Low oil investments and emergence of climate risk: the end is now or just business cycle as usual?

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Abstract
In this paper, we analyse the business cycle of aggregate oil and gas investments on the Norwegian continental shelf (NCS). Investments declined from 2013 to 2017. Two competing hypotheses emerged in the literature: 1)the downturn in investments is transitory and part of the cyclical nature of the business. or 2) the downturn is a permanent shock caused by the emergence of climate risk. As a step towards providing clarity to this issue, we apply various techniques to extract the business cycle of the NCS petroleum investments. We find that the recent recession was not more severe in terms of duration compared to previous crisis, but the decline in investments from peak to trough was more extreme than anything observed previously throughout the history of the Norwegian petroleum industry. The business cycle follows the dramatic change in the oil price in recent years. Additionally, we find that the size of an expansion has a significant empirical effect on the subsequent recession, and that the downturns last shorter than the upturns.

1. Introduction and background

The oil and gas industry experienced an unprecedently long, booming business cycle lasting for roughly a decade, almost double the duration of a regular boom period. This came to an end when oil prices fell markedly from 2014. While the oil price has begun its recovery, investment in development projects on the Norwegian Continental Shelf (NCS) 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 are holding investments back. This leads us to the following question: have Norwegian petroleum investments experienced a permanent negative shock from the emergence of climate risk, or is the market just going through a longer than usual business cycle? As part of providing an answer to this question, it is first necessary to provide a clearer picture of the characteristics of the business cycle throughout the 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.

To further elaborate on the two hypotheses; in the face of the empirical observations, conjectures of the oil adventure 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, Poudineh and West (2019) argue that climate risk, especially through the channel of regulatory risk causing an energy transition, has caused a significant increase in oil companies' discount rates. Consequently, aggregate investment will decrease. Reduction in investments is further argued to cause the value of oil and gas companies to plummet which might again trigger wide-spread economic downturn through contagion and the collapse of the petroleum service industry. A self-reinforcing cycle is argued, 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 investments. 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 latter 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 of 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.

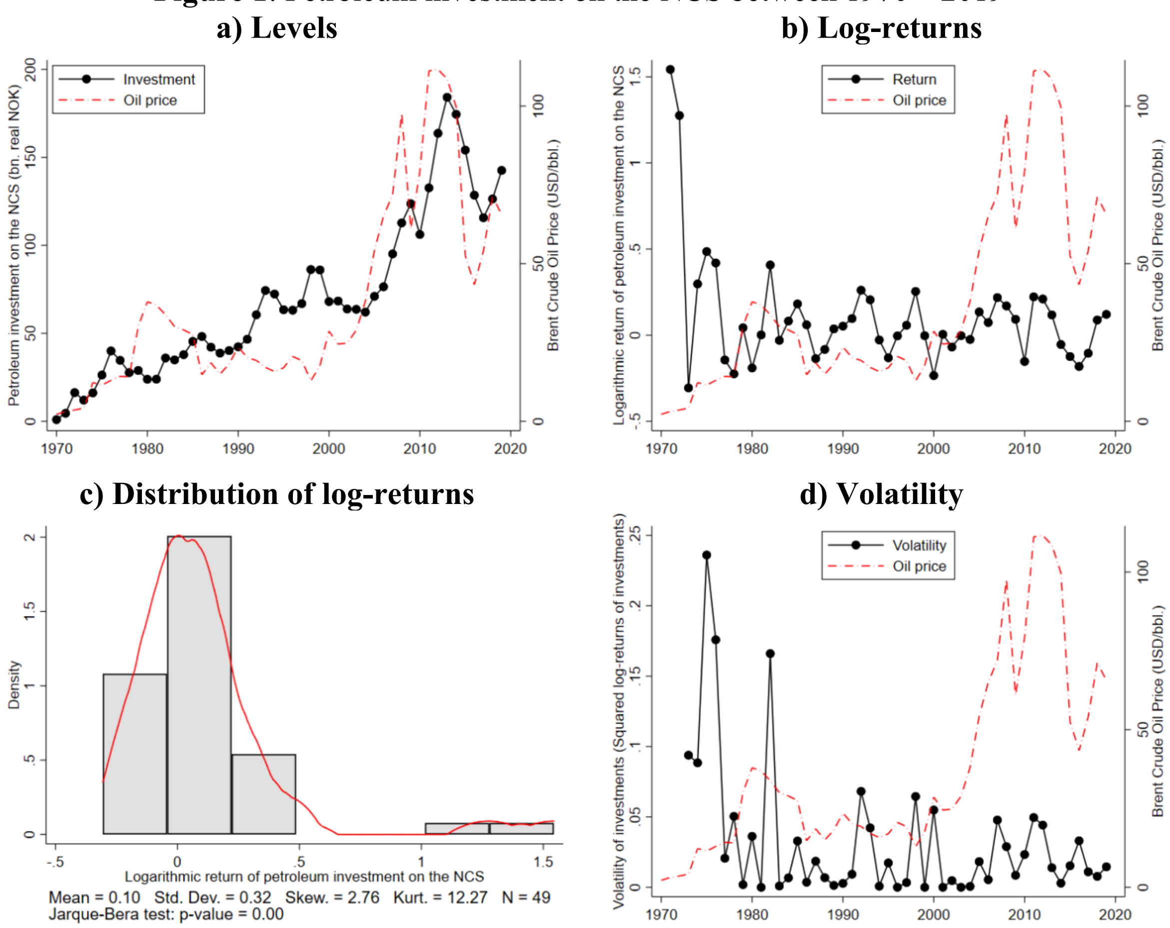
Looking at the second hypothesis. The relationship between petroleum companies' decision-making and level of debt has become a popular topic (Domanski et al.,2015; Gilje et al.,2017; Lehn and Zhu, 2016; Lips, 2018). Lehn and Zhu, for instance, investigate the effect of debt on the level of investments in the U.S. oil industry. They find that investment is inversely related to debt. In the ten-year booming cycle cost levels were increasing steeply. When combined with a steep reduction in the oil price, many companies experienced a negative cash flow. They were reluctant to cut dividends, so debt levels were increasing fast. The first priority after the cash flow again picked up has been to service stockholders and to reduce debt that had moved above critical levels. Balance sheets were to be improved before embarking on substantial investments. Oil companies got scared from experiencing a negative cash flow. As a result, global reserve replace rate has been record low. We now finally see signs that investments are picking up globally and that major oil companies enter into large long-term projects in deep water and LNG. An increase in the investment level will, if it does take place, undermine the hypothesis that the downturn in investments was due to climate risk.

For the remainder of this paper, we turn to the issue of analysing the business cycle of the oil and gas investments on the NCS. In Section 2, we present the data and provide descriptive statistics. One of the main goals here is to find the statistical properties of investments in order to determine the best approach to extract the business cycle. In Section 3, we present the obtained business cycle and describe its characteristics. Finally, in Section 4 we outline the methodology for further analysis aimed at investigating the two competing hypothesis. Section 5 concludes.

2. 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 2019. The inflation-adjusted investments are shown in Figure 1. The first hydrocarbon deposits of economic significant size, the Ekofisk field, was discovered in 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 the 2000. After a decline in annual development investments from 1999 to 2004, investments surged to levels never seen before. With the exception of a temporary setback in 2010, petroleum investment increased rapidly from 2004 to 2013. During this decade long boom, investments increased from 62 bn. NOK to 184 bn. NOK adjusted for inflation. Following the sharp decrease in oil prices from 2014, investments plummeted from its all-time high in 2013 to 115 bn. NOK in 2017. Oil and gas investments have since slowly begun to recover. In 2018, the declining trend was reversed as annual investment increased to 126 bn. NOK. Numbers for 2019 are at the time of writing tentative. Current estimates from the Norwegian Petroleum Directorate suggests an increase to 143 bn. NOK.

Figure 1: Petroleum investment on the NCS between 1970 – 2019



Data source: Norwegian Petroleum Directorate and Thomson Reuter Eikon. Panel (a) and (b) show petroleum investments (real bn. NOK) on the NCS between 1970 and 2019 in levels and logarithmic difference, respectively, plotted against Brent crude oil price (USD/bbl.). Distribution of log-returns, proxied through a histogram and Epanechnikov kernel density plot, with summary statistics is shown in panel (c). Panel (d) shows the volatility, proxied as the squared log-returns of investments.

Additional information regarding investments on the NCS can be found in Figure 1. Panel (a) shows the temporal development of the investments plotted against the Brent crude oil price (USD/bbl.). Analogously, panel (b) shows the development in the logarithmic returns of petroleum investments. In panel (c), the statistical distribution of the log-returns with additional summary and descriptive statistics are shown. Finally, panel (d) shows the volatility of investment. Volatility is here proxied as the squared log-returns of investments.

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. 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. If a variable y_t is stationary, it could be presented as an infinite moving average of past innovation terms. See Equation (1).

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

In the case of the presence of a deterministic trend, Equation (1) would change to include an expression of t the time index t – see Equation (2). 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.

$$y_t = \delta + \alpha_t + \theta(L)\varepsilon_t \tag{2}$$

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 (3), where the mean and variance would be $\mathbb{E}[y_t] = y_0$ and $var(y_t) = \sigma^2 t$ respectively.

$$y_t = y_{t-1} + \varepsilon_t \tag{3}$$

Various tests are avaiable for testing for stationarity. We apply four different test to obtain more robust results. Specifically, we look at the 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 (4). 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.

$$\Delta y_t = \alpha + \beta y_{t-1} + \delta t + \sum_{j=1}^{k} \zeta_j \Delta y_{t-j} + e_t \tag{4}$$

Analogously, the regression model for the Phillips-Perron test is given in Equation (5). If the ρ is not significantly less than one, then the time series y_t is deemed to be nonstationary.

$$y_\mathrm{t} = \alpha + \rho y_{t-1} + \delta t + u_t \tag{5}$$

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 of the 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. The null hypothesis is, however, 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 test

Variable	**No trend**				**Trend**			
	ADF	**DF-GLS**	**PP**	**KPSS**	**ADF**	**DF-GLS**	**PP**	**KPSS**
Investment	-1.17	-0.331	-0.98	2.19***	-3.65**	-3.438**	-2.57	2.19***
lnΔInvestment	-9.90***	-0.785	-7.01***	0.44*	-9.76***	-2.104	-6.69***	0.44***

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.

3. Analysis of business cycle

Based on the petroleum investment on the NCS, as shown in Figure 1, we attempt to extract the business cycle. Various approaches are available. One important aspect in regards 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 adopted 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 (6).

$$y_t = \tau_t + c_t \tag{6}$$

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). There is no obvious specification of τ_t, consider several alternatives:

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

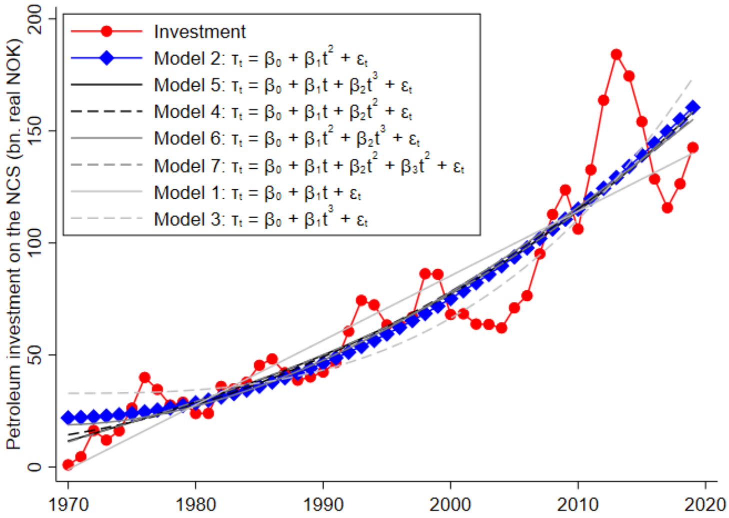
Figure 2 plots the oil and gas investments against the predicted regression line ($\hat{\tau}_t$) for each of the suggested models. Visual inspecting does not reveal an immediate best model specification. We therefore apply more rigorous testing. The optimal specification of τ_t, in terms of trade-off between model fit and parsimony, can be determined through applying information criteria. We consider three different criteria: Akaike, Hannan-Quinn and Schwarz's Bayesian – see Equations (7) – (9). As shown in Table 2, regardless of the choice of information criterion, model 2 is deemed the optimal model – which contains a constant term and a squared term of the time index.

$$\text{AIC} = -2\ln(L) + 2\text{k} \tag{7}$$

$$\text{BIC} = -2\ln(L) + k\ln(N) \tag{8}$$

$$\text{HQIC} = -2\ln(L) + 2k\ln(\ln(n)) \tag{9}$$

Figure 2: Petroleum investment and different 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

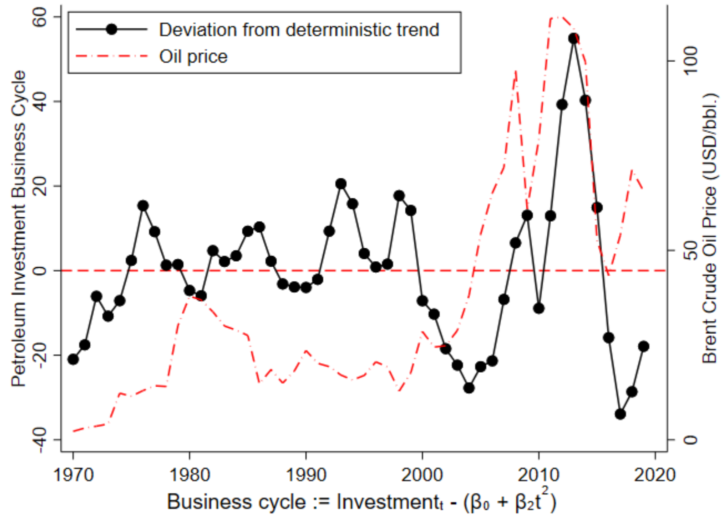
Specification	**AIC**	**HQIC**	**BIC**
Model 1	438.30	439.76	442.13
Model 2	431.45*	432.91*	435.28*
Model 3	443.21	444.67	447.04
Model 4	431.86	434.05	437.60
Model 5	431.54	433.73	437.28
Model 6	432.57	434.75	438.31
Model 7	433.54	436.45	441.19

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 innovation term of model 2. See Equation (10). Applying the described methodology, we obtain an estimation of the business cycle as shown in Figure 3.

$$\begin{gathered}\hat{\tau}_t = \hat{\beta}_0 + \hat{\beta}_1 t^2 + \hat{u} \\ \hat{c} \equiv \hat{u}_t = y_t - \hat{\tau}_t = y_t - \left(\hat{\beta}_0 + \hat{\beta}_1 t^2\right)\end{gathered} \tag{10}$$

Figure 3: Business cycle based on a deterministic trend component



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 maximums 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_{1984}, as seen in Figure 3. Arguably, 1982 should not be considered a business cycle peak. By the former definition both 1982 and 1984 would be considered as peaks, but under the latter definition only 1984 is. 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 achieve through visual inspection and qualitative reasoning.

Depending on preferences, either of the definitions could be feasible, we choose however to rely on the latter, i.e. only the observation with highest (lowest) value within a segment is considered a peak (trough). Applying this particular definition, we observe peaks in 1976, 1981, 1986, 1990, 1993, 2004, 2009, 2010 and 2013. Troughs occur in 1970, 1981, 1990, 2004, 2010 and 2017. As observed, the frequency and severity of the business cycles appears 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 also 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. 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 R.H.S, we find no evidence of a structural break. As the test is applied after trimming the sample with 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

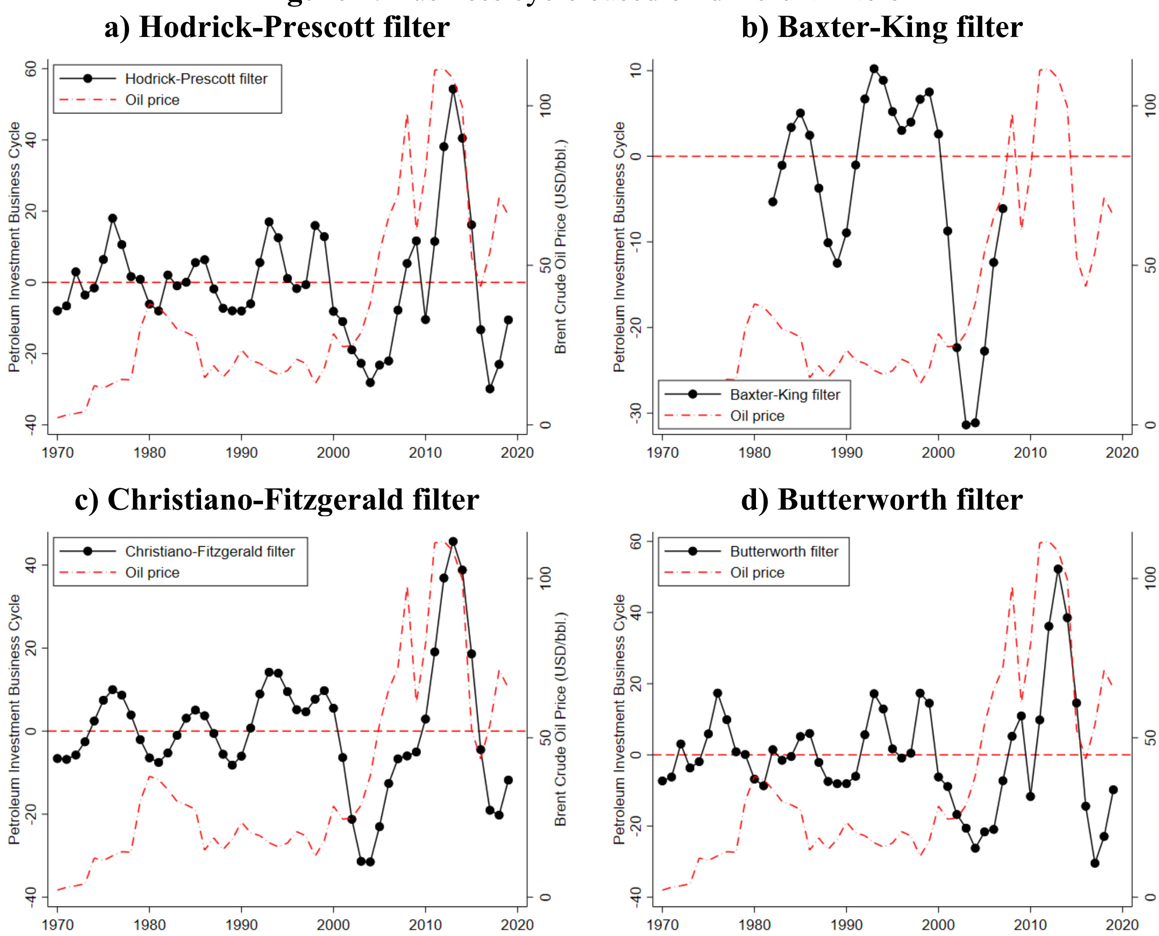
Test statistics and p-values for various structural break test with a null hypothesis of no structural break. The structural break test is applied with a rolling window scheme on the following regression equation: $\ln \Delta y_t = \beta_0 + \beta_1 \ln \Delta y_{t-1} + \beta_2 \ln \Delta x_{t-1} + \varepsilon_t$, where y_t denotes the petroleum investments 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 the petroleum investments is caused by a deterministic or stochastic trend. If we are dealing with a stochastic trend, the previous approach becomes inappropriate. Instead, a filter should be applied to the investments to extract the business cycle. However, as demonstrated by the Yule-Slutsky effect, peculiarities of the filter could generate a spurious business cycle when there is none. Consequently, rather than relying on a single approach, we opt for applying several different techniques in order 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 (11).

$$\min_{\tau_t} \left[\sum_{t=1}^{T} (y_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1} \{(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})\}^2 \right] \tag{11}$$

Figure 4 shows the obtained business cycle based on each of the above-mentioned four filters. Panel (a) displays the business cycle based on 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. When applying the Hodrick-Presscot 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 2007. 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 troughs are not present 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 4: Business cycle based on different filters

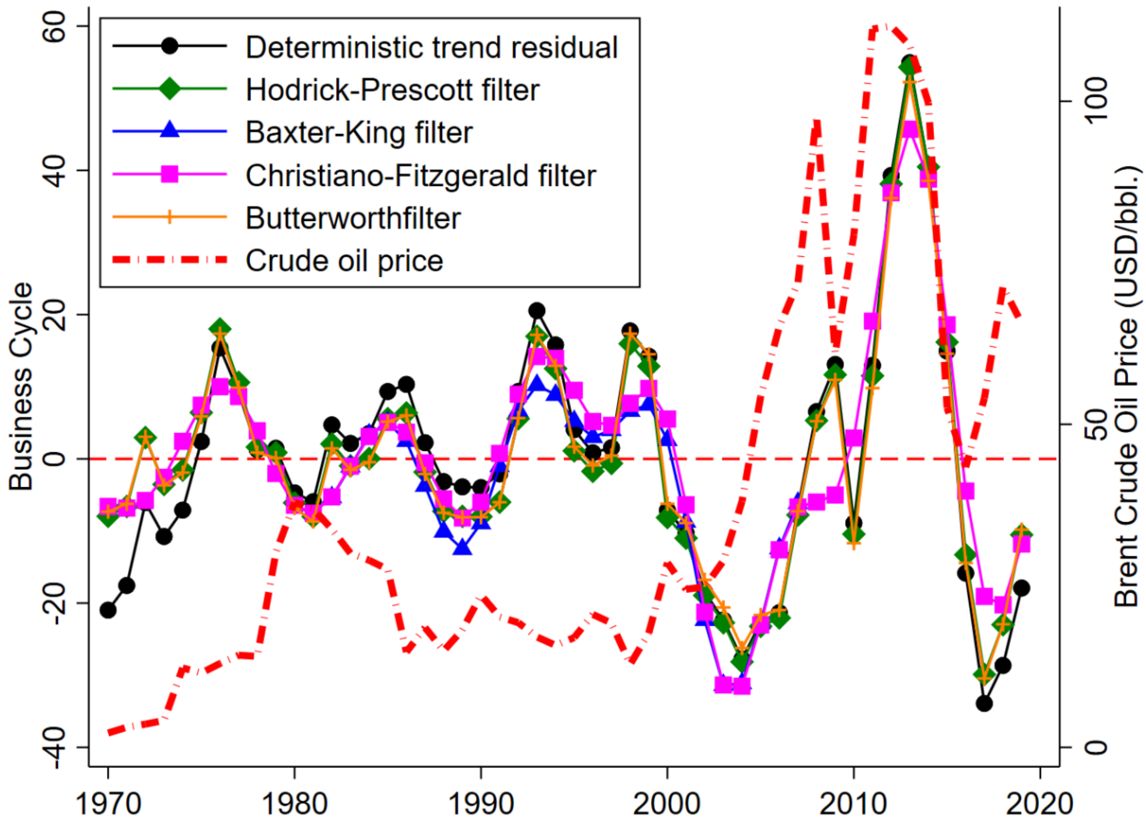


In Figure 5, we plot the business cycle based on the assumption of deterministic trend against the four different filters, which are based on the assumption of a stochastic trend. As shown, regardless of the methodology applied to obtain an estimate of the cyclical component ($\hat{c}_t$), i.e. the business 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 three 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	-148.47549	.	565.9875	47.21
1	27	19.507157	0.99909	230.0222	29.68
2	32	106.4821	0.97332	56.0723	15.41
3	35	134.51818	0.68906	0.0001*	3.76
4	36	134.51825	0		

Figure 5: Comparison of different business cycle measures



With the five proxies for the business cycle of the oil and gas investments on the NCS, we move on to provide summary statistics on the duration of the cycles (See Table 5). Beginning of the business cycle is derived 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 1.37. Shortest and longest recession lasted 3 and 6 years respectively. On the other hand, the duration expansions (time between a trough and subsequent peak) range between 1 and 11 years with an average and standard deviation of 5 and 3.67 years respectively. In regards to 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 regards 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 reaccessions, both for the Hodrick-Prescott and Butterworth we find a lower average – 3.5 and 2.88 years. For the Christiano-Fitzgerald filter, however, the average length of a recession is longer (5.5 years). Similar patterns are also found for expansions. Average expansions, based on a deterministic trend, is 5 years with a standard deviation of 3.67 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 6.25 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 3.13 years and 3 years for the latter. Nevertheless, the finding of 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 (1970-2019)			
Recession	4.40	1.34	-0.11	1.40	3	6	5
Expansion	5.00	3.67	0.85	2.66	1	11	5
P2P	9.25	5.12	0.43	1.85	4	16	4
T2T	9.40	3.21	0.41	1.83	6	14	5
				Hodrick-Prescott filter (1970-2019)			
Recession	2.75	1.16	0.51	3.16	1	5	8
Expansion	3.13	1.96	0.06	1.58	1	6	8
P2P	5.86	2.54	1.29	3.42	4	11	7
T2T	5.88	2.23	-0.82	2.22	2	8	8
				Baxter-King filter (1982-2007)			
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 (1970-2019)			
Recession	5.50	2.38	1.03	2.22	4	9	4
Expansion	6.25	3.20	1.08	2.28	4	11	4
P2P	12.33	6.66	0.69	1.50	8	20	3
T2T	11.75	3.30	-0.13	1.28	8	15	4
				Butterworth filter (1970-2019)			
Recession	2.88	1.25	0.24	2.40	1	5	8
Expansion	3.00	1.93	0.26	1.73	1	6	8
P2P	5.86	2.54	1.29	3.42	4	11	7
T2T	5.88	2.23	-0.82	2.22	2	8	8

Given these statistics, we turn to the question of whether the latest recession in the petroleum industry is particularly worse than the previous crisis. Regardless of approach, a peak was reached in 2013. As observed, the cyclical component was decreasing until 2017, where a local minimum was reached. Based on the available data, 2017 is regarded as a trough. Depending on what happens in the future beyond 2019, this might be changed. If the cyclical component does not continue to increase until exceeding zero and rather experience a double-dip recession, 2017 will be reclassified. Nevertheless, tentatively accepting the classification of 2017 as a trough, the recession lasted 4 years. As elucidated in Table 5, this recession was shorter in duration based on the deterministic trend and Christiano-Fitzgerald approach, but longer compared to Hodrick-Prescott, Baxter-King and Butterworth. In neither of the cases was the 2013-2017 recession deemed the longest recession. That honour goes to the recession ending in 2014. If 2017 truly was the end of the recession, then all things considered, it was a fairly typical downturn in terms of duration.

Returning to the issue of the status of 2017, the forecasts from the Norwegian Petroleum Directorate suggest a decrease in aggregate investments in 2020 compared to tentative numbers for 2019. On the contrary, more recent numbers from Statistics Norway are not as pessimistic. Assuming that investments do indeed decline in 2020, if the downturn is sufficiently severe, the recession starting in 2013 would become the longest based on all approaches with the exception of the Christiano-Fitzgerald filter. Whether the prediction will come true remains to be seen. Historically, the forecast accuracy of the official forecasts for aggregate petroleum investments reported in the National Budget is poor (Osmundsen and Lorentzen, 2017). A pseudo (ex post) out-of-sample forecast evaluation of the one year-ahead forecast shows that the National Budget performs significantly worse than predicting no change every year based on various statistical loss functions. For instance, the National Budget correctly predicts the direction of the investment growth 50 % of the time, which is as accurate as a coin flip. Hence, for the purpose of characterizing business cycles, the forecasts are of limited use.

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:

$$\begin{gathered} \Delta c_{Expansion} = |c_{1976} - c_{1970}| \\ and \\ \Delta c_{Recession} = |c_{1981} - c_{1976}|. \end{gathered} \tag{12}$$

In Figure 6, 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) 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 7 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 obtained through OLS is reported in Table 6. As shown, depending of the methodology, the correlation ranges from 0.75 to 0.85 – excluding the correlation of one 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. Definite answers cannot be provided, however, based on the presented analysis 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

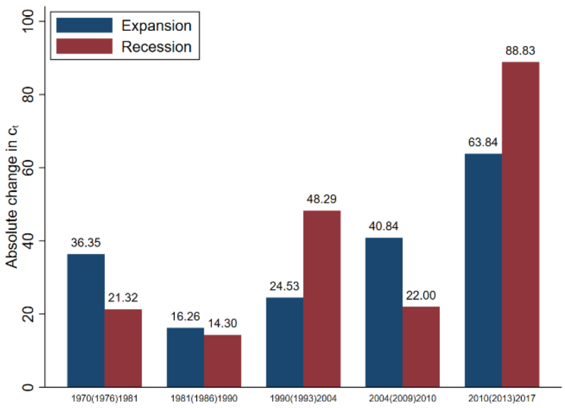
OLS β coefficient from regressing absolute change in cyclical component during expansion (trough to peak) on absolute change during subsequent recession:

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

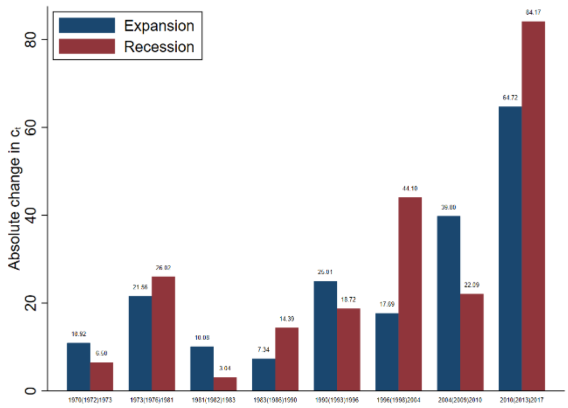
Asterisks denote a significance level of 10% (*), 5% (**) and 1% (***). Correlation coefficient between the dependent and independent variable is also reported.

Figure 6: Bar plot for change in cyclical component (Δc_t) throughout business cycle

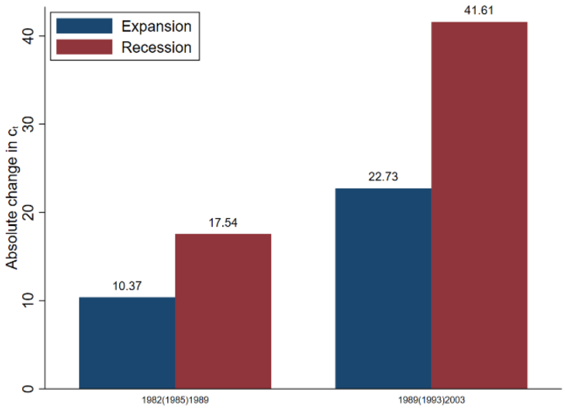
a) Deterministic trend



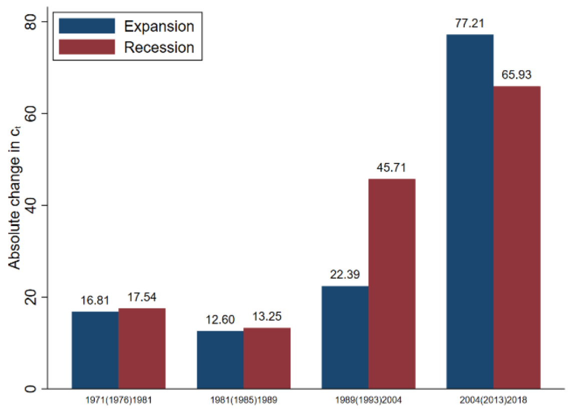
b) Hodrick-Prescott



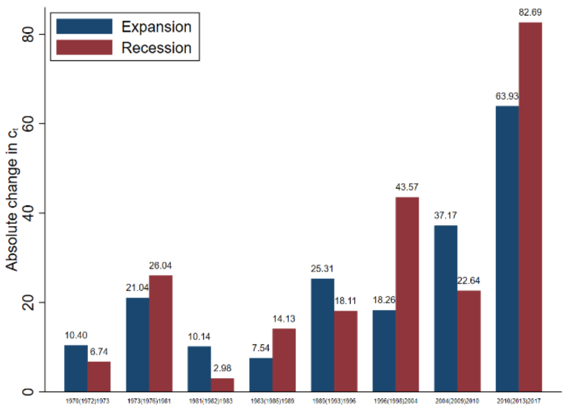
c) Baxter-King



d) Christiano-Fitzgerald



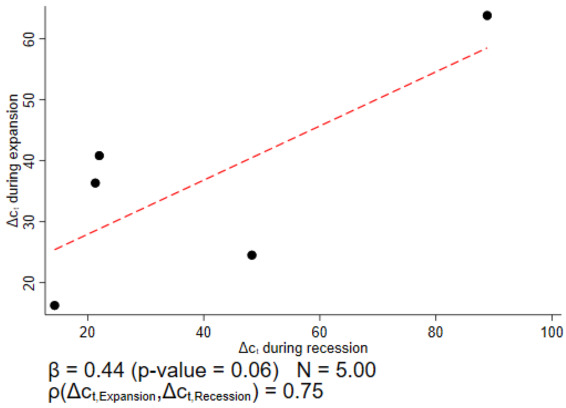
e) Butterworth



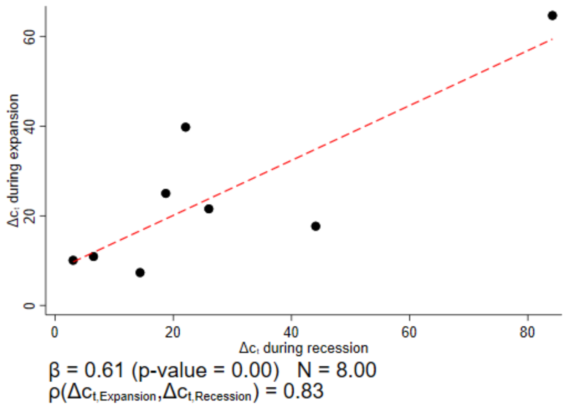
Bar plot for absolute change in cyclical component throughout each business cycle. Blue bars denote recessions (trough to peak) and red bars signify recessions (peak to trough). Labels on x-axis provides years for troughs and peak. For instance, 1970(1976)1981 means that the expansion occurred during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

Figure 7: Scatterplot for Δc_t during consecutive expansion and recession

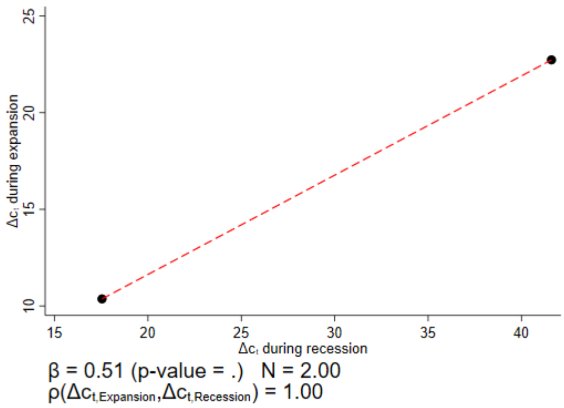
a) Deterministic trend



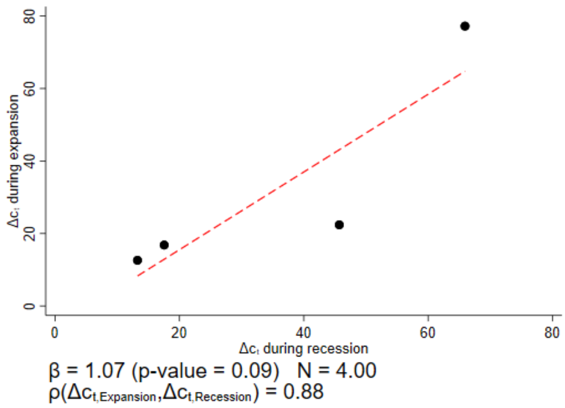
b) Hodrick-Prescott



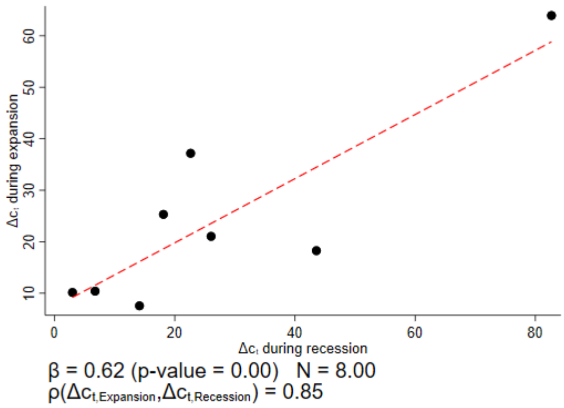
c) Baxter-King



d) Christiano-Fitzgerald



e) Butterworth



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.

4. Future analysis

In isolation, descriptive analysis of the past behaviour of the business cycle of Norwegian petroleum investments is not sufficient to obtain an answer to whether the recent downturn is transitory or permanent. To gain more clarity a more rigorous approach is necessary. For instance, an empirical analysis of the effect of debt on investments could contribute to elucidate further the nature of the recent downturn. Based on data from the Norwegian Petroleum Directorate, we intend to relate oil and gas investments on a company-year level to debt-to-equity ratio. That is, our econometric approach consists of applying a panel vector autoregressive a model on the following form:

$$y_{it} = \mu + \sum_{i=1}^{p} A_i y_{t-i} + Bx_{it} + \varepsilon_t. \tag{13}$$

Where y_{it} denotes the investment for company i at time t, and x is a matrix of explanatory variables which includes company debt and various control variables such as oil price, rig rates and proxies for industry cost level. If it is shown that investments are negatively related to debt, controlling for other relevant variables, it indicates that recent investment fluctuations are related to the business cycle.

5. Conclusion

From 2003 to 2013 the oil industry experienced an unprecedented long boom period. Unlike other industries the oil industry only had a minor setback due to the financial crisis in 2009. Although the global economy slowed down there was strong growth in Asia, particularly China. Since this region has a higher energy intensity than the regions with slow growth, oil demand kept rising. The long boom period gave an unprecedented increase in cost, e.g. due to a dramatic increase in rig rates (Osmundsen et al. (2015); Skjerpen et al. (2018)) and reduced drilling productivity (Osmundsen et al. (2010; 2012)). With a high cost level oil companies were exposed when the oil price plummeted in 2013. The cash flows became negative and the companies shielded dividend payments by increasing their debt rates. When oil prices started to rise again, oil companies prioritised to reduce their debt and to honour their obligations towards the share owners. Consequently, they rationed capital and investments have been slow to pick up. Consolidation of companies in the downturn has the same temporary effect on investments. Currently, the oil price is considerably higher than break-even prices for new projects and we see oil companies once again increase their investments. The dramatic investment cuts have reduced reserve replacement which may support a reasonably high oil price. Thus, there is a good explanation to the observed business cycles in recent years, following a known pattern, only more dramatic. However, it is still too early to conclude how this plays out.

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