Effect of the 2016 OPEC production cut announcement on the default likelihood of the oil industry and commercial banks

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Abstract: Using option pricing methodology, we provide evidence the oil and banking industries' default likelihood decreased following OPEC's November 2016 oil production cut announcement. The effect is present within several oil sub-industries and for the banks conducting business in states with the most oil production. In addition, for the oil industry we find the decrease in default likelihood is more pronounced for firms with higher leverage, low financial slack, small market value, and small book-to-market ratios. For commercial banks, banks with higher non-performing assets and provision for loan losses experienced a greater decline in default likelihood. In addition, similar to the oil industry, size and book-to-market are significant determinants of the change in default likelihood.

Keywords: market efficiency; event study; financial institutions; financial distress; energy.

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1 Introduction

During June of 2014, the front month futures contract price of West Texas Intermediate (WTI) oil reached almost $107 a barrel, then throughout 2015 and 2016 it declined steadily to a low of nearly $30 barrel in early 2016. Throughout the year of 2016, numerous news outlets began to question if the struggling oil industry had the ability to service their debt. US banks were already under pressure from near zero interest rates and prolonged low oil prices could potentially result in a negative effect on banks' energy loan portfolios performance. According to Singh and Shankar (2016), investors and regulators at the time were worried that the depressed oil prices were not only putting companies at risk but could also inflict job losses that could adversely affect the regional economies, and consequently a bank's whole loan portfolio.

Reporting for the *Wall Street Journal* in January of 2016, Olson and Ailworth (2016) claim oil prices plummeting toward 30 dollars a barrel could drive as many as one-third of American oil and gas producers toward bankruptcy by mid-2017. They mention North American producers were losing nearly $2 billion every week, and projections for losses on energy loans continued to rise. Ensign and Rapoport (2016) claim as many energy loans began to sour, several lenders were adding millions of dollars to reserves. As an example, Regions Financial Corp., at the time, said its' fourth quarter charge-offs increased by $18 million to $78 million from the prior quarter due to a single borrower from the energy industry. BOK Financial, a bank in Oklahoma, missed earnings expectations because its loan loss provisions would be greater than analysts expected. As a result, bank stock prices were down. For example, Zions Bancorp shares were down nearly 18% in about two weeks. However, other banks, such as Wells-Fargo, with only 2% of total loans in the energy field, felt the losses were manageable.

On 30 November 2016, OPEC cut their production levels, the first change in nearly eight years. With this announcement, the price of WTI rose 9.3% and Brent Crude rose 8.8%. The price of oil rebounded considerably, but would this give the oil industry and related banks a lifeline? In a 2 December 2016 *Wall Street Journal* article by Rapoport and Ensign (2016), the authors indicate as the price of crude rises, lenders' losses on the energy loans were expected to decline. On 1 December, regions financial stock price rose 2.2%, Zions Bancorp's stock price increased 1.6%, and others increased as well.

Although banks were in a much better place, caution was still the word of the day. What would be the financial effect on the oil and banking industry?

In this paper we seek to examine the change in financial distress surrounding the November 2016 OPEC production cut and the company specific factors which may affect the level of financial distress. Using a Black-Scholes-Merton (BSM) option pricing methodology, we find that the default likelihood (DL) of companies in the oil industry and banks in oil producing areas generally declined after OPEC's production cut. In addition, several firm specific variables such as leverage, size, financial slack, and return on assets are important determinants with regards to the size of the decrease. Furthermore, we find commercial banks operating with high expected exposure to oil related factors experience reduced DL.

2 Literature review

Loutia et al. (2016) examine the impact of OPEC's production decisions on both WTI and Brent Crude using event study methodology. They show the impact on oil prices from OPEC's production cuts are more significant than production increases, and the effect is less influential when prices are high. OPEC's dilemma is whether to attempt to keep prices low and prevent high oil cost producers from entering the market which, at the same time, could reduce their members' revenues. Schmidbauer and Rösch (2012) find OPEC decisions are anticipated by market players, and the pattern of impact is different with respect to the type of decision. Anticipation effects on volatility are highly pronounced for maintaining production and cuts to production, but do not exist for production increases. In addition, after effects were significant in all three cases. They conclude information leakage is crucial in determining volatility. Elyasiani et al. (2011) examine oil price shocks and industry stock returns. They find 9 of 13 industry excess returns have significant relation with the oil-futures return distribution. Oil-user industries such as chemicals and transportation are more impacted by oil return volatility than oil returns. In addition, depository institutions are affected by both oil return volatility and oil returns. Similar to other financial studies, they find the Fama-French (FF) factors SMB and HML show high significance as risk factors affecting excess returns. Sadorsky (1999) finds oil price changes affect economic activity, but changes in economic activity do little to impact oil prices. The author finds positive shocks to oil prices can dampen real stock returns. Basher and Sadorsky (2006) find oil price risk can affect emerging market stock returns. Their results are quite mixed. Using daily and monthly data, they find oil price increases have a positive increase on excess stock returns. However, when using weekly and monthly data, oil price decreases have positive impacts on the emerging market stock returns. Magyereh et al. (2020) suggest oil and gas companies' investments respond symmetrically to oil price changes indicating a financially healthier firm.

With all the uneasiness surrounding the oil markets, dramatic changes in oil prices potentially impact firm financial distress (DL). For measuring financial distress, Hillegeist et al. (2004) compare the Altman's Z-score, Ohlson's O-score, and the market-based BSM DL model. They find the BSM measure provides significantly more information than either of the others and recommend researchers use the BSM measure instead of the Z-score or O-score. Vassalou and Xing (2004) were the first authors to calculate default measures for individual firms and assess the effect of default risk on stock returns using the BSM measure. Similar to Fama and French (1996) who state the SMB and HML factors of the FF model (Fama and French, 1993) serve as a proxy for financial distress, they find the FF factors SMB and HML are related to default risk. For firms with high default risk, small firms have higher returns than large firms, and value stocks earn higher returns than growth stocks. Thus, size and book-to-market effects contain default related information. Fang and Zhong (2004) examine firm risk-shifting behaviour using the BSM measure and argue the market-based nature of this measure better captures potential risky behaviour by firms. Akhigbe et al. (2007) use a measure of DL based on the BSM option pricing to provide evidence Fed policy actions affect the financial distress of commercial banks. They find the measure of DL increases when the Fed increases interest rates through a tight money policy. In addition, they find it is more pronounced for banks with higher leverage, smaller size, and fewer growth opportunities measured by the market to book ratio. For a full review of empirical literature on the determinants and consequence of financial distress, see Habib et al. (2020).

3 Empirical hypotheses

Since Schmidbauer and Rösch (2012) find OPEC announcements indicating a decrease in production lead to higher expected oil prices along with the findings of Lin and Tamvakis (2010) who show negative production announcements lead to actual higher crude oil prices, we expect the probability of default will decrease for the oil and banking industry, since higher prices should enable them to better service their debt. Thus,

H1 The probability of default will fall after OPEC's production cut during the examined period.

In addition, since firms which have high leverage and/or less financial slack are inherently riskier, we expect firms with higher leverage or less financial slack may be associated with a greater decrease in the likelihood of default. Thus,

H2 Leverage (slack) is negatively (positively) related to the change in DL.

Vassalou and Xing (2004) find the FF SMB and HML factors are related to default risk, indicating small firms and value firms with high book-to-market may be more affected by a production change. Schmidbauer and Rösch (2012) show OPEC announcements increase oil price volatility in the short run, thus we posit this could adversely impact the DL of value firms in the near term. Alternatively, higher oil prices may allow value firms to take advantage of the opportunities provided by increased revenues, leading to a decline in financial distress. Thus,

H3 Size is positively related to the change in DL.

H4a Value (high book-to-market) firms are positively related to the change in DL.

H4b Value (high book-to-market) firms are negatively related to the change in DL.

Table 1 Summary statistics for the oil and banking industry

Variable	*Number*	*Mean*	*Median*	*Minimum*	*Maximum*
Panel a: oil industry					
Equity volatility	325	0.74298	0.58867	0.21591	3.91755
Asset volatility	325	0.33023	0.28073	0.02465	2.13153
Default measure	325	0.13442	0.01400	0.00000	0.98311
Dividend yield	325	0.02517	0.01287	0.00000	0.29897
Leverage	325	0.35294	0.33704	0.00000	1.41791
Financial slack	325	0.08508	0.03848	0.00000	1.00000
Operating ROA	325	0.33405	0.01965	–4.49880	125.211
FCF/TA	315	–0.1188	–0.04084	–17.1289	0.93076
BK/MKT	322	1.23184	0.67723	–13.41352	4.1858
Market value	325	6965.00	1029.23	0.696360	358591
Derivative dummy	325	0.55692	1.00000	0.00000	1.00000
Panel b: banking industry					
Variable	*Number*	*Mean*	*Median*	*Minimum*	*Maximum*
Equity volatility	305	0.28297	0.26370	0.15942	2.18234
Asset volatility	305	0.04019	0.03620	0.01078	0.56154
Default measure	305	0.00492	0.00003	0.00000	0.64304
Dividend yield	305	0.00255	0.00241	0.00000	0.00974
Leverage	305	0.03906	0.03059	0.00000	0.15618
Capital	305	0.11135	0.10608	0.00266	0.26674
ROE	305	0.19540	0.17571	0.00949	4.50562
NonPerf	305	0.00908	0.00651	0.00017	0.06536
PLL	305	0.00116	0.00092	–0.00474	0.02274
CHGNPA	302	–0.00107	–0.00061	–0.06347	0.02871
BK/MKT	305	0.68807	0.65255	0.07780	2.51316
Market value	305	4161.70	475.861	4.35600	282890

Notes: This table provides the default measure by industry along with its key inputs, equity volatility, asset volatility, and dividend yield, calculated as Compustat's total dividends divided by the firm's (market value + book value of liabilities). In addition, the explanatory variables for the cross-sectional analysis are included. Leverage is calculated as long-term debt divided by total assets, financial slack as cash and short-term investments divided by total assets, and operating ROA as earnings before interest and tax divided by total assets. FCF/TA is free cash flow divided by total assets and free cash flow is defined as operating activities net cash flow – cash dividends – capital expenditures. Market value ($ millions) is calculated as shares outstanding × price calculated from CRSP data as of day –2 prior to the announcement and BK/MKT is calculated as (book value per share from Compustat × price from CRSP) / market value. For the bank panel, capital is the ratio of book value to total assets. ROE is the ratio of earnings before interest and taxes to book value of equity. NonPerform is the ratio of total non-performing assets to total assets. PLL is the provision for loan losses divided by total assets, and CHGNPA is the ratio of the change in non-performing assets from the current year less the previous year to total assets. The derivative dummy is equal to 1 if the company uses derivatives and 0 if not.

As firms with low profitability might be more susceptible to default, we expect firms with low operating return on assets, return on equity (ROE), and free cash flow would benefit more from an increase in the price of oil, thus we expect a positive relation to default. In other words, the lower the profitability measure, the greater the decrease in the likelihood of default. Thus,

H5 Operating return on assets, ROE, and free cash flow to total assets are positively related to the change in DL.

The findings of Akhigbe et al. (2007) show highly capitalised banks are better able to absorb a negative economic shock; therefore, for the banks, we expect firms with low levels of capital, and high levels of either non-performing assets or provision for loan losses, to see a greater decrease in their probability of default. Thus,

H6 Capital (non-performing assets and provision for loan losses) are positively (negatively) related to the change in DL.

4 Methodology and data

4.1 Measuring DL and changes in DL

A European call option has several key features. First and foremost, it gives the holder the right to buy an underlying asset at an agreed upon strike price at expiration. Merton (1974) observed that owning equity is analogous to holding a call option on a firm's assets. Under this framework the underlying asset corresponds to the market value of the firm and the strike price is the face value of the firm's liabilities. At maturity, if the market value of the firm is more than the face value of the firm's liabilities, then the equity holders exercise their option, and as residual claimants on the assets of the firm, satisfy the demands of the debt holders and keep the residual value. However, if the market value of the firm is less than the face value of the firm's liabilities, then the equity holders will not exercise their option, thus letting the firm file for bankruptcy where equity holders receive nothing, and debt holders receive whatever value remains.

Previous research (Akhigbe et al., 2007; Hillegeist et al., 2004; Fang and Zhong, 2004; Vassalou and Xing, 2004) has applied the BSM framework, as described above, to calculate the DL of a firm. The DL measure used in the current study most closely follows Hillegeist et al. (2004), although the other aforementioned studies contain similar versions of these equations. Hillegeist et al. (2004) define the equation for valuing equity as a European call option on the value of the firm's assets as given in equation (1) below. The model adjusts for dividends paid by the firm, as they accrue to equity holders.

$$V_E = V_A e^{-qT} N(d_1) - X e^{-rT} N(d_2) + (1 - e^{-qT}) V_A \tag{1}$$

where $N(d_1)$ and $N(d_2)$ are the standard cumulative normal of d_1 and d_2, and

$$d_1 = \frac{\ln\left(\frac{V_A}{X}\right) + \left(r - q + \left(\frac{\sigma_A^2}{2}\right)\right)T}{\sigma_A \sqrt{T}}. \tag{2}$$

and

$$d_2 = d_1 - \sigma_A \sqrt{T}. \tag{3}$$

V_E is the daily value of the firm's market value of equity as reported by the Center for Research in Security Prices (CRSP), V_A is the current market value of assets, r is the risk-free rate of return as proxied by the US one-year treasury bill rate as reported by the Federal Reserve Economic Data (FRED) library at the Federal Reserve Bank of St. Louis, q is the dividend yield calculated as Compustat's total dividends divided by the firm's market value + book value of liabilities, X is the firm's total liabilities from Compustat, and σ_A is the standard deviation of asset returns. As explained in Hillegeist et al. (2004) the term $(1 - e^{-qT})V_A$ is required because it is the equity holders who receive the dividends and it equals 0 when q equals 0.

The DL measure, DL, for each firm per day is estimated as:

$$DL = N\left(-\frac{\ln\left(\frac{V_A}{X}\right) + \left(\mu - q - \left(\frac{\sigma_A^2}{2}\right)\right)T}{\sigma_A \sqrt{T}} \right) \tag{4}$$

where μ is the drift and calculated as the daily rolling mean of the change in the $\ln(V_A)$ over the previous year. Requiring daily values of V_A and σ_A creates a challenge as neither of these values are directly observable on a daily basis. However, as in Hillegeist et al. (2004), we are able to simultaneously estimate these values using a Newton search algorithm iterative process which takes equation (1) and the optimal hedge equation $\sigma_E = (V_A e^{-qT} N(d_1)\sigma_A) / V_E$.

In order to estimate V_A and σ_A, we calculate annualised estimates of σ_E as the standard deviation of daily equity returns using daily data for the past year multiplied by the square root of the number of trading days in a year (252). The initial value of σ_A is then calculated from the daily values of σ_E and V_E as $\sigma_A = \sigma_E V_E / (V_E + X)$. Using the search algorithm, the required parameters for each day are then calculated using equation (1) and the optimal hedge equation. From this process, we use the estimated daily values of V_A, σ_A, along with μ, T, and X, to calculate the DL value for each firm for each day with equation (4).

Our main analysis examines the change in DL surrounding OPEC's announcement on 30 November 2016, (day 0). We follow Akhigbe et al. (2007) and calculate the mean (median) DL over pre-event and post-event windows. Our pre-event mean daily DL measure is calculated using equation (4) over the 60-day period that ends two days prior to the event. We calculate our DL measure over two post-event windows, a short-term and a long-term window. The short-term post-event window runs from days –1 to +1, whereas the long-term post-event window is calculated over days +2 to +61. We report two estimates of the change in DL (ΔDL) to measure a short-term and long-term response to the policy. The first is the difference in the short-term post-event DL minus the pre-event DL. The second is the difference in the long-term post-event DL minus the pre-event DL.

Motivated by our hypotheses and previous research, we examine market value, book-to-market ratio, leverage, financial slack, operating return on assets, free cash flow to total assets, and a derivative dummy. We report summary statistics by industry in Table 1 along with the equity and asset volatility measures used in the DL calculations. Additionally, we include size and book-to-market which is consistent with Vassalou and Xing (2004), who find that SMB and HML from the FF three-factor model contain some default-related information, and Fama and French (1996), who state that the SMB and HML factors of the FF model (Fama and French, 1993) proxy for financial distress. We use CRSP data to calculate market value as shares outstanding multiplied by price as of 2 days prior to the event ($T - 2$). Book-to-market is calculated as (book value per share from Compustat times price from CRSP divided by market value). In addition, we believe that firms' leverage and profitability ratios may be important factors related to changes in the DL. Using Compustat data from the prior fiscal year, we calculate leverage as long-term debt divided by total assets, financial slack as cash and short-term investments divided by total assets, and operating return on assets as earnings before interest and taxes (EBIT) divided by total assets. Free cash flow is calculated as operating activities net cash flow less cash dividends and capital expenditures. Since many energy firms use derivatives to lock in prices for oil contracts, we use a dummy variable equal to one if Compustat's variables derivative assets or liabilities (long-term or current) are greater than zero. For the banking industry, similar to Akhigbe et al. (2007) we include leverage, capital, ROE, size (market value), and non-performing loans. Capital is calculated as the ratio of book value to total assets, ROE is the ratio of EBIT to book value of equity, and non-performing loans is the ratio of total non-performing assets to total assets. In addition, we include the change in non-performing assets over the year 2015 to 2016, and the provision for loan losses divided by total assets.

4.2 Data

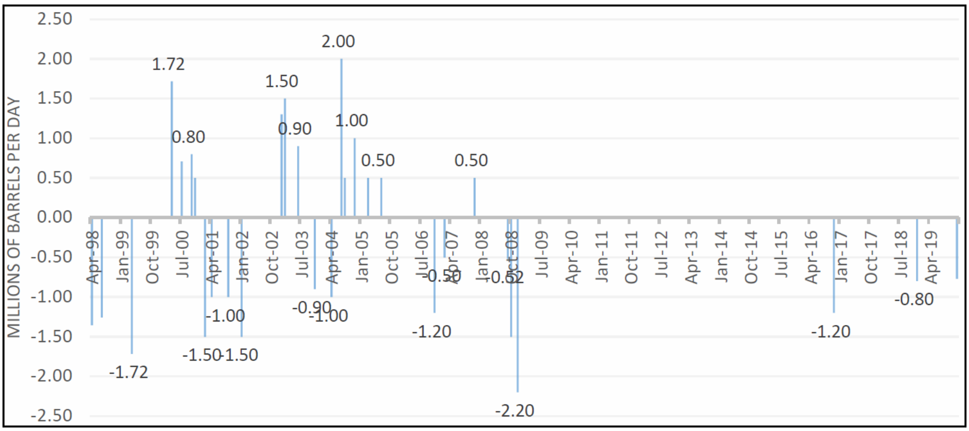
Our sample is comprised of two groups of firms, oil industry firms and banking industry firms. Table 1, panel A, provides the summary statistics for firms in the oil industry sample. We start with all energy industry firms in GIC sub-industries 10101010, 10101020, 10102010, 10102020, 10102030 and 10102040 from the Compustat database for the 2015–2016 financial statements. After a matching process with the CRSP database, we calculate the DL measure for the pre- and post-period to arrive at 325 firms. The sub-industries are as follows: oil and gas drilling (10101010), oil and gas equipment and services (10101020), integrated oil and gas (10102010), oil and gas exploration and production (10102020), oil and gas refining and marketing (10102030), and oil and gas storage and transportation (10102040). For these oil industry firms the mean DL measure is 0.13442 with a maximum of 0.98311, while the mean equity and asset volatility are 0.74298 and 0.33023, respectively. The mean leverage is 0.35294 and the mean financial slack measure is 0.08508. The mean operating return on assets is 0.33405 with a median of 0.01965, while the mean and median FCF to total assets is –0.1188 and –0.04084. The median book-to-market is 0.67723 and the median market value is 1,029.23 in millions of dollars. Finally, there are 181 firms which are represented as users of derivative contracts.

Panel B reports summary statistics for the 305 firms in the banking industry. To arrive at our sample, we follow a similar process to the oil industry sample. We begin with the universe of banks in the Compustat Bank Fundamentals database. After a matching process with the CRSP database, we calculate the default measure for the pre- and post-periods to arrive at 305 firms with valid data. For these banking firms the mean DL measure is 0.00492 with a maximum of 0.64304. The mean equity volatility is 0.28297 with a median of 0.2637 while the median asset volatility is 0.0362. The median dividend yield is 0.241%. The median leverage is 0.03059 and the median capital is 0.10608 with a maximum of 0.26674. In addition, the median non-performing loans to total assets is 0.00651 while the median provision for loan losses to total assets is

0.092%. Finally, the median market value is $475.861 in millions while the book-to-market value ratio ranges from 0.0778 to 2.51316.

Figure 1 shows the changes in OPEC's production from 1998–2019. As the chart indicates, during the period from 1998 through 2009 OPEC made regular and unpredictable changes to production with no changes from December 2008 through November 2016. The change in November of 2016 provides an obvious opportunity to examine the impact of a single change in production on the likelihood of firm default.

Figure 1 OPEC adjustments 1998–2019 (see online version for colours)



Source: https://www.reuters.com/article/global-oil-opec/timeline-opecs-oil-output-changes-since-the-1990s

5 Univariate and multivariate analysis

5.1 Univariate analysis

Panel A of Table 2 reports results for the entire oil industry. For this sample the mean pre-policy passage period DL is 0.14026 while the mean short-term policy action period and long-term policy action period DL are 0.12757 and 0.12859, respectively. This leads to a significant decrease in the change in DL after the OPEC announcement for both the short- and longer-term periods. The changes are –0.01269 and –0.01167. For the oil and gas drilling, oil and gas exploration and production, and oil and gas storage and transportation, we find significant decreases in the mean (median) DL indicator for both the short- and longer-term time periods. In panel B of Table 2, for oil and gas drilling the long-term decrease in the mean is –0.01873 or 7.8% lower relative to the pre-policy passage period DL of 0.23979. For the exploration and production group, the decrease in DL for the mean value is –0.02152 or 9.7% lower, while the change in the long-term is –0.01487 or 6.72% less. For panel D of Table 2, the integrated oil and gas industry, only the mean change in the long-term DL is significantly different than 0. Two groups, the oil and gas equipment and services (panel C of Table 2) and the oil and gas refining and marketing (panel D of Table 2), do not have significant ΔDL for the mean values, although the equipment and services do have a significant decrease in the median value. For the refining companies, the lack of significance can easily be justified, as an increase in the price of oil does not always mean an increase in profits. Their viability is determined by the crack spread, the difference between the price of oil and the price of petroleum products refined from it, such as gasoline and propane. Thus, if oil prices rise, with no change (or decreases) in refined products, their profit margins suffer. Hence, an oil price increase is not necessarily beneficial. In panel G of Table 2, for the oil and gas storage and transportation, the median decrease is –0.01355 for the long-term change while the mean decrease is –0.01339 or 17.86% lower. In general, we find support for Hypothesis 1.

Table 2 Changes in default likelihood surrounding the OPEC production cut by GIC sub-industry

Interval	*Sample size*	*Mean*	*Median*
Panel A: Oil industry combined			
DL: Pre-policy passage [–61, –2]	325	0.14026	0.01778
DL: Short-term policy action period [–1, +1]	325	0.12757	0.01197
DL: Longer-term policy action period [+2, +61]	325	0.12859	0.01186
Δ*DL*: Short-term [–61, –2] to [–1, +1]	325	–0.01269***	–0.01249***
Δ*DL*: Long-term [–61, –2] to [+2, +61]	325	–0.01167***	–0.01171***
Panel B: Oil and gas drilling (10101010)			
DL: Pre-policy passage [–61, –2]	19	0.23979	0.10338
DL: Short-term policy action period [–1, +1]	19	0.21475	0.08875
DL: Longer-term policy action period [+2, +61]	19	0.22106	0.08696
Δ*DL*: Short-term [–61, –2] to [–1, +1]	19	–0.02505***	–0.02582***
Δ*DL*: Long-term [–61, –2] to [+2, +61]	19	–0.01873**	–0.02021***
Panel C: Oil and gas equipment and services (10101020)			
DL: Pre-policy passage [–61, –2]	59	0.10162	0.01468
DL: Short-term policy action period [–1, +1]	59	0.09871	0.00987
DL: Longer-term policy action period [+2, +61]	59	0.09847	0.00911
Δ*DL*: Short-term [–61, –2] to [–1, +1]	59	–0.00291	–0.00199***
Δ*DL*: Long-term [–61, –2] to [+2, +61]	59	–0.00316	–0.00316**
Panel D: Integrated oil and gas (10102010)			
DL: Pre-policy passage [–61, –2]	20	0.05431	0.00020
DL: Short-term policy action period [–1, +1]	20	0.04630	0.00013
DL: Longer-term policy action period [+2, +61]	20	0.04319	0.00011
Δ*DL*: Short-term [–61, –2] to [–1, +1]	20	–0.00802	–0.00077***
Δ*DL*: Long-term [–61, –2] to [+2, +61]	20	–0.01112*	–0.01122***

Notes: This table reports the mean (median) DL measure over the pre-standard announcement period and two post announcement periods, and the mean (median) change in the default measure (Δ*DL*) as the difference between the post and preannouncement period DL. The post announcement periods include a short-term [–1, +1] and long-term [+2, +61]. The t-test (signed rank test) evaluates the null hypothesis that the mean (median) equals zero. ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

Table 2 Changes in default likelihood surrounding the OPEC production cut by GIC sub-industry (continued)

Interval	*Sample size*	*Mean*	*Median*
Panel E: Oil and gas exploration and production (10102020)			
DL: Pre-policy passage [–61, –2]	110	0.22117	0.05261
DL: Short-term policy action period [–1, +1]	110	0.19964	0.03309
DL: Longer-term policy action period [+2, +61]	110	0.20629	0.04671
Δ*DL*: Short-term [–61, –2] to [–1, +1]	110	–0.02152***	–0.02141***
Δ*DL*: Long-term [–61, –2] to [+2, +61]	110	–0.01487***	–0.01485***
Panel F: oil and gas refining and marketing (10102030)			
DL: Pre-policy passage [–61, –2]	25	0.10882	0.00985
DL: Short-term policy action period [–1, +1]	25	0.11049	0.01347
DL: Longer-term policy action period [+2, +61]	25	0.10244	0.01317
Δ*DL*: Short-term [–61, –2] to [–1, +1]	25	0.00167	0.01544
Δ*DL*: Long-term [–61, –2] to [+2, +61]	25	–0.00638	–0.00525
Panel G: Oil and gas storage and transportation (10102040)			
DL: Pre-policy passage [–61, –2]	92	0.07497	0.01019
DL: Short-term policy action period [–1, +1]	92	0.06512	0.00576
DL: Longer-term policy action period [+2, +61]	92	0.06158	0.00569
Δ*DL*: Short-term [–61, –2] to [–1, +1]	92	–0.00985**	–0.00974***
Δ*DL*: Long-term [–61, –2] to [+2, +61]	92	–0.01339**	–0.01355***

Notes: This table reports the mean (median) *DL* measure over the pre-standard announcement period and two post announcement periods, and the mean (median) change in the default measure (Δ*DL*) as the difference between the post and preannouncement period DL. The post announcement periods include a short-term [–1, +1] and long-term [+2, +61]. The t-test (signed rank test) evaluates the null hypothesis that the mean (median) equals zero. ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

In Table 3, we report the changes in DL surrounding the OPEC production cut for the banking industry. The mean pre-policy passage period DL for the entire banking industry in panel A is 0.00547. After the policy change, the mean DL is 0.0044 for the short-term and 0.00437 for the long-term. Although there is a decrease in the mean DL, it is not significantly different than 0. Since there may be some concern the election of a republican candidate for president and the possibility of decreased regulation in the banking industry may be causing an effect on the DL factors, we break the sample into banks in states with 65% of the US oil production in 2016 as noted by the United States Energy Information Administration (http://www.eia.gov/dnav/pet/pet_crd_crpdn_adc_mbbl_a.htm) website and banks in other states.[1]

The location of the banks is for their headquarters as stated in the Compustat database. In this group, Texas had approximately 41% of the production, Alaska 12.7%, Oklahoma 5.5%, and Colorado had 5.2%. In our sample, Texas has 13 banks Alaska, Oklahoma, and Colorado has 1, 3 and 3, respectively. For these 65% of banks, panel B shows the mean decreases in the DL are –0.00073 for the short-term and –0.00086 for the long-term. This is roughly a decrease of 35.1% and 41.34%, respectively. Although the median is significantly different than 0, the mean difference is not significant for the non 65% group. Thus, there is some evidence the DL is decreasing for the banks in states with oil production, which again supports Hypothesis 1.

Table 3 Changes in default likelihood surrounding the OPEC production cut for the banking industry

Interval	*Sample size*	*Mean*	*Median*
Panel A: Banking industry total			
DL: Pre-policy passage [–61, –2]	305	0.00547	0.00003
DL: Short-term policy action period [–1, +1]	305	0.00444	0.00003
DL: Longer-term policy action period [+2, +61]	305	0.00437	0.00002
Δ*DL*: Short-term [–61, –2] to [–1, +1]	305	–0.00103	–0.00105***
Δ*DL*: Long-term [–61, –2] to [+2, +61]	305	–0.00110	–0.00113***
Panel B: Banks in states with 65% of US Oil Production 2016 (TX, AK, OK, CO)			
DL: Pre-policy passage [–61, –2]	20	0.00208	0.00028
DL: Short-term policy action period [–1, +1]	20	0.00135	0.00016
DL: Longer-term policy action period [+2, +61]	20	0.00122	0.00016
Δ*DL*: Short-term [–61, –2] to [–1, +1]	20	–0.00073**	–0.00076***
Δ*DL*: Long-term [–61, –2] to [+2, +61]	20	–0.00086**	–0.00088***
Panel C: Banks not included in panel B			
DL: Pre-policy passage [–61, –2]	285	0.00570	0.00003
DL: Short-term policy action period [–1, +1]	285	0.00465	0.00002
DL: Longer-term policy action period [+2, +61]	285	0.00458	0.00002
Δ*DL*: Short-term [–61, –2] to [–1, +1]	285	–0.00105	–0.00107***
Δ*DL*: Long-term [–61, –2] to [+2, +61]	285	–0.00112	–0.00115***

Notes: This table reports the mean (median) *DL* measure over the pre-standard announcement period and two post announcement periods, and the mean (median) change in the default measure (Δ*DL*) as the difference between the post and preannouncement period DL. The post announcement periods include a short-term [–1, +1] and long-term [+2, +61]. The t-test (signed rank test) evaluates the null hypothesis that the mean (median) equals zero. ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

As a robustness check, we searched firm's 10 k's and 10 q's for mentions of the word 'energy'. From the sample of 305 banks, we found 78 banks which mention energy.[2] When we separated the group by banks which mention energy and those that do not, we did not find any significant difference in the mean change in the DL measure. However, out of the 20 banks with 65% of the oil production in the USA, 14 mention energy. Similar to the results for the 20 banks, there was a significant decrease in the mean change in DL.

5.2 Multivariate analysis

Using ordinary least squares (OLS), the cross-sectional regression results for the oil industry are presented in Table 4. Similar to Vassalou and Xing (2004), we remove firms with negative book-to-market decreasing the overall oil industry sample by 26 firms. For the entire industry, as expected we find operating ROA is positive and significantly different than 0.[3] Thus, firms with low operating profit are more likely to see a decrease in their probability of DL supporting our Hypothesis 5 that profitability is positively related to DL. This effect for ROA carries through to the integrated oil and gas industry, the exploration and production industry and refining and marketing industry. The size effect only occurs for the exploration and production industry. Leverage is significantly negative for the integrated group, meaning firms with high leverage will see larger decreases in the probability of default following OPEC's production cut supporting Hypothesis 2. In the equipment and services group, FCF to total assets is positive and significant, meaning firms with less free cash flow will see larger decreases in the default measure supporting Hypothesis 5. Similarly, firms with less financial slack are expected to see larger decreases in the ΔDL as expected under our second hypothesis, and this holds for the integrated and storage and transportation industries. Hypothesis 4a is supported by the significant positive relation between book-to-market and ΔDL. This relation indicates growth (low book-to-market) firms will be less impacted by OPEC's cut in production; whereas value firms that may be unable to quickly capitalise on higher oil prices experience an increase in DL in the short-term. We find no relation to ΔDL whether oil industry firms use derivatives or not.

In Table 5 we present the cross-sectional regressions for the banking industry. Unlike the oil industry firms, size is significantly positive in most cases, thus smaller banks have a greater decrease in the change in DL, providing support for Hypothesis 3. Like the oil industry, the book-to-market relation is significantly positive. For the Texas only banks, ROE is positive and significant, providing additional support for the fifth hypothesis, and suggesting firms with lower ROE, have a greater decrease in DL. For all banks and the Texas banks, the nonperforming loans as a percentage of total assets and provision for loan losses are significantly negative, as expected, supporting Hypothesis 6. In addition, for Texas banks, the change in non-performing loans is negative and significant indicating the likelihood of default is decreasing for those firms with a large increase in the change in non-performing assets. For the all banks group, as they have an increase in the change in non-performing assets, the DL rises. This may be due to the fact many banks in the whole sample do not hold many oil loans, thus they cannot benefit from the production cut and subsequent oil price increase.

6 Conclusions

During 2016, the price of oil reached its nadir at around \$30 a barrel. Across the USA and other oil producing countries, there was concern about its precipitous fall. Numerous articles written in The *Wall Street Journal* and other news outlets speculated on the ability of the oil industry to service their debt and how this might impact the banking industry which had provided billions of dollars in energy loans. In late 2016, OPEC made its first production cut in nearly eight years, thus providing some relief to the oil and banking industries. Using an option pricing methodology to calculate DL we find the probability of default for the energy related firms and banks with ties to energy decreased following OPEC's production cut.

Table 4 Results of cross-sectional analysis on the change in default likelihood of the oil industry

Variable	*1010xxxx*	*1010*	*1020*	*2010*	*2020*	*2030*	*2040*
	Complete industry	*Drilling*	*E&S*	*Integrated*	*E&P*	*R&M*	*S&T*
Intercept	–0.0275	–0.0957	0.0258	0.0217	–0.0836	0.0809	0.0040
	(–1.57)	(–0.99)	(0.51)	(1.30)	(–2.46)**	(0.56)	(0.16)
Leverage	–0.0187	–0.0777	–0.0052	–0.1321	0.0330	–0.0906	–0.0051
	(–1.50)	(–1.32)	(–0.17)	(–7.38)***	(1.20)	(–1.01)	(–0.34)
Operating ROA	0.0147	–0.0318	–0.0994	0.0671	0.0251	0.2210	0.0311
	(2.47)**	(–0.19)	(–1.52)	(3.95)***	(2.38)**	(1.76)*	(1.61)
FCF/total assets	–0.0013	0.0008	0.1386	0.0582	–0.0655	0.2019	
	(–0.52)	(0.01)	(2.35)**	(1.42)	(–1.94)*	(1.08)	
Financial slack	0.0144	–0.0697	–0.0234	0.2392	0.0682	–0.1180	0.0845
	(0.59)	(–0.32)	(–0.35)	(4.39)***	(1.59)	(–0.91)	(1.86)*
Size (Ln MV)	0.0016	0.0079	–0.0028	–0.0006	0.0043	–0.0051	–0.0009
	(1.44)	(1.19)	(–0.77)	(–0.58)	(1.96)*	(–0.65)	(–0.57)
BK/MKT	0.0017	0.0003	0.0029	–0.0042	0.0020	0.0121	–0.0011
	(2.01)**	(0.12)	(1.95)*	(–1.76)	(1.06)	(1.01)	(–0.53)
Derivative	–0.0020	0.0048	0.0160	–0.0097	–0.0084	–0.0047	–0.0030
	(–0.44)	(0.21)	(1.24)	(–1.58)	(–0.70)	(–0.21)	(–0.63)
N	286	19	55	20	88	24	81
Adj. R^2	0.0374	0.0027	0.1264	0.8679	0.0902	0.2460	0.0033
F-value	2.58**	1.01	2.12*	18.83***	2.23**	2.07	1.04

Notes: This table present ordinary least squares regression results on the change in long-term default likelihood after the OPEC announcement. The independent variables are defined as follows: leverage is calculated as long-term debt divided by total assets, financial slack as cash and short-term investments divided by total assets, and operating ROA as earnings before interest and tax divided by total assets. FCF/TA is free cash flow divided by total assets and free cash flow is defined as operating activities net cash flow – cash dividends – capital expenditures. Market value ($ millions) is calculated as shares outstanding × price calculated from CRSP data as of day –2 prior to the announcement and BK/MKT is calculated as (book value per share from Compustat × price from CRSP) / market value. The derivative dummy is equal to 1 if the company uses derivatives and 0 if not. T-values are in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively. In the S&T regression, FCF/TA was removed due to its high correlation (0.9661) with operating ROA.

From our multivariate analysis, we find across some of the oil sub-industries firms with high leverage, small size, low operating return on assets, low book-to-market (growth firms), and low financial slack benefited the most, with a significant relation to a decrease in the probability of default. For banks, those firms with high recorded non-performing loans and provisions for loan losses appear to have benefited the most with regards to a decrease in the DL indicator.

Table 5 Results of cross-sectional analysis on the change in default likelihood of the banking industry

Variable	*All banks*	*All banks*	*All banks*	*65% banks*	*Non-65%*	*Texas only*	*Texas only*	*Texas only*
Intercept	−0.0127	−0.0121	−0.0141	−0.0012	−0.0136	−0.0149	−0.0058	−0.0019
	(−2.96)***	(−2.83)***	(−3.25)***	(−0.26)	(−2.97)***	(−3.59)**	(−1.12)	(−0.34)
Leverage	−0.0182	−0.0170	−0.0189	−0.0097	−0.0211	0.0196	0.0025	−0.0099
	(−1.30)	(−1.22)	(−1.36)	(−0.68)	(−1.42)	(1.63)	(0.19)	(−0.81)
Capital	−0.0261	−0.0356	−0.0157	0.0163	−0.0262	0.01582	0.0037	−0.0279
	(−1.40)	(−1.93)*	(−0.83)	(0.74)	(−1.33)	(1.01)	(0.17)	(−0.96)
ROE	0.0014	−0.0058	0.0104	0.0140	0.0017	0.0834	0.0552	0.0424
	(0.86)	(−0.74)	(1.18)	(1.37)	(0.20)	(3.86)***	(2.21)*	(1.75)
NonPerform	−0.1214	−0.0838	−0.1254	−0.4966				
	(−1.88)*	(−0.61)	(−1.86)*	(−3.98)***				
CHGNPA	0.2778	−0.4111						
	(3.05)***	(−2.75)**						
PLL	−0.518	−1.2692						
	(−2.30)**	(−2.68)**						
BK/MKT	0.01757	0.0174	0.0151	−0.0037	0.0184	0.0079	0.0027	0.0020
	(7.19)***	(7.38)***	(6.65)***	(−1.18)	(7.12)***	(1.95)*	(0.61)	(0.47)
Size (Ln MV)	0.0009	0.0010	0.0007	−0.0001	0.0009	−0.0006	−0.0005	−0.0004
	(2.53)**	(3.17)***	(2.28)**	(−0.27)	(2.54)**	(−1.48)	(−1.02)	(−0.79)
N	304	304	301	20	284	13	13	13
Adj. R^2	0.1504	0.1554	0.1667	0.0564	0.1580	0.7547	0.5950	0.6056
F-value	9.94***	10.29***	11.00***	1.19	9.85***	7.15**	3.94*	4.07*

Notes: This table present ordinary least squares regression results on the change in long-term default likelihood after the OPEC announcement. The independent variables are defined as follows: leverage is calculated as long-term debt divided by total assets, capital is the ratio of book value to total assets. ROE is the ratio of earnings before interest and taxes to book value of equity. NonPerform is the ratio of total non-performing assets to total assets PLL is the provision for loan losses divided by total assets, and CHGNPA is the ratio of the change in nonperforming assets from the current year less the previous year to total assets. Market value ($ millions) is calculated as shares outstanding × price calculated from CRSP data as of day −2 prior to the announcement and BK/MKT is calculated as (book value per share from Compustat × price from CRSP) / market value. T-values are in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively. The total sample is 304 which is 1 less due to the removal of the company with the outlier ROE of 4.50. Without it the maximum ROE is 1.07.

We considered including the change in default for other OPEC announcements such as the increase in production in 2018; however, we believe the 2016 cuts were a clean event since there had been eight years between OPEC changes. Earlier production cuts were often followed by additional cuts (or increases) within just a few months, thus making a single change too 'noisy' to examine. In addition, the public story leading to the 2016 cut, with the media coverage throughout the year about potential energy loan losses, led to this being one of the most significant OPEC announcements in decades. We leave the investigation of the effect of other OPEC announcements on the oil and banking industry to further research.

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Notes

1 With California included in the oil-producing states (with about 5% of oil production), their inclusion led to a non-significant mean ΔDL. We conclude this could be due to the economic diversity of the state. In addition, although New Mexico, North Dakota and Wyoming had nearly 20% of production, no banks from this group were in the final sample due to missing data.

2 We attempted to pull numeric data on the bank energy loans from these SEC reports, however we found a very small number of firms include the dollar amounts of their energy loan portfolio.

3 The small sample size of our subsamples may explain why we do not find significance in each subsample, yet statistical significance in the full sample.