Structural properties of commodity futures term structures and their implications for basic trading strategies[1]

Rolf Duerr[§] Matthias Voegeli[‡]

December 4, 2009

Abstract

This paper examines the informational content of commodity futures term structures over time. Time series of commodity prices and returns are analyzed by means of static and rolling principal component analysis. We use weekly data from January 1998 to July 2009 of 23 commodity underlyings from Energy, Metals, Agriculture and Livestock. We find high stability of the principal components and their explanatory power over time. The first component identified as a level factor is paramount for the interpretation of term structure dynamics for most underlyings. This result suggests that an investor can exploit the information contained within the term structure and revealed by principal component analysis. We formulate three distinctive investment strategies based on term structure information which optimize roll yields. By creating portfolios according to a principal component ranking we significantly outperform a long-only benchmark.

Keywords: Futures term structure, Roll yield, Convenience yield, Contango, Backwardation, Commodity trading strategies, Principal component analysis

JEL: G11, G13, G12

[1]Submitted within the scope of the Research Seminar in Finance of the Swiss Institute of Banking and Finance (s/bf) at the University of St. Gallen

[§]University of St.Gallen, Weinhaldenstrasse 34, 8645 Jona, Switzerland. rduerr@gmx.ch

[‡]University of St.Gallen, Mullerstrasse 7, 8004 Zurich, Switzerland. matthias.voegeli@bluewin.ch

1 Introduction

The last decade has witnessed tremendous growth in commodity futures markets in terms of trading volume, the range of underlying commodities and the variety of contracts. Empirically, commodities are clearly different from conventional financial assets like equities or bonds. The existing literature (see for example Routledge, Seppi, and Spatt (2000) or Dincerler, Khoker, and Simin (2005)) proposes a set of stylized facts for commodities including:

1. Commodity futures prices with longer maturities are often below prices with shorter maturities. Carlson, Khokher, and Titman (2007) point out that without adjustment costs (i.e. in the form of a convenience yield), the futures term structure is upward sloping. A time-varying behaviour of futures prices is observable in that the constellation of upward or downward sloping term structure changes usually over time.

2. Spot and futures prices are mean reverting for many underlying commodities.

3. Commodity prices are heteroskedastic and price volatility is positively correlated with the degree of backwardation.

4. Commodity futures price volatility typically increases with decreasing time-to-maturity. This is known as the "Samuelson effect" (see Samuelson (1965)). Fama and French (1988) show a violation of this pattern when inventory is high.

5. Many commodities have seasonalities both in price levels and volatilities.

Our aim is to explore the informational content of the dynamics of futures term structures over a wide range of commodity underlyings, taking into account traded maturities up to twelve months. We identify the most important factors driving the stochastic process of commodity futures term structures by means of principal component analysis (PCA). Instead of formulating multi-factor models explaining and forecasting term structures (see Section 2), we aim to formulate generally applicable rules for investment strategies on the basis of the knowledge gained from the futures curve dynamics. Our contribution to existing literature is threefold: We apply PCA to study the dynamics of futures term structures for various commodities and rolling windows in a comprehensive way. We find economic explanations for the identified factors for each class of commodities. We formulate simple trading strategies based on the commodity-specific knowledge about the curve dynamics and form portfolios of underlyings with similar characteristics. We thereby offer a simple alternative to traditional commodity investments which suffer heavily from unfavorable roll-yields not taking into account any information contained in the futures term structure.

The remainder of this article is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the data we use in our investigation. Section 4 covers the methodology of PCA. Section 5 provides results and their interpretation from the PCA and the rolling PCA. In section 6 we propose three simple investment strategies to exploit the informational content of the term structure derived from our preceding analysis. Section 7 concludes.

2 Literature review

Existing literature differentiates between two alternative perspectives for the price formation of commodity futures prices. Kaldor (1939) developed the traditional theory of storage. Working (1949), Brennan (1958) and Williams (1986) elaborate on it. According to the theory of storage, futures prices are determined by the fundamental cost of carry relationship assuming no-arbitrage. Hence, the futures price F at time t for delivery of a commodity at T equals the spot price S plus interest foregone r and storage cost w less a convenience yield y:

$$F(t) = S(t)e^{(r+w-y)(T-t)} \tag{1}$$

The notion of convenience yield was first introduced by Kaldor (1939) as the value of physical goods held in inventories resulting from their inherent consumption use, accruing only to the owner of the physical good and not to the holder of the futures contract.

The alternative model views the commodity futures price as a combination of expected risk premium and a forecast of the future spot price:

$$F(t) = e^{-rp(T-t)}E_t[S(T)] \tag{2}$$

Cootner (1960) proposed this general risk-premium pricing model stating that the futures price equals the expected commodity spot price discounted by a risk premium rp to compensate for the price risk of the underlying.

Typically, the term structure of commodity futures is described by the convenience yield model which is derived from the theory of storage. The term structure is a representation of the inter-temporal price relationship between futures contracts with different maturities. The futures curve prevailing at date t for a given commodity i is a graphical representation of the set $F^i_{t,T}, T > t$ of futures prices for different traded maturities T. Denoting $cy = y - w$ (the convenience yield net of storage cost), Equation 1 implies that the futures curve at date t is an increasing or decreasing function of the maturity T , depending on the sign of $(r - cy)$. The former is called contango and the latter backwardation. In a backwardated market, futures contracts with shorter maturities are more expensive than contracts expiring later. The contango market represents the opposite situation.

The observation of the futures curve at date t is an important tool for market participants. According to the rational expectations hypothesis, the futures curve predicts the future spot price. Market participants can form their beliefs according to the futures term structure. Additionally, the inter-temporal price relationship expressed by the cost of carry Equation 1 allows to extract spot prices and convenience yields in order to uncover arbitrage opportunities. Lastly it allows exchanges and derivatives holders the marking-to-market of a portfolio of futures contracts.

After the pioneering work in the area of spot interest rate modeling by Vasicek (1977) and Cox, Ingersoll, and Ross (1981), there have been two similar approaches to the study of commodity prices. Seminal research from Brennan and Schwartz (1985), Gibson and Schwartz (1990) and Schwartz (1997) has focused on modeling the stochastic process for the spot price of commodities and other state variables such as the convenience yield. More recent studies of stochastic movements in commodity prices concentrate on modeling the whole term structure of either futures prices directly (e.g. Cortazar and Schwartz (1994)) or convenience yields (e.g. Miltersen and Schwartz (1998)). Cortazar and Schwartz propose the following dynamics for futures prices under the risk-neutral measure Q:

$$dF(t,T) = \sum_{i=1}^{n} \sigma_i(t,T)F(t,T)dW_t^i \tag{3}$$

or in integrated form:

$$F(t,T) = F(0,T)\exp\left(-\frac{1}{2}\sum_{j=1}^{K}\int_0^t \sigma_j^2(u,T)du + \sum_{j=1}^{K}\int_0^t \sigma_j(u,T)dW_j(u)\right) \tag{4}$$

where dW_1, dW_2, ..., dW_K are independent increments of Brownian motions under the risk-neutral measure and $\sigma_j(t,T)$ are the volatility functions of the futures prices. K is the number of risk factors identified. One possible way to identify risk factors is to apply PCA on the futures curve. Cortazar and Schwartz found that the factor structure of Copper futures curves are similar to the one of yield curve movements first described by Litterman and Scheinkman (1991). Clewlow and Strickland (2000) find that three factors explain over 98% of the variation of futures price dynamics from 1998 to 2000 in the case of Oil futures. Koekbakker and Ollmar (2005) examine forward curve dynamics of Nordic eletricity markets concluding that 10 factors explain 95% of the forward curve dynamics. Only recently, Chantziara and Skiadopoulos (2006) have tested wheter the term structure of Petroleum futures can be forecasted by means of principal component regression (PCR). They find small forecasting power.

3 Data

Our analysis covers 23 underlyings. They represent the commodity universe of the S&P Goldman Sachs Commodity Index (S&P GSCI) except for RBOB Gasoline and XB Gasoil. These two underlyings do not have enough observations since trading started only in 2006. The expiry of included futures contracts is limited to a maximum of 12 months as trading activity and liquidity decline sharply with increasing time to maturity. The data can be divided into four commonly used categories: Energy (WTI Crude Oil, Brent Crude Oil, Heating Oil, Gasoil, Natural Gas), Metals (Aluminium, Copper, Lead, Nickel, Zinc, Gold, Silver), Agriculture (Wheat, Kansas Wheat, Corn, Soybeans, Cotton, Sugar, Coffee, Cocoa) and Livestock (Feeder Cattle, Live Cattle, Lean Hogs). Details about the delivery months and exchanges are given in Table 1.

We use weekly price data of generic futures contracts as provided by Bloomberg, covering the period from January 1998 to July 2009. The price data refers to settlement prices at market closing on the last day of each trading week. Missing data points are replaced by linearly interpolating adjacent data points. Spot prices are not included in our data due to the inexistence of observable prices for most underlyings. By excluding spot prices from our analysis, we avoid the inconvenience of poor convergence performance between real spot and futures prices as recently observed by Irwin, Garcia, Good, and Kunda (2009).

3.1 Futures prices

Generic futures time series are constructed from actual futures prices by means of the relative to expiration roll method: I.e. the time series for the first generic futures contract $F^i_{t,1}$ uses price data from the current front contract with a time to maturity of one month. As soon as the front contract expires the first generic futures contract adapts the price of the second nearby contract

Table 1: Commodity futures contract specifications

Underlying	Exchange	Country	Price quotation[a]	Trading system	Expiry month											
					Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Brent Crude	ICE	U.K.	USD/bbl	O, E	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
WTI Crude	Nymex	U.S.	USD/bbl	O, E	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Heating Oil	Nymex	U.S.	USD/gal	O, E	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Gasoil	ICE	U.K.	USD/ton	O, E	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Natural Gas	Nymex	U.S.	USD/MMBtu	O, E	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Aluminium	LME	U.K.	USD/ton	O, E	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Copper	LME	U.K.	USD/ton	O, E	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lead	LME	U.K.	USD/ton	O, E	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Nickel	LME	U.K.	USD/ton	O, E	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Zinc	LME	U.K.	USD/ton	O, E	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Gold	Comex	U.S.	USD/oz	O, E		✓		✓		✓		✓		✓		✓
Silver	Comex	U.S.	Cents/oz	O, E	✓		✓		✓		✓		✓			✓
Wheat	Cbot	U.S.	Cents/bu	O, E			✓		✓		✓		✓			✓
Kansas Wheat	Cbot	U.S.	Cents/bu	O			✓		✓		✓		✓			✓
Corn	Cbot	U.S.	Cents/bu	O, E			✓		✓		✓		✓			✓
Soybeans	Cbot	U.S.	Cents/bu	O, E	✓		✓		✓		✓	✓	✓		✓	
Cotton	Nybot	U.S.	Cents/lb	O, E			✓		✓		✓			✓		✓
Sugar	Nybot	U.S.	Cents/lb	O, E			✓		✓		✓			✓		
Coffee	Nybot	U.S.	Cents/lb	O, E			✓		✓		✓		✓			✓
Cocoa	Nybot	U.S.	USD/ton	O, E			✓		✓		✓		✓			✓
Feeder Cattle	Cme	U.S.	Cents/lb	O, E	✓		✓	✓	✓			✓	✓	✓	✓	
Live Cattle	Cme	U.S.	Cents/lb	O, E		✓		✓		✓		✓		✓		✓
Lean Hogs	Cme	U.S.	Cents/lb	O, E		✓		✓		✓	✓	✓		✓		✓

[a] all price quotations are denominated in US Dollars.

Notes: ICE stands for Intercontinental Exchange, Nymex for New York Mercantile Exchange, LME for London Metal Exchange, Comex for New York Commodities Exchange, Cbot for Chicago Board of Trade, Nybot for New York Board of Trade, Cme for Chicago Mercantile Exchange. bbl stands for barrell, gal for gallon, bu for bushel, lb for pounds. O stands for open outcry and E stands for electronic.

which then becomes the new front contract. Accordingly, the time series for the second generic $F^i_{t,2}$ contract is derived from the futures prices of the actual second-nearby contract.

Per consequence, generic futures time series are characterized by a time-varying maturity. As long as the generic futures contract refers to the same actual futures contract, the maturity decreases weekly. However, at expiry the maturity of the generic futures contract jumps to the expiry date of the next-nearby contract. Depending on the commodity-specific trading months, a maximum of twelve generic futures contracts ($F^i_{t,1}$ to $F^i_{t,12}$) emerges. The commodity-specific futures expiry dates define the available number of generic futures contracts. By result, the complete future price term structure (with maturities $T \leq$ one year) can be spanned for any given week t in the data sample and for each underlying i.

Summary statistics for one- and twelve-month future price level series are depicted in Table 2 for each of the 23 commodities in the data sample. For 9 of 23 commodities, the arithmetic mean of the 12-month contract clearly exceeds the mean of the synthetic front contract, thus indicating on average a positive slope of the term structure exhibiting contango (Aluminium, Gold, Silver, Wheat, Kansas wheat, Corn, Cotton, Coffee, Cocoa). The opposite is true for Copper, Lead, Nickel, Zinc and Soybeans: these commodities tend to exhibit a backwardated futures term structure in our data sample. Energy underlyings, Sugar and Livestock tend to having identical means, thereby pointing to a flat term structure. Standard deviations of returns decrease with higher maturities in all cases except for energy. This is consistent with the "Samuelson effect" (see Samuelson (1965)), which hypothesizes an increase of the commodity futures price volatility with decreasing time to expiry. We tested the goodness-of-fit of departure from normality by means of the Jarque-Bera-test (see Jarque and Bera (1987)). Based on this, we can reject the null hypothesis of normality for prices of all maturities and underlyings at the 98% significance level exept for Cotton. We conducted an augmented Dickey-Fuller (ADF) test to examine if the time series of prices are stationary (see Dickey and Fuller (1979)). The null hypothesis stating that the series contains a unit root (and therefore is non-stationary) could not be rejected for all underlyings at a significance level of 95% as indicated in the last column. Thus we could not reject the hypothesis that the price time series are non-stationary.

Table 2: Summary statistics for price levels

Underlying	Mean		Skew.		Kurt.		JB	ADF
	$F^i_{t,1}$	$F^i_{t,12}$	$F^i_{t,1}$	$F^i_{t,12}$	$F^i_{t,1}$	$F^i_{t,12}$	$F^i_{t,1}$	$F^i_{t,1}$
Brent Crude	43.3 (27.2)	43.1 (28.6)	1.2	1.1	4.4	3.8	199	-1.1 (0.7)
WTI Crude	44.5 (26.9)	44.6 (28.0)	1.3	1.1	4.5	3.7	212	-1.3 (0.6)
Heating Oil	124.1 (77.0)	125.0 (80.1)	1.2	1.1	4.4	3.7	199	-1.3 (0.6)
Gasoil	385.5 (250.0)	386.9 (257.7)	1.3	1.2	4.6	4.0	237	-1.2 (0.7)
Natural Gas	5.4 (2.6)	5.7 (2.7)	0.8	0.4	3.6	2.0	71	-2.3 (0.2)
Aluminium	1797.7 (532.4)	1818.1 (523.3)	1.0	1.1	2.6	2.9	106	-1.46 (0.6)
Copper	3437.6 (2330.7)	3303.3 (2171.2)	1.0	1.1	2.5	2.5	108	-1.21 (0.7)
Lead	998.8 (749.1)	970.7 (705.2)	1.8	1.8	5.6	5.6	483	-1.37 (0.6)
Nickel	13814.9 (10170.1)	12872.3 (8860.2)	1.6	1.5	5.4	4.5	413	-1.39 (0.6)
Zinc	1502.6 (906.2)	1489.0 (801.4)	1.6	1.5	4.4	4.0	309	-1.25 (0.6)
Gold	463.9 (217.8)	476.5 (223.1)	1.0	1.0	2.7	2.5	106	0.33 (1.0)
Silver	7.9 (4.0)	8.1 (4.1)	1.1	1.1	2.9	2.9	113	-1.03 (0.7)
Wheat	393.7 (182.3)	419.3 (170.1)	1.9	1.9	6.0	6.0	585	-1.42 (0.6)
Kansas Wheat	424.1 (184.9)	437.7 (172.6)	1.9	2.0	6.2	6.6	604	-1.54 (0.5)
Corn	273.8 (103.4)	301.7 (106.4)	2.0	2.1	7.0	7.6	793	-1.63 (0.5)
Soybeans	687.7 (252.2)	670.9 (230.7)	1.6	1.7	4.9	6.0	337	-1.42 (0.6)
Cotton	55.0 (10.4)	60.3 (9.9)	0.1	0.3	2.7	3.3	4	-2.83 (0.0)
Sugar	9.2 (3.0)	9.4 (3.3)	0.9	0.9	3.5	3.0	87	-1.06 (0.7)
Coffee	95.2 (29.8)	103.5 (28.2)	0.0	-0.2	2.2	2.0	16	-2.56 (0.1)
Cocoa	1583.4 (534.4)	1625.9 (500.7)	0.6	0.6	3.2	3.1	43	-1.18 (0.7)
Feeder Cattle	93.3 (14.3)	92.2 (11.9)	0.1	0.2	1.8	1.9	36	-1.94 (0.3)
Live Cattle	79.2 (11.3)	80.2 (11.5)	0.1	0.8	1.8	3.0	34	-2.48 (0.1)
Lean Hogs	59.9 (10.6)	61.2 (9.3)	-0.4	1.2	3.1	5.1	13	-3.77 (0.0)

Notes: Values in brackets in the 'Mean'-column show standard deviations of price levels. JB indicates the value from the Jarque Bera test for normality. The critical value at the 1%-level is 9.2 and 6 at the 5%-level. ADF indicates the unit root test statistics from the augmented Dickey-Fueller test with the p-value in brackets. The critical value at the 1%-level is -3.4, at the 5%-level -2.9 and -2.6 at the 10%-level. N is equal to 605 weekly observations over the period from January 1998 to July 2009.

3.2 Futures returns

The returns used in the subsequent section to perform PCA are non-investable returns and as such not available for investors. They are directly based on the prices from the generic futures time series described in Section 2.1. We calculate logarithmic returns for each maturity time series T and commodity i as $r^i_T = ln(F^i_{t,T} - F^i_{t-1,T})$. The values $F^i_{t,T}$ and $F^i_{t-1,T}$ belong to the same futures price time series. The return calculation is similar to the S&P GSCI Spot Index which simply tracks the price of the nearby futures contracts.

Table 3: Summary statistics for returns

Underlying	Mean		Skew.		Kurt.		JB	ADF	t-stat
	$F^i_{t,1}$	$F^i_{t,12}$	$F^i_{t,1}$	$F^i_{t,12}$	$F^i_{t,1}$	$F^i_{t,12}$	$F^i_{t,1}$	$F^i_{t,1}$	$F^i_{t,1}$
Brent Crude	0.002 (0.05)	0.002 (0.03)	-0.8	-0.4	6.2	6.0	313	-23.6 (0.0)	1.15 (0.3)
WTI Crude	0.002 (0.06)	0.002 (0.03)	-0.7	-0.4	6.9	5.9	424	-24.3 (0.0)	0.97 (0.3)
Heating Oil	0.002 (0.06)	0.002 (0.03)	-0.2	-0.2	4.4	4.6	128	-23.9 (0.0)	0.95 (0.3)
Gasoil	0.002 (0.05)	0.002 (0.03)	-0.7	-0.5	4.7	4.2	132	-23.1 (0.0)	1.06 (0.3)
Natural Gas	0.001 (0.08)	0.001 (0.04)	0.1	-0.4	3.5	4.6	124	-24.1 (0.0)	0.28 (0.8)
Aluminium	0.000 (0.03)	0.000 (0.03)	-0.3	-0.8	5.8	7.9	230	-26.4 (0.0)	0.26 (0.8)
Copper	0.002 (0.04)	0.002 (0.04)	-1.0	-1.1	8.4	9.9	171	-11.3 (0.0)	1.26 (0.2)
Lead	0.002 (0.05)	0.002 (0.04)	-0.1	-0.2	5.9	8.1	960	-12.1 (0.0)	0.97 (0.3)
Nickel	0.002 (0.06)	0.002 (0.05)	0.1	0.2	5.2	5.7	598	-25.3 (0.0)	0.79 (0.4)
Zinc	0.001 (0.04)	0.001 (0.04)	-0.1	-0.1	5.4	5.3	1'182	-29.7 (0.0)	0.43 (0.7)
Gold	0.002 (0.03)	0.002 (0.03)	-0.0	-0.1	5.4	5.3	447	-26.2 (0.0)	1.88 (0.1)
Silver	0.001 (0.04)	0.001 (0.04)	-0.9	-1.0	6.2	6.5	329	-25.2 (0.0)	0.84 (0.4)
Wheat	0.001 (0.04)	0.001 (0.03)	0.2	-0.2	4.1	5.3	33	-25.6 (0.0)	0.45 (0.7)
Kansas Wheat	0.001 (0.04)	0.001 (0.03)	0.1	-0.0	4.3	6.1	232	-8.1 (0.0)	0.52 (0.6)
Corn	0.000 (0.04)	0.001 (0.03)	0.1	-0.1	5.6	6.8	163	-23.1 (0.0)	0.25 (0.8)
Soybeans	0.001 (0.04)	0.001 (0.03)	-1.1	-0.4	12.1	5.4	2'158	-15.9 (0.0)	0.53 (0.6)
Cotton	-0.000 (0.04)	-0.000 (0.03)	0.1	0.1	4.0	4.6	26	-23.9 (0.0)	-0.14 (0.9)
Sugar	0.001 (0.08)	0.001 (0.04)	6.3	-0.4	-45.3	4.5	5^8	-25.2 (0.0)	0.21 (0.8)
Coffee	-0.000 (0.05)	-0.000 (0.04)	0.4	0.5	6.0	5.9	75	-26.8 (0.0)	0.20 (0.8)
Cocoa	0.001 (0.05)	0.001 (0.04)	-0.2	-0.3	4.7	5.3	71	-16.9 (0.0)	0.50 (0.6)
Feeder Cattle	0.001 (0.02)	0.000 (0.01)	-0.5	-0.4	5.5	7.2	36	-25.8 (0.0)	0.59 (0.6)
Live Cattle	0.000 (0.03)	0.000 (0.02)	-0.6	-1.1	6.2	8.1	505	-20.1 (0.0)	0.41 (0.7)
Lean Hogs	-0.000 (0.06)	0.000 (0.03)	0.1	-0.3	8.3	9.2	749	-25.8 (0.0)	-0.02 (1.0)

Notes: Values in brackets in the 'Mean'-column show standard deviations of price levels. JB indicates the value from the Jarque Bera test for normality. The critical value at the 1%-level is 9.2 and 6 at the 5%-level. ADF indicates the unit root test statistics from the augmented Dickey-Fueller test with the p-value in brackets. The critical value at the 1%-level is -3.4, at the 5%-level -2.9 and -2.6 at the 10%-level. The last column shows values of t-statistics and probabilities in brackets. N is equal to 605 weekly observations over the period from January 1998 to July 2009.

Table 3 shows summary statistics for returns of one- and twelve-month contracts. Average returns are close to zero for all maturities and underlyings (consider t-values and probability of simple hypothesis test $H_0 : \mu = 0$). Standard deviations of distant-maturity contracts are lower than those for the front contracts for all commodities. Columns 'skewness' and 'kurtosis' show that return distributions of commodity futures are typically negatively skewed and have fat tails. We tested the goodness-of-fit of departure from normality by means of the Jarque-Bera-test (column 'JB'). We reject the null hypothesis of normality for returns of all maturities and underlyings at the 98% significance level. We also conducted an ADF test to examine if the time series of returns are stationary or non-stationary. The null hypothesis stating that the series contains a unit root could be rejected for all underlyings at a significance level of 99% as indicated in the 'ADF'-column. We reject the hypothesis of non-stationarity in our return time series and assume stationarity.

4 Methodology

We examine the basic properties of commodity term structures by means of PCA. Since different factors are influenced by the same driving forces, PCA can be used to reduce the dimensionality of a given data set by concentrating the information it contains into a few orthogonal factors, usually much less than existing in the original data set. In the case of our commodity futures prices PCA allows to condense the information available in the term structures to such relevant factors.

If we denote time by $t = 1, ..., T$ and let p be the number of variables. Such a variable is a $(T \times 1)$ vector $\mathbf{x}$. The purpose of PCA is to construct p artificial variables, the so-called principal components (hereafter PCs) as linear combinations of the $\mathbf{x}$ vectors orthogonal to each other, which reproduce the original variance-covariance structure. The first PC is constructed to explain as much of the variance of the original p variables, as possible. The second PC is constructed to explain as much of the remaining variance as possible, under the additional condition that it is uncorrelated with the first one. Subsequently further PCs follow the same pattern. Therefore PCA can be seen as a maximization problem where we maximize the explained variance of the original variables through the uncorrelated PCs. The coefficients with which these linear combinations are formed are called the loadings. In matrix notation:

$$Z = XA \tag{5}$$

where X is a $(T \times p)$ matrix, Z is a $(T \times p)$ matrix, and A is a $(p \times p)$ matrix of loadings. The first order condition of the maximization problem yields:

$$(X'X - lI)A = 0 \tag{6}$$

where l_i are the Lagrange multipliers and I is a $(p \times p)$ identity matrix. Equation 6 shows that the PCA is the calculation of the eigenvalues l_i, and the eigenvectors A of the variance-covariance matrix $S = X'X$. The variance explained by the *i-th* PC is given by the *i-th* eigenvalue divided by the sum of all eigenvalues. PCA therefore enables us to quantify the significance of the retrieved PCs.

Frachot, Jansi and Lacoste (1992) show that PCA yields more reliable results when it is applied to stationary time series. In order to gain insight into the structure of returns following investments in those commodities and to work with stationary data, we use time series of continuous returns. As shown in Section 3.2 for the time series of continuous returns the hypothesis of non-stationarity could be rejected. The series of returns for any given contract are also subject to a PCA. The PCA of both, weekly prices and weekly returns, covers the period from January 1998 to July 2009. In order to test the stability of the PCA results we further conduct PCA over a period of six years starting January 1998 to 2004 rolling forward in weekly steps and resulting in 294 datasets of PCA results.

5 Results

In this section we interpret the results of static as well as rolling PCA. According to those results we discuss the general properties of the different groups of commodities. We put special emphasis on the analysis of the time series of continuous returns.

5.1 Findings from Static Principal Component Analysis

Figure 1 and Table 4 summarize the main findings of the PCA. The PCA-results of the commodity prices and returns share four common characteristics:

1. If we plot the first principal component it approximates a straight horizontal line. It therefore affects any contract on the term structure by the same amount. The effect can be interpreted as a parallel shift of the curve. The explanatory power of the first PC is paramount and exceeds 90% of the variance for 20 out of 23 underlyings. The explanatory power of the first PC of returns is always below the explanatory power of the first PC of prices.

2. If we plot the second principal component it has a negative slope for most commodities (20 out of 23). It moves the shortest expiries into a different direction than the longer expiries and hence is best understood as a relative shift of the curve (change from contango to backwardation and vice verca). The negative slope of the second PC of most commodities shifts the short maturities up and the long maturities down pushing the curve towards backwardation. It therefore represents a steepness factor. Its explanatory power does not exceed 30% and on average it has a value lower than 5%.

3. The third principal component has little explanatory power, typically below the 1% level. If we plot it, it has a concave shape. Since it causes prices and returns of mid-maturity futures to move in the opposite direction of short- and long-maturity futures, it can be understood as a curvature factor.

4. Further principal components have nearly no explanatory power and no consistent interpretation since they do not share common characteristics.

These findings make sense from an economic point of view: The price structure of all commodities is mainly influenced by parallel shifts of the term structure with increasing or decreasing price levels. Taking Gold and Silver (whose term structure never left contango and whose prices tripled during the examined period) as an example, we observe first components with explanatory power in excess of 99% for returns as well as prices. However, if we look at agricultural goods with seasonal effects like Live Cattle whose prices changed little in the observed time-period, we count 56 transitions from contango to backwardation and vice versa. This corresponds to a relatively low explanatory power of the first component of 66.13% for returns and a relatively strong second component with an explanatory power of 14.8% for returns taking into account the frequent relative shifts of the curve and the relatively stable prices. WTI Oil is an example for the influence of the price level changes on the explanatory power of the first PC. Although the commodity changes 56 times from contango to backwardation and back, the first PC explains 96.4% of its variance for returns. Considering the massive price level movements (prices peaked in 2008 and collapsed again) this is a sensible result.

5.2 Findings from Rolling Principal Component Analysis

By means of rolling PCA we test the time-varying properties of PCs and the stability of their explanatory power. The results (see Table 5[2]) show stable first PCs and explanatory power over time. The relative standard deviation (mean divided by standard deviation) of the first PC is on average below the 1% level. The standard deviation of the explained variance is below the 5% level. The second PCs show a more heterogeneous picture: The lower the explanatory power of a component, the higher its standard deviation in a rolling analysis. Of all commodities, Metals have second PCs with the least significance. Therefore their second components exhibit the largest relative standard deviations. This however holds not true for all commodity classes:

[2]Figure 4 in the appendix shows a plot of the explanatory power of principal components over the 294 rolling PCAs

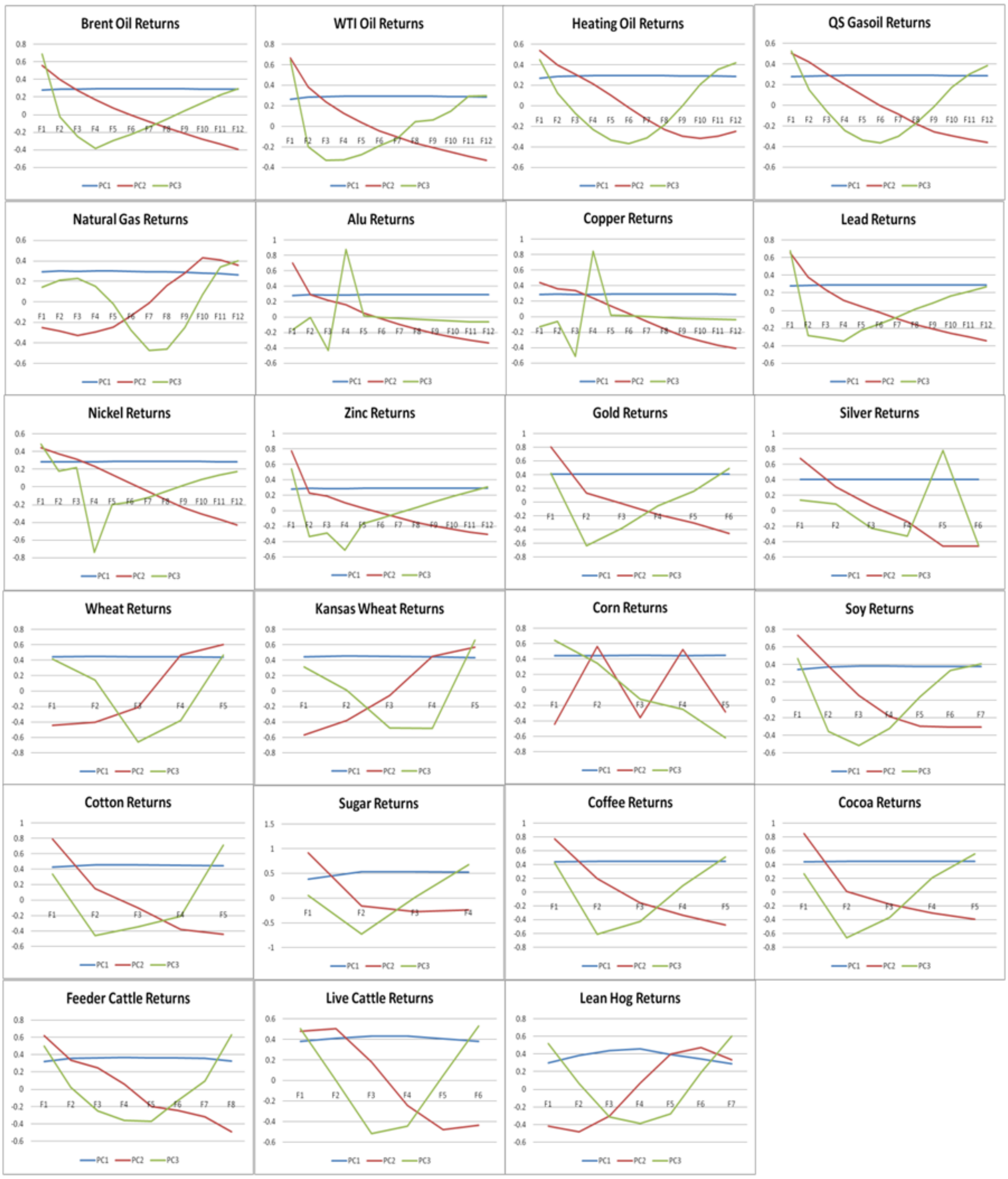

Figure 1: Results Principal Component Analysis: Graphical representation of the principal components 1-3 of all commodity return time series over the period of January 1998 to July 2009. The x-axis shows the factors, the y-axis the factor-loadings.

93% of the Cotton return variance is explained by its first PC but has a lower variance of this component over time than Lead explaining 97% of its return variance through its first PC. An economically useful explanation for third principal components is hard to obtain. Considering however the low explanatory power of third components, their contribution to the dynamics of commodity term structures can be neglected.

Table 4: Explanatory Power of Principal Components

(Weekly observations, N=605)

	Prices				Returns			
Underlying	PC1	PC2	PC3	Cummulative	PC1	PC2	PC3	Cummulative
Brent Crude	99.80%	0.20%	0.00%	100.00%	97.40%	2.20%	0.20%	99.80%
WTI Crude	99.70%	0.28%	0.01%	99.99%	96.40%	2.98%	0.49%	99.87%
Heating Oil	99.61%	0.30%	0.07%	99.98%	93.80%	3.60%	1.60%	99.00%
Gasoil	99.70%	0.27%	0.02%	99.99%	96.30%	2.67%	0.60%	99.57%
Natural Gas	95.50%	2.55%	1.10%	99.15%	77.27%	7.50%	5.00%	89.77%
Aluminium	99.77%	0.22%	0.01%	100.00%	98.14%	0.98%	0.43%	99.55%
Copper	99.92%	0.08%	0.00%	100.00%	99.25%	0.50%	0.14%	99.89%
Lead	99.92%	0.07%	0.00%	99.99%	97.77%	1.30%	0.50%	99.57%
Nickel	99.76%	0.23%	0.00%	99.99%	98.57%	1.12%	0.15%	99.84%
Zinc	99.92%	0.07%	0.01%	100.00%	98.50%	0.79%	0.35%	99.64%
Gold	99.99%	0.01%	0.00%	100.00%	99.93%	0.05%	0.02%	100.00%
Silver	99.99%	0.01%	0.00%	100.00%	99.86%	0.09%	0.03%	99.98%
Wheat	98.85%	1.00%	0.11%	99.96%	93.28%	3.19%	2.39%	98.86%
Kansas Wheat	99.04%	0.82%	0.09%	99.95%	91.91%	3.96%	2.57%	98.44%
Corn	99.71%	0.24%	0.03%	99.98%	95.20%	2.60%	1.30%	99.10%
Soybeans	98.86%	0.93%	0.15%	99.94%	92.02%	5.17%	1.47%	98.66%
Cotton	97.80%	1.70%	0.30%	99.80%	93.00%	4.06%	1.60%	98.66%
Sugar	98.82%	1.00%	0.10%	99.92%	82.30%	14.90%	2.20%	99.40%
Coffee	99.30%	0.60%	0.02%	99.92%	98.83%	0.80%	0.20%	99.83%
Cocoa	99.75%	0.20%	0.02%	99.97%	98.78%	0.96%	0.18%	99.92%
Feeder Cattle	97.80%	1.80%	0.30%	99.90%	86.50%	6.50%	3.70%	94.70%
Live Cattle	94.20%	4.00%	1.20%	99.40%	66.13%	14.80%	8.30%	89.23%
Lean Hogs	72.60%	17.30%	7.70%	97.60%	43.40%	25.20%	15.50%	84.10%

Notes: Explanatory power of principle components 1-3 of the prices and returns time series of 23 commodities comprising 605 weekly observations from January 1998 until July 2009. PC stands for principal component.

When we compare the movements of the term structure with rolling PCA-results, we gain insight into the composition of the PCs. Periods with either strong price movements, which lead to a parallel shift of the term structure, or periods with few changes in the slope and curvature of the term structure exhibit high explanatory power of the first principal components. Periods with rapid changes in the slope and curvature decrease the explanatory power of the first principal components and increase the explanatory power of the second and the third principal components. These findings support our understanding of the first three PCs as level-factor, steepness-factor and curvature factor.

Table 5: Standard Deviation of the Explanatory Power of Principal Components over Time

(Each PCA covering 312 weekly data points, N=294)

	Prices			Returns		
Underlying	S_PC1	S_PC2	S_PC3	S_PC1	S_PC2	S_PC3
Brent Crude	0.26%	0.25%	0.00%	0.85%	0.68%	0.10%
WTI Crude	0.26%	0.24%	0.01%	0.52%	0.41%	0.08%
Heating Oil	0.96%	0.54%	0.32%	1.60%	0.82%	0.48%
Gasoil	0.46%	0.32%	0.10%	0.92%	0.58%	0.23%
Natural Gas	2.87%	1.55%	0.79%	2.90%	0.65%	1.10%
Aluminium	0.18%	0.14%	0.01%	0.65%	0.19%	0.33%
Copper	0.03%	0.03%	0.00%	0.27%	0.23%	0.13%
Lead	0.18%	0.14%	0.01%	1.58%	1.03%	0.32%
Nickel	0.09%	0.10%-	0.00%	0.28%	0.30%	0.07%
Zinc	0.10%	0.09%-	0.00%	0.82%	0.26%	0.40%
Gold	0.02%	0.02%	0.00%	0.02%	0.01%	0.00%
Silver	0.04%	0.03%	0.00%	0.08%	0.04%	0.02%
Wheat	2.10%	1.77%	0.28%	1.69%	0.76%	0.78%
Kansas Wheat	2.86%	2.39%	0.36%	1.70%	0.87%	0.69%
Corn	1.27%	0.93%	0.21%	1.10%	0.89%	0.22%
Soybeans	1.43%	1.26%	0.25%	1.38%	1.14%	0.16%
Cotton	0.69%	0.64%	0.05%	0.90%	0.48%	0.30%
Sugar	0.55%	1.28%	0.25%	0.93%	0.75%	0.17%
Coffee	0.14%	0.14%	0.00%	0.27%	0.21%	0.05%
Cocoa	0.37%	0.35%	0.01%	0.08%	0.05%	0.03%
Feeder Cattle	1.61%	1.43%	0.13%	1.41%	0.44%	0.33%
Live Cattle	2.53%	1.38%	0.92%	2.85%	1.08%	1.05%
Lean Hogs	4.81%	2.74%	1.65%	2.71%	1.74%	0.79%

Notes: The stability of principle components is measured by 294 principal component analysis each covering 312 weekly data points, starting in January 1998 and moving one week ahead for each principal component analysis up to July 2009. The here shown standard deviation represents the second statistical moment of that distribution of PCA results. S_PC stands for standard deviation of the first principal component.

5.3 Different Groups of Commodities

In this section we discuss the characteristics of PCA-results of the four different commodity classes presented in chapter 5.2. The findings can be summarized as follows:

Explanatory power of the first PCs of Energy commodities can be found in the midfield compared to all underlyings with values between 77% to 97%. Natural gas with the lowest value exhibits strong seasonality over the different maturities of the term structure. This has a strong impact on the second and third principal components although natural gas is the only energy underlying whose term structure is consistently in contango. Heating Oil has less seasonality in spot prices but the term structure moves stronger between contango and backwardation. Brent, WIT Crude Oil and Gasoil exhibit no seasonality. The dominance of the first PC is caused by heavy price level movements from 2005 to 2009 with Oil reaching $150 per barrel. The second PC is downward sloping for all energy commodities except for Natural Gas.

Metals have first PCs with very high explanatory power which are stable over time. Their second PCs have a negative slope pushing the term structure towards contango. They are not affected by strong seasonal effects. Precious metals Gold and Silver are characterized as investment assets. The shape of the term structure is persistently in contango (near full carry) over time, explaining the dominance of the level factor over the steepness- and curvature-factor. The term structure of Industrial Metals - which can be classified as consumption commodities - exhibit steepness and curvature movements over time. The high explanatory power of the first component therefore points rather towards significant movements of price levels (parallel shifts) which dominate the second and third principal component.

Agricultural commodities show a rather heterogeneous picture. Coffee and Cocoa have very stable first PC with high explanatory power. Explanatory power of PC of Sugar and Kansas wheat is low. Cotton, Corn, Wheat and Soybeans have explanatory power around 94%. Second PC are evenly upward or downward sloping. Generally, the term structure of Agriculturals exhibits contango indicating high storage cost and perishability of the underlying. Lower explanatory power of Agriculturals can be explained with the less steep price level movements compared to Energy or Metals.

The first PCs of Lifestock clearly have the lowest and most unstable explanatory power of all underlyings. Their second and third components are more relevant. This reflects the demand- and supply-side seasonality of those products. Shocks on either side have a direct impact on the convenience yield which is reflected in regular changes of term structure shapes. Additionally, Livestock had little price level movements (parallel shifts) over the last twelve years. Therefore, the second and third factor have a higher impact explaining the variability of term structure dynamics.

6 Implications for Investment Strategies

The results obtained from the PCA give insights about the informational content of the futures term structure of commodities. We attempt to formulate simple investment strategies which exploit the unique characteristics of the futures curve of different underlyings.

Opposed to the non-investable returns we used in order to carry out PCA, we now turn our focus to returns that are available to investors. To construct a continuous time series of realizable futures returns throughout the sample period, a roll-over strategy has to be defined. Breeden (1980) and Young (1991) point to two possible approaches:

- Maturity date approach: The return time series can be constructed with respect to a specific maturity month T. Once a year, the contracts are rolled-over into the new contract. Per consequence, there will be one time series for each particular expiration month.
- Constant time to maturity approach: The time series is constructed with respect to a constant time to maturity $(T - t)$. The futures contract is rolled-over at each time the front-month contract expires. There will be one return time series for each time to maturity.

In empirical literature, the second approach is more commonly used (see Grauer and Litzenberger (1979), Breeden (1980) or Gorton and Rouwenhorst (2005)). The returns used for the analysis of the investment strategies are based on the constant time to maturity approach, i.e. the contracts are rolled-over or rebalanced as soon as the front-month contract expires. As it was the case with the generic futures price time series (see Section 2), the number of return time series per underlying and the holding period per contract depends on the number of delivery dates during the year. Hence, the number of return observations differs between the major classes of underlyings. We get 138 return observations for Energy and Metal commodities with a monthly holding period (from initially 605 price observations). The number of return observations for Agriculture and Livestock varies between 48 and 91 with holding periods per contract up to 4 months.

The total return of the constant time to maturity approach is the sum of the roll return and the change in the spot price. Roll returns are also called the gradient of the futures term structure. If the shape of the term structure (flat, contango or backwardation) does not change from one maturity date to the next, the total return stems solely from the roll-over mechanism. Hence, the return depends on the selected contract maturity of the yield curve and the direction of the position (long or short). Consider the following example: If today the futures curve of WTI Crude Oil is in contango (i.e. the longer maturity futures are higher priced than those on the short end of the curve) and we hold a long position in the front contract, we incur a negative roll yield (loss) when holding the contract until expiration and rolling it to the second-nearby contract. In case the term structure is in backwardation, we incur a positive roll yield (gain) on our position if the shape of the futures term structure and the spot price does not change.

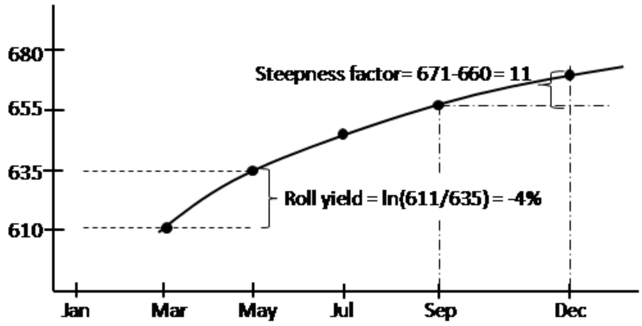

Figure 2: Term structure of Wheat as of January 2009

6.1 Investment rationale and strategies

In Section 5 we have concluded that a high first component (parallel shift) stems either from the fact that the shape of the term structure does not change much over time (and therefore the steepness and curvature factor are not important) or that the absolute shift of the price level is accounting for most of the variability of the curve and dominates other factors. With that in mind we formulate two simple objectives which are generally applicable to commodities investments. First, invest in those underlyings, where the shape of the term structure is persistent. This is true for commodities with high explanatory power of the first PC. Secondly, optimize the holdings by choosing maturities on the curve where the expected roll yield is highest. This is the case where the steepness of the curve between between maturity $T+1$ and T is highest. This optimizes the roll yield irrespective of the explanatory power of the first PC.

The steepness of the futures curve plays an important role in deciding which contract to choose on the term structure. Usually it is hard to implement a price prognosis into a trading strategy because futures prices already have these expectations factored in. If the futures term structure composed from futures with different maturities up to one year is in contango, then the market expects the spot price to rise in the future. In order to earn a positive return on a futures position, the spot/front price must increase more than is implied by the futures price. Figure 2 illustrates this effect. It shows the futures prices of different contract maturities for Wheat in January 2009. To earn a positive return on the May 09 contract (US Cents 635), the nearby March 09 contract (US Cents 611) must increase by more than 4% in 2 months. If the level of the futures curve would not change over time, we would face a loss of 4% in two months (24% per annum) with our long wheat position. This is the case for a futures term structure in contango. In backwardation, we would realize a return in the amount of the logarithmic difference between the May and March position if the spot price would be stable over time.

We therefore can optimize our roll yield by choosing the contract where we would earn/loose the most/least if the curve would be stable over time. This is the contract where the steepness factor is highest in case of backwardation and lowest in case of contango. We formulate the following three investment strategies choosing the optimal contracts either on the long or the short side:

1. *Directional 1 (long-only)*: This strategy buys different contracts depending on the shape of the futures term structure. In case of contango ($F^i_{t,1} < F^i_{t,12}$), we take a long position in the contract with the smallest slope, thereby minimizing roll losses. In case of backwardation ($F^i_{t,1} > F^i_{t,12}$), we buy the contract with the largest slope, thereby maximizing roll returns. This strategy has a clear long-bias but offers a return which is optimized for roll yields.

2. *Directional 2 (long-short)*: This strategy either buys or sells contracts depending on the shape of the curve but not simultaneously. An investor holds always either a long or a short position of the underlying. In case of contango, we sell the contract with the largest slope to receive the maximal roll yield. In case of backwardation, we buy the contract with the largest slope also to receive the maximal expected roll yield.

3. *Market neutral (long-short)*: To neutralize market movements we simultaneously buy and sell contracts of the same underlying with different maturities. In case the curve is in contango, we buy the contract with the smallest slope and sell the contract with the steepest slope. In case of backwardation, we buy the contract with the largest slope and sell the one with the smallest slope. Thereby an investor minimizes roll losses and maximizes roll returns.

As a *benchmark*, we use the following strategy: In accordance with the investment methodology of the S&P GSCI Excess Return Index, our benchmark buys and holds the available front contract until expiration. The contract is rolled-over to the next-nearest contract available. The monthly return of the benchmark depends on the front price change and the roll yield which itself depends on the steepness and the curvature of the term structure. We do not take into account transaction costs for our strategies since with the exception of Market neutral, the trading strategies have the same number of roll dates per contract as the benchmark and we would approximately incur the same transaction costs. The comparison of the investment

Table 6: Portfolios over Time

Period 1: 2001-2003				Period 2: 2004-2006			
Portfolio 1	Expl PC	Portfolio 2	Expl PC	Portfolio1	Expl. PC	Portfolio 2	Expl. PC
Gold	99.93%	QS Gasoil	94.54%	Gold	99.93%	Corn	92.41%
Silver	99.63%	Zinc	93.99%	Silver	99.61%	Heating Oil	91.66%
Cocoa	98.90%	Corn	92.85%	Copper	99.58%	Soy	90.19%
Coffee	98.47%	Lead	90.99%	Zinc	99.26%	Cotton	90.10%
Wheat	98.14%	Heating Oil	90.20%	Nickel	98.98%	Wheat	88.11%
Copper	98.13%	Sugar	90.04%	Cocoa	98.49%	Sugar	86.95%
Nickel	97.67%	Cotton	89.72%	Coffee	98.31%	Kansas Wheat	86.37%
Kansas Wheat	97.27%	Feeder Cattle	88.84%	Alu	98.00%	Natural Gas	84.46%
Soy	96.41%	Natural Gas	72.27%	Lead	97.23%	Feeder Cattle	77.97%
Alu	95.53%	Live Cattle	69.24%	WTI Oil	97.04%	Live Cattle	58.55%
Brent Oil	94.99%	Lean Hog	48.02%	Brent Oil	96.88%	Lean Hog	34.79%
WTI Oil	94.82%			QS Gasoil	94.75%		
Period 3: 2007-2009							
Portfolio 1	Expl PC	Portfolio 2	Expl PC				
Gold	99.95%	Lead	95.38%				
Silver	99.93%	Heating Oil	94.76%				
Coffee	99.53%	Corn	94.13%				
Cocoa	99.37%	Cotton	92.86%				
Brent Oil	98.79%	Kansas Wheat	92.07%				
Copper	98.66%	Soy	87.49%				
WTI Oil	98.51%	Feeder Cattle	82.36%				
Zinc	98.05%	Sugar	78.60%				
Alu	97.59%	Natural Gas	70.34%				
QS Gasoil	97.51%	Live Cattle	60.79%				
Nickel	96.73%	Lean Hog	43.30%				
Wheat	95.98%						

Notes: Portfolios for the three periods are constructed according to the ranking of the explanatory power of their first principal compoents according to a principal componentanalysis of the time series of returns of each specific commodity covering the three preceeding years. Expl. PC stands for explanatory power of the first principal component.

strategies with such a benchmark can be somewhat misleading since the number of open contracts per underlying and the direction of the position (long or short) can be different. This is most obvious in the case of the Directional 2- and the Market neutral-strategy. In practice however, such a simple benchmark is widely used for relative performance measurement as well as for replicating an investment strategy.

6.2 Portfolio construction

In order to test the obtained assumptions about the described commodities we implement the trading strategies over the period January 1998 - July 2009 with two portfolios of commodities in a dynamic setting. Portfolio one is an equally weighted portfolio of the twelve commodities with the highest explanatory power of the first PC out of our sample of 23 commodities. Similarly, portfolio two is an equally weighted portfolio of the remaining eleven commodities with the lowest explanatory power of their first PCs (see Table 6). The resulting PCA defines the ranking of PCs. Therefore the members of the portfolios are calculated every three years for the following three years. The portfolios are rebalanced every three years. According to our expectations, portfolio one should exceed the returns of portfolio two.

6.3 Returns of the Investment Strategies

Looking at the results of the investment strategies (Table 7, Figure 3) the following observations can be made:

All three investment strategies outperform the benchmark portfolio in every case (except for the market neutral strategy of portfolio one) over the whole investment period both in terms of returns and returns per standard deviation. Even commodities with relatively low explanatory power of first PCs exhibit superior returns when information implied in the term structure is accounted for.

Portfolio one performs significantly better (p-value>99.99%) than portfolio two in both directional strategies. This supports our hypothesis gained by the analysis of PCs.

Portfolio two and the benchmark outperform portfolio one when the market neutral strategy is applied. This can be explained by the special characteristics of commodities with high explanatory power of first PC's: As explained in Section 5, the explanatory power of first PCs is supported by strong price movements and stable term structures. The market neutral strategy is especially vulnerable to relative changes of the term structure since it buys and sells contracts of the same underlying with different maturities. If the strong explanatory power of the first PCs of portfolio one is mainly due to large price movements, its weak performance in a market neutral strategy is a possible consequence. Further, the benchmark, in the case of the market neutral strategy, is not well chosen since it does not reflect its risk-reducing non-directional approach.

The market neutral strategy exhibits low positive or low negative returns in every market condition. It is the investment strategy with the lowest standard deviations for both portfolios. The market neutral strategy for portfolio one exhibits the lowest standard deviation and return to standard deviation ratio of all strategies. The first directional strategy tends to be in line

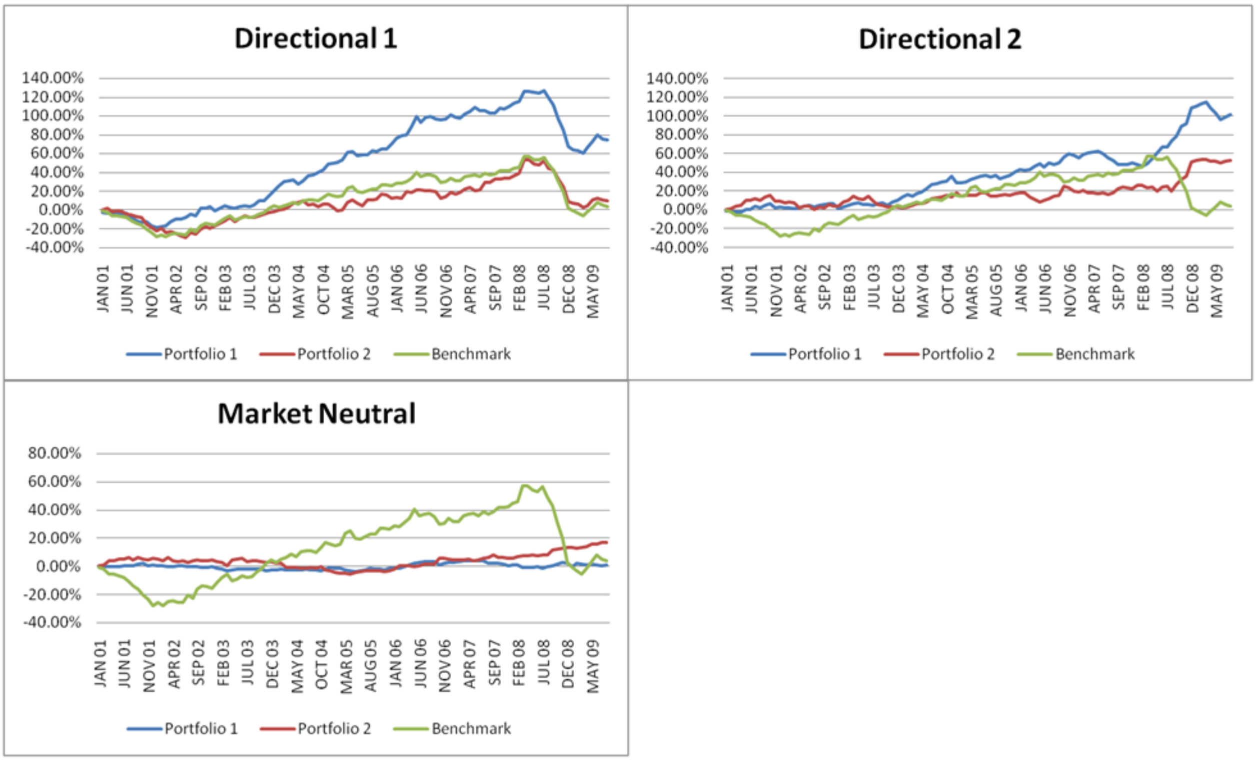

Figure 3: Returns of the Investment Strategies over the Period from January 2001- July 2009

with the general market development. It outperforms the benchmark portfolio for both portfolios exhibiting the highest standard deviation of all strategies. The second directional strategy profits from both strong up and down market movements. Negative returns do not occur. The strategy has the highest return to standard deviation ratio of all strategies.

The second and third statistical moments of the returns show that portfolio one has consistently lower skewness than portfolio two and lower kurtosis. Since low or even negative skewness reflects a higher probability of large negative returns and high kurtosis indicates unfavorable fat tails these findings are hard to interpret. However, they support the hypothesis of non-normality of commodity investment returns.

These findings support our hypothesis that the proposed commodity investment strategies create superior returns due to the information embedded in the term structure. The favorable characteristics of first PCs with high explanatory power contribute to this result and explain the significant better results of portfolio one (p-value>99.99%) in both directional strategies.

Table 7: Results of the two Portfolios and the Benchmarkportfolio

Strategy	Portfolio 1	Portfolio 2	Benchmark
Directional 1		Returns	
2001-2003	19.88%	-1.49%	4.26%
2004-2006	80.58%	20.08%	29.55%
2006-2009	-26.56%	-8.57%	-30.25%
Total	73.90%	10.02%	3.56%
Standard Deviation	4.47%	3.96%	3.67%
Skewness	-1.10	-0.39	-1.04
Kurtosis	6.50	6.53	7.36
Return per Standard Deviation	16.55	2.53	0.91
Directional 2		Returns	
2001-2003	9.67%	3.24%	4.26%
2004-2006	48.11%	16.25%	29.55%
2006-2009	43.55%	33.04%	-30.25%
Total	101.33%	52.52%	3.56%
Standard Deviation	3.38%	3.05%	3.67%
Skewness	0.77	1.20	-1.04
Kurtosis	7.66	8.44	7.36
Return per Standard Deviation	29.95	17.23	0.91
Market Neutral		Returns	
2001-2003	-2.81%	3.09%	4.26%
2004-2006	5.29%	1.77%	29.55%
2006-2009	-1.92%	11.81%	-30.25%
Total	0.56%	16.67%	3.56%
Standard Deviation	0.75%	1.15%	3.67%
Skewness	-0.43	0.53	-1.04
Kurtosis	4.33	4.99	7.36
Return per Standard Deviation	0.75	14.47	0.91

Notes: The table shows Returns and statistical moments of the different strategies with the different portfolios compared to the the benchmark-returns of a simple long only rolling strategy of all examined commodities. The Portfolios are rebalanced every three years.

In order to further test our results we examined the same investment strategies with three portfolios. They are again grouped according to the explanatory power of their first PC of the preceding three year period (Table 9, see appendix). The results are similar to the two portfolio case with two major difference: Portfolio three underperforms portfolio one and two in all strategies. Portfolio two outperforms portfolio one in the market neutral and the first directional strategy. Differences above the 90% of explanatory power of the first PC seem therefore not to contribute to superior returns. However, commodities with explanatory power of their first PCs below that level perform significantly worse than their peers given our set of strategies.

7 Conclusion

Principal component analysis (PCA) of commodity futures price term structures and the time series of their returns gives valuable insights about the dynamics of commodity futures prices and returns. We find that the first principal components (PCs) derived from our sample of 23 underlyings can be interpreted as level factors. The second PCs represent steepness factors and the third PCs curvature factors. For most underlyings, the explanatory power of the first PC is paramount. The explanatory power of further components is on average very low. Further, the explanatory power is stable over time. We find that the high explanatory power of the first PCs is mainly driven by strong price movements (parallel shifts) coupled with few relative movements (steepness and curvature) of the term structure from contango to backwardation and vice versa.

By ranking the underlyings according to the explanatory power of their first PCs we create two portfolios and three distinctive investment strategies exploiting the informational content of the commodity term structure and optimizing roll yields. The portfolio of commodities exhibiting relatively high explanatory power of the first PCs outperforms the portfolio of the commodities with relatively low explanatory power of the first PCs. Additionally, the proposed investment strategies outperform the simple front-roll-at-expiration strategy of the benchmark portfolio with the exception of the market neutral strategy. We show that investment strategies which exploit the information implied in the term structure gain superior returns compared to a basic investment strategy. This approach offers a promising alternative to investors who want to get exposure to commodity markets.

Several extensions and refinements are possible. On the level of PCA, longer maturities on the term structure can be taken into account at the expense of less liquidity in those contracts. PCA can be applied to a larger commodity sample. In analyzing the factor structure of commodity prices and returns we combine shocks to interest rates and convenience yields. Exploration into separating those effects might be of interest.

In relation with the portfolio construction process, transaction costs can be factored into the model. The selection and weighting of the underlyings can be coupled to some specific process. Rebalancing and correlation effects can be explored within the context of classical portfolio theory.

References

Breeden, D. T. (1980). Consumption risk in futures markets. *The Journal of Finance*, *35*, 503 – 520.

Brennan, M. J. (1958). The supply of storage. *The American Economic Review*, *48*, 50–72.

Brennan, M. J., & Schwartz, E. S. (1985). Evaluating Natural Resource Investments. *The Journal of Business*, *58*, 135 – 157.

Carlson, M., Khokher, Z., & Titman, S. (2007). Equilibrium exhaustible resource price dynamics. *The Journal of Finance*, *62*, 1663–1703.

Chantziara, T., & Skiadopoulos, G. (2006). Can the Dynamics of the Term Structure of Petroleum Futures be forecasted? Evidence from Major Markets. *Working Paper*.

Clewlow, L., & Strickland, C. (2000). *Energy Derivatives: Pricing and Risk Management* (1st ed.). London: Lacima Publications.

Cootner, P. H. (1960). Returns to speculators: Telser versus Keynes. *The Journal of Political Economy*, *68*, 396–404.

Cortazar, G., & Schwartz, E. S. (1994). The Valuation of Commodity Contingent Claims. *The Journal of Derivatives*, *1*, 27–39.

Cox, J. C., Ingersoll, J. E., Jr., & Ross, S. A. (1981). A Re-Examination of Traditional Hypotheses about the Term Structure of Interest Rates. *The Journal of Finance*, *36*, 769 – 799.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the Estimators for Autoregressive Time Series With a Unit Root. *Journal of the American Statistical Association*, *74*, 427 – 431.

Dincerler, C., Khokher, Z., & Simin, T. (2005). An empirical analysis of commodity convenience yields. *Working Paper*.

Fama, E. F., & French, K. R. (1988). Business cycles and the behavior of metals prices. *The Journal of Finance*, *43*, 1075–1093.

Frachot, A., Jans, D., & Lacoste, V. (1992). Factor Analysis of the Term Structure: A Probabilistic Approach. *Working Paper*.

Gibson, R., & Schwartz, E. S. (1990). Stochastic Convenience Yield and the Pricing of Oil Contingent Claims. *The Journal of Finance*, *45*, 959–976.

Gorton, G., & Rouwenhorst, K. G. (2005). Facts and fantasies about commodity futures. *Working Paper*.

Grauer, F. L. A., & Litzenberger, R. H. (1979). The Pricing of Commodity Futures Contracts, Nominal Bonds and Other Risky Assets under Commodity Price Uncertainty. *The Journal* *of Finance*, *34*, 69 – 83.

Irwin, S. H., Garcia, P., Good, D. L., & Kunda, E. L. (2009). *Poor convergence performance of cbot corn, soybean and wheat futures contracts: Causes and solutions.* Urbana-Champaign: Department of Agricultural and Consumer Economics, University of Illinois.

Jarque, C. M., & Bera, A. K. (1987). A Test for Normality of Observations and Regression Residuals. *International Statistical Review*, *55*, 163–172.

Kaldor, N. (1939). Speculation and economic stability. *The Review of Economic Studies*, *7*, 1–27.

Koekebakker, S., & Ollmar, F. (2005). Forward Curve Dynamics in the Nordic Electricity Market. *Managerial Finance*, *31*, 73–94.

Litterman, R. B., & Scheinkman, J. (1991). Common Factors Affecting Bond Returns. *The Journal of Fixed Income*, *1*, 54–61.

Miltersen, K. R., & Schwartz, E. S. (1998). Pricing of Options on Commodity Futures with Stochastic Term Structures of Convenience Yields and Interest Rates. *The Journal of Financial and Quantitative Analysis*, *33*, 33 – 59.

Routledge, B. R., Seppi, D. J., & Spatt, C. S. (2000). Equilibrium forward curves for commodities. *The Journal of Finance*, *LV*, 1297–1338.

Samuelson, P. A. (1965). Proof that properly anticipated prices fluctuate randomly. *Industrial Management Review*, *2*, 41–49.

Schwartz, E. S. (1997). The Stochastic Behavior of Commodity Prices: Implications for Valuation and Hedging. *The Journal of Finance*, *52*, 923–973.

Sharpe, W. F. (1994). The Sharpe Ratio. *Journal of Portfolio Management*, *21*, 49–59.

Vasicek, O. (1977). An equilibrium characterization of the term structure. *Journal of Financial Economics*, *5*, 177–188.

Williams, J. (1986). *The economic function of futures markets.* New York: Cambridge University Press.

Working, H. (1949). The theory of storage. *The American Economic Review*, *39*, 1254–1262.

Young, D. S. (1991). Macroeconomic forces and risk premiums on commodity futures. *Advances in Futures and Options Research*, *5*, 241–254.

A Appendix

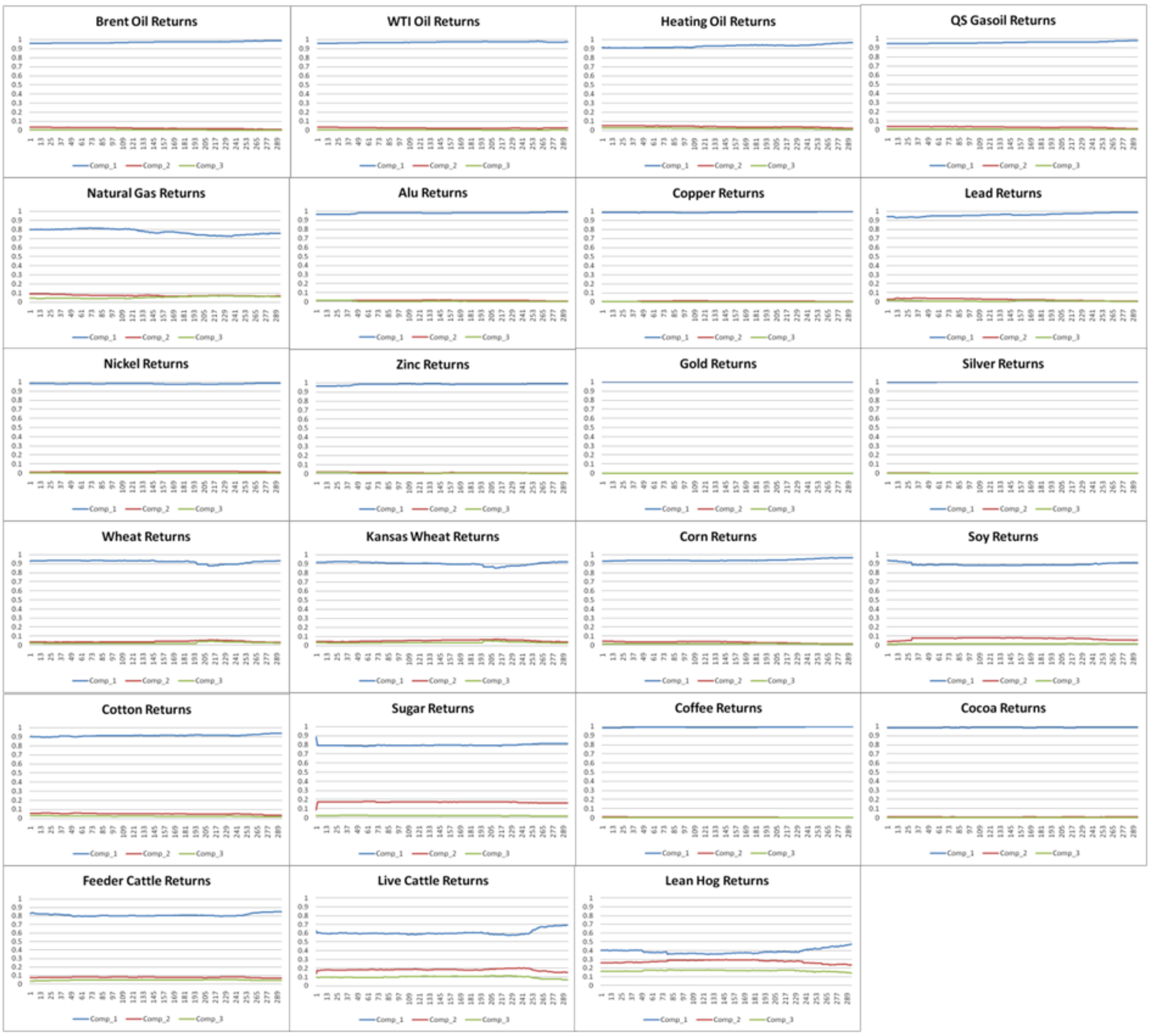

Figure 4: Results Rolling Principal Component Analysis: Explanatory Power of the Principal Components 1-3 of the Returns Time Series over 294 PCAs each Covering Six Years with Weekly Steps from January 1998 to August 2009

Table 8: Relative Standard Deviation of Principal Components over Time

(Each PCA covering 312 weekly data points, N=294)

	Prices			Returns		
Underlying	S_PC1	S_PC2	S_PC3	S_PC1	S_PC2	S_PC3
Brent Crude	0.10%	5.67%	28.36%	0.35%	37.49%	12.68%
WTI Crude	0.10%	1.64%	16.67%	0.29%	4.85%	25.22%
Heating Oil	0.17%	13.29%	2.33%	0.51%	63.72%	20.27%
Gasoil	0.09%	4.92%	3.33%	0.21%	163.84%	34.90%
Natural Gas	0.40%	10.78%	29.21%	2.01%	35.75%	16.80%
Aluminium	0.06%	13.85%	80.04%	0.64%	17.32%	48.98%
Copper	0.01%	5.52%	64.23%	0.22%	14.59%	9.43%
Lead	0.06%	9.86%	3.32%	0.71%	15.76%	49.67%
Nickel	0.03%	866.25%	132.89%	0.19%	5.86%	32.32%
Zinc	0.03%	252.24%	83.98%	0.65%	18.31%	11.65%
Gold	0.00%	1035.44%	9.41%	0.00%	29.37%	1.25%
Silver	0.01%	2575.31%	19.44%	0.03%	311.85%	285.70%
Wheat	0.53%	5.33%	11.12%	0.60%	7.34%	89.94%
Kansas Wheat	0.80%	7.72%	133.63%	0.71%	29.85%	24.82%
Corn	0.39%	4.37%	15.46%	0.17%	7.45%	2.15%
Soybeans	0.47%	14.97%	10.90%	0.60%	3.33%	26.69%
Cotton	0.25%	3.47%	12.67%	0.38%	4.52%	3.42%
Sugar	0.53%	7.50%	4.87%	1.09%	3.22%	31.57%
Coffee	0.06%	16.49%	12.43%	0.10%	5.59%	15.62%
Cocoa	0.14%	14.27%	31.44%	0.05%	12.69%	5.60%
Feeder Cattle	0.60%	9.95%	89.97%	1.08%	15.28%	19.21%
Live Cattle	1.24%	28.03%	6.36%	1.71%	1.42%	10.24%
Lean Hogs	8.55%	66.02%	11.09%	9.07%	72.85%	3.96%

Notes: The stability of principle components is measured by 294 principal component analysis each covering 312 weekly data points, starting in january 1998 and moving one week ahead for each principal component analysis up to July 2009. The here shown relative standard deviation represents the second statistical moment of that distribution of PCA results divided by its mean. S_PC stands for the relative standard deviation of the principal component. The relative standard deviation is the standard deviation divided by the mean of the specific component.

Table 9: Results with three Portfolios and the Benchmarkportfolio

Strategy	Portfolio 1	Portfolio 2	Portfolio 3	Benchmark
Directional 1		Returns		
2001-2003	21.66%	12.58%	-7.39%	4.26%
2004-2006	73.43%	54.94%	22.99%	29.55%
2006-2009	-15.63%	-30.59%	-6.17%	-30.25%
Total	79.46%	36.92%	9.43%	3.56%
Standard Deviation	4.66%	5.46%	3.67%	3.67%
Skewness	-0.55	-1.64	0.26	-1.04
Kurtosis	4.53	10.44	4.73	7.36
Return per Standard Deviation	17.04	6.77	2.57	0.91
Directional 2		Returns		
2001-2003	6.17%	14.52%	-1.98%	4.26%
2004-2006	45.15%	50.89%	-1.75%	29.55%
2006-2009	18.90%	76.84%	17.17%	-30.25%
Total	70.22%	142.24%	13.44%	3.56%
Standard Deviation	2.98%	5.04%	3.15%	3.67%
Skewness	0.76	1.54	0.02	-1.04
Kurtosis	6.91	10.80	4.85	7.36
Return per Standard Deviation	23.53	28.21	4.27	0.91
Market Neutral		Returns		
2001-2003	-0.69%	9.14%	-9.62%	4.26%
2004-2006	3.45%	18.74%	-13.50%	29.55%
2006-2009	1.30%	3.42%	9.87%	-30.25%
Total	4.06%	31.30%	-13.24%	3.56%
Standard Deviation	0.79%	1.16%	1.48%	3.67%
Skewness	0.26	0.25	0.22	-1.04
Kurtosis	7.43	5.17	4.68	7.36
Return per Standard Deviation	5.16	26.90	-8.96	0.91

Notes: The table shows Returns and statistical moments of the different strategies with the different portfolios compared to the the benchmark-returns of a simple long only rolling strategy of all examined commodities. The Portfolios are re-balanced every three years.