KEY DRIVERS OF EXPLORATION SUCCESS RATES ON THE NCS

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Introduction

A discovery is a petroleum deposit or several petroleum deposits, which have been discovered in the same well, in which through testing, sampling or logging there has been established a probability of the existence of mobile petroleum.[1] The definition covers both commercial and technical discoveries. A total of 53 exploration wells were spudded on the Norwegian continental shelf (NCS) in 2018. Many more wells were drilled in the North Sea (31) and the Norwegian Sea (15) than in 2017, while there has been a decline in the Barents Sea (7).[2] Both large and small exploration companies have contributed to the strong resource growth in the last few years. The Norwegian Petroleum Directorate (NPD) has estimated the undiscovered resources on the Norwegian shelf at approximately four billion standard cubic metres (Sm3) of recoverable oil equivalents. This corresponds to around 47 per cent of all the remaining resources on the shelf. By applying an econometric analysis on crossectional data from the NCS, we will determine key drivers of exploration success rates.

Iledare and Pulsipher (1999) analyse reserve additions in the mature onshore Lousiana, 1977-1994, finding that while technical progress in exploration is considerable it was not able to fully compensate for depletion. They consider both exploration and development wells and explain variations in added reserves. In their econometric model, among the explanatory factors are expected price of hydrocarbons, corporate income tax, severance tax, royalty, extraction and operating cost and the discount rate, and a time trend used as a proxy variable for technical progress.

Forbes and Zampelli (2000) use an econometric model on offshore US data from 1978 to 1995 to disentangle and quantify major factors affecting the commercial exploration success rate. They find that key drivers are oil and gas prices, drilling depth (affecting drilling cost), hydrocarbon type, stock of unexplored acreage, and technical advances (represented by a trend variable). We complement this article by focusing on the technical success rate, by introducing rig rates and drilling speed that are known to affect drilling cost (Skjerpen et al., 2018; Roll et al., 2012), by distinguishing between wildcat and appraisal wells, by using a data set that covers the three regions on the NCS.

Methodology

Pertaining to offshore exploration (wildcat) wells, we define technical success as a wellbore that is not a dry well and constitute a new discovery of previously unknown deposits of hydrocarbons. Technical success should not be confused with commercial success, which not only requires discovery but also a sufficiently large discovery size to constitute further development and commercialization[3]. Technical

[1] https://www.norskpetroleum.no/en/facts/discoveries/

[2] https://www.norskpetroleum.no/en/exploration/exploration-activity/

[3] A commercial success is not only a function of discovery size and reservoir quality It is also dependent on variables such as cost, available technology and oil price. A discovery might at the present be considered only a

success rates are important to study, for several reasons. Commercial success rates are contingent on several discretionary assumptions with respect to revenue and cost, and the commerciality status typically change with the business cycle. Technical success rates are to a larger extent an objective measure and represent the first step in a sequence for qualifying for a future development project. In addition, technical success rates represent crucial geological input to determine further exploration effort in or near a given location.

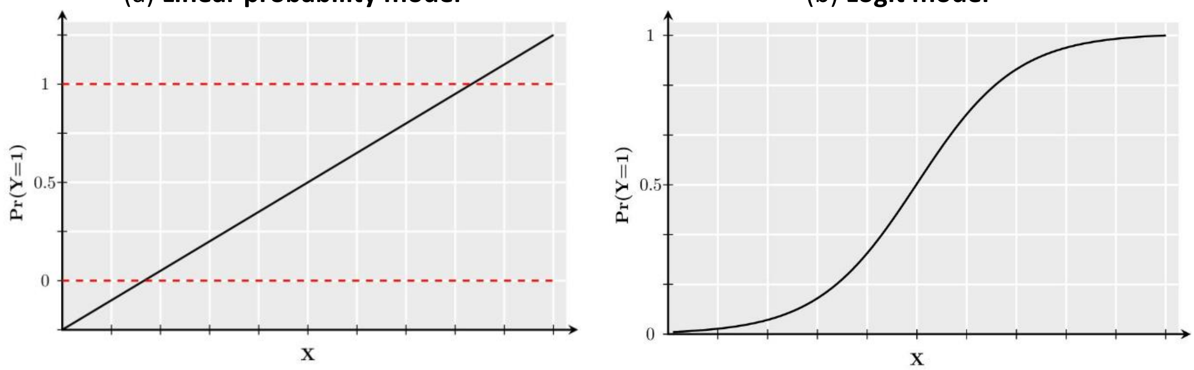
Let $success_i$ denote a dichotomous variable that is equal to one if a particular wildcat exploration well i on the NCS results in technical success and zero otherwise. See Equation (1).

$$Success = \begin{cases} 1 & if\ technical\ success \\ 0 & otherwise \end{cases} \tag{1}$$

Our econometric approach involves running a logit model, using robust standard error, with the conditional probability of $success$ being equal to 1, $\Pr(Success = 1|X)$, as the dependent variable and a set of independent explanatory variables. In order to avoid a violation of Kolmogorov's axioms of probability theory[4], it is not feasible to use a linear model estimated with ordinary least squares (OLS). See Figure 1 for an illustration of the differences between a linear and logit model, where the former violates the axioms of probability theory and the latter does not.

Figure 1: **Comparison of functional forms**

(a) **Linear probability model** (b) **Logit model**



Subfigure (a) shows the a linear functional form associated with running a OLS regression. On the other hand, Subfigure (b) shows a logistic function obtained by applying a logit regression.

The multivariate logit model is given as specified in Equation 2.

$$\begin{aligned} \Pr(Success = 1|X) &= F(\beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k) \\ &= \frac{1}{1 + e^{-(\beta_0 + \beta_{1 x_1} + \cdots + \beta_k x_k)}}, \\ & \quad or \\ \ln\left(\frac{\Pr(Success = 1|X)}{1 - \Pr(Success = 1|X)}\right) &= \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k \end{aligned} \tag{2}$$

technical discovery, but subsequently be retroactively reclassified as commercial if technological improvements allow for a higher extraction rate and/or the business cycle has become more favourable.

[4] Specifically, the probability of any event (E) in the event space (F) cannot be negative, $P(E) \in \mathbb{R}, P(E) \geq 0\ \forall\ E \in F$, and that the probability of an event from the entire sample space to occur is a hundred percent, $P(\Omega) = 1$.

As observed from Equation (2), the regression model is nonlinear in its parameters. Consequently, we cannot utilize ordinary least squares to estimate the coefficients. Hence, the maximum likelihood estimation approach must be utilized. The log-likelihood function to be maximized in this approach is shown in Equation (3). Depending on the difficulty of the log-likelihood function, a combination of the Newton–Raphson, Berndt–Hall–Hall–Hausman, Davidon–Fletcher–Powell and Broyden–Fletcher–Goldfarb–Shanno algorithms are applied.

$$\ln L = \sum_{j \in S} w_j \ln F(x_j b) + \sum_{j \notin S} w_j \ln\{1 - F(x_j b)\} \quad (3)$$

The model specification is based on both subject matter expertise and a more data driven approach. A set of potential variables is suggested based theoretical considerations, previous literature and dialogue with industry experts. The proposed variables are then subjected to a forward selection procedure where the model moves from its most parsimonious specification towards a specification including all variables. Variables are added incrementally based on which can provide the highest increase of the explanatory power conditional on all independent variables being statistically significant. Explanatory power is here measured in terms of McFadden's pseudo-R^2, which compares the estimated likelihood of the estimated model ($\ln \hat{L}(M_{Full})$) with the likelihood of an intercept only model ($\ln \hat{L}(M_{Intercept})$). Note that pseudo-$R^2$ does not have the same interpretation that is associated with the standard R^2. See Equation (4).

$$\text{Pseudo-}R^2 = 1 - \frac{\ln \hat{L}(M_{Full})}{\ln \hat{L}(M_{Intercept})} \quad (4)$$

The forward selection procedure is terminated either when all variables have been included or when any further inclusion causes any of the independent variables to be insignificant.

Data

Our data set was gathered from the Norwegian Petroleum Directorate and Thomson Reuters Eikon and consist mostly of wellbore information from exploration wells on the NCS between 1966 and 2019. Technical success is the main variable of interest in this study. The prevalence and development of technical success is shown in Figure 2. Subfigure (a) shows a bar plot indicating the absolute frequency of exploration effort (annual number of drilled wildcat wells) and the number of wells with technical success. As observed, there are large fluctuations in the number of wells drilled. Subfigure (b) shows the technical success rate, which is the ratio between number of successful wells and total drilled wells. While the success rate exhibits some variability, it appears to be on an upward sloping trend throughout the entire sample period. This can be illustrated by drawing a linear deterministic trend using ordinary least squares[5]. To address the possibility of nonlinearity, we apply locally weighted regression (LOWESS)[6]. As can be gleaned from the subfigure, the linear and nonlinear trends are

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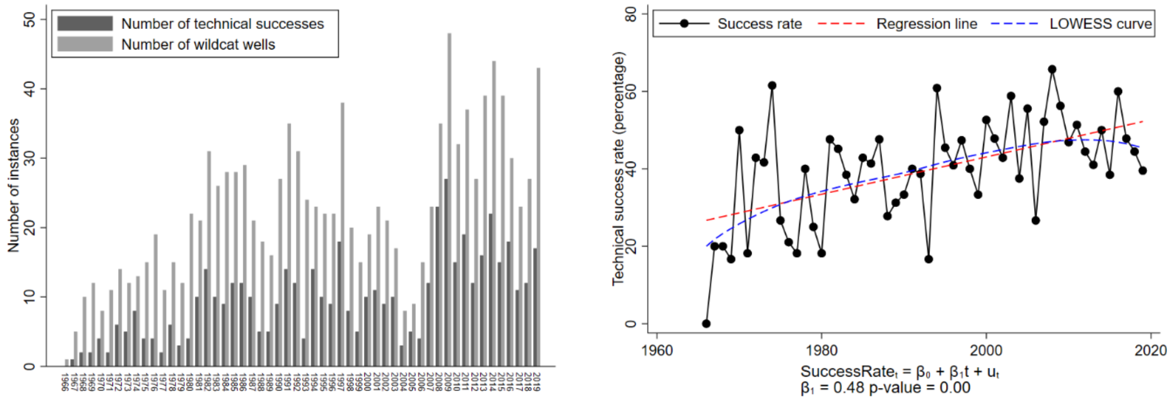
[5] Applying an OLS regression line in the pursuit causal inference would arguably violate Kolmogorov's axioms of probability theory. However, for the purpose of descriptive statistics, which limits itself to describe the data at hand, this is not an issue.

[6] For each observation of the dependent variable (y_i), as smoothed value (y_i^s) is estimated using the surrounding observations, $i \in [\max(1, i-k), \min(i+k, N)]$ $where\ k = \lfloor (N \times bwidth - 0.5)/2 \rfloor$. The weights ($x_j$) for the observations are given as follows: $w_j = \left\{1 - \left(\frac{|x_j - x_i|}{1.0001 \max(\min(i+k,N) - x_i, x_i - \max(1, i-k))}\right)\right\}^3$. y_i^s is then the weighted average of the sub-sample of surrounding observations.

predominantly coinciding. However, the success rate appears to have been experiencing a declining trend in the last decade according to this nonlinear specification.

Figure 2: **Exploration effort and technical success on the NCS (1966-2019)**

(a) **Number of wells and successes** (b) **Probability of success**

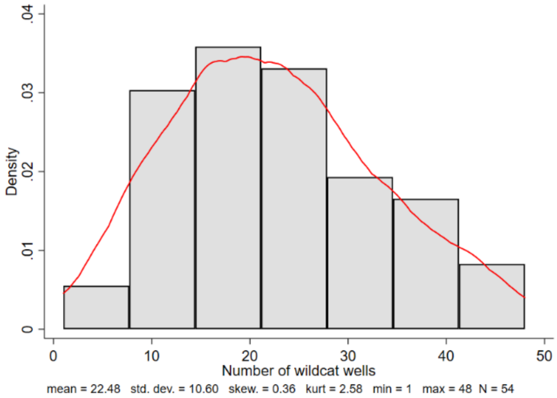


Subfigure (a) shows a bar plot for the number of technical successes and number of wildcat wells on the NCS between 1966 and 2019. Subfigure (b) shows the technical success rate (ratio between the number of successful wells and the total number of wells)

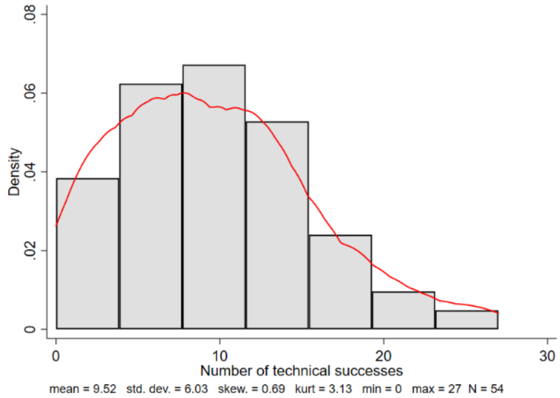
Figure 3 shows the statistical distribution of the annual number of wildcat wells, numbers of technical successful wells and the technical success rate. A histogram coupled with an Epanechnikov kernel density plot is used to approximate the distributions. Throughout the history of the petroleum industry on the NCS, the average number of wildcat wells is 22.48 with a standard deviation of 10.60. Exploration effort appears to follow a normal distribution as there is only a small amount of positive skewness and the tails are close to being mesokurtic. A Jarque-Bera normality test lends support to this notion. In terms of normality, similar results are found for the annual number of technical successes and success rate. On average, there are 9.52 success on the NCS per year with a standard deviation of 6.03. Analogously, the success rate is on average 39.46 percent with a standard deviation of 13.84 percentage points. It should be noted these statistics pertain to the entirety of the history of the Norwegian petroleum industry. As there appear to be a positive trend in the data, the prevalence of technical success tends to be higher towards the end of the sample period.

Figure 3: **Statistical distributions**

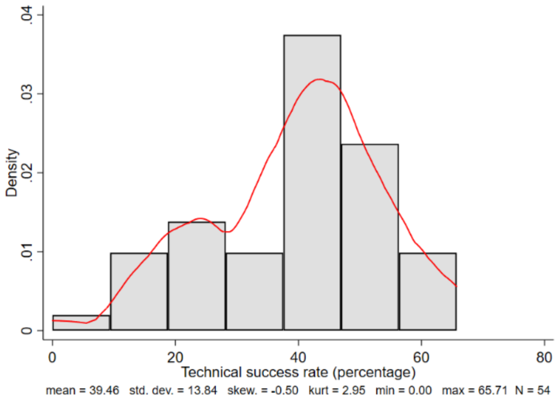
(a) **Number of wildcat wells**



(b) **Number of technical success**



(c) **Success rate**

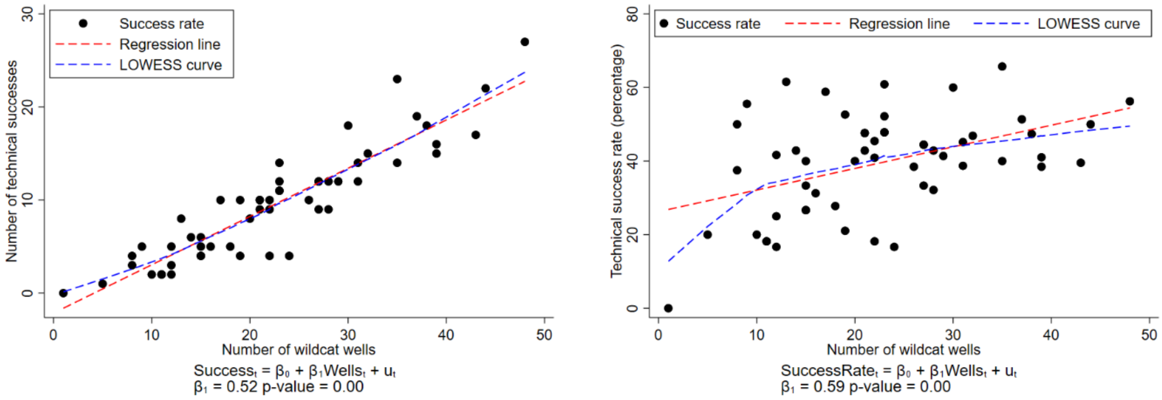


Statistical distribution is approximated through a histogram (where number of bins are equal to $\min\{\sqrt{N}, 10\ln(N)/\ln(10)\}$) and an Epanechnikov kernel density plot where the bandwidth is chosen such that the mean integrated squared error is minimized if the data were Gaussian and a Gaussian kernel were used.

Figure 4 shows the relationship between exploration success and exploration effort using a scatter plot with a fitted OLS regression line and a LOWESS curve. Subfigure (a) compares number of annual technical successes with the annual number of wildcat wells. As expected, the more wells that are drilled, the higher the number of successes tend to be. According to the estimated beta coefficient, an additional wildcat well tends to result in 0.52 additional success. Subfigure (b) substitutes the number of technical successful wells with the technical success rate. Analogously, an additional well tend to increase the annual success rate by 0.59 percent.

Figure 4: **Relationship between exploration effort and technical success**

(a) **Number of technical successes** (b) **Technical success rate**



Subfigure (a) shows the scatter plot between the number of technical successes and number of wildcat wells on the NCS between 1966 and 2019. An ordinary least regression line and a LOWSS (locally weighted scatterplot smoothing) curve is also added. Similarly, subfigure (b) shows the relationship between the technical success rate and number of wildcat wells.

To explain technical success rates, we are considering the following independent variables for our regression: Brent crude oil price (OilPrice), the year when the well was drilled (EntryYear), drilling depth (DrillingDepth) and drilling speed (DrillingSpeed). Table 1 shows the correlation between the dependent and independent variables.

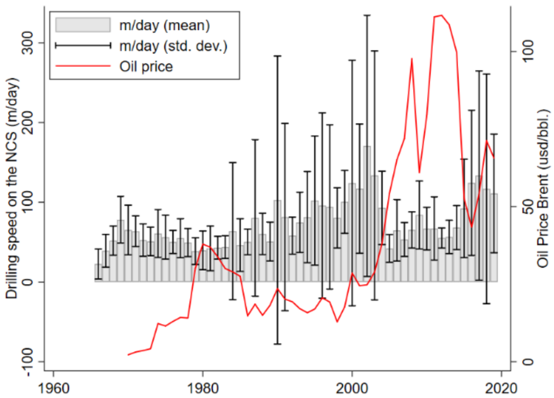
Table 1: **Correlation matrix**

	Success	DrillingSpeed	DrillingDepth	EntryYear	OilPrice
Success	1				
DrillingSpeed	-0.1533	1			
DrillingDepth	0.1376	0.0283	1		
EntryYear	0.0967	0.1833	-0.069	1	
OilPrice	0.0808	-0.0208	-0.0785	0.7486	1

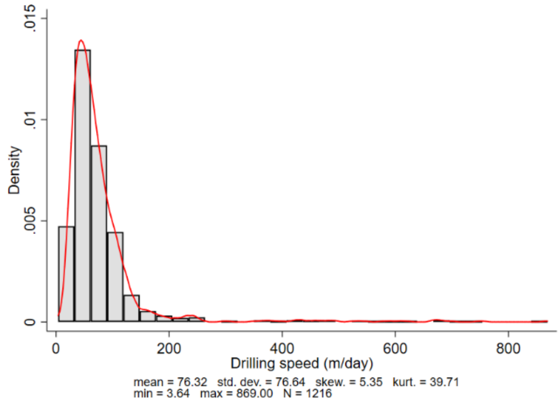
Drilling speed, measured in metre per day, is defined as the ratio between the drilling depth of a wildcat well and the number of days needed to complete the wellbore. Figure 5 illustrates different aspects of drilling speed of exploration wildcat wells on the NCS between 1966 and 2019. Subfigure (a) shows a bar plot of the annual average drilling speed with its standard deviation plotted against a time series of the oil price Brent (usd/bbl.). Subfigure (b) shows the statistical distribution of the drilling speed approximated through a histogram with an Epanechnikov kernel density estimate. The average drilling speed is 76.32 metres per day with a standard deviation of 76.64. As observed, drilling speed is clearly not normally distributed as there is positive skewness and leptokurtosis. A formal Jarque-Bera test confirms the non-normality. Subfigure (c) compares the statistical distribution of drilling speed conditional on being a dry well, and the drilling speed conditional on encountering hydrocarbons, i.e. technical success. As observed, there is some difference in the distributions. The average drilling speed for successful wells (62.86 metre/day) is lower than for unsuccessful wells (86.23 metre/day). Results from a Kolmogorov-Smirnov test suggests that these distributions are not coinciding as the null hypothesis of no difference in the maximum vertical distance of the cumulative distribution functions is rejected. One possible explanation for the observed difference could be that signs of hydrocarbons in the wellbore instigates well testing. This typically takes several days, thus reducing average drilling speed.

Figure 5: **Drilling speed of wildcat wells on the NCS (1966-2019)**

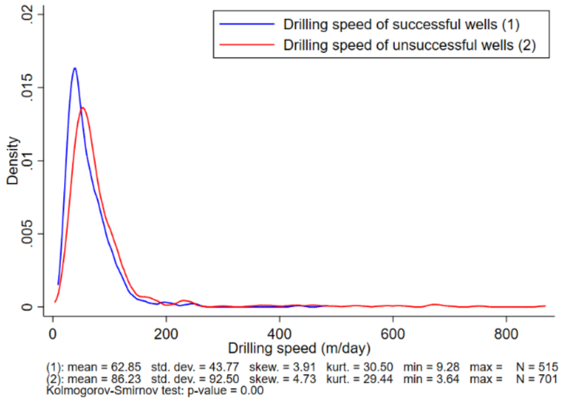
(a) **Annual average drilling speed**



(b) **Distribution of drilling speed**



(c) **Comparison between dry wells and successful wells**

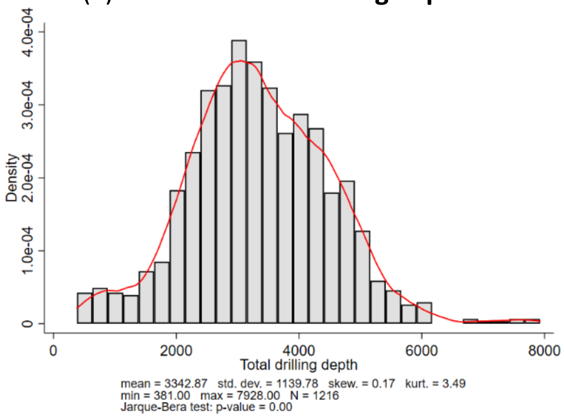


Subfigure (a) shows a bar plot displaying the annual average drilling speed and standard deviation of wildcat wells on the NCS between 1966 and 2019. The oil price is also added. Subfigure (b) shows the statistical distribution of drilling speed, which is approximated through a histogram (where number of bins are equal to $\min\{\sqrt{N}, 10\ln(N)\,/\,\ln(10)\}$) and an Epanechnikov kernel density plot where the bandwidth is chosen such that the mean integrated squared error is minimized if the data were Gaussian and a Gaussian kernel was used.

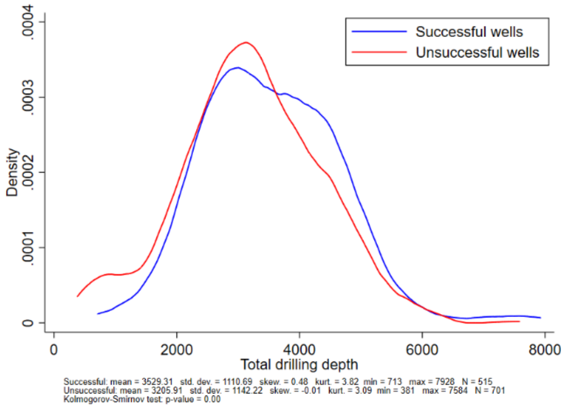
Figure 6 shows descriptive statistics for drilling depth, which is measured as the total measured length (metres) of wellbore from kelly bushing to total depth. Subfigure (a) shows the statistical distribution of drilling depth. The average drilling depth is 3342.87 metres with a standard deviation of 1139.78. There is some positive skewness (0.17) and leptokurtosis (3.49). A Jarque-Bera test suggest that drilling depth is not normally distributed. Subfigure (b) compares the statistical distribution of drilling depth conditional on the wellbore being successful with the statistical distribution of drilling depth for wells conditional on being unsuccessful. As observed there appears to be some difference. For instance, the average drilling depth of successful wells is 3529.31 metres and the drilling depth of unsuccessful wells is 3205.91. When applying a Kolmogorov-Smirnov test we find that these distributions indeed do not coincide. Subfigure (c) shows a scatter plot between drilling depth and year. Based on a simple OLS regression analysis, we can see that there is a significant downward trend in the data. The drilling depth for both successful and unsuccessful wells are decreasing, but based on an interaction effect we observe that the slope for successful wells is less steep[7].

Figure 6: **Drilling depth**

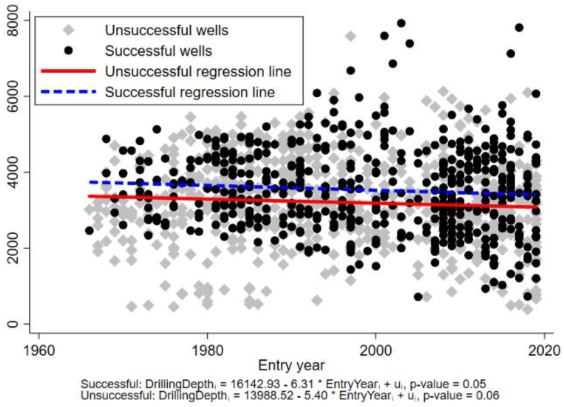
(a) **Distribution of drilling depth**



(b) **Comparison of distributions**



(c) **Temporal development in drilling depth**



Subfigure (a) shows the statistical distribution of drilling depth, which is approximated through a histogram (where number of bins are equal to $\min\{\sqrt{N}, 10\ln(N)\,/\ln(10)\}$) and an Epanechnikov kernel density plot where the bandwidth is chosen such that the mean integrated squared error is minimized if the data were Gaussian and a Gaussian kernel was used. Subfigure (b) compares the statistical distributions of the drilling depth of successful and unsuccessful wells using an Epanechnikov kernel density plot. Subfigure (c) shows a scatter plot between drilling depth and an initiation year of the drilling. The scatter plot distinguishes between successful and unsuccessful wells and adds an OLS regression lines based on both sub-samples.

Figure 7 shows the development in the crude oil price (Brent) and its relationship to the number of wildcat wells, the number of technical successes and the technical success rate. As shown in Subfigure (b), there is a positive and significant relationship between number of wells and the oil price. Hence, exploration effort on the NCS appears to follow the business cycle. Since the number of wildcat wells follows the oil price, it stands to reasons that the number of technical successes would be higher when to oil price is high compared to when it is low. On the other hand, Subfigure (d) shows that success rate also tends to increase with the oil price.

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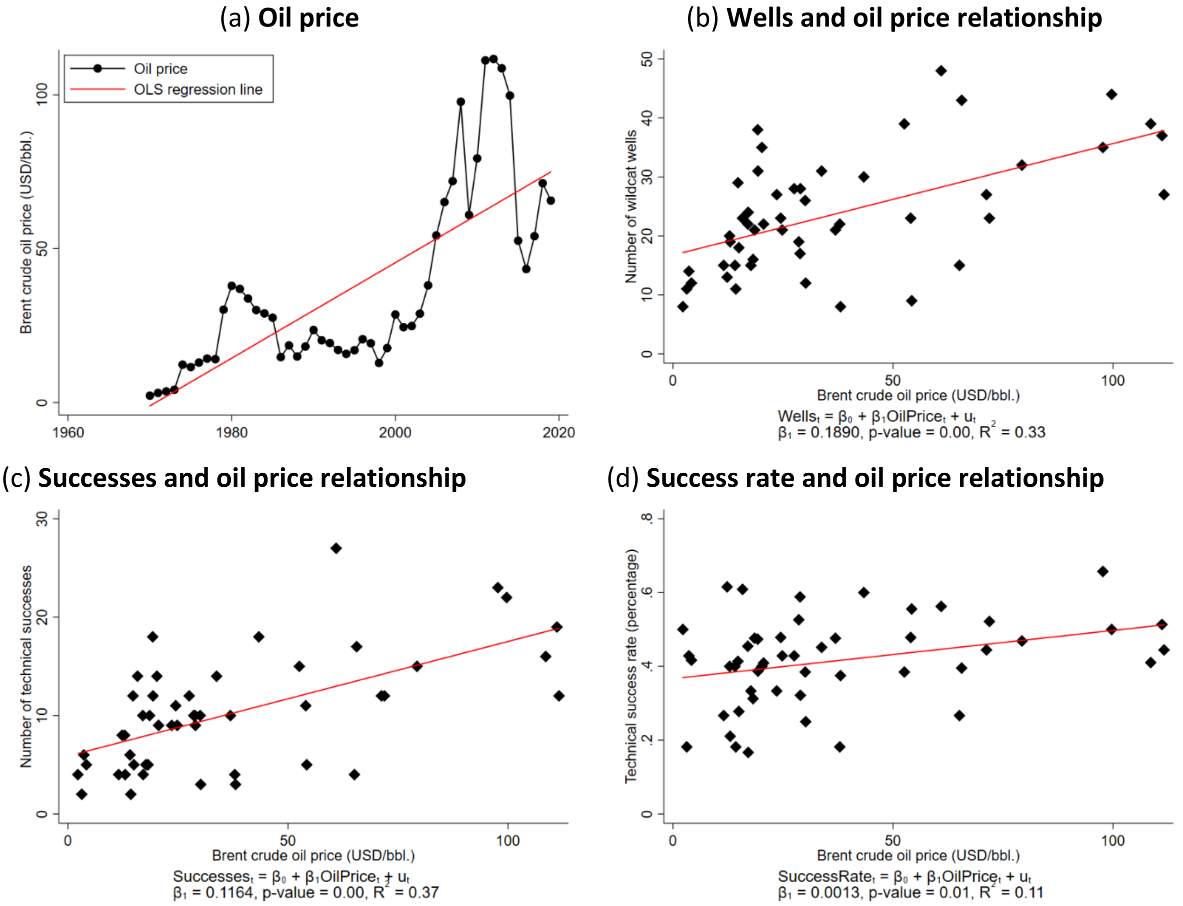
[7] $DrillingDepth_i = \beta_0 + \beta_1 EntryYear + \beta_2(Success \times EntryYear) + \varepsilon_i$

Figure 7: **Brent crude oil price**



Subfigure (a) shows a timeseries plot of Brent crude oil price (USD/bbl.) with a fitted OLS regression line. Subfigure (b) shows a scatter plot between well and oil price with a regression line. Analogously, Subfigures (c) and (d) substitute number of wells with number of technical successes and success rate respectively.

Results

We run a multivariate logit regression with technical success as the dependent variable and drilling speed of the wellbore, the year when the drilling was initiated, total drilling depth and the lagged oil price as the dependent variables. The regression equation is shown in Equation 5.

$$\ln\left(\frac{\Pr(Success_i = 1|X)}{1-\Pr(Success_i = 1|X)}\right) = \beta_0 + \beta_1 DrillingSpeed_i + \beta_2 EntryYear_i + \beta_3 TotalDepth_i + \beta_4 OilPrice_{t-1} + \varepsilon_i \quad (5)$$

Regression results for the multivariate logit model are shown in Table 2. As reported in the table, the pseudo-R^2 is 0.056. Contrary to the R^2 from a typical crossectional OLS regression, the pseudo-R2 does not have an intuitive interpretation. That being said, in absolute value, the goodness of fit is not particularly high. Nevertheless, given the difficulty of the issue at hand, the obtained results can be considered decent. Hence, the variables included in the multivariate model are important, but they do not explain the full story. The latter is as expected considering that that our specification does not include geological variables. The independent variables are sorted in order of importance in terms of addition to the pseudo-R^2. Drilling speed of the wildcat wells (metre per day) is the variable that provides the highest addition to pseudo-R2. It has an odds ratio (e^{β}) of approximately 0.9909. In other words, for each unit increase in drilling speed, the odds of technical success decrease by 0.91 percent ($= (1 - 0.9909) \cdot 100$). Care should be taken to not confuse probability and odds. Odds is the probability of an event occurring divided by the probability of the event not occurring, $p/(1-p)$. Hence, a unit increase in in drilling speed has a linear effect on the odds of success but a nonlinear effect on the probability of success. This finding coincides with our ex ante expectations. As observed in Figure 5 (c), there is an observable difference in average drilling time for successful and unsuccessful wildcat wells. As suggested by industry experts, sign of hydrocarbons necessitates additional testing which leads to idle time negatively impacting the average drilling speed of wellbore. In other words, the estimated odds ratio is only associational rather than causational due to the presence of endogeneity issues causing a violation of the population orthogonality condition. More specifically, following the suggested explanation there is a case of reverse causality. Lower drilling speed does not cause the probability of success to become higher, success is causing the drilling speed to become lower. However, there is also an explanation for this finding in terms of industrial economics. Higher drilling speed leads to lower drilling cost which may incentivise oil companies to take on more exploration risk, i.e. go for drilling targets with a lower probability of technical success but with larger reserves.

Table 2: **Multivariate regression results**

	OR	p-value
_cons	0.0000	0.00
DrillingSpeed	0.9909	0.00
EntryYear	1.0361	0.00
TotaldepthMDmRKB	1.0003	0.00
$OilPrice_{t-1}$	0.9950	0.09
N		1178
pseudo-R2		0.0560

Multivariate logit regression results with technical success as the dependent variable. Odds ratio is reported instead of beta coefficients. Model is specified through forward selection.

The second most important variable is the year when drilling was initiated. This variable has an odds ratio of approximately 1.0361, which implies that one unit increase in this variable increases the odds of success by 3.61 percent ($= (1 - 1.0361) \cdot 100$). Hence, coinciding with our prior expectations, for every year that passes, the chances of success increases. There are three forces likely at play here. First, when time evolves, the shelf become more mature, which may affect success rates. This is probably a rather involved relationship. At one point, there is so little oil left that it definitely has a negative exploitation effect. According to the NPD, half the Norwegian reserves remain, so the extent of this exploitation effect is uncertain. Another factor that is linked to maturity is that you get another mix of projects. While in the initial phase there is predominantly wildcats in new geological structures, with a larger fraction of satellite fields attached to existing infrastructure. Wells close to existing infrastructure often is in areas with more geological knowledge, so a higher technical success rate can be expected due to learning effects. Second, technology tends to improve over time, which is likely to increase the odds. Better seismics and geological models to a larger extent enable the companies to pick promising prospects. Third, we learn more about the geology of the area as time passes. With more knowledge, the decision-makers are expected to be better at locating petroleum deposits. While it seems reasonable to assume that technology and knowledge, which is proxied through drilling year, is monotonically increasing. The assumption of linear increase is more contentious. It could be argued that innovations are clustered and exhibits a more cyclical pattern. New technology is in all likelihood not implemented simultaneously across all companies either. However, based on descriptive statistics, see Figure 2 (b), there does indeed seem to be a linear trend in annual success rate. Caution should be exercised when applying this model result to decision-making. The results pertaining to the drilling year variable has good in-sample performance but they should not be extrapolated carelessly.

Total drilling depth is the third most important variable in our model. With an odds ratio of 1.0003 the odds of success increase by 0.3 percent ($= (1 - 1.0003) \cdot 100$) for each additional metre of drilling. The interpretation of this variable can be perplexing. Ex ante expectations regarding the relationship between technical success and drilling depth are mixed. Either there is petroleum in an area or there is not. Drilling an additional metre has no effect on the chances of success if there is no petroleum present. On the other hand, if there is a deposit of hydrocarbons, then it is possible that the wellbore is not sufficiently deep to reach the reservoir. Hence, drilling an additional metre would increase the probability of making a discovery. Consider for instance, wellbore 2/8-1 drilled by Amoco Norway Oil Company from 28.11.1967 to 02.07.1968, which drilled 2595 metres without making any discovery. Had they drilled an additional 43 metre they would have discovered what is known today as the Valhall field with its 200.36 million sm3 of oil equivalents. Valhall was discovered almost a decade later with wellbore 2/8-6 on 07.04.1975 with a drilling depth of 2669 metres. If we were to compare these to wellbores, then drilling depth has a positive effect on chances of success. A long well also has the potential to detect several layers or zones of petroleum, at different depths.

However, there could be a case of Reverse Tinkerbell effect pertaining to this finding. If every company began to believe and act upon this result, then it would subsequently vanish. Consider a related activity: onshore drilling for groundwater. Cabins are often built far away from existing infrastructure. Connection to the main water source is, consequently, frequently an issue. The solution is to drill for groundwater. While this appears to be a related problem, the relationship between finding groundwater and drilling depth tend to be negative. The reason is that decision-makers select a more or less random location and usually continue to drill until they reach maximum depth regardless of the circumstances. That is, they stop drilling when they either reach maximum depth or if they reach groundwater prior to reaching the maximum depth. In short, empirical results suggest that the probability of finding hydrocarbons on the NCS increases with drilling depth, but if this information is acted upon this relationship could be diminished or even vanish.

The last variable in our multivariate regression is lagged Brent crude oil price (usd/bbl.). It has an odds ratio of 0.9950, which means that one monetary unit increase in oil price is associated with a decrease in odds of success by 0.5 % ($= (1 - 0.9950) \cdot 100$). We use the lagged oil price to account for the fact that project sanction and project execution tend to not be contemporaneous events. Instead there is likely to be some extent of inertia. Oil price can be considered a proxy for the business cycle and subsequently also a proxy for a company's available cash flows. Our ex ante hypothesis is that oil and gas companies engage in cyclical behaviours pertaining to their decision-making which affect probability of success. Specifically, it could be that when oil price is high and companies are less financially constrained, they are more willing to undertake more novel and risky project in less mature areas, that typically has a lower technical success probability but a potential for larger reserves. On the other hand, when the oil price is low and companies are constrained, they prefer safer projects with higher chances of success. It is interesting to note that the descriptive statistics suggest a positive relationship between success rate and oil price, see Figure 7 (d). Running a univariate logit regression with the probability of technical success and the L.H.S. variable and lagged oil price the R.H.S. variable, we do indeed find a positive relationship. However, once we add EntryYear to our specification, the relationship becomes negative. Hence, the observed univariate relationship appears to be an artefact of endogeneity issues, specifically omitted variable bias which causes a violation of the population orthogonality condition - $\mathbb{E}(u|x)$. That is, since the correlation between oil price and EntryYear (0.7486) is positive and the latter has a positive effect in the independent variable, the bias in the coefficient of oil price is also positive. When looking at oil price throughout the last 50 years, it can be described a linear increasing trend. As including EntryYear is tantamount to adding a linear trend, it would seem that oil price is erroneously picking up the effect of technology and knowledge which EntryYear is a proxy for.

Conclusions

Our analysis indicates that learning and effects and technological advances have dominated maturity on the NCS, so that the technical success rate is still increasing. This is contrary to the findings of Ildedare and Pulsipher (1999) in mature onshore Louisiana. In addition, we find that the following factors are causing the technical success rates to increase: reduced drilling speed, increased drilling depth, and reduced oil price.

There are several probability measures for exploration. One is technical success rates, i.e., whether petroleum is discovered. This is of a geological nature. Another standard probability that combines commercial and geological features is the probability that an exploration wells leads to a discovery that is actually developed, i.e., the commercial success rate. There is also a third probability that puts more weight on the commercial side; the probability that the reservoir are developed, provided a technical discovery is made. In an extension of this paper we will analyse the drivers behind variation in these success rates over time, and the relation between them.

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