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Informational Efficiency in Futures Markets for Crude Oil

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Abstract

This paper develops a methodology to test whether recent developments on world oil markets are in line with the hypothesis of efficient markets. We treat the joint hypothesis problem as stated by Fama (1970), Fama (1991), that market efficiency can only be assessed in conjunction with a price model of market equilibrium. Data on spot and futures prices for Brent crude oil in the period 2002-2008 are used in combination with a multi factor model to investigate whether futures prices are efficient forecasts of future spot prices. The hypothesis of market efficiency is assessed by comparing the observed developments of crude oil spot prices to the ex-ante expected distributions of spot prices using the Rosenblatt transform. For the Brent crude oil futures market, the results are in line with the hypothesis of market efficiency in the short-term but during our sample period the hypothesis is refuted when forecast horizons of one year are considered. Our findings suggest that it can lead to rather wrong investment decisions when relying on longer-term crude oil futures prices and the information contained therein.

Keywords : Multi factor model, Informational efficiency, Oil market

JEL-Classification : G13, G14, Q40

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1 Introduction

The central role of crude oil markets in global economy still encourages research focused on the dynamics of crude oil prices. Oil as a primary energy carrier is needed for industrial production, the generation of heat and electricity and is the most important fuel in the transportation sector. A lot of research has been carried out which has underlined the huge impact of the oil price on the global economy. Standard economic theory suggests that prices should reflect scarcities of goods. Therefore high oil prices should indicate an existing, possibly transitory scarcity. Such high oil prices have then an important signalling function, inducing notably investments in exploration, production, transportation and demand side efficiency. However, if the oil price is affected by other factors than observed or anticipated changes in supply and demand, the scarcity signal of prices may be blurred, leading to inefficient decision making both upstream and downstream. Therefore the question of efficient market price formation on oil futures markets is not only of theoretical interest but has also implications for the wider economy.

Before the 1970ies, oil prices were determined by long-term contracts between international oil companies and oil producers. Price adjustments occurred only when these contracts were revised. In the eighties, the New York Mercantile Stock Exchange (NYMEX) introduced trade of crude oil products. Within the last 25 years oil markets became the most developed commodity markets. The advantage of high liquidity in crude oil markets has been accompanied by high oil-price volatility during the last decade. As stated by Shambora and Rossiter (2007) "the futures market for oil is the preferred trading arena for hedgers and speculators wishing to place their bets on that market's next move. The hundreds of millions of dollars wagered by these new players in the futures market is said to have resulted in higher prices and increased volatility." Increased volatility should however not be considered automatically as an indicator for market inefficiencies, but could be seen as a result of fast information processing and price discovery. Yet it is worth investigating whether recent price developments in crude oil futures markets, especially between 2004 and 2008, are only caused by fundamental changes in the equilibrium of supply and demand or put differently by rational information processing.

The main objective of this paper therefore is to test the hypothesis of efficient markets using the latest price developments and an advanced testing methodology. This methodology analyses the distribution of forecast errors under the null hypothesis of informational efficiency. To the best of our knowledge such a study has not been undertaken so far, while it provides clear indications that the joint hypotheses of efficient markets is not valid during recent years.

The remainder of this paper is organized as follows. Section 2 discusses price formation in the crude oil market. Informational efficiency in markets is addressed from a theoretical point of view and stylized facts of price movements are pointed out. A description of the methods and the tests applied in this study is presented in section 3. Section 4 describes the price model and the estimation methodology applied. Section 5 deals with the data used for the analysis and illustrates the empirical findings. Finally, concluding remarks are provided in section 6.

2 Price formation in the market for crude oil: theory and related literature

2.1 Informational efficiency in markets

The beginning of the discussion about efficient markets in modern economics may at least be traced back to Samuelson (1965). His main argument is already contained in the title of the article "Proof that properly anticipated prices fluctuate randomly".[1] The term "properly anticipated prices" means that current prices *P* include all relevant information denoted by Ω_t available at date *t* and reflect expectations made by market players concerning payoffs *X* of an asset.

$$P_t = E(X_t|\Omega_t) \tag{1}$$

This definition implies that all past and present price realizations of an asset are reflected in current prices and only this information is used to forecast future expected prices. Samuelson proves that "prices fluctuate randomly" and technically spoken, this consideration reduces to assuming a random walk for asset prices, meaning that prices should be not predictable.[2] It is important to note at this point that Samuelson develops his argument for the case of tradable assets like equity shares. To what extent this reasoning is applicable to commodity prices will be discussed subsequently.

Roberts (1967) is the first who distinguishes between several forms of informational efficiency. Fama (1970) adopts his taxonomy of weak-form, semi strong-form and strong-form efficiency. He defines weak-form efficiency, which is assumed in this article, as a theoretical construct where all past price information is incorporated in the price of an asset. In that case, the market is said to be weakly informational efficient. According to Samuelson's result an important implication is that prices follow a martingale and the best price estimator for tomorrow is the price of today. A more restrictive assumption is strong informational efficiency. This form requires that market prices reflect all public and private information available in the market, which can be hardly assumed in real world markets. In an additional article Fama redefines the categories used before. Since then, the class of weak-form tests mainly covers tests for return predictability (Fama, 1991).

A more accurate definition introducing the existence of an information set was provided by Jensen (1978) who defines "A market is efficient with respect to information set Ω_t if it is impossible to make economic profits by trading on the basis of information set Ω_t." Malkiel (1992) enhances this by "Formally, the market is said to be efficient with respect to some information set Ω_t, if security prices would be unaffected by revealing that information to all participants. Moreover, efficiency with respect to information set Ω_t, implies that it is impossible to make economic profits by trading on the basis of Ω_t." As concluded by Timmermann and Granger (2004) three issues are highlighted in these definitions which relate firstly to the importance of the information set Ω_t, secondly to the ability of market participants to exploit information from this set Ω_t and thirdly to the use of economic profits for testing the efficient market hypothesis (EMH).

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[1] One may note that efficiency as understood here should not be mixed up with Pareto-efficiency. Rather efficiency relies on the speed of information processing and the possibility of quick trades. Dimson and Mussavian (1998) point out, that economists sometimes talk about operational efficiency of markets, which can be interpreted as how resources are used for market operation. This interpretation is still different from Pareto-efficiency, which is about an efficient allocation through markets.

[2] In contrast Lucas (1978) has shown that even under the assumption of rational expectations among market participants equilibrium prices do not have to follow a random walk. The assumption of random walk price behavior is not a problem within our approach since we do not assume that crude oil spot prices have to follow a random walk.

This hypothesis has been repeatedly criticized based on various counterarguments. Notably various anomalies in stock markets have been observed like overreaction to new information (De Bondt and Thaler, 1985) or mean reversion (Lo and MacKinlay, 1988) in stock prices. The pure existence and observability of these anomalies still do not allow for excess returns. As Fama (1998) argues, the direction of over- or underreaction is not predictable and therefore excess returns based on assumed inefficiencies in the market are not possible which is in line with Malkiel (2003). The argument corresponds to the definition of informational inefficiency proposed by Masih and Masih (2002) which emphasises the capability of an investor to predict excess returns.

For crude oil obviously spot prices refer to the physical delivery of oil barrels. They are thus not prima facie asset prices[3]. Yet oil futures for a specific maturity are exchange traded assets and should therefore follow a random walk like other asset prices.[4] Otherwise excess returns might be possible and the Samuelson argument would not hold. Hence, using the information contained in futures price data is similar to using information contained in asset prices. Moreover there is a general interconnection between spot and futures markets due to the storability of the commodity. Assuming that new information moves both prices in spot and futures markets, there should be a link between the flow and processing of information and its impact on spot and futures prices. If the information flow is processed faster e. g. in the futures market, then a lead-lag relationship between futures and spot markets should exist. In this case, the futures market incorporates the information faster than the spot market and is said to lead the spot market. In real world markets, both hedgers and speculators will react to new information in the crude oil market by investing in futures rather than spot products. In general, as argued by Newbery (1992), the futures market should carry the function of price discovery. Gülen (1998) has found that in the time period from 1983 till 1995 light sweet crude oil futures traded at NYMEX play a significant role in price discovery and are unbiased predictors of the future spot price. Otherwise, futures market might provide opportunities for market manipulation. Silvapulle and Moosa (1999) consider a fictional case where e. g. the Organization of Petroleum Exporting Countries (OPEC) may find it profitable to invest in contracts in the futures market, in order to influence production decisions of competitors in the spot market. These analyses and others in the same vein suggest that using information contained in futures prices of crude oil is a reasonable choice in order to assess efficiency.

2.2 Stylized facts about price movements in crude oil markets

Numerous studies have investigated empirically the nature of price movements in oil markets. In contrast to commodity spot prices, Irwin et al. (1996) find futures prices not to be well described by a pure mean reversion process but rather by a random walk. In line with the findings of Irwin et al. (1996), Postali and Picchetti (2006) argue that a geometric Brownian motion, which is a random walk process, is suitable to describe the movement of oil prices because there are very low speeds of

[3] We would like to thank an anonymous referee who brought the necessity of the distinction between assets and commodities to our attention.

[4] Futures with a fixed maturity are martingales which means they are not mean reverting in the risk neutral measure. Assuming constant risk premia futures are also not mean reverting in the market measure. For a more detailed explanation see e. g. Dempster et al. (2008).

mean reversion.[5] On the other hand, Alvarez-Ramirez et al. (2002) find significant autocorrelation in Brent crude oil prices, which induces mean reverting behaviour in oil prices. Tabak and Cajueiro (2007) conclude that the random walk type behaviour in energy futures prices in general is still an unresolved matter of research. Thus, the empirical evidence to be found is mixed.

From a theoretical point of view, Pindyck (2001) argues that both mean reverting and random walk components are justified in the case of spot oil prices. On the one hand, the spot price should revert to its long-run marginal costs, in line with the theory of competitive markets, on the other hand these long-run marginal costs may be subject to stochastic shifts e.g. due to new resource estimates or technical change. Mean reverting behaviour thereby stems from fluctuations in the cost-of-carry, which represents the storage cost plus the interest paid to finance the asset minus the net benefit that accrues only to the owner of the physical asset, but not to the owner of a financial futures contract. In the commodities literature this is denoted as convenience yield and already Gibson and Schwartz (1990) have developed a two-factor oil price model incorporating a stochastic mean reverting convenience yield. Concerning the long-term price development of crude oil there is considerable uncertainty. Limited resources are on major reason, which lead to uncertainties about Hotelling-type scarcity rents (see e.g. Hamilton, 2009) or even fears about some coming "peak-oil". Yet technical change and exploration activities may extend the reserve basis and shift the peak of oil production. This makes predictions of future supply rather difficult, but for the stochastic properties the assumption of a random walk seems reasonable. A combination of mean reverting and random-walk components allows furthermore capturing Samuelson's maturity effect (Samuelson, 1965), the empirically observable effect of increasing volatility in oil futures as they get closer to expiry.

The stylized facts mentioned above have been incorporated in a multi factor model for oil prices in Schwartz and Smith, 2000. The equilibrium price level is captured by a random walk, whereas short-term deviations from the equilibrium are modelled through one mean reverting component. Along these lines, the oil prices are modelled in this article by a generalized combination of mean reversion and random walk components, as proposed for an n-factor setting by Cortazar and Naranjo (2006). So the basic assumption is not a random walk in oil spot prices but rather a price development driven by a combination of mean reverting and instationary factors.

Obviously there are a lot of fundamentals in crude oil markets which have to be considered when it comes to price modelling. Fundamental models with new information arrival are also able to produce stochastic spot price behaviour. Developing a fundamental (or structural) model of oil price formation could be a valuable alternative to the approach used here. Unfortunately a lot of fundamentals would be needed for a substantive model and many of these data are not available on a day-per-day basis. Moreover typically only information on current fundamentals is available and not available on expectation of market participants which are relevant for futures prices. Therefore we stick to the multi factor models based on spot and futures price series.

[5] However one may note that Postali and Picchetti (2006) similar to Pindyck (1999) use very long time series which capture the whole lifecycle of an oil field over several decades. In the present paper, much shorter time series are considered and the mean reverting behavior refers to short-term deviations.

3 Testing informational efficiency in crude oil markets

3.1 Existing test procedures

Alquist and Kilian (2010) are interested solely in the information contained in crude oil futures. Without taking the difference between the risk neutral and market measure into account they try to assess the ability of crude oil futures to forecast spot prices. Their empirical investigations suggest that oil futures prices should not be used for forecasting future oil spot prices because in a mean square prediction error sense they are not able to outperform simple no-change forecasts. The reason given is the high variability in futures prices which is caused by market fundamentals such as uncertainty about future oil supply shortfalls. This translates into fluctuations of the marginal convenience yield which has been pointed out in section 2.2. But their approach does not take the risk aversion of investors in oil futures market into account and is thus different from the approach proposed in this article which makes use of a formal framework for modelling both crude oil spot and futures prices.

Regarding the general assessment of efficiency in crude oil markets there has been considerable research. Usually, tests for informational efficiency are focusing on the random walk property of a commodity price series as pointed out in section 2. If the time series follows a random walk, the researcher concludes in such tests that the market is efficient, at least in the weak-form. As pointed out above, it is then not possible for an investor to make extra profits by using historical price data in order to predict future prices. Econometrically speaking, the investigation of the random walk behaviour is done under the null hypothesis of a unit root. However, Maslyuk and Smyth (2008) highlight that the class of unit root tests might suffer from neglected structural breaks in the time series. One or more structural breaks, which are not taken into account, will make an acceptance of the null hypothesis more likely. Thus, neglecting structural breaks might lead the researcher to accept the random walk behaviour, although the conclusion that markets are efficient and prices are outcomes of rational information processing is not necessarily warranted. Moreover, Cochrane (1988) argues that first-difference stationary time series, meaning they are integrated of order 1, are a combination of stationary and random walk components. The smaller the random walk component is, the more likely it is to reject the null hypothesis of random walk type behaviour. To our understanding testing for unit roots in crude oil price time series is thus not the most promising approach.

These shortcomings have led to the application of more advanced methods for the investigation of efficiency in oil markets, of which an overview is given in Table 1. Tabak and Cajueiro (2007) apply a Rescaled Range Hurst analysis (R/S analysis) to several rolling data windows of approximately four years, comprising the period from 1983 till 2004 for Brent crude oil. Since the R/S analysis assesses the random walk behaviour of the oil time series, any deviation from a random walk is connected with persistent (autocorrelation) or anti-persistent (mean reversion) price changes in the time series. The authors show that there is still autocorrelation in Brent crude oil spot returns but the autocorrelation is diminishing over time. Thus, they draw the conclusion that the market for Brent crude oil is becoming more efficient till 2004 – which is the time frame considered, and was highly inefficient in the eighties. This is to some extent in line with the findings of Maslyuk and Smyth (2008) who find that Brent crude oil prices are indeed characterised by a random walk process, though it is contradictory to the observation of autocorrelation in oil prices, but it supports Cochrane's assertion mentioned above.

Table 1: Overview of studies testing for efficiency in oil markets

Study	Data	Time Period			Method	Result
Maslyuk and Smyth (2008)	US WTI, UK Brent	Jan 1991 – Dec 2004	Spot and Futures (1, 3, 6)	Weekly	Unit root with endogeneous structural breaks	Non-stationary, weak-form efficient
Tabak and Cajueiro (2007)	US WTI, UK Brent	May 1983 – Jul 2004	Spot	Daily	Rescaled Range Hurst analysis	Becoming efficient, WTI more weak-form efficient than Brent
Alvarez-Ramirez et al. (2008)	US WTI, UK Brent, Dubai	1987 – 2007	Spot	Daily	Detrended Fluctuation Analysis	Short-term exploitable inefficiencies, long-term efficient
Elder and Serletis (2008)	US WTI	Jan 1994 - Jun 2005	Spot-month Futures	Daily	Semi-parametric wavelet estimator	Inefficient
Charles and Darné (2009)	US WTI, UK Brent	Jun 1982 – Jul 2008	Spot	Daily	Non-parametric variance ratio test	US WTI inefficient, UK Brent efficient
Cifarelli and Paladino (2010)	US WTI	Oct 1992 – Jun 2008	Spot and Futures (1, 2, 3, 4)	Weekly	ICAPM	Inefficient

Alvarez-Ramirez et al. (2008) use detrended fluctuation analysis (DFA) to detect autocorrelation in Brent crude oil over the period 1987 to 2007 as well. On the one hand, they confirm the findings of Tabak and Cajueiro (2007) that the long-term dependence is vanishing in oil markets, which means a movement towards efficiency. On the other hand, they still find autocorrelation for time horizons smaller than one month. Hence, they conclude that there is some evidence that the market exhibits inefficiencies in the short-term and becomes efficient in the long term. A conclusion that the results for the presence of autocorrelation in the crude oil market might depend on the method and dataset used seems to be appropriate. Elder and Serletis (2008) use a semi-parametric wavelet-based estimator and find that energy prices in general display long-term memory which is not consistent with the efficient market hypothesis. They use NYMEX spot-month futures prices for a sample period from 1994 to 2005. The long-term memory behaviour is anti-persistent which means that the time series follows a mean reverting process.

The same result arises from a study by Charles and Darné (2009). The West Texas Intermediate (WTI) crude oil market seems to be inefficient in the sub period of 1994 till 2008. Using non-parametric variance ratio tests they find weak-form efficiency for the Brent crude oil market in the period 1982 till 2008. The findings for WTI are supported by Cifarelli and Paladino (2010). They show that in the time span 1992 to 2008, the WTI crude oil market is informationally inefficient, concluding the market is not driven by fundamentals but by speculation. Except the last paper, these tests of informational efficiency however focus solely on the use of spot price data and disregard the information contained in futures prices. Although Cifarelli and Paladino (2010) uses futures prices, they focus on short-term efficiency of the markets, testing notably for feedback trading as one particular behavioural anomaly, which moves prices away from their fundamental values. In view of the discussion in section 2.1, asserting that crude oil spot prices are not asset prices, the idea of testing the random walk behaviour in oil spot prices is problematic and not adequate for assessing informational efficiency of crude oil markets to our understanding.

3.2 **Proposed test procedure**

Given the increasing importance of futures trading in oil markets, testing for the efficiency of these markets seems of particular importance. The proposed approach thereby aims at using realizations of spot prices in order to assess the efficiency of previously held futures markets. Put differently, the question of interest is: Which information is contained in crude oil futures prices? It is a common perception of market participants that futures prices contain information about future spot prices and this is taken as starting point in this paper.

Under the weak form hypothesis of market efficiency, any additional information received after the closing of the initial futures market with information set Ω_t should be random – in line with the Samuelson argument cited above. Therefore, if futures prices are rational or efficient forecasts of future spot prices under the risk neutral measure, forecast errors must have zero mean and forecast errors must be uncorrelated with any state variable in the information set Ω_t at time *t*.[6] Consequently realisations of spot prices S_T should scatter randomly around the expected spot prices $\mathrm{E}_{\mathrm{t}|\Omega_\mathrm{t}}[\mathrm{S_T}]$ derived using the information set Ω_t.[7] Any deviation of S_T from expected values is only due to unforeseeable informational shocks.

If a valid stochastic price model is available, which adequately describes the information contained in Ω_t, including the future stochasticity of prices, then this testing idea may be pushed one step fur-

[6] This follows directly from the assumption of rational expectations. Under rational expectations it holds that $\mathrm{S_T} = \mathrm{E}_{\mathrm{t}|\Omega_\mathrm{t}}[\mathrm{S_T}] + \epsilon_{\mathrm{t,T}}$, where $\epsilon_{\mathrm{t,T}}$ is a random error term which has a zero-mean expectational error and is independent of $\mathrm{E}_{\mathrm{t}|\Omega_\mathrm{t}}[\mathrm{S_T}]$.

[7] This does not mean that crude oil spot prices have to follow a random walk.

ther using the Rosenblatt transform (Rosenblatt, 1952). According to Rosenblatt, the transformation $F_{S_T|\Omega_t}(S_T)$ should lead to a uniform distribution for random realisations S_T, if $F_{S_T|\Omega_t}$ is the correct cumulative distribution function for S_T given the information set Ω_t. The uniformity of the resulting distribution may then for example be assessed using the Kolmogorov-Smirnov and Kuiper tests (see e. g. Crnkovic and Drachman, 1995, Diebold et al. , 1998, Benz and Trück, 2009).

The proposed testing procedure for market efficiency may thus be summarised as follows:

1. Identify a valid stochastic price model *M* describing the joint movements of spot and futures prices in the market considered.
2. For given information set Ω_t, estimate the parameter set $\boldsymbol{\Psi}$ for the price model *M.*
3. Determine the cumulative distribution $F_{S_T|\Omega_t}(\log S_T)$ for the log of the spot price S_T at forecast horizon *T-t* from the parameterized price model *M.* The log of the spot price is normally distributed with mean

$$\mathbf{E}[\log \mathbf{S_t}] = \boldsymbol{x_1(0) + \mu t + x_2(0) \cdot e^{-\kappa_2 t} + x_3(0) \cdot e^{-\kappa_3 t}} \tag{2}$$

and variance

$$\begin{aligned}\mathbf{Var}[\log \mathbf{S_t}] &= \sum_{i=1}^{3}\sum_{j=1}^{3} \boldsymbol{Cov}[\boldsymbol{x_i}, \boldsymbol{x_j}] \\ &= \boldsymbol{\sigma_1^2 t + \frac{\sigma_2^2}{2\kappa_2}\left(1-e^{-2\kappa_2 t}\right) + \frac{\sigma_3^2}{2\kappa_3}\left(1-e^{-2\kappa_3 t}\right) + 2\frac{\sigma_1\,\sigma_2\rho_{12}}{\kappa_2}\left(1-e^{-\kappa_2 t}\right)} \\ &\quad \boldsymbol{+2\frac{\sigma_1\,\sigma_3\rho_{13}}{\kappa_3}\left(1-e^{-\kappa_3 t}\right) + 2\frac{\sigma_2\,\sigma_3\rho_{23}}{\kappa_2+\kappa_3}\left(1-e^{-(\kappa_2+\kappa_3)t}\right)}\end{aligned} \tag{3}$$

4. Compute the Rosenblatt transform $F_{S_T|\Omega_t}(\log S_T)$ for the actually observed log of the spot price S_T.
5. Repeat steps 2 to 4 for a sufficient sample of points in time *t* with a constant forecast horizon *T-t.*
6. Compute Kolmogorov-Smirnov and Kuiper tests on the obtained sample of points $F_{S_T|\Omega_t}(\log S_T)$ to test the null-hypothesis of uniform distribution of the transformed forecast error.

If the null hypothesis is rejected in step 6, this rejects the joint hypotheses of predictability of expected spot prices and of validity of the price model *M* without shocks in the information set. Testing directly the weak-form hypothesis of market efficiency clearly is not possible (Fama, 1970, Fama, 1991), therefore the selection of an appropriate price model obviously is a key element in this testing procedure.

The advantage of this testing procedure is that it may be applied for different forecast horizons *T-t,* so that not only short term efficiency of markets may be tested. Another advantage is the use of distribution tests on interval forecasts, since it does not require any restriction to a predefined confidence level. Following Dowd (2008), the idea behind is rather to transform the data into forecast cumulative probability values, for which the entire distribution may be tested by means of the Kolmogorov-Smirnov and Kuiper tests. Hence, in assessing informational efficiency we are not concentrating on predictable patterns in spot prices but rather on the whole distribution of anticipated spot prices.

4 Modelling the price dynamics of crude oil

4.1 State-space model for oil prices

In line with the stylized facts summarized in section 2.2, a multi factor model for oil prices is taken as basis for our investigations, capturing both random walk and mean reverting price movements[8]. In a general form, spot and futures prices may be written as a function of several latent (unobservable) factors or state-variables, which exhibit the desired properties. The model of Cortazar and Naranjo (2006) describes the log of spot prices as an affine function of such latent factors and is therefore used as basis here. In order to estimate the unobserved state variables and parameters of the model, Kalman filter and maximum-likelihood techniques are used simultaneously. Finally, the multi factor model is applied to explain the stochastic behaviour of spot prices using all information available from futures prices. This modelling approach is in line with the assumption of weak informational efficiency of observable spot and futures prices.

This approach thus follows the work of Duffie et al. (2000) and Dai and Singleton (2000) who show how affine models are obtained from the traditional pricing approach based on the risk neutral probability measure. The model formulation with unobservable state variables capturing random walk and mean reverting components goes back to Schwartz and Smith (2000). As mentioned above their model focuses solely on long-term equilibrium prices (the random walk component) and short-term deviations (one mean reverting component) and does not model explicitly the convenience yield. This is in contrast with a further strand of literature in which state variables (e. g. convenience yield) are assumed to be observable or at least interpretable (see e. g. Gibson and Schwartz, 1990, Schwartz, 1997). Within the modelling framework used here it is nevertheless still possible to recover the convenience yield. The effect of storage and therefore the link between spot and futures prices is established via the mean reverting factors in the model. As shown by Cortazar and Naranjo (2006) the logarithm of the oil spot price S can be described as a sum of several latent factors[9] and a drift rate:

$$\log S_t = \mathbf{1}'\mathrm{x_t} + \mu t \tag{4}$$

where $\boldsymbol{x}_t$ is a vector of the state-variables and μ is the long-term growth rate[10], which is assumed constant over time. This multi factor model generalizes previous research of two- and three factor models (including Schwartz and Smith, 2000) to an arbitrary number of factors. Using futures prices, the dynamics of the state variables has to be described under the risk-neutral measure Q:

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[8] As noted by one reviewer it would be desirable to incorporate fundamentals such as spare capacity in our price model. Unfortunately to our knowledge at best monthly data on fundamentals are available which are difficult to combine with the daily price data we are using. Moreover under hypothesis of market efficiency the observable market prices should reflect all available fundamental information.

[9] Although the factors underlying the price dynamics of the log of the spot price are latent, they capture, since two of them are mean reverting, typical price behavior of oil markets such as short-term deviations from a long-term uncertain fundamental value. Including fundamental exogenous and endogenous variables in the model might improve the prediction of the price dynamics, but it would be difficult to obtain fundamental data for a sufficient long sample period and simultaneously at a high frequency.

[10] The constant drift could be interpreted as a Hotelling-type interest rate.

$$d\mathbf{x}_t = (-\mathrm{K}\mathbf{x}_t - \lambda)dt + \mathbf{\Sigma}d\mathbf{w}_t \tag{5}$$

where the diagonal of the matrix $\boldsymbol{K}$ contains mean reverting parameters κ_i, the diagonal of the matrix $\boldsymbol{\Sigma}$ contains diffusion parameters σ_{ii} and any two Brownian motions ω_{ij} have a correlation coefficient of ρ_{ij}. The market prices of risk $\boldsymbol{\lambda}$ are assumed to be real-valued constants.

We do not restrict the several latent factors to be independent of each other. Their correlations reflect the empirical observations of the futures term structure, which should be driven in an efficient market by expectations of agents about short- and long-term supply and demand. The economic reasoning behind this is straightforward. Suppose there is an event like oil spilling in offshore operations which affects both short-term market prices due to scarcity on the spot market and longer term expectations due to more dull prospects for deepwater exploration. Hence a positive (or negative) correlation for the latent factors is to be expected. Although the state variables are unobservable factors they can be interpreted economically as discussed in section 2.2. The first state variable follows a random walk, which is obtained by setting κ_1 equal to zero. Furthermore, this induces a unit root in the spot price process, which can be empirically observed under certain confidence levels in crude oil prices. The time-to-maturity effect or in general, the mean reverting effect, is reflected by the other state variables $\kappa_2 \ldots \kappa_n$. Each of these state variables reverts to λ_n/κ_n at a mean reversion rate given by $\kappa_2 \ldots \kappa_n$. The advantage of affine no-arbitrage term structure models is the small number of factors to capture the dynamics of the whole term structure of futures prices.

The random walk part is captured within our model by the first latent factor introduced above. It could be any fundamental influence pointed out before or even US-Dollar price movements. Since it is difficult to investigate the influence of the US-Dollar separately, we make use of the assumption that US-Dollar price movements should be incorporated immediately in crude oil prices. Hence, US-Dollar price movements are captured by the first factor and therefore incorporated in the model.[11]

In order to solve the equation for the process of the state variables, the assumption of arbitrage-free, efficient markets is used. Then the price of a futures contract F at time t equals the expected spot price S_T at maturity T under the risk-neutral measure Q (Cox et al. , 1981):

$$F(\mathbf{x}_t, t, T) = E_t^Q(S_T) \tag{6}$$

Applied to the Cortazar and Naranjo (2006) model, this provides the following solution for the futures prices:

$$F(\mathbf{x}_t, t, T) = \exp\left(x_1(t) + \sum_{i=2}^{N} e^{-\kappa_i(T-t)} x_i(t) + \mu t + \left(\mu - \lambda_1 + \frac{1}{2}\sigma_1\right)(T-t) - A(t,T) \right) \tag{7}$$

where $A(t,T) = \sum_{i=2}^{N} \frac{1-e^{-\kappa_i(T-t)}}{\kappa_i}\lambda_i + \frac{1}{2}\sum_{i\cdot j\neq 1}\sigma_i\sigma_j\rho_{ij}\frac{1-e^{-(\kappa_i+\kappa_j)(T-t)}}{\kappa_i+\kappa_j}$.

An important remark should be made here. Generally, additional factors should improve the model fit, but they also increase the computational burden of estimation substantially. Sometimes, a quite

[11] We would like to thank an anonymous referee who brought the influences from foreign exchange rates to our attention.

large number of factors might be necessary to fit the term structure of the forward curve and the volatility term structure.[12] Adding further state variables involves an inconvenient number of parameters, given that each additional factor contributes *3+(n-1)* more parameters where *n* is the new number of state variables.

4.2 Estimation methodology

A commonly used method to identify the above mentioned parameters is to cast the model in state-space form and use the Kalman filter in view of an error decomposition of the log-likelihood function. The Kalman filter has been repeatedly used to estimate stochastic models of commodity prices, interest rates and other economic time series. Harvey (1989) provides a complete textbook treatment of estimation, testing and model selection of models in state-space form. A more specific description of the approach used here is given in Cortazar and Naranjo (2006). In brief, the Kalman filter recursively calculates optimal estimates of the state variables using all past information. The state-space form consists of a transition and a measurement equation. The transition equation describes the stochastic process followed by the unobserved state variables. The measurement equation relates the vector of observable variables to a vector of state-variables. Particularly, the term structure of futures prices is observed at a specific date *t* for different maturities *T* and the measurement equation relates these observations to the state-variables. Solving the equations above leads to the measurement equation:

$$\mathbf{z}_t = \mathbf{H}_t\mathbf{x}_t + \mathbf{d}_t + \mathbf{v}_t \qquad \mathbf{v}_t \sim N(\mathbf{0}, \mathbf{R}_t) \tag{8}$$

where $\boldsymbol{z}_t$ is the vector of observed log-futures prices, $\boldsymbol{H}_t$ is the observation matrix, $\boldsymbol{x}_t$ is the vector of state variables, $\boldsymbol{d}_t$ is an input matrix of observations and $\boldsymbol{v}_t$ is a vector of serially uncorrelated Gaussian disturbances with mean zero and covariance matrix $\boldsymbol{R}_t$. The measurement equation assumes the existence of a linear relation between observed variables and state-variables. As noted above, in this model the logarithm of futures prices is a linear function of state variables. The subscript *t* indicates that the procedure works even for an incomplete panel of price observations because the equation allows a varying number of observations for each date.

The transition equation, which shows the evolution of the latent factors, has the following form:

$$\mathbf{x}_t = \mathbf{A}_t\mathbf{x}_{t-1} + \mathbf{c}_t + \boldsymbol{\varepsilon}_t \qquad \boldsymbol{\varepsilon}_t \sim N(\mathbf{0}, \mathbf{Q}_t) \tag{9}$$

where $\boldsymbol{A}_t$ is the state matrix, $\boldsymbol{c}_t$ is the input vector of transition, and $\boldsymbol{\varepsilon}_t$ is a vector of serially uncorrelated Gaussian disturbances with mean 0 and covariance matrix $\boldsymbol{Q}_t$. It allows for noise in the sampling data and is assumed to be constant over the whole sampling period. Given this state-space representation, the Kalman filter calculates optimal estimates $\boldsymbol{x}_t$ of state variables and the covariance matrix.

Finally, the estimation of model parameters $\boldsymbol{\Psi}$ is obtained by maximizing the log-likelihood function of innovations:

[12] As you can see from the RMSE provided in section 5.2 the fit of our model specification concerning term structure of prices and volatility term structure to real-world data is quite decent. An additional Principal Component Analysis has shown that in most of the cases three factors are sufficient to explain more than 99% of the variance in the data.

$$\log L(\boldsymbol{\Psi}) = -\frac{1}{2}\sum_t \log|\mathbf{F}_t| - \frac{1}{2}\sum_t \boldsymbol{\nu}_t' \, \mathbf{F}_t^{-1} \boldsymbol{\nu}_t \tag{10}$$

where $\boldsymbol{\Psi}$ represents a vector containing unknown parameters, $\mathbf{v_t}$ is the prediction error and has variance-covariance matrix $\mathbf{F_t}$. Hence, the estimation methodology obtains both, optimal values for the parameters, in order to describe the log of futures prices, and optimal values for the time series of latent factors, which sum up, completed by the long-term growth rate, to the log of spot prices for crude oil.

5 **Empirical Results**

5.1 **Data**

Our study is based on daily price data for Brent crude oil futures contracts, traded at IntercontinentalExchange (ICE) between the 4th of January 2000 and 31st of December 2008. Although futures contracts are traded up to consecutive 72 months in the future we decided to use only futures up to 36 month closest to maturity[13], because trading volumes for contracts with maturities for 'far months' are much smaller than for near months. These small numbers imply some thinness of the market and we suspect prices for far month contracts to be less reliable.[14] Furthermore we use Brent crude oil spot prices taken from Energy Information Administration (2011).

Table 2: Characteristics of the data

Year	Avg. No. of Daily Obs.	Mean Values of Futures Contracts and Spot Prices in US-$				
		All contracts	F1	F6	F12	Spot
2000	9	22.93	28.53	25.95	23.83	28.64
2001	9	22.37	24.86	24.11	23.00	24.42
2002	9	22.62	25.03	24.03	22.89	24.98
2003	9	24.58	28.48	26.63	24.91	28.90
2004	9	34.54	38.04	36.54	34.65	38.29
2005	9	55.19	55.25	56.50	55.83	54.58
2006	9	69.00	66.13	68.94	69.92	65.16
2007	9	72.24	72.66	73.28	73.24	72.44
2008	9	102.55	98.52	101.26	102.19	97.34

Table 2 characterises the data used for both model calibration and forecasting. On the basis of the mean values for the near-month, 6-month and 12-month futures (denoted as F1, F6 and F12) and for the spot prices it can be seen that there has been a sharp oil price increase in the observation period

[13] Notably contracts with maturities up to 1, 2, 3, 6, 9, 12, 18, 24 and 36 months. We do not use all available contracts in order to speed up the calculation but use as much as possible information contained in futures prices.

[14] Although, trading volumes for the 24 and 36 month contracts are low, we decided to use the information contained in these futures prices in order to distinguish the random walk and the mean reverting components of the model.

and during the last three years, the 12-month futures have had on average higher prices than the 1-month futures or spot prices which are almost the same.

A look at the volatility development for the 1-month and the 12-month contract reveals substantial differences between short- and long-term oil prices (cf. Figure 1). The volatility is computed as the standard deviation over 10 days of daily log-returns with the mean value of log price changes set to zero in line with Figlewski (1997). Figure 1 illustrates the maturity effect already described by Samuelson (1965), that volatility for futures which are close to maturity (notably F1, upper panel) is generally higher than the volatility of further-ahead futures (F12, lower panel). For the 12-month contract volatility never reaches the value of 6% as for short-term volatility. This is in line with the findings of section 2.2. Furthermore, there are volatility spikes, especially in the years before 2004 and in 2008. Between 2004 and 2008 the volatility is mostly below 4%, besides a sharp increase in fall 2008.

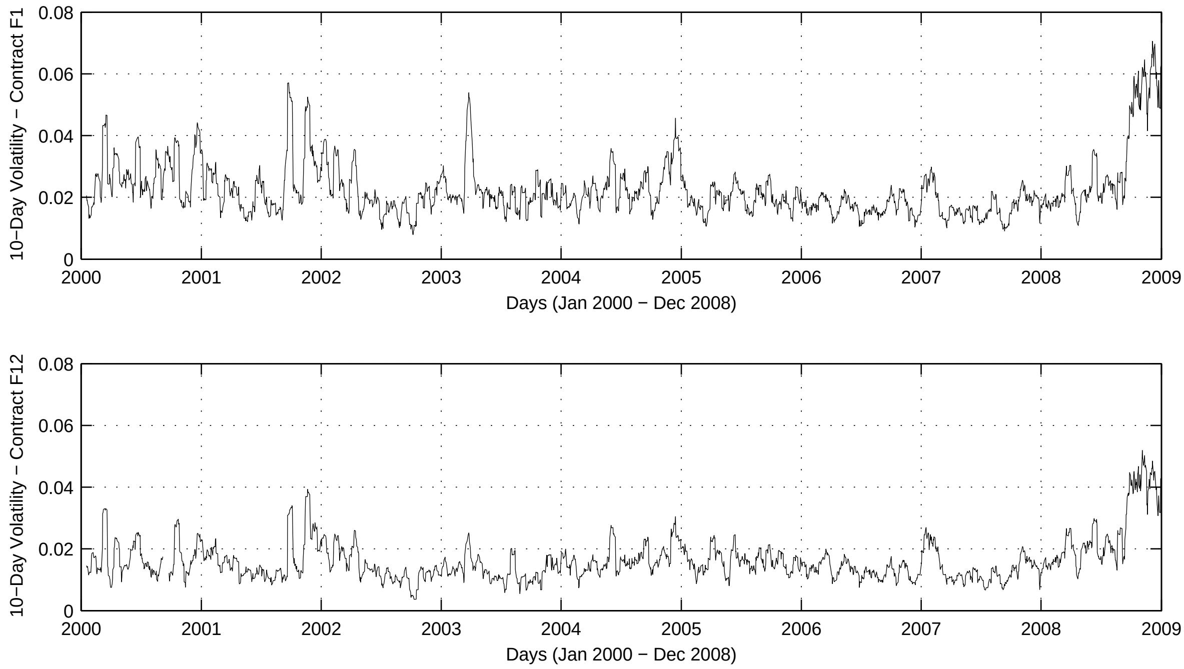

Figure 1: 10-Day volatility of the 1- and 12-month Brent futures (upper and lower panel)

Figure 2 depicts the price spreads between spot prices and 12 month Brent futures and between spot prices and 6 month Brent futures over the whole sample period including 2009 in order to get a picture of what happened after the beginning of the global economic and financial crisis. A positive price spread indicates time phases of backwardation, i.e. short term prices being above long term notations. Since there is no unique measure for backwardation, we decided to display two price differentials. During the sample period the oil market is mainly in backwardation but shifted to periods of contango in 2005/2006 and in fall 2008, although the start of the contango market depends on the measure of backwardation. In absolute values the difference is between -\$8 and +\$8 before fall 2008. After October 2008 this difference plunges to -\$20 and recovers in the subsequent months to -\$10. When considering relative values, the price spread is always between +30% and -30%. In line with the global financial crisis, which became evident in fall 2008, the increased price differential indicates that the information structure has changed dramatically, but it is not that obvious looking at the price spread of the spot price and 6 month futures.

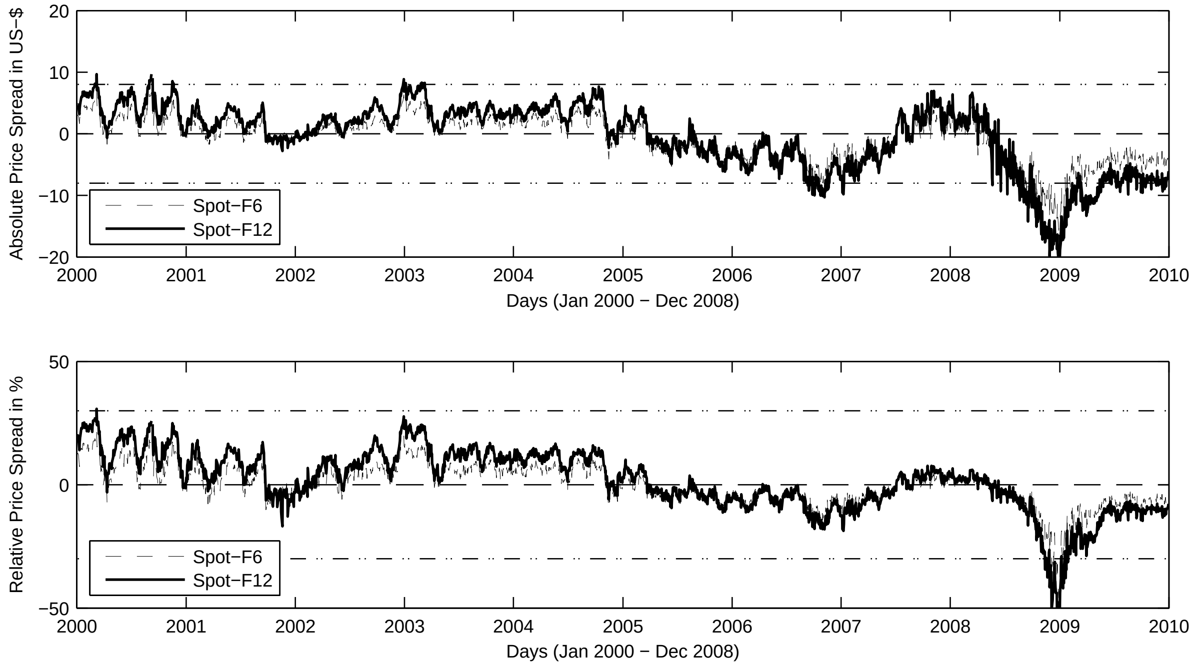

Figure 2: Absolute and relative price difference between spot price and 6-month (Spot-F6) and spot price and 12-month (Spot-F12) Brent futures (upper and lower panel)

5.2 Estimation results

The main concern of this study is to test whether deviations of spot prices from price forecasts derived from current crude oil futures prices are uniformly distributed. In order to do so, the estimation procedure described before is applied repeatedly to a rolling data window, where the in-sample period is fixed to two years. Although we use daily data, the parameter estimation is conducted once a week on Wednesdays, which means that the start and end date increase by 7 days each week. We decided to use a three-factor model including one random walk and two mean reverting components in order to capture both, the dynamics of the term structure of prices and the volatility structure over the whole sample period. This is necessary because the curvature of the term structure changes on the one hand with maturity and on the other hand over time, producing phases of backwardation or contango.

Table 3 shows averages of estimated parameters and their related standard errors. This is a summary of a total of 366 estimations from beginning of 2002 to end of 2008. Obviously the estimated values vary considerably over time, as can be seen from the standard deviations over time. At the same time the relation of mean parameter estimates to mean standard errors shows that the parameter estimates are mostly significant.

Table 3: Average estimates of model parameters and related standard deviations

Parameters	Mean		Standard deviation	
	Estimated Values		Estimated Values	
	Parameters	Standard errors	Parameters	Standard errors

κ_2	1.0996	0.0288	0.6888	0.0176
κ_3	2.2901	0.0794	1.0238	0.0589
λ_1	0.0225	0.0024	0.0179	0.0012
λ_2	0.0811	0.0485	0.2954	0.0596
λ_3	-0.1308	0.0676	0.3741	0.0675
μ	0.0003	0.0006	0.0003	0.0001
ξ	0.0000	0.0000	0.0000	0.0000
σ_1	0.2162	0.0087	0.0279	0.0023
σ_2	0.4629	0.0479	0.2866	0.0646
σ_3	0.3965	0.0478	0.2809	0.0659
ρ_{12}	0.0795	0.0705	0.2079	0.0216
ρ_{13}	0.0587	0.0777	0.2316	0.0215
ρ_{23}	-0.6556	0.0501	0.3047	0.0404

In order to assess the goodness-of-fit of the multi factor model Table 4 provides the average in-sample and out-of-sample root mean square errors (RMSE) and Bias for the term structure of futures prices and for each specific maturity. The RMSE is thereby computed as $\mathrm{RMSE_T} = \sqrt{\frac{1}{t}\sum_{i=1}^{t}\left(\mathrm{F(i, i+m)} - \hat{\mathrm{F}}\mathrm{(i, i+m)}\right)^2}$ and for the Bias similarly $\mathrm{BIAS_T} = \frac{1}{t}\sum_{i=1}^{t}\left(\mathrm{F(i, i+m)} - \hat{\mathrm{F}}\mathrm{(i, i+m)}\right)$.[15] The RMSE for the average fit of the volatility term structure and for each maturity is shown. For the in-sample period of two years the parameters and latent factors from the optimization procedure are used to compute the term structure of oil prices. For the out-of-sample period of one year, which fits to the longest forecast horizon used in section 5.3, the fitted in-sample parameters are used to obtain the state of the latent factors by running the Kalman filter again. Afterwards parameters and dynamics of latent factors are used to get the term structure of oil prices.

Table 4: In-sample and out-of-sample root mean square error (RMSE) and Bias for term structure of prices and root mean square error (RMSE) for volatility term structure at specific maturities

	Term Structure RMSE (US-$)	Term Structure Bias (US-$)	Volatility Term Structure RMSE (%)
In-sample (2 Years)	0.21	0.0040	1.09
F1	0.23	0.0038	1.16
F2	0.09	-0.0020	1.17
F3	0.18	0.0333	1.29
F6	0.21	0.0152	1.31
F9	0.13	-0.0072	1.22

[15] The computation of volatility is almost the same. Futures prices just have to be changed with volatility.

F12	0.17	-0.0178	1.21
F18	0.25	0.0418	0.85
F24	0.27	-0.0325	0.81
F36	0.23	-0.0068	0.56
Out-of-sample (1 Year)	0.24	0.0182	-
F1	0.28	-0.0109	-
F2	0.10	0.0027	-
F3	0.23	0.0587	-
F6	0.22	0.0518	-
F9	0.14	0.0194	-
F12	0.19	-0.0068	-
F18	0.31	0.0150	-
F24	0.29	-0.0050	-
F36	0.28	0.0186	-

The results indicate that the overall fit of the multi factor model to real world historical prices is quite good. The pricing error in absolute terms is quite small, the in-sample RMSE corresponds to an average error of 0.21 US-$ and the out-of-sample error to 0.24 US-$. Using an average in-sample oil price over all contracts of 56.92 US-$ the absolute pricing error translates in relative terms to 0.37%. Furthermore the modelled futures prices are not biased. On average the term structure of volatility is fitted with an error of less than 2%, which is a quite good result because it accounts for all maturities and for the whole sample period. We want to point out that volatility is estimated only from futures prices and no additional information is used, which makes a volatility fit for each maturity, especially in the mid-term, a rather demanding task (cf. Figure 4).

Table 5: Average estimates of latent factors and related standard deviations

Latent Factors	Mean Estimated Values		Standard deviation	
	Factor	Standard error	Factor	Standard error
x_1	3.4926	0.0031	0.5913	0.0011
x_2	0.3038	0.0193	0.3948	0.0159
x_3	-0.1626	0.0189	0.3279	0.0156

Table 5 shows average estimates of latent factors and related standard errors. The evolution of the latent factors over time is plotted in Figure 3. Obviously the latent factor 1 which corresponds to the random walk component is lower in the first years than in the later years. The sum of the mean-reverting latent factors 2 and 3 oscillates around zero as expected and the standard errors remain below 0.01 over the entire sample period[16].

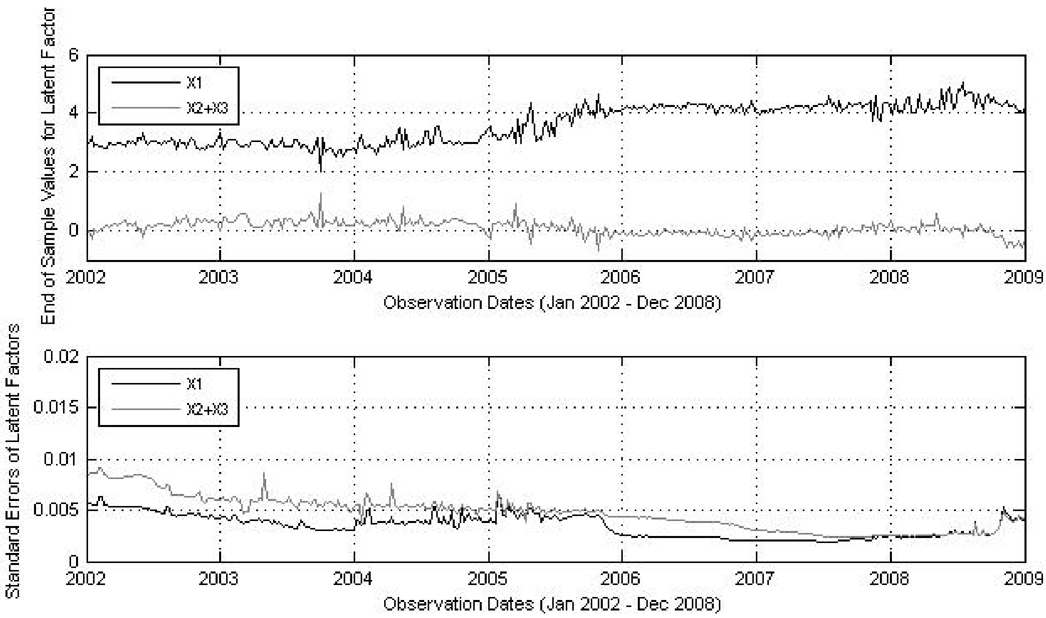

Figure 3: Evolution of latent factors over time from 2002 to end of 2008

Additionally Figure 4 provides two examples both of the in-sample fit of futures prices and of the volatility term structure for two specific dates 11th December 2002 and 10th September 2008 where the market is in backwardation respectively in contango. Obviously the multi factor model is in general well-suited to describe the observed price patterns. Under the weak-form hypothesis of market efficiency we only slightly stretch the results by claiming that the multi factor model also adequately describes the information content available in the market.[17]

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[16] This is not always true if the factors 2 and 3 are considered individually. Due to identification and/or multicollinearity problems, sometimes high standard errors occur. Yet for the price forecasts and the price distributions only the sum of the three factors is relevant, hence the insignificance of individual parameter estimates does not pose problems.

[17] Other authors including notably Schwartz (1997) and Cortazar and Naranjo (2006) have investigated several model specifications. Following the results of their investigations we adopt a three-factor model.

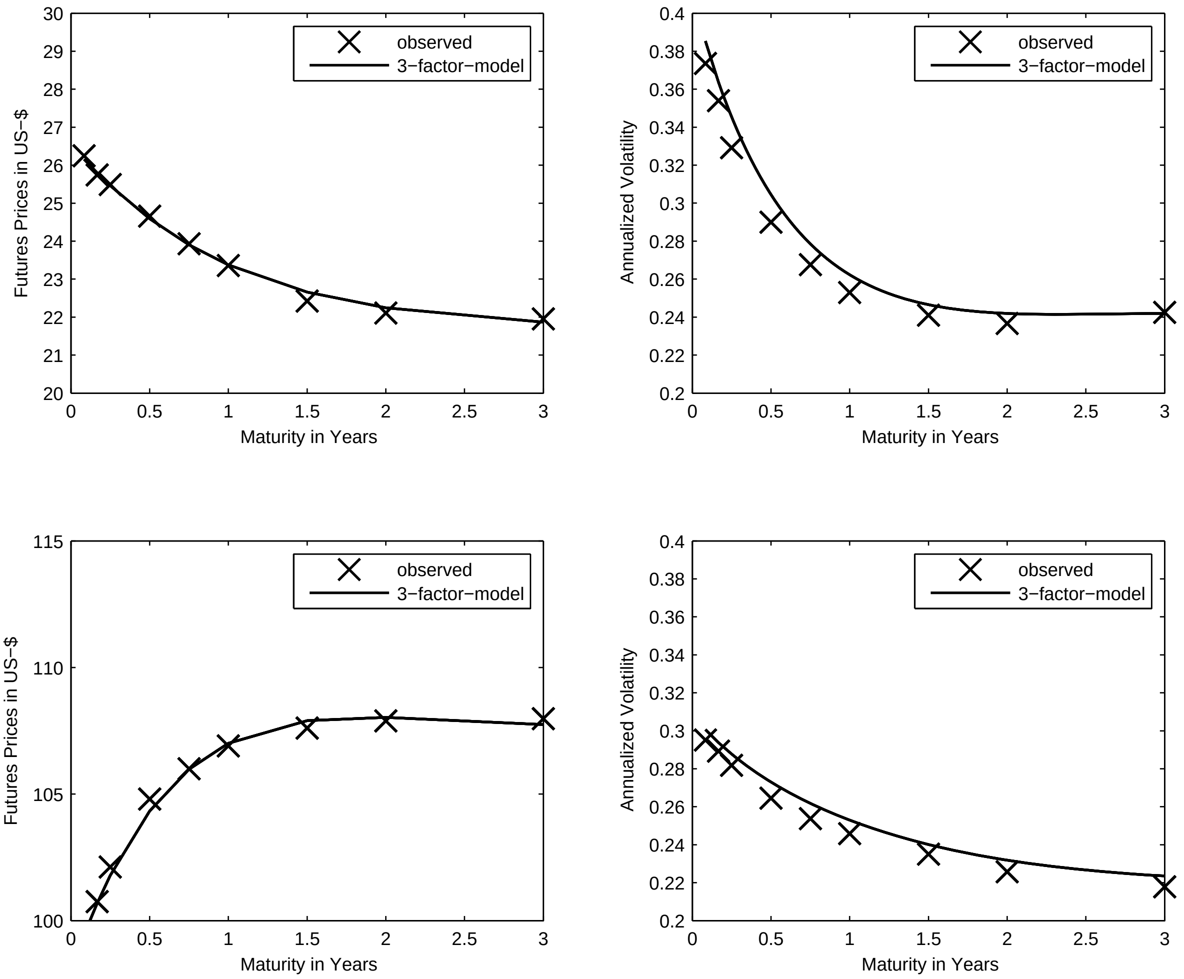


Figure 4: In-sample fit of the term structure of prices and volatility on 11-Dec-2002 (upper panel) and 10-Sep-2008 (lower panel)

5.3 **Test results**

Given this good fit to existing time series information, the key question is whether the model is able to describe at least on average adequately the future development of spot prices. In order to answer this question, we compare the spot price distribution derived from the fitted model for some forecast horizon with the actual later observations of the spot prices itself, as described in section 3.2. The approach tests the ability of the futures market to treat available information efficiently so that new information leads to random price movements. We are using forecast horizons of one week and one year over the whole in-sample period from 2002 to 2008 from which we obtain 366 points for the distribution evaluation.

Figure 5 shows the spot price dynamics between 2002 and 2008 as well as the daily log-returns of oil prices. We do not suspect any structural breaks from the graphical inspection of the time series, except for summer and fall 2008. Hence, we apply the new methodological approach from section 3 on the whole sample period and on two subsamples of equal length, namely from January 2002 to December 2004 and from January 2005 to December 2007, excluding the sharp price movements in 2008 due to the global financial and economic crisis.

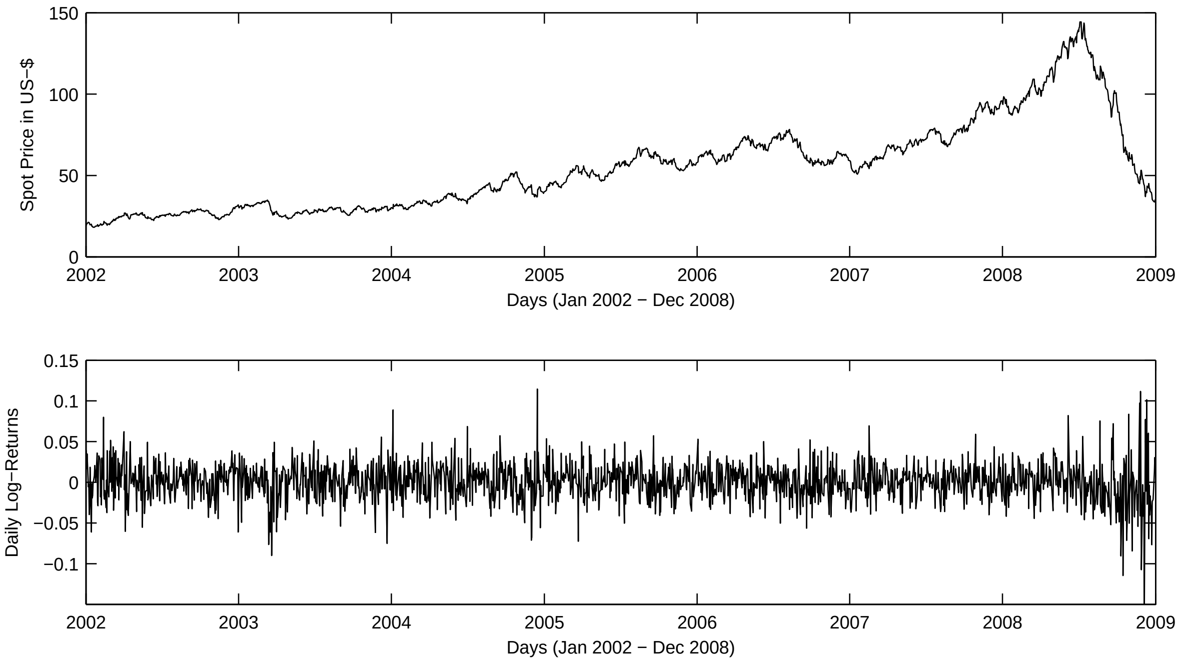
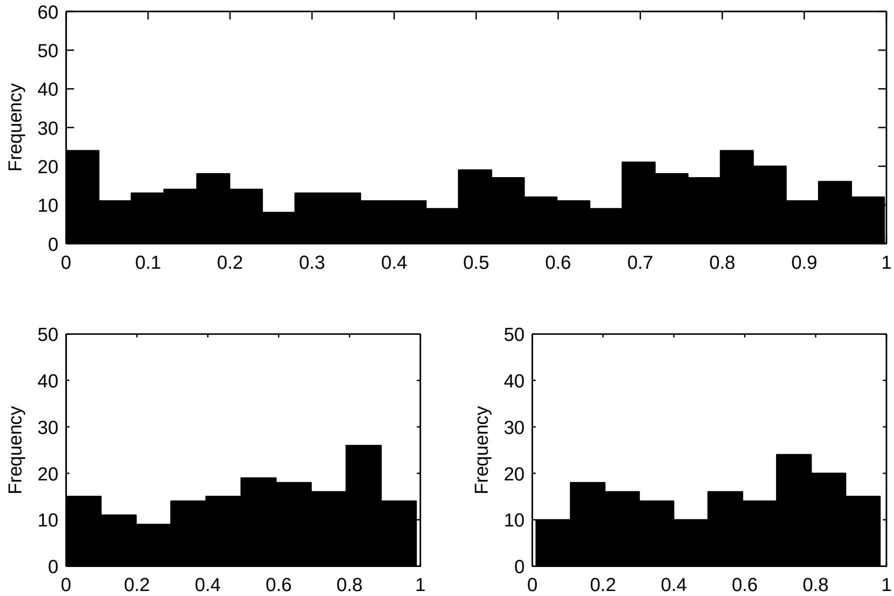


Figure 5: Spot prices (upper graph) and daily log-returns of spot prices (lower graph) between 2002 and 2008

Our results for the one week forecast[18] (cf. Figure 6) indicate that observed spot prices as compared to the ex-ante expected distributions are rather uniformly distributed within the whole sample and the two subsamples. This indicates that the short-term behaviour of oil prices during that time period is in line with the hypothesis of efficient markets. The information contained in futures prices fits to short-term dynamics of the spot price process.



[18] We are not running in the problem of overlapping forecast periods by using a one week forecast. Hence, the assumption of independent and identically distributed (iid) Rosenblatt-transformed spot prices S_T seems to be reasonable. Due to the weekly prediction update the one year forecast horizons overlap and therefore Rosenblatt-transformed spot prices S_T are no longer iid (see Dowd, 2008). Even though the standard test procedure for uniformity had to be augmented in this case, especially allowing for the dependence structure (namely auto-correlation) of spot prices we do not expect the qualitative results to be changed.

Figure 6: Histograms of the Rosenblatt transform for one week forecast over whole sample period (upper panel) and subsample 1 (lower panel – left) and subsample 2 (lower panel – right)

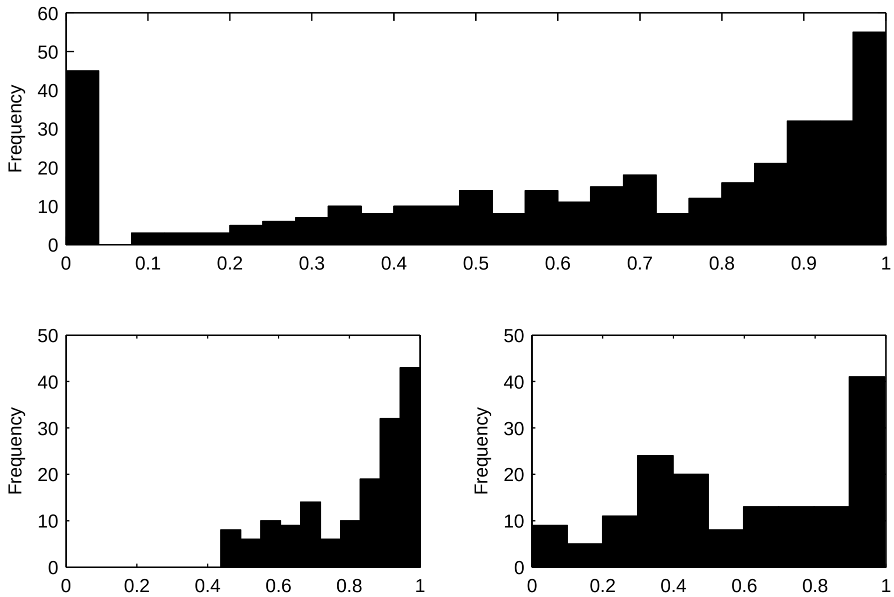


Figure 7: Histograms of the Rosenblatt transform for one year forecast over whole sample period (upper panel) and subsample 1 (lower panel – left) and subsample 2 (lower panel – right)

For the one year forecast of the whole sample period and the two subsamples the hypothesis of uniformly distributed price observations as compared to ex-ante distributions is obviously not valid (cf. Figure 7). Observed prices are disproportionally found in the upper and lower quantiles of the ex-ante distribution. For subsample 1, observations are mainly found in the upper quantiles of the distribution indicating that the constant rise in oil prices during that time period has not been expected ex-ante. During the second subsample period between 2005 and 2007 interval forecasts are covering all quantiles, but realised spot prices are found especially in the upper quantiles but also to a non-negligible proportion in the lower quantiles. Hence, observations are not in line with the assumption of efficient and prices repeatedly overshoot, yet partly also undershoot ex-ante expected price ranges.

These graphically derived findings are underpinned by a Kolmogorov-Smirnov test (K-S test) and the related Kuiper test. The statistic for the Kolmogorov-Smirnov test is computed as $V_{KS} = max\left(\left| F_{S_T|\Omega_t}(S_T) - F(u)\right|\right)$ where $F_{S_T|\Omega_t}(S_T)$ is the Rosenblatt-transformed empirical distribution function of spot prices and $F(u)$ denotes the cumulative distribution function of the uniform distribution. The test statistic for Kuiper's test is $V_K = D^+ + D^-$ where D^+ is defined as $\mathrm{D}^+ = \max\left(F_{S_T|\Omega_t}(S_T) - F(u)\right)$ and D^- as $\mathrm{D}^- = \max\left(F(u) - F_{S_T|\Omega_t}(S_T)\right)$. The null hypothesis of both tests is that realized spot prices are from the same continuous distribution as the ex-ante price expectations derived from futures prices. The results summarized in Table 6 clearly indicate that this hypothesis is rejected for the one year forecasts, whereas it is not invalidated for the one week forecasts. Correspondingly the longer term efficiency of crude oil markets, which is crucial for capital allocation decisions, is strongly in question.

Table 6: Results for Kolmogorov-Smirnov and Kuiper tests

	KS test statistic	Kuiper test statistic
One Week Forecast, whole sample 2002 - 2008	0.0574	0.0956
One Week Forecast, subsample 1, 2002 – 2004	0.1019	0.1338
One Week Forecast, subsample 2, 2005 – 2007	0.0764	0.11146
One Week Forecast, subsample 3, 2008	0. 3269***	0. 3846***
One Year Forecast, whole sample, 2002 – 2008	0. 2322***	0.3279***
One Year Forecast, subsample 1, 2002 – 2004	0. 4777***	0.4841***
One Year Forecast, subsample 2, 2005 – 2007	0. 1592**	0.1975**
One Year Forecast, subsample 3, 2008	0. 6731***	0.6731***

Asterisk denote rejection of the null hypothesis at 1%***, 5%** or 10%* level for n=366 observations (whole sample), n=157 (subsamples 1 and 2) und n=52 (subsample 3).

Table 6 includes additionally test results for a third subsample, consisting from predictions derived based on information available during the year 2008. Here the hypothesis of efficient and structurally invariant markets is clearly rejected. One year forecasts are found to be far from uniformly distributed and most observations are in the 0.1-Quantile of the ex-ante price distribution (cf. Figure 8). This indicates that the big drop in fall 2008 has not been expected nor was contained in the ex ante expected uncertainty range and the subsequent price recovery to previous price levels in 2009 has not been fast enough to fit to ex ante expectations. In the case of one week forecasts, observed prices are disproportionally higher or lower than expectations based on oil futures prices, but overall the graphical impression is closer to a uniform distribution, although both the Kolmogorov-Smirnov and the Kuiper test statistic reported in Table 6 refute the hypothesis of identical distributions. Hence the events of 2008 may only be interpreted as the result of a structural break unless the hypothesis of market inefficiency is abandoned from the outset. Yet the results for the preceding periods indicate that the joint hypothesis of market efficiency without structural breaks is even refuted for earlier, less turbulent periods of recent oil price developments. Only in the short-term, market efficiency is less questionable.

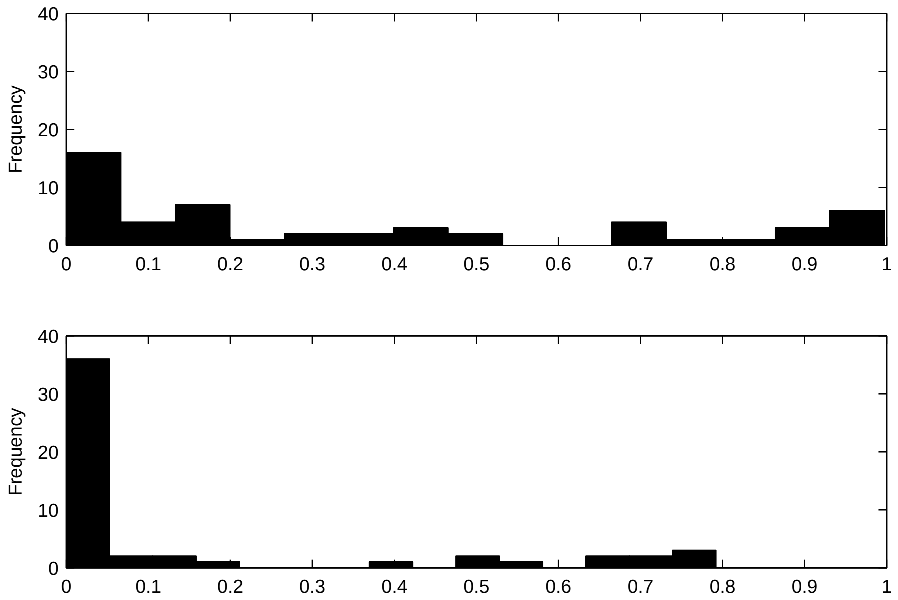


Figure 8: Histograms of the Rosenblatt transform for one week forecast (upper panel) and one year forecast (lower panel) for subsample 3

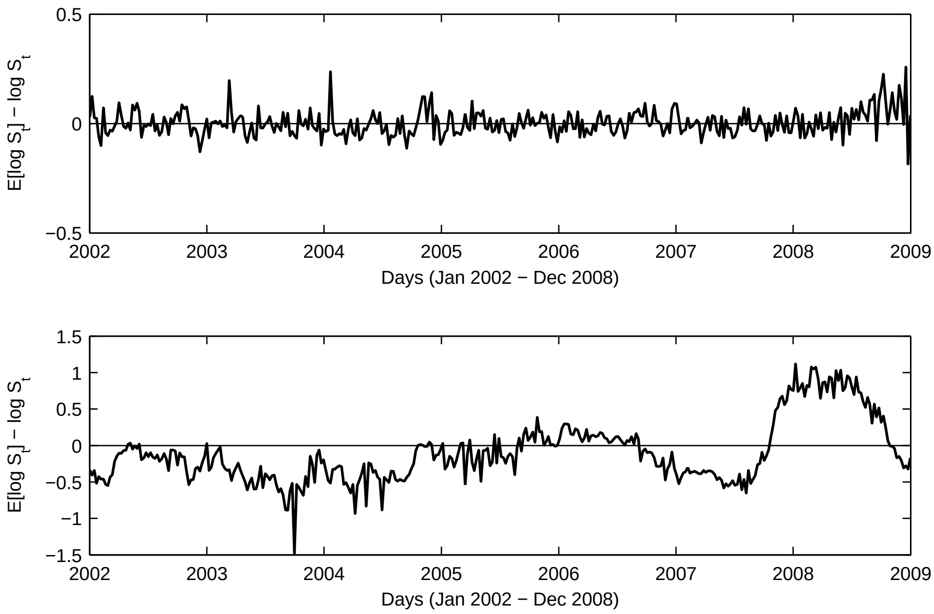


Figure 9: One week forecast errors (upper panel) and one year forecast errors (lower panel) over the whole sample period

The results are confirmed by Figure 9 which displays the difference between the expected values of the log of the spot price and the realised values when using the expected values from one week and one year forecast. The figure clearly confirms that in the case of the one week forecast the forecast errors scatter almost randomly around zero where in the case of the one year forecast prices show phases with huge negative (2003-2005) and positive deviations (2008).

6 Summary and Conclusions

The approach developed here allows for testing the joint hypothesis of efficient and structurally invariant markets. A separate test of both hypotheses is hardly possible. An application of traditional tests for structural breaks would be implicitly or explicitly based on the assumption of continued informational efficiency. On the other hand a pure test of the hypothesis of informational efficiency would require a fully non-parametric approach which is hardly achievable. Yet, maintaining the hypothesis of informational efficiency while allowing for structural breaks is only defendable, if the structure of the information flow has been altered fundamentally in the analysed period. This is certainly an arguable hypothesis for the period after mid 2008, when the global financial and economic crisis became evident. Yet the assumption of fundamentally changed information structures for summer 2006 or even earlier periods seems hardly justifiable.

The testing approach therefore evaluates the information contained in futures prices and their ability to predict future spot prices using a general three-factor model to describe this information content. The analysis has shown that the Brent oil market seems to be efficient in the short-term, presumably because financial traders arbitrage away biased expectations for the short term. Yet in the longer term, the open positions held by some fundamental traders are probably outweighed by traders arbitraging along the forward curve. The resulting forward curve then reflects rather expectations of arbitrage-freeness of financial traders than fundamental market expectations. Investors have to be aware of this issue when it comes to investment decisions.

In general, the interval forecast used here is mainly affected by volatility contained in oil futures. We are aware of the fact that the assumption of time independent parameters for a forecast horizon of one year is not fully convincing. However, using a model with time-varying volatility, e. g. a GARCH approach, should not affect our main results. The volatility in GARCH models reverts with a certain speed to its long-term value meaning that the one year forecast interval is hardly affected. Using implied volatility from option prices instead might be an alternative worth investigations, yet this might again be biased due to the thinness of the market for long-term maturities and the necessary assumptions on the underlying option price model. The assumption of constant risk premia might affect the results. The main problem concerning the estimation is that the process of expected spot prices is not observable. The risk premia which are estimated via the measure change between risk-neutral futures prices and real-world expected spot prices might therefore be biased. Time-varying (possibly price level depending) risk premia might overcome this problem but this issue has to be left for future research

In conclusion, prices provide appropriate signals for investment decisions or valuation in ideal markets. Yet the analysis has shown that longer-term futures prices might not only be affected by randomly arriving fundamental information. Admittedly, it is difficult to distinguish between the influence of fundamentals and to which extent futures prices are affected by speculative behaviour of market participants. In the risk-neutral and arbitrage-free world of financial markets, such as the oil futures market, there appears thus to be a substantial danger that future prices do not incorporate sufficient fundamental information. Yet then using futures prices of oil for valuation of real oil investments might lead to rather wrong decisions. In other words, building on castles in the air is dangerous when it comes down to drilling wells in the ground.

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