Hovedoppgave for cand.oecon-graden

How do oil prices affect oilrig activity?

An empirical investigation

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Preface

This thesis has been written during my stay at Statistics Norway as a student assistant. I am grateful to Statistics Norway for providing me with office space and facilities. The thesis is a contribution to the project "Oljemarkedet i det 21. århundre" ("The Oil Market in the 21. Century"), which is founded by Norges Forskningsråd (The Research Council of Norway).

I would like to thank my two supervisors, Knut Einar Rosendahl and Terje Skjerpen at Statistics Norway, for excellent guidance along the way, and a special thanks to Skjerpen for leading me through the econometric rough waters. I am grateful to Petter Vegard Hansen for valuable comments and support during the process, and to Marius Holm Rennesund for excellent proofreading (any remaining mistakes are of course my own responsibility). Finally, thanks to Morten Henningsen. You know why.

Oslo, February 3rd, 2004.

Contents

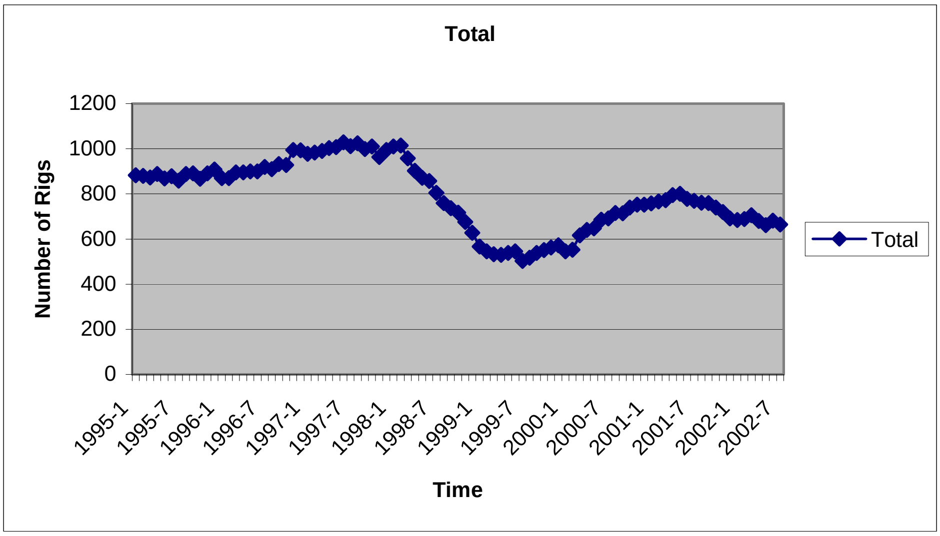
1. Introduction

In this thesis, I want to study how changes in crude oil prices affect the level of oilrig (drilling) activity. Rig activity is a preparation for future production of oil (or gas), either through exploration for new fields or development of existing fields. Thus, the current rig activity is an indicator of the future level of oil production. Moreover, rig activity is more flexible than oil production, and will therefore presumably react quicker to changes in prices and other external conditions than actual production does. There have been several studies of the relationship between oil production and oil prices, but very few have discussed the relationship between drilling activity and oil prices. However, Iledare (1995) models and estimates how the drilling activity for natural gas and the reserve additions in West Virginia respond to changes in the expected wellhead price, taxes, resource depletion and reserve-life index. In this thesis I will only focus on the drilling rigs employed in exploration and development of oil, and not of natural gas.

Expectations about future profitability of producing oil will clearly be important for the level of rig activity in most regions of the world. For Non-OPEC countries, which are more or less price takers in the oil market, future profitability is to a large extent determined by future oil prices. Furthermore, expectations about future oil prices often seem to be closely related to the current oil price, or at least the oil price level over the last couple of years. That is, expectations seem to be rather adaptive (although often with a time trend). Consequently, my hypothesis is that there is a long-run relationship between oilrig activity and oil price. I want to test this hypothesis, and also examine in what way oil prices affect rig activity, e.g., what, if any, are the immediate effects of oil price changes. In this way, the results may also tell us something about the oil companies' expectations about future profitability. As the data are separated into six different oil-producing regions, I further want to compare the different regions' reactions to changes in oil prices. The regions I will analyse are the United States, Europe, Asia Pacific, Latin America, the Middle East and Africa (these regions will be further specified in Section 3.1).

Figure 1 plots the total oilrig activity in the period 1995:1-2002:7 (monthly data). We observe that the oilrig activity level has varied from a minimum value during the period of 503 (1999:7), to a maximum of 1028 (1997:6).

Figure 1: Total oilrig activity



A plot of the six regions separately (Fig. 2) shows that the regions differ somewhat in their pattern. In the US and in Latin America, rig activity shows much more volatility than the four remaining regions. The US data start in January 1992, whereas for the other regions, I only have data since January 1995.

Figure 2: Oilrig activity in different regions

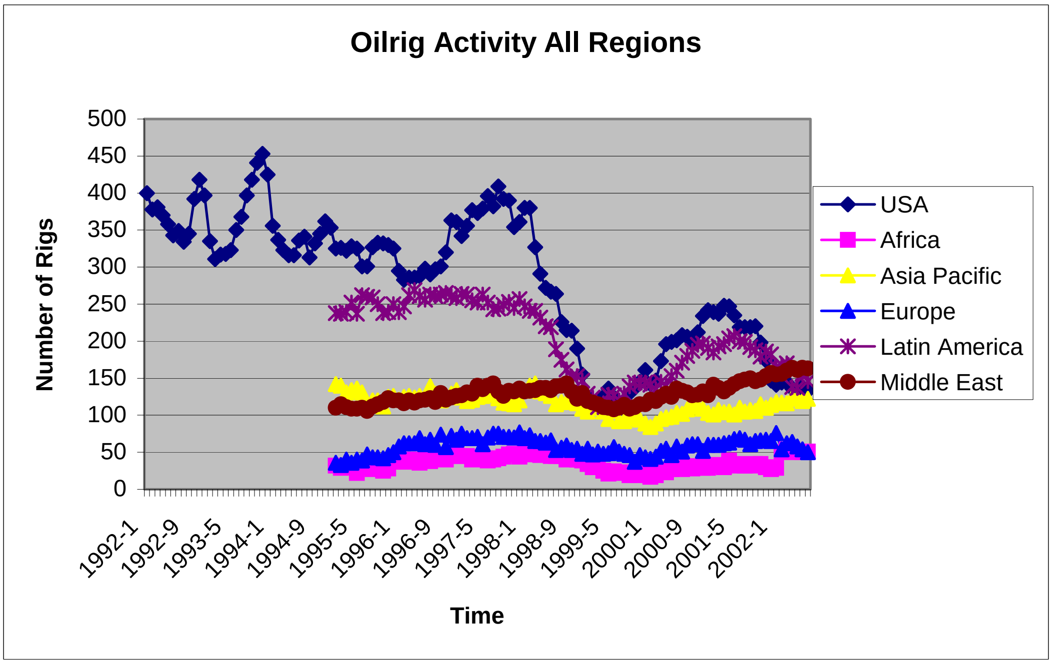


Table 1 reports descriptive statistics (mean and standard deviation) for both the total rig activity and for the separate regions. This shows that the US has by far the highest number of active oilrigs, although by looking at Figure 2, we observe that since 1998, the US activity level has declined, and is now close to at least a couple of the other regions (in particular Latin America). During this period there was a substantial reduction in oilrig activity, following a large decrease in oil prices. Africa and Europe have the smallest number of oilrigs. Although I analyse the different regions separately, note that the rig market is partly international, and that rigs may be transported from one region to another. Oil companies hire more rigs when they want to increase the activity, but usually it will take some time from the decision to increase rig activity is made, until the rig is in place and operating.

Table 1: Descriptive statistics for oilrig activity level

	Mean	Standard deviation
Total*	790.68	153.39
US	353.97	144.44
Europe	57.736	10.914
Middle East	129.43	14.721
Latin America	202.46	49.273
Africa	35.484	9.385
Asia Pacific	115.96	13.338

*Mean and standard deviation calculated for the period 1995:1-2002:7

Other factors than prices may also affect the oilrig activity. There may be seasonal variations, due to weather conditions or companies' spending patterns - high activity at the end of a year to fulfil commitments, and correspondingly low activity at the start of a year before new contracts are made. Furthermore, there is a limited number of available rigs, and these are used both for oil and natural gas. Thus, if many of the rigs are being utilised in natural gas exploration, this leaves fewer rigs for use in the oil industry. Technological progress, making it easier to exploit existing wells or reducing the number of wells needed to develop a field, could have a negative impact on the number of rigs needed. On the other hand, it may increase the profitability of extracting oil, and therefore increase rig activity. Factors like local taxation policies, political unrest and government sanctions may also have an impact. Finally, some regions or countries are mature (i.e., they have reached their production peak), and will therefore experience decreasing activity over time, whereas other regions or countries have only recently opened up for exploration and will therefore show increasing activity. Some of these factors, like technological change and maturity of the region, are unobservable factors (or factors for which adequate time series do not exist), which must be proxied using some kind of time trend.

The model I will estimate in this thesis is a time series regression model where the dependent variable is oilrig activity, and real oil price is the explanatory variable. I assume that producers will want to observe the price over some time before deciding whether to change the activity level, in coherence with the assumption of adaptive expectations. I have therefore computed smoothed prices for the last 3, 6, 12, 24, 30 and 36 months[1] and have, for all regions, investigated the consequences of operating with different smoothing assumptions. Econometric results for three model versions are reported for each region (except Europe, for which only one model version turned out to be stable). To ease the comparison, the model version using smoothed prices over 12 months is reported for all regions, although its significance level varies between regions. All variables are on logarithmic form, as this makes it possible to interpret the price coefficients as elasticities.

The models assume that oil price is (weakly) exogenous for the oilrig activity level. However, the oil price is strongly affected by the existence and policies of OPEC (Organization of the Petroleum Exporting Countries). According to their homepage (OPEC (2003a)), "*One of OPEC's primary missions is to achieve stable oil prices, which are fair and reasonable for oil producers and consumers*". This is done by controlling the production level. OPEC is currently operating with a price band of $22-28 per barrel of crude oil. The price band was introduced in March 2000, as a response to the observed large reduction in oil prices during 1998-1999. If the price should go beyond this level, OPEC will increase production (and thereby probably also increase the oilrig activity level), thus increasing supply and lowering prices, whereas production (and activity level) will be reduced if the oil price should fall below the target. Hence, the OPEC-countries can hardly be perceived to be price takers, regarding the price as given. Therefore, the regions with a significant number of OPEC-members, or with major OPEC-producers, have been estimated both with and without the OPEC-countries, to see if this influences the results in any way. The hypothesis is that Non-OPEC regions should react sooner and/or more heavily (larger long-run effects) to oil price

[1] Prices are computed by taking the mean of the last 3, 6, etc. months, including the current month.

changes than when the OPEC-countries are included. However, OPEC's success at stabilising oil prices has been quite variable over the years, and some OPEC-countries have a quite small share of the total production. Thus, the existence of OPEC-countries in some of the regions may not have such a large influence on the results after all, as the estimation results will show.

I have monthly data on oilrig activity (number of rigs in operation) and the price of oil for six regions. The length of the series varies over regions. Unit root-testing of the data revealed that it was appropriate to treat oilrig activity and smoothed prices as non-stationary, which led to a host of problems needing to be resolved. Chapter 2 discusses the theoretical aspects of these problems, and presents the concepts of non-stationarity, unit roots and cointegration. Chapter 3 presents the empirical model used in the estimations. The point of departure is an Autoregressive Distributed Lag-model (ADL-model), which is reparameterised into an Equilibrium Correction Model (ECM) to test for cointegration between the non-stationary variables. I also introduce a stochastic trend (following the STSM-tradition (Structural Time Series Model, Harvey et al. (1986)), and Harvey (1989)), as this turns out to have an impact on the cointegration properties of the variables.

The estimation results for the regions are reported in Chapter 4. Both short-run and long-run price elasticities are estimated. In the short run, significant price effects on the oilrig activity are only obtained for the US, Latin America and Non-OPEC Middle East. In the long run, the largest effect is in the US, more than twice the size of the effect in Europe. A possible explanation may be that the US has a much smaller degree of governmental involvement in the oil industry than many of the countries in the other regions, and that this makes the oil companies operating in the US more flexible. Chapter 5 concludes, and sums up some of the shortcomings and problems with the econometric results.

The model is estimated in STAMP 6.2 (cf. Koopman et al. (1999)). Unit root tests of the variables (Section 3.2) and evaluation of the stability of the dynamic models (Sections 4.2.1 and 4.2.2) are performed in TSP 4.5 (cf. Hall and Cummins (1999)).

2. Theory

2.1 Stationarity, Non-stationarity and Unit Roots

When estimating time series models, one usually requires that the variables are stationary to obtain valid inference. According to Greene (2003, p. 612), "*[a] stochastic process* y_t *is weakly stationary or covariance stationary if it satisfies the following requirements:*

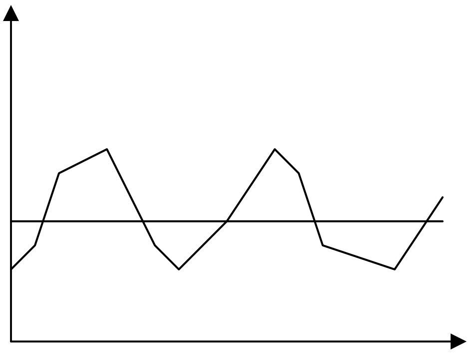
1) $E[y_t]$ *is independent of t.*

2) $Var[y_t]$ *is a finite, positive constant, independent of t.*

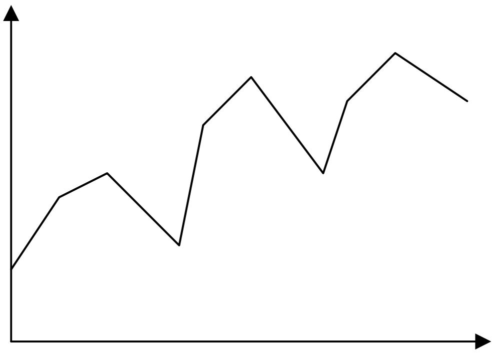
3) $Cov[y_t, y_s]$ *is a finite function of* $|t-s|$*, but not of t or s.*"

The last condition implies that as long as the distance between the observations is the same, the covariance is equal over the entire sample. Strong stationarity requires that the joint distribution of $(y_t, y_{t+1}, ..., y_{t+h})$ is equal to the joint distribution of $(y_s, y_{s+1}, ..., y_{s+h})$ for any *t*, *s* ($t \neq s$), and *h*. For my purpose, weak stationarity will suffice. Stationarity thus implies that the observations are fluctuating around an equilibrium level. Even though the observations, being random, may well deviate from this at some points during the sample, they will have a tendency to revert to a certain level (cf. Fig. 3a). Non-stationary variables, on the other hand, fluctuate randomly, with no tendency to revert to any specific level (cf. Fig. 3b). Typically, non-stationary variables have increasing variance over time, with corresponding increasing fluctuations. As the t-value for the OLS-estimator is given by $t = \frac{\hat{\beta} - \bar{\beta}}{\sqrt{\hat{\mathrm{var}}(\hat{\beta})}}$ (where $\hat{\beta}$ is the estimated coefficient and $\bar{\beta}$ is the value that the coefficient has under H_0), an increasing variance will affect the asymptotic properties of the estimator - $\hat{\beta}$ will not be efficient. If this problem is disregarded, it may lead to so-called spurious regression, which means that one rejects the null hypothesis of no relationship between two variables that in reality are completely independent. Numerous simulations have illustrated this problem; the classic reference is Granger and Newbold (1974). They simulated two completely independent variables 100 times and regressed them on each other, and in 76 of the 100 replications the null hypothesis of no relationship between the variables was rejected. Thus there is a great risk of making a Type I-error, falsely rejecting H_0, when H_0 is true, when the variables are non-stationary.

Figure 3: Examples of stationarity and non-stationarity



3a: Stationary



3b: Non-stationary

Non-stationarity implies that at least one of the roots of the equation's lag polynomial is on the unit circle - i.e., that the variable has one or more unit roots[2]. An example is the simple random walk with drift[3],

(1) $y_t = \varphi + y_{t-1} + \varepsilon_t$,

where $\varepsilon_t \sim WN(0,\sigma^2)$. By substituting recursively for y_{t-1}, one gets

(1') $y_t = \sum_{i=0}^{\infty} (\varphi + \varepsilon_{t-i})$,

which is the sum of an infinite number of random variables. The variance of y_t will thus be infinite, and y_t is then obviously non-stationary. It can be shown that (1) in fact has a unit root: by collecting all $y's$ on the left-hand side and using the lag operator ($Ly_t = y_{t-1}$, $L^2 y_t = y_{t-2}$, etc.), one gets

(2) $(1-L)y_t = \varphi + \varepsilon_t$.

The lag polynomial is thus $(1-L)$. The root of the lag polynomial is obtained by equating it to zero. $(1-L)=0$ implies one root equal to 1, hence y_t has a unit root. When there is a unit root in a time series, a random shock will have permanent effects (thus causing the non-stationarity).

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2 If the dependent variable only has one lag, there will be only one unit root.

3 Closely following Greene (2003, p. 631).

2.1.1 Unit Root Tests

There are several tests for unit roots (and hence, non-stationarity) in time series data. Among these are the (Augmented) Dickey-Fuller test (ADF)[4] and the Phillips-Perron (PP) test (see Greene (2003, pp. 643-645)). Both the ADF-test and the PP-test distinguish between three different cases: an AR (autoregressive)-model (random walk), an AR-model with a constant, and an AR-model with a constant and time trend:

(a) $\Delta y_t = \delta y_{t-1} + u_t$

(b) $\Delta y_t = \beta_0 + \delta y_{t-1} + u_t$

(c) $\Delta y_t = \beta_0 + \beta_1 t + \delta y_{t-1} + u_t$

The null hypothesis is that $\delta = 0$ [5], which implies that y_t has a unit root. If H_0 is rejected, the variable is assumed to be stationary. As the critical values are affected by the inclusion of constant and trend, different critical values for the three different cases have been tabulated (these are the same for both tests). The ADF-test can only be used on models with an autoregressive process, whereas the PP-test is more general, and also works well on moving average (MA) processes. Then again, the ADF-test has better small sample properties than the PP-test. These tests both have non-stationarity as the null hypothesis. However, there has been a discussion in the literature as to what should be the null hypothesis when testing for unit root. The practice of having non-stationarity as H_0 is largely based on Nelson and Plosser's findings (Nelson and Plosser (1982)), where they examined 14 macroeconomic time series (e.g. GNP, wages, consumer prices, etc.). They found that none of these series could be characterised as stationary, thus concluding that this was the "normal" or most common behaviour for macroeconomic variables. Still, tests with stationarity as the null hypothesis have also been developed, among these is the KPSS-test (Kwiatkowski et al. (1992)). The tests mentioned above are still widely used and I will also use them in my analysis, although there has been a fair amount of criticism towards them. See e.g. Maddala and Kim (1998) for a comprehensive review and discussion of different unit root tests.

In an infinite time horizon perspective, there is a big difference between the properties of a unit root time series and a stationary series. However, the estimated sample periods will

[4] The Augmented DF-test is necessary if there is autocorrelation in the residuals. The idea is to include as many lags as are needed to obtain a white noise error term, and then test for unit root. In the case of no autocorrelation, an ordinary DF-test will suffice.

[5] Derived from $y_t = \rho y_{t-1} + u_t$, subtracting y_{t-1} from each side gives $\Delta y_t = (\rho - 1) y_{t-1} + u_t$. Denoting $(\rho - 1) = \delta$, a unit root $\rho = 1$ is equivalent to $\delta = 0$.

necessarily have to be finite. Hamilton (1994, sec. 15.4) discusses the notion that as long as one is dealing with finite samples, it may be very difficult, in practice impossible, to distinguish a unit root process from a stationary process. He also gives a mathematical exposition of this. If the true process is a unit root, there may be a stationary process with a root close to, but not quite equal to, unity, which will be impossible to distinguish from a unit root process by testing. Conversely, a stationary process (with a true root close to, but not equal to, unity) may be impossible to distinguish from a unit root process when running unit root-tests. Thus, with finite samples, there may be a risk of making Type I- or Type II-mistakes. Hamilton argues (pp. 515-516) that this may not be so serious, and that "[…] *the goal of unit root tests is to find a parsimonious representation that gives a reasonable approximation to the true process, as opposed to determining whether or not the true process is literally I(1)* [non-stationary]." The reader should keep this in mind when I get to the stationarity analysis of the variables in Section 3.2.

2.2 Cointegration

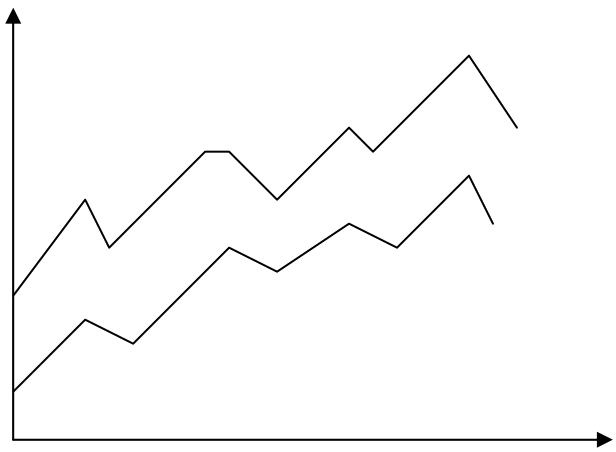
An issue closely related to non-stationarity is integration. A non-stationary variable that becomes stationary by differencing it once, is said to be integrated of order 1. Returning to the simple autoregressive model from Section 2.1.1, moving y_{t-1} in (1) to the left-hand side (thus obtaining the difference of y_t), one gets

(3) $\Delta y_t = y_t - y_{t-1} = \varphi + \varepsilon_t$,

which consists of the mean φ and the stationary error term ε_t $(E(\varepsilon_t) = 0)$, hence, Δy_t is stationary. This again implies that y_t is integrated of order 1. Correspondingly, a variable that has to be (first-) differenced *d* times before becoming stationary is integrated of order *d*. In fact, the number of unit roots in a variable's lag polynomial corresponds to its order of integration - a variable that has to be differenced once to become stationary will only have one unit root, whereas an I(2)-variable will have two unit roots. According to Greene (2003, p. 632), *"An I(1) series in its raw (undifferenced) form will typically be constantly growing, or wandering about with no tendency to revert to a fixed mean. […] An I(2) series is growing at an ever-increasing rate. […] Series that are I(3) or greater are extremely unusual, but they do exist"*. Thus, in most cases, the researcher faces the problem of having to determine whether the variables concerned are I(0), I(1) or I(2).

As mentioned in Section 2.1, a regression between two non-stationary variables will typically show spurious effects. However, provided that the variables are integrated of the same order, there may be a linear combination of the variables that is stationary. If this is the case, the variables are cointegrated, and it is then possible to make valid inference (estimations will be efficient). To illustrate, if we have two I(1)-series, they may look something like in Figure 4:

Figure 4: Example of cointegrated variables



Although the two series grow randomly, the distance between them is fairly constant, and this relationship makes it possible to obtain efficient estimates. It should be noted that two I(1)-variables by no means need to be cointegrated, the point is that in order to obtain cointegration, the variables in question have to be integrated of the same order.

2.2.1 Cointegration Tests

Several tests for cointegration have been suggested in the literature, both for single-equation models and for systems. The Engle-Granger two-step approach for single equation models with only one cointegrating relation (Engle and Granger (1987)) is to do a static regression between the variables in interest, and then do an ADF-test on the residuals from this regression. If the residuals are stationary, one can conclude that the variables are cointegrated. However, this test requires higher critical values than an ordinary t-test. These values are tabulated in MacKinnon (1991). The Engle-Granger approach has been criticised for having low power, and is now regarded as somewhat "outdated". Another cointegration test, which better accommodates the dynamics that are often present in the models, is the so-called dynamic approach, or ECM approach. The relevant critical values are the ones reported in Banerjee et al. (1998). I will describe this test more fully in Chapter 3, as this is the test I use in my analysis. Cointegration can also be tested for within a system framework, cf. for instance Johansen (1995) who uses a VAR-approach. While the single equation methods require that there is only one cointegrating relation, a situation with more than one cointegrating relation can be dealt with by a system method. However, this method usually requires a further specification of restrictions in order to fully identify the adjustment parameters. Since I only use two observable variables (i.e., oilrig activity and oil price) in the empirical models, little is gained by pursuing a system approach, and hence I will stick to single equation methods.

2.3 Stochastic Trend

As mentioned in Chapter 1, there are several unobservable factors that may contribute to the oilrig activity level. As disregarding these factors may lead to problems with the diagnostic tests of the estimated model, due to unexplained variation, it is important to somehow try to include them in the model. Earlier, the effects of such unobservable factors were often approximated by a linear, deterministic trend. This is obviously a strong assumption. Factors like technical progress or political conditions will not necessarily show a systematic, deterministic pattern. Therefore, the assumption of a deterministic trend has become an increasingly contested area in time series econometrics. Harvey et al. (1986) introduced the concept of a modelled, stochastic trend in a so-called Structural Time Series Model, a concept that is increasingly being used. A stochastic time trend allows the trend to change over time, and it is therefore well suited to approximate the effects of several unobservable factors influencing the dependent variable in different directions, and with different impact. In my model, it will also play an important role for the cointegration properties of the variables.

A stochastic trend is driven by random disturbances and can move in any direction. The stochastic trend is specified as:

(4) $\mu_t = \mu_{t-1} + \beta + \eta_t \qquad \eta_t \sim NIID(0, \sigma_\eta^2)$,

where β is the slope of the trend, assumed to be constant, and η_t is the level disturbance. The larger the variance σ_η^2, the larger are the movements in the trend. The stochastic trend may have different specifications, β may for instance be constrained to zero. If so, the stochastic trend is as a random walk. If both σ_{η}^{2} and β are non-zero, the specification will be a random walk with drift. It should be noted that the model with deterministic time trend emerges as a special case of the model with stochastic trend (if $\sigma_{\eta}^{2}=0$). Hence the specification of a stochastic trend does not exclude the possibility of modelling a deterministic trend, if this is an appropriate simplification. In Section 3.2 I will show how equation (4) is included in the econometric model.

As mentioned in Chapter 1, there is reason to believe that seasonal variation may be a factor that influences the oilrig activity level. It is possible to include a stochastic seasonal component, which may degenerate to fixed seasonality under certain restrictions. However, as the sample period is perceived to be too short to detect stochastic seasonality, I will not go into the details of this. I did try to estimate all regions with stochastic seasonality included, but it was not significant for any of the regions. See Koopman et al. (1999) or Harvey (1989) for further information on this subject. An important point to note is that, if stochastic seasonality were present, this would also influence the critical values of the integration tests. As I will come back to later, the seasonality tests were not significant for fixed seasonality either, with UK as the only exception (see Section 4.2.2). Thus, judged from this, there seems to be no seasonal variations affecting the oilrig activity level.

3. Data and Estimation Method

3.1 Data

The data for active oilrigs have been collected from the Baker Hughes Rig Counts (cf. Baker Hughes (2002)). The Rig Count is a census of the number of drilling ('rotary') rigs actively exploring for or developing oil or natural gas. A rig is counted as active in the US weekly census if it is drilling or "turning to the right", whereas in the monthly international rig count the rig is regarded as active if it is drilling at least 15 days during the month counted. Thus, rigs that are drilling less than 15 days during the month (in the international counts), are in transit between locations, are rigging up or are being used in non-drilling activities, are not included. This makes the Baker Hughes counts a good indicator of current rig activity and the number of wells being drilled, rather than a measure of the rig fleet's capacity.

For the US, I have weekly oilrig activity data from July 1987 until July 2002 (from Baker Hughes: US Rig Reports), which has been converted into monthly data[6]. For some other regions in the world (Europe, the Middle East, Latin America, Africa and Asia Pacific), I have monthly oilrig activity data for the period January 1995 until July 2002 (Baker Hughes: New International). The most important region not covered by the census is the former Soviet Union. Canada has neither been analysed, as there is no separate oilrig activity data for this region. The census also reports the number of active rigs divided by countries within regions. I have chosen to look at Norway and the United Kingdom specifically, to see if their reactions to oil price changes differ.

Weekly price data for the oil prices Brent Blend, US WTI, Nigeria and Dubai have been collected from PIW[7] since 1986. These have been converted into monthly data. I use the US WTI (West Texas Intermediate) price for the US and Latin America, Brent Blend for Europe, Dubai for the Middle East and Asia Pacific, and Nigeria for Africa. These prices are all nominal, and reported in dollars. The price data are spot prices, i.e., the prices in an open market with immediate delivery. However, a lot of the crude oil production is sold in the

[6] By taking the average of the relevant weeks in a month.
[7] Petroleum Intelligence Weekly

futures market, with futures prices that are set for delivery of a specific quantum on a given date. Thus, a plausible theory would be that the oil producers are more concerned with the futures prices (which are the prices they are actually paid) rather than the spot prices. However, futures prices and spot prices follow each other quite closely (see Pindyck (2001)), and since there are better time series for spot prices than futures prices, the use of spot prices seems justified.

The real prices have been calculated using a price index for all manufacturing industries in the US from the American Bureau of Labor Statistics[8]. This is a monthly index from January 1992. This price index, although American, has been used for all regions, mainly because I have been unable to find any price indices for the other regions. There is of course no apparent reason why the other regions should follow the same price development as the United States, however since all oil prices are reported in dollars, this seems like a good approximation (for lack of better alternatives). Moreover, the oil is often exported, and the income is used to pay for imports. The imports price will to a large degree be affected by the price index used here. Hence, the sample period is 1992:1-2002:7 for the US region (the period is shortened because the price index starts in 1992), and 1995:1-2002:7 for the other regions. In terms of number of observations, this is quite satisfactory (around 126 for the US, and around 90 for the other regions - the exact number depends on the number of included lags), although it should be noted that they do not cover a particularly long period in terms of years, which may be somewhat problematic. As I have available price data from the period before 1995, the use of e.g. the 36-month smoothed price does not shorten the sample period for any of the regions except the US, where the sample period starts with the first available real price.

When analysing the US oilrig activity the price of natural gas was included as an explanatory variable. As the same rigs are used for both oil and gas, a high gas price should have a negative impact on the oilrig activity, as this probably would increase the number of rigs used for gas. However, this variable turned out to be highly insignificant, and as it did not affect the other coefficients in any substantial way, it has not been included in the reported estimations. For the other regions, I did not have sufficient data to test this.

[8]Taken from BLS (2003).

The estimated regions consist of the following countries (an asterisk* refers to OPEC countries):

- The United States
- Europe: Denmark, France, Germany, Netherlands, Hungary, Italy, Norway, Poland, Romania, Turkey, United Kingdom, (former) Yugoslavia, "others".
- The Middle East: Abu Dhabi*, Dubai*, Egypt, Iran*, Kuwait*, Oman, Pakistan, Qatar*, Saudi Arabia*, Sudan, Syria, Yemen, "others".[9]
- Latin America: Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Mexico, Peru, Trinidad, Venezuela*.
- Africa: Algeria*, Angola, Congo, Gabon*, Libya*, Nigeria*, South Africa, Tunisia, "others".
- Asia Pacific: Australia, Brunei, India, Indonesia*, Japan, Malaysia, Myanmar, New Zealand, Offshore China, Papua New Guinea, Philippines, Taiwan, Thailand, Vietnam, "others".

3.2 Estimation Method

As mentioned in Section 2.1.1, macroeconomic time series variables are often, at least according to Nelson and Plosser, non-stationary. I therefore need to investigate the stationarity properties of the variables. Unit root tests[10] reveal that for all regions, the (log-transformed) oilrig activity is integrated of the first order. Neither the ADF-test nor the PP-test reject the null hypothesis of I(1) for the level series, whereas for the differenced series, the null hypothesis of I(2) against the alternative hypothesis of I(1) is rejected, in all regions. On the other hand, for the smoothed price variables, the picture is not as clear. The (PP-) tests of all the level series do not reject the hypothesis of I(1), but the tests of the differenced series are somewhat unclear as to the rejection of the hypothesis of I(2), in most situations. It might seem like the smoothing of the prices influences the stationarity properties of the variables, giving the series I(2)-characteristics. I also performed unit root tests on the "non-smoothed" prices, and these tests were far more conclusive about the I(1)-property of all the price variables. However, there are a number of different tests for stationarity, and numerous papers (e.g. Leybourne and Newbold (1999)) have shown that these can give different results for the

[9] Note: Egypt and Sudan are included in the Middle East region, although they geographically belong to the African continent. Also note that as Iraq has been under UN sanctions the entire sample period, it has not been included.

[10] Unit root tests were performed in TSP 4.5 (Hall and Cummins (1999)).

same sample. Both the ADF-test and the PP-test have been criticised for having low power, tending not to reject H_0 when this in fact should be rejected (cf. the discussion in Section 2.1.1). The KPSS-test (Kwiatkowski et al. (1992)) was performed on one of the series (US 12month) which neither ADF nor PP could reject as I(2), however this test concluded that it (the differenced series) could not be rejected as I(1). Thus, different tests gave different conclusions about the stationarity properties of the same series. In addition to this, the small size of my sample might influence the stationarity tests, making it more difficult to draw conclusions about the stationarity of the series. The upshot of all this is that, due to the uncertainty of the tests, I have chosen to base my analysis on the assumption that the variables are I(1), even though the unit root tests do not fully substantiate such an assumption. In addition to this, I assume that the oil price variables are weakly exogenous for the parameters in the estimated model.[11]

The point of departure is an Autoregressive Distributed Lag Model (ADL-model), which models the dependent variable as a function of its own lagged value(s), and the current and lagged value(s) of the explanatory variable. It is thus a model well suited to capture the dynamics of a market such as the oilrig market. The most general version of the model that is used in my estimations is an ADL(3,3)-model, i.e. a model with three lags of the dependent and three lags of the independent variable. The model is then as follows:

(5) $y_t = b_0 + b_1 y_{t-1} + b_2 y_{t-2} + b_3 y_{t-3} + b_4 x_t + b_5 x_{t-1} + b_6 x_{t-2} + b_7 x_{t-3} + \varepsilon_t$.

Given that y_t and x_t both are I(1), we cannot get valid inference from this model unless y_t and x_t are cointegrated. To find out if they are, a convenient reparameterisation of the ADL-model is the Equilibrium Correction Model, or ECM-model. This reparameterisation makes it easy to test for cointegration and to obtain long-run elasticities when cointegration is present. Utilising the lag operator, Eq. (5) is equivalently given by

(6) $(1 - b_1 L - b_2 L^2 - b_3 L^3) y_t = b_0 + (b_4 + b_5 L + b_6 L^2 + b_7 L^3) x_t + \varepsilon_t$.

Rewriting the lag polynomial for *y* gives[12]

[11] For definition of weak exogeneity, see Engle et al. (1983).
[12] See Hamilton (1994, p. 517) for this alternative representation of the autoregressive process.

(7) $(1-b_1L-b_2L^2-b_3L^3)=(1-\rho L)-(\zeta_1L+\zeta_2L^2)(1-L)$,

where I define $\rho=b_1+b_2+b_3$, $\zeta_1=-(b_2+b_3)$ and $\zeta_2=-b_3$.
Equivalently for *x*,

(8) $(b_4+b_5L+b_6L^2+b_7L^3)=(b_4+\gamma L)-(\eta_1L+\eta_2L^2)(1-L)$,

where $\gamma=b_5+b_6+b_7$, $\eta_1=b_6+b_7$ and $\eta_2=b_7$.
Inserting Eqs. (7) and (8) into Eq. (6) gives

(9) $(1-\rho L)y_t-(\zeta_1L+\zeta_2L^2)\Delta y_t=b_0+(b_4+\gamma L)x_t-(\eta_1L+\eta_2L^2)\Delta x_t+\varepsilon_t$,

where I utilise the fact that $(1-L)y_t=\Delta y_t$, and equivalently for x_t. Multiplying throughout and rearranging gives:

(10) $y_t=b_0+\rho y_{t-1}+\zeta_1\Delta y_{t-1}+\zeta_2\Delta y_{t-2}+b_4x_t+\gamma x_{t-1}-\eta_1\Delta x_{t-1}-\eta_2\Delta x_{t-2}+\varepsilon_t$.

By subtracting y_{t-1} from both sides of the equation and adding and subtracting b_4x_{t-1} to the right hand side, and rearranging, I obtain the ECM-representation[13]:

(11) $\Delta y_t=-\lambda[y_{t-1}-\tau x_{t-1}-\alpha]+\zeta_1\Delta y_{t-1}+\zeta_2\Delta y_{t-2}+b_4\Delta x_t-\eta_1\Delta x_{t-1}-\eta_2\Delta x_{t-2}+\varepsilon_t$,

where $\lambda=1-\rho$, $\tau=\dfrac{\gamma-b_4}{\lambda}$, and $\alpha=\dfrac{b_0}{\lambda}$. The term in brackets is the equilibrium correction term, which measures the magnitude of the past disequilibrium, and represents a linear combination of y and x that is stationary. In the case when no lags of the differenced dependent variable are included (i.e., $\zeta_1=\zeta_2=0$), the parameter λ (the adjustment parameter) tells us how fast the model returns to its steady-state after having been in disequilibrium. If λ is not significantly different from zero, the null hypothesis of no cointegration cannot be rejected, which again implies that there is no meaningful long-term

[13] See Hendry and Juselius (2000).

relationship between the variables. This is thus the ECM-approach for testing for cointegration (cf. Section 2.2.1). Reparameterisation of Eq. (11) gives

(12) $\Delta y_t = b_0 + \zeta_1 \Delta y_{t-1} + \zeta_2 \Delta y_{t-2} + b_4 \Delta x_t + \eta_1^* \Delta x_{t-1} + \eta_2^* \Delta x_{t-2} + \lambda^* y_{t-1} + \theta x_{t-1} + \varepsilon_t$,

where $\eta_1^* = -\eta_1$, $\eta_2^* = -\eta_2$ and $\lambda^* = -\lambda$. Defining $\theta = \lambda\tau$, the long-term effect of a change in x is thus simply obtained by $\omega = \frac{\theta}{-\lambda^*}$ (see Bårdsen (1989)). Since all variables are on logarithmic form, this is equivalent to the long-run price elasticity. The short-term (immediate) effect of a price change on the oilrig activity level is obtained directly from b_4. However, since the price variables are smoothed, b_4 will have to be divided by the relevant number of months (three for the smoothed 3-month price, etc.) to obtain the short-run elasticity related to a change in the non-smoothed price.

I now have the ECM-model. The ECM-specification of the ADL-model (Eq. (12)) was initially estimated in PcGive, with deterministic time trend included (both linear and quadratic), to allow for the unobservable effects that also may influence the oilrig activity. However, using this specification the two observed variables did not seem to be cointegrated, and the models for some of the regions failed on several of the diagnostic tests (these tests will be further described in Section 4.1). As mentioned in Section 2.3, a stochastic trend may constitute a better approximation for the unobservable factors influencing the oilrig activity. This led me to investigate further by estimating the regions with stochastic trend included, using the STAMP-program (Koopman et al. (2000)). The inclusion of a stochastic trend did provide me with a significant adjustment parameter in most regions. Thus, introducing a stochastic trend in the model, I replace the constant term from Eq. (11) with the stochastic trend process μ_t defined in section 2.3 (Eq. (4)), which gives

(13) $\Delta y_t = -\lambda[y_{t-1} - \tau x_{t-1} - \delta\mu_t] + \zeta_1 \Delta y_{t-1} + \zeta_2 \Delta y_{t-2} + b_4 \Delta x_t - \eta_1 \Delta x_{t-1} - \eta_2 \Delta x_{t-2} + \varepsilon_t$,

where $\delta = \frac{1}{\lambda}$. According to Harvey (1989, p. 373) this is still a valid representation of the ECM-model, although it contains a non-stationary unobserved component. Introducing a stochastic trend in an ECM-model has e.g. been done in Sarantis and Stewart (2001). In the same way as above (cf. Eq. (12)), this may be rewritten as

(14) $\Delta y_t = \zeta_1 \Delta y_{t-1} + \zeta_2 \Delta y_{t-2} + b_4 \Delta x_t + \eta_1^* \Delta x_{t-1} + \eta_2^* \Delta x_{t-2} + \lambda^* y_{t-1} + \theta x_{t-1} + \mu_t + \varepsilon_t$.

Recalling from Section 2.3 that the stochastic trend is specified as

(4) $\mu_t = \mu_{t-1} + \beta + \eta_t$,

I now have a model consisting of equations (14) and (4). The terms ε_t ("irregular component") and η_t ("level component") are normally distributed, mutually uncorrelated white-noise disturbances with zero means and variances σ_ε^2 and σ_η^2, respectively. As mentioned, the stochastic trend may have different specifications, β may for example be constrained to zero. It is possible to do hypothesis tests on the significance of σ_η^2, although this involves non-standard inference. To ensure that the error terms in fact were normally distributed, irregular interventions (corresponding to dummy variables for outlier values) were necessary in a couple of the regions. A level intervention, corresponding to a step dummy variable, was included for Africa.[14]

The estimation of the stochastic trend is quite complex, and as it would go far beyond the scope of my thesis, I will not go into the technical details of this. Suffice it to say that the regression parameters and hyperparameters (the variance of the stochastic components) are estimated by Maximum Likelihood (ML), utilising that the model can be written in the state space form. The estimate of the final state can be obtained by running the Kalman filter, whereas optimal (smoothed) estimates of the states at other points in time using all sample information requires the use of backward Kalman filter recursions. The numerical calculations are performed by the STAMP-program. See Harvey (1989) and Koopman et al. (1999) for a thorough explanation of the approach.

In the situation with no lags of the dependent variable, the coefficient for the lagged rig activity variable in (log-transformed) level (λ^*) needs to be between (-2) and 0 for the

[14] See Harvey (1989, p. 397) for further discussion on intervention analysis.

dynamic model to be stable. This again implies that the coefficient of the lagged dependent variable when the equation is written on level form has an absolute value less than one[15]. If the coefficient is between 0 and (-1), the disequilibrium term will go monotonically towards zero, whereas if it is between (-2) and (-1), there will be an "overshooting" effect, where the disequilibrium will cycle around zero, with gradually smaller cycles, until reaching zero. If the coefficient turns out to be outside this interval, the model is explosive. However, when lags of the differenced dependent variable are included, the stability condition is somewhat more complicated (see Lütkepohl (1990, p.11)). The way to proceed is to write the dynamic model in level and put it on the companion form. One then obtains a VARX model of order one, and one needs to find the eigenvalues of the coefficient matrix of the lagged endogenous variables. Now, stability requires that all the eigenvalues have modulus less than one. The eigenvalues have been calculated numerically in TSP 4.5 for the regions concerned.

[15] See Johansen (1995, p. 46) for reference.

4. Empirical Analysis

4.1 Introduction

Estimations have been done in STAMP 6.2 (Structural Time Series Analyser, Modeller and Predictor), which allows estimation with a stochastic trend. As mentioned in Section 2.2, the variables need to be cointegrated in order for the long-run relationship between oilrig activity and oil prices to exist. I test this by inspecting the t-value for the lagged oilrig activity variable in the model (cf. Section 3.2). The critical t-values are reported in Banerjee et al. (1998, Table 1, Panel B). At a 5% level of significance, the critical value is about 3.75, whereas at 1% significance, the critical value is about 4.35.[16] For all regions, with a couple of exceptions that I will come back to, the estimations show t-values at a satisfactory (significant) level, thus it seems fairly safe to conclude that oilrig activity and price are in fact cointegrated (when a stochastic trend is present), and the results of the estimations have a meaningful interpretation. Regarding the differenced variables, the usual t-test[17] will suffice. I will also use the t-test for the lagged independent variable (x_{t-1}), although the exact critical values here are difficult to determine. Note that, due to the differences in the interpretation of the t-values for the various variables, I have chosen to report the t-values themselves in the tables rather than the standard errors or the p-values.

The diagnostic tests reported in the tables are the following[18]: the *Normality* test statistic is the Bowman-Shenton statistic, which has a χ^2 distribution with two degrees of freedom, the 5% critical value is 5.99 (1%: 9.21). The *H(h)* is a test statistic for heteroskedasticity, calculated as the ratio of the squares of the last *h* residuals to the squares of the first *h* residuals, where *h* is the closest integer of *T/3* (and *T* is the number of observations). It has an *F* distribution with *(h,h)* degrees of freedom, the critical value (5%) for the US is 1.69, whereas for the rest of the regions the critical value is 1.84 (due to different *T's*). *DW* is the Durbin-Watson test statistic of autocorrelation in the residuals. Since the estimated model includes lag(s) of the dependent variable, this test does not provide much information, as it will tend to be biased towards 2

[16] The inclusion of the stochastic trend affects the critical values somewhat, the critical values are therefore approximations.
[17] Critical values: 5% 1.98; 1% 2.62.
[18] Koopman et al. (1999, p. 119).

(Gujarati (1995, pp. 424-425)). *Q(p,q)* is the Box-Ljung test statistic on the first *p* autocorrelations, which is tested against a χ^2 distribution with *q* degrees of freedom, where *q* is given as *p+1* less the number of included variance components (irregular and/or level component). Critical values with *q=8* are 20.09 (1%) and 15.51 (5%), with *q=7* 18.48 and 14.07, respectively (the correct q-value is given in each of the tables). As we are dealing with an ADL-model, with lags of the dependent variable included, it would have been optimal to have an LM-test for autocorrelation (Breusch-Godfrey test) instead, as this often is a more suitable test for autocorrelation in such a model (Maddala and Kim (1998, p. 19)). Unfortunately, the STAMP-program does not perform this test. R^2 is the coefficient of determination.

Regarding the stochastic trend specification, STAMP reports the variance of the stochastic components, and the significance level of the components in the final state. A non-zero variance of σ_η^2 indicates a stochastic level, whereas the significance of the slope component β in the final state has determined whether or not it should be included. However, I do not have the significance level of the variances, thus it is difficult to tell whether the variance is in fact significantly different from zero. For most of the regions analysed, σ_η^2 seems to be non-zero, whereas β is insignificant in the final state. For these regions, the stochastic trend has thus been specified as a random walk. For one of the regions, though, the trend appears to be deterministic, with no variance of σ_η^2, but with μ and β significant in the final state, and can hence be represented by an intercept and a linear deterministic trend. I will come back to this in Section 4.2, where I go through the estimation results for the regions. In Section 4.3 I present the long-run price elasticities, and discuss the observed differences between the regions.

4.2 Results

For each region, I report the model version with 12-month prices, and two other model versions that seem to work well (judging by the diagnostic tests and significance level of the estimates). In the tables, "3mnth", "6mnth" etc. refer to the smoothed prices, whereas Δx_t, Δx_{t-1} etc. refer to the coefficients. The dummy variables are denoted as e.g. DI00.1, where

'DI' represents the type of dummy (in this case an impulse dummy, 'DS' is used in the case of a step dummy), the two first digits represent the year, and the last digit(s) represent the month in the relevant year. Hence, DI00.1 indicates an impulse dummy for January 2000.

4.2.1 The United States

For the US, initial estimations reveal a high degree of autocorrelation in the residuals. To correct for this, two lags of the differenced oilrig activity variable are included (corresponding to including three lags of the dependent variable in the initial ADL-specification, cf. Section 3.2). As mentioned in Section 3.2, including lags of the differenced dependent variable complicates the interpretation of the coefficient value for the lagged dependent variable (λ^*) when it comes to evaluating the stability of the model. However, numerical calculations of the eigenvalues in TSP reveal that the model is stable for all three smoothing alternatives for the price (all modulus values are less than 1). Inspection of the residuals from the estimated models reveals a very significant outlier value for January 2000, which is corrected for by introducing a dummy variable for this month, as this improves the diagnostic test of normality substantially. A possible explanation for this outlier may be that insecurity surrounding the new millennium led to decreased activity. Abraham (2001, p. 204) mentions that the decrease in drilling activity in the first quarter of 2000 may have been caused by American oil companies waiting for OPEC's response to the lower oil prices observed in 1998-1999, in addition to a general problem of attracting investment capital. Regarding the stochastic trend, this is specified as a random walk. When it comes to lags of the differenced independent variable, there are some differences between the three model versions (according to smoothing assumptions) as to which number of lags is optimal, as can be seen from the table. The diagnostic tests are satisfactory for all three models (no indication of non-normality[19], heteroskedasticity or autocorrelation). The results are reported in Table 2:

[19] After including the January 2000-dummy.

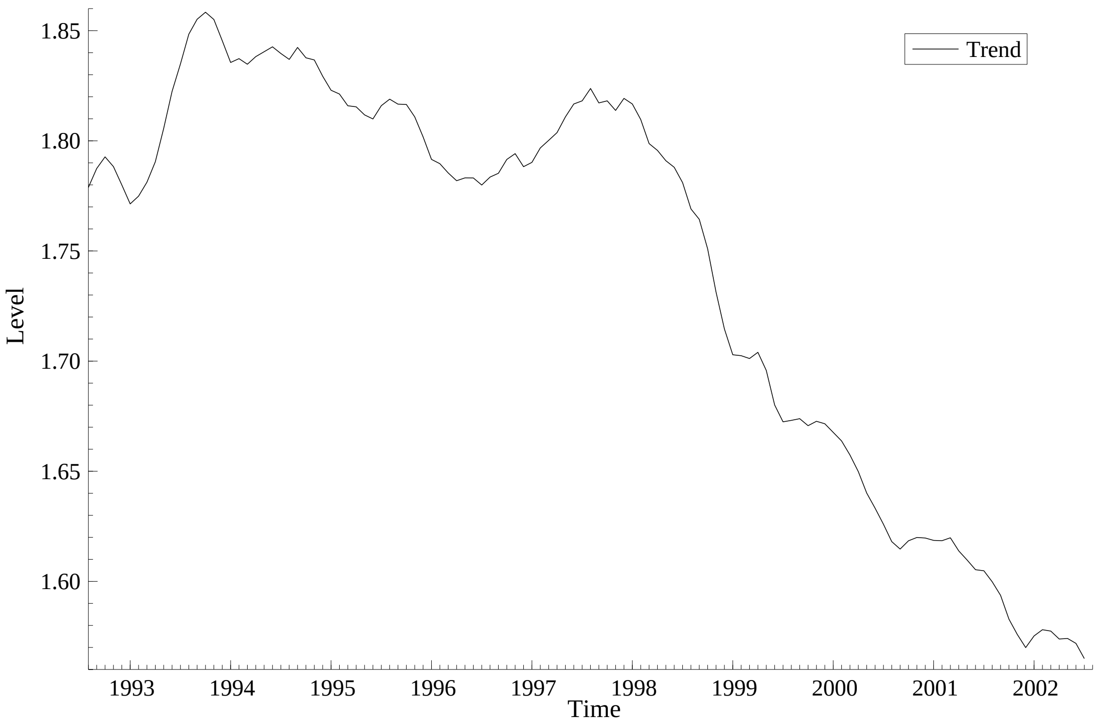
Table 2: Estimation results for US oilrig activity

	3mnth		6mnth		12mnth	
	Estimate	*t-value*	Estimate	*t-value*	Estimate	*t-value*
Δy_{t-1}	0.350	*4.642*	0.421	*5.411*	0.366	*4.545*
Δy_{t-2}	-0.264	*-3.256*	-0.337	*-4.090*	-0.141	*-1.637*
Δx_t	0.495	*3.507*	0.914	*2.546*	0.517	*0.860*
Δx_{t-1}			-0.600	*-1.647*		
Δx_{t-2}	-0.528	*-3.166*				
y_{t-1}	-0.207	*-3.872*	-0.201	*-3.561*	-0.571	*-5.795*
x_{t-1}	0.380	*5.055*	0.346	*4.244*	0.831	*4.155*
DI00.1	-0.208	*-4.270*	-0.203	*-3.927*	-0.179	*-3.955*
Diagnostics:						
Std. Error	0.051		0.054		0.053	
Normality	0.334		2.137		1.630	
H(39)	0.579		0.634		0.772	
DW	2.040		1.987		2.042	
Q(9,8)	3.639		2.348		3.006	
R^2	0.488		0.452		0.466	

The short-run price effects (Δx_t) are highly significant for 3mnth and 6mnth, with coefficient values of 0.495 and 0.914, respectively. Dividing these coefficients by the respective number of months, a short-run elasticity of around 0.15 is obtained (for both models). The 12mnth coefficient, on the other hand, is insignificant. Thus, in the 3mnth and 6mnth model specifications, price changes seem to have a significant, immediate effect, whereas for the 12mnth specification, price changes are not significant. As we know that it necessarily will have to take some time from the decision of increasing the number of rigs is made until the rigs are in place and operating, it does seem somewhat puzzling that the activity change appears so quickly. Observe that the dummy variable for January 2000 is highly significant for all three models, and it is (as expected) negative.

To provide an example of how the stochastic trend may look, the estimated stochastic trend for the US model version based on the 6mnth-prices is presented graphically in Figure 5:

Figure 5: Estimated stochastic trend for US 6mnth



As can be observed from the figure, the stochastic trend increases during the first period of the sample, before decreasing quite steadily, except for a temporary increase during 1997. The US region is mature (the large fields have already been developed), and should therefore a priori show decreasing activity. However, during the 1990's, the amount of proven reserves in the Gulf of Mexico increased substantially, and the production also increased. This may explain the observed increase in the stochastic trend during the first months of the sample period, whereas the maturity of the US region seems to be the dominating effect thereafter, as indicated by the decreasing trend.

4.2.2 Europe

The stochastic trend for Europe is also specified as a random walk. One lag of the differenced dependent variable is sufficient to get rid of the autocorrelation in the residuals. Hence again (as for the US) dynamic stability will not only involve the evaluation of the adjustment parameter (λ^*). The model versions based on the 6mnth, 12mnth and 24mnth price periods seem to work best, however stability calculations in TSP show that the two latter models are unstable. I have therefore only reported the results for the model using the 6mnth price alternative in Table 3:

Table 3: Estimation results for European oilrig activity

	6mnth	
	Estimate	*t-value*
Δy_{t-1}	-0.725	*-7.733*
Δx_t	0.282	*0.558*
Δx_{t-1}	-0.815	*-1.563*
y_{t-1}	-0.241	*-3.391*
x_{t-1}	0.152	*2.610*
Diagnostics:		
Std. Error	0.089	
Normality	2.025	
H(29)	1.157	
DW	2.050	
Q(8,7)	3.012	
R^2	0.387	

The short-run effect of an oil price change (based on the smoothed price) in Europe is highly insignificant, with a t-value of 0.56. Hence, as opposed to the US, Europe seems to be quite insensitive to price changes in the short run. The λ^* -coefficient (y_{t-1}) is significant at around 10%.

In order to investigate Europe more closely, I have done estimations for Norway and the United Kingdom separately, to see if they appear to respond differently to price changes. Norway has a stronger governmental involvement in the oil industry than the UK has, which may cause some differences. However, it proves very troublesome to find a good specification for these two sub-regions. For both countries it is necessary to introduce dummy variables for highly significant outlier values, however I have been unable to find good explanations for these (Norway: June 1996, UK: July and October, 1999). Still, with these dummies included, the diagnostic tests are quite satisfactory for both countries. Note that when investigating the stochastic specification, the UK actually has significant fixed, seasonal effects, which would correspond to including a dummy for each month of the year. This is somewhat surprising, as none of the other regions (including Norway and Europe as a whole) appear to have neither stochastic nor fixed seasonality. Both countries are characterised by a stochastic trend specified as a random walk. The necessary number of lags of the differenced price variable varies somewhat between the countries. An interesting feature is that for Norway and the UK, there is no need for lags of the differenced dependent variable to correct for autocorrelation, as opposed to for Europe as a whole. Moreover, the models seem to be stable for both countries, and for all price-smoothing alternatives - again as opposed to for Europe as a whole. The results are presented together in Table 4 on the next page, to ease the comparison.

Table 4: Estimation results for Norway and United Kingdom (t-values in parentheses).

	Norway			United Kingdom		
	6mnth	12mnth	24mnth	6mnth	12mnth	24mnth
Δx_t	0.935 (1.116)	0.354 (0.219)	6.105 (1.909)	0.364 (0.463)	0.951 (0.691)	2.095 (0.805)
Δx_{t-2}				-1.631 (-1.950)	-4.255 (-3.053)	
y_{t-1}	-1.278 (-14.718)	-1.245 (-13.927)	-1.312 (-15.404)	-1.124 (-12.174)	-1.048 (-11.580)	-1.084 (-11.721)
x_{t-1}	0.248 (0.501)	0.686 (1.616)	0.763 (0.919)	0.180 (0.512)	0.756 (2.022)	1.491 (2.454)
DI96.6	-0.663 (4.806)	-0.674 (-4.786)	-0.645 (-4.797)			
DI99.7				-0.315 (-2.600)	-0.369 (-3.038)	-0.332 (-2.673)
DI99.10				-0.679 (-5.376)	-0.707 (-5.828)	-0.726 (-5.768)
Diagnostics:						
Std. error	0.163	0.162	0.161	0.125	0.120	0.131
Normality	2.507	2.172	2.036	3.409	3.969	3.118
H(29)	0.671	0.603	0.677	1.507	1.181	1.751
DW	1.830	1.777	1.860	2.050	2.025	2.029
Q(8,7)	6.562	6.716	9.531	5.140	6.726	8.124
R^2	0.526	0.533	0.840	0.653	0.688	0.630

The short-run price elasticities are, as for Europe, insignificant, with the exception of Norway when using the 24mnth price alternative, which is almost significant at 5%. However, this coefficient value is very high (6.105), and does seem somewhat implausible. Thus, estimating these two countries separately have unfortunately not brought much new insight, apart from the observation that changes in oil prices do not seem to have any significant short-run effect on oilrig activity for either of these countries (if we disregard the model version for Norway using smoothed prices over 24 months). The adjustment parameter (λ^*) is below (-1), indicating that there is an "overshooting effect" in the adjustment process: a deviation from equilibrium in one period will be corrected for the next period by more than one hundred per cent. A possible explanation may be that when the oil companies decide to increase rig activity after an observed price increase, they may want to increase the rig activity somewhat more than what the price increase actually reflects, in expectations of further price increases. Equivalent reasoning can be used in the case of a price decrease. Also note that for Norway, the $\theta's$ (x_{t-1}) are insignificant, whereas the θ – coefficients are significant in the two model versions of UK using the 6mnth and 12mnth prices. This may affect the calculation of the long-run coefficients, which I will come back to in Section 4.3.

4.2.3 Asia Pacific

The Asia Pacific region includes one OPEC-member, Indonesia. However, Indonesia does not belong to "core-OPEC"[20], and it has the third smallest quota in the organisation (quotas effective as of November 1, 2003)[21]. This may explain why I get more or less the same results when estimating the Asia Pacific region with and without Indonesia. Therefore, I only report the results from the estimations for Asia Pacific as a whole. Asia Pacific is characterised by a stochastic trend specified as a random walk. No lags of the dependent variable are needed, whereas the number of necessary lags of the independent variable differ somewhat between the different model versions. All diagnostic tests are satisfactory, apart from the R^2-values, which are somewhat on the low side. The estimation results are reported in Table 5 (on the next page):

[20] Which consists of Saudi Arabia, Kuwait, Qatar and the United Arab Emirates (Abu Dhabi and Dubai).
[21] OPEC (2003b)

Table 5: Estimation results for Asia Pacific

	12mnth		24mnth		36mnth	
	Estimate	*t-value*	Estimate	*t-value*	Estimate	*t-value*
Δx_t	0.096	*0.148*	0.986	*0.774*	1.034	*0.444*
Δx_{t-1}	-0.815	*-1.244*	-2.26	*-1.776*	1.082	*0.455*
Δx_{t-2}					-3.722	*-1.590*
y_{t-1}	-0.474	*-5.295*	-0.734	*-7.189*	-1.049	*-9.630*
x_{t-1}	0.082	*1.242*	0.375	*1.973*	1.037	*1.692*
Diagnostics:						
Std. Error	0.050		0.050		0.051	
Normality	0.058		0.082		0.168	
H(29)	0.605		0.643		0.519	
DW	1.949		1.903		1.999	
Q(8,7)	4.355		5.842		6.430	
R^2	0.110		0.115		0.075	

All the short-run coefficients are highly insignificant. Thus, like Europe, the Asia Pacific region appears to be insensitive to oil price changes in the short run. We should also note that the θ – coefficients, which are needed in the calculation of the long-run coefficients, for the most part are insignificant (apart from the coefficient obtained in the model version using the 24mnth oil prices, which is very close to being significant at 5%). This may affect the significance level of the long-run coefficients. As observed for Norway and the UK, there seems to be overshooting in the model version based on the 24mnth price (cf. the estimated λ^* – value in the row for y_{t-1}).

4.2.4 Latin America

Latin America has been estimated both including and excluding the OPEC-member Venezuela, which does not necessarily behave as a price taker in the oil market (cf. the discussion in Chapter 1). Venezuela is the largest producer among the Latin American countries, and it is also one of the major OPEC-countries, with currently the third largest quota, after Saudi Arabia and Iran. Starting with Latin America including Venezuela, the stochastic trend degenerates to an intercept and a linear trend in the two models based on 3mnth and 6mnth prices, whereas the stochastic trend is specified as a random walk in the model based on the 12mnth prices. Thus, the stochastic trend specification actually differs between the different models. Latin America is the only region where a deterministic trend may seem like a good approximation. I have included a dummy variable for April 2002. This month there was an attempted coup d'état against president Hugo Chavez in Venezuela, which greatly affected the oil industry in the country, causing a sharp decline in the oilrig activity (OGJ (2002) and Abraham (2002, pp. 273-276)). With this dummy included, all diagnostic tests are fairly satisfactory. The results are as follows:

Table 6: Estimation results for Latin America

	3mnth		6mnth		12mnth	
	Estimate	*t-value*	Estimate	*t-value*	Estimate	*t-value*
Δx_t	0.221	*1.807*	0.305	*1.627*	0.169	*0.389*
y_{t-1}	-0.077	*-2.301*	-0.096	*-2.201*	-0.418	*-4.908*
x_{t-1}	0.124	*4.667*	0.132	*3.696*	0.359	*3.164*
DI02.4	-0.198	*-4.216*	-0.181	*-3.843*	-0.175	*-4.057*
Diagnostics:						
Std. Error	0.042		0.043		0.046	
Normality	0.129		0.597		0.070	
H(29)	1.509		1.622		1.394	
DW	2.219		2.131		2.079	
Q(8,8)	4.049		3.898		3.245	
R^2	0.392		0.374		0.284	

The significance level of the short-run coefficients differs somewhat between the three models. In the model version with 3mnth prices it is significant at the 10% level. Using the 6mnth prices it is significant at slightly more than 10%. In the model with 12mnth prices it is not significant at all. Thus, we observe a similar effect as for the US region. Comparing with the US coefficients, Latin America does not react as strongly to oil price changes in the short run as the US does. It should be noted that the t-values of the oilrig activity coefficients in the two models based on 3mnth and 6mnth prices are not sufficiently high (in absolute value) to conclude that the variables are cointegrated. Moreover, the λ^* – coefficients are very close to zero (cf. the y_{t-1} -row), which means that although the models satisfy the stability requirements, the adjustment towards equilibrium will be quite slow. However, the oilrig activity and the 12mnth-price do seem to be cointegrated.

Turning to the estimation of Non-OPEC Latin America, there is no significant outlier value for this region (as expected, since Venezuela was the cause of the irregularity), and the diagnostic tests are satisfactory, apart from the low R^2 -values. Note that for the 3mnth price, I have included two lags of the differenced lagged rig activity to get rid of the autocorrelation in the residuals. The stochastic trend specification is a random walk in all the three models, as opposed to for Latin America as a whole, where a deterministic trend was obtained in the model versions based on 3mnth and 6mnth prices.

Table 7: Estimation results Non-OPEC Latin America[22]

	3mnth		6mnth		12mnth	
	Estimate	*t-value*	Estimate	*t-value*	Estimate	*t-value*
Δy_{t-1}	-0.293	*-2.608*				
Δy_{t-2}	-0.299	*-2.678*				
Δx_t	0.161	*0.907*	0.147	*0.337*	0.692	*0.883*
Δx_{t-1}			-0.562	*-1.261*	-1.028	*-1.303*
y_{t-1}	-0.278	*-2.910*	-1.040	*-9.504*	-1.031	*-9.488*
x_{t-1}	0.265	*3.174*	0.706	*3.389*	1.001	*4.007*
Diagnostics:						
Std. Error	0.060		0.061		0.060	
Normality	1.203		0.445		0.619	
H(29)	1.503		1.549		1.439	
DW	1.935		1.991		2.006	
Q(8,7)	1.954		3.420		2.938	
R^2	0.183		0.123		0.160	

[22] Excluding Venezuela.

Here, the short-run coefficients are all far from significant. The short-run coefficients in the two models based on 3mnth and 6mnth prices are smaller than those obtained when Venezuela was included in the region. This is somewhat counterintuitive. However, using the 12mnth prices the short-run elasticity is larger than the corresponding coefficient in Table 6 (although both are highly insignificant). For the two models with 6mnth and 12mnth prices there is evidence of cointegration, but in the case with 3mnth prices, the lagged oilrig activity coefficient is too low to conclude with cointegration. This lack of cointegration makes the results harder to interpret.

4.2.5 The Middle East

The Middle East region comprises quite a few OPEC-countries, and the assumption of exogenous price for this region is obviously somewhat troublesome, as mentioned in Chapter 1. In order to get an impression of how this affects the region, I have again estimated the region both including and excluding the OPEC-countries. Starting with the entire Middle East region (both OPEC and Non-OPEC), the trend specification is yet again a random walk. The diagnostic tests are satisfactory, apart from low R^2 -values. There are no significant outlier values. The results are reported in Table 8:

Table 8: Estimation results for the Middle East, including the OPEC countries

	12mnth		24mnth		30mnth	
	Estimate	*t-value*	Estimate	*t-value*	Estimate	*t-value*
Δx_t	0.071	*0.156*	0.280	*0.313*	1.202	*1.015*
Δx_{t-1}	-0.699	*-1.530*	-0.969	*-1.084*	-1.720	*-1.470*
y_{t-1}	-1.171	*-10.965*	-1.197	*-11.150*	-1.184	*-10.978*
x_{t-1}	0.280	*2.035*	0.653	*2.994*	0.831	*2.921*
Diagnostics:						
Std. Error	0.035		0.035		0.035	
Normality	2.487		2.754		3.122	
H(29)	0.928		0.908		0.862	
DW	2.042		2.034		2.051	
Q(8,7)	3.550		4.284		5.371	
R^2	0.139		0.172		0.169	

As we have seen for most of the other regions, the short run price coefficients are all highly insignificant, hence an oil price change will not have any immediate effects on the oilrig activity level in the Middle East. Again, we observe an overshooting effect.

I have also estimated models for Non-OPEC Middle East. Here, the diagnostic tests are not as satisfactory, there is e.g. a problem with both normality and autocorrelation of the residuals in the model version with the 24mnth price, which I am unable to correct for. The stochastic specification is still just a random walk.

Table 9: Estimation results for the Middle East, excluding the OPEC countries[23]

	12mnth		24mnth		30mnth	
	Estimate	*t-value*	Estimate	*t-value*	Estimate	*t-value*
Δx_t	1.137	*1.694*	3.263	*2.530*	3.261	*1.914*
y_{t-1}	-1.220	*-11.660*	-1.214	*-11.535*	-1.209	*-11.690*
x_{t-1}	0.510	*2.314*	0.826	*2.479*	0.923	*1.959*
Diagnostics:						
Std. Error	0.054		0.053		0.054	
Normality	5.184		6.518		4.074	
H(29)	0.705		0.682		0.681	
DW	2.016		2.008		2.010	
Q(8,7)	5.299		9.386		6.251	
R^2	0.158		0.190		0.154	

Here, the short-run price coefficients in the models based on 24mnth and 30mnth prices are in fact significant, and very high (both at 3.26). The short-run price elasticity using 12mnth prices is somewhat less significant, with a value of 1.14. According to this, the Non-OPEC Middle East seems to react quite substantially to price changes, and far more heavily than the Middle East as a whole, which makes sense intuitively. There is the same overshooting effect of the lagged oilrig activity coefficient (λ^*) that I found for the region as a whole.

[23] Saudi Arabia, Iran, Abu Dhabi, Dubai, Qatar and Kuwait.

4.2.6 Africa

For the Africa-region, there are quite a few problems with the tests for autocorrelation and normality, which may lead to inefficiency of the estimates. The stochastic trend is specified as a random walk. Due to a redefinition of the variables in the dataset for Africa, the number of active oilrigs increases substantially in February 2002, and this increase persists for the rest of the sample. Therefore, I have included a step dummy from 2002:2. The results of the estimations are given in Table 10:

Table 10: Estimation results Africa

	12mnth		24mnth		36mnth	
	Estimate	*t-value*	Estimate	*t-value*	Estimate	*t-value*
Δx_t	0.587	*0.540*	2.541	*1.223*	5.175	*1.272*
Δx_{t-1}	-3.105	*-2.791*	-3.215	*-1.553*	4.517	*1.111*
y_{t-1}	-1.048	*-11.468*	-1.130	*-12.188*	-1.151	*-11.962*
x_{t-1}	0.713	*2.630*	1.733	*3.748*	1.863	*1.946*
DS02.2	0.661	*6.389*	0.642	*6.302*	0.563	*5.250*
Diagnostics:						
Std. Error	0.103		0.102		0.106	
Normality	8.676		10.357		10.491	
H(29)	0.518		0.660		0.651	
DW	2.177		2.143		2.133	
Q(8,7)	5.522		7.060		13.597	
R^2	0.401		0.416		0.370	

None of the short-run elasticities are significant. Thus, oil price changes do not seem to have an immediate effect on the oilrig activity level in Africa, either. We observe the same "overshooting effect" as for quite a few of the other regions.

As the Africa-region includes several OPEC-countries, I have done estimations with these removed, to see if this changes the results. There are problems with the normality tests, though the rest of the tests are satisfactory. Dummies for outliers were experimented with, but were not included in the final estimations, as they led to autocorrelation of the residuals. In addition, the 2002:2-dummy for Africa was caused by the redefinition of variables for Algeria and Libya, which both are OPEC-countries, hence it is reasonable that this dummy should not be included here.

Table 11: Estimation results Non-OPEC Africa

	12mnth		24mnth		36mnth	
	Estimate	*t-value*	Estimate	*t-value*	Estimate	*t-value*
Δx_t	2.978	*0.544*	0.603	*0.132*	24.164	*1.974*
Δx_{t-1}	-8.493	*0.085*				
y_{t-1}	-0.634	*-6.314*	-0.721	*-6.958*	-0.795	*-7.627*
x_{t-1}	1.073	*3.025*	2.189	*3.014*	3.712	*2.126*
Diagnostics:						
Std. Error	0.451		0.455		0.457	
Normality	18.315		19.437		16.483	
H(29)	0.601		0.677		0.651	
DW	1.967		1.964		1.983	
Q(8,7)	3.657		4.890		5.292	
R^2	0.268		0.246		0.242	

The short-run coefficient using the model with 36mnth prices is significant, but extremely high (at 24.164). Remember that the normality problems may cause inefficient estimates. It does seem highly unlikely that a price increase should lead to an instant 24-fold increase in the oilrig activity. However, note that this region in total has a very limited number of active oilrigs, and this may cause a problem for the inference. Another aspect is that some of the African countries are quite unstable, with regime changes and other political instability that may influence the oil industry. This may explain why it is difficult to obtain significant estimates for Africa. Here, we do not observe the "overshooting" effect that was seen for Africa as a whole.

4.3 Long-term Effects

As shown above, the short-run effects of oil price changes are for the most part insignificant, except for the US, Latin America and Non-OPEC Middle East, where there are significant short-run effects for a couple of the model versions. The insignificant short-run effects may well be explained by the time lag from a price change is observed, until the rig activity level is actually changed (due to e.g. adaptive expectations or an inflexible rig market). However, in the long run there is reason to believe that price changes will have an effect on the oilrig activity level. The long-run price elasticities are reported in Table 12.[24] As noted in Section 4.2, most of the $\theta's$ and $\lambda^{*}'s$ for the different regions are significant. However, since the long-run elasticity is calculated as the ratio between two coefficients (multiplied with (-1)), one would need the covariance between the estimators of θ and λ^{*} to calculate the standard errors and significance level of the long-run coefficients. Unfortunately, STAMP does not report this covariance, hence the correct significance level cannot be calculated. The long-run elasticities are therefore reported without t-values.

Table 12: Long-run price elasticities

	3mnth	6mnth	12mnth	24mnth	30mnth	36mnth
USA	1.836	1.721	1.455			
Europe		0.631				
Norway		0.194	0.551	0.582		
United Kingdom		0.160	0.721	1.375		
Asia Pacific			0.173	0.511		0.989
Latin America	1.610	1.375	0.859			
Non-OPEC Latin America	0.953	0.679	0.971			
Middle East			0.239	0.546	0.702	
Non-OPEC Middle East			0.418	0.680	0.763	
Africa			0.518	1.427		1.762
Non-OPEC Africa			1.692	3.036		4.669

[24] Calculated as $\omega = \frac{\theta}{-\lambda^{*}}$, where θ is the lagged price coefficient, and λ^{*} is the lagged oilrig activity coefficient (cf. Eq. (12)).

Theoretically, the long-run price elasticities should be fairly similar for all the different models within a region. Table 12 shows that this is not necessarily the case for all regions, which perhaps reflects the relative uncertainty of the coefficients. Some points can still be made. The US has by far the highest long-run price elasticity[25], and it is fairly stable, around 1.5. If the price on crude oil increases (permanently) from $25 to $30, equivalent to a 20 per cent increase, this will in the short run bring about an oilrig activity increase of around 3 per cent[26], whereas in the long run, the activity increase will be 30 per cent[27]. The US oil industry is driven by commercial interests (private companies), and there is a small degree of governmental regulation. Also, as the region is mature, there are many small oil fields with high unit costs, which only will be developed when the oil price is sufficiently high. Moreover, the US rig market is fairly flexible, making it easier to increase the rig activity quickly. These are all factors that may explain the observed swift reaction.

Europe's long-run elasticity (which I only have calculated for one price period, as the models for the other price periods were unstable) is around 0.6, less than half of the US. Here, a price increase from $25 to $30 will only induce a 12 per cent[28] increase in oilrig activity in the long run. As already mentioned, this may be due to the governmental involvement in the region. In Europe (especially Norway), the governments are much more involved in the oil industry, either directly or through taxation, and a large governmental involvement may cause delays in the decision-making process, thus contributing to a slower reaction to price changes. E.g., if some of the oil companies' profits will have to be paid as taxes to the government, there is reason to believe that a larger oil price change will be required before the companies decide to increase the rig activity level, compared to a situation where the companies keep all profits to themselves. Also, governments may be concerned with ensuring a stable development of the oil industry, rather than focusing on profits only. Another aspect is that the European rig market is less flexible than e.g. the US rig market. The European oil industry is mainly offshore, with a predominance of long-term contracts (especially in Norway, cf. OGJ (2003, p. 52)), making swift adaptation to oil price changes difficult. When it comes to the country-specific long-run elasticities in Norway and the UK, these vary quite a bit between the three different models, but overall, the UK seems to be somewhat more price sensitive than Norway. Comparing the UK and Norway long-run elasticity using 12mnth prices with the

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[25] If one disregards Non-OPEC Africa, where there are problems with inefficient estimates.
[26] Using the calculated short-run elasticity of 0.15 (cf. p.24), the change is thus calculated 0.2*0.15.
[27] 0.2*1.5.
[28] 0.2*0.6.

European long-run elasticity in the model based on 6mnth prices, Norway is somewhat below, whereas the UK is a bit above.

The Asia Pacific elasticities vary quite a lot, but comparing e.g. the long-run elasticities obtained when using 12mnth and 24mnth prices with those obtained in other regions using similar prices, Asia Pacific does not seem to be particularly sensitive to oil price changes. The oil industry in this region is quite regulated (more so than most Western countries), which may explain the relative price insensitivity of the region.

The Latin America region is a mix of countries with a large governmental involvement in the oil industry (e.g. Mexico), and countries that are more privatised, with international companies operating (e.g. Brazil). The long-run coefficients vary quite a lot for this region as well. The elasticities obtained using 3mnth and 6mnth prices are higher than the respective coefficients for Non-OPEC Latin America, which is slightly counterintuitive (cf. the discussion in Section 4.2.4). However, sticking to a model version with 12mnth prices, the long-run elasticity is largest when Venezuela is not included, although the difference is not very large (0.859 vs. 0.971). Comparing with the other regions, Latin America (both with and without Venezuela) is somewhat more price sensitive than Europe, but the region is less sensitive than the US.

In the Middle East region, the Non-OPEC Middle East long-run elasticities are slightly larger than the long-run elasticities for the Middle East as a whole. Thus, the Non-OPEC region is somewhat more price sensitive than when OPEC is included - corresponding well to the discussion of the short-run effects (Tables 8 and 9). However, these elasticities are all fairly low compared to most of the other regions, at about the same level as Asia Pacific.

The African long-run elasticities also have quite a large range, and they are substantially higher than Asia Pacific's. The Non-OPEC Africa elasticities are implausibly high, but remember that there were problems with the diagnostic tests of the two Africa-regions, which makes the estimates for θ and λ^* somewhat unreliable. Hence, these long-run coefficients should not be interpreted too literally.

5. Conclusion

This study uses monthly data on oil prices and oilrig activity for six regions in the world to estimate the effect of prices on activity. I use an Equilibrium Correction Model that allows for a stochastic trend, and obtain estimates of both short-run and long-run adaptation to price changes. Results show that in the short run, only the US, Latin America and Non-OPEC Middle East regions have significant reactions to oil price changes. For the rest of the regions, the short-run coefficients are far from significant. Regarding the long-run effects, the US region has the highest long-run elasticity at around 1.5. Thus, a one per cent increase in the oil price will induce a 1.5 per cent increase in the oilrig activity level. Europe's long-run elasticity is, at 0.6, less than half the US elasticity. Asia Pacific and the Middle East are the least price sensitive regions. One possible explanation for this is the varying degree of governmental involvement and regulation in the regions, whereas varying flexibility in the rig market is another factor that possibly plays a part. The regions with OPEC-countries have also been estimated with these countries removed, and the estimation results indicate that the OPEC-countries do seem to be somewhat less sensitive to price changes (do not consider the oil price as exogenous). An interesting extension would be to calculate the speed of adjustment, i.e., how long it takes for the different regions to approximately reach the long-run level.

There are methodological problems with a few of the regions, making the results somewhat uncertain. The non-stationarity of the data poses problems, and establishing the "true" integration order of a variable may be a difficult task. Hence, my assumption of I(1)-variables is crucial for the estimations. Also, the inclusion of a stochastic trend, to allow for the unobservable factors, seems to play an important part for the conclusion that prices and activity are cointegrated. Before the introduction of a stochastic trend, cointegration was rejected for most of the regions.

It is apparent that the models have varying success for the different regions. It proves for instance very difficult to obtain satisfactory diagnostic tests for Africa, which indicates that the model specification for this region is not adequate. In addition to this, e.g. Asia Pacific and the Middle East have low R^2-values. A point to note is the fairly short sample period available for estimation (in terms of years), which may explain some of the difficulties. It would be interesting to test the models for a longer sample period. Moreover, the estimated regions are as defined in the Baker Hughes rig counts, and although the countries within the specified regions are more or less geographically close, there may be large variations within regions with respect to organisation of the oil industry, political stability, etc. This may be another explanation for the models' varying degree of success.

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