.1644	-0.1026	0.3487	0.1318
Panel D: Ranking Period of 12 Months					
H = 1	0.5425	0.4127	0.6148	0.7465	0.5709
H = 3	0.2603	0.2822	0.2651	0.6323	0.3768
H = 6	-0.0693	0.1234	-0.2640	0.2687	0.0463
H = 12	-0.0520	0.0475	-0.7817	-0.0757	-0.1679

The table reports the reward-to-risk ratios of the momentum portfolios over 4 consecutive sub-periods and over the whole sample. The reward-to-risk ratio is measured as the portfolio's annualized mean divided by its annualized standard deviation. *H* is the holding period of the momentum strategy.

Figure 2.1 looks at the performance of the zero-cost winner minus loser portfolios over increasing holding periods. Consistent with Rouwenhorst (1998) and Jegadeesh and Titman (2001), the average return of the momentum portfolios for a given ranking period is U-shaped, suggesting that the initial positive relative strength (over horizon of up to 12 months as reported in Table 2.2) is followed by first a negative performance (over horizons of 18 to 24 months) and then a zero average return (beyond 24 months). This indicates that after the initial price continuation, a subsequent price correction takes place. This is consistent with the idea that transactions by short-term momentum traders temporarily move prices away from long-term equilibrium, eventually causing prices to overreact. Once the overreaction is acknowledged, the market is in for a correction (Barberis et al., 1998; Daniel et al., 1998; Hong and Stein, 1999). This adjustment occurs over horizons of 18 to 24 months. Note however that this interpretation should be treated with some caution, as the returns over holding periods of 18 and 24 months, though mostly negative, are insignificant.

Figure 2.1. Average momentum returns over different holding periods



The figure presents the average returns of momentum portfolios for 4 ranking periods and for holding periods of increasing length. *t*-ratios for the significance of the mean are reported in parentheses.

Table 2.4 tests the sensitivity of the momentum results to the technique used to calculate futures returns. Relative to Table 2.2, Table 2.4 assumes that i) the roll-over date is set to the second last Wednesday before maturity (as opposed to the last trading day of the month before maturity), and ii) at the time of the roll-over, the contracts whose maturity is the furthest away is used (as opposed to the contact with the second nearest maturity). The momentum strategies in Table 2.4 perform well at the 10% level for 8 combinations of ranking and holding periods. Across these 8 momentum strategies, the winners outperformed the losers by an average of 7.38% a year. The momentum profits in Table 2.4 are therefore less significant in both economic and statistical terms than those reported in Table 2.2. Although momentum persists, the profitability of the trading strategy is found to be sensitive to the way futures prices are compiled. It is likely also that the 7.38% average return is, at least in part, a compensation for the illiquidity of maturing contracts and contracts with far distant maturities. Net of liquidity risk, the profits of the relative-strength strategies are expected to further decrease.

Table 2.4. Sensitivity of momentum profits to return definition

	Holding Period of 1 Month			Holding Period of 3 Months			Holding Period of 6 Months			Holding Period of 12 Months		
	Winners	Losers	Momentum	Winners	Losers	Momentum	Winners	Losers	Momentum	Winners	Losers	Momentum
Panel A: Ranking Period of 1 Month												
Mean	0.0237	-0.0701	0.0938	0.0040	-0.0537	0.0577	-0.0100	-0.0327	0.0227	-0.0123	-0.0456	0.0333
	(0.70)	(-2.17)	(2.23)	(0.15)	(-2.09)	(2.18)	(-0.43)	(-1.34)	(1.13)	(-0.57)	(-2.03)	(2.51)
Standard deviation	0.1705	0.1634	0.2136	0.1337	0.1300	0.1337	0.1176	0.1225	0.1009	0.1082	0.1120	0.0660
Reward-to-risk ratio	0.1387	-0.4290	0.4390	0.0298	-0.4134	0.4317	-0.0854	-0.2672	0.2249	-0.1139	-0.4072	0.5041
Panel B: Ranking Period of 3 Months												
Mean	0.0421	-0.0730	0.1150	0.0040	-0.0583	0.0623	-0.0120	-0.0401	0.0280	-0.0119	-0.0552	0.0433
	(1.24)	(-2.33)	(2.61)	(0.13)	(-2.05)	(1.72)	(-0.46)	(-1.52)	(0.98)	(-0.52)	(-2.28)	(2.15)
Standard deviation	0.1718	0.1586	0.2225	0.1513	0.1435	0.1822	0.1315	0.1319	0.1435	0.1132	0.1204	0.1000
Reward-to-risk ratio	0.2449	-0.4601	0.5171	0.0266	-0.4061	0.3418	-0.0916	-0.3039	0.1954	-0.1051	-0.4584	0.4327
Panel C: Ranking Period of 6 Months												
Mean	0.0092	-0.0598	0.0689	-0.0029	-0.0478	0.0449	-0.0184	-0.0505	0.0321	-0.0175	-0.0426	0.0251
	(0.27)	(-1.89)	(1.62)	(-0.09)	(-1.56)	(1.16)	(-0.65)	(-1.72)	(0.95)	(-0.73)	(-1.62)	(1.00)
Standard deviation	0.1718	0.1591	0.2137	0.1583	0.1534	0.1934	0.1421	0.1468	0.1693	0.1187	0.1300	0.1242
Reward-to-risk ratio	0.0533	-0.3758	0.3227	-0.0184	-0.3114	0.2320	-0.1295	-0.3441	0.1896	-0.1474	-0.3274	0.2018
Panel D: Ranking Period of 12 Months												
Mean	0.0289	-0.0815	0.1105	0.0028	-0.0717	0.0745	-0.0158	-0.0430	0.0272	-0.0362	-0.0252	-0.0110
	(0.85)	(-2.44)	(2.51)	(0.09)	(-2.25)	(1.89)	(-0.57)	(-1.39)	(0.76)	(-1.33)	(-0.90)	(-0.35)
Standard deviation	0.1703	0.1664	0.2195	0.1559	0.1583	0.1962	0.1380	0.1532	0.1770	0.1337	0.1372	0.1557
Reward-to-risk ratio	0.1699	-0.4900	0.5031	0.0181	-0.4529	0.3798	-0.1144	-0.2805	0.1536	-0.2707	-0.1834	-0.0709

The mean and standard deviation are annualized. The reward-to-risk ratio is measured as the ratio of the annualized mean to the annualized standard deviation. *t*-ratios for the significance of the mean are in parentheses. The difference with Table 2.2 is that we switch to the most distant (in place of the nearby) contract and use weekly (in place of monthly) settlement prices. Our definition of returns assumes that we hold the first contract up to two weeks before maturity, at which time we roll our long position to the contract whose maturity is the furthest away.

2. 4. 2. Risk-based explanations

The remainder of Section 2.4 focuses on the 13 momentum strategies that are profitable at the 10% level in Table 2.2. This section tests whether the profits then identified are a compensation for risk. With this in mind, Table 2.5 displays the sensitivities of each portfolio returns to the bond, equity and commodity futures markets and, subsequently, the abnormal performance of the momentum strategies (α in (2.1)). The results indicate that both the winners and losers are sensitive to the risk factors. While the returns of 11 out of 13 momentum strategies follow the ups and downs of S&P-GSCI, the relative-strength portfolios are truly neutral to the risks present in the bond and equity markets. As a result, the adjusted-R^2 of the momentum regressions are very low.

Table 2.5. Static risk model

	Holding Period of 1 Month			Holding Period of 3 Months			Holding Period of 6 Months			Holding Period of 12 Months		
	Winners	Losers	Momentum	Winners	Losers	Momentum	Winners	Losers	Momentum	Winners	Losers	Momentum
Panel A: Ranking Period of 1 Month												
α	0.0299	-0.0788	0.1087	0.0214	-0.0674	0.0889	0.0132	-0.0670	0.0802	-0.0071	-0.0648	0.0577
	(0.83)	(-2.27)	(2.10)	(0.81)	(-2.69)	(2.79)	(0.58)	(-2.89)	(3.48)	(-0.36)	(-3.12)	(3.49)
β_B	-0.1470	-0.0558	-0.0912	-0.0804	-0.1387	0.0583	-0.0608	-0.1180	0.0572	-0.0536	-0.1059	0.0524
	(-1.55)	(-0.61)	(-0.67)	(-1.16)	(-2.10)	(0.70)	(-1.03)	(-1.95)	(0.95)	(-1.05)	(-1.94)	(1.21)
β_M	0.0733	0.1552	-0.0819	0.0920	0.1451	-0.0531	0.1180	0.1189	-0.0010	0.0926	0.1205	-0.0279
	(1.07)	(2.34)	(-0.83)	(1.83)	(3.03)	(-0.88)	(2.74)	(2.70)	(-0.02)	(2.49)	(3.05)	(-0.89)
β_C	0.5270	0.5452	-0.0181	0.5552	0.4524	0.1028	0.5227	0.4551	0.0675	0.4978	0.4321	0.0657
	(8.83)	(9.45)	(-0.21)	(12.70)	(10.86)	(1.94)	(13.85)	(11.82)	(1.76)	(15.22)	(12.42)	(2.37)
$\bar{R}^2$	20.51%	23.49%	-0.50%	35.18%	29.93%	0.55%	39.97%	33.14%	0.35%	44.53%	35.72%	1.48%
Panel B: Ranking Period of 3 Months												
α	0.0832	-0.0668	0.1500	0.0482	-0.0661	0.1144	0.0215	-0.0613	0.0828	0.0130	-0.0503	0.0631
	(2.42)	(-1.94)	(3.02)	(1.59)	(-2.19)	(2.70)	(0.84)	(-2.34)	(2.53)	(0.63)	(-2.12)	(2.58)
β_B	-0.0766	-0.1503	0.0737	-0.0297	-0.1571	0.1274	-0.0280	-0.1183	0.0903	-0.0376	-0.1339	0.0963
	(-0.85)	(-1.66)	(0.57)	(-0.37)	(-1.99)	(1.15)	(-0.42)	(-1.73)	(1.06)	(-0.69)	(-2.13)	(1.49)
β_M	0.0827	0.1486	-0.0660	0.1379	0.1292	0.0087	0.1368	0.1102	0.0266	0.0551	0.1132	-0.0581
	(1.26)	(2.26)	(-0.70)	(2.39)	(2.25)	(0.11)	(2.81)	(2.21)	(0.43)	(1.39)	(2.49)	(-1.24)
β_C	0.5961	0.3786	0.2175	0.6150	0.3992	0.2159	0.5730	0.4192	0.1538	0.5212	0.4068	0.1145
	(10.45)	(6.61)	(2.64)	(12.24)	(7.97)	(3.08)	(13.35)	(9.56)	(2.82)	(14.93)	(10.16)	(2.77)
$\bar{R}^2$	26.52%	13.85%	1.45%	33.98%	18.75%	2.57%	38.38%	24.45%	2.16%	43.10%	27.14%	2.58%
Panel C: Ranking Period of 6 Months												
α	0.0209	-0.1085	0.1294	0.0127	-0.0821	0.0948	0.0134	-0.0820	0.0954			
	(0.59)	(-2.98)	(2.56)	(0.40)	(-2.48)	(2.09)	(0.49)	(-2.72)	(2.39)			
β_B	0.0039	-0.1065	0.1104	0.0007	-0.1050	0.1058	-0.0520	-0.0836	0.0316			
	(0.04)	(-1.12)	(0.84)	(0.01)	(-1.22)	(0.90)	(-0.73)	(-1.07)	(0.31)			
β_M	0.0925	0.1592	-0.0667	0.1141	0.0982	0.0159	0.1113	0.1281	-0.0168			
	(1.38)	(2.31)	(-0.69)	(1.92)	(1.57)	(0.19)	(2.13)	(2.24)	(-0.22)			
β_C	0.6327	0.4789	0.1538	0.6206	0.4481	0.1725	0.5616	0.4635	0.0981			
	(10.81)	(7.93)	(1.83)	(11.84)	(8.11)	(2.28)	(12.18)	(9.19)	(1.47)			
$\bar{R}^2$	28.09%	18.29%	0.40%	32.37%	18.34%	1.06%	33.89%	22.96%	-0.25%			
Panel D: Ranking Period of 12 Months												
α	0.0587	-0.1019	0.1604	0.0222	-0.0757	0.0978						
	(1.70)	(-2.83)	(3.11)	(0.78)	(-2.25)	(2.16)						
β_B	-0.0068	-0.0857	0.0789	-0.0066	-0.1319	0.1254						
	(-0.07)	(-0.91)	(0.58)	(-0.09)	(-1.48)	(1.04)						
β_M	0.0434	0.1612	-0.1178	0.0235	0.1313	-0.1077						
	(0.66)	(2.35)	(-1.20)	(0.43)	(2.03)	(-1.24)						
β_C	0.6177	0.4117	0.2060	0.5759	0.3940	0.1819						
	(10.69)	(6.82)	(2.38)	(12.00)	(6.92)	(2.38)						
$\bar{R}^2$	27.55%	14.49%	1.37%	32.51%	14.61%	1.62%						

Table 2.5. Continued

The table reports coefficient estimates from (2.1). α measures abnormal performance, β_B, β_M and β_C measures the sensitivities of returns to the excess returns on Datastream government bond index, the S&P500 composite index and S&P-GSCI, respectively. *t*-ratios are in parenthesis. To facilitate comparison with Table 2.2, α has been annualized. $\overline{R}^2$ is the adjusted goodness of fit statistic.

On average, the annualized abnormal returns of the 13 profitable momentum strategies equal 10.18%,[11] ranging from a low of 5.77% for the 1-12 strategy to a high of 16.04% for the 12-1 strategy. The 13 profitable strategies of Table 2.2 have positive and significant α in Table 2.5. Therefore, the winner-loser profits cannot be described as a compensation for exposure to the risks we considered.[12] As in Table 2.2, the momentum pattern is mainly driven by the losers: at the 10% level, all 13 losers have negative and significant alphas, while only 2 winners have positive and significant alphas. This result corroborates the conclusions of Hong et al. (2000) from equity markets.

As a robustness check, Table 2.6 investigates whether the average returns of Table 2.2 are a compensation for time-varying risks. The possibility indeed remains that the profitability of the momentum strategies is driven by the winners having higher systematic risks than the losers in up-markets and lower systematic risks than the losers in down-markets. If this is the case, the momentum profits identified in Table 2.2 could simply be a return for exposure to time-varying risks. To test this, model (2.2) conditions the measures of abnormal performance and risks on business cycle variables. For model (2.2) to be well-specified, the hypotheses that $\alpha_1 = 0$, $\beta_1 = \{\beta_{B1}, \beta_{M1}, \beta_{C1}\} = 0$ and $\alpha_1 = \beta_1 = 0$ have to be rejected. Table 2.6 reports the *p*-values of these tests and α_0, the conditional abnormal performance of the momentum portfolios.

[11] The average abnormal performance in Table 2.5 (10.18%) is slightly higher than the average return reported in Table 2.2 (9.38%). The difference is due to the fact that (1) the momentum strategies have a positive commodity beta and (2) the commodity index offered a negative excess return over the period considered (-2.82%).

[12] They are not compensation to the Fama and French (1993) SMB and HML factors either. Adding the momentum factor of Carhart (1997) to the sets of risk factors included in (2.1) reduces the size and significance of the abnormal return (α). This result is expected as both the momentum factor of Carhart and our relative-strength portfolios are formed by consistently buying recent winners and selling recent losers. The results from these models are available on request from the authors.

Table 2.6. Conditional risk model

	α_0		$p(\alpha_1 = 0)$	$p(\beta_1 = 0)$	$p(\alpha_1 = \beta_1 = 0)$
	Estimate	t-ratio			
Panel A: Ranking Period of 1 Month					
H = 1	0.0992	1.93	0.12	0.01	0.00
H = 3	0.0770	2.60	0.33	0.00	0.00
H = 6	0.0738	3.67	0.02	0.00	0.00
H = 12	0.0586	3.94	0.60	0.00	0.00
Panel B: Ranking Period of 3 Months					
H = 1	0.1303	2.74	0.45	0.00	0.00
H = 3	0.1093	2.95	0.18	0.00	0.00
H = 6	0.0834	2.94	0.75	0.01	0.03
H = 12	0.0704	3.12	0.06	0.10	0.01
Panel C: Ranking Period of 6 Months					
H = 1	0.1232	2.69	0.71	0.00	0.00
H = 3	0.0916	2.31	0.50	0.03	0.04
H = 6	0.1034	2.98	0.67	0.25	0.51
Panel D: Ranking Period of 12 Months					
H = 1	0.1676	3.38	0.93	0.04	0.12
H = 3	0.1079	2.53	0.61	0.26	0.14

α_0 measures the conditional abnormal performance of the momentum portfolio. To facilitate comparison with Table 2.2, α_0 has been annualized. $p(\alpha_1=0)$, $p(\beta_1=0)$ and $p(\alpha_1=\beta_1=0)$ are p-values associated with the hypotheses that the measures of abnormal performance and/or risk are constant. H is the holding period of the momentum strategy.

The results indicate that, out of the 13 profitable strategies we consider, 2 have time-dependent measures of abnormal performance and 10 have time-dependent measures of risk at the 10% level. Additionally, the evidence suggests that α_1 and β_1 are jointly significant for 10 strategies at the 5% level. These results ultimately indicate that restricting the measures of risk and abnormal performance to be constant as in (2.1), instead of conditioning them on business cycle variables as in (2.2), might lead to poor conclusions on abnormal performance. The annualized conditional measures of abnormal performance (α_0) range from 5.86% for the 1-12 strategy to 16.76% for the 12-1 strategy, with an average at 9.97%. All 13 strategies have significant α_0 at the 10% level, an indication that the abnormal performance identified in Table 2.2 is not merely a compensation for time-varying risks.

2. 4. 3. Backwardation and contango

This section analyzes in more details the characteristics of the futures contracts that the momentum strategies recommend trading. Following Erb and Harvey (2006), this chapter hypothesizes that the momentum strategies buy backwardated contracts and sell contangoed contracts. If hedgers are net short, the futures price has to rise as maturity approaches to entice speculators to open long positions. Conversely, if hedgers are net long, the futures price has to fall as maturity approaches to entice speculators to open short positions. The increase (decrease) in the futures price over the life of the contract is referred to as normal backwardation (contango) (for more on this, Keynes, 1930; Hicks, 1939; or, more recently, Miffre, 2000). This suggests that the momentum profits could be driven by long positions in backwardated contracts and short positions in contangoed contracts. To test this hypothesis, we relate the buy and sell recommendations of the trading rule first, to the roll-returns of commodity futures and second, to the term structure of average futures prices.

To measure whether a market is in backwardation or contango, roll-returns of each commodity futures are calculated by relating the futures price on the nearest contract to the futures price on the most distant contract as follows: $R_t = P_{Nearest,t} / P_{Distant,t} - 1$. A positive roll-return R_t indicates that the market is backwardated, as the time t futures price on the nearest contract then exceeds the time t futures price on the most distant contract. Conversely, a negative roll-return suggests that the market is in contango. For each momentum strategy, dummy variables that assign positive values to the commodity futures that are bought and negative values to the commodity futures that are sold are created. The actual values assigned to the dummy depend on the number of times the specific contract is bought or sold. For example, if in a given month the strategy buys (sells) 3 aluminum contracts, the aluminum dummy equals 3 (-3) for that specific month. Similarly, if the strategy ignores aluminum futures, the position dummy equals 0. For each commodity in each strategy, we then calculate the correlation between the roll-returns and the position dummies. A positive and significant correlation indicates that the momentum strategy buys backwardated contracts and sells contangoed contracts, while a negative and significant correlation suggests the opposite.

The correlations between the roll-returns and the position dummies are reported in Table 2.7 for each of the 31 commodity futures and each of the 13 profitable momentum strategies. The last column reports the average correlations per commodity futures across strategies. The last row presents the average correlations per strategy across commodity futures. The mean correlation across both strategies and commodity futures equals 39.31%. 86.85% (85.61%) of the correlations are positive and significant at the 5% (1%) level.[13] These results indicate that the momentum strategies buy backwardated contracts and sell contangoed contracts. This proposition is strongly supported for light crude oil, lumber, oats, soybean oil and unleaded gas for which the average correlations across strategies exceed 55%. The adequacy of the hypothesis is also born out by the fact that the average correlations across commodities are positive, ranging from a low of 23.63% for the 1-1 strategy to a high of 45.68% for the 3-12 strategy.

[13] Note that this result is not sensitive to the definition of roll-return. When roll-returns are measured as in Erb and Harvey (2006) as a function of the price differential between the nearest and second nearest contracts, 78.43% (74.40%) of the correlations between the position dummies and the roll-returns are positive and significant at the 5% (1%) level.

Table 2.7. Correlations between roll-returns and position dummies: Backwardation and contango

	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	
Aluminium	28% *	2%	2%	-18%	2%	4%	3%	-11%	3%	3%	1%	2%	1%	1.77%
Cocoa	28% *	44% *	54% *	59% *	37% *	44% *	47% *	51% *	43% *	44% *	42% *	51% *	54% *	45.89%
Coffee	29% *	44% *	55% *	59% *	40% *	47% *	55% *	63% *	50% *	52% *	53% *	56% *	58% *	50.78%
Copper	18% *	31% *	40% *	52% *	39% *	47% *	56% *	72% *	49% *	58% *	63% *	68% *	72% *	51.06%
Corn	23% *	42% *	57% *	65% *	44% *	54% *	64% *	67% *	56% *	61% *	64% *	55% *	58% *	54.70%
Cotton	26% *	41% *	48% *	53% *	37% *	44% *	46% *	49% *	46% *	45% *	43% *	52% *	50% *	44.61%
Diammonium Phosphate	17%	30% *	58% *	64% *	13%	32% *	64% *	65% *	50% *	66% *	67% *	60% *	61% *	49.76%
Feeder Cattle	20% *	27% *	27% *	22% *	40% *	41% *	45% *	45% *	37% *	34% *	28% *	32% *	38% *	33.49%
Frozen Pork Bellies	25% *	34% *	36% *	47% *	39% *	41% *	42% *	51% *	41% *	40% *	43% *	43% *	43% *	40.46%
Gold	3%	1%	0%	4%	3%	0%	-2%	7%	3%	3%	5%	4%	6%	2.71%
Heating Oil	25% *	33% *	42% *	53% *	28% *	32% *	44% *	56% *	40% *	43% *	49% *	48% *	50% *	41.86%
Lean Hogs	21% *	35% *	44% *	55% *	30% *	38% *	45% *	51% *	45% *	49% *	51% *	48% *	51% *	43.31%
Light Crude Oil	32% *	46% *	54% *	64% *	46% *	50% *	53% *	62% *	62% *	63% *	61% *	61% *	63% *	55.21%
Live Cattle	29% *	45% *	40% *	26% *	47% *	50% *	42% *	27% *	38% *	32% *	20% *	27% *	24% *	34.29%
Lumber	51% *	69% *	76% *	69% *	62% *	64% *	62% *	58% *	67% *	61% *	52% *	66% *	60% *	62.80%
Milk	29% *	41% *	48% *	45% *	53% *	54% *	51% *	45% *	60% *	55% *	47% *	51% *	48% *	48.18%
Natural Gas	39% *	53% *	58% *	64% *	53% *	51% *	57% *	56% *	52% *	51% *	47% *	54% *	50% *	52.67%
Oats	38% *	52% *	64% *	66% *	47% *	55% *	65% *	66% *	61% *	64% *	66% *	67% *	66% *	59.77%
Orange Juice	15% *	20% *	22% *	32% *	31% *	37% *	43% *	53% *	34% *	38% *	41% *	45% *	47% *	35.13%
Palladium	24% *	35% *	41% *	44% *	36% *	41% *	47% *	50% *	38% *	41% *	44% *	41% *	42% *	40.36%
Platinum	13% *	21% *	29% *	33% *	34% *	40% *	47% *	55% *	32% *	35% *	36% *	40% *	41% *	35.14%
Regular Gas	32% *	18%	2%	26% *	38% *	16%	-2%	12%	-2%	-10%	-3%	26%	24%	13.68%
Silver	13%	17% *	21% *	25% *	19% *	23% *	28% *	34% *	27% *	29% *	33% *	31% *	33% *	25.68%
Soybean Meal	29% *	50% *	60% *	63% *	44% *	52% *	55% *	56% *	52% *	56% *	56% *	58% *	58% *	52.88%
Soybean Oil	29% *	51% *	61% *	65% *	45% *	54% *	62% *	64% *	54% *	59% *	61% *	56% *	59% *	55.40%
Soybeans	16% *	31% *	37% *	47% *	35% *	44% *	53% *	52% *	47% *	54% *	52% *	46% *	49% *	43.39%
Sugar	31% *	46% *	58% *	71% *	46% *	54% *	60% *	67% *	52% *	54% *	54% *	58% *	59% *	54.70%
Unleaded Gas	44% *	55% *	56% *	65% *	51% *	47% *	53% *	58% *	57% *	57% *	60% *	62% *	60% *	55.78%
Western Plywood	-8%	-27% *	-28% *	-36% *	-19%	-36% *	-46% *	-51% *	-40% *	-55% *	-53% *	-42% *	-42% *	-36.98%
Wheat	18% *	28% *	41% *	51% *	30% *	37% *	42% *	56% *	46% *	49% *	53% *	56% *	62% *	43.91%
White Wheat	-7%	13%	37% *	35% *	8%	25% *	35% *	30% *	30% *	37% *	37% *	26% *	34% *	26.25%
Average	23.63%	33.13%	40.04%	44.21%	34.16%	38.08%	42.46%	45.68%	39.67%	40.93%	41.07%	43.50%	44.48%	39.31%

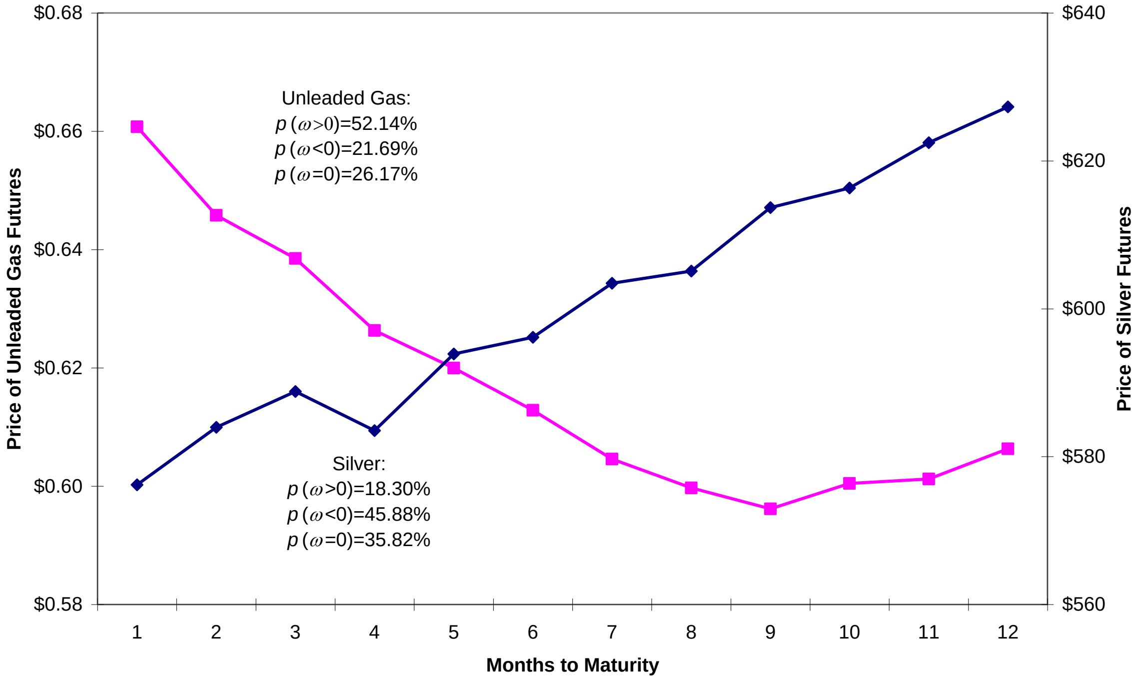
R is the ranking period, *H* is the holding period of the momentum strategy. The roll-return is measured as a function of the time *t* price differential between the nearest contract and the most distant contract. The position dummies assign positive values to the commodity futures that are bought, negative values to the commodity futures that are sold and a value of 0 to the commodity futures that are neither bought, nor sold. * indicates that the correlation is significant at the 5% level (using Pearson correlation test).

A closer look at the results in Table 2.7 reveals that the correlations between the roll-returns and the position dummies are negative and mainly significant for western plywood, suggesting that the momentum strategies buy western plywood in contangoed markets and sell it in backwardated markets. The correlations in Table 2.7 are insignificantly different from zero for the futures on aluminum, gold and regular gas, an indication that the momentum profits do not depend on whether these markets are in backwardation or contango. This suggests that dropping the futures on western plywood, aluminum, gold and regular gas from the set of contracts on which the momentum strategies is implemented could further enhance the profitability of the trading rule.

The term structure of futures prices can also be used to reveal whether a market is backwardated or contangoed. A backwardated market has a downward-sloping term structure, as the time t futures prices of nearby contracts exceed that of more distant contracts. Conversely, a contangoed market has an upward-sloping term structure, as, in this case, prices of distant contracts exceed prices of nearby contracts. Figure 2.2 pictures the term structure of average futures prices of two commodities (unleaded gas and silver) as the average futures prices across contracts 1 to 12 months before maturity.[14] The plots clearly suggest that unleaded gas tend to be on average in backwardation over the period January 1979 – September 2004, while silver was contangoed more often than not. Figure 2.2 also presents $p(\omega>0)$, $p(\omega<0)$ and $p(\omega=0)$, the percentages of times the 13 momentum strategies buy, sell or ignore each of the two commodity futures. In line with our hypothesis that the momentum strategies buy backwardated contracts and sell contangoed contracts, we bought unleaded gas futures, a backwardated contract, 52.14% of the times and sold silver futures, a contangoed contract, 45.88% of the times.

[14] Because most futures contracts do not trade for more than one year, the term structure of average prices is estimated with reference to the 12 months before maturity. Average prices on contracts with maturities exceeding 12 months are meaningless as then too few observations are considered.

Figure 2.2. Term structure of average futures prices: Unleaded gas and silver



The figure presents the average prices of unleaded gas and silver futures 1 to 12 months before maturity. $p(\omega>0)$ is the percentage of long positions across the 13 profitable momentum strategies, $p(\omega<0)$ is the percentage of short positions across the 13 profitable momentum strategies and $p(\omega=0)$ is the percentage of times the 13 momentum strategies disregard the commodity futures.

2. 4. 4. Momentum, diversification and inflation hedge

Commodity futures are well-known for their properties as risk diversifiers. Table 2.8 reports the correlations between the momentum returns and the returns of traditional asset classes. Across the 13 profitable strategies, the average correlation between the momentum returns and the returns of the S&P500 composite index is -0.02, ranging from a low -0.06 (for the 12-1 and 12-3 strategies) to a high of 0.05 (for the 3-6 strategy). The correlations between the momentum returns and the Treasury-bill or Treasury-bond rates are equally low with averages at 0.03 and 0.04, respectively. None of the correlations with the S&P500 returns, the Treasury-bond or Treasury-bill rates are significant at the 5% level. These results corroborate the evidence in Table 2.5 on the lack of sensitivity of the momentum returns to equity and bond returns. 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 total risk of their equity and/or fixed-income portfolios.

Table 2.8. Diversification and inflation hedge

	US T-Bill	US T-Bond	S&P500	Commodity	Inflation
Panel A: Ranking Period of 1 Month					
H = 1	0.09	-0.04	-0.05	-0.01	0.03
H = 3	0.00	0.03	-0.04	0.11 **	-0.02
H = 6	0.01	0.06	0.02	0.10 **	-0.06
H = 12	0.00	0.06	-0.03	0.14 *	-0.05
Panel B: Ranking Period of 3 Months					
H = 1	0.00	0.03	-0.03	0.15 *	-0.01
H = 3	0.03	0.07	0.03	0.18 *	-0.04
H = 6	0.03	0.07	0.05	0.16 *	-0.04
H = 12	0.03	0.07	-0.05	0.16 *	0.02
Panel C: Ranking Period of 6 Months					
H = 1	0.07	0.05	-0.02	0.11 **	-0.01
H = 3	0.03	0.06	0.03	0.13 *	-0.03
H = 6	0.05	0.02	0.00	0.09	0.01
Panel D: Ranking Period of 12 Months					
H = 1	0.03	0.02	-0.06	0.14 *	0.02
H = 3	0.01	0.05	-0.06	0.14 *	0.04
Average	0.03	0.04	-0.02	0.12	-0.01

The table reports correlations between the returns of momentum portfolios and the returns of different asset classes. *H* is the holding period of the momentum strategy. * and ** indicate that the correlation is significant at the 1 and 10% level, respectively (using Pearson correlation test).

The correlations between the momentum returns and the S&P-GSCI excess returns are mainly positive and significant. This backs up the evidence in Table 2.5 of positive and significant loadings of the momentum returns on the S&P-GSCI excess returns. The positive correlations and loadings can in turn be explained by the relatively high weighting of S&P-GSCI towards energy derivatives (Erb and Harvey, 2006) and the long positions of momentum portfolios in backwardated energy markets (as evidenced, for example, in Figure 2.2).

Table 2.8 also reports the correlations between the momentum returns and the percentage change in the consumer price index (used as a proxy for short-term unexpected inflation). The correlations are insignificant and range from -0.06 to 0.04. This indicates that the strategies do not offer a hedge against short-term unexpected inflation. The incremental returns and the added benefits of diversification come at the cost of losing the inflation hedge that is naturally provided by commodities (Bodie and Rosansky, 1980; Bodie, 1983). This result corroborates the evidence in

Erb and Harvey (2006) who question the ability of excess commodity futures returns to act as an inflation hedge.

2. 5. Contrarian Strategies

Table 2.9 reports summary statistics of returns of long-term contrarian strategies. A contrarian strategy advocates that the losers (winners) in the ranking period will turn into winners (losers) in the holding period. As a result, a contrarian strategy that tactically allocates wealth towards the long-term underpriced losers and away from the long-term overpriced winners should be profitable.

The results in Table 2.9 indicate that the systematic rebalancing of commodity futures using a contrarian approach is not a source of abnormal returns in commodity futures markets. There is no evidence that past winners turn into losers over ranking and holding periods that range from 2 to 5 years. In the meantime, past losers systematically keep losing (the average return of the loser portfolios ranges from -5.12% to -0.72% a year). As a result, none of the contrarian strategies is profitable. There is even evidence that a momentum strategy is profitable at the 10% level, if the ranking period is set to 5 years and the holding period to 3 or 5 years.

The contrarian pattern identified in stock markets over long-term horizons by De Bondt and Thaler (1985) is not present in commodity futures markets. For price reversals to occur in commodity futures markets, contracts would need to switch every 2 to 5 years from backwardation to contango. Then, the winners in the ranking period (namely, in backwardated markets) would become losers in the holding period (namely, in contangoed markets). Conversely, if markets switched every 2 to 5 years from contango to backwardation, the losers in the ranking period (namely, in contangoed markets) would become winners in the holding period (namely, in backwardated markets). In both cases, a contrarian strategy would be profitable. The lack of price reversals in commodity futures markets is therefore possibly due to the fact that commodity futures markets do not switch over horizons of 2 to 5 years from backwardation to contango (or, conversely, from contango to backwardation).

Table 2.9. Summary statistics of returns of contrarian strategies

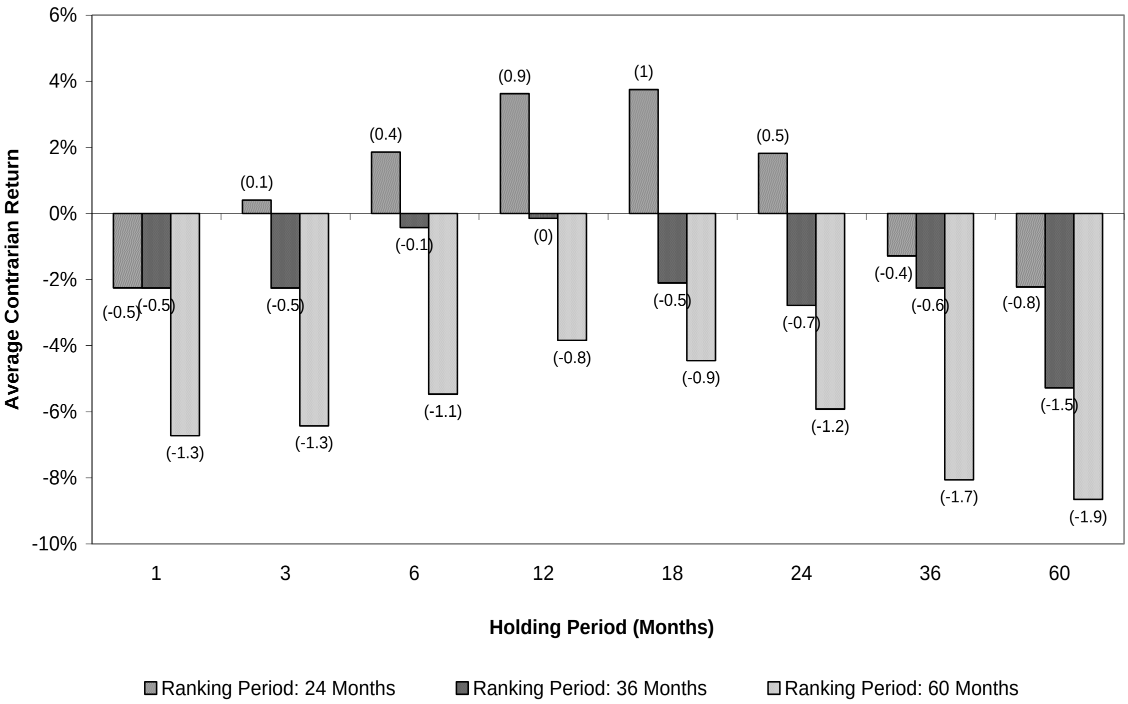
	Holding Period of 2 Years			Holding Period of 3 Years			Holding Period of 5 Years		
	Winners	Losers	Contrarian	Winners	Losers	Contrarian	Winners	Losers	Contrarian
Panel A: Ranking Period of 2 Years									
Mean	-0.0254	-0.0072	0.0182	-0.0130	-0.0259	-0.0129	0.0037	-0.0186	-0.0223
	(-0.87)	(-0.24)	(0.50)	(-0.46)	(-0.91)	(-0.41)	(0.14)	(-0.66)	(-0.80)
Standard deviation	0.1366	0.1406	0.1680	0.1294	0.1299	0.1442	0.1177	0.1212	0.1206
Reward-to-risk ratio	-0.1856	-0.0513	0.1080	-0.1002	-0.1990	-0.0894	0.0315	-0.1531	-0.1846
Panel B: Ranking Period of 3 Years									
Mean	-0.0129	-0.0407	-0.0278	0.0011	-0.0215	-0.0226	0.0214	-0.0314	-0.0528
	(-0.41)	(-1.24)	(-0.68)	(0.04)	(-0.68)	(-0.59)	(0.73)	(-1.00)	(-1.55)
Standard deviation	0.1438	0.1494	0.1867	0.1376	0.1408	0.1704	0.1240	0.1323	0.1436
Reward-to-risk ratio	-0.0893	-0.2723	-0.1490	0.0082	-0.1526	-0.1326	0.1726	-0.2376	-0.3679
Panel C: Ranking Period of 5 Years									
Mean	0.0353	-0.0239	-0.0592	0.0475	-0.0331	-0.0806	0.0354	-0.0512	-0.0866
	(0.99)	(-0.68)	(-1.22)	(1.34)	(-0.96)	(-1.72)	(0.95)	(-1.58)	(-1.88)
Standard deviation	0.1548	0.1520	0.2106	0.1490	0.1461	0.1980	0.1481	0.1286	0.1829
Reward-to-risk ratio	0.2281	-0.1573	-0.2812	0.3188	-0.2269	-0.4073	0.2391	-0.3979	-0.4734

The mean and standard deviation are annualized. The reward-to-risk ratio is measured as the ratio of the annualized mean to the annualized standard deviation. *t*-ratios for the significance of the mean are in parentheses.

The absence of price reversals may also be due to the fact that many commodity futures have had negative average returns over the period considered, with an equally-weighted portfolio of the 31 futures yielding an average return merely equal to -2.64% a year. As a result, the loser portfolios keep losing not simply over the short run (as in Tables 2.1, 2.2 and 2.3) but also over longer horizons (in Table 2.9). Possibly for the same reason, we barely found any evidence of price continuation in the momentum winners in Tables 2.1, 2.2 and 2.3.

Figure 2.3 pictures the average returns of the contrarian strategies over increasing holding periods. For a given ranking period, the relationship between average contrarian return and holding period is n-shaped, suggesting that the contrarian strategies perform better for intermediate holding periods. The contrarian strategies with a 5-year ranking period offer the most negative returns, while the strategies with a 2-year ranking period perform relatively better. These contrarian returns are however insignificant at the 10% level, making even these strategies unprofitable.

Figure 2.3. Average contrarian returns over different holding periods



The figure presents the average returns of contrarian portfolios for 3 ranking periods and for holding periods of increasing length. *t*-ratios for the significance of the mean are reported in parentheses.

2. 6. Conclusions

This chapter looks at the performance of 56 momentum and contrarian strategies in commodity futures markets. We build on the research of Erb and Harvey (2006) who focus on one momentum strategy. While contrarian strategies do not work, 13 momentum strategies are found to be profitable in commodity futures markets over horizons that range from 1 to 12 months. Our tactical allocation in commodity futures markets generates an average return of 9.38% a year. Interestingly, a portfolio that equally weights the 31 commodity futures considered in the study lost 2.64% a year over the same period. The momentum returns are also found to have low correlations with the returns of traditional asset classes, making therefore our relative-strength portfolios good candidates for inclusion in well-diversified portfolios.

While the momentum profits are not a compensation for risk (whether it is constant or time-dependent), they are related to the backwardation and contango theories. The results indeed indicate that the momentum strategies buy backwardated contracts and sell contangoed contracts. This result implicitly suggests that a momentum strategy that consistently trades the most backwardated and contangoed contracts is likely to be profitable. In the next chapter we are trying to investigate this suggestion.

In the next chapter we test the possibility that the momentum profits may be eroded by transaction costs or may be a compensation for thin trading and market frictions (as in Lesmond et al., 2004). The annual turnover and trading costs of these strategies is tested and a net return is being reported.

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

3. 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. Gorton and Rouwenhorst (2006) show that the high basis portfolio of commodities, the one with the high roll-return in their study, outperforms the low basis portfolio, the one with the low roll-return). In a similar way, Erb and Harvey (2006) and our research of the first chapter 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.[15]

This chapter 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

[15] 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).

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.

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 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.

This chapter proceeds as follows. Section 3.2 presents the dataset. Sections 3.3 and 3.4 analyze the profits of the individual momentum strategies and term structure strategies, while Section 3.5 studies the performance of strategies that jointly exploit momentum and term structure signals. Section 3.6 provides robustness checks and Section 3.7 concludes.

3. 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. All contracts used in this chapter and their performance and descriptive characteristics are presented in Table 3.1. It entails the start date of inclusion for each contract and the exchange it is traded.

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.

On the performance side, nickel has the highest average annual return standing at 0.269, surpassing unleaded gas at 0.24, in direct contrast to cocoa and wheat that show the lowest returns at -0.061 and -0.053, respectively. Natural gas and sugar are the most volatile commodities compared to feed cattle that exhibits the lowest volatility.

Table 3.1. Momentum Strategies: Summary Statistics

Commodity	Ann.Mean	Ann.Volatility	Exchange	Ticker	Start Date
Aluminum	0,0296	0,1630	LME	LA	24/7/1997
Brent Crude	0,1806	0,3294	ICE	LCR	7/12/1988
Cocoa	-0,0614	0,2911	NYBOT	NCC	29/12/1978
Coffee	0,0295	0,3907	NYBOT	NKC	29/12/1978
Copper	0,1216	0,2420	LME	LP	24/7/1997
Corn	-0,0497	0,2263	CBT	CC.	29/12/1978
Cotton	0,0036	0,2444	NYBOT	NCT	29/12/1978
Crude Oil	0,1433	0,3305	NYMEX	NCL	30/3/1983
Diammonium	-0,0038	0,1460	CBT	CDP	21/10/1991
Diammonium	0,1089	0,0859	CME	CDI	7/6/2004
Feed Cattle	0,0287	0,1454	CME	CFC	29/12/1978
Froz. Pork	0,0001	0,3884	CME	CPB	2/1/1979
Gas Oil	0,1394	0,3238	ICE	LLO	6/4/1981
Gasoline Unleaded	0,2399	0,4020	NUMEX	NHU	3/12/1984
Gold	-0,0022	0,1866	CMX	NGC	29/12/1978
Heating Oil	0,1880	0,3721	NYMEX	NHO	29/12/1978
Kansas Wheat	0,0208	0,2002	Kansas City BOT	KKW	29/12/1978
Lead	0,1157	0,2460	LME	LL	24/7/1997
Lean Hogs	0,0408	0,2606	CME	CLH	29/12/1978
Live Cattle	0,0708	0,1621	CME	CLC	29/12/1978
Lumber	-0,0434	0,3089	CME	CLB	29/12/1978
Milk	-0,0457	0,1960	CME	CFM	25/3/1996
Natural Gas	0,0879	0,5366	NYMEX	NNG	3/4/1990
Nickel	0,2692	0,3594	LME	LN	24/7/1997
Oats	-0,0188	0,3247	CBT	CO	29/12/1978
Orange Juice conc.	0,0129	0,2939	NYCE	NJO	29/12/1978
Palladium	0,0732	0,3637	NYMEX	NPA	29/12/1978
Platinum	0,0557	0,2591	NYMEX	NPL	29/12/1978
Silver	0,0231	0,3592	CMX	NSL	29/12/1978
Soybean meal	0,0409	0,2426	CBT	CSM	29/12/1978
Soybean oil	-0,0119	0,2571	CBT	CBO	29/12/1978
Soybeans	-0,0174	0,2224	CBT	CS.	29/12/1978
Sugar	-0,0319	0,4434	NYBOT	NSB	29/12/1978
Tin	0,1066	0,2026	LME	LT	24/7/1997
Wheat	-0,0535	0,2165	CBT	CW.	29/12/1978
White Wheat	0,0246	0,1764	MGE	MNW	31/1/1991
Zinc	0,0543	0,2514	LME	LX	24/7/1997

Ann.Mean: Annualized arithmetic mean/return
Ann.Volatility: Annualized standard deviation (volatility)

This chapter 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).[16] 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.[17] 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 3.3 to 3.6), but also the return earned on the collateral in excess of any margin call. This chapter 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).

[16] 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.

[17] 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.

3. 3. Single-Sort Strategies Based on Momentum

3. 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).[18] In the previous chapter we extend this finding to futures markets. This chapter 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 the first chapter of this thesis *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 being held (shorted) that combines the *H* overlapping winner

[18] 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).

(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 our previous chapter. 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.[19]

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

$$R_{Pt} = \alpha + \beta_B \left(R_{Bt} - R_{ft}\right) + \beta_M \left(R_{Mt} - R_{ft}\right) + \beta_C \left(R_{Ct} - R_{ft}\right) + \varepsilon_{Pt} \tag{3.1}$$

where R_{Pt} is the excess return (without the return of the collateral) 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.[20]

3. 3. 2. Performance evaluation and risk management

Table 3.2 reports summary statistics for the 13 winners (Panel A), 13 losers (Panel B) and 13 momentum portfolios (Panel C) outlined above.[21] Table 3.3 sets out the parameter estimates and significance tests for equation (3.1). Despite differences in the samples employed, the evidence confirms the main findings of our first chapter,

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[19] 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.

[20] 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.

[21] The Ljung-Box test unambiguously suggests that the monthly returns summarized in Table 3.2 are not autocorrelated despite arising from an overlapping-portfolio strategy. This is because (as explained in Section 3.3.1) the December return of, say, a 6-3 strategy is obtained as the *average* of the 3 winner (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.

namely, that trend-following is a reliable source of returns in commodity futures markets.

Table 3.2. 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 3.3. 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 (3.1). 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 3.2, 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 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 3.2, Panel A generate a positive and significant average return across strategies of 8.75% a year. In contrast, the losers in Table 3.2, Panel B generate a negative (albeit insignificant) average return at -1.46%. Hence, over the 1979-2007 period, the profitability of momentum strategies appears to be driven by the winners.[22]

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).[23] 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

[22] Similarly, the maximum 12-month rolling returns of the winner portfolios in Table 3.2, 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 3.2, Panel B (at 43.33% on average).

[23] Cornish-Fisher Value-at-Risk is a measure of the likely loss at a given confidence level (quintile) that takes the higher moments (skewness and kurtosis) of non-normal distributions into account through the use of a Cornish and Fisher (1937) expansion, better approximating the shape of the true distribution. Cornish-Fisher VaR will give a larger loss estimate than traditional VaR when returns are negatively skewed or highly kurtotic, penalizing both negative skewness and excess kurtosis.

of the portfolios. [24] The results in Panel C of Table 3.2 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 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 (3.1).[25] The results in Table 3.3 suggest that, in line with our first chapter, 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.[26] 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).

[24] Sortino ratio is a variation of the Sharpe ratio. Similarly, it measures the risk-adjusted return but differentiates harmful volatility from volatility in general by replacing standard deviation with downside deviation in the denominator.

[25] 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.

[26] 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 3.2.

3. 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 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 0.5% estimate of Jegadeesh and Titman (1993) or the more conservative 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 important to assess the impact of trading costs on the momentum profits. Three elements influence the buying and selling of a commodity contract in our strategies and hence, the strategies' turnover in direct comparison with the benchmark's turnover. These are: *a*) the rolling of contracts as maturity approaches, which is something in common with the benchmark. The difference may arise because of the selected constituents of our strategies, their different allocations in the portfolios and their possibly different maturities compared to the constituents of the benchmark; *b*) the change in the constituents of the active portfolios at the time of portfolio construction, in case there is a change; and *c*) the monthly rebalancing to equal weights of the prior constituents, in case there is no change in portfolio construction.[27] 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.[28] The results are reported in the last two rows of Table 3.2, Panel C. A turnover statistic of 1 indicates that we buy and sell the

[27] The monthly rebalancing to equal weights of the constituents that continue to be part of the portfolio is minimal compared to the other two transaction costs and is not considered in this study.

[28] 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.

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).

Once we know how many times we buy and sell our portfolios in a year, we calculate the average trading costs per round-trip. A futures trader's position turnover typically incurs the transaction costs of the commissions, the full bid–ask spread witnessed in the market and any price impact from his own trading flows. We limit our analysis of trading costs to the measurement of round-trip transaction costs, proxied by the bid–ask spread, and ignore our own possible price impact and commissions.[29] In commodity futures markets transaction costs vary across commodity contracts and across time, dependent on liquidity and trading volume. Because of no access to the appropriate databases and in order to decrease the complexity of the calculations, we use only one common round-trip trading cost and this is the conservative upper range of 0.033% of Locke and Venkatesh (1997), expressed as a percentage of the notional portfolio value. Locke and Venkatesh obtained trade register data from the Commodity Futures Trading Commission (CFTC) and directly calculated effective bid–ask spreads for 12 different futures contracts on the Chicago Mercantile Exchange (CME) over the period January 1, 1992, through June 30, 1992. Thus, comparing the liquidity of commodity futures over this period to the liquidity over the whole period of our study, can give us valuable information on the conservatism of using Locke and Venkatesh round-trip trading costs.[30] As it can be observed in Figure 3.1, the lower average trading volume of commodity futures in this specific period, compared to the whole, reinforces the conservatism and the probability of overestimation of our selected trading costs. Of course, the overall higher trading volume does not limit the possibility that the superior performance of our trading strategies is a compensation for a lack of liquidity only in the selected portfolio constituents or only at the time of each selection, rather than a lack of liquidity of all commodities under study. This possibility is fully addressed, when performing robustness analysis checks in section 3.6.1.

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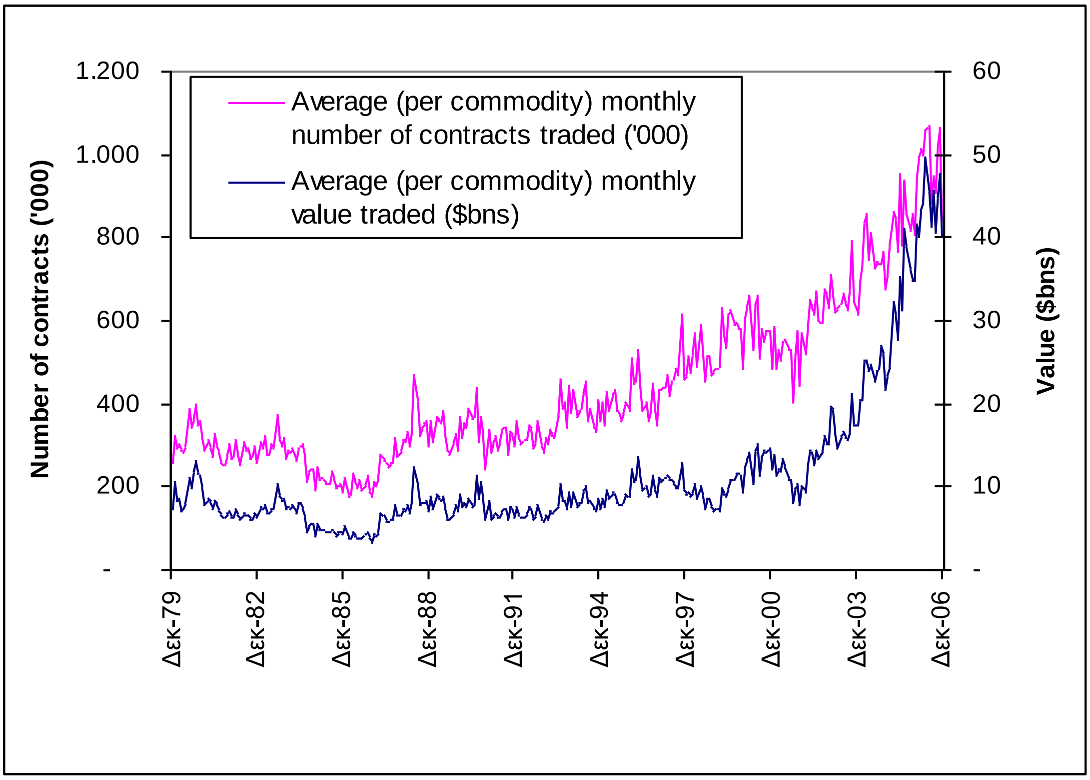
[29] Large traders can negotiate extremely low commissions taking into account the rebates received.

[30] Liquidity can be proxied by the total $ trading value or the total number of contracts traded. It can be also proxied by the ratio of absolute return to its $ trading volume averaged over a given period, called the Amihud ratio (Amihud, 2002). Intuitively, the latter one can be interpreted as the daily price response associated with one $ of trading volume.

Figure 3.1. Commodity Futures Liquidity



The liquidity of commodity futures is measured both in total $ value terms of the commodities traded and in total number of contracts traded. The average value and number of contracts traded across all commodities studied in this chapter are presented above.

Table 3.2 reports estimates of the net momentum returns after accounting for transaction costs. 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.

3. 4. Single-Sort Strategies Based on Term-Structure

3. 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 an indication or result of the market being in 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 an indication or result of the market being in 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 an 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:

$$R_t = \left[\ln\left(P_{t,n}\right) - \ln\left(P_{t,d}\right)\right] \times \frac{365}{N_{t,d} - N_{t,n}} \tag{3.2}$$

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 (3.2) 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 rebalancing 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 rebalances 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).

3. 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 3.4. 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 3.4 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 3.2. As with momentum in Table 3.2, 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.

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 $TS_{3,i}$.

Table 3.4. 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.

Second, analysing 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 3.C) suggesting that, for 4 out of the 6 term structure strategies considered, the EOM and 15M returns are undistinguishable. 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 3.4 and Table 3.5 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.[31]

Third, and as in Table 3.2, the active strategies on average bear substantially more risk than the passive benchmark. For example, the annualized volatility, downside volatility and 99% Cornish-Fisher Value-at-Risk (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.[32] 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.

[31] 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 frequency, over the time period and for the cross section covered in our study, we cannot test this hypothesis directly.
[32] The results for the reward-to-risk ratios are consistent with Erb and Harvey (2006).

The multifactor model estimates are reported in Table 3.5. For virtually all of the 7 profitable term structure strategies identified in Table 3.4, the returns of the long-short portfolios follow the ups and downs of the S&P GSCI but are unrelated to the S&P500 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 3.4, 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.

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.

Table 3.5. 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 (3.1). 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.

3. 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 3.5.1), analyzes its performance (Section 3.5.2) and investigates the ability of the combined portfolio to serve as a tool for risk diversification (Section 3.5.3).

3. 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 first chapter). 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 3.6 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%.

Table 3.6. 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.

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.

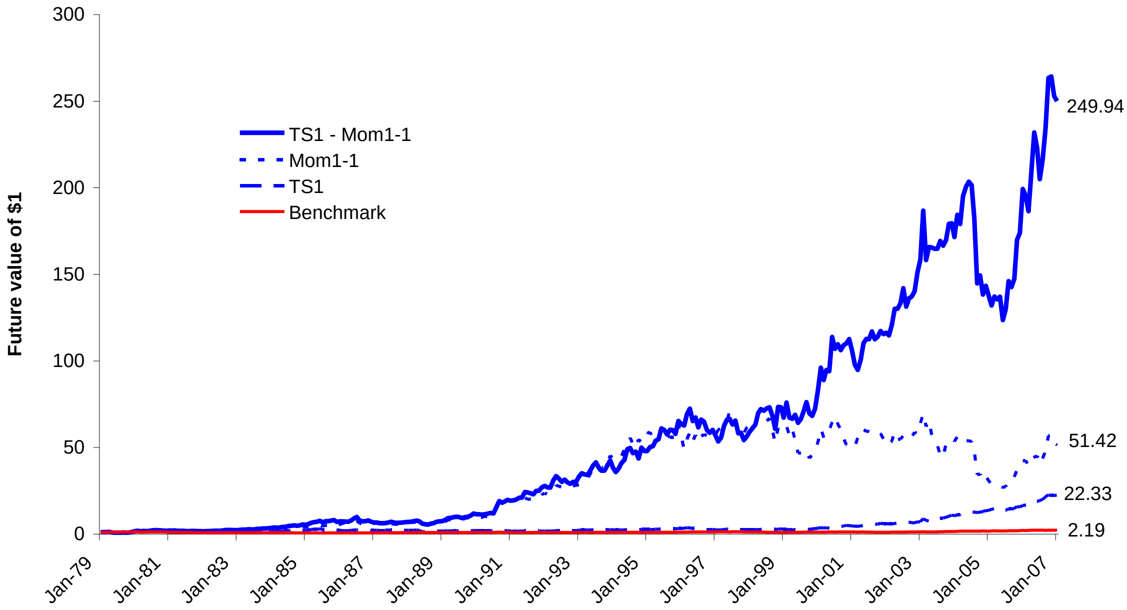
The choices of one-month holding period (H=1) and monthly rebalancing were dictated by the fact that, as illustrated in Tables 3.1-3.4, the momentum strategies with H=1 and the TS_1 strategy stand out as the most profitable.[33] Following the evidence of Tables 3.1 and 3.2, the ranking periods (R) are 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 3.6. 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.

[33] Given the superior performance of TS_1 (versus TS_2) shown in Tables 3.3 and 3.4, 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.

3. 5. 2. Performance evaluation, risk management and transaction costs

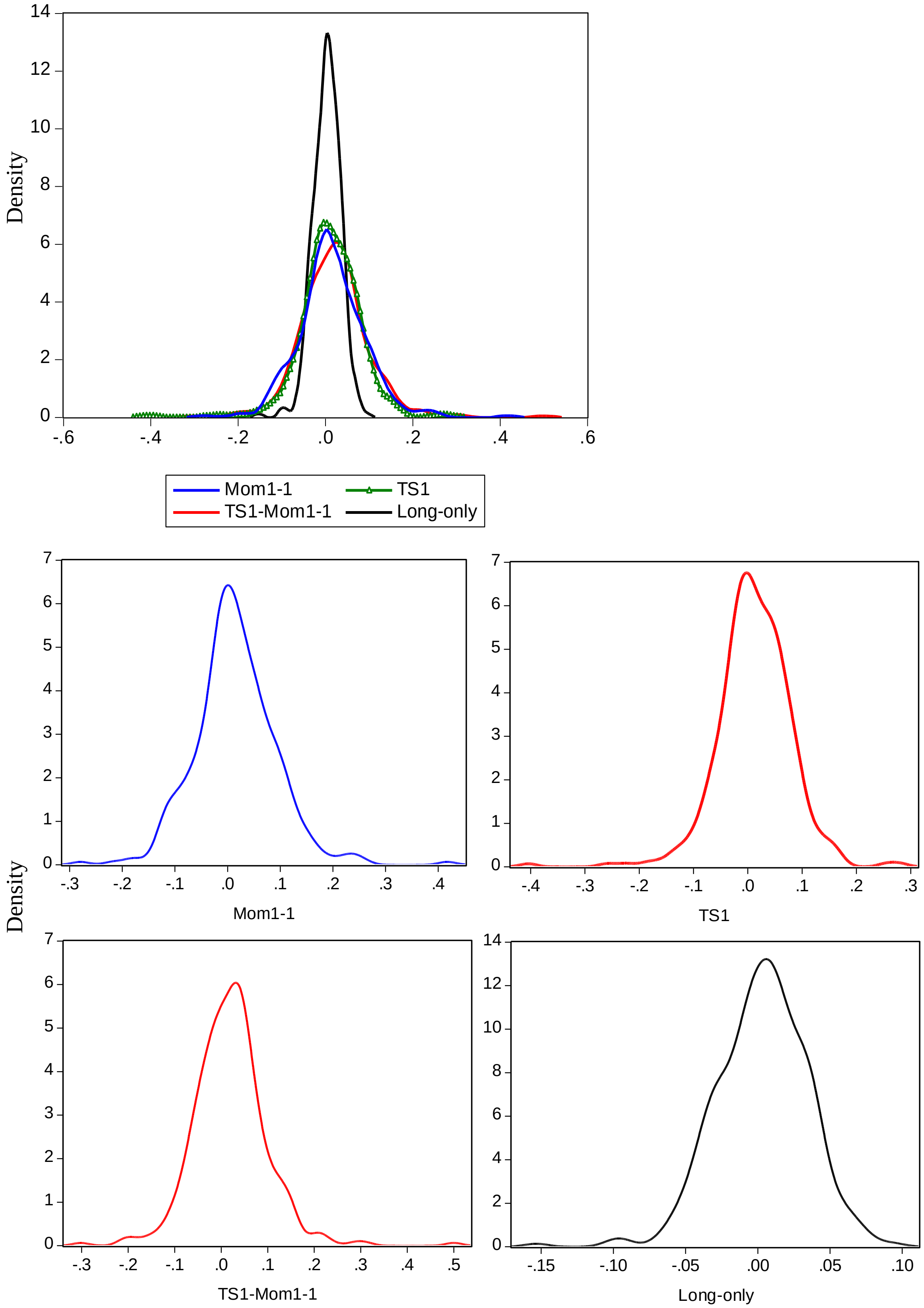
Figure 3.2 plots the future value of \$1 invested in TS_1-$Mom_{1\text{-}1}$, $Mom_{1\text{-}1}$, TS_1 and the passive benchmark. Figure 3.3 plots the corresponding return distribution. Both figures bear out the outstanding performance and very high risk of the active double- or single-sort strategies relative to the passive benchmark. Figure 3.2 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.

Figure 3.2. 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 3.3. Returns Distributions



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.

Table 3.7 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 3.1 and 3.3) at 10.53% and 12.28%, respectively.

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 3.1 and 3.3 for the single-sort strategies.

Table 3.7. 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 (3.1). 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.

Relative to the individual baseline strategies (c.f. Tables 3.1 and 3.3), 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 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).[34] 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 3.3) 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 simple risk-adjusted basis, the most

[34] 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.

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 3.7, Panel B). Consistent with the individual trading strategies in Tables 3.2 and 3.4, 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 3.3) and the TS-only strategies (c.f. Table 3.5), 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.

3. 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 3.8 through the Pearson correlation coefficient (and significance t-statistics) between their returns and those of traditional asset classes.

Table 3.8. 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.

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 3.7) 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 3.7). 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.

3. 6. Robustness Analysis

In this section, we investigate whether the superior profits of the double-sort portfolios are a compensation for liquidity risk (Section 3.6.1), withstand alternative specifications of the risk-return trade-off (Sections 3.6.2 and 3.6.3) and are robust to an extended sample that takes into account the credit crunch (Section 3.6.4).

3. 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 3.9, 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 3.5.

Table 3.9. 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** (2.37)
Average	*0.1937*			*0.1594*				
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** (3.69)
Average	*0.1786*			*0.1654*				

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.

If the success of the proposed combined strategies in Section 3.3.5 is partly an artifact of liquidity risk, then the *HV* portfolios in Table 3.9 should underperform the corresponding double-sort portfolios in Table 3.7. 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 3.7 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 3.9 (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 3.9; 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_{1-1} and *LV*-TS_1-Mom_{1-1} portfolios (19.81% and 17.63%; Table 3.9) are lower than the unconditional mean return of the TS_1-Mom_{1-1} double-sort portfolio (23.55%; Table 3.7). 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-Mom_{1-1} (23.55%). Clearly this is not the case. One possible explanation for this puzzle relates to the diversification return of Erb and Harvey (2006).[35] The latter comes from frequently rebalancing a portfolio of commodity futures to equal weights and equals

$$\frac{1}{2}\left(1-\frac{1}{K}\right)\bar{\sigma}^2\left(1-\bar{\rho}\right),$$ [36]

where K is the number of assets in the portfolio, $\bar{\sigma}^2$ is the average variance of the constituents and $\bar{\rho}$ is their average correlation. Clearly, the diversification return rises with K and $\bar{\sigma}^2$ and falls with $\bar{\rho}$. 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.

3. 6. 2. 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.[37]

[35] 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.
[36] Erb and Harvey, 2006, p.86.
[37] 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.

The coefficient estimates and significance *t*-ratios, set out in Appendix 3.A, 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.

3. 6. 3. 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 (3.3) that allows for the measures of risk and abnormal performance in (3.1) to vary over time as a function of Z_{t-1}, a vector of pre-specified zero-mean information variables (Christopherson et al., 1998).[38]

$$\begin{aligned} R_{Pt} = \alpha_0 + \alpha_1 Z_{t-1} + \\ \beta_{B0}\left(R_{Bt} - R_{ft}\right) + \beta_{B1}\left(R_{Bt} - R_{ft}\right)Z_{t-1} + \\ \beta_{M0}\left(R_{Mt} - R_{ft}\right) + \beta_{M1}\left(R_{Mt} - R_{ft}\right)Z_{t-1} + \\ \beta_{C0}\left(R_{Ct} - R_{ft}\right) + \beta_{C1}\left(R_{Ct} - R_{ft}\right)Z_{t-1} + \varepsilon_{Pt} \end{aligned} \tag{3.3}$$

The results, reported in Appendix 3.B, indicate the presence of time variation in the risk and performance measures of the multifactor model (3.1). 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 (3.1), 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 (3.1), the average alpha of the active strategies is of similar magnitude as previously

[38] 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.

reported. A total of 19 out of 31 strategies have positive and significant α at the 5% level in Appendix 3.B versus 23 in Tables 3.2, 3.4 and 3.6. 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.

3. 6. 4. 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. Bearing this in mind, we extend the dataset until the end of November 2008 and report in Table 3.10 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-$Mom_{1\text{-}1}$, and the benchmark equal 18.31%, 14.65%, 23.15% and 2.42%, respectively.

Table 3.10. Performance over an Extended Sample: January 1979 – November 2008

	$Mom_{1\text{-}1}$			TS_1			TS_1 - $Mom_{1\text{-}1}$			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. $Mom_{1\text{-}1}$ 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.

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 extended sample January 1979-November 2008, Mom1-1, TS1 and TS1-Mom1-1 present reward-to-risk ratios of 0.69, 0.62 and 0.84, while the reward-to-risk ratio of the benchmark is at 0.20. The reward-to-risk ratio of the benchmark over the original period (January 1979-January 2007) was standing higher at 0.31 with the reward-to-risk ratios of Mom1-1, TS1 and TS1-Mom1-1 lower at 0.57, 0.59 0.85, respectively (Table 3.2, 3,4, 3.7).

3. 7. Conclusions

This chapter 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 of our first chapter, 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, 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 next chapter provides a thorough analysis of how these three types of active strategies and a new one based on the maturity of the contracts can be used in a long-only framework in commodity futures markets. We create enhanced indices based respectively on momentum, term structure, a combination of these two signals and the time-to-maturity of the contracts.

Appendix

Appendix 3.A. 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 (3.1) 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.

Appendix 3.B. Conditional Risk-Adjusted Performance

	α	*t*- statistic	p_1	p_2	p_3
Panel A: Momentum-Only Strategies					
Mom $_{1-1}$	**0.1657**	3.5333	0.3140	0.0000	0.0000
Mom $_{1-3}$	**0.0915**	3.1236	0.0777	0.0000	0.0000
Mom $_{1-6}$	**0.0619**	2.9704	0.1153	0.0071	0.0118
Mom $_{1-12}$	**0.0548**	3.4013	0.1100	0.0003	0.0003
Mom $_{3-1}$	**0.1408**	2.9240	0.0804	0.0000	0.0000
Mom $_{3-3}$	0.0795	1.9434	0.1137	0.0179	0.0088
Mom $_{3-6}$	0.0587	1.8776	0.0259	0.0005	0.0002
Mom $_{3-12}$	**0.0533**	2.1431	0.1101	0.0343	0.0231
Mom $_{6-1}$	0.0888	1.8588	0.0367	0.0015	0.0007
Mom $_{6-3}$	0.0673	1.5476	0.0483	0.0017	0.0013
Mom $_{6-6}$	**0.0853**	2.1970	0.0194	0.0218	0.0059
Mom $_{12-1}$	**0.1288**	2.6145	0.0300	0.0007	0.0002
Mom $_{12-3}$	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* $_{1-1}$	**0.2348**	4.9103	0.6343	0.0000	0.0000
TS_1 - *Mom* $_{3-1}$	**0.2133**	4.2339	0.0767	0.0000	0.0001
TS_1 - *Mom* $_{12-1}$	**0.2019**	4.0643	0.0156	0.0002	0.0001
Mom $_{1-1}$ - TS_1	**0.2319**	4.8324	0.4506	0.0000	0.0000
Mom $_{3-1}$ - TS_1	**0.1867**	3.5762	0.1410	0.0550	0.0590
Mom $_{12-1}$ - 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.

Appendix 3.C. EOM vs 15M portfolio formation

	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 EOM and 15M returns and significance *t*-statistic. Panel B reports 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.

4. Traditional and Enhanced Commodity Indices: Momentum, Term Structure and Maturity Signals

4. 1. Introduction

Indices are generally regarded as the simplest and most cost efficient way to acquire exposure to the underlying markets. In commodity markets the first index goes back to 1957 and was created by the Commodity Research Bureau (CRB) as a broad indicator of commodity price movements. Many indices followed. The traditional or first-generation indices tend to hold the most active contracts and promise a passive, long-only exposure to commodities. These indices are often considered as sub-optimal since they are long-only, rebalance infrequently and fail to take into account the term structure of commodity prices. To remedy these problems, a plethora of second-generation indices has emerged with each of these indices trying to outperform their first-generation counterparts by using market signals of influence to the commodity markets or by accurately reflecting on the propensity of commodity markets to be either in backwardation or in contango.

We are seeing these days a proliferation of customized indices and it has become increasingly more difficult for investors to tell them apart. The risks that these financial innovations bear are well hidden behind their complex technical specifications. The constituents, the allocations and the rolling procedures which influence the returns and risks, can be extremely different. These differences can become the true risk contributors rather than commodity prices. Indices become in reality strategies and this lack of knowledge on the indices and of research on the influencing factors behind them, poses difficulties for index comparison and investment decisions.

The first objective of this chapter is to provide a comparative review of the first and second generation indices that are offered to investors today, highlighting in the process their differentiating factors: the number of assets that are being hold, the weighting scheme, the rolling technique and contract schedule and the rebalancing frequency. Shining more light on the index world of commodities is considered of high importance especially after the renewed interest in commodity markets from investors.

The second objective is to propose a theoretical framework to facilitate choosing among commodity indices based on the factors that turn these indices into strategies. The goal is to assess the magnitude of the influence that these factors can have on the long-only commodity world. Apart from the momentum and term structure factors that were examined in a long-short framework in the previous chapters, a new time to maturity factor is found to exhibit a pivotal role influencing the performance of commodities. All factors are now considered in a long-only framework. New enhanced indices are proposed that not only provide long-only investors with similar risk exposure to the commodity market as do the S&P-GSCI or the DJ-UBSCI but also offer a performance that is higher than that of these two traditional indices.[39] These enhanced indices present different asset allocation than their traditional counterparts, with weightings based on momentum signals, term structure signals, the combination of both prior signals or the time-to-maturity signals of the contracts. Bearing in mind the asset allocation constraints of many traditional asset managers, the chapter assesses the tracking ability and alpha potential of these enhanced indices in a long-only framework. The results indicate that the long-only modified indices have very high correlation ranging from 95% to 99% with their traditional counterparts, suggesting that they are suitable tools to track the ups and downs of commodity markets. With alphas ranging from 0.49% to 6.18% a year, the enhanced indices also exhibit superior performance relative to the baseline S&P-GSCI and DJ-UBSCI.[40] The enhanced index that is found to outperform the most employs target maturities far away from the present seeking to capture what we call “time alpha”. By shining light on the technical characteristics of commodity indices and the factors they try to take advantage of, investors can assess the real, hidden risks behind the indices and facilitate choosing amongst them.

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[39] The choice of the S&P-GSCI and DJ-UBSCI was dictated by the fact that these two indices are heavily traded. JPMorgan estimates that there are $50bn in funds tracking the S&P-GSCI and $25bn tracking the DJ-UBSCI (5th Jan 2009, Financial Times). Although most investors trade through swaps, as of May 2004, the S&P-GSCI represented 86 percent of the combined open interest of the three indices, the DJ-UBSCI accounted for 10 percent, and the CRB made up the remaining 4 percent of open interest.

[40] When referred to the returns of the S&P-GSCI, the DJ-UBSCI and enhanced versions of thereof, we mean the excess returns of these indices. The returns of all the indices in this paper are fully collateralized, but we have not included the return of the collateral in our analysis.

This chapter proceeds as follows. Section 4.2 provides a comparative review of the first- and second-generation indices that are present in the market at the time of writing. Section 4.3 presents the dataset. Section 4.4 presents the S&P-GSCI and DJ-UBSCI indices and their replication approach. Sections 4.5, 4.6, 4.7 and 4.8 introduce the enhanced indices based respectively on momentum, term structure, a combination of these two signals and the time-to-maturity of the contracts. Finally section 4.9 concludes.

4. 2. Comparative Review of First and Second-Generation Indices

4. 2. 1. Traditional Commodity Indices

A short description follows of the most widely-used traditional indices.[41]

Standard & Poor's Goldman Sachs Commodity Index

S&P GSCI (former GSCI) was launched in 1991 and it currently consists of 24 constituents whose weight is based on the global production of commodities. It is heavily weighted toward energy. Weights rebalance every January. Rolls take place every month in a conventional front to second-month roll-schedule (see Table 4.1) over a five-day window between the fifth and ninth business days.

Table 4.1. Predefined Active Contracts

Commodity (Contract)	Designated Contract Expirations at Month Begin	
	GSCI	DJAIG
Wheat (Chicago)	H H K K N N U U Z Z Z H	H H K K N N U U Z Z Z H
Wheat (Kansas)	H H K K N N U U Z Z Z H	
Corn	H H K K N N U U Z Z Z H	H H K K N N U U Z Z Z H
Soybeans	H H K K N N X X X X F F	H H K K N N X X X X F F
Oil (Soybean)		H H K K N N Z Z Z Z F F
Coffee "C"	H H K K N N U U Z Z Z H	H H K K N N U U Z Z Z H
Sugar #11	H H K K N N V V VH H H	H H K K N N V V VH H H
Cocoa	H H K K N N U U Z Z Z H	H H K K N N U U Z Z Z H
Cotton #2	H H K K N N Z Z Z Z Z H	H H K K N N Z Z Z Z Z H
Lean Hogs	G J J M M N Q V V Z Z G	G J J M M N Q V V Z Z G
Cattle (Live)	G J J M M Q Q V V Z Z G	G J J M M Q Q V V Z Z G
Cattle (Feeder)	H H J K Q Q Q U V X F F	
Oil (WTI Crude)	G H J K M N Q U V X Z F	H H K K N N U U X X F F
Oil (#2 Heating)	G H J K M N Q U V X Z F	H H K K N N U U X X F F
Oil (RBOB)	G H J K M N Q U V X Z F	H H K K N N U U X X F F
Oil (Gasoline)	G H J K M N Q U V X Z F	H H K K N N U U X X F F
Oil (Brent Crude)	H J K M N Q U V X Z F G	
Oil (Gasoil)	G H J K M N Q U V X Z F	
Natural Gas	G H J K M N Q U V X Z F	H H K K N N U U X X F F
Aluminum (High Gd. Prim.)	G H J K M N Q U V X Z F	H H K K N N U U X X F F
Copper - Grade A	G H J K M N Q U V X Z F	H H K K N N U U Z Z Z H
Standard Lead	G H J K M N Q U V X Z F	
Primary Nickel	G H J K M N Q U V X Z F	H H K K N N U U X X F F
Zinc (Special High Grade)	G H J K M N Q U V X Z F	H H K K N N U U X X F F
Tin	G H J K M N Q U V X Z F	
Gold	G J J M M Q Q Z Z Z Z G	G J J M M Q Q Z Z Z Z G
Silver	H H K K N N U U Z Z Z H	H H K K N N U U Z Z Z H
Platinum	J J J N N N V V V F F F	
Orange Juice	H H K K N N U U X X F F	

[41] The sources of information for all the indices of the paper include the index manuals mentioned in the appendix and the websites of the service providers.

The table contains the futures months included in the S&P-GSCI and DJ-UBSCI at the beginning of each calendar month, starting with January. The letter codes are F (January), G (February), H (March), J (April), K (May), M (June), N (July), Q (August), U (September), V (October), X (November) and Z (December).

Dow Jones-UBS Index

DJ-UBS Commodity Index (former DJ-AIGCI) was launched in 1998 and it currently has 19 components. Their weight is based on the liquidity and production of the commodities over the last 5 years. Weights change every January. Rolls take place every month in a conventional front to second contract according to the roll-schedule (see Table 4.1) over a five-day window between the sixth and tenth business days.

Thomson Reuters/Jefferies CRB

Thomson Reuters/Jefferies CRB index was launched in 1957 and it currently consists of 19 constituents. Throughout its history it has undergone major revisions. The liquidity, the importance and the diversification of commodities are the main factors that determine the weightings of the index. The rebalancing process currently follows a nearby rollover schedule.

Rogers International Commodity Index

RICI was launched in 1998. It is one of the most diverse commodity indices with 36 constituents from eleven exchanges and denominated in four different currencies. The weight of each constituent is based on liquidity and consumption patterns in the developed and developing world. The rolling procedure is following the conventional front (most active) to second contract.

There have been various studies on commodity indices and their significance. Georgiev (2001) examines the inflation hedging properties of S&P-GSCI (former GSCI), DJ-UBSCI (former DJ-AIGCI) and S&P Commodity indices and finds that adding a commodity index to a diversified portfolio of assets can enhance risk-adjusted returns. Jensen et al. (2002) and Nihman and Swinkels (2003) confirm the favorable diversification properties of the S&P-GSCI and its subindices.

Regardless of these attractive properties for investors, a major criticism against commodity indices is that they fail to fulfill their primary purpose, namely, to accurately reflect the entire asset class. The construction and calculation methodology, the portfolio weightings, the transaction fees vary significantly from one index to another. While their goal would suggest similar exposures, their risk-return characteristics vary widely, to the extent that Erb and Harvey (2006) argue that commodity indices are in reality strategies. Akey (2007) documents vast differences in the performance of 6 commodity indices, e.g. the spread between the top and bottom performers was more than 1300 basis points in 2005 and the associated risk measures varied even further. The historical returns of commodity indices have been the subject of debate as well. The composition of these indices has changed substantially since they started trading. And Erb and Harvey (2006) criticize the pre-trading hypothetical returns of these indices arguing that the actual returns are the tangible ones. The backfilled history could entail subjective construction biases.

4. 2. 2. Second Generation Commodity Indices

Second generation indices have been introduced to solve some of the problems inherent in the first generation ones. For instance, short-term supply and demand disconnects and cyclical production cycles influence the shape of the commodities term structure. These changing term structure curves effectively imply that the traditional approach of rolling commodity futures on a pre-defined schedule is simply not using all the available information. Commodity markets can either trade in backwardation or in contango but the traditional indices do not position themselves favorably in this respect, i.e. they do not exploit the dynamic nature of commodity curves.

Commodities, as an asset class, exhibit idiosyncratic properties. For instance, regardless of the general direction of the market, commodities are likely to experience sharp drawdowns and sudden price volatility. Traditional commodity indices cannot protect themselves from severe price movements since they do not have the ability to drastically change their allocation. They cannot take advantage of the changing trends both in the general direction of the commodity market and in the cross section of the same market.

With different constituents relative to the traditional indices and different rebalancing frequency and weighting methodology, the second generation commodity indices have been designed so as to give investors a wider and more accurate exposure to commodities. More often than not, their target has shifted towards outperforming the traditional indices. The most well-known second generation indices are described just below.

Bache Commodity Index

The BCI was launched in 2007 and it currently has 19 components. Commodities are selected because of their importance to the sector and to the overall market. It employs a momentum allocation strategy and weights rebalance daily. Rolls take place every month in a conventional front to second contract according to the roll-schedule.

Diapason Commodities Index

The DCI was introduced in 2006 and it currently consists of 48 commodities. The original feature of this index is that it includes more assets than any other, offering investors the best diversification possible at the possible expense of a lack of liquidity. The weights of each commodity depend on liquidity and trade significance. The index is following the conventional roll from the front to the second contract based on a predefined roll-schedule.

Barclays Capital (former Lehman Brothers) Commodity Index Family

Barclays Capital LBCI was launched in 2006 and it currently consists of 20 components. It is rebalanced annually. Rolls take place between the fifth and ninth business days each month. It operates within the most liquid part of the relevant commodity futures curves. The Barclays Capital LBCI PB (pure beta) index was constructed in 2007 around the concept of providing the best proxy for commodities spot returns. Negative roll-yield is minimized by utilizing a weighting methodology that naturally underweights commodities that have been in contango and overweights commodities in backwardation on a daily basis.

Barclays Capital Commodity Index Family

The Commodities Out-performance Roll-Adjusted Liquid Strategy (CORALS) index was launched in 2008. It uses a systematic allocation model that feeds fundamental and technical data combined with a risk-based optimizer to produce an optimum monthly allocation (long or short) to 12 individual commodity indices of the S&P-GSCI. The Barclays Capital Momentum Alpha Index is adjusting its exposure according to historical alpha, it positions itself on the point of the commodity curve with the highest historical out performance. The Commodity Based Alpha Trading Strategy (COMBATS) is another recent innovation from Barclays Capital that was introduced in October 2009. It is trying to extract commodity alpha from long-short positions in a basket of ten commodity futures. It is a market neutral strategy that is going long the Barclays Capital Momentum Alpha Indices and short the corresponding nearby index. Finally, the Barclays Capital Roll-Yield index has been introduced, that is positioning its exposure according to the roll-yield of each commodity contract, buying the contract with the highest positive roll-return in backwardated term structures and selling the lowest negative roll-return in contangoed term structures.

Deutsche Bank liquid Commodity Index Family

The DBLCI was launched in 2003. It consists of 6 components. Crude and heating oil futures contracts are rolled monthly and aluminum, gold, corn and wheat futures contracts annually. This rolling procedure was adopted to account for the historical tendency of the energy curves to be in backwardation and the metal and agricultural curves to be in contango. The DBLCI-MR (mean-reversion) was launched in 2003 and it has no annual rebalancing. Instead, the rebalancing of the individual commodity weights is dependant on its performance relative to the past. It is generally known as mean-reverting investing. The DBLCI-OY (optimal yield) was launched in 2006. The index does not select the futures contracts on a pre-defined schedule (contract table). It is designed to roll each commodity to the futures contract that has the highest roll-yield. It either maximizes the positive roll-yield in backwardated term structures or minimizes the negative roll-yield in contangoed markets. DBLCI-OY Broad and Balanced indices have extended the number of constituents to 14.

Merrill Lynch Commodity Index Extra

MLCX was launched in 2006 and it currently consists of 18 components which are sorted by liquidity and then weighted by the importance of each commodity in the global economy. It is designed to roll semi-continuously over a 15-day window from a second to third-month futures contract from the first through the fifteenth business day of the month. Compared to other indices MLCX overweights downstream commodities (such as soybean meal and gasoline) and underweights upstream commodities (such as grains, oilseeds and softs). This is to reflect the fact that downstream (upstream) commodities tend to be more often than not in backwardation (contango).

JPMorgan Commodity Index Family

The Investable Global Asset Rotator (IGAR) index was launched in 2006. It is rebalanced by using an investment strategy that is generally known as momentum investing. The weighting of the constituents (24 individual commodity sub-indices of the S&P GSCI) is selected on the assumption that if certain constituents performed well in the past they will continue to perform well in the future and if they performed badly they will continue to do so. The JPMorgan Commodity Curve Index (JPMCCI), launched in 2007, invests along the entire length of the futures curve in proportion to the open interest of each contact of the 35 commodities that it follows.

UBS Bloomberg Constant Maturity Commodity Index Family

The UBS Bloomberg Constant Maturity Commodity Index (CMCI) family was launched in 2007 and it currently consists of 28 components. It is weighted using global economic weights, global consumption and liquidity. It differs from the rest of the indices as it targets a constant maturity, with contract maturities ranging from 3 months to 5 years depending on the index considered. It holds two contracts simultaneously and adjusts proportions relative to time to maturity.

DCI BNP Paribas Enhanced Index

The DCIBGL was launched in 2007 and it currently consists of 48 components. Its weights are based on trade volume and liquidity. It is reweighed annually. This index uses the forward curve roll-optimization process for 17 commodity contracts on the last 3 business days of each month. To achieve this optimization process an algorithm is selecting the optimum contracts of each commodity on which the index will roll every month.

MorningStar Commodity Index Family

Five indices were launched in 2007. Long-Only Commodity, Short-Only, Long-Short, Long-Flat, Flat-Short. They consist of 20 commodities and they employ a methodology based on momentum. According to the rolling procedure, contracts that are at least two months from delivery are selected.

By using term structure and market signals the second generation indices try to capture part of the returns of commodity-based active management strategies. Akey (2005) makes a case in favor of active investing suggesting that inefficiencies and alpha opportunities could be exploited. He shows that commodity futures traders produce more favorable returns than traditional commodity indices. A proper use of market timing, tactical trading and market selection could offer superior returns to investors. Both Till and Eagleeye (2003) and Erb and Harvey (2006) suggest that investing in the S&P-GSCI when in backwardation (as opposed to contango) produces higher returns than when following a buy-and-hold strategy. Erb and Harvey (2006) further examine the S&P-GSCI returns in a momentum framework. They buy (short) the S&P-GSCI for one month if the return over the previous year was positive (negative). In a more fundamental approach, Jensen et al. (2002) link the S&P-GSCI performance to the monetary environment. More specifically, they show that under restrictive monetary conditions the S&P-GSCI returns are four times larger than the corresponding returns under expansionary conditions. Nihman and Swinkels (2003) also show that the GCSI performance is linked to macroeconomic variables. Vrugt et al. (2007) consider both fundamental (e.g. monetary environment, business cycle) information and market sentiment factors when trying to forecast S&P-GSCI returns.

4. 3. Data

The dataset from Bloomberg spans the period October, 24 1988 to November, 20 2008. It consists of the daily prices for all the maturities of the 30 commodity futures contracts that form the two major commodity indices, the S&P GSCI and the DJ-UBSCI, and the daily prices of the two excess return indices themselves. Their constituent lists can be found in table 4.2.

Table 4.2. Commodity Characteristics

Commodity	Ticker	Exchange	Start Date
Aluminum	LA	LME	03/01/1989
Brent Crude	CO	ICE	19/07/1991
Cocoa	CC	NYBOT	03/01/1989
Coffee	KC	NYBOT	03/01/1989
Copper	LP	LME	03/01/1989
Copper NYMEX	HG	CMX-NYMEX	30/08/1990
Corn	C	CBT	21/12/1988
Cotton	CT	NYBOT	03/01/1989
Crude Oil	CL	NYMEX	22/11/1988
Feed Cattle	FC	CME	29/11/1988
Gas Oil	QS	ICE	31/07/1989
Gasoline	HU	NYMEX	01/12/1988
Gasoline RBOB	XB	NYMEX	04/10/2005
Gold	GC	CMX-NYMEX	29/12/1988
Heating Oil	HO	NYMEX	01/12/1988
Kansas Wheat	KW	Kansas City BOT	23/12/1988
Lead	LL	LME	03/01/1989
Lean Hogs	LH	CME	29/12/1988
Live Cattle	LC	CME	29/12/1988
Natural Gas	NG	NYMEX	23/07/1990
Nickel	LN	LME	03/01/1989
Orange Juice	JO	NYMEX	17/11/1988
Platinum	PL	NYMEX	01/11/1988
Silver	SI	CMX-NYMEX	02/12/1988
Soybean Oil	BO	CBT	24/10/1988
Soybeans	S	CBT	22/11/1988
Sugar	SB	NYBOT	03/01/1989
Tin	LT	LME	01/08/1989
Wheat	W	CBT	03/01/1989
Zinc	LX	LME	01/07/1991

Normal font denotes the S&P-GSCI index, italics the DJ-UBSCI index and bold refers to both.

These two indices were created officially in 1991 and 1998 but have been backfilled by the index providers. We use the closing prices of the futures contracts for LME futures (aluminum, copper, nickel, zinc, lead and tin) expiring on the third

Wednesday of each month. Before December 2000 most of the LME futures did not exist, so we have used daily forward contracts of fixed maturity available in Bloomberg and have interpolated the daily prices of theoretical futures contracts on the LME.

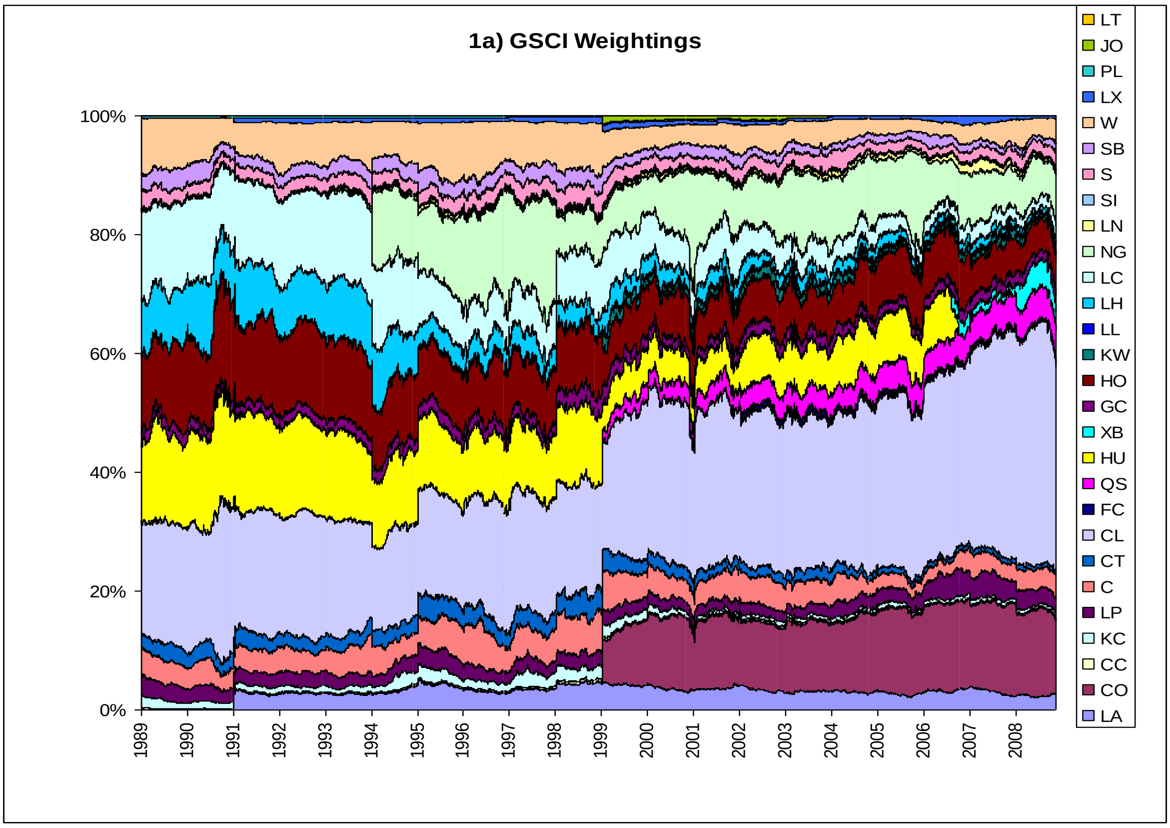
For each commodity index, we have acquired from Bloomberg its constituent indices, consisting of the returns of each underlying commodity that follows the exact index rolling procedures. The crude oil constituent DJ-UBSCI index, for example, is an index that follows the exact rolling procedures of the DJ-UBSCI but measures the returns of crude oil only. Using the returns of these constituent indices and the annual weighting allocation of the two indices going back to the beginning of the study we have calculated the daily weighting of each index component. Effectively we have tried to mimic the portfolio construction once a year based on the constituents of the index and the weights allocated to each constituent without backfilling of today's asset allocation.

4. 4. Methodology and Replication of the Baseline S&P-GSCI and DJ-UBSCI Indices

4. 4. 1. S&P-GSCI index methodology and replication

We follow the methodology detailed in Standard & Poor's GSCI manual (2007) to replicate the S&P-GSCI Excess Return Index. The S&P-GSCI index is a production-weighted index of the prices of exchange-traded, liquid physical commodity futures contracts. Throughout its history the weighting of the index has been skewed towards the petroleum sector (see Figure 4.1a). The return of the index is calculated based on the returns of the commodity futures contracts that are designated for each commodity each month. In general, at the beginning of the expiration month, futures contracts that are expiring that month are rolled (exchanged) for contracts with the next applicable expiration month. Details on the roll-schedule are provided in Table 4.1. As seen there, certain commodities roll more frequently than others. Energy and industrial metals are rolled forward more frequently while agricultural and livestock commodities are rolled forward less frequently. The less frequent rollers have on average a longer life expectancy, an expiry date that is further away from the present. The roll-period last for 5 days and occurs on the fifth through the ninth business day of the month at a rate of 20% per day dollar weighted. The S&P-GSCI has specific S&P-GSCI business days and specific daily contract reference (settlement) prices, as referred to in the manual. We have replicated the exact rolling procedures described in the index methodology (Standard & Poor's, 2007). In order to achieve greater accuracy we have used all the commodities (live or dead) from the launch of the index till today. The time span is from 04/01/1989 until the 20/11/2008.

Figure 4.1a: S&P-GSCI weightings



The results suggest that overall the S&P-GSCI replication exercise has been a successful one. The last two columns of Table 4.3 (Panel A) report summary statistics for both the S&P-GSCI and our replicated version. On the return side we witness the exact same annualized geometrical mean and a slight difference of the level of 0.14% on the annualized arithmetic mean. Testing the significance of this difference, we find it to be insignificantly different to 0 with a t-stat of 1.17. The risk-adjusted annualized alpha (relative to the S&P-GSCI) is significant but at a level of 0.22% only. In terms of risk, we have identical annualized volatility and all the rest of the statistics are also extremely close. The correlation with the S&P-GSCI stands at 0.9992 and is not significantly different from 1 (t-stat=-0.30). The annualized tracking error derived from the regression of our replicated version against the S&P-GSCI index stands at 0.83%, while the beta stands at 0.9987 and not significantly different from 1 (t-stat=-0.65). The success of our S&P-GSCI replication is analyzed in Appendix 4.A (c.f. columns 1 and 2) constituent by constituent. Most of the constituents have been replicated with highly precise accuracy and the largest discrepancy in annualized returns corresponds to lean hogs with a 0.4% difference between replicated and actual returns.

Table 4.3. Momentum and Term Structure Enhanced S&P-GSCI Indices: Summary Statistics

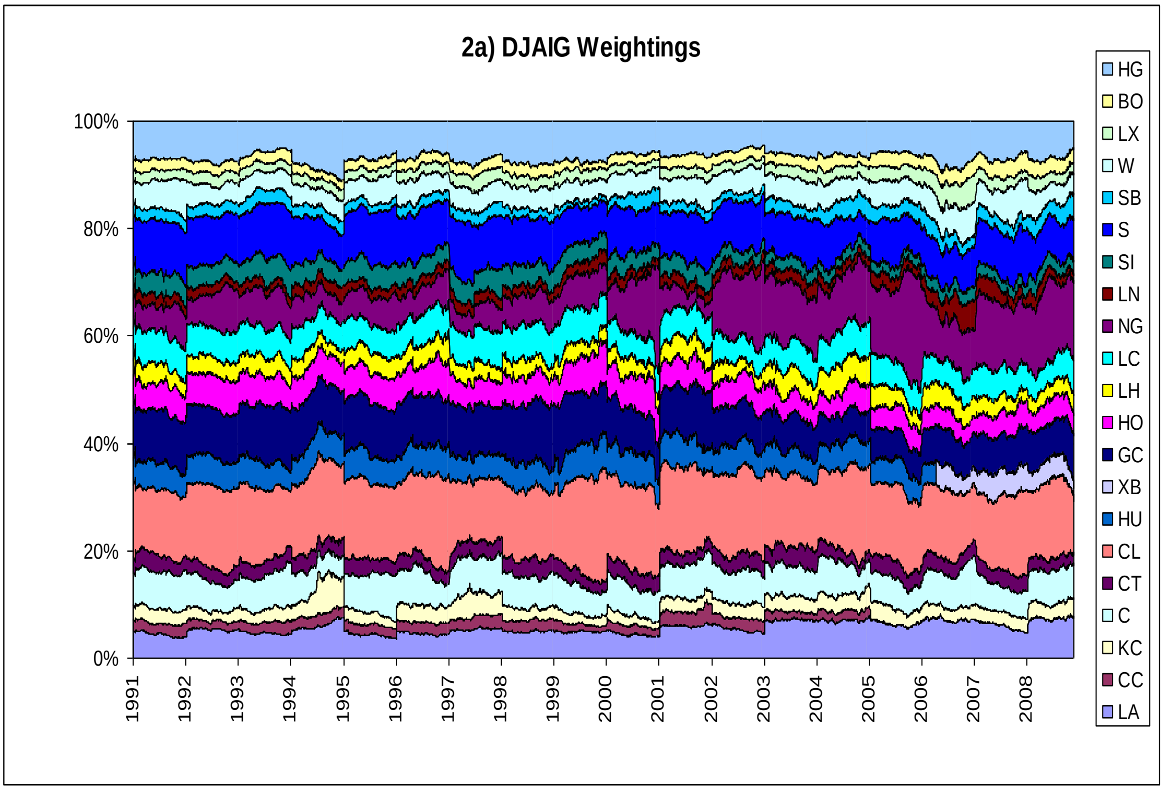
	Mom(real)	Mom(grad)	TS(real)	TS(grad)	Mom/TS(real)	Mom/TS(grad)	TS/Mom(real)	TS/Mom(grad)	GSCI replication	GSCI
Panel A: GSCI index and enhanced versions										
Annualized arithmetic mean	0.0574	0.0499	0.0561	0.0636	0.0506	0.0526	0.0715	0.0675	0.0382	0.0368
Annualized geometric mean	0.0355	0.0283	0.0336	0.0414	0.0287	0.0310	0.0492	0.0454	0.0148	0.0148
Annualized volatility	0.2111	0.2110	0.2075	0.2047	0.2104	0.2087	0.2078	0.2068	0.2125	0.2126
Reward/risk ratio	0.2720	0.2363	0.2701	0.3105	0.2406	0.2521	0.3441	0.3266	0.1799	0.1730
Skewness	-0.1035	-0.1036	-0.2048	-0.2240	-0.1018	-0.1218	-0.1038	-0.1381	-0.2513	-0.2637
Kurtosis	5.8355	5.6806	5.9240	5.8541	5.6923	5.6722	5.6688	5.6177	5.4322	5.4148
99% VaR (Cornish-Fisher)	0.1866	0.1843	0.1884	0.1855	0.1839	0.1828	0.1813	0.1811	0.1874	0.1877
Best month	0.2418	0.2381	0.2373	0.2329	0.2416	0.2381	0.2447	0.2379	0.2230	0.2223
Worst month	-0.2840	-0.2814	-0.2870	-0.2823	-0.2802	-0.2786	-0.2766	-0.2758	-0.2817	-0.2825
% of positive months	0.5523	0.5607	0.5272	0.5230	0.5397	0.5439	0.5439	0.5397	0.5230	0.5272
Maximum drawdown	-0.5814	-0.5804	-0.5830	-0.5761	-0.5744	-0.5741	-0.5674	-0.5683	-0.5924	-0.5927
Max 12M rolling return	0.6920	0.7021	0.7504	0.7260	0.7307	0.7277	0.7333	0.7249	0.7123	0.7075
Min 12M rolling return	-0.4317	-0.4273	-0.3979	-0.3737	-0.4078	-0.4024	-0.3939	-0.3922	-0.4203	-0.4201
Correlation with GSCI	**0.9774**	**0.9843**	**0.9763**	**0.9811**	**0.9837**	**0.9849**	**0.9806**	**0.9827**	**0.9992**	**1.0000**
Ho: Correlation=0	(71.21)	(85.97)	(69.44)	(78.12)	(84.09)	(87.67)	(77.08)	(81.65)	(395.95)	
Ho: Correlation=1	(-1.64)	(-1.37)	(-1.69)	(-1.50)	(-1.40)	(-1.34)	(-1.52)	(-1.44)	(-0.30)	
Annualized Alpha with GSCI	**0.0211**	0.0138	**0.0192**	**0.0266**	0.0141	**0.0162**	**0.0343**	**0.0305**	**0.0022**	
	(2.04)	(1.58)	(2.14)	(3.33)	(1.64)	(2.02)	(3.75)	(3.62)	(1.85)	
Tracking Error with GSCI	0.0447	0.0373	0.0450	0.0397	0.0380	0.0362	0.0408	0.0384	0.0083	
Beta with GSCI	**0.9708**	**0.9772**	**0.9532**	**0.9445**	**0.9736**	**0.9669**	**0.9586**	**0.9560**	**0.9987**	
Ho: Beta=0	(57.10)	(70.61)	(52.13)	(45.69)	(63.04)	(68.96)	(54.30)	(55.65)	(506.14)	
Ho: Beta=1	(-1.72)	(-1.65)	(-2.56)	(-2.68)	(-1.71)	(-2.36)	(-2.34)	(-2.56)	(-0.65)	
Panel B: Spread between enhanced-GSCI and GSCI										
Annualized arithmetic mean	**0.0199**	0.0129	**0.0174**	**0.0245**	0.0131	**0.0150**	**0.0327**	**0.0288**		
	(1.96)	(1.52)	(1.67)	(2.62)	(1.51)	(1.81)	(3.45)	(3.22)		
Annualized geometric mean	0.0189	0.0122	0.0163	0.0236	0.0123	0.0143	0.0318	0.0280		
Annualized volatility	0.0451	0.0375	0.0460	0.0413	0.0383	0.0368	0.0416	0.0394		
Reward/risk ratio	0.4421	0.3437	0.3784	0.5931	0.3412	0.4072	0.7863	0.7313		
Skewness	0.9854	0.8068	-0.0364	-0.3260	0.7338	0.6549	1.0305	0.7868		
Kurtosis	6.2684	5.5521	4.9374	9.2800	5.8583	4.7418	5.7264	5.8195		
99% VaR (Cornish-Fisher)	0.0260	0.0226	0.0373	0.0476	0.0249	0.0222	0.0217	0.0247		
Best month	0.0607	0.0421	0.0476	0.0467	0.0526	0.0446	0.0480	0.0447		
Worst month	-0.0407	-0.0367	-0.0445	-0.0671	-0.0305	-0.0312	-0.0307	-0.0371		
% of positive months	0.5397	0.5146	0.5607	0.5439	0.5188	0.5397	0.5439	0.5272		
Maximum drawdown	-0.1164	-0.1588	-0.1064	-0.0773	-0.1825	-0.1362	-0.0475	-0.0516		
Max 12M rolling return	0.2007	0.1534	0.1797	0.2011	0.1727	0.1476	0.2490	0.2235		
Min 12M rolling return	-0.0658	-0.0558	-0.0782	-0.0639	-0.0640	-0.0597	-0.0307	-0.0405		
Correlation with GSCI	**-0.1379**	**-0.1294**	**-0.2164**	**-0.2857**	**-0.1467**	**-0.1914**	**-0.2113**	**-0.2370**		
	(-2.14)	(-2.01)	(-3.41)	(-4.59)	(-2.28)	(-3.00)	(-3.33)	(-3.76)		

Significance *t*-ratios in parentheses. Bold denotes statistically significant at the 10% level or better. The spread is defined as the return from the enhanced S&P-GSCI (former GSCI) minus the return from the baseline S&P-GSCI.

4. 4. 2. DJ-UBSCI index methodology and replication

We follow DJ-AIGCI Index Handbook (2006) to replicate the DJ-UBSCI (former DJ-AIGCI) Excess Return Index. The DJ-UBSCI is both a liquidity and production-weighted index of the prices of exchange-traded, physical commodity futures contracts. Contrary to the S&P-GSCI, the index has been designed to achieve more diversification and less concentration to specific commodities. No commodity sector can have more than 33% allocation to the index and no individual commodity more than 15%. The DJ-UBSCI weightings are depicted in Figure 4.2a. Each month the index replaces the contracts that have near-term expirations with contracts that have more-distant expirations following a specific designated contracts table (see Table 4.1, col. 3). Some differences can be observed in the designated contracts tables of the S&P-GSCI and the DJ-UBSCI. The energy sector rolls less frequently in DJ-UBSCI than in S&P-GSCI meaning that its energy contracts expire further away from the present. The roll-period lasts for 5 days and occurs on the 6th through the 10th business day of the month at a rate of 20% per day dollar weighted. To replicate with accuracy the exact methodology described above we have used all the commodities of the DJ-UBSCI from the launch until the present. The time span is from 04/01/1991 to 20/11/2008.

Figure 4.2a: DJ-UBSCI weightings



The summary statistics in Table 4.4, Panel A suggest that the DJ-UBSCI replication is even sharper than that of the S&P-GSCI. The difference between the annualized return of the DJ-UBSCI and the replicate one is 0.1%. We find this difference to be statistically insignificant with a t-stat at the level of 1.63. All the risk measures are almost identical. The correlation with the DJ-UBSCI stands at 0.9998 and is not significantly different from 1 (t-stat=-0.13). The regression gives out an annualized alpha of 0.1% which is barely significant at the 10% level, with a tracking error of 0.26% and a beta of 1.0003 which is not significantly different to 1 (t-stat=0.21). As Appendix 4.B shows, the largest discrepancy between the annualized return of the replicated S&P-GSCI and the actual S&P-GSCI (at 0.55%) is observed for zinc contracts. With this replication exercise in place, the rolling procedure of the S&P-GSCI and DJ-UBSCI indices is modified in terms of when/where to roll, what contract table and weighting scheme to follow in search for alpha.

Table 4.4. Momentum and Term Structure Enhanced DJ-UBSCI Indices: Summary Statistics

	Mom(real)	Mom(grad)	TS(real)	TS(grad)	Mom/TS(real)	Mom/TS(grad)	TS/Mom(real)	TS/Mom(grad)	DJAIG replicated	DJAIG
Panel A: DJAIG index and enhanced versions										
Annualized arithmetic mean	0.0403	0.0343	0.0254	0.0407	0.0297	0.0367	0.0473	0.0450	0.0207	0.0197
Annualized geometric mean	0.0285	0.0229	0.0138	0.0290	0.0180	0.0252	0.0356	0.0335	0.0106	0.0096
Annualized volatility	0.1571	0.1554	0.1543	0.1503	0.1562	0.1546	0.1508	0.1503	0.1452	0.1451
Reward/risk ratio	0.2564	0.2205	0.1647	0.2707	0.1902	0.2372	0.3135	0.2997	0.1426	0.1356
Skewness	-0.5042	-0.5180	-0.6096	-0.6276	-0.5683	-0.5494	-0.5794	-0.5874	-0.6624	-0.6811
Kurtosis	5.5596	5.5570	6.3234	6.2428	5.6574	5.6958	5.7203	5.7296	6.0249	6.1399
99% VaR (Cornish-Fisher)	0.1451	0.1437	0.1520	0.1417	0.1462	0.1449	0.1420	0.1417	0.1407	0.1419
Best month	0.1148	0.1210	0.1282	0.1244	0.1307	0.1315	0.1154	0.1170	0.1213	0.1208
Worst month	-0.2224	-0.2196	-0.2320	-0.2245	-0.2244	-0.2217	-0.2184	-0.2171	-0.2115	-0.2134
% of positive months	0.5302	0.5302	0.5395	0.5535	0.5535	0.5488	0.5535	0.5535	0.5395	0.5302
Maximum drawdown	-0.4952	-0.5017	-0.5028	-0.4828	-0.5048	-0.5009	-0.4815	-0.4828	-0.4941	-0.4960
Max 12M rolling return	0.4718	0.4449	0.4131	0.3826	0.4014	0.4258	0.4088	0.4040	0.3742	0.3734
Min 12M rolling return	-0.3442	-0.3369	-0.3515	-0.3220	-0.3507	-0.3422	-0.3214	-0.3196	-0.3345	-0.3373
Correlation with DJAIG	**0.9575**	**0.9673**	**0.9662**	**0.9701**	**0.9695**	**0.9712**	**0.9690**	**0.9721**	**0.9998**	**1.0000**
Ho: Correlation=0	(48.43)	(55.69)	(54.68)	(58.31)	(57.70)	(59.53)	(57.23)	(60.43)	(813.21)	
Ho: Correlation=1	(-2.15)	(-1.88)	(-1.91)	(-1.80)	(-1.82)	(-1.76)	(-1.83)	(-1.74)	(-0.13)	
Annualized Alpha with DJAIG	**0.0196**	0.0138	0.0049	**0.0198**	0.0090	**0.0161**	**0.0263**	**0.0241**	**0.0010**	
	(1.87)	(1.50)	(0.53)	(2.35)	(1.00)	(1.84)	(2.89)	(2.74)	(1.68)	
Tracking Error with DJAIG	0.0454	0.0395	0.0399	0.0366	0.0384	0.0369	0.0374	0.0354	0.0026	
Beta with DJAIG	**1.0366**	**1.0355**	**1.0272**	**1.0058**	**1.0432**	**1.0346**	**1.0068**	**1.0066**	**1.0003**	
Ho: Beta=0	(49.44)	(62.56)	(46.04)	(44.95)	(58.72)	(63.07)	(53.56)	(53.56)	(639.91)	
Ho: Beta=1	(1.75)	(2.15)	(1.22)	(0.26)	(2.43)	(2.11)	(0.36)	(0.35)	(0.21)	
Panel B: Spread between enhanced-DJAIG and DJAIG										
Annualized arithmetic mean	**0.0204**	0.0146	0.0055	**0.0199**	0.0099	**0.0168**	**0.0264**	**0.0242**		
	(1.87)	(1.54)	(0.58)	(2.29)	(1.08)	(1.90)	(2.96)	(2.87)		
Annualized geometric mean	0.0193	0.0138	0.0047	0.0192	0.0092	0.0161	0.0257	0.0236		
Annualized volatility	0.0456	0.0397	0.0400	0.0365	0.0388	0.0372	0.0373	0.0353		
Reward/risk ratio	0.4472	0.3668	0.1369	0.5456	0.2553	0.4517	0.7083	0.6857		
Skewness	0.5118	0.5075	0.1451	0.1820	0.2113	0.4764	0.7760	0.7126		
Kurtosis	3.4109	3.3963	5.2134	6.0126	3.9866	3.8684	4.5324	4.7027		
99% VaR (Cornish-Fisher)	0.0256	0.0223	0.0315	0.0304	0.0267	0.0225	0.0203	0.0205		
Best month	0.0406	0.0344	0.0537	0.0528	0.0439	0.0441	0.0504	0.0488		
Worst month	-0.0340	-0.0287	-0.0380	-0.0405	-0.0367	-0.0261	-0.0213	-0.0218		
% of positive months	0.5256	0.5116	0.5302	0.5209	0.5116	0.5209	0.5116	0.5302		
Maximum drawdown	-0.1321	-0.1533	-0.1749	-0.0988	-0.2000	-0.1346	-0.0826	-0.0698		
Max 12M rolling return	0.1702	0.1467	0.1738	0.1872	0.1686	0.1676	0.2153	0.2169		
Min 12M rolling return	-0.0897	-0.0819	-0.0950	-0.0566	-0.0823	-0.0630	-0.0526	-0.0514		
Correlation with DJAIG	**0.1164**	**0.1299**	0.0988	0.0230	**0.1616**	**0.1351**	0.0265	0.0272		
	(1.71)	(1.91)	(1.45)	(0.34)	(2.39)	(1.99)	(0.39)	(0.40)		

Significance *t*-ratios in parentheses. Bold denotes statistically significant at the 10% level or better. The spread is defined as the return from the enhanced DJ-UBSCI (former DJ-AIGCI) minus the return from the baseline DJ-UBSCI.

4. 5. Momentum Enhanced Indices

We assess the performance of the S&P-GSCI and DJ-UBSCI enhanced by signals based on the constituents' returns, referred to as the momentum effect in our previous chapters and in the literature (see Erb and Harvey, 2006). In a nutshell, if certain constituents performed well (relatively to the rest) in the past they will continue to perform well in the future. If the constituents performed badly (relatively to the rest) in the past they will continue to do so. To capture this pattern, the weightings of the winner (loser) constituents are adjusted upwards (downwards). We adopt the 1-month ranking, 1-month holding strategy (referred to as Mom1-1 in the previous chapters) in our subsequent analysis. On every start of the roll-period (5th for the S&P-GSCI or 6th for the DJ-UBSCI business day of the month), we measure the return that each constituent had the preceding month. We then rebalance the index to the original index weightings (S&P-GSCI or DJ-UBSCI) with the weighting adjusted upwards for each constituent if its previous month's performance has been above the median performance and downwards if it has been below the median performance.

First, the downward adjustment of each component's weight is limited since in this setting short-selling an index constituent is not possible. Secondly, the weighting of each component should increase or decrease according to its previous month's relative performance so that the weighting of the commodity that had the highest return increases more than the weighting of the commodity that had the second highest return and so forth. There are two critical steps in this rebalancing process which are explained below.

The new weightings are constructed according to the "real" relative performance of the constituents of each index. Hereafter, we refer to each index enhanced by this "real" momentum effect as Mom(real) Index. The weights for the constituents with below-or- equal-to-median return are adjusted to reflect their "real" relative performance as follows

$$wreal_{i,t} = wo_{i,t} - \frac{p \times \sum_{i=1}^{m} wo_{i,t} \times (-(r_{i,t} - \max_{i=1}^{m} r_{i,t}))}{\sum_{i=1}^{m} (-(r_{i,t} - \max_{i=1}^{m} r_{i,t}))} \tag{4.1}$$

where the subscript i(=1 to m) refers to the constituents that have exhibited returns below or equal to the median previous month's return; t is the roll-date (5th or 6th business day according to the index); $wreal_{i,t}$ is the real weighting of the i constituent after the adjustment on the t roll-date ($wreal_{i,t}$ >= 0); *wo* is the original index weighting for the commodity at that roll-date; p is the percentage by which we want the weighting of the below-the-median commodities as a whole to fall (we adopt p= 50% so that if, say, the *wo* of the below the median commodities aggregated as a group is 50%, then we target to reduce it by 50%, making their *wreal*=25%); r is the return of the constituent contract over the previous month; and *maxr* is the maximum return of the below or equal to median constituents.

We measure all the new weightings for the below the median return contracts in order to calculate the maximum allowed increase for the group of contracts with above the median return. The weights for the constituents with above the median return are then adjusted as

$$wreal_{j,t} = wo_{j,t} + \frac{(\sum_{i=1}^{m} wo_{i,t} - \sum_{i=1}^{m} wreal_{i,t}) \times (r_{j,t} - \min_{j=1}^{n-m} r_{j,t})}{\sum_{j=1}^{n-m} (r_{j,t} - \min_{j=1}^{n-m} r_{j,t})} \tag{4.2}$$

where n is the total number of constituents for each index; j(=1 to n-m) are the constituents that have exhibited returns above the median previous month's return; and *minr* is the minimum return of the below or equal to median constituents.

Between roll-dates, the constituents' weights evolve naturally based on their performance as

$$w_{i,t} = \frac{w_{i,t-1}(1+r_{i,t})}{1+\sum_{i=1}^{n}(w_{i,t-1}(1+r_{i,t}))} \tag{4.3}$$

Following this “real” relative performance rebalancing method, the weighting of the constituents can be significantly influenced by outliers or extreme points. To mitigate this potential problem and to test the sensitivity of the results to the weight-adjustment method employed, we have designed a second approach which we call “gradual” (grad) weight-adjusting where the new weights are obtained according to the gradual relative performance of the constituents of each index. Therefore we refer to each index enhanced by this “gradual” momentum effect as Mom(grad) Index. This approach is as follows.

First, the weights for the constituents with below-or-equal-to-median return are adjusted as

$$wgrad_{i,t} = wo_{i,t} - \frac{p \times \sum_{i=1}^{m} wo_{i,t} \times (m - position_{i,t} + 1)}{\sum_{i=1}^{m}(m - position_{i,t} + 1)} \tag{4.4}$$

where *i, j, n, m, t, wo* and *p* are as described above after equation (4.2); $wgral_{i,t}$ is the gradual weighting of the *i* constituent after the adjustment on the *t* roll-date ($wgral_{i,t}$ >= 0), *position* is the position of the constituent from highest to lowest when above the median. So it takes the number 1 if it had the highest performance the previous month. When below or equal to median it is the position of the constituent from lowest to highest. So it takes the number 1 if it had the lowest performance the previous month.

We measure all the new weightings for the below the median return contracts in order to calculate the maximum allowed increase for the group of contracts with above the median return. The weights for the constituents with above the median return are adjusted accordingly as

$$wgrad_{j,t} = wo_{j,t} + \frac{\left(\sum_{i=1}^{m} wo_{i,t} - \sum_{i=1}^{m} wgrad_{i,t}\right) \times (n\text{-}m - position_{j,t} + 1)}{\sum_{j=1}^{n-m} (n\text{-}m - position_{j,t} + 1)} \tag{4.5}$$

Between roll-dates, weights evolve naturally according to their performance as indicated in (4.3).

The evolution of the weights throughout the period of study of this chapter, and the differences in this respect between the traditional indices and the most successful momentum-enhanced ones are depicted in Figures 4.1(a,b) and 4.2(a,b). Panels A of Tables 4.3 and 4.4 report summary statistics for, respectively, the S&P-GSCI and DJ-UBSCI indices enhanced by the momentum effects using both adjusting methods. Summary statistics for the spread (or differential return) between the enhanced indices and the traditional ones are reported in Panels B of Tables 4.3 and 4.4. In all cases the enhanced indices have outperformed the traditional ones by an average of 1.64% against the total return of 3.68% of the S&P-GSCI and an average of 1.75% against the total return of 1.97% for the DJ-UBSCI. The average correlations with the S&P-GSCI and the DJ-UBSCI stand at 0.9809 and 0.9624. In statistical term the former ones are not significantly different from 1, when the latter ones are. In terms of risk, the volatility, kurtosis and 99% Cornish-Fisher Value-at-Risk (VaR) of the probability distributions remain virtually unchanged.

Figure 4.1b: Momentum Enhanced S&P-GSCI weightings (top performing strategy)

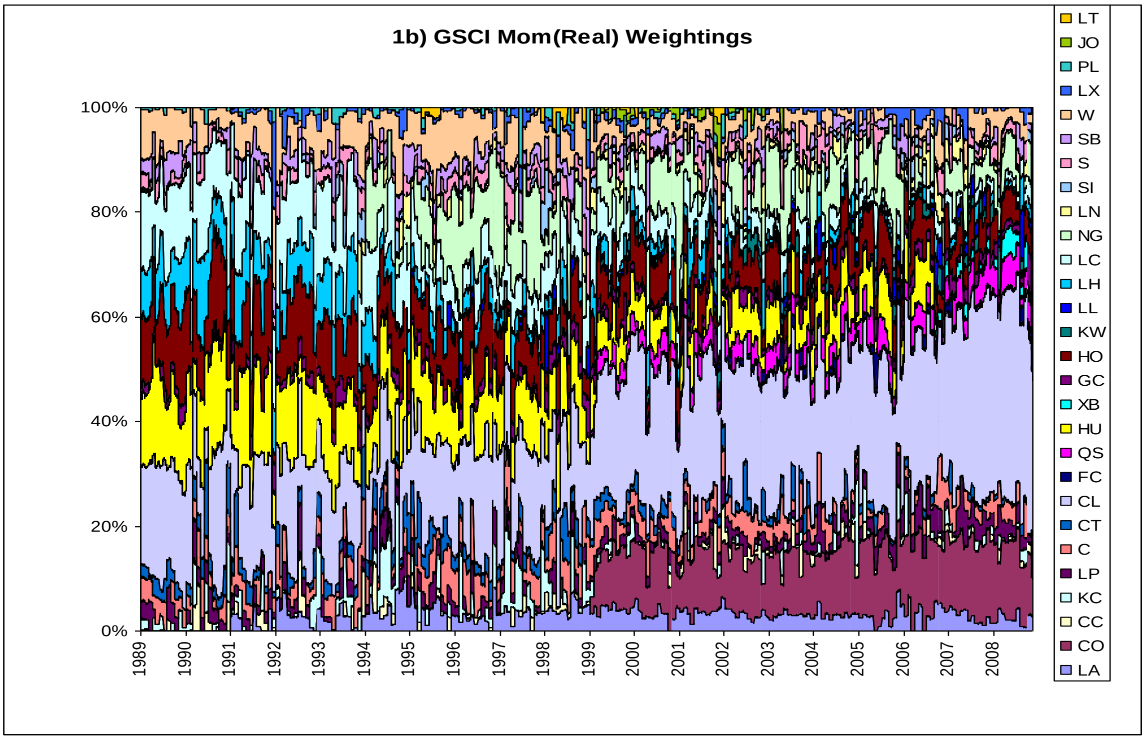
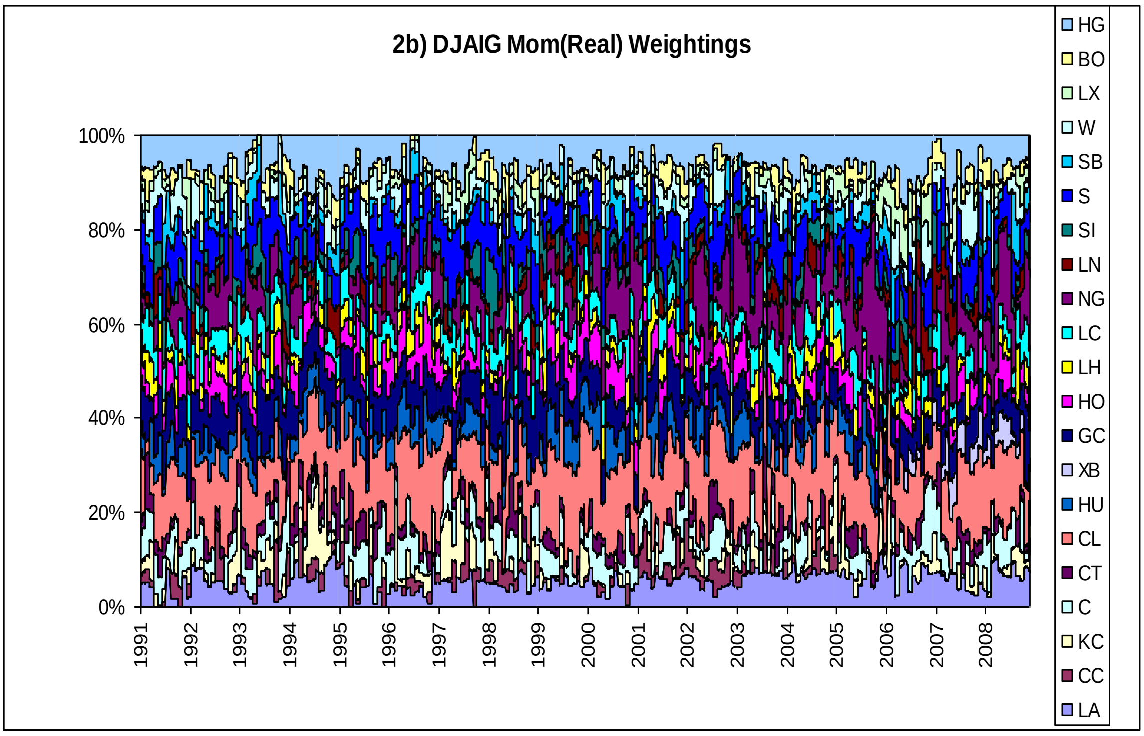


Figure 4.2b: Momentum enhanced DJ-UBSCI weightings (top performing strategy)



The skewness of the probability distributions of the enhanced strategies is visibly higher. The highest reward-to-risk ratio for the indices corresponds to the Mom(real) S&P-GSCI case at 0.272, and for the spreads it corresponds to Mom(real) DJ-UBSCI index at 0.4472. In contrast, the reward-to-risk ratios of the S&P-GSCI and DJ-UBSCI are much lower at 0.1730 and 0.1356, respectively. An interesting finding is the different sign of the correlations (all significant) between the two momentum spreads and the baseline indices which suggest that when the S&P-GSCI return increases the momentum spread decreases and the opposite holds for the DJ-UBSCI. Alongside a favorable spread and a similar or lower volatility sophisticated investors are also interested in the alpha, the tracking error and the beta of the regression of the enhanced indices on the traditional ones seeking to ensure that the enhanced strategies are not being rewarded for taking more systematic risk. The regression analysis confirms the outperformance of the enhanced indices. Mom(real) ranks top with a statistically significant outperformance of 2.11% against the S&P-GSCI and 1.96% against the DJ-UBSCI with tracking errors of 0.0447 and 0.0454 respectively. The alpha of the Mom(grad) indices is also positive albeit insignificant. At the 10% level we reject the hypothesis that the betas relative to the baseline benchmark are 1 in all cases. Our enhanced S&P-GSCI indices have lower betas against the S&P-GSCI (average betas stand at 0.9740) than the enhanced DJ-UBSCI indices against the DJ-UBSCI (average betas stand at 1.0361) suggesting that on average the former indices have lower allocation towards energy commodities than their baseline index and the latter ones have on average higher allocation to energy commodities that their baseline index. This difference helps explains the opposite behavior of the spreads against the baseline indices, witnessed in the correlations.

All correlations and betas between the enhanced and traditional indices are close to 1. These results, along with the low tracking errors, indicate that our enhanced replicating indices can be used to gain similar exposure to commodity markets as the one typically provided by the baseline indices themselves.

4. 6. Term Structure Enhanced Indices

In this section we assess the performance of the S&P-GSCI and DJ-UBSCI indices enhanced by information taken from the term structure of their constituents referred to as term structure effect in the previous chapter and in the literature (see Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006). Accordingly, if certain constituents are in relative backwardation (positive roll in relation to the rest of the constituents) they will perform well in the future, so their weightings are adjusted upwards. If they exhibit relative contango (negative roll in relation to the rest of the constituents) they will underperform in the future, in which case their weightings are adjusted downwards. In our subsequent analysis we adopt the term structure strategy referred to as TS1 in the previous chapter. Accordingly, on every start of the rolling period (5th or 6th business day according to the index), we measure the roll-return that each constituent contract has with the next contract. We then rebalance each of the index constituents' weightings upwards (downwards) if its roll-return has been above (below-or-equal) the median roll-return.

These enhanced index weightings have been constructed in accordance to the "real" relative roll- returns of the constituents of each index; therefore, we refer to the resulting index as TS(real) Index. The weights of the constituents with below-or-equal to the median roll-return are, firstly, adjusted as

$$wreal_{i,t} = wo_{i,t} - \frac{p \times \sum_{i=1}^{m} wo_{i,t} \times (-(roll_{i,t} - \max_{i=1}^{m} roll_{i,t}))}{\sum_{i=1}^{m} (-(roll_{i,t} - \max_{i=1}^{m} roll_{i,t}))} \tag{4.6}$$

where i (=1 to m) are the constituents that exhibited roll-returns below and equal to the median roll-return; t, $wreal_{,,}$ wo and p are as described after equation (4.2); *roll* is the roll-return of the constituent contract with the next contract at roll- date; and *maxroll* is the maximum roll-return of the below or equal to median constituents.

To calculate the maximum allowed increase of weightings for the group of contracts with above the median roll-return, we measure all the new weightings for the below the median roll-return contracts. Second, the weights of the constituents with above the median roll-return are adjusted as follows:

$$wreal_{j,t} = wo_{j,t} + \frac{\left(\sum_{i=1}^{m} wo_{i,t} - \sum_{i=1}^{m} wreal_{i,t}\right) \times \left(roll_{j,t} - \min_{j=1}^{n-m} roll_{j,t}\right)}{\sum_{j=1}^{n-m} \left(roll_{j,t} - \min_{j=1}^{n-m} roll_{j,t}\right)} \qquad (4.7)$$

where n is the total number of constituents for each index, j (=1 to n-m) are the constituents that have exhibited roll-returns above the median roll-return; *minroll* is the minimum roll-return of the below or equal to median constituents.

Between roll-dates, weights evolve naturally according to (4.3).

To mitigate the influence of outliers (or extreme points) and to robustify the results to the weighting method, we deploy a second gradual ("grad") method to adjust weights using equations (4.4) and (4.5), as in the momentum framework. The only difference is that now the distinctive factor is not the return of the previous month (momentum) but the roll-return on the roll-date following the term structure effect as in (4.6) and (4.7). Hereafter, we refer to the resulting index as TS(grad) Index. Between roll-dates, weights evolve following (4.3).

Figure 4.1c and Figure 4.2c present the evolution of the weights throughout the period of the study according to the most successful TS weighting scheme. Summary performance measures for the TS-enhanced indices are set out in tables 4.3 and 4.4 (panels A and B). All TS indices outperform the traditional ones by an average of 2.09% against the S&P-GSCI and 1.27% against the DJ-UBSCI. The average correlations with the S&P-GSCI and the DJ-UBSCI stand very high at 0.9787 and 0.9681 respectively. At the 5% level, we systematically fail to reject the hypothesis that these correlations equal 1, suggesting that the enhanced indices do a good job at tracking the ups and downs of the baseline indices. In contrast with the momentum-enhanced indices, the gradual adjustment of the weights has a more favorable effect on the performance than the real adjustment. The S&P-GSCI TS(grad) index is in the lead with 2.45% annualized difference in returns against the S&P-GSCI (t-stat of 2.62) and an annualized return of 6.36% against the 3.68% of the S&P-GSCI. This outperformance does not come at the expense of higher risk. The overall volatility and kurtosis of the distributions are virtually unchanged while the skewness has noticeably increased reducing the 99% VaR measures. The same TS(grad) strategy has almost doubled the highest reward-to-risk ratio at the level of 0.311 against the 0.173 for the S&P-GSCI. A closer look at the statistics for the spread confirms the superiority of S&P-GSCI TS(grad) with a reward-to-risk ratio of 0.59. The sign of the correlations between the spreads and the returns of the traditional indices are in line with the momentum enhancement but in absolute terms the correlation increases for the S&P-GSCI and decreases for the DJ-UBSCI becoming insignificant in the latter case. In terms of the risk-adjusted returns, S&P-GSCI TS(grad) remains the top ranked index with an annualized alpha of 2.66% (t-stat = 3.33), a tracking error of 3.97% and a beta of 0.9445 that is significantly different from 1 (t-stat=-2.68).

Figure 4.1c: Term structure enhanced S&P-GSCI weightings (top performing strategy)

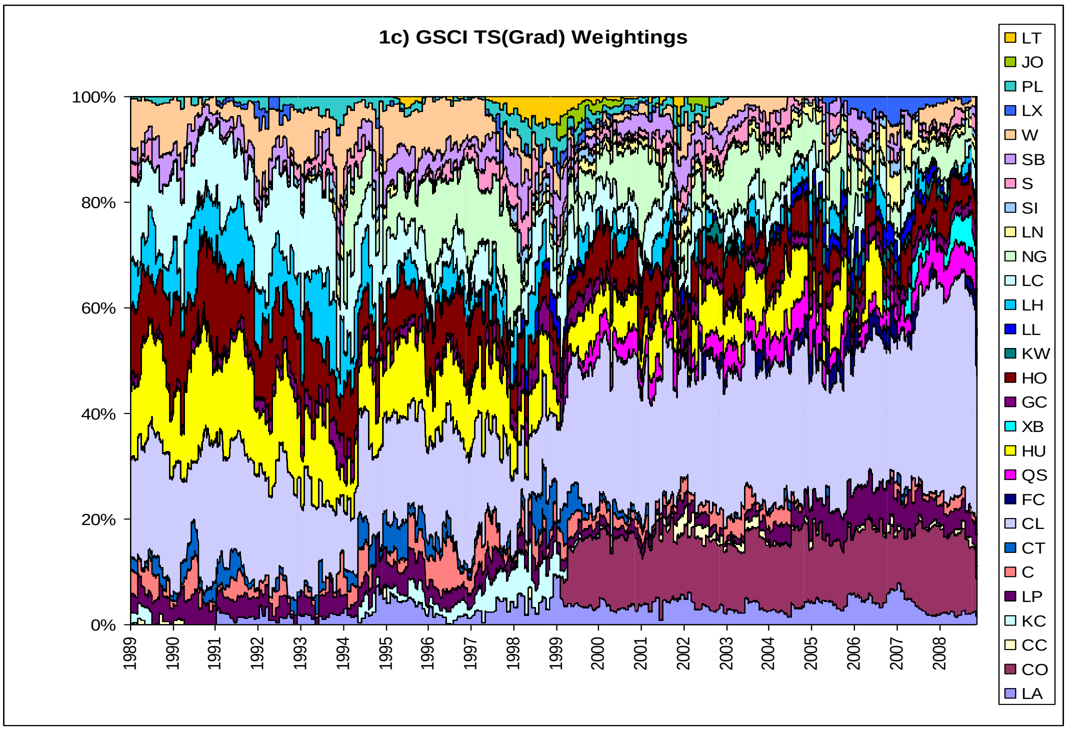
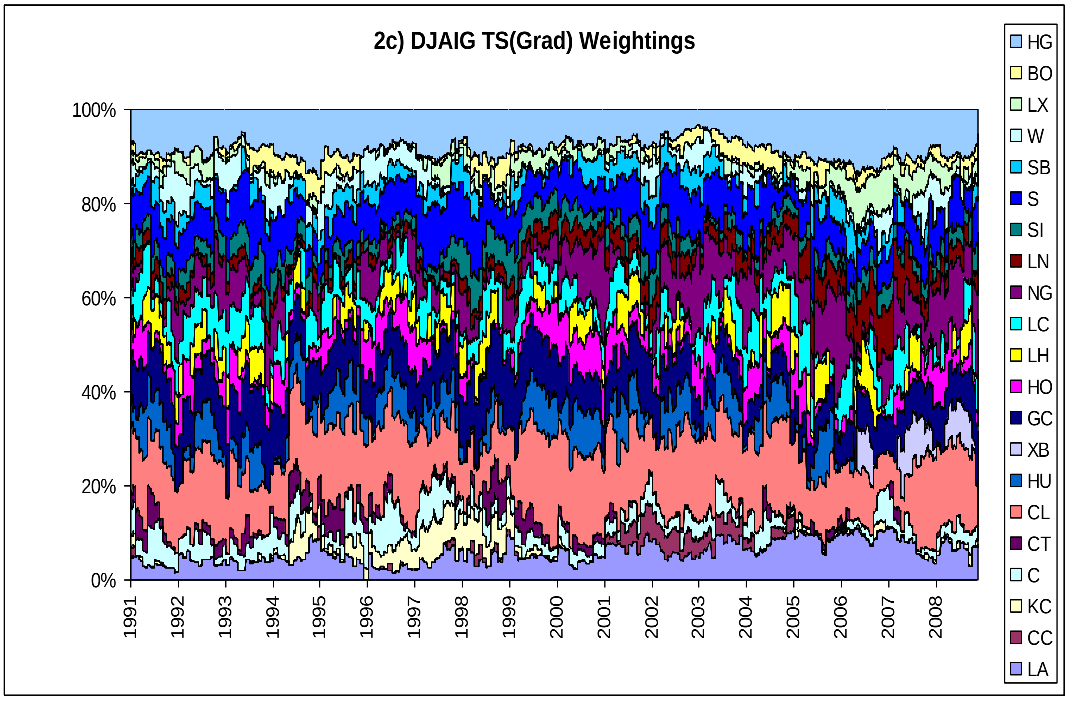


Figure 4.2c: Term structure enhanced DJ-UBSCI weightings (top performing strategy)



4. 7. Momentum and Term Structure Enhanced Indices

The performance of S&P-GSCI and DJ-UBSCI enhanced by the combination of momentum and term structure signals is being assessed in this section. If certain constituents are in relative backwardation (positive relative roll) and at the same time exhibit relative superior performance (momentum), they will perform well in the future so their weights are adjusted upwards. If they exhibit relative contango (negative relative roll) and relative inferior performance (momentum), they will underperform in the future and so their weights are adjusted downwards.

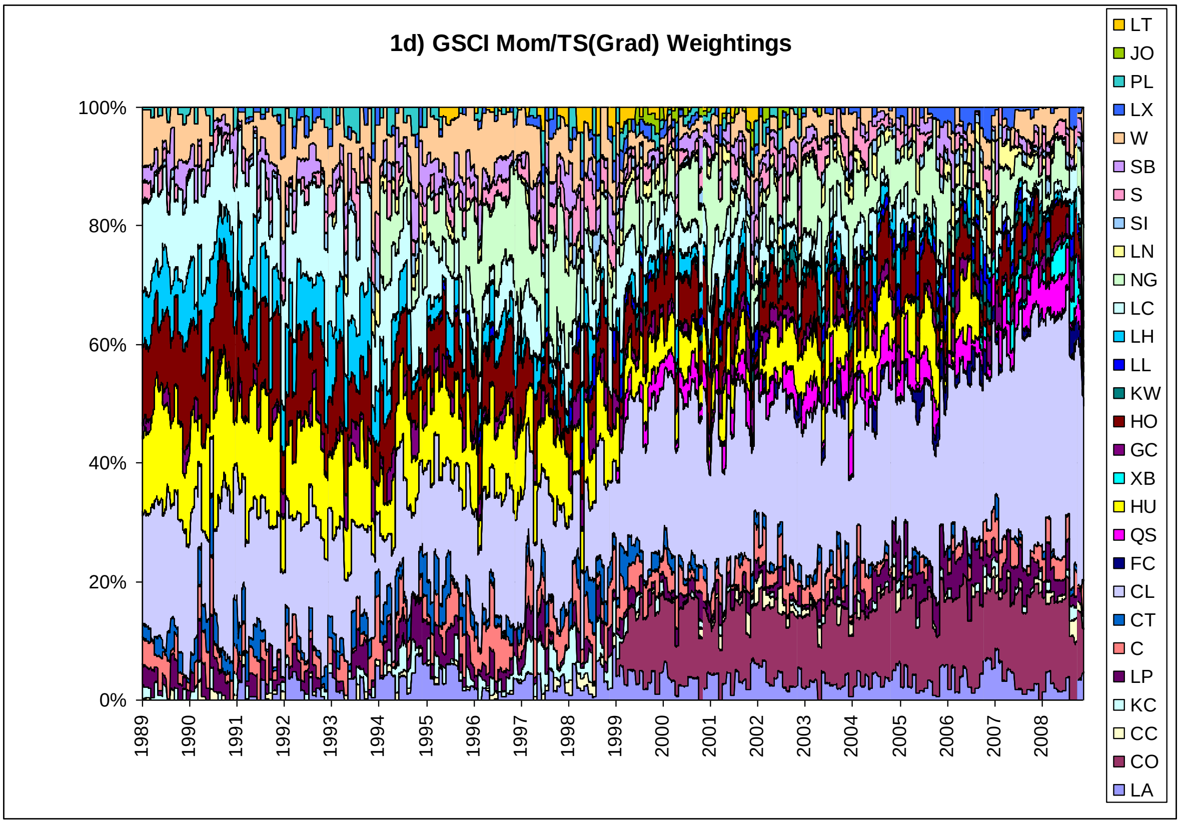
We assess two separate strategies referred to as Mom/TS and TS/Mom using the same terminology of previous sections. In the Mom/TS case, we initially sort the constituents according to their previous month's returns (momentum) and find the median return. After splitting the commodities into two groups (above/below the median return), the initial weightings are adjusted. We increase the weightings of the positive momentum group and decrease the weightings of the negative momentum group but only according to their relative roll-return inside each group. Thus we "weight" both the momentum and the term structure effects. The relative roll-return is used as the distinctive factor following equations (4.6) and (4.7). For example, if the S&P-GSCI allocates x% to corn and corn is in the winner portfolio, our enhanced strategy will allocate more than x% to corn with the exact weighting calculated as in equation (4.6). Vice versa, if the S&P-GSCI allocates y% to wheat and wheat is in the loser portfolio, our enhanced strategy will allocate less than y% to wheat, with the exact weighting calculated as in equation (4.7). Hereafter, the terminology Mom/TS(real) and the Mom/TS(grad) refers to the indices based, respectively, on the "real" and "gradual" weighting schemes.

Next, we combine again the momentum and term structure signals but in reverse order. The constituents are sorted according to their relative roll-returns to find the median roll-return and they are divided into two groups according to that median. The initial weightings inside each group are then adjusted according to the previous month's returns using equations (4.1) and (4.2). Momentum is now the relative distinction factor. As above, the results are presented for both TS/Mom(real) and TS/Mom(grad) indices.

Figure 4.1(d,e) and Figure 4.2(d,e) present the evolution of the weights throughout the period according to the most successful combined weighting schemes. Summary statistics of the combined weighting strategies are reported in Tables 4.3 and 4.4. So far these strategies generate the most favorable results. The average outperformance of the enhanced indices is 2.24% against the S&P-GSCI and 1.93% against the DJ-UBSCI. The average correlations stand at 0.983 and 0.9704, respectively. The former ones are statistically indifferent to 1 when the latter ones are statistically different. In both adjustment methods the TS/Mom strategies outperform the Mom/TS strategies. The strategy with the highest annualized outperformance is the S&P-GSCI TS/Mom(real) with a mean spread of 3.27% (t-stat = 3.45) making an annualized return of 7.15%, which almost doubles the S&P-GSCI return of 3.68%. Volatility, VaR, drawdown, worst month and min 12m return of this enhanced index are lower than those of the traditional index, while the skewness is less negative. The reward-to-risk ratio stands at 0.344 against the 0.173 of the index and the 0.786 of the spread.

The empirical properties of the remaining combined indices are qualitatively similar to those of the S&P-GSCI TS/Mom(real). DJ-UBSCI TS/Mom(real) produces an annualized return of 4.73% against the 1.97% of the traditional (DJ-UBSCI) index and a reward-to-risk ratio of 0.3135 against the 0.1356 of the index and the 0.7083 of the spread. A closer look at the correlations of the spreads against the traditional indices suggests that the sign is negative and significant for S&P-GSCI and positive and significant, except for 2 spreads, for DJ-UBSCI. Among the 8 combined (or double-enhanced) index strategies, 6 have significantly positive alphas which are 2.46% on average. Tracking errors stay low and betas are close to 1. The betas of the enhanced benchmarks relative to the traditional indices range from 0.956 to 0.9736 against the S&P-GSCI and from 1.0066 to 1.0432 against the DJ-UBSCI. We systematically reject the null that the betas equal 1 for the S&P-GSCI enhanced indices. For the DJ-UBSCI enhanced indices the Mom/TS ones reject the null hypothesis but the TS/Mom ones fail to reject it, suggesting they are insignificantly different to 1. The tracking errors of the enhanced portfolios are low, ranging from 3.62% to 4.08% for the S&P-GSCI ones and from 3.54% to 3.84% for the DJ-UBSCI ones. All this suggests that passive managers interested in our enhanced indices for strategic asset allocation can take comfort in knowing that our approach is closely replicating the risk of the benchmarks and at the same time is providing enhanced returns.

Figure 4.1d,e: Momentum and term structure enhanced S&P-GSCI weightings (top performing strategies)



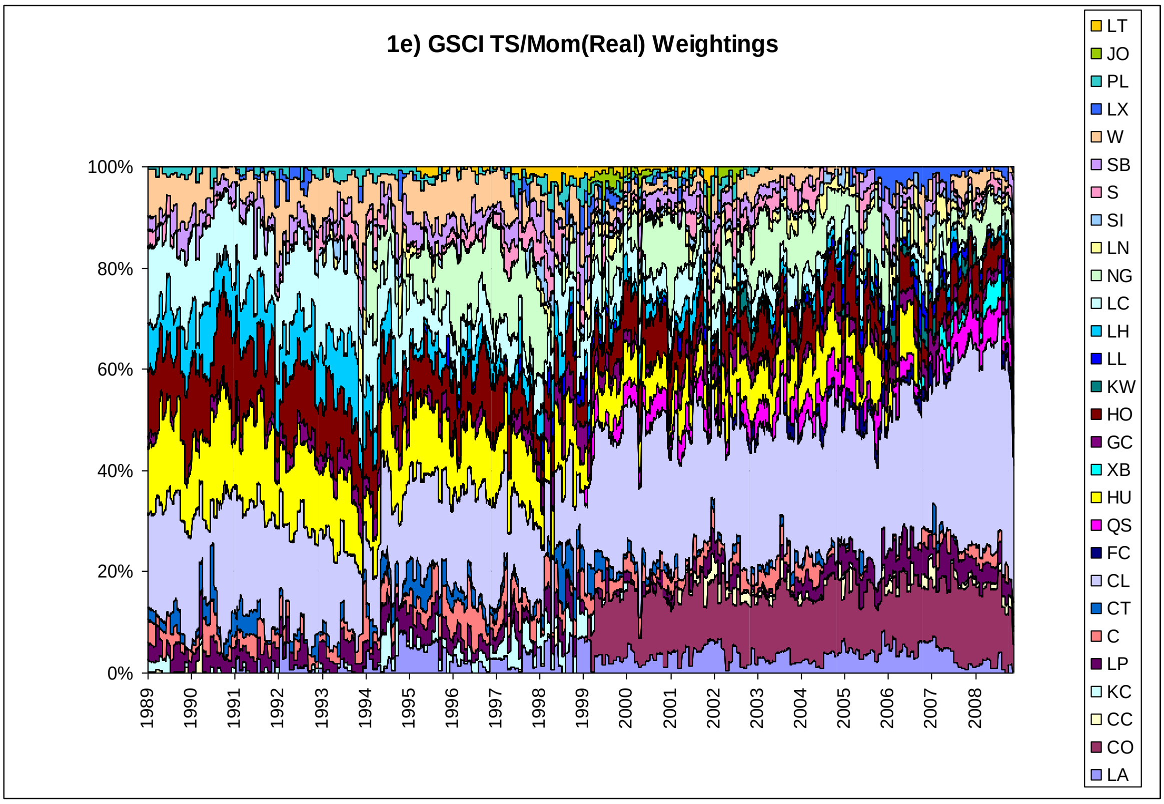
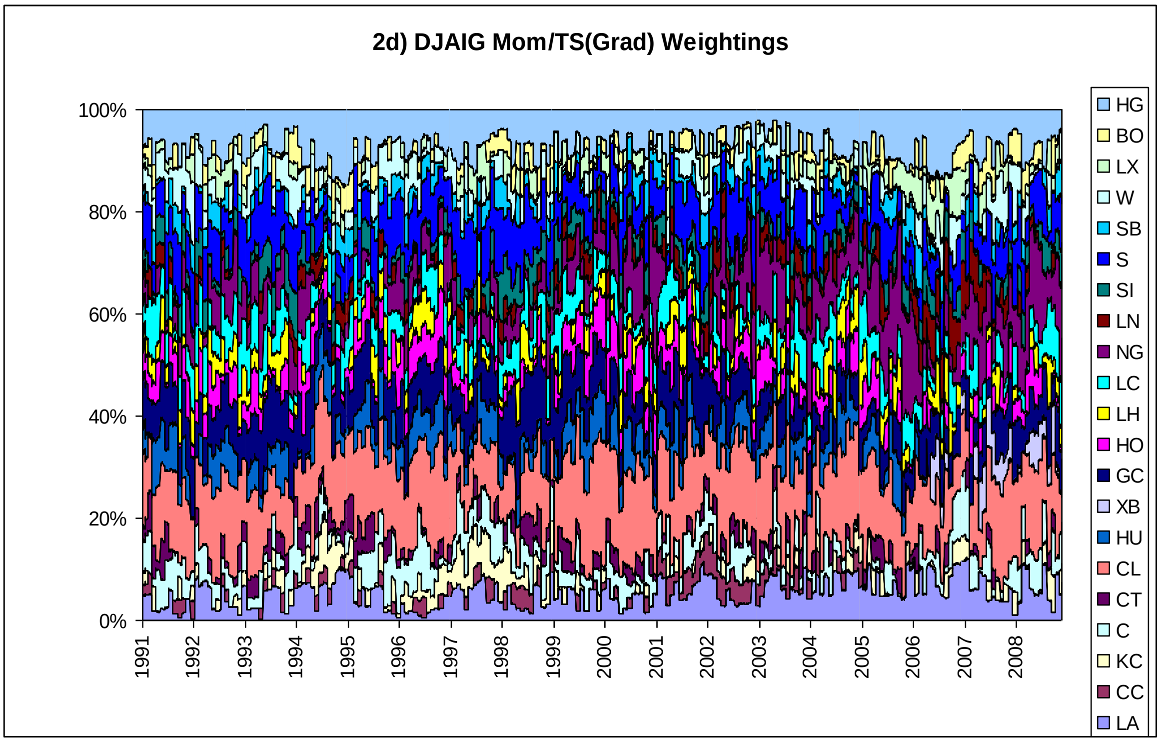
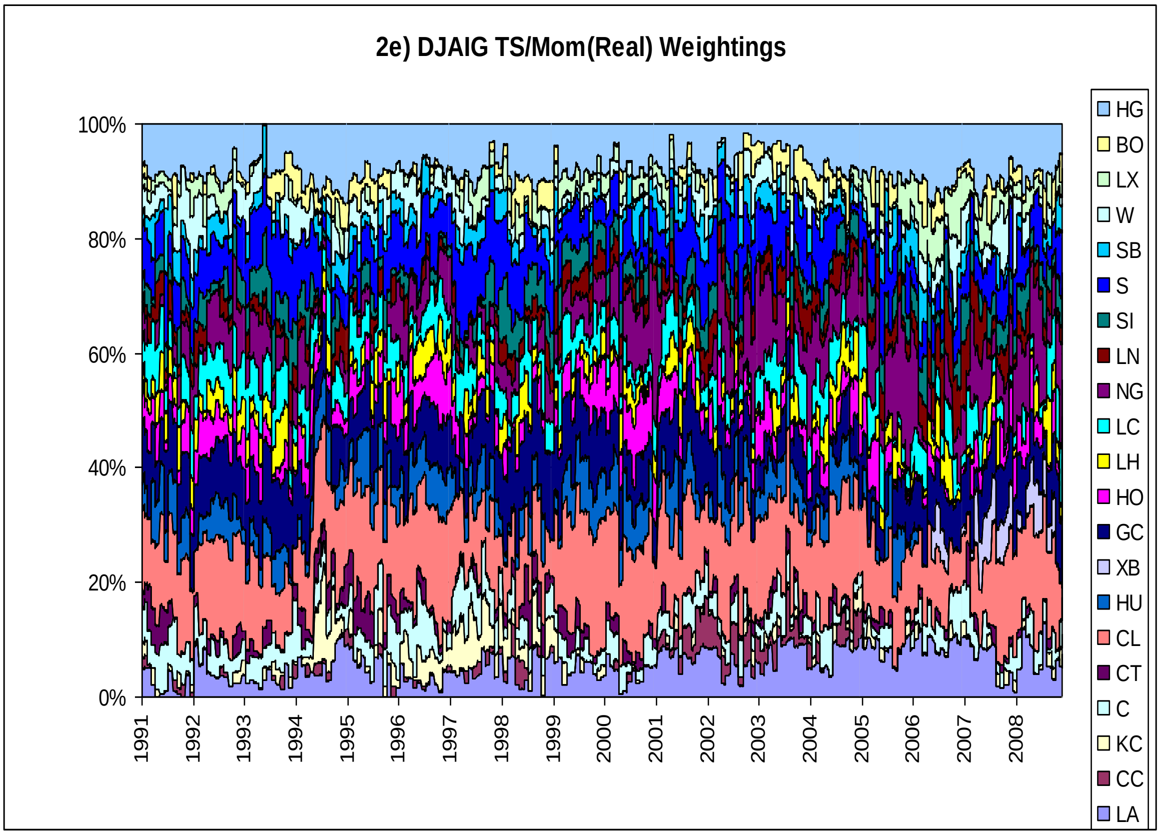


Figure 4.2d,e: Momentum and term structure enhanced DJ-UBSCI weightings (top performing strategies)





The preceding analysis suggests that our enhanced benchmarks can be used for both strategic and tactical asset allocations. The strategic benefits come from successfully replicating the index and thus offering investors with as good an indicator of commodity price movements as the traditional indices. Yet, the added value comes from the tactical benefits of our enhanced indices that can generate excess returns of up to 3.27% (t-stat of 3.45) in the case of TS/Mom(real) for the S&P-GSCI.

4. 8. Maturity / Time Alpha Enhanced Indices

This section furthers our analysis by investigating the role of the commodity contracts' maturity on the performance of the S&P-GSCI and DJ-UBSCI indices. The objective is to assess whether the maturity or "time" alpha signals can provide investors increased diversification across commodity maturities.

Traditional approaches employed by commodity indices rolling from the front to the second contract on a pre-defined schedule are subject to the changing nature of the term structure. In addition, the term structure of the forward price volatility generally declines with time to expiration of the futures contract (Samuelson, 1965). Therefore, traditional indices can exhibit significant roll-losses, extreme volatility and returns that can be quite different from the commodity spot returns. Instead of rolling the constituents according to the traditional S&P-GSCI and DJ-UBSCI approaches, we roll into the specific futures contracts in the term structure curve of each constituent that will give us an average maturity (expiry) of 3, 6, 9 and 12 months. We create 4 different maturity indices for each traditional index. The weightings and the rest of the rolling parameters remain the same but the specific commodity contracts vary.

For the aluminum in the S&P-GSCI 3m, we hold the third contract rolling into the forth, spending on average for the whole period of the analysis 69% of the time on the third contract, 31% of the time on the forth and having an average time to maturity of 2.83 months. For the S&P-GSCI 3m we target 3-month maturity for all constituents. For aluminum in the S&P-GSCI 6m we target 6-month maturity. We hold the 6th contract and roll to the 7th one, spending on average for the whole period of the analysis 69% of the time on the 6th contract, 31% of the time on the 7th and having an average time to maturity of 5.82 months. More details on the target maturities and time spent in each contract can be found in Appendices 4.A and 4.B.

In trying to target much higher maturities, for some commodities we simply cannot hold contracts very far inside the term structure curve either because these contracts do not exist or because they did not exist at some point in the period of the analysis. It is typical in that case to ignore commodities that do not have contracts on the far end of the curve (eg, 5-year UBS Bloomberg Constant Maturity Commodity Index). To preserve the diversification properties of our enhanced indices and maintain as high a correlation with the traditional benchmarks as possible, we took a different route and decided to include contracts that are the closest to the target maturity.

The summary statistics in Tables 4.5 and 4.6 suggest that the further away from the present, the further inside the curve and the longer maturity contracts we use, the higher the returns of the enhanced indices, the lower the volatility and the higher the downside protection. The annualized return is 3.68% for the S&P-GSCI, 8.66% for the S&P-GSCI 3m, 8.75% for the S&P-GSCI 6m, 8.69% for the S&P-GSCI 9m and 8.83% for the S&P-GSCI 12m. The further away from the present, the volatility decreases significantly and despite the worse readings for the skewness and kurtosis of the distributions of returns, the 99% VaR decreases. Maximum drawdown, minimum 12-month returns and worst-month statistics exhibit better values. The reward-to-risk ratio of the S&P-GSCI (at 0.173) is more than trebbled to 0.5753 by the S&P-GSCI 12m. The correlations of the enhanced indices with the S&P-GSCI stand high at 0.9779 for the S&P-GSCI 3m, 0.9436 for the S&P-GSCI 6m, 0.9208 for the S&P-GSCI 9m and 0.913 for the S&P-GSCI 12m. All are statistically different from 1. Turning our attention to the spread, the average outperformance of the 4 enhanced indices against the S&P-GSCI stands at 4.74% with the reward-to-risk ratio jumping to 0.9838 for the spread of the S&P-GSCI 3m index. Given their lower betas against the baseline indices, the spread of these indices is negatively correlated with the traditional indices suggesting that when the performance of the traditional indices improves the outperformance of the enhanced indices decreases and vice versa. The annualized alphas of the indices against the S&P-GSCI are even higher than the annualized returns of the spreads and their volatilities are much lower as well. The average alpha of the maturity-enhanced indices stands at 5.76% and the average tracking error at 5.51%. Betas range from 0.6592 to 0.8791 and are significantly different from 1. This suggests that the abnormal performance of the maturity enhanced indices comes at the cost of a tracking that is not as good as with the baseline indices.

Table 4.5. Maturity Enhanced S&P-GSCI Indices: Summary Statistics

	GSCI	GSCI 3m	GSCI 6m	GSCI 9m	GSCI 12m
Panel A: GSCI index and enhanced versions					
Annualized arithmetic mean	0.0368	0.0866	0.0875	0.0869	0.0883
Annualized geometric mean	0.0148	0.0668	0.0719	0.0733	0.0754
Annualized volatility	0.2126	0.1911	0.1691	0.1578	0.1535
Reward/risk ratio	0.1730	0.4531	0.5172	0.5508	0.5753
Skewness	-0.2637	-0.4380	-0.6200	-0.7105	-0.7287
Kurtosis	5.4148	6.5498	7.6158	8.1703	8.3765
99% VaR (Cornish-Fisher)	0.1877	0.1879	0.1814	0.1762	0.1737
Best month	0.2223	0.2206	0.1834	0.1543	0.1458
Worst month	-0.2825	-0.2721	-0.2595	-0.2525	-0.2486
% of positive months	0.5272	0.5858	0.5816	0.5649	0.5816
Maximum drawdown	-0.5927	-0.5844	-0.5641	-0.5442	-0.5336
Max 12M rolling return	0.7075	0.7546	0.7976	0.8137	0.8023
Min 12M rolling return	-0.4201	-0.3700	-0.3234	-0.2844	-0.2710
Correlation with GSCI	1.0000	0.9779	0.9436	0.9208	0.9130
Ho: Correlation=0		(71.93)	(43.88)	(36.35)	(34.46)
Ho: Correlation=1		(-1.63)	(-2.62)	(-3.13)	(-3.28)
Annualized Alpha with GSCI		**0.0515**	**0.0574**	**0.0595**	**0.0618**
		(4.79)	(3.56)	(3.31)	(3.35)
Tracking Error with GSCI		0.0401	0.0561	0.0617	0.0627
Beta with GSCI		**0.8791**	**0.7504**	**0.6836**	**0.6592**
Ho: Beta=0		(34.26)	(18.44)	(14.85)	(14.03)
Ho: Beta=1		(-4.71)	(-6.13)	(-6.87)	(-7.25)
Panel B: Spread between enhanced-GSCI and GSCI					
Annualized arithmetic mean		**0.0467**	**0.0476**	**0.0470**	**0.0484**
		(4.30)	(2.69)	(2.25)	(2.21)
Annualized geometric mean		0.0456	0.0445	0.0427	0.0436
Annualized volatility		0.0475	0.0771	0.0912	0.0958
Reward/risk ratio		0.9838	0.6170	0.5158	0.5051
Skewness		-0.3053	-0.4597	-0.4328	-0.3951
Kurtosis		7.8465	5.1403	4.3010	4.1525
99% VaR (Cornish-Fisher)		0.0500	0.0687	0.0757	0.0782
Best month		0.0659	0.0740	0.0809	0.0842
Worst month		-0.0553	-0.0771	-0.0839	-0.0864
% of positive months		0.6485	0.5816	0.5900	0.5816
Maximum drawdown		-0.0897	-0.1768	-0.2451	-0.2624
Max 12M rolling return		0.1701	0.2704	0.3296	0.3466
Min 12M rolling return		-0.0723	-0.1483	-0.1722	-0.1811
Correlation with GSCI		**-0.5406**	**-0.6880**	**-0.7377**	**-0.7566**
		(-9.89)	(-14.59)	(-16.82)	(-17.81)

Significance *t*-ratios in parentheses. Bold denotes statistically significant at the 10% level or better. The spread is defined as the return from the enhanced S&P-GSCI (former GSCI) minus the return from the baseline S&P-GSCI.

Table 4.6. Maturity Enhanced DJ-UBSCI Indices: Summary Statistics

	DJAIG	DJAIG 3m	DJAIG 6m	DJAIG 9m	DJAIG 12m
Panel A: DJAIG index and enhanced versions					
Annualized arithmetic mean	0.0197	0.0497	0.0595	0.0618	0.0629
Annualized geometric mean	0.0096	0.0396	0.0510	0.0541	0.0557
Annualized volatility	0.1451	0.1381	0.1265	0.1202	0.1157
Reward/risk ratio	0.1356	0.3595	0.4707	0.5142	0.5438
Skewness	-0.6811	-0.7728	-0.8632	-0.8485	-0.8888
Kurtosis	6.1399	6.7854	7.9853	8.7129	9.0936
99% VaR (Cornish-Fisher)	0.1419	0.1418	0.1405	0.1393	0.1372
Best month	0.1208	0.1230	0.1208	0.1196	0.1168
Worst month	-0.2134	-0.2068	-0.1986	-0.1953	-0.1914
% of positive months	0.5302	0.5814	0.5953	0.5814	0.5535
Maximum drawdown	-0.4960	-0.4904	-0.4752	-0.4542	-0.4415
Max 12M rolling return	0.3734	0.4277	0.5021	0.5384	0.5266
Min 12M rolling return	-0.3373	-0.3147	-0.2766	-0.2347	-0.2234
Correlation with DJAIG	1.0000	0.9898	0.9603	0.9381	0.9297
Ho: Correlation=0		(101.64)	(50.21)	(39.54)	(36.83)
Ho: Correlation=1		(-1.04)	(-2.08)	(-2.61)	(-2.79)
Annualized Alpha with DJAIG		**0.0299**	**0.0418**	**0.0453**	**0.0472**
		(4.84)	(3.62)	(3.38)	(3.38)
Tracking Error with DJAIG		0.0197	0.0354	0.0417	0.0427
Beta with DJAIG		**0.9422**	**0.8372**	**0.7770**	**0.7414**
Ho: Beta=0		(60.57)	(23.79)	(18.11)	(16.68)
Ho: Beta=1		(-3.72)	(-4.63)	(-5.20)	(-5.82)
Panel B: Spread between enhanced-DJAIG and DJAIG					
Annualized arithmetic mean		**0.0287**	**0.0384**	**0.0406**	**0.0417**
		(5.62)	(3.76)	(3.20)	(3.05)
Annualized geometric mean		0.0285	0.0375	0.0392	0.0401
Annualized volatility		0.0213	0.0425	0.0527	0.0568
Reward/risk ratio		1.3479	0.9042	0.7713	0.7347
Skewness		0.3920	-0.3254	-0.2658	-0.1658
Kurtosis		5.6089	4.1574	3.4773	3.4222
99% VaR (Cornish-Fisher)		0.0159	0.0343	0.0397	0.0416
Best month		0.0269	0.0369	0.0435	0.0478
Worst month		-0.0172	-0.0408	-0.0400	-0.0423
% of positive months		0.6977	0.6372	0.5721	0.5860
Maximum drawdown		-0.0357	-0.1128	-0.1490	-0.1552
Max 12M rolling return		0.1113	0.2156	0.2680	0.2854
Min 12M rolling return		-0.0314	-0.1011	-0.1238	-0.1205
Correlation with DJAIG		**-0.3932**	**-0.5561**	**-0.6138**	**-0.6608**
		(-6.24)	(-9.76)	(-11.35)	(-12.85)

Significance *t*-ratios in parentheses. Bold denotes statistically significant at the 10% level or better. The spread is defined as the return from the enhanced DJ-UBSCI (former DJ-AIGCI) minus the return from the baseline DJ-UBSCI.

Summary statistics for the constituents of the maturity-enhanced GCSI indices are shown in Appendix 4.A (columns 3-6). The most outstanding constituents in terms of both higher returns and lower volatilities are the natural gas contracts with an annualized difference in returns of 20.45% between the 1-month and 3-month maturities. This difference rises to 24.77% for the S&P-GSCI 12m. Brent crude, lean hogs and wheat contracts follow in showing increased performance over the medium to the longer end of the term structure. In precious metals we have not seen any significant return differences along the curve. Among the 28 constituents of the S&P-GSCI, only copper has presented higher returns on the front end of the curve rather than the back end on average. Perhaps because of increased liquidity risk, the tendency for the returns of most of the constituents is to increase the higher the maturity we target. And the dispersion of the returns of all of the constituents decreases the higher the maturity we target.

Qualitatively similar results are obtained for the four maturity-enhanced DJ-UBSCI indices. Their average annualized return is 5.85% while the DJ-UBSCI yields 1.97% with a difference in their returns that is significant at the 1% level (Table 4.6, Panel B). The volatility of their returns is significantly lower and all other risk measures are more favorable than those for the traditional DJ-UBSCI index. The reward-to-risk ratio increases more than four times from 0.1356 (DJ-UBSCI) to 0.5438 (DJ-UBSCI 12m). All these results confirm that our enhanced versions can be used for tactical asset allocation. The correlation between the returns of the DJ-UBSCI and the returns of the DJ-UBSCI different maturity indices is high and stands at 0.9545 on average while the betas range from 0.7414 to 0.9422. All but one of the correlations and all the betas are significantly different from 1. The tracking errors, albeit higher than in Tables 4.3 and 4.4, only range from 1.97% to 4.27%. This suggests that while targeting longer maturity contracts, the benefits from enhanced performance do come at the price of higher tracking error (relative to the baseline replication). Still the correlations and betas are close enough to 1 to suggest that the enhanced indices do follow the ups and downs of the DJ-UBSCI and thus can be used for strategic asset allocation. The spreads show an average annualized return of 3.74% with an average annualized dispersion of returns of 4.33%. The DJ-UBSCI 3m spread is the top performer index strategy with an impressive reward-to-risk ratio of 1.3479. It yields positive monthly returns 70% of the time and has a ratio of Max 12m rolling return/Min 12m rolling return of almost 4. The correlations between the spreads and the baseline index remain negative. The picture is even better when we assess the risk-adjusted alpha. The average annualized alpha stands at 4.11% (t-stat equal or above 3.38) with an average tracking error of 3.49%.

Constituent by constituent, the main findings are qualitatively similar to those for the S&P-GSCI. As Appendix 4.B illustrates, natural gas contracts exhibit the highest annualized difference in returns at 11.55% between the 1-month and 3-month maturities and at 14.89% between the 1-month and 12-month maturities. Lean hogs, wheat, live cattle, corn and gasoline follow. Precious metals, again, do not yield significant return differences along the curve. From the 21 constituents of the DJ-UBSCI only copper contracts have presented higher returns on the front side of the curve rather than the back side and sugar contracts have given mixed results. The returns for most of the constituents increase the higher the maturity we target. And the dispersion of the returns of all of the constituents decreases the higher the maturity we target.

4. 9. Conclusion

This paper contributes to the commodity markets literature by providing a thorough analysis of the trading performance of the two traditional commodity indices, S&P-GSCI and DJ-UBSCI, and different enhanced versions thereof. Following our first chapter, the first type of enhancement refers to the momentum effect. The more momentum is embedded in the weight allocation, the better the risk-adjusted performance of the indices. Following the term structure signaling approach of our second chapter the second type of enhancement consists of tactically allocating more (less) weight towards the constituents that are in backwardation (contango). The third type of enhancement is a combination of the two previous approaches. Momentum and term structure signals jointly exploited appear to improve significantly the risk-adjusted performance of the traditional indices. Finally, a maturity-type enhancement that expands the traditional indices across the commodity curve, delivers the highly profitable option of holding longer term maturities instead of shorter term ones.

The analysis demonstrates how different trading parameters, rolling procedures and technical specifications of indices can have a significant impact on the risk-adjusted returns of long-only commodity-trading strategies. Our results favor the momentum- and term structure-based index parameterization. Unambiguous evidence is provided to conclude that the longer the maturity contracts used, the higher the risk-adjusted returns. There are implications for calendar spreads as well. Our results favor the longer maturity legs.

Appendix

Appendix 4.A. Constituents of S&P-GSCI Index and Enhanced Versions: Summary Statistics

	04/01/1989-20/11/2008	GSCI	GSCI replicated	GSCI 3m	GSCI 6m	GSCI 9m	GSCI 12m
Aluminum	An.Ret	-3.11%	-2.87%	-1.54%	0.09%	0.39%	0.63%
	Real Ret	-4.87%	-4.58%	-3.17%	-1.40%	-0.96%	-0.64%
	SD	18.9%	18.9%	18.3%	17.3%	16.5%	15.9%
	69%/31% of time at contract			3 4	6 7	9 10	12 13
	Expiry/Maturity (months)		1.10	2.83	5.82	8.77	11.67
	Price Range		1022.75 3306.5	1037.64 3318	1059.25 3356.5	1081.27 3390	1103.74 3413.5
	MinR/MaxR		-7.93% 7.70%	-7.89% 7.55%	-7.74% 7.43%	-7.44% 7.30%	-7.15% 7.16%
Brent Crude	An.Ret	24.22%	24.28%	28.42%	29.25%	29.06%	29.06%
	Real Ret	17.80%	17.66%	22.29%	24.15%	24.17%	24.17%
	SD	33.1%	33.1%	31.3%	28.4%	27.8%	27.8%
	74%/26% of time at contract			3 4	6 7	7 8	7 8
	Expiry/Maturity (months)		1.40	2.77	5.72	6.68	6.68
	Price Range		10.05 146.6	10.43 147.18	10.93 148.38	11.08 148.51	11.08 148.51
	MinR/MaxR		-12.98% 9.72%	-12.25% 9.70%	-10.77% 9.85%	-10.49% 9.85%	-10.49% 9.85%
Cocoa	An.Ret	-4.04%	-4.08%	-2.42%	-2.23%	-2.06%	-1.92%
	Real Ret	-8.47%	-8.38%	-6.48%	-5.96%	-5.59%	-5.29%
	SD	30.2%	30.3%	29.2%	27.9%	27.1%	26.5%
	90%/10% of time at contract			2 3	3 4	4 5	5 6
	Expiry/Maturity (months)		2.12	3.91	6.24	8.56	10.91
	Price Range		694 3275	714 3275	736 3252	758 3207	779 3197
	MinR/MaxR		-9.52% 12.92%	-9.48% 12.92%	-9.48% 9.96%	-9.51% 9.58%	-9.46% 9.13%
Coffee	An.Ret	-3.53%	-3.56%	-3.43%	-4.00%	-3.40%	-3.33%
	Real Ret	-10.50%	-10.39%	-9.56%	-9.23%	-8.30%	-7.79%
	SD	38.3%	38.5%	36.3%	33.5%	32.3%	30.7%
	84%/16% of time at contract			2 3	3 4	4 5	6 7
	Expiry/Maturity (months)		2.11	4.05	6.38	8.70	13.44
	Price Range		42.5 314.8	45.15 273.8	46.7 244	48.15 244.4	51.25 246.4
	MinR/MaxR		-13.23% 26.15%	-13.16% 26.15%	-12.41% 20.97%	-12.59% 20.06%	-12.88% 18.53%
Copper	An.Ret	7.44%	7.43%	7.09%	7.14%	7.37%	7.62%
	Real Ret	4.20%	4.20%	4.07%	4.36%	4.73%	5.02%
	SD	24.7%	24.7%	23.9%	22.9%	22.3%	22.1%
	68%/32% of time at contract			3 4	6 7	9 10	12 13
	Expiry/Maturity (months)		1.05	2.84	5.84	8.79	11.71
	Price Range		1329.75 8804	1335.5 8756	1351.75 8645	1368.25 8525	1383.5 8421
	MinR/MaxR		-9.87% 12.64%	-9.87% 12.61%	-9.79% 12.48%	-11.73% 12.38%	-15.52% 17.41%
Corn	An.Ret	-7.82%	-7.79%	-5.36%	-3.48%	-2.32%	0.64%
	Real Ret	-10.24%	-10.10%	-7.63%	-5.63%	-4.28%	-0.92%
	SD	22.5%	22.5%	22.0%	21.2%	20.1%	17.7%
	86%/14% of time at contract			2 3	3 4	4 5	6 7
	Expiry/Maturity (months)		1.93	4.00	6.33	8.65	13.39
	Price Range		174.75 768.25	187 768.25	198.75 788	207 805	220 815.75
	MinR/MaxR		-6.69% 7.35%	-6.58% 7.35%	-6.42% 7.14%	-6.27% 6.96%	-6.12% 6.56%
Cotton	An.Ret	-6.45%	-6.57%	-5.39%	-3.86%	-2.78%	-2.72%
	Real Ret	-9.04%	-9.06%	-7.72%	-5.89%	-4.53%	-4.00%
	SD	23.3%	23.3%	22.3%	20.7%	19.1%	16.3%
	90%/10% of time at contract			2 3	3 4	4 5	6 7
	Expiry/Maturity (months)		2.39	3.85	6.27	8.67	13.33
	Price Range		28.52 113.84	30.22 107.45	31.25 102.25	32.25 95.53	34.95 98.44
	MinR/MaxR		-6.68% 6.78%	-7.09% 7.06%	-6.62% 6.78%	-6.09% 7.48%	-6.07% 7.04%
Crude Oil	An.Ret	15.81%	15.77%	17.06%	15.98%	14.63%	13.87%
	Real Ret	9.35%	9.02%	12.12%	12.09%	11.27%	10.74%
	SD	33.9%	34.4%	29.2%	26.0%	24.4%	23.6%
	56%/44% of time at contract			3 4	6 7	9 10	11 12
	Expiry/Maturity (months)		0.63	2.97	5.96	8.92	10.86
	Price Range		10.72 145.78	11.61 146.43	12.19 146.93	12.58 146.69	12.81 146.34
	MinR/MaxR		-31.89% 14.54%	-24.74% 10.20%	-19.22% 10.43%	-15.03% 10.56%	-12.87% 10.52%
Feed Cattle	An.Ret	0.38%	0.52%	2.61%	6.79%	5.66%	5.66%
	Real Ret	-0.70%	-0.57%	1.52%	5.89%	4.88%	4.88%
	SD	14.7%	14.7%	14.6%	13.0%	12.2%	12.2%
	58%/42% of time at contract			2 3	4 5	5 6	5 6
	Expiry/Maturity (months)		1.67	2.95	5.68	7.28	7.28
	Price Range		71.225 119.15	73.325 119.15	73.775 119.15	74.25 118	74.25 118
	MinR/MaxR		-5.82% 3.15%	-5.82% 3.19%	-5.36% 3.20%	-4.84% 3.20%	-4.84% 3.20%

	04/01/1989-20/11/2008	GSCI	GSCI replicated	GSCI 3m	GSCI 6m	GSCI 9m	GSCI 12m
Gas Oil	An.Ret	25.26%	25.10%	27.01%	27.20%	27.66%	27.66%
	Real Ret	19.03%	18.65%	21.22%	22.59%	23.48%	23.48%
	SD	32.6%	32.5%	30.5%	27.2%	25.8%	25.8%
	86%/14% of time at contract			3 4	6 7	8 9	8 9
	Expiry/Maturity (months)		1.28	2.66	5.61	7.53	7.53
	Price Range		91.25 1333.75	94.25 1340.5	102 1353.25	107 1347.5	107 1347.5
	MinR/MaxR		-13.45% 8.16%	-12.83% 8.13%	-11.00% 7.91%	-9.81% 7.71%	-9.81% 7.71%
Gasoline	An.Ret	17.70%	17.89%	20.20%	18.85%	18.85%	18.85%
	Real Ret	11.24%	11.31%	15.75%	15.25%	15.25%	15.25%
	SD	33.7%	33.8%	27.4%	24.8%	24.8%	24.8%
	24%/76% of time at contract			3 4	6 7	6 7	6 7
	Expiry/Maturity (months)		0.89	3.27	6.25	6.25	6.25
	Price Range		32.92 240.9	37.04 214.37	39.65 203.78	39.65 203.78	39.65 203.78
	MinR/MaxR		-25.78% 12.94%	-21.84% 8.26%	-19.01% 7.38%	-19.01% 7.38%	-19.01% 7.38%
Gasoline RBOB	An.Ret	-12.23%	-12.10%	-12.32%	-8.64%	-6.19%	-6.62%
	Real Ret	-20.20%	-19.04%	-18.14%	-13.77%	-11.22%	-11.68%
	SD	40.4%	40.4%	36.9%	33.9%	33.1%	33.3%
	24%/76% of time at contract			3 4	6 7	9 10	11 12
	Expiry/Maturity (months)		0.88	3.13	5.63	7.76	8.96
	Price Range		103.99 358.77	112.09 350.2	132.19 356.07	136.26 375.72	129.04 373.62
	MinR/MaxR		-10.74% 12.49%	-10.30% 11.51%	-9.43% 10.08%	-9.26% 10.30%	-9.53% 11.12%
Gold	An.Ret	0.09%	0.07%	0.14%	0.13%	0.02%	0.02%
	Real Ret	-1.09%	-1.10%	-1.03%	-1.04%	-1.14%	-1.14%
	66%/34% of time at contract	15.3%	15.3%	15.3%	15.3%	15.2%	15.2%
	%time at 1 / 2 contract			2 3	3 4	5 6	5 6
	Expiry/Maturity (months)		2.16	3.71	5.70	9.63	9.63
	Price Range		253.9 1008.8	254.2 1008.8	254.9 1012.5	257.3 1018.5	257.3 1018.5
	MinR/MaxR		-7.46% 9.23%	-7.46% 9.23%	-7.49% 9.11%	-7.38% 9.00%	-7.38% 9.00%
Heating Oil	An.Ret	11.33%	11.49%	13.88%	14.40%	14.20%	14.20%
	Real Ret	5.27%	5.29%	9.22%	10.60%	10.80%	10.80%
	SD	33.6%	33.7%	28.8%	25.9%	24.6%	24.6%
	25%/75% of time at contract			3 4	6 7	9 10	9 10
	Expiry/Maturity (months)		0.88	3.28	6.27	9.22	9.22
	Price Range		29.52 411.16	31.41 418.06	34.16 426.7	36.81 421.15	36.81 421.15
	MinR/MaxR		-29.60% 13.94%	-24.47% 9.03%	-21.06% 8.53%	-19.98% 8.33%	-19.98% 8.33%
Kansas Wheat	An.Ret	-2.53%	-2.46%	0.84%	5.27%	5.87%	5.87%
	Real Ret	-5.98%	-5.78%	-2.43%	2.17%	3.03%	3.03%
	SD	26.3%	26.3%	25.7%	24.5%	23.3%	23.3%
	86%/14% of time at contract			2 3	3 4	4 5	4 5
	Expiry/Maturity (months)		1.83	3.96	6.25	8.49	8.49
	Price Range		259.25 1337	270.25 1308	282 1274.5	291 1280	291 1280
	MinR/MaxR		-8.10% 7.83%	-7.08% 7.83%	-6.56% 7.99%	-6.18% 8.00%	-6.18% 8.00%
Lead	An.Ret	6.76%	6.76%	8.37%	9.37%	9.11%	9.41%
	Real Ret	2.34%	2.32%	4.15%	5.53%	5.45%	5.77%
	SD	29.1%	29.1%	28.2%	26.7%	26.1%	26.0%
	72%/28% of time at contract			3 4	6 7	9 10	12 13
	Expiry/Maturity (months)		1.14	2.82	5.81	8.74	11.62
	Price Range		406 3940	412.5 3878	423.75 3776	432.5 3680	440 3590
	MinR/MaxR		-11.42% 13.70%	-11.31% 13.51%	-11.13% 13.25%	-10.82% 13.16%	-10.50% 13.03%
Lean Hogs	An.Ret	-5.92%	-5.52%	1.71%	5.70%	5.06%	5.06%
	Real Ret	-8.38%	-7.94%	-0.53%	4.27%	4.08%	4.08%
	SD	22.8%	22.8%	21.1%	16.5%	13.7%	13.7%
	80%/20% of time at contract			2 3	4 5	6 7	6 7
	Expiry/Maturity (months)		1.36	2.93	6.10	9.19	9.19
	Price Range		27.225 90.878	33.375 87.804	35.325 86.225	38.9 97.375	38.9 97.375
	MinR/MaxR		-6.65% 7.12%	-5.60% 5.58%	-5.36% 4.86%	-4.19% 4.64%	-4.19% 4.64%
Live Cattle	An.Ret	0.13%	0.22%	3.68%	2.06%	1.28%	1.28%
	Real Ret	-0.76%	-0.66%	2.93%	1.55%	0.93%	0.93%
	SD	13.3%	13.3%	12.0%	10.0%	8.3%	8.3%
	70%/30% of time at contract			2 3	3 4	5 6	5 6
	Expiry/Maturity (months)		1.72	3.64	5.63	9.57	9.57
	Price Range		54.8 109.675	57.65 112.4	59.3 114.55	60.25 117.7	60.25 117.7
	MinR/MaxR		-6.16% 3.77%	-6.35% 3.44%	-4.06% 2.75%	-3.94% 2.98%	-3.94% 2.98%
Natural Gas	An.Ret	-9.10%	-9.09%	11.37%	12.60%	15.36%	15.69%
	Real Ret	-20.71%	-20.38%	3.63%	7.90%	11.83%	12.66%
	SD	51.3%	51.5%	38.0%	29.2%	24.9%	23.1%
	37%/63% of time at contract			3 4	6 7	9 10	11 12
	Expiry/Maturity (months)		0.77	3.16	6.14	9.06	10.98
	Price Range		1.323 15.427	1.423 15.131	1.548 14.516	1.66 13.162	1.706 12.183
	MinR/MaxR		-15.38% 20.64%	-13.00% 11.44%	-10.49% 9.23%	-7.31% 8.94%	-7.50% 8.84%

	04/01/1989-20/11/2008	GSCI	GSCI replicated	GSCI 3m	GSCI 6m	GSCI 9m	GSCI 12m
Nickel	An.Ret	8.98%	9.22%	10.44%	12.20%	12.14%	12.04%
	Real Ret	2.83%	2.91%	4.17%	6.32%	6.53%	6.54%
	SD	34.2%	34.5%	34.2%	32.8%	32.0%	31.7%
	70%/30% of time at contract			3 4	6 7	9 10	12 13
	Expiry/Maturity (months)		1.11	2.82	5.80	8.74	11.62
	Price Range		3742.06 52850	3801.19 52200	3855.62 49900	3910.83 47510	3966.83 45140
	MinR/MaxR		-16.69% 14.06%	-16.55% 13.96%	-14.77% 13.83%	-13.48% 13.71%	-12.59% 13.59%
Silver	An.Ret	0.76%	0.78%	0.87%	1.09%	1.18%	1.13%
	Real Ret	-2.73%	-2.68%	-2.58%	-2.33%	-2.16%	-2.19%
	SD	26.3%	26.4%	26.3%	26.1%	25.8%	25.7%
	67%/33% of time at contract			2 3	3 4	5 6	6 7
	Expiry/Maturity (months)		2.11	3.70	5.70	9.62	11.49
	Price Range		3.51 20.785	3.55 20.785	3.573 20.885	3.633 21.065	3.637 21.095
	MinR/MaxR		-13.75% 11.35%	-13.75% 11.49%	-13.55% 11.35%	-13.36% 11.34%	-13.28% 11.35%
Soybeans	An.Ret	0.99%	0.96%	1.41%	1.33%	1.38%	2.32%
	Real Ret	-1.50%	-1.53%	-1.00%	-0.93%	-0.75%	0.31%
	SD	22.3%	22.3%	21.9%	21.3%	20.6%	19.9%
	80%/20% of time at contract			2 3	4 5	5 6	6 7
	Expiry/Maturity (months)		1.94	3.02	6.33	7.99	9.63
	Price Range		411.5 1631	410 1649	415 1631	419 1644.75	426 1649.25
	MinR/MaxR		-7.08% 6.92%	-7.03% 6.96%	-6.86% 7.30%	-6.81% 7.29%	-6.80% 7.32%
Sugar	An.Ret	5.22%	5.25%	5.83%	6.33%	5.41%	3.98%
	Real Ret	0.29%	0.28%	0.84%	2.51%	2.35%	1.32%
	SD	31.0%	31.1%	31.1%	27.1%	24.3%	22.7%
	75%/25% of time at contract			1 2	2 3	3 4	4 5
	Expiry/Maturity (months)		2.09	2.47	5.40	8.04	10.90
	Price Range		4.08 19.3	4.08 19.3	4.56 19.26	5.03 18.44	5.08 18.32
	MinR/MaxR		-10.71% 10.45%	-10.71% 10.45%	-10.39% 9.26%	-10.04% 7.83%	-9.65% 8.44%
Wheat	An.Ret	-6.53%	-6.47%	-2.47%	1.38%	1.67%	1.67%
	Real Ret	-9.53%	-9.36%	-5.27%	-1.25%	-0.70%	-0.70%
	SD	25.1%	25.1%	24.1%	23.0%	21.7%	21.7%
	%time at 1 / 2 contract			2 3	3 4	4 5	4 5
	86%/14% of time at contract		1.83	4.00	6.33	8.65	8.65
	Price Range		230.75 1282.5	242.75 1250	252.5 1251.5	263 1257.5	263 1257.5
	MinR/MaxR		-8.05% 8.85%	-7.91% 8.85%	-7.86% 8.68%	-7.80% 8.55%	-7.80% 8.55%
Zinc	An.Ret	-1.43%	-1.22%	-0.03%	1.95%	2.34%	2.62%
	Real Ret	-4.60%	-4.43%	-3.09%	-0.91%	-0.32%	0.07%
	SD	25.3%	25.7%	24.9%	23.8%	22.9%	22.4%
	70%/30% of time at contract			3 4	6 7	9 10	12 13
	Expiry/Maturity (months)		0.85	2.84	5.82	8.77	11.66
	Price Range		724 4594	744 4532	759.25 4380	773 4212	783.75 4039
	MinR/MaxR		-11.75% 9.96%	-11.63% 9.56%	-10.36% 8.97%	-9.76% 8.45%	-9.50% 8.16%
Platinum	An.Ret	N/A	5.22%	5.52%	5.17%	5.17%	5.17%
	Real Ret	N/A	2.96%	3.24%	2.93%	2.93%	2.93%
	SD	N/A	20.8%	20.9%	20.7%	20.7%	20.7%
	79%/21% of time at contract			1 2	2 3	2 3	2 3
	Expiry/Maturity (months)		2.40	2.15	5.16	5.16	5.16
	Price Range		333.1 2276.1	333.1 2276.1	333.8 2279.9	333.8 2279.9	333.8 2279.9
	MinR/MaxR		-9.16% 7.92%	-9.16% 7.92%	-9.04% 7.64%	-9.04% 7.64%	-9.04% 7.64%
Orange Juice	An.Ret	N/A	-5.97%	-5.75%	-5.25%	-5.23%	-5.23%
	Real Ret	N/A	-9.94%	-9.26%	-8.28%	-8.02%	-8.02%
	SD	N/A	29.4%	27.5%	25.5%	24.5%	24.5%
	91%/9% of time at contract			2 3	3 4	5 6	5 6
	Expiry/Maturity (months)		1.63	3.21	5.20	9.14	9.14
	Price Range		54.65 208.15	56.8 206.65	58.5 204.5	63.55 203.3	63.55 203.3
	MinR/MaxR		-8.88% 17.09%	-8.88% 16.27%	-8.60% 7.65%	-17.85% 22.97%	-17.85% 22.97%
Tin	An.Ret	N/A	2.24%	2.35%	2.34%	2.35%	2.38%
	Real Ret	N/A	-0.25%	-0.05%	0.06%	0.11%	0.11%
	SD	N/A	22.2%	21.8%	21.2%	21.0%	21.2%
	69%/31% of time at contract			3 4	6 7	9 10	12 13
	Expiry/Maturity (months)		1.12	2.83	5.82	8.78	11.69
	Price Range		3611 25340	3635 25300	3670 25180	3698 25090	3723 25015
	MinR/MaxR		-10.83% 16.22%	-10.81% 15.62%	-10.58% 14.94%	-10.36% 14.55%	-10.18% 14.45%

An.Ret: Annualized arithmetic mean
Real Ret: Annualized geometric mean
SD: Annualized standard deviation (volatility)
Min R/ Max R: Minimum Return / Maximum Return

Appendix 4.B. Constituents of DJ-UBSCI Index and Enhanced Versions:

Summary Statistics

	04/01/1991-20/11/2008	DJAIG	DGAIG replicated	DJAIG 3m	DJAIG 6m	DJAIG 9m	DJAIG 12m
Aluminum	An.Ret	-2.44%	-2.46%	-1.50%	0.11%	0.40%	0.62%
	Real Ret	-4.14%	-4.14%	-3.14%	-1.38%	-0.95%	-0.64%
	SD	18.7%	18.6%	18.3%	17.3%	16.5%	15.9%
	69%/31% of time at contract			3 4	6 7	9 10	12 13
	Expiry/Maturity (months)		1.57	2.83	5.82	8.77	11.67
	Price Range		1022.7 3306.5	1037.64 3318	1059.25 3356.5	1081.27 3390	1103.74 3413.5
	MinR/MaxR		-7.89% 7.70%	-7.89% 7.55%	-7.74% 7.43%	-7.44% 7.30%	-7.15% 7.16%
Cocoa	An.Ret	-2.80%	-2.84%	-1.14%	-0.95%	-0.96%	-0.95%
	Real Ret	-7.15%	-7.06%	-5.13%	-4.64%	-4.45%	-4.29%
	SD	29.9%	29.8%	28.7%	27.5%	26.8%	26.2%
	90%/10% of time at contract			2 3	3 4	4 5	5 6
	Expiry/Maturity		2.12	3.90	6.23	8.54	10.88
	Price Range		694 3275	714 3275	736 3252	758 3207	779 3197
	MinR/MaxR		-9.50% 10.50%	-9.48% 10.38%	-9.48% 9.96%	-9.51% 9.58%	-9.46% 9.13%
Coffee	An.Ret	-0.77%	-0.74%	-0.56%	-1.31%	-0.92%	-1.08%
	Real Ret	-8.12%	-8.02%	-7.10%	-6.91%	-6.14%	-5.80%
	SD	39.1%	39.2%	37.0%	34.2%	33.0%	31.3%
	84%/16% of time at contract			2 3	3 4	4 5	6 7
	Expiry/Maturity		2.12	4.05	6.38	8.68	13.40
	Price Range		42.5 314.8	45.15 273.8	46.7 244	48.15 244.4	51.25 246.4
	MinR/MaxR		-13.23% 26.15%	-12.97% 26.15%	-12.41% 20.97%	-12.59% 20.06%	-12.88% 18.53%
Copper NYMEX	An.Ret	6.98%	6.61%	7.86%	8.75%	8.87%	8.87%
	Real Ret	3.55%	3.19%	4.48%	5.72%	6.07%	6.07%
	SD	25.5%	25.5%	25.2%	23.8%	22.8%	22.8%
	34%/66% of time at contract			3 4	6 7	9 10	9 10
	Expiry/Maturity (months)		2.14	3.22	6.24	9.21	9.21
	Price Range		60.6 406.35	60.85 406.35	61.55 402.9	62.35 398.55	62.35 398.55
	MinR/MaxR		-11.05% 12.25%	-10.81% 12.20%	-10.75% 12.18%	-10.66% 12.10%	-10.66% 12.10%
Corn	An.Ret	-7.71%	-7.65%	-4.87%	-2.91%	-1.86%	1.19%
	Real Ret	-10.19%	-10.06%	-7.24%	-5.15%	-3.88%	-0.40%
	SD	23.1%	23.0%	22.5%	21.6%	20.4%	17.8%
	86%/14% of time at contract			2 3	3 4	4 5	6 7
	Expiry/Maturity (months)		1.92	3.99	6.31	8.62	13.34
	Price Range		174.75 768.25	187 768.25	198.75 788	207 805	220 815.75
	MinR/MaxR		-6.69% 7.35%	-6.58% 7.35%	-6.42% 7.14%	-6.27% 6.96%	-6.12% 6.56%
Cotton	An.Ret	-9.20%	-9.07%	-7.83%	-6.13%	-5.10%	-4.52%
	Real Ret	-11.80%	-11.62%	-10.21%	-8.21%	-6.91%	-5.85%
	SD	23.9%	23.8%	22.9%	21.2%	19.6%	16.7%
	90%/10% of time at contract			2	3 4	4 5	6 7
	Expiry/Maturity (months)		2.40	3.84	6.24	8.63	13.27
	Price Range		28.52 113.84	30.22 107.45	31.25 102.25	32.25 95.53	34.95 98.44
	MinR/MaxR		-6.68% 6.78%	-7.09% 7.06%	-6.62% 6.78%	-6.09%	-6.07%
Crude Oil	An.Ret	12.14%	12.17%	14.14%	13.77%	13.00%	12.44%
	Real Ret	6.23%	6.30%	9.46%	10.13%	9.89%	9.57%
	SD	32.7%	32.5%	28.8%	25.4%	23.6%	22.7%
	56%/44% of time at contract			3 4	6 7	9 10	11 12
	Expiry/Maturity (months)		1.17	2.97	5.96	8.90	10.84
	Price Range		10.72	11.61	12.19	12.58	12.81
	MinR/MaxR		-31.89%	-24.74%	-19.22%	-15.03%	-12.87%
Gasoline	An.Ret	16.39%	16.33%	18.36%	17.82%	17.82%	17.82%
	Real Ret	10.65%	10.63%	14.17%	14.48%	14.48%	14.48%
	SD	31.6%	31.6%	26.8%	23.9%	23.9%	23.9%
	24%/76% of time at contract			3 4	6 7	6 7	6 7
	Expiry/Maturity (months)		1.40	3.27	6.24	6.24	6.24
	Price Range		32.92	37.04	39.65	39.65	39.65
	MinR/MaxR		-25.78%	-21.84%	-19.01%	-19.01%	-19.01%
Gasoline RBOB	An.Ret	-22.86%	-22.34%	-13.53%	-11.73%	-8.83%	-8.39%
	Real Ret	-29.53%	-27.85%	-18.92%	-16.42%	-13.38%	-12.94%
	SD	38.3%	38.2%	35.8%	33.0%	31.9%	31.9%
	24%/76% of time at contract			3	6	9	11
	Expiry/Maturity (months)		1.37	3.17	5.80	8.12	9.51
	Price Range		112.09	112.09 350.2	132.19	136.26	129.04
	MinR/MaxR		-10.61% 11.89%	-10.30% 11.51%	-9.43% 10.08%	-9.26% 10.30%	-9.53% 11.12%

	04/01/1991-20/11/2008	DJAIG	DGAIG replicated	DJAIG 3m	DJAIG 6m	DJAIG 9m	DJAIG 12m
Gold	An.Ret	1.10%	1.08%	1.17%	1.17%	1.08%	1.08%
	Real Ret	-0.08%	-0.09%	-0.01%	-0.01%	-0.08%	-0.08%
	SD	15.3%	15.3%	15.3%	15.3%	15.2%	15.2%
	66%/34% of time at contract			2	3	5 6	5 6
	Expiry/Maturity (months)		2.16	3.70	5.69	9.61	9.61
	Price Range		253.9 1008.8	254.2 1008.8	254.9 1012.5	257.3 1018.5	257.3 1018.5
	MinR/MaxR		-7.46%	-7.46%	-7.49%	-7.38%	-7.38%
Heating Oil	An.Ret	9.41%	9.38%	11.01%	12.40%	12.85%	12.85%
	Real Ret	3.85%	3.80%	6.57%	8.82%	9.69%	9.69%
	SD	32.2%	32.2%	28.5%	25.4%	23.8%	23.8%
	25%/75% of time at contract			3	6	9	9
	Expiry/Maturity (months)		1.39	3.28	6.26	9.20	9.20
	Price Range		29.52	31.41	34.16	36.81	36.81
	MinR/MaxR		-29.60% 13.66%	-24.47% 9.03%	-21.06% 8.53%	-19.98% 8.33%	-19.98% 8.33%
Lean Hogs	An.Ret	-7.83%	-7.60%	0.42%	5.23%	4.88%	4.88%
	Real Ret	-10.30%	-10.06%	-1.87%	3.77%	3.87%	3.87%
	SD	23.4%	23.3%	21.4%	16.7%	13.9%	13.9%
	80%/20% of time at contract			2 3	4 5	6 7	6 7
	Expiry/Maturity (months)		1.35	2.91	6.05	9.11	9.11
	Price Range		27.225 90.101	33.375 86.125	35.325 86.225	38.9 97.375	38.9 97.375
	MinR/MaxR		-6.65% 7.12%	-5.60% 5.58%	-5.36% 4.86%	-4.19% 4.64%	-4.19% 4.64%
Live Cattle	An.Ret	-0.95%	-0.98%	3.19%	1.82%	0.95%	0.95%
	Real Ret	-1.90%	-1.90%	2.41%	1.28%	0.59%	0.59%
	SD	13.8%	13.6%	12.3%	10.3%	8.5%	8.5%
	68%/32% of time at contract			2	3	5	5
	Expiry/Maturity (months)		1.74	3.66	5.65	9.58	9.58
	Price Range		54.8 109.675	57.65 112.4	59.3 114.55	60.25 117.7	60.25 117.7
	MinR/MaxR		-6.16% 3.77%	-6.35% 3.44%	-4.06% 2.75%	-3.94% 2.98%	-3.94% 2.98%
Natural Gas	An.Ret	-1.40%	-1.38%	10.17%	11.05%	13.33%	13.51%
	Real Ret	-11.19%	-11.05%	3.30%	6.91%	10.21%	10.80%
	SD	45.4%	45.4%	35.9%	27.6%	23.6%	22.0%
	39%/61% of time at contract			3 4	6 7	9 10	11 12
	Expiry/Maturity (months)		1.34	3.14	6.13	9.07	11.01
	Price Range		1.079 15.378	1.145 15.131	1.195 14.516	1.3 13.162	1.3 12.183
	MinR/MaxR		-15.38% 14.93%	-13.00% 11.44%	-10.49% 9.23%	-7.31% 8.94%	-7.50% 8.84%
Nickel	An.Ret	6.38%	6.37%	7.39%	9.01%	9.04%	9.05%
	Real Ret	0.85%	0.75%	1.76%	3.73%	4.00%	4.10%
	SD	32.7%	32.9%	32.8%	31.5%	30.8%	30.5%
	69%/31% of time at contract			3 4	6 7	9 10	12 13
	Expiry/Maturity (months)		1.81	2.83	5.82	8.77	11.67
	Price Range		3758.6 52200	3801.19 52200	3855.62 49900	3910.83 47510	3966.83 45140
	MinR/MaxR		-16.59% 13.96%	-16.55% 13.96%	-14.77% 13.83%	-13.48% 13.71%	-12.59% 13.59%
Silver	An.Ret	3.80%	3.82%	3.90%	4.16%	4.26%	4.23%
	Real Ret	0.04%	0.06%	0.16%	0.46%	0.63%	0.64%
	SD	27.1%	27.1%	27.0%	26.8%	26.5%	26.4%
	67%/33% of time at contract			2 3	3 4	5 6	6 7
	Expiry/Maturity (months)		2.10	3.70	5.69	9.60	11.46
	Price Range		3.51 20.785	3.55 20.785	3.573 20.885	3.633 21.065	3.637 21.095
	MinR/MaxR		-13.75% 11.35%	-13.75% 11.49%	-13.55% 11.35%	-13.36% 11.34%	-13.28% 11.35%
Soybeans	An.Ret	3.36%	3.32%	4.11%	3.58%	3.24%	3.64%
	Real Ret	0.74%	0.71%	1.57%	1.20%	1.02%	1.56%
	SD	22.7%	22.6%	22.2%	21.5%	20.8%	20.1%
	81%/19% of time at contract			2	4	5 6	6 7
	Expiry/Maturity (months)		1.92	3.00	6.31	7.96	9.59
	Price Range		411.5 1631	410 1649	415 1631	419 1644.75	426 1649.25
	MinR/MaxR		-7.08%	-7.03%	-6.86%	-6.81% 7.29%	-6.80% 7.32%
Soybean Oil	An.Ret	-0.48%	-0.24%	-0.37%	1.98%	2.69%	3.05%
	Real Ret	-3.09%	-2.84%	-2.88%	-0.39%	0.49%	0.91%
	SD	23.0%	23.0%	22.6%	21.7%	20.8%	20.5%
	78%/22% of time at contract			2 3	4 5	6 7	7 8
	Expiry/Maturity (months)		2.17	2.68	5.58	8.46	9.92
	Price Range		14.38 70.82	14.64 70.82	14.98	15.41	15.66
	MinR/MaxR		-6.89% 8.42%	-6.89% 8.42%	-6.74% 8.05%	-6.65% 7.59%	-6.62% 7.46%

	04/01/1991-20/11/2008	DJAIG	DGAIG replicated		DJAIG 3m		DJAIG 6m		DJAIG 9m		DJAIG 12m	
Sugar	An.Ret	5.57%	5.50%		6.09%		6.29%		5.20%		3.66%	
	Real Ret	0.63%	0.63%		1.22%		2.60%		2.22%		1.11%	
	SD	31.0%	30.7%		30.7%		26.6%		23.9%		22.3%	
	75%/25% of time at contract				1	2	2	3	3	4	4	5
	Expiry/Maturity (months)		2.09		2.47		5.40		8.03		10.88	
	Price Range		4.08	19.3	4.08	19.3	4.56	19.26	5.03	18.44	5.08	18.32
	MinR/MaxR		-10.71%	10.45%	-10.71%	10.45%	-10.39%	8.54%	-10.04%	7.83%	-9.65%	8.44%
Wheat	An.Ret	-4.36%	-4.27%		-0.16%		3.92%		3.93%		3.93%	
	Real Ret	-7.59%	-7.44%		-3.22%		1.03%		1.34%		1.34%	
	SD	26.0%	26.0%		25.0%		23.8%		22.4%		22.4%	
	86%/14% of time at contract				2	3	3	4	4	5	4	
	Expiry/Maturity (months)		1.82		3.99		6.31		8.62		8.62	
	Price Range		230.75	1282.5	242.75	1250	252.5	1251.5	263	1257.5	263	1257.5
	MinR/MaxR		-8.05%	8.85%	-7.91%	8.85%	-7.86%	8.68%	-7.80%	8.55%	-7.80%	8.55%
Zinc	An.Ret	-0.23%	-0.78%		-0.03%		1.95%		2.34%		2.62%	
	Real Ret	-3.37%	-3.84%		-3.09%		-0.91%		-0.32%		0.07%	
	SD	25.2%	25.0%		24.9%		23.8%		22.9%		22.4%	
	70%/30% of time at contract				3	4	6	7	9	10	12	13
	Expiry/Maturity (months)		1.76		2.84		5.82		8.77		11.66	
	Price Range		730.75	4556	744	4532	759.25	4380	773		783.75	4039
	MinR/MaxR		-11.69%	9.56%	-11.63%	9.56%	-10.36%	8.97%	-9.76%	8.45%	-9.50%	8.16%

An.Ret: Annualized arithmetic mean
Real Ret: Annualized geometric mean
SD: Annualized standard deviation (volatility)
Min R/ Max R: Minimum Return / Maximum Return

5. Concluding Remarks

5. 1. What have we Learned

The thesis presents evidence that idiosyncratic characteristics do exist in commodity futures markets and that they can form the basis for highly profitable trading strategies clearly outperforming equally-weighted indices. The presence of relative price continuation and reversal is tested and profitable momentum strategies in the short-term up to one year are identified. Evidence of a strong link between momentum strategies and the term structure of the commodity curve is presented. Commodities that are included in the best relative performers of past periods tend to be in a backwardated state and commodities with the worst relative performance tend to be in a contango state. This implicitly suggests that the state of the term structure can play an important role in explaining the variability of returns in commodity markets. Examining further the suggestion, profitable term structure strategies that allocate wealth towards relatively backwardated commodities and away from relatively contangoed commodities are identified.

The two types of strategies, momentum and term structure, are shown to exhibit low correlations suggesting they are independent. By combining signals from prior price action and from prices of contracts along the curve help generate superior double-sort strategies that alongside the previous two are independent to the returns of traditional asset classes, making them good candidates-diversifiers for inclusion in investment portfolios. Lack of liquidity, transaction costs, macroeconomic risk factors or time-variation in risks do not provide a probable explanation for the profitability of the strategies. The strategies are also robust to the recent commodity market turmoil and the extreme volatility experienced in commodity markets.

The role of momentum, term structure and the new time to maturity/expiry factors are examined in a long-only framework. The design of enhanced versions of the traditional S&P-GSCI and DJ-UBSCI indices is fruitful. With risk parameters close to the traditional indices, the enhanced indices can be used in direct investment for return enhancement and diversification purposes and in a theoretical framework to facilitate choosing among commodity indices.

5. 2. Extensions for Future Research

The risk management analysis highlights the fact that the long-short momentum and term structure 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.

Previous research by Basu et al. (2006) shows that the information contained in the Commitment of Traders (COT) can successfully be used for commodity market timing. In another interesting paper, Basu and Miffre (2009) try to explain momentum and term structure strategies by creating portfolios of commodities chosen by hedgers and speculators. A cross section analysis of the COT report data (open interest, volume, liquidity of each cluster of traders) in terms of momentum (winners and losers), term structure (backwardated and contangoed) and "time alpha" (back-end versus front-end spread) constitutes an interesting avenue for future research. Based on the outcome, more accurate timing strategies on commodity futures could be created mixing momentum, term structure, and maturities with COT data.

Inventory data could play a significant role in explaining inefficiencies in commodity markets. Following Gorton et al. (2008) who present evidence that prior commodity futures returns and the futures basis reflect the state of inventories, novel trading strategies could be tested mixing momentum, term structure and maturities with information on inventories.

It must be noted that possible liquidity tradeoffs for the enhanced indices have not been investigated in depth. However, the commodities reflected in the DJ-UBSCI represent over $1.9 trillion of annual world production with an annual futures trading volume exceeding $15 trillion.[42] The notional value outstanding of banks' OTC commodity derivatives contracts is a record $9.0 trillion.[43] The momentum, term structure and combined indices, all have the same maturity as the traditional indices. The weights change dynamically but, as illustrated in the second chapter, liquidity does not seem to play a role in the profitability of momentum, term structure and combined strategies. For the maturity-enhanced indices the weights remain the same as in the traditional indices but the liquidity in most commodity contracts drops quickly after the third month, resulting in wider bid-offer spreads. However, the outperformance is significant and possible explanations for part of it could be attributed to the asymmetric behavior of participants in the markets when commodity prices increase or decrease (implied positive relationship of the outperformance of the back-end strategies with the volatility of the front-end), to the changing nature of the term structure, to the stability of the back-end of the curve (due to supply and demand dynamics) and to the minimum roll-costs of the longer maturity contracts among others. As solely the front-end of the term structure provides investors with adequate liquidity, it is likely that the improved performance of the maturity enhanced strategies is in part a fair compensation for taking on liquidity risk. A detailed analysis of the liquidity premium in such indices constitutes an interesting avenue for future research.

[42] As stated in the DJ-UBS Commodity Index (2009) manual.
[43] According to IFSL research (2008).

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