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Abstract

We analyse business cycles of oil and gas investment on the Norwegian continental shelf. Investment declined steeply from 2014 until 2017, following business cycle-induced cost increase and a subsequent dramatic drop in the oil price. Two competing hypotheses emerged in the literature, as to whether the downturn is transitory and part of the cyclical nature of the business, or if it is a permanent shock caused by the emergence of climate risk. We apply various techniques to extract the cyclical component of petroleum investment. The results show that the recent recession was not more severe in terms of duration compared to previous crises, and that it was transitory. However, the change in cyclical component from peak to trough was more extreme than anything observed previously. After an upturn of only two years and while the capital-intensive parts of the supplier industry were not yet recovered, in March 2020 the pandemic COVID-19 and oil price war caused another dramatic oil price reduction. We discuss the counter-cyclical tax policy passed by the Norwegian Parliament in light of the oil companies' practice of capital rationing and an explicit aim of ensuring the survival of the supplier industry.

1.0 Introduction and background

The Norwegian oil and gas industry experienced a very long, booming business cycle lasting for roughly a decade, from 2004 to 2013, only broken by a minor set-back under the financial crisis. Whereas other industries were hit hard by the financial crisis, the effect was small and brief for the petroleum industry. An explanation provided is that whereas the OECD-area

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went into decline, the financial crisis had small effect on Asian countries. Since countries in Asia have higher oil demand per unit of GDP than OECD-countries, the net effect on oil demand thus was low. The oil industry therefore experienced a nine-year boom cycle, which is unprecedented. This ended abruptly when oil prices fell markedly from mid-2014. When the oil price began its recovery a few years later, investment in petroleum development projects on the Norwegian Continental Shelf (NCS) and other extraction countries was slow to follow suit.

Two competing hypotheses emerged. On one hand, it was argued that petroleum investment will never recover, and what we are observing is the beginning of the end due to the emergence of climate risk. On the other hand, it is possible that a prolonged upturn is followed by a longer downturn, where the build-up of cost level and debt over the long boom period initially held investment back when the oil price picked up again. This leads us to the following question: has Norwegian petroleum investment experienced a permanent negative shock from the emergence of climate risk, or is the industry just going through a business cycle that is longer than usual?

As part of providing an answer to this question, it is first necessary to provide a clearer picture of the business cycle throughout history of the petroleum industry on the NCS. Only when an adequate understanding of the past has been achieved can we proceed to investigate the permanency of the latest recession. In the face of empirical observations, conjectures of the oil industry reaching its end has become common. It has been postulated in recent literature that the emergency of climate risk has irreparably caused a decrease in investment activity. In the context of the petroleum industry, risk caused by CO_2-driven climate change is often referred to as climate risk. In a qualitative study on companies operating on the NCS, Oslo Economics (2017) finds that climate risk affects their risk assessment through six channels: market risk, regulatory risk, technological uncertainty, physical risk and reputational risk. Fattouh al. (2019) argue that climate risk, especially through the channel of regulatory risk (inducing energy transition), has caused a significant increase in oil companies' discount rates. Consequently, aggregate investment will decrease. Decreasing investment is further argued to reduce the value of oil and gas companies, which might again trigger wide-spread economic downturn through contagion and the collapse of the petroleum service industry. Fattouh et al. argue for a self-reinforcing cycle, i.e., fossil fuel prices are believed to increase due to underinvestment, increased prices would in a further instance increase the speed of energy transition, which would result in even higher discount rates and lower investment.

This hypothesis has proven itself to be challenging to test through empirical modelling. Henriques and Sadorsky (2010) come close by relating stock returns on energy companies to environmental sustainability through extending CAPM to include the energy price. The beta coefficient of the energy price is decomposed into energy price volatility, environmental sustainability (ES) and company size. Two issues prevent us from concluding that climate risk would have a similar significant effect without further investigation. First, as ES is a broader concept than climate risk, it would be incorrect to assume that what is true for the whole must be true for all its parts. Second, the approach of Henriques and Sadorsky (2010) would at best only address the effect of climate risk through the market risk channel.

Relevant to the second hypothesis, the relationship between petroleum companies' decision-making and level of debt has become a popular topic (Domanski et al., 2015; Gilje et al.,2017; Lehn and Zhu, 2016; Lips, 2018). Lehn and Zhu investigate the effect of debt on the level of investment in the U.S. oil industry. They find that investment is inversely related to debt.

In what can be argued to effectively be a nine-year booming cycle from 2004 to 2013, cost levels were increasing steeply. The one-year downturn in 2009 was not enough to dampen cost inflation. The high growth in China relieved the oil industry for what would have been a traditional downcycle at this time, and cost continued to rise. When combined with a steep reduction in the oil price in 2014, many companies experienced a negative cash flow. They were reluctant to cut dividends, so debt levels were increasing fast. First priority after the cash flow again picked up was to service stockholders and to reduce debt that had moved above critical levels. Balance sheets were to be improved before embarking on substantial investment. As a result, global reserve replacement rate has been a record low. First in 2017 we finally saw signs that investment was picking up globally and that major oil companies were entering into large long-term projects in deep water and LNG. Several significant development projects were sanctioned on the NCS that year. Such increase in the investment level contributes to undermine the hypothesis that the downturn in investment was a permanent response, primarily due to climate risk, but it does not rule out that climate risk played a part.

Cyclicality in petroleum investment is closely related with cyclicality in revenue (fluctuations in the oil price) and cyclicality in cost. As both revenue and cost have a cyclical response to oil price change, the net effect is to dampen fluctuations in return on investment in response to oil price changes.

As for cost, drilling cost is particularly cyclical, and they may represent as much as half the cost of a development project (Osmundsen et al., 2010). According to Skjerpen et al. (2018) rig rates at the NCS tripled (312 % increase) between 2000 and 2013. In the same period, there was a large reduction in drilling speed measured by meter per day (Osmundsen et al., 2010, 2012). The joint effect of souring rig rates and decreasing drilling speed was a dramatic increase in drilling cost. In the following downturn, this effect was reversed by an increase in drilling speed and decreasing rig rates. An additional factor that generates cyclical cost is that boom periods have larger cost overruns in development projects (Dahl et al., 2017; Lorentzen et al., 2017).

The investment decisions of oil companies over the business cycle are analysed in Osmundsen et al. (2020). In periods of strain on the cash flow, oil companies ration capital by demanding a breakeven price for new projects that is considerably lower than the expected oil price. This is equivalent to raising the rate of return requirement for new investment. Unlike the assumption in Fattouh al. (2019), that this is a permanent response to the emergence of climate risk, Osmundsen et al. (2020) document that oil companies change their breakeven price systematically over the business cycle, so that the effective rate of return requirement is reduced again when the cash flow situation is restored. Capital rationing is not a new phenomenon, it is the standard response from oil companies to business cycles. Thus, this is business as usual in terms of investment methodology, but with more dramatic impact in recent years. We actually saw capital rationing on the NCS even before the oil price peaked in 2014. A boom cycle of effectively nine years led to so large cost increases that new projects were not profitable even at a record high oil price. By scaling down investment at a time of low cash flow, oil companies were able to pay dividends and reduce debt that had reached an uncomfortable level. Reduced investments also led to reduced cost in the supply industry through reduced demand. Once again there was ample access to skilled personnel, excess supply of rigs and supply vessels, there was available capacity at construction sites, and productivity rose. These are a normal sequence of events in a petroleum industry business cycle, only more dramatic this time.

For the remainder of this paper, we turn to the issue of analysing the business cycle of oil and gas investments on the NCS. Section 2 provides a brief coverage of relevant theory. In Section 3, we present the data and provide descriptive statistics. One of the main goals here is to find the statistical properties of investments to determine the best approach to extracting the business cycle. In Section 4, we present the obtained business cycle and describe its characteristics. Section 5 concludes.

2.0 Theory

The aim of this paper is to elucidate the business cycles of the Norwegian petroleum industry by using aggregate capital expenditure from development projects on the Norwegian continental shelf (NCS). Identifying the business cycle of a timeseries (y_t), such as petroleum investments, is not a straightforward process. To provide the necessary background, we will provide a brief coverage of relevant theory. For a comprehensive coverage, see Bjørnland and Thorsrud (2015).

We begin by considering a generic time series (y_t), such as the solid, black line in Figure 1. By eyeballing this time series, we can clearly observe an upward sloping trend and a certain cyclicality. According to theory, this times series (y_t) can be decomposed into two components: (1) a trend component (τ_t) and (2) a cyclical component (c_t), see Equation (1).

$$y_t = \overbrace{\tau}^{\substack{trend\\component}} + \underbrace{c_t}_{\substack{cyclical\\component}} \tag{1}$$

The cyclical component is colloquially referred to as the business cycle. To find the cyclical component we re-arrange Equation (1).

$$c_t = y_t - \tau_t \tag{2}$$

That is, we find the cyclical component by subtracting the trend component from the time series of interest. See Equation (2). While y_t is observable, the trend component τ_t is not. Consequently, we first have to determine the type of trend and its characteristics before the cyclical component can be calculated. We will return to issues of the trend component in sections 3 and 4. For the time being, let us assume the simplest case: a linear deterministic trend. Under this assumption, the trend can be estimated using regression analysis, where we attempt to explain the time series of petroleum investment in terms of the time index. Since petroleum investments are observed on an annual frequency, the time index will be the calendar year. The regression model is shown in Equation (3).

$$y_t = \beta_0 + \beta_1 TimeIndex_t + \varepsilon_t \tag{3}$$

The two parameters in the regression model are estimated using ordinary least squares. This method works by choosing values for β_0 and β_1 coefficients such that the squared sum of the residuals (ε_t) are minimized. Specifically, this objective is achieved when:

$$\hat{\beta}_1 = \frac{Covar(y_t, TimeIndex_t)}{Var(TimeIndex)} = Corr(y_t, TimeIndex_t) \cdot \frac{std.dev.(y_t)}{std.dev.(TimeIndex_t)} \tag{4}$$

and

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \overline{TimeIndex}. \tag{5}$$

In other words, the estimate of the slope beta coefficient ($\hat{\beta}_1$) is the ratio between the covariance between the times series and the time index, and the variance of the time index. Alternatively, it is the correlation between the time series and the time index multiplied with the ratio of the standard deviations of these two variables. See Equation (4). The estimate of the intersection slope ($\hat{\beta}_0$) is a function of the slope estimate and the averages of the time series and time index. See Equation (5). With these estimates, we can calculate the predicted value of the time series ($\hat{y}_t$). See Equation (6).

$$\hat{y}_t = \hat{\beta}_0 + \hat{\beta}_1 \overline{TimeIndex}. \tag{6}$$

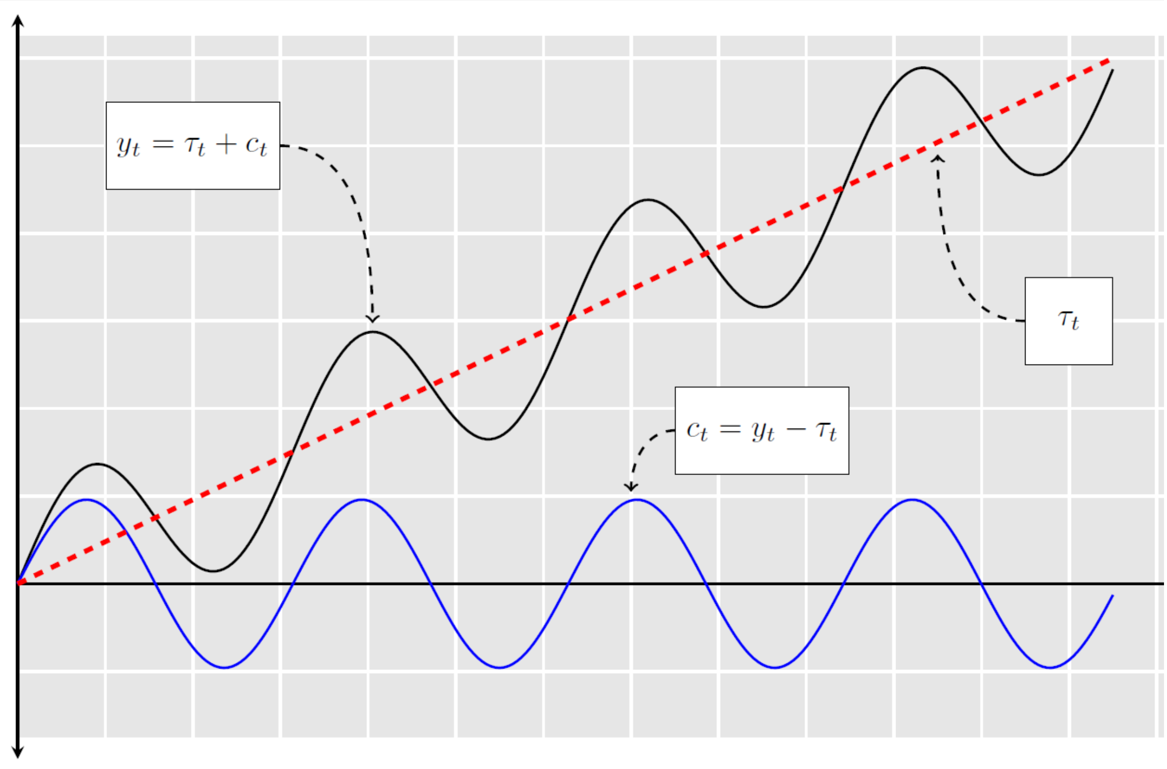
The predicted value of the time series ($\hat{y}_t$) is the equivalent of the trend component (τ_t). The difference between the actual and predicted values of the time series is equal to the residual (ε_t) from Equation (3). This residual or error term is in this context a measure of the business cycle. Hence, we have that,

$$\varepsilon_t = y_t - \hat{y}_t = y_t - \left(\hat{\beta}_0 + \hat{\beta}_1 \overline{TimeIndex}\right) \tag{7}$$

where $c_t \equiv \varepsilon_t$ and $\tau_t \equiv \hat{y}_t$.

In figure 1, the dashed red line is the predicted value of the solid black line, i.e., the trend component, which we get by applying Equation (6). The solid blue line is obtained by applying Equation (7) and represents the cyclical component. As established in Equation (1), the dashed red line and solid blue line sums up to the solid black line.

Figure 1: Diagrammatic illustration of a generic time series



Generic illustration of business cycles. The x-axis represents time, and the y-axis could be any measure of interest such as monetary units. The black line represents an arbitrary time series (y_t), which is a combination of a deterministic trend (τ_t) and a cyclical (c_t) component. The trend component is here represented by a dashed red line and the cyclical component by a blue line.

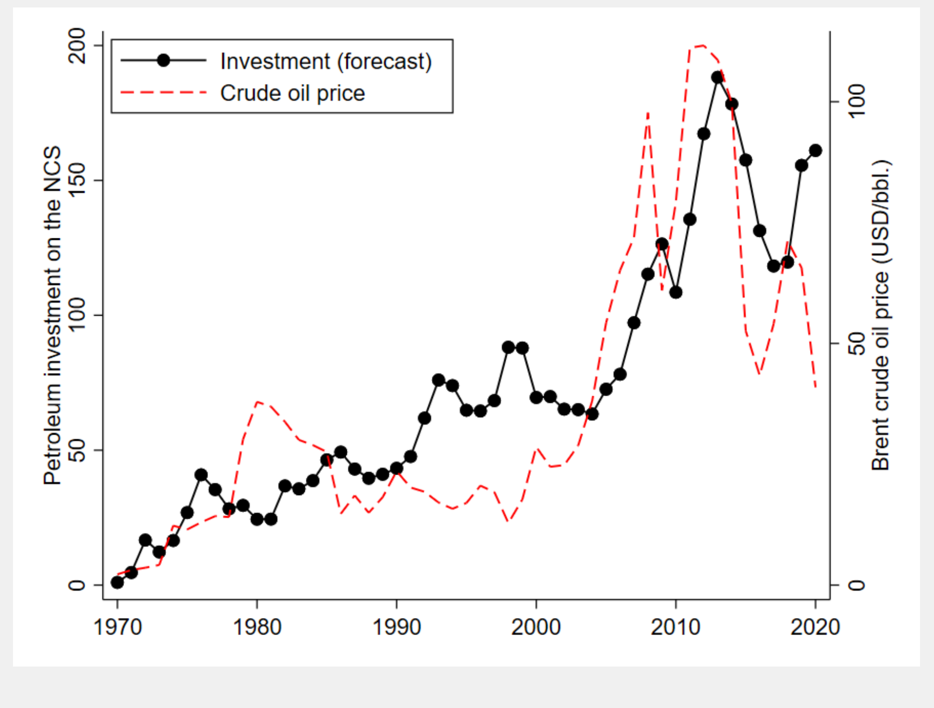
The example under consideration is trivial as it relies on assumption which have not been verified. Consequently, it should only serve as a pedagogical illustration. First, the cyclical component consists of identical cycles both in terms of duration and severity. In reality, this is seldom the case. Business cycles typically differ quite extensively in both length and severity. Second, the considered example does not exhibit any noise. Outside the realm of simulated data, there would be a third component to Equation (1): idiosyncratic noise. Third, the trend is not necessarily linear. In practice, the trend could take on any functional form or perhaps even be stochastic. In the case of a stochastic trend, the regression approach is no longer feasible. As shown by Nelson and Kang (1982), erroneously assuming a deterministic trend could lead to spurious business cycles. In other words, the methodology can produce a business cycles that does not exist. In the case of a stochastic trend, more advanced methodologies are necessary, such as the Baxter and King (1999) band-pass filter, the Christiano and Fitzgerald (2003) band-pass filter, Hodrick–Prescott high-pass filter and Butterworth high-pass filter.

3.0 Data and descriptive statistics

The main variable of interest is the aggregate oil and gas development investments on the Norwegian Continental Shelf (NCS) between 1970 and 2020. Capital expenditure on development investments on the Norwegian continental shelf (NCS) was extracted from the web page of the Norwegian Petroleum Directorate (NPD).

The inflation-adjusted investments are shown in Figure 2. The first hydrocarbon deposits of economic significant size, the Ekofisk field, was discovered in December of 1969. Investments dedicated to developing the NCS quickly followed suit from 1970. Oscillation around a stable linear trend can be observed from the start of the sample period until the beginning of 2000. After a decline in annual development investments from 1998 to 2004, investments surged to levels never seen before. Except for a temporary setback in 2010, petroleum investment increased rapidly from 2004 to 2013. During this decade long boom, investments increased from 63 bn. NOK to 188 bn. NOK adjusted for inflation. Following the sharp decrease in oil prices from 2014, investments plummeted from its all-time high in 2013 to 118 bn. NOK in 2017. Oil and gas investments have since slowly begun to recover. From to 2017 to 2019, we observe an increase in investments from 118 bn. NOK to 156 bn. NOK. Tentative numbers for 2020 suggest an annual investment of 161 bn. NOK.

Figure 2: Oil and gas investment on the NCS (1970-2020)



The inflation-adjusted petroleum investments on the Norwegian continental shelf between 1970 and 2020, actual figures and forecast for 2020. The investment is plotted against the Brent crude oil price (USD/bbl.).

Before embarking on an analysis of the business cycle of petroleum investments, it is crucial to determine whether the variable of interest, oil and gas investments on the NCS, is stationary. A time series is said to be stationary if both its first and second order moment are time invariant. That is, the time series' average and variance does not change over time. A stationary times series will fluctuate around a given value. By visually inspecting petroleum investments, we can clearly observe that it is nonstationary, i.e., the first and/or second order moment are not time invariant. To properly extract the business cycle, however, we need to know if the nonstationarity is caused by the presence of a deterministic or stochastic trend. Both types of trends stay true to their name. If petroleum investment has a deterministic trend, then this could for instance mean that the time series increases by a fixed amount every time period, i.e. a linear deterministic trend. A deterministic trend is any trend that can be described by a functional form with the time index as the input. A stochastic trend, on the other hand, is a trend that evolves randomly. If a variable y_t is stationary, it could be presented as an infinite moving average of past error terms. See Equation (8).

$$\begin{gathered} y_t = \delta + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \theta_3 \varepsilon_{t-3} + \cdots \\ y_t = \delta + \theta(L) \varepsilon_t \end{gathered} \tag{8}$$

In the case of the presence of a deterministic trend, Equation (8) would change to include an expression of the time index t – see Equation (9). Consequently, the first order moment would be dependent on time, $\mathbb{E}[y_t] = \delta + \alpha t$. On the other hand, the deviation from the expectation would remain invariant, $y_t - \mathbb{E}[y_t] = \delta + \alpha t + \theta(L)\varepsilon_t - (\delta + \alpha_t) = \theta(L)\varepsilon_t$. That is, the time series y_t is stationary around a long-run trend, i.e. trend stationary.

$$y_t = \delta + \alpha t + \theta(L) \varepsilon_t \tag{9}$$

A time series with a stochastic trend could take on several different forms. The simplest case is that of a random walk model, see Equation (10), where the mean and variance would be $\mathbb{E}[y_t] = y_0$ and $var(y_t) = \sigma^2 t$ respectively.

$$y_t = y_{t-1} + \varepsilon_t \tag{10}$$

Various tests are avaiable for testing for stationarity. We apply four different tests to obtain more robust results. Specifically, we look at augmented Dickey-Fuller (ADF) test, Dickey-Fuller Genealized Least Squares (DF-GLS) test, Phillips-Perron (PP) test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. The regression model for the ADF and DF-GLS are shown in Equation (11). The null hypothesis here is the presence of a unit root, i.e. nonstationarity, which would be the case if β is insignificantly different from zero.

$$\Delta y_t = \alpha + \beta y_{t-1} + \delta t + \sum_{j=1}^{k} \zeta_j \Delta y_{t-j} + e_t \tag{11}$$

Analogously, the regression model for the Phillips-Perron test is given in Equation (12). If the ρ is not significantly less than one, then the time series y_t is deemed to be nonstationary.

$$\mathrm{y_t} = \alpha + \rho y_{t-1} + \delta t + u_t \tag{12}$$

Table 1 shows the results from the four above mentioned stationarity tests, both with and without a deterministic component, when applied to petroleum investment and the logarithmic growth in investments. In the case of investment when applying the ADF test, the null hypothesis is not rejected when we do not include a deterministic trend and is rejected when a deterministic trend is included. This implies that petroleum investments are trend stationary, i.e., the nonstationarity is caused by the presence of deterministic trend. The DF-GLS test yields similar results. The PP test on the other hand, does not reject the null hypothesis regardless of whether the deterministic component is included. However, the null hypothesis is rejected when the test is applied to the logarithmic return of the petroleum investments. In other words, the PP test suggests that petroleum investments are nonstationary due to the presence of a stochastic trend. The KPSS test, which has a switched null hypothesis compared to the preceding tests, concludes that both investment and logarithmic returns on investments are nonstationary regardless of whether a deterministic component is included.

Table 1: Stationarity testing of petroleum investments (1970-2020)

	No trend				**Trend**			
Variable	**ADF**	**DF-GLS**	**PP**	**KPSS**	**ADF**	**DF-GLS**	**PP**	**KPSS**
$Investment$	-1.10	-0.282	-0.80	2.26***	-3.66**	-3.459**	-2.65	2.26***
$\Delta \ln Investm$	-9.93***	-0.752	-7.07***	0.43*	-9.78***	-2.141	-6.79***	0.43***

Stationarity test statistics and corresponding significance levels for oil and gas investments on the NCS and logarithmic returns of investments between 1970 and 2019. Tests include: augmented Dickey-Fuller (ADF), Dickey-Fuller Genealized Least Squares (DF-GLS), Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS). Trend signifies whether a deterministic component is added in the test. Asterisks denote a significance level of 10 % (*), 5 % (**) and 1 % (***).

In short, in consensus with visual inspection, the applied tests do indeed confirm that the petroleum investment time-series are nonstationary. They are, however, inconclusive on whether the nonstationarity of investments is caused by a stochastic or deterministic trend.

4.0 Analysis of business cycles

4.1 Plotting business cycle

Based on petroleum investment on the NCS, as shown in Figure 2, we attempt to extract the business cycle. Various approaches are available. One important aspect in regard to selecting an appropriate methodology pertains to whether the variable in question contains a deterministic or stochastic trend. As described in the preceding section, the battery of nonstationarity tests applied failed to reach a consensus. Hence, we adopt the strategy of applying a wide spectre of approaches based on different assumptions. We then compare the obtained business cycles to gain insight into whether the results are robust.

Beginning with the tentative assumption of the presence of a deterministic trend, let the annual inflation-adjusted petroleum investment on the Norwegian Continental Shelf (NCS) at time t be denoted as y_t. To find the business cycle, we separate y_t into two components: a trend component (τ_t) and cyclical component (c_t). See Equation (1).

The trend component can be interpreted as the long-run evolution of petroleum investments on the NCS and the cyclical component as the business cycle. While τ_t is expected to be nonstationary, either due to a stochastic or deterministic trend, the cyclical component c_t should be stationary. If the trend is deterministic, τ_t can be estimated through a simple ordinary least squares regression as a function of the time period (t). In Figure 1, we assumed a liner trend, for illustration. We have no theoretical reason to assume this to be the case. As there is no obvious specification of τ_t, we consider several alternatives:

- Model 1: $y_t = \beta_0 + \beta_1 t + \varepsilon_t$
- Model 2: $y_t = \beta_0 + \beta_1 t^2 + \varepsilon_t$
- Model 3: $y_t = \beta_0 + \beta_1 t^3 + \varepsilon_t$
- Model 4: $y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \varepsilon_t$
- Model 5: $y_t = \beta_0 + \beta_1 t + \beta_2 t^3 + \varepsilon_t$
- Model 6: $y_t = \beta_0 + \beta_1 t^2 + \beta_2 t^3 + \varepsilon_t$
- Model 7: $y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_3 t^3 + \varepsilon_t$

Figure 3 plots the oil and gas investments against the predicted regression line ($\hat{\tau}_t$) for each of the suggested models. Visual inspection does not reveal an immediate best model specification. We therefore apply more rigorous testing. The optimal specification of τ_t, in terms of trade-off between model fit and parsimony, can be determined by applying information criteria. We consider three different criteria: Akaike, Hannan-Quinn and Schwarz's Bayesian – see Equations (13) – (15).

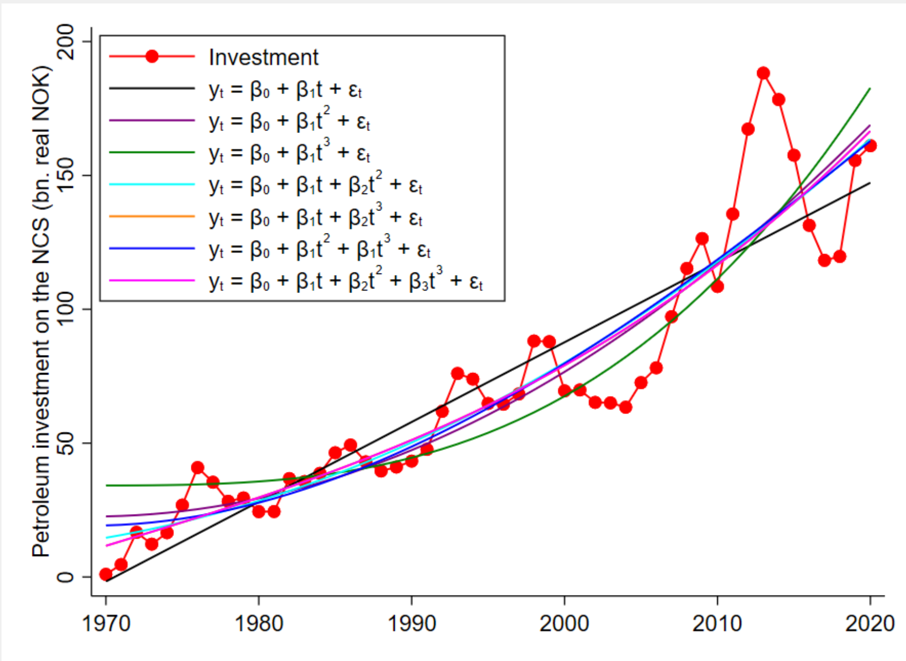
$$\mathrm{AIC} = -2\ln(L) + 2\mathrm{k} \tag{13}$$

$$\mathrm{BIC} = -2\ln(L) + k\ln(N) \tag{14}$$

$$\mathrm{HQIC} = -2\ln(L) + 2k\ln(\ln(n)) \tag{15}$$

As shown in Table 2, regardless of the choice of information criterion, model 2 is deemed the optimal model. It contains a constant term and a squared term of the time index. It should be noted that these results are only valid in-sample. There is no strong reason or evidence to suggest that this established deterministic trend will have external validity. That is, a squared trend is not necessarily valid for the future.

Figure 3: Petroleum investment and various deterministic trends



Data source: Norwegian Petroleum Directorate. Oil and gas investment on the NCS between 1970 and 2019 plotted against different specifications of a deterministic trend.

Table 2: Model specification with information criteria

Specification	AIC	HQIC	BIC
Model 1	450.03	451.50	453.89
Model 2	442.65*	444.13*	446.51*
Model 3	455.37	456.85	459.24
Model 4	442.94	445.15	448.73
Model 5	442.67	444.88	448.46
Model 6	443.65	445.86	449.44
Model 7	444.67	447.62	452.39

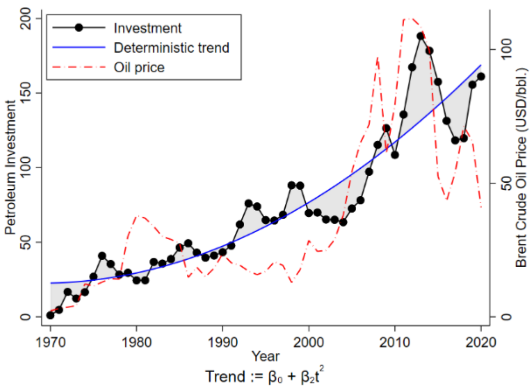
Model specification of deterministic trend based on Akaike (1974), Hannan-Quinn and Schwarz's (1978) Bayesian information criteria. The L.H.S variable is the inflation adjusted petroleum investments on the NCS from 1970 to 2019. The R.H.S consists of a linear (t), squared (t^2) and cubed (t^3) time-period terms. Asterisk (*) denotes the optimal model.

With the given estimate of the trend component ($\hat{\tau}_t$), the business cycle is obtained by taking the difference between the investments (y_t) and the trend, or simply the error term of model 2; see Equation (16). Applying the described methodology, we obtain an estimation of the business cycle as shown in Figure 4.

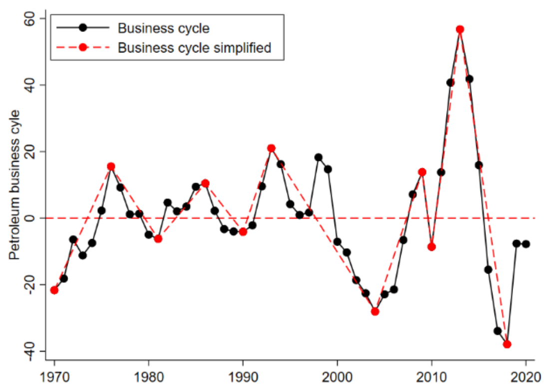
$$\hat{\tau}_t = \hat{\beta}_0 + \hat{\beta}_1 t^2 + \hat{u}$$
$$\hat{c} \equiv \hat{u}_t = y_t - \hat{\tau}_t = y_t - \left(\hat{\beta}_0 + \hat{\beta}_1 t^2\right) \quad (16)$$

Figure 4: Petroleum business cycle in Norway (1970-2020)

(a) Investment with deterministic trend



(b) Business cycle



Subfigure (a) shows the petroleum investments on the NCS between 1970 and 2020; the estimated trend and oil price (USD/bbl.). The grey area between the investment and trend is business cycle. The business cycle is shown explicitly in subfigure (b). Using the established definition, the peaks and trough are highlighted in red.

Based on the obtained cyclical component $\hat{c}_t$, i.e., the business cycle, we proceed to identify the peaks and troughs. There are several approaches available. A peak (trough) is by definition a local maximum (minimum). However, not all local maxima should be classified as peaks. A data point should only be classified as a peak if it is a local maximum and if it has a value-exceeding zero. On the one hand, we could declare all data points adhering to this condition as a peak. On the other hand, it might be sensible to only declare the data point with the highest value within a segment of continuous positive values to be a peak. Applying the latter definition has both its advantages and disadvantages. Consider for instance c_{1982} and c_{1986}, as seen in Figure 4(b). Arguably, 1982 should not be considered a business cycle peak. By the former definition both 1982 and 1986 would be considered as peaks, but under the latter definition only 1986 is selected. On the contrary, if we look at c_{1993} and c_{1998}, an argument could be made that both are peaks. Our definition, however, will only declare 1993 as a peak. In short, by adhering to a strict definition, we might end up with either too many or too few peaks than what we would obtain through visual inspection and qualitative reasoning.

Depending on preferences, either definition could be feasible. However, we choose for now to rely on the latter, i.e., only the observation with highest (lowest) value within a segment is considered a peak (trough). Later we will determine peaks and throughs by four different filters from the business cycles literature. Applying this definition, we observe peaks in 1976, 1986, 1993, 2009, and 2013. Troughs occur in 1970, 1981, 1990, 2004, 2010 and 2018. As observed from Diagram 4(b), the frequency and severity of the business cycles appear to follow a rather predictable pattern for the first 2/3 of the sample. From 1998 to 2004, petroleum investments experienced an unusually long and severe downturn. This recession was immediately followed by an unusually long and considerable upturn from 2004 to 2013 – interrupted only briefly in 2010.

The change in behaviour of the business cycles towards the final third of the sample period could be indicative of a structural break. If there is a lack of parameter stability, interaction effects for level and slope of the deterministic trend (τ_t) should be included to give a more accurate approximation of the business cycle (c_t). However, if there is no genuine structural break, the proposed modification could cause us to infer a spurious business cycle, which is known in the literature at the Nelson-Kang critique. Hence, we undertake structural break tests. Modelling the logarithmic return of investments as an autoregressive distributed lag (ADL) model, with a first order lag of the dependent variable and log-returns of crude oil price on the right-hand side, we find no evidence of a structural break. As this test is structured with a trimming the sample by 15 %, any potential structural break after 2012 cannot be captured.

Table 3: Structural break test

Test	statistic	p-value
Supremum Wald	4.5492	0.8572
Average Wald	1.7642	0.7720
Exponential Wald	1.1848	0.7273
Supremum likelihood-ratio	1.8383	1.0000
Average likelihood-ratio	0.637	1.0000
Exponential likelihood-ratio	0.3438	1.0000

Test statistics and p-values for various structural break tests with a null hypothesis of no structural break. The structural break test is applied with a rolling window scheme on the following regression equation: $\ln \Delta y_t = \beta_0 + \beta_1 \ln \Delta y_{t-1} + \beta_2 \ln \Delta x_{t-1} + \varepsilon_t$, where y_t denotes petroleum investment and x_t the Brent crude oil price. A trimming of 15 % was applied both at the beginning and at the end of the sample period.

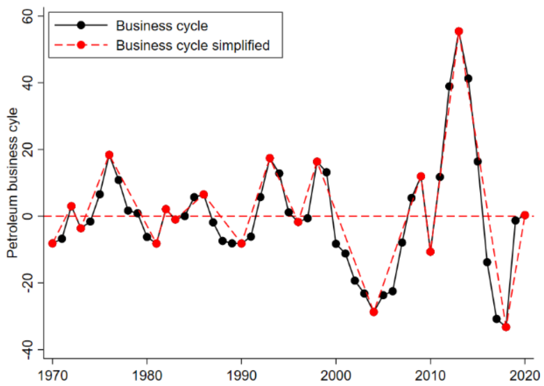
As noted previously, the choice of methodology depends on whether the nonstationarity of petroleum investment is caused by a deterministic or stochastic trend. If we are dealing with a stochastic trend, the former approach becomes inappropriate. Instead, a filter should be applied to investments to extract the business cycle. However, as demonstrated by the Yule-Slutsky effect, peculiarities of the filter could generate a spurious business cycle. Consequently, rather than relying on a single approach, we opt for applying several different techniques to ensure more robust results. Specifically, we utilize the Hodrick-Prescott (1997), Baxter-King (1999) band pass, Christiano-Fitzgerald (2003) and Butterworth (1930) filters. The Hodrick-Prescott approach is the most popular filter in the literature. The business filter is here obtained as the solution to the minimization problem shown in Equation (17).

$$\min_{\tau_t} \left[\sum_{t=1}^{T} (y_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1} \{(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})\}^2 \right] \tag{17}$$

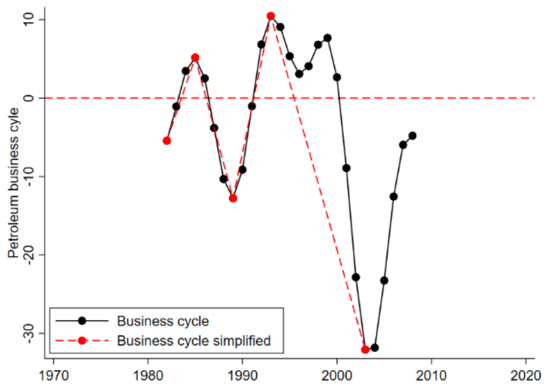
Figure 5 shows the obtained business cycle based on each of the four filters. Panel (a) displays the business cycle based on the Hodrick-Prescott filter. As observed, it appears to coincide predominantly with the business cycle obtained from assuming a deterministic trend. There are, however, some notable differences. For instance, under the paradigm of a deterministic trend, the two local maximums in 1993 and 1998 were contained within the same uninterrupted segment of observation exceeding zero. Hence, only one of these were declared a peak. Figure 5 depicts the business cycle based on the assumption of a stochastic trend, based on four different filters. When applying the Hodrick-Prescot filter, the local minimum in 1996 now falls below zero and both the 1993 and 1998 maxima are declared as peaks. Panel (d) with the Butterworth filter behaves in a similar manner compared to the business cycle obtained by a deterministic trend. Panel (b) shows the Baxter-King filter, which due to trimming does not extend past 2008. Based on the available data, however, the business cycle appears to be less erratic compare to the preceding filters. Finally, panel (c) shows the Christiano-Fitzgerald filter. Based on visual comparison, it appears to largely coincide with the Baxter-King filter. By virtue of being less erratic, most of the more ambiguous peaks and troughs are not identified when this filter is applied. In disagreement with the preceding filters, the Christiano-Fitzgerald filter does not regard the downturn in investments in 2010 as a recession.

Figure 5: Petroleum business cycle (1970-2020)

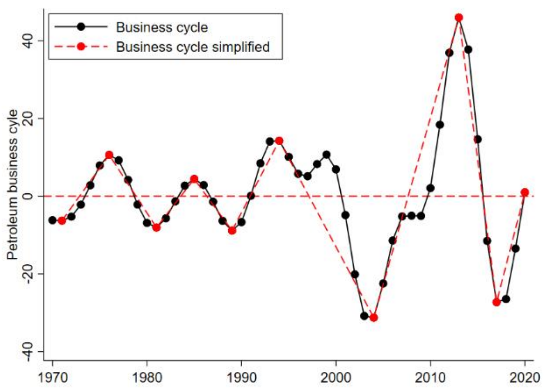
(a) Hodrick-Prescott



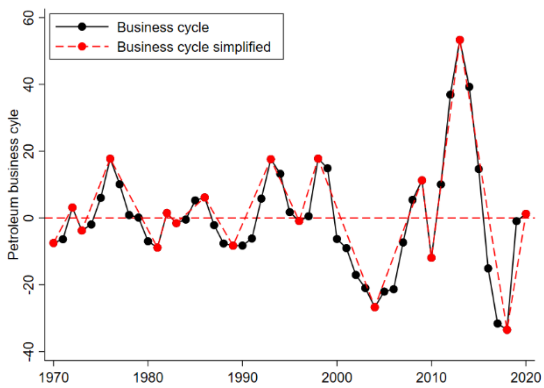
(b) Baxter-King



(c) Christiano–Fitzgerald



(d) Butterworth



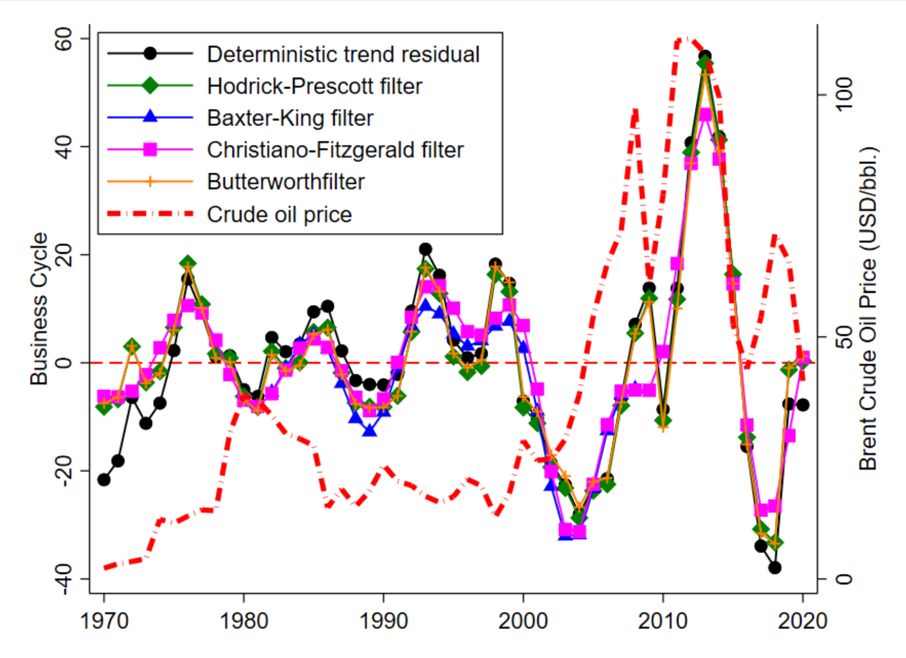
Business cycle estimated using four different types of filters.

In Figure 6, we present a joint plot of the business cycle determined by the four different filters based on the assumption of a stochastic trend. As shown, regardless of the methodology applied to obtain an estimate of the cyclical component ($\hat{c}_t$), i.e., the business cycle, all five approaches are predominantly coinciding. To confirm this, we apply the Johansen cointegration test – see Table 4. Excluding the Baxter-King filter due to its reduced sample range, we find evidence of four cointegrated equations, which lends support to the notion that these approaches are in agreement.

Table 4: Johansen test for cointegration

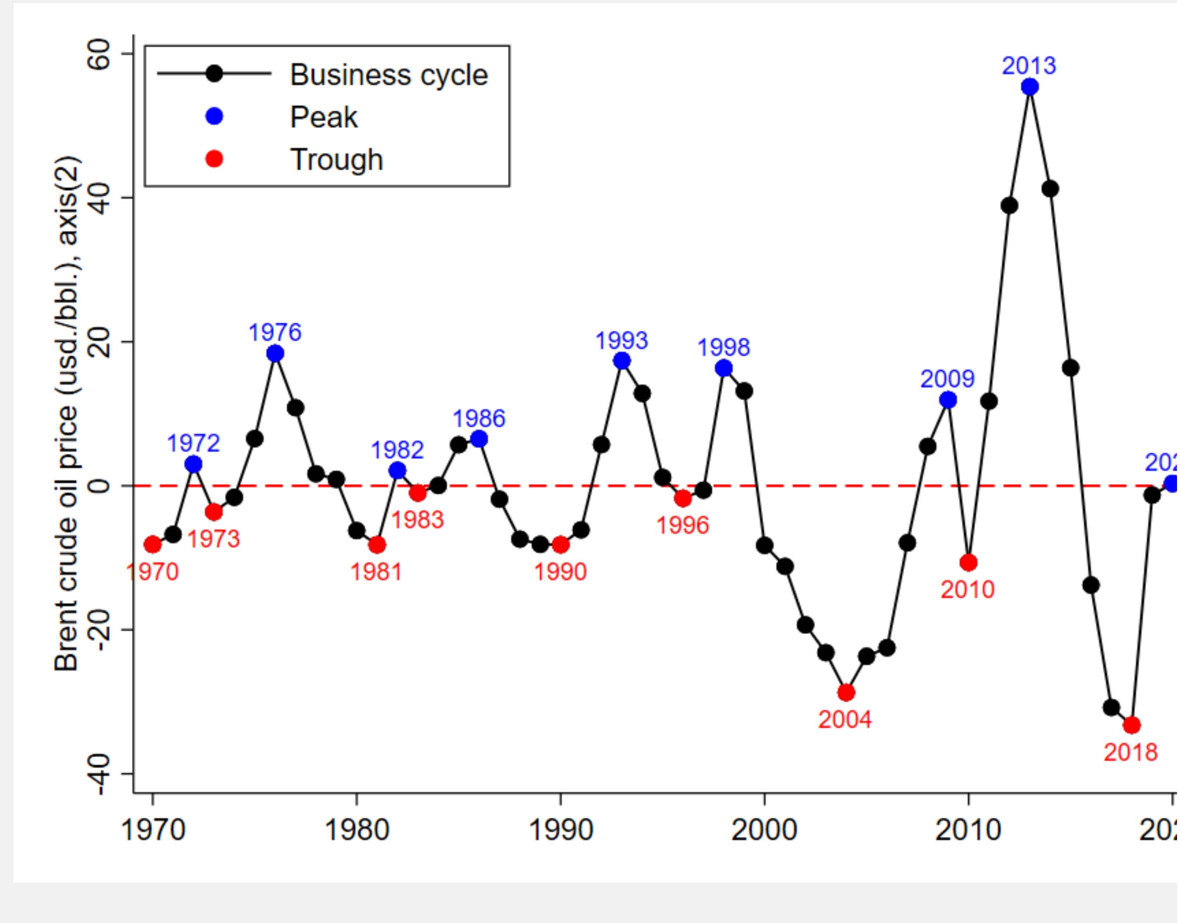
Maximum rank	Params	LL	Eigenvalue	trace statistics	5% critical value
0	20	-199.33829	.	541.4714	47.21
1	27	-37.616869	0.99776	218.0286	29.68
2	32	29.698894	0.92115	83.3971	15.41
3	35	66.18287	0.7476	10.4291	3.76
4	36	71.39742	0.17862		

Figure 6: Comparison of different business cycle measures



With all the approaches predominantly coinciding, it would be acceptable to choose one of the filters. If we were to make such a choice, it would be the Hodrick-Prescott filter which is the standard filter to use.

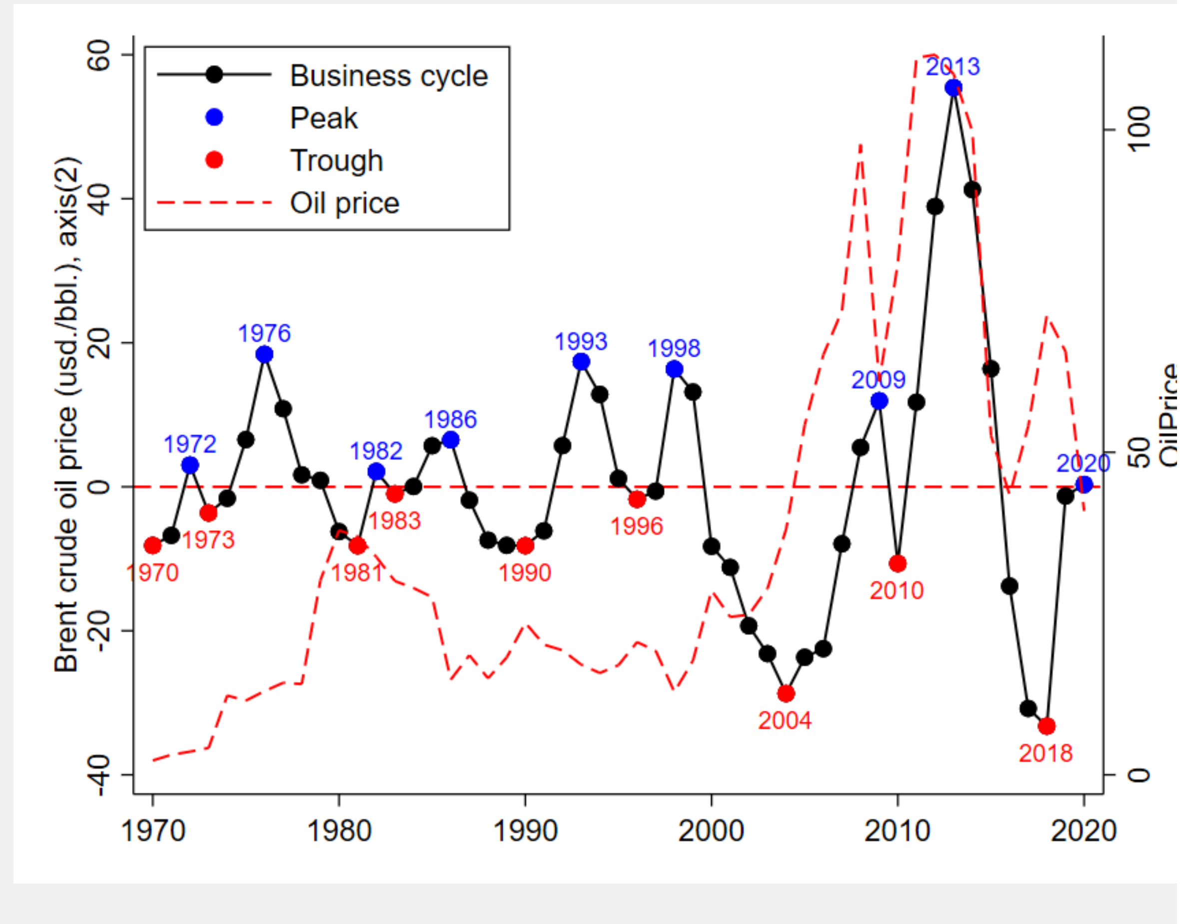
Figure 7: Business cycle in the Norwegian petroleum industry using Hodrick-Prescott filter



Petroleum business cycle (1970-2020), using the Hodrick-Prescott filter.

We use the results from the Hodrick-Prescott filter in our policy discussions. In Figure 8 we plot the business cycle together with Brent blend.

Figure 8: Business cycle in the Norwegian petroleum industry using Hodrick-Prescott filter



Shows the cyclical component for the aggregate, development investments in oil and gas projects on the Norwegian continental shelf between 1970 and 2020. The cyclical component was elucidated using the Hodrick-Prescott filter. The Brent crude oil price (usd./bbl.) is also included.

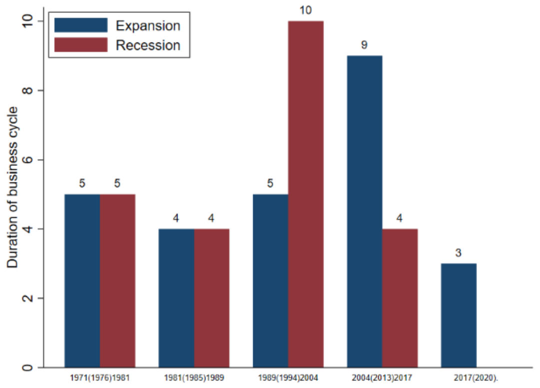
Not surprisingly, the diagram depicts a clear relation between the business cycle and the oil price. Cointegration tests on our sample confirm this. We find that aggregate investment on the NCS and the oil price are cointegrated. We also find that investment is cointegrated with a lagged oil price. The figure indicates that the fit is best with a lagged oil price from year 2000. (However, the sample is too small to test for subsamples.) This makes sense, with a more volatile oil price, oil companies wait to see if a price change appears to be more permanent.

4.2 Length of business cycle

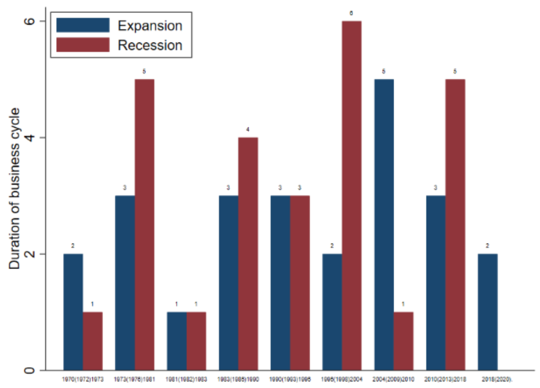
With the five proxies for the business cycle of the oil and gas investment on the NCS, we move on to provide summary statistics on the duration of the cycles (See Table 5 and Figure 9).

Figure 9: Bar plot for comparison of duration of expansion and subsequent recession

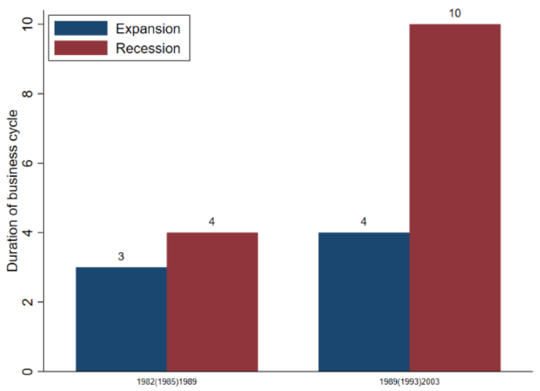
a) Deterministic trend



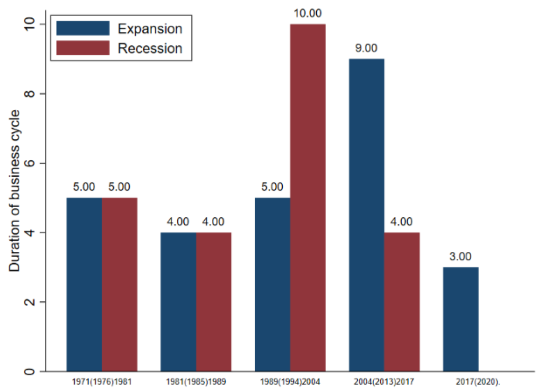
b) Hodrick-Prescott



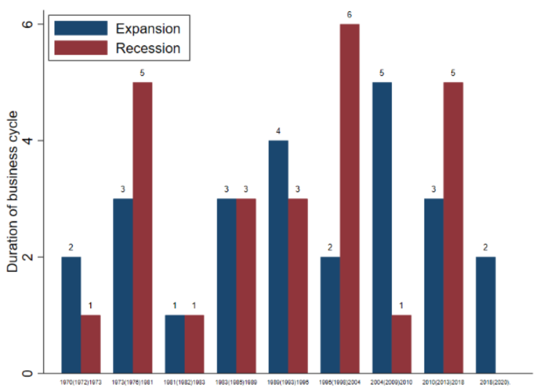
c) Baxter-King



d) Christiano-Fitzgerald



e) Butterworth



Bar plot for duration of business cycles. Blue bars denote expansions (trough to peak) and red bars signify recessions (peak to trough). Labels on x-axis provides years for troughs and peak. For instance, 1970(1976)1981 means that the expansion occurred during 1970 to 1976, where the former is a trough and the latter a peak, and that the subsequent recession lasted from 1976 to 1981.

Beginning with the business cycle based on the assumption of a deterministic trend, the average length of a recession (time between a peak and a subsequent trough) is 4.4 years with a standard deviation of 1.34. Shortest and longest recession lasted 3 and 6 years respectively. On the other hand, the duration of expansions (time between a trough and subsequent peak) range between 1 and 11 years with an average and standard deviation of 5.2 and 3.63 years, respectively. As for the length of a full cycle, either measured as the length between two subsequent peaks (P2P) or troughs (T2T), a business cycle is found to last around 9 years.

Interestingly, in regard to duration of the business cycles, we find some variation across the different proxies. While the deterministic trend approach finds an average length of 4.4 years for recessions, both for the Hodrick-Prescott and Butterworth filters we find a lower average, 2.67 and 2.78 years. For the Christiano-Fitzgerald filter, however, the average length of a recession is longer (5.2 years). Similar patterns are also found for expansions. Average expansions based on a deterministic trend is 5.2 years with a standard deviation of 3.63 years. The shortest expansion lasted for only 1 year while the longest lasted for 11 years. In other words, the typical expansion is longer than the typical recession. Expansions based on the assumption of a stochastic trend deviate somewhat from findings based on a deterministic trend. Based on the Baxter-King and Christiano-Fitzgerald filters, the average expansion is found to be longer, 7 and 5.75 years, respectively. For the Hodrick-Prescott and Butterworth filters, however, the average expansion is found to be shorter. Specifically, for the former, an average expansion lasts for 3.25 years and 3.13 years for the latter. Nevertheless, the finding that recessions tending to be shorter than expansions holds true regardless of approach. Additional statistics for the length of a whole business cycle, measured as peak-to-peak (P2P) and trough-to-trough (T2T) is also included in Table 5.

Table 5: Summary statistics for length of business cycles

	Mean	Std. Dev.	Skew.	Kurt.	Min	Max	N
Deterministic trend (1970-2020)							
Recession	4.40	1.34	-0.11	1.40	3	6	5
Expansion	5.20	3.63	0.70	2.59	1	11	5
P2P	9.25	5.12	0.43	1.85	4	16	4
T2T	9.60	3.05	0.36	2.00	6	14	5
Hodrick-Prescott filter (1970-2020)							
Recession	2.67	1.12	0.70	3.42	1	5	9
Expansion	3.25	2.05	-0.04	1.41	1	6	8
P2P	6.00	2.39	1.14	3.38	4	11	8
T2T	6.00	2.33	-0.80	2.14	2	8	8
Baxter-King filter (1982-2008)							
Recession	3.50	0.71	0.00	1.00	3	4	2
Expansion	7.00	4.24	0.00	1.00	4	10	2
P2P	8.00	.	.	.	8	8	1
T2T	10.50	4.95	0.00	1.00	7	14	2
Christiano-Fitzgerald filter (1970-2020)							
Recession	5.20	2.28	1.00	2.70	3	9	5
Expansion	5.75	2.87	1.07	2.25	4	10	4
P2P	11.00	5.42	1.05	2.26	7	19	4
T2T	11.50	3.11	0.00	1.48	8	15	4
Butterworth filter (1970-2020)							
Recession	2.78	1.20	0.44	2.54	1	5	9
Expansion	3.13	2.03	0.15	1.48	1	6	8
P2P	6.00	2.39	1.14	3.38	4	11	8
T2T	6.00	2.33	-0.80	2.14	2	8	8

Summary statistics for length of business cycles derived from five different methods. P2P is short for peak-to-peak. Analogously, T2T is trough-to-trough.

4.2 Severity of business cycle

Given these statistics, we turn to the question of whether the latest recession in the petroleum industry is considerably worse than previous crises. Regardless of approach, a peak was reached in 2013. For the filters, we find a peak in 2013 with a trough in 2018. The Christiano-Fitzgerald deviates somewhat by classifying 2017 as the trough. In other words, the latest recession was either 4 or 5 years, depending on the filter. The deterministic approach, however, as of 2020 still has a negative cyclical component. Hence, it is unclear if 2018 will be declared as trough for this approach or if investment will double dip. As elucidated by Table 5, the latest recession was shorter than the average recession according to the Christiano-Fitzgerald approach. For the remaining filters, on the other hand, the recession was longer than average. Assuming 2018 is the local minimum for the deterministic approach, the duration of the recession was on average.

While the recent crisis might not be worse in terms of duration compared to previous recessions, there is an argument to be made that it was more severe. To investigate this, we take a closer look at the relationship between the absolute change in the cyclical component during an expansion ($\Delta c_{t,Expansion}$) to the absolute change during the immediate recession ($\Delta c_{t,Recession}$). For instance, if a trough occurs in 1970 and the subsequent peak and trough occurs in 1976 and 1981 respectively, then:

$$\Delta c_{Expansion} = |c_{1976} - c_{1970}|$$
$$and \tag{18}$$
$$\Delta c_{Recession} = |c_{1981} - c_{1976}|.$$

In Figure 10, we show a bar plot for each pair of $\Delta c_{t,Expansion}$ and $\Delta c_{t,Recession}$ that constitute each business cycle. Regardless of the approach utilized to obtain the cyclical component, there are three noteworthy findings.

First, the severity of each business cycle tends to increase throughout the sample period. That is, the increase during expansions and decrease during recessions appear to become larger. Second, adhering to this pattern, the last recession (2013-2017/2018) was the most severe observed in the entire history of the petroleum industry on the NCS. However, the expansion preceding this recession, was also the largest to occur. Third, the size of $\Delta c_{t,Recession}$ appears to be related to the size of the preceding $\Delta c_{t,Expansion}$. In other words, the larger the expansion, the more sever the recession tends to be. To pursue this point further, in Figure 11 we show a scatterplot between each pair of $\Delta c_{t,Expansion}$ and $\Delta c_{t,Recession}$with an added regression line. The correlation coefficient (ρ) and the beta coefficient (β) obtained through OLS is reported in Table 6. As shown, depending on the methodology, the correlation ranges from 0.75 to 0.88 – excluding the correlation of 1 for the Baxter-King filter that has only two observations.

Inspecting the regression results, again with the exception of the Baxter-King filter, the coefficient is significant in all cases. For instance, take the coefficient from the deterministic trend approach, if the increase in the cyclical component from trough to peak during an expansion increases by one bn. NOK, then the reduction to the subsequent trough is expected to be 0.44 bn. NOK larger. Hence, the notion that the severity of the last recession is evidence of a permanent negative shock is brought into question. Based on the obtained results, an alternative interpretation is that the unusually severe recession is product of an unusually large expansion. Based on the presented analysis, definite answers cannot be provided, however, as we cannot convincingly claim causality or fulfilment of the population orthogonality condition – $\mathbb{E}[u|x] = 0$.

Table 6: Relationship between Δc_t from subsequent expansion and recession

Approach	$\boldsymbol{\rho}$	$\boldsymbol{\beta}$	**N**
Deterministic trend	0.7521	0.4418*	5
Hodrick-Prescott filter	0.8345	0.6129***	8
Baxter-King filter	1.0000	0.5136	2
Christiano-Fitzgerald filter	0.8803	1.0726*	4
Butterworth filter	0.8545	0.6229***	8

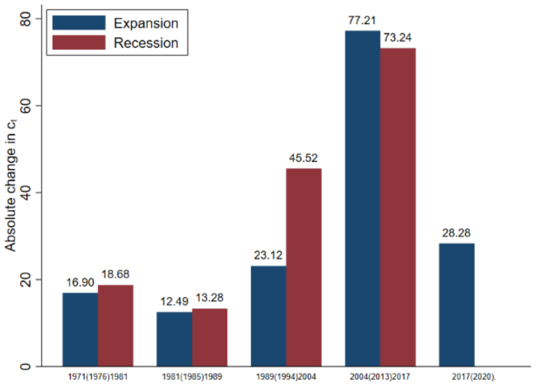
OLS β coefficient from regressing absolute change in cyclical component during expansion (trough to peak) on absolute change during subsequent recession:

$$\Delta c_{t,Expansion} = \beta_0 + \beta_1 \Delta c_{t,Recession} + \varepsilon_t$$

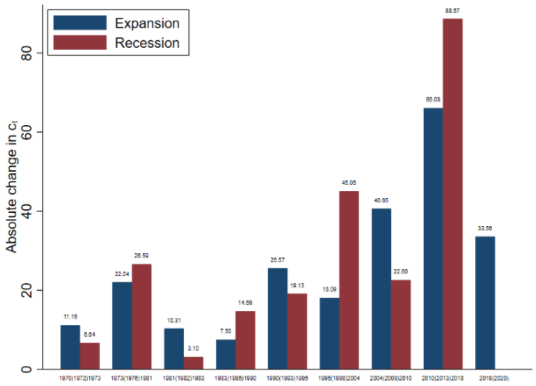
Asterisks denote a significance level of 10% (*), 5% (**) and 1% (***). Correlation coefficient between the dependent and independent variable is also reported.

Figure 10: Bar plot for change in cyclical component (Δc_t) throughout business cycle

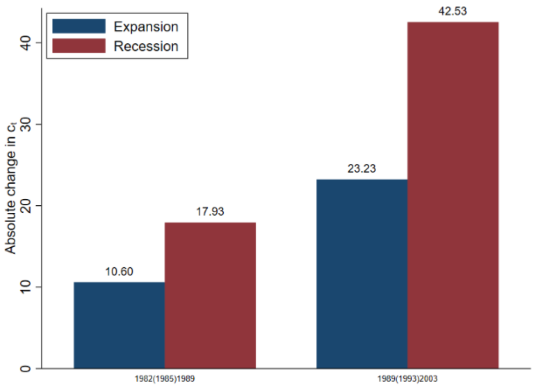
a) Deterministic trend



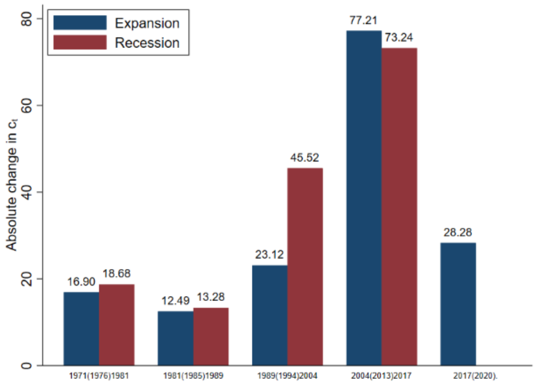
b) Hodrick-Prescott



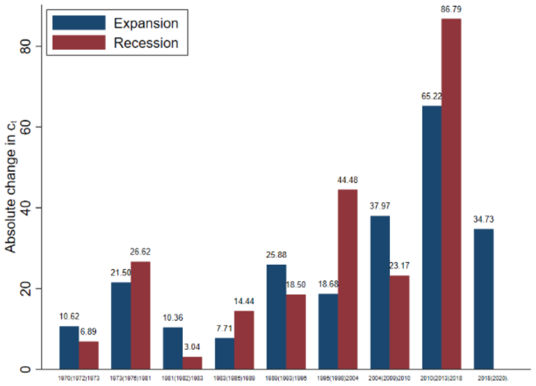
c) Baxter-King



d) Christiano-Fitzgerald



e) Butterworth

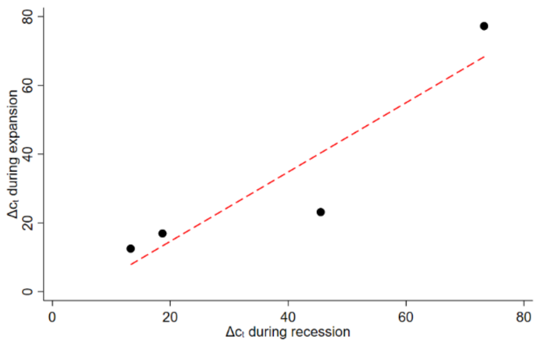


Bar plot for absolute change in cyclical component throughout each business cycle. Blue bars denote recessions (trough to peak) and red bars signify recessions (peak to trough). Labels on x-axis provides years for troughs and peaks. For instance, 1970(1976)1981 means that the expansion occurred during 1970 to 1976, where the former is a trough and the latter a peak, and that the subsequent recession lasted from 1976 to 1981.

The full cycle starting in 2010 and ending in 2018, has a duration that is on average. However, it exhibits the largest change in investment. The same applies if we look at the change in investment in the expansion and the recession separately. The change in investment is even higher if we define the start of the full cycle to be in 2004, since the 2009-downturn due to the Financial crisis only lasted for one year.

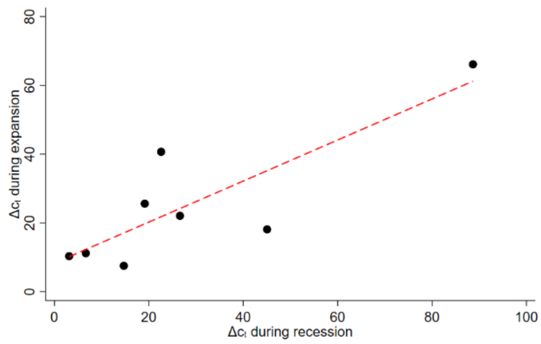
Figure 11: Scatterplot for Δc_t during consecutive expansion and recession

a) Deterministic trend



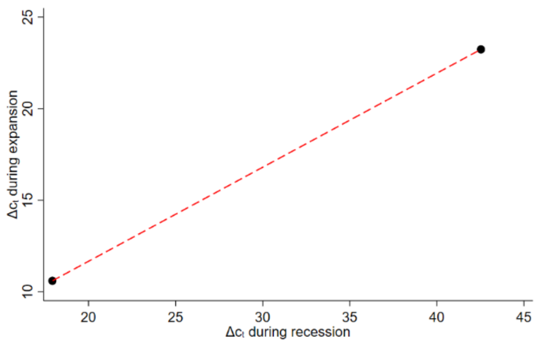
β = 1.01 (p-value = 0.05) N = 4.00
$\rho(\Delta c_{t,Expansion}, \Delta c_{t,Recession})$ = 0.92

b) Hodrick-Prescott



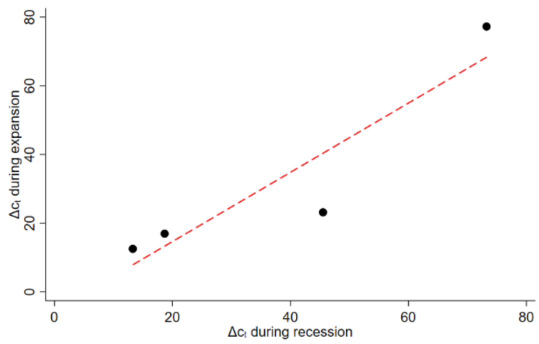
β = 0.60 (p-value = 0.00) N = 8.00
$\rho(\Delta c_{t,Expansion}, \Delta c_{t,Recession})$ = 0.84

c) Baxter-King



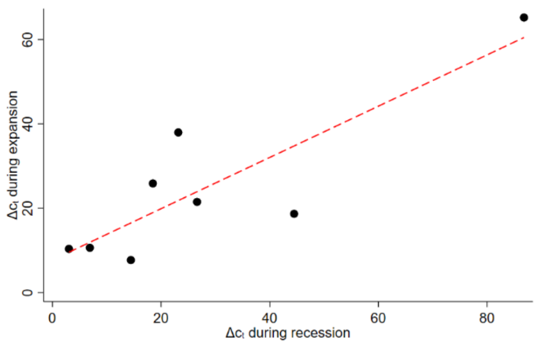
β = 0.51 (p-value = .) N = 2.00
$\rho(\Delta c_{t,Expansion}, \Delta c_{t,Recession})$ = 1.00

d) Christiano-Fitzgerald



β = 1.01 (p-value = 0.05) N = 4.00
$\rho(\Delta c_{t,Expansion}, \Delta c_{t,Recession})$ = 0.92

e) Butterworth



β = 0.61 (p-value = 0.00) N = 8.00
$\rho(\Delta c_{t,Expansion}, \Delta c_{t,Recession})$ = 0.86

Scatterplot between change in cyclical component ($\Delta c_{t,Expansion}$) during expansion (trough to peak) and the change ($\Delta c_{t,Recession}$) during the immediate recession (peak to trough). Red dashed line is the fitted OLS regression line. Coefficient from regression with corresponding p-value and correlation coefficient is also reported.

5.0 Conclusion

We have analysed the business cycle of oil and gas investment on the Norwegian continental shelf for the entire period of oil activity (1970-2020). As for the duration of the cycles, we find that they are typically in the range of 3 to 5 years for recessions and 3 to7 years for expansions. There was practically a nine-year boom from 2004 to 2013, which marks an outlier. There is no clear pattern that oil investment has become more cyclical over time when we only look at duration of cycles. However, we find that the severity of each business cycle tends to increase throughout the sample period. That is, the increase during expansions and decrease during recessions appear to become larger. Second, adhering to this pattern, the last recession (2014 -2017) was the most severe observed in the entire history of the petroleum industry on the NCS. However, the expansion preceding this recession, was also the largest to occur. We find that the size of a recession tends to be related to the size of the preceding expansion. The dramatic fall in investment starting in 2014 is thus explained as a combined response to a reduction in the steep oil price reduction and an unprecedented cost increase during the long and large expansion leading up to the recession. The findings support the hypothesis that this is not a permanent shock, but a dramatic business cycle. Investment on the NCS started increasing again in 2017 and was back to mid-cycle level by 2019. Costs were down and the oil price increased. In March 2020, however, the industry was once again hit hard, this time by a combination of the COVID-19 pandemic and oil price war.

The demanding situation in the Norwegian petroleum industry facing COVID-19 is unparalleled. The upswing that culminated in 2013 was twice the regular length of a boom cycle, resulting in dramatic cost growth and debt build-up. The decline was abrupt and hard. After only a couple of years of boom, before the industry had recovered, it was hit by another tough crisis in 2020.

The oil companies and the supplier industry are affected differently. The oil companies are set up to withstand this type of fluctuation. They usually operate with high margins, a relatively low debt ratio, and handle the problems associated with declining cash flow by stopping activities that can be cancelled or postponed. The supplier industry typically has low margins, higher debt and less flexibility, and was much more exposed to what looked like a potential doble-dip, starting in 2020. The extensive division of labour between oil companies and suppliers (Sasson and Blomgren, 2011) means that the brunt of activity reduction is borne by the suppliers. The supplier industry consists of both labour- and capital-intensive segments (Blomgren and Quale, 2019) and the effects of activity reduction will vary accordingly. The labour-intensive parts of the supplier industry handle downturns through immediate reductions in use of hired personnel and/or furloughing or downsizing of own personnel. The capital-intensive parts of the supplier industry, e.g., the important rig and shipping companies, have high levels of debt and thus less flexibility in these situations. When the COVID-19 crisis and the oil price war struck, the capital-intensive suppliers had not yet recovered from the 2014-2017 crisis. A large part of the contracts of oil services are on contracts with medium to long term duration, with limited cost escalation, so at the initial phase of the upturn contracts still were at low rates. In addition, overcapacity made an immediate raise in rates unlikely.

If the crisis were to persist, there would be a short-term rise in unemployment from activity reductions among the labour-intensive suppliers and the possible closure of many of the capital-intensive suppliers. It would also present future capacity challenges as many specialized companies are part of integrated supply chains. Closures, loss of skills and bottlenecks would make it difficult to rebuild once the oil price increased again. We would see cost growth, a decline in quality and a lower Norwegian share of deliveries to the NCS.

The business cycle in the petroleum industry became a key topic in the Norwegian Parliament. It took the position that in this particular situation much was to be gained in limiting the decline of the supplier industry. The remedy enacted was a temporary change in petroleum taxation. The underlying assumption was that this is a temporary crisis; oil demand picks up again when the pandemic is defeated, and the oil war comes to an end. Expected oil prices were downgraded but were still well above breakeven costs on the Norwegian shelf. To understand why this situation still became a crisis, it is important to understand how some decisions depend on future oil prices, while others depend on the current price. Due to lead times in the industry - from project development and sanctioning it takes several years before production. The average lead time on the NCS is 3.3 years, see Lorentzen et. al. (2017). Thus, it is not the current oil price that is relevant for investment decisions. However, the problem was that companies were capital rationing since their cash flow relied on the current oil price. Projects were not approved even if they were considered profitable in net present value terms. In addition, the planning of future projects stopped or slowed down. Combined with the fact that some large development projects were near completion, this meant that the NCS could soon see a new and long-lasting downturn that significant parts of the supplier industry not could withstand.

Temporary changes were made in tax depreciations so that tax payments were deferred. With prevailing price expectations, many oil companies on the Norwegian shelf would fall out of tax position. An increase in liquidity was therefore conditional on the companies receiving the tax balance even if they were not in a tax position. The combination of tax deferrals and refund of negative tax balances caused a significant improvement in the liquidity of the oil companies, resulting in less capital rationing. Earlier tax depreciations also had the effect of reducing the breakeven prices, making it easier to sanction projects. The state will receive its tax revenue, but a few years later.

The state here acts counter-cyclically and will be able to profit from the realization of profitable projects, by reducing unemployment and maintaining the capacity of the supplier industry. They succeeded in reducing the immediate cutbacks in the supplier industry and in accelerating development projects on the NCS, thus maintaining economic activity and employment at a time when other industries struggled under COVID-19. By maintaining capacity, mass unemployment was avoided. The same applied to cost increases when the oil market recovers, as supplier capacity was maintained.

Under normal circumstances, counter-cyclical measures are not to be recommended. Boom periods inevitably generate cost increases that need to be dealt with, and periodical downturns are needed for capacity adjustments and cost cuts. If governments intervene to reduce a normal downturn, they may also reduce necessary adjustments and thus only postpone the problem. Often, government would also act too slowly. Measures are enacted too late and they may actually end up reinforcing cyclicality by adding new investment in a boom cycle. This particular situation was different. Cost were already dramatically cut in the steep 2014-2017 recession, and the industry was ready for a normal upturn. This was stopped in 2020 by a powerful combination of COVID-19 and a price war for oil. This setback was extraordinary and not a regular cyclical pattern. The Norwegian Parliament also reacted very quickly, so the tax package had correct timing. There is still the danger that investment may become too high in the coming few years. Limitations on the duration of the tax package and limits on the number of projects that are sufficiently mature to be sanctioned, suggested that this would not pose a problem. However, with petroleum industry business cycles you never know, so this remains to be seen.

The temporary tax package seems to have succeeded in generating new activity. A number of development projects that was delayed are now set to be sanctioned. Increased activity reduces the payment of unemployment benefit. The net fiscal effect, however, is negative in the short run. The tax deferrals are large. The Government will recoup these funds later as higher tax depreciations today means lower depreciations and thereby higher tax payments in a few years. Norway was able to undertake this policy due to its large Petroleum wealth fund. The fund also reduces the fiscal impact of cyclicality in the petroleum industry, by isolating the fiscal budget from fluctuations in government take, as the petroleum revenue used in the budget does not come from the current activity but is taken from the fund.

Although we cannot rule out that climate risk played a role, our findings are that the dramatic downturn in Norwegian petroleum investment after 2014 is consistent with the traditional business cycle pattern of increasing cost in the boom cycle, and tight capital rationing and lead times in projects delaying the upturn when the oil price began to increase

again. By decisive and adequate response, the Norwegian parliament seems to have stopped a double-dip emerging from the 2020 combined COVID-19 and price war crisis.

Cyclicality is an essential although sometimes ignored element to understand the petroleum industry. Thus, our analysis sheds some light on how to analyse this industry. It is important to bear in mind cyclicality in all economic analysis related to the oil industry. For instance, if return on capital in the petroleum industry is to be compared to returns in other industries, a selective choice of period of analysis may determine the outcome; see Emhjellen and Osmundsen (2020). If you want the petroleum industry to look unprofitable, you choose return observations from a downcycle. Would it like it to look robust and profitable, choose data from a boom cycle. Only by using data from one or several full cycles, will you get a correct answer.

The cyclicality of petroleum investment is to a large degree driven by the oil price, often with a lag. The risk for investors in oil companies, however, is reduced by a corresponding cyclicality in cost, also this with a lag. For instance, when the oil price goes down, we see cost reductions in terms of lower rig rates, higher drilling speed, and lower cost overruns. This dampens the negative effect on capital return. Inversely, the increase in capital return when the oil price increases is dampened by an increase in cost.

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