SMC UNIVERSITY
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Survival Analysis of Canadian Oil and Gas Firms

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Abstract

In the context of oil price fluctuations inducing boom and bust cycles, this empirical study is a survival analysis of the Canadian oil and gas exploration and production (E&P) industry. The population includes 540 public Canadian E&P firms that have their headquarters and production activity in Canada, and the data covers the periods of Q1-2002 to Q1-2016 representing over 15,850 firm-quarter observations. The method is an extended Cox model with repeating events, allowing for the use of time-varying predictor variables and the analysis is executed in R, a free statistical software. The study introduces a new definition of financial distress as two consecutive quarters of negative operating cash flow to total assets ratio, develops a baseline model with financial ratios and industry-specific covariates and tests three hypotheses. The first two hypotheses examine the extent to which hedging and company size respectively correlate to the state of financial distress, and the third hypothesis explores how being financially distressed contributes to being a target in a merger and acquisitions (M&A) transaction. The findings show that a hedging firm is 18.5 times less exposed to the hazard of financial distress than a non-hedging firm; and with each unit size increase, a firm is 1.18 times less likely to experience financial distress, but financial distress is not a valid predictor of the hazard of being an M&A target. This study provides a new perspective supporting the use of hedging and size increase for increasing corporate resilience in Canadian oil and gas firms.

Key words: Bankruptcy, Canadian oil and gas, Cox proportional hazards model, extended Cox model, financial distress, financial ratios, financial ratios history, firm size, hedging, M&A, survival analysis

Declaration - Signature

"I declare in lieu of an oath that I have written this doctoral thesis by myself, and that I did not use other sources or resources than stated for its preparation. I declare that I have clearly indicated all direct and indirect quotations, and that this thesis has not been submitted elsewhere for examination purposes or publication."

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I certify that I have read this dissertation and that, in my opinion, it is fully adequate in scope and quality as a doctoral thesis.

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List of Abbreviations

2P	Proved Reserves and Probable Reserves
BOE	Barrel of Oil Equivalent
CAD	Canadian Dollar
CAPP	Canadian Association of Petroleum Producers
CCI	Canadian Crude Index
CI	Confidence Interval
DACF	Debt Adjusted Cash Flow
EBITDAX	Earnings before Interest, Tax, Depreciation, Amortization and Exploration
E&P	Exploration and Production
EV	Enterprise Value
FCF	Free Cash Flow
FD	Financially Distressed
HR	Hazard Ratio
JWN	JuneWarren-Nickle's (Energy Group)
LR	Likelihood Ratio
M&A	Merger and Acquisition
MDA	Multi Discriminant Analysis
NFD	Non-Financially Distressed
OCF/TA	Operating Cash Flow Over Total Assets
O&G	Oil and Gas
P/E	Price Earnings (ratio)
PH	Proportional Hazard

PSAC	Petroleum Services Association of Canada
ROA	Return on Assets
ROE	Return on Equity
RRR	Reserves Replacement Rate
SD	Standard Deviation
TSX	Toronto Stock Exchange
TSXV	Toronto Stock Exchange Venture
USD	United States Dollar
WC/TA	Working Capital over Total Assets
WTI	West Texas Intermediate

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Dedication

To my wife and soulmate Gloria, and to my sons Alec, Evan and Noah.

Your love and support fuel my energy and enable me to manage distress and build resilience, while enjoying the booms and surviving the busts in the cycles of life.

Chapter 1: Overview

Survival Analysis of Canadian Oil and Gas Firms

Survival analysis is an advanced statistical technique of multi-linear regression analyses that serves for calculating the correlation of a predictor to an event, predict the likelihood over time of the hazard of the event and alternatively predict the probability of survival over time. The technique originated in medical sciences and has since been applied toward corporate failure and bankruptcy predictions using a specific survival analysis approach, the semi-parametric Cox proportional hazards (Cox PH) model (Deepa, n/a; Klein & Kleinbaum, 2012; Laine & Reyes, 2014; Yamazaki, 2013). Cox (1972) published the eponymous Cox PH model that uses only the value of the covariates – and thus does not require any indexing to prior distributions – for a regression analysis, provided the PH assumption is satisfied. The PH assumption requires that the values of the covariates remain constant over time. The specific outputs of a Cox PH model are the hazard function which gives the instantaneous potential per unit of time for failure to occur, given that the firm has survived up to that time, and the survival functions or cumulative hazards functions. When the covariates values change with time, the Cox PH model must be extended to satisfy the PH assumption. This research applies an extended Cox PH model that accommodates changes in the covariates' values during the study period, and accepts the repetition of the hazard event (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012). The method is an extended Cox model with repeating events that this research applies to a central concept of financial distress for a population of 540 Canadian oil and gas firms based on 15,850 firm-quarters spanning the reporting period of Q1-2002 to Q1-2016. This overview chapter provides an economic context for the research with the problem statement, describes the purpose of the research and its significance, lays out a summary of the research design, stipulates the hypotheses, frames the assumptions and limitations and lists the operational definitions of this study before concluding with a summary (Cox, 1972; Deepa, n/a; Fox, 2008; Klein & Kleinbaum, 2012; Laine & Reyes, 2014; Yamazaki, 2013).

Problem Statement

The problem is the dire financial distress situation Canadian oil and gas firms face during bust cycles (CAPP, 2016; Jakeman & Tertzakian, 2016; Millington, 2016; PSAC, 2016). Twenty Canadian oil and gas firms have filed for bankruptcy in the two years from September 2014 to August 2016 and several others are in financial distress (Haynes & Boone, 2016; Office of the Superintendent of Bankruptcy Canada, 2016). Canada has a commodity-driven economy that is highly sensitive to the health of its oil and gas industry. In Canada, the province of Alberta has, with 4.1 million barrels, the world's third largest reserves of crude oil, following Saudi Arabia and Venezuela. Alberta counts for more than 80% of the country's oil and gas production but the industry is active in 12 out of 13 Canadian provinces and territories (CAPP, 2016). The oil and gas industry in Canada follows boom and bust cycles and it is reactive to the volatility of the price of oil, booming when the price stays high and busting when it is low (Jakeman & Tertzakian, 2016; Millington, 2016). Alberta's economy has been thriving with high levels of investment, sustained infrastructure development, full employment and even a shortage of skilled laborers since 2002; this long boom cycle has been synchronized with a steady rise in oil prices until June 2014 at USD 105.54 (Jakeman & Tertzakian, 2016; Macrotrends, 2016; Millington, 2016). The economy was in crisis in 2001 when the oil price fell from USD 45.78 in November 2000 to USD 26.02 in November 2001. The price of oil peaked in June 2008 at USD 151.72, then briefly dipped in January 2009 at USD 46.86 and remained high above USD 80.00 until it started going down after June 2014 reaching a floor of USD 28.50 in January 2016

(Macrotrends, 2016). Canada is a net exporter of oil and every annualized dollar increase in the price of oil barrel represents a CAD 1.7B GDP increase for the period of 2015-2021 per Millington (2016). Jakeman & Tertzakian, (2016) estimated that the industry sustains over 440,000 direct and indirect jobs in September 2016 down from 500,000 in 2014 when the annual capital spending was CAD 81B and sustained low oil prices would risk eliminating 116,000 over the next five years. Natural Resources Canada (2017) estimated the oil and gas related jobs at 191,415 direct jobs, 518,133 indirect jobs, and 203,065 oil and gas construction jobs. As of Q2 2016 the industry's nominal cash flow is the lowest since the 1990s, investment is reduced to legacy spending, production has declined, employment has fallen following systemic layoffs throughout the industry at large and the whole Albertan economy has considerably slowed down (Jakeman & Tertzakian, 2016). Thus, the Canadian economy is largely driven by its oil and gas industry which follows boom and bust cycles. Millington (2016) estimated that the national GDP could be 23% lower if the price of oil remains low on average and grows slowly to reach only USD 51.00 by 2021 compared to a base case of USD 73.00. Canada exports 97% of its production to the USA where the oil and gas industry is also feeling the impact of low prices with a 379% spike in corporate bankruptcies in the oil and gas sector in 2015 (CAPP, 2016; Dionne, Plastino & Shaked, 2016). Many Canadian oil and gas firms are heavily indebted, illiquid, insolvent or outright bankrupt and the industry's distress ripples through the entire economy. While intuitively understandable and their impact practically observable, the drivers of the economic survival of Canadian oil and gas firms are not dynamically analyzed and documented in the literature and this study aims at contributing to fill that gap (CAPP, 2016; Dionne, et al., 2016; Haynes & Boone, 2016; Jakeman & Tertzakian, 2016; Macrotrends, 2016;

Millington, 2016; Natural Resources Canada, 2017; Office of the Superintendent of Bankruptcy Canada, 2016; PSAC, 2016).

Purpose of Research

The purpose of this quantitative empirical study is to assess the relationship of explanatory variables to the survival time of Canadian oil and gas firms through an extended Cox model with repeating events (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012), that allows to estimate and interpret the cumulative hazard or the survivor function these predictor variables represent for the dependent variable. In survival analysis, the hazard function gives the instantaneous potential per unit of time for the event of financial distress to occur, given that the firm has survived up to that time. The survivor function gives the probability that a firm survives longer than some specified time (Fox, 2008; Klein & Kleinbaum, 2012). This quantitative study uses a sample of 540 public Canadian exploration and production (E&P) firms having published quarterly financial reporting for the period covering the first quarter of 2002 (Q1-2002) until the first quarter of 2016 (Q1-2016), and representing over 15,850 firm-quarters of data collected. The methodology is quantitative and the method is an extended Cox model with repeating events, which allows for the use of time-dependent covariates and the reoccurrence of the state of financial distress for the same firm (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012). For the first two hypotheses in this study, the dependent variable is financial distress, for which the researcher introduces a new definition in this study as two consecutive quarters of a negative ratio of operating cash flow divided by total assets (OCF/TA); and for the third hypothesis, it is the status of being an M&A target. As a preamble to the central hypotheses, this study includes the development of a baseline model for which the dependent variable is financial distress and the independent variables are covariates including financial ratios for liquidity, solvency, profitability, valuation, efficiency, energy and size. The study aims to assess to what extent each covariate in the baseline model influences financial distress, and for the hypotheses, understand if hedging helps to prevent financial distress, if small size aggravates financial distress and if financially distressed firms are more prone to being merged or acquired (Cox, 1972; Fox; 2008; Klein & Kleinbaum, 2012).

Survival is the time until the event of financial distress happens, and in this study the event of financial distress can happen multiple times for the same firm (Fox, 2008; Klein & Kleinbaum, 2012). The researcher uses a survival analysis technique known as the extended Cox model, with repeating events, which allows for including time-dependent covariates in the independent variables (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012). The independent variables are covariates predictors combining in a vector that is a function of proportional hazards characterizing the dependent variable of financial distress. As an alternative to a vector, the survival analysis can also use univariate predictors to individually test the independent variables. The literature on bankruptcy, corporate failure and financial distress is large and has evolved through successive research paradigms providing multiple analytical techniques (Aziz & Dar, 2006; Horrigan, 1968). Starting with financial ratios analysis, these methods include the univariate analysis by Beaver (1966), the multiple discriminant analysis (MDA) by Altman (1968), the conditional probability models by Ohlson (1980) or Zmijewski (1984) and many alternative intelligent techniques such as neural networks, decision trees, support vector machines or multidimensional scaling, and have in common to perform a binary pass/fail snapshot analysis and prediction. On the contrary, this study is a survival analysis, a statistical technique that is more dynamic, uses larger data and provides more analytical depth as well as predictive power in understanding the determinants of survival. Survival analysis is a regression analysis technique widely used in epidemiology, biostatistics and to a lesser extent engineering, finance and social sciences (InfluentialPoints, 2016; Pereira, 2014). The methods to perform a survival analysis can be parametric with an assumption that the underlying distribution of the survival times follows a probability distribution such as exponential, Weibull and lognormal distributions; nonparametric like the Kaplan-Meier graphical representation of survival curves used for univariate analyses; and semi-parametric like the Cox PH model (Klein & Kleinbaum, 2012). The Cox PH model is the approach that finance and social empirical studies commonly use (Chancharat, Davy, McCrae & Tian, 2007; Chen & Lee, 1993; Chong, He, Li & Zhang, 2010; Pereira, 2014) . The preference for this method lies in its semi-parametric property that dispenses from assuming and defining a probability distribution for the survival times; therefore unlike the more cumbersome parametric models, the baseline hazard in a semi-parametric survival analysis is an unspecified function. Additionally, the Cox PH model also derives its success from the fact that it is statistically robust and delivers results very close to the parametric models (Klein & Kleinbaum, 2012). To be valid, the Cox PH model requires the satisfaction of the proportional hazard assumption: the hazard ratio (HR) is constant over time or more specifically the hazard for one firm is proportional to the hazard for any other firm and the proportionality remains constant, independent of time. The PH assumption verifies naturally for covariates that remain constant over the study period such as sex, geographic location or other stable attributes that social studies often use. However, when the values of the covariates change for each firm over the study period, that means that the covariates fluctuate with time, and the model no longer satisfies the PH assumption. Such predictor variables are time-dependent covariates and require extending the original Cox PH model with a unique time coefficient or a stratification of the data to mitigate the fluctuating impact of time on the predictors (Cox, 1972;

Fox, 2008; Klein & Kleinbaum, 2012). The independent variables in this study are time-dependent and the method is a Cox extended model (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012). This research revolves around the key construct of financial distress with an ad hoc definition. The theoretical foundations include a review of the theory on financial distress and corporate failure starting from the origins of financial ratios until the current state of research, and a literature review of the specific constructs for the hypotheses: hedging, firm size, and merger and acquisitions (Altman, 1968; Aziz & Dar, 2006; Beaver, 1966; Chancharat, et al., 2007; Chen & Lee, 1993; Chong, et al., 2010; Cox, 1972; Fox, 2008; Horrigan, 1968; InfluentialPoints, 2016; Klein & Kleinbaum, 2012; Ohlson,1980; Pereira, 2014; Zmijewski, 1984).

This research includes a review of 26 studies on bankruptcy and financial distress which allow the researcher to confirm the conclusions of Outecheva (2007) that the literature agrees on recognizing that there is no universally and commonly agreed upon definition of financial distress, the main construct of interest of this study. Multiple definitions and measures exist in diverse empirical studies and each researcher designed their own construct to fit the purpose of their research (Outecheva; 2007). In this study, the researcher introduces a new definition of financial distress as two consecutive quarters of negative OCF/TA. This definition is, to the best of the researcher's knowledge, original in the literature and it stems from a rationale with multiple elements. The E&P sector in oil and gas is a cash-intensive and asset-heavy business with long lead times and a strong dependency on assets productivity and profitability to ensure a level profitability that grants endogenous long-term sustainability including assets renewal, covering the cost of capital, profit redistribution, strategic growth and potential share buy-backs (CAPP, 2016; Jakeman & Tertzakian, 2016; Harp Jr. & Howard, 2009; PSAC, 2016). That long range sustainability and profitability relies on a backbone of sufficient, well maintained, upgraded, well run and reliable asset base. This requires a continuous significant level of capital investment and the return on that investment in turns demands to “sweat the assets” (Harrison, 2005) to produce efficiently enough in order to generate the cash flow that maintains the profitability, sustainability and growth necessary in a competitive sector that is highly sensitive to the externality of low oil prices. OCF/TA is an asset efficiency ratio measuring the cash flow generated by the assets. With the consideration of survival, as opposed to investing in an E&P stock for a quick profit opportunity, the fundamental value of the E&P firms relies on their assets. Bankers and other refinancers know this and as long as the assets are productive enough, E&P firms can access refinancing in case of a temporary liquidity shortfall. Therefore in a context of oil price volatility, E&P firms can experience a low or even negative asset efficiency ratio during one reporting period without necessarily needing to take strategic action for correcting the impact on profitability and sustainability. They are expected as required, to be able to generally refinance and access cash in the period following the reporting of a negative asset efficiency ratio. But when the negative ratio repeats in a subsequent contiguous quarter, the firm’s ability to sustain its profitability on the sole strength of its assets weakens considerably. At that stage, the company may already be experiencing liquidity tension or close to it but it is not yet completely illiquid or insolvent or even bankrupt. The company is in financial distress, not yet in financial death. That state of financial distress includes liquidity tension and the firm is in what Outecheva (2007) described as a “death struggle”. In that stage, in accordance with the definition of Hillier, Jaffe, Jordan, Ross and Westerfield (2012), the firm needs to take strategic corrective action and as Davydenko (2013) framed, potentially access external refinancing. The death struggle can ultimately result in a resurrection, a merger or a bankruptcy. The definition of financial distress using two consecutive quarters of negative asset efficiency ratio is distinct from alternative definitions in the literature, especially those that simply use the legal filing for bankruptcy as a threshold, illiquidity or insolvency. This definition ties into the asset-heavy and cash-intensive nature of the E&P business, includes access to refinancing during temporary operational hiccups or externalities, and intends to capture the structural failure endangering the self-sustaining profitability. This definition also includes the need for strategic action while the firm can still fight for its survival, provided its management possesses the financial and strategic acumen to recognize and acknowledge the severity of the distress at that moment. This study first analyzes the extent to which non-collinear ratios of liquidity, solvency, profitability and industry-specific indicators contribute to financial distress. Then, as hedging is a practice more or less in use in the industry, the study aims at understanding whether hedging provides a protection against financial distress. The oil and gas industry in Canada is very diverse in terms of participants size, and large with several thousands of companies operating in E&P (CAPP, 2016; PSAC, 2016); and while not all firms are public, there is a large enough span of sizes to try to understand if size impacts financial distress and if smaller firms are more exposed to its hazard. For all these questions, the dependent variable is financial distress and the independent variables are the vectors of covariates that relate best to the specific question of interest. For the last question this study explores, the consideration shifts to the fact that in a still growing industry with several actors and where the fundamental value lies in the reserves, there is a concurrent level of mergers and acquisitions which reflects a natural evolution toward industry consolidation and which seems to be an integral part of the value chain for smaller players. In this context, the study seeks to observe whether being financially distressed influences merging or being acquired. For this last question, the dependent variable is the status of M&A in a

Heaviside function and the independent variable is primarily the financial distress status and secondarily a vector of covariates including liquidity, solvency, profitability and valuation ratios (CAPP, 2016; Davydenko 2013; Harp Jr. & Howard, 2009; Harrison, 2005; Hillier et al., 2012; Jakeman & Tertzakian, 2016; Outecheva, 2007; PSAC, 2016).

This study contributes to the literature on multiple levels. The first includes the construct of interest and the method, the second is on the industry and the country, and the third level is about the questions this research analyzes. The paradigm of defining financial distress is neither established nor unified (Outecheva, 2007), and in the post-positivist approach governing this study, there is a clear attempt at proposing an original definition of financial distress that builds on an industry, a finance, and a strategic rationale while leveraging existing literature inputs from Davydenko (2013), Outecheva (2007), Hillier et al. (2012) and others before them. Although the E&P industry characteristics influence it, this definition of financial distress is eligible to fit several other industries or for a generic use. The method of an extended Cox model (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012), is to the best of the researcher's knowledge, a first in survival analyses focusing on oil and gas, and the sample size is also unprecedentedly large; both of these originalities contribute to the existing empirical knowledge. Another level of contribution is the focus on Canada and the oil and gas E&P sector in Canada. This study is the first attempt since Chen and Lee (1993), to the best of the researcher's knowledge, at running a survival analysis on oil and gas; their study used a Cox PH model, not an extended Cox model, thus did not include time-dependent covariates, and it did not focus on Canada. Their study used a smaller sample size of 175 firms observed over three years including 67 distressed firms, while this research has a larger sample of 540 firms observed over 14 years. While Chen and Lee (1993) used a Cox PH model with the assumption that the proportionality of covariates remains constant over time, they did recommend for future research to use time-dependent covariates. Comparatively, the larger sample of this study over a longer time and the inclusion of time-dependency should yield greater accuracy. Finally the questions relating to hedging and M&A this study explores, are original and should feed into the significance of the study (Chen & Lee, 1993; Cox, 1972; Davydenko, 2013; Fox, 2008; Hillier et al., 2012; Klein & Kleinbaum, 2012; Outecheva, 2007).

Significance of the Study

The significance of this research derives from its originality and its practical use for the business world. The originality of this research is about the country, the industry, the methodology and the hypotheses. To the best of the researcher's knowledge, this study is the first survival analysis using time-dependent covariates focused on E&P firms in Canada. The practical use of this research will be of benefit to oil and gas managers, engineering, procurement and contracting managers (EPCM), other servicing suppliers to E&P companies, or creditors and analysts. Managers will better understand the state of financial distress this study proposes and still have an opportunity to act upon it with strategic action before the company becomes insolvent and is forced to file for bankruptcy. EPCM and servicing companies representing 195,415 jobs in Canada (Natural Resources Canada, 2017) will have an interest in managing their prospective counterparty risk before engaging into material or long-term deals with E&P firms in financial distress. Creditors and analysts will benefit a better perspective in assessing the viability and distress level of firms while making refinancing decisions or recommendations on the stocks (CAPP, 2016; Davydenko, 2013; Natural Resources Canada, 2017; PSAC, 2016).

The state of financial distress in this study follows what Outecheva (2007) calls a death struggle and includes the need for a strategic corrective action that Hillier et al. (2012) stressed in their definition of financial distress. In that state, firms are becoming illiquid or even insolvent but they are not yet in default or bankrupt. They need to take drastic action to reduce costs, restructure, divest, ally, merge, devise a new strategy or business plan and show strong management commitment and focus, to leverage their tangible assets and improve profitability. Firms in financial distress still have time to take such corrective action and secure refinancing along with sending the right confidence signals to the market to avoid entering receivership. Actual default occurs when the firm misses on a payment by its due date and Davydenko (2013) reported that 62% of defaults on bonds occur in the 30 days preceding one of the two semi-annual scheduled payments of June and December, including 29% on the actual payment date. This study should therefore provide a new helpful perspective to the stakeholders directly involved in diagnosing financial distress and taking decisive action to save it with a prospective of improved profitability based on efficient assets and convincing managerial focus. There are more than 250 E&P firms trading in Canada that represent about 12% of the TSX, about 500,000 jobs, CAD 72B in revenue, CAD 80B in capital investment and CAD 17B in royalty payments (Jakeman & Tertzakian, 2016; TMX, 2016). This survival analysis on their financial distress based on the efficiency of their assets, which drives their liquidity, solvency and long-term profitability will be directly beneficial to all of them, especially right before and during cycles busts (CAPP, 2016; Davydenko, 2013; Jakeman & Tertzakian, 2016; Hillier et al., 2012; Outecheva, 2007; TMX, 2016).

The hedging literature reveals varied reasons for hedging and a wide span of hedging levels. Jin and Jorion (2006) and Lookman (2004) concluded that hedging does not increase firm value in oil and gas. This study will complement the analytical portfolio of oil and gas managers when they optimize their decision to hedge part or all their production, factoring in the varied strategic objectives to hedge or not and the expertise and transaction costs it requires. They will now have an empirical reference shining light on whether hedging helps prevent a structural and serious but manageable state of financial distress. Practitioners intuitively expect firm size to influence resilience and while the literature does provide some insights, this study will provide a tangible reference specific to Canadian oil and gas firms as no other exists so far. Investment bankers and managers consider M&A at the deal and transaction level, focusing on the deal size, the premium, the synergies, the industry consolidation or redesign and the comparatives. Economists considering M&A may have a wider perspective and correlate the cycles of M&A activity to others such as boom and busts cycles in oil and gas. Financial economists and scholars have analyzed M&A as a bankruptcy avoidance strategy (Kyimaz, 2006) or found similar predictive keys between bankruptcy and M&A (Powell & Yawson, 2007). Any or all, of these inquisitive minds with an interest in M&A should find in this study empirical material that will help understand patterns, predictors, and plan action, timing, and valuation strategies in a volatile and competitive industry where the slightest information asymmetry can be a decisive competitive advantage (Jin & Jorion, 2006; Kyimaz, 2006; Lookman, 2004; Powell & Yawson, 2007).

This study is original in its method and its scope. The Canadian oil and Gas E&P industry is important to the national economy, with CAD $142B in 2015 nominal GDP representing 7.7% of Canadian GDP, and 709,548 direct and indirect jobs representing 3.9% of total employment (Natural Resources Canada, 2017). In a recent study, Millington (2016) estimated that every Canadian dollar gain in annualized WTI price represents approximately CAD 1.7B increase in GDP for the period of 2014-2021 (Millington, 2016). Additionally, CAPP (2016) estimated that for every two job additions in Canadian oil and gas, an equivalent new job appears in the US

(CAPP, 2016). Thus, oil and gas impacts several stakeholders in an intricate value chain that includes 518,133 directs jobs and 195,415 indirect jobs of oil and gas construction or EPCM, to which additional sectors such as railroad transportation or other services (e.g. hospitality in oil and gas driven centers like Calgary in Alberta) are also tributary (Natural Resources Canada, 2017). This study will be of great and varied interest to all managers, practitioners, analysts, scholars and other stakeholders involved in Canadian Oil and Gas, and probably beyond. However, it remains that to validate its significance this research needs a strong, complete, defendable and replicable design (CAPP, 2016; Millington, 2016; Natural Resources Canada, 2017).

Research Design

The description of the research design below situates the methodology in the literature and introduces the method of survival analysis, describes the population, defines the concept of financial distress and expands on the actual statistical analysis procedure at the core of this study. This quantitative research uses published financial data statements as independent variables that the researcher cannot control, alter or manipulate to change the dependent variable. Therefore, this research is a non-experimental study. This research inscribes in the field of analysis on corporate failure and bankruptcy prediction which has originated with financial ratios analysis in the early twentieth century and gradually evolved until maturing as a paradigm with Beaver's univariate analysis (Beaver, 1966) and Altman's Z-score (Altman, 1968) using a multi-discriminant analysis. The paradigm shifted in the early 1980s with conditional probability models by Ohlson (1980) and Zmijewsky (1984), and opened to several alternatives methods since then, including intelligent techniques such as neural networks, decision trees, support vector machines or multidimensional scaling. All these predictive techniques have in common to adopt a binary pass/fail approach which is a limit that motivated early pioneers in applying survival analysis to corporate failure, among them Chen and Lee (1993). Survival analysis is a statistical technique widely used in epidemiology, biostatistics and to a lesser extent engineering and finance that allows for a better understanding of the time-to-event and the impact of covariates on the survival time (InfluentialPoints, 2016; Pereira, 2014, Klein & Kleinbaum, 2012). The literature abundantly documented the limits of MDA and other probabilistic models and Davydenko (2013) summarized a preference for survival analysis by many empiricists in asserting that "hazard analysis has become the instrument of choice in empirical studies predicting default and bankruptcy" (Davydenko, 2013, p.25). The methods to perform a survival analysis can be parametric, semi-parametric or non-parametric. Parametric methods require defining a baseline hazard as they carry an assumption that the underlying distribution of the survival times follows a probability distribution such as exponential, Weibull, lognormal, log-logistic or gamma distributions. Semi-parametric models do not hold that assumption and do not require the use of a probability distribution for defining a baseline hazard, and the most popular method is the Cox proportional hazards model proposed by Cox (1972). They allow for only using the covariates. Nonparametric models like the Kaplan-Meier graphical representation of survival curves or the life-table method are mainly used for univariate analyses. The survival analysis method of choice in finance and social sciences is the Cox PH model. The preference for the method stems from it not requiring a baseline function as opposed to the more cumbersome parametric models and it being statistically robust in delivering results very close to the parametric models (Klein & Kleinbaum, 2012). The Cox PH model requires the satisfaction of the proportional hazard assumption: the hazard ratio (HR) is constant over time or more specifically the hazard for one firm is proportional to the hazard for any other firm and the proportionality remains constant, independent of time. This underlying assumption means that the covariates the study uses are time-independent. When the value of some covariates changes with time and makes the proportionality of covariates inconstant, those covariates are time-dependent. Those do not generally satisfy the PH assumption and the Cox PH model is not appropriate for a survival analysis involving time-dependent or time-varying covariates. The appropriate semi-parametric method for time-dependent covariates is the extended Cox model. The extension of the Cox PH model for time-dependent covariates consists in either stratifying the data in homogenous time-independent blocks or adding a time coefficient to the Cox PH model (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012). The theoretical foundations of survival analysis, the Cox PH model and the extended Cox model with a time coefficient lead the way below to the specific research technique for this study (Altman, 1968; Beaver, 1966; Chen and Lee, 1933; Cox, 1972; Davydenko, 2013; Fox, 2008; InfluentialPoints, 2016; Klein & Kleinbaum, 2012; Ohlson 1980; Pereira, 2014; Zmijewsky, 1984).

This study is a quantitative analysis using a sample of 540 Canadian E&P firms publicly traded on the TSX anytime between Q1-2002 and Q1-2016. The sample includes only firms that meet the following criteria: they are in the upstream oil and gas business of exploration and production (E&P); they are headquartered in Canada; their production takes place in Canada; and they are publicly traded in Canada, on the TSX or the TSXV. The quarterly financial reporting of these public 540 firms represents 14 years of data and 15,850 firm-quarters. While Canadian oil and gas firms have not benefitted from being the focus of any other survival analysis, to the best of the researcher's knowledge, authors have worked on Canadian business failure prediction models and reported that "a major obstacle in Canadian business failure prediction research is the scarcity and poor organization of available data" (Boritz, Kennedy & Sun, 2007, p. 147).

Davydenko (2013) used the databases of Moody's, Merrill Lynch, LSTA/LPC Mark-to-Market Pricing Database, Mergent's Fixed Income Securities Database, Thomson Reuters and Compustat to perform a survival analysis using Cox PH, focused on bond default and insolvency of 306 public Canadian firms. The study in this research has a different focus than Davydenko's (2013) credit analysis and requires financial statement data for all firms in the sample. The primary data source for this research is Canoils, a privately-owned database started in 1985 and focused exclusively on Canadian Oil and Gas companies. Canoils belongs to the JuneWarren-Nickle's Energy Group (JWN) a publishing firm that provides paying access to Canoils to professional subscribers such as oil and gas corporations, credit analysts and banks, media or educational institutions. JWN graciously granted the researcher a free access to the data for this study (Boritz et al., 2007; Davydenko, 2013).

The financial literature does not provide a universally accepted standard definition of the notion or status of financial distress. This post-positivist research focuses on this notion and defines it as two consecutive quarters of negative ratios of operating cash flows to total assets, a definition that builds on the work of Outecheva (2007) and Hillier et al. (2012) with the intent to capture the quintessential state of short and long-term risk to the resilience, growth and profitability of E&P firms. This definition of financial distress is the central construct of interest of this study for which the researcher selects predictor variables including a Heaviside function for hedging, a proxy in the form of the natural logarithm of total assets for firm size, another Heaviside function for M&A, and liquidity ratios, profitability ratios, solvency ratios, valuation ratios, energy ratios and efficiency proxies for the baseline model (Outecheva, 2007; Hillier et al., 2012).

The core statistical analysis of this study consists in collecting the data (see appendix B), building the relevant financial ratios for each firm-quarter (see appendix C), laying out the data for use in R, the statistical software running the survival analysis (see appendix D), coding R (see appendix E), running an extended Cox model and interpreting the results (see appendix F). The study explores three hypotheses and precedes them with a baseline model. Prior to running the survival analyses this study focuses on, the study includes a descriptive statistics section that analyses the data through standard statistical values such as the mean, the median or the standard deviation. The baseline foundational model includes a vector of covariates that allows determining the correlation to financial distress of liquidity, solvency and profitability ratios. For each analysis in the baseline model and the three hypotheses, the result interpretation starts with appraising the model validity through the following goodness of fit tests: likelihood ratio test, Wald test, score (logrank) test, concordance and R-square. If the model goodness of fit is satisfactory, the next phase in interpreting the results consists in verifying whether the rejection or lack thereof of the null hypothesis by reading the p-value which must be lower than 0.05, reading the HR which must be different from one, and ensuring that the confidence interval (CI) is also different from one, for concluding to the rejection of the null hypothesis. Provided the null hypothesis is rejected, the analysis then progresses to interpret the regression, typically by reading the point estimate hazard ratio (HR) in a survival analysis along with its CI, or by reading directly the regression coefficient with its CI for continuous predictor variables. The hazard ratio describes the relationship between the covariate and financial distress and gives the instantaneous potential per unit of time (quarter in this study) for failure (financial distress) to occur, given that the firm has survived up to that quarter. The HR tells how strong is the relationship of the predictor variable to the dependent variable by showing how many times the independent variable for firms exposed to the event (e.g. financially distressed firms) correlates to the event more (or less) than it does for the whole population including censored firms. The analysis may also include a visual representation of the survival curve or its alternative cumulative hazard curve which is a curve of the regression analysis for all the data in the model. This curve is the hazard function which gives a conditional failure rate with a scale from zero to infinity and the survivor function gives the probability that a firm survives longer than some specified time. Chapter 3 of this study contains a detailed mathematical description of the Cox PH and the extended Cox models this study uses (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012).

In summary, the research objective is to:

- Collect the financial reporting data, verify it and build the financial ratios for each firm and each quarter in Excel.
- Analyze in Excel the descriptive statistics of the data.
- Layout the data in Excel for use in R, the statistical software this study uses to perform the survival analysis, as a CSV file.
- Code and run the survival analyses in R for each predictor variable or vector of covariates as required.
- Assess the model's goodness of fit and proceed further only if the model is valid.
- Check if the model rejects the null hypothesis and proceed further only if it does.
- Interpret the HR or the regression coefficient.
- Run and interpret the cumulative hazard curve.

The research design establishes the key constructs of survival analysis, financial distress, population and analytical procedure, and this analytical framework serves to test the substantial research hypotheses of this study.

Research Hypotheses

The baseline model serves to construct in Excel the observations of financial ratios and other proxies for each firm and each period. This represents over 15,850 observations and for each predictor variable, the baseline model tests a null hypothesis of no correlation and no predictive ability to the dependent variable of financial distress. The preparation work of the baseline model helps for the data analysis and data layout of the hypotheses this study researches.

The first question R1 is: does the presence of an active hedging policy influences financial distress? The hypotheses formulating question R1 are:

- Null hypothesis $H1_0$: Hedging has no influence on preventing financial distress.
- Alternative hypothesis $H1_a$: Hedging does influence the prevention of financial distress.

For research question R1, the dependent variable is financial distress and the independent variable is a Heaviside function identifying the presence of hedging in percentage of BOE hedged with “1” and the absence of hedging with “0”. The sample size for this research question differs from the baseline models as it includes a shorter time frame starting in Q1-2007 and ending in Q1-2016. The Q1-2007 starting period reflects the beginning of a compulsory reporting of hedging activity for Canadian oil and as firms as required by the National Instrument 51-101 Standards of Disclosure for Oil and Gas Activities (NI 51-101). The sample size for this hypothesis is 515 firms and 11,005 observations. The null hypothesis is rejected if

HR and CI are different from one and the p-value is smaller than 0.05 (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012; Ontario Securities Commission, 2016).

The second research question R2 is whether firm size influences financial distress? The hypotheses for this question are:

- Null hypothesis $H2_0$: Smaller size does not influence financial distress.
- Alternative hypothesis $H2_a$: Smaller size influences financial distress.

The dependent variable remains financial distress and the independent variable is company size measured as the natural log of total assets. The sample size is the same as the baseline model's. For R2 too, the null hypothesis is rejected if HR and CI are different from one and the p-value is smaller than 0.05 (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012).

The third research question R3 is: does being financially distressed influences being an M&A target? The hypotheses are:

- Null hypothesis $H3_0$: Financial distress does not influence the propensity to be an M&A target.
- Alternative hypothesis $H3_a$: Financial distress is a catalyst to being an M&A target.

The dependent variable is a proxy for M&A activity in the form of a Heaviside function of "1" for M&A activity and "0" for the lack of M&A activity. The sample size is 166 firms and 175 events, some firms having more than one transaction during the period of study of Q1-2002 to Q1-2016. An event is a status of being a target in an M&A completed transaction. Consistent with the first two hypotheses, the null hypothesis is rejected if HR and CI are different from one and the p-value is smaller than 0.05 (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012).

The baseline model of this study intends to capture the specifics structural factors that contribute to a distressed state that may endanger the going concern of Canadian oil and gas firms and thus require a transformational strategic action. This foundational analysis is important to enabling a focus on the three research hypotheses that shed light on precise external and managerial factors relevant to the oil and gas industry. The constructs of interest and the method of this study are open to interpretation and therefore require a context of assumptions and limitations for grounding this research.

Assumptions and Limitations

This study takes place in a post-positivist paradigm where the methodology is a non-experimental quantitative design using a precise statistical analysis and the axiology includes the researcher's worldview in selecting and defining the key constructs of interest. The assumptions and limitations framing this research are methodological, theoretical, specific to the research topic, and relate to the method of the extended Cox model. They include the sampling, the definition of financial distress and the selection of the predictor variables, the method of survival analysis, the interpretation metrics and the specific assumptions around the proxies for the hypotheses and oil and gas metrics.

The scope of this study restricts the sample to Canadian oil and gas E&P firms that have their headquarters and production in Canada and that are publicly listed on the Canadian stock exchange, the TSX. As companies report their financial statements quarterly, the metric in use for the frequency and the volume of data is the firm-quarter. In the literature, the firm-month is a metric that appears in empirical studies (Chen & Lee, 1993; Davydenko, 2013), but this study uses firm-quarter since it corresponds to the frequency of reporting and the size of the sample of 540 firms over 14 years yields a statistically significant sample of more than 15,850 firm-quarters. The sample size for the baseline model is 15,836 firm-quarters, the sample size for the first hypothesis on hedging is 11,005 firm-quarters; it is 15,854 firm-quarters for the second hypothesis on firm size, and 3,698 firm-quarters for the third hypothesis on M&A. To simplify the language in this study, the researcher uses a generic 15,850 firm-quarters when referring to an overall sample size (Chen & Lee, 1993; Davydenko, 2013).

Theoretically, the researcher's view and choices characterize the central constructs of financial distress definition and selection of covariates. A review of the literature shows that there is no consensus on the definition of financial distress. Over the past century, the notion appeared under various phrases and the variety of criteria authors have used include asset value, bankruptcy, default, liquidity, insolvency, dividend reduction, restructuring, profitability, stock market value, lay-offs, sales growth reduction or distressed exchange offers. Noting this heterogeneity, Outecheva (2007) posited that "the state of the art in the theory of financial distress is rather to interpret it as dependent on the purpose of research under a particular point *[sic]* of view" (Outecheva, 2007, p.18). In this study, the researcher defines financial distress as two consecutive quarters of negative operating cash flow to total assets ratio. The intent of this definition is to fit a cash-intensive industry with long lead times where companies must "sweat the assets" (Harrison, 2005) to make them generate the cash flow that can sustain their renewal and the overall profitability of the firm. Financial health depends on assets efficiency and a negative ratio of OCF/TA in any quarter should alarm company management while still leaving time for refinancing, which is possible and normally accessible in an integrated economic value chain where banks recognize the value of collaterals in oil and gas firms, typically heavy and valuable production equipment or reserves. This access to refinancing is consistent with Davydenko's approach to financial distress (Davydenko, 2013). However, when a firm suffers a second consecutive quarter of asset inefficiency, it falls into financial distress, a stage where liquidity is a potential problem that may worsen, where the firm is not yet systematically in technical default or even insolvent, but where management needs to take material and strategic action such as restructuring, strategic partnerships, lay-offs, reorganization accompanied with a sound and credible project and financial strategy. Following Turetsky and McEwen (2001) and Whitaker (1999), Outecheva (2007) called this phase death struggle, where the fate of the company could either go towards a renewed positive momentum or a filing for bankruptcy; and Hillier et al. (2012) defined that a firm in financial distress needs to take strategic action, consistent with Platt and Platt (2002), Andrade and Kaplan (1998) and Brown, James and Mooradian (1992). The definition of financial distress as two consecutive quarters of negative OCF/TA ratio fits asset heavy industries such as exploration and production (E&P) in oil and gas, and leverages the contributions of Davydenko (2013), Outecheva (2007), Hillier et al. (2012) and their predecessors. With similarity to the variety existing in defining financial distress, the choice of predictor variables is also very diverse in the literature and in this study the researcher's own selection is ontologically personal. Seeking completeness, mutual exclusivity and relevance, the researcher identifies liquidity, solvency, profitability, valuation, energy, size, and operational efficiency ratios that best combine into vectors of covariates for the baseline model and each research question in this study. Additionally, the researcher assumes the directional effect, as positive or negative, of each financial distress predictor on the hazard ratio. This study has an axiological assumption of being value laden with the researcher's worldview in defining financial distress, selecting the financial distress predictors and assuming their directional contribution to the hazard rate. This axiological assumption also extends to more specific topics at the core of the hypotheses being tested (Andrade and Kaplan, 1998; Brown, James and Mooradian, 1992; Davydenko, 2013; Harrison, 2005; Hillier et al., 2012; Outecheva, 2007; Platt and Platt, 2002; Turetsky and McEwen, 2001; Whitaker, 1999).

The methodology of this empirical study is quantitative with a survival analysis statistical method (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012). The techniques of survival analysis can be parametric, semi-parametric or non-parametric. The survival analysis method of this study is a semi-parametric approach that is consistent with existing empirical analyses using survival analysis in finance and social sciences. Being semi-parametric, the method does not require any assumption about the distribution of survival times that would depend on previous periods' observations. Therefore, the semi-parametric technique does not have any baseline hazard; rather, it depends exclusively on the vector of covariates, and where those covariates fluctuate over time, the model is extended to include a time coefficient. The method is the Cox extended model, an extension of the Cox PH model that includes time-varying covariates (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012).

Additionally, the confidence intervals set for use in this study are at 95%, a rate that could be higher for more precise appreciations or on the contrary lower as required, but a rate that is standard in survival analyses and in financial empirical analyses. The p-value is small when inferior or equal to 0.05 and large when superior to 0.05. The hazard ratio interpretation is that a HR of 1 means that there is no relationship between the covariate and the event, a HR superior to 1 means that the hazard for the exposed firms is as many times as that of unexposed firms (for example a HR of 5 for a covariate means that for exposed firms it contributes to the event 5 times as much as the censored firms), and a HR of less than 1 also carries the same proportionality of exposure between exposed and unexposed firms. For hedging and for M&A, the analysis in this study relies on a Heaviside function with a value of 1 when the event occurred and zero when it did not (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012).

The oil and gas industry metrics this study uses are 2P for reserves, BOE for production, WTI for oil price index and USD for oil price currency. In oil and gas, reserves are classified in three categories. The first is 1P or proved reserves, the second is 2P or proved reserves plus probable reserves, and the third is 3P or proved reserves plus probable reserves plus possible reserves. A common practice in the financing industry or managerial analyses and forecasting is to use 2P, a measure that is not as conservative as 1P and not as generous as 3P (Arthur, Levine, Taylor & Tolleth, 2014; Harp, Jr. & Howard, 2009; Society of Petroleum Engineers, 2007). Thus, to remain consistent with industry practice, this research uses 2P as the metric for oil and gas reserves. Oil and gas firms produce either oil only, gas only or both, in various proportions, and tend to have very diverse approaches to hedging their production. The frequency, continuity and proportion of the production hedged vary greatly from one firm to another. In this study, the proxy for hedging is the percentage of barrels of oil equivalent (BOE) hedged, a unit of energy consistent with practitioners' preference in banking and oil and gas, and that captures the total production of a company, whether in gas or in oil. When providing this perspective to situate the context, the price of oil and gas is in US dollars and for the West Texas Intermediate (WTI) index. Oil price reports come in three main benchmark indices representing several dozens of oil types and assays: WTI, Brent crude and Dubai & Oman crude or Fateh. The indices represent the gravity of the oil as light or heavy, its sulfur level, as sweet or sour, and its production site that determines its transportation, as off shore or in-land. A Canadian index exists since 2014. The Canadian Crude Index (CCI) represents the heavy sour crude produced in Canada, especially in the oil sands, but this index is too recent for providing the trend and historical data this study needs, and WTI is one of the most commonly used oil price benchmarks globally and certainly in North America. Therefore, this study refers to the WTI in USD for the boom and bust perspective of oil prices fluctuations impacting Canadian oil and gas E&P producers (Arthur et al. 2014; Harp, Jr. & Howard, 2009; Natural Resources Canada, 2017; Society of Petroleum Engineers, 2007).

Several types of measures and approximations exist in the literature for company size. The most common in empirical studies and survival analyses is the natural logarithm of total assets, a metric that fits the objective of this study for an asset heavy industry; that remains consistent with the conceptual approach of financial distress definition in this study; and that is practical for use in a vector of covariates. The proxy for company size is thus, consistently with the literature, the natural logarithm of total assets (Log Assets) (Altman & Hotchkiss, 2006; Aziz & Dar, 2006; Chancharat et al., 2007; Charalambous et al.; Chen & Lee, 1993; Chong et al., 2010; Dang & Li, 2015; Fitzpatrick & Ogden, 2011; Gentry, Newbold & Whitford, 1985; Nikitin, 2003; Ohlson, 1980; Peat, 2007; Prantl, 2003; Raj & Rinastiti, 2002; Rommer, 2004; Shumway, 2001).

Mergers and acquisitions in this study come through the lens of financial distress and the approach of interest to understanding whether financial distress influences the M&A activity, requires viewing it from the perspective of the target. M&A is eligible for measurement and scoping only for target companies, public firms, for the period of observation going from Q1-2002 to Q1-2016, and excludes companies with foreign production, headquartered outside of Canada, cancelled deals and companies with incomplete data.

This study is laden with the choices of the researcher and includes an ad hoc definition of financial distress, ad hoc selections of predictor variables, hedging and M&A proxy variables, and literature-aligned standards and assumptions for the use of a semi-parametric survival analysis model, a 95% confidence interval, the interpretation of the p-value, the proxy for firm size, reserves, oil price index and Heaviside function (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012). Throughout the study as required, the researcher provides rationales and explanations for the use of any such assumption and definition to help clarify their sense, use and context as would the provision of operational definitions that follows (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012).

Operational Definitions

Several concepts and notions appear throughout this study. They pertain to the industry, the research key construct of financial distress and the method of survival analysis. Some have a straightforward definition and others need to be more explicitly laid out in the context of this study. Table 1 provides in alphabetical order an overview of the operational definitions further explained below and attaches each concept to a primary category and a secondary category to help situate each concept in the study. Then an explanation of all notions follows, as they fit in this study.

Table 1

Overview of the operational definitions

Notion	Primary Category	Secondary Category
2P	Oil and gas	Reserves
Bankruptcy	Corporate distress	Failure
Baseline model	Survival analysis	Cox PH model / Extended Cox model
BOE	Oil and gas	Reserves / Production / Hypothesis 1
Censoring	Survival analysis	Extended Cox model
Conditional probability models	Corporate distress analysis	Failure prediction
Corporate failure	Corporate distress analysis	Failure
Covariates	Survival analysis	Extended Cox model
Cox PH model	Survival analysis	Extended Cox model
Death struggle	Corporate distress analysis	Financial distress concept
Decision trees	Corporate distress analysis	Failure prediction
Default	Corporate distress analysis	Failure
DuPont Analysis	Corporate distress analysis	Financial analysis
E&P	Oil and gas	Industry / Scope
Economic distress	Corporate distress analysis	Financial distress concept
Extended Cox model	Survival analysis	Extended Cox model
Failure in survival analysis	Survival analysis	Cox PH model
Financial distress	Corporate distress analysis	Financial distress concept
Hazard function	Survival analysis	Cox PH model
Hazard ratio	Survival analysis	Cox PH model
Heaviside function	Survival analysis	Statistics
Hedging	Oil and gas	Hypotheses
Intelligent techniques	Corporate distress analysis	Failure prediction
Multicollinearity	Survival analysis	Statistics
PH assumption	Survival analysis	Cox PH model
Predictor	Survival analysis	Extended Cox model
Semi-parametric	Survival analysis	Cox PH model
Survival analysis	Survival analysis	Cox PH model
Survivor function	Survival analysis	Cox PH model
Time-dependent / Time-varying	Survival analysis	Extended Cox model
TSX and TSXV	Oil and gas	Industry / Scope
Vector of covariates	Survival analysis	Statistics
WTI	Oil and gas	Industry / Price

A detailed explanation of each concept in the list of notions in the first column of table 1 follows below in the same alphabetical order.

- 2P: Proved reserves plus probable reserves. There are three levels of reserves estimation in oil and gas: 1P or proved reserves, 2P or the sum of proved reserves and probable reserves, and 3P or the sum of proved, probable and possible reserves. The most common reserve estimate in the industry and in finance is 2P as it represents the most acceptable balance between the too conservative1P and the too optimistic 3P (Harp, Jr. & Howard, 2009; Society of Petroleum Engineers, 2007).
- Bankruptcy: legal insolvency that can ultimately result in a liquidation and foreclosure or in a restructuring. Most of the North American academic literature on business failure refers to the American bankruptcy chapters when mentioning bankruptcy, making it a benchmark for most readers. The Code of Laws governs bankruptcy laws in the U.S.A. and includes titles which in turn include chapters. Three chapters deal with bankruptcy. Chapter 7 is for liquidation, the most common filing used for personal bankruptcy, although also accessible and sometimes used by businesses as well. Chapter 11 is for restructuring businesses and corporations, allowing them to be rehabilitated and continue as a going concern while their debt load becomes a separate legal estate for which a plan will be negotiated and implemented with creditors; companies benefit a “bankruptcy protection” under Chapter 11 thanks to the creation of this separate legal estate. Chapter 13 or the Wage Earner Plan allows individuals to develop a plan to repay their debt partially or completely while they can keep their assets, as opposed to Chapter 7’s liquidation. In Canada, there are no chapters to refer to bankruptcy laws and instead of one Code of Laws there are several Acts governing bankruptcies. The Bankruptcy and Insolvency Act (BIA) governs bankruptcies for most the businesses and the Office of the Superintendent of Bankruptcy (OSB), a federal office. The Companies Creditors’

Arrangement Act (CCAA) governs the restructuration or liquidation of businesses with more than CAD 5M in liabilities that commit an act of bankruptcy including defaulting on a creditor's payment when due. The Winding Up and Restructuring Act applies to financial institutions. The Wage Earner Protection Act applies to individuals. The Farmer Debt Mediation Act applies to farmers. The Canada Transportation Act regulates railroads bankruptcies. The Act of interest for this study with its scope of public oil and gas companies is the CCAA which is the closest equivalent to Chapter 11 in the U.S. However, the CCAA bears the following notable differences: the filing can be voluntary but requires the commitment of a bankruptcy act, unlike in Chapter 11; a CCAA filing does not create a separate legal estate; under CCAA, the debtor cannot disclaim a collective bargaining agreement (CBA) unlike in Chapter 11 where this provision is a considerable help for restructuring and renegotiate labour contracts; a CCAA filing does not grant the debtor any exclusivity period to file a plan (120 days after the petition date in Chapter 11, that the court may extend for up to 18 months) or to solicit acceptances (180 days after the petition date in Chapter 11, that the court may extend for up to 20 months). Overall, where Chapter 11 has specific statutory requirements and seems more designed for the continuity of the business which can save jobs and be more beneficial to the economy as a going concern, the CCAA is more general and open to the Canadian judge's will, and seems more concerned with fairness to creditors and all stakeholders rather than privileging a going concern compromise. This bankruptcy paradigm in Canada contributes to the definition of financial distress in this study in situating the firm into a death struggle before it files for bankruptcy, as the intent of restructuring and taking strategic action is economic and managerial rather than legal with the safety net of a Chapter 11 protection as can be the case in the U.S. (Blakes Canadian Lawyers, 2016; Office of the Superintendent of Bankruptcy Canada, 2016; United States Courts, 2017).

- Baseline model: In this study, the baseline model is an extended Cox model with repeating events that explores the existing relationship of selected covariates including liquidity, solvency, profitability and activity-specific ratios to the state of financial distress, regardless of any hypothesis and research question. The baseline model builds the financial ratios observations and the structure of the collected data layout for the survival analysis in R, the statistical software that computes the survival analysis regression for the large amount of observations. As such, the baseline model serves to prepare the data for the specific hypotheses of this study (Klein & Kleinbaum, 2012).
- BOE: Barrel of oil equivalent. One barrel of 42 U.S. gallons or approximately 159 litres of crude oil contains 5.8 million British thermal units (MBtus) or 1,700 kilowatt-hours (kWh) of energy, and 6,000 cubic feet of natural gas (6 mcf) have the energy equivalent of one barrel of crude oil. BOE (also referred to as COE for Crude Oil Equivalent) is a standard unit for measuring, reporting and analyzing the energy a production and exploration firm can access or produce (BP, 2016; US Energy Information Administration, 2017).
- Censoring: Censoring is a key concept in survival analysis data observation, consisting in identifying and removing from the sample tested the observations for which the event did not occur during the observation period (i.e. the firm did not go into financial distress since it started reporting its financial information, until the end of the study period in Q1-2016), the subjects lost to observation during the observation period or withdrawn from the study (i.e. the firm stopped reporting). This censoring is a right-censoring, which is

the most common in statistical analysis. Left-censoring occurs when the true survival time is less than or equal to the observed survival time, which happens when the event occurs for other reasons than the dependent variable event being observed. All censoring in this study is a right-censoring (Klein & Kleinbaum, 2012).

- Conditional probability models: Conditional probability is the probability of an event based on the occurrence of another event. The conditional probability models this study mentions are logit and probit, both binary classification models. The probit model (from the combination of probability and unit) is a regression analysis that uses the maximum likelihood procedure and can result in only two values such as pass or fail; hence it is binary. Like probit, the logit model is a logistic regression with a categorical dependent variable and a cumulative logistic function used for the independent variables. That function takes the form of a S curve and captures growth with an exponential initial stage that slows down and eventually stops at maturity. In this study, the references to these models are mainly in the literature review about the O-score model by Ohlson (1980), a logit model, and the Zmijewski's probit model (Zmijewski, 1984). Incidentally, it is interesting to note in the context of this study that it was also Cox (1958) who developed the logit model, 14 years before his other seminal contribution of proportional hazard survival analysis that is the generic method of quantitative analysis in this study (Balcaen & Ooghe, 2006; Ohlson, 1980: Zmijewski, 1984).
- Corporate failure: in the context of this study, the phrase is a synonym to bankruptcy, economic, or financial failure. The researcher employs it in a generic sense to situate, introduce or illustrate predictive analysis from its origin in the early 20th century up to now. The phrase "corporate failure" in this study does not pretend to any specific and

rigorous measurable or attributive definition, as several authors and schools of thought may have used it with various meaning based on the needs of their specific researches (Outecheva, 2007).

- Covariates: a covariate is an independent variable that may have a predictive impact on the result being observed. In regression analysis and thus survival analysis, synonyms for covariates include predictors or explanatory variables (Klein & Kleinbaum, 2012).
- Cox PH model: Cox (1972) developed a semi-parametric survival analysis that now bears his name. The model is a proportional hazards regression analysis that does not require to be indexed like a parametric model. As such, the analysis depends entirely on the vector of covariates deemed to influence the event. The Cox PH model requires the satisfaction of the proportional hazard or PH assumption that the value of the covariates remains constant over time. The tests for verifying the PH assumption are graphical (log-log survivor curves: if the curves are parallel the PH assumption is satisfied; or a comparison of observed and predicted survivor curves: if the curves are close the PH assumption is satisfied); goodness-of-fit (GOF): if the p-value is large the PH assumption is satisfied; or Schoenfeld residuals: if they are flat or nil the PH assumption is satisfied. If the PH assumption is not satisfied, then the value of the covariates varies with time and is time-dependent or time-varying. One solution for that is to stratify the model by splitting the dataset into sub-samples, each with their own baseline hazards, and then estimate the partial likelihood of each stratum before summing them all for the total model output. Another solution consists in adding a time coefficient to the model and turn it into an extended Cox model. This study uses an extended Cox model. The key outputs of a Cox PH model are the hazard ratios (HR) and the survivor functions or cumulative hazard

functions. Chapter 3 of this study provides a detailed mathematical description of the Cox model and the extended Cox model (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012).

- Crude oil: In this study, the reference to crude oil is from a standardized and generic benchmark perspective to discuss oil prices and cycles. The reference benchmark is the WTI index. Technically, several dozens of oil types exist based on their location, transportability, viscosity as low or high density and sulphur content as sweet for less sulphur or sour for more sulphur. The measurement of oil is in barrels and one barrel is 42 U.S. gallons or approximately 159 litres. Crude oil is fluid and easier to extract than the bitumen from the oil sands that constitutes the bulk of Canada's oil reserves. Oil sands are a mixture of sand, clay, water and bitumen and the bitumen is so viscous that it requires heating for extraction and the addition of diluent for transportation. The province of Alberta in Western Canada has the world's largest reserves of oil sands before Venezuela, the USA or Russia, and the total area actively mined in Alberta is 904km^2, about the size of Berlin in Germany. Another alternative to conventional crude oil extraction is hydraulic fracturing also known as fracking, a very recent method less than ten years in development (Arthur et al. 2014; Harp, Jr. & Howard, 2009; CAPP, 2016; PSAC, 2016; Society of Petroleum Engineers, 2007).
- Death struggle: A stage of corporate financial distress that Outecheva (2007) introduced in her doctoral dissertation. Whitaker (1999) and McEwen and Turestsky (2001) originally posited that financial distress is not a single event and Outecheva (2007) built on it to propose subsequent phases in the process of being financially distressed. Following an early impairment, a deterioration of performance, failure and then insolvency, the firm enters the death struggle when it defaults and faces the risk of

bankruptcy; the firm is insolvent and its existence is at risk. The death struggle phase precedes a debt restructuring and then recovery or on the contrary a bankruptcy (Outecheva, 2007). This study borrows from that interpretation for its definition of financial distress (McEwen and Turestsky, 2001; Outecheva, 2007; Whitaker, 1999).

- Decision trees: A classification method that uses a visual graph of alternative possibilities which incorporate probabilities of outcomes. Decision trees are a tool that several disciplines use including operations research, decision learning, and binomial option pricing in finance, which can lead to the Black-Scholes formula, real options analysis or investment decisions and competing projects. The method is also one of the bankruptcy prediction techniques and as such it relies on algorithms for data mining (Altman et al.; Bhattacharya, Gepp & Kumar, 2010; Chen, 2011; Hosseini & Rashidi, 2013).
- Default: A firm is in default when it misses a due payment on a specific date. The firm can be illiquid before that date but it defaults only when it misses the payment. Davydenko (2013) analyzed that defaults on bond coupon payments occur mostly in the 30 days or less before the semi-annual payment dates in June and December (Davydenko, 2013). Default can also happen with suppliers, contractors, employees or on preferred stocks dividends. Default is one of many criteria present in the literature to define corporate failure or financial distress, including Beaver (1966) or Andrade and Kaplan (1998) (Andrade and Kaplan, 1998; Beaver, 1966; Davydenko, 2013).
- DuPont Analysis: The DuPont analysis or DuPont identity is a breakdown of a firm's return on equity into net margin, asset turnover ratio and leverage, allowing for a better understanding of the drivers of the return on equity. The formula was developed in the DuPont Corporation a century ago and contributed to the development of financial ratios

which later became foundational to bankruptcy and corporate failure predictive analysis (Castellano, 2015; Horrigan, 1968).

- E&P: Exploration and Production is the upstream industry of the oil and gas sector that also includes the midstream companies focusing on transportation such as pipeline companies, the downstream companies focusing on distribution with refineries and gas stations networks, and integrated oil and gas companies which activities span across those distinctions. More than 1,000 E&P companies exist in Canada, including about 250 publicly traded, where the oil and gas activity is mainly upstream and midstream as over half of the production is exported to the US refineries on the Gulf coast and the rest is exported to Asia or Europe. The scope of this study is Canadian E&P companies that have their production and headquarters in Canada, and that are listed on the TSX (PSAC, 2016; TMX, 2016).
- Economic Distress: Davydenko (2013) defined economic distress as insolvency which is a low market asset values relative to debt, and distinguished it from financial distress that he defined as illiquidity or low cash reserves relative to current liabilities (Davydenko, 2013). Like the concepts of financial distress or corporate failure, economic distress does not benefit in the literature a standard and commonly accepted definition. The concept may be interpreted by the researcher as they wish, often indistinctly from or amalgamating with financial distress. However, it carries a longer term and more structural impact on the firm resilience than does the narrower definition of financial distress tied to illiquidity or default only, that the literature often proposes. In this study, economic distress is close enough to the definition of financial distress based on the structural ability to generate enough cash from the operations to ensure the going concern

sustainability and the long-term profitability of the firm, to be indistinct. The phrase is however rarely employed, as opposed to its synonym financial distress (Davydenko, 2013).

- Extended Cox model: An extension of the Cox PH model that includes a time coefficient for time-varying covariates. When the proportional hazards assumption of proportionality constancy over time does not hold for some covariates, those change value with time. To run the model with time-sensitive covariates, the researcher can stratify the data in homogenous blocks satisfying the PH assumption before summing them all or add a time coefficient to the time-varying covariates. The latter is the extended Cox model (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012).
- Failure in survival analysis: The event of interest, which in this study is the occurrence of the state of financial distress, or the event of being an M&A target for the third hypothesis. The key indicator of failure in survival analysis is the hazard function (Klein & Kleinbaum, 2012).
- Financial Distress: Two consecutive quarters of negative operating cash flow to total assets ratio (OCF/TA). The literature provides several definitions for financial distress but there is no universal standard and each researcher selects the most pertinent definition to their study. This definition is original and designed to fit a capital-intensive and asset heavy industry such as oil and gas E&P with long lead times and assets life cycles. The resilience of the business depends on its self-sustainability which fuels the capacity of the assets to generate enough cash to insure short term funding liquidity as well as cash for reinvestment, growth and competition, or even profitability. The metric of OCF/TA is an asset efficiency ratio that should be a low positive percentage. In an industry as exposed

to the externality of crude oil prices as E&P, this definition captures the structural reliance on self-funding through a profitable use of the assets representing the core value enabler of the business, while allowing management to take corrective action if the first quarter presents a negative asset efficiency ratio. When a second consecutive quarter confirms the alarming trend, the company is in financial distress. As such, it can still fight this death struggle by taking strategic corrective action in the form of restructuring, reorganization, strategic partnerships, strategic portfolio management, focus, and refinancing by leveraging its reserves as a precious collateral and presenting a well crafted new management vision. This definition evolves from contributions to the literature by Outecheva (2007) for the death struggle, Davydenko (2013) for the possibility to access refinancing, which thus discounts illiquidity as an exclusive measure of financial distress, and Hillier et al. (2012) for the requirement to take strategic action as a gauge of severity (Davydenko, 2013; Hillier et al, 2012; Outecheva, 2007).

- Hazard function: The instantaneous potential per unit time for the event to occur, if the firm has survived up to that time. The hazard function gives a conditional failure rate and focuses on the odds of failing. The hazard function is a key output of survival analysis (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012).
- Hazard ratio: The hazard for one firm divided by the hazard for a different firm, which corresponds to the vector of covariates for one firm relative to the same vector for another firm. The hazard ratio is the measure of effect in survival analysis, expressed as the exponential of the regression coefficient for each covariate and used to measure the relationship between the dependent variable and the covariates (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012).

- Heaviside function: A discontinuous step function adapted from differential equations in calculus to represent binary choices in the form of 0 and 1 representing the absence or presence of an event. In this study, the hypotheses on hedging and M&A use a Heaviside function (Dobrushkin & Gourley, 2014; Klein & Kleinbaum, 2012).
- Hedging: a risk management investment designed to mitigate potential adverse price movements of an asset. Oil and gas prices are volatile and producers may use derivative contracts to offset those price fluctuations on part or all their production. The main derivatives in use in oil and gas include futures, which lock in the price of the future production and both sellers and buyers are obligated to honor the future price; swaps of floating price for a fixed price for a defined period of time with periodic cash flows exchanges or swaps; put options that fix a price floor and give the buyer the right but not the obligation to buy; and costless collars that combine two options such as being long (buying) on a put, and short (selling) on a call therefore creating a floor and a ceiling. The hedging focus in this study is on the existence of hedging and not on the specific strategies and derivatives of Canadian oil and gas producers (Haushalter, 2000, 2001; Iqbal, 2015; Jin & Jorion, 2006; Mercatus Energy Advisors, 2016).
- Intelligent techniques: artificial intelligent techniques relying on algorithms and computer processing power to generate, emulate or apply logic. In corporate failure and bankruptcy prediction, intelligent techniques are distinct from statistical techniques such as univariate or multivariate discriminant analyses, conditional probabilities or survival analysis. Finance is only one of many applications and research fields where intelligent techniques are experimented. The techniques are constantly evolving and expanding but in corporate failure the main techniques are machine learning techniques including decision trees,

neural networks and support vector machines among others (Balcaen and Ooghe, 2006; Blocher, Ko & Lin, 2001; Charalambous, Charitou and Neophytou, 2004: Chong & Wilson, 1995; Ravi & Ravi, 2007).

- Multicollinearity: in statistical analysis multicollinearity refers to two or more predictors in a regression analysis that are strongly correlated, and thus one can be predicted from the others quite accurately. The Cox PH model and the extended Cox model rely on an assumption of non-multicollinearity and each analysis should test this assumption or alternatively use univariate analyses, rather than vectors, to eliminate the risk of multicollinearity (Cox, 1972; Fox, 2008; InfluentialPoints, 2016; Klein & Kleinbaum, 2012).
- PH assumption: Proportional hazard assumption central to the Cox PH model. The validity of the model relies on the assumption that the covariates remain constant over time and therefore the proportionality of hazards or hazard ratios among the firms in the sample also remain constant. Graphic methods such as the parallelism of log-log survival curves or the closeness of predicted and observed survival curves, goodness-of-fit test using p-values, or Schoenfeld residuals are the tests for verifying the PH assumption. If the assumption does not hold, the covariate varies with time and the model must be stratified in homogenous blocks for which the PH assumption is verified, or extended with a time factor for the time-dependent covariates (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012).
- Predictor: a predictor is a synonym for a covariate in survival analysis (Klein & Kleinbaum, 2012).

- Semi-parametric: a regression model that combines parametric and non-parametric components. The Cox PH model is a semi-parametric model because its baseline function does not need to be specified. A survival model uses a baseline function and a vector of covariates. The baseline hazard function in the Cox PH model is a time component that does not involve the explanatory variables, while those are time-independent and normally satisfy the Cox PH assumption. The Cox PH formula is the product of the time-dependent baseline hazard function and the exponential expression of the vector of covariates. When the vector is equal to zero, its exponential is 1 and therefore the remaining time-dependent factor is the baseline hazard function. In the Cox PH model, that baseline hazard function is unspecified and the regression applies only to the exponentials of the covariates. That property of keeping the baseline hazard function unspecified is what makes the Cox PH model a semi-parametric model, and why the PH assumption must be satisfied. In parametric models, the baseline hazard function is the assumption that an underlying distribution of the survival times follows a probability distribution such as exponential, increasing or decreasing Weibull and lognormal distributions. Non-parametric models provide graphical representations of the distribution such as the Kaplan-Meier model (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012).
- Survival analysis: or time-to-event analysis, survival analysis is a statistical technique for analyzing prospectively the duration until an event of interest occurs. The technique is a regression analysis that relies on the key notions of hazard function, hazard ratio, survivor function, censoring, proportional hazard (PH), PH assumption and vector of covariates or predictors. Klein and Kleinbaum (2012) listed three goals to survival analysis: a) estimate and interpret survivor functions and hazard functions, b) compare

survivor and hazard functions, and c) assess the relationship of explanatory variables to survival time. The technique is mainly used in epidemiology and biostatistics, but also in engineering, social studies and finance (InfluentialPoints, 2016; Pereira, 2014). The specific methods to do a survival analysis can be parametric, semi-parametric or graphical. This study, consistent with existing research in survival analysis applied to finance, uses a semi-parametric method extended from the generic Cox Proportional Hazard model to allow for the use of time-varying covariates and for the repetition of the dependent variable during the study period. The method for this study is an extended Cox model with repeating events (Cox, 1972; Fox, 2008; InfluentialPoints, 2016; Klein & Kleinbaum, 2012; Pereira, 2014).

- Survivor function: In survival analysis, this key construct of interest is a function that gives the probability that a subject (a firm in this study) survives longer than a specified time. The function focuses on surviving or not failing as opposed to the hazard function that focuses on the failure time. The survival function is a decreasing curve or step function when using real data that also serves for testing the PH assumption (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012).
- Time-dependent: or time-varying covariates define the nature of explanatory variables or predictors or covariates for which the values fluctuate during the study. The Cox PH model is based on the PH assumption and the constancy of the proportions among the individuals in the sample. This is the case for example for individuals' sex or firms' headquarters location in some studies, both of which are time-independent or time-invariant covariates. When the values fluctuate, such as for financial ratios for example, the covariates' value vary along different periods during the study and they are thus time-

dependent or time-varying predictors. A Cox PH model with time-dependent covariates does not initially satisfy the PH assumption and requires a stratification into homogenous blocks of time-invariant covariates to be later consolidated, or to be extended with a time coefficient for the time-varying explanatory variables (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012).

- Time-varying: synonym to time-dependent (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012).
- TSX and TSXV: Toronto Stock Exchange and TSX Venture Exchange. Both are Canadian stock exchanges providing a primary and a secondary market for Canadian oil and gas firms. They are part of the TMX Group Limited based in Toronto, Canada. The TSX serves the senior equity market and the TSXV for more junior firms, is in Calgary, Alberta (TXM, 2016).
- Vector of covariates: a vector is a matrix with only one column or one row, and a vector of covariates is thus a linear matrix including all the ordered explanatory variables used in a survival analysis or a Cox PH model (Anonymous, 2003; Klein & Kleinbaum, 2012).
- WTI: West Texas Intermediate. Oil price reports come in three main benchmark indices representing several dozens of oil types and assays: WTI, Brent crude and Dubai & Oman crude or Fateh. The indices represent the gravity of the oil as light or heavy, its sulfur level, as sweet or sour, and its production site that determines its transportation, as off shore or in-land. The WTI is the benchmark reference for oil and gas prices in North America. This study refers to WTI prices (Arthur et al., 2014; Harp, Jr. & Howard, 2009; Society of Petroleum Engineers, 2007).

Summary

In a context of boom and bust cycles driven by the fluctuations in the price of oil and gas, Canadian oil and gas producers leading the Albertan economy are in severe financial distress during bust phases. Since mid-2014, oil prices are low and the province has suffered dozens of bankruptcies, massive layoffs, a halt in major capital projects investments, a drastic reduction in production and a harsh economic recession (Jakeman & Tertzakian, 2016; Macrotrends, 2016; Millington, 2016). Over the past century, the analytical methods to study and predict corporate failure, bankruptcy and financial distress have evolved and matured, going through a few different paradigms until the current use of a variety of artificial intelligence techniques and the application of survival analysis methods borrowed from epidemiology and biostatistics (Aziz & Dar, 2006; Horrigan, 1968; InfluentialPoints, 2016). This research is a survival analysis with the intent to study the relationship of explanatory variables to the state of financial distress in a population of publicly traded Canadian oil and gas exploration and production firms headquartered and producing in Canada. The method for this quantitative study is a semi-parametric extended Cox model with repeating events. This technique uses a multi linear regression analysis of proportional hazards within the sample population with the exclusive use of predictors, and no baseline hazard, while accounting for the time factor of varying predictor values and accepting the repetition of the event of financial distress (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012). The research uses a sample of 540 firms with quarterly public reporting of financial statements from Q1-2002 until Q1-2016, representing 15,850 firm-quarters. To the best of the researcher's knowledge, this sample size is unprecedented in similar studies, specifically for Canadian oil and gas firms for which this is the first survival analysis, the first Cox PH model extended to include time-varying covariates and to allow for the repetition of the event. This originality contributes to the significance of this study as do its practical applications in opening the way to further analyses of the impact of different predictors alone or combined, the specific definition of financial distress unique to this study and the pragmatic understanding it allows stakeholders in the E&P sector, such as suppliers, partners, investors, regulators or customers, at capturing the resilience, solidity, economic fragility or strength, growth, profitability and overall survival and potential of Canadian E&P firms. In the absence of a universally established definition, the researcher defines the central notion of financial distress in this study as two consecutive quarters of a negative ratio of operating cash flows to total assets. This definition intends to capture the state where a firm in this capital-intensive industry characterized by long lead times is not generating sufficient cash flows from its operations to sustain its liquidity requirements, which endangers its solvency and profitability by impeding the ability to reinvest healthily in its essential asset base. In that state, firms need to consider significant strategic actions to survive, or face complete failure in the form of bankruptcy or insolvency. The design of the study uses the foundation of a baseline model and explores three hypotheses as research questions. The baseline model explores the causal relationship of liquidity, solvency, profitability and operational predictors to financial distress and has a sample size of 15,836 quarter-firms. The first hypothesis studies whether the presence of hedging influences financial distress and uses a sample of 515 firms, with 11,005 quarter-firm observations for the period of Q1-2007 to Q1-2016. The second hypothesis is on the impact of size on financial distress and has the same sample size as the baseline model with 15,854 quarter-firms. The third hypothesis focuses on whether being financially distressed is a factor in being the target of a merger and acquisition transaction and uses a sample of 166 firms involved in such transactions between Q1-2002 and Q1-2016, with 175 M&A transactions and 3,698 quarter-firm events of financial distress. The analysis consists in collecting the data, building the observations in Excel, laying out the data for the statistical software, coding the software, running the survival analysis, verifying the models' validity, testing the null hypothesis, interpreting the regression results and interpreting the cumulative hazards function curves. This research exists within a post-positivist paradigm where the axiological assumption includes the values and interpretations of the researcher in framing the key constructs of interest. Therefore, this study is laden with several assumptions and limitations stemming from the choice of the method, the definition of financial distress, the units and metrics, and the scope. An explanation of all assumptions and limitations enables to better contextually situate the research and facilitate its replicability. As this study bears multiple specificities related to the oil and gas industry, corporate failure and the statistics of survival analysis, it includes definitions or explanations for several key notions, some of which have evolved with the science of financial distress itself. With such a strong contextual framework and potential significance due to its originality, this study requires a solid rooting in the academic literature on the central construct of financial distress and the satellite concepts explored in the research questions (Aziz & Dar, 2006; Cox, 1972; Fox, 2008; Horrigan, 1968; InfluentialPoints, 2016; Jakeman & Tertzakian, 2016; Klein & Kleinbaum, 2012; Macrotrends, 2016; Millington, 2016; Outecheva, 2007).

Chapter 2: Literature Review

Oil price shocks create financial distress on Canadian oil and gas firms and there is a need to analyze and understand the determinants of such distress (Jakeman & Tertzakian, 2016; Millington, 2016, CAPP, 2016; PSAC, 2016). However, the specific questions of interest for this study evolve around the pertinence of hedging and size as determinant of financial distress and the impact of financial distress as a driver of merger and acquisition activity. Research on corporate failure is rich and varied but empirical studies do not unanimously converge in adopting one reference approach for studying financial distress and predicting it (Outecheva, 2007). There is room for subjective selection and interpretation of the inputs, yet the analysis must abide by the rigor of the scientific approach. This reality defines the post-positivist paradigm of this analysis. The current state of knowledge and research in corporate failure has gradually evolved from the apparition of financial ratios over a century ago to their use for predicting bankruptcy until the first paradigm of linear multiple discriminant analysis started in 1968, followed by a second paradigm of conditional probabilities models in the early 1980s (Altman, 1968; Horrigan, 1968; Ohlson, 1980; Zmijewski; 1984). Both have become references still in use today and both present limitations and restrictions. Several alternative techniques, mainly leveraging artificial intelligence also attempt to accurately predict financial distress but only proportional hazards as used in survival analysis and as enabled for business analysis by Cox (1972) offer more than a binary answer (Chen & Lee, 1993). This literature review targets completeness in setting the historical and broad stage of the evolution of financial distress analysis starting as far as 1892 (Castellano, 2015; Marshall, 1892) and leveraging over 180 references. The rest of this chapter comes in three sections. The first establishes the research paradigm and its assumptions. The second roots the theoretical orientation of the study comprised of eight subsections encompassing the buildup of the analytical paradigms, their descriptions and limitations, the alternatives techniques, survival analysis, hedging, size and merger and acquisitions. The third section proposes a critique of the existing research using the necessary understanding of the framework set in section two to arrive at the adoption of the survival analysis methodology for this study (Altman, 1968; Beaver, 1966; Castellano, 2015; Cox, 1972; Chen & Lee, 1993; Horrigan, 1968; Jakeman & Tertzakian, 2016; Marshall, 1892; Millington, 2016, CAPP, 2016; Outecheva, 2007; PSAC, 2016).

Research Paradigm Assumptions

A post-positivist paradigm governs this dissertation, with the following ontological, epistemological, axiological, rhetorical and methodological assumptions. The ontology of this research is that financial distress is a tangible reality, observable and measurable. Yet, that reality can fluctuate and change depending on the definition used to determine financial distress. Bisman (2010) determined that “accounting is a human artefact, and decision-making is inextricably bound to facets of human cognition” (Bisman, 2010, p.14) and as financial ratios variables are constructs of accounting, they are inherently reflective of the valuation and recognition choices made for the reporting of financial statements, albeit in full compliance of the required accounting principles and standards. Therefore, data is fallible but it is possible to capture the reality of financial distress. Epistemologically, this research is etic, dualist and objective. The researcher performs this study on historical data and is completely independent from the oil and gas companies analyzed, individually or as a group, in the past or the present. To gain knowledge about the hazard of financial distress and survival of Canadian oil and gas companies, this study applies an extended Cox model with repeating events that is nomothetic, objective and uses a quantifiable statistical analysis. Axiologically, this study is value laden with the researcher's worldview of defining financing distress and selecting how many and what variables to use. This influence stems from (a) an absence of a universally accepted set of financial ratios or definitions required as a paradigm for a survival analysis of financially distressed companies, (b) the liberty to select and include market data and firm characteristics, and (c) a lack of formal and irrevocable generally accepted definition of the state of financial distress. The rhetorical assumption of this study is that the researcher uses an impersonal, formal and strict language based on the rules of statistical and financial recognition, measurement and disclosure. The researcher is writing from the perspective of a disinterested scientist. The last assumption governing this research is methodological: the researcher performs this empirical research through a quantitative technique using a specific statistical analysis selected based on the research question. The perspective of understanding the time to failure and the probabilities of survival based on time-varying covariates guide the choice of using a semi-parametric extended Cox model. The statement of the research objective is clear and the study uses verifiable hypotheses to formulate it. Internal and external validity is central as the researcher explores causal relationships within a macro-economic context and for an entire industrial sector (Abawi, 2008; Bisman, 2010; Guba & Lincoln, 1994; Johnson & Onwuegbuzie, 2004; Miller, 2002; Trochim, 2006).

These assumptions are meant to establish a paradigm for this quantitative research where scientific rigor and agnosticism guide data collection, statistical analysis, argumentation and reporting while acknowledging the influence of the researcher's values in choosing definitions and selecting variables. This paradigm inscribes in continuity with the literature on corporate failure that grounds this research and helps frame its theoretical foundations.

Theoretical Orientation

Originally, the development of financial ratios occurred gradually. The business objective behind their apparition was to analyze and compare performance and then the need to monitor credit and corporate risk turned them into the preferred tool for financial distress analysis and prediction. Beaver (1966) initiated a new paradigm for bankruptcy prediction that included Altman's MDA (Altman, 1968) and the conditional probability models pioneered by Ohlson (1980) and Zmijewski (1984) but those classical models had several restrictive assumptions and alternative techniques have since been proposed including neural networks, non-computing techniques and intelligent techniques such as support vector machines or decisions trees. Among them, one technique proved superior in allowing for a dynamic time-to-event analysis of corporate survival as opposed to the traditional pass/fail binary prediction alternative methods offer. This analytical method is a semi-parametric survival analysis Cox (1972) developed that is mainly used in biostatistics, epidemiology and to a lesser extent engineering, finance and social studies (InfluentialPoints, 2016; Pereira, 2014). The technique is a proportional hazards regression analysis one can extend for time-varying covariates. Survival analysis assumes that there is no multicollinearity and that the hazards remain proportional among covariates and the extended Cox model of this study allows to estimate the relevance of covariates, the hazard they represent for financial distress and predict survival on a time-continuum. Using vectors of relevant predictors, the extended Cox model can analyze the questions of interest for this study around the determinants of financial distress, the impact of hedging and size on financial distress and the causality of financial distress on mergers and acquisitions. This section presents the theoretical foundations of this research by reviewing the literature with eight subsections. The first three pose the framework with a historical review of the origin of financial ratios and their use in bankruptcy prediction, a review of the classical paradigms of corporate failure analysis, and the alternative techniques used. The fourth and fifth focus on survival analysis with its superiority over classical models and its empirical use in oil and gas and in Canadian literature, and an overview of the diversity characterizing the definition of financial distress. The last three are a literature review of hedging, firm size and M&A as they relate to the research problem of financial distress and survival of Canadian Oil and Gas firms (Altman, 1968; Beaver, 1966; Cox, 1972; InfluentialPoints, 2016; Ohlson, 1980; Pereira, 2014; Zmijewski, 1984).

Financial Ratios: Origins and First Use in Bankruptcy Prediction

A review of the academic literature in bankruptcy and corporate failure performed for this research reveals that Beaver (1966) is the most systematically and frequently cited reference for anchoring the origins of bankruptcy predictability, but long before him several authors had already built the foundations he used to publish his seminal article. Initial works focused on the use of financial ratios, then more empirical studies analyzed ratios' predicting power confirming the emergence of a few specific ratios while evolving towards cash flow analysis in the last decade before Beaver (1966) (Beaver, 1966; Castellano, 2015; Horrigan, 1968).

The roots of corporate financial health analysis through financial ratios trace back as far as the late nineteenth century and it took them about three decades until 1920 to take hold. Foulke (1961) situated the first appearance of financial ratios no later than 1891 and Horrigan (1968) analyzed that credit analysis that developed with the emergence of the American financial sector, was the real catalyst for the use of financial ratios, especially in the last decade of the nineteenth century. Two studies marked the development of financial ratios, both in the 1910's. The first is the DuPont Analysis. In 1914, Donaldson Brown developed a ratio "triangle" system to analyze operating results and return on investment. Brown was an electrical engineer without any formal training in finance who had previously gained exposure to and reported on business challenges at the DuPont Corporation. Brown built his inspiration for the "triangle" on a similar approach published by Marshall (1892) (Castellano, 2015; Horrigan, 1968; Marshall, 1892). The second was a compilation of seven ratios for 981 firms by Wall (1919) that raised the following comment from Horrigan (1968):

> His results would be vulnerable to criticism by today's standards; but his study was historically significant because it was a widely-read *[sic]*, overt departure from the customary usage of a single ratio with an absolute criterion. Wall had, in effect, popularized *[sic]* the ideas of using many ratios and using empirically determined relative ratio criteria (Horrigan, 1968, p.286).

Financial distress analysis and predictability originates from the need to monitor credit worthiness and corporate risk. That monitoring expanded in breadth and sophistication thanks to financial ratios and by the 1920s, there were both enough public data for empirical studies and shared financial knowledge of financial ratios to give rise to bankruptcy prediction studies. The specific use of financial ratios for understanding and predicting corporate failure started during the great depression and established the first empirical bases of bankruptcy analysis. Following Wall's study (1919), the use of financial ratio gained in popularity and innovation as it widely proliferated in the 1920s (Horrigan, 1968). Bliss (1923) was the first to explore the predictive power of ratios by attempting to capture the complete business activity of any corporation through a system of ratios, based on the assumptions that they were good indicators of the structural relationships within a company. Duning and Wall (1928) pioneered the formalization of financial analysis by using ratios (Beaver, Correia & McNichols, 2010; Bliss, 1923; Duning & Wall, 1928; Horrigan, 1968). Foster and Ramser (1931) studied 173 firms and 11 ratios to formalize financial analysis. Fitzpatrick (1932) randomly selected 20 firms that had failed during the period of 1920 to 1929 and pair matched them using fiscal year, sales volume, asset size, product line and financial soundness as criteria. He analyzed each pair three to five years prior to the failure and concluded on the importance of each of the 13 ratios used for his analysis while specifically singling out net worth to debt and net profits to net worth as the best indicators of failure. In 1934, Dodd and Graham (1934) published “Security Analysis” and contributed to formalizing financial analysis using ratios. Smith and Winakor (1935) used 10 years of data to analyze 183 firms with 21 ratios and were the first to praise the ratio of working capital to total assets’ accuracy, steadiness and predictive power of failure. Merwin (1942) analyzed a larger sample of 900 small corporations using six years of data. He identified three ratios useful to predict failure for up to five years prior to discontinuance: a) net working capital to total assets, b) net worth to total debt, and c) the current ratio. For Horrigan (1968), “Merwin’s study was the first sophisticated analysis of ratio predictive power, and the findings of the study still appear to be credible” (Horrigan, 1968, p.289). Hickman (1958) used data from 1900 to 1943 and identified the net profits to sales ratio and times-interest-earned as useful predictors of default on corporate bonds issues. Halcrow, Jacoby and Saulnier (1958) used credit information from RFC for the years 1934 to 1951 to determine the predictive power of current ratio and net worth to debt ratios for loan defaults. Walter (1957) and Donaldson (1962) shifted the analysis of failure on technical cash insolvency and pioneered the use of cash flow analysis towards bankruptcy prediction based on the fundamental principle that the value of an economic concern is the net present value of its expected future cash flows. Thus, from Wall (1919) to Merwin (1942) the following series of five observations follows. First, financial ratios gained in popularity and sophistication. Second, the advent of ratios contributed to the formalization of financial analysis.

Third, there was the publication of the first empirical studies attempting to predict failure by using ratios. Fourth, the ratio of working capital to total assets started to emerge as a reliable predictor of failure. Fifth, Merwin (1942) produced the first solid predictive analysis of corporate failure, twenty-four years before Beaver (1966). All this preamble to Beaver (1966) constituted necessary stepping stones to his ground-breaking article, about which it is interesting to note the following prescient comment from Horrigan (1968) "this study will undoubtedly become a landmark for future research in ratio analysis" (Horrigan, 1968, p.291). Indeed, the landmark turned out a major paradigm shift in corporate failure prediction (Beaver et al.; Bliss, 1923; Duning & Wall, 1928; Dodd & Graham, 1934; Donaldson, 1962; Fitzpatrick, 1932; Foster & Ramser, 1931; Foulke; 1961; Halcrow et al., 1958; Hickman, 1958; Horrigan, 1968; Merwin, 1942; Smith & Winakor, 1935; Wall, 1919; Walter, 1957).

Classical Paradigms of Corporate Failure Analysis

From Beaver (1966) to Zmijewski (1984), the classical paradigms of multiple discriminant analysis (MDA) and conditional probability models have dominated corporate failure predictive analysis. Beaver (1966) wrote a seminal article that stands as a milestone in corporate failure literature. He used a stronger statistical technique than Merwin (1942), the naive Bayes approach, on 79 matched pair companies using data from 1954 to 1964 (Pereira, 2014; Horrigan, 1968). Beaver (1966) used a univariate analysis, taking each ratio one at a time with its own cut-off point to make a predictive classification of failure or success. He used 30 ratios and a cash flow approach, and considered the firm as a reservoir of liquid assets, drained by cash outflows and supplied by cash inflows. The reservoir serves to balance cash flow variations and failure is a consequence of its exhaustion when the firm can no longer honor its financial obligations. For Beaver (1966), failure meant the incapacity to honor financial obligations as they come due, and the operational application of this principle translated into the occurrence of any of the following events “bankruptcy, bond default, an overdrawn bank account, or non-payment of a preferred stock dividend” (Beaver, 1966, p.71). He identified working capital to debt as the best predictive ratio, followed by net income to total assets. The univariate analysis from Beaver (1966) opened the way to what would become one of the base reference techniques in bankruptcy prediction, Altman’s Z-score (Beaver, 1966; Horrigan, 1968; Merwin, 1942; Pereira, 2014; Zmijewski, 1984).

Altman (1968) used the linear discriminant analysis that Fisher (1936) had originally introduced to combine five ratios into a single function called the Z-score that required only one cut-off point but depended on restrictive assumptions. With 33 matched pairs of bankrupt and non-bankrupt firms and data from 1946 to 1965, Altman (1968) calculated discriminant factors for each ratio. The technique called MDA relies on the main assumption of dichotomy meaning that data groups are discrete, identifiable and non-overlapping. Additionally, MDA has three restrictive assumptions: multivariate normality, equal dispersion matrices, and inclusion of prior probability of failure and misclassification costs (Balcaen & Ooghe, 2006). The first assumption of normality tends to be subject to violation in MDA as financial ratios have the propensity to be asymmetric and skewed to the right. However, within a specific industry group, Deakin (1976) observed a more normal distribution (Balcaen & Ooghe, 2006; Deakin, 1976; McLeay & Omar, 2000). Authors using MDA have forced the normalization by using several transformation techniques including reciprocal or logarithmic transformations, log-transformation, square root and lognormal transformation, or windsorizing, which consists in trimming the outliers (Balcaen & Ooghe, 2006). The second restrictive assumption requires the variance-covariance matrices to be equal between the failing and non-failing group otherwise the mean variables between both groups fail the significance tests. A violation of this assumption can be mitigated by using a variant of MDA, the quadratic MDA but Balcaen and Ooghe (2006) observed that quadratic MDA is a complex procedure only relevant for large data samples with relatively small numbers of independent variables and very large dispersions in variance-covariance matrices (Balcaen & Ooghe, 2006). The third assumption that requires factoring in the determination of the optimal cut-off point for the function, the costs of type I and type II errors and the probability of dispersion between both data groups, serves to ensure accuracy and generalizability of the function result (Balcaen & Ooghe, 2006). The Z-score is still popular and the simplicity of its use in the form of a single function with fixed factors, only requiring financial ratios input must have contributed to its success. Scholars like Deakin (1977), Edmister (1972), Eisenbeis (1977), Joy and Tollefson (1975) or Tafler (1982) have been aware of its restrictive assumptions and worked on them extensively and in 1980 conditional probability models shifted the paradigm of bankruptcy prediction analysis (Altman, 1968; Balcaen & Ooghe, 2006; Deakin, 1976, 1977; Edmister, 1972; Eisenbeis, 1977; Fisher, 1936; Joy & Tollefson, 1975; McLeay & Omar, 2000; Tafler, 1982).

Conditional probability models appeared as alternatives to MDA for bankruptcy prediction analysis. The most popular is the O-score (Ohlson, 1980), a method that uses a logit score to predict bankruptcy. Martin (1977) was the first to use the logit model to predict bank failure. The second type of model is a probit analysis proposed by Zmijewski (1984). These models provide non-linear maximum likelihood estimations obtained from assumptions on the probability distribution of failure conditional on firm characteristics. Those assumptions are a logistic distribution for the most popular logit analysis and a cumulative normal distribution for probit analysis (Balcaen & Ooghe, 2006). Ohlson (1980) broke away from the tradition of using matched pairs with a sample of 105 bankrupt industrial firms and 2,058 non-bankrupt industrial firms from 1970 to 1976. He used nine variables based on previous literature and issued a linear function with parameters and a single cut-off score used to classify firms with the group they are the closest to in terms of dichotomous failed/non-failed status. As they allow the use of disproportional samples, conditional probability models are less statistically demanding than MDA, but like MDA, type I and type II error rates are the statistics of choice for measuring the accuracy of their classification. Logit analysis relies on two assumptions: the dependent variable must be dichotomous, and the optimal cut-off probability should factor in the cost of type I and type II error rates. The logit score is an intuitively comfortable value between zero and one resembling a probability of failure but the models are highly sensitive to multicollinearity and outliers (Balcaen & Ooghe, 2006; Martin, 1977; Ohlson, 1980; Zmijewski, 1984). The course of this research indicates that the Z-score and the O-score are the most compared to techniques in empirical studies, but over the years since the early seventies there have been many alternative techniques proposed for financial distress and bankruptcy prediction (Balcaen & Ooghe, 2006; Martin, 1977; Ohlson, 1980; Zmijewski, 1984).

Other Techniques Used in Bankruptcy Prediction

Corporate failure prediction has used several techniques besides MDA and conditional probabilities, and among them neural networks stand out for their relative frequency in the literature. The neural network technique is a non-statistical approach coming from neural computing, an artificially intelligent system using a network of interconnected units called artificial neurons. The original idea driving the development of neural networks was to mimic the human brain's neural architecture and to emulate its functioning; and in many other disciplines than finance researchers explore the application of this field (Chong & Wilson, 1995).

The technique consists in teaching computers to develop algorithms based on provided samples (Blocher, Ko & Lin, 2001; Chong & Wilson, 1995; Ravi & Ravi, 2007). Several studies concluded in the superiority of neural networks over statistical methods including Charalambous, Charitou and Neophytou (2004), Chong and Wilson (1995), Han, Kwon and Lee (1996), Hansen and Messier (1991), Kiang and Tam (1992), Odom and Sharda (1990), and Sharda and Wilson (1994). However, Boritz, Kennedy and De Miranda e Albuquerque (1995) found that rather than the panacea, neural networks show only discrete bubbles of superior performance compared to MDA and conditional probability models. Neural networks are part of iterative learning models as are inductive learning systems that develop rules from given samples and composite rules induction systems applied by Blocher et al., Altman, Frydman and Kao (1985) and Hansen and Messier (1991). Support vector machines, or SVM, are supervised learning algorithms used for outlier detection, classifications and regression analysis (Erdogan, 2013; Lai, Yen & Zhou, 2014). Like SVM, composite rule induction system is also a supervised learning technique central to machine learning and relying on making inferences from a dataset (Blocher et al., 2001). Multidimensional scaling is a visualization technique relying on ordination of related data displayed in a distance matrix (Chipulu, Jayasekera & Khoja, 2016; Garcia-Cestona, Mar-Molinero & Sagarra, 2015; Mar-Molinero & Neophytou, 2004; Mar-Molinero & Serrano-Cinca, 2001). Multiple criteria linear programming is a data mining technique evolving from linear discriminant analyses used for decision-making involving several criteria (Kou, Kwak & Shi, 2012). Decision trees are a non-parametric data mining technique classifying data in an arborescence, which then serves as input for decision analysis (Altman et al., 1985; Bhattacharya et al., 2010; Chen, 2011; Hosseini & Rashidi, 2013). Isotonic separation is a data separation and classification method originally developed in medical research and relying on the key assumption of monotonic consistency of data. Ravi and Ravi (2007) also identify soft computing subsuming seamless hybridization of other computing techniques (Ravi & Ravi, 2007). Non-computing techniques include managerial decision based approach (Peat, 2007) and factor analysis (Caruthers, Mingo & Pinches, 1973). The gambler's ruin model (Wilcox, 1971, 1976), the catastrophe theory (Fletcher, Ryan & Scapens, 1981; Fabozzi, Francis & Hastings, 1983) and the contingent claims models (Cram, Hillegeist, Keating & Lundstedt, 2004) also belong to this category. At last, the other approaches to corporate failure prediction include operational research, evolutionary approaches, simple-intuitive models (Ooghe, Spaenjers & Vandermoere, 2009), and survival analysis often referred to as dynamic event history analysis in social sciences. All but survival analysis are binary classification techniques and none of the approaches mentioned above has so far successfully imposed itself as the next unequivocal paradigm in corporate failure analysis as have the Z-score and the O-score. But survival analysis presents unique and distinctive characteristics in the way it approaches corporate failure prediction and benefits greater credit than any of these alternative techniques (Altman et al., 1985; Bhattacharya et al., 2010; Blocher et al., 2001; Boritz,et al., 1995; Caruthers et al., 1973; Charalambous et al., 2004; Chen, 2011; Chipulu et al., 2016; Chong & Wilson, 1995; Cram et al., 2004; Erdogan, 2013; Fabozzi et al., 1983; Fletcher et al., 1981; Garcia-Cestona et al., 2015; Han et al., 1996; Hansen & Messier, 1991; Hosseini & Rashidi, 2013; Kiang & Tam, 1992; Kou et al., 2012; Lai et al., 2014; Mar-Molinero & Neophytou, 2004; Mar-Molinero & Serrano-Cinca, 2001; Odom & Sharda, 1990; Ooghe et al., 2009; Peat, 2007; Sharda & Wilson, 1994; Ravi & Ravi, 2007; Wilcox, 1971, 1976).

Survival Analysis

Survival analysis is a statistical technique widely used in biostatistics and to a lesser extent in mechanical engineering and social studies (InfluentialPoints, 2016; Pereira, 2014). Using historical data, survival analysis generates on a time continuum the probabilities of survival or survivor function, and the probability of instantaneous failure along the continuum provided the entity has survived so far or hazard function. Survival analysis can take the form of multiple models but the most frequently used are the parametric proportional hazard models, the Cox semi-parametric PH model and the accelerated failure time models. Proportional hazards models rely on the stable proportionality over time of the hazard of each predictor variable within the sample population. They are a regression analysis of univariate or multiple covariate predictors such as financial ratios and market data where the covariates do not show multicollinearity. In parametric models, the data requires fitting a specific statistical distribution with the assumption that the hazard follows that distribution (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012). Cox (1972) developed a semi-parametric approach to proportional hazards analysis by removing the necessity to define the probability of a baseline function. This simplification of removing the need for prior distributions has made of the Cox semi-parametric PH model the preferred survival analysis corporate failure prediction technique. When the values of the predictor covariates remain constant over time, such as sex or geographic location for example, the covariates are time-invariant. When the values of some covariates change over time, as can be expected for financial ratios, those covariates are time varying and the Cox PH model requires the inclusion of a time coefficient for these covariates to extend the original model (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012). Lane, Looney and Wansley (1986) pioneered the use of the Cox PH model in corporate failure prediction by doing a survival analysis on the duration between balance sheet date and official disclosure of bank failure. The first studies applying survival analysis for corporate failure used time-invariant covariates. They also systematically justified the use of the Cox PH model by comparing their results with the classical alternatives of MDA and conditional probability models (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012; Lane et al.; Laitinen & Luoma, 1991; Chen & Lee, 1993; Henebry, 1996; Whalen, 1991).

Several finance research papers have addressed the superiority of survival analysis over the classical binary models of MDA, logit and probit (Agarwal & Bauer, 2014; Beaver et al., 2010; Chen & Lee, 1993; Davydenko, 2013; LeClere, 2005; Pereira, 2014; Shumway, 2001; Whalen, 1991; Yamazaki, 2013). The early authors noted two attributes in praising the technique. The first is the ability to estimate how long a firm may survive as opposed to the binary lens used in classical models that answers only whether the firm survives. The second is that survival analysis does not require any assumption about the distributional properties of the data, which is the multivariate normality restrictive assumption underlying MDA (Chen & Lee, 1993; Whalen, 1991). Shumway (2001) made a landmark assertion praising the superiority of hazard models for bankruptcy prediction in a frontally critical paper of previous methods, and has since become a commonly cited reference in survival analyses empirical studies. He specifically asserted that “static” models have a selection bias due to the use of data for the year prior to failure as opposed to computing from all the years available in the sample, thus he contended that “static models do not adjust for period at risk, but hazard models adjust for it automatically” (Shumway, 2001, p.102). He also noted the benefits of using time-varying covariates that allow to capturing changes in corporate health, a point LeClere (2005) also emphasized. The third benefit of hazard models Shumway (2001) listed is the compounding effect of using more data than in binary models as all sample years are used and thus they are more accurate. Beaver et al. (2010) acknowledged the advantages of hazard analysis. Agarwal and Bauer (2014) specifically attested to the superiority of hazard models over the Z-score and contingent claims. Yamazaki (2013) recognized the statistical power of proportional hazard models for analyzing and estimating events risks. Pereira (2014) considered survival analysis more useful and accurate than alternative approaches. In addition, for Davydenko (2013) "hazard analysis has become the instrument of choice in empirical studies predicting default and bankruptcy" (Davydenko, 2013, p.25). The superiority of survival analysis for a more meaningful and accurate predictability of corporate failure is recognized in the literature. The classical binary or static models carry heavy assumptions easily violated or require additional mitigating transformations. Comparatively, hazard models offer increased accuracy thanks to the inclusion of larger data, they remove the selection bias and the multivariate normality of data requirement, and above all, they give the probability of surviving up to a certain time along with the probability of failure at that time, respectively the survivor and the hazard functions. The Cox proportional hazards model has imposed itself as the method of choice over parametric models in business-related empirical studies and its validation in the literature participates in its selection for this research. The financial literature shows a wide and frequent use of the now asserted technique of survival analysis in corporate failure prediction. Yet, its use has so far remained marginal in both oil and gas studies and Canadian literature (Agarwal & Bauer, 2014; Beaver et al., 2010; Chen & Lee, 1993; Davydenko, 2013; LeClere, 2005; Pereira, 2014; Shumway, 2001; Whalen, 1991; Yamazaki, 2013).

Empirical studies document the use of survival analysis to predict financial distress for several industries but seldom for oil and gas and to the best of the researcher's knowledge never for Canadian Oil and Gas firms. This research has identified 67 business related empirical survival studies using a proportional hazard method, including 18 published in the last five years (appendix A). 41 of these studies used an all-industry sample data and 15 focused on banking. Only one was on Oil and Gas (Chen & Lee, 1993) and two by Canadians without however any specific focus on Canada (Chen & Lee, 1993; Davydenko, 2013). Chen and Lee (1993) were inspired by the oil price decline of 1981 and used three years of data for a sample of 175 firms including 67 financially distressed (Chen & Lee, 1993). They used a definition of financial distress consistent with Beaver (1966) as the first event of any of the following: a) filing for bankruptcy or going into receivership, b) defaulting on debt payment, and c) suspending preferred stock dividends. They concluded to the usefulness of the Cox PH model as compared to logit and found that financial structure, the ability to find reserves, size and diversification between oil and gas are important determinants of survival time for oil and gas companies, but cash flow is not. Their survival analysis used time-independent covariates and they suggested future research to include time-dependent financial ratios as well as consider mergers as alternative causes for exit (Chen & Lee, 1993). Research on business failure in Canada has relied on the use of MDA. Altman and Levallee (1980), Legault and Veronneau (1986) and Springate (1978) developed each MDA Canadian business failure prediction models. Boritz, Kennedy and Sun (2007) compared them to the reference Z-score and O-Score models to assess their applicability to the Canadian business environment and noted that “a major obstacle in Canadian business failure prediction research is the scarcity and poor organization of available data” (p. 147). Davydenko (2013) used a Cox PH model with a sample of 30,744 firm-months to insist on the use of market data rather than book values, especially for very distressed firms and demonstrate that insolvency is a much stronger trigger of default than illiquidity, except for constrained firms, as illiquidity can be mitigated by external refinancing (Davydenko, 2013). He defined insolvency as a low ratio of market asset values to debt and illiquidity as low ratio of cash reserves to current liabilities. He also asserted that the timing of default, found to concentrate on two calendar months, June and December, and more specifically in the thirty days preceding those bond scheduled payment semi-annual dates, is by far best determined by the market value of assets (Davydenko, 2013). Scholar empirical analyses have made of survival analysis and more specifically the Cox proportional hazards model their preferred instrument, away from the classical binary approaches. Yet the technique appears only twice in Canadian studies and only once in Oil and Gas, using time-independent covariates. Chen and Lee (1993) justified their analysis by the external oil price shock impacting oil and gas firms and Davydenko (2013) following Shumway (2001) insisted on the use of market data for very distressed firms. The criteria defining distressed firms are not consistent in the literature and this key construct of interest for this study requires a focused review of its own (Altman & Levallee, 1980; Beaver, 1966; Chen & Lee, 1993; Boritz et al., 2007; Davydenko, 2013; Legault & Veronneau, 1986; Springate, 1978; Shumway, 2001).

Financial Distress

The financial literature is very heterogeneous in defining financial distress. This diversity shows in the meaning and the criteria used to measure the cut-off point used for sampling studies. Financial distress is distinct from insolvency for Davydenko (2013) who related it to illiquidity, whereas insolvency is economic distress, for Purnanandam (2008) who viewed it as transitory stage from solvency to insolvency, and for Outecheva (2007) who put it on a sequential process where they are different phases of a cycle (Davydenko, 2013; Outecheva, 2007; Purnanandam, 2008). Both financial distress and insolvency are also distinct from default which is characterized by the failure to make a payment on a specific due date and bears a legal liability. A firm can be in a state of insolvency at any point in time and for a long period before triggering the default by missing a payment. Davydenko (2013) placed most defaults in the month preceding the semi-annual bond payments dates of June and December, but the actual insolvency may have been prevalent for a much longer time before defaulting (Davydenko, 2013). Similarly, bankruptcy is also distinct from financial distress, insolvency and default, as filing for bankruptcy is a legal proceeding that varies from one country to another and that may not only be motivated by the consequences of financial and economic distress, but also by strategic and restructuring purposes without necessarily entailing financial distress (Gilbert, Menon & Schwartz, 1990; Outecheva, 2007). The two main avenues to defining financial distress are values and flows. Value-based insolvency relates to assets versus debts in terms of net worth, and flow-based insolvency is the actual inability to pay debt when it comes due (Hillier et al., 2012). Several authors use multiple criteria to define financial distress, some use only one and many do not formally distinguish between financial distress, default, failure and bankruptcy. Financial distress is a default on due payment for Beaver (1966), Andrade and Kaplan (1998), Ross (2005), Chen and Lee (1993), Anderson and Sundaresan (1996) and Kim, Ramaswamy and Sundaresan (1993). Hillier et al. and Whitaker (1999) related financial distress to illiquidity and insufficient cash flows to cover current obligations. Liquidity is also the criteria for McEwen and Turetsky (2001) who measured it by a change in cash flow from positive to negative, and for Asquisth, Gertner and Scharfstein (1994) who determined a cut-off in terms of Ebitda falling below 80% of interest expenses. A decrease in asset value defines financial distress for Black and Cox (1976), Leland (1994), Longstaff and Schwartz (1995), Purnanandam (2008) who measured it as the market value of assets falling below 66% of the face value of debt, and Davydenko (2013) who argued that access to refinancing discounts illiquidity as the main trigger of failure. Chen and Lee (1993) used an interruption in preferred dividends as a classification criterion for financial distress, while Hillier et al. used a more general reduction in dividend payment. Another criterion of Chen and Lee (1993) is the actual filing for bankruptcy, and so do Pereira (2014), Davydenko (2013) and Chancharat, Davy, McCrae and Tian (2007). Restructuring is a sign of financial distress for Andrade and Kaplan (1998), Brown et al. (1992), Platt and Platt (2002), Hillier et al. who include it in a more generic required corrective action to be taken by the firm, and Chancharat et al. Other authors used a decrease in profitability to define financial distress. For Altman and Hotchkiss (2006), it is the return on invested capital falling below the cost of capital in a significant and continuous manner. Platt and Platt (2002) considered several years of operating loss, as did Denis and Denis (1995) with three consecutive years and Gilbert et al., Whitaker (1999) and Shumway (2001) considered a drop in the firm's stock market returns, in line with Opler and Titman (1994) who specified it at 30% or more of the median stock return. Other criteria used in the literature include lay-offs (Hillier et al., 2012; Platt & Platt, 2002), distressed exchange offers (Davydenko, 2013) and a decrease in sales growth (Opler & Titman, 1994). The list of criteria used to define financial distress thus includes assets value, illiquidity, default, dividend reduction, bankruptcy filing, restructuring, profitability, stock market value, lay-offs, sales and debt refinancing. However, financial distress is not a single event, rather, it is part of a sequence of subsequent stages (Outecheva, 2007; McEwen & Turetsky, 2001; Whitaker, 1999). Outecheva (2007) described corporate financial distress as a cycle starting with early impairment, which is a strategic level of danger where the firm is still solvent. The cycle continues with a distressed but solvent phase with operational impacts manifested as a deterioration of performance affecting profitability followed by failure, insolvency and default where the firm is illiquid. In the next phase, the firm is insolvent: it starts with bankruptcy along with a death struggle between liquidation, takeover or survival, which takes the form of restructuring the troubled debt and eventually regaining solvency to be in the last stage of the cycle, recovery (Outecheva, 2007). Failure, a term mainly used in predictive statistical models, default, insolvency and bankruptcy appear indistinctly in the financial literature as synonyms to financial distress and while some authors stressed the semantic distinctions many others did not seem to note the diversity of meanings. The criteria used to define and measure the state of financial distress are very diverse but the two main approaches are illiquidity triggering default and insolvency measured through assets relative to debt. While financial distress may come as insolvency for many in the literature, some authors also stressed it as a preceding phase to actual insolvency. Outecheva (2007) provided an accurate synthesis of the difficulty in defining financial distress:

> Different approaches to the definition of the term "Financial Distress" show how versatile, complex, and sometimes even controversial this economic category is. The state of the art in the theory of financial distress is rather to interpret it as dependent on the purpose of research under a particular point *[sic]* of view: operational, legal, etc., which leads to using this term interchangeably with other similar financial definitions (Outecheva, 2007, p.18).

The definition of financial distress is very heterogeneous but invariably firms in distress tend to see their stock value drop and their gearing increase, two consequential attributes of hedging authors have largely documented among others (Altman & Hotchkiss, 2006; Anderson & Sundaresan, 1996; Andrade & Kaplan, 1998; Asquisth et al., 1994; Beaver, 1966; Black & Cox, 1976; Brown et al., 1992; Chancharat et al. 2007; Chen & Lee, 1993; Davydenko, 2013;

Denis & Denis, 1995; Gilbert et al., 1990; Hillier et al., 2012; Kim et al., 1993; Leland, 1994; Longstaff & Schwartz, 1995; McEwen & Turetsky, 2001; Mooradian 1992; Opler & Titman, 1994; Outecheva, 2007; Pereira, 2014; Platt & Platt, 2002; Purnanandam, 2008; Ross, 2005; Shumway, 2001; Whitaker, 1999).

Hedging

The reasons to hedge are varied and the presence and level of hedging also fluctuate especially in oil and gas. The literature on hedging has evolved since Miller and Modigliani (1958) and eventually focused on the reasons for hedging, among which financial distress. Miller and Modigliani (1958) provided the foundation for this literature in denying the pertinence of hedging, as they assumed that corporate financial policy is irrelevant. Several authors disagreed with this postulate and from 1960 to the early 1980s, the literature focused on how to hedge, at a time that was concomitant with the development and multiplication of financial derivatives instruments and contracts. Mayers and Smith Jr. (1982) followed by Smith Jr. and Stulz (1985) and Froot, Scharfstein and Stein (1993) shifted this paradigm with landmark papers on the reasons for hedging. Those include a reduction in the cost of financial distress, tax optimization, risk aversion, avoiding underinvestment and maximizing growth opportunities, correlation with leverage or correlation with firm value increase. Chowdhry and Schwartz (2012) referred to a long-standing puzzle in the risk management literature as to why firms chose not to hedge their exposure to the risks representing the highest negative impact on their cash flow. They asserted that firms should hedge the variance in cash flow using specific transaction exposures for known and contracted cash flow amounts, rather than hedge the cost of financial distress, that is, hedge the probability of bankruptcy as opposed to its impact (Chowdhry & Schwartz, 2012). Following DeMarzo and Duffie (1995), Breeden and Viswanathan (2016) also considered a reduction in cash flow volatility as an objective in hedging because it shines light on managerial performance. They posited too that firms do not consider hedging all risks but only the marginal risks that stand the firm apart from similar firms, the risks out of managerial control, which can affect the superior managerial ability and performance, or simply put, firms hedge to lock in performance (Breeden & Viswanathan, 2016). Jin and Jorion (2006) analyzed the hedging activities of 119 oil and gas producers from 1998 to 2001 and concluded that hedging has no impact on market value in oil and gas. They explained that due to the homogeneity of the industry and the facility to identify and hedge commodity risk exposure, hedging does not reduce the stock price sensitivity to oil and gas prices, and speculated that hedging in this industry must thus lie in management's will to maximize personal utility (Jin & Jorion, 2006). Lookman (2004) also concluded that the impact of hedging on firm valuation is marginal in an empirical study based on 364 year-firm of oil and gas producers. He found that for undiversified firms facing primary risk (commodity risk), hedging was associated with high agency costs, lower firm value and bad management, while for diversified firms mainly hedging secondary risks (foreign exchange and interest rate risks) it was the opposite, but overall the impact on firm value was marginal (Lookman, 2004). Pincus and Rajgopal (2002) considered income smoothing with discretionary accrual choices in an absence of markets to hedge the operational risk of unsuccessful drilling and found that managers make such decisions based on their existing hedging. They also confirmed the finding by Haushalter (2000) that oil and gas producers do not hedge all their exposure. Haushalter (2000, 2001) observed a wide variety in the hedging policies of oil and gas producers, some not hedging at all, some doing it only partially and others hedging 100% of their production. He positively correlated the level of hedging of oil and gas firms to financing costs and leverage, economies of scales in hedging and negatively to basis risk, which is the risk of low correlation between changes in the value the oil and gas being hedged and the value of the derivatives used for hedging. He concluded that firms with higher leverage and thus higher financing cost tend to hedge more; firms facing lower basis risk also tend to hedge more; and as hedging is a costly process requiring specific expertise and economies of scales in transaction costs, larger firms tend to hedge more (Haushalter, 2000, 2001). Iqbal (2015) also found that oil and gas firms show a higher level of debt than non-hedge firms before entering hedging and subsequently their debt decreases (Iqbal, 2015). The literature shows that firms engage into hedging for more reasons than mitigating an exposure, and even when they do, especially for oil and gas producers, there is no industry uniformity in hedging policy. Hedging is demanding in expertise and transaction costs and bears basis risk, therefore it may not be accessible or favored by companies below a certain size, especially in oil and gas where it does not increase firm value through stock appreciation. As the benefits of hedging are already embedded in the stock price in that industry, the incentive to hedge must then be specific such as locking in managerial performance, covering only precise cash flow exposure or mitigating a high leverage that comes with higher refinancing cost. So not all oil and gas firms hedge, those who do may do it only partially and be large enough, yet those with high leverage should have an incentive to hedge and high leverage is a factor in leading to financial distress. The hedging literature reveals a similarity to financial distress analysis through hazard models: it is not a binary hedge/non-hedge simple proposal; rather, the factors used are heterogeneous and may fluctuate with time. Firm size is one of these evolving factors and a corporate failure predictive variable frequently used in empirical studies (Allayannis & Weston, 2001; Breeden & Viswanathan, 2016; Campello, Lin, Ma & Zou, 2011; Carter, Rogers & Simkins, 2006; Chowdhry & Schwartz, 2012; DeMarzo & Duffie, 1995; Dolde, 1995; Froot et al., 1993; Haushalter, 2000, 2001; Haushalter, Heron & Lie, 2002; Iqbal, 2015; Jin & Jorion, 2006; Lookman, 2004; Mayers & Smith Jr., 1982; Miller & Modigliani, 1958; Nance, Smith Jr. & Smithson, 1993; Pincus & Rajgopal, 2002; Smith Jr. & Stulz, 1985; Purnanandam, 2008)

Firm Size

Firm size is a popular variable used in bankruptcy prediction and a review of literature helps shining light on its predictive power and its measurement. For Chancharat et al. (2007) firm size increase directly correlates to increased probability of failure. On the contrary, many other studies found that smaller firms have a larger exposure to financial distress (Aziz & Dar, 2006; Fitzpatrick & Ogden, 2011; Raj & Rinastiti, 2002; Shumway, 2001). Rommer (2004) formulated two hypotheses to relate the effect of size to the trigger of financial distress. The first is that firm size follows a U-shaped statistic where small firms lack resilience to shock and are thus exposed at one branch, while at the other branch large firms lack flexibility and nimbleness to quickly monitor their employees and communicate internally. The second is like the scholar consensus considering that firm size inversely correlates to bankruptcy risk. Altman and Hotchkiss (2006) considered the major corporate failure of the early 2000s and for them "size is no longer a proxy for corporate health" (Hotchkiss, 2006, p. 4). While most authors agree that firm size has strong failure predictive power, the metric of choice for measuring it varies in the literature. Charalambous et al. (2004) listed 43 previous empirical studies on corporate failure in which 17 used asset size for pair matching (with industry and/or sales). Total assets and its natural logarithm are common proxies used for company size (Chancharat et al. 2007; Gentry et al., 1985; Peat, 2007; Raj & Rinastiti, 2002; Chong et al., 2010; Ohlson, 1980), but less frequently used proxies include sales and its natural log (Chen & Lee, 1993), market capitalization (Shumway, 2001) and headcount (Nikitin, 2003; Prantl, 2003). Dang and Li (2015) who reviewed 100 empirical papers in an analysis of firm size measurement in corporate finance confirm these frequencies. They found that total assets, total sales and market value of equity along with their natural log appeared as size proxy in 85 out of 87 papers using single measures (the other 13 with multiple measures served for robustness check in the study). Of the 85 papers, 49 used total assets, 20 used market capitalizations, 16 used total sales and two used the number of employees, or respectively their natural log. They found a strong correlation of 0.92 between the log of assets and the log of sales, while however, warning that the measures of firm size are not interchangeable (Dang & Li, 2015). Reviewing the literature on firm size thus reveals three conclusions. Most studies find strong financial distress predictive power to firm size. They conclude to a positive correlation between decreasing size and probability of failure. The natural log of total assets is the preferred proxy for firm size. As with hedging, firm size can also be a factor in mergers and acquisition (Altman & Hotchkiss, 2006; Aziz & Dar, 2006; Chancharat et al., 2007; Charalambous et al., 2004; Chen & Lee, 1993; Chong et al., 2010; Dang & Li, 2015; Fitzpatrick & Ogden, 2011; Gentry et al., 1985; Nikitin, 2003; Ohlson, 1980; Peat, 2007; Prantl, 2003; Raj & Rinastiti, 2002; Rommer, 2004; Shumway, 2001).

Mergers and Acquisitions

The literature on mergers and acquisitions is vast and varied but several authors have explored the relationship between financial distress and M&A, especially to see in M&A a bankruptcy avoidance strategy and correlate solvency fragility to increased takeover risk. Vazirani (2015) listed six temporal waves, four theories and seven motives for M&A. The waves listed start as early as 1893 for the first and end with the last from 2003 to 2007, a wave of M&A driven by leverage buyouts, private equity financing, collateralization and syndicated debt. Vazirani (2015) also anchored the study of M&A activity into four theories: the capital market school focused on wealth creation derived from M&A, the strategic management school centered on diversification strategy, the organizational behavior school and the process perspective. Those theories shelter the following motives for M&A: inefficient management, synergy or horizontal mergers, diversification, agency problems, tax considerations, market expansion, and purchase of assets below their replacement costs (Vazirani, 2015). One or more of these motives may specifically relate to bankruptcy avoidance. Shrieves and Stevens (1979) analyzed that newly merged companies improved their solvency ratios over that of both pre-merger entities. Dickerson, Gibson and Tsakalotos (2003) used a sample of UK companies to find in pre-emptive acquisitions a defense mechanism against hostile takeover and a great influence against the probability of bankruptcy. Similarly, for Billingsley, Johnson and Marquette (1988) debt capacity and tax benefits drive the choice between merger and bankruptcy, while Stiglitz (1972) saw a higher risk of hostile takeover in firms with high debt-to-equity ratio, equated to high bankruptcy risk (Billingsley et al., 1988; Stiglitz, 1972). Erel, Jang and Weisbach (2015) studied a large sample of European companies to report that indeed, being acquired lifted the financial constraints of the target firms, especially when they are small, who no longer need to hoard cash for strategic capital investments, become less sensitive to cash flow fluctuation and tend to increase investment (Erel et al., 2015). For Pastena and Ruland (1986), among distressed firms, those merging are larger and have lower financial leverage than those filing for bankruptcy, as well high ownership concentration is a factor indicating a stronger propensity to merge than to default (Pastena & Ruland, 1986). Kyimaz (2006) supported the bankruptcy avoidance argument by observing that the divestiture announcement resulted in higher wealth gains for distressed firms and firms with higher leverage (Kyimaz, 2006). Peel and Wilson (1989) also found in acquisitions an alternative to bankruptcy and Powell and Yawson (2007) shone light on how well the variables used to predict takeovers are similarly useful for bankruptcy prediction. Parnes (2009) analyzed the objective of enhancing credit worthiness for both the acquirer and the target as a motive for corporate acquisitions and distressed firms (Parnes, 2009). In Canada, Cohen, Gupta, Uffner and Wach (2009) focused on income funds that originated in the oil and gas sector in the 1980s. Those funds were tax exempt and the authors reported that they have represented a significant level of activity and importance in Canadian mergers and acquisitions, for tax optimization purposes, until a 2006 tax policy removed their flow-through entity tax advantages (Cohen, et al., 2009). M&A have regularly taken place intensely in economic waves throughout modern history and while growth and wealth optimization purposes often motivate them, several researchers have demonstrated that they also take place to avoid bankruptcy and tend to improve solvency and leverage. A reason for seeking an M&A partner can also be tax benefits and in Canada, many such motivated M&A took place in the oil and gas sector through income funds until those lost their tax shelter status in 2006. However, in an industry largely sensitive to the fluctuation of the price of oil and gas, survival motivated M&A along with solvency, leverage and creditworthiness are still arguably fueling Canadian Oil and Gas M&A activity (Billingsley et al., 1988; Cohen et al., 2009; Dickerson et al., 2003; Erel et al., 2015; Kyimaz, 2006; Parnes, 2009; Pastena & Ruland, 1986; Peel & Wilson, 1989; Powell & Yawson, 2007; Shrieves & Steven, 1979; Stiglitz, 1972; Vazirani, 2015).

Ever since ratios have started being used in financial analysis, they have proven as a solid backbone of preferred metrics still used in most of financial distress and bankruptcy prediction analyses alongside with additional market and firm characteristics data (Horrigan, 1968). In the life cycle of corporate failure prediction, the classical approaches best exemplify the growth stage of analytical capabilities (Balcaen & Ooghe, 2006). They have imposed themselves as a reference focal point in the literature, and while alternatives are still regularly proposed, survival analysis is a paradigm shift representing both maturity and depth of analysis unlike any other technique (Agarwal & Bauer, 2014; Beaver et al., 2010; Chen & Lee, 1993; Davydenko, 2013; LeClere, 2005; Pereira, 2014; Shumway, 2001; Whalen, 1991; Yamazaki, 2013). Survival analysis permits to enrich the analysis with specific vantage points such as hedging, firm size and M&A. The results of any survival analysis are nonetheless a function of the criteria used to define financial distress. The literature is not consensual on the subject and researchers may fit it to their specific purposes, hence the axiological assumption stipulated above for this study (Outecheva, 2007). Hedging has varied motives and policies; it is costly and does not contribute to increasing corporate wealth in oil and gas (Haushalter, 2000, 2001; Iqbal, 2015). Ad hoc risk management motivates hedging by those oil and gas firms that are large enough to effectively manage it and amortize its cost. The literature consensually points to an understanding that smaller firms are more prone to financial distress than large ones, and among other measures uses mostly the natural logarithm of total assets to measure firm size (Aziz & Dar, 2006; Dang & Li, 2015; Fitzpatrick & Ogden, 2011; Raj & Rinastiti, 2002; Shumway, 2001). Several motives justify M&A activity, but bankruptcy avoidance for financially distressed companies has been documented in the literature beyond or concurrently to expansion, growth and wealth creation, along with the will to improve leverage, optimize tax or improve creditworthiness similarly to the same impulse that originated financial distress prediction analysis almost a century ago (Kyimaz, 2006; Parnes, 2009; Powell & Yawson, 2007). The theoretical foundation for this research takes roots in a rich and varied literature that has evolved along the life cycle of corporate distress analysis. Yet despite the strengths of its roots and the quality of its analyses, it is still open to critiques considering the research problem of this study, critiques that are necessary to pave the way to the selected methodology and subsequent analysis performed (Agarwal & Bauer, 2014; Aziz & Dar, 2006; Balcaen & Ooghe, 2006; Beaver et al., 2010; Chen & Lee, 1993; Dang & Li, 2015; Davydenko, 2013; Fitzpatrick & Ogden, 2011; Haushalter, 2000, 2001; Horrigan, 1968; Iqbal, 2015; Kyimaz, 2006; LeClere, 2005; Outecheva, 2007; Parnes, 2009; Pereira, 2014; Powell & Yawson, 2007; Raj & Rinastiti, 2002; Shumway, 2001; Whalen, 1991; Yamazaki, 2013).

Critique of Previous Research

To the best of the researcher's knowledge, there is no specific precedent to studying the determinants of corporate failure in the Canadian oil and gas industry. This study nonetheless anchors in a generic body of work in financial distress predictive analysis. This theoretical orientation suffers weaknesses, and the consideration of these limits contributes to the selection of the methodology for this research. The first critique expressed below pertains to authoring and credit, the second explores the abusive use of classical references and its consequences, and the third critique ties into the covariates used in financial distress analysis.

The literature on corporate failure is abundant and varied. While this field of research is matured, and has already evolved through a few distinct eras, the research performed for this literature review reveals an incorrect and persistent tendency by most authors to give exclusive credit for the origins of this branch of corporate finance research to Beaver (1966). Indeed, as Horrigan (1968) foresaw, the work of Beaver (1996) did become a landmark publication and it rightfully deserves the credit commensurate with the importance of the breach it represented. However, as described above, Beaver (1966) stood on the shoulders of others before him rather than creating ex-nihilo. Yet, there is rarely any mention of the predecessors to Beaver (1966) and it requires a focused research effort intent on understanding the origins of the stepping-stone

Beaver (1966) used to unravel the foundations he stood on. Whether the systematic and easy reference to Beaver (1966) seeking to plant the origins of research in corporate failure and give credibility to the literature review in most papers flows out of mimesis or whether it has become the orphan child of the requirement to limit references to the past five years, the literature in general perpetuates a compounding ignorance. Although not enough credit goes to his predecessors, Beaver (1966) himself opened his seminal article with this first sentence "At the turn of the century, ratio analysis was in its embryonic state." (Beaver, 1966, p.71) and cited in footnotes a reference from 1908 as well as the historical research performed by Horrigan (as cited in Beaver, 1966) for his 1963 unpublished dissertation. The question of replicating preceding studies then emerges as whether so many who cited Beaver (1966) have read his paper? One of the key factors to the solidity and success of Beaver's (1966) paper was the novelty of its stronger statistical analysis than ever proposed before in similar research contexts. Beaver (1966) did express in a footnote to the second introductory line of his paper his gratitude to H. Roberts for his help with statistical expertise, but the contribution of this expert to this seminal paper seems to have vanished in history. Similarly, little to no reference appears in the literature about the fact that Altman (1968) found his inspiration in Fisher (1936) who originally pioneered linear discriminant analysis. Again, only purposeful research allows reaching such depths and the unverifiable suspicion may arise that the publication of Fisher's (1936) work in the Annals of Eugenics stewarding prejudice against racial, disabled and ethnic groups may have contributed to blackballing any reference to his inspirational contribution to MDA. If this suspicion holds true, it is worth denouncing, as the value of a scientific contribution should stand on its own, regardless of the personal views of their author. Academic research and publication steward high standards of ethics and integrity; it is also the ultimate scientific and epistemological reference, one supposed to be complete and accurate. Gradually and collectively failing to give due credit, not in the way of improperly citing an author, but more subtly by not acknowledging the theoretical foundations of seminal works is a surreptitious asphyxiation of said foundations until they eventually fade away, and that is worthy of criticism. Shortsightedness in giving due credit can also morph into another collective flaw where corporate failure predictive analyses tend to systematically use the classical models as reference benchmarks (Altman, 1968; Beaver, 1966; Horrigan, 1968; Fisher, 1936).

For benchmark analyses, predictions and new techniques, the constant references in the literature are the Z-score and the O-score, respectively by Altman (1968) and Ohlson (1980). However, the classical techniques are laden with limitations and while their merit in advancing the field deserves a consistent and full acknowledgement, they should no longer be the systematic focal point used to gauge the validity of empirical studies, especially when alternative techniques like survival analysis are there to provide more analytical depth. Classical models result in binary classifications of failure or non-failure that do not provide insights into the relative weight, contribution and influence of the determinants, and mainly rely on data from the last year preceding bankruptcy. Until Ohlson (1980) used logit to introduce his conditional probability model, MDA models like preceding analyses used pair matching, often with small sample sizes including the Z-score with 33 matched pairs. Both attributes of small sample size and pair matching considerably limit the generalizability of these models and should caution against making of them the obligatory references. MDA has restrictive assumptions largely identified in the literature and reported by Balcaen and Ooghe (2006), requiring demanding transformations, and conditional probabilities models are also limited by their sensitivity to outliers and the risk of multicollinearity. The well-established limits and restrictions of MDA, logit and probit should caution against using them to assert the validity of empirical studies on corporate failure and financial distress analysis. Survival analysis relies on a larger period than the year preceding failure, explains the impact of the covariates to survival time, and the Cox PH model has the proportional hazard assumption of proportionality over time and the assumption that there is no multicollinearity among covariates. Each multivariate study should test both assumptions. Yet, even with survival analysis, the results are a function of both the covariates and the definitions used (Altman, 1968; Balcaen & Ooghe, 2006; Ohlson, 1980).

More than a century after the emergence of financial ratios and their use in assessing business performance and predicting corporate failure and bankruptcy there is still no consensus on the ontology of financial distress analysis. Dang and Li (2015) noted that the empirical literature fails to provide rationales for defining or selecting measures of firm size (Dang & Li, 2015). They make a criticism that may also be valid for the determinants of failure. Solvency and liquidity are generally central to bankruptcy prediction but the ratios used vary from one study to another; as well, the use of market data and firm characteristics also fluctuate. Shumway (2001) made an impact when he championed the use of market data for survival analysis. Davydenko (2013) insisted on solvency over liquidity and market data over book values. Altman (1968) used four variables, Beneish (1999) eight, and five in another version, Ohlson (1980) nine and Zmijewski (1984) three, while other authors used varying combinations of ratios, market data and firm characteristics. Business practitioners such as the DBRS credit agency assess oil and gas firms' risk through profitability and cash flow, competitive landscape, stability, regulation and inherent industry specific considerations, all with their specific series of ratios, and with a clear acknowledgement of multicollinearity:

> Although there is an overlap in some instances (to some degree, in the long term all five factors tend to profitability and stability), DBRS has found that considering these five measures in a separate fashion is a useful way of approaching this analysis (DBRS, 2011, p5).

So, whether in research papers or in business, there are potentially as many ways to measure financial distress as there are studies and this lack of consistent and solid framework limits the generalizability and replicability of several analyses. Here too, mimesis is an accepted and recurring habit in scholar publications when ratios selection flows out of popularity in previous studies, rather than through a transparent and clearly explained rationale. Like the variety of covariates found in the literature, the definition of what constitutes a state of financial distress is also unbound and fluctuates from one author to another. In this regard, a major criticism applies to the use of a strictly legal definition of bankruptcy, especially for studies made in the US, as companies may file for Chapter 11 or Chapter 7 bankruptcy filing to reorganize themselves or for other strategic reasons (Blakes Canadian Lawyers, 2016). The legal definition lens of financial distress is thus a limitation when analyzing and predicting financial distress, as within a sample, not all stressed companies may file for bankruptcy and not all of those who file, are effectively distressed economically, meaning with their going concern capability at risk. Davydenko (2013) distinguished two schools: one using economic distress based on the market value of assets going below the face value of debt to trigger insolvency, and one focused on current obligations with a shorter-term world view of financial distress (Davydenko, 2013). Many authors analyzing bankruptcy and financial distress do not even define their acception of the failure status. While the absence of boundaries framing predictive analyses of financial distress increases the freedom to explore new techniques and innovate, it can be detrimental to the scientific rigor, the generalizability and the consistency of such analyses. To the best of the researcher knowledge, only one empirical study applied a survival analysis to study corporate failure in oil and gas. In that study, Chen and Lee (1993) used time-invariant covariates but they did recommend for further research to use time-varying covariates (Beneish, 1999; Blakes Canadian Lawyers, 2016; Chen & Lee, 1993; Dang & Li, 2015; Davydenko, 2013; DBRS, 2011; Ohlson, 1980; Shumway, 2001; Zmijewski, 1984).

The absence of an undisputed paradigm for corporate failure analysis beckons researchers into omitting to appropriately acknowledging the stepping-stones that enabled the main paradigms of their favorite references, Altman (1968) and Ohlson (1980). They ignore the well-documented restrictions and limitations of both approaches and continue referencing them to seek validity for any new empirical study, often using intelligent techniques that provide a binary answer to the prediction of failure. The definitions used for failure and the selection of predictive variable fluctuate and are not always rationalized. This study falls within a post-positivist paradigm that defines its boundaries, subjectivity and limits. Within that framework, an empirical analysis seeking to understand the determinants of financial distress beyond a binary answer, using more than a single year preceding failure data, and factoring in the changes over time of the variables, requires using a Cox Proportional Hazards model with time-varying covariates or more precisely an extended Cox model with repeating events (Altman, 1968; Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012; Ohlson, 1980).

Chapter 3: Methodology

This study requires a specific and detailed methodology description to set the paradigm within which the survival analysis takes place in the next chapter. This chapter provides this description and includes seven sections. The first section is the research design that introduces and elaborates on the concept of financial distress, explains the predictor variables used in the baseline model of this study and describes the baseline model. The second section proposes the research hypotheses and includes the specific technique variations from the baseline model for each hypothesis. The third section explains the population and sampling strategy, followed by a description of the research instrument in section four, including its mathematical development. The fifth section discusses data collection and the sixth deals with the descriptive statistics of the data. The last section is a summary concluding this chapter.

Research Design

This study is a quantitative research using the statistical technique of survival analysis on a sample of 540 Canadian oil and gas exploration and production firms. Although there are several methods in survival analysis, this study uses the semi-parametric approach of Cox (1972), known as the Cox extended model allowing for the use of time-dependent covariates with repeating events (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012). The research instrument section below contains a detailed description of this model and its theoretical foundations. The overall problem guiding the research in this study is about the financial fragility of oil and gas producers whose profitability and sustainability is impacted by the external factor of oil and gas prices. The whole oil and gas industry in Canada follows boom and bust cycles and the survival of the firms in that sector is the central focus of this research inspired by the current severe bust cycle started with the mid-2014 drop in oil prices (CAPP, 2016; Jakeman &

Tertzakian, 2016; Macrotrends, 2016; Millington, 2016). The nature of the problem and the question of survival analysis focused on a specific sector within an industry in a country require the use of tangible data, and the methods available to analyze corporate failure are diverse and well established in academic literature. Among them, survival analysis is a robust statistical technique central to biostatistics and epidemiology (InfluentialPoints, 2016). Financial empiricists have applied it to research on corporate failure to gain a richer set of perspectives and answers than the previously available paradigms offering binary answers. They have consistently used the semi-parametric model proposed by Cox (1972) and this research inscribes in that tradition (Chen & Lee, 1993; Davydenko, 2013; LeClere, 2005; Pereira, 2014; Shumway, 2001). Therefore, a survival analysis of Canadian oil and gas firms demands actual data and a robust, academically proven and accepted statistical method, a requirement that leads to the choice of a quantitative methodology for this study. The design of this research includes the prerequisite description of the notion of financial distress and the selection of the predictors ahead of the actual survival analysis per se (Chen & Lee, 1993; Cox, 1972; Davydenko, 2013; Fox, 2008; InfluentialPoints, 2016; Klein & Kleinbaum, 2012; LeClere, 2005; Pereira, 2014; Shumway, 2001).

Definition of Financial Distress

The notion of financial distress suffers multiple definitions and interpretations in the literature and each researcher adapts it to their purpose (Outecheva, 2007). This study is not different in that regard and as financial distress is the key construct of interest around which the whole analysis evolves, it must be precisely defined and the rationale for its definition must also be clearly laid out. The purpose of the research is to analyze the relationship of predictor variables to the event of financial distress. The governing paradigm of this study is post-positivist and the axiological assumption is that the researcher's world view permeates it, specifically regarding the definition of the central key construct notion of financial distress (Outecheva, 2007).

For this research, the definition of financial distress is two consecutive quarters of negative operating cash flow to total assets (OCF/TA). To the best of the researcher's knowledge, this definition is original in the literature. The rationale for the selection of this definition stems from the cash-intensive and asset-heavy nature of the oil and gas E&P sector and a deliberate distinction between bankruptcy, insolvency, illiquidity and financial distress. E&P firms require numerous, large, and expensive equipment in remote exploration sites with camps, air travel and lodging accommodations; and continuous capital expenditure for maintenance, upgrades and expansion projects. Their business is very tangible and cash-intensive. They invest heavily in exploring oil reserves in areas they pay royalties to exploit, and they use large capital expenditures and operating expenses to extract, produce and transport the crude oil to the downstream refineries. The province of Alberta in Canada has the worldwide third largest reserves of crude oil, its oil reserves lie primarily in oil sands which unlike light crude found in Saudi Arabia or in the North Sea for example are more expensive to extract (CAPP, 2016; Natural Resources Canada, 2017). Canada's E&P industry needs considerable cash to operate and that vital cash needs to be generated by its operations. In other words, E&P firms need to "sweat the assets" (Harrison, 2005) to survive, especially during and immediately following low oil prices periods and bust times fueling economic recessions (CAPP, 2016; Harrison, 2005; Jakeman & Tertzakian, 2016; Millington, 2016; Natural Resources Canada, 2017; PSAC, 2016).

The ratio of OCF/TA is an asset efficiency ratio that measures how well the assets generate cash. This ratio shows the quintessential capability of an E&P firm to autonomously and continuously operate and grow as a going concern. The threshold for a healthy OCF/TA ratio is not standardized and it is industry-specific. In some industries, a ratio of 10% is recommended by investors and analysts looking for an upward trend profit opportunity (Financial Analysis Hub, 2016). The context of this study is specific and far removed from an investment outlook. Rather, it is about survival during a recession. Therefore, for this research, the consideration of the dire economic environment, the possibility to access refinancing, the tangible value of the assets collaterals and the value of the reserves for Canadian E&P firms lead the researcher to consider that when seeking to survive, firms reduce their capital investments and expansion and thus need only a positive OCF/TA ratio. Additionally, the industry-specific propensity to rise and fall with boom and bust cycles, is not foreign to banks and creditors, and those stakeholders discern systemic externalities such as oil prices impacting the whole sector from mismanagement or individual underperformance. They are thus supposedly more inclined to refinance those firms suffering the impact of cyclical externalities even when their asset efficiency is minimal, yet not negative. The researcher considers that in an integrated commodity-driven economy such as Canada’s where oil and gas is a key resource, such flexibility from banks participates from their own long-term strategy and governance as they must conservatively manage their own risk by limiting proprietary exposure and complying with Basel III requirements (CAPP, 2016; Financial Analysis Hub, 2016; Jakeman & Tertzakian, 2016; Millington, 2016; Natural Resources Canada, 2017; PSAC, 2016).

The choice of using two consecutive quarters of negative OCF/TA follows the assumption that even before the first quarter’s financial statements are published, management starts taking the measure of liquidity drying up and whether or not they already seek refinancing before that quarter's publication, the disclosure of the illiquidity risk sends a strong signal to creditors and bankers with a potential impact on their credit worthiness, risk and cost of capital. Management can still leverage its strong collaterals during the second quarters and convincingly promote a strong strategic change including restructuring plans, reorganization, divestiture, joint venture, lay-offs, renegotiation, along with a firm executive commitment and new strategic plan, to access refinancing. Firms failing to be alarmed by a negative asset efficiency ratio and take consequent strategic action right away fall into financial distress if the OCF/TA ratio is negative for a second consecutive quarter. They are then illiquid or rapidly draining on their liquidity and need urgent refinancing to jump start a newly balanced alignment between their cost base, their assets, their profitability and their cash flow. This state of financial distress may correspond to what Outecheva (2007) calls the death struggle but it respects the fact that E&P firms must use their assets to generate the cash flow required for their survival and long-term profitability (Outecheva; 2007).

This definition of financial distress differs from illiquidity stricto sensu as firms can still access refinancing as documented by Davydenko (2013). This definition is also distinct from insolvency because technical insolvency is triggered by a default on a due payment. Until the payment date, the firm is not officially insolvent. Davydenko (2013) analyzed that 62% of Canadian firms default in the 30 days before the two semi-annuals bond coupons months of June and December including 29% on the actual date. The semi-annual calendar for coupons creates a temporal bias for defaults that skews the operational inefficiency of assets at producing cash that this research attempts to champion. At last, the definition of financial distress in this study also varies from bankruptcy as bankruptcy or receivership in Canada is a legal rather than an economic state that may or may not be reflective of actual illiquidity and growing risk of insolvency and that also may be entered for strategic reasons more so than survival economic ones. In any event, receivership may not offer the consistency required in capturing financial distress for several firms over many years. Bankruptcy may be an outcome of the death struggle and therefore a subsequent stage (Blakes Canadian Lawyers, 2016; Davydenko; 2013; Outecheva, 2007).

This study's definition of financial distress as two consecutive quarters of negative OCF/TA ratio captures a state where the firm is in liquidity trouble and faces insolvency risk but it can still turn the odds of failure around through drastic action. Diagnosing financial distress at that stage is ultimately of a greater interest to the industry professionals and all their stakeholders including banks. With the notion of financial distress defined, the next foundational component of the study is the predictor variables used in this study (Hillier et al., 2012; Outecheva, 2007).

Predictor Variables

Table 2 lists all the independent covariates that contribute to calculating the regression coefficients and hazard ratios in this study. The choice of predictors in the table reflects the objective of being complete, exclusive and specific. Completeness refers to the categories of financial ratios and proxies titled as liquidity, solvency, profitability, valuation, efficiency, energy and size. Exclusivity is about avoiding unnecessary redundancy in the ratios and proxies selected. For example, the quick ratio is a liquidity ratio predictor similar enough to the current ratio, ceteris paribus, to make its inclusion redundant. Specificity aims at capturing the proxies and ratios that are uniquely relevant to the oil and gas industry and without which the list of predictors would be incomplete. Those include for example the use of EBITDAX in proxies X8 and X13, the use of probable reserves in proxy X15, and the proxies X16 to X18.

Table 2

Determinants of Financial Distress

Predictor Proxy	Predictor	Definition	Effect on HR
Financial Distress			
X1	Operating Cash Flow / Total Assets	Operating Cash Flow / Total Assets	-
Liquidity			
X2	Working Capital / Total Assets	(Current Assets - Current Liabilities) / Total Assets	-
X3	Current Ratio	Current Assets / Current Liabilities	-
Solvency			
X4	Solvency Ratio	(Net Income + DDA) / Total Liabilities	-
X5	Shareholders Equity Ratio	Market value of Equity / Total Assets	-
X6	Debt-to-Assets Ratio	Total Debt / Total Assets	+
X7	Debt-to-Equity Ratio	Total Debt / Shareholders' Equity	+
X8	Debt-to-EBITDAX	Total Debt / (EBITDA + Exploration Costs)	+
Profitability			
X9	Return on Assets (ROA)	Net Income / Average Total Assets	-
X10	Return on Equity (ROE)	Net Income / Average Total Equity	-
X11	Operating Profit Margin	Operating Profit / Revenue	-
Valuation			
X12	P/E Price-Earnings Ratio	Market Value per Share / Earnings per Share	-
X13	EV/EBITDAX	Enterprise Value / EBITDAX	-
X14	EV/DACF	Enterprise Value / Debt Adjusted Cash Flow	-
X15	EV/FCF	Enterprise Value / Free Cash Flow	-
X16	EV/2P	Enterprise Value / Probable Reserves	-
Efficiency			
X17	Operating Costs per BOE	Operating Costs / Annual Production of BOE	+
Energy			
X18	Production to Reserves	Production / Reserves	-
X19	RRR - Reserve Replacement Rate	(Increase in Reserves + Production) / Production	-
Size			
X20	Natural Log of Total Assets	Log (total Assets)	-

Note: DDA: Depreciation, Depletion & Amortization
BOE: Barrels of Oil Equivalent

With the dependent variable of financial distress established and the covariates listed, the prerequisites to designing the actual steps of the analysis are complete. Consistent with practitioners' approaches to conducting survival analyses prior to exploring hypotheses and given the context of an industry exposed to boom and bust cycles along with the anchoring of this study in the century long tradition of using financial ratios to measure corporate health and risk, this study establishes a baseline model as a prelude to the three hypotheses central to this research.

Baseline Model

The baseline model covers the main categories of financial ratios traditional to standard ratio analysis, in continuity and coherence with the literature and theoretical foundations of corporate distress analysis. The baseline model grounds the theoretical approach that will be used for the hypotheses and offers a wider perspective on the original topic of Canadian oil and gas firm survival analysis than would the hypotheses taken exclusively.

The survival analysis in this study follows a rigorous and established statistical method more than four decades old. The research instrumentation section in this chapter provides a description of the theoretical foundations of the Cox PH model and the extended Cox model (Cox, 1972; Fox; 2008; Klein & Kleinbaum, 2012). The actual regression analyses of the baseline model, using over 15,850 firm-quarters, are performed in R, a statistical software specifically designed for conducting survival analyses among other capabilities. The Cox PH model assumes an absence of multicollinearity and builds its strength and originality on the proportional hazards assumption that keeps the hazard ratio constant across the firms being tested and over time. A common practice in survival analysis consists in testing a vector of covariates and run the regressions with several predictor variables in the same function (Cox, 1972; Fox; 2008; Klein & Kleinbaum, 2012). However, in this study the researcher performs a series of univariate extended Cox models with repeating events to prevent any risk of multicollinearity and confounding, and maximize the understanding of the potential correlation between each predictor and the dependent variable of financial distress. To reach the results this study seeks to analyze, this quantitative research follows a technique that includes a long preparatory work in Excel followed by the running of the survival analysis in R. The research technique for the baseline model consists in the following steps:

1. Collect the raw and public financial and market data for Canadian oil and gas E&P firms that are traded on the TSX, headquartered in Canada and having their E&P activity located in Canada. This data is graciously provided to the researcher by JuneWarren Nickle's Energy Group (JWN), a publishing firm specializing in gathering, managing and leasing operational and financial data on the Canadian oil and gas industry. The researcher obtains the data in Excel format (see appendix B).
2. Verify and clean-up the raw data by removing firms with incomplete data, firms with foreign headquarters or foreign production that may have been included in the data query despite the original filters in selecting the data from the JWN database.
3. Check the accuracy of the data by visually reconciling financial statement lines on the balance sheet and income statement of a 5% sample of firms, between 25 and 30, with the reporting in PDF format that the TSX makes available on its website for the past five years. In case of significant discrepancy, consult back with JWN and alternatively consider another source as required. In case of satisfactory reconciliation, proceed with the rest of the analysis.
4. Build in Excel the financial ratios listed in table 2 for each firm and each quarterly period in the sample (see appendix C).
5. Use the table of OCF/TA ratio built in step 4 to identify the status of financial distress for each firm during the period it reported financial statements between Q1-2002 and Q1-2016.
6. Identify and label as "FD" any firm that experienced two or more consecutive quarters of negative OCF/TA, or "No FD" any firm that has not.

7. Identify and label as "active" all firms still reporting their financial statements in Q1-2016, or "inactive" if they are no longer.
8. Use the labels of steps 6 and 7 to filter data subgroups and calculate the following descriptive statistics for each ratio and each subgroup: number of firms N, mean, median and standard deviation.
9. Layout the data for use in R. This includes presenting data in continuous columns for each variable, building the periods with the first one for each firm numbered as zero and removing all periods where the firm is inactive. The covariate data layout for R is prepared in Excel and then saved as a CSV file for use in R (see appendix D).
10. Prepare a separate Excel file with the start and end date number of quarters within the analysis time frame for each firm (i.e. a firm starting in Q2-2005 has a start number of 10 as this is the tenth period after Q1-2002). This file is required for the survival analysis in R and is also saved as a CSV file (see appendix D).
11. In R, code and run the univariate survival analyses (see appendix E).
12. Analyze the descriptive statistics from R, including the number of observations used in the regression analyses and the number of dependent variable events (see appendix F).
13. Analyze the models' goodness of fit and validity through the likelihood ratio test, the Wald test, the score (logrank) test, the concordance and the R-square values returned by R.
14. Analyze whether the null hypothesis is rejected or fails to be rejected through the z-score, the p-value, the hazard ratio or the coefficient or regression as required, and the confidence intervals.

15. Interpret the hazard ratio or the coefficient of regression for the variables that reject the null hypothesis.
16. Stratify the data around oil price major shifts during the study period to analyze the potential impact of such price changes on the dependent variable of financial distress.
17. Run a univariate survival analysis with the stratification as independent variable. Interpret the results in the form of a cumulative hazard curve.
18. If the stratification rejects the null hypothesis of no oil price impact on financial distress, rerun the survival analysis on the variables that rejected the null hypothesis in step 14. Interpret the results.

The baseline model is designed to analyze the pertinence and strength of standard financial ratios and industry specific variables on the dependent variable of financial distress as defined in this study. The baseline model uses over 15,850 firm-quarter observations from 540 firms over the periods of Q1-2002 to Q1-2016. The baseline model also serves as a reference for the hypotheses of this study. The next section poses the three hypotheses of this research and completes accordingly the specific technique for each one of them.

Research Hypotheses

The baseline model attempts to understand the extent to which representative and exclusive standard financial ratios correlate in a survival analysis to the dependent variable of financial distress defined as two consecutive quarters of negative OCF/TA. Thus, for each predictor variable, the baseline model tests a null hypothesis of no correlation and no predictive ability to the dependent variable of financial distress. Beyond that baseline though, the central research questions of this study are the following three hypotheses.

The first question R1 is: does the presence of an active hedging policy influences financial distress? The hypotheses formulating question R1 are:

- Null hypothesis $H1_0$: Hedging has no influence on preventing financial distress.
- Alternative hypothesis $H1_a$: Hedging does influence the prevention of financial distress.

For research question R1, the dependent variable is financial distress and the independent variable is a Heaviside function identifying the presence of hedging in percentage of BOE hedged with "1" and the absence of hedging with "0". The sample size for this research question differs from the baseline models as it includes a shorter time frame starting in Q1-2007 and ending in Q1-2016. The Q1-2007 starting period reflects the beginning of a compulsory reporting of hedging activity for Canadian oil and gas firms as required by the National Instrument 51-101 Standards of Disclosure for Oil and Gas Activities (NI 51-101) (Ontario Securities Commission, 2016). The sample size for this hypothesis is 515 firms and over 11,000 observations. The changes in technique from the baseline model are:

1. Perform step 4 for with the percentage of BOE hedged by all firms in each quarter and build a Heaviside function status identifying the companies that hedged as "1" and those that did not as "0".
2. Repeat steps 6 to 14 for this data sample.
3. Perform the interpretation in step 15 for the hedging predictor variable.
4. Omit subsequent steps 16 to 18.

The result analysis consists primarily in verifying the validity of the model through the goodness of fit test in step 13, and the following steps 14 and 15 on the rejection of the null hypothesis, should the model be valid. Specifically, an HR different from 1 or a large p-value of more than 0.05 would reject the null hypothesis $H1_0$ and an HR equal to 1 or a small p-value of less than 0.05 would fail to reject $H1_0$ (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012; Ontario Securities Commission, 2016).

The second research question R2 is whether firm size influences financial distress? The hypotheses for this question are:

- Null hypothesis $H2_0$: Smaller size does not influence financial distress.
- Alternative hypothesis $H2_a$: Smaller size influences financial distress.

The dependent variable remains financial distress and the independent variable is company size measured as the natural log of total assets. The sample size is the same as the baseline model's and the changes in technique from the baseline model are:

1. Perform step 4 with the natural log of total assets for each company and each period.
2. Repeat steps 6 to 15 for company size.
3. In step 16 stratify the data around company size to gain precision on the results.
4. Repeat steps 17 and 18 accordingly.

Like R1, the result analysis consists primarily in verifying the validity of the model through the goodness of fit test in step 13, and the following steps 14 and 15 on the rejection of the null hypothesis, should the model be valid. For R2 too, an HR different from 1 or a large p-value of more than 0.05 would reject the null hypothesis $H2_0$ and an HR equal to 1 or a small p-value of less than 0.05 would fail to reject $H2_0$ (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012).

The third research question R3 is: does being financially distressed influences being an M&A target? The hypotheses are:

- Null hypothesis $H3_0$: Financial distress does not influence the propensity to be an M&A target.

- Alternative hypothesis $H3_a$: Financial distress is a catalyst to being an M&A target.

The dependent variable is a proxy for M&A activity in the form of a Heaviside function of "1" for M&A activity and "0" for the lack of M&A activity. The sample size is 166 firms and 175 events, some firms having more than one transaction during the period of study of Q1-2002 to Q1-2016. An event is a status of being a target in an M&A completed transaction. The changes in technique from the baseline model are:

1. Like step 1, collect M&A transaction data from JWN.
2. Filter the data to remove transactions that are private, cancelled, incomplete, about foreign production and duplicated.
3. Repeat steps 6 to 14 for this data sample.
4. Perform the interpretation in step 15 for the financial distress predictor variable.
5. If the model is valid and the null hypothesis rejected, rerun the model with a vector of covariates including predictors X9 to X16. Validate model's goodness of fit and interpret the correlation of the predictor variables to the status of M&A target.

Consistent with the previous two hypotheses, the result analysis is first a check of model validity and second a review of the null hypothesis rejection or not. a HR different from 1 or a large p-value of more than 0.05 would reject the null hypothesis $H3_0$ and an HR equal to 1 or a small p-value of less than 0.05 would fail to reject $H3_0$ (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012).

These three hypotheses leverage the baseline model design which is an underlying basis for framing the paradigm of financial ratios as predictors of financial distress as defined in this study, in the context of a survival analysis of Canadian oil and gas firms. With a 14-year span, 540 firms and over 15,850 observations for the baseline model, the statistical sample of this study is large, significant and aiming at ensuring the validity and the credibility of this study. The next section expands on the logic governing the sampling strategy of this study.

Population and Sampling Strategy

The population for this study is specific and focused, consisting in public Canadian oil and gas exploration and production firms. The sampling strategy backs onto the specific business cycles characterizing this industry through oil price fluctuations. The firms included in the sample are all listed on the TSX, headquartered in Canada and have their production in Canada as well. Canada is a country with a commodity-driven economy in which the oil and gas sector plays a major role. The province of Alberta with its oil sands has the world's third largest reserves behind Saudi Arabia and Venezuela. The Canadian oil and gas industry is mainly upstream, exploring, extracting, producing and shipping oil and gas for refining mainly - 97% of Canadian oil is exported to the USA, per Natural Resources Canada (2017) - in the USA (CAPP, 2016; Jakeman & Tertzakian, 2016; Millington, 2016; Natural Resources Canada, 2017; PSAC, 2016). The revenue stream of the capital-intensive oil and gas E&P sector in Canada is largely tributary to the international price of oil and gas. This dependency impacts profitability and submits the whole sector and the industry to boom and busts cycles when the oil price fluctuates. During high prices, E&P firms, the oil and gas industry, Alberta and Canada experience growth and enjoy a boom. On the contrary when the oil prices dip significantly and remain low, revenues decrease, investments are minimized, layoffs occur and an economic recession takes hold, materializing the bust phase of the boom and bust cycle (Jakeman & Tertzakian, 2016; Millington, 2016). A long boom cycle commenced in 2002 when oil prices started climbing up following a rough bust phase in 2000 and 2001 with a price as low as USD 26.02 per barrel in November 2001. This boom cycle lasted until June 2014 and during that period the oil price peaked at USD 151.72 in June 2008, then dipped briefly at USD 46.86 in January 2009 due to the international financial crisis and the uncertainty it brought, and then it remained high above USD 80.00. In June 2014, it was at USD 105.54 and went continuously down in the next year and a half until it reached a floor of USD 28.50 in January 2016. Since the end of World War II there have been several oil price cycles: until 1974, the price of the barrel was relatively steady under USD 30.00; in March 1974, the first boom started with a price at USD 50.15 and lasted until July 1980 at USD 113.25; then a bust followed until March 1986 with a low price of USD 22.33. From March 1986 until November 1998, the price was more volatile with large fluctuations including a spike at USD 70.64 in September 1990 and a dip at USD 23.07 in December 1993 and a record low of USD 16.44 in November 1998. The price then jolted up steeply in the next two years reaching USD 45.40 in August 2000. This period was followed by another year and half bust until November 2001 at USD 26.02. From there a long boom started until June 2014 with only one exception in the second half of 2008. The cycle is in a bust since June 2014 (Macrotrends, 2016). Graphs 1 and 2 show the graphic representations of the oil price cycles for the past 70 years and 20 years, respectively (CAPP, 2016; Jakeman & Tertzakian, 2016; Millington, 2016; Macrotrends, 2016; Natural Resources Canada, 2017; PSAC, 2016).

Figure 1. 70-year Historical Chart of Crude Oil Prices

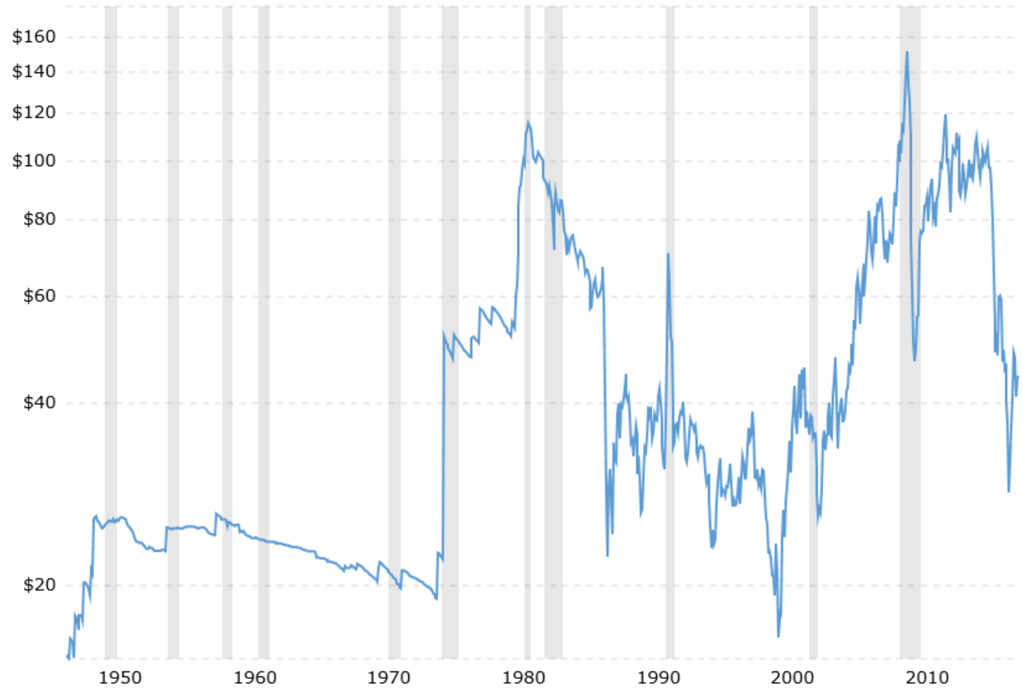

Figure 1. Chart of the WTI crude oil prices in USD from January 1st, 1946 to October 1st, 2016, showing the volatility of oil prices (Macrotrends, 2016).

Figure 2. 20-year Historical Chart of Crude Oil Prices

Figure 2. Chart of the WTI crude oil prices in USD from January 1st, 1998 to October 1st, 2016, showing the oil price growth and drops triggering the cycles of booms and busts (Macrotrends, 2016).

The sampling strategy for this study considers these business cycles and aims at gathering a large sample size while covering a period long enough to give significance to the results. The data available to the researcher is from January 2002 until March 2016. The start of data availability in 2002 coincides with the beginning of the latest and longest boom cycle and the end of the period includes the current bust cycle (Macrotrends, 2016). This 14-year period is the longest used in a similar survival analysis, to the best of the researcher's knowledge. All firms in the sample are publicly traded in Canada on the Toronto Stock Exchange (TSX) or the TSX Venture (TSXV) in Calgary, and therefore all firms submit quarterly financial reporting. The sample thus consists of an initial pull of 608 firms reduced to 540 eligible firms representing up to 15,854 firm-quarters for the largest number of observations on the size variable (Macrotrends, 2016).

Research Technique

The methodologies employed to analyze business failure and corporate financial distress have matured and evolved over the past century. The first ones were financial ratios analysis followed by univariate and multi-discriminant analyses (MDA), conditional probability models and many alternative intelligent techniques such as neural networks, decision trees, support vector machines or multidimensional scaling (Balcaen & Ooghe, 2006; Horrigan, 1968). However, all these techniques perform a binary pass/fail snapshot analysis and prediction, as opposed to survival analysis, a statistical technique that is more dynamic, uses larger data including several years before the event, and provides more analytical depth as well as increased predictive power in understanding the determinants of survival (Agarwal & Bauer, 2014; Beaver et al., 2010; Chen & Lee, 1993; Davydenko, 2013; LeClere, 2005; Pereira, 2014; Shumway, 2001; Whalen, 1991; Yamazaki, 2013). Survival analysis is a regression analysis technique widely used in epidemiology, biostatistics and to a lesser extent engineering and finance (InfluentialPoints, 2016; Pereira, 2014). Survival analysis allows for a better understanding of the time-to-event and the impact of predictor variables on the survival time. The limits of MDA and other probabilistic models have been well documented in the literature and Davydenko (2013) summarized a preference for survival analysis by many empiricists in asserting that "hazard analysis has become the instrument of choice in empirical studies predicting default and bankruptcy" (Davydenko, 2013, p.25). The methods to perform a survival analysis can be parametric, semi-parametric or non-parametric. Parametric methods require defining a baseline hazard as they carry an assumption that the underlying distribution of the survival times follows a probability distribution such as exponential, Weibull, lognormal, log-logistic or gamma distributions. Semi-parametric models do not hold that assumption and do not require the use of a probability distribution for defining a baseline hazard, and the most popular method is the Cox proportional hazards model proposed by Cox (1972). They allow for only using the covariates without a baseline hazard defined out of a past probability distribution. Nonparametric models like the Kaplan-Meier graphical representation of survival curves or the life-table method are mainly used for univariate analyses (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012). The survival analysis method of choice generally used in finance and social sciences is the Cox PH model, which can accommodate univariate or covariate analyses. The method is preferred because it does not require a baseline function as opposed to the more cumbersome parametric models and it is statistically robust, delivering results very close to the parametric models (Klein

& Kleinbaum, 2012). The Cox PH model requires the satisfaction of the proportional hazard assumption: the hazard ratio (HR) is constant over time or more specifically the hazard for one firm is proportional to the hazard for any other firm and the proportionality remains constant, independent of time. This underlying assumption means that the covariates used in the study are time-independent. When the value of some independent variables changes with time and makes the proportionality of those predictors inconstant, these predictor variables are said to be time-dependent. The PH assumption is generally not satisfied with time-dependent covariates and the Cox PH model is not appropriate for a survival analysis involving time-dependent or time-varying covariates. The appropriate semi-parametric method for time-dependent covariates is the extended Cox model. The extension of the Cox PH model for time-dependent covariates consists in either stratifying the data in homogenous time-independent blocks or adding a time coefficient to the Cox PH model. When the observation of the dependent variable, such as financial distress in this study, happens more than once, the extended model can include such repeating events and R, the software conducting the survival analysis in this study can run extended Cox models with repeating events, either focusing on univariate or covariates analyses. When the independent variables are ratios, changes over time in the numerator and denominator of the ratios can influence the output of a survival analysis using a vector of covariates (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012). In studies like this one, the researcher may therefore seek to minimize the risk of confounding and ensure the absence of multicollinearity by running univariate analyses that can more accurately expose the prediction ability and impact of the independent variable on the dependent variable. In this study, the researcher mainly elects to using such a method consisting in univariate extended Cox model with repeating events, but the theoretical foundations of survival analysis, the Cox PH model and the extended Cox model with a time coefficient developed below include vectors of covariates for completeness and standardization of the mathematical models (Agarwal & Bauer, 2014; Balcaen & Ooghe, 2006; Beaver et al., 2010; Chen & Lee, 1993; Cox, 1972; Davydenko, 2013; Fox, 2008; Horrigan, 1968; InfluentialPoints, 2016; Klein & Kleinbaum, 2012; LeClere, 2005; Pereira, 2014; Shumway, 2001; Whalen, 1991; Yamazaki, 2013;).

The general objectives of survival analysis are to estimate and interpret the probability of survival over time through the survivor function, the instantaneous risk of failure or death event at any time through the hazard function, and perform comparative analyses involving both functions (Klein & Kleinbaum, 2012). Survival analysis is a regression analysis of several observations for which a series of explanatory variables or predictors are covariates that additively and proportionately contribute to the event. The researcher selects the covariates and tests whether and to what extent they contribute to the event. The cornerstone of the analysis is the hazard function made of two components: a baseline hazard and a vector of covariates. Estimating the hazard function requires defining the baseline hazard probability distribution and calculating the maximum likelihood function for the covariates. The Cox PH model does not require the baseline hazard, making it a semi-parametric model. The mathematical foundations that explain the tools and procedure of survival analysis in the general context of this study follow below (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012).

Let t be the time when financial distress occurs and T the corporate survival time following the event of financial distress. T is therefore a random variable that is non-negative ($T \geq 0$). At time t, the instantaneous risk of financial distress event is a density function:

Instantaneous risk of financial distress: $$f(t) = \lim_{\Delta t \to 0} \frac{P(t \leq T < t + \Delta t)}{\Delta t}$$ Equation 1 where T is a random non-negative ($T \geq 0$) variable indicating the time to failure of a firm

t is a specific value for T;

Δt is a time interval

Given that instantaneous risk of financial distress, the probability that a firm survives longer than time t units is a cumulative density function measured from t to infinity called the survival function:

Survival function: $S(t) = P(T \geq t) = 1 - f(t)$ Equation 2

For the firms surviving longer than time t, the probability of financial distress in the next instant is a conditional failure rate given as the hazard function:

Hazard function: $h(t) = \lim_{\Delta t \to 0} \frac{P(t \leq T < t + \Delta t | T \geq t)}{\Delta t}$ Equation 3

The hazard function focuses on the happening of the failure event and describes the evolution over time of the immediate rate of failure of a firm; it is therefore the conditional probability of failure in the next instant or per unit of time, given that the firm was not yet in financial distress at time t. The numerator is the probability that the random variable associated with a survival time T lies between t and t+Δt subject to T being greater or equal to t. And the hazard function h(t) is the limit of that probability over the time interval Δt, as Δt approaches zero, or the instantaneous potential per unit of time for the financial distress to occur, given that the firm has survived up to time t (Chen & Lee, 1993; Klein & Kleinbaum, 2012; Pereira, 2014).

The hazard function has a baseline component and a vector of covariates component. The combination of both components means that the hazard is a function of the natural course of events as represented by the passing of time, ceteris paribus, and the specific impact of the covariates. In the absence of any such specific impact, the value of the covariates is reduced to nil and the hazard only depends on the baseline component. In parametric models, the baseline hazard is calculated as a probability distribution using past data that can take the form of an exponential, a Weibull, a lognormal, a log-logistic or a gamma distribution. The baseline hazard function then defined is only a function of time and is independent of the covariates. On the contrary, the second component of the hazard function that is the vector of covariates does not involve time, but only the values of the explanatory variables. The baseline hazard is denominated h0(t) as the baseline hazard that is a function of time, and the vector of covariates is a function C(βiXi) representing the values β1, β2, ...βp of p explanatory variables X1, X2,...Xp aggregated as the vector X=(X1, X2, ...Xp). For i firms, the hazard function expresses as:

Hazard function: $h(t|X) = h_0(t)\, C(\beta_i X_i)$ Equation 4

Where *$h(t|X)$* is a function of time t and covariates X

$h_0(t)$ is the baseline hazard function, involving only time t

$C(\beta_i X_i)$ is a function of the vector of explanatory variables, not involving time t

β_i is the value of the vector of covariates X_i

X_i is the vector of covariates $X = (X_1, X_2, ...X_p)$

Equation (4) means that the hazard function varies by a ratio of C(βiXi) from the baseline hazard: for any two firms A and B, the hazard of falling into financial distress of A is relatively higher or lower than that of B by the ratio of C(βAXA)/ C(βBXB), where βA and βB are the values of the explanatory variables XA and XB respectively. Thus, the hazard for firm A is proportional to that of firm B and the values of the βs affect the survival time proportionally. The model is a proportional hazard model as the hazard for any observation i is a fixed proportion of the hazard of any other observation at any point in time.

Proportionality: $\mathrm{HR}\ (A{:}\ B) = C(\beta_A X_A) \,/\, C(\beta_B X_B)$

$$= \beta(A\text{-}B)$$

$$= \beta_1(X_{A1}-X_{B1}) + \beta_2(X_{A2}-X_{B2}) + \ldots + \beta_p\,(X_{Ap}-X_{Bp}) \quad \text{Equation 5}$$

The function C(Xiβi) is thus a sum of relative risks of the predictors or explanatory variables and as this relative risk cannot be negative it can be written as the exponential of the linear combination of p predictors assumed to act additively on log h(t). The hazard function then becomes:

Hazard function: $$h(t|X) = h_0(t)\, e^{C(\beta i X i)} \quad \text{Equation 6}$$

Equivalently: $$h(t|X) = h_0(t) \exp\,(\beta_1 X_1 + \beta_2\, X_2 + \ldots\ \beta_p X_p) \quad \text{Equation 7}$$

With the exponentiation now introduced, the proportionality of hazards for two firms A and B can be expressed as the following hazard ratio from equation (5):

Proportionality: $\mathrm{HR}(A{:}B) = e^{\beta A} \,/\, e^{\beta B}$

$$= e^{[\beta(A\text{-}B)]}$$

$$= \exp[\beta_1(X_{A1}-X_{B1}) + \beta_2(X_{A2}-X_{B2}) + \ldots + \beta_p(X_{Ap}-X_{Bp})]$$

Equation 8

When the values β's of the vector of covariates are zero, the second component of the function becomes e^0, which is equal to 1, and the function is reduced to its baseline hazard component to become:

Baseline Hazard $h(t) = h_0(t)$ Equation 9

And when the baseline hazard function is not specified, the hazard function becomes a semi-parametric model that depends only on the vector of covariates. In the Cox PH model the baseline hazard function is unspecified and the hazard ratio becomes the following semi-parametric equation:

Semi-parametric Cox PH HR $HR(X) = e^{(\beta 1X1+ \beta 2X2 +\ldots \beta pXp)}$ Equation 10

Then, the goal becomes the estimation of the β's. That estimation requires maximizing the likelihood function (ML), which is the joint probability of the observed data. However, in the Cox PH model, only the probabilities of the financially distressed firms are considered, not those of the censored firms. Censoring is a key component of survival analysis and censored firms are those within the data sample that did not experience the event of financial distress by Q1-2016, or those for which data was not available and were therefore lost to follow-up up to Q1-2016, or those that were removed from the observation of financial distress event for other reasons than failure to financial distress, such as delisting from the TSX or being acquired or merged with another firm. Including only the uncensored data in the ML function turns it into a maximization of the partial likelihood function L(β) expressed as:

Partial Likelihood: $L(\beta)= \prod_{i=1}^{k} \mathbf{Lj} = \prod_{i=1}^{k} \exp(\beta xi) / \sum \exp(\beta xj)$ Equation 11

where $L(\beta) = L_1 \times L_2 \times \ldots L_k$ Equation 12

L(β) is the product of several likelihoods, one for each k financial distress time, and Lj is the portion of L(β) for the j^{th} financial distress time. Maximizing the partial likelihood function consists in maximizing the natural logarithm of L: Log L and calculate the partial derivatives of Log L with respect to each predictor in the model, a process done by iteration in a step wise manner.

The objective of the Cox PH analysis is to find the point estimate for the hazard ratio (HR), the confidence interval, test the significance of effect and test the PH assumption. The point estimate HR is the value that describes the relationship between the predictor and the event of financial distress. HR is the exponential of the regression coefficient provided in the model output. The confidence interval for HR is generally a 95% confidence interval. The test for significance of effect is the p-value or the likelihood ratio or the Wald statistics or the score (logrank) test. Testing the PH assumption involves either graphical methods such as log-log survivor curves or predictor survivor curves, or a p-value goodness-of-fit test or the use of Shoenfeld residuals (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012).

The standard Cox PH model output is a table listing for each covariate the regression coefficient, its standard deviation, the p-value, the hazard ratio (the exponential of the regression coefficient) and the confidence interval at 95% over two columns. The Interpretation of the results passes through the p-value to assess the significance of the results in validating or infirming the null hypothesis: a small p-value of 5% or less strongly indicates to reject the null hypothesis; on the contrary, a large p-value above 5% fails to reject the null hypothesis whereas a p-value close to the 5% cut-off is marginal and can be interpreted either way. The hazard ratio indicates whether there is a relationship between the covariate and the event. A hazard ratio of 1 means that there is no such relationship, as opposed to a larger number meaning a stronger relationship, as many times the number as the relationship for censored or unexposed data; and conversely a value below 1 indicates a lesser relationship to the event than unexposed data. The survival curves provide a graphical representation of the step function of each covariate, showing an ever-decreasing chance of survival as time passes starting from the event. Alternatively, the cumulative hazard curves show an increasing hazard rate with time, built out of applying the regression equation to the actual data being analyzed. Another way to appreciate the survival curves is the table of survival probabilities used to graph the step functions. The confidence interval gives a measure of precision for the point estimate HR, the wider the interval the less precise (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012).

When the value of the predictors covariates varies with time and the PH assumption is not satisfied, the covariates are time-dependent and each observation has then a unique covariate vector Xi(t) that includes a time component. The Cox PH model becomes an extended Cox model to include the time factor for each covariate observation. The exponential component for the vector of covariates now includes the original β factors as in the Cox PH model, for the time-independent covariates represented by Xi, and a time factor Δ for the time-dependent covariates represented by Xj(t). The model formula in equation (7) then becomes:

Time-dependent hazard function: $h(t|X(t)) = h_0(t)\ \exp[\sum\beta_i X_i + \sum\Delta_j X_j(t)]$ Equation 13

where $X(t) = (X_1, X_2,\ldots, X_{p1}, X_1(t), X_2(t), \ldots, X_{p2}(t))$

with $X_1, X_2,\ldots,X_{p1}$ being time-independent predictor covariates

and $X_1(t), X_2(t), \ldots,X_{p2}(t)$ being time-dependent predictor covariates

The proportionality of firm A's hazards relative to firm B discussed in equations (5) and (8) now includes for both firms the set of time-independent covariates and the set of time-dependent covariates. For each covariate, the factor β applies to the difference of (A-B) included in the generalized Xi in equation (13) as in the Cox PH model, but it also includes the extension with the time factor Δ applying to the time-dependent covariates of (A(t) – B(t)) included in the generalized Xj(t) in equation (13). An important underlying assumption of the extended Cox model is that the hazard at time t depends on the value of Xj(t) at that same time. Another important feature of the model to understand is that the time coefficient Δ does not vary with time itself; it is rather a unique time-independent factor representing the corresponding time-dependent predictors blending in all observations for those predictors. Still maintaining the semi-parametric characteristic of the Cox PH model and keeping the baseline hazard unspecified, the hazard ratio in equation (10) becomes for the extended Cox model:

Time-dependent Hazard Ratio $HR(t) = \exp[\sum\beta_i[A_i-B_i] + \sum \Delta_j[A_j(t)-B_j(t)]]$ Equation 14

where A_i is the time-independent covariate i for firm A

B_i is the time-independent covariate i for firm B

$A_j(t)$ is the time-dependent covariate j for firm A

$B_j(t)$ is the time-dependent covariate j for firm B

Aj(t)-Bj(t) is a function of time and the coefficient Δ is the unique overall time factor that applies to it. Δ being a single number, e^{Δ} is therefore a fixed number. In the extended Cox model, the maximum likelihood function ML allows the hazard to vary over time as the baseline hazard cancels similarly to the Cox PH model. When there are time-independent covariates, the extended Cox model allows testing the PH assumption for time-independent covariates by adding a function of time.

PH assumption in extended Cox model

$$h(t,X(t)) = h_0(t) \ \exp[\sum\beta_i X_i + \sum\Delta_i X_i g_i(t)] \qquad \text{Equation 15}$$

where $g_i(t)$] is a function of time for the i^{th} variable and can take different forms such as zero (as in the Cox PH model), a value of time t, Log t or a Heaviside function with t=1 or t=0.

The result output and interpretation is the same for the extended Cox model as described for the Cox PH model above (Cox, 1972; Chancharat et al, 2007; Klein & Kleinbaum, 2012; Pereira, 2014).

The tools used to apply this statistical research instrument are Excel and R. Excel serves to import the raw data query from the JWN's Canoils database, build the financial ratios, prepare the data descriptive statistics, and lay out the data for R. R is a free integrated suite of software environment and programs for statistical computing and graphics. The software requires programming skills but thanks to its wide popularity, multiple methods for using it have been published including several peer-reviewed papers. The research technique of this study is a solid statistical method that has been established for over four decades allied with the computing powers of Excel and the robust R environment and programming language (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012). Both Excel and R are necessary for computing 14 years of quarterly data for 62 metrics and 608 firms, which is the amount of raw data initially collected for this study.

Data Collection Procedures

This research does not use any primary data, only secondary data. This is due to the nature of financial information this study requires, which consists in publicly reported financial statements detailed information, production and energy data, and mergers and acquisition activity data. Canadian researchers have previously reported on the difficulty to gather financial corporate data for empirical studies in corporate failure (Boritz, Kennedy & Sun, 2007). Financial statements information for publicly traded companies is available on the TSX website but it covers only the past five years and comes in a PDF format. Five years of data is not enough for the scope of this research and the PDF format is not practical for extracting and analyzing data. Yet, oil and gas is an important industry in Canada and any or all data pertaining to it is valuable for strategic and competitive analysis purposes. The data required for the scope of this study exists but it is generally privately owned. JuneWarren-Nickle's (JWN) is a publishing firm established over 75 years ago, that specializes in Canadian oil and gas. At the core of their business, JWN collects, analyzes, secures, and sustains oil and gas data to make them available to professional subscribers such as oil and gas corporations, credit analysts and banks, media or educational institutions. For this study, JWN graciously granted the researcher a free access to their Canoils database for the duration of one year. The researcher signed a non-disclosure agreement before getting access to Canoils and benefitted the required training from JWN experts in accessing and retrieving data from Canoils. Before running a data query the researcher dressed a list of financial ratios and industry indicators that could be relevant to this research. Then, the researcher queried a multi-criteria selection in Canoils to retrieve the initial batch of data for the baseline model. The criteria were a) oil and gas companies publicly listed on the TSX or the TSXV; b) Exploration and Production companies; c) companies headquartered in Canada; d) companies with their oil and gas production in Canada; and e) quarterly and annual data from Q1-2002 to Q1-2016. This query returned 62 data items for 608 firms. Upon review of the data, the researcher removed 63 firms from the sample because their data was incomplete or missing, and an additional five firms because their productions were not located in Canada. The final sample is 540 firms and up to 15,859 firm-quarters observations for the 14 years' time of data used in the scope of this study. The period of Q1-2002 to Q1-2016 covers 57 quarters and potentially 30,894 firm-quarters for the 540 firms in the sample, but many firms have not been publicly reporting quarterly data for the entire period as they started and/or stopped after Q1-2002 and before Q1-2016. The total number of reported firm-quarters is 15,859 for the sample of 540 firms. As a precaution and to verify data accuracy, the researcher reconciled key balance sheet and income statement figures for a random sample of 27 firms representing 5% of the total sample of 540 firms with their PDF data available on the TSX website. The reconciliation matched with more than 99% accuracy and the difference attributed to rounding and foreign exchange translation impact is deemed immaterial. Therefore, the data from Canoils is accurate and acceptable for this study. Table 3 shows the sample selection process and the split of data population within the total sample of 540 firms (Boritz et al., 2007; JWN, 2016; TXM, 2016).

Table 3

Sample selection process - Baseline Model

Total available sample		
Canadian Oil and Gas E&P firms publicly listed in Canada, headquartered in Canada and with their production in Canada		608
Substract firms with incomplete data	63	
Substract firms with production located outside of Canada	5	
Total available sample		540
Sample breakdown A: Active/Inactive in Q1-2016		
Firms no longer reporting financial statements in Q1-2016, including		335
Firms that did not experience financial distress - Censored	89	
Firms that did experience financial distress - Censored	246	
Firms still actively reporting financial statements in Q1-2016, including		205
Firms that did not experience financial distress - Censored	51	
Firms that did experience financial distress	154	
Total		540
Sample breakdown B: Financially Distressed / Non-Financially Distressed		
Firms that did not experience financial distress, including		140
Firms no longer reporting financial statements in Q1-2016 - Censored	89	
Firms still actively reporting financial statements in Q1-2016 - Censored	51	
Firms that did experience financial distress, including		400
Firms no longer reporting financial statements in Q1-2016 - Censored	246	
Firms still actively reporting financial statements in Q1-2016	154	
Total		540

The same sample remains valid for testing the second hypothesis in this study about firm size impact on financial distress hazard. The baseline sample also serves as a sampling starting point for the first hypothesis about hedging. Canadian oil and gas firms were not required to report on their risk management practice with actual data on the volume and percentage of production hedged before Q1-2007. The regulatory and accounting standard National Instrument 51-101 Standards of Disclosure for Oil and Gas Activities (NI 51-101) introduced in 2003 evolved to include this requirement as of Q1-2007 (Ontario Securities Commission, 2016). The shorter time than the baseline model starting in Q1-2002 resulted in the removal of 25 firms from the baseline sample. The total sample size for the first hypothesis is thus 515 firms. The third hypothesis requires a different sample focusing on the M&A transactions involving the same population of Canadian oil and gas E&P firms headquartered in Canada, listed on the TSX and with their production in Canada. For M&A data, the researcher makes an initial query on Canoils that returns 573 oil and gas announced deals on conventional and unconventional assets for the period of Q1-2002 to Q1-2016. All deals are corporate transactions and with Canadian targets and as the same firms can be involved in more than one transaction over time, the sample consists in transactions rather than firms. For each transaction, the data of interest is the financial distress status of the target firm one quarter before the time of the transaction and the vector of covariates also at one quarter before the M&A transaction. The assumption of considering the quarter before the transaction obeys to data quality purposes: at the time of the transaction, 120 firms did not publish any financial reports and their covariate information is missing, whereas one quarter before the transaction, only 26 firms did not report their financial statements. The time of the transaction means the quarter during which the deal is announced. In one instance, a target firm is involved in two transactions in the same quarter; but as the first transaction consisted in the acquisition of 19.8% of the shares of the target and the second transaction one month later is the acquisition of the remaining 80.2% of shares by the same acquirer, this acquisition in two steps is considered as one transaction in this study. The perspective required for testing this hypothesis is that of target companies and the sample available out of the original list of 573 transactions is 166 firms targeted with 175 transactions. Of the 573 transactions, 222 involved public firms but 47 transactions are not eligible for inclusion in the sample due to cancelled status, incomplete data, foreign production, duplication in the dataset or post Q1-2016 announcement date. After this selection, the total number of transactions is 175. As some firms went through more than one M&A deal throughout the period, there are more transactions than firms and the total number of firms eligible for the sample is 166. Table 4 provides a breakdown of this sampling selection process (JWN, 2016; Ontario Securities Commission, 2016; TMX, 2016).

Table 4

Sample selection process - M&A target firms

Total available sample		
M&A transactions in Canada Oil and Gas E&P		573
Substract "unspecified" targets	31	
Substract other private targets transactions	320	351
Total public firms target transactions		222
Substract "cancelled" transactions	13	
Substract firms with incomplete data	27	
Substract firms with foreign production	1	
Substract post Q1-2016 announced transactions	5	
Substract duplicate transaction	1	47
Total sample of transactions		175
Substract multiple transactions for same firms		9
Total sample of firms		166

Descriptive Statistics

The dataset of this study is large and its use is varied as it serves for a baseline model and three hypotheses. This section is an analysis of the descriptive statistics of the data presented in relevant population groups with the number of firms N, the mean and the median values, and the standard deviation SD for each covariate predictor pertinent to that hypothesis or the baseline model. The statistics also include information on the censored firms and on comparative volume data for hedging and size. The population groups include all firms, financially distressed and non-financially distressed, and active and inactive firms. The section starts with the baseline model and continues with each of the three hypotheses.

Baseline model

For the total population of the baseline model table 5 displays a summary abstract of table 3 focusing on the number of censored firms in the total sample. 386 firms are censored out of 540 representing a proportion of 72%.

Table 5

Baseline model - Censored firms and active financially distressed firms

Total sample	540
Firms not in distress and no longer reporting financial statements in Q1-2016	89
Firms not in distress and still actively reporting financial statements in Q1-2016	51
Firms in financial distress and no longer reporting financial statements in Q1-2016	246
Total censored firms	386
Baseline model active firms in financial distress	154

The key statistical characteristic of the data population of 540 firms is its dispersion. All predictors in the baseline model show a very large standard deviation (SD) which calls for caution when looking at the mean of any predictor in this large data sample. Table 6 shows these descriptive statistics along with significant differences between the mean and the median as a further indication of the data dispersion and the impact of strong outliers shifting the mean away from the median. Remaining mindful of the large SD, the X1 proxy shows that on average firms fall short by about 4% of generating enough cash flow to sustain their total assets. The two liquidity proxies do exhibit directionally opposed means with X2 indicating a strong state of illiquidity relative to total assets while X3 indicates that current assets cover current liabilities more than seven times. The median for X3 does however point to 50% of the data population having current assets worth only 85% of their current liabilities and thus being illiquid. Both proxies are calculated differently, one using the difference between current assets and current liabilities while the other uses their ratio. The data are very volatile even for the same firm over different periods and the variations compound at different rates between both metrics, which for a large population of over 15,850 observations can yield significant differences of the averages and allow for outliers and volatility to show a current ratio mean of 7.62 times while X2 is negative at (0.97). Overall the solvency ratios show on average a high level of debt and the profitability ratios are all negative, including their median. The SD is particularly large for X11 and X8 pointing to significant disparities in the operating costs including exploration costs, their leveraged financing and the ability to be operationally profitable. The average operating cost per BOE is $21.27 but for this proxy also the SD is large, confirming the disparity and dispersion of the 15,850 observations.

Table 6

Descriptive statistics for the baseline model - All firms

Predictor Proxy	Predictor	All Firms N	Mean	Median	SD
Financial Distress					
X1	Operating CashFlow / Total Assets	540	(0.04)	0.01	1.11
Liquidity					
X2	Working Capital / Total Assets	540	(0.97)	(0.01)	15.06
X3	Current Ratio	540	7.62	0.85	58.34
Solvency					
X4	Solvency Ratio	540	(0.46)	0.01	6.13
X5	Shareholders Equity Ratio	540	2.65	0.87	40.72
X6	Debt-to-Assets Ratio	540	0.78	0.10	12.69
X7	Debt-to-Equity Ratio	540	3.64	0.06	427.81
X8	Debt-to-EBITDAX	540	(6.61)	-	965.42
Profitability					
X9	Return on Assets (ROA)	540	(0.14)	(0.01)	5.96
X10	Return on Equity (ROE)	540	(0.15)	(0.01)	10.73
X11	Operating Profit Margin	540	(11.69)	(0.18)	8,407.70
Efficiency					
X17	Operating Costs per BOE	540	21.27	12.15	199.92
Energy					
X18	Production to Reserves	540	0.0017	0.0005	0.0185
X19	RRR - Reserve Replacement Rate	540	0.0017	0.0005	0.0185

As the overall data is dispersed, table 7 provides a split perspective of the descriptive statistics by the population of distressed and non-distressed firms. There are about three times as many financially distressed firms as non-financially distressed firms and except for X8, all predictors are considerably less dispersed for non-distressed firms. For these firms, the liquidity ratios are directionally aligned with respectively -0.14 for X2 and 0.98 for X3 and show on average a state of very moderate illiquidity. The solvency ratios are also healthier and show a relatively moderate indebtedness compared to financially distressed firms. The mean for X8 is negative at -26.67 and may reflect large self-funded exploration costs the non-distressed firms incurred, but the large SD for this proxy tempers this reading. At about $11.00 of operating cost per BOE, these firms are on average more efficient. The more concentrated data with mean and median closer, and the direction and values of the predictors for non-financially distressed firms indicate a validation of the definition and the metric selected for the state of financial distress in this study.

Table 7

Descriptive statistics for the baseline model – FD and NFD firms

Predictor Proxy	Predictor	Financially Distressed N	Mean	Median	SD	Non-Financially Distressed N	Mean	Median	SD
Financial Distress									
X1	Operating CashFlow / Total Asse	400	(0.06)	(0.00)	1.21	140	0.04	0.04	0.70
Liquidity									
X2	Working Capital / Total Assets	400	(1.23)	0.02	17.02	140	(0.14)	(0.03)	4.87
X3	Current Ratio	400	9.69	1.17	66.68	140	0.98	0.61	2.15
Solvency									
X4	Solvency Ratio	400	(0.63)	(0.04)	7.01	140	0.09	0.08	0.22
X5	Shareholders Equity Ratio	400	3.16	0.89	46.62	140	1.01	0.83	0.93
X6	Debt-to-Assets Ratio	400	0.96	0.02	14.53	140	0.21	0.20	0.13
X7	Debt-to-Equity Ratio	400	4.63	-	490.00	140	0.47	0.36	0.69
X8	Debt-to-EBITDAX	400	(0.34)	-	193.70	140	(26.67)	4.31	1,947.83
Profitability									
X9	Return on Assets (ROA)	400	(0.19)	(0.02)	6.83	140	0.00	0.01	0.05
X10	Return on Equity (ROE)	400	(0.20)	(0.02)	12.29	140	0.00	0.01	0.17
X11	Operating Profit Margin	400	(16.54)	(0.53)	10,008.95	140	(0.05)	0.15	1.55
Efficiency									
X17	Operating Costs per BOE	400	26.14	14.27	242.52	140	10.99	9.93	6.71
Energy									
X18	Production to Reserves	400	0.0014	0.0004	0.0139	140	0.0025	0.0007	0.0266
X19	RRR - Reserve Replacement Rate	400	0.0014	0.0004	0.0139	140	0.0025	0.0007	0.0266

Tables 8 and 9 further split the financially distressed and non-financially distressed firms respectively into active and inactive firms to get a more precise sense of the descriptive statistics. Financially distressed and active firms show a more negative X1 predictor and a significantly higher X7 proxy than inactive firms, although with a large SD for X7. Those active firms also exhibit a positive mean for X11 but the dispersion is very large around this statistic. X17 is also higher for active firms with, again, a large SD. For non-financially distressed firms in table 9, the data is, consistently with table 7, less dispersed and the only notable difference between active and inactive firms appears in X8 where inactive firms have a negative mean of -68.72 with a very large SD. The profitability ratios are on average very close between both groups of active and inactive firms, albeit being negative for the latter. The operating costs per BOE are very close between both categories and overall, the distinction between financially distressed and non-financially distressed firms seem to be impervious to the active or inactive status of the firms. Thus, the main split of relative importance is between financially distressed and non-financially distressed firms as opposed to active and inactive firms.

Table 8

Descriptive statistics for the baseline model – FD firms: active and inactive

		Financially Distressed							
Predictor		Active Firms				Inactive Firms			
Proxy	Predictor	N	Mean	Median	SD	N	Mean	Median	SD
Financial Distress									
X1	Operating CashFlow / Total Assets	154	(0.09)	(0.01)	1.50	246	(0.04)	(0.00)	0.88
Liquidity									
X2	Working Capital / Total Assets	154	(1.62)	0.06	20.29	246	(0.90)	(0.00)	13.61
X3	Current Ratio	154	8.79	1.55	50.42	246	10.46	0.95	77.90
Solvency									
X4	Solvency Ratio	154	(0.78)	(0.06)	8.71	246	(0.51)	(0.02)	5.13
X5	Shareholders Equity Ratio	154	3.60	0.95	52.63	246	2.78	0.84	40.78
X6	Debt-to-Assets Ratio	154	1.31	0.00	19.18	246	0.66	0.05	8.78
X7	Debt-to-Equity Ratio	154	9.73	-	722.28	246	0.28	0.01	11.48
X8	Debt-to-EBITDAX	154	(0.29)	-	211.97	246	(0.38)	-	176.57
Profitability									
X9	Return on Assets (ROA)	154	(0.22)	(0.03)	9.84	246	(0.16)	(0.02)	1.90
X10	Return on Equity (ROE)	154	(0.04)	(0.02)	6.24	246	(0.33)	(0.02)	15.71
X11	Operating Profit Margin	154	8.85	(0.68)	14,820.84	246	(37.38)	(0.43)	1,503.77
Efficiency									
X17	Operating Costs per BOE	154	31.45	14.08	364.83	246	22.25	14.38	66.80
Energy									
X18	Production to Reserves	154	0.0012	0.0004	0.0113	246	0.0015	0.0005	0.0158
X19	RRR - Reserve Replacement Rate	154	0.0012	0.0004	0.0113	246	0.0015	0.0005	0.0158

Table 9

Descriptive statistics for the baseline model – NFD firms: active and inactive

		Non-Financially Distressed							
Predictor		Active Firms				Inactive Firms			
Proxy	Predictor	N	Mean	Median	SD	N	Mean	Median	SD
Financial Distress									
X1	Operating CashFlow / Total Asse	51	0.04	0.04	0.03	89	0.04	0.03	1.07
Liquidity									
X2	Working Capital / Total Assets	51	(0.04)	(0.02)	0.14	89	(0.27)	(0.06)	7.40
X3	Current Ratio	51	1.00	0.68	1.62	89	1.03	0.49	2.78
Solvency									
X4	Solvency Ratio	51	0.09	0.08	0.19	89	0.09	0.08	0.25
X5	Shareholders Equity Ratio	51	1.09	0.92	0.86	89	0.90	0.73	1.01
X6	Debt-to-Assets Ratio	51	0.22	0.21	0.12	89	0.19	0.19	0.14
X7	Debt-to-Equity Ratio	51	0.51	0.39	0.74	89	0.42	0.32	0.62
X8	Debt-to-EBITDAX	51	4.75	4.31	108.86	89	(68.72)	4.28	2,974.40
Profitability									
X9	Return on Assets (ROA)	51	0.01	0.01	0.05	90	(0.00)	0.00	0.05
X10	Return on Equity (ROE)	51	0.01	0.02	0.14	89	(0.01)	0.01	0.20
X11	Operating Profit Margin	51	0.02	0.17	0.86	89	(0.14)	0.11	2.16
Efficiency									
X17	Operating Costs per BOE	51	11.08	10.05	6.03	89	10.86	9.78	7.53
Energy									
X18	Production to Reserves	51	0.0008	0.0006	0.0007	89	0.0052	0.0008	0.0420
X19	RRR - Reserve Replacement Rate	51	0.0008	0.0006	0.0007	89	0.0052	0.0008	0.0420

Indeed, by removing the distress status and splitting the firms only into active and inactive in table 10, it appears that both groups present similar statistics except for X7, X8 and X11, all with large SD.

Table 10

Descriptive statistics for the baseline model – Active and inactive firms

Predictor Proxy	Predictor	Active Firms N	Mean	Median	SD	Inactive Firms N	Mean	Median	SD
Financial Distress									
X1	Operating CashFlow / Total Assets	205	(0.05)	0.01	1.27	335	(0.02)	0.01	0.92
Liquidity									
X2	Working Capital / Total Assets	205	(1.18)	-	17.23	335	(0.78)	(0.02)	12.65
X3	Current Ratio	205	6.60	0.95	42.91	335	8.59	0.77	69.93
Solvency									
X4	Solvency Ratio	205	(0.53)	0.00	7.40	335	(0.39)	0.01	4.60
X5	Shareholders Equity Ratio	205	2.90	0.93	44.67	335	2.41	0.81	36.56
X6	Debt-to-Assets Ratio	205	1.00	0.10	16.28	335	0.57	0.10	7.87
X7	Debt-to-Equity Ratio	205	7.14	0.05	612.53	335	0.31	0.07	10.29
X8	Debt-to-EBITDAX	205	1.13	-	188.81	335	(14.00)	-	1,337.31
Profitability									
X9	Return on Assets (ROA)	205	(0.15)	(0.01)	8.35	335	(0.13)	(0.01)	1.71
X10	Return on Equity (ROE)	205	(0.03)	(0.01)	5.29	335	(0.26)	(0.01)	14.08
X11	Operating Profit Margin	205	5.78	(0.16)	11,966.03	335	(28.31)	(0.20)	1,308.12
Efficiency									
X17	Operating Costs per BOE	205	23.44	11.92	284.33	335	19.32	12.38	57.91
Energy									
X18	Production to Reserves	205	0.0011	0.0005	0.0091	335	0.0024	0.0005	0.0245
X19	RRR - Reserve Replacement Rate	205	0.0011	0.0005	0.0091	335	0.0024	0.0005	0.0245

Hypothesis 1 - Hedging

The sample of population on which the first research question is tested is a subgroup of 515 firms within the sample of the baseline model. As such, the descriptive statistics of the baseline model are equally valid for hypothesis 1 even though the hedging statistics starts in Q1-2007, five years later than the baseline model. Table 11 shows an additional marginal statistic relevant to this hypothesis with the percentage of production hedged by group and sub-groups. The distribution of data for hedging percentage is very dispersed as indicated by the large standard deviations. The large dispersion is especially apparent for firms that are still active and financially distressed. With the caution imposed by large SD on interpreting mean data, these averages reveal that financially distressed and inactive firms hedged less than 10% of their production while non-financially distressed firms hedged over 27% of their production with a median and SD close to the mean.

Table 11

Descriptive statistics hypothesis 1 – Percentage of production hedged

Classification	N	Mean	Median	SD
All firms	515	12.91%	0.00%	162.49%
Financially distressed firms	389	9.09%	0.00%	181.87%
Non-financially distressed firms	126	27.49%	26.61%	26.50%
Active firms	205	17.10%	0.00%	219.72%
Inactive firms	310	7.96%	0.00%	20.77%
Financially distressed and active firms	154	11.86%	0.00%	254.06%
Financially distressed and inactive firms	235	6.21%	0.00%	19.92%
Non-financially distressed and active firms	51	32.29%	32.15%	26.97%
Non-financially distressed and inactive firms	75	17.80%	0.00%	22.63%

Hypothesis 2 - Size

The marginal descriptive statistic of interest for hypothesis two is the size of the sample companies, which are the same as those in the baseline model. Table 12 lists the mean, median and SD by groups and subgroups for this sample, in dollars and in the natural logarithm proxy used for the survival analysis testing in this study. The size of non-financially distressed firms is very dispersed, as is that of active firms: there are thus firms of all sizes these descriptive statistics show to not be financially distressed. Financially distressed firms have a more concentrated distribution and show an average of a much smaller size with about $162M in total assets than non-financially distressed firms with a mean of $1.247B. While the Log proxy serves for the survival analysis, the actual dollar value is a metric that provides a more intuitive reading of the descriptive statistics for total asset size in the sample of 540 firms.

Table 12

Descriptive statistics hypothesis 2 – Total assets size

Classification	Total Assets (000)'$ N	Mean	Median	SD	Log Total Assets N	Mean	Median	SD
All firms	540	1,247,191	33,857	5,610,173	540	10.52	10.43	2.81
Financially distressed firms	400	161,982	14,916	671,194	400	9.60	9.61	2.33
Non-financially distressed firms	140	4,734,152	655,507	10,734,860	140	13.48	13.39	2.10
Active firms	205	2,125,891	47,740	7,661,668	205	10.88	10.77	3.15
Inactive firms	335	408,846	26,748	2,015,364	335	10.18	10.19	2.40
Financially distressed and active firms	154	165,116	12,525	581,791	154	9.53	9.44	2.44
Financially distressed and inactive firms	246	159,301	16,752	739,143	246	9.66	9.73	2.22
Non-financially distressed and active firms	51	7,166,980	1,510,864	13,172,158	51	14.36	14.23	1.81
Non-financially distressed and inactive firms	89	1,428,430	169,719	4,139,956	89	12.28	12.04	1.84

Hypothesis 3 – M&A

With a smaller sample than the baseline model, the population of firms used for hypothesis 3 shows less dispersion for the financial distress and profitability proxies. On the contrary, the valuation proxies are very dispersed, especially X14 which includes leverage. Table 13 shows that on average for the population of firms that were a target in an M&A transaction, they were moderately distressed and unprofitable.

Table 13

Descriptive statistics hypothesis 3 M&A – All firms

Predictor Proxy	Predictor	All Firms N	Mean	Median	SD
Financial Distress					
X1	Operating CashFlow / Total Assets	166	(0.00)	0.02	0.85
Profitability					
X9	Return on Assets (ROA)	166	(0.06)	(0.00)	0.62
X10	Return on Equity (ROE)	166	(0.01)	(0.01)	1.87
X11	Operating Profit Margin	166	(1.31)	(0.07)	431.90
Valuation					
X12	P/E Price-Earnings Ratio	166	52.11	(3.85)	2,573.67
X13	EV/EBITDAX	166	13.50	18.94	1,680.55
X14	EV/DACF	166	217.44	21.06	11,813.40
X15	EV/FCF	166	(28.81)	(9.82)	1,301.77
X16	EV/2P	166	0.52	0.04	4.55

A closer look at the split between those that were financially distressed and those that were not, shows in table 14 that the large dispersion in X11 still apparent for all firms is due to the financially distressed firms with a SD of 542.82 in stark contrast to the SD of 1.60 for non-financially distressed firms. The same comparison also applies to X14. However, the opposite trend exists for X1 where the financially distressed data are more concentrated. Between both groups, the most significant comparative differences are in the valuation predictor descriptive statistics with X12 being negative at -41.70 for non-financially distressed firms and positive at 99.28 for financially distressed firms where the means and median are also volatile for X13, X14 and X15.

Table 14

Descriptive statistics hypothesis 3 M&A – FD and NFD firms

Predictor		Financially Distressed				Non-Financially Distressed			
Proxy	Predictor	N	Mean	Median	SD	N	Mean	Median	SD
Financial Distress									
X1	Operating CashFlow / Total Asse	100	(0.02)	0.01	0.58	66	0.04	0.04	1.21
Profitability									
X9	Return on Assets (ROA)	100	(0.09)	-	0.76	66	0.00	0.00	0.04
X10	Return on Equity (ROE)	100	(0.01)	(0.01)	2.28	66	(0.00)	0.01	0.18
X11	Operating Profit Margin	100	(2.02)	(0.29)	542.82	66	(0.08)	0.12	1.60
Valuation									
X12	P/E Price-Earnings Ratio	100	99.28	(9.06)	2,848.13	66	(41.70)	20.79	1,911.97
X13	EV/EBITDAX	100	(18.05)	10.88	1,710.66	66	76.24	25.29	1,617.85
X14	EV/DACF	100	312.01	17.41	14,469.00	66	28.91	24.86	645.84
X15	EV/FCF	100	(53.40)	(10.39)	1,215.96	66	20.21	(8.29)	1,457.18
X16	EV/2P	100	0.50	0.03	4.02	66	0.57	0.04	5.43

Within the financially distressed group of firms, active firms, with a small size of 11, appear in table 15 to be driving the data dispersion of the financially distressed group of firms. Inactive firms however lead the volatile statistics except for X12 and X16.

Table 15

Descriptive statistics hypothesis 3 M&A – FD firms: active and inactive

		Financially Distressed							
Predictor		Active Firms				Inactive Firms			
Proxy	Predictor	N	Mean	Median	SD	N	Mean	Median	SD
Financial Distress									
X1	Operating CashFlow / Total Assets	11	(0.01)	(0.00)	0.11	89	(0.02)	0.01	0.63
Profitability									
X9	Return on Assets (ROA)	11	(0.11)	(0.02)	0.37	89	(0.09)	(0.01)	0.81
X10	Return on Equity (ROE)	11	(0.11)	(0.02)	2.59	89	0.01	(0.01)	2.22
X11	Operating Profit Margin	11	35.43	(0.75)	1,264.33	89	(9.41)	(0.24)	194.81
Valuation									
X12	P/E Price-Earnings Ratio	11	534.40	(3.34)	6,191.59	89	19.49	(10.79)	1,595.49
X13	EV/EBITDAX	11	(2.77)	0.32	555.60	89	(20.90)	13.38	1,847.97
X14	EV/DACF	11	(51.79)	15.36	1,371.71	89	380.58	17.74	15,762.24
X15	EV/FCF	11	(11.78)	(4.90)	201.15	89	(61.22)	(11.19)	1,322.38
X16	EV/2P	11	0.95	0.03	6.27	89	0.40	0.04	3.35

Only two firms are non-financially distressed and active as showing in table 16. This sample size is too small for descriptive statistics reading and the inactive firms statistics provide all the substance of the non-financially distressed firms in table 14.

Table 16

Descriptive statistics hypothesis 3 M&A – NFD firms: active and inactive

		Non-Financially Distressed							
Predictor		Active Firms				Inactive Firms			
Proxy	Predictor	N	Mean	Median	SD	N	Mean	Median	SD
Financial Distress									
X1	Operating CashFlow / Total Asse	2	0.03	0.03	0.02	64	0.04	0.04	1.24
Profitability									
X9	Return on Assets (ROA)	2	(0.01)	0.00	0.05	64	0.00	0.00	0.04
X10	Return on Equity (ROE)	2	(0.10)	0.00	0.52	64	0.00	0.01	0.14
X11	Operating Profit Margin	2	(0.10)	0.10	0.70	64	(0.07)	0.12	1.63
Valuation									
X12	P/E Price-Earnings Ratio	2	157.47	19.46	706.17	64	(52.26)	20.95	1,954.84
X13	EV/EBITDAX	2	34.86	26.85	36.09	64	78.30	25.28	1,657.72
X14	EV/DACF	2	34.91	24.75	27.34	64	28.61	24.89	661.72
X15	EV/FCF	2	482.12	(21.89)	5,134.89	64	(2.82)	(7.88)	961.44
X16	EV/2P	2	0.03	0.03	0.02	64	0.60	0.04	5.58

Of the total sample of 166 firms in table 17, 13 only are active and 153 are inactive. This last subgroup therefore drives the statistics for both the financially distressed and non-financially distressed subgroups and for all the firms. Active firms show a positive average operating profit margin with a large SD and very high X12, also with a large SD, compared to inactive firms.

Table 17

Descriptive statistics hypothesis 3 M&A – Active and inactive firms

Predictor Proxy	Predictor	Active Firms N	Mean	Median	SD	Inactive Firms N	Mean	Median	SD
Financial Distress									
X1	Operating CashFlow / Total Assets	13	(0.01)	0.00	0.11	153	(0.00)	0.02	0.90
Profitability									
X9	Return on Assets (ROA)	13	(0.10)	(0.02)	0.35	153	(0.06)	(0.00)	0.65
X10	Return on Equity (ROE)	13	(0.11)	(0.01)	2.43	153	0.01	(0.00)	1.78
X11	Operating Profit Margin	13	30.33	(0.49)	1,169.89	153	(5.70)	(0.04)	151.24
Valuation									
X12	P/E Price-Earnings Ratio	13	481.46	(2.15)	5,746.75	153	(6.42)	(4.32)	1,733.87
X13	EV/EBITDAX	13	2.20	2.73	517.87	153	15.05	19.98	1,781.76
X14	EV/DACF	13	(40.48)	16.92	1,279.22	153	253.10	21.44	12,594.53
X15	EV/FCF	13	52.83	(5.96)	1,860.48	153	(40.08)	(10.21)	1,204.45
X16	EV/2P	13	0.82	0.03	5.82	153	0.48	0.04	4.33

The descriptive statistics in this study are different from the actual survival analysis in the next chapter, but they are important to understand the data. There are three times as many financially distressed firms as non-distressed and overall the data is highly dispersed, especially for financially distressed firms. The distinction between active an inactive status is not very relevant, but it provides a deeper level of reading when looking at groups of distressed and non-distressed firms, such as for example for non-financially distressed and active firms that hedge more and are larger in size than any other category. The valuation metrics for the 166 firms in the third hypothesis sample are highly dispersed; notably, X14 – EV/DACF – is very volatile for distressed and inactive firms. Overall the data shows a large dispersion and the descriptive statistics above are not sufficient to analyze any correlation, regression or causal relationships between the predictors and financial distress, which calls for a more robust method such as a survival analysis.

Summary

The focal point of this research is the definition of financial distress as two consecutive quarters of the ratio of operating cash flows to total assets. This definition is unique to this study and intends to capture the ability of public E&P firms in a capital intensive and asset-heavy industry with long lead times to generate from their operations enough cash to build resilience, reinvest in productive assets, be profitable and secure their going concern prospective. The study is an extended Cox model with repeating events for which a baseline model serves to analyze the extent to which predictor ratios in financial distress, liquidity, solvency and profitability contribute to creating a state of financial distress (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012). Building on the baseline model, three hypotheses are tested, respectively to understand whether hedging contributes to reduce the hazard of financial distress; whether larger size also contributes to a reduction in financial distress hazard; and whether financial distress is an aggravating factor in being a target of an M&A transaction. The baseline model uses a population of 540 public Canadian E&P firms with production and headquarters in Canada, with quarterly reporting covering the period of Q1-2002 to Q1-2016 or over 15,850 firm-quarters. For the first hypothesis on hedging the period is Q1-2007 to Q1-2016 as firms were not compelled to report their hedging status before Q1-2007, and the sample is a subset of the baseline sample, of 515 firms. The second hypothesis uses the same sample as the baseline model and the third hypothesis has a smaller sample of 166 firms. A descriptive statistical analysis reveals that the data is highly dispersed and the split between financially distressed and non-financially distressed firms is more relevant than the distinction between active and inactive firms. 400 firms are financially distressed representing 74% of the baseline sample of 540 firms and the 140 non-financially distressed show significantly less dispersed predictors. Similarly, the descriptive statistics reveal that non-financially distressed firms hedge a larger percentage of their production and have a larger size. The valuation ratios for the third hypothesis are also highly dispersed and the non-financially distressed firms have better profitability ratios. The overall significant dispersion of the data limits the accuracy of the descriptive statistics and stresses the need for a stronger analytical method to run the regressions with the proportionality that only a Cox PH model enables, and to capture the time impact on the predictors by extending the model, while also including the repetition of the event of financial distress. Following the presentation of the research design, the sample data and their descriptive analyses discussed above, the next chapter precisely addresses this requirement of a more robust method and uses the extended Cox model with repeating events to analyze the baseline model and the three hypotheses of this study (Cox, 1972; Fox, 2008; JWN, 2016; Klein & Kleinbaum, 2012).

Chapter 4: Analysis and Presentation of Results

The survival analysis consisting in a Cox extended model with repeating events designed for this study is performed in the free statistical software R (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012). This chapter reports on the results of the analysis and includes three sections. The first is a presentation of the descriptive statistics returned by R. The second and longer sections details the results and includes four subsections, one for the baseline model and one for each of the three hypotheses this study tests. The last section is a summary of the results (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012).

Descriptive Statistics from R

The statistics summarized in table 18 are issued by the R software upon running the survival analysis models. The baseline model is carried out of a total sample of 15,836 quarter-firms. A certain number of observations are deleted “due to missingness” as showing in the second column for each univariate analysis. The percentage of events is the number of events divided by N, the number of observation used for the analysis. The comparatively small N for X18 and X19 result from the fact that the observations for these predictors are annual rather than quarterly. For the baseline model, the event of financial distress represents an average of about 20% of N. There is virtually no observation deleted for the hypotheses and the percentage of financial distress events are 33.1% and 21.3% respectively for the first two hypotheses of hedging and size, and only 4.7% for the event of M&A in the population of distressed firms for the third hypothesis.

Table 18

Descriptive Statistics from R

Predictor	N	Observat. deleted	Total Sample	Number of Events	% of Events
Baseline Model					
X1_OCF/TA	11,719	4,117	15,836	3,372	28.8%
X2_WC/TA	15,805	31	15,836	3,368	21.3%
X3_Current Ratio	15,799	37	15,836	3,365	21.3%
X4_Solvency Ratio	15,795	41	15,836	3,370	21.3%
X5_Shareholders'Equity Ratio	14,650	1,186	15,836	3,200	21.8%
X6_Debt to Assets Ratio	10,396	5,440	15,836	1,790	17.2%
X7_Debt to Equity Ratio	10,387	5,449	15,836	1,790	17.2%
X8_Debt to Ebitdax	10,374	5,462	15,836	1,789	17.2%
X9_Return on Assets	15,801	35	15,836	3,372	21.3%
X10_Return on Equity	15,773	63	15,836	3,368	21.4%
X11_Operating Profit Margin	12,760	3,076	15,836	2,225	17.4%
X17_Operating Cost per BOE	11,308	4,528	15,836	1,771	15.7%
X18_Production to Reserves	2,641	13,195	15,836	365	13.8%
X19_Reserves Replacement Rate	2,642	13,194	15,836	365	13.8%
Hypothesis 1 Hedging	11,005	6	11,011	3,647	33.1%
Hypothesis 2 Size	15,849	5	15,854	3,372	21.3%
Hypothesis 3 M&A	3,698	0	3,698	175	4.7%

The value of N for all predictors in table 18 is large enough to carry out the survival analysis and expect to test the goodness of fit and the validity of the model. Similarly, the number of events appear sufficiently significant to test the null hypotheses of the baseline model and the three hypotheses. The detail of the results below formally answers those intuitive observations for the baseline model and the hypotheses.

Details of Analysis and Results

The results of the Cox extended model with repeating events (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012), as returned by R, are listed for the baseline model first, followed by each of the three hypotheses this study is testing. The baseline model results include the statistical validity or goodness of fit, the survival analysis testing the null hypothesis and a stratification using the price of oil to get a glimpse at any strong correlation between that externality and financial distress and whether it accentuates or not the predictors results initially returned without the stratification of oil pricing. The results for each hypothesis also explore the model validity first and upon validation, the actual survival analysis results (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012).

Survival Analysis of the Baseline Model

Table 19 provides a summary of the validity of the baseline model. R returns five different tests for the goodness of fit of the regression analysis. Concordance measures the probability that a randomly selected firm that experienced financial distress has a higher risk score than a firm that did not experience financial distress. This index can take a value between 0.5 and one with 0.5 meaning that the probability is not better predicted than pure chance and one showing perfect predictability; above 0.7 the model is good and above 0.8 the model is strong. The R-square shows the data concentration or dispersion around the fitted regression line with a value between 0 and 100%. The higher the value the higher the goodness of fit and the more precise the prediction from the model. The likelihood ratio test, the Wald test and the score (logrank) test measure the goodness of fit of nested models. Their values can range from zero to infinity, the higher, the better the fit of the model and the lower the p-value which represents the probability that the result is due to chance. When all three tests agree, the goodness of fit is strong and the results of the analysis are reliable; when they do not, statisticians favor the likelihood ratio for interpreting the model’s validity (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012).

Table 19

Baseline Model Statistical Validity

Predictor	Concord.	R-square	Likelihood Ratio Test	Likelihood Ratio p-value	Wald test Test	Wald test p-value	Score (logrank) test Test	Score (logrank) test p-value	All tests agree	Goodness of Fit
Financial Distress										
X1_OCF/TA	0.847	0.029	349.70	0.0001	547.40	0.0001	699.80	0.0001	Yes	Yes
Liquidity										
X2_WC/TA	0.489	0.011	175.90	0.0001	204.10	0.0001	216.90	0.0001	Yes	Yes
X3_Current Ratio	0.642	0.010	159.70	0.0001	181.00	0.0001	189.20	0.0001	Yes	Yes
Solvency										
X4_Solvency Ratio	0.693	0.011	167.70	0.0001	201.50	0.0001	224.80	0.0001	Yes	Yes
X5_Shareholders'Equity Ratio	0.590	0.009	133.20	0.0001	147.70	0.0001	154.20	0.0001	Yes	Yes
X6_Debt to Assets Ratio	0.521	0.008	86.53	0.0001	113.50	0.0001	139.10	0.0001	Yes	Yes
X7_Debt to Equity Ratio	0.470	0.007	68.23	0.0001	77.71	0.0001	79.64	0.0001	Yes	Yes
X8_Debt to Ebitdax	0.647	0.007	71.75	0.0001	81.22	0.0001	81.59	0.0001	Yes	Yes
Profitability										
X9_Return on Assets	0.663	0.009	147.30	0.0001	160.50	0.0001	164.80	0.0001	Yes	Yes
X10_Return on Equity	0.630	0.009	147.20	0.0001	160.50	0.0001	164.90	0.0001	Yes	Yes
X11_Operating Profit Margin	0.678	0.011	146.70	0.0001	199.70	0.0001	206.20	0.0001	Yes	Yes
Efficiency										
X17_Operating Cost per BOE	0.619	0.008	93.66	0.0001	106.70	0.0001	110.20	0.0001	Yes	Yes
Energy										
X18_Production to Reserves	0.568	0.014	37.88	0.0001	37.20	0.0001	36.72	0.0001	Yes	Yes
X19_Reserves Replacement Rate	0.567	0.014	36.74	0.0001	0.32	0.0001	37.46	0.0001	No	Yes

While the concordance and the R-square present average to low values, except for the C-index for X1, the three other tests are all high above zero and agree, with small p-values (as a small exception X19 Wald test disagrees with the other two tests). Therefore, the baseline model returns a solid goodness of fit for all predictors and its survival analysis results are trustworthy. With the model validity established, the focus can now advance to the actual results of the baseline model survival analysis summarized in table 20. To increase the accuracy of the regression, the researcher elects to run for each predictor a univariate survival analysis regression and test the following null hypothesis: the predictor variable does not contribute to predicting financial distress. The alternative hypothesis is that the predictor variable does help predicting financial distress. A p-value of more than 0.05 or a confidence interval value of one fail to reject the null hypothesis. Under the null hypothesis, the pattern of the data tested is random and takes the form of a normal curve. A large or low z-score contribute to rejecting the null hypothesis as the pattern is in the tail of the curve. The baseline model tests fourteen variables. For nine of these variables, the null hypothesis is rejected, indicating a valid correlation between the predictor and the state of financial distress. For the other four variables, the null hypothesis fails to be rejected. Table 20 lists all variables and their respective results.

Table 20

Baseline Model Survival Analysis

Predictor	z	p-value	Confidence Interval Lower .95	Confidence Interval Upper .95	Reg. coeff.	Hazard ratio	Reject null hyp.
Financial Distress							
X1_OCF/TA	-5.9646	0.0000	0.9549	0.9769	-0.0347	0.9659	Yes
Liquidity							
X2_WC/TA	-6.3181	0.0000	0.9954	0.9976	-0.0035	0.9965	Yes
X3_Current Ratio	3.8240	0.0001	1.0003	1.0008	0.0006	1.0006	Yes
Solvency							
X4_Solvency Ratio	-6.2530	0.0000	0.9911	0.9953	-0.0068	0.9932	Yes
X5_Shareholders'Equity Ratio	3.3157	0.0009	1.0003	1.0010	0.0006	1.0006	Yes
X6_Debt to Assets Ratio	6.4036	0.0000	1.0023	1.0043	0.0033	1.0033	Yes
X7_Debt to Equity Ratio	1.9656	0.0494	1.0000	1.0070	0.0035	1.0035	No
X8_Debt to Ebitdax	-3.3635	0.0008	0.9995	0.9999	-0.0003	0.9997	Yes
Profitability							
X9_Return on Assets	-0.3674	0.7130	0.9918	1.0056	-0.0013	0.9987	No
X10_Return on Equity	-0.2683	0.7880	0.9969	1.0024	-0.0004	0.9996	No
X11_Operating Profit Margin	-9.0307	0.0000	0.9993	0.9996	-0.0006	0.9994	Yes
Efficiency							
X17_Operating Cost per BOE	3.3852	0.0007	1.0003	1.0012	0.0007	1.0007	Yes
Energy							
X18_Production to Reserves	-0.5660	0.0007	0.0000	6,920.090	-3.5899	0.0276	No
X19_Reserves Replacement Rate	-0.5661	0.5710	0.0000	6,887.063	-3.5890	0.0276	No

As the outcome of the analysis is not binary but rather continuous for the variable tested, the regression coefficient is the intercept of interest for interpreting the survival analysis results, rather than the hazard ratio, included in table 19 for information purpose only. This interpretation is the following for X1: the estimate of the change in the log of the hazard in financial distress is -3.47% per unit of change of OCF/TA. This interpretation applies only to the variables for which the null hypothesis is rejected and deserve attention under the perspective of the directional effect on financial distress presented in table 2. Thus, the rate given by the regression coefficient is the estimate of the decrease in the log of the hazard in financial distress per unit of change in X1 (-3.47%), X2 (-0.035%), X4 (-0.068%), X5 (-0.006%) and X11 (-0.006%). A unit increase in any of these ratios reduces the log of the hazard in financial distress by their respective percentage of regression coefficient. Alternatively, for X6 (0.033%) and X17 (0.007%) the positive rates indicate, as directionally expected, a decrease in the log of the hazard in financial distress per unit of change in these predictors. Counterintuitively, for X3 (-0.006%) an increase in current ratio tends to also increase the hazard of financial distress, and for X8 (-0.003%) an increase in debt relative to Ebitdax decreases, rather than increases, the risk of financial distress, albeit as with these variables, in very modest proportions.

The price of oil is a strong externality that impacts the oil and gas industry, as explained above in chapter three. While this economic observation is not central to this study, the researcher takes the opportunity of having available data and survival analysis processing capability to test the baseline model variables that rejected the null hypothesis considering an oil price change. This part of the analysis requires a stratification that starts by running a histogram of company starts by quarter, further aggregated by year as showed in figure 3 (company starts refers to company starting to publish quarterly results as a public E&P company listed in the TSX).

Figure 3. Histogram of Company Starts by Year

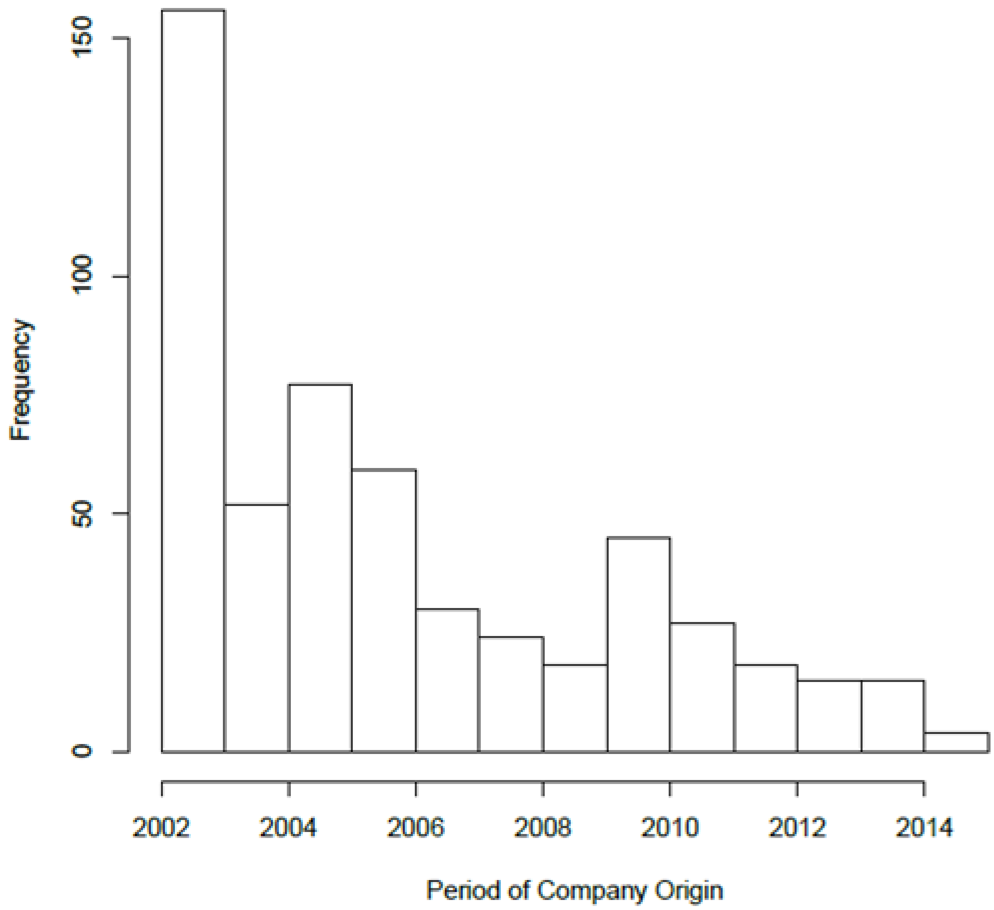

Figure 3. Histogram showing the number of Canadian oil and gas firms starting to be publicly traded on the TSX by year. The first year of 2002 corresponds to the first year of the sample size in this study and includes all companies that were already trading on the TSX as of Q1-2002. Adapated from data provided by JuneWarren Nickle's (2016) (JWN, 2016; TMX, 2016).

The histogram in table 3 shows 13 periods for each year between 2002 and 2015. To stratify this histogram relative to the price of oil, the researcher refers to the historical chart of crude oil prices in figure 2. This chart shows two major price inflection points during the period of interest in this study: Q3-2008 and Q3-2014, each marking a severe inflection in the chart and the price of oil.

Figure 2. 20-year Historical Chart of Crude Oil Prices

Figure 2. Chart of the WTI crude oil prices in USD from January 1st, 1998 to October 1st, 2016, showing the oil price growth and drops triggering the cycles of booms and busts (Macrotrends 2016).

With these two dates, the researcher further consolidates the histogram into three strata, each representing the company starts for the periods of Q1-2002 to Q2-2008, Q3-2008 to Q2-2014, and Q3-2014 to Q4-2015. The resulting histogram in figure 4 shows a very small stratum for the last period and the researcher elects to merge it with the second stratum.

Figure 4. Histogram of Stratified Company Starts by Period

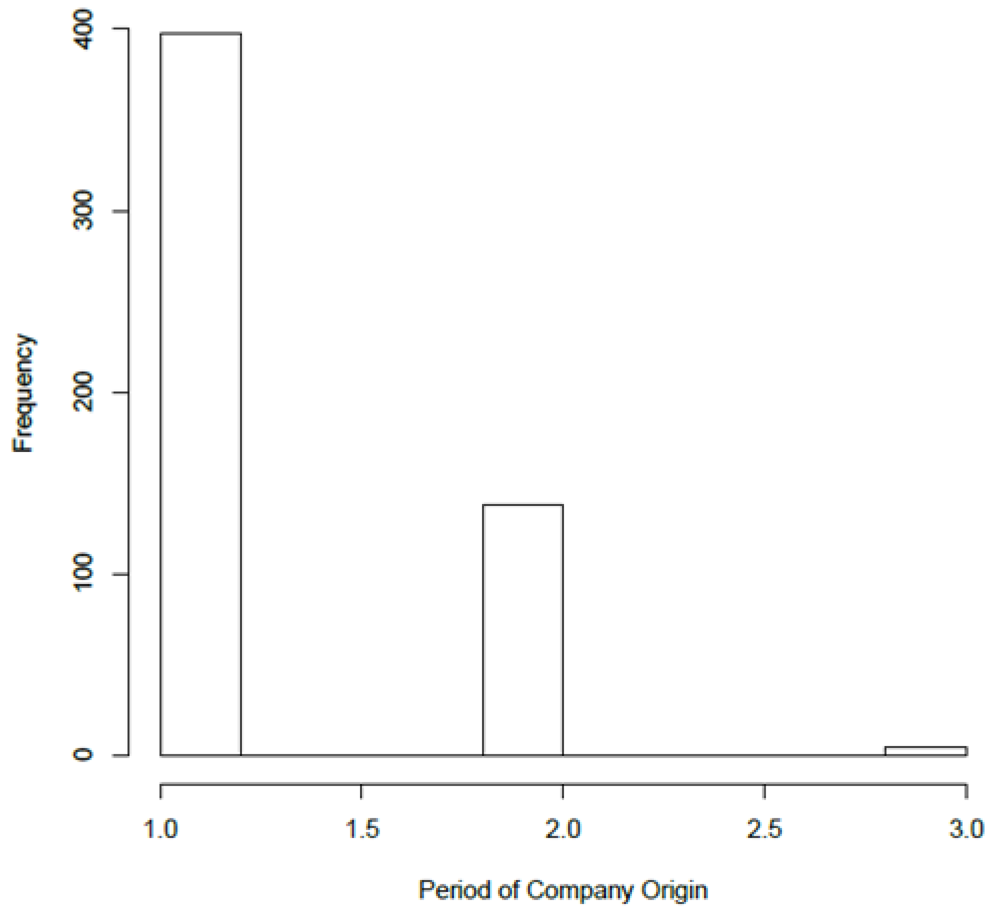

Figure 4. Histogram of oil and gas firms becoming publicly traded on the TSX, aggregated into three strata from the histogram in figure 3.

With only two strata representing company starts before and after the steep price correction of the end Q2-2008, a univariate survival analysis using only this stratification as a predictor shows in figure 5 a higher cumulative hazard of distress for companies that started after Q3-2008 in stratum two (blue) compared to the companies in stratum one (red) that started between Q1-2002 and Q2-2008. The distinct and higher sloped blue stratum compared to the red stratum indicates a higher risk of financial distress hazard for the firms that started post Q2-2008, and the colored halo around the curve indicates a larger confidence interval and more volatility for that same blue stratum two compared to the red stratum one. The table of number of firms at risk below the graph shows the number of firms entering the sample, therefore starting to be publicly traded, each year, that are at risk of experiencing financial distress. For stratum two for example, 142 firms became active in the sample in the second half of 2008 and eight in the last year preceding Q1-2016.

Figure 5. Period Cumulative Hazard

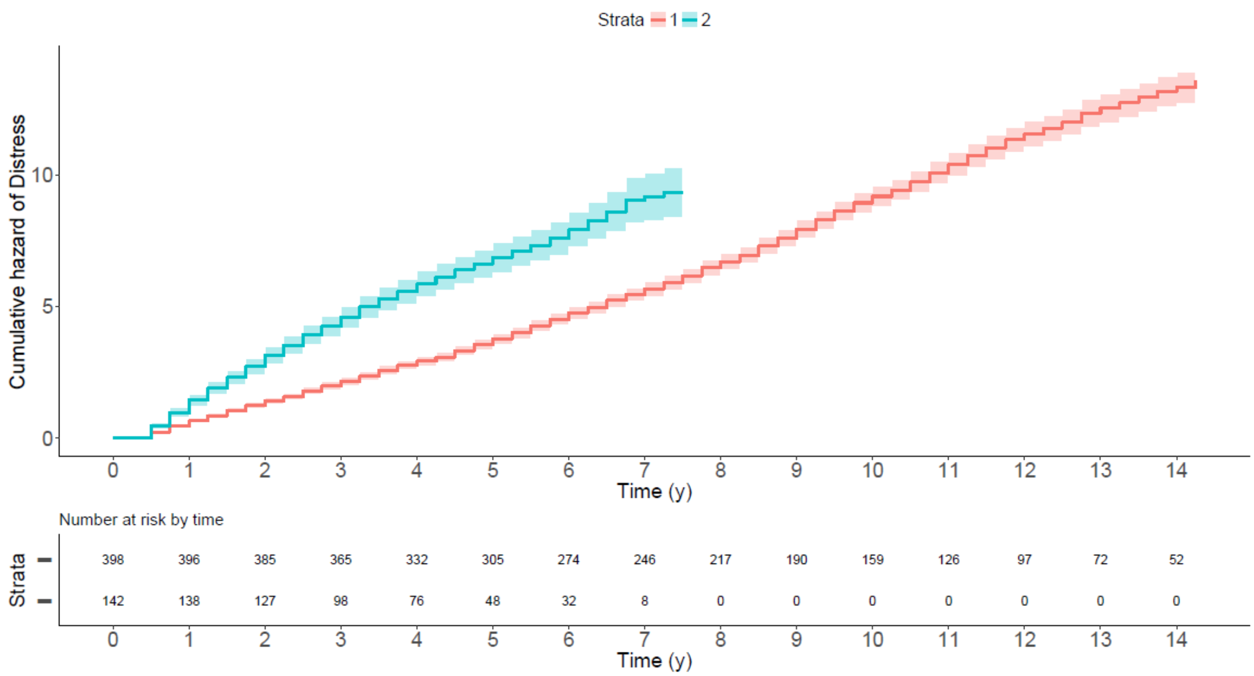

Figure 5. Cumulative hazard curves showing the increased risk of financial distress for firms that started (became public) since Q2-2008, in blue, compared to firms that started between Q1-2002 (including those that were already active and public by then) and Q1-2008.

The researcher then runs the survival analysis using the stratified model for the baseline predictor variables that did reject the null hypothesis to understand if the change in oil price contributes to further changing the baseline model results summarized in table 20. For this test, the null hypothesis is: the change in oil price in June 2008 does not affect the correlations found in the baseline model valid predictors. The alternative hypothesis is that the June 2008 variation in oil price changes the correlations found in the baseline model valid predictors.

The results summarized in table 21 show that except for X1, there is no evidence of change due to the oil price drop. For X1, the regression coefficient increases from -0.0347 to -1.5464, representing a 44.5 times increase and thus a significant decrease in risking financial distress per unit increase of OCF/TA following the decrease in oil price.

Table 21

Baseline Model Stratified Survival Analysis

Predictor	z	p-value	Confidence Interval Lower .95	Confidence Interval Upper .95	Reg. coeff.	Reject null hyp.
Financial Distress						
X1_OCF/TA	-14.6165	0.0000	0.1731	0.2621	-1.5464	Yes
Liquidity						
X2_WC/TA	1.9598	0.0500	1.0000	1.0450	0.0220	No
X3_Current Ratio	1.0508	0.2934	0.9996	1.0013	0.0005	No
Solvency						
X4_Solvency Ratio	0.2794	0.7800	0.9949	1.0068	0.0008	No
X5_Shareholders'Equity Ratio	1.2770	0.2016	0.9961	1.0186	0.0073	No
X6_Debt to Assets Ratio	-1.3423	0.1800	0.9337	1.0129	-0.0279	No
X8_Debt to Ebitdax	1.2037	0.2287	0.9996	1.0016	0.0006	No
Profitability						
X11_Operating Profit Margin	3.1448	0.0017	1.0002	1.0010	0.0006	No
Efficiency						
X17_Operating Cost per BOE	-1.6115	0.1071	0.9971	1.0003	-0.0013	No

Table 22 and figure 6 are example outputs of the R survival analysis and cumulative hazard curve. The appendices to this study contain additional outputs.

Table 22

Sample output of R Survival Analysis

Predictor: X1_OCF/TA	Coef	Std. Err.	Exp(coef)	Exp(-coef)	z	P > |z|	Lower .95	Upper .95
Final Data Period 22	0.6191	0.0479	1.8573	0.5384	12.9286	0.0000	1.6909	2.0400
Final Data X1_OCF.TA	-0.0347	0.0058	0.9659	1.0354	-5.9646	0.0000	0.9549	0.9769
Final Data Period 22: Final Data X1_OCF.TA	-1.5464	0.1058	0.2130	4.6946	-14.6165	0.0000	0.1731	0.2621

n = 11,719, number of events = 3,372 (4,117 observations deleted due to missingness)	
Concordance	0.847 (se = 0.008)
R-square	0.029 (max possible = 0.953)
Likelihood Ratio test	349.7 on 3 degrees of freedom p = 0.0001
Wald test	547.4 on 3 degrees of freedom p = 0.0001
Score (logrank) test	699.8 on 3 degrees of freedom p = 0.0001

Figure 6. Sample Cumulative Hazard Curve – Stratified OCF/TA

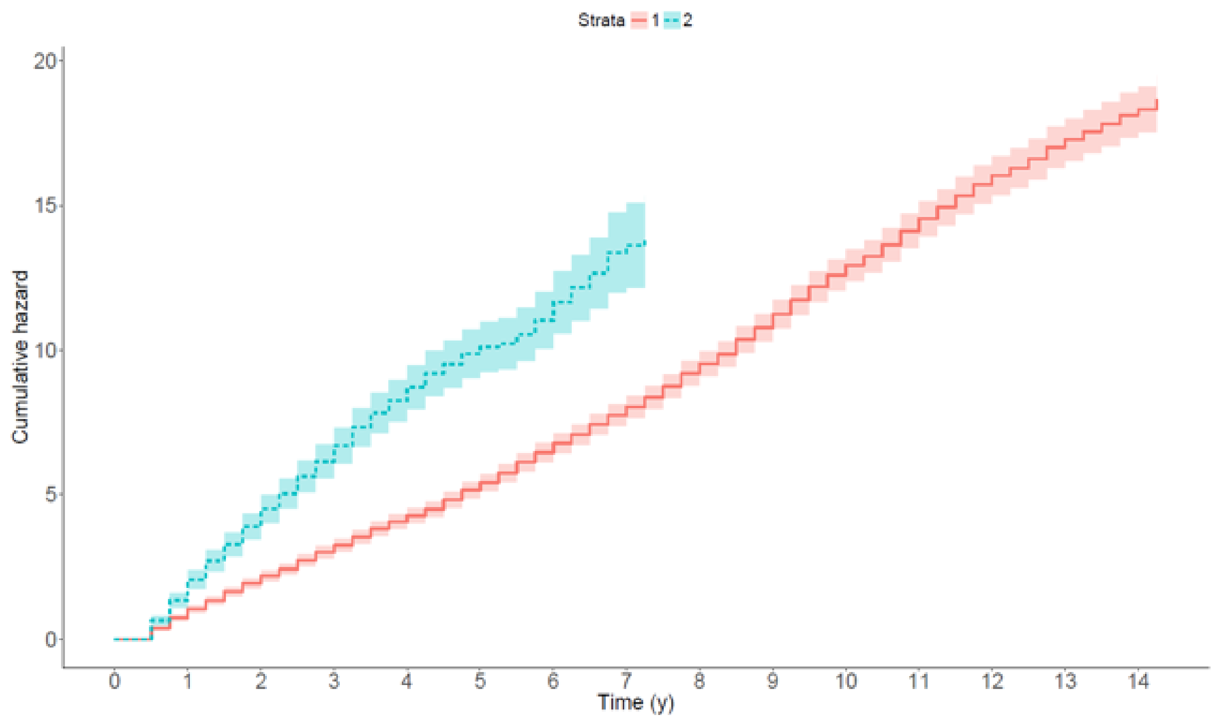

Figure 6. Sample representation of the cumulative hazard showing an increased risk of financial distress for stratum two firms over stratum one firms, using OCF/TA as a predictor.

The baseline model is not the focus of this study, unlike the three hypotheses tested below, but it provides a general context for the survival analysis of the Canadian oil and gas firms using a new definition of financial distress. The univariate models, ran on sample of quarter-firms ranging from 2,641 to 15,805 are valid and present a strong goodness of fit making their results reliable. Those results show the existence of a predictive correlation between nine variables and financial distress, however the values of the regression coefficients are very small. A stratification around the time of the June 2008 drastic oil price drop shows that the firms that started after that period are more exposed to financial distress than those that existed before. Additionally, the stratification fails to reveal any change in the original survival analysis due to the change in oil price, except for the only variable that is inherently tied to the definition of financial distress used in this study. This contextual baseline model analysis provides a background for the three hypotheses that make the focus of this research.

Hypothesis 1 – Hedging

The survival analysis for the hedging hypothesis uses a sample of 11,005 quarter-firms and shows very decisive results in rejecting the null hypothesis. The goodness of fit is strong and observable through the very low z-score confirmed with an extremely low p-value. Additionally, the likelihood ratio test is high and in agreement with the Wald test and the score (logrank) test (all exhibiting low p-values too). The confidence interval of 0.0436 and 0.0669 is far removed from one and narrow, indicating a high level of precision with very little volatility for the predictive accuracy of the correlation of hedging to hazard of financial distress. Table 23 shows the results of the survival analysis. As explained in chapter 3, when the point estimate or hazard ratio is one, there is no relationship between the predictor and the event, a number larger than one indicates as many times the hazard for the sample of non-censored firms compared to the total sample and a number lower than one conversely means as fewer chances of hazard. As opposed to the baseline model, where the output is not binary, the hedging hypothesis uses a Heaviside function identifying the presence of hedging in percentage of BOE hedged with “1” and the absence of hedging with “0”. Therefore, the right correlation to read is the point estimate given by the hazard ratio. HR is 0.0540, a value that is 18.5130 times lower than one. This means that the null hypothesis is rejected and that the firms that hedged had more than 18.5 times less chances to be exposed to the hazard of financial distress.

Table 23

Hypothesis 1 Hedging - Survival Analysis Results

Predictor: Hedging	Coef	Std. Err.	Exp(coef)	Exp(-coef)	z	P > |z|	Lower .95	Upper .95
Final_dataStart	0.0292	0.0024	1.0297	0.9712	12.3917	0.0000	1.0249	1.0344
Final_dataHedging	-2.9185	0.1093	0.0540	18.5130	-26.7015	0.0000	0.0436	0.0669

n = 11,005, number of events = 3,647 (6 observations deleted due to missingness)

Concordance	0.713 (se = 0.007)
R-square	0.174 (max possible = 0.976)
Likelihood Ratio test	2,101.0 on 2 degrees of freedom p = 0.0001
Wald test	861.8 on 2 degrees of freedom p = 0.0001
Score (logrank) test	1,513.0 on 2 degrees of freedom p = 0.0001

Figure 7 represents the cumulative hazard curves of both populations of firms. The hedging firms have a rather flat and consistently low curve in blue, indicating their low level of exposure to financial distress. The non-hedging firms' red curve show on the contrary an increasing and higher cumulative hazard with limited volatility in the form of a narrow confidence interval throughout. Thus, for hypothesis one, the survival analysis shows a strong correlation between the hedging activity and the event of financial distress: hedging firms are 18.5 times less exposed to the hazard of financial distress than non-hedging firms.

Figure 7. Hypothesis 1 Hedging - Cumulative Hazard Curve

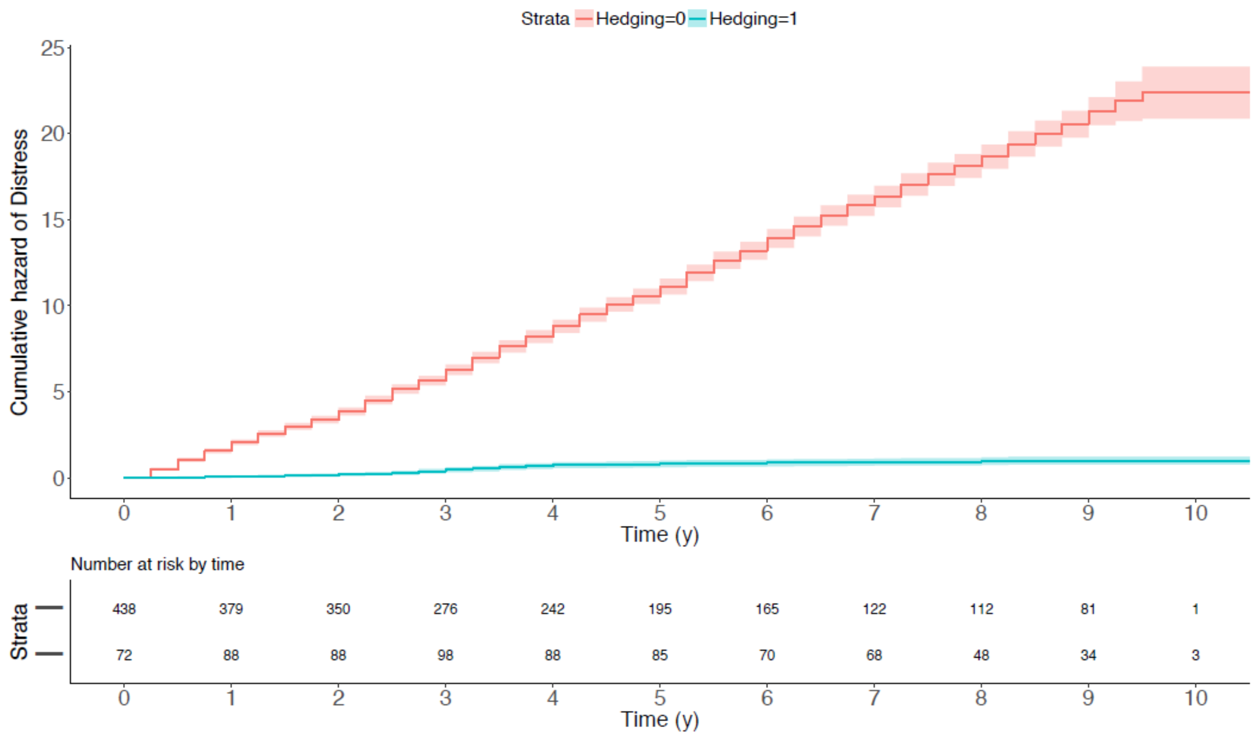

Figure 7. Cumulative hazard curves showing a higher risk of financial distress for firms that had no hedging policy, in red, compared to firms that had an active hedging policy, in blue.

Table 24 shows that for 2,794 firms that hedged, only 86 experienced financial distress, that is 3.07%; and for 8,211 non-hedging firms, 3,561 did experience financial distress, a proportion of 43.37%. These statistics provide a different perspective that further confirms the results of HR and the cumulative hazard curve in table 23 and figure 7.

Table 24

Hypothesis 1 Hedging - Survival Analysis Descriptive Statistics from R

Predictor: Hedging	Records	N.Max	N. Start	Events	Median	0.95LCL*	0.95UCL**
Final_data hedge = 0	8,211	438	438	3,561	0.5	0.50	0.50
Final_data hedge = 1	2,794	100	72	86	4.0	3.25	6.25

Notes * LCL: Lower Confidence Limit

** UCL: Upper Confidence Limit

Hypothesis 2 – Size

The second hypothesis is tested on a large sample of 15,849 quarter-firms with only five observations deleted from the total sample due to missingness. The interpretation of the survival analysis results starts with the validity of the model, then the testing of the null hypothesis and a stratification by size to further understand the results.

Table 25 shows the return of the analysis performed in R. The z-score of -26.6573 is very low and the p-value is extremely small. The confidence interval around the hazard ratio of 0.8469 is very narrow at 0.8367 and 0.8573, and the likelihood ratio test is positive at 926.4, in agreement with the Wald test and the score (logrank) test (all of which have very small p-values too). Therefore, the model is valid and its strong goodness of fit makes its results reliable. The correlation coefficient is negative at -0.1661 and the hazard ratio is below 1 at 0.8469, indicating that the null hypothesis is rejected. For each unit of change in size, the estimate of change in the log of the hazard in financial distress is -16.61%. In other words, using the point estimate HR, each increment in size reduces the hazard of financial distress by 1.1807.

Table 25

Hypothesis 2 Size - Survival Analysis Results

Predictor: Size	Coef	Std. Err.	Exp(coef)	Exp(-coef)	z	P > |z|	Lower .95	Upper .95
Final_dataStart	0.0209	0.0014	1.0211	0.9794	14.4394	0.0000	1.0182	1.0240
Final_dataX20_Size	-0.1661	0.0062	0.8469	1.1807	-26.6573	0.0000	0.8367	0.8573

n = 15,849, number of events = 3,372 (5 observations deleted due to missingness)

Concordance	0.676 (se = 0.007)
R-square	0.057 (max possible = 0.91)
Likelihood Ratio test	926.4 on 2 degrees of freedom p = 0.0001
Wald test	932.2 on 2 degrees of freedom p = 0.0001
Score (logrank) test	930.4 on 2 degrees of freedom p = 0.0001

Having already tested the hypothesis and confirmed that the null hypothesis of no correlation between size and financial distress is rejected, the researcher performs a stratification of the sample by initially dividing the size by five to obtain five groups. Figure 8 shows the sequence of histograms leading to the final three strata. The second histogram shows that both extremes of very small and very large companies are very small in numbers and can thus be merged with the closest strata, delivering a final stratification of three strata visible in the third histogram in figure 8.

Figure 8. Hypothesis 2 Size – Stratification Histograms

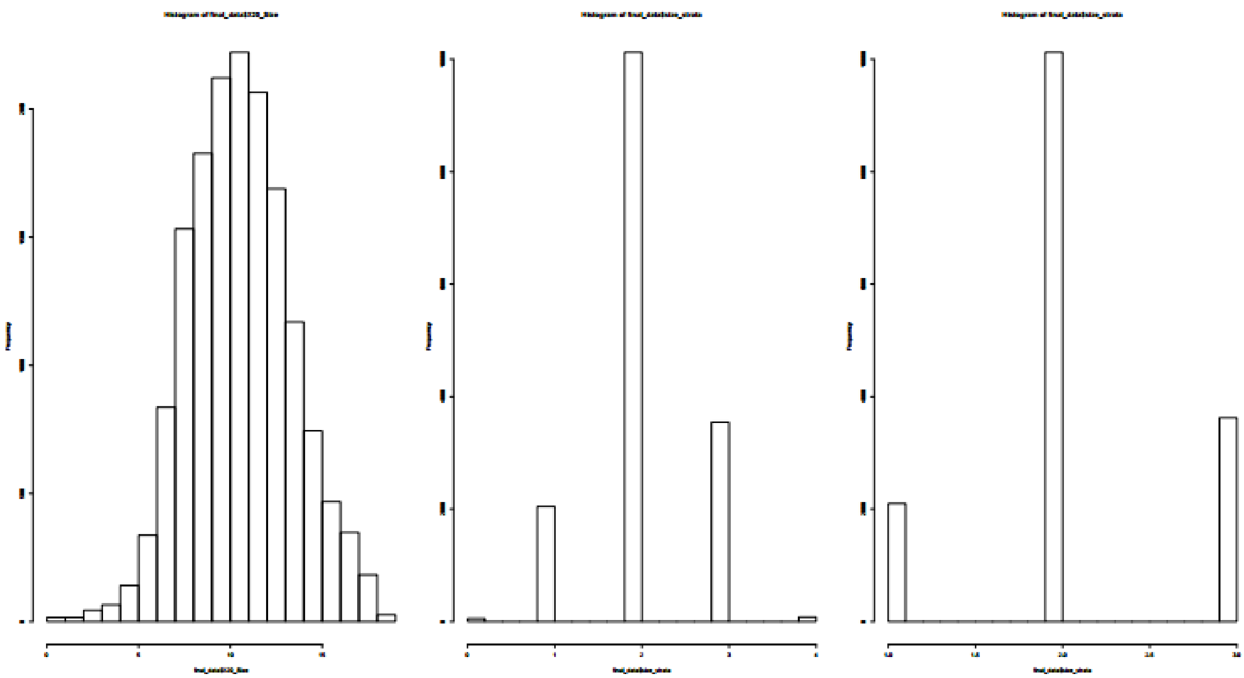

Figure 8. Three histograms representing the stratification of firm sizes from 19 categories to five strata and ultimately to three strata.

The stratification objective is not to test the null hypothesis, which is already confirmed as rejected. Rather, it is to gain further perspective on the impact of size in the hazard of financial distress through the cumulative hazard curve that presents a good visual in figure 9.

Figure 9. Hypothesis 2 Size – Stratified Cumulative Hazard Curve

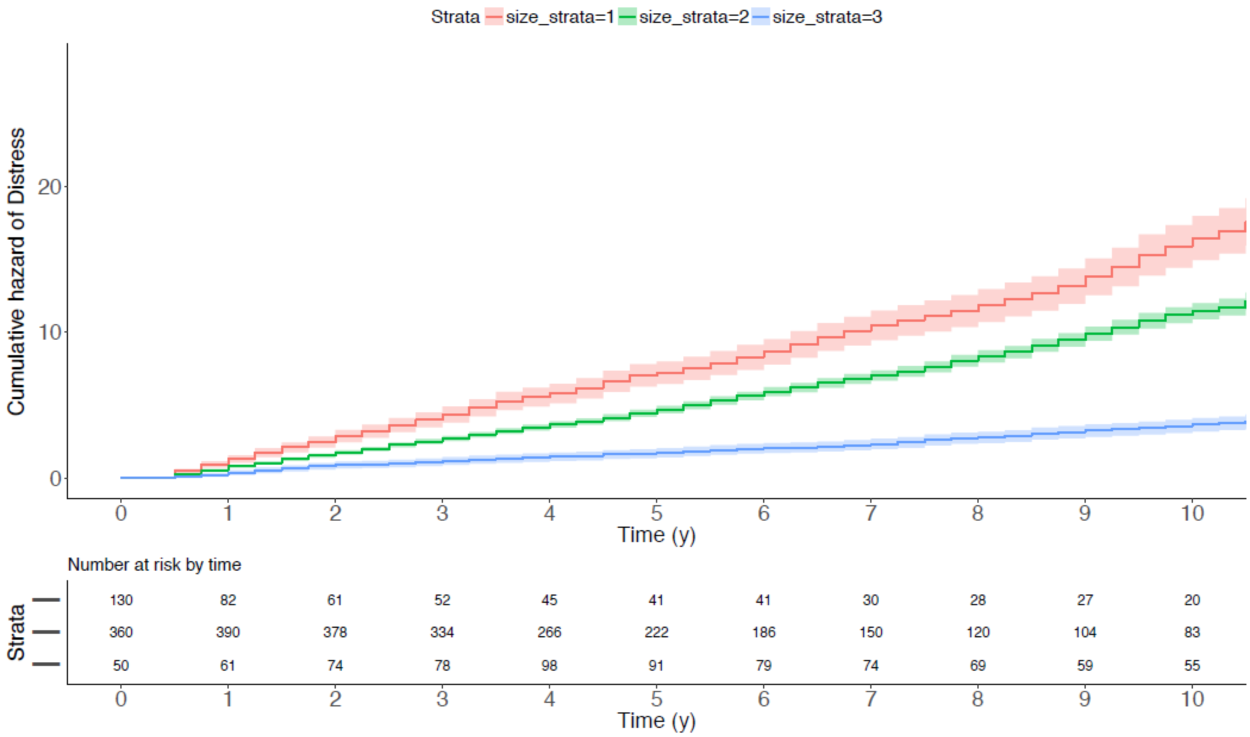

Figure 9. Cumulative hazard curves for all three strata tested in hypothesis two.

The three curves confirm the survival analysis by showing for stratum one in red, the strata of the smallest firms, a higher and slightly steeper cumulative hazard along with a larger confidence interval and volatility. Alternatively, the blue curve for the larger firms of stratum three is flatter and narrower, showing a lesser exposure to financial distress thanks to their larger size. And the larger sample of stratum two representing the middle of the histogram, is the green curve sandwiched between the other two strata, with a lower hazard than stratum one red curve firms and a higher hazard than stratum three blue curve larger firms.

Table 26

Hypothesis 2 Size - Survival Analysis Descriptive Statistics from R

Predictor: Size	Records	N.Max	N. Start	Events	Median	0.95LCL	0.95UCL
Final_data_Size_Strata = 1	2,099	130	130	688	0.75	0.75	0.75
Final_data_Size_Strata = 2	10,124	390	360	2,367	1.00	1.00	1.00
Final_data_Size_Strata = 3	3,626	100	50	317	1.75	1.25	2.25

Notes * LCL: Lower Confidence Limit
** UCL: Upper Confidence Limit

Table 26 reveals that for each stratum, the percentage of events to records is respectively 32.78% for stratum one, 23.38% for stratum two, and 8.74% for stratum three. These statistics further confirm the rejection of the null hypothesis and the existence of the inverse correlation between size increase and financial distress hazard.

Hypothesis 3 – M&A

The third hypothesis of this study explores the existence of a correlation between the state of financial distress and the event of being a target of an M&A activity. The sample size is 3,698 financially distressed quarter-firms for 175 M&A events involving 166 target firms. As with the previous two hypotheses, the analysis starts with the goodness of fit before accepting the results of the null hypothesis rejection or not. Table 27 shows the survival analysis results from R.

Table 27.

Hypothesis 3 M&A - Survival Analysis Results

Predictor: Financial Distress	Coef	Std. Err.	Exp(coef)	Exp(-coef)	z	P > |z|	Lower .95	Upper .95
Final_dataStart	0.0484	0.0075	1.0496	0.9527	6.4353	0.0000	1.0342	1.0652
Final_data_Fin.Dist.	-0.2216	0.2029	0.8012	1.2481	-1.0925	0.2750	0.5383	1.1924

n = 3,698, number of events = 175

Concordance	0.676 (se = 0.026)
R-square	0.01 (max possible = 0.334)
Likelihood Ratio test	37.9 on 2 degrees of freedom p = 0.0001
Wald test	41.4 on 2 degrees of freedom p = 0.0001
Score (logrank) test	42.9 on 2 degrees of freedom p = 0.0001

The concordance is 0.676, a value above 0.5 the threshold for a model being not better at predicting the outcome than chance, and just shy of 0.7, the minimum limit for a good model. This metric indicates a model that is at best acceptable but not good. The likelihood ratio is 37.9 on two degrees of freedom with a very small p-value (i.e. the LR value is trustworthy), and it agrees with the Wald test and the score (logrank) test. All these tests have positive but relatively low values, confirming the acceptability but weakness of the model. The R-square is very low at 0.01 and shows that the model's data is not close to the fitted regression line and does not provide any meaningful distinction between the explained variation and the total variation. The R-square of 0.01 also reveals that the model would not be good at providing any precise prediction. Figure 10 shows how the cumulative hazard curves for the stratum representing the sample population that did not experience the event of being an M&A target has an indistinct path from that of those financially distressed firms that were an M&A target.

Figure 10. Hypothesis 3 M&A – Cumulative Hazard Curve

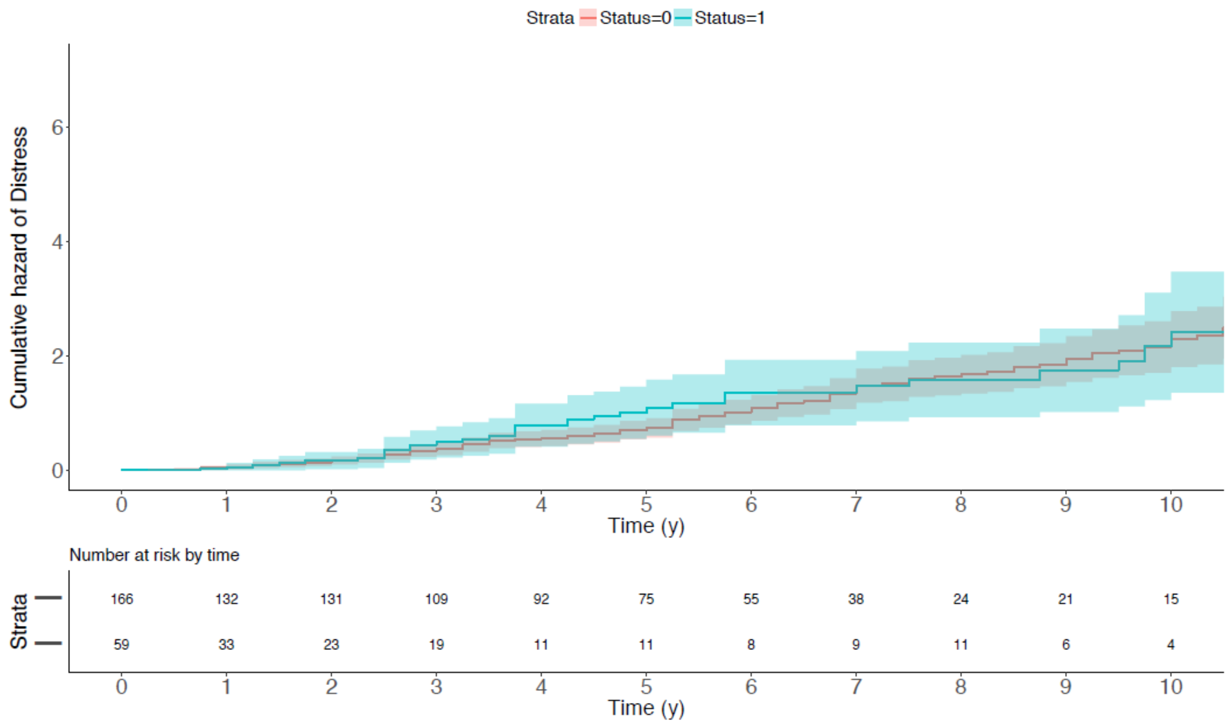

Figure 10. Cumulative hazard curves for hypothesis 3 showing the absence of a causal relationship between financial distress and the event of being an M&A target.

The graph also shows that the confidence intervals are large, especially the blue one for the M&A target firms. This graph provides a visual representation of the R-square results. Overall, with a positive and low LR confirmed by the Wald test and the score (logrank) test and a concordance superior to 0.5, the model is valid; but the low results of these tests and the very low R-square caution that the model is very weak. The model for hypothesis three is valid but very weak; it is however valid enough to proceed to the next step of the analysis and check the null hypothesis. The p-value of 0.2750 is largely superior to the threshold of 0.05 and indicates that the probability that the pattern of the M&A activity relative to the state of financial distress being created by some random process is too high to reject the null hypothesis. The model for hypothesis three is very weak yet valid, but the null hypothesis fails to be rejected and this survival analysis does not show a causal relationship between financial distress and the event of being an M&A target.

Despite the lack of null hypothesis rejection for the model of the univariate analysis, the researcher also runs a model using a vector of covariates including valuation metrics. Table 28 shows the results of this analysis.

Table 28.

Hypothesis 3 M&A Vector of Covariates - Survival Analysis Results

Predictor: Financial Distress	Coef	Std. Err.	Exp(coef)	Exp(-coef)	z	P > |z|	Lower .95	Upper .95
Final_dataStart	0.0641	0.0324	1.0662	0.9379	1.9805	0.0477	1.0007	1.1360
Final_dataStatus	0.5513	0.9119	1.7355	0.5762	0.6046	0.5455	0.2905	10.3670
X1-OCF/TA	0.1891	1.1660	1.2082	0.8277	0.1622	0.8712	0.1229	11.8753
X9_ROA	3.5240	3.8610	33.9198	0.0295	0.9127	0.3615	0.0175	65615.03
X10_ROE	0.5308	0.4091	1.7003	0.5881	1.2975	0.1945	0.7626	3.7910
X11_Op. Prof.	0.0017	0.0269	1.0017	0.9983	0.0627	0.9500	0.9503	1.0559
X12_P.E	0.0002	0.0007	1.0002	0.9998	0.3135	0.7436	0.9989	1.0015
X13_EV/Ebitdax	0.0032	0.0010	1.0032	0.9968	3.1142	0.0019	1.0012	1.0052
X14_EV/DACF	0.0017	0.0017	1.0017	0.9983	0.9959	0.3192	0.9984	1.0050
X15_EV/FCF	0.0035	0.0021	1.0035	0.9965	1.6910	0.1029	0.9994	1.0075
X16_EV/2P	-1.1680	9.1790	0.3110	3.2156	-0.1272	0.2031	0.0000	548.1740

n = 547, number of events = 23 (3,151 observations deleted due to missingness)

Concordance	0.782 (se = 0.076)
R-square	0.046 (max possible = 0.186)
Likelihood Ratio test	25.5 on 11 degrees of freedom p = 0.007619
Wald test	17.9 on 11 degrees of freedom p = 0.0837
Score (logrank) test	28.0 on 11 degrees of freedom p = 0.003295

R ran this model for 547 observations of financial distress only, with 23 events of being an M&A target, and censored 3,151 observations. The concordance shows a good model and the LR is positive, the model is valid. Regarding the null hypothesis that the covariates have no predictive value for the event of being an M&A target, the results in table 28 confirm those of table 27 with one exception. The p-value is too high for all covariates but one to reject the null hypothesis. That exception is the X13_EV/Ebitdax covariate with a p-value of 0.0019 and a narrow confidence interval that is also different from one. The interpretation of this result is that for each unit of change in the ratio of EV/Ebitdax, the estimate of change in the log of the hazard in being an M&A target is 1.0032. The overall result for hypothesis 3 remains nonetheless that the null hypothesis is not rejected.

Summary of Results

This study focuses on three hypotheses for which table 29 provides a summary of results.

Table 29

Summary of results

Hypothesis	Coeff	HR	HR Times	z	p-value	Confidence Interval Lower .95	Confidence Interval Upper .95	Accept Model	Reject Null
H1 - Hedging	-2.9185	0.0540	18.5130	-26.7015	0.0000	0.04360	0.06692	Yes	Yes
H2 - Size	-0.1661	0.8469	1.1807	-26.6573	0.0000	0.83666	0.85735	Yes	Yes
H3 - M&A	-0.2216	0.8012	1.2481	-1.0925	0.2750	0.53833	1.19243	Yes	No

Albeit a baseline model serves as a foundation to explore for the first time the existence of strength of the correlation between standard financial ratios and the hazard of financial distress as defined in terms of two consecutive quarters of negative OCF/TA efficiency ratio, table 29 does not include this baseline model. Suffice to say about the baseline model that the results of the univariate Cox extended model survival analyses (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012) do show a correlation between nine financial ratios (out of 15) and the event of financial distress hazard, but this correlation remains very small. The stratification visible in figure 6 shows that the oil price shock of June 2008 is a distinct shift in the exposure to financial distress between firms that started their activity after date (higher hazard) and those that had started before (lower hazard). However, this shift does not alter the initial results of the baseline model and thus fail to amplify the already low correlations for the nine valid predictor variables.

The study results in table 29 show that the models are valid for all three hypotheses and allow to check the null hypothesis. For hypotheses one and two, the null hypotheses are rejected, and for the hypothesis three it is not. The results for hypothesis one show that a hedging firm is 18.5 times less likely to experience the hazard of financial distress than a non-hedging firm. The results for hypothesis two indicate that the estimate of the change in the log of the hazard in financial distress is -16.61% per unit of increase in size, therefore, the larger the firm the less likely it is to experience financial distress. The results for hypothesis three are that financial distress is not a reliable predictor variable of the event of being an M&A target. With the results of the study now available, disclosed and interpreted statistically, this research reaches the point to review the entire study, discuss the results and offer recommendations, in the last chapter of conclusions and recommendations (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012).

Chapter 5: Conclusions and Recommendations

This research concludes with this chapter, following an opening with an overview chapter before a literature review to provide an exhaustive background to this study, and a methodology chapter leading to the presentation and analysis of the results. This ultimate part starts with a summary of the key points in this research, follows with a discussion of the results, then a section on the conclusion and practical recommendations and closes with recommendations for future research.

Summary of the Results

The content in this study, building up to this concluding chapter, is vast and varied. This section proposes a refresher summary of the key components of this study, including the problem statement, the significance of the study, the literature review findings, the methodology and the results.

Summary of the problem statement

An economic context with severe impact on the Canadian oil and gas sector sets the background of this study. The problem this context sheds light on and that drives this research is the dire financial distress Canadian oil and gas firms experience during bust cycles. The Canadian economy is commodity driven, and among other commodities such as grain, coal, phosphate or gold and diamond to name a few, oil and gas play a significant role sustaining almost a million jobs, driving the province of Alberta and representing over CAD 81B in annual investment (CAPP, 2016; Millington, 2016; PSAC, 2016). The oil and gas industry in Canada follows boom and bust cycles and is sensitive to the volatility of the price of oil on the international markets, conventionally reported in USD for the WTI index. Since the mid-1970's there have been a series of cycles and the period of interest in this study from Q1-2002 to Q1-

2016 includes an oil price growth that peaked at USD 151.72 in June 2008, fell sharply right after in the context of the 2008 and 2009 financial recession, resumed with a growing but volatile growth and fell again in June 2014, starting one of the most severe bust cycles this industry has experienced, epitomized with a January 2016 oil price floor of USD 28.50 (Macrotrends, 2016). Canada is a net exporter of oil and per Millington (2016), every annualized dollar increase in the price of oil barrel represents a CAD 1.7B GDP increase for the period of 2015-2021. In Calgary, the Canadian oil and gas capital located in Alberta where the oil sands producing 97% of Canadian oil are located, employers in all sectors have implemented massive lay-offs, hiring and investment freezes, and many companies have been struggling to survive (CAPP, 2016; PSAC, 2016). This bust cycle started in the second half of 2014 and in early 2017, it is still not recovering as an economic leading indicator consisting in the city's downtown offices occupancy rate shows that 30% of the available office space is empty (Avison Young, 2007; Macrotrends, 2016). In the two years from September 2014 to August 2016, 20 Canadian oil and gas firms have filed for bankruptcy and several others have and still are experiencing financial distress (Haynes & Boone, 2016; Office of the Superintendent of Bankruptcy Canada, 2016). These two notions are distinct and this study's introduction of a new financial distress definition contributes to its significance (Avison Young, 2007; CAPP, 2016; Haynes & Boone, 2016; Macrotrends, 2016; Millington, 2016; Office of the Superintendent of Bankruptcy Canada, 2016; PSAC, 2016).

Summary of the significance of the study

The significance of this study is multifold. The scope, originality, method, and practical use to the business world contribute all to the importance of this research. The scope of this study pertains to the importance of the oil and gas industry in Canada that materially permeates the value chains of several other sectors including transportation, construction, banking, hospitality and retail among others with $142B of 2015 nominal GDP (7.7% of Canadian GDP) and 709,548 direct and indirect jobs (3.9% of national employment) (Natural Resources Canada, 2017). The scope also relates to the size of the sample: 540 firms with public quarterly financial data during a 14-year period and representing a sample size of more than 15,850 observations. This study is original in its focus on Canadian oil and gas, its use of an extended Cox model with repeating events (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012), its use of a new and clearly rationalized definition of financial distress that leverages the existing literature, and the hypotheses of hedging, size and M&A it explores. Testing hedging as a minimizing factor of Canadian oil and gas firms' financial distress hazard is a novelty in the existing literature; testing size in the same context is a confirmation of the literature consensus for an original scope (Aziz & Dar, 2006; Fitzpatrick & Ogden, 2011; Raj & Rinastiti, 2002; Shumway, 2001); and testing the impact of financial distress on the status of being a target in Canadian oil and gas M&A activity is also an original attempt that may contribute to the design of future research for more decisive results. The method of an extended Cox model with repeating events is a survival analysis technique that gives this study a depth and breadth alternative binary bankruptcy predictive analyses cannot match, especially with such a large sample and for the dynamic perspective of understanding the time to the event (Chen & Lee, 1993; Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012). To practitioners, along with scholars, this study provides a new helpful perspective through the definition of financial distress when making diagnoses, appreciating profitability and going concern capability during bust cycles, and ultimately making strategic decisions. This study contributes to oil and gas managers' understanding of the importance of their assets' efficiency and capacity to autonomously generate cash, secure solvency, long term profitability and growth through sustained capital investment. Similarly, this study also contributes to managers' understanding of the importance of hedging and size for preventing financial distress. The significance of this study also stems from being framed within a clearly stated post-positivist paradigm, in the tradition of several quantitative studies that are part of the literature review of this research (Aziz & Dar, 2006; Chen & Lee, 1993; Cox, 1972; Fitzpatrick & Ogden, 2011; Fox, 2008; Klein & Kleinbaum, 2012; Natural Resources Canada, 2017; Raj & Rinastiti, 2002; Shumway, 2001;).

Summary of the literature review

The literature review of this study starts by providing a contextual and historical framework of the evolution of the use of financial ratios as the main predictive tool in corporate failure. This introduction serves to better understand the two main paradigms of multi-discriminant analysis (MDA) and conditional probabilities models that remain literature benchmarks and that preceded the variety of alternative methods mainly using intelligent techniques. In the rich field of corporate failure predictive approaches, survival analysis stands apart in its ability to assess the hazard. The literature review also includes the notion of financial distress and the current state of research on the three topics of the hypotheses, hedging, size and M&A.

The use of financial ratios started at the turn of the past century and evolved in the 1920's with the first empirical studies geared towards credit worthiness (Horrigan, 1968). More studies, larger and more focused followed, up to the early sixties, but it was Beaver (1966) who set off the main paradigm shift in bankruptcy prediction, rapidly followed by Altman (1968) with the MDA developed Z-score. Ohlson (1980) and Zmijewski (1984) shifted the MDA paradigm towards the logit and probit conditional probabilities models. MDA carried restrictive assumptions requiring demanding transformations, and while logit an probit were less demanding but very sensitive to multicollinearity and outliers, both methods are intuitively comfortable and popular among neophytes (Balcaen & Ooghe, 2006). The advent of increased computing power and data processing capabilities enabled alternative techniques to enter the field of bankruptcy and corporate failure prediction. Those include neural networks, support vector machines or decision trees among others. Until Ohlson (1980), empirical studies used pair matching and all but survival analysis, rely on a pass/fail binary response (Altman, 1968; Balcaen & Ooghe, 2006; Beaver, 1966; Horrigan, 1968; Ohlson, 1980; Zmijewski, 1984).

Cox (1972) proposed a semi-parametric approach to survival analysis that social sciences and finance researchers adapted from biostatistics and epidemiology to gain superiority in bankruptcy and corporate failure prediction over the binary results providing techniques (Cox, 1972; InfluentialPoints, 2016; Pereira, 2014). That superiority stems from the use of larger data, longer time-frame, the proportional hazards assumption, the assumption of no multicollinearity, the hazard ratio and the survival rate showing survival or hazard probabilities over time. Of the 67 business-related survival analyses using a proportional hazards method this research has found, only two are Canadian: Chen and Lee (1993) did the only published Cox PH survival analysis on a sample of 175 firms including 67 financially distressed; and more recently Davydenko (2013) focused on credit analysis with a large sample of 30,744 firm-months. Chen and Lee (1993) used time-independent covariates and suggested future research to include time-dependent financial ratios as well as consider M&A as alternative causes for exit. Among other findings, they reported that cash flow is not an important determinant of survival time for oil and gas companies. They used a definition of financial distress aligned with Beaver's (1966) and based on bankruptcy, default, or suspension of preferred dividends (Beaver, 1966; Chen & Lee, 1993; Cox, 1972; Davydenko, 2013; InfluentialPoints, 2016; Pereira, 2014).

The literature is very heterogeneous in defining financial distress and the criteria include asset value decrease, illiquidity, insolvency and default, dividend reduction, bankruptcy filing, restructuring, drop in profitability, stock market value, lay-offs, sales decrease and debt refinancing. Outecheva (2007) described financial distress as a cycle starting with early impairment when the firm is still solvent followed by a deterioration of performance affecting profitability, the firm still being solvent; then insolvency and default where the firm is illiquid. In a subsequent phase, the firm is firmly insolvent and faces a death struggle characterized by an exit choice of liquidation, takeover or survival. Survival happens through a restructuring of the troubled debt leading back to solvency which starts the last stage of the cycle, recovery. Hillier et al. (2012) included in the state of financial distress the need for management to take decisive strategic action to correct the downhill course or save the company. Despite a very large number of studies on financial distress over several decades, there is still no consensus on a standard definition; rather, Outecheva (2007) concluded that "the state of the art in the theory of financial distress is…to interpret it as dependent on the purpose of research under a particular point *[sic]* of view" (Outecheva, 2007, p.18). (Hillier et al., 2012; Outecheva, 2007).

The hedging literature initially focused on how to hedge, from the 1960's until the early 1980's before shifting to the reasons for hedging which include a reduction in the cost of financial distress among other motives. For Chowdry and Schwartz (2012), firms should hedge the probability of bankruptcy through specific transaction exposure rather than its impact. Breeden and Viswanathan (2016) found that firms hedge to lock in performance. With a focus on oil and gas, Jin and Jorion (2006) analyzed that hedging does not increase market value.

Lookman (2004) had also reached the same conclusion, adding that for undiversified firms facing primary (commodity) risk, hedging was associated with high agency costs, lower firm value and bad management. Haushalter (2000, 2001) reported that oil and gas producers do not hedge all their exposure and that firms with high leverage and thus higher financing cost, tend to hedge more; firms with lower basis risk also tend to hedge more; and as hedging is a costly process requiring specific expertise and economies of scales in transaction costs, larger firms tend to hedge more (Breeden & Viswanathan, 2016; Chowdry & Schwartz, 2012; Haushalter, 2000, 2001; Jin & Jorion, 2006; Lookman, 2004).

Firm size is a frequent topic in the corporate failure literature and there is a scholar consensus that firm size has strong failure predictive power and that firm size inversely correlates to bankruptcy risk (Aziz & Dar, 2006; Fitzpatrick & Ogden, 2011; Raj & Rinastiti, 2002; Shumway, 2001). For Rommer (2004), firm size follows a U-shaped statistic where small firms lack resilience to shock and are thus exposed at one branch, while at the other branch large firms lack flexibility and nimbleness to quickly monitor their employees and communicate internally. In a review of 100 empirical papers Dang and Li (2015) found that the most frequent measure of firm size is the natural logarithm of assets. Thus, a review of firm size literature decisively shows that firm size is a good predictor of financial distress, the risk decreases with size and the measure for size is Log assets (Aziz & Dar, 2006; Dang & Li, 2015; Fitzpatrick & Ogden, 2011; Raj & Rinastiti, 2002; Rommer, 2004; Shumway, 2001).

Several authors considering the relationship between financial distress and M&A saw in M&A a bankruptcy avoidance strategy and correlated solvency fragility to increased takeover risk (Jin & Jorion, 2006; Kyimaz, 2006; Lookman, 2004; Powell & Yawson, 2007). Dickerson et al. (2003) found in pre-emptive acquisitions a defense mechanism against hostile take-over and a great influence against the probability of bankruptcy. Before them, Stiglitz (1972) had seen a higher risk of hostile take-over in firms with high debt-to-equity ratio, which he equated to high bankruptcy risk. For Erel et al. (2015), being acquired lifts the financial constraint of the target firm. Powell and Yawson (2007) found that the variables used to predict takeovers are similarly useful for bankruptcy prediction. In Canada, Cohen et al. (2009) identified a surge in oil and gas M&A activity for tax optimization purposes following a 2006 fiscal policy change (Cohen et al., 2009; Dickerson et al., 2003; Erel et al., 2015; Jin & Jorion, 2006; Kyimaz, 2006; Lookman, 2004; Powell & Yawson, 2007; Stiglitz, 1972).

Summary of the methodology

The key construct of interest of this study is the notion of financial distress defined as two consecutive quarters of negative operating cash flow to total assets ratio. Exploration and production (E&P) of oil and gas, especially in Canada where oil sands are more expensive to exploit than light crude fields elsewhere in the world, is a capital intensive, asset heavy and long lead time industry (CAPP, 2016). This definition of financial distress leverages the notion of death struggle by Outecheva (2007) and the necessity of strategic action put forth by Hillier et al. (2012) while putting the emphasis on asset efficiency. The efficient use of the productive assets should generate the cash flow necessary to sustain profitability and reinvest in the assets to grant growth. The first quarter of negative OCF/TA is an alert about the going concern of the firm which should trigger strategic corrective action; a second consecutive period puts the firm in financial distress, a state where it still can take corrective action and a state that can become chronic with repetitive events for several quarters (CAPP, 2016; Hillier et al., 2012; Outecheva, 2007).

This study builds a baseline model and tests three hypotheses. The baseline model includes a vector of covariates with select ratios for liquidity, solvency, profitability and industry-specific variables. Setting up a baseline model is a common practice in survival analysis, as is the use of vectors of covariates when there are multiple independent variables (Fox, 2008; Klein & Kleinbaum, 2012). In this study, however, the actual testing of the baseline model consists in a series of univariate analyses on each predictor variable. This approach yields higher precision and eliminates the potential risk of multicollinearity or confounding a vector may carry. Each of these analyses tests the null hypothesis that the independent predictor variable has no effect on the hazard of financial distress. The baseline model uses the public financial quarterly reporting from Q1-2002 to Q1-2016 for a sample of 540 of Canadian oil and gas E&P firms traded on the TSX, with headquarters and production in Canada. This represents a sample size of 15,836 firm-quarters observations. JuneWarren Nickle's (JWN) a Canadian oil and gas publishing firm graciously offered the data to the researcher, and the researcher reconciled for accuracy a sample of the data with PDF financial statements available on the TSX website (Cox, 1972; Fox, 2008; JWN, 2016; Klein & Kleinbaum, 2012).

The technique of the study includes two phases: a data preparation in Excel and the actual survival analysis in R. The raw data in Excel format serves to build the financial ratios and the dependent variable of financial distress for each firm and each period, present the data, calculate descriptive statistics and prepare the data layout for R. The same data and Excel preparation serves, with required adjustments, for the three hypotheses of this study. The first hypothesis tests whether having a hedging activity, determined from the existence of percentage of BOE hedged, and measured through a Heaviside function of "1" for the presence of hedging and "0" if the firm did not hedge in that period, helps reduce the hazard of financial distress. The null hypothesis is that hedging has no impact on financial distress. The sample size is 515 firms over the period of Q1-2007 to Q1-2016 representing 11,005 firm-quarter observations. The second hypothesis is that size measured in Log assets impacts financial distress and the null hypothesis is that size has no effect on financial distress. The same sample as the baseline model serves to test this hypothesis and the total number of observations is 15,849 firm-quarters. For the third hypothesis, the dependent variable is not the financial distress but the status of being a target in an M&A activity, measured through a Heaviside function. Financial distress is the independent variable and the null hypothesis is that being financially distressed has no effect on being an M&A target. The data for this activity includes 166 firms, 175 M&A events and 3,698 financial distress observations. The second phase of the technique is the survival analysis in R, a statistical software specifically designed to carry out survival analyses among other capabilities (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012).

The survival analysis in this study is an extended Cox model with repeating events. This is a semi-parametric model, thus one that does not require a baseline hazard from a previous probabilistic distribution but instead uses only the exponentiation of the changes in the covariates to perform a regression analysis between the independent and the dependent variables. The Cox PH model uses the assumption that the hazard ratio remains constant among the population for each predictor variable. When that proportional hazard assumption is violated, that means that the value of the predictor changes with time, which is the case for the financial ratios and other variables this study uses. A time coefficient, directly calculated by R, serves then to reinstate the PH assumption and such a model is an extended Cox model. The model output includes the z-score, the p-value, the regression coefficient, the hazard ratio and the confidence intervals at 95% along with goodness of fit statistics and cumulative hazard curves. The design of this study includes stratifications on the baseline model to test the potential impact of oil price shocks, and on the size hypothesis to gain further precision on the results. The study consists in collecting and preparing the data, running the analysis in R, interpret the model validity and interpret the survival analysis results. A hazard ratio of 1 means that the null hypothesis fails to be rejected and a HR of more than one means that the hazard is as many times higher for exposed firms than censored firms, and vice versa for HR of less than one. The HR interpretation must follow the directional impact of the predictor on the dependent variable (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012).

This study includes descriptive statistics that reveal that the data is highly dispersed and the distinction between financially distressed and non-financially distressed is more relevant than that of active and inactive firms. 74% of the 540 firms in the baseline model or 400 are financially distressed and the remaining 140 non-financially distressed firms show much less distressed predictors. For the populations of the hedging and size hypotheses, non-financially distressed firms hedge a larger percentage of their production and have a larger size. The valuation ratios for the third hypothesis are also highly dispersed and the non-financially dispersed firms have better profitability ratios.

Summary of findings

This study generates three key findings for the hypotheses it tests, and two additional ancillary findings for the baseline model and the impact of oil price shock on the hazard of financial distress:

- The first hypothesis shows the most significant finding of this study. The model presents a solid goodness of fit and is valid. The null hypothesis is rejected and the alternative hypothesis is accepted, meaning that a hedging firm is 18.5 times less likely to experience financial distress than a non-hedging firm.

- For the second hypothesis, too, the model passes the goodness of fit test and is valid. The null hypothesis is rejected and the valid alternative hypothesis means that the estimate of the change in the log of the hazard in financial distress is -16.61% per unit of increase in size. With each unit size increase, a firm is 1.18 times less likely to experience financial distress.
- The model for the third hypothesis on the impact of financial distress on being an M&A target is weak but valid, but the null hypothesis is not rejected. The p-value is 0.2750 which means that the chance of the regression analysis pattern being a random process is 27.5%. This percentage is significantly higher than the 5% threshold below which the null hypothesis is rejected. Thus, financial distress is not a valid predictor of the event and hazard of being an M&A target.

In addition to the key results of the hypotheses, this research also sheds light on the following two findings.

- The baseline model is valid and the null hypothesis is rejected for nine predictors out of 14. However, the correlation between those variables and the dependent variable of financial distress is very small. For eight predictors, the estimate of the change in the log of the hazard in financial distress is less than 0.1% per unit of change in the predictor.
- A stratification around the oil price shock of June 2008 shows that the variable predictor of oil price change has an impact on financial distress: the companies that started after Q2-2008 have a higher cumulative hazard of financial distress than those that started before. However, upon applying that stratification to the nine valid predictors of the

baseline model, it appears that the change in oil price fails to have any impact on the initial results of the baseline model.

The whole study, as developed in the previous chapters and summarized above, unrolls to identify the interest for this study, situating the theoretical foundation, designing a methodology and presenting the results of the survival analysis. This construction leads to the essential objective of critically discussing the results, in compliance with the rhetorical assumption of a disinterested scientist that contributes to the post-positivist paradigm governing this research.

Discussion of the Results

This section covers four parts, one for each of the hypotheses on hedging, firm size and M&A, and the last one for the ancillary results from the baseline model and the oil price shock.

Discussion of the Findings on Hedging and Financial Distress

The most significant result of this study is the importance of hedging on reducing the hazard of structural financial distress. Against a literature background that focuses on the reasons for hedging without specifically including survival and resilience, this result invites the addition of a new reason to the existing portfolio. Finance practitioners and firm managers consider that “cash is king” and apparently, so do hedging scholars, as Chowdhry and Schwartz (2012) referred to firms not hedging their exposure to the risks representing the highest negative impact on their cash flow as a long-standing puzzle in the risk management literature. They argued that firms should hedge the probability of bankruptcy as opposed to its impact. The result of this study supports their conclusion while offering a deeper perspective on two levels: the first is the focus on the self-sustained ability to generate cash, not just the existence of the cash; and the second is the continuity in hedging rather than a transaction-based hedging practice. Cash inflow can have indiscriminate catalysts building its strength, such as the externality of a strong oil price, the sales of assets, other exceptional events, or the successful outcome of a refinancing strategy leveraging existing or future collaterals, or taking advantage of favorable economic conditions such as lower interest rates. Cash outflow may be variably severe, ceteris paribus, depending on management practice, efficiency or poor treasury and financial strategy including over gearing. Cash is king, indeed, but risk managing a projected cash flow that nets such positives and negatives and which prospective analysis requires assumptions that may prove somewhat accurate, does not cover the same depth of hedging effectiveness as the result of this study implies. The definition of financial distress this study uses puts the emphasis of corporate resilience on the firm's ability to generate the cash it needs to survive, grow and thrive on the efficiency of its assets. This is different from the variety of factors listed above that can indiscriminately generate the cash flow that the existing literature focuses on, including the conclusions of Chowdhry and Schwartz (2012). They also argued for specific transaction hedging, while the result of this study using over 11,000 firm-quarters to indicate that hedging firms are 18.5 times less likely to face the hazard of financial distress, tends to support the effectiveness of a continuous and embedded hedging strategy for oil and gas firms. Survival analysis enables the use of very large data samples and this study is taking full advantage of it, but a large population often comes as dispersed data, as the descriptive statistics in this study revealed for this sample. The corollary of this dispersion may be a different or wider focus than the underlying literature reference studies, especially when those did not use the same method. This study does not explore the pertinence of diversification or bad management as Lookman (2004) studied, and does not focus either on the proportion of production hedged as did Haushalter (2000, 2001). The Heaviside function this study uses only pertains to the existence of hedging, not its proportions, continuity, strategy or importance within a firm's risk management practice. Yet, the results are decisively strong. Similarly, this study does not specifically focus on the effectiveness of hedging marginal risk that allows management to lock in performance as considered by DeMarzo and Duffie (1995) and Breeden and Viswanathan (2016). However, the result of this study shows that hedging contributes to building structural strength, which reflects sound management, and which my contribute to infirming the conclusions of Jin and Jorion (2006) and Lookman (2004) that minimize the impact of hedging on firm's stock and valuation, for good management and sophisticated risk management must inevitably build a premium on the stock of the hedging companies that are 18.5 times less exposed to the anemia and shock of financial distress. That sophistication appears in the cost, the expertise and even the larger size that hedging requires as Haushalter (2000, 2001) has posited (Breeden & Viswanathan, 2016; Chowdhry & Schwartz, 2012; DeMarzo & Duffie, 1995; Haushalter, 2000, 2001; Jin & Jorion, 2006; Lookman, 2004).

Discussion of the Findings on Firm Size and Financial Distress

The results of this study confirm the three conclusions of the literature review on firm size impact on financial distress, respectively on relevance, correlation and metric. With a very significant sample size of 15,849 quarter-firms, the model in this study has a strong goodness of fit as the very low p-value, the low z-score, the narrow confidence interval and the positive likelihood ratio confirmed by the Wald test and the score (logrank) test) indicate. This confirms the strong predictive power of firm size on financial distress as most the numerous studies in the often tested variable of firm size in corporate finance and financial distress has found. These studies, including Aziz and Dar (2006), Fitzpatrick and Ogden (2011), Raj and Rinastiti (2002), Rommer (2004), and Shumway (2001), have also concluded to a positive correlation between decreasing size firm and probability of failure. The result of this research confirms this scholar consensus in finding that for each unit of change in size, the estimate of change in the log of the hazard in financial distress is -16.61%. Thus, as the literature has established, this study confirms that with size increase, firms decrease their hazard of financial distress. In a meta-analysis of 100 empirical papers, Dang and Li (2015) found an overwhelming preference for the metric of Log assets for measuring size in corporate finance. This study remains consistent with this consensus and uses the same metric of Log assets. However, among the confirmations of the previous literature findings, this study dissents with the hypothesis by Rommer (2004) that firm size follows a U-shaped statistic in positively correlating to resilience against financial distress. Rommer (2004) hypothesized that small firms lack resilience to shock and are exposed at one branch of the U, while at the other branch, large firms lack flexibility and nimbleness to quickly monitor their employees and communicate internally. This study includes a stratification which results confirm the initial finding that the larger a firm, the less cumulative hazard it exhibits for financial distress; this result does not support the U-shape hypothesis Rommer (2004) formulated. While the variable of size has been tested in numerous studies and may not be as original as the hedging variable discussed above, the contribution of this study in this mature field lies in the novelty of the population of Canadian oil and gas E&P firms, including the sample size, and the originality of the definition of financial distress aiming to capture the structural weakness of firms this study introduces. With a statistically solid method of a Cox extended model with repeating events, a large sample size, a new population and a new definition of financial distress, this study adds a modest stone to the already high wall of studies on firm size impact on corporate health (Aziz & Dar, 2006; Cox, 1972; Dang & Li, 2015; Fitzpatrick & Ogden, 2011; Fox, 2008; Klein & Kleinbaum, 2012; Raj & Rinastiti, 2002; Rommer, 2004; Shumway, 2001).

Discussion of the Findings on Financial Distress and M&A

Several authors have explored the relationship between financial distress and M&A, especially to see in M&A a bankruptcy avoidance strategy and correlate solvency fragility to increased takeover risk. Those include Dickerson et al. (2003), Erel et al. (2015), Pastena and Ruland (1986), Kyimaz (2006), and Peel and Wilson (1989). This study attempts to explore the causal relationship between being structurally financially distressed and being a target in an M&A transaction. The sample size of 175 M&A events for 166 firms and 3,698 distressed firm-quarters is statistically significant and the method of a Cox extended model with repeating events is also statistically solid (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012). The model is weak but valid and it results in failing to reject the null hypothesis. Structural financial distress in terms of two consecutive quarters of negative OCF/TA asset efficiency ratio is not a valid predictor of the hazard for a firm to be a target in an M&A transaction. A model using a vector of profitability and valuation covariates returns the same results except for one predictor, EV/Ebitdax, which shows a relatively weak correlation indicating that a distressed firm has only a 0.32% hazard increase for every decrease in its EV/Ebitdax ratio. Powell and Yawson (2007) analyzed that the variables used to predict takeovers are similarly useful for bankruptcy prediction. The results of this study do not reconcile with their finding, and begs the question of the fit of the definition of financial distress that captures a deep structural weakness, for shining light on a potential M&A target. This question covers the alternative or concomitant potential design limitations or flows that led the testing of this hypothesis. Several externalities such as synergies, opportunistic consolidations, portfolio management, managerial vision and action among others may be factors of trigger and completion of an M&A transaction. Those are external to the concept of financial distress in this study, one that depicts a firm as vulnerable.

While the status of financial distress may not be the prime trigger that attract a predator firm, like a wounded prey would, it should still impact the valuation of the target firm and reflect in a valid model showing positive correlations between financial distress and being an M&A target. This intuitively expected causality does not show in the testing of this third hypothesis despite using a vector of valuation covariates. The epistemology of this research is epic, dual and objective, and the researcher acknowledges, with no vested interest and an agnostic lens, the result of this hypothesis (Cox, 1972; Dickerson et al., 2003; Erel et al., 2015; Fox, 2008; Klein & Kleinbaum, 2012; Pastena & Ruland, 1986; Powell and Yawson, 2007; Kyimaz, 2006; Peel & Wilson, 1989).

Discussion of the Findings on Financial Ratios, Oil Price Shock and Financial Distress

The baseline model result, preliminary to the central hypotheses of this research, shows that the univariate extended Cox models with repeating events are valid and nine financial ratios predictor variables do correlate to the status of financial distress, albeit with low values. The literature review in this study explores the background of the use of financial ratios for predicting financial distress, including the main paradigms and models that have governed this field of research. Against that mature and varied literature backdrop, this study introduces a new structural definition of financial distress, but the standard financial ratios of liquidity, solvency and profitability only moderately predict the anemic state of this financial distress. Refinancing, debt restructuring, or other managerial action that does not reflect the firm's inner ability to generate going concern, reinvestment, profitability and growth cash flow from its operating assets may contribute to the counterintuitive small regression coefficients. Alternatively, and despite the precaution of running univariate analyses, the use of ratios in a survival analysis compounds the confounding effect of the numerator and the denominator changes over time. This baseline analysis is not central to this study; it situates the context of financial distress and provides an increased perspective for introducing the hypotheses of this study. A more sophisticated survival analysis that would warrant a whole study would be of value to more precisely analyze the results of the baseline model, including the oil price impact that the stratification highlighted. The data in this study is very dispersed but statistically significant, covering 14 years and amounting to over 15,850 firm-quarter observations (JWN, 2016). The extreme dispersion of the data is another factor that may call for specific stratifications or for an even more precise sample that includes size as a selection criterion. The results of the baseline model show both a useful confirmation of the correlation between financial ratios and the structural strength of the firm and a contrast with past studies that used other methods and found stronger correlations. They also hint at the potential limits of using ratios in a survival analysis. Ultimately, this baseline model opens a new alternative for further consideration, provided, unlike in this study, it be central to that effort (Cox, 1972; Fox, 2008; JWN, 2016; Klein & Kleinbaum, 2012).

The problem statement that opens this study refers to the impact of oil price fluctuations on the boom and bust cycles the Canadian oil and gas industry goes through. The stratification around one price shock shows indeed a clear distinction between the hazard of financial distress for firms that had been active prior to that price shock and the hazard of financial distress for firms that started only after that price drop. Although this observation is not the focus of this study, it contributes to showing that the structural weakness the key construct of interest of financial distress establishes in this study, does correlate to the externality of oil price fluctuations. The context of this specific oil price shock is a larger global financial recession, rather than purely endogenous to oil and gas. This context may have had an impact on the higher financial distress hazard of the firms that started past that date, due to other factors such as access to debt, general economic contraction, managerial vision and momentum in times of generalized economic duress which can alter confidence levels and strategic decisions, or else. Thus, this finding does not prove the correlation but solidly points to its existence, and it would require a more specifically designed study to further establish it. However, this directional finding is important to relate the overall study to the context of the original problem statement and assert that the resilience, long term survival, profitability and growth ought to be considered through a deeply rooted financial distress metric as this study does, and evolve from the binary paradigms of bankruptcy prediction, in continuation of the work of Outecheva (2007) as well as Turetsky and McEwen (2001) and Whitaker (1999) (Outecheva, 2007; Turetsky & McEwen, 2001; Whitaker, 1999).

The variety of topics this survival analysis covers provides the opportunity to discuss the results and findings on the foundational baseline model and all three hypotheses of this study. This discussion is disinterested, objective and non-complacent, to the best of the researcher's capability and leads to the conclusion of this study, along with practical recommendations.

Conclusion and Practical Recommendations

The Canadian economy is tributary to its commodities, among which oil and gas exploration and production plays a key role (CAPP, 2016; Millington, 2016; Natural Resources Canada, 2016). The E&P sector is sensitive to boom and bust cycles and during the latter, oil and gas firms go through dire economic challenges (CAPP, 2016; Jakeman & Tertzakian, 2016; Millington, 2016; PSAC, 2016). This study uses an established statistical method that contrasts with alternative approaches within a field of research that has theoretically and empirically matured throughout a century and landmarked a few paradigms along the way (Balcaen & Ooghe, 2006; Cox, 1972; Fox, 2008; Horrigan, 1968; Klein & Kleinbaum, 2012). The theory and practical application of financial distress predictive analysis is still evolving and not yet consolidated under one unequivocally accepted technique. So is the definition of financial distress, and this research introduces a new one that captures the deficient capability of asset heavy, capital intensive and long lead time firms in the oil and gas industry to generate from their assets' efficiency the economic strength to remain a going concern, reinvest intelligently, be profitable and grow. The Canadian oil and gas industry is very diverse in firm and asset size, leverage, and overall management sophistication. This diversity shows in the extreme dispersion of the data in this study; the sample size is statistically significant, covering up to 14 years of financial reporting for 540 firms and giving over 15,850 observations of firm-quarters. Within a post-positivist research paradigm, this quantitative study thus uses large data, reviews extensively the existing literature and applies a solid statistical technique. The empirical findings of this research result in two practical recommendations for Canadian oil and gas managers and stakeholders (Balcaen & Ooghe, 2006; CAPP, 2016; Cox, 1972; Fox, 2008; Horrigan, 1968; Jakeman & Tertzakian, 2016; Klein & Kleinbaum, 2012; Millington, 2016; Outecheva, 2007; PSAC, 2016;).

The first recommendation is to hedge. In an industry that is so exposed to the external fluctuations of oil price, this study shows that hedging is a valid risk management strategy to prevent structural financial distress. Not hedging for stock price appreciation, or valuing exceptional managerial performance, but for embedding resilience at the core of the business in a structured, systematic, permanent and sophisticated way that honors the vision, expertise, cost and long term unwavering stability it may require. Smaller companies may consider expanding their own capabilities to create or increase their hedging strategy, consider pooling their needs to respond to the sophistication good hedging requires, or externalize the function to expert advisory and consulting firms. Larger firms that already hedge may gain from the perspective of this research the will to be more systemic with a longer-term view when managing their hedging strategy. This includes hedging for core resilience, through cash flows naturally but not just for transactional cash flows, and resisting the temptation to hedge speculatively. The higher the proportion of its production a firm hedge, the better its financial ratios and the lower its cumulative hazard of financial distress. The same goes for size.

The second recommendation is to seek size. This study confirms the results of several empirical studies that larger firms are less exposed to financial distress than smaller ones (Aziz & Dar, 2006; Fitzpatrick & Ogden, 2011; Raj & Rinastiti, 2002; Shumway, 2001). The Petroleum Services Association of Canada estimates at more than 1,000 the number of upstream oil and gas companies in Canada, doing exploration and production (PSAC, 2016). This includes 252 public companies listed on the TSX and the TSXV with 10 seniors (producing more than 100,000 BOE per day), 41 intermediates (10,000 to 100,000 BOE/d), 48 juniors (1,000 to 10,000 BOE/d) and 153 emerging juniors (0 to 1,000 BOE/d) (TMX, 2016). The industry is far from being mature and consolidated, and the smaller the firm, the less its management systems including long term strategy, risk management, financial management and operations are sophisticated, leaving them more exposed to the adverse winds of oil price fluctuation or any event that can test their resilience. All these smaller firms, especially the two-third of E&P firms in the industry that are private along with the emerging juniors and the juniors would be well-advised to seize consolidation opportunities and increase size to minimize the hazard of structural financial distress (Aziz & Dar, 2006; Fitzpatrick & Ogden, 2011; PSAC, 2016; Raj & Rinastiti, 2002; Shumway, 2001; TMX, 2016).

As the definition of financial distress in this study touches the core strength of oil and gas firms, they should proactively include the consideration of building inner resilience, minimize the risk of vegetating in a limbo anemic financially distressed state, in their decision to merge, consolidate and go beyond joint ventures concerns. The scope of this study is larger than the two practical recommendations above, and while the data is large, the technique solid and the hypotheses diverse and supplemented with a baseline model, this study reveals several avenues for future research.

Recommendations for Future Research

This research covers many topics and opens the following opportunities for empirical future research.

- Hedging: following the strong benefit of hedging in minimizing the hazard of financial distress this study reports, future research may focus on risk management strategies including the proportions hedged or the continuity of the hedging and their impact on corporate resilience in the Canadian oil and gas industry; financial derivatives Canadian oil and gas firms use; and the motivation and factors guiding the hedging strategies in Canadian oil and gas, including risk appetite and corporate governance influence or managerial change following a merger, take-over or change in executive leadership.
- M&A: the validity of the null hypothesis in this study points to the opportunity of further exploring the causal factors to M&A activity in the Canadian oil and gas industry, to complement the tax optimization objective Cohen et al. (2009) reported on following a policy change, considering the broader literature background of bankruptcy avoidance and solvency fragility (Cohen et al.; 2009).

- Baseline model: the results of this study indicate to the need to explore the impact of ratios' numerator and denominator changes in affecting the correlation between the independent variables and the dependent variable in an extended Cox model, and performing a similar analysis to the baseline model in this study accordingly (Cox, 1972; Fox, 2008; Klein & Kleinbaum, 2012).
- Oil price fluctuation and financial distress: the stratification around one price shock in this study points toward a strong correlation between oil price and financial distress, however a more focused study may use more than one stratification around one shock, and use other dependent variables than financial distress, such as financial ratios.
- Financial distress: future research may consider how fitting the definition of financial distress this study introduces for capital intensive and heavy asset industries may be to different industries with different characteristics.
- Industry: the population for this study is limited to the E&P sector, but a similar study could include or focus on the dependent industries of EPCM (engineering, procurement and construction management), oil and gas services, transportation (i.e. rail and road), or hospitality and tourism among others; future research may also seek to understand to what extent oil price induced economic recessions, such as the one Alberta is experiencing since mid-2014, influences the diversification of the oil and gas industry in renewable energies.
- Oil prices: as a leading and very influential externality to the financial health of oil and gas firms, oil prices offer several areas of focus for future research. The first is the impact of new technology on oil prices. The second is the influence of futures on oil prices. And the third uses the assumption of oil prices staying low for an extended period (as of Q2-

2017, prices have been relatively low for almost three years) to ask what strategies should oil firms apply to secure their long-term survival and strengthen their resilience? (Macrotrends, 2016).

The Canadian oil and gas industry is important, varied, exposed and still growing. While empirical data may require efforts to gather, this industry offers a much larger potential for diverse and impactful academic research than currently exists. This study humbly opens a small window on the potential for future research, and may hopefully inspire for embracing these opportunities.

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Appendices

Appendix A

List of Survival Analysis Studies

Table A

List of Survival Analysis Studies

Authors	Year	Country	Industry	Focus
Agarwal and Bauer	2014	UK	All	Comparative analysis Hazard Models, Z-score, contingent claims
Alves, Kalatis and Mathias	2014	Brazil	Banking	Private banks in Brazil
Amendola, Restaino and Sensini	2015	Italy	All	Competing risks, hazard model
An and Qi	2012	USA	Other	Competing risks, mortgage duration
Anderson, Burkhauser, and Butler	1989	USA	Other	Work and health after retirement
Andes, Hill and Perry	1996	USA	All	Financial distress
Anstis, Bradbury and Nash	1989	Australia	All	Survival analysis accuracy
Aonuma and Kijima	1998	Japan	All	Prepayment valuation
Audretsch and Mahmood	1995	USA	All	New firm survival
Baba and Goko	2009	Switzerland & Japan	Hedge Funds	Survival analysis
Batta and Wan	2014	USA	All	Impact of equity misvaluation
Bhattacharjee, Higson, Holly and Kattuman	2009	UK	All	Business exit, failures and acquisitions
Bhattacharjee and Han	2014	China	All	Survival analysis
Botman, van Giersbergen and van der Goot	2009	Netherlands	Internet	IPOs
Braga, Bressan, Colosimo and Fully Bressan	2006	Brazil	Banking	Credit Unions
Buehler, Jaeger and Kaiser	2012	Switzerland	All	Survival analysis
Chancharat, Davy, McCrae and Tian	2007	Australia	All	Survival analysis
Charalambakis	2015	Grece	All	Survival analysis
Charalambakis and Garrett	2016	Greece and UK	All	Comparative study US-Indian-UK firms
Chen and Lee	1993	Canada and Hong Kon	Oil and Gas	Survival analysis
Chen, Ho, Lin and Tsai	2012	Taiwan	All	Credit rating
Chong, Li, He and Zhang	2010	Hong Kong	All	Competing risk analysis, Hong Kong firms
Ciochetti, Deng, Lee, Shilling and Yao	2003	USA	Real Estate	Commercial mortgage default, originator bias
Coffinet, Pop and Tiesset	2013	France	Banking	Option prices
Crapp and Stevenson	1987	Australia	All	Survival analysis
Davydenko	2013	Canada	All	Credit analysis
DeYoung	2003	USA	Banking	New entrants in commercial banking
Duffie, Saita and Wang	2007	USA	All	Stochastic covariates
Foster and Zurada	2013	USA	All	Loan defaults
Han and Hausman	1990	USA	All	Competing risks
Henebry	1996	USA	Banking	Cash flow addition
Henebry	1997	USA	Banking	Temporal stability of PH models
Honjo	2000	Japan	All	New firms
Janot	2001	Brazil	Banking	In Portuguese
Laitinen	2005	Finland	All	Financial distress prediction, Finnish firms
Laitinen and Luoma	1991	Finland	All	Survival analysis
Lane, Looney and Wansley	1986	USA	Banking	Survival analysis
LeClere	2000	USA	All	Financial distress
LeClere	2005	USA	All	Time varying covariates
Lee and Urrutia	1996	USA	Insurance	Comparative analysis Hazard Models, Logit
McEwen and Turetsky	2001	USA	All	Ex ante predictors of financial distress
Moeller and Molina	2003	USA	All	Financial management, issuance of high-yield bonds
Nikitin	2003	USA	All	Indonesian financial crisis
Noga and Schnader	2013	USA	All	Book-tax differences
Oz and Yelkenci	2015	USA & Turkey	All	Comparative study prediction models, Turkey
Parker, Peters and Turetsky	2002	USA	All	Corporate governance
Partington and Kim	2015	Australia	All	Survival analysis
Partington, Stevenson, Torbey and Wong	2006	USA	All	Chapter 11, duration and payoff
Pereira	2014	Portugal	All	Survival analysis
Porath	2006	Germany	Banking	German saving banks and credit cooperatives
Prantl	2003	Germany	All	New firms, voluntary liquidation, post-reunification

List of Survival Analysis Studies (continued)

Authors	Year	Country	Industry	Focus
Quigley	1987	USA	Real Estate	Interest rate variation, mortgage prepayment, household mobility
Raj and Rinastiti	2002	USA	Banking	Asian perspective, factors of influence
Rocha	1999	Brazil	Banking	In Portuguese
Rommer	2004	Danmark	All	Exploratory analysis
Rommer	2005	Danmark	All	Comparative analysis, French, Italian and Spanish firms
Sales	2005	Brazil	Banking	In Portuguese
Schwartz and Torous	1989	USA	Finance	Mortgage-backed securities
Shang, Shanling and Slaughter	2010	USA	Software	Survival analysis
Shumway	2001	USA	All	Comparison with
Stepanova and Thomas	2002	Switzerland & UK	Other	Personal Loan
Sueyoshi	1992	USA	All	Competing risks
Sugimura	2002	Japan	Other	Mortgage loans
Whalen	1991	USA	Banking	Usefulness of porportional hazards model
Wheelock and Wilson	1995	USA	Banking	Determinants of failure
Wheelock and Wilson	2000	USA	Banking	Determinants of failure
Yamazaki	2013	Japan	All	Survival analysis

Appendix B

Abstract of Raw Data

Table B

Abstract of Raw Data

Compar	Company	Folder	Data Item	Data Iter	1st Qtr 2002	2nd Qtr 2002	3rd Qtr 2002
2025	Artisan Energy Corporation	Oil & Gas Operating Analysis\Price Benchmark Analysis \Natural	AECO-C - per mcf	FN6103	2.037773693	2.790771334	2.000995611
2025	Artisan Energy Corporation	Oil & Gas Operating Analysis\Price Benchmark Analysis \Natural	NYMEX - per mcf	FN6102	2.325250566	3.267434796	3.126175516
2025	Artisan Energy Corporation	Oil & Gas Operating Analysis\Price Benchmark Analysis \Natural	Henry Hub - per mcf	FN7590	2.487444768	3.295637437	3.109897525
2025	Artisan Energy Corporation	Oil & Gas Operating Analysis\Price Benchmark Analysis \Nat. Ga	Natural Gas Price Realization as % of AEC	FN7644			
2025	Artisan Energy Corporation	Oil & Gas Operating Analysis\Price Benchmark Analysis \Nat. Ga	Natural Gas Price Realization as % of NYM	FN7646			
2025	Artisan Energy Corporation	Oil & Gas Operating Analysis\Price Benchmark Analysis \Nat. Ga	Natural Gas Price Realization as % of Hen	FN7648			
2025	Artisan Energy Corporation	Oil & Gas Operating Analysis\Hedging Contracts Outstanding	% Oil/NGL Hedged	FN5598	0	0	0
2025	Artisan Energy Corporation	Oil & Gas Operating Analysis\Hedging Contracts Outstanding	% Natural Gas Hedged	FN5599	0	0	0
2025	Artisan Energy Corporation	Oil & Gas Operating Analysis\Hedging Contracts Outstanding	% BOE Hedged	FN5600	0	0	0
2025	Artisan Energy Corporation	Oil & Gas Operating Analysis\Reserve Replacement Ratios\2P Re	Total Additions less Sales	FN6058			
43	Aspen Group Resources Corp.	Corporate Financial Data\Company Details	Headquartered Country	FN4020	Canada	Canada	Canada
43	Aspen Group Resources Corp.	Corporate Financial Data\Balance Sheet ('000)\Assets	Cash & Equivalents	FN4307	38.0844695	51.4510932	12.58218
43	Aspen Group Resources Corp.	Corporate Financial Data\Balance Sheet ('000)\Assets	Short Term Investments	FN4309		0	0
43	Aspen Group Resources Corp.	Corporate Financial Data\Balance Sheet ('000)\Assets	Trade Receivables	FN4310	5148.863374	4563.811942	2853.719362
43	Aspen Group Resources Corp.	Corporate Financial Data\Balance Sheet ('000)\Assets	Total Current Assets	FN4317	6774.158006	6396.664889	4010.258632
43	Aspen Group Resources Corp.	Corporate Financial Data\Balance Sheet ('000)\Assets	Total Assets	FN4328	107478.7185	106630.891	88483.2508
43	Aspen Group Resources Corp.	Corporate Financial Data\Balance Sheet ('000)\Liabilities	Total Current Liabilities	FN4340	14396.33515	10995.32632	11519.07261
43	Aspen Group Resources Corp.	Corporate Financial Data\Balance Sheet ('000)\Liabilities	Total Liabilities	FN4352	38774.81858	38752.10935	35223.19925
43	Aspen Group Resources Corp.	Corporate Financial Data\Balance Sheet ('000)\Equity	Total Shareholders Equity	FN4367	68624.38933	67878.78168	53260.05155
43	Aspen Group Resources Corp.	Corporate Financial Data\Income Statement ('000)\Revenue	Total Revenue (Net)	FN4381	3660.846983	3756.216262	2306.955694

Appendix C

Abstracts of Excel Data Preparation

Table C1

Data Preparation – WC/TA

	A	B	C	D	E	G	H	I	J	K	L	M	N	O	P
1															
2		FD/No FD	Active/Ina	Firm #	Firm Code	Ratio	Q1-02	Q2-02	Q3-02	Q4-02	Q1-03	Q2-03	Q3-03	Q4-03	Q1-04
5					X2										
6		FD	Inactive	1	2021	WC/TA									
7		FD	Active	2	1587	WC/TA	0.18	0.21	0.24	(0.02)	(0.06)	0.07	0.02	(0.35)	(0.35)
8		FD	Inactive	3	1931	WC/TA									
9		No FD	Inactive	4	9043	WC/TA									
10		No FD	Inactive	5	1086	WC/TA									
11		FD	Active	6	1617	WC/TA									
12		No FD	Active	7	48	WC/TA	(0.04)	(0.29)	(0.34)	(0.29)	(0.31)	(0.36)	(0.32)	(0.23)	(0.28)
13		FD	Active	8	1919	WC/TA									
14		FD	Active	9	2007	WC/TA									
15		No FD	Inactive	10	981	WC/TA									
16		FD	Active	11	847	WC/TA									0.98
17		FD	Inactive	12	1605	WC/TA									
18		FD	Inactive	13	24	WC/TA	0.08	0.10	0.08	0.10	0.18	0.23	0.29	0.23	0.28
19		FD	Inactive	14	1594	WC/TA									
20		FD	Inactive	15	1620	WC/TA									
21		FD	Active	16	1469	WC/TA									
22		FD	Active	17	8489	WC/TA									
23		FD	Inactive	18	1855	WC/TA									
24		FD	Active	19	846	WC/TA									
25		FD	Active	20	879	WC/TA								0.05	0.25
26		FD	Inactive	21	1215	WC/TA									
27		FD	Inactive	22	1316	WC/TA									
28		FD	Inactive	23	1040	WC/TA					(0.33)	(0.37)	(0.36)	(0.20)	(0.24)
29		FD	Inactive	24	1881	WC/TA									
30		FD	Active	25	29	WC/TA	0.52	0.49	0.49	0.53	0.47	0.46	0.41	0.59	0.60
31		FD	Inactive	26	1923	WC/TA									
32		FD	Inactive	27	956	WC/TA								(0.46)	(0.36)

Table C2

Data Preparation – Debt/Ebitdax

	A	B	C	D	E	G	AZ	BA	BB	BC	BD	BE	BF	BG	BH	BI	BJ
1																	
2		FD/No FD	Active/Ina	Firm #	Firm Code	Ratio	Q1-13	Q2-13	Q3-13	Q4-13	Q1-14	Q2-14	Q3-14	Q4-14	Q1-15	Q2-15	Q3-15
3831		FD	Active	518	1926	D/Ebitdax	-	-	-	-	-	-	-	-	-	-	-
3832		FD	Inactive	519	929	D/Ebitdax											
3833		FD	Inactive	520	825	D/Ebitdax											
3834		No FD	Inactive	521	827	D/Ebitdax											
3835		FD	Inactive	522	1238	D/Ebitdax	(25.90)	20.34	(9.75)								
3836		FD	Active	523	1233	D/Ebitdax	(13.88)	60.50	16.92	(140.11)	29.70	(4.81)	16.53	(5.87)	(149.74)	(161.71)	(8.35)
3837		No FD	Inactive	524	864	D/Ebitdax											
3838		No FD	Active	525	1606	D/Ebitdax	7.68	5.61	5.63	6.72	6.31	2.59	3.65	2.42	13.20	7.22	12.02
3839		FD	Inactive	526	925	D/Ebitdax											
3840		FD	Inactive	527	1210	D/Ebitdax											
3841		FD	Active	528	1853	D/Ebitdax	-	-	-	(1.39)	(2.19)	(1.92)	(1.40)	1.97	(3.69)	(3.01)	(3.35)
3842		FD	Inactive	529	1924	D/Ebitdax	-	-	-	-	-	-	-	-	-	-	-
3843		FD	Inactive	530	906	D/Ebitdax											
3844		No FD	Inactive	531	1135	D/Ebitdax											
3845		No FD	Inactive	532	774	D/Ebitdax	-										
3846		No FD	Inactive	533	778	D/Ebitdax	16.05	19.30	20.85								
3847		FD	Active	534	8649	D/Ebitdax						-	-	-	-	-	-
3848		FD	Active	535	1002	D/Ebitdax	(323.93)	(264.15)	792.78	(67.09)	(393.86)	828.01	(80.39)	(33.14)	(133.33)	(392.77)	(126.47)
3849		FD	Active	536	868	D/Ebitdax	13.98	6.16	10.78	6.48	8.69	4.92	3.25	2.53	11.97	63.46	8.59
3850		FD	Active	537	867	D/Ebitdax	6.86	1.56	9.49	23.77	10.01	-	-	(11.19)	(1.69)	592.87	12.77
3851		FD	Active	538	3943	D/Ebitdax	-	-	(3.51)	0.60	1.26	1.88	0.76	0.67	2.25	(0.75)	(0.72)
3852		No FD	Active	539	783	D/Ebitdax	6.83	6.28	9.00	11.82	7.78	9.45	8.82	4.23	29.80	20.33	(2.15)
3853		No FD	Inactive	540	911	D/Ebitdax											

Appendix D

Abstracts of Data Layout for R

Table D1

Data Layout for R – Hypothesis 3, CSV File.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	N	Firm.Code	Quarter	Period	MAStatus	Status	X1_OCF/T.	X9_ROA	X10_ROE	X11_OP Pr	X12_P/E	X13_EV/El	X14_EV/D.	X15_EV/F(	X16_EV/2P
2	1	1086	Q4-05	0	0	0	0.2	0.04	0.13	0.57		0.31	0.5	1.79	0
3	1	1086	Q1-06	1	0	0	0.12	0.04	0.09	0.63	54.88	12.12	18	43.78	
4	1	1086	Q2-06	2	0	0	0.2	0.04	0.08	0.68	64.85	9.5	17.44	-113.96	
5	1	1086	Q3-06	3	0	0	0.1	0.02	0.07	0.67	47.07	11.04	17.87	348.3	
6	1	1086	Q4-06	4	0	0	0.1	0.02	0.04	0.57	83.5	15.21	23.69	-29.61	0.03
7	1	1086	Q1-07	5	0	0	0.06	0.03	0.06	0.58	61.57	13.01	21.18	121.83	
8	1	1086	Q2-07	6	0	0	-0.02	0.03	0.07	0.65	57.36	12.41	22.88	261.58	
9	1	1086	Q3-07	7	0	0	0.09	0.04	0.08	0.64	50.17	10.74	20.41	-291.85	
10	1	1086	Q4-07	8	0	0	0.11	0.05	0.1	0.71	36.36	10.52	17.98	178.36	0.04
11	1	1086	Q1-08	9	0	0	0.06	0.06	0.12	0.74	27.59	8.98	15.89	59.22	
12	1	1086	Q2-08	10	0	0	0.16	0.06	0.13	0.77	27.16	7.97	16.13	55.4	
13	1	1086	Q3-08	11	0	0	0.07	0.05	0.1	0.75	18.24	5.72	10.1	-204.67	
14	1	1086	Q4-08	12	0	0	0.04	0	0	0.39	939.34	11.51	12.03	-14.66	0.02
15	1	1086	Q1-09	13	1	0	0.01	0	0	0.37	690.47	13.67	17.41	-25.92	
16	1	1086	Q2-09	14	0	0	0.05	0.01	0.02	0.49	177.86	18.38	26.44		
17	2	981	Q3-05	0	0	0	0.04	0.01	0.01	0.26		-5.33	-4.58	2.48	
18	2	981	Q4-05	1	0	0	0.02	0.01	0.01	0.33	130.05	30.68	27.52	-17.75	0.11
19	2	981	Q1-06	2	0	0	0.02	0	0	0.05	4688.92	51.64	43.23	-5.98	

Table D2

Data Layout for R – Hypothesis 1, Start End CSV file.

	A	B	C	D
1	Firm.Code	Start	End	
2	2021	20	34	
3	1587	0	36	
4	1931	0	30	
5	9043	32	34	
6	1086	0	36	
7	1617	12	36	
8	48	0	36	
9	1919	18	36	
10	2007	8	36	
11	981	0	36	
12	847	0	36	
13	1605	16	27	
14	24	0	18	
15	1594	0	26	
16	1620	4	19	
17	1469	4	36	
18	8489	28	36	
19	1855	20	36	
20	846	0	36	
21	879	0	36	
22	1215	3	26	

Appendix E

Abstract of Survival Analysis Coding in R

Hypothesis 2 - Size

```
#H2.R

#Analysis.R
setwd('~/Dropbox/UCBC/COULIBALY-2016-10/Thursday/')
require(survival)
require(plyr)
require(survminer)
#Read in and summarize data.

baseline <- read.csv('H2 Size 7Nov2016.csv', header=TRUE)
str(baseline)
hist(baseline$X20_Size)
summary(baseline$N)
summary(as.factor(baseline$Period))

baseline_tic <- read.csv('Start End H2 Size 7Nov2016.csv')
str(baseline_start_end)
summary(baseline_start_end)
tail(baseline_start_end)
str(baseline_tic)
baseline_tic$year <- round(baseline_tic$Start/4)+2002

baseline_tic$period <- ifelse(baseline_tic$Start <= 26, 1, NA)
baseline_tic$period <- ifelse(baseline_tic$Start <= 50 & baseline_tic$Start > 26, 2, baseline_tic$period)
baseline_tic$period <- ifelse(baseline_tic$Start > 50, 3, baseline_tic$period)
baseline_tic$period2 <- ifelse(baseline_tic$period > 1, 2, baseline_tic$period)
baseline_tic$period <- as.integer(baseline_tic$period)
# hist(baseline_tic$period, main='Histogram of Company Starts by Period', xlab="Period of Company Origin")
# hist(baseline_tic$year, main='Histogram of Company Starts by Year', xlab="Period of Company Origin")
# hist(baseline_tic$Start, xlab='Quarter of Company Origin', main='Histogram of Company Starts by Quarter', breaks=12)
# baseline_tvc <- baseline[c('Period', 'Status', 'Firm.Code', 'X1_OCF.TA', 'X2_WC.TA')]

final_data <- merge(baseline, baseline_tic, by='Firm.Code', all.x=TRUE)
final_data <- arrange(final_data, Firm.Code, Period)
head(final_data, 50)
names(final_data)
final_data$Period.End <- final_data$Period + 1

surv.obj <- Surv(final_data$Period/4, final_data$Period.End/4, final_data$Status)

#surv.obj
hist(final_data$X20_Size)
final_data$size_strata <- round(final_data$X20_Size/5)
hist(final_data$size_strata)
final_data$size_strata <- ifelse(final_data$size_strata == 0, 1, final_data$size_strata)
final_data$size_strata <- ifelse(final_data$size_strata == 4, 3, final_data$size_strata)


summary(final_data)
summary(coxph(surv.obj ~ final_data$Start + final_data$X20_Size)) #$coefficients[2]

fit <- survfit(coxph(surv.obj ~  strata(final_data$size_strata)))
fit
```

Appendix F

Abstract of Survival Analysis Output from R

Hypothesis 3 – M&A Vector of Covariates

```
Call:
coxph(formula = surv.obj ~ final_data$Start + final_data$Status +
    final_data$X1_OCF.TA + final_data$X9_ROA + final_data$X10_ROE +
    final_data$X11_OP.Prof + final_data$X12_P.E + final_data$X13_EV.Ebitdax +
    final_data$X14_EV.DACF + final_data$X15_EV.FCF + final_data$X16_EV.2P)

  n= 547, number of events= 23
   (3151 observations deleted due to missingness)

                                coef  exp(coef)   se(coef)      z Pr(>|z|)
final_data$Start           6.409e-02  1.066e+00  3.236e-02  1.980  0.04765 *
final_data$Status          5.513e-01  1.736e+00  9.119e-01  0.605  0.54547
final_data$X1_OCF.TA       1.891e-01  1.208e+00  1.166e+00  0.162  0.87120
final_data$X9_ROA          3.524e+00  3.390e+01  3.861e+00  0.912  0.36151
final_data$X10_ROE         5.308e-01  1.700e+00  4.091e-01  1.297  0.19448
final_data$X11_OP.Prof    -1.686e-03  9.983e-01  2.689e-02 -0.063  0.95003
final_data$X12_P.E         2.212e-04  1.000e+00  6.762e-04  0.327  0.74355
final_data$X13_EV.Ebitdax  3.164e-03  1.003e+00  1.016e-03  3.113  0.00185 **
final_data$X14_EV.DACF     1.686e-03  1.002e+00  1.693e-03  0.996  0.31918
final_data$X15_EV.FCF      3.347e-03  1.003e+00  2.052e-03  1.631  0.10285
final_data$X16_EV.2P      -1.168e+01  8.424e-06  9.179e+00 -1.273  0.20305
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

                          exp(coef) exp(-coef) lower .95 upper .95
final_data$Start          1.066e+00  9.379e-01 1.001e+00     1.136
final_data$Status         1.736e+00  5.762e-01 2.905e-01    10.368
final_data$X1_OCF.TA      1.208e+00  8.277e-01 1.229e-01    11.878
final_data$X9_ROA         3.390e+01  2.949e-02 1.751e-02 65640.067
final_data$X10_ROE        1.700e+00  5.882e-01 7.626e-01     3.791
final_data$X11_OP.Prof    9.983e-01  1.002e+00 9.471e-01     1.052
final_data$X12_P.E        1.000e+00  9.998e-01 9.989e-01     1.002
final_data$X13_EV.Ebitdax 1.003e+00  9.968e-01 1.001e+00     1.005
final_data$X14_EV.DACF    1.002e+00  9.983e-01 9.984e-01     1.005
final_data$X15_EV.FCF     1.003e+00  9.967e-01 9.993e-01     1.007
final_data$X16_EV.2P      8.424e-06  1.187e+05 1.295e-13   548.174

Concordance= 0.782  (se = 0.076 )
Rsquare= 0.046   (max possible= 0.186 )
Likelihood ratio test= 25.53  on 11 df,   p=0.007619
Wald test            = 17.91  on 11 df,   p=0.0837
Score (logrank) test = 27.95  on 11 df,   p=0.003295
```