Caught in a Debt Trap:

Financial Distress and Oil Production Decisions

Yanan Li[1]

Wenjun Wang[2]

Abstract

The research investigates the causal effects of financial distress on corporate production within the oil industry framework. The identification strategy capitalizes on the exogenous shock from the 2014 oil price collapse and pre-existing firm-level variations in debt maturity structures. Employing a difference-in-difference methodology, the study reveals that firms facing greater rollover risk in 2014 significantly expanded production in the post-crisis period. This effect is particularly pronounced among firms with lower cash reserves, higher capital intensity, and increased levels of secured debt. The findings offer policy insights into the dramatic declines in commodity prices witnessed during the oil crisis and its subsequent impact.

JEL: L11, G30, O13

Key Words: oil production; financial distress; rollover risk

[1] Business School, Beijing Normal University. E-mail: yananli@bnu.edu.cn
[2] Investment Banking Division, Agricultural Bank of China. E-mail: wenjunwang00@gmail.com

1 Introduction

Production is a fundamental aspect of firms' daily operations, facilitating the transformation of inputs such as raw materials, labor, and capital into final goods (Hitomi, 1996). As global economic uncertainty rises and the costs of goods increase, corporations increasingly prioritize production planning to mitigate the effects of adverse shocks. For instance, multinational firms have been observed to shift production across different regions to counteract the impact of elevated tariffs (Flaaen et al., 2020; Houde and Wang, 2022). Production activities are intrinsically linked to financial operations and are key drivers of corporate financial performance (Wang et al., 2021). The interplay between financing and production decisions is especially critical in the post-pandemic landscape, marked by escalating corporate debt levels and heightened financial vulnerabilities (Aldasoro et al., 2021). Despite its significance, this area remains insufficiently explored. Consequently, this paper examines how financial distress influences corporate production decisions, with a specific focus on the oil industry.

The relationship between financial distress and firm production is complex and resists simple, deterministic predictions. Theoretical models suggest that this relationship may be nonlinear. On one hand, financial distress typically leads to a reduction in output, as mounting debt obligations diminish a firm's ability to borrow, thereby necessitating a cutback in debt-driven investments (Povel and Raith, 2004). On the other hand, financial constraints might paradoxically prompt an increase in production, as firms seek to enhance cash flows to meet debt obligations and stave off insolvency (Brander and Lewis, 1988; Domanski et al., 2015). A case in point is the Texas-based oil company Magnum Hunter, which declared bankruptcy in December 2014 but accelerated oil production under Chapter 11 to generate sufficient revenue for its creditors,[3] resulting in a one-third increase in production between mid-2014 and the end of 2015.[4] However, empirical studies on this intersection are sparse and often yield inconclusive results (Lehn and Zhu, 2016; Lips, 2019; De Ridder, 2019), highlighting the need for further investigation.

Our empirical analysis capitalizes on the dramatic decline in oil prices in 2014, one of the most significant in history, which introduced a sudden, industry-wide shock to the oil sector. This collapse

[3] Chapter 11 provides protection for a bankrupt firm from creditors, by allowing the firm to continue operation and work on plans to repay its creditor.
[4] See the news report in https://oilprice.com/Energy/Energy-General/Why-Are-Bankrupt-Oil-Companies-Still-Pumping.html

nearly paralyzed the lending market for oil companies and, when combined with impending debt maturities, significantly heightened rollover risk for many firms. Utilizing a difference-in-difference framework, we examine how firms adjusted their production in response to this financial distress. Our identification strategy treats the abrupt credit deterioration experienced by the oil industry in 2014 as a natural experiment, allowing us to explore the causal impact of financial distress on corporate production decisions.

The dataset utilized in this analysis comprises a comprehensive sample of publicly traded firms in the North American oil sector over the period from 2009 to 2016, derived from the Compustat database. The oil industry presents several key advantages for examining the relationship between debt and production. First, crude oil is relatively homogeneous compared to most manufactured goods, making oil production straightforward to measure and comparable across different firms (Rauch, 1999; Eichengreen et al., 2016). Second, the industry is notably reliant on debt financing. The debt levels within the oil and gas sector surged from approximately $1 trillion in 2006 to around $2.5 trillion by 2014, reflecting an annual growth rate of 15% (Domanski et al., 2015). This substantial increase in borrowing was fueled by the accommodative monetary policies initiated in 2008, along with strong investor confidence in the oil market, leading oil firms to extensively tap into credit markets.

Our primary measure of financial distress is designed to capture the ex-ante rollover risk faced by firms, calculated as the ratio of current liabilities to total sales at the close of 2013. This measure is informed by recent research that leverages variations in firms' preexisting levels of debt maturing during crises (Almeida et al., 2012; Carvalho, 2015; Duval et al., 2020; Chen and Duchin, 2024). In periods of severe credit tightening, firms with a larger proportion of debt maturing during a crisis encounter greater rollover risk compared to firms whose debt is primarily due over a longer horizon (He and Xiong, 2012). Given that the 2014 oil price shock was unanticipated, it is improbable that firms would have strategically adjusted their debt maturity structures at the end of 2013 to mitigate potential rollover risk in 2014. Thus, a firm's debt composition prior to the crisis can be considered exogenous to its subsequent outcomes. The identification strategy rests on the assumption that, in the absence of the shock, firms with varying levels of rollover risk would have exhibited parallel trends in the outcome variables, after accounting for observed firm characteristics. We confirm through our data that this parallel trends assumption is valid.

We employ a difference-in-difference methodology to examine the effects of financial distress on production. Our empirical model incorporates controls for a comprehensive set of time-varying firm characteristics, including size, leverage, and market-to-book ratio, alongside firm and year fixed effects. The results indicate that rollover risk significantly influenced production decisions in the aftermath of the oil price collapse. Specifically, a one-standard-deviation increase in the proportion of debt maturing in 2014 is associated with a 14.27 percent rise in oil production relative to pre-crisis levels. To bolster the robustness of our baseline findings, we conduct several additional tests. To mitigate endogeneity concerns, we create an alternative measure of rollover risk by excluding short-term debt from current liabilities, and the results remain consistent. We further apply a propensity score matching (PSM) technique to address potential endogeneity arising from unobserved firm-specific factors, such as future growth prospects. Additionally, we perform two placebo tests based on alternative crisis years, confirming that firms with varying rollover risk outside the narrow window surrounding the 2014 oil crisis did not display differential production behavior. To rule out the possibility that our findings are driven solely by lower prices, we include an interaction term between a production cost indicator and the crisis variable in our baseline regression, confirming that the observed effects are not attributable to price fluctuations.

We further investigate the heterogeneity in the production effects of rollover risk by examining the roles of cash holdings, capital intensity, and secured debt. Our analysis reveals that firms with lower cash reserves, higher capital intensity, and greater levels of secured debt experienced heightened rollover risk during the oil price crisis, leading to a more pronounced increase in production. These heterogeneous effects underscore our primary finding that the production response is driven by rollover risk, which poses a significant threat to highly leveraged firms. Lastly, we empirically test the mechanism through which financially distressed firms amplify production to generate additional revenue, thereby fulfilling their debt obligations.

This paper contributes to the expanding literature on the consequences of corporate financial distress. Prior research has explored various strategies firms use to navigate financial difficulties, including investing in riskier projects, employing derivatives for hedging, reducing corporate payouts, and increasing tax avoidance (Acharya and Viswanathan, 2011; Acharya, 2013; Bliss et al., 2015; Li et al., 2018; Chen and Duchin, 2019; Juelsrud and Nenov, 2019). However, the impact on production outcomes has been less studied. Our research addresses this gap by demonstrating that distressed firms may respond to financial challenges by ramping up production.

Additionally, our study advances the literature on debt maturity and rollover risk. Prior work has established that firms with shorter debt maturities face heightened default risks during credit crises (He and Xiong, 2012b). Existing research has shown that increased rollover risk compels firms to cut capital expenditures, liquidate assets at distress prices, and engage in risk-shifting behaviors (Almeida et al., 2012; He and Xiong, 2012b; Chen and Duchin, 2024). Our findings expand on this literature by emphasizing production outcomes, revealing that firms with higher rollover risk not only experience these pressures but also respond by increasing production and becoming more aggressive in the market.

Our paper also enriches the understanding of reserve-based lending, a common financing arrangement in the oil industry (Azar, 2017). Previous studies have indicated that the use of secured debt leads to more frequent asset sales among distressed firms compared to their less stressed counterparts, especially during crises when collateral values drop and secured creditors assert their claims (Gilson et al., 2016; Carey and Gordy, 2021; Ma et al., 2022). The heterogeneous impacts observed in our study are consistent with these findings. Specifically, a higher proportion of secured debt, which increases the cost of default, results in greater rollover risk and has a more significant impact on production.

Our research is related to the study by Gilje et al. (2020), which provides evidence that highly leveraged firms in the oil and gas sector expedite project completion, potentially at the expense of long-term project value. However, our study differs in several key aspects. First, while Gilje et al. (2020) focus on investment decisions and use well completion time as their dependent variable, we concentrate on production decisions, capturing output from both newly drilled and existing wells. Second, the mechanism we propose differs: Gilje et al. (2020) suggest that high-leverage firms complete wells early to boost collateral value and enhance their negotiating position in credit discussions. In contrast, we argue that financially distressed firms increase production primarily to generate revenue for servicing maturing debt. Third, whereas Gilje et al. (2020) limit their sample to 69 public oil companies utilizing fracking technology, our study uses a broader sample of listed oil companies, offering a more comprehensive analysis of the relationship between financial distress and production decisions.

The remainder of the paper is organized as follows. Section 2 provides an overview of the institutional background and a review of relevant literature. Section 3 describes the data used in the analysis. Section 4 outlines our identification strategy. Section 5 presents the empirical results. Section 6 explores the underlying mechanisms driving the observed effects. Finally, Section 7 offers concluding remarks.

2 Institutional Background, Literature Review and Hypothesis Development

2.1 Institutional Background

The 2014 oil price crisis represents one of the greatest oil price declines in modern history (Baumeister and Kilian, 2016). The WTI oil price fell from an average of $110 per barrel in mid-2014 to a low of $29 in January 2016, a decrease of 73.6% (see Figure 1). The magnitude of the slump was unprecedented, surpassing the 56% cumulative decline of the 1986 oil price collapse and the 67% cumulative decline during the 2008 financial crisis.

The 2014 oil price crisis was caused by an oversupply of crude oil coupled with reduced demand. On the supply side, increases in oil production in the US and Canada have caused an oversupply of crude oil (Chen and Duchin, 2024). The shale revolution greatly increased oil production in the U.S. Meanwhile, extraction from oil sands created an energy boom for Canada, whose oil reserve ranked third in the world. The surge in oil production from these two countries brought about a dramatic decline in oil imports, creating downward pressure on global oil prices. Furthermore, on the demand side, large commodity-importing countries, such as China, India and Brazil, experienced an economic slowdown since 2010. For example, in 2014, China's economic growth hit a record low in 24 years as its real estate market cooled down and the local government struggled with a heavy debt burden. Thus, the weakening global economy led to reduced demand for crude oil, pressing the oil price to further decline. Oil prices continued to decline until February 2016, when the OPEC countries coordinated on a production freeze and North American producers started to reduce oil production. These actions contributed to the subsequent rise in crude oil prices. In mid-2018, the WTI oil price recovered to above $70 per barrel.

The 2014 oil price drop led to severe credit tightening for oil firms. As oil prices plummeted, oil producers faced a substantial reduction in their revenues and profitability. Many had incurred significant debt to finance exploration and production during the prior period. With the sudden and prolonged decline in oil prices, servicing this debt became more challenging, raising concerns about their ability to meet interest and principal payments. Credit rating agencies also downgraded the creditworthiness of numerous oil firms, making it costlier to borrow and further eroding their financial stability. Reduced cash flows and liquidity concerns, exacerbated by asset write-downs, heightened the risk of financial distress and potential defaults. As lenders and investors became more cautious, the cost of borrowing increased, and terms for new debt issuance became more stringent, creating a credit squeeze for oil firms. Data on oil and gas firms released by the management consulting firm EnerCom Inc. showed that at least 42 oil and gas companies in the U.S. filed for bankruptcy following the 2014 oil crisis.[5]

2.2 Literature Review

Our work is closely related to the literature on how a firm's financial status affects its production planning. We summarize the related theoretical and empirical works separately.

Early theoretical studies include Brander and Lewis (1986) and Brander and Lewis (1988). While Brander and Lewis (1986) focus on the effects of limited liability in creating the connection between finance and production, Brander and Lewis (1988) consider bankruptcy cost as the source of the strategic interactions. They both find that firms have incentives to increase production if they use more debt. However, subsequent theoretical studies arrive at different conclusions. Parsons (1997) extends the model in Brander and Lewis (1988) and finds that in some cases, debt may make the firm conservative in setting output levels. Povel and Raith (2004) and Agliari et al. (2006) show that a financially constrained firm is incentivized to limit its bankruptcy risk by reducing its debt positions; thus, it underinvests and has output levels lower than that of an unconstrained firm.

Empirical studies on the impact of financial frictions on production decisions are limited and arrive at mixed conclusions. Lips (2018) uses a panel vector autoregressive approach to analyze the relationship between debt and production decisions for oil firms. He shows that financial leverage has no impact on contemporaneous production but may decrease production in subsequent quarters. In contrast, Gilje et al. (2020) show that highly levered firms are more likely to accelerate the completion of oil wells to start production early. Both of these two studies use debt–asset ratios to measure the extent of firms' financial distress, noting potential endogeneity concerns that firms might self-select into high or low debt-to-asset groups. However, our proxy for financial distress (rollover risk) is more likely to be exogenous to firm-level unobservables, hence yielding a causal estimation.

---

[5] See the link: https://www.oilandgas360.com/17-85-billion-in-oil-and-gas-bankruptcies-in-2015/

2.3 Hypothesis Development

Rollover risk, also known as refinancing risk, refers to the risk associated with soon-to-maturing debt (Acharya et al., 2011; Lobo et al 2022). Firms with shorter debt maturity usually face greater default risks during credit crises (He and Xiong, 2012), exacerbating their financial distress. The literature has found that elevated rollover risk forces firms to cut capital expenditures, sell assets at fire-sale prices and engage in risk-shifting (Almeida et al., 2012; He and Xiong, 2012; Chen and Duchin, 2024). A firm with higher rollover risk may have strong motivations to ramp up its production when its debt is soon-to-maturing. The driving force behind this action is that the producer must gain enough revenue to pay off the maturing debt to avoid bankruptcy.

The dramatic decline in oil prices in 2014 provides us with a perfect setting to test this prediction. The 2014 oil price collapse led to a significant reduction in operating cash flow for oil producing companies. Many firms experienced record-high losses, and some even became insolvent. Given concerns about rapidly rising credit risk, banks froze credit lines for the oil industry, and the bond market liquidity for petroleum firms also dried up. The interruption in external financing brought unprecedented difficulties to producers regarding rolling over debt, triggering more financial pressure on affected firms. We predict that distressed oil producers are expected to increase their production. Therefore, our hypothesis is as follows:

H1: *Firms with high rollover risk substantially increase oil production following the 2014 oil price crisis.*

We test this hypothesis empirically in the following sections.

3 Data and Variables

3.1 Sample Construction

To investigate firms' production behavior around the 2014 oil price shock, we select a full sample spanning an eight-year window from 2009 to 2016 for publicly traded oil firms in North America (including the United States and Canada). The start of our sample period in 2009 witnessed the recovery of the global oil market from the 2008 financial crisis, while the end of the sample period in 2016 was when the oil price began to rebound from its 2014 plummet.

The primary source of data for this analysis is Compustat, where the financial data are available on an annual basis. Following Acharya et al. (2013), we restrict the analysis to Exploration & Production firms with a Standard Industrial Classification (SIC) code of 1311. These firms are primarily engaged in exploration and production activities (Crude Petroleum and Natural Gas)[6]. We have included both currently active and inactive firms in the sample and have not imposed any restriction on firms reporting data for all years. Application of unbalanced panel data, which admits the possibility of both entry and exit, mitigates potential selection and survivorship bias.[7]

Firm-level oil production data also comes from Compustat but in a different segment, *Industry Specific Annual*. This segment contains industry-specific datasets, including data specific to the oil and gas industry, such as oil production and total proven oil reserves. For the information on oil production, some firms report it as average production per day, and some firms report it as total production per year, while other firms report both. We choose total production per year as the variable for oil production, as it has fewer missing observations. In cases that this information is not available, we transform average production per day to total production per year (see Appendix B for more details). After this data imputation, the share of observations with missing production values is around 20%. Missing production values is not a big concern in the analysis, because most firms with missing production values are junior miners or pure exploration companies that are not supposed to have positive production. We also conduct a check in Appendix C to show that missing production values cannot be predicted by rollover risk, hence are not driving the results.

We merge these two datasets on financial information and production, and then exclude firms that have observations only in pre-crisis or post-crisis periods. This gives 366 firms with 2307 observations in total during 2009-2016. Further, we drop observations with nonpositive production, which yields 310 firms with 1818 observations. To minimize the effect of extreme values on the empirical results, we winsorize the production variable and rollover risk variable at 1% and 99%. We also drop firm-year observations with missing or extreme values on control variables, such as firms with market-to-book ratios higher than 100. All these procedures lead to a final sample with 272 distinct firms and 1622 firm-year observations during 2009-2016.

3.2 Measures of Key Variables

[6] Firms in SIC 2911 (Petroleum Refining) are not included in the analysis. This is because most of them are vertically integrated oil firms that mainly engage in refining businesses, whereas oil price shocks are expected to have a larger influence on producing rather than on refining.

[7] We carefully examine the pattern of bankruptcy in our sample. We collect bankruptcy filings on publicly traded oil firms following the 2014 oil price crisis from the UCLA-LoPucki Bankruptcy Research Database. Consistent with Chen and Duchin (2024), we find no public firms in the oil sector filed for bankruptcy in 2014. Six and eleven firms filed for bankruptcy in 2015 and 2016, respectively. Since these bankrupt firms were all observed in 2014, we have at least one pre-treatment and one post-treatment observations for the same firm, thus mitigating the concern on sample selection bias.

3.2.1 Production

We use the natural logarithm of a firm's annual oil production as the dependent variable. It is defined as follows:

$$Prod_{it} = Log(Production_{it}) \tag{1}$$

where $Production_{it}$ denotes the amount of oil (millions of barrels) produced by firm *i* in year *t*.

3.2.2 Rollover Risk

Following Duval et al. (2020), we capture firm-level financial distress by a firm's ex ante debt rollover risk, measured as the proportion of precrisis debt that was arranged to mature during the crisis. Specifically, we derive the rollover risk using the ratio of current liabilities to total sales at the end of 2013. This measure is in a similar vein as that used in recent studies that exploit variation in the precrisis debt maturity structure (Almeida et al., 2012; Carvalho, 2015; Chen and Duchin, 2024; Li and Zheng, 2020). As the 2014 oil price shock was unexpected, it is arguably true that firms did not self-select into a particular deb maturity structure before the crisis. In other words, firms were unlikely to intentionally adjust the proportion of maturing debt before the crisis to prevent potential future rollover risk. Therefore, the variation in the financial position at the end of 2013 is exogenous to firm production decisions after the crisis.

3.3 Control Variables

Following Chod and Lyandres (2011) and Hsu et al. (2010), we include firm size, financial leverage, and market-to-book ratio as control variables. We define firm size as the natural logarithm of a firm's total asset. Larger firms have more physical capital and they are expected to manufacture more goods. Financial leverage is measured as the ratio of total liability divided by total assets. Debt taking may boost production, as firms could use borrowed funding to expand investment and increase production capacity (Campello, 2006). Market-to-book is defined as the ratio of the summation of the market value of equity and the book value of debt to book assets. Firms with higher market-to-book ratios face lower borrowing costs and find it easier to raise debt for production expansion (Chen and Zhao, 2006).

3.4 Summary Statistics

Table 1 presents summary statistics of production, rollover risk, and other firm-level characteristics. Firm-level oil production has a mean value of 8.23 million barrels per year and a median of 1.09

million barrels per year. The mean value of the natural logarithm of firm-level oil production is -0.21, and its median value is 0.09. The measure of rollover risk exhibits considerable variations across firms. The ratio of current liabilities divided by total sales in 2013 has an average value of 1.00 with a standard deviation of 2.34. Table 1 also summarizes the statistics for the control variables. Firm size, calculated as the natural logarithm of total assets, has a mean value of 6.26. The mean value for firm leverage is 0.31, indicating that, on average, firms' total debt accounts for 31% of book assets. On average, we have market-to-book ratios larger than one.

4 Identification Strategy

By employing a difference-in-difference method, we analyze firms' production decisions around the oil crisis. We design the analysis based on the debt maturity structure at the end of 2013. The measure is inspired by recent studies that utilize the differential across firms in preexisting levels of maturing debt during crises (Almeida et al. 2012; Carvalho, 2015; Duval et al. 2020). Due to severe credit tightening, firms with a larger proportion of debt maturing within a year face higher rollover risk than do firms whose debt is mostly maturing further out (He and Xiong, 2012). We compare the pre- and post-crisis change in production for firms with different degrees of rollover risk (that is, preexisting debt maturity structures), controlling for firm attributes and year and firm fixed effects. The identification assumption is that without the oil price shock, oil production in firms with different rollover risks would follow the same trend. As the 2014 oil price plummet was unexpected, it is unlikely that firms systematically adjusted their debt maturity structures at the end of 2013 to prevent potential rollover risk in 2014. Therefore, a firm's debt structure before the crisis is arguably exogeneous to potential firm outcomes.

The specification of the regression is as follows:

$$Prod_{it} = \alpha_0 + \alpha_1 RO_i \times Crisis_t + \alpha_1 X_{it} + \kappa_i + \varphi_t + \varepsilon_{it} \quad (2)$$

where $Prod_{it}$ is the oil production for firm *i* in year *t*, measured as the natural logarithm of oil production in year *t*. The variable RO_i is the rollover risk facing firm *i* during the crisis, measured as the relative size of current liabilities to total sales at the end of 2013. $Crisis_t$ is a time indicator that equals one for observations during 2014-2016 and zero during 2009-2013. X_{it} represents the set of control variables, including firm size, financial leverage, and market-to-book ratio. The variables κ_i

and φ_t are firm-fixed and year-fixed effects, respectively. ε_{it} is the error term with standard errors clustered at the firm level.

The key assumption for a difference-in-difference regression is that treated and control firms have parallel trends in the absence of the treatment. To examine this assumption, we plot the production trends for firms with different degrees of rollover risk in Figure 2. The figure shows that before the crisis, low rollover risk firms (long dashed lines) and high rollover risk firms (solid lines) experienced a similar production trajectory. However, during the 2014 oil price crisis, the production for high rollover risk firms increased considerably and surpassed that of the other firms. This implies that the parallel trend assumption is likely to hold in our empirical analysis.

5 Empirical Results

5.1 Baseline Results

Table 2 reports the estimated effect of rollover risk at the outset of the oil price crash on production. In Column 1, the model includes firm fixed effects and a subset of controls (only firm size); in Column 2, the model includes firm fixed effects and a whole set of control variables; in Column 3, the model includes both firm and year fixed effects, as well as a whole set of controls. Our variable of interest is the interaction term between the ex-ante rollover risk and the crisis indicator, which captures the impact of rollover risk on firm production behavior following the oil price crash.

The results in Columns 1-3 consistently show that firms with greater rollover risk (that is, a larger ratio of current liabilities to total sales) substantially increased oil production following the crisis. The results hold after we control for time-invariant firm fixed effects and time-specific effects (year fixed effects). The impacts are significantly positive at the 1% level across all models. Column 3 shows that a one-standard-deviation increase in the share of debt maturing in 2014 led to a 14.27 (0.061*2.34*100) percent increase in production in the post-crisis period.

Our empirical results show that rollover risk has a significant impact on firms' production decisions.[8] This is aligned with other studies that find that the structure of debt maturity affects firms'

[8] Our results also imply that oil firms are underproducing in normal times. In North America, most wells are pumped because the subsurface reservoir pressure is not sufficient to make the oil flow to the surface (Rao, 2018). Operators of existing oil wells adjust their production by slowing down or accelerating the pumping units. However, usually operators do not set the pumping speed at the well's maximum flow for two reasons. First, pumping is costly. Pumping involves a fixed cost, such as the cost of pumping equipment rental, and an operating cost, such as for labor and the electricity consumed to drive the pump. Most firms face a convex cost in producing oil from existing oil wells (Rao, 2018; Anderson et al., 2018), which makes the well's optimal extraction rate lower than its maximum flow. Second, underproducing is helpful in extending the economic life of wells. A well's maximum flow decays when more oil is extracted, as extraction reduces reservoir pressure (Hotelling, 1931; Anderson et al., 2018). To maintain reservoir pressure for a longer period and gain

investment behavior. For example, Chen and Duchin (2024) find that firms with large current liabilities positions expanded investments in risky financial assets by approximately 50 percent more than did other firms after the 2014 oil crisis. Almeida et al. (2012) also highlight the significant impact of the maturity structure and find that firms with a higher share of long-term debt maturing during the 2007 credit crisis reduced their investments by 18 percent more than did otherwise similar firms.

In addition, in Table 2, we find that some control variables have significant impacts on firm production. For instance, the coefficient on firm size is positive and statistically significant at the 1% level, suggesting that larger firms produced more crude oil. Firm leverage is significantly positively correlated with production, indicating that firms taking more debt expanded production to a larger extent. The coefficient on the market-to-book ratio is also significantly positive, suggesting that high-value firms achieved greater production, perhaps due to higher borrowing capacities.

5.2 Robustness Checks

5.2.1 Alternative Measures of Rollover Risk

When constructing our key variable, debt rollover risk, we have included both long-term debt and short-term debt scheduled to mature in 2014. A concern with this variable is that it may not be exogenous to firm outcomes. While long-term debt was prescheduled long before the 2014 oil price crisis, the short-term debt scheduled to mature in 2014 might still bear some endogeneity concerns – firms might rearrange the debt structure of 2014 before the crisis based on their expectations for future economic and financial conditions.[9] To assuage this concern, we conduct a robustness check by excluding short-term debt from current liabilities to measure firms' exposure to unexpected oil price shocks, following Duval et al. (2020).

We re-estimate our baseline model with rollover risk measured as the ratio of current liabilities excluding short-term debt at the end of 2013 to total sales in 2013. Consistent with our main results, the coefficients on the interaction term remain significantly positive in all three models (Table 3), and their magnitudes are close to the results in our baseline regression. These exercises strengthen the confidence in our main findings.

---

steady output, operators could choose to underproduce at the early stage of production. This strategy reduces the rate of decay in production from wells and ultimately increases the well's total production.

[9] Despite the merit of a higher likelihood of being exogenous, using long-term debt has a potential disadvantage. Large firms have greater access to long-term debt such as bonds than do small firms; therefore, focusing only on long-term debt creates selection problems. As a consequence, in our baseline analysis, we do not use the measure solely based on long-term debt.

5.2.2 A Matched Difference-in-difference Approach

When constructing our key variable, debt rollover risk, we include current liabilities at the end of 2013. While the oil price slide is largely unforeseen, the amount of current liabilities that firms decided to hold in 2013 might still be driven by future expected economic conditions or firms' unobservable characteristics. For example, firms with better prospects may raise more debt to exploit these growth opportunities, thus leading to higher production. Ideally, we should identify firm- or project-level sources of heterogeneous investment opportunities. However, such data are prohibitively difficult to gather. Therefore, we try to match control and treatment firms with variables likely to be correlated with growth opportunities, such as total proven reserves, as well as the control variables mentioned in our baseline regression. We first apply Propensity Score Matching (PSM) to generate comparable treated and control groups, and then conduct a difference-in-difference regression based on this matched sample.

When applying PSM, we first estimate a probit model. The dependent variable, high rollover risk, is an indicator of whether a firm's rollover risk is above the sample median. It equals one if the firm's rollover risk is above the sample median and zero otherwise. The probit model includes total proven reserve and all control variables from Equation (2). Using propensity scores estimated from the probit model and nearest-neighbor matching, we match between treated and control firms (following Smith and Todd 2005). Covariates are matched with a 1:4 nearest-neighbor algorithm.[10] The final matched sample has 119 treated firms and 131 control firms. Then, we run the difference-in-difference regression as in Equation (2) to estimate the causal effect of rollover risk on firm production using the matched sample. The estimation results are reported in Table 4. Consistent with our main results, in columns (1) - (3), the coefficients of the interaction term *High Rollover Risk*Crisis* remain positive at conventional levels of significance. Specifically, Column (3) shows that the coefficient of the interaction term is 0.271. Considering that the gap in average rollover risk between treated firms (firms with high rollover risk) and control firms (firms with low rollover risk) is 1.64, this coefficient implies that a one-standard-deviation increase in the share of debt maturing in 2014 resulted in a 38.7 percent (0.271/1.64*2.34) increase in oil production relative to that before the crisis. The results of these exercises are largely comparable with the baseline results. This further supports that our main

[10] Our results are robust to the use of different numbers (that is, the parameter *K*) of the neighbors.

results are not driven by unobserved firm-level factors, especially future growth prospects, between the treated and control groups.

5.2.3 Placebo Test

To further strengthen our findings, we perform two falsification tests by assuming a crisis year immediately before and after the sharp price decline. In these tests, we verify that there is a null production effect of larger proportions of debt maturing in the hypothetical crisis year.

We first conduct the test using the 2009-2013 sample, assuming 2009-2012 as the pre-event period and 2013 as the event year. The firm's rollover risk variable is the ratio of current liabilities to total sales at the end of 2012. Column 1 in Table 5 shows estimates from the preferred model, including a full set of fixed effects and covariates. As we expected, there is no statistically significant impact of maturing debt on production because of the lack of credit tightening in 2013.

Similarly, we conduct another test using the 2013-2016 sample, assuming 2013-2014 as the preevent period, 2015 as the event year, and 2016 as the post-event period. We similarly define the rollover risk variable—the relative size of current liabilities to total sales at the end of 2014. Again, the result is not statistically significant, as shown in Column 2 of Table 5.

Both of these tests suggest that firms with different rollover risks largely follow similar trends outside the windows around the 2014 oil price collapse. This reinforces the validity of our identification strategy that the differential change in production between firms with different rollover risks was driven by the 2014 oil crisis.

5.2.4 Controlling for the Price Effect

There may be concerns that overproduction is merely the result of a lower price effect rather than financial distress. To alleviate these concerns, we control for the price effect in our regression and check whether it drives the main results. Firms with higher extraction costs are more vulnerable to substantial oil price declines (Baumeister and Kilian, 2016), as a decrease in oil prices squeezes their profit more than it does the profits of firms with lower production costs. In the extreme case, the oil price crisis could even lead to a negative profit for high cost firms. Therefore, if overproduction is merely the result of a lower price effect, then we expect firms with higher extraction costs to increase production to a larger extent.

Given that production cost data are not available in the dataset, we use a firm's exposure to fracking as a proxy for its production cost. Shale oil drilling and extraction is far more expensive than conventional oil extraction, as it involves more drilling rigs and skilled labor (Kilian, 2016; Smith, 2018). However, it is difficult to exactly identify a shale oil producer in our data, as listed oil and gas firms do not disclose their production composition in terms of shale oil and nonshale oil. To address this data limitation, we define a firm as having high exposure to fracking if it describes itself as a shale oil producer in its annual financial reports. We create an indicator that takes the value of one if the firm has high exposure to fracking and zero otherwise. Then, we add the interaction between this indicator and the crisis variable to the baseline regression.

Table 6 reports the estimated results. It shows that the interaction term *Rollover Risk*Crisis* continues to be significantly positive; however, the interaction term between *Fracking* and the *Crisis* variable is positive but not significant. This alleviates the concern that our main finding is driven by the price effect. This analysis reaffirms the baseline results that firms with higher financial distress exhibited a stronger production increase.

5.3 Heterogeneous Effects

We provide cross-sectional evidence on the established relationship between financial distress and production planning. These analyses enhance the conclusion of our empirical model.

5.3.1 The Role of Cash Holdings

We first examine whether the extent of cash holdings attenuates the relationship between financial distress and production planning. When a firm has difficulties rolling over its debt, it may be forced to search for sources of expensive funding. However, one way to mitigate this risk is to hold excess cash holdings (Brunnermeier and Yogo, 2009). Firms can draw from their cash reserves and pay down some of the maturing debt (Bianchi et al. 2018; Bosch-Rosa, 2018). If firms have sufficiently large cash holdings to settle their debt that is due, they do not have to roll over the debt (Liu et al. 2021a). As documented by Edwards et al. (2016), firms with more cash holdings are less likely to be affected by increased financial distress. Therefore, we expect that firms with fewer cash reserves are more sensitive to the 2014 oil price crisis, and hence more likely to increase production.

We sort firms into two subsamples on the basis of their pre-crisis cash holdings, which are proxied by cash and short-term investments divided by total assets (Bliss et al. 2015; Amberg et al., 2021). A firm is sorted into the high (low) group if its averaged cash reserve during 2011-2013 is above (below) the sample median. We re-estimate the DID Equation (2) for each group of firms. Panel A of Table 7 shows that the overproduction effect of rollover risk following the 2014 oil crisis is more pronounced in firms with lower cash holdings, as evidenced by the significant and larger coefficient in Column 2 relative to that in Column 1. Our results suggest that the production increases following the oil crisis were mainly driven by highly levered firms with poor cash holdings. This strengthens our key finding that the interaction of firm-level rollover risk in 2014 and the oil price plummet plays an important role in post-crisis production changes.

5.3.2 Capital Intensity

In this subsection, we investigate whether capital intensity moderates or exacerbates the overproduction effect of roller risk. During periods of oil price declines, smaller rigs can shut down temporarily and then restart once the price rises; however, larger and capital-intensive drilling operations cannot be shed as easily due to their high adjustment costs. Considering that most property, plant and equipment are sunk costs, firms continue to produce as long as they are able to cover short-term variable costs (Pindyck, 1990). Recent studies find that firms with higher capital intensity experienced worse losses during economic downturns, such as the pandemic, as these firms have less flexibility with respect to reducing costs (Alfaro et al., 2020). Therefore, the overproduction effect of rollover risk may be pronounced in firms with high capital intensity. We expect that more capital-intensive firms are more sensitive to the 2014 oil price crisis; thus, they are more likely to increase their production.

We classify firms into two subsamples based on their capital intensity at the baseline, which is measured as the averaged ratio of net property, plant and equipment (PPE) over sales during 2011-2013 (Pindado et al. 2010; Carrión-Flores and Innes, 2010). A firm is sorted into the high (low) capital-intensive group if its capital intensity is above (below) the sample median. We re-estimate DID Equation (2) for each group of firms. Panel B of Table 7 shows that the overproduction effect of rollover risk following the 2014 oil crisis is stronger in firms with higher capital intensity, as evidenced by the significant and larger coefficient in Column 3 relative to that in Column 4. This corroborates our key finding that firm-level rollover risk and the oil price drop play an important role in post-crisis production changes.

5.3.3 The Role of Secured Debt

The extent to which a firm is exposed to rollover risk may be positively associated with its share of secured debt. Reserve-based lending is commonly used in the oil industry, and the loan facility available to the borrower is secured by its proven oil reserve (Azar, 2017). Creditors use crude oil prices to evaluate reserves; however, the dramatic oil price collapse reduces collateral value. Secured creditors may be concerned with the erosion of their collateral and are highly motivated to push for debt repayment (Carey and Gordy, 2021), thus exacerbating producers' rollover risk. Recent studies show that the greater use of secured debt results in more sales in distressed firms than in otherwise unstressed firms, as secured creditors enforce their rights to collateral (Gilson et al., 2016; Ma et al., 2022). Therefore, the overproduction effect of rollover risk may be pronounced in firms with greater uses of secured debt. We expect that firms with more secured debt are more sensitive to the 2014 oil price crisis; thus, they are more likely to increase their production.

To analyze the role of secured debt, we supplement the main analysis sample with a second dataset, Capital IQ, which has information on firm-level debt structures.[11] Capital IQ has compiled comprehensive and detailed information on firm debt structures by going through financial footnotes in firms' SEC 10-K filings (Colla et al., 2013). Following Colla et al. (2013) and Ma et al. (2022), we construct our measure of the secured debt ratio as the sum of the outstanding amount of drawn bank revolvers, term loans, secured bonds and notes, capital leases, and other secured debt divided by the total debt amount. A firm is sorted into the high (low) secured debt group if its average ratios of secured debt during 2011-2013 are above (below) the sample median. We re-estimate the DID Equation (2) for each group of firms, respectively. Panel C of Table 7 reports the regression results. The coefficient on the interaction term *Rollover Risk*Crisis* is positively significant in Column 5 and larger than that in Column 6, suggesting that the impact of rollover risk during the oil price crisis was exacerbated in firms with greater secured debt. This confirms our key finding that the urgency to roll over maturing debt drives post-crisis production.

6 Mechanism

In this section, we empirically test the potential channel through which a firm's elevated rollover risk translates into increased production. As outlined in our hypothesis development in Section 2.3, we posited that increased rollover risk prompts firms to increase production to cope with exacerbated default risk following the 2014 oil price crisis. As the credit market for the oil industry came to a sudden halt following the 2014 oil price plunge, most producers faced deteriorating refinancing

[11] We link Capital IQ to the Compustat dataset by unique firm ID: Global Company Key. We remove firm-year observations if the difference between total debt provided by Compustat and the summation of the debt components provided by Capital IQ is greater than 10% of total debt (as in Colla et al., 2013).

conditions (Chen and Duchin, 2024). To meet debt obligations, they had to resort to internally generated revenue by producing more barrels of crude oil. We therefore test whether firms with higher rollover risk indeed exhibit a larger degree of default risk. This empirical validation could help to bolster our central finding that firms ramp up production to fulfill the obligations associated with maturing debt.

Empirically, we examine the impact of rollover risk on firms' default probability. We use measures based on Altman Z-score to capture a firm's default risk (Altman, 1968; Agarwal and Taffler, 2007; Almamy et al, 2016).[12] A lower Z-score indicates a greater default potential. Following Nguyen et al. (2020), Wu and Tian (2022), we define our dependent variable *High Default* as a binary variable indicating the bottom quartile of Z-score distribution within the sample. Table 8 shows the impact of rollover risk on firms' default risk. In Columns 1-2, the coefficients of interest *Rollover Risk*Crisis* are positive at conventional levels of significance. The results suggest that highly leveraged firms are particularly susceptible to default risk when confronted with adverse financial shocks. This supports our main finding that boosting sales through increased production could be a viable strategy for handling their maturing debt obligations during financial distress.

7 Conclusion

Our paper empirically examines the effect of financial distress on firms' production planning. Exploiting the firm-level variation in the preexisting exposure to the 2014 oil price decline, we find that firms with larger proportions of soon-to-mature debt at the outset of the crisis considerably expanded their production after the crisis. While many studies document changes in other operational perspectives related to financial distress, such as inventory management, supply chain solutions and pricing strategies (Chao et al., 2008; Luo and Shang, 2015; Birge et al., 2017; Jin et al., 2018), our findings complement this literature by highlighting that firms might manage rollover risk by adjusting production decisions. We also demonstrate the role of cash holdings, capital intensity and secured debt in moderating the production effect.

Our findings also have important implications for understanding the plummets in commodity prices during the oil crisis and its aftermath. We have found that higher debt rollover risk causes a

[12] The formula for Altman Z-score is Z = 1.2*X1+ 1.4*X2 + 3.3*X3 + 0.6*X4 +0.99*X5, where X1 = working capital/total assets, X2 = retained earnings/total assets, X3 = EBIT/total assets, X4 = market value of equity/total liabilities, X5 = total sales/total assets.

large increase in oil production. The additional production from oil producers was found to have a significant negative impact on global oil prices in 2014 (Baumeister and Kilian, 2016; Gundersen, 2020). Our findings also resonate with the recent dynamics of oil production during the great 2020 pandemic. Despite a sharp drop in oil prices in March 2020, the global oil industry continued to pump nearly record-high volumes, adding millions of barrels of oil to inventories. Among the many explanatory factors of this oversupply phenomenon, an explanation drawn from our analysis is that firms facing high rollover risk were forced to increase production and take aggressive strategies in the product market. Therefore, our study provides important implications for policymakers—it is necessary to help financially distressed producers obtain credit during the crisis, which helps alleviate the overproduction effect and stabilize commodity prices.

One potential limitation of our study is that we use a sample from the oil industry, and the results may not generalize to other sectors. Future research would benefit from extending the analysis to study industries involving agricultural and metal-based commodities. In addition, the connection between financial condition and production decisions could be analyzed by interacting with more underlying factors such as information asymmetry, credit concentration and public offering (e.g., Chod and Lyandres, 2011; Saidi and Streitz, 2021).

References

Agliari, Anna, Domenico Delli Gatti, Mauro Gallegati, and Stefano Lenci. "The complex dynamics of financially constrained heterogeneous firms." *Journal of Economic Behavior & Organization* 61, no. 4 (2006): 784-803.

Acharya, Viral V., Douglas Gale, and Tanju Yorulmazer. "Rollover risk and market freezes." *The Journal of Finance* 66, no. 4 (2011): 1177-1209.

Acharya, Viral V., Lars A. Lochstoer, and Tarun Ramadorai. "Limits to Arbitrage and Hedging: Evidence from Commodity Markets." *Journal of Financial Economics* 109, no. 2 (2013): 441–65.

Agarwal, Vineet, and Richard J. Taffler. "Twenty‐five years of the Taffler z‐score model: Does it really have predictive ability?." *Accounting and Business Research* 37, no. 4 (2007): 285-300.

Aldasoro, Iñaki, Bryan Hardy, and Nikola Tarashev. "Corporate debt: post-GFC through the pandemic." (2021).

Alfaro, Laura, et al. Aggregate and firm-level stock returns during pandemics, in real time. No. w26950. National Bureau of Economic Research, 2020.

Almamy, Jeehan, John Aston, and Leonard N. Ngwa. "An evaluation of Altman's Z-score using cash flow ratio to predict corporate failure amid the recent financial crisis: Evidence from the UK." *Journal of Corporate Finance* 36 (2016): 278-285.

Almeida, Heitor, Murillo Campello, Bruno Laranjeira, and Scott Weisbenner. "Corporate Debt Maturity and the Real Effects of the 2007 Credit Crisis." *Critical Finance Review* 1, no. 1 (2012): 3-58.

Amberg, Niklas, Tor Jacobson, Erik von Schedvin, and Robert Townsend. "Curbing Shocks to Corporate Liquidity: The Role of Trade Credit." *Journal of Political Economy* 129, no. 1 (2021): 182–242.

Anderson, Soren T., Ryan Kellogg, and Stephen W. Salant. "Hotelling under pressure." *Journal of Political Economy* 126, no. 3 (2018): 984-1026.

Azar, Amir. "Reserve base lending and the outlook for shale oil and gas finance." Columbia Center on Global Energy Policy working paper (2017).

Baumeister, Christiane, and Lutz Kilian. "Understanding the Decline in the Price of Oil since June 2014." *Journal of the Association of Environmental and Resource Economists* 3, no. 1 (2016): 131-158.

Bianchi, Javier, Juan Carlos Hatchondo, and Leonardo Martinez. "International Reserves and Rollover Risk." *American Economic Review* 108, no. 9 (2018): 2629–70.

Birge, John R., Rodney P. Parker, Michelle Xiao Wu, and S. Alex Yang. "When Customers Anticipate Liquidation Sales: Managing Operations under Financial Distress." *Manufacturing & Service Operations Management* 19, no. 4 (2017): 657–73.

Bliss, Barbara A., Yingmei Cheng, and David J. Denis. "Corporate payout, cash retention, and the supply of credit: Evidence from the 2008–2009 credit crisis." *Journal of Financial Economics* 115.3 (2015): 521-540.

Bosch-Rosa, Ciril. "That's how we roll: an experiment on rollover risk." *Journal of Economic Behavior & Organization* 145 (2018): 495-510.

Branch, Ben. "The costs of bankruptcy: A review." *International Review of Financial Analysis* 11, no. 1 (2002): 39-57.

Brander, James A., and Tracy R. Lewis. "Oligopoly and financial structure: The limited liability effect." *The American Economic Review* (1986): 956-970.

Brander, James A., and Tracy R. Lewis. "Bankruptcy costs and the theory of oligopoly." *Canadian Journal of Economics* (1988): 221-243.

Brunnermeier, Markus K, and Motohiro Yogo. “A Note on Liquidity Risk Management.” *American Economic Review* 99, no. 2 (2009): 578–83.

Campello, Murillo. "Debt financing: Does it boost or hurt firm performance in product markets?." *Journal of Financial Economics* 82, no. 1 (2006): 135-172.

Carey, Mark, and Michael B. Gordy. “The Bank as Grim Reaper: Debt Composition and Bankruptcy Thresholds.” *Journal of Financial Economics* 142, no. 3 (2021): 1092–1108.

Carvalho, Daniel. "Financing constraints and the amplification of aggregate downturns." *The Review of Financial Studies* 28, no. 9 (2015): 2463-2501.

Carrión-Flores, Carmen E., and Robert Innes. "Environmental innovation and environmental performance." *Journal of Environmental Economics and Management* 59.1 (2010): 27-42.

Chao, Xiuli, Jia Chen, and Shouyang Wang. “Dynamic Inventory Management with Cash Flow Constraints.” *Naval Research Logistics* 55, no. 8 (2008): 758–68.

Chen, Zhiyao, and Ran Duchin. "Do Nonfinancial Firms Use Financial Assets to Take Risk?." *The Review of Corporate Finance Studies* 13, no. 1 (2024): 1-37.

Chen, Long, and Xinlei Zhao. "On the relation between the market-to-book ratio, growth opportunity, and leverage ratio." *Finance Research Letters* 3.4 (2006): 253-266.

Chod, Jiri, and Evgeny Lyandres. “Strategic Ipos and Product Market Competition.” *Journal of Financial Economics* 100, no. 1 (2011): 45–67.

Colla, Paolo, Filippo Ippolito, and Kai Li. "Debt specialization." *The Journal of Finance* 68, no. 5 (2013): 2117-2141.

Dasgupta, Sudipto, Erica XN Li, and Dong Yan. "Inventory behavior and financial constraints: Theory and evidence." *The Review of Financial Studies* 32.3 (2019): 1188-1233.

Deng, Shiming, Chaocheng Gu, Gangshu (George) Cai, and Yanhai Li. "Financing Multiple Heterogeneous Suppliers in Assembly Systems: Buyer Finance vs. Bank Finance." *Manufacturing & Service Operations Management* 20, no. 1 (2018): 53－69.

De Ridder, Maarten. Intangibles investment and the persistent effect of financial crises on output. Cambridge INET working paper, 2019.

Domanski, Dietrich, Jonathan Kearns, Marco J. Lombardi, and Hyun Song Shin. "Oil and debt." BIS Quarterly Review March (2015).

Duval, Romain, Gee Hee Hong, and Yannick Timmer. "Financial frictions and the great productivity slowdown." *The Review of Financial Studies* 33, no. 2 (2020): 475-503.

Eckbo, B. Espen, Karin S. Thorburn, and Wei Wang. "How costly is corporate bankruptcy for the CEO?." *Journal of Financial Economics* 121, no. 1 (2016): 210-229.

Edwards, Alexander, Casey Schwab, and Terry Shevlin. "Financial constraints and cash tax savings." *The Accounting Review* 91, no. 3 (2016): 859-881.

Eichengreen, Barry, Livia Chiţu, and Arnaud Mehl. "Network effects, homogeneous goods and international currency choice: New evidence on oil markets from an older era." *Canadian Journal of Economics*/Revue canadienne d'économique 49, no. 1 (2016): 173-206.

Ferriani, Fabrizio, Filippo Natoli, Giovanni Furio Veronese, and Federica Zeni. “Risk Premium in the Era of Shale Oil.” SSRN Electronic Journal, 2019.

Flaaen, Aaron, Ali Hortaçsu, and Felix Tintelnot. "The production relocation and price effects of US trade policy: the case of washing machines." *American Economic Review* 110, no. 7 (2020): 2103-27.

Hotelling, Harold, "The Economics of Exhaustible Resources," *Journal of Political Economy 39*, no. 2 (1931): 137–175

Gundersen, Thomas S. "The impact of US supply shocks on the global oil price." *The Energy Journal* 41, no. 1 (2020): 151-174.

Gilje, Erik, Elena Loutskina, and Daniel Murphy. "Drilling and debt." *The Journal of Finance* 75, no. 3 (2020): 1287-1325.

Gilson, Stuart C., Edith S. Hotchkiss, and Matthew G. Osborn. "Cashing out: The rise of M&A in bankruptcy." Available at SSRN 2547168 (2016).

He, Zhiguo, and Wei Xiong. "Rollover risk and credit risk." *The Journal of Finance* 67, no. 2 (2012): 391-430.

Houde, Sebastien, and Wenjun Wang. The incidence of the US-China solar trade war. No. 22/372. Economics Working Paper Series, 2022.

Hitomi, Katsundo. Manufacturing systems engineering: a unified approach to manufacturing technology, production management and industrial economics. CRC Press, 1996.

Hsu, Hung‐Chia, Adam V. Reed, and Jörg Rocholl. "The new game in town: Competitive effects of IPOs." *The Journal of Finance* 65, no. 2 (2010): 495-528.

Jin, Wei, Jianwen Luo, and Qinhong Zhang. "Optimal Ordering and Financing Decisions under Advance Selling and Delayed Payment for a Capital-Constrained Supply Chain." *Journal of the Operational Research Society* 69, no. 12 (2018): 1978–93.

Kashyap, Anil K., Jeremy C. Stein, and David W. Wilcox. 1993. "Monetary Policy and Credit Conditions: Evidence from the Composition of External Finance." *American Economic Review* 83 (1):78–98.

Kilian, Lutz. "The Impact of the Shale Oil Revolution on U.S. Oil and Gasoline Prices." *Review of Environmental Economics and Policy* 10, no. 2 (2016): 185–205.

Lehn, Kenneth, and Pengcheng Zhu. "Debt, investment and production in the US oil Industry: An analysis of the 2014 oil price shock." Available at SSRN 2817123 (2016).

Li, Wu-Lung, and Kenneth Zheng. "Rollover risk and managerial cost adjustment decisions." *Accounting & Finance* 60, no. 3 (2020): 2843-2878.

Lips, Johannes. "Debt and the Oil Industry-Analysis on the Firm and Production Level." Available at SSRN 3026063 (2018).

Liu, Ya, Buhui Qiu, and Teng Wang. "Debt rollover risk, credit default swap spread and stock returns: Evidence from the COVID-19 crisis." *Journal of Financial Stability* 53 (2021a): 100855.

Lobo, Gerald J., Myungsoo Son, and Hakjoon Song. "How Do Auditors Respond to Clients' Rollover Risk?." *Journal of Accounting, Auditing & Finance* (2022): 0148558X221115120.

Luo, Wei, and Kevin Shang. "Joint Inventory and Cash Management for Multidivisional Supply Chains." *Operations Research* 63, no. 5 (2015): 1098–1116.

Ma, Song, Joy Tianjiao Tong, and Wei Wang. "Bankrupt Innovative Firms." *Management Science* 68, no. 9 (2022): 6971–92.

Nguyen, Justin Hung, Cameron Truong, and Bohui Zhang. "The price of carbon risk: Evidence from the kyoto protocol ratification." Available at SSRN 3669660 (2020).

Parsons, John E. “A Note on Bankruptcy Costs and the Theory of Oligopoly.” *The Canadian Journal of Economics* 30, no. 2 (1997): 397.

Pástor, Ľuboš, Robert F. Stambaugh, and Lucian A. Taylor. "Dissecting green returns." *Journal of Financial Economics* 146, no. 2 (2022): 403-424.

Povel, Paul, and Michael Raith. “Financial Constraints and Product Market Competition: Ex Ante vs. Ex Post Incentives.” *International Journal of Industrial Organization* 22, no. 7 (2004): 917–49.

Pindado, Julio, Valdoceu De Queiroz, and Chabela De La Torre. “How Do Firm Characteristics Influence the Relationship between R&D and Firm Value?” *Financial Management* 39, no. 2 (2010): 757–82.

Pindyck, Robert. “Irreversibility, Uncertainty, and Investment,” 1990.

Rao, Nirupama L. “Taxes and US Oil Production: Evidence from California and the Windfall Profit Tax.” *American Economic Journal: Economic Policy* 10, no. 4 (2018): 268–301.

Rampini, Adriano A., Amir Sufi, and S. Viswanathan. "Dynamic risk management." *Journal of Financial Economics* 111, no. 2 (2014): 271-296.

Rauch, James E. "Networks versus markets in international trade." *Journal of International Economics* 48, no. 1 (1999): 7-35.

Saidi, Farzad, and Daniel Streitz. “Bank Concentration and Product Market Competition.” *The Review of Financial Studies* 34, no. 10 (2021): 4999–5035.

Smith, James L. “Estimating the Future Supply of Shale Oil: A Bakken Case Study.” *Energy Economics* 69 (2018): 395–403.

Smith, Jeffrey, and Petra E. Todd. "Does Matching Overcome Lalonde's Critique of Nonexperimental Estimators?" *Journal of Econometrics* 125, no. 1-2 (2005): 305-53.

Wang, Jiao, Lima Zhao, and Arnd Huchzermeier. “Operations-Finance Interface in Risk Management: Research Evolution and Opportunities.” *Production and Operations Management* 30, no. 2 (2021): 355–89.

Wu, Yuhui, and Yanan Tian. "The price of carbon risk: Evidence from China’s bond market." *China Journal of Accounting Research* 15, no. 2 (2022): 100245.

Figures and Tables

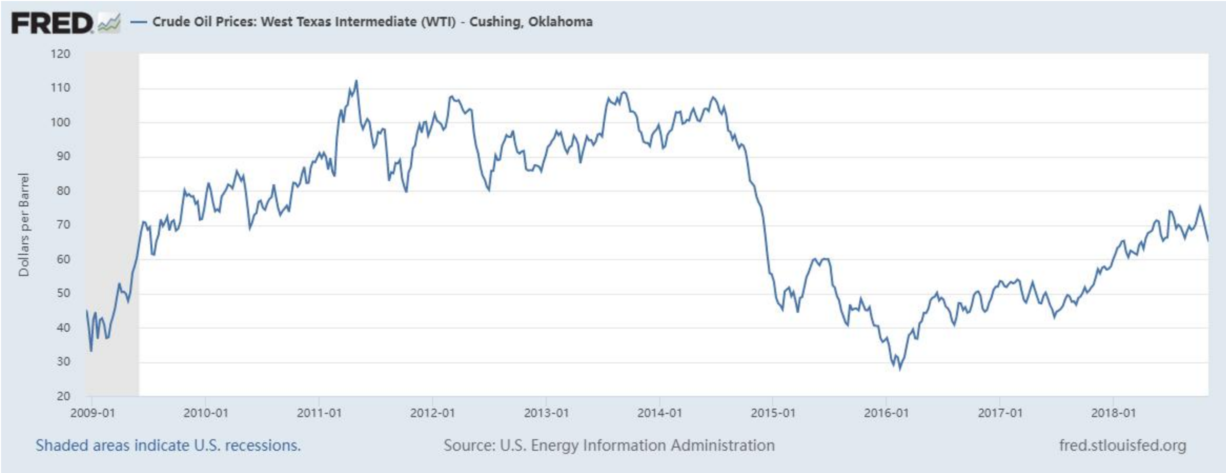

Figure 1　WTI Oil Price

Notes: This figure plots the WTI oil price (USD per barrel) from Jan 2009 to mid-2018.

Source: U.S. Energy Information Administration, FRED

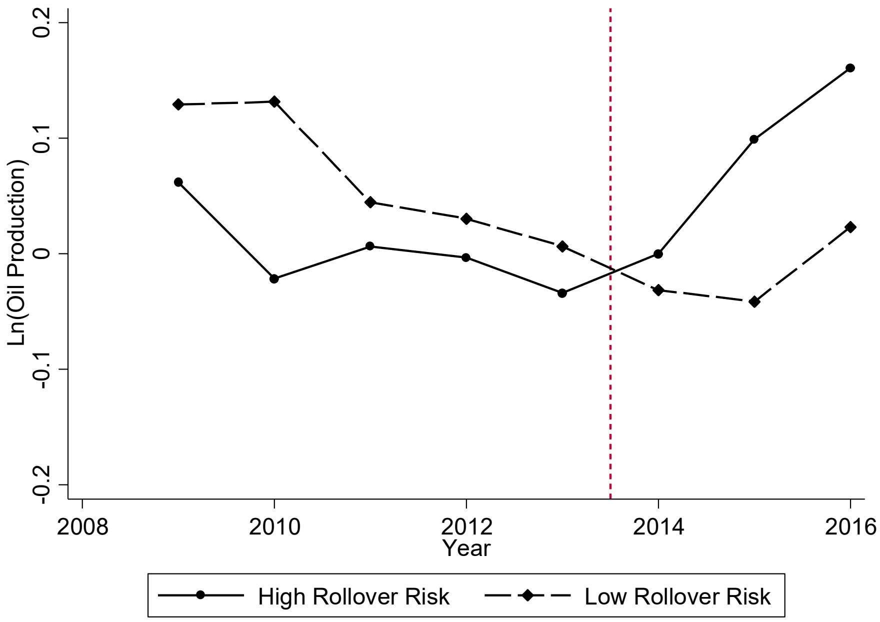

Figure 2   Trends in production for firms with different rollover risks

Notes: We plot oil production in firms with different levels of rollover risk (measured as the ratio of current liabilities to total sales at the end of 2013). "*High Rollover Risk*" indicates firms that are above the 50th percentile of the distribution of rollover risk. "*Low Rollover Risk*" indicates firms below the 50th percentile of the same distribution. The *y-axis* is the natural logarithm of oil production for the firms.

Table 1 Summary Statistics

Variables	Mean	SD	25th percentile	Median	75th percentile
Production (million barrel)	8.23	22.65	0.15	1.09	4.72
Ln(Production)	-0.21	2.54	-1.89	0.09	1.55
Rollover Risk	1.00	2.34	0.30	0.45	0.87
Firm Size	6.26	2.25	4.80	6.34	7.84
Leverage	0.31	0.41	0.11	0.25	0.40
Market-to-book	1.28	1.84	0.69	0.97	1.45
Observations	1622				

Notes: This table presents the summary statistics of the key variables during the sample period (2009-2016).

Table 2 Impact of Rollover Risk on Production

Dependent variable	*Ln(Production)*		
	(1)	(2)	(3)
Rollover Risk × Crisis	0.050***	0.048***	0.061***
	(0.018)	(0.018)	(0.018)
Crisis	0.341***	0.276***	
	(0.057)	(0.057)	
Firm Size	0.772***	0.845***	0.824***
	(0.067)	(0.067)	(0.072)
Leverage		0.415***	0.347***
		(0.073)	(0.068)
Market-to-book		0.028*	0.035**
		(0.015)	(0.017)
Constant	-5.215***	-5.807***	-5.560***
	(0.420)	(0.433)	(0.464)
Firm Fixed Effect	Yes	Yes	Yes
Year Fixed Effect	No	No	Yes
Observations	1,622	1,622	1,622
R-squared	0.946	0.949	0.950

Notes: The dependent variable is the natural logarithm of firms' annual production. "Rollover Risk" is measured as the ratio of current liabilities to total sales at the end of 2013. "Crisis" is an indicator that takes the value of zero in the period 2009-2013 and one in 2014-2016. See Appendix A for more details on variable constructions. Column (1) includes fixed effect and a subset of controls (only firm size); Column (2) includes firm fixed effect and a whole set of controls; Column (3) includes both firm and year fixed effects, as well as a whole set of controls. Standard errors in parentheses are clustered at the firm level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3 Robustness Check: Alternative Measures of Rollover Risks

Dependent variable	*Ln(Production)* (1)	(2)	(3)
Rollover Risk (excluding Short-term Debt) × Crisis	0.064**	0.058**	0.077**
	(0.030)	(0.029)	(0.031)
Crisis	0.337***	0.273***	
	(0.058)	(0.058)	
Full Controls	No	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes
Year Fixed Effect	No	No	Yes
Observations	1,597	1,597	1,597
R-squared	0.946	0.949	0.950

Notes: This table examines the robustness of our main results to using different measures of rollover risks. "Rollover Risk (excluding Short-term Debt)" is the amount of current liabilities excluding short-term debt divided by total sales at the end of 2013. "Crisis" is an indicator that takes the value of zero in 2009-2013 and one in 2014-2016. Column (1) includes fixed effect and a subset of controls (only firm size); Column (2) includes firm fixed effect and a whole set of controls; Column (3) includes both firm and year fixed effects, as well as a whole set of controls. Standard errors in parentheses are clustered at the firm level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4 Results from a matched difference-in-differences model

Dependent variable	*Ln(Production)* (1)	(2)	(3)
High Rollover Risk × Crisis	0.276**	0.240**	0.271**
	(0.126)	(0.118)	(0.120)
Crisis	0.334***	0.267***	
	(0.076)	(0.088)	
Full Controls	No	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	No	No	Yes
Observations	1,294	1,294	1,294
R-squared	0.936	0.939	0.941

Notes: This table reports the result for the difference-in-difference regression based on the propensity score matching subsample. We employ the nearest-neighbor matching method to ensure that the differences in firm attributes between firms with high rollover risk and firms with low rollover risk are insignificant. Covariates are matched with a 1:4 nearest-neighbor algorithm. Column (1) includes firm fixed effect and a subset of controls (only firm size); Column (2) includes firm fixed effect and a whole set of controls; Column (3) includes both firm and year fixed effects, as well as a whole set of controls. Standard errors in parentheses are clustered at the firm level. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5 Placebo Tests: Altering Crisis Years

Dependent variable	*Ln(Production)*	
	(1)	(2)
Maturing Debt × Crisis	-0.026	0.018
	(0.046)	(0.015)
Full Controls	Yes	Yes
Firm Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
R-squared	0.965	0.979
Observations	919	897
Subsample	2009-2013	2013-2016

Notes: This table presents two placebo tests by assuming the crisis year to be 2013 (Column 1) and 2015 (Column 2). Column (1) uses the 2009-2013 sample, assuming 2009-2012 as the pre-crisis period and 2013 as the post-crisis period. "Maturing Debt" in Column (1) is the amount of current liabilities divided by total sales at the end of 2012. Column (2) uses the 2013-2016 sample, assuming 2013-2014 as the pre-crisis period and 2015-2016 as the post-crisis period. "Maturing Debt" in Column (2) is the amount of current liabilities divided by total sales at the end of 2014. Standard errors in parentheses are clustered at the firm level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6 Controlling for the Price Effect

Dependent variable	*Ln(Production)*		
	(1)	(2)	(3)
Rollover Risk × Crisis	0.054***	0.051***	0.063***
	(0.018)	(0.018)	(0.018)
Crisis	0.308***	0.243***	
	(0.066)	(0.066)	
Fracking*Crisis	0.167	0.163	0.135
	(0.117)	(0.114)	(0.115)
Full Controls	No	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes
Year Fixed Effect	No	No	Yes
Observations	1,622	1,622	1,622
R-squared	0.947	0.949	0.950

Notes: "Fracking" is a dummy variable that equals one if the firm is a shale oil producer and zero otherwise. Column (1) includes firm fixed effect and a subset of controls (only firm size); Column (2) includes firm fixed effect and a whole set of controls; Column (3) includes both firm and year fixed effects, as well as a whole set of controls. Standard errors are clustered at the firm level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7 Heterogeneous Impacts

Variables	Panel A: Cash Holdings		Panel B: Capital Intensity		Panel C: Secured Debt	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
Rollover Risk × Crisis	0.015	0.140***	0.069**	-0.013	0.104***	0.007
	(0.047)	(0.046)	(0.027)	(0.101)	(0.026)	(0.066)
Full Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	757	782	738	801	481	612
R-squared	0.951	0.937	0.913	0.973	0.915	0.963

Notes: The dependent variable is the natural logarithm of firms' annual production. In Panel A, we measure cash holdings by using cash and short-term investment divided by total assets. A firm is sorted into the high (low) group if its averaged cash reserve during 2011-2013 is above (below) the sample median. In Panel B, we measure capital intensity by net PPE divided by total sales. A firm is sorted into the high (low) group if its averaged capital intensity during 2011-2013 is above (below) the sample median. In Panel C, we measure the ratio of secured debt by using secured debt divided by total debt. A firm is sorted into the high (low) group if its averaged ratio of secured debt during 2011-2013 is above (below) the sample median. All standard errors in parentheses are clustered at the firm level. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8 Mechanical Channels

Dependent variable	High Default	
	(1)	(2)
Rollover Risk × Crisis	0.033***	0.023**
	(0.011)	(0.011)
Full Controls	No	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	1,538	1,538
R-squared	0.570	0.596

Notes: This table reports the regression for mechanical channels. Our dependent variables is *High Default*, which equals one if the firm's Z-score is within the bottom quartile within the sample, and zero otherwise. "Rollover Risk" is measured as the ratio of current liabilities to total sales at the end of 2013. "Crisis" is an indicator that takes the value of zero in the period 2009-2013 and one in 2014-2016. Standard errors in parentheses are clustered at the firm level. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix A: Variable Definition

Production = firm-level oil production per year.

Prod = natural logarithm of firm-level oil production

Rollover Risk= total current liabilities divided by total sales at the end of 2013.

Reserve = firm-level total proven oil reserve.

Firm Size = natural logarithm of total book assets.

Leverage = total debt divided by total book assets.

Market-to-book = the sum of the equity and total debt divided by total book assets.

Cash Holdings = cash and short-term investment divided by total assets.

Capital Intensity = net property, plant and equipment (PPE) divided by sales.

Secured Debt = ratio of secured debt divided by total debt.

Appendix B: Details on Production Data

In this appendix, we provide more details on the production data used in our analysis. Firm-level oil production data come from Compustat, but in a different segment *Industry Specific Annual*. In this segment, Compustat offers industry-specific datasets, including data specific to the oil and gas industry, such as oil production and total proven oil reserve. During 2009-2016, there are 598 unique firms with 2902 observations in the production data. We find that 47% of these observations have production levels of zero or are altogether missing. To take full advantage of the limited data, we adopt a transformation method to gain more data points.

Regarding data reporting, there are three types of firms. Table B1 gives one example. The first type of firms only reports their production data as average production per day, such as firm A. The second type of firms only reports their production data as total production per year, such as firm B. The third type of firms reports their production data as both total production per year and average production per day, such as firm C.

In cases where annual production is unavailable (that is, for the first type of firms), we transform average production per day to total production per year. Total production per year is calculated as average production per day multiplied by 365. For a leap year, the average production per day is multiplied by 366. See the added data points on total production per year for firm A in Table B2. After this transformation, we have 2215 observations with positive production, accounting for 76% of total firm-year observations during 2009-2016.

Table B1 An example of data reporting on production

	Year	Total production per year (1,000 barrel)	Average production per day (1,000 barrel)
Firm A	2009		279
	2010		289
	2011		249
	2012		284
	2013		225
	2014		220
	2015		238
	2016		191
Firm B	2009	294	
	2010	291	
	2011	279	
	2012	298	
	2013	258	
	2014	286	
	2015	257	
	2016	215	
Firm C	2009	101,735	278.726
	2010	117,900	322.934
	2011	124,100	339.945
	2012	128,800	352.026
	2013	126,515	346.617
	2014	116,948	320.405
	2015	106,568	284.357
	2016	100,744	275.257

Table B2 Transforming production per day to total production per year

	Year	Total production per year (1,000 barrel)	Average production per day (1,000 barrel)
Firm A	2009	**101,835**	279
	2010	**105,485**	289
	2011	**90,885**	249
	2012	**103,944**	284
	2013	**82,125**	225
	2014	**80,300**	220
	2015	**86,870**	238
	2016	**69,906**	191
Firm B	2009	294	
	2010	291	
	2011	279	
	2012	298	
	2013	258	
	2014	286	
	2015	257	
	2016	215	
Firm C	2009	101,735	278.726
	2010	117,900	322.934
	2011	124,100	339.945
	2012	128,800	352.026
	2013	126,515	346.617
	2014	116,948	320.405
	2015	106,568	284.357
	2016	100,744	275.257

Appendix C: Examining the Pattern of Missing Production Values

The production data is missing for around 20% of the firm-year observations, raising the concern that missing values might confound our results. If the absence of firms from the sample is systematically correlated with the rollover risk measure, then our sample bears sample selection issue. To address this concern, we conduct a regression analysis to examine if missing values for firm production could be predicted by financial distress. We do the analysis based on the originally merged dataset between the financial data and production data (i.e, the sample before dropping observations with missing production values), and run the following regression,

$$ProdMissing_{it} = \alpha_0 + \alpha_1 RO_i * Crisis_t + \ \alpha_1 X_{it} + \kappa_i + \varphi_t + \varepsilon_{it}$$

where $ProdMissing_{it}$ is a dummy variable which equals one if the firm-year observation is missing production, and zero otherwise. The independent variable and control variables are the same as those in our baseline regression. The variables κ_i and φ_t are firm-fixed and year-fixed effects, respectively. ε_{it} is the error term with standard errors clustered at the firm level.

Table C1 reports the estimation result. It shows the coefficient on the interaction term *Rollover Risk* × *Crisis* is insignificant, suggesting that missing production values are largely random across firms, and are not determined by firms' financial distress. Therefore, our main findings are unlikely driven by the sample selection problem that arises from missing production information.

Table C1 Examining the Pattern of Missing Production Values

VARIABLES	*Production Missing*
Rollover Risk × Crisis	-0.011
	(0.009)
Full Controls	Yes
Firm FE	Yes
Year FE	Yes
Observations	1,874
R-squared	0.735

Notes: After dropping missing values on rollover risk and control variables, 1,874 out of 2,307 observations enter into the regression. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.