CRUDE OIL SPOT PRICES AND THE MARKET'S PERCEPTION OF INVENTORY NEWS*

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Abstract

Market news and announcements are among the driving forces behind crude oil price fluctuations. Our paper focuses on investigating the impact of certain inventory news, regularly provided by the US Energy Information Administration (EIA). We use the discrepancy between crude oil inventory forecasts and actual inventory levels as a proxy for investor perception of inventory news. Technically, our analysis rests on a two-step model: Firstly, a measure of the market's perception, on a weekly basis, of inventory news is obtained as the deviation between actual inventory and forecast. Then, the series of daily crude oil spot prices is fitted to a regression model with GARCH residuals, where covariates render the impact of inventory news. Our findings suggest that there is an asymmetry with respect to the sign of the discrepancy between inventory forecasts and actual inventory levels. Furthermore, we find that a pronounced impact of the market's perception on crude oil prices has only begun to appear in recent years.

Key words: Crude oil spot prices; inventory news; market's perception; ARIMA forecast; GARCH with covariates; WTI crude

1 Introduction

Since the late 1980s, crude oil prices are among the most volatile products and commodities, see e.g. Regnier [9]. Extreme swings in crude oil prices use to be linked to geopolitical events, and economic turmoil. The role of the OPEC uses to be questioned, and possible effects of the cartel's announcements of decisions have been analysed (e.g. Fattouh [3], Schmidbauer & Rösch [10]). One clue to understand the recent zig-zag of prices, however, seems to be the uncertainty about market fundamentals. While demand shocks are blamed by Wirl [11], supply factors are brought forth by Gallo et al. [4]. According to Kaufmann [7], there is impact of changes in both market fundamentals on crude oil prices, with major speculative pressure interfering from 2004 onwards, when prices rapidly increased. Effects of refining capacity and inventories on crude oil prices and transmissions in the energy supply chain are investigated by Kaufmann et al. [5, 6]. Their results indicate little evidence of an effect of higher refinery utilization, while a rise in crude inventories

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could effectively lower prices. On the other hand, prices affect inventory management practices, such that higher prices lead to lower inventories and increasing refinery utilization.

The "swings" in crude oil prices appear to be "coupled with counter-swings" in inventories. — This perception is adopted by some short-run forecasting models of monthly crude oil prices by Ye, Zyren & Shore [12, 14]. They focus on concepts of "normal" and "relative" (in the sense of deviation from the "normal") levels of market indicators such as demand, field production, net imports, and inventory. Empirically, Ye, Zyren & Shore [13] found that the demand elasticity with respect to short-run market price fluctuations is much less than the short-run inventory elasticity in the US, while the supply elasticity due to long production chains is virtually zero. Their conclusion is that trends in inventory, together with seasonal patterns, reflect the supply/demand balance and affect crude prices in the long-run, while deviations from the "normal level" affect the price behaviour in the short run.

On days when weekly US ending stocks of crude and petroleum products are released, headlines like "Sharp rise in US inventories weighs on oil"[1] or vice versa "Oil prices increase after US inventories decline"[2] in economic news catch the reader's eye. The weekly oil report by the US Energy Information Administration, usually released on Wednesdays, is awaited by market analysts as well as by investors, who draw conclusions from changes in inventory on the current oil market supply and demand fundamentals.

In our study, we investigate the role of weekly inventory data on the very day of their release as determinants of expectation and volatility of daily crude price changes:

- In which way do inventory data on the very day of their release bear on oil prices?
- In particular: Do prices respond to the markets' perception of deviation from some consensus forecast?

An ARIMA model provides us with a forcast of inventories levels; the residuals of this model render the markets' perception of deviation, which can be classified according to magnitude and sign. We study the residuals' impact on conditional expectation and volatility of oil price changes on the basis of a combination of regression and GARCH models.

We restrict this paper to the investigation of US crude inventory releases and their impact on the behaviour of WTI price changes. Our empirical basis consists of data from the period January 1999 through December 2010, which is split into two six-year periods in order to account for the remarkable rise of prices during the recent six years in comparison to the early years in this period (see Kaufmann [7]).

This paper is organized as follows. WTI price and news release data used in the present study are introduced in Section 2. A proxy for the market's perception of inventory data released is obtained and used as covariate in models for conditional expectation and volatility of WTI price changes; this methodology is the subject of Section 3. Empirical results are reported in Section 4. Finally, conclusions are drawn in Section 5.

2 Data

The time series of daily WTI spot prices (in USD/barrel) and price changes in percent are shown in Figure 1. Prices are available at the website of the US Energy Information Administration (EIA).[3] Weekly US ending stocks of crude oil, petroleum products, and of the strategic petroleum reserve are posted on the website after 10:30 a.m. Eastern Time on Wednesdays. For weeks

[1] FT, 2010-01-15
[2] FT, 2006-12-14
[3] http://eia.doe.gov

starting with public holidays, the release is delayed by one day. Figure 2 displays three series of weekly ending stocks (in thousand barrels) on the day of release.

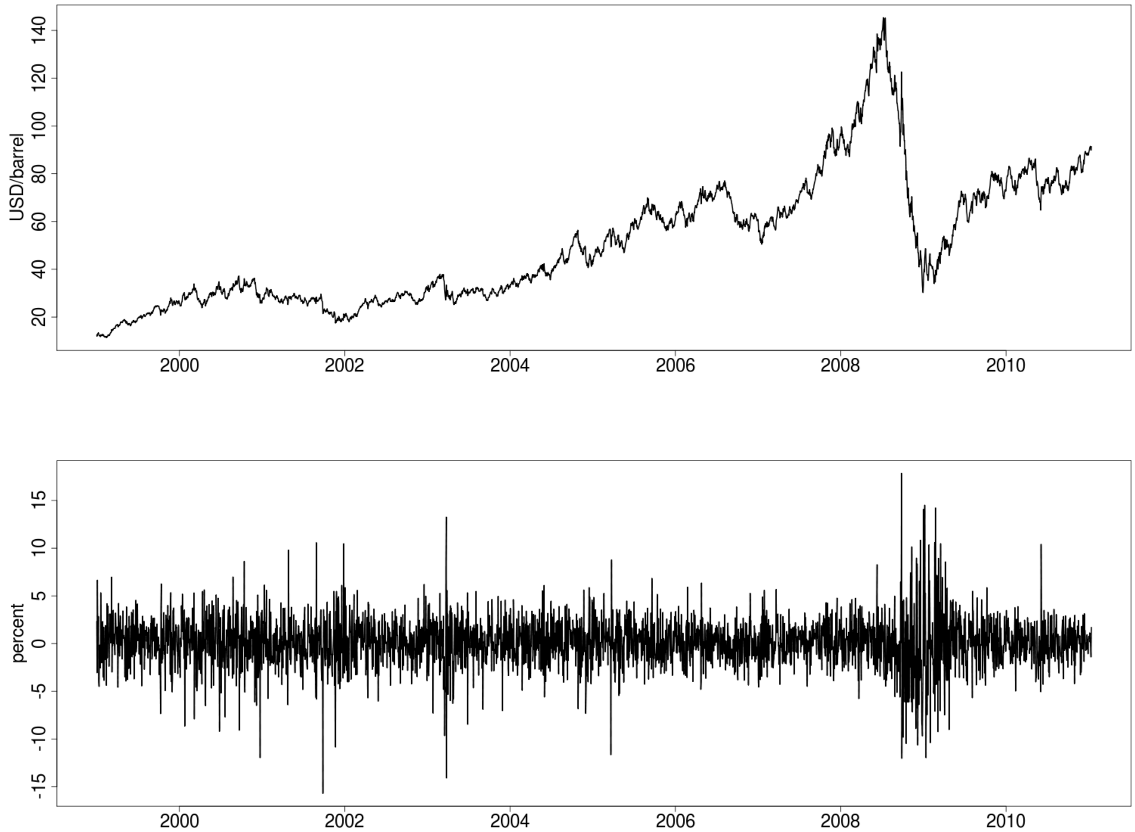

Figure 1: Daily WTI spot prices / price changes

3 Modeling the Effect of Inventory Release Data

The idea of the present investigation is that the market perception of deviations of released inventory data from forecasted values can have an effect on the conditional (using past information) expectation of the return on crude oil prices, as well as on its conditional volatility. Our analysis proceeds in three steps.

In the first step, we obtain forecast errors of crude oil inventory levels on a weekly basis, according to EIA information policy. We assume that the market's perception of inventory news, at the time of its release, is adequately expressed as (standardized) difference between actual inventory and last week's forcast. Specifically, the forecast is obtained using an ARIMA(p,d,q) model

$$\left(1-\sum_{i=1}^{p}\phi_i L^i\right)(1-L)^d x_t = \left(1+\sum_{i=1}^{q}\theta_i L^i\right)\epsilon'_t \tag{1}$$

to 260 data points (covering five years). Here, (x_t) is the series of weekly inventory levels as reported, L designates the lag operator, and the integers p, d, and q refer to the order of the autoregressive, integrated, and moving average parts of the model, respectively, and (ϵ'_t) should be white noise. For a release date t_0, model (1) is fitted [4] to the series $x_{t_0-260}, \ldots, x_{t_0-1}$ to obtain forecast $\hat{x}_{t_0}$, the forecast error being $\eta'_{t_0} = x_{t_0} - \hat{x}_{t_0}$. Division of η'_{t_0} by the model's

[4] All computations were carried out in R [8].

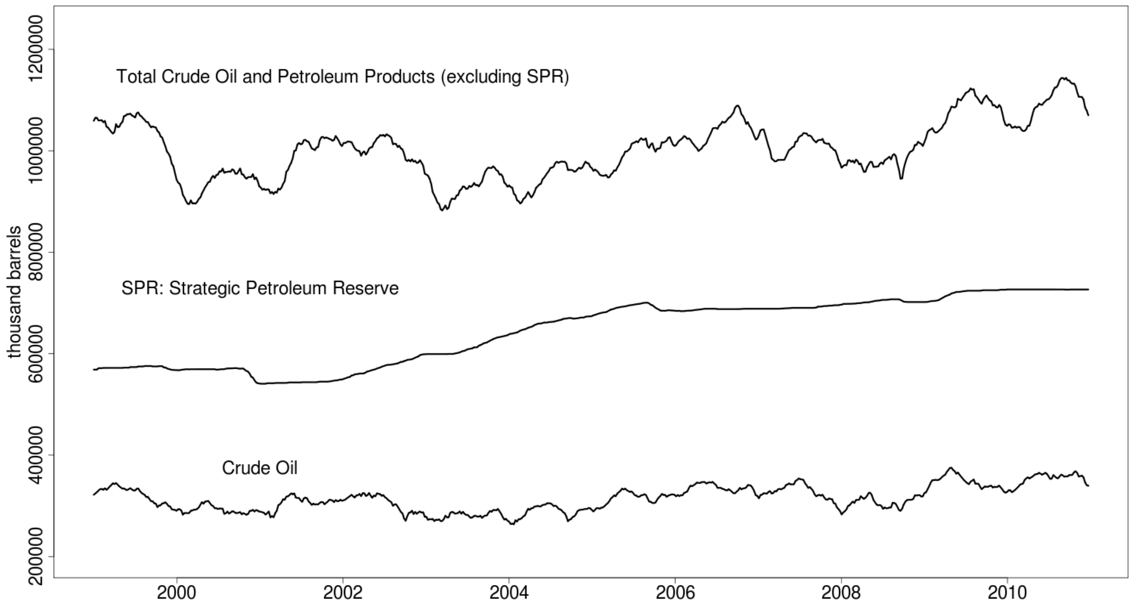

Figure 2: Weekly US ending stocks

estimated standard error results in η_{t_0}, which can be used as a standardized proxy for the market's perception of inventory news x_{t_0}, in the light of last week's expectation. The series (η_t) can then, by re-indexing, be converted into a *daily* series (d_t) by substituting 0 for each day without news release. For further use as covariates in expectation and volatility models, two series are derived from (d_t):

$$
\begin{aligned}
d_{\text{pos},t} &= \begin{cases} d_t & \text{if inventory data was released on day } t \text{ and } d_t > 0, \\ 0 & \text{otherwise,} \end{cases} \\
d_{\text{neg},t} &= \begin{cases} |d_t| & \text{if inventory data was released on day } t \text{ and } d_t < 0, \\ 0 & \text{otherwise,} \end{cases}
\end{aligned} \tag{2}
$$

so that $d_{\text{pos},t}$ ($d_{\text{pos},t}$) is non-zero for those days on which inventory reported exceeds (undercuts, respectively) the forecast.

In the second step, the variables in (2) are plugged into a regression model, together with a dummy variable indicating whether a day belongs to a bull period, that is, to a period of increasing price trend:

$$
d_{\text{bull},t} = \begin{cases} 1 & \text{if day } t \text{ belongs to a bull period,} \\ 0 & \text{otherwise,} \end{cases} \tag{3}
$$

We say that a day belongs to a bull period if the smoothed WTI price series is increasing from $t-1$ to t. A linear filter with linearly increasing, one-sided (backward-looking) weights was used for smoothing. The regression model, with daily returns in percent on the WTI crude spot price, r_t, as dependent variable, reads:

$$
r_t = c + \sum_{i \in \text{pos,neg,bull}} b_i d_{it} + \epsilon_t \tag{4}
$$

(The series (r_t) was not found to have significant autocorrelation.) The residuals (ϵ_t) of the regression model (4) will be heteroskedastic (see Figure 1), and we therefore use a GARCH model, again with covariates $d_{\mathrm{pos},t}$, $d_{\mathrm{neg},t}$ and $d_{\mathrm{bull},t}$:

$$\epsilon_t = \nu_t \cdot \sqrt{h_t}, \tag{5}$$
$$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta h_{t-1} + \sum_{i \in \mathrm{pos,neg,bull}} \gamma_i d_{it}, \tag{6}$$

which constitutes the third step of the analysis. Equation (4) specifies the conditional expectation of r_t, with the standardized residuals from the inventory forecasting model, and the bull indicator as regressors; equation (6) expresses the conditional volatility of returns.[5] Here (ν_t) is Gaussian white noise with $\mathrm{var}(\nu_t) = 1$. The conditional variance of r_t is thus allowed to depend on the variables d_{it}, $i =$ pos, neg, bull.

4 Empirical Results

Based on equations (1), (4), (5) and (6), a model for WTI price returns and volatility can now be constructed step by step. In the following, we display and compare the estimation results concerning the two six-year periods preceding/starting with January 2005.

A. ARIMA model for crude inventories

An ARIMA(2,1,0) model fitted to the 260 most recent data points is used to produce a weekly forecast of crude inventories data.

The series of observed deviations of actual inventory levels from last week's forecasts is shown in Figure 3; in our approach the standardized values serve as a proxy for the market's perception of inventory news.

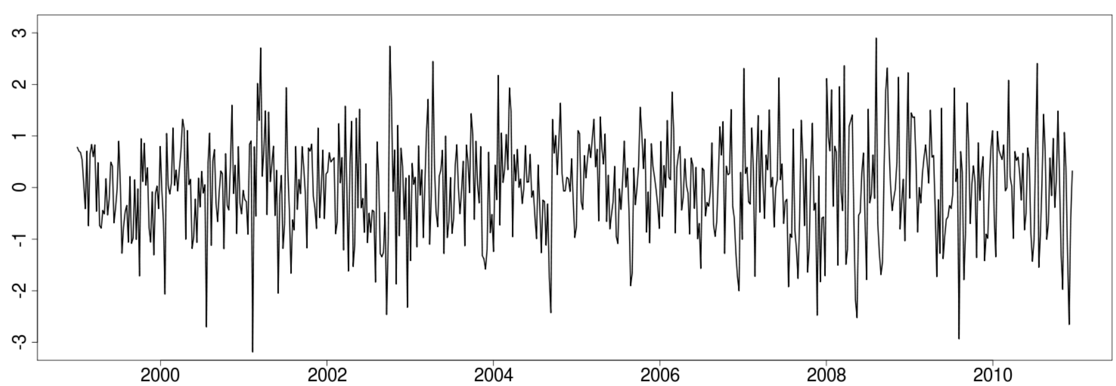

Figure 3: Differences between inventories and ARIMA forecast, standardized values

B. Regression model for the expected return on WTI prices

In the next step, we fit a regression model to the sequence of crude returns w.r.t. the variables $d_{\mathrm{pos},t}$ and $d_{\mathrm{neg},t}$ in (2) and the bull indicator $d_{\mathrm{bull},t}$ in (3). Estimation results for this model when differentiating between time periods are:

[5]Equation (6) is the conditional variance specification of a GARCH(1,1) process, see Engle [2], Bollerslev [1], with covariates added on.

time period 1999 – 2004:

	estimate	std. error	t value	$\Pr(>\lvert t\rvert)$	
c	-0.1143	0.1197	-0.955	0.339745	
b_{pos}	-0.8393	0.2396	-3.503	0.000473	***
b_{neg}	0.2815	0.2232	1.261	0.207536	
b_{bull}	0.3935	0.1416	2.780	0.005504	**

(7)

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1

Residual standard error: 2.547 on 1493 degrees of freedom
Multiple R-squared: 0.01541, Adjusted R-squared: 0.01343
F-statistic: 7.787 on 3 and 1493 DF, p-value: 3.691e-05

time period 2005 – 2010:

	estimate	std. error	t value	$\Pr(>\lvert t\rvert)$	
c	-0.2372	0.1191	-1.992	0.04653	*
b_{pos}	-0.5324	0.2155	-2.470	0.01361	*
b_{neg}	0.5200	0.2189	2.376	0.01764	*
b_{bull}	0.4975	0.1433	3.472	0.00053	***

(8)

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1

Residual standard error: 2.639 on 1505 degrees of freedom
Multiple R-squared: 0.01738, Adjusted R-squared: 0.01542
F-statistic: 8.875 on 3 and 1505 DF, p-value: 7.861e-06

Deviations from the inventory forecasts impact on crude returns significantly and on the very day of the release of the data. This can be observed for both time periods in the case of positive deviations. A surplus in inventories as compared to the forecast leads to a decline in returns. However, if inventories fall below the forecast, returns on crude appear to climb significantly only in the second, and more recent time period. A pushing factor of expectations during the whole time period is the bull period indicator.

C. Augmenting the regression model with a GARCH process

The residual series from the regression model in (**B**) is further analyzed on the basis of a GARCH process. Including the deviation variables $d_{\text{pos},t}$ and $d_{\text{neg},t}$, together with the bull indicator $d_{\text{bull},t}$ in the conditional variance specification amounts to a GARCH(1,1) process with covariates. While the best models w.r.t. the AIC criterion lack the bull indicator, deviations from the inventory forecasts enter the model at least in the recent time period. Estimation results are:

time period 1999 – 2004:

	estimate	std. error	t value	$\Pr(>\lvert t\rvert)$
α_0	0.75051677	0.35567828	2.110100	0.0348
α_1	0.09413724	0.02662844	3.535215	0.0004
β	0.79006641	0.07592156	10.406351	0.0000

(9)

AIC: 6962.968

time period 2005 – 2010:

	estimate	std. error	t value	$\Pr(>\lvert t \rvert)$
α_0	0.06069598	0.05460840	1.111477	0.2664
α_1	0.09052375	0.01937349	4.672559	0.0000
β	0.88006640	0.02510933	35.049385	0.0000
γ_{pos}	0.89066259	0.34447568	2.585560	0.0097
γ_{neg}	0.39632961	0.25625780	1.546605	0.1220

AIC: 6726.063

(10)

For the time period 2005 – 2010, it turns out that both $d_{\text{pos},t}$ and $d_{\text{neg},t}$ should be included in the GARCH specification when AIC is used as the criterion for model optimization, even though $d_{\text{neg},t}$ has no significant impact at the 10% level.

5 Summary and Conclusions

The purpose of our study was to ascertain possible effects of the weekly release of US inventories data on the expectation and volatility behavior of WTI spot price changes in a daily time horizon. We apply a regression model with GARCH residuals, where covariates indicate the day of release as well as the amount of positive/negative deviation from the weekly forecast of crude inventories. The forecast is derived from an ARIMA specification for the series of inventory levels. The empirical basis of the investigation consisted of data from January 1999 through December 2010, which was split into two six-year periods for comparison reasons.

A schematic comparison of the two periods under consideration is given in the following table (an asterisk indicates significance at the 5% level).

time period	impact on… expectation			impact on… volatility		
	positive inventory	negative deviation	bull period	positive inventory	negative deviation	bull period
1999 – 2004	*		*			
2005 – 2010	*	*	*	*		

Our findings suggest that there is more pronounced impact of the market's perception of deviation on the behaviour of daily WTI price changes in the period from 2005 through 2010. There is an asymmetry w.r.t. the direction of deviation. An unexpected surplus of inventories implies a much higher volatility of price changes than if the forecast was undercut.

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