Distance to Default: Oil Corporates and Hedging Strategy

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ABSTRACT

The addition and rapid growth of North American shale oil production on global supply channels coincided with the recent global oil price collapse. Independent oil producers have shown themselves to be instrumental in the tight oil production growth and movement towards US oil independence. Predicting the industry's capability to maintain and further develop domestic shale oil production requires an understanding of financial and operational resilience. Equity investors, like debt providers, have contributed to firm capital structure scalability in a cyclical industry. The risk of firm default during an energy price trough is critical for equity and debt valuations. This paper investigates the effect of hedging programs by a homogeneous group of independent, domestic-focused tight oil producers on firm distance to default. In order to determine if hedge programs influence firm financial distress metrics, forty-four domestic tight oil producers were analyzed over a five-year period (2011-2015), utilizing a balanced fixed effect panel model. Results conclude that hedge volumes exhibit a significant positive interaction with firm distance to default, supporting previous research.

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1.0 INTRODUCTION

Production growth from exploration and production (E&P) tight oil producers in North America between 2010 and 2015 surprised all but the most knowledgeable industry insiders. Shale and tight oil production grew from 0.8 million to 4.9 million barrels per day (BPD) in this period, going from 15% to 52% of total US crude oil production (Energy Information Administration, 2015). This exceptional growth pattern spurred many long-term forecasts predicting the United States would be oil independent by 2017. The addition of this production caused the global supply curve to shift left under a constant demand pattern, resulting in lower prices. The price of crude oil declined dramatically in the second half of 2014, and as of May 2016, sixty independent producers had filed for bankruptcy or reorganization protection (Hals, 2016). This includes twelve of the forty-four firms in this study that filed during 2016. Small- to medium-sized shale producers (private and public) contribute an estimated one million BPD to domestic production, making them an important supplier group (Morse, 2015). Given this, assessment of such producers' resilience is a worthy area of inquiry. The time period under study, due to a severe negative price innovation, proved an excellent opportunity to observe firm performance, default probabilities, and the characteristics of effective hedge programs.

The hedging strategies of US-based independent tight oil producers studied here over a five-year period that includes both stable and volatile crude oil price periods will illuminate a crucial question: Do hedge programs provide a positive contribution to reduce default probabilities and the likelihood of bankruptcy? The literature review did not reveal any other comprehensive, hand-collected data study of domestic, undiversified tight oil firm financing and hedging strategies and their impact on firm default probability. The findings of this paper will contribute important information on a new independent producer group to existing research in the area of hedging strategies and their effect on financial distress metrics. This research will provide the investor community with information that will help them consider the allocation of debt- or equity-structured funding to this specific E&P segment. Bank lenders, who require minimum production hedging in their covenant structures, will benefit from an empirical study of hedging programs and firm default risk.

The research hypothesis suggests that a study sample of independent, domestic, non-diversified tight oil producers, with higher levels of hedging ratios, have a lower probability of default as measured by distance to default than those producers with a lower hedging ratio. To test this hypothesis, I created a sample of non-diversified independent tight oil producers, with and without credit ratings, with market capitalization values between 100 million and 11 billion as of June 30, 2015. A fixed effect panel model, with quarterly frequency, is used to evaluate the impact of hedging on distance to default, while controlling for firm size, leverage ratio, profitability, investment, and production costs. Publicly traded companies were selected, as comprehensive data is available on the Securities and Exchange Commission (SEC) Electronic Data Gathering, Analysis and Retrieval (EDGAR) website and in quarterly financial reports mandated by SEC market risk[1] disclosure requirements. While E&P producers extract a combination of crude oil, natural gas, and natural gas liquids, this study selected firms with more than 50% of their revenue derived from crude oil sales. This allows for a homogeneous, controlled evaluation of the hedging effects on the firm sample during a period of price stability and a period with negative price shocks in global oil prices during Q3-2014 (Figure 1).

Figure 1: Historical WTI Crude Oil Prompt Futures Prices USD/Bbl (2011-2016)

As Jin and Jorion (2006) note in their study of hedging policies on oil and gas producer firm value, this group selection allows for a focused approach and strong homogeneity. By selecting domestic-focused tight oil producers, this research further emphasizes a homogeneous nature of study. The companies selected are focused on E&P and

[1] Since 1997, the SEC Financial Reporting Release 48 requires all publicly traded companies to disclose, on an annual basis, possible and actual risk exposures including all derivatives products used for hedging and speculation.

commodity sales only in North America and are registered corporations in the United States. This ensures that tax and federal subsidy programs are consistent across the sample group.[2]

Hedging activity and the sophistication of hedging strategies correlate to the corporate leverage ratio (Domanski, 2015). Aretz and Bartram (2010) found 65% of all US-based firms used derivatives. Corporate hedging strategies also have a link to debt borrowing structure obligations and covenants. This demands minimum hedge volumes to ensure stable cash flow streams are available to service outstanding debt, and maximum hedge volume limits to discourage speculation.

The high-yield corporate debt market, and in particular the US E&P sector, is attractive for investors seeking higher yields with a known risk exposure. Since 2009, when government interest rate policy resulted in a downward shift to the term structure of interest rates, investor demand for high-yield returns has supported the growth of the corporate high-yield bond market. These channels of high-yield funding and strong global oil prices have supported E&P tight oil drilling and production growth activity.

The time period for shale and horizontal discovery to commercial production can be as short as six weeks; this process also has a much shorter production life cycle than conventional wells (Kilian, 2016). As a result, many more independent producers are taking on a larger portfolio of shale plays and becoming larger corporate entities, consequently requiring further external funding. Access to debt markets varies based on the size and credit rating of the independent producers. Larger firms with credit ratings can access the public debt capital markets, assuming investor demand for these types of debt products. Many firms have no credit rating due to firm size or firm financial health, thereby limiting borrowing channels to banking relationships and private placement.

Crude oil is a cyclical commodity with high price peaks and low price troughs. Low prices

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[2] State level industry or government subsidy information could have a varied effect across the producer sample group, albeit firms are concentrated in six states.

can create financial stress for producers and default risk for debt obligations. Distance to default measured using Moody's KMV model,[3] based on Merton's 1974 bond valuation model, has been applied extensively to corporate firms and is a forward-looking measure of how far away a firm is from bankruptcy by comparing asset net worth to firm market volatility. Empirical estimates of default probability via this model structure out-perform accepted benchmarks such as agency debt ratings (Kealhofer, 2003). This approach is particularly useful for firms with no credit ratings and no market-traded credit default products.

The remainder of this paper is organized as follows: Section 2 reviews existing research and outlines this paper's contribution. Section 3 describes the data and empirical models and methodology the study uses. Section 4 reports the empirical results and discusses the robustness of the methodology. Finally, Section 5 summarizes the key findings.

2.0 LITERATURE REVIEW

Economic theory, derived from Miller and Modigliani's Irrelevance Proposition (1958), states that a corporate financing policy, which includes hedging policy, should have no effect on firm economic performance or value under perfectly efficient markets. Shareholders may prefer that a corporate firm does not hedge so that they can participate in the risk exposure that a firm incurs, such as oil price risk for an oil producer (Smith and Stulz, 1985). The literature has noted market imperfections such as financial distress and bankruptcy costs, corporate tax, external financing that is costlier than internal WACC,[4] information asymmetry between managers and shareholders, and agency problems (Hubbard, 1997). These market imperfections provide the rationale for considering risk management programs.

Firm risk falls into two categories: asset price risk, such as commodity, interest rate, or foreign exchange; and firm operation risk, such as geographic and product diversification (Allayannis et al., 2001). This study focuses on a homogeneous, undiversified group of US

[3] The KMV model (Kealhofer, McQuown, Vasicek) is a proprietary model and database owned by Moody's Analytics.
[4] WACC is the weighted average cost of capital and refers to the cost of funding for a firm.

market-focused oil producers and therefore considers only asset commodity price risk. In a study of oil producers, Haushalter (2000) noted that corporate risk management can reduce the unexpected costs of financial distress and underinvestment in capital projects. The use of hedging is directly related to the firm's financing costs and reduces bankruptcy costs (Haushalter et al., 2002). The greater the financial leverage, the more apt managers are to manage asset price risk. Economies of scale, hedging costs, and basis price risk[5] are all relevant to the hedging structures selected. Contrary to this finding, Hahnenstein and Roder (2003) suggest that hedging does not reduce the probability of bankruptcy. Full-cover hedging is not required or sufficient to minimize a company's probability of bankruptcy, thereby indicating that cash flow variance minimizing hedging is different from strategies to reduce the probability of bankruptcy.

Mnasri et al. (2013) presented an empirical study for North American oil and gas producers on the impact of maturity term structure of hedging programs on firm value and firm risk. Their results showed a non-monotonic relationship between maturity structure and financial distress. This supports the research of Fehle and Tsyplakov (2005), who found that firms do not initiate or modify existing risk management policies when they are far removed from financial distress or deeply in financial distress. They also found that transaction costs are an important determinant of a firm's risk management decisions. The popularity of three-way collars[6] in recent years allows E&P firms to access hedging products at little cost, albeit adding significant tail risk to their portfolios, which may not be fully considered (Mnasri et al., 2013).

Distance to default literature commenced with Merton's seminal paper (1974) on methods to price corporate liabilities. Merton treats corporate debt as an option-like financial instrument based on the model structure of Black Scholes (1973). This provides a real-time credit measure of firm liabilities, thereby reducing reliance on quarterly or annual corporate reports. As a firm's asset value evolves over time, debt obligation is honored when the cumulative asset value stays above the promised payout; if not, default occurs.

[5] Basis price risk is the differential between the production facility location and the liquid market trading location.
[6] A three-way collar is a standard costless collar with the addition of an out-of-the-money short put.

KMV Corporation extended Merton's model to calculate expected default frequency using a distance to default measure for each firm (Kealhofer, 2003). The primary focus of the KMV model is probability of firm default rather than valuation of debt as per Merton. Bharath and Shumway (2008) found that KMV's distance to default approach was not a sufficient statistic for firm default probability, but serves as a good functional form to forecasting defaults. Distance to default structural form continues to be a relevant input in firm default research (Duffie et al., 2007; Duan et al., 2012). The common use of cross default provisions in debt covenants means that default is a company-wide event, not debt obligation specific (Bohn and Crosbie, 2003). Moody's KMV model and the Altman Z score (1968), the industry accepted credit risk modelling tools, must be broadly disseminated in risk management departments and used in conjunction with other tools in the risk analysis process, such as traditional ratio analysis. Both KMV and Altman Z score models provided insight to the Enron default in advance of credit ratings (Azadinamin, 2012).

Oil option market volatility has always been skewed in the downside risk direction, due to the large magnitude of producer hedging activity combined with an absence of consumer hedge activity. Between 2011 and 2014 the put skew steepened, perhaps supported in large part by increased producer hedging (Cortazar et al., 2015). A steeper volatility curve for out-of-the-money put protection results in a higher cost for hedging. The growth of independent producers participating in the tight oil sector could explain the amplification of the put skew, as lenders demand a minimum level of hedging to ensure cash flow for debt servicing. To reduce hedging costs, producers may select strike levels that provide less protection (Mnasri et al., 2013) or inadvertently put on speculative positions (three-way collars or bull put spreads[7]). In this study, 36% percent of the firms used three-way collars to hedge oil and gas production. The delta equivalent valuation for these three-way collars eroded to near zero after the oil price break in Q3-2014, proving this structure does not guarantee downside price protection.

[7] A bull put spread consists of a short sale put and a long put purchase at a lower strike price. The strategy of the bull put is to collect option premiums with the expectation of a rising price market.

This paper's research will contribute to the existing literature by providing evidence on the importance of hedging strategies among US-based shale-focused independent oil producers to default probabilities. This will provide important insight to a new industry where project scale and duration makes shale producers appear similar to manufacturing companies, unlike the historical model of E&P companies. Future domestic shale oil production depends on the resiliency of these small- to medium-sized independent producers.

3.0 METHODOLOGY

3.1 Model Approach

3.1.1 Statistical Properties of Stock Price Returns and Hedging

Independent crude oil producers' revenues and subsequent earnings are exposed to significant market risk. Prior to the study of hedging programs for this sample, the relationship between stock price returns and energy price returns will be analyzed (as per Jin and Jorion, 2006).

The firm's stock returns were modelled as a dependent variable using a two-factor model with S&P 500 futures market returns as a control variable: firstly, with oil price returns (1), and secondly, with gas price returns (2). Sample selection criteria limited the sample to firms that secure the majority of their revenue from oil production sales. During the study time series, oil prices experienced a significant negative innovation commencing in Q3-2014. I expect oil price returns to be a statistically significant influence on stock returns and have no expectation that gas prices will prove statistically significant. Finally, a three-factor model was used to observe the firm's stock return interaction with oil and gas futures price returns simultaneously, again using SP-500 returns as a control variable (3).

$$R_{i,t} = \alpha_i + \beta_{mkt,i} * R_{mkt,t} + \beta_{oil,i} * R_{oil,t} + \varepsilon_{i,t} \quad (1)$$

$$R_{i,t} = \alpha_i + \beta_{mkt,i} * R_{mkt,t} + \beta_{gas,i} * R_{gas,t} + \varepsilon_{i,t} \quad (2)$$

$$R_{i,t} = \alpha_i + \beta_{mkt,i} * R_{mkt,t} + \beta_{oil,i} * R_{oil,t} + \beta_{gas,i} * R_{gas,t} + \varepsilon_{i,t} \quad (3)$$

Next, the firm stock returns were regressed against the hedging ratio and ratio of proven reserves to market value of equity (4), as per Rajgopal (1999). This will indicate the importance of the hedge ratio and magnitude of proven reserves on firm stock returns.

$$R_{i,t} = \alpha_i + \beta_{mkt} * R_{mkt,i} + \left(\gamma_1 + \gamma_2 * \Delta_{oil,i} + \gamma_3 * \frac{Oil\ Reserve_i}{MW\ Equity_i}\right) * R_{oil,t} + \beta_{gas} * R_{gas,t} + \varepsilon_{i,t} \quad (4)$$

3.1.2 Fixed Effect Panel Model: Distance to Default

Previous literature on the importance of hedging or not hedging has focused on firm value represented by the Tobin Q, usually described as a ratio of market equity value to book equity value for a specific industry or firm, as the dependent variable. Hedging ratio is the primary RHS independent variable. Control variables include firm size, firm profitability, firm investments, leverage, and production cost. Allayannis and Weston's (2001) seminal paper provided the framework for this study. Jin and Jorion (2006) noted that the model structure Allayannis and Weston (2001) used could have several sources of endogeneity. To address this, they concentrated on the homogenous market of oil and gas producers while maintaining the model structure of RHS control variables. I believe that Jin and Jorion (2006) did not entirely eliminate endogeneity, however, as LHS and RHS variables have similar sources of endogeneity. I proceed by implementing a distance to default measurement, instead of Tobin Q, for each firm, as my research is focused on survival rather than firm value for this volatile industry group (5). This dependent variable should not create endogeneity concerns in the model structure.

$$Distance\ to\ Default_i = \alpha_i + \beta_i * Hedge\ Ratio\ Production_i + \sum_j \gamma_j\ Control\ Variable_j + \varepsilon_{i,j} \quad (5)$$

Where:

$$Hedge\ Ratio\ Production = \frac{Delta\ Hedge\ Volume_{i,t}}{Annual\ Prodution_{\ i,t+1}} \quad (6)$$

$$Hedge\ Ratio\ Reserves = \frac{Delta\ Hedge\ Volume_{i,t}}{Annual\ Reserves_{\ i,t+1}} \quad (7)$$

Control Variables Used:

1. *Firm Size: Log Total Assets*
2. *Leverage Ratio: Total Debt/Market Value Equity*
3. *Profitability: Return on Assets % ttm (Trailing 12-month Value)*
4. *Investment Growth (CAPEX / Total Assets)*
5. *Expense Cost per Share*

Jin and Jorion (2006) used credit rating and access to financial markets as control variables, which are not relevant for this study as the majority of firms have no credit rating and all firms access hedging products through their lending relationships and the broker dealer market.

3.1.3 Naïve Distance to Default

Distance to default, using the KMV model, is a normalized ordinal measure of default risk for an individual firm, based on Merton's (1974) debt valuation model, which estimates the number of standard deviations moves required to bring a firm to default within a specific time horizon. It uses a structural approach to calculate expected default probability, providing a real-time view of the credit monitoring process, as opposed to quarterly or annual ratio analysis. Distance to default measures and compares a firm's net worth, based on market equity valuation, to the firm's market volatility (8). Distance to default is similar to bond ratings in that it does not indicate the exact default probability. The KMV model provides actual expected default frequency (EDF) by comparing distance to default results to a proprietary database of historical default observations. This database, and hence EDF valuations, is not available for this research due to funding restrictions. The key assumption in the distance to default structural model is that all relevant information for determining default risk is contained in the expected firm market value of assets, default point, and asset volatility, which requires efficient liquid markets. Nevertheless, distance to default application for this study of firm hedging is appropriate, as all firms are publicly traded in liquid markets and balance sheet statements provide transparency on the short-term and long-term debt obligations for each firm. One critique is that the distance to default structure does not distinguish between types of debt such as seniority, collateralization, covenants, and convertibility. I believe that this critique will not hinder the results of this homogeneous study group.

$$d_f = \frac{E(V_t) - d^*}{\sigma_V} \tag{8}$$

where: $E(V_t)$ *is expected firm value*

σ_V *is firm asset market volatility*

$d^* = short.term\ debt + \frac{1}{2} * long.term\ debt$

In order to manage the challenges of calculating σ_V , I implemented the naïve distance to default measure (9) presented in Bharath and Shumway (2008), defined as:

$$Naïve\ dd = \frac{ln\frac{E+F}{F} + (r_{i,t-1} - 0.5 Naïve\ \sigma_v^2)T}{Naïve\ \sigma_v \sqrt{T}} \tag{9}$$

where E represents the value of the market equity calculated as the product of the stock price at the end of each quarter and the number of shares outstanding; F is the face value of debt; $r_{i,\,t-1}$ is the return of equity of the firm, i, in the previous period

$$\sigma_v = \frac{E}{E+F}\sigma_e + \frac{F}{E+F} Naïve\sigma_d \tag{10}$$

and $Naïve\ \sigma_d = 0.05 + 0.25 * \sigma_e$ and T is the forecast horizon of one quarter. The inputs for the distance to default model of Bharath and Shumway (2008) are sources from financial statements and equity market historical data.

3.2 DATA

3.2.1 Sample Description

This study examines the impact of financing strategies and hedging on firm value and firm distress on a homogenous undiversified group of forty-four independent, domestic-focused tight oil producers (Appendix A) from 2011 to 2015. This study is the first to focus on smaller-sized US domestic independent producers and benefits from a quarterly frequency instead of annual observations. This testing should provide a comprehensive understanding of the effectiveness of hedging as a risk management tool with good statistical intensity.

To support the homogeneous and undiversified sample criteria, firms were selected from the SEC Standardized Industry Classification (SIC) classification 1311 (Crude Petroleum and Natural Gas Production)[8] with oil sales contribution of more than 50% of firm revenue during 2013-2014 and market capitalization between 100 million and 11 billion USD during the study time period. Total crude oil production volume for this sample was approximately 2% of global production during this time period, amounting to 2.2 million BPD in 2014 and 2.5 million BPD in 2015.[9] Quarterly data was meticulously hand-collected, reviewed, and cross-referenced for accuracy from 10-K financial reports from the SEC EDGAR system and from the Thomson Reuters EIKON database. Data include key financial statement metrics and commodity price hedge programs, in the form of annual production, proven reserves, and financial hedges. Data validation is satisfied as SEC regulation mandates that public firms disclose corporate risks, such as credit, market, and operational, and proven developed and undeveloped reserves. Firms have a choice of reporting market risk in tabular, sensitivity, or value at risk forms. All firms in this sample provided tabular data, allowing for detailed delta equivalent hedge volume to be determined for each quarter of the study time period.

During the extraction of crude oil, producers also extract natural gas and natural gas liquids (NGL) as either primary or secondary products. The overall hedge ratio includes natural gas and NGL hedges with oil hedges since all three products contribute to the producer's earnings. A specific crude oil-only hedge ratio is also used to test robustness of the overall hedge ratio and to determine if the oil production-specific firm selection will respond more significantly to an oil-specific hedge ratio (Figure 2). Hedge ratios were calculated by summing the linear exposure products to the option positions on a delta basis using the Modified Black Scholes model (Black and Scholes, 1973), using the historical implied third prompt month option volatility.[10] Hedge position and forward sales with no guaranteed fixed prices, such as basis hedges or volumetric forwards, were not included in the delta equivalent hedge calculation because a floor price is not guaranteed.

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[8] SEC SIC for Crude, Petroleum and Natural Gas producers
[9] Data from 10-K company reports cross referenced with Reuters EIKON data, author's calculations.
[10] The use of third-month volatility, sufficiently removed from short-term market stress situations, to calculate options positions of all tenors is believed to be sufficiently precise for the hedge deltas.

Figure 2: Average Firms' Delta Hedge Production vs. Next Year Production/Reserves

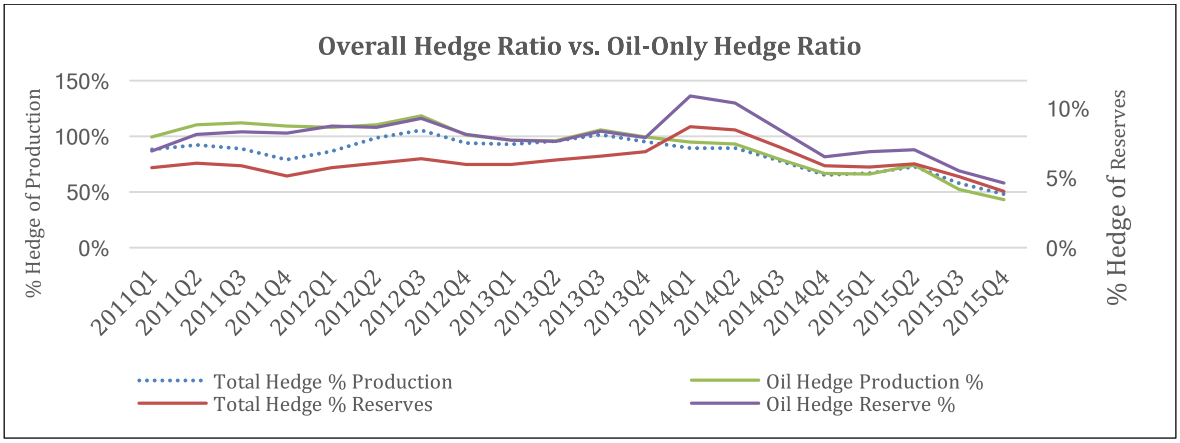

Table 1: Summary of Firm Characteristics

	Observations	Mean	Std. Dev.	Min	Max
Company	880			1	44
WTI Oil	880	84.42	21.90	37.04	109.62
WTI_Vol_3M	792	0.2813	0.1180	0.1304	0.5496
Bankruptcy*	880	0.2727	0.4456	0	1
Market Cap	849	2,659.86	3,600.00	4.06	29412
Total Assets	859	3,692.50	4,051.69	2.8	18927
ROA	840	0.1172	2.4200	-29.1	35.9
Revenue	868	292.95	732.33	-126.5	13601
Ops Exp	868	323.86	740.91	-332.8	12729
Hedge_Prod	824	0.8653	0.8206	0	5.46
Hedge_Dummy_150+	839	0.1585	0.3654	0	1
Hedge_ Dummy_0+	839	0.9261	0.2618	0	1
BV Reserve/MV Equity	849	2.0850	4.7653	0	97.29
Permian Basin	880	0.4318	0.4956	0	1
TobinQ	859	1.4100	0.7203	0.304	6.866
Capex_TA	859	0.0776	0.0805	0	1.202
Distance to Default	839	4.131	2.155	0.156	14.95
D/E	848	2.4060	12.6900	0	339

* Observed December 2016, 12 months after sample period, as percentage
\+ Binary variable for hedging dummy based on 150% production, 0% production

Hedge activity was found in 92.6% of the firm time periods (Table 1). All firms had some form of hedge activity during the five-year time series. Hedge ratios greater than 150% were found during 16% of the firm quarterly time periods. This does not necessarily indicate that 150% of hedges were in the current or the following year. Rather, this figure represents the aggregate delta hedge volume over all future years. Some firms hedge forward one year, while other firms hedge forward in a declining volume pattern over multiple years. Crude oil-only hedge ratio and reserves were calculated to compare the significance of oil-specific hedging, as this study sample focused on firms with majority oil production revenue exposure.

Oil producers have two choices for exploration cost accounting under US accounting rules: a full cost or a successful efforts approach. Full cost allows firms to capitalize all costs incurred in the exploration, regardless of the operability of the well. Successful efforts means that only costs associated with a successful well are capitalized, a more conservative method. To manage this different accounting structure, this study uses EBITDAX[11] as a comparable measure in the leverage ratio.

Independent producers in the sample are mainly focused on tight oil extraction and are present in all the major shale play regions in the United States, with the highest firm presence in the Permian Basin. The Permian Basin is known to have one of the lowest exploration and lifting costs (Maugeri, 2013).

3.2.2 Descriptive Statistics

Oil producers implement hedging policies to limit downside price risk exposure, using derivative instruments such as forwards, futures, options, and collars. Producer price hedging strategies are based on expected annual production in future years. The US oil futures and options markets have superior liquidity and transparency, which provides low transaction costs for implementing a hedge. To access oil futures markets, non-investment grade companies tend to transact directly with their lending banks, which reduces costly collateral agreements for credit risk and allows for right way risk[12] between the producer and the lending bank. The early termination of hedging has occurred in the past, driven by a firm's desire to lock in profit margins from the hedge transactions, to support operating profits. Over recent price declines, lenders have required tight oil producers in financial distress to terminate in-the-money hedges, to direct cash flow for mandatory debt repayments.

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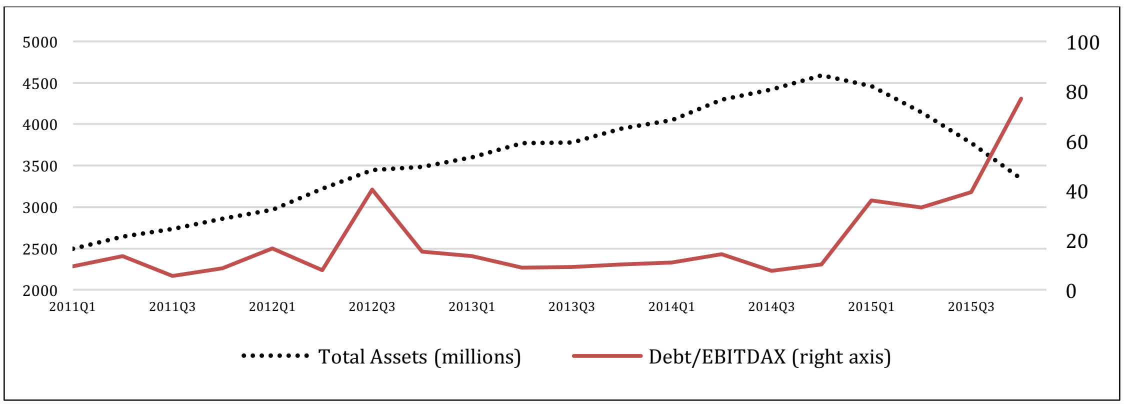
[11] EBITDAX is equal to EBITDA for full cost method firms. Firms in this study are evenly split between selections of full cost or successful efforts accounting. Adjusted EBITDAX was calculated for all firms.
[12] Right way risk refers to risk that goes against the client book but in favor of the derivative or debt issuer.

Standard E&P corporate valuation is based on net present value of fixed assets, which are always a function of proven reserves and sometimes a function of unproven reserves.[13] More complex corporate valuation methods use an option pricing mechanism which includes some percentage of unproven reserves in the valuation. Corporate lending analysts consider proven reserves paramount in determining borrowing authorization amounts. The firm asset valuation process uses proven reserve volumes multiplied by a banker-generated price deck, which references the market futures price curve. A shift lower in the energy futures price curve will move the price deck lower and result in a reduction in proven reserve valuation. This, in turn, reduces the asset value backing or collateralizing the debt instruments (Figure 3).

Figure 3: Total Assets and D/EBITDAX: Firm Study Sample Average



4.0 EMPIRICAL RESULTS

4.1 Firm Stock Returns Sensitivities to Oil and Gas Prices

Tables 2 and 3 provide results for the two-factor models and the three-factor model, respectively. Results indicate that there is a highly significant interaction of S&P 500 future returns and WTI oil returns on firm's stock returns in both a pooled OLS and FE panel approach. The coefficient of S&P 500 return is 1.15, indicating that the firms' stock returns are more volatile than the market returns. If the market returns increase by 1%, the average of firm stock returns increases by 1.15%.

[13] Total reserves consist of proven developed, proven undeveloped, and unproven undeveloped reserves. Proven reserves include proven developed and proven undeveloped. Market futures prices are a factor in determining the viability of reserves designated proven.

Table 2: Two-Factor Model with WTI Oil Returns and HH Gas Returns

Two-Factor Model		WTI_Return	HH_Return
WTI_Return		0.8160	
	t-stat	5.1800	
	P>|t|	0.0000***	
HH_Return			0.3317
	t-stat		2.1000
	P>|t|		0.0360**
S&P 500_Return		1.1541	2.0352
	t-stat	2.9800	5.7500
	P>|t|	0.0030***	0.0000***

** Significance at 5% level ***Significance at 1% level

The three-factor model shows that firm stock returns increase by 0.78% if WTI oil price returns increase by 1%. This is a strong, significant relationship. For HH gas prices, a 1% increase in gas prices results in a 0.17% increase in stock returns with low significance and can be removed as a key influence on firm stock returns. This result is consistent with the sample selection criteria, which focused on firms with strong revenue from oil production.

Table 3: Three-Factor Model with WTI Oil Returns and HH Gas Returns

Three-Factor Model		WTI_Return	HH_Return	SP500_Return
Coefficient		0.7802	0.1668	1.2037
	t-stat	4.8700	1.0500	3.1000
	P>|t|	0.0000***	0.2950	0.0020***

** Significance at 5% level ***Significance at 1% level

4.2 Firm Stock Return: Hedge Ratio Production and BV Reserve / MV Equity

The fixed effects panel model (table below) and the OLS pooled regression (not shown) provide consistent results showing that hedge ratio production is not statistically significant and book value of reserves is statistically significant. S&P 500 and WTI returns continue to exhibit statistically significant patterns in this model. The insignificance of the hedge ratio inverts the findings of both Jin and Jorion (2006) and Acharya et al. (2013). However, the proven reserve valuation with stock return valuation accords with the findings of Acharya (2013) and Boyer and Filion (2007). Equity market participants make investment decisions based on several sources of firm information, such as future revenue streams. This market dynamic is confirmed with t-stat significance between WTI price returns and firm natural resource reserves. Limited investor access to updated hedge volumes and a time constraint on aggregation and analysis of this data from annual reports may explain why hedge ratios do not statistically predict firm stock return.

Table 4: Panel FE Results: Hedge Ratio Production and BV Reserve / MV Equity

Stock_Return	SP500_Return	WTI_Return	Hedge_Prod_Roil	BVRES_MVE_ROIL	HH_RETURN
Coefficient	1.2302	0.5237	-0.1526	0.0497	0.1400
t-stat	3.1300	2.2700	-0.6600	2.1500	0.8700
P>|t|	0.0020***	0.0240**	0.5080	0.0320**	0.3840

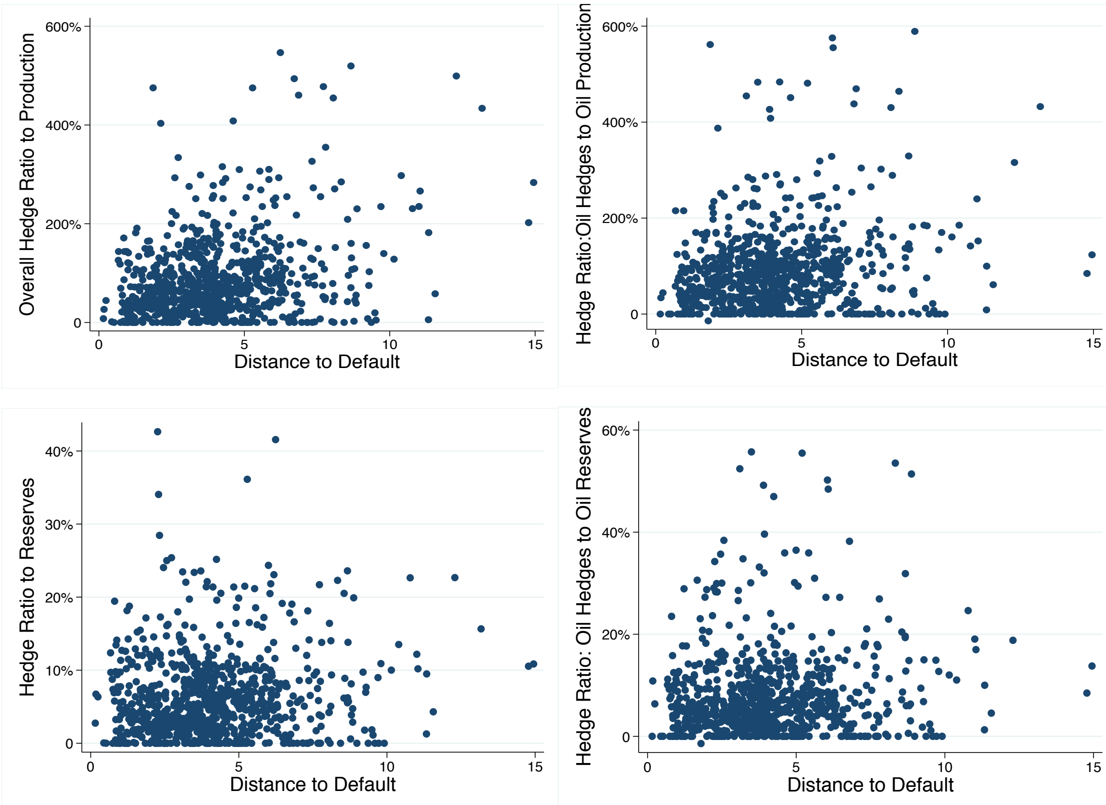
Hedge_Prod_Roil is the hedge ratio of production multiplied by WTI oil return; BVRES_MVE_ROIL is book value reserves divided by market value equity multiplied by WTI oil return.
** Significance at 5% level ***Significance at 1% level

4.3 Fixed Effect Panel Model: Naïve Distance to Default

Model results with log Tobin Q as the dependent variable find that the hedging ratio is statistically significant with a low magnitude of influence in the coefficient. This result is contrary to the findings of Jin and Jorion (2006) and supports the findings of earlier literature. As previously mentioned, the concern of endogeneity in the model structure reduces its relevance.

The magnitude of the hedge is statistically significant for distance to default with a coefficient value of 0.8931, indicating a .89% increase in number of standard deviations in distance to default with a 1% increase in hedge ratio (Table 5). The number of standard deviation that represents distance to default values plotted against hedge ratio to annual production confirms that higher hedge ratios result in a larger distance to default metric (Figure 4).

Figure 4: Hedge Ratios vs. Distance to Default



This is particularly relevant in this particular study time period given the exposure to a large negative innovation in global oil prices. In the twelve months after the study time period, twelve of the forty-four firms declared some form of default or bankruptcy protection and two firms were acquired by the same independent oil producer.[14] This provides a unique situation with complete firm data immediately prior to a default event, which can allow for investigation into the contributing factors to the erosion of distance to default for these firms (Figure 5).

[14] The two firms acquired both had hedge ratios in the top 10% of the sample. Acquisition occurred at the end of 2015, indicating that these firms were acquired for their hedge book rather than their proven reserves or operating efficiency.

Figure 5: Quarterly Distance to Default Ratio for Sample Firms

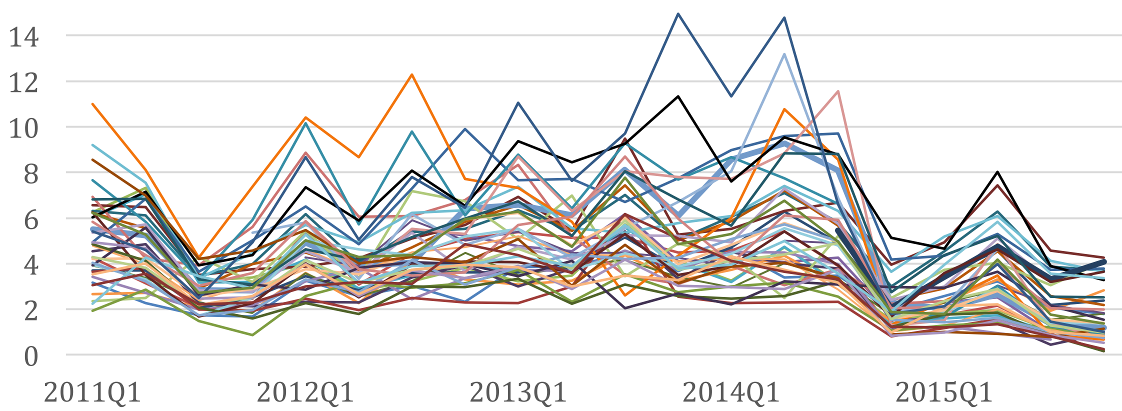


Table 5: Fixed Effect Panel: Naïve Distance to Default

	Naïve dd		
Observations	783		
# Groups	44		
	Coefficient	t-Stat	P>|t|
LOG_TA	0.3718	--1.0700	0.2850
ROA	0.0448	0.8500	0.3980
HEDGE_PROD	0.8931	-6.6800	0.0000***
CAPEX_TA	0.4843	0.9705	0.6180
OPSEXP_SHARE	-0.0763	-4.5800	0.0000***
D_E	-0.0140	-2.6500	0.0080***
cons	4.8468	4.1500	0.0000***

Hedge_Prod is the hedge ratio: delta hedge position divided by next year annual production; LOG_TA is the natural log of firm's total assets, ROA is the trailing 12 month return on assets, CAPEX_TA is the capital expenditure divided by total assets, OPSEXP_SHARE is the operating expense divided by number of shares, D_E is the debt equity ratio.
* Significance at 10% level ** Significance at 5% level ***Significance at 1% level

4.4 Strength of Results

The regression model for WTI oil returns and S&P 500 returns against stock returns was analyzed with monthly, quarterly, and annual data frequencies with consistent model results. The coefficient magnitude and sign were consistent for all independent variables under a pooled OLS and FE panel models to evaluate oil price and market return significance to individual stock returns.

The FE panel models for firm value and distance to default were executed on an annual frequency as a robustness confirmation with quarterly frequency results. Several representations of leverage were used for independent model variable, including

D/EBITDAX and LTD/MV CAPITAL to support and interpret the similarities and differences with the debt/equity selected independent leverage variable.

4.4.1 Probit Model Results

As an extension to the distance to default model results, I ran a probit model with bankruptcy—surveyed at December 2016, one year after the study time period—as the binary dependent variable. This is an alternative approach to observe the interaction of hedge ratio magnitude and bankruptcy outcomes for firms.

The data used in this research provides a rare opportunity to immediately analyze potential contributors to bankruptcy for these firms. Some may argue that the overall sample is small, as is the subset of firms ultimately declaring bankruptcy; nevertheless, the data provides an opportunity for detailed analysis of these firms in a homogeneous sample. Results will be useful for evaluating bankruptcy on different firm samples in the future. This model does not contain an independent variable capturing management structure; this is the weakness of the model. Further work on this model will include a variable to identify managerial ownership. The strategy and timing of the bankruptcy is not under consideration here, as there are many reasons for the actual timing of the announcement. A future model should give further consideration to identifying model parameters to represent this aspect. In this study, I take a snapshot of all firms, one year later, in an on-going low global oil price environment, to observe the number of firms that have used some form of bankruptcy protection. This is relevant for both debt and equity investors. It could be argued that equity investors have more to lose, and data has shown that although the firms in this sample are sub-investment grade, many large institutional investors have been allocating equity funding to these firms.

Model results (Table 6) indicate that firm capital structure and a hedging dummy representing overall hedging, equal to 150% of next year's production, are statistically significant contributors to a firm's bankruptcy. Lender covenants typically require firms to hedge 50% of next year's production (Anderson, 2012). A threshold of more than 150% implies the future three years of 50% hedge ratio, assuming constant production. From my model observations, higher hedge ratios are key to larger distance to default positions and firm value. Is there a constraint that limits firms' capability to increase their hedge ratios? Experts suggest lender covenants can limit speculative activity if they have upper limit hedge ratios at 80%-90% per production year (Anderson, 2012). No firms with lender borrowing instruments had hedge ratios near this level on a per annum basis over several years. It could be argued that three-way collars and put spreads are themselves speculative, as the lower price protection is removed during large negative price innovations.

In this model, I added a binary variable to represent Permian Basin production exposure,[15] to capture the lifting and producing costs for a barrel of oil. This is a different metric than the operating expenses per share independent variable. Permian is a binary independent variable, equal to 1 if a firm is present in the Permian Basin and 0 if a firm has no operations in the basin. While this is a statistically significant and interesting result in the probit model, more research is required to confidently conclude that Permian operational presence is key to minimizing the probability of bankruptcy.

Table 6: Probit Model Results with Marginal and Overall Significance

Observations	805		Correctly Classified =		70.51%
Pseudo R2 =	0.1942				
	Coefficient	z-Stat	P>|z|	means	dy/dx
LOG_TA	-0.1062	-1.0800	0.2800	3.3432	-0.0343
TIE	-0.0011	-0.9500	0.3400	7.0737	-0.0004
D_E	0.0149	2.2000	0.0280**	2.0286	0.0048
PERMIAN	-1.0510	-9.0300	0.0000***	0.4194	-0.3396
OPSEXP_SHARE	-0.0126	-1.1100	0.2670	3.5909	-0.0041
ROA	-0.0128	-0.2700	0.7867	-0.0460	-0.0041
HEDGE_DUMMY_150	0.3063	2.2100	0.0270**	0.1704	0.0989
cons	0.1170	0.3600	0.7220		

** Significance at 5% level ***Significance at 1% level

5.0 CONCLUSIONS

Overall sample firm stock price returns have a beta higher than the market. A 1% increase in the stock market return will result in a return of 1.15% for the sample firm stock returns. This is consistent with investors' perception of firms' riskiness. WTI oil future price

[15] Tight oil lifting and producing costs are lower in the Permian Basin compared to other shale plays (Maugeri 2013).

returns are statistically significant with stock price returns and with a coefficient of 0.78; a 1% increase in WTI returns contributes to a .78% increase in stock returns. Hedge ratio size did not have a statistically significant relationship with stock returns, which is contrary to previous literature. Proven reserves were statistically significant with stock returns, which is consistent with previous literature. Future work should include utilization of a binary hedge independent dummy variable to verify the result and create a direct comparison with model structures in previous literature.

Hedge ratio volume was statistically significant to the distance to default dependent variable. Distance to default provides a real-time measure for hedge ratio importance to firm financial resilience and default probability and is the primary input to the default probability calculations used by ratings agencies. As the hedge volume decreases the distance to default narrows. The twelve firms declaring default in 2016 all experienced erosion of distance to default valuation towards the terminal period of the study time series. This in itself is interesting, as the firms in this study have no external activity that could create disturbances in the sample data, unlike larger international or integrated oil producers.

Firm capital structure is statistically significant at the 1% level for the distance to default panel model and the probit bankruptcy model. This paper focused on the hedge ratio importance for default distress. I believe that capital structure plays an equally important role. Further model analysis focused on the debt structure based on firm size and earnings volatility will be valuable to future research.

The discussion of bankruptcy as a key tool in a firm’s risk management strategy will contribute to the growing conversations on understanding why firms declare pre-organized bankruptcy terms and how they use bankruptcy as a heavy-handed tool in negotiations with creditors.

The hedging requirements of lenders is relevant and effective to reduce revenue volatility and support distance to default metrics. While important for debt holders, it is equally important for equity holders, as institutional investors are active participants in this sector.[16] Further discussion is warranted on the impact of capital structure on distance to default. Many firms liquidated their hedge positions during adverse price environments to increase operating revenues or to satisfy lender cash flow requests. If hedges remained active during the negative price innovation, the number of firms defaulting might be lower. Future research could support these findings by researching another highly homogenous sample group in the oil and gas sector to test the robustness of results.

[16] Study sample firms, 50.3% of outstanding common equity owned by traditional investment managers, 8.73% by inside company members /individuals, 2.25% by government pension funds, 0.53% by corporate pension funds.

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Appendix A: List of Firms in Study Sample

Symbol	Company Name	Market Cap (Million USD)	Management Ownership %
AXAS	Abraxas Petroleum Corporation	313.3	8.92
AREX	Approach Resources Inc.	285.5	9.10
BBG	Bill Barrett Corporation	455.9	2.44
BCEI	Bonanza Creek Energy, Inc.	995.5	2.70
BBEP	BreitBurn Energy Partners, L.P.	1,118.0	1.35
CPE	Callon Petroleum Company	515.8	1.84
CRZO	Carrizo Oil & Gas, Inc.	2,551.5	6.03
XEC	Cimarex Energy Co	10,855.7	1.60
CWEI	Clayton Williams Energy, Inc.	664.1	51.14
CRK	Comstock Resources, Inc.	166.1	20.33
CXO	Concho Resources Inc.	11,024.0	1.16
CLR	Continental Resources Inc.	10,810.0	76.99
DNR	Denbury Resources Inc.	2,505.7	2.04
EROC	Eagle Rock Energy Partners, L.P.	397.8	
ESTE	Earthstone Energy, Inc.	287.8	7.23
EOX	Emerald Oil, Inc.	39.6	2.35
EGN	Energen Corporation	4,974.3	0.62
EXXI	Energy XXI Ltd.	314.5	3.03
EPM	Evolution Petroleum Corporation, Inc.	250.4	10.73
GDP	Goodrich Petroleum Corporation	154.9	15.70
HK	Halcon Resources Corporation	684.8	2.53
LPI	Laredo Petroleum, Inc.	2,964.4	1.22
LGCY	Legacy Reserves LP	673.4	7.23
LINE	Linn Energy, LLC	3,537.3	0.85
LRE	LRR Energy, L.P.	217.3	
MCEP	Mid-Con Energy Partners, LP	169.0	7.10
MUR	Murphy Oil Corporation	7,560.1	5.65
NFX	Newfield Exploration Company	5,885.3	0.88
NOG	Northern Oil and Gas, Inc.	431.3	8.77
OAS	Oasis Petroleum Inc.	2,273.1	3.24
PE	Parsley Energy, Inc.	2,492.7	16.40
PVA	Penn Virginia Corporation	322.3	1.31
PNRG	PrimeEnergy Corporation	138.4	47.23
QEP	QEP Resources, Inc.	3,305.3	0.78
REN	Resolute Energy Corporation	81.3	14.91
SD	Sandridge Energy Inc.	566.3	0.94
SM	SM Energy Company	3,322.6	1.70
SGY	Stone Energy Corporation	768.1	3.59
SFY	Swift Energy Company	97.0	4.61
SYRG	Synergy Resources Corporation	1,195.7	9.72
TPLM	Triangle Petroleum Corporation	382.2	2.50
VNR	Vanguard Natural Resources LLC	1,267.0	1.03
WRES	Warren Resources, Inc.	60.9	6.45
WLL	Whiting Petroleum Corporation	6,591.2	0.03