Does the Tail Wag the Dog? Tail Risks and Real Investment*

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This study investigated corporate investment decisions under output price uncertainty. Although significant skewness and kurtosis are prevalent in security price fluctuations, existing literature predominantly quantifies uncertainty solely by price change volatility. Firms may react to tail risks and reverse the implications of the traditional model. To examine the impact of tail risks on choices, our analysis focuses on oil companies, examining their investment behaviors in oil well operations—covering production, mothballing, drilling, and closure—against skewness and kurtosis in WTI crude oil price changes. The empirical results show that tail risks significantly affect firms' investment and disinvestment timing choices, affecting optimal investment decisions and values with potential impacts of up to $10 million annually. The results show a 27% difference in oil well closure decisions attributable to skewness variations and that adopting such models can lead to investment choices differing by as much as 50%. We found a significant impact of skewness and kurtosis when accounting for hedging strategy, financial constraints, and the term structure of oil prices.

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1. Introduction

Output price change uncertainty plays a central role in modern theories of investment choice and the valuation and exercise of real options (Dixit (1989, 1991)); Dixit and Pindyck (1994)). These features can provide incentives to delay investments and abandon unprofitable investments. The Real Options Valuation (ROV) model predicts that output price uncertainty affects investment choices by influencing the value of the "delay" option, which presents investors in real assets with the option to defer decisions until future uncertainties in prices decline. However, this prediction does not consider the "shape" of the price change uncertainty – i.e., the tail risks in price uncertainty, but merely controls for price volatility as the measure for "output price uncertainty". A typical assumption is that output price changes have a normal distribution; however, this is not always true. Corrado and Su (1996) identify significant non-normality in S&P 500 index prices, and Diavatopoulos et al. (2012) find similar results in stock returns. Nonnormality of price changes of commodities is also evident (Ferderer, 1996; Dai et al., 2021). A positive output price shock may cause firms to begin production, whereas a negative shock could motivate firms to shut down production. When we expect large price changes as "outliers", compared with cases where price changes are more likely to be around their expected values, investment decisions may differ. The pioneering work by Bernanke (1983) indicates that the "bad side" of price uncertainty determines the value of the "delay" option, calling for a study of the differentiated impacts of positive and negative price uncertainty. In this study, we specify and estimate models of investment choice that allow us to test the influence of tail risk in output prices on oil firms' decisions regarding oil well production, shutting-in, drilling, and closure.

Oil exploration and production is a sector in which there can be substantial uncertainty surrounding future oil prices and significant sunk costs of investment and where output price changes exhibit non-normal behavior. Thus, the investment and production behaviors of firms operating in this sector provide an ideal setting for studying the impact of expected skewness and kurtosis on these decisions. Oil price changes exhibit high volatility (Ferderer (1996)) but also nonzero skewness and excess kurtosis. Many existing studies (Dai et al. (2021)) demonstrate the existence of nonzero skewness in oil prices, which we confirm along with the presence of excess kurtosis, calling for a revisit of the empirical relations between investment and production decisions and the moments of the price change distribution, accounting for higher-order moments. We empirically examined oil firms' investment choices when facing price uncertainties. The decisions of oil firms to open new wells, close existing wells, or temporarily shut-in wells are examined regarding asymmetry and extreme cases in output price change distributions. The empirical findings suggest that asymmetry and outliers in output price changes are significant factors in firms' investment decisions, either proceeding immediately with projects or delaying them. Skewness can cause a 27% difference in the (dis)investment choices for well closure when skewness increase by one standard deviation. These impacts remain significant even after controlling for heterogeneity among oil wells, locations, information spillover effects, hedging decisions, and financial constraints. A decision model incorporating the tail risks of asymmetry and outliers shows significantly different predictions (up to approximately 50% and a $10 million potential value loss) from a model that excludes these factors. The impact of tail risk on investment choices is significant, even when compared to the effects of the standard deviation of price changes. This suggests that the significant effects of tail risks on investments should be extended to broader investment considerations.

We examine oil firms' investment decisions from January 2010 to September 2019. This includes monthly data from approximately 600,000 individual oil wells in five U.S. states–California, Pennsylvania, Oklahoma, Texas, and South Dakota–totaling 53 million observations. The validity of this rich dataset allows us to comprehensively examine oil-well investment choices. We control for the location, drilling type, depth, age, productivity, drilling cost, and maintenance cost of each oil well. Additionally, by linking to oil well operators' firm identification, we obtain data on the financial performance and characteristics of the decision-makers, including leverage, hedging strategies, and standard error clusters, in the estimated models to examine how firms' operations and finances affect investment choices. The data provide insights into the production status and timelines of drilling and closing each oil well investment project, and the financial condition of the operators.

While a company's quarterly or yearly capital expenditure provides a glimpse into its capital spending decisions, a deeper understanding requires disaggregated microlevel data observed at a higher frequency. First, we measure the data monthly and provide information on new investment (drilling), disinvestment (abandonment), and shut-in (producing or mothballing) choices. Second, the primary uncertainty these companies face is price uncertainty, reflected in the distributional characteristics of oil prices. Third, the examined dataset allows for comparing choices across different geographical locations and states. The dataset examined included up to 53 million observations that span ten years and multiple geographic areas and states in the United States. Statistical approaches involve estimating Cox proportional hazards models structured to investigate the choice to drill and shut down (abandon) and dynamic panel probit models to investigate the choice to continue producing or temporarily stop production.

In the existing literature on real investments using capital investment data, firms' output prices, such as wholesale output prices, are rarely observable and quantifiable at a high frequency. For instance, Moel and Tufano (2002) use yearly data on the opening and closing of gold mines to examine how price volatility affects decisions while Doshi et al. (2018) study quarterly data. An important exception is Kellog (2014) who studies monthly data. Furthermore, the physical realized volatility, skewness and kurtosis of output prices may not accurately reflect market beliefs about the future values of these parameters. To resolve this issue, we use WTI crude oil option prices from the CME to estimate the option-implied risk-neutral distribution's central moments of oil prices at the market level. WTI oil options are actively traded on the CME, with a wide range of strike prices compared to call and put options. From the settlement prices of these options, we can recover the market investors' perceived riskiness of WTI crude oil prices and capture the asymmetry and outliers of the oil price change distribution from the amounts investors pay for calls and puts over different strike prices. For WTI oil options with different maturity terms, we can extract the moments of oil price changes over different investment horizons that match the investment horizons for oil well decisions on opening, closing, and shutting. Following Bakshi et al. (2003, BKM), we estimate the risk-neutral volatility, skewness, and kurtosis of oil price changes daily over a wide range of investment horizons from January 2010 to September 2019.

Our results show that the expected skewness and kurtosis of the price change distribution are important determinants of oil producers' investment activity decisions, consistent with the predictions of the option pricing theory accounting for higher-order moments. The results suggest that option-implied higher-order moments are proxies for jump or crash risks in output prices (oil futures prices) and leptokurtic risk. These characteristics have a significant impact on the propensity to choose to switch between "producing" or "mothballing." Our results show that when option-implied oil price skewness increases by one standard deviation, the propensity to exercise a real option for irreversible investment decisions increases (e.g., re-opening a mothballed oil well). When the implied kurtosis in oil prices increases by one standard deviation, the likelihood of investment increases. The propensity to close an oil well immediately increased by 27.51% when the skewness increased by one standard deviation, and the propensity to drill a new well increased by 5.73% when the kurtosis increased by one standard deviation. The potential value loss if not adopting a tail risk-incorporated decision model counts towards $879,860, a possible monthly value diff, and a $10,558,320 value difference per year for an average oil firm. Finally, our main results are more consistent with decision-makers following value-maximizing decision rules than imposing their individual investor preferences for skewness and kurtosis.

In addition to estimating the potential value loss for oil firms, we also consider the impacts of firms' financial conditions, including leverage, hedging strategies, and other potential factors, such as the shape of the term structure of oil prices and oil well heterogeneity. We manually collect each oil well's hedging positions and annual oil production and find that hedging strategies do not alter the conclusion that tail risks are important for oil firms. Fewer leveraged firms respond to changes in tail risk when making oil investment decisions. We also test the robustness of the results using the realized distribution moments of oil price changes. We find results similar to the main results using risk-neutral distribution moments, suggesting that the proxies for oil prices do not matter significantly.

Kellogg (2014) shows that volatility in oil prices affects oil firms' investment decisions by delaying their drilling activities if volatility increases, which is consistent with the predictions of Real Options Valuation (ROV). Decarie (2020) demonstrates that natural gas firms respond to various market factors. Doshi et al. (2018) showed that financial constraints affect oil drilling decisions. This paper is the first to show how the asymmetry and outliers, the higher-order moments of price distributions, affect the 'shape' of the uncertainty when controlling for volatility and how they impact investment choices. The primary question we ask, and answer is accomplished through the specification and estimation of discrete choice models utilizing a comprehensive sample of over 53 million well-month observations of micro-level oil well drilling and the operational decisions of operators in five major oil-producing states. The utility of such data has not gone unnoticed, forming the basis for the investigations by Kellogg (2014), Gilje (2019), Anderson et al. (2018), and Décaire et al. (2020). Oil and gas producers tend to expand drilling and completion activities only when prices are high and, at the same time, do not rapidly close or plug wells when prices are below the marginal cost of production. To our knowledge, this is the first study to investigate the implications of non-normal output prices on firms' investment and production decisions.

Section 2 presents a brief review of real investment theory and the implications of price uncertainty in the presence of irreversible investment decisions. Section 3 presents an economic model of investment choice and develops hypotheses on the relationship between the real options exercise and implied skewness and kurtosis. In Section 4, an econometric framework is developed to test the hypotheses, and the data are discussed. Section 5 presents and discusses the empirical results. Section 6 presents the summary and conclusions.

2. Real Investments and Tail Risks

2.1 Irreversible Real Investments and Price Uncertainties

Real investment decisions have four important characteristics. First, the investment is entirely or partially irreversible. In other words, investments involve sunk costs. Secondly, investments involve risky payoff streams. Third, new information arrives over time, which can influence the expectations of future risky payoffs. Fourth, most investment opportunities do not necessarily disappear if not taken up immediately. That is, the investment decision involves whether to invest and when.

The study of real investment activity and the theory of optimal investment choice by firms has a long and rich history (see Caballero (1999), Girardi (2021), and references therein). The foundations of the optimal decision rule for firms' investment choices stem significantly from the Fisher Separation Theorem

(Fisher (1930)) and Hirshleifer (1958, 1970), while the work of Tobin and Brainard (1976) and Hayashi (1982) significantly impacts the study of such choices under uncertainty. These frameworks lead us to what is commonly referred to as the net present value rule (NPV). However, the implications of sunk costs and future uncertainty play an important role in what many would call the modern theory of investment under uncertainty, highlighting the value of real options (ROV) embedded in investment and production opportunities.

While the NPV rule does not explicitly indicate the relationship between uncertainty (price volatility) and real investment (Samis et al. (2005)), Dixit and Pindyck (1994) amongst others show that accounting for the option to change investment and production (the real options valuation ROV approach) suggests that an increase in uncertainty can lead to investment postponement. The underlying well-known principle is that an option's value increases as expected volatility increases. The ROV predicts that more significant price uncertainty leads to an increase in the real option's value and postponement of the option's exercise (Bernanke (1983), Dixit and Pindyck (1994), Abel et al. (1996)).

The relationship between price uncertainty and investment choices has been the theme of numerous studies focusing on other (than oil) industries and general industry sectors. Drakos and Konstantinou (2013) present a connection between price uncertainty and investment decisions in the manufacturing industry. By examining capital investment decisions, Doshi et al. (2018) show that the tendency to follow real options exercising rules depends on firm size. They find that larger firms are less likely to follow these rules, as they mainly hedge output price risk and avoid detrimental price movements and uncertainty. Other studies on real options include Pindyck (1993) on the effects of cost and technology uncertainty on real options investment; Aizenman and Marion (1993a, 1993b) on the impacts of policy and macroeconomic uncertainty on investments; Lensink and Morrissey (2000), who examine the investment-uncertainty relationship at the aggregate level; Leahy and Whited (1995), Kang et al. (2014), and Gulen and Ion (2016), who examine the influences of policy uncertainty on investment; Jens (2017) who discuss political uncertainty effects.[‡]

Studies on the relationship between uncertainty and oil investment include Mohn and Misund (2009) at the aggregate level and Yang et al. (2008) at the micro and firm levels. Studies focusing on the impact of price volatility on investment include Elder and Serletis (2010), Yoon and Ratti (2011), Ahmadi et al. (2019), Phan et al. (2019), Cao et al. (2020), Maghyereh and Abdoh (2020), and Doshi et al. (2018), consistently find that price uncertainty negatively affects investment. However, some recent studies do not support the negative uncertainty-investment relationship. For instance, Miao and Wang (2007) showed that

[‡] Gulen and Ion (2016) find evidence of a negative relationship between firm capital investment and policy uncertainty captured by a news-based index.

uncertainty is positively associated with investment when the market is incomplete and risk cannot be perfectly hedged. Lambrecht (2017) surveys the literature.

2.2 Skewness, Kurtosis, and Investment

The option to "delay" investment or divestment increases in value when volatility increases when price changes follow Geometric Brownian motion (Dixit and Pindyck (1994))[§]. However, this assumption does not explicitly address the case whn price changes exhibit non-normality.

Although the study of skewness and kurtosis in financial security returns has a long history (Conrad et al., 2013), the literature largely ignores the implications of skewness and kurtosis on real investment activity. One exception is Schneider and Spalt (2016), who show the relationship between project return skewness and investment decisions, but not within the framework of the ROV. Boyarchenko and Levendorskiĭ (2002) and Boyarchenko (2004) derive the optimal exercising rules of RO assuming a jump-diffusion price process and suggest that their model potentially indicates a skewness-kurtosis and investment relationship.[**] Bernanke's theoretical development of his "Bad News Principal" (Bernanke (1983)) indicates that only adverse price shocks matter in the optimal timing of real investment.

2.3 Tail Risks and Oil Real Investments

Myers (1977) indicates that Real Options Valuation explains the "conservative" leverages of firms with market investment opportunities and real options whose value is negatively related to risky debt. Aguerrevere (2009) highlights the importance of real options in influencing investment decisions under different market conditions. Mayers (1998) analyzed the convertible bond value using the ROV. Compared

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[§] The Geometric Brownian Motion can be denoted as: $dP/P = \alpha dt + \sigma dz,$ where α is the drift parameter and σ is the variance parameter, the measure for uncertainty risk.

[**] A separate literature has focused on the implications of skewness and kurtosis of financial security returns. One strand of the literature reveals that the relationship between equity investment and probability distribution skewness and kurtosis depends on forms of investor utilities (Brunnermeier and Parker (2004)). For example, Kraus and Litzenberger (1976) show investors' preference for positive skewness in the equity market, suggesting a non-quadratic form of investor utility. Another strand of studies explains the influences of skewness and kurtosis on investor preferences. For instance, Harvey and Siddique (2000) find that investors require a positive premium for systematic skewness, and Boyer et al. (2010) find a negative return premium for idiosyncratic skewness. While the previously mentioned studies use central return moments, others focus on the risk-neutral moments of returns. For instance, Conrad et al. (2013) reveal that more positive risk-neutral skewness is strongly related to lower subsequent returns. Bali and Murray (2013) show that risk-neutral skewness is negatively related to the equity portfolio returns. Both studies suggest investors' tendency to hold assets with positive skewness. Furthermore, Bali and Murray (2013) show that, although both sides of skewness influence asset returns, left-hand side skewness is remarkably priced into skewness assets by investors. Bali and Murray (2013) point out that exposure to skewness can be asymmetric by decomposing the left- and right-hand sides of skewness risk. Studies on implied higher moments and security price include Datta et al. (2017). Kurtosis is strongly related to investors' preferences and returns premiums. Related studies include Dittmar (2002) focus on the investor's preference on kurtosis, and other studies like Arouri and Nguyen (2010), Diavatopoulos et al. (2012), and Bachmann and Bayer (2014) explore the relationship of investment and both skewness and kurtosis.

with capital investment data, oil well drilling, closing activities, and crude oil prices have become rich data for exploring investment problems. First, a company's capital investment data have a low observation frequency and are reported every quarter. Second, company-level data are unable to observe output prices directly. By contrast, oil well drilling, production, and closing records from Oklahoma, Texas, Pennsylvania, North Dakota, and California were reported to agencies every month, with observable price distribution moments from options markets as an ideal setting for examining real investment choices and price uncertainties.

Kellogg (2011) and Covert (2015) examined learning and productivity in well-drilling and fracking, respectively. Molls (2001) studied Oklahoma oil well production and found that sunk costs and historic price change volatility helped explain oil well drilling decisions. Moel and Tufano (2002) found that gold mining's entry and exit options exercising behaviors are negatively related to uncertainty. Kellogg (2014) studied oil well-drilling activity in Texas and concluded that it is strongly affected by price uncertainty, measured as price change volatility. He found greater volatility was associated with a higher probability of postponing drilling activity. Using drilling data from similar oil wells, Décaire et al. (2020) found that an information spillover effect influences drilling activity. Specifically, drilling in neighboring oil fields encourages oil-well drilling in adjacent areas. However, these studies do not control for price uncertainty. Doshi et al. (2018) studied quarterly investment expenditures of energy companies and documented an inverse relationship between oil price volatility and aggregate quarterly expenditures among smaller firms. Boomhower (2019) and Muehlenbachs (2015) studied firms' decisions to abandon or environmentally remediate no longer productive wells. Anderson et al. (2018) studied production and drilling activities in Texas and found that, while the expected price influences drilling activity, it does not affect productions. Chen and Linn (2017) study rig activity in the U.S. and find that rig activity in developed economies is positively related to oil futures prices. A more recent study (Bloom et al. (2022)) shows that the skewness of sales growth survey predictions by manufacturers does not explain changes in capital investment.

3. Option Valuation with Higher Order Moments

3.1 Real Options Pricing and Modified B-S Model

The Black and Scholes call option pricing model is expressed as:

$$C_{ROV,BS} = SN(d_1) - Ke^{-rt}N(d_2)$$

where *S* is the underlying asset's current value, *K* is the exercise price of the real option, *N(x)* is the normal c. d. f., and d1 and d2 are parameters that depend on the log price change volatility (Hull (2003)).

Jarrow and Rudd (1982), Corrado and Su (1996a, 1996b), and Brown and Robinson (2002) develop option valuation models in which the log-price change distribution of the underlying asset may exhibit higher-order moments, that is skewness and kurtosis, which deviate from the parameters of the normal distribution. The call option price when the log price change distribution of the underlying asset exhibits skewness and kurtosis is equal (Brown and Robinson (2002)).[‡‡]

$$C = C_{BS} + \mu_3 \cdot Q_3 + (\mu_4 - 3) \cdot Q_4$$

where μ_3 and μ_4 represent the skewness and raw kurtosis of the log-price change distribution, respectively. Parameters Q_3, and Q_4 are linear functions of option moneyness. If skewness equals 0, kurtosis equals 3, and volatility is positive, the model reduces to the Black-Scholes price. Therefore, the exercise of real options may be influenced by expected future volatility, skewness, and kurtosis.

3.2 Oil Well Lifecycle - Drilling, Producing, Mothballing, and Shutdown

The life cycle of an oil well comprises several stages, from testing to plugging. 1) First, a seismic survey of an oil well usually includes testing for the estimated quantity of expected total production and the measured depth of the oil reserve. On average, it takes approximately three months to complete the drilling process.[§§] 2) After drilling ends and the well is completed, production may begin, and the oil well moves to its second stage, "producing." At this stage, oil producers consider the expected oil price (and distribution moments) and the cost of maintaining production to decide on production status. 3) Mothballing is a temporary suspension of production. When facing bad news for production, such as price shocks or surges in operating costs, producers can move the oil-producing well. 4) Mothballing status is an intermediate status between "producing" and "shut down" but it requires a medium level of maintaining cost to keep this status. The benefit of maintaining the "mothballing" status is that oil producers still have the option to resume production. 5) The last stage of an oil well is "shutdown" – when producing or maintaining the well is no longer economical or when the oil wells are exhausted. Re-opening a plugged oil well is generally not possible and, where possible, is extremely costly.

4. Value Maximizing Choices

4.1 The Choice Problem

Define the objective function for each oil producer as γ:

$$\gamma = \max_{prod} V(P, Q, C, \mathbb{C}, \theta, O)$$

[‡‡] $Q_3 = \frac{1}{3!} S_0 \sigma \sqrt{t}[(2\sigma\sqrt{t} - d)n(d) + \sigma^2 t N(d)]$ and $Q_4 = \frac{1}{4!} S_0 \sigma \sqrt{t}[(d^2 - 1 - 3\sigma\sqrt{t}(d - \sigma\sqrt{t}))n(d) + \sigma^2 t^{3/2} N(d)]$, where S_0 is the underlying asset price, σ is stochastic volatility, $n(d)$ and $N(d)$ are p.d.f. and c.d.f. of $d = \frac{\ln(\frac{S_0}{K}) + (r + \sigma^2/2)t}{\sigma\sqrt{t}}$ (Brown and Robinson, 2002, eq.3&4).

[§§] For a detailed description of the drilling process see https://production-technology.org/.

where P is the oil price change, which may reflect higher-order moments, and Q denotes the quantity of crude oil output. C represents the costs incurred in each period, reflecting the well, production, or mothballing status. $\mathbb{C}$ is the one-time investment (disinvestment) cost (e.g., drilling or closing costs). The vector θ includes oil well characteristics, such as reserve and productivity. Real option choices are subsumed in vector O. O allows the producer to shift from one status to another; an example of such a shift is changing from an undrilled field to drilling a new oil well or shutting down the production of a producing oil well. Such shifts change the production status of an oil well, and the available options depend on the status of the well.

We denote the multi-period dynamic problem of investment choices for the oil producer as the solution to the following Bellman equation,[†††] expressed as current profit plus the value of future expected profits, assuming optimal continuing choices after one production period:

$$\gamma = \max_{prod} E_t\big(V(P, Q, C, \mathbb{C}, \theta, O)\big) = \max_{prod}\left(\pi(P_t, Q_t, C, \mathbb{C}, \theta | \mathbb{I}_t) + \frac{1}{(1+r)} E_t(V_{t+1} | prod_t)\right)$$

where $\mathbb{I}_t$ denotes the information set of the producer at time t. For instance, consider the criteria for continuing in the mothball state or switching to production. The difference in the objective function between choosing to resume production for an oil well and continuing to move the well is[‡‡‡]

$$\begin{aligned}\Delta V_t(Status_{t-1} = m) & \\ &= \breve{\pi}(P_t, Q_t, \theta) - C^p - \mathbb{C} + C^m \\ &+ \frac{1}{(1+r)}\big(E_t(V_{t+1} | Status_t = p) - E_t(V_{t+1} | Status_t = m)\big)\end{aligned}$$

where m denotes the status, the producer faces when making their decisions, m is the mothballing. If the producer chooses to resume production (where p is producing), the difference in the producer's expected profit would be current profit $\breve{\pi}$ minus the difference in the operating costs ($-C^p + C^m$), minus the one-time transition cost $-\mathbb{C}$, along with the difference in expected future profits. Ideologically, such a difference in expected profits, ΔV_t, will be determined by the distribution function of the oil price changes, P_t, which incorporates skewness and kurtosis that influences the output prices the producer may retain. Similar criteria can be identified for the choice to drill or postpone drilling and the choice to continue production versus complete shutdown.

4.2 Exercises of an American Real Option

[†††] Molls (2001) presents a similar specification.
[‡‡‡] Appendix B gives more details for the derivation of the equations.

Boyarchenko and Levendorskii (2000, 2002) and Boyarchenko (2004) solve the theoretical framework of asymmetry in output prices and optimal exercise prices, suggesting that skewness and kurtosis potentially affect an American real option exercise's threshold by affecting the parameters of price asymmetry. Theories predict that skewness negatively affects the likelihood of exercising, and kurtosis effects decrease the trigger threshold.

The issue of non-normality in output prices when determining the optimal real options exercise policy has been addressed in the existing literature. Researchers have utilized real analysis methods, starting by defining the specifications of the underlying price process and then solving for the optimal exercise prices and their relationship to the parameters in the process specification. This approach follows the framework established by Dixit and Pindyck (1994), with variations in assumptions for the underlying price-generating process. Relevant references include McDonald and Siegel (1986), Kjærland (2007), Darby et al. (1999), and Nielsen (2002). Other methods, such as using binary lattices to solve the real options problem, are discussed in works like Smith (2005).

We did not directly explore the underlying processes that may give rise to skewness and kurtosis. However, empirical simulations show that a general model incorporating mean reversion and random jumps in addition to Brownian motion produces data exhibiting skewness and kurtosis for reasonable parameters. Such models have been found to fit oil futures price change data.[§§§]

4.3 Empirical Models

The economic choice model involves a set of optimal actions. Therefore, a natural framework for analysis is a choice-based empirical model that captures the state of a well and the characteristics of the output price change distribution along with other factors that should influence future cash flows, such as costs and production capacity. The first model involves continuing in the mothball state versus beginning production. Thus, we propose the following econometric model for the resumption problem:

$$Prod_{i,t} = \Phi(\alpha_0 + \beta_1 \cdot Price_t + \beta_{2,3} \cdot \{Prod_{i,t-1}\} \cdot Volatility_t + \beta_{3,4} \cdot \{Prod_{i,t-1}\} \cdot Skewness_t + \beta_{5,6} \cdot \{Prod_{i,t-1}\} \cdot Kurtosis_t + \Delta \cdot Controls_{i,t} + \varepsilon_{i,t}) \quad (1)$$

[§§§] In the double exponential jump-diffusion process suggested by Kou (2002), the intensity of jumps on either side changes the higher-order distribution of prices. A greater intensity of jumps in the lower side decreases skewness and any non-zero jump intensity increases the excess kurtosis of distribution. A more recent study by Boyarchenko and Levendorskiĭ (2000) derives the theory for the optimal exercising rule under the Lévy processes of prices which they suggest could solve the real options problems with skewed prices and outliers, as well as Asmussen, Avram, and Pistorius (2004) who derive the put options with Lévy processes. See also Merton (1976), Bates (1997), Zhang (1997), Arnold and Crack (2000), Gukhal (2001), Lewis (2001), Kou and Wang (2004), Levendorskiĭ (2005), and Sepp (2008).

where $Prod_{i,t}$ denotes the production status for oil well i in month t and $Price_t$, $Volatility_t$, $Skewness_t$, $Kurtosis_t$ are the expected level, volatility, skewness, and kurtosis of oil price changes, respectively.

$Prod_{i,t}$=*1* for producing and =*0* for mothballing. A panel binary dependent variable model can be used to examine the relationship between the distribution moments and choices.

The choice to drill and shut down involves irreversible investment choices; that is, such decisions cannot be reversed. For example, a drilled oil well will not recover to its original condition without incurring significant costs, and for a closed oil well is almost impossible. The decisions to drill and shut down occur only once for each oil well. Thus, they are comparable to the occurrence of hazard events and can be written as a proportional hazard model:[****]

$$Drilling_{i,t} = \Phi(\alpha_0 + \beta_1 \cdot Price_t + \beta_2 \cdot Volatility_t + \beta_3 \cdot Skewness_t + \beta_4 \cdot Kurtosis_t + \Delta \cdot Controls_{i,t} + \varepsilon_{i,t}) \tag{2}$$

and

$$Shutdown_{i,t} = \Phi(\alpha_0 + \beta_1 \cdot Price_t + \beta_2 \cdot Volatility_t + \beta_3 \cdot Skewness_t + \beta_4 \cdot Kurtosis_t + \Delta \cdot Controls_{i,t} + \varepsilon_{i,t}) \tag{3}$$

Here, $Drilling_{i,t}$ and $Shutdown_{i,t}$ denote the start of the drilling activities or the state of a closed oil well.

Table 1 shows the predictions of the signs of the coefficients according to the modified Black-Scholes option pricing model and ROV. It also shows the predictions of the coefficients of other important controls for the models, which we introduce in Section 4.

(Insert Table 1. Here)

5. Data and Methods

(Insert Table 2 here.)

5.1 Oil Well Investment and Production Data

5.2 Records of Oil Wells' Drilling, Production, and Closing Dates

Oil well production rates, dates, date production begins, and date production ends are obtained from Enverus.[‡‡‡‡] Data obtained include a well identifier code (a unique well identification 14-digit number:

[****] Décaire et al. (2020) use Cox proportional model.

[‡‡‡‡] Enverus.com. we am grateful to Enverus for providing us with access to their well production and cost datasets and especially to Ms. Annie Shen and Mr. Jason Eleson for their very generous help.

American Petroleum Institute, short for "API"), the well's operator company's names, the well's monthly oil production rates, gas production rates, and water production rates, well's measured depth in tens of thousands of feet, a well lease identifier (and lease names), the basin where the well is located, well's field name, and location's county and state names, total drilling costs, the date drilling begins (the spud dates), the dates when the well begins production (the completion dates), well's peak production rates, well's first 6-months' and first 12-months' production rates, and age of the well measured as the number of months from the first production date, and the date a well is closed off so that it stops producing (the "last production" dates).

Records of more than 600,000 oil wells were obtained from Texas, North Dakota, Oklahoma, California, and Pennsylvania. According to their monthly oil production rates and the first and last production months, we constructed the production histories/statuses for each of the 600,000 oil wells every month. The earliest date was January 2010, and the last was September 2019.[§§§§]

(Insert Table 3 here.)

5.3 Oil Futures Prices and Implied Moments

We use BKM's (Bakshi, Kapadia, and Madan (2003)) risk-neutral model-free option-implied central moments to estimate current beliefs about future volatility, skewness, and kurtosis of the oil price change distribution. These estimates are constructed from futures and futures' options prices.

Daily crude oil futures prices and options on futures prices (LO) were obtained from the Chicago Mercantile Exchange (CME) Group Datasets (End-of-Day Complete database). The data were used to compute a proxy for the expected oil price and option-implied volatility, skewness, and kurtosis at future time horizons. Only option prices with maturities between 10 and 180 days–the most liquid options contracts–are utilized, as contracts expiring or far from maturity are traded thinly, and their settlements are noisier. Options and futures prices clearly out of line relative to the averages are assumed to be recording errors and excluded. Risk-free rates were obtained from the OptionMetrics files using the WRDS. Risk-free rates were extrapolated and interpolated to ensure sufficient data for maturities spanning 10-180 days.

We follow Chang, Christoffersen, and Jacobs (2013) and Ruan and Zhang (2018) in computing the risk-neutral central moments of the price change distribution. First, the data are filtered by a) dropping

[§§§§] The spud date identifies when drilling begins and investment costs are incurred. The production status histories, allow recovery of the investment decisions (choices between producing and mothballing) of oil producers through every oil well's entire production history during the ten-year period studied. The histories allow identification of the investment date (which we classify as the spud date) and the decisions to temporarily suspend production and to abandon (shut in) a well. The production histories therefore provide information on the state of the well at any date. Each oil wells' drilling and shutdown profiles are constructed from the well spud dates and their last production dates.

option prices lower than 3/8 (minimum tick), b) dropping deep-in-the-money options (put options with an exercise price higher than 103% of the futures price and call options with an exercise price lower than 97% of the futures price), and c) dropping prices on days with fewer than two put or call prices and/or options prices violating arbitrage conditions.[*****] Second, to expand the option prices set from the CME option settlement prices, we expand the moneyness range within a date and maturity using the moneyness values of existing observations. The expansion uses a cubic spline interpolation method. We expand the moneyness for each date and maturity to the range between 0.0001 and 3 and use the implied volatility (from the CME's modified Black-Scholes option pricing model) to interpolate and extrapolate the implied volatilities in that range. Third, we use implied volatilities to infer option prices using the Black-Scholes option in the futures pricing model to obtain a smooth option price function in the moneyness 0.0001 and 3 range for each date and maturity. [†††††]

We computed the 18-month BKM risk-neutral implied central moments. Kellogg (2014) points out that "18 months" is a typical horizon for oil operators to observe prices. Décaire et al. (2020) use similar measures for price and volatility. Also, Slade (2001) mentions that "Most firms use a long-run commodity price" for decision purposes. These producers usually consult forecasted long-run output prices for investment decisions according to survey results with copper producer managers. Specifically, using futures prices, we estimate the term structure of oil return realized central moments and then compute 10-180 days central moments to interpolate the one-month maturity central moments.[‡‡‡‡‡] Then, the one-month central moments and term structure were used to extrapolate the 18-month maturity central moments. However, we use the one-month price and central moments for the production examination model because the transition between production and mothballing can occur immediately.

We assume that the physical timing to drill or shut down is not immediate but that the time between the formal evaluation and the actual implementation of the choice occurs with a lag.[§§§§§] Three-month lags in the estimated central moments are employed in the analyses presented later for the drilling and shutdown examination models.[******] We calculate the 18-month forward central moments using the average of the 18-month maturity futures settlement prices. Both the 18-month and the one-month oil prices were deflated and scaled by 100 to fit the scale of risk-neutral moments. Oil producers can observe the monthly average

[*****] Arbitrage conditions: excluding observations of option prices when a call option's price is greater than or equal to present value of futures prices or when a call options' price is lower than or equal to the present value of futures prices minus present value of strike prices.
[†††††] For more detail on the trapezoidal integration of central moments, please see p.587-588 of Ruan and Zhang(2018).
[‡‡‡‡‡] The method follows Kellogg (2014, Appendix A).
[§§§§§] This follows Kellogg (2014) – it usually takes three months to commence drilling after decision.
[******] Computation details are available upon request.

forward price and distribution moments to determine whether to continue production or shut it. Our sample is every month for each well; we can only observe the changes in the oil well-producing states in the months.

6. Empirical Results

6.1 The Choice to Drill or Defer

The examination of the drilling decision is similar to that of Kellogg (2014) and Décaire et al. (2020), except that we account for the influence of the skewness and kurtosis of the price change distribution, in addition to volatility and study a sample that spans multiple producing states of the United States. We examine the relationship between drilling an "infill oil well" and the magnitude of price distribution moments to explore the effects of price uncertainty on irreversible investment decisions, as the uncertainty affects investment options value.[††††††] To identify infill wells, we exclude the first wells in a field (exploratory wells) and retain only the first drilled wells whose spud dates are between March 2010 and September 2019, when oil price data are available in our dataset. We dropped wells with spud dates before or in March 2010 or shut them down after September 2019. Undrilled fields were identified as "unexercised options" with *drilling*=0 throughout the date range for all months up to the spud date, at which we assigned *drilling* = 1.

(Insert Table 4 here.)

The analysis of the option to drill when considering infill drilling has the feature that as new wells are drilled, the availability of new drilling options decreases. As Kellogg (2014) points out, a probit specification (or the linear probability model) is not an appropriate structure to account for this dynamic, and Décaire et al. (2020) agree with their analyses. However, the Cox proportional hazards model fits the described settings.[‡‡‡‡‡‡]

We construct the dataset of the unexercised "drilling" options by assigning *drilling=0* for the months between the beginning of a lease's production and the last month before drilling. The dependent variable *drilling=1* during the spud month. Thus, the months with *drilling=0* are when the wells remain

[††††††] Schlumberger describes infill drilling as "The addition of wells in a field that decreases average well spacing. This practice both accelerates expected recovery and increases estimated ultimate recovery in heterogeneous reservoirs by improving the continuity between injectors and producers. As well spacing is decreased, the shifting well patterns alter the formation-fluid flow paths and increase sweep to areas where greater hydrocarbon saturations exist." https://glossary.slb.com/en/terms/i/infill_drilling

[‡‡‡‡‡‡] The Cox proportional-hazards model (Cox, 1972) is a model used for investigating the association between the survival time of an entity, person, etc., and one or more predictor variables. Basically, it is formulated to model how a set of specified factors influence the rate of a particular event happening (e.g., drilling a well) at a particular point in time. This rate is commonly referred as the hazard rate. See Cameron and Trivedi (2005, Ch. 17) for a review of the Cox Proportional Hazard Model.

undrilled, and the months with *drilling=1* are when the wells are drilled. Each well enters the data when it becomes available for drilling (when the first well in the lease spuds, oil producers can prepare an infill oil well to boost oil production). Months after the spud dates were truncated.[§§§§§§] This oil well has *drilling=0* for the months after it enters the sample up to the month of drilling; however, after, it is no longer an opportunity, as it has been drilled. Hence, on any date until drilling, there is a probability that it will be drilled, conditional on the economic factors prevailing at that time. Hence, this dynamic fits the Cox model well.

Column (1) of Table 4 reports the estimation results. The results indicate that price is positively related to the probability of drilling, and volatility is negatively associated with likelihood. These conclusions are consistent with the existing literature on real investment . The finding that price (volatility) is positively (negatively) related to the probability of drilling is consistent with the results presented by Moel and Tufano (2002), Kellogg (2014), and Décaire et al. (2020). Anderson et al. (2018) found that oil well production does not respond to price changes.

We find evidence that higher-order moments influence the choice to drill. Column (2) of Table 4 shows that when the kurtosis increases by 1.00, the probability of drilling a new oil well increases by 26.24% (an exponential of 0.233). This finding suggests that tail risk in the price distribution of output influences the decision to invest.

We also find that a well's oil reserve is an essential determinant of drilling decisions – *reserve* has a positive and significant coefficient (0.65 and p-value <0.001). The higher the potential of a productive oil well, the higher the probability of drilling. Oil producers expect a higher production rate from wells with high reserves, and high-reserve oil wells are more likely to generate higher profits. The expected profit affects both the delay option and immediate investment values. However, the "immediate investment" value increases more than the "delay option," causing a higher likelihood of drilling a high reserve oil well. We expect the drilling cost to have a negative coefficient as the cost decreases the project value. An increase in drilling cost is analogous to an increase in the option strike price, thereby reducing the delay option value. However, the immediate investment value decreases more than the delay option value.

It is worth noting that most oil wells were drilled far enough from the expiration of the oil well leases; that is, the exercise of real investment options is more of a choice by oil producers to maximize expected payoffs than having to keep at least one oil well active to maintain a lease. In an alternative examination, we exclude oil wells that were drilled close to the expiration of oil leases (drilled within one

[§§§§§§] The hazard model will not use the months after the event happens (when the dependent variable is 1). Also, the hazard model will not use any unexercised options for estimation. These observations (after exercised and never exercised options) contain no useful information for estimating the hazard model.

year from the expiration of original leases) and the main conclusion that skewness and kurtosis matter to drilling choices still holds. [†††††††]

6.2 The Choice to Permanently Shutdown (plug) or Continue Producing

We define the time of a "shutdown" (*shutdown=1*) as the last month of production for the oil well. *Shutdown=0* until the final month of production, beginning with the first production date and ending the month before closing. *Shutdown=0* when the well begins to produce. The well had one *shutdown=1* in its last production month. We exclude the months when wells stop producing in the middle of their lives but then resume, as these constitute temporary shut-ins (mothballing). The cost of re-opening a permanently shutdown well is prohibitive, and as mentioned earlier, switching to mothball status would cause a shift from no periodic maintenance cost to a per-period cost, which would make no economic sense.

(Insert Table 5 here.)

Column (1) reports the 5. The results indicate that the price is negatively related to the probability of closing an oil well. We show that price is positively related to the likelihood of drilling, increasing the expected payoff from drilling an oil well. Such value increases are more for "immediate investment" than "delay option," as the latter is discounted more by time. Similarly, when prices decrease, oil producers are likelier to close down oil wells because the decline in oil prices will make an operating oil well unprofitable. Thus, when the opposite occurs, oil producers are less likely to close their oil wells. Oil producers have two choices: the first is to shut down oil wells immediately, and the second is to postpone the shutdown plan. Both become less attractive as the oil price increases; however, the first choice is even less appealing to producers, as the increase in oil price affects the expected payoffs from the first choice more than the second. Thus, oil producers are more likely to postpone shutdowns when oil prices increase. We also find that the coefficient of *volatility* is negative, indicating that increased expected volatility leads to an increased value for the delay option and has a lower probability of selecting shut-in. When price volatility is high, there is a better chance that a price increase will make the shutdown plan unattractive. Therefore, producers tend to delay shutting wells down if price volatility increases the delay option value. The choice is negatively related to volatility, and the empirical results suggest that *volatility* is negatively related to the probability of shutdown, consistent with the ROV predictions. In summary, the empirical results for price and volatility are consistent with the existing literature and predictions when prices are volatile and investment is irreversible..

Skewness and kurtosis are positively related to the probability of oil-well shutdowns, consistent with the prediction of real options valuations. In Column (6), the coefficient of skewness is significant at

[†††††††] Results available upon request.

the 1% level. This finding suggests that when price skewness increases (i.e., increases in the probability of positive price jumps), producers are more likely to shut down oil wells immediately. This finding seems counterintuitive at first. However, the put option value decreases, suggesting that waiting for the shutdown plan to proceed is not worth waiting. The expected payoff from the immediate shutdown does not change with skewness but is related to the expected price. This result is consistent with the immediate shutdown value being greater than the waiting value. To summarize, we find that extreme positive shocks accelerate a close-down plan and that outliers on both sides decrease the value of making such decisions immediately.

It was also found that (oil well) depth was positively related to the shutdown. Deeper wells have higher operating costs than shallower wells; thus, they are more likely to become optimal for the shutdown. We include *basin* in the econometric model to show that the dummies are significant explanatory variables for investment decisions. We use *last12* as a proxy for well productivity. If the oil well remains productive, the expected payoffs from future production will be higher than those from a less effective oil well. We show that *last12*, i.e., the well's last 12-month production rate, is negatively associated with the propensity to close the well. The production rate of an oil well decays exponentially with time. Thus, even for the same well, profitability changes over time. A more productive newer well is more profitable for maintenance in the production state than a less effective older well.

6.3 The Choice to Produce or Mothball

Column (1) of Table 6 reports the panel probit estimation results in which the choice variable is defined as follows: The dependent variable here is the oil well's production status, and $prod = 1$ for "producing" and $prod = 0$ for "mothballing." The estimated coefficient on *Price* is positive and significantly different from zero (0.437 and significant at 1%), as is the lagged production status, *l.prod* (0.302 significant at 1%). Note that the value of "immediate investment" and "delay option" increase with price. However, increases in output price have a more substantial impact on "immediate investment" than on the "delay option." This conclusion is intuitive. The "delayed" cash flows are discounted, and price increases should have a smaller impact on the more discounted cash flows than on the less discounted ones. For a producing well, the value of the put option of "mothballing" the oil well decreases with increased output price, making it less attractive to shut in the wells, thus leading to the positive coefficient of price. An increase in price volatility increases the put option value. The fact that lagged production status and volatility affect choice is consistent with producers recognizing the presence of sunk costs and future uncertainty.

(Insert Table 6 here.)

In column (2), the coefficient on "mothballing" lagged status and skewness is positive (0.045) and significant (with a p-value < 0.001). A higher skewness leads to the acceleration of immediate investment and a stronger propensity to re-open (a mothballed oil well). The interaction of "producing" lagged status and kurtosis has a negative and significant coefficient (-0.163 at 1%), and the coefficient of the interaction of "mothballing" lagged status and kurtosis is positive and significant (0.120 at 1%). Increases in kurtosis accelerate investment, suggesting that an increase in kurtosis reduces the value of the delay option and makes postponing investments less optimal. The results indicate that asymmetry and dispersion have significant impacts on investment propensity.

The coefficient on *age* is negative and significant (-0.360 and p-value <0.001), indicating that older wells are less profitable, consistent with older wells being less productive and more costly to operate. Thus, the results for *age* are consistent for models that include and exclude higher-order moments in the price distribution. We find that the coefficient of *depth* is negative and significant. The estimated coefficient on the variable cumulative oil production *cumulative oil production* is positive and statistically significant. However, the estimated coefficient of the reserve variable is not significantly different from zero. However, the reserve becomes significant and positive in the unreported results, excluding basins, drilling types, and depth in the empirical model. The estimated coefficient of the lagged production status, *l.prod,* is positive and significant. This finding suggests that lagged production status is an essential determinant of production status.

The empirical results revealed that tail risk significantly impacts oil firms' investment decisions. Changes in skewness affect oil producers' decisions to close, while changes in kurtosis lead to different likelihoods of closing an operating oil well. The results indicate that the marginal effect of kurtosis is as large as that of volatility. It is important to incorporate tail risks into decision models. The next section investigates the economic significance of tail risk for oil firms.

6.4 The Impacts of Tail Risks versus Volatility

6.4.1 Three-Way Sorting

As Kellogg (2014) and Moel and Tufano (2002) indicated, the volatility of oil price changes significantly influences decisions regarding mine drilling and closing. It is imperative to ascertain the relative importance of tail risks compared to volatility in shaping these decisions. Hence, the central research question arises: To what extent do skewness and/or kurtosis affect real investment decisions relative to volatility? Alternatively, this question can be reformulated as follows. How do value-maximizing choices differ from the existing model that exclusively considers volatility as a measure of uncertainty?

Initially, we examine periods during which volatilities are approximately equivalent but with varying levels of tail risk. In other words, we summarize the percentage of oil producers opting to commence drilling for new or close operating wells when volatilities are nearly identical. Still, the skewness and/or kurtosis differ. Table 7 illustrates the percentage of oil wells drilled in months, in which volatilities are categorized into four distinct portfolios (portfolio 1, which is the lowest volatility, and Portfolio 4, which is the highest volatility). The oil wells within each volatility portfolio are divided into three sub-portfolios: those in months with skewness exceeding the 75th percentile, those with skewness below the 25th percentile, and those between. The oil wells are divided into three sub-portfolios within each skewness portfolio based on kurtosis. The drilling model data findings indicate that when skewness is held constant within the intermediate portfolio, the percentage of drilled oil wells tends to increase consistently as kurtosis increases across various volatility portfolios. However, when kurtosis remains in the intermediate portfolio, and we examine the sub-portfolios based on volatility and skewness, we observe that in the lowest volatility portfolios, the percentage of drilled wells increases with skewness. This trend holds for the highest volatility portfolios. However, for portfolios characterized by intermediate levels of volatility, the relationship exhibits non-monotonic behavior. By contrast, for the shutdown model, we do not discern any consistent monotonic relationship between volatility, skewness, and kurtosis. Statistics about production status indicate that approximately 89.74% of the month-well observations within a sample are associated with active production. When skewness was segregated into percentiles at the 25th and 75th levels, the average percentage of monthly wells engaged in production was 88.66% for skewness values below the 25th percentile and 90.39% for skewness values exceeding the 75th percentile. The 25th percentile of volatility is measured at 0.243, whereas the 75th percentile is registered at 0.376. In cases of low volatility, an increase in skewness corresponds to a higher likelihood of oil wells being in production status.

(Insert Table 7 here.)

6.4.2 Reversed Choices - The Importance of Tail Risks

This subsection explores the possibility of oil firms reversing their investment decisions based on the impact of skewness and kurtosis on optimal choices. Specifically, it investigates when firms might change their production choices because models incorporating skewness and kurtosis could yield different outcomes than those considering only volatility as a source of price uncertainty. We estimate the likelihood of exercising an investment option using two different models: 1) an empirical model that predicts the likelihood of exercising a drilling option based on the volatility of price changes (the Simplified Model) and 2) an empirical model that predicts the likelihood using volatility, skewness, and kurtosis (the Complete Model). The median of exercised cases establishes a cutoff: probabilities at or above the median are predicted as “drilling,” while those below are predicted as “not drilling.”

First, we examine the choice of drilling by comparing the complete model - a model that incorporates the skewness and kurtosis of oil price changes, as in our main specification–and the simplified model, based on the main specification but without the variables for the skewness and kurtosis of oil price changes. We compared the predictions of the drilling choices of the two models (complete and simplified). We first ran a regression analysis of the complete model and predicted the hazard rate from the model's estimates. The predicted hazard rates were summarized for the statistical distribution median (50^{th} percentile value). When the predicted hazard rate is larger than the median, the oil well is predicted to be drilled; when the predicted hazard rate is lower than the median, we predict that the oil well will remain in-drilled as an open option. The simplified model's predicted hazard rate is also summarized for its median to predict the actions taken, and when its predicted hazard rate is greater than the median of the predicted hazard rate, the oil well is predicted to be drilled; if the rate is lower than the median, we predict that it is not drilled. According to the complete model, 73.28% of the sample was predicted to be drilled, and 72.80% was predicted to be drilled using the simplified model; 1.44% of samples have different predictions between the two models. We find that the percentage of different predictions (well-month observations) is about 2-5% before 2015 but is close to 0% between 2015 and 2018.

(Insert Table 8 here.)

The shutdown choice is predicted similarly: when the Cox proportional hazard model predicts a greater-than-median hazard rate, the oil well is predicted to be closed; otherwise, it is predicted to remain in operation. In the predicted shutdown choices, 31.55% were predicted to be closed based on the complete model, and 7.71% were predicted to be closed based on the simplified model. There are 23.85% predictions in which the simplified model (with only the volatility variable to measure uncertainty) predicts remaining operational, but the complete model (with skewness and kurtosis) is predicted to be closed. Figure 2 shows the percentages of different predictions between the complete and simplified models, calculated as the proportion of well-month observations with different predicted actions (closed vs. stay-operating). According to this figure, the percentage of different predictions increased in the 2010s. From 2016 to 2019, the percentage was approximately 50%.

(Insert Figure 2 here.)

The choices between production and mothballing are fitted using a different statistical model in our main specification: the panel probit model. Thus, choices were predicted using a panel probit model. The choices are predicted based on two alternative specifications: complete and simplified. In the simplified specification, the skewness and kurtosis variables of the oil price changes were not included. The complete model predicts 45.13% of the well-month observations to be produced, and the simplified model predicts a production of 50.02 %. A 4.89% sample is predicted to be produced by the simplified model but predicted to be mothballed by the complete model. Figure 2 shows the trend in the percentage of monthly observations for different predictions. The percentage of different predictions between the complete and simplified models gradually increased over time. This figure increased by approximately 5.5% in 2019.

6.4.3 Potential Value Loss When Ignoring Tail Risks

The following sections estimate the possible loss of value for oil producers. The potential value loss was estimated following the methods of Décaire et al. (2020) to estimate the oil well project value. We follow similar assumptions as Décaire et al. (2020) but alter the specifications for oil drilling investment decisions. The potential loss estimation by Décaire et al. (2010) was for natural gas wells. Following Décaire et al. (2020) in estimating asset value for natural gas wells,[‡‡‡‡‡‡‡] the net profit per barrel is calculated as, $P[(1-\varphi-\rho)-\tau(1-\varphi-\rho-\theta)]$, where φ is operating costs, ρ is royalty rates, τ is effective tax rate, and θ is depreciation rate. Value of an oil well is calculated as $V = E[Q]\frac{\Pi}{\mu+\omega}$, where μ is discount rate, and ω is depletion rate. $E[Q]$ is estimated as the predicted production rate obtained from a regression of the annual production rate of the first infill well on the annual production rate of the second well. The coefficient was then used to estimate the production rates of the infill wells in the sample. The drilling cost was the average drilling cost of the sample. Here are the parameters of inputs: φ = 12.3%, ρ = 28.6%, τ = 34%, θ = 40%, μ = 10%, and ω = 15%.[§§§§§§§]

The average well value was estimated to be approximately $2,913,058 per year. Dividing this value by 12 estimates a $242,754 monthly value. Referring to our estimated difference in the percentage of different predictions from the complete and simplified models (assuming a 2.5% difference), oil producers will obtain a $6,068 value difference if not using the complete model that incorporates tail risks per well per month. The sample's average number of oil well options per operator is 145; on average, each oil operator is holding 145 open oil well options per month. This counts towards $879,860 possible value differences per month and $10,558,320 value differences per year. The average annual net income of oil firms in our sample is $1,002,000,000. This suggests that 1.05% of annual earnings could have changed if operators simply adopted a decision model incorporating tail risk into oil price changes.

6.5 Physical Moments and Even Higher-Order Moments

[‡‡‡‡‡‡‡] Please see p.36 4.3.1 Estimating the underlying asset value of Décaire et al. (2020).

[§§§§§§§] Sources of input parameters:
φ: https://www.investopedia.com/ask/answers/071615/what-are-average-operating-expenses-oil-and-gas-sector.asp
ρ: https://www2.deloitte.com/content/dam/Deloitte/global/Documents/Energy-and-Resources/dttl-er-US-oilandgas-guide.pdf
τ: https://www.api.org/-/media/files/policy/taxes/dm2018-086_api_fair_share_onepager_fin3.pdf
θ: https://www.plantemoran.com/explore-our-thinking/insight/2022/08/the-tcja-100-percent-bonus-depreciation-starts-to-phase-out-after-2022
μ: Decaire et al. (2020).
ω: esimated from $\frac{Prod_{t=2}}{Prod_{t=1}} = e^{-w}$.

6.5.1 Physical Price Distributions

Notably, most oil producers use physical oil prices as price benchmarks rather than futures (option-implied) prices or distribution moments. First, most oil producers (70% in our sample) hedge some of their crude oil positions in the case of high uncertainty in oil markets; from drilling to the production of crude oil, oil price uncertainty cannot be fully reduced but can be alleviated by entering financial contracts. Second, some small oil producers find it too costly to enter these financial contracts and may use physical prices as their benchmarks. Thus, we examined the moments of physical price changes. The volatility, skewness, and kurtosis of the physical price changes are estimated from the physical price changes (1-st futures WTI crude oil price changes) and are calculated as the standard deviation, skewness, and kurtosis of price changes on an annual rolling basis. The spot prices from six months before to six months after the dates were used to compute the price changes' standard deviation, skewness, and kurtosis. This computation follows the methodology for computing the term structure of volatility outlined in Kellogg (2014). Then, the daily moments were averaged monthly to measure the distribution moments of the physical oil price changes.[********] According to the empirical results, physical price change distributions have similar coefficient signs and significance to the BKM risk-neutral moments estimated from options and futures prices.[††††††††]

(Insert Table 9 here.)

6.5.2 Interaction Terms - Nonlinear Relationship

It is plausible to assert that the influence of kurtosis may be contingent on the magnitude of skewness, as these effects exhibit the potential for mutual interaction. For instance, in the event of positive skewness, an increase in kurtosis could enhance the probability of encountering favorable developments in the future. Consequently, in this subsection, we conduct an empirical analysis incorporating an interaction term encompassing skewness and kurtosis into our regression models.

The outcomes derived from the production model substantiate that, in cases where both skewness and kurtosis are higher, oil producers tend to choose to produce over mothballing strategies. Importantly, the statistical significance of the interaction term is manifested in both the mothballing and production statuses. Nevertheless, when we considered the drilling model, the interaction term, although not statistically significant, exhibited a positive coefficient. Turning to the shutdown model, the interaction

[********] For example, the 1-st WTI crude oil futures prices from 180 days before Jan 1, 2015 to 180 days after Jan 1, 2015 are calculated to their daily price changes; then the daily price changes in the 360 days are summarized its distribution standard deviation, skewness, and kurtosis; the statistical summaries are used as Jan 1, 2015 physical price changes' volatility, skewness, and kurtosis. Each trading date of Jan 2015 are calculated volatility, skewness, and kurtosis in a similar way, then the daily moments are simply averaged to their monthly estimates.

[††††††††] In an unreported robustness test, we use 18-month (one-month) physical moments to replace the risk-neutral moments. The results are similar to these using the concurrent physical moments.

term had a noteworthy negative coefficient that was statistically significant. This empirical evidence implies that in situations in which both distribution moments experience an increase, oil producers tend to opt for the deferral of shutdown decisions.

(Insert Table 10 here.)

6.5.3 Even-Higher-Order Dimensions and Asymmetries in Price Distribution

Because oil price distributions may not follow a normal distribution and exhibit significant skewness and kurtosis in our sample, it is important to suggest whether oil price changes exhibit even higher-order moments in the distribution. Next, we empirically examine the asymmetry in the price change distribution on whether the oil producer responds only to changes in the odd-order central moments (skewness and fifth-order moments). Two alternative hypotheses examine whether oil producers respond only to moments describing the asymmetry in the oil price change distribution:

H0: Oil investment decisions only respond to odd-order central moment changes in oil price change distribution.

H1: Oil investment decisions are explained by changes in odd-or and even-order central moments.

The rationale under this null hypothesis is that oil producers do not maximize expected payoffs by choosing a choice with a higher payoff but simply dislike the asymmetry in the oil price change distribution. If this null hypothesis is supported by the empirical results for oil investment choices and oil price change distribution moment changes, the reason could be explained by the oil producers' preference over positive skewness (and over positive/negative even higher-order central moments).

Since Jarrow and Rudd (1982), Corrado and Su (1986), and Brown and Robinson (2002) developed the skewness- and kurtosis-adjusted option pricing models, higher-order moments (order >5) have not yet been derived. Thus, we respond to an estimation of the higher-order moments on the realized distribution of the central moments. This estimation uses a 360-day rolling window to estimate the realized distribution of the central moments for oil price changes. The p-th order central moments are calculated as $R_{p,t} = \frac{\sum_{n=1}^{N}(\Delta Price - \overline{\Delta Price})^p}{n-1}$, where n=t-180 to t+180. The empirical results suggest that all moments matter, not just odd- or even-order moments, in oil drilling decisions.

(Insert Table 11 here.)

6.6 The Impact of Financial Constraints on Oil Investments and Uncertainty

6.6.1 Hedging

As previously mentioned, many oil producers hedge their positions in crude oil. In this subsection, we examine whether hedging choices influence oil producers' responses to changes in tail risk. The hedging ratio of oil production is calculated as the ratio of hedging derivatives to total oil production over a fiscal year cycle. The derivative positions for hedging and annual total oil production were manually collected from 10-k. The average hedging ratio was 44.97%, and the ratio was highly skewed, with a median of 30.10% and a standard deviation of 32.90%. Approximately 38% of the firm-year sample has a hedging ratio of 0 %. Table 12 suggests that the interactions between the hedging ratio and the distribution moments (volatility, skewness, and kurtosis) are insignificant at the 5% level for drilling decisions. [‡‡‡‡‡‡‡‡] We find significant impacts of hedging ratios on the producing status choices between producing and mothballing in the production model sample. When we split our sample into hedgers and non-hedgers based on whether the firms have nonzero hedging positions, we found no significant differences between the two groups. Thus far, the results show that hedging strategies do not significantly change firms' choices when facing tail risk.

(Insert Table 12 here.)

6.6.2 Leverage

Next, exploring whether financially constrained oil firms are more likely to respond to changes in tail risk-skewness and kurtosis in oil price changes is important. If oil producers are concerned about the potential value loss from making decisions that are not value-maximizing, they should be particularly cautious when their financial conditions are more tangential. The measure of financial constraints is the leverage of the oil well operator[§§§§§§§§]. Firms closer to bankruptcy or insolvency are more likely to be concerned about potential value losses. The rationale is that oil producers should be more cautious about their investment decisions. Financial constraints are proxied by operator leverage. The data used to calculate leverage were collected from Compustat through the WRDS,[*********] show that the interactions of volatility are significant and negative, suggesting that leveraged firms are more likely to delay drilling plans when

[‡‡‡‡‡‡‡‡] Following Doshi, et a. (2018) and Adam, et cl. (2017), the endogeneity issue with leverage ratio may be resolved with the Inverse Mills Ratio (and capital investment), which is predicted from the serial correlation coefficient in taxable incomes, the instrument variable for hedging ratio. In an unreported robustness result, we split our sample into two groups: hedgers and non-hedgers and run the main model separately for each subgroup for drilling decisions. Non-hedgers do not respond to changes in skewness and kurtosis of oil price changes but respond to changes in predicted hedging ratios (coefficient of Inverse Mills Ratio is negative and significant at 1%); hedgers respond to changes in skewness negatively but the coefficient for the Inverse Mills Ratio is not significant.

[§§§§§§§§] They are those reported as the main operator of the oil wells by Enverus.

[*********] Leverage is calculated as short-term debt (dlcq) plus long term debt (dlttq) divided by total equity (seqq). All items on quarterly basis.

uncertainty increases. However, more leveraged oil producers are reluctant to shut down operating oil wells when the skewness changes.

(Insert Table 13 here.)

6.7 Term Structure of Oil Prices: Contango and Backwardation

The shape of the term structure of oil prices may affect oil producers' choices. For example, if oil prices are expected to increase, oil producers may become more optimistic about oil drilling projects. Following the measure in Miffre and Rallis (2007) and the term in Kolb (1992), we use roll-return (R) to measure the shape of the term structure of oil prices. R is defined as $\mathrm{R_t} = P_{Nearest,t}/P_{Distant,t} - 1$. Thus, a higher *R* suggests higher oil prices in nearer terms and lower oil prices in more distant terms. As *R* increases, the term structure becomes more of a contango than a backwardation. The regressions of models, including *R* suggest that when facing a more contango term structure in oil prices, oil producers are more likely to choose to delay drilling and shutdown plans. A dummy variable, *Contango* = 1 for negative *R*, shows a positive but insignificant coefficient. The regressions of production status on variables and, including the term structure measures, show that oil producers are less likely to resume production, and the dummy variable shows a positive and significant coefficient, suggesting a significant impact of the shape of the term structure of oil prices on investment choices for oil producers.

(Insert Table 15 here.)

6.8 Robustness

6.8.1 Unobserved Heterogeneity in the Production/Temporary Shut-in (Mothball) Model

We investigate whether unobserved heterogeneity across wells affects the main results presented in Tables 4-6. There may exist substantial unobserved heterogeneous differences among oil wells that determine production statuses. Determinants other than depth, age, drilling type, or basin may affect the profitability of the oil wells, such as operating costs. Using a robust model controlling for unobserved heterogeneity, we implement the simple initial condition solution proposed by Wooldridge (2005) to solve the unobserved heterogeneity issue in random-effects panel probit model. In addition to the initial model's specification, we include add the lagged values (initial conditions) of the dependent variable, cumulative oil production, and age's initial values, and averages of cumulative oil production and age to control unobserved heterogeneity among wells. We find that the empirical results rarely change.

6.8.2 The Influence of Nearby Drilling Activity

Décaire et al. (2020) find that the propensity for oil producers to decide whether to drill a new oil well is influenced by the drilling activity of neighbor producers, suggesting that an information spillover effect influences producers decisions to drill. We construct measures of proximity in the following manner: using the arrangement of sections within a lease,[†††††††††] we can identify the "neighbors" of an oil well with the section numbers. A section can have up to eight neighbors. For instance, section 16 has neighbor sections 8, 9, 10, 15, 17, 20, 21, and 22. However, some sections have fewer neighbors within the lease. For instance, section 1 only has neighbor sections 2, 11, and 12. A well lease can be identified by its range and township values which, along with section numbers, are available from the Enverus' database. After identifying each well's neighbors, we count the number of drilled options among these neighbors. These are the number of exercised options around the well. This number serves as a source of spillover information, as it indicates the productivity of the oil wells and reserve underground. We am able to split between the oil well's firm's own drilled neighboring wells and drilled wells from other firms. Both numbers are included in the empirical model to examine the effect of proximity options exercises on oil well drilling decisions. Including these measures of proximity in the base drilling model, we find that our basic results regarding the relation between the choice to drill, volatility, skewness and kurtosis are unchanged. However, we do find that proximity does matter in our sample, that the probability of drilling is positively related to proximity.

7. Summary and Conclusions

By focusing on production histories for all oil wells domiciled in California, North Dakota, Pennsylvania, Texas, and Oklahoma from 2010 to 2019 and relating the changes in producing status to oil price moments (volatility, skewness, and kurtosis), we show that oil producers account for higher order oil price moments consistent with the predictions of value maximizing behavior in the presence of real options (price change uncertainty and sunk costs). The choices to produce or temporarily shut down, are determined by expected skewness, kurtosis and volatility of the price change distribution in addition to other well-specific characteristics. The choice to continue producing or permanently shut down are determined by expected skewness and volatility. The choice to drill or wait to drill is determined however only by expected kurtosis and volatility. The evidence overall indicates that sunk costs matter in the presence of future price uncertainty. The choices of the oil producers in the sample are consistent with value maximizing behavior in the presence of real options, however not all choices are influenced by skewness and kurtosis despite the fact that in theory the value of the real options involved are influenced by those parameters of the price change distribution.

[†††††††††] An example of the map of the arrangements of section within a well lease can be accessed: https://www.geomore.com/locating-wells/.

References

Abel, A. B., Dixit, A. K., Eberly, J. C., & Pindyck, R. S. (1996). Options, the value of capital, and investment. *The Quarterly Journal of Economics*, *111*(3), 753-777.

Aguerrevere, F. L. (2009). Real options, product market competition, and asset returns. *The Journal of Finance*, *64*(2), 957-983.

Ahmadi, M., Manera, M., & Sadeghzadeh, M. (2019). The investment-uncertainty relationship in the oil and gas industry. *Resources Policy*, *63*, 101439.

Aizenman, J., & Marion, N. P. (1993b). Macroeconomic uncertainty and private investment. *Economics Letters*, *41*(2), 207-210.

Aizenman, J., & Marion, N. P. (1993a). Policy uncertainty, persistence and growth. *Review of International Economics*, *1*(2), 145-163.

Al-Harthy, M. H. (2007). Stochastic oil price models: Comparison and impact. *The Engineering Economist*, 52(3), 269-284.

Anderson, S. T., Kellogg, R., & Salant, S. W. (2018). Hotelling under pressure. *Journal of Political Economy*, 126(3), 984-1026.

Arnold, T., & Crack, T. F. (2000). Option pricing in the real world: a generalized binomial model with applications to real options. *Available at SSRN 240554*.

Arouri, M. E. H., & Nguyen, D. K. (2010). Oil prices, stock markets and portfolio investment: Evidence from sector analysis in Europe over the last decade. *Energy Policy*, *38*(8), 4528-4539.

Asmussen, S., Avram, F., & Pistorius, M. R. (2004). Russian and American put options under exponential phase-type Lévy models. *Stochastic Processes and Their Applications*, *109*(1), 79-111.

Bachmann, R., & Bayer, C. (2014). Investment dispersion and the business cycle. *American Economic Review*, *104*(4), 1392-1416.

Backus, D. K., Foresi, S., & Wu, L. (2004). Accounting for biases in Black-Scholes. *Available at SSRN 585623*.

Bakshi, G., Kapadia, N., & Madan, D. (2003). Stock return characteristics, skew laws, and the differential pricing of individual equity options. *The Review of Financial Studies*, *16*(1), 101-143.

Baldwin, C. Y. (1982). Optimal sequential investment when capital is not readily reversible. *The Journal of Finance*, *37*(3), 763-782.

Bali, T. G., & Murray, S. (2013). Does risk-neutral skewness predict the cross section of equity option portfolio returns?. *Journal of Financial and Quantitative Analysis*, 1145-1171.

Bates, D. S. (1997). The skewness premium: Option pricing under asymmetric processes. *Advances in Futures and Options Research*, *9*, 51-82.

Bennouna, K., Meredith, G. G., & Marchant, T. (2010). Improved capital budgeting decision making: evidence from Canada. *Management Decision*.

Berger, P. G., Ofek, E., & Swary, I. (1996). Investor valuation of the abandonment option. *Journal of Financial Economics*, *42*(2), 259-287.

Bernanke, B. S. (1983). Irreversibility, uncertainty, and cyclical investment. *The Quarterly Journal of Economics*, *98*(1), 85-106.

Block, S. (2007). Are "real options" actually used in the real world?. *The Engineering Economist*, *52*(3), 255-267.

Bloom, N., Bond, S., & Van Reenen, J. (2007). Uncertainty and investment dynamics. *The Review of Economic Studies*, *74*(2), 391-415.

Boomhower, J. (2019). Drilling like there's no tomorrow: bankruptcy, insurance, and environmental risk. *American Economic Review*, 109(2), 391-426.

Borland, L., & Bouchaud, J. P. (2004). A non-Gaussian option pricing model with skew. *Quantitative Finance*, *4*(5), 499-514.

Boyarchenko, S. (2004). Irreversible decisions and record-setting news principles. *American Economic Review*, 94(3), 557-568.

Boyarchenko, S. I., & Levendorskiĭ, S. Z. (2000). Option pricing for truncated Lévy processes. *International Journal of Theoretical and Applied Finance*, 3(03), 549-552.

Boyarchenko, S. I., & Levendorskiĭ, S. Z. (2002). Perpetual American options under Lévy processes. *SIAM Journal on Control and Optimization,* 40(6), 1663-1696.

Boyer, B., Mitton, T., & Vorkink, K. (2010). Expected idiosyncratic skewness. *The Review of Financial Studies*, *23*(1), 169-202.

Brown, C. A., & Robinson, D. M. (2002). Skewness and kurtosis implied by option prices: A correction. *Journal of Financial Research*, *25*(2), 279-282.

Brunnermeier, M. K., & Parker, J. A. (2005). Optimal expectations. *American Economic Review*, *95*(4), 1092-1118.

Caballero, R. J. (1999). Aggregate investment. *Handbook of Macroeconomics*, *1*, 813-862.

Cameron, C. & A. Trivedi (2005). Microeconometrics: Methods and Applications. Cambridge University Press, Cambridge, UK.

Cao, H., Guo, L., & Zhang, L. (2020). Does oil price uncertainty affect renewable energy firms' investment? Evidence from listed firms in China. *Finance Research Letters*, *33*, 101205.

Carruth, A., Dickerson, A., & Henley, A. (2000). What do we know about investment under uncertainty?. *Journal of Economic Surveys*, *14*(2), 119-154.

Chang, B. Y., Christoffersen, P., & Jacobs, K. (2013). Market skewness risk and the cross section of stock returns. *Journal of Financial Economics*, *107*(1), 46-68.

Chang, B. Y., Christoffersen, P., Jacobs, K., & Vainberg, G. (2012). Option-implied measures of equity risk. *Review of Finance,* 16(2), 385-428.

Chen, F., & Linn, S. C. (2017). Investment and operating choice: Oil and natural gas futures prices and drilling activity. *Energy Economics*, 66, 54-68.

Chen, J., Hong, H., & Stein, J. C. (2001). Forecasting crashes: Trading volume, past returns, and conditional skewness in stock prices. *Journal of Financial Economics*, *61*(3), 345-381.

Claerbout, J., & Muir, F. (2008). Hubbert math. *Sepstanford.edu*.

Conrad, J., Dittmar, R. F., & Ghysels, E. (2013). Ex ante skewness and expected stock returns. *The Journal of Finance*, *68*(1), 85-124.

Cooper, I. (2006). Asset pricing implications of nonconvex adjustment costs and irreversibility of investment. *The Journal of Finance*, *61*(1), 139-170.

Corrado, C. J., & Su, T. (1996a). Skewness and kurtosis in S&P 500 index returns implied by option prices. *Journal of Financial Research*, *19*(2), 175-192.

Corrado, C. J., & Su, T. (1996b). S&P 500 index option tests of Jarrow and Rudd's approximate option valuation formula. *Journal of Futures Markets: Futures, Options, and Other Derivative Products*, *16*(6), 611-629.

Covert, T. (2015). Experiential and social learning in firms: the case of hydraulic fracturing in the Bakken Shale. *Available at SSRN 2481321.*

Cox, D. R. (1972). Regression models and life-tables. *Journal of the Royal Statistical Society: Series B (Methodological)*, 34(2), 187-202.

Cox, J. C., & Ross, S. A. (1976). The valuation of options for alternative stochastic processes. *Journal of Financial Economics,* 3(1-2), 145-166.

Dai, Z., Zhou, H., Kang, J., & Wen, F. (2021). The skewness of oil price returns and equity premium predictability. *Energy Economics*, *94*, 105069.

Datta, D. D., Londono, J. M., & Ross, L. J. (2017). Generating options-implied probability densities to understand oil market events. *Energy Economics*, 64, 440-457.

Davis, G. A., & Cairns, R. D. (2017). The odd notion of "reversible investment". *Journal of Banking & Finance*, *81*, 172-180.

Décaire, P. H., Gilje, E. P., & Taillard, J. P. (2020). Real option exercise: Empirical evidence. *The Review of Financial Studies*, *33*(7), 3250-3306.

Dias, J. C., Larguinhob, M., & Braumannc, C. A. (2015). Entry and Exit Decisions under Uncertainty for a Generalized Class of One-Dimensional Diffusions. In *Real Options Conference. Athens and Monemvasia*.

Diavatopoulos, D., Doran, J. S., Fodor, A., & Peterson, D. R. (2012). The information content of implied skewness and kurtosis changes prior to earnings announcements for stock and option returns. *Journal of Banking & Finance*, *36*(3), 786-802.

Dittmar, R. F. (2002). Nonlinear pricing kernels, kurtosis preference, and evidence from the cross section of equity returns. *The Journal of Finance*, *57*(1), 369-403.

Dixit, A. (1989). Entry and exit decisions under uncertainty. *Journal of Political Economy*, *97*(3), 620-638.

Dixit, A. (1991). Irreversible investment with price ceilings. *Journal of Political Economy*, *99*(3), 541-557.

Dixit, R. K., & Pindyck, R. S. (1994). *Investment Under Uncertainty*. Princeton university press.

Doshi, H., Kumar, P., & Yerramilli, V. (2018). Uncertainty, capital investment, and risk management. *Management Science*, *64*(12), 5769-5786.

Drakos, K., & Konstantinou, P. T. (2013). Investment decisions in manufacturing: assessing the effects of real oil prices and their uncertainty. *Journal of Applied Econometrics*, *28*(1), 151-165.

Elder, J., & Serletis, A. (2010). Oil price uncertainty. *Journal of Money, Credit and Banking*, *42*(6), 1137-1159.

Ferderer, J. P. (1996). Oil price volatility and the macroeconomy. *Journal of Macroeconomics*, *18*(1), 1-26.

Figlewski, S. (2016). What goes into risk-neutral volatility? Empirical estimates of risk and subjective risk preferences. *The Journal of Portfolio Management*, 43(1), 29-42.

Fisher, I. (1930). *Theory of interest: as determined by impatience to spend income and opportunity to invest it.* Augustusm Kelly Publishers, Clifton.

Gilje, E. P. (2019). Does local access to finance matter? Evidence from US oil and natural gas shale booms. *Management Science*, *65*(1), 1-18.

Girardi, D. (2021). The neoclassical theory of aggregate investment and its criticisms.

Greene, W. H. (2003). *Econometric analysis*. Pearson Education India.

Gukhal, C. R. (2001). Analytical valuation of American options on jump-diffusion processes. *Mathematical Finance*, *11*(1), 97-115.

Gulen, H., & Ion, M. (2016). Policy uncertainty and corporate investment. *The Review of Financial Studies*, *29*(3), 523-564.

Harvey, C. R., & Siddique, A. (2000). Conditional skewness in asset pricing tests. *The Journal of Finance*, *55*(3), 1263-1295.

Hausman, J. (1999). The effect of sunk costs in telecommunications regulation. In *The new investment theory of real options and its implication for telecommunications economics* (pp. 191-204). Springer, Boston, MA.

Hayashi, F. (1982). Tobin's marginal q and average q: A neoclassical interpretation. *Econometrica: Journal of the Econometric Society*, 213-224.

Hirshleifer, J. (1958). On the theory of optimal investment decision. *Journal of Political Economy*, *66*(4), 329-352.

Hirshleifer, J. (1970). *Investment, interest, and capital.*

Holland, A. S., Ott, S. H., & Riddiough, T. J. (2000). The role of uncertainty in investment: An examination of competing investment models using commercial real estate data. *Real Estate Economics*, *28*(1), 33-64.

Hull, J. C. (2003). Options futures and other derivatives. Pearson Education India.

Jarrow, R., & Rudd, A. (1982). Approximate option valuation for arbitrary stochastic processes. *Journal of Financial Economics*, *10*(3), 347-369.

Jens, C. E. (2017). Political uncertainty and investment: Causal evidence from US gubernatorial elections. *Journal of Financial Economics*, *124*(3), 563-579.

Jin, Y., & Jorion, P. (2006). Firm value and hedging: Evidence from US oil and gas producers. *The journal of Finance,* 61(2), 893-919.

Jurczenko, E., Maillet, B., & Negréa, B. (2004). A note on skewness and kurtosis adjusted option pricing models under the Martingale restriction. *Quantitative Finance*, *4*(5), 479-488.

Kaminski, V. (2012), *Energy Markets*. Risk Books, Incisive Media, London, UK.

Kang, W., Lee, K., & Ratti, R. A. (2014). Economic policy uncertainty and firm-level investment. *Journal of Macroeconomics*, *39*, 42-53.

Kellogg, R. (2014). The effect of uncertainty on investment: Evidence from Texas oil drilling. *American Economic Review*, *104*(6), 1698-1734.

Kellogg, R. (2011). Learning by drilling: Interfirm learning and relationship persistence in the Texas oilpatch. *The Quarterly Journal of Economics*, 126(4), 1961-2004.

Kolb, R. W. (1992). Is normal backwardation normal?. *The Journal of Futures Markets* (1986-1998), 12(1), 75.

Kogan, L. (2001). An equilibrium model of irreversible investment. *Journal of Financial Economics*, *62*(2), 201-245.

Kou, S. G. (2002). A jump-diffusion model for option pricing. *Management Science*, *48*(8), 1086-1101.

Kou, S. G., & Wang, H. (2004). Option pricing under a double exponential jump diffusion model. *Management Science*, *50*(9), 1178-1192.

Keynes, J. M. (2015). Vom Gelde (A treatise on money) (pp. 1-656). Duncker und Humblot.

Kraus, A., & Litzenberger, R. H. (1976). Skewness preference and the valuation of risk assets. *The Journal of Finance*, *31*(4), 1085-1100.

Lambrecht, B. M. (2017). Real options in finance. *Journal of Banking & Finance*, *81*, 166-171.

Leahy, J. V., & Whited, T. (1995). The effect of uncertainty on investment: Some stylized facts.

Lensink, R., & Morrissey, O. (2000). Aid instability as a measure of uncertainty and the positive impact of aid on growth. *The Journal of Development Studies*, *36*(3), 31-49.

Levendorskiĭ, S. (2005). Perpetual American options and real options under mean-reverting processes. *Available at SSRN 714321*.

Lewis, A. L. (2001). A simple option formula for general jump-diffusion and other exponential Lévy processes. *Available at SSRN 282110*.

List, J. A., & Haigh, M. S. (2010). Investment under uncertainty: Testing the options model with professional traders. *The Review of Economics and Statistics*, 92(4), 974-984.

Lukawski, M. Z., Anderson, B. J., Augustine, C., Capuano Jr, L. E., Beckers, K. F., Livesay, B., & Tester, J. W. (2014). Cost analysis of oil, gas, and geothermal well drilling. *Journal of Petroleum Science and Engineering*, *118*, 1-14.

Maghyereh, A., & Abdoh, H. (2020). Asymmetric effects of oil price uncertainty on corporate investment. *Energy Economics*, *86*, 104622.

Majd, S., & Pindyck, R. S. (1987). Time to build, option value, and investment decisions. *Journal of Financial Economics*, *18*(1), 7-27.

Mayers, D. (1998). Why firms issue convertible bonds: the matching of financial and real investment options. *Journal of Financial Economics*, *47*(1), 83-102.

McDonald, R., & Siegel, D. (1986). The value of waiting to invest. *The Quarterly Journal of Economics*, *101*(4), 707-727.

Merton, R. C. (1976). Option pricing when underlying stock returns are discontinuous. *Journal of Financial Economics*, *3*(1-2), 125-144.

Miao, J., & Wang, N. (2007). Investment, consumption, and hedging under incomplete markets. *Journal of Financial Economics*, 86(3), 608-642.

Miffre, J., & Rallis, G. (2007). Momentum strategies in commodity futures markets. *Journal of Banking & Finance*, 31(6), 1863-1886.

Moel, A., & Tufano, P. (2002). When are real options exercised? An empirical study of mine closings. *The Review of Financial Studies*, 15(1), 35-64.

Mohn, K., & Misund, B. (2009). Investment and uncertainty in the international oil and gas industry. *Energy Economics*, *31*(2), 240-248.

Molls, B. M. (2001). *An empirical investigation of investment under uncertainty with sunk costs: Oil production in Oklahoma*. The Pennsylvania State University.

Muehlenbachs, L. (2015). A dynamic model of cleanup: Estimating sunk costs in oil and gas production. *International Economic Review*, 56(1), 155-185.

Myers, S. C. (1977). Determinants of corporate borrowing. *Journal of Financial Economics*, *5*(2), 147-175.

Phan, D. H. B., Tran, V. T., & Nguyen, D. T. (2019). Crude oil price uncertainty and corporate investment: New global evidence. *Energy Economics*, *77*, 54-65.

Pindyck, R. S. (1986). Irreversible investment, capacity choice, and the value of the firm. *National Bureau of Economic Research.*

Pindyck, R. S. (1990). Irreversibility, uncertainty, and investment. *National Bureau of Economic Research.*

Pindyck, R. S. (1993). Investments of uncertain cost. *Journal of Financial Economics*, *34*(1), 53-76.

Potters, M., Cont, R., & Bouchaud, J. P. (1998). Financial markets as adaptive systems. *Europhysics Letters*, *41*(3), 239.

Raimi, D., Krupnick, A. J., Shah, J. S., & Thompson, A. (2021). Decommissioning orphaned and abandoned oil and gas wells: New estimates and cost drivers. *Environmental Science & Technology*, 55(15), 10224-10230.

Ruan, X., & Zhang, J. E. (2018). Risk-neutral moments in the crude oil market. *Energy Economics*, *72*, 583-600.

Samis, M., Davis, G. A., Laughton, D., & Poulin, R. (2005). Valuing uncertain asset cash flows when there are no options: A real options approach. *Resources Policy*, *30*(4), 285-298.

Schneider, C., & Spalt, O. (2016). Conglomerate investment, skewness, and the CEO long-shot bias. *The Journal of Finance*, *71*(2), 635-672.

Sepp, A. (2008). VIX option pricing in a jump-diffusion model. *Risk Magazine*, 84-89.

Slade, M. E. (2001). Valuing managerial flexibility: An application of real-option theory to mining investments. *Journal of Environmental Economics and Management*, 41(2), 193-233.

Tobin, J., & Brainard, W. C. (1976). Asset markets and the cost of capital. *Cowles Foundation Discussion Papers*. 659.

Tsekrekos, A. E. (2010). The effect of mean reversion on entry and exit decisions under uncertainty. *Journal of Economic Dynamics and Control*, *34*(4), 725-742.

Wooldridge, J. M. (2005). Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity. *Journal of Applied Econometrics*, *20*(1), 39-54.

Yang, M., Blyth, W., Bradley, R., Bunn, D., Clarke, C., & Wilson, T. (2008). Evaluating the power investment options with uncertainty in climate policy. *Energy Economics*, *30*(4), 1933-1950.

Yoon, K. H., & Ratti, R. A. (2011). Energy price uncertainty, energy intensity and firm investment. *Energy Economics*, *33*(1), 67-78.

Zhang, X. (1997). Valuation of American options in a jump-diffusion model. *Numerical Methods in Finance*, 93-114.

TABLE 1. Coefficient Sign Predictions of Choice Determinants for Choice Models

Table 1. shows the predicted relationships between the empirical model variables as discussed in section 3 and the probability of oil producers choosing "producing" ("drilling" or "shutdown") status at t according to the developed economic and empirical models in 4.3, 4.4, and 4.5. These relationships are indicated by the modified Black-Scholes option pricing model and Real Options Valuation as discussed in section 3. The first column shows the names of the variables in these empirical models (as in equations (1), (2), and (3)). Columns 3-5 show the predicted relationships between the variables and the probability of choosing "producing" as in the production model, and the probability to choose "drilling" in the drilling model, as well as the probability to choose to close the oil well in the shutdown model. In particular, the relationship between the probability and price moments for the production model depends on lagged status, so column 2 gives the lagged status of oil wells. In the second column, lagged producing status is given as signs of predicted coefficients depending on lagged status.

Model	Production		Drilling	Shutdown
Variable	Lagged Production State at t-1	Probability of Selecting "Producing" State at t	Probability of Selecting "Drilling" at t	Probability of Selecting "Shutdown" at t
Lagged Status(= "Producing")		Positive		
Price		Positive	Positive	Negative
Volatility	*Producing*	Positive	Negative	Negative
	Mothballing	Negative		
Skewness	*Producing*	Positive	Positive	Positive
	Mothballing	Negative		
Kurtosis	*Producing* *Mothballing*	Positive or Negative	Positive or Negative	Positive or Negative
Horizontal Drilling		Positive or Negative	Positive or Negative	Positive or Negative
Directional Drilling		Positive or Negative	Positive or Negative	Positive or Negative
Undetermined Drilling		Positive or Negative	Positive or Negative	Positive or Negative
Basins		Positive or Negative	Positive or Negative	Positive or Negative
Age		Negative		
Depth		Negative	Negative	Positive
Productivity		Positive	Positive	Negative
Total Costs		Positive	Negative	Negative

TABLE 2. Life Cycle of An Oil Well

Table 2. describes the six stages of the life cycle of an oil well – 1. Seismic survey; 2. Drilling; 3. Producing; 4. Mothballing, 5, Producing (Resuming), and 6. Shutdown. The second column describes the definition of each stage and the last column explains the situations in which each stage would be chosen.

Oil well life cycle stage	Define	When to choose the stage
1. Seismic Survey	Tests of oil well expected total production and operating cost	Oil producers to test oil reserve and reservoir depth
2. Drilling	Use rigs to open a new well and stabilize wellbore with cement and steel	Reservoir is detected; maintaining leasing a field
3. Producing	Pump up crude oil products and sell at market (future) prices	Expected revenue from selling is higher than operating cost; well is not exhausted or dry
4. Mothballing	Temporarily stop production of an oil well but maintain the option to re-open it later	Expected revenue is lower than operating cost but may becomes greater than cost in the future
5. Producing (Resuming)	Resume production after mothballing when prices are better	Resume production of oil well if expected revenue becomes greater than costs
6. Shutdown	Permanently close a well by plugging in wellhead with cement	Well is exhausted; too costly to maintain an active oil well

Table 3. Statistical Summary

Data consists of oil wells in California, Pennsylvania, North Dakota, Oklahoma, and Texas. Dates range monthly from Jan 2010 to Jun 2019. "Prod"=1 for producing well-month observations and "Prod"=0 for mothballing. Age is the number of months in production from the completion date. Cum. oil production indicates the cumulative oil production measured in bbl. Price is the one-month maturity WTI futures prices (scaled by 100 and deflated by CPI). Volatility, skewness, and kurtosis are BKM's (Bakshi et al. (2003)) option-implied risk-neutral central moments computed from WTI crude oil futures prices and option prices. *Reserve* is the total tested oil potential in bbl. *Depth* is in tens of thousands of feet. Drilling type dummies include directional, horizontal, vertical, and undetermined drilling types. *Last12* is the oil well's last 12-months' production rate and it is only for the shutdown dataset. *Exer(drilling) (exer(shutdown))* is the drilling varible in the drilling(shutdown) dataset and it is equal to one for spud (shutdown) month. The variables *age*, *cum. oil production*, *reserve*, *depth*, and *last12* are taken natural logarithm. The last panel summarizes the dummies for the wellheads' located basins.

Variable	Obs	Mean	Std. dev.	Min	Max
		controls			
age	53,562,491	5.165	1.173	0.000	6.945
cumulative oil	49,811,453	10.277	1.861	0.000	17.649
reserve	11,986,651	3.892	1.667	-4.605	9.736
depth	47,080,572	8.220	0.780	2.996	10.127
last12	46,437,694	5.566	2.076	0.000	13.857
		one-month price and moments			
price_deflated	53,562,491	0.587	0.285	0.151	1.444
kurtosis	53,562,491	1.155	1.090	-0.289	4.700
skewness	53,562,491	-0.157	0.398	-0.993	0.609
volatility	53,562,491	0.210	0.058	0.100	0.401
		18-month price and moments			
price_deflated	48,374,905	0.579	0.281	0.189	1.454
kurtosis	50,144,399	0.363	0.240	0.008	1.212
skewness	50,144,399	-0.285	0.197	-0.876	0.406
volatility	50,144,399	0.239	0.068	0.109	0.569
		well status dummy			
exer(drilling)	5,516,130	0.394	0.489	0.000	1.000
exer(shutdown)	50,144,399	0.002	0.048	0.000	1.000
prod	53,561,751	0.917	0.275	0.000	1.000
		percent (%)			
		drilling types			
directional	1,729,569	3.42%			
horizontal	2,423,340	4.80			
undetermined	33,018,806	65.38			
vertical	13,329,828	26.39			

Basins percent (%)					
production		shutdown		drilling	
CA coast	20.67%	*CA coast*	2.71	*CA coast*	2.71
CA offshore	0.56	*CA offshore*	0.01	*CA offshore*	0.01
other-California	18.35	*other-California*	0.01	*other-California*	0.01
Sacramento	1.69	*Sacramento*	0.00	*Sacramento*	0.00
San Joaquin	11.35	*San Joaquin*	3.69	*San Joaquin*	3.69
Ozark uplift	0.02	*Anadarko*	14.39	*Anadarko*	14.39
eastern shelf	4.36	*Appalachian*	8.00	*Appalachian*	8.00
Forth Worth	11.47	*Arkoma*	1.09	*Arkoma*	1.09
gulf coast central	5.75	*Burgos-Rio Grande*	0.00	*Burgos-Rio Grande*	0.00
gulf coast west	4.61	*central basin*	13.85	*central basin*	13.85
Hollis-Hardeman	0.44	*Cherokee platform*	9.08	*Cherokee platform*	9.08
Kerr	2.17	*Delaware*	2.33	*Delaware*	2.33
Llano uplift	0.03	*east Texas*	1.63	*east Texas*	1.63
midland	15.39	*east Texas coastal*	0.00	*east Texas coastal*	0.00
northwest shelf	2.82	*eastern shelf*	4.79	*eastern shelf*	4.79
Pala Duro	0.30	*Fort Worth*	7.38	*Fort Worth*	7.38
Val Verde	0.02	*gulf coast central*	4.78	*gulf coast central*	4.78
		gulf coast west	5.25	*gulf coast west*	5.25
		Hollis-Hardeman	0.42	*Hollis-Hardeman*	0.42
		Kerr	0.72	*Kerr*	0.44
		Llano uplift	0.04	*Llano uplift*	0.04
		midland	16.79	*midland*	16.79
		northwest shelf	2.60	*northwest shelf*	2.60
		other-Texas	0.00	*other-Texas*	0.00
		Ozark uplift	0.04	*Ozark uplift*	0.04
		Palo Duro	0.35	*Palo Duro*	0.35
		Val Verde	0.05	*Val Verde*	0.05

Table 4. The Choice to Drill or Defer

Table 4. panels (1)-(2) show results of the regression of the real option exercise on price, central moments, and controls using the Cox hazard model. The regressions examine the impacts of the determinants on exercise of real options of oil well entry. The regression equation is Equation (2). The dependent variable "exer" dummy=1 for "drilling" months and =0 for the months before exercising of the options. The option-implied risk-neutral central moments (volatility, skewness, and kurtosis) are computed using BKM (2003). Well depth is measured in tens of thousands of feet. "horizontal drilling" and "directional drilling" are drilling types. "Arkoma", "east Texas", … are basin dummies. Drilling costs, *cost_def*, are sums of drilling, completion, tie-in, and transportation costs and are deflated. The variables, *depth*, *cost_def*, and *reserve* are taken natural logarithms. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

	(1)				(2)			
*drilling=1 for spud month and =0 for prior months								
dependent variable: drilling	coefficient	robust SE	p		coefficient	robust SE	p	
price	2.015	0.074	0.000	***	1.827	0.104	0.000	***
volatility	-4.098	0.194	0.000	***	-4.272	0.199	0.000	***
skewness					-0.085	0.074	0.253	
kurtosis					0.233	0.084	0.005	***
depth	0.256	0.049	0.000	***	0.253	0.050	0.000	***
cost_def	-0.564	0.037	0.000	***	-0.562	0.037	0.000	***
reserve	0.165	0.011	0.000	***	0.165	0.011	0.000	***
horizontal drilling	0.327	0.136	0.016	**	0.323	0.136	0.017	**
vertical drilling	0.263	0.135	0.052	*	0.262	0.262	0.053	*
			Basins					
Burgos-Rio Grande	-41.836	1.004	0.000	***	-41.835	1.004	0.000	***
Central basin platform	0.658	0.055	0.000	***	0.660	0.055	0.000	***
Delaware	0.711	0.046	0.000	***	0.710	0.046	0.000	***
East Texas	-0.401	0.130	0.002	***	-0.401	0.130	0.002	***
East Texas coastal	-42.227	0.766	0.000	***	-42.231	0.765	0.000	***
eastern shelf	-0.156	0.085	0.088	*	-0.145	0.085	0.088	*
Fort Worth	-0.016	0.058	0.780		-0.017	0.058	0.770	
gulf coast central	-0.325	0.061	0.000	***	-0.323	0.061	0.000	***
gulf coast west	0.189	0.040	0.000	***	0.186	0.040	0.000	***
Hollis-Hardeman	0.188	0.155	0.446		0.119	0.156	0.443	
Kerr	0.107	0.234	0.647		0.108	0.234	0.644	
Llano uplift	0.114	1.062	0.914		0.108	1.061	0.919	
midland	0.745	0.038	0.000	***	0.747	0.038	0.000	***
northwest shelf	-0.199	0.227	0.380		-0.197	0.227	0.385	
Palo Duro	0.098	0.263	0.708		0.098	0.263	0.710	
Val Verde	0.827	0.450	0.066	*	0.833	0.447	0.063	
Arkoma	-0.480	0.479	0.316		-0.476	0.479	0.320	
Cherokee platform	-0.485	0.083	0.000	***	-0.484	0.083	0.000	***
obs	1,080,596				1,080,596			
# of wells	27,152				27,152			
log likelihood	-85,863.227				-85,854.493			

Table 5. The Choice to Shutdown or Continue Producing

Table 5. panels (1)-(2) show results of the regression of the real option exercise on price, central moments, and controls using the Cox hazard model. The regressions examine the impacts of the determinants on exercise of real options of oil well exits. The regression equation is Equation (3). The dependent variable "shutdown" dummy=1 for "shutdown" months and =0 for the months before exercising of the options. The option-implied risk-neutral central moments (volatility, skewness, and kurtosis) are computed using BKM (2003). Well depth is measured in tens of thousands of feet and taken natural logarithm. "horizontal drilling" and "directional drilling" are drilling types. "Arkoma", "east Texas", … are basin dummies. Proxy for shutdown costs, *cost_def*, are sums of drilling, completion, tie-in, and transportation costs and are deflated (drilling costs and shutdown costs are positively correlated). The variable *last12* is the well's lastest 12-month production rate in bbl. The variables *cost_def* and *last12* are taken natural logarithms. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

	(1)				(2)			
*shutdown=1 for shutdown month and =0 for prior months								
dependent variable: shutdown	coefficient	robust SE	p		coefficient	robust SE	p	
price	-4.027	0.082	0.000	***	-5.148	0.123	0.000	***
volatility	-6.139	0.267	0.000	***	-6.397	0.253	0.000	***
skewness					1.373	0.102	0.000	***
kurtosis					1.459	0.097	0.000	***
depth	0.250	0.039	0.000	***	0.247	0.039	0.000	***
cost_def	-0.412	0.023	0.000	***	-0.406	0.023	0.000	***
last12	-0.124	0.010	0.000	***	-0.125	0.010	0.000	***
horizontal drilling	-0.102	0.085	0.229		-0.115	0.084	0.172	
vertical drilling	-0.117	0.068	0.088	*	-0.117	0.068	0.087	*
			Basins					
other-California	-0.619	0.947	0.513		-0.631	0.948	0.506	
San Joaquin	0.381	0.078	0.000	***	0.378	0.078	0.000	***
Anadarko	0.360	0.092	0.000	***	0.352	0.092	0.000	***
Appalachian	-0.557	0.168	0.001	***	-0.567	0.168	0.001	***
Arkoma	0.365	0.244	0.134		0.357	0.243	0.143	
Burgos-Rio Grande	6.017	0.188	0.000	***	5.983	0.187	0.000	***
central basin platform	-0.545	0.103	0.000	***	-0.547	0.102	0.000	***
Cherokee platform	0.707	0.010	0.000	***	0.701	0.101	0.000	***
Delaware	0.092	0.102	0.369		0.084	0.102	0.411	
east Texas	-0.393	0.205	0.056	*	-0.387	0.204	0.057	*
east Texas coastal	4.615	0.419	0.000	***	4.564	0.411	0.000	***
eastern shelf	-0.353	0.137	0.010	**	-0.357	0.137	0.009	***
Forth Worth	-0.081	0.100	0.415		-0.088	0.099	0.377	
gulf coast central	0.009	0.133	0.946		0.008	0.132	0.952	
gulf coast west	-0.161	0.103	0.117		-0.161	0.102	0.115	
Hollis-Hardeman	-0.322	0.148	0.030	**	-0.327	0.148	0.027	**
Kerr	-1.574	0.270	0.000	***	-1.582	0.270	0.000	***
Llano uplift	-0.625	0.244	0.010	**	-0.625	0.247	0.012	**
midland	-0.212	0.091	0.021	**	-0.221	0.091	0.016	**
northwest shelf	-0.848	0.178	0.000	***	-0.843	0.178	0.000	***
other-Texas	-35.092	-	-		-35.106	-	-	
Palo Duro	0.560	0.246	0.023	**	0.552	0.245	0.024	**
Val Verde	0.510	0.526	0.332		0.514	0.525	0.328	
obs		9,037,487				9,037,487		
# of wells		126,890				126,890		
log likelihood		-193,846.06				-193,589.24		

Table 6. The Choice to Produce or Mothball

Table 6. estimation results of producing status on price, central moments, and controls using the random-effects panel probit model. The regressions examine the impacts of the determinants on exercise of real options of oil well production. The model specification in Equation (1). The dependent variable, *prod*, =1 for "producing" and =0 for "mothballing". L.prod =1: lagged producing status is "producing" and =0: lagged producing status is "mothballing". The option-implied risk-neutral central moments (volatility, skewness, and kurtosis) are computed using BKM (2003). Well depth is measured in tens of thousands of feet, and well age is measured in months. "horizontal drilling" and "vertical drilling" are drilling types and "directional drilling" is the benchmark. "Ardmore", "Delaware", … are basin dummies. The variables, *age*, *depth*, *reserve*, and *cumulative oil production* are taken natural logarithms. The reported ρ is the proportion of panel-level variance in the total variance of dependent variable. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

	(1)			(2)		
*prod=1 for producing and prod=0 for mothballing						
dependent variable: prod	coefficient	robust SE	p	coefficient	robust SE	p
l.prod	0.302	0.021	0.000 ***	8.510	0.522	0.000 ***
price	0.437	0.022	0.000 ***	0.451	0.023	0.000 ***
{l.prod=0}×vol	0.460	0.041	0.000 ***	0.237	0.055	0.000 ***
{l.prod=1}×vol	0.577	0.034	0.000 ***	0.973	0.044	0.000 ***
{l.prod=0}×skewness				0.045	0.012	0.000 ***
{l.prod=1}×skewness				0.065	0.012	0.000 ***
{l.prod=0}×kurtosis				0.120	0.012	0.000 ***
{l.prod=1}×kurtosis				-0.163	0.012	0.000 ***
age	-0.346	0.012	0.000 ***	-0.350	0.012	0.000 ***
depth	-1.360	0.036	0.000 ***	-1.363	0.036	0.000 ***
reserve	-0.015	0.010	0.106	-0.016	-0.016	0.096 *
cumulative oil production	0.746	0.012	0.000 ***	0.747	0.747	0.000 ***
horizontal drilling	0.371	0.062	0.000 ***	0.362	0.362	0.000 ***
vertical drilling	-0.640	0.065	0.000 ***	-0.635	-0.635	0.000 ***
undetermined	1.284	0.067	0.000 ***	1.279	1.279	0.000 ***
			Basins			
CA offshore	1.204	0.106	0.000 ***	1.206	0.106	0.000 ***
other-California	0.936	0.037	0.000 ***	0.935	0.037	0.000 ***
Sacramento	1.040	0.046	0.000 ***	1.039	0.046	0.000 ***
San Joaquin	1.261	0.103	0.000 ***	1.262	0.103	0.000 ***
eastern shelf	1.238	0.115	0.000 ***	1.237	0.115	0.000 ***
Forth Worth	0.503	0.068	0.000 ***	0.504	0.068	0.000 ***
gulf coast central	1.056	0.098	0.000 ***	1.053	0.098	0.000 ***
gulf coast west	1.623	0.045	0.000 ***	1.622	0.045	0.000 ***
Hollis-Hardeman	1.362	0.164	0.000 ***	1.362	0.164	0.000 ***
Kerr	0.613	0.169	0.000 ***	0.605	0.169	0.000 ***
Llano uplift	0.666	0.457	0.145	0.666	0.455	0.143
midland	1.772	0.042	0.000 ***	1.771	0.042	0.000 ***
northwest shelf	1.256	0.178	0.000 ***	1.258	0.178	0.000 ***
Palo Duro	1.646	0.271	0.000 ***	1.645	0.270	0.000 ***
Val Verde	-0.023	0.366	0.000 ***	-0.025	0.366	0.946
constant	6.747	0.347	0.000 ***	2.817	0.452	0.000 ***
obs		7,829,827			7,829,827	
# of wells		124,652			124,652	
log likelihood		-731,463.77			-730,965.92	

Table 7. Percentages of Well Statuses Triple-Sorted by Volatility, Skewness, and Kurtosis

Table 7 shows the statistical summary of the average percentage of oil wells in the status of drilling, shutdown, or producing, sorted by volatility, skewness, and kurtosis. The volatility of oil price changes is sorted into four portfolios: below 25th percentile of time-series, 25-50th percentile, 50-75th percentile, and above 75th. Within each volatility portfolio, we sort the percentile into nine subportfolios based on below 25th percentile, above 75th percentile and in the middle of the skewness and kurtosis of oil price changes. For drilling model sample, we dropped observations after the third month of drilling.

drilling model			
	percentage of drilled well-month obs		2.76%
	volatility ≤25^{-th} percentile		
	kurtosis ≤25-th	25^{-th}≤kurtosis≤75^{-th}	kurtosis ≥75^{-th}
skewness ≤25-th	-	1.98%	-
25^{-th}≤skewness≤75^{-th}	0.81%	1.42%	2.08%
skewness≥75^{-th}	-	1.82%	-
	25^{-th} percentile≤volatility≤50^{-th} percentile		
	kurtosis ≤25-th	25^{-th}≤kurtosis≤75^{-th}	kurtosis ≥75^{-th}
skewness ≤25-th	-	0.69%	-
25^{-th}≤skewness≤75^{-th}	0.82%	1.46%	2.25%
skewness≥75^{-th}	-	1.29%	-
	50^{-th} percentile≤volatility≤75^{-th} percentile		
	kurtosis ≤25-th	25^{-th}≤kurtosis≤75^{-th}	kurtosis ≥75^{-th}
skewness ≤25-th	-	1.17%	-
25^{-th}≤skewness≤75^{-th}	0.63%	9.94%	2.27%
skewness≥75^{-th}	-	1.41%	-
	volatility ≥75^{-th} percentile		
	kurtosis ≤25-th	25^{-th}≤kurtosis≤75^{-th}	kurtosis ≥75^{-th}
skewness ≤25-th	-	0.66%	-
25^{-th}≤skewness≤75^{-th}	0.62%	13.01%	-
skewness≥75^{-th}	-	-	-
shutdown model			
	percentage of closed well-month obs		0.89%
	volatility ≤25^{-th} percentile		
	kurtosis ≤25-th	25^{-th}≤kurtosis≤75^{-th}	kurtosis ≥75^{-th}
skewness ≤25-th	-	0.18%	0.20%
25^{-th}≤skewness≤75^{-th}	0.28%	0.29%	0.23%
skewness≥75^{-th}	-	0.23%	
	25^{-th} percentile≤volatility≤50^{-th} percentile		
	kurtosis ≤25-th	25^{-th}≤kurtosis≤75^{-th}	kurtosis ≥75^{-th}
skewness ≤25-th	-	0.34%	0.33%
25^{-th}≤skewness≤75^{-th}	0.38%	0.27%	0.16%
skewness≥75^{-th}	0.35%	0.30%	0.16%
	50^{-th} percentile≤volatility≤75^{-th} percentile		
	kurtosis ≤25-th	25^{-th}≤kurtosis≤75^{-th}	kurtosis ≥75^{-th}
skewness ≤25-th	-	0.30%	-
25^{-th}≤skewness≤75^{-th}	0.32%	0.21%	0.19%
skewness≥75^{-th}	-	0.14%	0.17%
	volatility ≥75^{-th} percentile		
	kurtosis ≤25-th	25^{-th}≤kurtosis≤75^{-th}	kurtosis ≥75^{-th}
skewness ≤25-th	-	0.37%	0.21%
25^{-th}≤skewness≤75^{-th}	0.32%	0.30%	-
skewness≥75^{-th}	0.37%	0.40%	4.37%

Table 7. Percentages of Well Statuses Triple-Sorted by Volatility, Skewness, and Kurtosis (continued)

production model			
	percentage of producing well-month obs		89.74%
	volatility ≤25-th percentile		
	kurtosis ≤25-th	25-th≤kurtosis≤75-th	kurtosis ≥75-th
skewness ≤25-th	88.72%	88.18%	-
25-th≤skewness≤75-th	90.34%	91.50%	-
skewness≥75-th	90.80%	-	-
	25-th percentile≤volatility≤50-th percentile		
	kurtosis ≤25-th	25-th≤kurtosis≤75-th	kurtosis ≥75-th
skewness ≤25-th	-	91.98%	86.80%
25-th≤skewness≤75-th	91.78%	89.50%	-
skewness≥75-th	92.07%	89.71%	-
	50-th percentile≤volatility≤75-th percentile		
	kurtosis ≤25-th	25-th≤kurtosis≤75-th	kurtosis ≥75-th
skewness ≤25-th	-	84.21%	82.90%
25-th≤skewness≤75-th	-	89.00%	83.01%
skewness≥75-th	-	87.20%	84.47%
	volatility ≥75-th percentile		
	kurtosis ≤25-th	25-th≤kurtosis≤75-th	kurtosis ≥75-th
skewness ≤25-th	-	91.54%	88.98%
25-th≤skewness≤75-th	-	91.43%	90.45%
skewness≥75-th	-	91.19%	82.11%

Table 8 Predictions from A Complete Model and A Simplified Model

Table 8 shows the results of the predictions for drilling activities, shutdown activities, and producing status of oil wells based on two alternative models - a complete model that incorporate the skewness and kurtosis of oil price changes, and a simplified model that excludes the tail risk variables, but everything else kept same. The predictions from Cox models are based on the medians of the hazard rate of dependent variable = 1.

Drilling			
Proportion of drilled well-month obs	2.76%		
Predicted drilled well-month obs from complete model	73.28%		
Predicted drilled well-month obs from simplified model	72.80%		
Predicted drilled and undrilled obs (drilled=1)		simplified model	
		0	1
complete model	0	80.48%	0.00%
	1	1.44%	18.08%
Percentage of different predictions	1.44%		
Shutdown			
Proportion of closed well-month obs	0.27%		
Predicted closed well-month obs from complete model	31.55%		
Predicted closed well-month obs from simplified model	7.71%		
Predicted closed and operating obs (closed=1)		simplified model	
		0	1
complete model	0	68.45%	0.00%
	1	23.85%	7.71%
Percentage of different predictions	23.85%		
Production			
Proportion of producing well-month obs	89.74%		
Predicted producing well-month obs from complete model	45.13%		
Predicted producing well-month obs from simplified model	50.02%		
Predicted producing and mothballing obs (producing=1)		simplified model	
		0	1
complete model	0	49.98%	4.89%
	1	0.00%	45.13%
Percentage of different predictions	4.89%		

Table 9 Physical Moments to Replace Implied Moments

In Table 9, we estimate the main result models with the physical distribution central moments (volatility, skewness, and kurtosois) to replace the option-implied central moments in results Table 4-6. The physical moments are estiamted from a 360-day rolling window of oil spot price changes to estimate the realized distribution second, third, and fourth central moments. The daily estimates are averaged over monthly to matched with the monthly oil status. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

drilling model				
dependent variable: drilling = 1 for drilled				
	coefficient	robust SE	p-value	
price_def	2.026	0.074	0.000	***
volatility	-51.216	1.636	0.000	***
skewness	0.175	0.034	0.000	***
kurtosis	-0.015	0.007	0.030	**
controls	Yes			
obs	1,080,596			
wells	27,152			
log pseudolikelihood	-85,400.29			
shutdown model				
dependent variable: shutdown = 1 for closed				
	coefficient	robust SE	p-value	
price_def	-3.648	0.075	0.000	***
volatility	-101.00	1.793	0.000	***
skewness	0.477	0.037	0.000	***
kurtosis	0.062	0.010	0.000	***
controls	Yes			
obs	9,037,487			
wells	126,890			
log pseudolikelihood	-190,716.29			
production model				
dependent variable: prod = 1 for producing				
	coefficient	robust SE	p-value	
l.prod	0.242	0.025	0.000	***
price_def	0.435	0.022	0.000	***
l.{prod=mothballing}×l.volatility	3.585	0.687	0.000	***
l.{prod=producing}×l.volatility	10.440	0.727	0.000	***
l.{prod=mothballing}×l.skewness	0.116	0.010	0.000	***
l.{prod=producing}×l.skewness	-0.008	0.010	0.390	
l.{prod=mothballing}×l.kurtosis	0.009	0.002	0.000	***
l.{prod=producing}×l.kurtosis	-0.004	0.002	0.817	
controls	Yes			
obs	7,829,827			
wells	124,652			
log pseudolikelihood	-731,277.70			

Table 10. Non-Linear Effects of Tail Risks

In Table 10, the models adding the interaction of skewnss and kurtosis are reported, as well as the results adding the squared skenwess, kurtosis, and the interaction. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

drilling model

dependent variable: drilling = 1 for drilled

	coefficient	robust SE	p-value		coefficient	robust SE	p-value	
price_def	1.832	0.104	0.000	***	2.861	0.131	0.000	***
volatility	-4.291	0.203	0.000	***	-4.162	0.208	0.000	***
skewness	-0.2	0.182	0.272		1.759	0.379	0.009	***
kurtosis	0.284	0.117	0.016	**	-4.533	0.336	0.000	***
skewness×kurtosis	0.144	0.219	0.510		-1.518	0.381	0.000	***
skewness^2					3.703	0.392	0.000	***
kurtosis^2					3.097	0.211	0.000	***
skewness^2×kurtosis^2					-2.701	0.327	0.000	***
controls	Yes				Yes			
obs	1,080,596				1,080,596			
wells	27,152				27,152			
log pseudolikelihood	-85,854.26				-85,727.19			

shutdown model

dependent variable: shutdown = 1 for closed

	coefficient	robust SE	p-value		coefficient	robust SE	p-value	
price_def	-5.152	0.124	0.000	***	-4.554	0.140	0.000	***
volatility	-6.388	0.251	0.000	***	-5.826	0.260	0.000	***
skewness	2.036	0.196	0.000	***	4.990	0.347	0.000	***
kurtosis	1.062	0.143	0.000	***	0.470	0.339	0.165	
skewness×kurtosis	-1.080	0.263	0.000	***	-1.990	0.293	0.000	***
skewness^2					4.091	0.387	0.000	***
kurtosis^2					-0.708	0.387	0.067	*
skewness^2×kurtosis^2					-0.348	0.476	0.464	
controls	Yes				Yes			
obs	9,037,487				9,037,487			
wells	19,338				19,338			
log pseudolikelihood	-193,572.62				-193,416.93			

production model

dependent variable: prod = 1 for producing

	coef	robust SE	p-value		coef	robust SE	p-value	
l.prod	-2.343	7.571	0.757		-32.826	20.219	0.104	
price_def	0.456	0.023	0.000	***	0.451	0.023	0.000	***
l.{prod=mothballing}×l.volatility	0.267	0.057	0.000	***	0.271	0.059	0.000	***
l.{prod=producing}×l.volatility	0.990	0.045	0.000	***	1.003	0.047	0.000	***
l.{prod=mothballing}×l.skewness	-3.750	0.637	0.000	***	0.759	1.249	0.543	
l.{prod=producing}×l.skewness	-2.515	0.619	0.000	***	-3.797	1.270	0.003	***
l.{prod=mothballing}×l.kurtosis	-0.971	0.185	0.000	***	-5.053	1.040	0.000	***
l.{prod=producing}×l.kurtosis	-0.904	0.179	0.000	***	-1.295	1.032	0.210	
l.{prod=mothballing}×l.skewness×l.kurtosis	0.123	0.021	0.000	***	0.104	0.021	0.000	***
l.{prod=producing}×l.skewness×l.kurtosis	0.084	0.020	0.000	***	0.094	0.022	0.000	***
l.{prod=mothballing}×skewness^2					-0.228	0.053	0.000	***
l.{prod=mothballing}×kurtosis^2					0.070	0.017	0.000	***
l.{prod=mothballing}×skewness^2×kurtosis^2					-[36]	-	-	
l.{prod=producing}×skewness^2					0.055	0.053	0.298	
l.{prod=producing}×kurtosis^2					0.005	0.017	0.776	
l.{prod=producing}×skewness^2×kurtosis^2					-	-	-	
controls	Yes				Yes			
obs	7,829,827				7,829,827			
wells	124,652				124,652			
log pseudolikelihood	-730,922.51				-730,906.10			

[36] The interactions of lagged status and skewness and kurtosis are dropped due to multicollinearity.

Table 11 Higher-Order Moments

Table 11 reports the results of drilling, shutdown, and producing and mothballing decisions related to the changes in higher-order (2th to 8th-) distribution moments, estimated from oil price changes realized moments. Ri gives the i-th distribution moments of oil price changes. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

drilling model								
dependent variable: drilling = 1 for drilled								
	Coef	Robust SE	p-value		Coef	Robust SE	p-value	
price_def	2.315	0.071	0.000	***	2.289	0.069	0.000	***
R2	-1.983	0.238	0.000	***	-1.256	0.612	0.040	**
R3	0.001	0.000	0.000	***	0.006	0.000	0.000	***
R4	0.067	0.018	0.004	***	-0.644	0.167	0.000	***
R5					-0.820	0.048	0.000	***
R6					1.195	0.124	0.000	***
R7					2.569	0.176	0.000	***
R8					-3.926	0.311	0.000	***
controls	Yes				Yes			
obs	1,080,596				1,080,596			
wells	27,152				27,152			
log pseudolikelihood	-86,001.51				-85,633.46			
shutdown model								
dependent variable: shutdown = 1 for closed								
	Coef	Robust SE	p-value		Coef	Robust SE	p-value	
price_def	-3.382	0.087	0.000	***	-2.730	0.082	0.000	***
R2	-4.929	0.269	0.000	***	-11.393	0.769	0.000	***
R3	0.001	0.000	0.000	***	0.009	0.000	0.000	***
R4	0.145	0.024	0.000	***	1.238	0.197	0.000	***
R5					-1.138	0.068	0.000	***
R6					0.512	0.145	0.000	***
R7					3.470	0.239	0.000	***
R8					-3.700	0.389	0.000	***
controls	Yes				Yes			
obs	9,037,487				9,037,487			
wells	126,890				126,890			
log pseudolikelihood	-193,772.48				-192,040.08			

*production model's estimates failed due to limited data variability.

Table 12 Hedging Strategies and Investment Choices Under Tail Risks

Table 12 shows the empirical regression results of the main models adding the hedging ratio of firms. Hedging ratio is calculated as the fiscal year's hedging derivatives' positions to the production quantity in oil of the main operator of oil wells. Hedging ratios are manually collected from 10-k. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

hedging ratio	mean	median	S.D.	min	max							
obs=415	44.97%	30.10%	66.64%	0%	682.54%							
drilling model												
dependent variable: drilling = 1 for drilled					non-hedgers				hedgers			
	coefficient	robust SE	p-value		coefficient	robust SE	p-value		coefficient	robust SE	p-value	
price_def	3.174	0.205	0.000	***	2.003	0.555	0.000	***	3.379	0.227	0.000	***
volatility	-3.189	0.420	0.000	***	-3.929	0.952	0.000	***	-2.505	0.397	0.000	***
skewness	-0.380	0.165	0.021	**	0.841	0.532	0.114		-0.520	0.156	0.001	***
kurtosis	-0.102	0.187	0.584		0.244	0.563	0.665		0.058	0.170	0.733	
hedging ratio	-0.339	0.118	0.004	***								
hedging ratio×volatility	0.799	0.527	0.130									
hedging ratio×skewness	0.078	0.161	0.630									
hedging ratio×kurtosis	0.332	0.216	0.125									
inverse mills ratio					-4.06×10^{-29}	1.14×10^{-29}	0.000	***	-5.75×10^{-29}	9.76×10^{-29}	0.556	
controls	Yes				Yes				Yes			
obs	242,923				41,653				201,270			
wells	7,570				1,837				6,729			
log pseudolikelihood	-20,773.24				-2,181.60				-17,511.92			
shutdown model												
dependent variable: shutdown = 1 for closed					non-hedgers				hedgers			
	coefficient	robust SE	p-value		coefficient	robust SE	p-value		coefficient	robust SE	p-value	
price_def	-7.273	0.269	0.000	***	-6.298	0.472	0.000	***	-7.709	0.346	0.000	***
volatility	-6.047	0.468	0.000	***	-6.188	0.88	0.000	***	-3.168	0.425	0.000	***
skewness	2.296	0.229	0.000	***	2.512	0.340	0.000	***	2.343	0.274	0.000	***
kurtosis	2.049	0.197	0.000	***	2.585	0.302	0.000	***	2.206	0.214	0.000	***
hedging ratio	-0.705	0.145	0.000	***								
hedging ratio×volatility	5.656	0.534	0.000	***								
hedging ratio×skewness	0.993	0.160	0.000	***								
hedging ratio×kurtosis	0.761	0.185	0.000	***								
inverse mills ratio					-7.67×10^{-25}	9.07×10^{-25}	0.398		1.47×10^{-38}	3.23×10^{-39}	0.000	***
controls	Yes				Yes				Yes			
obs	1,963,502				594,765				1,336,994			
wells	32,677				12,035				26,692			
log pseudolikelihood	-34,468.601				7,795.92				-24,153.22			

Table 12 Hedging Strategies and Investment Choices Under Tail Risks (continued)

production model												
dependent variable: prod = 1 for producing					non-hedgers				hedgers			
	coefficient	robust SE	p-value		coefficient	robust SE	p-value		coefficient	robust SE	p-value	
l.prod	7.586	2.121	0.000	***	3.152	4.748	0.507		6.660	2.387	0.005	***
price_def	0.746	0.086	0.000	***	0.233	0.199	0.241		0.565	0.068	0.000	***
l.{prod=mothballing}×l.volatility	0.062	0.241	0.796		-0.650	0.405	0.108		1.214	0.176	0.000	***
l.{prod=producing}×l.volatility	1.026	0.152	0.000	***	1.013	0.294	0.001	***	0.714	0.127	0.000	***
l.{prod=mothballing}×l.skewness	0.246	0.078	0.002	***	-0.239	0.177	0.176		0.241	0.062	0.000	***
l.{prod=producing}×l.skewness	0.157	0.048	0.001	***	0.443	0.109	0.000	***	-0.115	0.044	0.008	***
l.{prod=mothballing}×l.kurtosis	0.061	0.053	0.250		0.063	0.098	0.517		0.033	0.058	0.576	
l.{prod=producing}×l.kurtosis	-0.149	0.051	0.003	***	-0.226	0.108	0.037	**	-0.063	0.044	0.156	
hedging ratio	2.878	1.722	0.095	*								
hedging ratio×l.{prod=mothballing}×l.volatility	1.571	0.294	0.000	***								
hedging ratio×l.{prod=producing}×l.volatility	-0.380	0.152	0.012	**								
hedging ratio×l.{prod=mothballing}×l.skewness	-0.005	0.069	0.941									
hedging ratio×l.{prod=producing}×l.skewness	-0.286	0.050	0.000	***								
hedging ratio×l.{prod=mothballing}×l.kurtosis	-0.106	0.049	0.031	**								
hedging ratio×l.{prod=producing}×l.kurtosis	-0.011	0.051	0.834									
inverse mills ratio					-4.54×10^{-37}	8.75×10^{-38}	0.000	***	-2.16×10^{-39}	2.18×10^{-39}	0.323	
controls	Yes				Yes				Yes			
obs	1,504,422				402,912				1,101,511			
wells	26,906				9,804				22,182			
log pseudolikelihood	-87,288.14				-24,508.72				-62,415.97			

Table 13 Impact of Financial Leverage on Investment Choices under Tail Risks

Table 13 reports the regression results of the impact of tail risks on investment choices of oil wells adding the financial leverage of main operators. Financial leverage is calculated as debt-to-equity ratio where data were obtained from Compustat.

	coefficient	robust SE	p-value	
drilling model				
dependent variable: drilling = 1 for drilled				
price_def	2.475	0.163	0.000	***
volatility	-4.237	0.314	0.000	***
skewness	-0.203	0.114	0.074	*
kurtosis	0.133	0.218	0.299	
leverage	0.032	0.015	0.033	**
leverage×volatility	-0.077	0.024	0.001	***
leverage×skewness	0.021	0.027	0.431	
leverage×kurtosis	0.003	0.015	0.846	
controls	Yes			
obs	395,760			
wells	11,675			
log pseudolikelihood	-32,960.31			
shutdown model				
dependent variable: shutdown = 1 for closed				
	coefficient	robust SE	p-value	
price_def	-5.606	0.202	0.000	***
volatility	-6.208	0.367	0.000	***
skewness	1.714	0.173	0.000	***
kurtosis	1.669	0.159	0.000	***
leverage	-0.032	0.028	0.263	
leverage×volatility	-0.043	0.049	0.381	
leverage×skewness	-0.169	0.055	0.002	***
leverage×kurtosis	0.001	0.029	0.982	
controls	Yes			
obs	3,321,885			
wells	52,188			
log pseudolikelihood	-55,807.49			
production model				
dependent variable: prod = 1 for producing				
	coefficient	robust SE	p-value	
l.prod	12.057	1.459	0.000	***
price_def	0.415	0.076	0.000	***
l.{prod=mothballing}×l.volatility	0.221	0.177	0.210	
l.{prod=producing}×l.volatility	0.939	0.123	0.000	***
l.{prod=mothballing}×l.skewness	0.150	0.044	0.001	***
l.{prod=producing}×l.skewness	-0.042	0.032	0.184	
l.{prod=mothballing}×l.kurtosis	0.150	0.034	0.000	***
l.{prod=producing}×l.kurtosis	-0.170	0.030	0.000	***
leverage	0.018	0.135	0.892	
l.{prod=mothballing}×l.volatility×leverage	0.005	0.022	0.811	
l.{prod=producing}×l.volatility×leverage	-0.043	0.020	0.033	**
l.{prod=mothballing}×l.skewness×leverage	-0.008	0.010	0.366	
l.{prod=producing}×l.skewness×leverage	-0.016	0.007	0.016	**
l.{prod=mothballing}×l.kurtosis×leverage	0.002	0.005	0.724	
l.{prod=producing}×l.kurtosis×leverage	0.004	0.006	0.431	
controls	Yes			
obs	2,521,038			
wells	43,675			
log pseudolikelihood	-121,859.79			

Table 14 Term Structure Shape and Investment Under Tail Risks

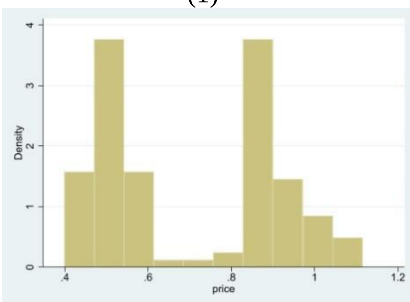
In Table 14, the variables for the shape of term structure of oil prices are added to the main models. R is defined as $\mathrm{R_t} = P_{Nearest,t}/P_{Distant,t} - 1$. So higher *R* suggests a higher oil prices at nearer terms and lower oil prices at more distant terms. Contango = 1 for negative R,

drilling model								
dependent variable: drilling = 1 for drilled								
	Coef	Robust SE	p-value		Coef	Robust SE	p-value	
price_def	1.829	0.104	0.000	***	1.825	0.105	0.000	***
volatility	-4.576	0.254	0.000	***	-4.292	0.267	0.000	***
skewness	-0.127	0.078	0.102		-0.087	0.076	0.254	
kurtosis	0.245	0.084	0.003		0.233	0.084	0.005	
R	-0.447	0.216	0.039	**				
contango					0.004	0.032	0.907	
controls	Yes				Yes			
obs	1,080,596				1,080,596			
wells	27,152				27,152			
log pseudolikelihood	-85,852.40				-85,854.49			
shutdown model								
dependent variable: shutdown = 1 for closed								
	Coef	Robust SE	p-value		Coef	Robust SE	p-value	
price_def	-5.005	0.124	0.000	***	-5.182	0.123	0.000	***
volatility	-9.160	0.322	0.000	***	-6.624	0.319	0.000	***
skewness	0.887	0.115	0.000	***	1.368	0.102	0.000	***
kurtosis	1.391	0.103	0.000	***	1.484	0.098	0.000	***
R	-3.527	0.237	0.000	***				
contango					0.044	0.036	0.216	
controls	Yes				Yes			
obs	9,037,487				9,037,487			
wells	126,890				126,890			
log pseudolikelihood	-193,226.02				-193,586.96			
production model								
dependent variable: prod = 1 for producing								
	Coef	Robust SE	p-value		Coef	Robust SE	p-value	
l.prod	8.514	0.522	0.000	***	8.602	0.521	0.000	***
price_def	0.503	0.026	0.000	***	0.481	0.024	0.000	***
l.{prod=mothballing}×l.volatility	-0.017	0.051	0.741		0.112	0.054	0.037	**
l.{prod=producing}×l.volatility	0.708	0.042	0.000	***	0.844	0.044	0.000	***
l.{prod=mothballing}×l.skewness	0.033	0.013	0.007	***	0.020	0.012	0.100	
l.{prod=producing}×l.skewness	0.050	0.012	0.000	***	0.036	0.012	0.002	***
l.{prod=mothballing}×l.kurtosis	0.122	0.012	0.000	***	0.102	0.012	0.000	***
l.{prod=producing}×l.kurtosis	-0.160	0.012	0.000	***	-0.183	0.012	0.000	***
R	-0.529	0.051	0.000	***				***
contango					0.063	0.005	0.000	***
controls	Yes				Yes			
obs	7,829,827				7,829,827			
wells	124,652				124,652			
log pseudolikelihood	-730,791.62				-730,792.31			

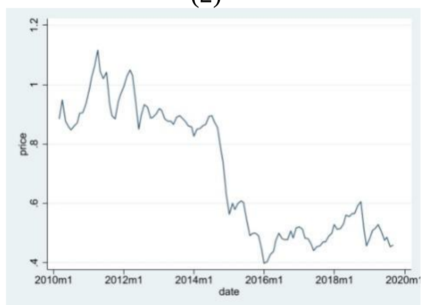
Figure 1. Oil Price and Central Moments

Figure 1. (1) and (2) show the histogram of three-month lagged 18-month oil futures price and graph of the price to date, respectively; (3) and (4) shows the histogram of 18-month three-month lagged option-implied volatility and graph of the volatility to date, respectively; (5), (6), (7), and (8) shows the histograms of 18-month three-month lagged option-implied skewness and kurtosis and the graphs of the central moments to dates, respectively. Oil price is scaled by 100 and deflated by CPI. (9)-(11) shows the average percentage of drilled, closed, or producing number of wells over time. (12)-(14) shows the average control variables.

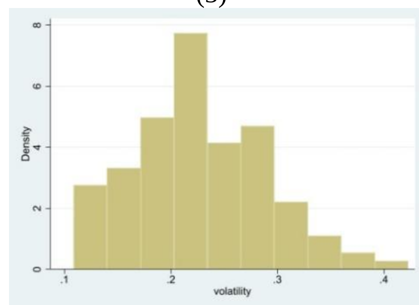
(1)



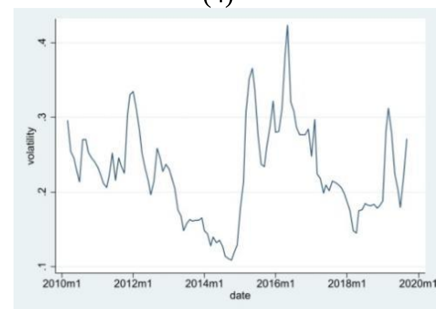
(2)



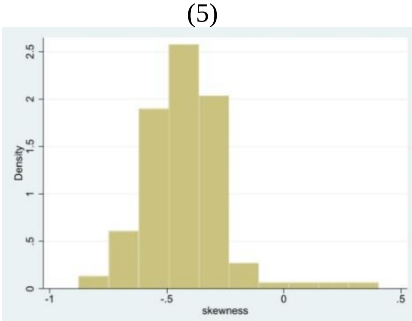
(3)



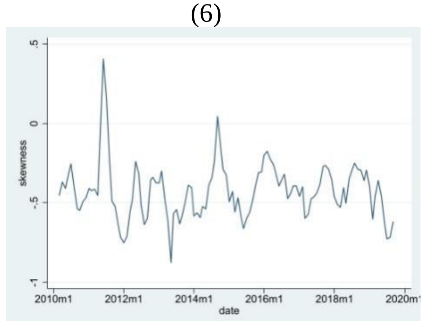
(4)



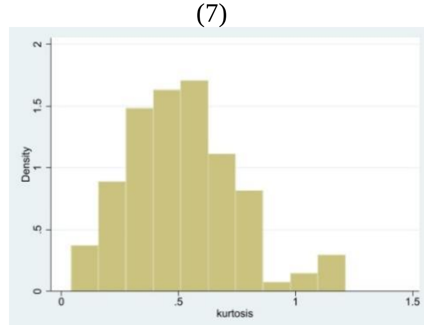
(5)



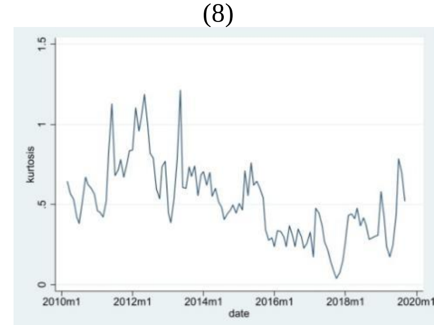
(6)



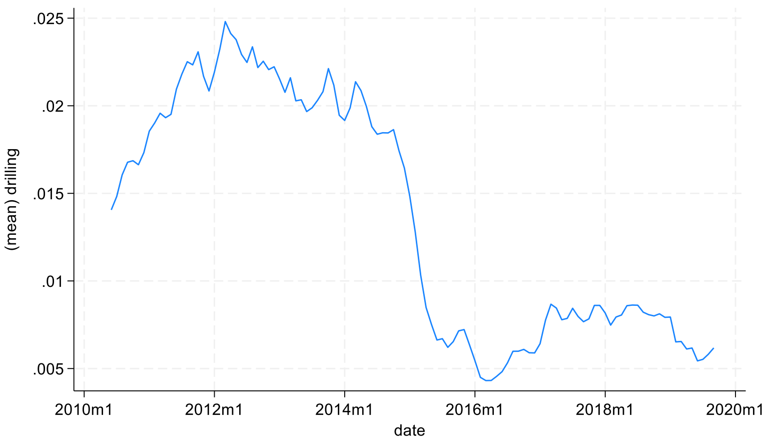
(7)



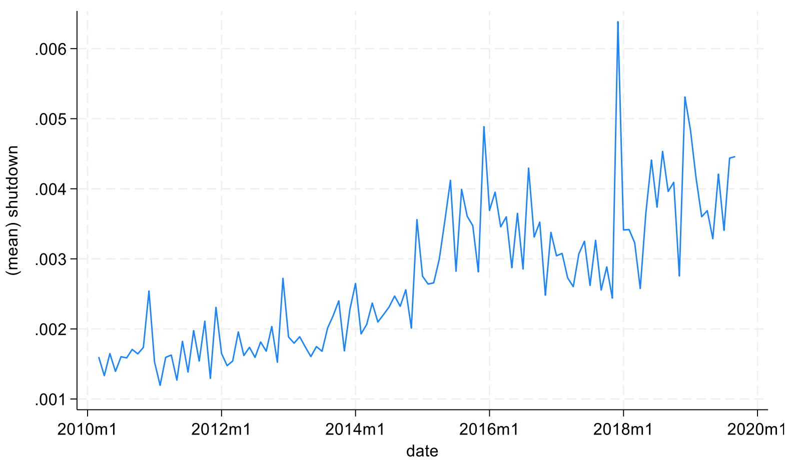
(8)



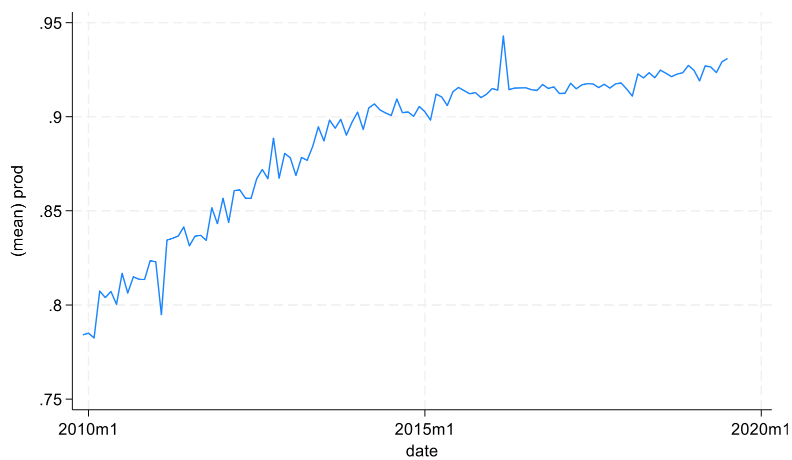
(9) Percentage of drilled wells



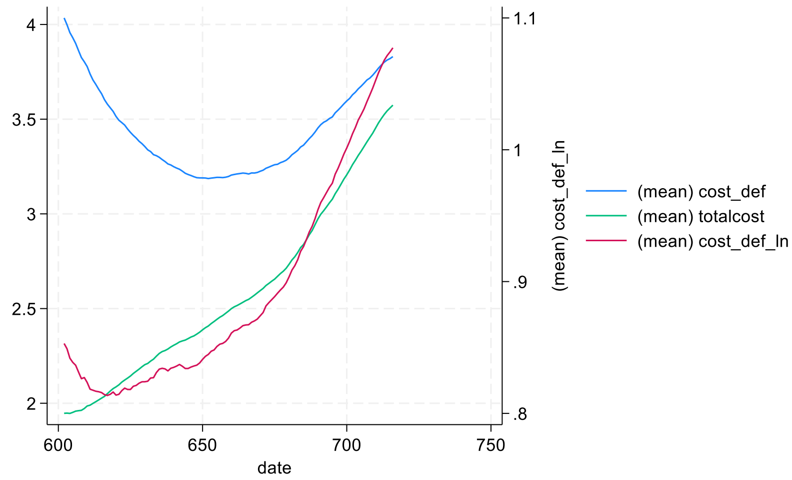
(10) Percentage of Closed Wells



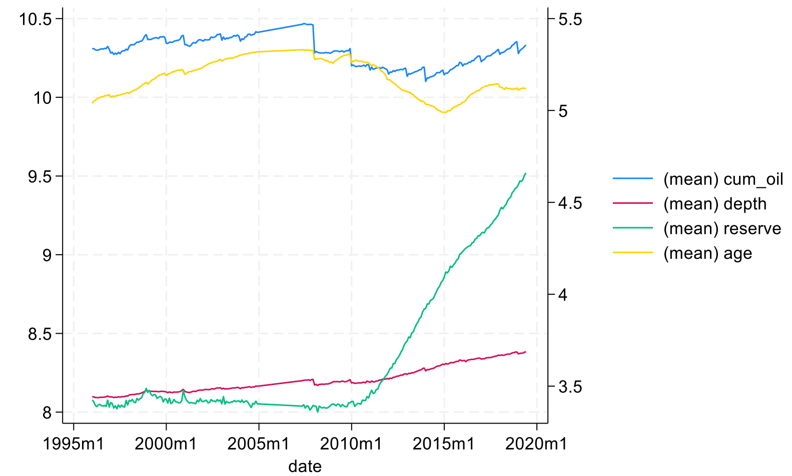
(11) Percentage of Producing Wells



(12) Average Drilling Cost (Deflated), Cost in $, and Log of Cost



(13) Average Cumulative Oil Production, Well Depth, Reserve, and Age



(14) Average Latest 12-Month Oil Production

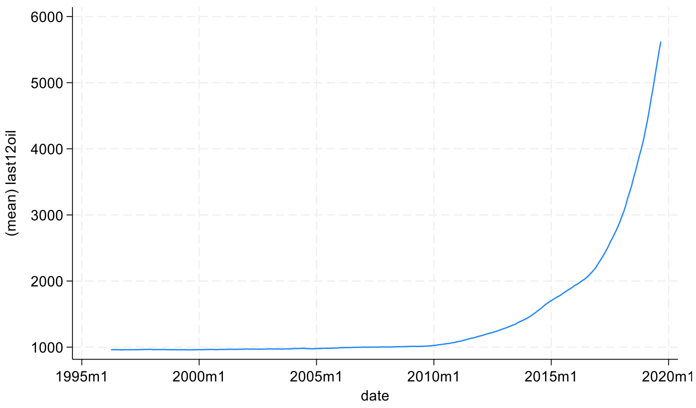
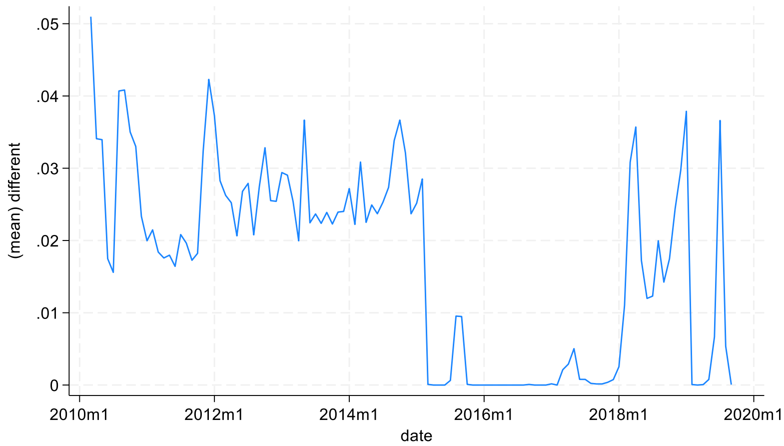


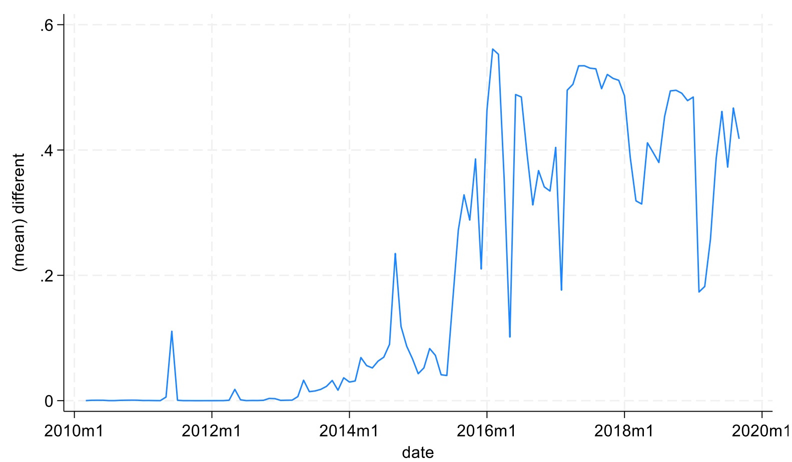
Figure 2. The Percentage of Different Predictions Between the Complete and the Simplified Models

Figure 2 displays the time-series of the percentage of observations with different predictions from the complete model that includes skewness and kurtosis and the simplified model that does not.

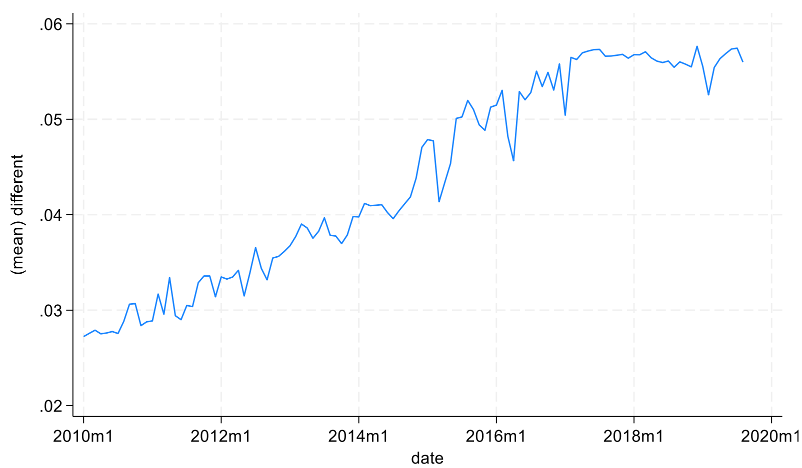
(a) Drilling Predictions



(b) Shutdown Predictions



(c) Production Predictions



Appendix A. Computation of BKM Option-Implied Risk-Neutral Central Moments

We obtain crude oil (symbol: CL) options on futures prices and futures prices from the CME Group Datasets (End of Day Complete database). Only option prices with maturities between 10 and 180 days are used, which are the most liquid options contracts. We manually dropped some outliers when the prices is 100 times greater than average, which is identified as data input error. Risk-free rates are obtained from the OptionMetrics files. Risk-free rates are extrapolated and interpolated to ensure sufficient risk-free rates for maturities of 10-180 days. We follow Chang, Christoffersen, and Jacobs (2013) and Ruan and Zhang (2018), when computing the risk-neutral central moments. We filter data by dropping option prices lower than 3/8 (minimum tick) and deep-in-the-money options (put options with an exercise price higher than 103% of futures price and call options with an exercise price lower than 97% of futures price) as well as drop days with fewer than 2 puts or calls prices, and the options prices violating the spot-futures arbitrage condition. We expand moneyness for each date and maturity to the range between 0.0001 and 3 and use the implied volatility (from CME's modified Black-Scholes option pricing model) to interpolate and extrapolate implied volatilities in that range. Next, we use the implied volatility to infer option prices using the Black-Scholes options on futures model to obtain a smooth option price in the moneyness 0.0001 and 3 for each date and maturity. With futures price and option prices in the moneynesses range [0.0001,3], we calculate option implied volatility, skewness, and kurtosis following Bakshi, Kapadia, and Madan (2003) using the trapezoidal integration following Chang, Christoffersen, and Jacobs (2013) and Ruan and Zhang (2018). We then compute the 18-month BKM risk-neutral central moments. We use futures prices to estimate the term structure of oil return realized central moments, then use the 10-180 days central moments to interpolate the one-month maturity central moments. We then use the one-month central moments and term structure to extrapolate 18-month maturity central moments. The last step is to take three-month lags of the central moments for drilling and shutdown model moments. The methods are similar to those employed by Kellogg (2014) when computing forward looking implied volatilities.

Appendix B. Derivation of Solution to the Profit Function

We begin with a discussion of the choices regarding the producing status of a well, under the assumption that the status is chosen by selecting those decisions that are value maximizing at each future date over the expected life of the well. Assume the well has been drilled and completed and from that point on could either be producing or not producing (we will take up the decision to drill later). Assume a risk-neutral expected-payoff maximizing representative producer who must decide whether to make an irreversible investment when the producer's oil well's current status is "mothballing", i.e., production is temporarily shut-in. Define the state of a well as *prod=p* for "producing" and *prod=m* for "mothballing", respectively. The producer may immediately re-open the oil well and re-start production incurring an irreversible (sunk) investment cost, but will then receive the net payoffs from produced crude oil based upon a random future stream of output prices P,operating costs C^p, and production volumes Q. The cost to switch from mothballed to producing is assumed to equal $\mathbb{C}^{m,p}$ and is not recoverable. However, the producer may choose to defer the decision – use the "delay option" to delay the decision to a future date. By waiting the producer can observe an updated price level resolving uncertainty from *t* to to *t+1*.

Similarly, the producer can choose to temporarily shut in an operating well, that is, to change to "mothballing" when current status is "producing". The revenues from production (as discussed previously, a function of output prices P, operating costs C^p, and production volumes Q) will be sacrificed and the representative producer maintain the oil well by costing maintenance cost C^m. The producer may choose to defer the decision with the "delay option" to postpone until next date. Price uncertainty is resolved by using the "delay option". To summarize, we assume that if a well is producing an operating cost is incurred and if the well is mothballed a maintenance cost is incurred each period. The operating cost of the producing well is C^p and the maintaining cost of the mothballed well is C^m. The operating cost is incurred only when *prod=p*, and the maintaining cost is incurred each period only when *prod=m*. The value of the immediate choice to switch equals the discounted expected payoff stream less the switching cost $\mathbb{C}^{p,m}$ (the net present value of the immediate choice). Assume that for a given well, C, $\mathbb{C}$, and θ are static parameters for each well where θ includes observed and unobserved other variables affecting investment value. Assume that $\mathbb{C} = \mathbb{C}^{m,p} = \mathbb{C}^{p,m}$.

Define the value function $V(P, Q, C, \theta, O(\mathbb{C}))$, where value depends upon future oil prices P and the distribution of those prices, production quantity Q, operating cost C^p, maintaining cost C^m, other well characteristics θ, and the options to "mothball" and to "produce" which are exercised at an investment cost $\mathbb{C}$. If the state of the well is mothballed then the option to switch to production is in force and if the state of the well is producing the option to switch to mothballing in is force. The options have values denoted as $O^m(P, Q, C^m, \mathbb{C}, \theta)$ and $O^p(P, Q, C^p, \mathbb{C}, \theta)$ which arise from the options to switch from "producing" to "mothballing" and from "mothballing" to “producing”, respectively. So the value function consists of three components: the profit that depends on P_t and Q_t, the costs C^p or C^m, and the real options O^m or O^p. The producer faces a multiperiod problem of selecting production as well as the optimal policy for exercising the options. The producer is assumed to follow a policy that maximizes an expected payoff function by choosing the optimal investment time *t* to exercise the option to switch, conditional on the current state of the well and an optimal policy concerning production.

Assume for illustration that the current state is $prod$ = m (mothballing). The optimal choice to switch or continue with the current state of the well (that is delay switching) will define an optimal investment trigger price P*. If the actual price exceeds the trigger price then the option would be exercised. That trigger price will be a function of the expected future distributional characteristics of the price change distribution. Define the implicit objective function γ where the optimal policy defines the selection of the state of the well at each date as:

$$\gamma = \max_{prod} V(P, Q, C, \mathbb{C}, \theta, O)$$

where P represents the expected price distribution at *t*, Q is the set of quantities produced each period over the production horizon of the well, C represents the operating cost ($denoted\ C^p$) stream of each period, including both fixed and variable cost if $prod = p$, and the cost of maintaining the well if $prod = m$ ($denoted\ C^m$). $\mathbb{C}$ is the switching investment cost. The vector θ contains both observed and unobserved well characteristics that affect production decisions, and O is the set of options the producer faces in each period (for instance, $O = O^p\ if\ prod = m$). The behavior and distribution of P is assumed to be exogenously determined and is a function of time *t* and depends both on the expected price change, and the anticipated volatility, skewness, and kurtosis reflected in the price distribution.

$$P = P(\mu, \sigma, sk, k|t)$$

where μ is the expected change, σ is volatility, sk is skewness, and k is the kurtosis of the price change distribution. Oil prices are determined in a world market and so this assumption conforms to both the actual market environment and the data (Kaminski (2012), U.S. Energy Information Administration https://www.eia.gov/energyexplained/oil-and-petroleum-products/prices-and-outlook.php).[37]

Define the multi-period dynamic problem of the producer as:

[37] It is worth pointing out that a process for oil prices that exhibits mean reversion and random jumps as well as a continuous stochastic error, as has been found in the literature (Al-harthy (2007)) produces a price change distribution that exhibits both non-zero skewness and excess kurtosis for reasonable parameter values.

$$\gamma = \max_{prod} E_t\big(V(P, Q, C, \mathbb{C}, \theta, O)\big) = \max_{prod}\left(\pi(P_t, Q_t, C, \mathbb{C}, \theta | \mathbb{I}_t) + \frac{1}{(1+r)} E_t(V_{t+1} | prod_t)\right)$$

where $\frac{1}{(1+r)}$ is the discount factor, $\pi(P_t, Q_t, C, \mathbb{C}, \theta | \mathbb{I}_t)$ is the profit function at *t* given the current information set and $E_t(V_{t+1} | prod_t)$ is the expectation of the continuing value function at *t+1* given the producing status choice at *t*, $prod_t$ assuming an optimal policy subsequent to *t+1*, where we have assumed that the expectation exists and that the price process is exogenous to the firm.[38] The value function at *t* can be rearranged to contain two maximized terms: the first term is the profit function at *t*, and the second is the discounted expected value function at *t+1* given producing status choice at *t* and an optimal policy following *t*. The production state *prod* is selected at *t* to maximize the sum of the two terms. The investment choice at *t* therefore depends upon the production state at *t-1*. If the representative oil producer chooses $prod_t = p$ when $prod_{t-1} = p$, the above equation becomes:

$$V_t(prod_t = p, prod_{t-1} = p) = \pi(P_t, Q_t, C, \mathbb{C}, \theta | \mathbb{I}_t) + \frac{1}{(1+r)} E_t(V_{t+1} | prod_t = p)$$

$$= \breve{\pi}(P_t, Q_t, \theta) - C^p + \frac{1}{(1+r)} E_t(V_{t+1} | prod_t = p)$$

$\breve{\pi}(P_t, Q_t, \theta) - C^p = \pi(P_t, Q_t, C, \mathbb{C}, \theta | \mathbb{I}_t)$ for $prod_t = p$ when $prod_{t-1} = p$.

We henceforth drop the notation for the information set $\mathbb{I}_t$ as it is implicit.

When $prod_{t-1} = m$ and the representative producer chooses $prod_t = p$, the value function becomes:

$$V_t(prod_t = p, prod_{t-1} = m) = \breve{\pi}(P_t, Q_t, \theta) - C^p - \mathbb{C} + \frac{1}{(1+r)} E_t(V_{t+1} | prod_t = p)$$

$\breve{\pi}(P_t, Q_t, \theta) - C^p - \mathbb{C} = \pi(P_t, Q_t, C, \mathbb{C}, \theta | \mathbb{I}_t)$ for $prod_t = p$ when $prod_{t-1} = m$. The only difference is that transitioning from "mothballing" to "producing" incurs a one-time sunk cost $\mathbb{C}$. Similarly if the representative producer chooses $prod_t = m$ when $prod_{t-1} = m$, the value equation is:

$$V_t(prod_t = m, prod_{t-1} = m) = -C^m + \frac{1}{(1+r)} E_t(V_{t+1} | prod_t = m)$$

If the representative producer chooses $prod_t = m$ when $prod_{t-1} = p$:

$$V_t(prod_t = m, prod_{t-1} = p) = -C^m - \mathbb{C} + \frac{1}{(1+r)} E_t(V_{t+1} | prod_t = m)$$

[38] The reader will recognize this as a Bellman equation. Molls (2001) presents a similar specification.

where C^m is the maintenance cost in "mothballing" periods, and the only difference between the two equations is the term $-\mathbb{C}$, the one-time transitioning cost from "producing" to "mothballing".

The well operator is assumed to select the choice that maximizes value conditional on the current state of the well (m or p). Therefore, if maximizing behavior is assumed, the choice observed implies that choice has the largest current value, this of course also implies the choice carries with it an optimal policy going forward. Mothballing incurs a per period cost while a complete shut down does not, hence it would never be optimal to switch from complete shutdown to the mothball state.

When $prod_{t-1} = m$, the difference in the value equation between choosing $prod_t = p$ and choosing $prod_t = m$ will equal:

$$\Delta V_t(prod_{t-1} = m)$$

$$= \breve{\pi}(P_t, Q_t, \theta) - C^p - \mathbb{C} + \frac{1}{(1+r)} E_t(V_{t+1}|prod_t = p)$$

$$-\left(-C^m + \frac{1}{(1+r)} E_t(\mathbb{V}_{t+1}|prod_t = m)\right)$$

$$= \breve{\pi}(P_t, Q_t, \theta) - C^p - \mathbb{C} + C^m + \frac{1}{(1+r)}\big(E_t(V_{t+1}|prod_t = p) - E_t(V_{t+1}|prod_t = m)\big)$$

When $prod_{t-1} = p$, the difference in the value equation between choosing $prod_t = p$ and choosing $prod_t = m$ equals:

$$\Delta V_t(prod_{t-1} = p)$$

$$= \breve{\pi}(P_t, Q_t, \theta) - C^p + \frac{1}{(1+r)} E_t(V_{t+1}|prod_t = p)$$

$$-\left(-C^m - \mathbb{C} + \frac{1}{(1+r)} E_t(V_{t+1}|prod_t = m)\right)$$

$$= \breve{\pi}(P_t, Q_t, \theta) - C^p + \mathbb{C} + C^m + \frac{1}{(1+r)}\big(E_t(V_{t+1}|prod_t = p) - E_t(V_{t+1}|prod_t = m)\big)$$

The difference is twice the one-time transitioning cost from "mothballing" to "producing" (or from "producing" to "mothballing"), $2\mathbb{C}$.[39]

If there were no sunk costs associated with switching between production and mothballing then switching would be costless and instantaneous. In that case the future continuation value vanishes because the lagged state, that is the state coming into time *t*, will have no influence on future decisions. In the

[39] We assume that the transitioning cost from "mothballing" to "producing" is the same as the cost from "producing" to "mothballing", as a consequence, the difference between these two equations is twice the cost. If the transitioning costs are different ($\mathbb{C}^{mp}$ *and* $\mathbb{C}^{pm}$), the difference between these two equations become $\mathbb{C}^{mp}$+$\mathbb{C}^{pm}$.

presence of sunk costs however, the lagged production state matters for the current choice of production state. If sunk switching costs are zero, the firm will produce if current profit is positive and will shut down if profit is negative. Mothballing would never occur since mothballing incurs a per period cost. Conversely the larger are the non-recoverable switching sunk costs, the more important is the lagged production status for the current period production choice.

The value effect from the optimal choice to switch from production to mothballing, or vice versa therefore implicitly defines a decision rule. The decision to switch will depend upon the distributional properties of future price changes and the remaining parameters of the model including the cost of switching. The profit function is determined by the oil price, quantity produced, and well characteristics, $\breve{\pi}(P_t, Q_t, \theta)$. Given that the price is a random variable it can be characterized by the parameters of its probability distribution which we define as the expected future price, volatility, skewness, and kurtosis at *t*, conditional on the information set at time *t*. In addition, the difference in value function $(-C^p + \mathbb{C} + C^m)$ is related to the operating cost, maintaining cost, as well as the transition cost. We re-write the difference in the value function ΔV_t as reduced form equations:

$$\Delta V_t(prod_{t-1} = m) = \gamma_0^m + \gamma_P^m \cdot P_t + \gamma_Q^m \cdot Q_t + \gamma_C^m \cdot C + \gamma_\theta^m \cdot \theta + \gamma_{C^m}^m \cdot C^m + \gamma_{\mathbb{C}}^m \cdot \mathbb{C} + \varepsilon_t^m$$

and:

$$\Delta V_t(prod_{t-1} = p) = \gamma_0^p + \gamma_P^p \cdot P_t + \gamma_Q^p \cdot Q_t + \gamma_C^p \cdot C + \gamma_\theta^p \cdot \theta + \gamma_{C^m}^p \cdot C^m + \gamma_{\mathbb{C}}^p \cdot \mathbb{C} + \varepsilon_t^p$$