ESSAYS IN EMPIRICAL CORPORATE FINANCE

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ESSAYS IN EMPIRICAL CORPORATE FINANCE

For my family

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ABSTRACT

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This dissertation goal is to deepen our understand about firms' resource allocation decisions. In the first chapter, using an NPV-based revealed-preference strategy, I find that idiosyncratic risk affects the discount rate that firms use in their capital budgeting decisions. I exploit quasi-exogenous within-region variation in project-specific idiosyncratic risk and find that, on average, firms inflate their discount rate by 5 percentage points (pp) in response to an 18pp increase in idiosyncratic risk. Moreover, these discount rate adjustments are negatively associated with measures of firm profitability. I then explore how proxies for costly external financing and agency frictions relate to discount rate adjustments. Consistent with theoretical predictions, firms appear to adjust their discount rate to account for both frictions.

In the second chapter, which is joint work with Erik Gilje and Jérôme Taillard, We study when and why firms exercise real options. Using detailed project-level investment data, we find that the likelihood that a firm exercises a real option is strongly related to peer exercise behavior. Peer exercise decisions are as important in explaining exercise behavior as variables commonly associated with standard real option theories, such as volatility. We identify peer effects using localized exogenous variation in peer project exercise decisions and find evidence consistent with information externalities being important for exercise behavior.

In the third chapter, I empirically measure the effect of ownership concentration on firms' risk-taking behavior. In support of the existing theory, I find that firms choose riskier

projects when their ownership concentration increases. To obtain a causal interpretation of the results, I use the merger of financial holdings as an exogenous shock to firms' level of ownership concentration.

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CHAPTER 1 : Capital Budgeting and Idiosyncratic Risk

One of the most important financial decisions managers face is selecting the best projects among competing investment proposals. Traditional corporate finance theory holds that, when evaluating projects, firms' discount rates should account for the projects' systematic risk, but not their idiosyncratic risk (Bogue and Roll, 1974; Myers and Turnbull, 1977; Constantinides, 1978). Similarly, textbooks warn managers about the temptation of incorporating a "fudge factor" when calculating discount rates in an attempt to compensate for idiosyncratic risk[1], on the grounds that this kind of adjustment can significantly distort the firms' overall allocation of capital. Despite these warnings, surveys conducted by the Association for Financial Professionals (AFP) showed that nearly half of all respondents had manually adjusted their discount rates to account for project-specific risk (Jacobs and Shivdasani, 2012). In surveys, many managers report setting discount rates that are systematically and substantially greater than the cost of capital (Poterba and Summer, 1995; Graham and Harvey, 2001; Graham et al., 2015; Jagannathan et al., 2016). These revelations are worrisome, considering that even small deviations from the *true* discount rate can have sizable effects on managers' decision to pursue a given project. In spite of the focus given to calculating discount rates in managerial training, and the central role it plays in firms' internal allocation of capital, there has been relatively little empirical investigation of managers' actual behavior. This study is among the first to (i) provide causal empirical evidence about how managers adjust their projects' discount rates with respect to idiosyncratic risk, (ii) document the consequences of idiosyncratic risk pricing for firm performance, and (iii) shed light on the economic factors that affect those adjustments.

Measuring firms' discount rates, as well as the level of idiosyncratic risk associated with

[1] The classical corporate finance textbook of Brealey and Myers (1996) discuss this as follows: "We have defined risk, from the investor's viewpoint, as the standard-deviation of portfolio return or the beta of a common stock or other security. But in everyday usage risk simply equals bad outcome. People think of the risks of a project as a list of things that can go wrong. For example: ... A geologist looking for oil worries about the risk of a dry hole. ... Managers often add fudge factors to discount rates to offset worries such as these. This sort of adjustment makes us nervous."

individual projects, presents significant empirical challenges. First, firms do not report this information. Second, it is not usually possible to observe firms' individual investment decisions. Third, it is generally difficult to compare the investment set across and within firms, limiting researchers' ability to control for confounding factors that might affect the calculation of discount rates. Finally, it is rarely possible to obtain precise estimates of individual projects' expected cash flow.

I overcome these challenges by employing a comprehensive and detailed dataset of onshore vertical gas wells drilled in the United States between 1983 and 2010. Each new well represents a project. Together, the data covers $53 billion in capital expenditures on 114,969 distinct projects. The dataset has a number of advantages. Specifically, the institutional setting makes it possible to forecast individual projects' cash flows and capital expenditures, and to fully characterize each firm's investment portfolio annually. In addition, the projects are homogeneous and tend to have similar characteristics, which allows meaningful comparisons across projects. For instance, every project in the sample is undertaken using similar drilling technology for which the production function is simple and transparent, meaning that it is possible to easily compute projects' expected monthly production. All projects also produce the same resource, natural gas, further simplifying cross-project comparisons. And finally, the natural gas industry offers an especially rich literature on project-level production forecasting techniques, which means that the dataset is well suited to obtaining plausible estimates of expected cash flow for each project.

First, I provide evidence that firms inflate their annual discount rates by an average of 3.8 to 6.0 percentage points (pp) in response to a one-standard-deviation increase in projects' idiosyncratic risk. This adjustment is economically meaningful, considering that the average firm in the sample has an estimated weighted average cost of capital (WACC) of 9.6pp. Obtaining this result requires measures of projects' idiosyncratic risk and project-specific discount rates. I measure idiosyncratic risk using a novel method based on the geographic cross-sectional dispersion of projects' idiosyncratic productivity shocks. Specifically, I define each project's idiosyncratic productivity shock as the ratio of the first-year production forecast error over the drilling cost, and then estimate the dispersion of that measure at the regional level every year. I measure discount rates using a revealed-preference strategy based on the net present value (NPV) rule. This process has four steps. First, for each well a firm drills during a given year, I estimate the well's expected cash flows using forecasts of the well's production and natural gas prices. Second, I use those forecasts to compute the project's expected internal rate of return (IRR). Third, I separate all projects within each firm-year subsample into two portfolios depending on whether their level of idiosyncratic risk is above or below the median for that firm-year. And fourth, I estimate the firm's discount rate to be the lowest expected IRR across projects in each of these portfolios. The logic is that the firm's discount rate must be at least that low, otherwise those marginal projects would not have been undertaken. After assessing wells' idiosyncratic risk and discount rates, I then test the validity of both measures by performing multiple sanity checks. Comparing discount rates across the two firm portfolios, I find a significant relation between discount rates and idiosyncratic risk.

Then, I investigate the consequences of idiosyncratic risk pricing on firms' performance. I introduce a novel measure of idiosyncratic risk pricing to directly test its effects on performance metrics. Precisely, the measure of idiosyncratic risk pricing corresponds to the firm-year discount rate adjustment for a one-unit increase in projects' idiosyncratic risk. I find that for the average firm, a one-standard-deviation increase in the price of idiosyncratic risk is negatively correlated with firms' gross profit margin (-5.1pp), investment rate (-0.8pp), year-over-year asset growth (-0.7pp) and gross profitability (-0.5pp). These results show that adjusting discount rates to account for idiosyncratic risk has important negative consequences.

Finally, I ask *why* managers attempt to account for idiosyncratic risk by adjusting discount rates. Various theories associate managers' motives to adjust their discount rate to external influences (frictions between the firms and the financial market) and to internal ones (frictions between managers and their superiors). It is important to note that the results presented in this final part of the paper correspond to correlations, as I do not have exogenous variation for the costly external financing and agency friction proxies.

With respect to the external frictions theory, Froot et al. (1993) predict that in a world with costly external financing, managers would adjust their discount rates to account for risks that cannot be offloaded to the financial market. That is, they predict that if firms cannot fully diversify their exposure to idiosyncratic risk at the firm level, then they should adjust their discount rates to account for those sources of risk. The authors' logic is that if the firm is hit by a bad idiosyncratic shock, such as drilling multiple bad wells that fail to produce enough cash flows to fund their operations next period, it has two options. The firm can either reduce its investment next period, or turn to the financial market and raise capital, but at a premium because of the costly external financing constraint. Then, managers should take this additional financing cost into account for projects with greater exposure to idiosyncratic risk ex-ante, and adjust their discount rate accordingly. To test this hypothesis empirically, this study builds on Hennessy and Whited (2007) by constructing six proxies of costly external financing and measuring their relation to firms' pricing of idiosyncratic risk. When using Hennessy and Whited (2007)'s favored proxy of costly external financing, the results are consistent with the prediction made by Froot et al. (1993). Specifically, a one-standard-deviation increase in the cost of external financing is associated with an average increase of 2.3pp in firms' pricing of idiosyncratic risk. Although the results using the other proxies are not always statistically significant, they are mainly directionally consistent with the theoretical prediction.

To examine the role of internal frictions, I relate the pricing of idiosyncratic risk to the size of field managers' budget. A manager with a larger budget is arguably more diversified and therefore faces less total idiosyncratic risk. Simultaneously, Diamond (1984) predicts that risk-averse managers with larger budgets should exhibit a lower idiosyncratic risk premium[2]. In line with Diamond (1984)'s prediction, I find that managers' budget size is strongly related to the pricing of idiosyncratic risk: a one-standard-deviation in firms' average managerial budget size is associated with a 1.16pp reduction in the price of idiosyncratic risk.

To mitigate endogeneity concerns, I use several strategies, including multiple sets of fixed effects and an instrumental variable. With regard to the fixed effect strategy, the nature of the research design makes it possible to control for factors varying at the frequency of the firm-year, because I construct two idiosyncratic risk portfolios per firm-year. For instance, in a given year, a firm may systematically select regions that are riskier, hence the need for a firm-year fixed effect. In addition, I also include an idiosyncratic risk portfolio fixed effect, as there may be a selection effect where some unobserved variables (e.g., managers' experience) may systematically be associated to better or riskier regions (i.e., regions with better potential projects, lower risk of bad drilling outcomes). However, the use of those fixed effects does not eliminate the possibility of a within-firm omitted-variable bias. Confounding variation occurring within a given firm-year, such as variation in managers' characteristics may still be correlated with idiosyncratic risk, which is why I also use an instrumental variable. To better illustrate how my instrumental variable strategy solves this problem, I consider two types of within-firm omitted variables: (i) the variables correlated with projects' geographic characteristics, and (ii) variables uncorrelated with projects' geographic characteristics. For instance, field managers' overall bargaining power might vary across firms, which could impact how firms assign managers based on their experience to different regions, which corresponds to a source of variation related to (i). Alternatively, the production uncertainty associated with wells drilled by unexperienced managers is higher irrespective of their assigned region, since their ability to properly forecast wells' outcome or operate the drilling equipment is lower than the experienced managers, which corresponds to (ii). In both cases, managers' experience would likely be correlated with projects' risk-

[2]Diamond (1984) highlights that a sufficient condition to obtain this phenomenon is to assume that managers have a DARA utility function. This assumption is relatively general since a large class of models assume that managers have a CRRA utility function, and CRRA utility implies DARA utility.

iness, and thus would be correlated with the overall level of idiosyncratic risk measured for their associated wells' outcomes. Failing to account for the managers' experience would thus lead to a within-firm omitted-variable bias. To deal with this form of omitted variable, it is necessary that the instrumental variable and the fixed effects strategies account for both sources of variation. To address these types of within-firm omitted variables, I use the following instrument for a well's idiosyncratic risk: the largest idiosyncratic productivity shock experienced by any of a firm's peers within each township-year[3]. After controlling for the portfolios' selection effect and the firm-year factors, the information content of peers' idiosyncratic productivity shocks should be uncorrelated with the within-firm omitted variables. Put differently, the instrumental variable assumption in this paper is that the relative level of characteristics of a firms' managers and its peers' managers is randomly distributed within an idiosyncratic risk portfolio. Finally, to satisfy the relevance condition, it is reasonable to assume that the largest idiosyncratic productivity shocks among peer firms would have, on average, a positive relation with the idiosyncratic risk measure, which equals the dispersion of idiosyncratic productivity shocks for each township-year.

The rest of this paper proceeds as follows. Section 1 presents an overview of the literature. Section 2 offers background information on the natural gas industry. Section 3 outlines the data used in the study. Sections 4 to 6 explain the measurement of managers' expectations, firms' discount rates, and projects' idiosyncratic risk, respectively. Section 7 discusses the results and the instrumental variable strategy. Section 8 reports the robustness analysis. Section 9 offers concluding remarks.

1.1 Literature Review

Although there is a robust theoretical and survey-based literature on capital budgeting and project evaluation, this is the first observational study of how managers adjust their

[3] I use the wells' township to determine the wells' respective region. Townships are defined as 6 miles by 6 miles squares of land by the American Public Land Survey System (see Figure 6.1). It is important to note that not all states use the Public Land Survey System. For states not using this system, I construct *synthetic* township, and assign wells to those township using the wells' GPS coordinates.

discount rates to account for idiosyncratic risk. I summarize in detail the existing literature addressing each of the paper's three core contributions, as I introduced them in the previous section.

First, by showing that firms appear to price idiosyncratic risk, this study provides direct empirical backing for the discussions of capital budgeting (e.g., Poterba and Summer (1995), Graham and Harvey (2001), Graham et al. (2015), and Jagannathan et al. (2016)). Those survey-based papers document and discuss the existence of a puzzling gap between firms' estimated weighted cost of capital (WACC) and the discount rates reported in their surveys. The present study provides a direct causal estimate based on firms' actual choices, of how idiosyncratic risk affects discount rates. In doing so, this paper also contributes to the theoretical literature providing guidance on the proper way to compute discount rates (e.g., Bogue and Roll (1974), Myers and Turnbull (1977), and Constantinides (1978)). This paper establishes both that managers appear to include a project-level idiosyncratic risk premium in the calculation of discount rates, and that doing so has adverse consequences on performance.

Second, my paper also relates to Kruger et al. (2015) who document a different mistake firms make when computing discount rates. Kruger et al. (2015) show that a firm often applies a unique discount rate to its projects, even when projects face different levels of systematic risk. While Kruger et al. (2015) show that firms adjust their discount rate too little, I find they adjust too much. Also, when Kruger et al. (2015) focus on systematic risk, I focus on idiosyncratic risk. The two papers show that these distinct mistakes both have adverse effects on firms' performance.

Third, this paper contributes to the literature studying the effect of idiosyncratic risk on firms' behaviors. Panousi and Papanikolaou (2012) point out that firms reduce their overall level of investment when their firm-level exposure to idiosyncratic risk increases, which is plausibly suboptimal from the standpoint of a well-diversified investor. The authors identify managers' remuneration and ownership structure as important factors to rationalize the observed phenomenon. My paper relates to Panousi and Papanikolaou (2012)'s main contribution by providing direct evidence as to which capital-budgeting lever is altered by managers when taking into account project-level idiosyncratic risk: the discount rate. At the same time, I identify additional attributes of the firm that appear to be relevant in understanding why idiosyncratic risk is accounted for in the discount rate, enriching our comprehension of firms' response to idiosyncratic risk. Also, my results suggest not only that the overall level of idiosyncratic risk experienced at the firm level matters, but that the exposure of specific local managers to project-level idiosyncratic risk can ultimately have firm-wide impacts. Finally, my setting enables me to directly relate the intensity at which firms price idiosyncratic risk to negative performance outcomes, such as lower gross profit margins.

Fourth, this study also contributes to the extensive literature on the effects of costly external financing on firms' choices[4]. Most directly related to this paper is Froot et al. (1993), who study how costly external finance affects the relation between capital budgeting and risk management. The authors predict that firms facing costly external financing should adjust their discount rates to account for risks that cannot be hedged or diversified. Supporting this view, I find that firms facing high costs of external finance do in fact adjust their discount rate to manage risk.

In addition to these research areas, there are other strands of literature that address how corporate policies and the characteristics of firms affect managers' risk tolerance. Two prior findings are especially relevant. The first of these is that compensation contracts play a significant role in mitigating risk tolerance misalignment between managers and their superiors (Ross, 1973; Holmstrom and Weiss, 1985; Lambert, 1986). A rich empirical literature indicates that market-based compensation contracts affect managers' risk tolerance (Agrawal and Mandelker, 1987; Tufano, 1996; Guay, 1999; Rajgopal and Shevlin, 2002; Coles et al., 2006; Armstrong and Vashishtha, 2012; Gormley et al., 2013), while theoretical

[4]This literature extends at least back to Miller and Orr (1966). Notable contributions include Fazzari and Petersen (1993), Hennessy and Whited (2007), Lyandres (2007), and Bolton et al. (2011), among others.

work suggests that such contracts can shift managers' focus from maximizing long-term value to pursuing short-term benefits (Narayanan, 1985; Bolton et al., 2006). Similarly, empirical findings show that market-based compensation can induce excessive risk taking in managers (Bebchuk and Spamann, 2010; Dong et al., 2010; Hagendorff and Vallascas, 2011). Overall, these results suggest that owners solely using wage contracts to align their managers' decisions with their preferences might also subject their firms to potential drawbacks. Of greater immediate relevance, Holmstrom and Costa (1986) provide a theoretical argument suggesting that capital budgeting policies can be used to complement compensation contracts in order to more successfully align managers' decisions with those of their supervisors. The present study contributes to this literature by empirically identifying the size of managers' budgets as a tool to alter risk tolerance. Specifically, the findings reported here suggest that it is possible to increase the idiosyncratic risk tolerance of a manager by increasing the size of his allocated budget, in line with the diversification effect proposed by Diamond (1984).

1.2 Natural Gas Industry: Institutional Background

1.2.1 Project Overview: The Drilling Technology

Two prominent technologies exist to drill natural gas wells: vertical drilling and horizontal drilling (see Figure 1). In this paper, I focus specifically on vertical-drilling technology. Vertical drilling is the principal technology employed during the period analyzed for this study, representing roughly 90% of all natural gas wells in the dataset. Horizontal drilling is more recent, and has only gradually gained mainstream appeal during the later part of the sample period. Additionally, it is easier to obtain precise production forecasts for wells drilled using vertical drilling technology, as horizontal wells are substantial more complex and technologically advanced (Ma et al., 2016). For example, Covert (2015) provides a clear illustration of the high level of detail necessary to properly characterize expected monthly production for horizontally drilled wells. Obtaining information at this level of detail is simply not possible when dealing with a relatively long-term dataset for the entire United States. At the same time, good production forecasts for vertical wells can be produced using information available from major data providers such as DrillingInfo. For all of these reasons, the study focuses exclusively on vertically drilled wells.

1.2.2 The Life Cycle of Natural Gas Fields

The commercial life cycle of natural gas has two stages: exploration and development. According to the *U.S. Energy Information Agency* (i.e., EIA), the exploration stage involves documenting the geological potential of the field in question, and determining its economic viability. Once a firm has sufficient information for confirming the economic potential of the field, it is classified as a proven reserve[5] and the development stage begins.

This study focuses on the development stage, during which firms still face a high level of idiosyncratic risk despite having established that the field in question is a proven reserve. They do not yet know (i) the exact delineation of the natural gas field, (ii) the structure of the rock formations within it, (iii) the production potential of each drilling location, or (iv) the technical expertise required to optimally extract the resource. For firms drilling wells, this lack of knowledge translates into tangible operational risks, such as the risk of drilling a dry hole[6]. For example, Figure 2 illustrates the development of the Panhandle field in Texas over the period between 1960 and 2010. Figure 2.1 represents the initial estimation of the field boundary, while Figure 2.2 represents the field's finalized boundary 50 years later. There are substantial differences between the expected and realized boundaries. Large sections that were initially identified as promising appear to have had limited potential ultimately. This example provides a clear illustration of how idiosyncratic risk remains at the micro-level even after a field's economic potential has been confirmed at the macro-level.

[5] The American Bar Association's definition of proven reserves is as follows: The amount of oil and gas is estimated with reasonable certainty to be economically producible. source: American Bar Association, Oil and Gas Glossary, 2019.

[6] A dry hole is a well that fails to produce enough natural gas to be economically viable.

1.2.3 The Structure of Natural Gas Exploration and Production Firms

Oil and gas companies establish their strategies at the uppermost levels of the corporate hierarchy (Graham et al., 2015), but surveying, wells' selection, and specific drilling decisions require advanced technical expertise and site-specific information (Kellogg, 2011; Covert, 2015; Decaire et al., 2019). For this reason, lower-level managers, geologists, and engineers tend to evaluate and select projects (Bohi, 1998), working within the confines of strategic guidelines from their superiors. Additionally, oil and gas firms tend to organize their operational units by regions. For example, energy companies' shareholder communication documents (e.g., 10-K) provide examples of how those geographical formations affect operations' structure (see Figure 3). Finally, by allocating their total budgets across multiple regional units, firms expose the key on-the-ground decision-makers (i.e., the junior managers) to the risks of only a relatively small number of specific projects. This creates a divide between idiosyncratic risk diversification measured at the firm level, and diversification measured at the level of individual managers, potentially creating incongruities in risk preferences.

1.3 The Dataset

The present study uses a dataset provided by DrillingInfo[7] covering all natural gas wells drilled in the United States between 1983 and 2010 (see Figure 4). Ultimately, the dataset contains 30,420,544 month-well observations used to estimate the well production function, a total of 114,969 distinct gas wells, and 369 distinct firms. The dataset includes monthly production for each project along with a set of projects' characteristics such as rock formation features, wells' GPS location, the royalty rate[8] and the depth of the well. I augment

[7]DrillingInfo is a trusted data provider for multiple federal agencies reporting on environment and energy matters. Studies conducted by the U.S. Environmental Protection Agency (EPA) and the U.S. Energy Information Administration (EIA) *Inventory of U.S. Greenhouse Gas Emissions and Sinks, 1990-2016* by the EPA and *Petroleum Supply Monthly (PSM)* by the EIA use this dataset, for example.

[8]The royalty rates correspond to an expense computed as a percentage of the well's revenue that goes directly to the land owners leasing the land for a given well. The royalty rate estimates are based on royalty percentages obtained from DrillingInfo for the leases signed in the United States in a given year.

these data points with two hand-collected datasets. The first covers per-project capital expenditures including per-foot drilling costs, obtained from public filling from regulatory pooling documents[9], and estimated operational costs, as in (Decaire et al., 2019). The second is drawn from the EIA and corresponds to the three-year natural gas price forecasts and two alternative sources of natural gas prices (the Bloomberg natural gas futures prices, and the EIA wellhead state's natural gas prices). The EIA is a federal reporting agency producing an annual economic analysis for the oil and gas industry[10]. For public firms, the dataset is further augmented using Compustat. Finally, the information needed to compute each firm's weighted cost of capital is drawn from the 10-year risk-free rate available on the Saint-Louis Federal Reserve website, the Kenneth French oil and gas industry return, the Robert Shiller price-earnings ratio, and credit rating information from Capital IQ.

Finally, I make several refinements to the dataset. I restrict the analysis to firms drilling at least 10 wells in a given year[11]; because discount rates are estimated from the lower boundary of the firms' portfolios, it is reasonable to focus on firms that are at least moderately active during the year of analysis. For less-active firms, it is harder to distinguish between the firms' discount rate and the quality of their opportunity set when using the revealed-preference strategy. This adjustment drops only 5% of wells in the initial sample. Additionally, all township-year subgroups with fewer than three wells drilled are removed, because the measure of idiosyncratic risk employed here relies on the standard-deviation for each township-year set. Finally, any wells with missing information are dropped from the dataset, along with any wells for which the initial production date is prior to the drilling date, as those clearly contain data entry errors.

[9] I hand collected per-foot drilling cost for a subset of wells covering the full sample period. Then, following Kellogg (2014) I obtain the drilling cost estimate by multiplying the well's vertical depth with the per-foot drilling cost.

[10] More specifically, the U.S. Energy Information Administration (EIA) is a statistical and analytical agency housed within the U.S. Department of Energy. The EIA collects, analyzes, and disseminates independent and impartial energy information to promote sound policymaking, efficient markets, and public understanding of energy and its interaction with the economy and the environment. The EIA is the nation's premier source of energy information and, by law, its data, analyses, and forecasts are independent of approval by any other officer or employee of the U.S. government. Source: `https://www.eia.gov/about/mission_overview.php`

[11] The main result is robust to alternative cut-off value of 6 and 14, for example.

The firms in the sample are relatively large, with an average total value of active wells of \$229.2 million. On average, the total annual drilling budget is \$60.3 million. The average firm invests \$11.3 million per year for a given field, or \$19.4 million per year for a given state (see Table I). The average vertical gas well in the dataset costs \$465,653 and produces 570,049 thousand cubic feet of natural gas over its lifetime. Together, these numbers indicate that the average firm in the sample is large and experienced, and it operates in multiple geographical areas in a given year.

1.4 Firms' Expectations

To estimate a firm's discount rate, I must first estimate each well's expected cash flows. Since cash flows equal well output times the price of natural gas, I need to estimate firm's expectations of each variable.

In general, computing the expected production quantities independently from expected prices leads to potential biases. In most situations, projects' production flow is endogenously correlated with prices, such that the expected cash flow can be expressed as:

$$E[p_z \cdot q_{j,z,m}] = E[p_z] \cdot E[q_{j,z,m}] + Cov(p_z; q_{j,z,m}), \tag{1.1}$$

where p_z is the price of natural gas at timze z, and $q_{j,z,m}$ is the natural gas production of well j at time z and age m (in months). If $Cov(p_z; q_{j,z,m}) \neq 0$ it would indicate that expected production flow and natural gas prices are jointly determined. However, in the case of gas wells, once the decision to drill has been made, the well's monthly production is determined by geophysical factors and is therefore independent of the state of the economy. In the case of vertical oil wells, Anderson et al. (2018) show that firms do not alter production rates or delay production due to oil price changes. Indeed, once a well starts producing, managers have little ability to influence the production level without risking damage to the well. What this means is that effectively, production flow depends on local geophysical parameters such as the local rock type, the density of the natural gas deposit, and so forth, rather than on economic variables affecting natural gas prices. For this reason, I assume that the production flow is not correlated with variables that affect gas prices. Further supporting this assumption, the correlation between realized natural gas prices and wells' realized production flow is just -0.0034 in my sample[12]. Thus, estimating expected quantities and expected prices independently should not result in biased outcomes. The process through which I obtain these estimates is described below.

1.4.1 Firms' Expected Production

Monthly production of vertical gas wells can be approximated using a petroleum-engineering model such as the Arp model (Fetkovich, 1996; Li and Horne, 2003). The Arp model is the classical production-forecasting equation, and nowadays is taught in most energy engineering courses (e.g., the University of Pennsylvania course Engineering in Oil, Gas and Coal). According to the Arp model, the predicted monthly quantities produced by well j equal

$$q_{j,m} = A_j(1 + b\theta m)^{\frac{-1}{b}}, \tag{1.2}$$

where m corresponds to the number of months since the well has been drilled, A_j corresponds to the well's baseline production level, and b and θ are decline-rate elasticity parameters. To approximate the Arp model, I linearize this equation to obtain a regression (see Appendix 10.2 for the full derivation):

$$\ln(q_{j,m}) = \alpha_0 + \alpha_1 + A_j + \sum_{k=1}^{K} \beta_k m^k + \epsilon_{j,m}, \tag{1.3}$$

where α_0 and α_1 are dummy variables for the first and second months of production, used to account for ramping production[13], K is the order of the linear approximation (i.e., 7),

[12] This statistic corresponds to the correlation of the realized natural gas prices)i.e., the wellhead spot price provided on the EIA website) with the realized within-well's production flow computed for the entire well-month sample.

[13] A well's ramping period usually corresponds to the first two months of production, during which firms' engineers optimize and adjust the well's production to reach peak long-term capacity (Dennis, 2017). Pro-

and $\epsilon_{j,m}$ is the regression's error term.

The production baseline (i.e., A_j) represents the expected quantity of gas that will be initially produced by the well. I allow A_j to depend on the firm's total experience (i.e., the total number of wells the firm has drilled before well j), the firm's local experience (i.e., the number of wells the firm has drilled in the given township at the time of drilling j), the level of local information available (i.e., the total number of wells that have been drilled in the township at the time of drilling j), a firm-year fixed effect, and a township-year fixed effect such that:

$$A_j = \ln(\text{Firm's Local XP}_j) + \ln(\text{Firm's Total XP}_j) + \ln(\text{Local Info}_j) + \alpha_{i,t} + \alpha_{p,t} \quad (1.4)$$

Where i identifies the firms that drilled well j, p identifies the township in which the well is drilled, and t is the year the well is drilled.

Several recent papers motivate the addition of these controls for the Arp estimation (Covert, 2015; Decaire et al., 2019; Hodgson, 2019). Firms' experience levels, peer effects, and local access to information influence the quality and type of projects a firm will undertake. More experienced firms are more likely to produce high-quality wells and to identify regions with better potential. Equally, regions with more activity are more likely to have wells of higher quality, while at the same time affording more precise information about how best to extract the resource. Because the goal of this part of the analysis is both to obtain precise estimates of the wells' expected production flow and to deliver a reasonable measure of the wells' idiosyncratic productivity shocks, it is important to control for factors that capture those characteristics.

Finally, to obtain the wells' expected production flow, I proceed in two steps. First, I use the Arp model to estimate regression (3), using a sample of 30,420,544 month-well realized output (see Table XIX). Then, I use the Arp model estimates to obtain a measure

duction then gradually declines until the well is dry.

of the managers' expectation for each well in the sample. Figure 5[14] provides a graphical illustration for the median well production function over time and contrasts it with the estimated production output. These expectations constitute the basis of the analysis to obtain a measure of the discount rate, and a measure of the wells' idiosyncratic risk.

1.4.2 Firms' Expected Price

I define the expected gas prices using the EIA's yearly three-year natural gas price forecast, at the time of drilling the well[15]. The EIA forecast is closely followed by governmental organizations, financial institutions, and energy companies. Section 9 explores alternative price specifications, such as the Bloomberg natural gas futures prices and wellhead spot prices varying at the level of individual states, and how these affect the results reported below. The EIA data are preferable to those other options for two reasons, however. First, the EIA three-year natural gas forecast has been published consistently since 1983, while the Bloomberg three-year natural gas futures contracts started trading only in 1995. Thus, the longer period for the EIA forecast allows the analysis to extend over a correspondingly greater duration. Second, although the wellhead state-by-state prices provide information on price variation across states during a given year, which helps to take into account cross-sectional variation of natural gas prices, those wellhead prices fail to account for managers' future expectations about price variation, making them unsuitable for the analysis. Finally, the EIA three-year forecast horizon is well matched to the present study, as the discounted half-life[16] for projects in the sample is 31 months.

[14] The ramping up period, encompassing the first two months of production, is excluded in order to capture production decline from peak production to termination.

[15] A similar assumption for the prices is used in Kellogg (2014), Covert (2015) and Decaire et al. (2019).

[16] The discounted project half-life corresponds to the amount of time required for managers to obtain half of the discounted project's expected cash flow.

1.5 Estimating Firms' Discount Rates Using a Revealed Preference Strategy

1.5.1 Estimating Projects' Expected Rates of Return

To obtain estimates of firms' discount rates, I proceed in four steps. First, for each well a firm drills during a given year, I estimate the well's expected cash flows using forecasts of the well's production and natural gas prices. Second, I use those forecasts to compute the expected IRR (μ_j) of each project j by solving the equation

$$\sum_{m=1}^{M} \frac{1}{(1+\mu_j)^m}\,\mathbb{E}[q_{j,m}]\,\mathbb{E}[p_j] - C_j = 0, \tag{1.5}$$

were $\mathbb{E}[q_{j,m}]$ corresponds to the expected monthly production for well j at age m (in months)[17], $\mathbb{E}[p_j]$ corresponds to the EIA 3-year natural gas price forecast at the time of drilling well j net of operating costs and royalty rate[18], and C_j corresponds to the initial drilling cost incurred when the well is established. And as a final parameter, the average well in the sample produced for a total of 264 months (i.e., M=264).

1.5.2 Estimating Firm-Year Discount Rates

In the third step of the revealed preference strategy, for each firm in a given year, I split the wells into two portfolios based on their level of idiosyncratic risk. Projects with a measure of idiosyncratic risk above (below) the firm-year median are put in the high (low) idiosyncratic risk portfolio. Finally, the discount rates are estimated with the projects' lowest expected performance in each of the portfolios for each firm-year. The logic is that the firm's discount

[17] I adjust the expected quantities from the Arp model for the probability of having no production during a given month. Adjusting for the probability of no production is necessary since the Arp regression uses the natural logarithmic value of the well production, thus excluding production event equal to 0. More specifically, $\mathbb{E}[q_{j,m}] = \mathbb{E}[q_{j,m} * (1 - Pr(\text{zero production in month } m))]$. I follow the methodology developped by Covert (2015) to adjust the production estimates for the zero production events. According to this method, I estimate a linear probability model to estimate the probability of having a no-production event, such that the probability of a month with zero production is 0.028 in the first year, 0.029 in the second year, 0.031 in the third year.

[18] $\mathbb{E}[p_j] = \mathbb{E}[\text{Gas Price}_j]$ * (1- Royalty$_j$ - Operational Cost)

rate for that risk profile must be at least this low; otherwise these projects would not have been undertaken. Precisely, the estimated discount rate corresponds to the average expected IRR among the projects contained in the lowest 5^{th} percentile of the portfolios' expected IRR distribution. In Section 9, I explore several alternative discount rate cut-off definitions, and the results are not economically or statistically affected.

Estimating discount rates based on two firm-year portfolios in this way provides multiple benefits. First, it simplifies the task of building a direct measure of the price of idiosyncratic risk for a given firm-year in order to directly test the effect of idiosyncratic risk pricing on firms' performance (see Section 7). Second, it makes it possible to include a regression specification that controls for a firm-year fixed effect. However, to show that the results are not sensitive to this research design choice, I provide an alternative specification where I estimate the discount rate from one portfolio per firm-year in Section 9. The results are robust to this specification.

In this study, I only observe the set of projects each firm completes in a given year. In other words, I observe a truncated distribution of projects' expected IRR, because it is not possible to observe the expected return for projects the firms did not pursue (i.e., those that are not completed). At the same time, a firm may not have had investment opportunities with an expected IRR sufficiently close to the firm's discount rate. This means that my estimate constitutes an upper bound for the firms' discount rate. To mitigate concerns about this upper bound, I restrict the analysis to a subset of firms that drill at least 10 wells in a given year. The intuition is that for firms that drill many wells, the marginal well is more likely to represent the firms' lower bound (i.e., the firm's discount rate). Then, to validate that the estimates accurately capture the main features attributed to firms' discount rates, I conduct a robustness test. First, I restrict the analysis to the subset of firms whose full capital structure is observed. For that group, I compute the WACC. I obtain an estimate for the cost of equity in two steps. First, I use the one-year[19] oil and

[19]Results are robust when using CAPM betas computed with other horizons, such as two-year and three-year horizons.

gas industry capital asset pricing model (CAPM) beta computed at the monthly frequency, obtained from Kenneth French's industry return data[20]. Then, I multiply this variable by the expected equity premium, estimated from the earning-to-price ratio obtained from the Robert Shiller's website[21]. Finally, to obtain the cost of debt, I collect the firms' yearly credit rating from Capital IQ (see Appendix 10.1.). Table II presents the results of this test. There is a positive and statistically significant correlation between the discount rate estimates and the firms' WACC. Coefficient β_1 indicates that a one-percentage point increase to the firm WACC results in a 1.3 to 1.5pp increase in the discount rate[22]. The results presented in columns 3 and 4 of Table II suggest that the idiosyncratic risk premium is added to the discount rate on top of the WACC, and also that the discount rate measure behaves in a manner consistent with variations in the cost of capital.

1.6 Measure of Wells' Idiosyncratic Risk

To estimate projects' average idiosyncratic risk, I proceed in three steps. First, I define the well's idiosyncratic productivity shock, denoted ζ_j, as the well's first-year cash-flow forecast error attributable to quantity uncertainty scaled by the well's drilling cost:

$$\zeta_j = \frac{\sum_{m=1}^{m=12} \mathbb{E}[p_j] * q_{j,m} - \sum_{m=1}^{m=12} \mathbb{E}[p_j] * \mathbb{E}[q_{j,m}]}{Cost_j} \tag{1.6}$$

$$= \frac{\mathbb{E}[p_j]}{Cost_j} * \sum_{m=1}^{m=12} [q_{j,m} - \mathbb{E}[q_{j,m}]] \approx \frac{\mathbb{E}[p_j]}{Cost_j} * \sum_{m=1}^{m=12} \underbrace{\epsilon_{j,m}}_{(*)} . \tag{1.7}$$

Where (*) roughly corresponds to the Arp model forecast error over the first year of production. These well-level productivity shocks possess a set of characteristics well suited to capture the idiosyncratic production shock. The source of the forecast error captures

[20] The oil and gas industry return is available within the 49 industries' returns breakdown. I verify the robustness of the results using the various industry breakdowns available on the Kenneth French website, and I obtain similar results in all cases.

[21] I estimate the expected equity premium from the fitted value of the regression $[\frac{E_t}{P_t} - rf_t] = \alpha + \beta[\frac{E_{t-1}}{P_{t-1}} - rf_{t-1}] + \epsilon_t$, estimated for the period 1983 to 2010. In an alternative specification, I use Fama and French (2002)'s estimate of the equity premium (4.32%) for the entire sample period, and the results are statistically robust and remain qualitatively similar, although the coefficients are slightly smaller.

[22] In all specifications, the value of 1 is included for the coefficient β_1's confidence interval.

the source of variation to well's profitability attributable to the wells' annual production, holding expected prices constant. I obtain wells' expected production using the Arp model, which controls for the firm-year fixed effect and township-year fixed effect, indicating that the idiosyncratic shocks are orthogonal to the firm-year and township-year information sets. Also, Gilje and Taillard (2016a) show that wells' drilling costs are homogeneous within a year, further supporting the idea that the Arp production forecast errors drive the variation in productivity shocks at the firm-year level. Then, it is reasonable to assume that well-diversified investors will perceive such a source of uncertainty as purely idiosyncratic. To support this claim, Table XX presents the results of a regression of the market excess return on the wells' idiosyncratic productivity shocks. In all regression specifications, the coefficient associated with the idiosyncratic productivity shocks is not significant, which indicates that there exists no correlation between the well's idiosyncratic productivity shocks and the market excess returns. In a CAPM based framework, having the well's shocks uncorrelated with the market excess return[23] provides evidence in favor of the idiosyncratic nature of the shocks. Considering that the CAPM is the most likely asset pricing model used by the average investor (Berk and van Binsbergen, 2016), using this framework for the analysis appears reasonable.

Second, I measure the idiosyncratic risk for each township-year by computing the cross-sectional dispersion of the local wells' idiosyncratic productivity shocks. The strategy is designed to only capture the quantity uncertainty contribution to the cash flow uncertainty. It is useful to note that I achieve this by only using expected prices in ζ_j calculation, ignoring the price shock from the calculation. This is to ensure that idiosyncratic risk is truly calculated from local idiosyncratic shocks. This provides a measure of idiosyncratic risk at the township-year level that can be attributed to each well that is drilled in the specific township in that given year (see Figure 6.1). Third, to obtain a measure for the firm-year-portfolio level, I take the average of the idiosyncratic risk for all the projects completed. Ultimately, the sample average of the projects' average idiosyncratic risk is

[23] In the CAPM framework, the investor's stochastic discount rate is a function of the market excess return.

equal to 10pp, and its standard-deviation is 18pp.

This measure of idiosyncratic risk has several appealing features. First, it corresponds to the level of productivity uncertainty managers face in the first year for 1$ of invested capital. Second, firms tend to pay attention to the drilling outcomes in their wells' closed vicinity (Decaire et al., 2019), suggesting that the level of cross-sectional dispersion for the township-year likely reflects the level of well's idiosyncratic risk as assessed by local managers. Third, the analysis is conducted at a yearly frequency. Thus, working with first-year risk provides a measure of risk that is computed at the frequency of the study's analysis. And finally, the information contained in the productivity forecasting errors, ζ_j, is plausibly orthogonal to the characteristics of the managing firm. The Arp regression controls include a firm-year fixed effect and a township-year fixed effect as well as the firm's local experience, the firm's global experience, and the amount of local information available at the time of drilling. Thus, the information contained in a given well's productivity forecasting errors likely corresponds to information that is orthogonal to the firm-year and geographic characteristics already assessed by the model.

To verify the validity of the Arp regression specifications, it is first necessary to test whether there is any spatial correlation between the production forecast errors across wells. The goal of the test is to make sure that variation in forecasting errors is not driven by other important spatial-economic factors omitted from the Arp model. I assess spatial correlations using the Moran's I coefficient, which ranges in value from -1 to 1. A coefficient equal to zero indicates no spatial correlation, while positive coefficients imply clustering of forecasting errors. In the present context, a positive Moran's I would suggest that the Arp model has omitted spatial factors. However, the estimate of Moran's I is close to zero, at 0.01, suggesting that the Arp model properly captures relevant spatial factors. Finally, Figure 7 plots the distribution of the wells' idiosyncratic productivity shocks. The idiosyncratic productivity shocks distribution is centered at zero (i.e., the median value is 0.0007), but it is slightly leptokurtic.

Next, in order to confirm that the above measure of idiosyncratic risk is positively related to a greater occurrence of poor drilling outcomes, I examine the number of dry holes per township-year. For township-year subgroups in the upper half of the idiosyncratic risk distribution, there are on average 0.39 dry holes drilled; for township-years in the lower half, this value is 0.04. This corresponds to a one order of magnitude difference between the comparison groups, strongly suggesting that township-years with greater idiosyncratic risk consistently experience higher rates of negative drilling outcomes. To control for additional factors, I also estimate a Poisson regression[24]. Table XXI displays a positive and statistically significant relationship between projects' idiosyncratic risk and the probability of drilling a dry hole across all specifications. Specifically, a one-standard-deviation increase in the idiosyncratic risk measure is associated with 1.4 additional dry holes drilled in the township-year. This result provides further empirical support for the relationship between the measure of idiosyncratic risk and adverse drilling outcomes.

1.7 Results

1.7.1 Do Managers Price Idiosyncratic Risk?

To test whether managers price idiosyncratic risk, I first estimate an OLS regression of firms' discount rates and projects' idiosyncratic risk. The regression includes two observations per firm-year, one for each of the firm's high- and low-idiosyncratic risk portfolios. To simplify the interpretation of the regression coefficient across all the regression specifications in the paper, I scale the regressor of interest by its regression-sample standard-deviation[25]. Table III shows that managers appear to positively price idiosyncratic risk. Column 1 presents the simple regression with one control, the portfolios' potential differential exposure to systematic risk (See Appendix 10.3. for a complete discussion). Columns 2 to 5 introduce a

[24] A Poisson regression is the appropriate model when the dependent variable is a count variable, such as the number of dry holes in a township-year (Greene, 2003).

[25] To scale a regressor by a constant does not alter the statistical properties of the estimate (Greene, 2003). This strategy has the added benefit of directly providing me with the magnitude for the effect of a one-standard-deviation increase in the projects' idiosyncratic risk.

set of controls and show that the regression results are robust to those further specifications. Column 6 includes a firm-year fixed effect, to control for the time-varying characteristics of firms, and Column 7 adds the idiosyncratic risk portfolio fixed effect. The source of variation in those regression is the relationship between average projects' idiosyncratic risk and the discount rates estimated for high- and low-risk firm-year portfolios. For the average firm, a one-standard-deviation increase in idiosyncratic risk results in a 6.7 to 8.0pp increase in the discount rate.

1.7.2 Instrumental Variable

The fixed effects included in the above regressions address a few endogeneity concerns. Specifically, the firm-year fixed effect accounts for the fact that, in a given year, a firm may systematically select regions that are riskier. At the same time, the idiosyncratic risk portfolio fixed effect helps address the idea that there might be a selection effect such that some unobserved variables (e.g., managers' experience) might systematically be associated to better or riskier regions (i.e., regions with better potential projects, lower risk of bad drilling outcomes). However, the fixed effect strategy does not account for the managers' heterogeneity within the idiosyncratic risk portfolios, which could plausibly vary by firms. Thus, the previous OLS regression may suffer from a within-firm omitted-variable bias.

To address these additional endogeneity concerns, I take an instrumental-variable approach. The strategy is implemented in two steps. First, each well is associated with its corresponding township-year peers' largest project's idiosyncratic productivity shock. Figure 6 provides a graphical example – with three firms (identified in **Red**, **Blue**, and **Black**) – of how these shocks are identified for one particular township-year; for the wells drilled by the Red firm, the associated peer's shock is 0.23. Then, I define the instrumental variable as the average value of those associated peers' shocks computed at the level of each firm-year portfolio.

The relevance of the instrumental variable has to do with how the idiosyncratic risk variable is calculated. In this study, the idiosyncratic risk corresponds to the cross-sectional dispersion of all the project-specific productivity shocks occurring within a township-year such that:

$$\text{Idiosyncratic Risk}_{p,t} = f(\zeta_j^{Red}, \zeta_j^{Blue}, \zeta_j^{Black}) \tag{1.8}$$

From the example in Figure 6, the projects' idiosyncratic risk measure for the wells drilled in that particular township-year, 0.129, corresponds to the standard-deviation of the 10 idiosyncratic productivity shocks. From the standpoint of the Red firm, the largest idiosyncratic productivity shock experienced by its Blue and Black peers in the township-year is 0.23. Then, given how the idiosyncratic risk variable is constructed, it is reasonable to assume that, on average, those peers' shocks will be correlated with the idiosyncratic risk variable. Panel A of Table VII reports the first stage of the instrumented regression, which provides empirical support for this assumption. The values of β_1 indicate that there is a positive relationship between idiosyncratic risk levels and the size of the largest idiosyncratic productivity shock that affects a firm's peers within a given township-year. Additionally, to address potential concerns about weak instruments, the bottom section of Panel A reports the Kleibergen-Paap first-stage F-statistic. For each regression specification, the statistic's value is substantially greater than the minimum threshold, $\sim$10, alleviating concerns regarding the presence of a weak instrument.

To satisfy the exclusion restriction, I use the peers' idiosyncratic productivity shocks within each township. From the Arp regression, I obtain the peers' idiosyncratic shocks after controlling for firm-year factors, township-year factors, as well as the firms' experience and information set. Then, if managers' assignment to specific regions is affected by these characteristics, the Arp model should make the information content of peers' shocks uncorrelated with those variables (see Section 7 for the full discussion of the idiosyncratic shocks). Then, after applying the fixed effect strategy in the instrumented regression, the peers' managers' characteristics should be uncorrelated with the firm's managers' characteristics within a portfolio's risk profile. As a sanity check, I verify if this assumption is supported empirically for the whole sample. In the context of Figure 6, this corresponds to testing if the idiosyncratic productivity shocks of the *Red* firm (0.05, -0.1) are correlated with the largest peer's idiosyncratic productivity shock, 0.23. More specifically, I regress each well's own idiosyncratic shock on their associated largest peers' idiosyncratic productivity shock, for the entire sample (i.e., the 114,969 distinct wells). While there exists no way to technically test for the exclusion restriction, the absence of correlation is generally reassuring. Table VIII reports the regression results of the firm's own idiosyncratic productivity shocks on the largest peers' idiosyncratic productivity shock in each township-year. I find no statistical relationship between the two types of shocks, across all the regression specifications. Perhaps the most relevant specification is the one presented in column 8, because it addresses more directly the underlying assumption of the instrumental variable strategy: the absence of correlation between firms' managers' characteristics and its peers' characteristics within a township of a given risk level. Specifically, column 8 suggests that there exists no statistical relationship between the shocks within a given township, providing support for the instrument assumption.

Panel B of Table VII reports the results of the second stage of the instrumented regression. The coefficients are slightly smaller in magnitude than the results obtained from the reduced-form regression, but they remain economically meaningful. For the instrumented regression, a one-standard-deviation increase in a project's idiosyncratic risk results in an increase of 5.2 to 6.7pp in the firm's discount rate, compared to 7.1 to 8.6pp for the reduced-form regression.

Regarding the sign of the endogeneity bias, I find that the coefficient of interest (β_1) of the instrumented regression is smaller than the one in the reduced-form regression presented in Table VI, across all specifications (see Appendix C). The direction of the bias for the coefficient of interest (β_1^*) depends on (i) the covariance between the managers' experience and the level of idiosyncratic risk associated with the wells, and (ii) β_2, the linear relationship between managers' experience and the firms' discount rate. Ultimately, multiple within-firm omitted variables could be affecting my analysis, with some having opposing effects on the direction of the endogeneity bias. In this sense, the goal of the following discussion is to provide a concrete example to illustrate the type of omitted variables that appear to ultimately dominate the direction of the endogeneity bias observed in the reduced-form regression.

For (i), it is plausible that more experienced managers get assigned to better regions (i.e., better prospect, lower production risk) because of their greater bargaining power within the firm or that, given their higher level of experience, the outcome of their wells is less uncertain because they know better how to optimally extract the natural gas. In this specific framework, this would suggest a negative relationship between the managers' level of experience and the observed idiosyncratic risk variable. For (ii), to obtain a reasonable explanation on the sign of β_2, it is helpful to look at it from a career concern standpoint. More experienced managers have a longer list of realizations, which suggests that each additional signal is less likely to have a large effect on how the firms' superiors update their belief of the experienced managers' worth. In this case, bad drilling outcomes are less likely to negatively affect how superiors value experienced managers than how they value unexperienced managers. Chevalier and Ellison (1999) provide empirical evidence in favor of this career concern explanation, showing that on average, less experienced managers are more likely to get fired for bad performance. This suggests that for a similar level of exposure to idiosyncratic risk, more experienced managers would require a smaller idiosyncratic risk premium than their less experienced counterparts, implying that the sign of β_2 should be negative. Ultimately, the combined effect of these variables would suggest that the reduced-form regression suffers from an upward bias because of omitted variables such as managers' experience. In other words, the coefficient obtained in the reduced-form regression may overestimate the magnitude of the discount rate adjustment to account for idiosyncratic risk, when compared to the true coefficient.

1.7.3 Idiosyncratic Risk Premiums and Firm Performance

The previous results have implications for firms' performance. If managers inflate their discount rate when faced with a high level of idiosyncratic risk, firms would then underinvest in wells with a high level of idiosyncratic risk. As a consequence, pricing idiosyncratic risk could have negative consequences for firms' performance, while abstaining from doing so should be correlated with relatively better performance. However, there is little empirical evidence linking firms' discount rate adjustment to adverse performance.

I directly examine that relationship here. To test for the effect of idiosyncratic risk pricing on firms' performance (e.g., gross profit margins, gross profitability, asset growth (YoY), and investment rate), it is necessary to develop a measure of firms' pricing of idiosyncratic risk, to directly use it as a regressor. To construct this variable, I define the numerator as the difference between the discount rates of the high idiosyncratic risk portfolio and the low idiosyncratic risk portfolio, and I define the denominator as the difference between the idiosyncratic risk measures of the two portfolios[26], such that:

$$\text{Price of Idiosyncratic Risk}_{i,t} = \frac{\text{Discount Rate}_{i,t,High} - \text{Discount Rate}_{i,t,Low}}{\text{Idiosyncratic Risk}_{i,t,High} - \text{Idiosyncratic Risk}_{i,t,Low}}$$

where High and Low corresponds to the two firm-year portfolios sorted on the exposure to idiosyncratic risk. Effectively, this measure gives the discount rate change that corresponds to a one-unit increase in average projects' idiosyncratic risk, for each firm at a yearly frequency.

Table IX relates firms' price of idiosyncratic risk to their performance. For the average firm, a one-standard-deviation increase in the price of idiosyncratic risk has a statistically significant and sizable negative effect on the gross profit margins (-5.1pp), gross profitability (-0.5pp), investment rate (-0.8pp) and year-over-year asset growth (-0.8pp). The negative relationship between firms' performance and the firms' pricing of idiosyncratic risk suggests

[26]The calculation details are available in Appendix A.1.

that idiosyncratic risk pricing is related to one or more forms of resource misallocation.

1.7.4 Mechanisms

This section explore several potential mechanisms that might induce managers to adjust discount rates to account for idiosyncratic risk. The mechanisms relate to theories that focus on either external pressures (frictions between the firm and the financial market) or internal pressures (frictions between managers and their superiors).

The Cost of External Funding and Idiosyncratic Risk Pricing

Firms dispose of multiple tools to manage their exposure to risk. While most of the discussion in the literature has focused on the use of financial derivatives, other mechanisms have long been acknowledged. Studying the interaction between risk management and capital budgeting, Froot et al. (1993) make the empirical prediction that managers would adjust their discount rate to account for risk that cannot be offloaded in the financial market in the presence of costly external financing. Risks that cannot be hedged expose the firm to variability in cash flows. In the context of this paper, this can be understood as drilling wells that would not produce enough natural gas (e.g., a dry hole). If the projects that a firm pursues fail to produce cash flow, the firm may then have to turn to external markets to raise additional funds and continue its operations. However, if the cost of marginal funds increases with the amount raised, the firm might have to limit its investment in the next period or raise capital from increasingly expensive sources. In this sense, greater variability in the wells' outcome exposes firms to a greater probability of having to raise external funds at a premium. Since this source of risk directly translates into a greater cost of capital, Froot et al. (1993) suggest that managers should adjust their discount rate calculations accordingly.

Obtaining a measure of the cost of external financing is challenging, as researchers do not directly observe this variable. To test the hypothesis, this study builds on the work done by Hennessy and Whited (2007), which provides empirically-based guidance for selecting the best proxy of costly external financing. The core of their analysis focuses on firms' size as well as three indexes: (i) the Cleary index, (ii) the Whited-Wu index, and (iii) the Kaplan-Zingales index. In general, they conclude that firm size is the best proxy for the costs of external financing, where larger firms face a lower costs of external financing than do their smaller counterparts. They also, however, find that the Cleary index and Whited-Wu index properly capture most of the dynamics attributed to the cost of external financing, but fail to behave adequately with respect to the costs of bankruptcy, making them inaccurate overall proxies for the cost of external financing. Finally, the authors note that the Kaplan-Zingales index improperly captures most of the dynamics attributed to the cost of external financing. On this basis, the authors conclude that firm size is the best proxy for costly external financing, noting that the three indexes are better suited to act as proxies for the need for external funding rather than for its cost.

All four of these potential proxies are included here, in an effort to be fully transparent. In addition, the present study includes firms' status (i.e., public or private) and the Hadlock-Pierce index as additional proxies. Private ownership status has been associated with higher financing frictions in the finance literature (Gao et al., 2013) and thus has the potential to be informative here. Also, there is empirical evidence suggesting that the Hadlock-Pierce index captures firms' financial constraints. Although the index has not been tested in the Hennessy and Whited (2007)'s costly external financing horse race analysis, it is closely related to the firm's size proxy discussed by Hennessy and Whited (2007) as it is a function of firm size and age.

Table VII and Tables XXII to XXVI present the results of each of the six proxies of costly external financing. For each table, the coefficient β_2 measures the effect of costly external financing on firms' pricing of idiosyncratic risk. Columns 5 through 8 of each table present the results when two variables are instrumented: (i) the projects' idiosyncratic risk variable and (ii) the interaction of projects' idiosyncratic risk with the relevant proxy of costly external financing (i.e., β_1 and β_2).

Table VII reports the results of firm size. Consistent with the analysis of Froot et al. (1993), it shows that as the cost of external funding decreases, firms tend to price idiosyncratic risk less aggressively. The results are robust across all specifications, for both reduced form and the instrumented regression. On average, a one-standard-deviation reduction in firm size results in a 2.3pp increase in the price of idiosyncratic risk[27]. Columns 2, 3, 4, 6, 7, and 8 introduce a proxy for firms' diversification[28], which corresponds to the firm-level idiosyncratic risk diversification among all the projects that are drilled for a given firm-year. The diversification variable is included because firms' size has been associated with several other characteristics of firms, such as their ability to diversify sources of idiosyncratic risk (Demsetz and Strahan, 1997). The firms' annual budget diversification variable is constructed in a similar spirit to the diversification index in Seru (2014) (see Appendix 10.1.), and a larger value of the variable indicates that a larger share of the idiosyncratic risk is diversified at the firm level.

Table XXII reports the results for the Hadlock-Pierce index, which are directionally consistent with the section hypothesis, and statistically significant. Namely, when the Hadlock-Pierce index increases, which indicates that firms are more financially constrained, firms' price idiosyncratic risk more aggressively. Table XXIII presents mixed results for the effect of firms' ownership status. For the specifications excluding a fixed effect at the firm level, the results are consistent with the prediction made by Froot et al. (1993), such that private firms' price idiosyncratic risk more than public firms, but the difference is not statistically significant. Tables XXIV to XXVI report the Cleary, Whited-Wu and Kaplan-Zingales indexes results. They are directionally consistent with the theoretical prediction developed in Froot et al. (1993), but they are not all statistically different from zero.

To provide additional evidence supporting this channel, I test how sensitive in the discount rate adjustment for more- and less-diversified firms, in the sense of idiosyncratic risk. The underlying assumption of (Froot et al., 1993) is that firms should adjust their discount rate

[27]From Table VII: β_2*Average *Scaled* Idiosyncratic Risk*σ_{Asset}= -0.01*0.6*383.8=-2.3.

[28]Appendix 10.1. provides the details of the calculations involved.

to account for projects' idiosyncratic risk, if this source of risk is not diversified at the firm level. To address that, I split the sample into two subsamples. I take a set

Overall, the results presented in this section suggest that the cost of external financing can have a meaningful impact on how firms adjust their discount rates. Focusing on Hennessy and Whited (2007)'s favored measure, the results indicate that costly external financing can induce managers to price the undiversified quantities of idiosyncratic risk. It is reasonable to assume that this proxy imperfectly captures attributes associated with firms' cost of external financing, and thus it could ultimately suffer from endogeneity bias. However, most of the additional proxies tested in this section provide results that are directionally consistent with that theoretical prediction (despite not being all statistically significant), lending further strength to that finding.

Managers' Budget Size Diversification and Idiosyncratic Risk Pricing

Survey evidence collected by Graham et al. (2015) suggests that specific investment decisions are formulated at the lower level of the hierarchical structure, while budget allocation is decided by the firms' superiors. Geanakoplos and Milgrom (1991) suggest that delegating investment decision-making to the agents with the highest amount of information regarding a specific decision improves resource allocation. Empirically, the delegation of authority has been linked to team specialization (e.g., Caroli and Reenen (2001); Colombo and Delmastro (2004); Acemoglu et al. (2007)), where workers in jobs that require technical skills usually benefit from a greater level of authority. In the context of gas exploration and production companies, this approach increases the likelihood that people most familiar with the local rock formation specificity will make investment decisions with limited interference (Bohi, 1998). However, the decoupling between the capital allocation choice and the decision to invest in specific projects, known as the delegation process, has been argued as a potential source of agency conflict between managers and their superiors (Aghion and Tirole, 1997). From the lens of Aghion and Tirole (1997), to delegate land surveying and project selection can be beneficial for firms since specialized on-site managers are more likely to generate quality information and then identify better drilling opportunities. However, by giving managers a high level of autonomy, there is a risk that managers might try to abuse their authority and misrepresent the full set of available wells when pitching them to the firms' superiors, if monitoring is costly. For example, managers might prefer to avoid pitching projects with an associated idiosyncratic risk measure that exceeds their preferred level, although those wells could be value creating from the firms' standpoint. This could be the case if managers are evaluated, and ultimately *rewarded* or *punished*, by demonstrating their ability to generate production forecasts that are, on average, in line with the wells' realized production. For the firms, managers' ability to produce reliable production forecasts on average can be appealing since it facilitates the efficient allocation of resources. Firms' superiors might value this type of ability in managers' performance reviews. Thus, for managers, choosing wells with a higher level of idiosyncratic risk increases the probability of being wrong in the production forecast (above or below) of a given well, which could increase their risk of receiving bad evaluations. Although my dataset does not enable me to observe managers' compensation contracts or if they get fired or promoted based on their forecasting performance, Table VIII provides empirical evidence suggesting that firms' resource allocation responds to forecasting *mistakes*. Precisely, the regression results reported in Table VIII indicate that firms allocate a smaller share of the annual budget in the following period to managers for which the realized production diverges more from the expected production in the current period. This result is robust when controlling for a region-year fixed effect, a factor that captures regions' overall production potential and quality.

A direct consequence of the delegation process is that firms' high-level decision-makers allocate the firm's total budget across multiple managers, each tasked with evaluating, selecting, and pitching projects to the firms' superiors that should, in principle, maximize the firm's value. The fact that managers receive a fraction of the firm's budget can result in a loss of diversification at the manager level, in the sense used by Diamond (1984). The general response from the finance and economic literature to this type of agency friction is to design a compensation contract that would mitigate the friction. However, given the complex nature of real life situation, it appears reasonable to think that such wage contract might not feasible in practice. In this sense, Holmstrom and Costa (1986) suggest that capital budgeting policies can play a partial role. For a risk-averse manager, if projects' idiosyncratic productivity shocks are not perfectly correlated among themselves, being granted a larger budget has two effects. First, it reduces the total quantity of idiosyncratic risk they face. And second, it decreases the manager's idiosyncratic risk premium. The insight developed in Diamond (1984) would suggest that firms in which managers have larger budgets should, all things being equal, price idiosyncratic risk less aggressively.

That hypothesis is directly tested here. First, I construct a measure to proxy for managers' idiosyncratic risk diversification: managers' budget size. Natural gas exploration and production companies organize their activities into regional units. Although it is difficult to delineate the exact region covered by each manager, it is still possible to develop multiple proxies of managers' budgets based on a plausible definition of region of activity. The procedure followed here considers two potential scenarios that represent a lower and an upper boundary for the size of their assigned territory, such that managers could either be assigned to a specific field or to a specific state. Assuming that managers are assigned to specific gas fields is a reasonable lower boundary, as each field possesses unique characteristics for which the required technical expertise cannot be directly mapped onto other locations (Kellogg, 2011). These particularities create a steep learning curve for managers taking on new fields and limit managers' ability to transfer their knowledge. At the other extreme, using states as managers' assigned territories presents a plausible upper boundary. Indeed, it matches job postings' regions of assignment and how organizations determine the territory of their regional units. For each of these two scenarios, I then estimate the managers' budget size in two steps. First, I calculate the total cost for all wells drilled in a given field or state for each firm and year. Then, I define average managers' budget as the average value across all fields/states at the firm and year level. This provides me with the average budget size of the firms' managers in that given year, for each of two possible methods of measuring the budget allocation.

Table IX presents the results of the regression assuming that individual fields define managers' region of activity. Coefficient β_2 measures the effect of managers' budget size on firms' pricing of idiosyncratic risk. In line with Diamond's proposal, managerial budget size appears to have a meaningful impact on idiosyncratic risk pricing. A one-standard-deviation increase in average budget size results in a reduction of 1.16pp[29] in the price of idiosyncratic risk. Table XXVII presents the results of the same tests when managers are assumed to operate at the level of an entire state. The results are robust to this alternative specification for the region of activity; the relationship is similar in both cases. Finally, Table XXIIX shows a positive and statistically significant relationship between managerial budget size and projects' levels of idiosyncratic risk. This is further evidence suggesting that managers' risk tolerance increases as a result of increasing budget size.

To further support the agency channel effect, I test how the effect of managers' budget size varies as a function of agency friction. To do so, I construct a measure of agency friction building on the insight that proximity facilitates monitoring and information acquisition by the firm's superiors. A rich empirical literature presents evidence illustrating the benefits of proximity in reducing the cost of acquiring information and improving monitoring. Giroud (2013) presents evidence suggesting that proximity between firms' headquarters and plants reduces agency conflict by improving the ability of superiors to go on-site and directly monitor plants' managers. Similarly, Coval and Moskowitz (1999) and Coval and Moskowitz (2001) show results with mutual fund managers, where proximity enables funds' managers to obtain better results with the shares of firms located geographically closer, suggesting better monitoring capabilities and access to private information. I obtain the measure of proximity by calculating the median distance between the wells drilled by a firm in a given year[30]. In the context of this literature, a greater median distance between the

[29]From Table IX: β_2*Average *Scaled* Idiosyncratic Risk*$\sigma_{\text{Managers' Budget}}$= -0.11*0.6*17.6=-1.16.

[30]In a first step, I measure the distance between all the wells a firm drilled in a given year. Then, the agency friction value is defined as the median value of those distances, for each firm-year.

firms' wells indicates greater difficulty in monitoring the quality of projects for the firms' superiors, thus corresponding to a greater level of agency problem. Given this, if budget size affects managers' risk tolerance through the agency channel, one would expect that the effect of budget size be more salient in firms experiencing greater agency conflict. Table X reports the results of this additional test. The variable of interest is associated with the coefficient β_3. The negative coefficient suggests that as firms face more agency problems (i.e., a greater distance between the wells), the effect of budget size in mitigating the agency friction becomes stronger.

The results reported in this section suggest that managers' budget size has a meaningful effect on managers' risk tolerance, ultimately reducing managers' pricing of idiosyncratic risk. It suggests that, for the average firm, the set of available tools to alter managers risk tolerance extends beyond compensation contracts. By shifting the allocation of resources among its managers, firms can provide a form of insurance for those who are, for instance, overly risk-averse.

Costly External Financing and Agency Frictions

To further explore how the two mechanisms affect the price of idiosyncratic risk, I investigate their combined effect. Table XI reports the results of the regression that includes proxies for both mechanisms as well as their interaction term. Across all specifications and for both proxies of managers' budget size (i.e., aggregation at the field or state level), I find that the price of idiosyncratic risk (β_1) is positive and statistically significant, such that a one-standard-deviation increase is associated with a 10.5 to 12.7pp increase in the discount rate. In addition, including both mechanisms simultaneously does not eliminate their individual contribution. Particularly, both mechanisms (β_2 and β_6) are statistically and economically significant, and their magnitudes are closed to the ones obtained in Tables VII, IX and Table XXVII. These results provide additional evidence suggesting that both mechanisms operate jointly on frictions associated with the firms' price of idiosyncratic risk. Perhaps more interesting is the coefficient β_7, which represents the contribution of the interaction between the two mechanisms to the price of idiosyncratic risk. The coefficient is positive and statistically significant, although its magnitude is almost zero[31]. To interpret this coefficient, it is useful to look at a simple case. For a fixed level of idiosyncratic risk, we can look at two firms with different sizes: 0 or 1. In this example, managers' budget size will be less effective in reducing the price of idiosyncratic risk ($\beta_6 + \beta_7$) for larger firms (i.e., firms of size 1). I interpret this result such that, when holding the level of idiosyncratic risk constant, the marginal benefit for increasing the size of managers' budget is smaller for firms that are less exposed to costly external financing frictions. A similar reasoning can be applied to firms' size.

1.8 Robustness Analysis

In this section, I conduct several robustness tests to rule out alternative explanations.a

1.8.1 The Effect of Real Options

One potential concern with the strategy adopted here for estimating firms' discount rates is whether it adequately accounts for important aspects of firms' project selection. For example, managers might use a real option investment threshold, rather than project cost, to calculate projects' NPV; the real option literature (Dixit and Pindyck, 1996) explicitly considers idiosyncratic risk when determining optimal exercise thresholds. If this is the case, failing to account for the firm projects' *optionality feature* could substantially alter the nature of the above results.

Empirical evidence suggests that managers behave in a way that is directionally consistent with real option theory (Bloom et al., 2007; Kellogg, 2014; Decaire et al., 2019), although they also systematically exercise their investment opportunities prior to the real option recommendation. Brennan and Schwartz (1985) (in the case of gold mines), Kellogg (2014)[32]

[31] I divided the variable by 1000 to increase the coefficient magnitude and show digits in the regression table.
[32] See Figure 10 of Kellogg (2014).

(on oil wells), and Decaire et al. (2019) (on shale gas wells) provide empirical evidence in support of this claim. This suggests that managers do not follow the recommendation of real option theory strictly–a situation that is further supported by multiple survey-based studies (Graham and Harvey, 2001; Jacobs and Shivdasani, 2012; Graham et al., 2015). Instead, in more than 90% of cases, managers prefer more straightforward and less capricious valuation strategies such as NPV and IRR when selecting projects (Graham and Harvey, 2001), with little mention of the use of real options. In this light, it is reasonable to assume that managers acknowledge to some extent the value and importance of operational flexibility, but real option models might be too stylized to properly capture the *exact* dynamic. Nonetheless, I use two methods here to ensure that the present results are robust to the effect of operational flexibility and real option.

First, to directly alleviate the concern that this study is biased by a *operational flexibility* factor, I repeat the above analysis using a restricted sample of projects that are minimally likely to be affected. Precisely, I focus on wells for which managers have little time to drill, since real option valuation directly depends on the flexibility of a project's timing. Speaking generally, the more time the managers have to decide when to invest in their projects, the more the real option is worth. Now, there are two ways a firm can obtain the right to develop a plot of land in the United States. It can either acquire a lease, providing the exclusive right to the plot during a certain period, which is, on average, three years, or it can "hold [the development rights] by production". This means that as long as a firm has an actively producing well on the plot, they are entitled to further develop it until they fully deplete the available reserves of natural gas. In these cases, firms usually have 20 years or more to drill additional wells. Papers investigating real option behavior have traditionally focused on projects whose lands are controlled through this second mechanism, because the real option phenomenon is more salient in those cases (Decaire et al., 2019). However, when operating on a leased plot of land, oil and gas exploration companies tend to drill their first well immediately prior to the expiration of the lease (Herrnstadt et al., 2019). Thus, for those first wells, the effective value of the option-to-wait at the time of drilling is marginal. Effectively, as the real option time to expiration converges toward zero, its value also converges to zero. Given this, the first strategy used here is to limit the analysis to only those wells that are the first to be drilled on a given plot of land. For those wells, managers faced limited operational flexibility.

The second strategy is to adjust the revealed preference strategy described above to directly account for the *real option* value. This is done by modifying the decision rule used when estimating each project's expected IRR. Rather than assuming that firms choose to invest whenever a project's expected cash flow is greater than its cost, the new rule assumes that firms use a real option optimal exercise threshold that increases along with a project's level of idiosyncratic risk such that the decision rule becomes (see Appendix 10.5 for a detailed explanation of the real option calculation):

$$\sum_{m=1}^{M} \frac{1}{(1+\mu_j)^m} \, \mathbb{E}[q_{j,m}] \, \mathbb{E}[P_j] - V_j^* = 0 \tag{1.9}$$

Where V^* is the real option optimal exercise threshold as specified by Dixit and Pindyck, such that $V_j^* = \frac{\beta_j^1}{\beta_j^1 - 1} C_j \geq C_j$.

There are two limitations to this strategy, however. The first is related to the amount of time to expiration for each project. Because this information is not observed for most wells in the dataset, the most conservative approach is to assume that firms have an infinite time horizon to exercise their options for all projects. The real option optimal threshold is increasingly sensitive to projects' risk as the time to expiration increases, thus giving each project an effectively infinite duration before expiration corresponds to a more conservative scenario here (Dixit and Pindyck, 1996). The second limiting factor is related to the measure of idiosyncratic risk. There could be concerns that the measured level of the idiosyncratic risk is too low, and that it does not properly capture the total quantity of idiosyncratic productivity risk faced by the firms. In turn, this would bias the real option test. To test the robustness of the results with the calibrated real option, I design a kill test. Precisely, when calibrating the real option optimal threshold, I increase the measure of idiosyncratic productivity risk to find at which level my core result is no longer statistically significant. Multiplying the magnitude of idiosyncratic productivity risk magnifies the difference between the riskier wells and the less risky ones, ultimately widening the difference between the real option exercise threshold, which reduces the difference between the estimated expected IRRs.

Table XII presents the results of the first strategy and Table XXIX present the results of the robustness test for the real option effect. Both regressions are qualitatively and statistically similar to the primary results described in earlier sections, suggesting that a operational flexibility or real option effect is not significantly altering the reported outcomes. Not surprisingly, the regression coefficients are lower in all specifications, suggesting that some of the observed variation might be partially attributable to those phenomenon. Also, the number of observations in both tables is lower than that in the main regression tables. For Table XII, it is because most of the projects evaluated in this analysis are infill wells (i.e., wells drilled when the plot of land is *held by production*), which reduces the number of firms included in the sample. Similarly, for Table XXIX, the number of observations for the real option calibration specification is lower than the one for the main specification, because implied volatility data is not available on Bloomberg before the year 2000. Finally, the results of the kill test indicate that the core results of this paper are robust to the real option calibration up to an increase of 28.8% of the idiosyncratic risk.

1.8.2 The Effect of Firms' Leverage

The cost of debt for a given firm increases with the total amount of risk incurred at the firm level (Merton, 1974), including both systematic and idiosyncratic forms of risk. Taksler (2003) presents empirical evidence in favor of Merton's theory, which is roughly that a firm's weighted cost of capital should account for the firm's idiosyncratic risk, through its debt component. To test for this alternative interpretation, I design a separate regression that includes firms' market leverage and an interaction term of market leverage with project-level idiosyncratic risk, including only those firms for which the relevant information is available.

Table XIII reports the results of that test, which are that the effects of leverage on the price of projects' idiosyncratic risk does not economically or statistically alter the above results. Also, consistent with the effect of leverage discussed in Merton (1974), the coefficient of the interaction between firms' leverage and the projects' average idiosyncratic risk (i.e., β_5) is positive, but not statistically significant in all regression specifications. The directional effect is consistent with the phenomenon discussed by Merton, such that idiosyncratic risk should be priced by the debt component of firms' capital structure.

1.8.3 Asset Pricing and the Idiosyncratic Risk Premium

A well-established asset pricing literature has found that firms' returns may account for idiosyncratic risk. For example, Goyal and Santa-Clara (2003) found a positive relationship between the quantity of idiosyncratic risk measured at the firm level and the returns on the market, while Ang et al. (2009) finds that firms with high past idiosyncratic volatility have low future average returns. This literature has discussed the role of investors lack of diversification and the role of real options to explain the idiosyncratic risk premium. There is a possibility that the results observed in my study are affected by this dynamic. However, three pieces of evidence presented in the previous sections provide reassuring evidence regarding such concerns. First, Table II coefficient β_2 indicates that firms price idiosyncratic risk after controlling for the WACC or the cost of equity, which proxies for the *idiosyncratic risk premium* discussed in the asset pricing literature. Second, Table XXIII shows that the results are robust to firms' listing status (i.e., private or public), ruling out the idea that the observed phenomenon is driven by a stock market effect, since it is observed for both types of firms. Finally, the mechanisms explored in this paper indicate that a plausible explanation for the observed dynamic is attributable to firms' internal frictions, steering away from a solely financial market effect.

1.8.4 Alternative Price Specifications

The study's primary results are also robust to two alternative price specifications. The first alternative uses the three-year Bloomberg natural gas futures contract prices rather than EIA three-year forecast[33]. In the second specification, the EIA regional wellhead prices are used to account for price heterogeneity across states (see Figure 8). Effectively, the price firms obtain for selling their product can vary across regions, depending on the *quality* of the resource and the distance it must be transported in order to reach a refinery site. Tables XIV and XV report the results of these two additional specifications. In both cases, the primary results are not qualitatively or quantitatively altered.

1.8.5 Alternative Discount Rate Thresholds

I introduce two alternative threshold specifications to address the concern that the results of the analysis can be materially affected by the threshold used to estimate the firm-year portfolios' discount rate. Determining a reasonable threshold is important in this analysis, because two sources of bias can potentially affect the discount rate estimate. First, the projects' expected IRR are obtained using a noisy measure of the managers' *true* expectations. Figure 9 provides a graphical illustration of the effects of measurement noise on the observed firm-year portfolio's expected IRR distribution. For this reason, observations situated on the very left portion of the distribution proxy for the discount rate with measurement error. Thus, it is reasonable to extend the discount rate threshold slightly beyond the minimum value of the distribution. Second, taking value too far on the right side of the distribution would fail to capture the features associated with the discount rate, as it would more likely capture dynamics associated with the firm's average profitability and its opportunity set. Table XVII presents the main results with two alternative threshold specifications, to show that the results are robust. Columns 1 to 3 present the results using only the lowest bound of the expected IRR distribution, and columns 4 to 6 present the

[33] The number of observations is smaller than the main specification used above, because Bloomberg's three-year natural gas futures prices are only available from 1995 to 2010, which presents a restricted sampling window.

results using the observations in the 2.5th lowest percentile of the distribution.

1.8.6 Results by Time Period

Finally, I verify that managers price idiosyncratic risk consistently period by period. Precisely, Table XVIII reports the results for the price of idiosyncratic risk, evaluated per decade (i.e., [1983-1990), [1990-2000), [2000-2010]). The table shows that managers consistently adjust their discount rate to account for idiosyncratic risk, across the three decades. This indicates that the main specification results are not driven by specific events associated with one particular time period. Rather, the effect is economically significant across all three decades.

It is interesting to note that the price of idiosyncratic risk has been steadily declining over time, across all regression specifications. Although the goal of this paper is not to explain the time trend for the price of idiosyncratic risk, future research investigating the underlying drivers of such phenomenon would be interesting.

1.9 Conclusion

Choosing discount rates for new investment projects is a fundamental topic in corporate finance, yet we have almost no evidence on how managers make these choices in practice. This study helps fill this gap by analyzing the relation between projects' idiosyncratic risk and firms' project-specific discount rates. The primary findings are that (i) managers adjust their discount rates upward when faced with increased idiosyncratic risk; (ii) pricing idiosyncratic risk is negatively related to several measures of firm performance; (iii) managers appear to adjust their discount rate calculation to account for their exposure to undiversified unhedgeable risk, when facing costly external financing; and (iv) capital budgeting policies, and specifically the size of managers' budget, appear to provide firm owners with an additional lever to adjust managers' effective risk tolerance to desired levels.

An interesting implication of these results relates to the role of alternative tools for aligning managers' preferences. Most of the theoretical and empirical work in finance focuses on compensation contracts as the main means of insuring managers against the potential negative outcomes of specific projects. Echoing the theoretical insights provided by Holmstrom and Costa (1986), this analysis finds that capital budgeting policies, such as the size of managers' budget, can supplement contracts and other tools, and may even help to achieve this goal more efficiently.

1.10 Appendix

1.10.1 Variable Definition

In this appendix, I define how each variable discussed in the paper is constructed. Subscript i corresponds to a specific firm, t corresponds to the year, j indicates a specific well, f refers to a region (i.e., a field or a state), p refers to a township, and k refers to the two portfolios at the firm-year level sorted on the idiosyncratic risk. A subscript with a minus sign, such as $X_{\text{-}i}$, indicates that the firm's own observations are excluded from the observations used in the calculation of the specific variable.

Gas Well Variables

1. # of Wells in a Township-Year: $\mathrm{N}^{j}_{p,t}$ = Count the number of projects per township p and year t

2. # of Active Regions: $\mathrm{N}^{f}_{i,t}$ = Count the number of fields or states the firm is active in during the year

3. # of Projects per Firm-Year Portfolio: $\mathrm{N}^{j}_{i,t,k}$ = Count the number of projects per firm i, year t, and portfolio k

4. Cost_j = The drilling cost of well j

5. Township-Year Average Well's $\mathrm{Cost}_{p,t} = \frac{\sum_{p,t} Cost_j}{N^{j}_{p,t}}$

6. $\mathrm{Asset}_{i,t} = \sum_i Cost_j$, for all producing wells on year t for firm i

7. $\mathrm{Budget}_{i,t} = \sum_{i,t} Cost_j$, for all the wells drilled on year t for firm i

8. Managers' $\mathrm{Budget}_{f,i,t} = \sum_{f,i,t} Cost_j$, for all the wells drilling on year t for firm i in

region (i.e., field or state) f

9. Average Managers' Budget at the Firm Level$_{i,t,f}$ $= \frac{\sum_{i,t} \text{Managers' Budget}_{i,t,f}}{N^{f}_{i,t}}$

10. Natural Gas Price$_t$ $= P_t$

11. Operational Cost (%) $= OP$

12. Royalty Rate$_t$ (%) $= R_t$

13. Yearly Gas Production$_{i,t}$ (in 1,000 cf) $= Q_{i,t}$

14. Operating profit$_{i,t}$ $= P_t Q_{i,t} * (1 - R_t - OP) - Budget_{i,t}$

15. Gross Profit Margin$_{i,t}$ (%) $= \frac{OperatingProfit_{i,t}}{P_t Q_{i,t}} * 100$

16. Gross Profitability$_{i,t}$ (%) $= \frac{OperatingProfit_{i,t}}{Asset_{i,t}} * 100$

17. Assets Growth$_{i,t+1}$ (YoY) (%) $= \frac{Asset_{i,t+1}}{Asset_{i,t}} * 100$

18. Investment Rate$_{i,t+1}$ (%) $= \frac{Budgeti,t+1}{Asset_{i,t}} * 100$

19. Discount Rate: DR$_{i,t,k}$ = Lower *region* of the firm-year portfolio's expected IRR distribution.

20. Project's Productivity Shock: $\zeta_j = \frac{\sum_{m=1}^{m=12} \mathbb{E}[p_t] * q_{j,m} - \sum_{m=1}^{m=12} \mathbb{E}[p_t]\,\mathbb{E}[q_{j,m}]}{Cost_j}$

21. Township-Year Idiosyncratic Risk: IR$_{k,t}$ $= = \frac{1}{N^{j}_{p,t}-1} \sum_{p,t} (\zeta_j - \bar{\zeta}_{p,t})^2$

22. Projects' Average Idiosyncratic Risk: Average IR$_{i,t,k}$ $= \frac{1}{N^{j}_{i,t,k}} \sum_{i,t,k} IR_{k,t}$

23. Price of Idiosyncratic Risk$_{i,t}$ $= \frac{DR_{i,t,High} - DR_{i,t,Low}}{\text{Average IR}_{i,t,High} - \text{Average IR}_{i,t,Low}}$, where High and Low

corresponds to the two firm-year portfolios sorted on the exposure to idiosyncratic risk

24. Largest Peers' Projects' Idiosyncratic Productivity Shock: Max Peer $\text{IPS}_{p,t} = max_{p,t}[\zeta_{-j}]$

25. Average Largest Peers' Projects' Idiosyncratic Productivity $\text{Shock}_{i,t,k} = \frac{1}{N^{j}_{i,t,k}} \sum_{i,t,k} \text{Max Peer IR}_{p,t}$

26. Annual Firm's Budget $\text{Diversification}_{i,t} = \frac{N^{j}_{i,t}-1}{\sum_{i,t}(\zeta_j-\bar{\zeta}_{i,t})^2}$

Financial Market Variables

For the regressions using Compustat variables or other financial market variables, the variable definitions are below. Names are denoted by their Xpressfeed pneumonic in bold, when available.

1. Total Book Assets = **at**

2. Total Debt = **dltt** + **dlc**

3. Market Value of Equity: $\text{MVE}_{i,t}$ = **pstk** + **csho*prcc_c**

4. Market Leverage = $\frac{\text{Total Debt}_{i,t}}{\text{MVE}_{i,t}+\text{Total Debt}_{i,t}}$

5. β^{OG}_t = One year CAMP Oil and Gas Industry beta, computed at the monthly frequency.

6. Risk-free Rate: rf_t = 10-year risk-free rate from St-Louis Federal Reserve.

7. Industry Cost of Equity: $\text{r}^{E}_t = rf_t + \beta^{OG}_t * (E(\frac{E_t}{P_t}) - rf_t)$

8. Cost of Debt: $\text{r}^{D}_{i,t}$ = Interest rate of trading bonds from firms of equivalent credit rating.

9. Weighted Average Cost of Capital: $\text{WACC}_{i,t} = \frac{\text{MVE}_{i,t}}{\text{MVE}_{i,t}+\text{Total Debt}_{i,t}} * \text{r}_t^E + \frac{\text{Total Debt}_{i,t}}{\text{MVE}_{i,t}+\text{Total Debt}_{i,t}} * r_{i,t}^D$

10. Cash Flow: $\text{CF} = \frac{\textbf{oancf}+\textbf{intpn}}{\textbf{at}}$

11. $\text{TLTD} = \frac{\textbf{dltt}+\textbf{dlc}}{\textbf{at}}$

12. $\text{TDIV} = \frac{\textbf{dvp}+\textbf{dvc}}{\textbf{at}}$

13. $\text{CASH} = \frac{\textbf{che}}{\textbf{at}}$

14. Market-to-book Ratio: $\text{Q} = \frac{\text{MVE}+\text{Total Debt}-\textbf{txditc}}{\textbf{at}}$

15. DIVPOS = is indicator that equals one if the firm pays dividends, and zero otherwise.

16. $\text{LNTA} = \ln(\textbf{at})$

17. Three-digit Industry YoY Sales Growth: $\text{ISG} = \frac{\sum_{3\ digit\ SIC} \textbf{sale}_{i,t+1}}{\sum_{3\ digit\ SIC} \textbf{sale}_{i,t}}$

18. Own-firm Real Year-over-Year (YoY) Sales Growth: $\text{SG} = \frac{\text{Real } \textbf{sale}_{i,t+1}}{\text{Real } \textbf{sale}_{i,t}}$

19. $\text{CURAT} = \frac{\textbf{act}}{\textbf{lct}}$

20. $\text{COVER} = \frac{\textbf{oibdp}-\textbf{dp}}{(\textbf{xint}+\textbf{dvp})/(1-\tau\_c)}$, where τ_c is the tax rate.

21. $\text{IMARG} = \frac{\textbf{ni}}{\textbf{sale}}$

22. $\text{SLACK} = \frac{\textbf{che}+0.5*\textbf{invt}+0.7*\textbf{rect}-\textbf{dlc}}{\textbf{ppent}}$

Costly external financial variables

In the paper, I use four indexes to proxy for the level of costly external financing by firms. To construct each of the first three proxies (Cleary Index, Whited-Wu Index, Kaplan-Zingales index), I process the data following the methodology presented in Hennessy and Whited (2007). Finally, for each index to have the same interpretation, I follow the recommendation of Hennessy and Whited (2007) and multiply the Cleary index by -1, such that it is increasing with the likelihood of facing costly external finance. Finally, to construct the Hadlock-Pierce index, I follow the methodology presented in Hadlock and Pierce (2010).

The indexes are constructed in the following way:

$$\begin{aligned} \textit{Kaplan-Zingales index} &= -1.001909 * CF + 3.139193 * TLTD - 39.36780 * TDIV \quad (1.10) \\ &\quad - 1.314759 * CASH + 0.2826389 * Q \\ \textit{Whited-Wu index} &= -0.091 * CF - 0.062 * DIVPOS + 0.021 * TLTD - 0.044 * LNTA \quad (1.11) \\ &\quad + 0.102 * ISG - 0.035 * SG \\ \textit{Cleary index} &= -0.11905 * CURAT - 1.903670 * TLTD + 0.00138 * COVER \quad (1.12) \\ &\quad + 1.45618 * IMARG + 2.03604 * SG - 0.04772 * SLACK \\ \textit{Hadlock-Pierce index} &= -0.737 * log(Asset_{2004}) + 0.043 * log(Asset_{2004})^2 + 0.040 * Age \quad (1.13) \end{aligned}$$

Where *Age* is measured using the year in which a firm drills its first well in the *DrillingInfo* raw data sample, which starts in 1885.

1.10.2 Linearized ARP model

To estimate the Arp model using a OLS regression, I linearize the equation such that:

$$q_{j,m} = A_j(1 + b\theta m)^{\frac{-1}{b}} \tag{1.14}$$

$$\ln(q_{j,m}) = \ln(A_j) - \frac{1}{b}\ln(1 + b\theta m) \tag{1.15}$$

$$\ln(q_{j,m}) = \alpha_0 + \alpha_1 + A_j + \sum_{k=1}^{K} \beta_k m^k \tag{1.16}$$

Where the last step is obtained by doing a Taylor expansion of the term $ln(1 + b\theta m)$. For a fixed m sufficiently small, the expansion terms converge to zero, since the product of b and θ is close to zero. In other words, I can approximate the hyperbolic decline curve using a K^{th} order polynomial. Finally, I include two dummy variables, α_0 and α_1, equal to 1 for the first and second month of the well's production and zero otherwise, to account for the well's production ramp-up patterns (Dennis, 2017).

1.10.3 Well's Differential Exposure to Systematic Risk Factors

Wells in my analysis could have different exposure to some *potential* systematic risk factors (e.g., natural gas prices). For example, wells with a greater level of idiosyncratic risk are associated with a greater discount rate, for a given firm-year. Consequently, it is reasonable to expect that, on average, more risky wells produce larger quantities of natural gas than their smaller counterparts, all things being equal. Empirically, the correlation between wells' level of idiosyncratic risk and their associated level of production is 0.2. Now, wells producing greater quantities of natural gas are mechanically more exposed to natural gas prices, a potential systematic risk factor. This relationship can potentially alter how I interpret this study's core result, since it would imply that wells with a greater level of idiosyncratic risk are probably more exposed to systematic risk factors (i.e., natural gas prices), confounding idiosyncratic and systematic risk factors.

To illustrate how wells with different production levels could have a different exposure to natural gas prices, I use a simple example, such that:

$$p_z * q_{j,z,m} = \beta_{Well'sPriceExposure} p_z + \epsilon_{j,z,m} \tag{1.17}$$

Where p_z corresponds to the price of natural gas at time z, and $q_{j,z,m}$ is well j production at age m (in months). We can then derive the expression for the coefficient $\beta_{Well'sPriceExposure}$, such that:

$$\begin{aligned} \beta_{Well'sPriceExposure} &= \frac{cov(p_z * q_{j,z,m}; p_z)}{var(p_z)} && (1.18)\\ &= \frac{\mathbb{E}[p_z^2 * q_{j,z,m}] - \mathbb{E}[q_{j,z,m} * p_z] * \mathbb{E}[p_z]}{var(p_z)} && (1.19)\\ &= \frac{\mathbb{E}[q_{j,z,m}](\mathbb{E}[p_z^2] - \mathbb{E}[p_z]^2)}{var(p_z)} && (1.20)\\ &= \mathbb{E}[q_{j,z,m}] && (1.21) \end{aligned}$$

Where I use the fact that wells' production flow is independent from the natural gas price process to obtain equation 19. Section IV provides an expansive discussion and some empirical support in favor of this assumption. This simple framework confirms the intuition that wells with a greater level of production flow may be more exposed to natural gas prices. This can potentially confound the *true* effect of idiosyncratic risk in the main analysis.

That being said, the quantity of risk is not the only relevant aspect to consider in this scenario. The price of this *potential* systematic risk factor is equally important in characterizing the consequence of a different exposure to systematic risk. There exists mixed evidence on the size of a natural gas risk premium or, to a more general extant, the risk premium of an *energy* factor. First, from a CAPM standpoint, the risk premium of natural gas is virtually zero[34]. The sample average one-year CAPM monthly beta coefficient for natural gas is 0.004. Computing the measure over alternative horizons does not significantly alter the resulting coefficients such that the two-year horizon beta coefficient is 0.003, the three-year beta is 0.003, and the four-year beta is 0.003. Second, when looking at other asset pricing models, such as models derived from the arbitrage pricing theory (APT), there exists little consensus for the existence of an *energy* factor priced by the market. On one side, Chen et al. (1986) and Kilian and Park (2009), among others, find little evidence in favor of an energy factor. Chen et al. (1986) find that oil price risk is not separately valued in the stock market, while Kilian and Park (2009) find limited explanatory power for oil supply and demand shocks in explaining stock returns. On the other side, Chiang et al. (2014) and Ready (2017) provide evidence in favor of an energy factor priced by the market.

Given the lack of general agreement in academic research for the existence of a priced energy risk factor, I include the wells' differential exposure to this *potential* systematic risk factor in my main specification. To do so, I use the results derived in equation 21. Precisely, for each firm-year portfolio, I measure the average production of the wells that were drilled, to proxy for their average exposure to natural gas prices.

[34] Berk and van Binsbergen (2016) provide empirical evidence suggesting that the representative investor utilizes the CAPM to determine the risk premium.

1.10.4 Sign of the Endogeneity Bias

To guide the analysis of the endogeneity bias sign in the reduced-form regression, it is useful to look at a simple regression case to work within an intuitive framework. For illustration's sake, one can take the example that managers with different level of experience might not be randomly allocated among the two firm-year portfolios (i.e., the high and low idiosyncratic risk portfolios), such that *Managers' Experience* would be part of the *true* data generating process:

$$\text{Discount Rate}_{i,t,k} = \beta_1 \text{Idiosyncratic Risk}_{i,t,k} + \beta_2 \text{Managers' Experience}_{i,t,k} + \epsilon_{i,t,k} \quad (1.22)$$

In the case where *Managers' Experience* is omitted from the *true* regression model, the reduced-form regression would then be:

$$\text{Discount Rate}_{i,t,k} = \beta_1^* \text{Idiosyncratic Risk}_{i,t,k} + \epsilon(\text{Managers' Experience})_{i,t,k} \quad (1.23)$$

In this simplified example, the expression of the *biased* reduced-form β_1^* can be defined as:

$$\beta_1^* = \beta_1 + \beta_2 \frac{cov(\text{Idiosyncratic Risk}_{i,t,k}; \text{Managers' Experience}_{i,t,k})}{var(\text{Idiosyncratic Risk}_{i,t,k})} \quad (1.24)$$

From this simple example, one can note that the direction of the bias for the coefficient of interest (β_1^*) depends on (i) the covariance between the managers' experience and the level of idiosyncratic risk associated with the wells, and (ii) β_2, the linear relationship between managers' experience and the firms' discount rate.

1.10.5 Revealed Preference Strategy with Real Option

To account for the real option effect, I adjust the firms' decision rule, such that I no longer assume that it is optimal to invest when the expected discounted cash flows of the wells are greater than the cost (C_j), but I assume that the wells are exercised when the discounted cash flows are greater than the real option optimal threshold (V_j^*), such that:

$$\sum_{m=1}^{M} \frac{1}{(1+\mu_j)^m} \mathbb{E}[q_{j,m}]\,\mathbb{E}[P_j] - V_j^* = 0 \tag{1.25}$$

To compute the real option optimal threshold (V_j^*), I follow the methodology introduced in Dixit and Pindyck (1996, Chapter 5) such that:

$$V_j^* = \frac{\beta_j^1}{\beta_j^1 - 1} * C_j \tag{1.26}$$

$$\beta_j^1 = \frac{1}{2} - \frac{r_t - \delta}{\sigma_j^2 + \omega_t^2} + \sqrt{[\frac{(r_t - \delta)}{\sigma_j^2 + \omega_t^2} - \frac{1}{2}]^2 + \frac{2r_t}{\sigma_j^2 + \omega_t^2}} \tag{1.27}$$

where C_j denotes the well's drilling cost, r denotes the 10-year risk-free rate, δ corresponds to the project's dividend rate, σ_j^2 is the project's idiosyncratic risk, and ω_t^2 is the natural gas risk.

I follow Brennan and Schwartz (1985) and set the dividend rate (i.e., δ) equal to the natural gas convenience yield. I compute the convenience yield using the natural gas spot and Bloomberg Natural Gas Future prices. Precisely, I obtain the sample average natural gas convenience yield (i.e., δ) such that:

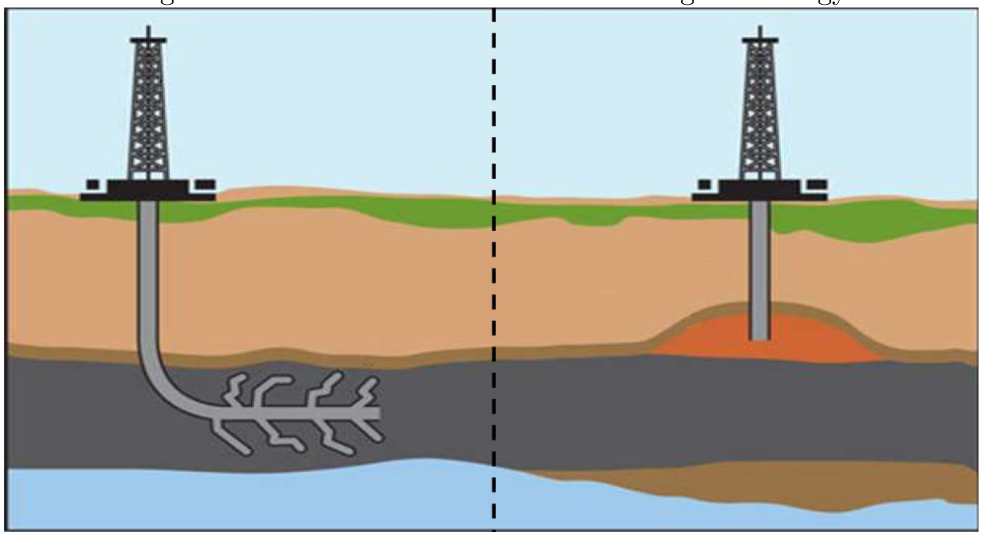
$$\delta = \frac{1}{11} \sum_{t=2000}^{2010} [r_t + \frac{1}{3}(1 - \frac{F_t}{S_t})] \tag{1.28}$$

Where t is the year during which the convenience yield is measure, F_t is the Bloomberg three-year Natural Gas Future Price, and S_t is the spot price.

Finally, I define the project's risks as the combination of the project's idiosyncratic risk (σ_j^2) and price risk (ω_t^2). The project's idiosyncratic risk is the same measure as the one I use throughout the paper. The measure of price risk corresponds to the three-year Bloomberg Natural Gas Futures contract implied volatility. Kellogg (2014) has an extensive discussion on which measure of price uncertainty is best to use in a real option calibration, and concludes that using implied volatility derived from financial derivatives is optimal. However, the financial option for the three-year horizon contracts are not available on Bloomberg before 2000. For this reason, the number of observations used in the regression of this section is smaller than that of the main specification.

Figures

Figure 1: Vertical versus Horizontal Drilling Technology



This figure provides a graphical illustration of the difference between horizontal and vertical wells. Vertical wells represent the older technology, predominantly used in the first part of the American oil and gas development (i.e.; 1900-2005). During the analyzed period, 89% of the gas wells drilled in my sample were completed using the vertical technology.

Figure 2: Panhandle Field (Texas) Development Progress between 1961-2010

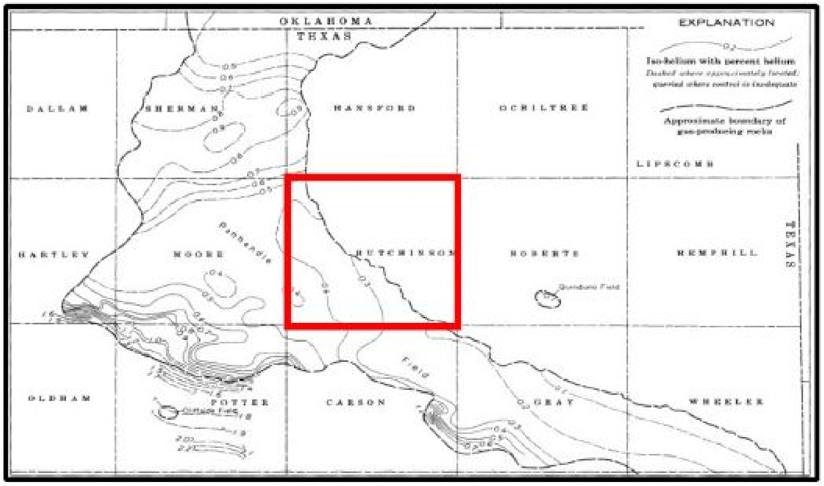


Figure 2.1. 1961 map of approximate boundary of Panhandle oil and gas field producing region. Source: *Anderson and Hinson, 1961; Boone 1958; and G.B. Shelton, U.S. Bureau of Mines, written communication, 1958* .

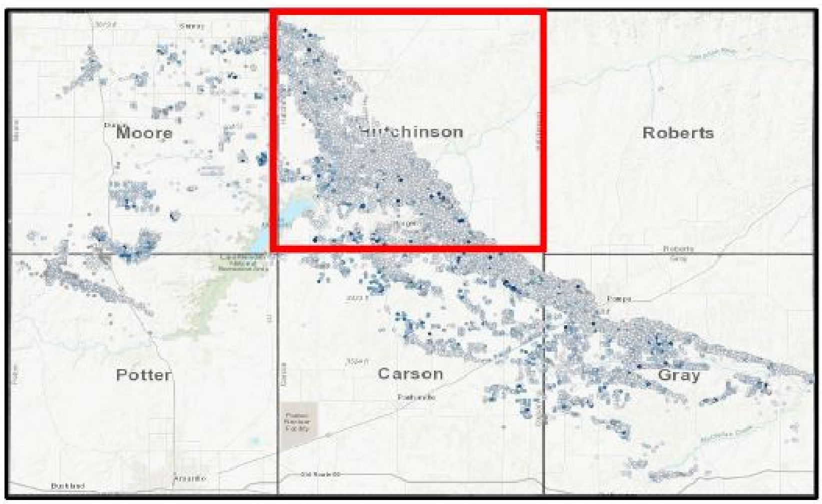


Figure 2.2. 2010 map of cumulative oil and gas wells drilled in the Panhandle field. Each dot represents an individual well. Wells' quality is indicated by a color code. Darker shade of blue indicates wells that were among the most productive of the region, while dots color coded in gray indicate lower level of productivity.

This panel of figures plots the evolution of the Panhandle field development over the period 1961 to 2010. Figure 2.1. provides the initial expectation of the field boundary, based on geological surveys. Figure 2.2. provides an updated view of the field development. The red square indicates the Hutchinson county to help align the surveyor map with the 2010 map.

Figure 3: Excerpt from Energy Firms' 10-K Statement for Ongoing U.S. Activities

UNITED STATES

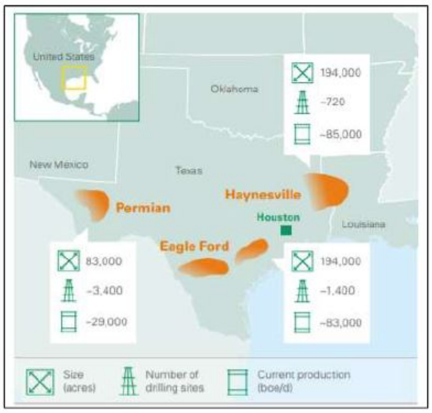
ExxonMobil's year-end 2018 acreage holdings totaled 12.1 million net acres, of which 0.8 million net acres were offshore. ExxonMobil was active in areas onshore and offshore in the lower 48 states and in Alaska.

During the year, 554.6 net exploration and development wells were completed in the inland lower 48 states. Development activities focused on liquids-rich opportunities in the onshore U.S., primarily in the Permian Basin of West Texas and New Mexico and the Bakken oil play in North Dakota. In addition, gas development activities continued in the Marcellus Shale of Pennsylvania and West Virginia, the Utica Shale of Ohio and the Haynesville Shale of East Texas and Louisiana.

ExxonMobil's net acreage in the Gulf of Mexico at year-end 2018 was 0.7 million acres. A total of 3.5 net exploration and development wells were completed during the year.

Participation in Alaska production and development continued with a total of 7.3 net development wells completed.

Panel 3.1: U.S. Upstream Business of Exxon Mobil Corporation (2018).
This figure presents an example of how energy firms break down their exploration and production activities in the United-States. There is a strong focus on geographical detail, often refering to states or fields to define their upstream activities.



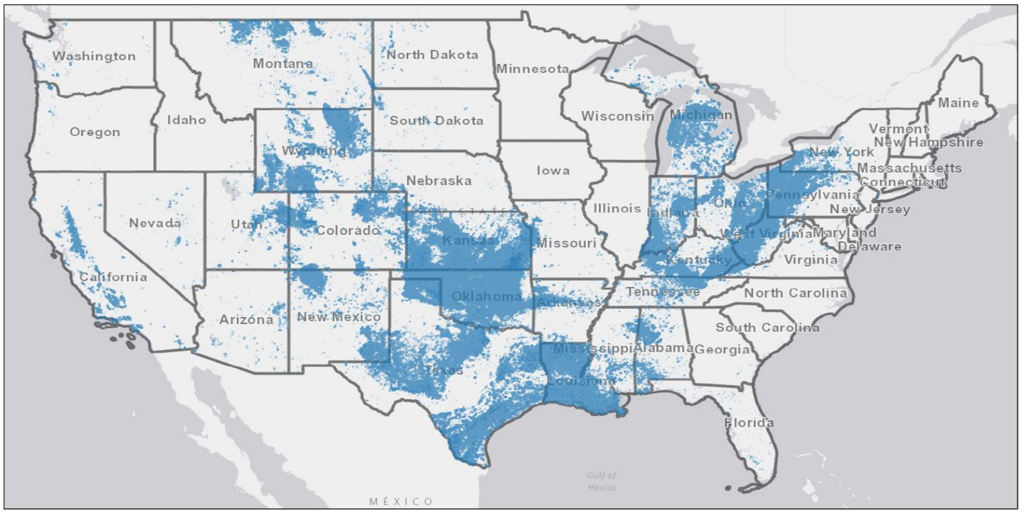
Permian	• Delaware sub-basin of the Permian in West Texas. • 83,000 acres with around 3,400 drilling sites. • Current production – around 29,000boe/d (~70% liquids).
Eagle Ford	• Karnes Trough and Eagle Ford in South Texas. • 194,000 acres with 1,400 gross drilling locations. • Current production – around 83,000boe/d (~70% liquids).
Haynesville	• East Texas and Louisiana. • 194,000 acres with 720 gross drilling locations. • Current production – around 85,000boe/d, all gas.

As at 31 December 2018.

Panel 3.2: U.S. Upstream Business of British Petroleum Plc. (2018).
This figure presents how British Petroleum Plc. breaks down its upstream operations (i.e., exploration and production) in the United-States.

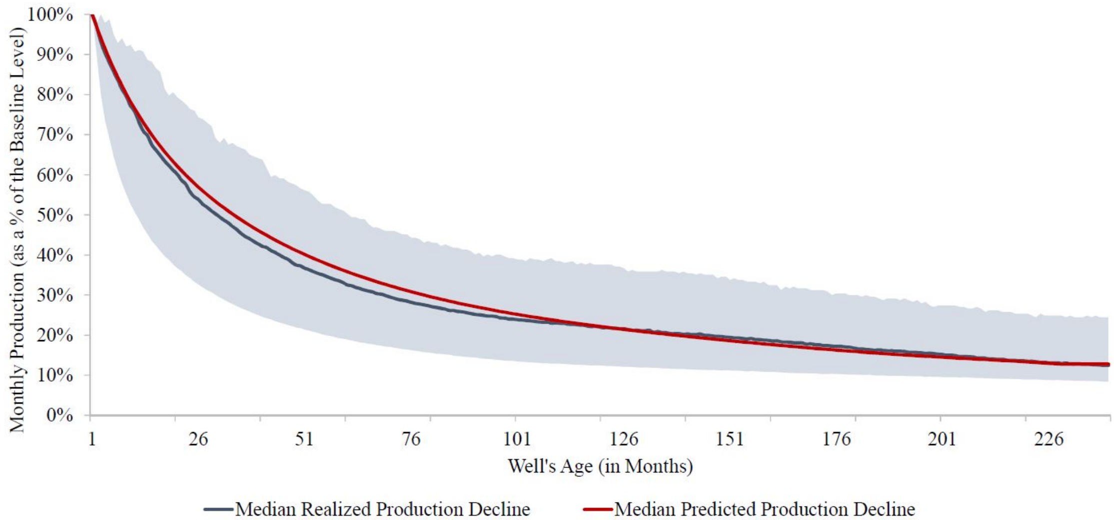
The figures in the two above panels present examples of how energy firms break down and discuss their activities. Those firms rely heavily on geographical boundaries to define their operations, referring to man-made boundaries (i.e., states) or naturally occurring ones (i.e., geological structure) in most cases.

Figure 4: Geographic Distribution of the Vertical Gas Wells



This figure plots the sample of wells included in the analysis. The total sample includes 114,696 vertical gas wells drilled over the period ranging from 1983 to 2010. The map provides information on the regions with the most activity during the analyzed period.

Figure 5: Expected and Realized Well's Production Decline Over Time



This figure plots the wells production decline level over time. The blue line corresponds to the median empirical production, the red line corresponds to the hyperbolic Arp prediction and the shaded area represent the 10th and 90th confidence interval.

Figure 6: Variables Constructed Using the Township-Year Idiosyncratic Productivity Shocks

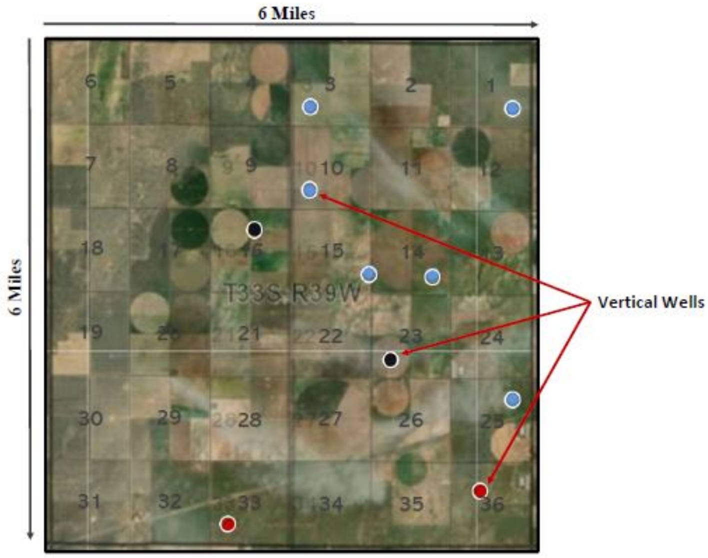


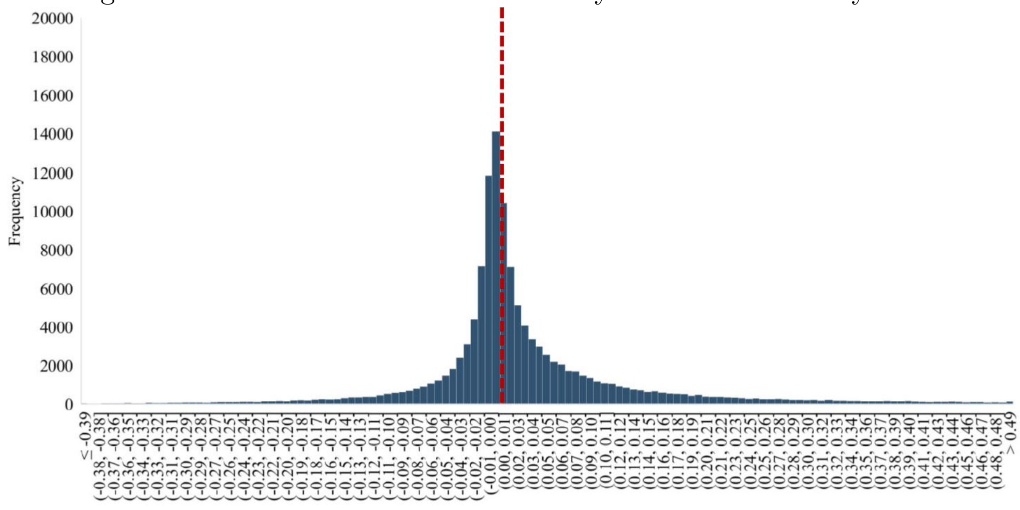
Figure 6.1. Bird Eye View of a Township-Year (Kansas)
This figure plots the wells drilled in the township (33S-39W) in Kansas, for the year 1990 to 1991. A township is a 6 miles by 6 miles square of land. In the Public Land Survey System, each township is constituted of 36 1-squared mile sections. The colored circles represent distinct wells drilled by the three active firms in the township-year (Occidental Petroleum, Linn Energy, and Merit Energy).

	Idiosyncratic Productivity Shocks (ς)		
	Occidental Petroleum	**Linn Energy**	**Merit Energy**
	Red	Blue	Black
(ς_1) Well 1	0.05	-0.22	0.23
(ς_2) Well 2	-0.1	0.1	0.03
(ς_3) Well 3		0.01	
(ς_4) Well 4		0.12	
(ς_5) Well 5		-0.04	
(ς_6) Well 6		0.14	
Largest Peer's Idiosyncratic Productivity Shock	0.23	0.23	0.14
Projects' Idiosyncratic Risk: 0.129			

Figure 6.2: Realized Idiosyncratic Productivity Shocks, Idiosyncratic Risk, and Instrumental Variable
This table presents an example of the realized idiosyncratic productivity shocks for the wells drilled in the township-year, for the three active firms. Sigma (ς) represents the wells' specific idiosyncratic shocks. For each well drilled in the township-year, I determine the well's level measure of idiosyncratic risk, *Projects' Idiosyncratic Risk*, as the cross-sectional standard deviation measured for the township-year (e.g., 0.129). Finally, the instrumental variable, *Largest Peers' Idiosyncratic Productivity Shock*, corresponds to the largest idiosyncratic shocks experienced by a firm's peers. For example, for the Red firm, the largest peers' idiosyncratic shock is 0.23, experienced by the Black firm.

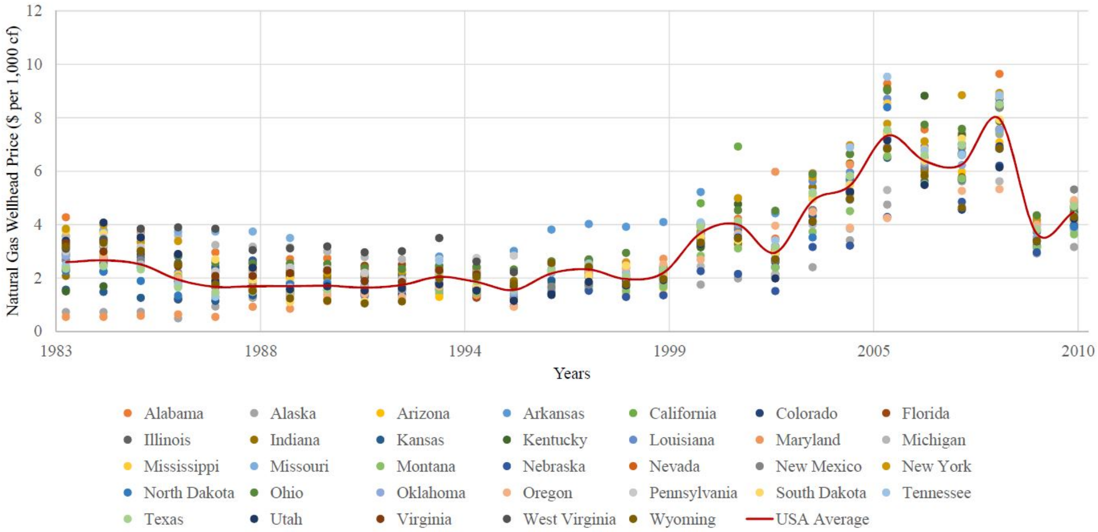
Figure 6.1. presents a simplified example of wells being drilled in a given township-year. In this example, three firms (i.e., Red, Blue, and Black) were active in the township during that specific year. The adjacent table (Figure 6.2) reports an illustrative example of the potential idiosyncratic productivity shock, measured for each well. The instrumental variable used in the paper, Average Largest Peers' Idiosyncratic Productivity Shock, corresponds to the biggest shock that was measured for the firm's peers in its wells' township-year, averaged at the firmyear porfolio level. To obtain the Projects' Average Idiosyncratic Risk , I take the average value of Projects' Idiosyncratic Risk for each firmyear porfolio.

Figure 7: Distribution of the Well's Idiosyncratic Productivity Shocks



This figure plots the distribution of the well's idiosyncratic productivity shocks. The total sample includes 114,696 vertical gas wells drilled over the period ranging from 1983 to 2010. values to the right of the red dashed line indicate positive shocks, while value to the left indicate negative shocks.

Figure 8: Natural Gas Wellhead Price by Region over Time



This figure plots the evolution of yearly natural gas wellhead prices for each producing state over time. Source: `https://www.eia.gov/dnav/ng/ng_prod_whv_a_EPG0_FWA_dpmcf_a.htm`

Figure 9: Firm-Year Portfolio's Projects' Expected IRR Distribution

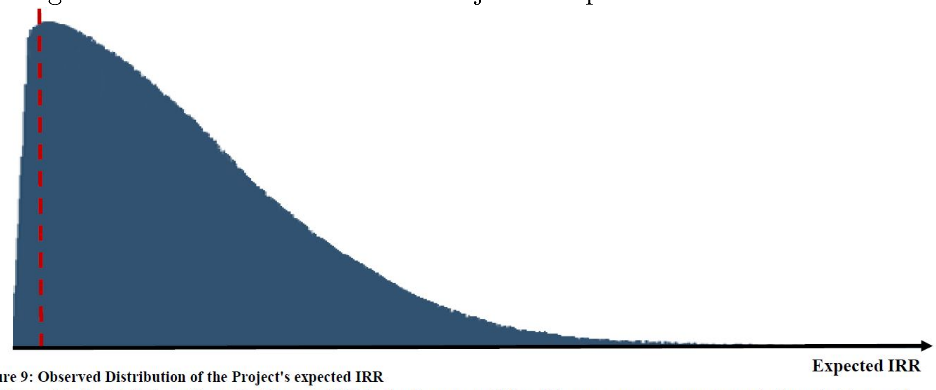


Figure 9: Observed Distribution of the Project's expected IRR
This figure plots the distribution of the projects' expected IRR for the firm-year portfolios. If there was no measurement error in the projects' expected IRR, the observed distribution would cut sharply at the red dotted line. However, because of measurement error in the projects' expected IRR, the tails of the distribution are fatter, and the left tail of the distribution extends beyond the firms *true* cut-off value.

This figure plots the distribution of the projects' expected IRR for the firm-year portfolios. If there was no measurement error in the projects' expected IRR, the observed distribution would cut sharply at the red dotted line. However, because of measurement error in the projects' expected IRR, the tails of the distribution are fatter, and the left tail of the distribution extends beyond the firms true cut-off value.

Tables

Table 1: Summary Statistics of Firms' and Wells' Characteristics

This table reports summary statistics of exploration and production gas companies included in the sample. The time period of the sample is from 1983 to 2010. The sample consists of all firms drilling at least 10 gas wells in the year of analysis, and wells drilled in township-year with at least 3 wells. I exclude from the analysis all wells with missing fields, and wells for which the first production date occurs before the drilling date, as they correspond to data entry error. Panel A reports summary statistics of the firm's characteristics. Panel B reports well-level characteristics used to estimate the Arp model.

	Observation	Mean	Median	Std. Dev.
Panel A: Firm Level Data				
Assets (In millions $)	3,946	229.17	84.87	383.79
Annual Budget (In millions $)	3,946	60.34	22.95	108.80
Annual Budget per Field (In millions $)	3,946	11.30	6.07	17.57
Annual Budget per State (In millions $)	3,946	19.37	10.30	30.09
Number of Firms	369			
	Observation	Mean	Median	Std. Dev.
Panel B: Well Level Data				
Drilling Cost ($)	114,696	465,652.90	402,357.30	299,580.20
Drilling Cost ($ per foot)	114,696	79.07	81.48	6.94
Royalty Rate (%)	114,696	17.32%	18.75%	2.83%
Operational Cost (%)	114,696	20.00%	20.00%	0.00%
Well Total Gas Production (in 1,000 cf)	114,696	570,049.90	177,654.50	1,608,979.00
EIA three-year forecast gas prices (Per 1,000 cf)	114,696	4.05	3.37	1.83

Table 2: Firms' Discount Rate and The Cost of Capital

This table reports coefficient estimates from an OLS regression for the relation between the cost of capital and firms' discount rate, and t-statistics robust to heteroskedasticity and within-firm dependence in bracket. The period of the sample is from 1983 to 2010. The unit of observation in the underlying table is at the firm i, and year t level. The *Industry Cost of Equity* is calculated using the oil and gas industry beta, computed at the monthly frequency on a one-year horizon basis, multiplied by the expected market excess return. The oil and gas industry returns are obtained from Kenneth French web site. Market excess return is approximated using the earning-to-price ratio obtained from Robert Shiller web site. The risk-free rate is the 10-year risk-free rate, obtained from the St-Louis Federal Reserve website. Finally, to compute the *weighted average cost of capital* (WACC), I obtain the cost of debt using firms credit rating reported in Capital IQ. See appendix A.2 for the full methodological details. The variable *Project's Average Idiosyncratic Risk* is scaled by its standard deviation to simplify the lecture of the table and facilitate its comparison with the other regression tables. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Discount Rate (%)$_{i,t,k}$			
	(1)	(2)	(3)	(4)
(β_1) WACC (%)$_{i,t}$	1.403***	1.549***	1.367***	1.325**
	[2.88]	[2.80]	[3.13]	[2.40]
(β_2) Project's Average Idiosyncratic Risk$_{i,t,k}$			11.862***	9.989**
			[3.06]	[2.43]
Firm Fixed Effect$_i$	No	Yes	No	Yes
R-Squared	0.011	0.298	0.152	0.383
F-Statistic	8.308	7.831	19.800	13.866
Observations	748	748	748	748

Table 3: Managers' Project's Idiosyncratic Risk Pricing

This table reports coefficient estimates from an OLS regression for the effect of projects' idiosyncratic risk on firms' discount rate, and t-statistics robust to heteroskedasticity and within-firm dependence in bracket. The time period of the sample is from 1983 to 2010. The unit of observation in the underlying table is at the firm i, year t and portfolio k level. *Project's Average Idiosyncratic Risk* denotes the average projects' idiosyncratic risk measure for each firm-year portfolio (i.e., the high or low idiosyncratic risk portfolio). The variable *Average Natural Gas Production Level* correspond to the wells' total production averaged at the firm-year porfolio level. The variable *Project's Average Idiosyncratic Risk* is scaled by its standard deviation to simplify the lecture of the table and facilitate its comparison with the other regression tables. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Discount Rate (%)$_{i,t,k}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(β_1) Projects' Average Idiosyncratic Risk$_{i,t,k}$	7.968***	7.059***	7.042***	7.013***	7.014***	7.110***	6.681**
	[3.60]	[3.06]	[3.08]	[3.07]	[3.07]	[3.22]	[2.58]
(β_2) Average Natural Gas Production Level$_{i,t,k}$	0.361	0.396*	0.398*	0.403*	0.403*	0.384	0.378
	[1.60]	[1.72]	[1.72]	[1.75]	[1.75]	[1.54]	[1.49]
(β_3) Budget$_{i,t}$			0.008		0.002		
			[0.80]		[0.24]		
(β_4) Assets$_{i,t}$				0.008	0.007		
				[1.40]	[1.62]		
Firm Fixed Effect$_i$	Yes	Yes	Yes	Yes	Yes	No	No
Year Fixed Effect$_t$	No	Yes	Yes	Yes	Yes	No	No
Firm-Year Fixed Effect$_{i,t}$	No	No	No	No	No	Yes	Yes
Portfolio Fixed Effect$_k$	No	No	No	No	No	No	Yes
R-Squared	0.451	0.470	0.471	0.471	0.471	0.738	0.738
F-Statistic	6.942	4.690	6.727	3.671	5.782	6.151	3.713
Observations	3,946	3,946	3,946	3,946	3,946	3,946	3,946

Table 4: Instrumented Regression - Managers' Project's Idiosyncratic Risk Pricing

This table reports the effects of project-level idiosyncratic risk on firms' discount rate based on the exogenous measure of Projects' Average Idiosyncratic Risk from an instrument, and t-statistics robust to heteroskedasticity and within-firm dependence in bracket. The time period of the sample is from 1983 to 2010. The unit of observation in the underlying table is at the firm i, year t, and portfolio k level. The results in Panel A report the first stage coefficient estimates of a two stage OLS regression which uses the average of the firm's peers' largest idiosyncratic productivity shocks of each wells, to instrument for the variable Projects' Average Idiosyncratic Risk. The bottom of Panel A reports the first stage F-statistic on the instrument for the two-stage least-square regression. Panel B reports the second stage regression results of the instrumented model. *Projects' Average Idiosyncratic Risk* denotes the average projects' idiosyncratic risk measure for each firm-year portfolio (i.e., the high or low idiosyncratic risk portfolio). The variable Project's Average Idiosyncratic Risk is scaled by its standard deviation to simplify the lecture of the table and facilitate its comparison with the other regression tables. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Panel A: First Stage	Projects' Average Idiosyncratic Risk$_{i,t,k}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(β_1) Average Largest Peers' Projects' Idiosyncractic Shock$_{i,t,k}$	0.698***	0.706***	0.706***	0.706***	0.706***	0.797***	0.746***
	[11.52]	[11.66]	[11.65]	[11.65]	[11.64]	[14.38]	[13.22]
(β_2) Budget$_{i,t}$			0.000		0.000		
			[0.93]		[0.30]		
(β_3) Assets$_{i,t}$				0.000	0.000		
				[0.89]	[0.53]		
(β_4) Average Natural Gas Production Level$_{i,t,k}$	0.009	0.033***	0.033***	0.033***	0.033***	0.047***	0.033***
	[1.15]	[4.72]	[4.84]	[4.77]	[4.81]	[5.98]	[4.12]
Firm Fixed Effect$_i$	Yes	Yes	Yes	Yes	Yes	No	No
Year Fixed Effect$_t$	No	Yes	Yes	Yes	Yes	No	No
Firm-Year Fixed Effect$_{i,t}$	No	No	No	No	No	Yes	Yes
Portfolio Fixed Effect$_k$	No	No	No	No	No	No	Yes
R-Squared	0.750	0.792	0.792	0.792	0.792	0.903	0.908
Kleibergen-Paap First Stage F-Statistic	111.833	145.591	103.829	97.303	76.646	193.544	104.833

Panel B: Instrumented Regression	Discount Rate (%)$_{i,t,k}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(β_1) Projects' Average Idiosyncratic Risk$_{i,t,k}$	3.819**	4.271***	4.254***	4.231***	4.232***	6.013***	5.102***
	[2.31]	[2.67]	[2.63]	[2.62]	[2.62]	[4.20]	[3.08]
(β_2) Budget$_{i,t}$			0.008		0.004		
			[0.74]		[0.36]		
(β_3) Assets$_{i,t}$				0.006	0.005		
				[1.21]	[1.28]		
(β_4) Average Natural Gas Production Level$_{i,t,k}$	1.075**	1.386***	1.394***	1.399***	1.400***	0.604**	0.451**
	[2.05]	[2.67]	[2.63]	[2.65]	[2.64]	[2.58]	[2.02]
Firm Fixed Effect$_i$	Yes	Yes	Yes	Yes	Yes	No	No
Year Fixed Effect$_t$	No	Yes	Yes	Yes	Yes	No	No
Firm-Year Fixed Effect$_{i,t}$	No	No	No	No	No	Yes	Yes
Portfolio Fixed Effect$_k$	No	No	No	No	No	No	Yes
R-Squared	0.435	0.461	0.461	0.461	0.461	0.730	0.731
F-Statistic	10.022	13.903	12.531	10.131	9.581	32.996	11.198
Observations	3,946	3,946	3,946	3,946	3,946	3,946	3,946

Table 5: Firms' Idiosyncratic Shocks and Peers' Largest Idiosyncratic Shock In Township-Year

This table reports coefficient estimates from an OLS regression for the effect of largest peers' projects' idiosyncratic risk on firms' own idiosyncratic risk, and t-statistics robust to heteroskedasticity, within-firm and within-township dependence in bracket. The time period of the sample is from 1983 to 2010. The unit of observation in the underlying table is at the well j level. Largest Peers' Project's Idiosyncratic Shock denotes the largest projects' idiosyncratic productivity shock of the firms' peers measured for each township-year. The variable *Firm's Project's Idiosyncratic Shock* corresponds to the idiosyncratic productivity shock measured for each well individually. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Firms' Projects' Idiosyncractic Shock$_j$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(β_1) Largest Peers' Projects' Idiosyncractic Shock$_{i,t,p}$	0.044	0.065	0.022	0.043	0.043	0.042	0.017	0.039
	[1.33]	[1.63]	[1.49]	[1.30]	[1.30]	[1.33]	[0.57]	[0.39]
Firm Fixed Effect$_i$	Yes	No	No	Yes	Yes	No	No	No
Year Fixed Effect$_t$	No	Yes	No	Yes	Yes	No	No	No
Township Fixed Effect$_p$	No	No	Yes	No	Yes	No	Yes	No
Firm-Year Fixed Effect$_{i,t}$	No	No	No	No	No	Yes	Yes	Yes
Township-Year Fixed Effect$_{p,t}$	No	No	No	No	No	No	No	Yes
R-Squared	0.105	0.045	0.233	0.112	0.112	0.223	0.336	0.567
F-Statistic	1.758	2.651	2.212	1.689	1.689	1.759	0.329	0.155
Observations	114,969	114,969	114,969	114,969	114,969	114,969	114,969	114,969

Table 6: Firms' Performance and Managers' Idiosyncratic Risk Pricing

This table reports coefficient estimates from an OLS regression for the effect of the price of idiosyncratic risk on firms' performance, and t-statistics robust to heteroskedasticity and within-firm dependence in bracket. The time period of the sample is from 1983 to 2010. The unit of observation in the underlying table is at the firm *i* and year *t* level. The variable *Price of Idiosyncratic Risk* corresponds to the firm's price of idiosyncratic risk computed at a yearly frequency. The dependent variables correspond to the firm *gross profit margin* (%), the *gross profitability* (%), the *YoY asset growth* (%), and the *investment rate* (%), and are winsorized at the 1 and 99 percentiles. The variable *Project's Average Idiosyncratic Risk* is scaled by its standard deviation to simplify the lecture of the table and facilitate its comparison with the other regression tables. Detailed calculation of the four dependent variables is available in appendix A.1. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Gross Profit Margin $(\%)_{i,t}$		Gross Profitability $(\%)_{i,t}$		YoY Asset Growth $(\%)_{i,t+1}$		Investment Rate $(\%)_{i,t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(β_1) Price of Idiosyncratic Risk$_{i,t}$	-5.053**	-5.110**	-0.511**	-0.501**	-0.745*	-0.747*	-0.811*	-0.814*
	[-2.47]	[-2.54]	[-2.04]	[-1.98]	[-1.71]	[-1.71]	[-1.67]	[-1.67]
(β_2) Budget$_{i,t}$		-0.020		-0.055*		0.017		0.024
		[-0.26]		[-1.76]		[1.25]		[1.36]
(β_3) Assets$_{i,t}$		-0.092***		0.008		-0.000		-0.002
		[-3.02]		[0.62]		[-0.05]		[-0.30]
Firm Fixed Effect$_i$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect$_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.530	0.539	0.808	0.809	0.414	0.415	0.431	0.432
F-Statistic	6.097	8.397	4.144	3.259	2.935	2.447	2.801	2.297
Observations	1,973	1,973	1,973	1,973	1,973	1,973	1,973	1,973

Table 7: Managers' Project's Idiosyncratic Risk Pricing and Firms' Size

This table reports coefficient estimates from an OLS regression for the effect of projects' idiosyncratic risk on firms' discount rate, and t-statistics robust to heteroskedasticity and within-firm dependence in bracket. The time period of the sample is from 1983 to 2010. The unit of observation in the underlying table is at the firm i, year t, and portfolio k level. Project's Idiosyncratic Risk denotes the average projects' idiosyncratic risk measure for each firm-year portfolio (i.e., the high or low idiosyncratic risk portfolio). The variable *Firm's Diversification* denotes how much of the wells' idiosyncratic risk drilled in a given year is diversified at the firm's level. The instrumented regression contains up to three instrumented variables, the *Projects' Average Idiosyncratic Risk*, the *Projects' Average Idiosyncratic Risk * Assets*, and for some specifications the *Projects' Average Idiosyncratic Risk * Diversification*. The variable Project's Average Idiosyncratic Risk is scaled by its standard deviation to simplify the lecture of the table and facilitate its comparison with the other regression tables. Detailed calculation of each variable is available in appendix A.1. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Discount Rate (%)$_{i,t,k}$							
	Reduced Form Regression				Instrumented Regression			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(β_1) Projects' Average Idiosyncratic Risk$_{i,t,k}$	3.813***	4.144***	4.832***	4.355***	4.669***	5.001***	6.300***	5.903***
	[4.29]	[4.34]	[4.41]	[4.04]	[3.74]	[3.69]	[4.37]	[3.97]
(β_2) Projects' Average Idiosyncratic Risk$_{i,t,k}$ * Assets$_{i,t}$	-0.004**	-0.004**	-0.007***	-0.007***	-0.008***	-0.008***	-0.010***	-0.010***
	[-2.42]	[-2.34]	[-2.89]	[-2.81]	[-3.05]	[-3.08]	[-3.82]	[-3.74]
(β_3) Assets$_{i,t}$	0.007*	0.007*			0.011**	0.011**		
	[1.92]	[1.92]			[2.23]	[2.23]		
(β_4) Budget$_{i,t}$	-0.006	-0.006			-0.006	-0.006		
	[-1.05]	[-1.09]			[-1.03]	[-1.07]		
(β_5) Firm's Diversification$_{i,t}$		0.005				0.006		
		[0.48]				[0.55]		
(β_6) Projects' Average Idiosyncratic Risk$_{i,t,k}$ * Firm's Diversification$_{i,t}$		-0.030**	-0.019	-0.032		-0.031*	-0.023	-0.033
		[-2.10]	[-1.28]	[-1.45]		[-1.83]	[-1.39]	[-1.55]
(β_7) Average Natural Gas Production Level$_{i,t,k}$	0.860***	0.861***	0.768***	0.637***	0.833***	0.834***	0.680***	0.599***
	[6.25]	[6.26]	[4.56]	[3.70]	[5.22]	[5.24]	[3.59]	[3.27]
Firm Fixed Effect$_i$	Yes	Yes	No	No	Yes	Yes	No	No
Year Fixed Effect$_t$	Yes	Yes	No	No	Yes	Yes	No	No
Firm-Year Fixed Effect$_{i,t}$	No	No	Yes	Yes	No	No	Yes	Yes
Portfolio Fixed Effect$_k$	No	No	No	Yes	No	No	No	Yes
R-Squared	0.717	0.718	0.880	0.881	0.717	0.717	0.879	0.880
F-Statistics	19.280	13.940	25.857	16.659	19.470	14.463	27.323	17.736
Kleibergen-Paap First Stage F-Statistics	N.A.	N.A.	N.A.	N.A.	56.022	34.302	73.83	62.783
Observations	3,946	3,946	3,946	3,946	3,946	3,946	3,946	3,946

Table 8: Year-over-Year Managers' Share of Firm's Budget Variation

This table reports coefficient estimates from an OLS regression for the managers' budget change YoY on the annual region's forecast dispersion, and t-statistics robust to heteroskedasticity, within-firm and within-region (i.e., field or state) dependence in bracket. The time period of the sample is from 1983 to 2010. The unit of observation in the underlying table is at the firm i, year t, and region f level. The sample used in the below regression only includes observations from firms that were *active in more than one region* during the analyzed year. The variable Region's Forecast Dispersion denotes the standard deviation of a firm's wells' drilled in a specific region in a given year. The variable *Managers' Budget Change YoY* corresponds to the change in the managers' share of the firm's budget between two years. For example, a value of 5% would indicate that the firm's budget allocation to the manager's region increased by 5% YoY. The variable *Region's Forecast Dispersion* is scaled by its standard deviation to simplify the lecture of the table and facilitate the comparison between the two potential regions of assignment. Detailed calculation of the regression variables is available in appendix A.1. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Managers' Share of Firm's Budget Change YoY (%)$_{i,t+1,f}$							
	Managers' Budget (Region = Field)				Managers' Budget (Region = State)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(β_1) Region's Forecast Dispersion$_{i,t,f}$	-2.651	-2.246	-5.736**	-6.385*	-5.507*	-5.368*	-9.721**	-7.561*
	[-1.60]	[-1.34]	[-2.10]	[-1.81]	[-1.84]	[-1.77]	[-2.29]	[-1.70]
(β_2) Assets$_{i,t}$	0.030	0.039			-0.001	0.004		
	[1.05]	[1.31]			[-0.03]	[0.09]		
(β_3) Budget$_{i,t}$	0.019	0.003			-0.003	-0.001		
	[1.56]	[0.23]			[-0.17]	[-0.02]		
Firm Fixed Effect$_i$	Yes	Yes	No	No	Yes	Yes	No	No
Year Fixed Effect$_t$	No	Yes	No	No	No	Yes	No	No
Firm-Year Fixed Effect$_{i,t}$	No	No	Yes	Yes	No	No	Yes	Yes
Region-Year Fixed Effect$_{i,t}$	No	No	No	Yes	No	No	No	Yes
R-Squared	0.09	0.11	0.49	0.54	0.04	0.05	0.23	0.25
F-Statistic	8.315	2.643	4.428	3.262	1.134	1.075	5.227	2.874
Observations	6,374	6,374	6,374	6,374	4,419	4,419	4,419	4,419

Table 9: Managers' Project's Idiosyncratic Risk Pricing and Managers' Budget - Fields

This table reports coefficient estimates from an OLS regression for the effect of projects' idiosyncratic risk on firms' discount rate, and t-statistics robust to heteroskedasticity and within-firm dependence in bracket. The time period of the sample is from 1983 to 2010. The unit of observation in the underlying table is at the firm i, year t, and portfolio k level. *Project's Average Idiosyncratic Risk* denotes the average projects' idiosyncratic risk measure for each firm-year portfolio (i.e., the high or low idiosyncratic risk portfolio). The variable *Managers' Average Budget* corresponds to the managers budget size averaged at the firm-year level, when assuming that managers are assigned to distinct fields. The instrumented regression contains two instrumented variables, the *Projects' Average Idiosyncratic Risk* and the *Projects' Average Idiosyncratic Risk * Managers' Average Budget*. The variable Project's Average Idiosyncratic Risk is scaled by its standard deviation to simplify the lecture of the table and facilitate its comparison with the other regression tables. Detailed calculation of the regression variables is available in appendix A.1. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Discount Rate (%)$_{i,t,k}$							
	Reduced Form Regression				Instrumented Regression			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(β_1) Projects' Average Idiosyncratic Risk$_{i,t,k}$	6.410***	6.409***	7.426***	6.872***	6.512***	6.509***	8.300***	7.861***
	[3.43]	[3.43]	[3.59]	[3.31]	[3.71]	[3.71]	[4.65]	[4.18]
(β_2) Projects' Average Idiosyncratic Risk$_{i,t,k}$ * Managers' Average Budget$_{i,t}$	-0.061**	-0.061**	-0.118***	-0.119***	-0.064**	-0.064**	-0.110***	-0.109***
	[-2.09]	[-2.09]	[-2.99]	[-2.96]	[-2.34]	[-2.33]	[-3.57]	[-3.45]
(β_3) Assets$_{i,t}$	0.002	0.002			0.002	0.002		
	[0.68]	[0.82]			[0.64]	[0.81]		
(β_4) Budget$_{i,t}$		-0.002				-0.002		
		[-0.26]				[-0.26]		
(β_5) Managers' Average Budget$_{i,t}$	0.044	0.047			0.046	0.049		
	[1.37]	[1.40]			[1.29]	[1.27]		
(β_6) Average Natural Gas Production Level$_{i,t,k}$	1.270***	1.269***	0.711**	0.552	1.263***	1.262***	0.571*	0.477
	[5.63]	[5.59]	[2.14]	[1.64]	[4.44]	[4.42]	[1.81]	[1.50]
Firm Fixed Effect$_i$	Yes	Yes	No	No	Yes	Yes	No	No
Year Fixed Effect$_t$	Yes	Yes	No	No	Yes	Yes	No	No
Firm-Year Fixed Effect$_{i,t}$	No	No	Yes	Yes	No	No	Yes	Yes
Portfolio Fixed Effect$_k$	No	No	No	Yes	No	No	No	Yes
R-Squared	0.615	0.615	0.836	0.836	0.615	0.615	0.835	0.836
F-Statistic	9.105	10.592	18.681	11.492	10.105	11.071	21.383	12.241
Kleibergen-Paap First Stage F-Statistic	N.A.	N.A.	N.A.	N.A.	70.322	70.293	114.279	90.530
Observations	3,946	3,946	3,946	3,946	3,946	3,946	3,946	3,946

Table 10: Managers' Project's Idiosyncratic Risk Pricing and Managers' Budget - Agency Effect

This table reports coefficient estimates from an OLS regression for the effect of projects' idiosyncratic risk on firms' discount rate, and t-statistics robust to heteroskedasticity and within-firm dependence in bracket. The time period of the sample is from 1983 to 2010. The unit of observation in the underlying table is at the firm i, year t, and portfolio k level. *Project's Average Idiosyncratic Risk* denotes the average projects' idiosyncratic risk measure for each firm-year portfolio (i.e., the high or low idiosyncratic risk portfolio). The variable *Managers' Average Budget* corresponds to the managers budget size averaged at the firm-year level. Column (1) to (4) reports the results when assuming that managers are assigned to specific fields, and columns (5) to (8) report to results when assuming that managers are assigned to different states. The variable *Distance* denotes the median distance between the firms' wells drilled during a given year in hundreds of miles, *winsorised at the* 5^{th} *and* 95^{th} *percentile*. The variable *Project's Average Idiosyncratic Risk* is scaled by its standard deviation to simplify the lecture of the table and facilitate its comparison with the other regression tables. Detailed calculation of the regression variables is available in appendix A.1. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Discount Rate $(\%)_{i,t,k}$							
	Managers' Budget (Region = Field)				Managers' Budget (Region = State)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(β_1) Projects' Average Idiosyncratic Risk$_{i,t,k}$	7.429***	7.393***	8.298***	8.118***	7.249***	7.216***	7.965***	7.789***
	[3.37]	[3.35]	[3.55]	[3.21]	[3.38]	[3.36]	[3.49]	[3.14]
(β_2) Projects' Average Idiosyncratic Risk$_{i,t,k}$ * Managers' Average Budget$_{i,t}$	-0.062*	-0.057	-0.089**	-0.093**	-0.037	-0.030	-0.044*	-0.046*
	[-1.68]	[-1.64]	[-2.09]	[-2.24]	[-1.61]	[-1.46]	[-1.82]	[-1.96]
(β_3) Projects' Average Idiosyncratic Risk$_{i,t,k}$ * Managers' Average Budget$_{i,t}$ * Distance$_{i,t}$	-0.088**	-0.092**	-0.087*	-0.084*	-0.044**	-0.048**	-0.044*	-0.043
	[-2.44]	[-2.38]	[-1.88]	[-1.73]	[-2.16]	[-2.22]	[-1.67]	[-1.55]
(β_4) Assets$_{i,t}$		0.003				0.005		
		[0.56]				[1.03]		
(β_5) Budget$_{i,t}$		0.006				0.010		
		[0.71]				[1.03]		
(β_6) Managers' Average Budget$_{i,t}$	0.097*	0.072			0.047*	0.013		
	[1.86]	[1.49]			[1.83]	[0.51]		
(β_7) Distance$_{i,t}$	0.295	0.336			0.314	0.330		
	[0.55]	[0.63]			[0.59]	[0.61]		
(β_8) Managers' Average Budget$_{i,t}$ * Distance$_{i,t}$	0.037	0.031			0.006	0.007		
	[0.70]	[0.61]			[0.20]	[0.26]		
(β_9) Projects' Average Idiosyncratic Risk$_{i,t,k}$ * Distance$_{i,t}$	0.229	0.278	0.673	0.587	0.295	0.359	0.762	0.683
	[0.23]	[0.28]	[0.62]	[0.51]	[0.30]	[0.35]	[0.70]	[0.59]
(β_{10}) Average Natural Gas Production Level$_{i,t,k}$	0.886***	0.902***	0.578***	0.547***	0.884***	0.911***	0.600***	0.570***
	[4.31]	[4.28]	[3.49]	[3.41]	[4.35]	[4.34]	[3.66]	[3.53]
Firm Fixed Effect$_i$	Yes	Yes	No	No	Yes	Yes	No	No
Year Fixed Effect$_t$	Yes	Yes	No	No	Yes	Yes	No	No
Firm-Year Fixed Effect$_{i,t}$	No	No	Yes	Yes	No	No	Yes	Yes
Portfolio Fixed Effect$_k$	No	No	No	Yes	No	No	No	Yes
R-Squared	0.624	0.624	0.840	0.840	0.624	0.625	0.840	0.840
F-Statistic	4.309	4.169	8.964	6.096	4.085	3.839	9.192	6.314
Observations	3,946	3,946	3,946	3,946	3,946	3,946	3,946	3,946

Table 11: Managers' Project's Idiosyncratic Risk Pricing, Internal Agency Frictions and Costly External Financing

This table reports coefficient estimates from an OLS regression for the effect of projects' idiosyncratic risk on firms' discount rate, and t-statistics robust to heteroskedasticity and within-firm dependence in bracket. The time period of the sample is from 1983 to 2010. The unit of observation in the underlying table is at the firm i, year t, and portfolio k level. *Project's Average Idiosyncratic Risk* denotes the average projects' idiosyncratic risk measure for each firm-year portfolio (i.e., the high or low idiosyncratic risk portfolio). The variable *Firm's Diversification* denotes how much of the wells' idiosyncratic risk drilled in a given year is diversified at the firm's level. The variable *Managers' Average Budget* corresponds to the managers budget size averaged at the firm-year level. Column (1) to (4) reports the results when assuming that managers are assigned to specific fields, and columns (5) to (8) report to results when assuming that managers are assigned to different states. The variable *Project's Average Idiosyncratic Risk* is scaled by its standard deviation to simplify the lecture of the table and facilitate its comparison with the other regression tables. Detailed calculation of the regression variables is available in appendix A.1. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Discount Rate (%)$_{i,t,k}$							
	Managers' Budget (Region = Field)				Managers' Budget (Region = State)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(β_1) Projects' Average Idiosyncratic Risk$_{i,t,k}$	10.542**	10.531**	12.428**	11.880**	11.077**	11.059**	12.678**	12.143**
	[2.49]	[2.50]	[2.39]	[2.31]	[2.52]	[2.54]	[2.40]	[2.32]
(β_2) Projects' Average Idiosyncratic Risk$_{i,t,k}$ * Assets$_{i,t}$	-0.015*	-0.015**	-0.018**	-0.017**	-0.016**	-0.015**	-0.019***	-0.018***
	[-1.96]	[-1.98]	[-2.45]	[-2.40]	[-2.09]	[-2.10]	[-2.68]	[-2.65]
(β_3) Assets$_{i,t}$	0.016*	0.015**			0.019*	0.018*		
	[1.74]	[1.99]			[1.76]	[1.89]		
(β_4) Managers' Average Budget$_{i,t}$	0.068	0.063			0.043	0.035		
	[1.02]	[1.02]			[0.95]	[0.89]		
(β_5) Managers' Average Budget$_{i,t}$ * Assets$_{i,t}$	-0.000	-0.000			-0.000	-0.000		
	[-1.45]	[-1.51]			[-1.60]	[-1.61]		
(β_6) Projects' Average Idiosyncratic Risk$_{i,t,k}$ * Managers' Average Budget$_{i,t}$	-0.111*	-0.111*	-0.220**	-0.217**	-0.106**	-0.105**	-0.154**	-0.153**
	[-1.75]	[-1.79]	[-2.09]	[-2.07]	[-2.00]	[-2.02]	[-2.05]	[-2.02]
(β_7) Projects' Average Idiosyncratic Risk$_{i,t,k}$ * Managers' Average Budget$_{i,t}$ * Assets$_{i,t}$ / 1000	0.021	0.021	0.034*	0.033*	0.016*	0.016**	0.023**	0.022**
	[1.59]	[1.64]	[1.87]	[1.82]	[1.94]	[1.98]	[2.21]	[2.17]
(β_8) Budget$_{i,t}$		0.003				0.006		
		[0.26]				[0.52]		
(β_9) Firm's Diversification$_{i,t}$	0.003	0.003			0.001	0.001		
	[0.24]	[0.24]			[0.10]	[0.09]		
(β_{10}) Projects' Average Idiosyncratic Risk$_{i,t,k}$ * Firm's Diversification$_{i,t}$	-0.082*	-0.082*	-0.072	-0.086	-0.083*	-0.083*	-0.073	-0.087
	[-1.68]	[-1.69]	[-1.30]	[-1.36]	[-1.72]	[-1.73]	[-1.33]	[-1.39]
(β_{11}) Average Natural Gas Production Level$_{i,t,k}$	1.202***	1.204***	0.504	0.361	1.209***	1.215***	0.515	0.375
	[3.89]	[3.83]	[1.51]	[1.06]	[3.89]	[3.81]	[1.55]	[1.10]
Firm Fixed Effect$_i$	Yes	Yes	No	No	Yes	Yes	No	No
Year Fixed Effect$_t$	Yes	Yes	No	No	Yes	Yes	No	No
Firm-Year Fixed Effect$_{i,t}$	No	No	Yes	Yes	No	No	Yes	Yes
Portfolio Fixed Effect$_k$	No	No	No	Yes	No	No	No	Yes
R-Squared	0.470	0.470	0.737	0.737	0.472	0.472	0.737	0.738
F-Statistic	2.642	4.289	9.531	6.280	2.501	3.986	9.314	6.085
Observations	3,946	3,946	3,946	3,946	3,946	3,946	3,946	3,946

Table 12: Managers' Project's Idiosyncratic Risk Pricing - Real Option Effect (1)

This table reports coefficient estimates from an OLS regression for the effect of projects' idiosyncratic risk on firms' discount rate, and t-statistics robust to heteroskedasticity and within-firm dependence in bracket.. The time period of the sample is from 1983 to 2010. The unit of observation in the underlying table is at the firm *i*, year *t*, and portfolio *k* level. In this regression specification, the analysis is only performed on a subsample of projects for which the time to expiration is expected to be close to zero, making the real option optimal exercise threshold (V*) close to the projects investment cost (I). The variable *Project's Average Idiosyncratic Risk* is scaled by its standard deviation to simplify the lecture of the table and facilitate its comparison with the other regression tables. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Discount Rate (%)$_{i,t,k}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(β_1) Projects' Average Idiosyncratic Risk$_{i,t,k}$	6.228***	5.256***	5.230***	5.243***	5.232***	5.514***	4.241***
	[5.32]	[4.51]	[4.51]	[4.51]	[4.50]	[4.89]	[3.28]
(β_2) Budget$_{i,t}$			0.006		0.008		
			[1.56]		[1.60]		
(β_3) Assets$_{i,t}$				0.001	-0.001		
				[0.91]	[-0.46]		
(β_4) Average Natural Gas Production Level$_{i,t,k}$	0.288***	0.288***	0.289***	0.290***	0.288***	0.229**	0.189*
	[3.20]	[3.23]	[3.25]	[3.29]	[3.25]	[2.33]	[1.93]
Firm Fixed Effect$_i$	Yes	Yes	Yes	Yes	Yes	No	No
Year Fixed Effect$_t$	No	Yes	Yes	Yes	Yes	No	No
Firm-Year Fixed Effect$_{i,t}$	No	No	No	No	No	Yes	Yes
Portfolio Fixed Effect$_k$	No	No	No	No	No	No	Yes
R-Squared	0.64	0.67	0.67	0.67	0.67	0.84	0.84
F-Statistic	15.082	12.093	8.220	8.255	6.242	14.700	6.632
Observations	1,642	1,642	1,642	1,642	1,642	1,642	1,642

Table 13: Managers' Project-Level Idiosyncratic Risk Pricing - Leverage Effect

This table reports coefficient estimates from an OLS regression for the effect of projects' idiosyncratic risk on firms' discount rate, and t-statistics robust to heteroskedasticity and within-firm dependence in bracket. The time period of the sample is from 1983 to 2010. The unit of observation in the underlying table is at the firm i, year t, and portfolio k level. The *Leverage* variable corresponds to the firms' market leverage calculated using the firm 10-k annual statement and stock market data. Detailed calculations are available in appendix A.2. The analysis is restricted to the set of firms available in Compustat for which the necessary variables were available. The variable *Project's Average Idiosyncratic Risk* is scaled by its standard deviation to simplify the lecture of the table and facilitate its comparison with the other regression tables. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Discount Rate (%)$_{i,t,k}$			
	(1)	(2)	(3)	(4)
(β_1) Projects' Average Idiosyncratic Risk$_{i,t,k}$	6.110**	6.261**	4.372**	4.416**
	[2.53]	[2.53]	[2.13]	[2.04]
(β_2) Budget$_{i,t}$		-0.010		
		[-1.34]		
(β_3) Assets$_{i,t}$	0.002	0.008		
	[0.38]	[1.15]		
(β_4) Leverage$_{i,t}$	-6.581	-5.588		
	[-1.25]	[-1.06]		
(β_5) Leverage$_{i,t}$ * Projects' Average Idiosyncratic Risk$_{i,t,k}$	6.459	6.184	17.000**	17.319**
	[0.77]	[0.72]	[2.13]	[2.16]
(β_6) Average Natural Gas Production Level$_{i,t,k}$	0.371*	0.368*	0.313	0.322
	[1.78]	[1.79]	[1.42]	[1.29]
Firm Fixed Effect$_i$	Yes	Yes	No	No
Year Fixed Effect$_t$	Yes	Yes	No	No
Firm-Year Fixed Effect$_{i,t}$	No	No	Yes	Yes
Portfolio Fixed Effect$_k$	No	No	No	Yes
R-Squared	0.644	0.631	0.828	0.828
F-Statistic	5.039	4.920	9.000	5.404
Observations	918	918	918	918

Table 14: Managers' Project's Idiosyncratic Risk Pricing - Futures Price

This table reports coefficient estimates from an OLS regression for the effect of projects' idiosyncratic risk on firms' discount rate, and t-statistics robust to heteroskedasticity and within-firm dependence in bracket. The time period of the sample is from 1995 to 2010. The unit of observation in the underlying table is at the firm i, year t, and portfolio k level. *Project's Average Idiosyncratic Risk* denotes the average projects' idiosyncratic risk measure for each firm-year portfolio (i.e., the high or low idiosyncratic risk portfolio). In this regression specification, the project's internal rate of return is estimated using the *36-month Bloomberg Natural Gas Futures* prices instead of the EIA three-year price forecast. The variable *Project's Average Idiosyncratic Risk* is scaled by its standard deviation to simplify the lecture of the table and facilitate its comparison with the other regression tables. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Discount Rate (%)$_{i,t,k}$				
	(1)	(2)	(3)	(4)	(5)
(β_1) Projects' Average Idiosyncratic Risk$_{i,t,k}$	7.153***	7.149***	7.145***	7.304***	6.228***
	[3.74]	[3.75]	[3.74]	[4.24]	[3.29]
(β_2) Budget$_{i,t}$	-0.003		-0.006		
	[-0.52]		[-0.80]		
(β_3) Assets$_{i,t}$		0.001	0.003		
		[0.12]	[0.48]		
(β_4) Average Natural Gas Production Level$_{i,t,k}$	0.736*	0.736*	0.737*	0.763	0.728
	[1.76]	[1.76]	[1.76]	[1.37]	[1.30]
Firm Fixed Effect$_i$	Yes	Yes	Yes	No	No
Year Fixed Effect$_t$	Yes	Yes	Yes	No	No
Firm-Year Fixed Effect$_{i,t}$	No	No	No	Yes	Yes
Portfolio Fixed Effect$_k$	No	No	No	No	Yes
R-Squared	0.548	0.548	0.548	0.784	0.784
F-Statistic	6.504	5.021	5.332	8.985	5.404
Observations	3,416	3,416	3,416	3,416	3,416

Table 15: Managers' Project's Idiosyncratic Risk Pricing - EIA State's Wellhead Price

This table reports coefficient estimates from an OLS regression for the effect of projects' idiosyncratic risk on firms' discount rate, and t-statistics robust to heteroskedasticity and within-firm dependence in bracket. The time period of the sample is from 1983 to 2010. The unit of observation in the underlying table is at the firm i, year t, and portfolio k level. *Project's Average Idiosyncratic Risk* denotes the average projects' idiosyncratic risk measure for each firm-year portfolio (i.e., the high or low idiosyncratic risk portfolio). In this regression specification, the project's internal rate of return is estimated using the wellhead spot price specific to each state (Source: https://www.eia.gov/dnav/ng/ng_prod_whv_a_epg0_fwa_dpmcf_a.htm) instead of the EIA price forecast. The variable *Project's Average Idiosyncratic Risk* is scaled by its standard deviation to simplify the lecture of the table and facilitate its comparison with the other regression tables. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Discount Rate (%)$_{i,t,k}$				
	(1)	(2)	(3)	(4)	(5)
(β_1) Projects' Average Idiosyncratic Risk$_{i,t,k}$	7.162***	7.158***	7.166***	7.200***	6.410***
	[3.32]	[3.31]	[3.29]	[3.40]	[2.76]
(β_2) Budget$_{i,t}$	0.007		0.008		
	[0.70]		[0.49]		
(β_3) Assets$_{i,t}$		0.002	-0.001		
		[0.68]	[-0.15]		
(β_4) Average Natural Gas Production Level$_{i,t,k}$	0.690*	0.692*	0.689*	0.547*	0.519
	[1.82]	[1.83]	[1.84]	[1.67]	[1.56]
Firm Fixed Effect$_i$	Yes	Yes	Yes	No	No
Year Fixed Effect$_t$	Yes	Yes	Yes	No	No
Firm-Year Fixed Effect$_{i,t}$	No	No	No	Yes	Yes
Portfolio Fixed Effect$_k$	No	No	No	No	Yes
R-Squared	0.469	0.469	0.469	0.738	0.739
F-Statistic	6.512	5.117	6.083	7.701	4.737
Observations	3,946	3,946	3,946	3,946	3,946

Table 16: Managers' Project's Idiosyncratic Risk Pricing - Alternative Design

This table reports coefficient estimates from an OLS regression for the effect of projects' idiosyncratic risk on firms' discount rate, and t-statistics robust to heteroskedasticity and within-firm dependence in bracket. The time period of the sample is from 1983 to 2010. The unit of observation in the underlying table is at the firm i, and year t level. *Projects' Average Idiosyncratic Risk* denotes the average projects' idiosyncratic risk measure for each firm-year, scaled by its standard deviation (i.e., one portfolio per firm-year). The variable *Project's Average Idiosyncratic Risk* is scaled by its standard deviation to simplify the lecture of the table and facilitate its comparison with the other regression tables. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Discount Rate $(\%)_{i,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
(β_1) Projects' Average Idiosyncratic $\text{Risk}_{i,t}$	11.043***	7.015***	5.689***	5.695***	5.679***	5.678***
	[6.49]	[6.45]	[5.81]	[5.82]	[5.80]	[5.79]
(β_2) $\text{Budget}_{i,t}$				-0.003		-0.007
				[-0.80]		[-1.11]
(β_3) $\text{Assets}_{i,t}$					0.002	0.004
					[0.59]	[1.06]
(β_4) Average Natural Gas Production $\text{Level}_{i,t,k}$	0.689***	0.040	0.155**	0.153**	0.156**	0.153**
	[3.39]	[0.64]	[2.50]	[2.49]	[2.55]	[2.52]
Firm Fixed Effect_i	No	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect_t	No	No	Yes	Yes	Yes	Yes
R-Squared	0.320	0.718	0.745	0.746	0.746	0.746
F-Statistic	29.718	21.326	22.429	14.992	16.697	12.601
Observations	1,973	1,973	1,973	1,973	1,973	1,973

Table 17: Managers' Project's Idiosyncratic Risk Pricing - Alternative Threshold Value

This table reports coefficient estimates from an OLS regression for the effect of projects' idiosyncratic risk on firms' discount rate, and t-statistics robust to heteroskedasticity and within-firm dependence in bracket. The time period of the sample is from 1983 to 2010. The unit of observation in the underlying table is at the firm i, year t level, and portfolio k level. The columns' titles refer to the firm-year porfolio percentiles of the idiosyncratic risk distribution used to compute the estimated discount rate. For example, the columns with *Minimum Bound* indicate that only to lowest projects' expected IRR was used to estimate the discount rate. *Projects' Average Idiosyncratic Risk* denotes the average projects' idiosyncratic risk measure for each firm-year, scaled by its standard deviation (i.e., one portfolio per firm-year). The variable *Project's Average Idiosyncratic Risk* is scaled by its standard deviation to simplify the lecture of the table and facilitate its comparison with the other regression tables. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Discount Rate (%)$_{i,t,k}$							
	Minimum Bound				0^{th} to 2.5^{th} Percentile			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(β_1) Projects' Average Idiosyncratic Risk$_{i,t,k}$	6.372***	6.402***	6.672***	6.070**	6.623***	6.625***	6.849***	6.261**
	[2.92]	[2.92]	[3.03]	[2.50]	[2.98]	[2.98]	[3.05]	[2.51]
(β_2) Budget$_{i,t}$		0.001				0.004		
		[0.04]				[0.24]		
(β_3) Assets$_{i,t}$		-0.002				-0.001		
		[-0.54]				[-0.22]		
(β_4) Average Natural Gas Production Level$_{i,t,k}$	0.669*	0.663*	0.493*	0.471*	0.659*	0.658*	0.494*	0.472*
	[1.94]	[1.93]	[1.80]	[1.68]	[1.91]	[1.93]	[1.81]	[1.69]
Firm Fixed Effect$_i$	Yes	Yes	No	No	Yes	Yes	No	No
Year Fixed Effect$_t$	Yes	Yes	No	No	Yes	Yes	No	No
Firm-Year Fixed Effect$_{i,t}$	No	No	Yes	Yes	No	No	Yes	Yes
Portfolio Fixed Effect$_k$	No	No	No	Yes	No	No	No	Yes
R-Squared	0.463	0.463	0.730	0.731	0.464	0.464	0.731	0.731
F-Statistic	5.246	10.583	5.147	3.335	5.542	7.739	5.186	3.363
Observations	3,946	3,946	3,946	3,946	3,946	3,946	3,946	3,946

Table 18: Managers' Project's Idiosyncratic Risk Pricing - Time Trend

This table reports coefficient estimates from an OLS regression for the effect of projects' idiosyncratic risk on firms' discount rate, and t-statistics robust to heteroskedasticity and within-firm dependence in bracket. The time period of the sample is from 1983 to 2010. The unit of observation in the underlying table is at the firm i, year t and portfolio k level. *Project's Average Idiosyncratic Risk* denotes the average projects' idiosyncratic risk measure for each firm-year portfolio (i.e., the high or low idiosyncratic risk portfolio). Specifically, the variables $Decade_{1990}$ and $Decade_{2000}$ denote dummy variables equal to 1 if the observation occured in that decade, and zero otherwise. The variable *Project's Average Idiosyncratic Risk* is scaled by its standard deviation to simplify the lecture of the table and facilitate its comparison with the other regression tables. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Discount Rate $(\%)_{i,t,k}$					
	(1)	(2)	(3)	(4)	(5)	(6)
(β_1) Projects' Average Idiosyncratic Risk$_{i,t,k}$	8.261***	8.251***	8.266***	8.242***	9.515***	8.670***
	[2.71]	[2.70]	[2.72]	[2.70]	[3.01]	[2.68]
(β_2) Budget$_{i,t}$		-0.002		-0.004		
		[-0.44]		[-1.01]		
(β_3) Assets$_{i,t}$			0.002	0.003		
			[0.71]	[1.10]		
(β_4) Projects' Average Idiosyncratic Risk$_{i,t,k}$ * Decade$_{1990}$	-2.257	-2.250	-2.272	-2.268	-2.888	-3.297
	[-0.94]	[-0.93]	[-0.95]	[-0.95]	[-1.17]	[-1.35]
(β_5) Projects' Average Idiosyncratic Risk$_{i,t,k}$ * Decade$_{2000}$	-4.608	-4.593	-4.624	-4.594	-5.843*	-5.723*
	[-1.56]	[-1.55]	[-1.57]	[-1.56]	[-1.87]	[-1.82]
(β_6) Average Natural Gas Production Level$_{i,t,k}$	0.282***	0.282***	0.284***	0.284***	0.208**	0.184**
	[3.56]	[3.55]	[3.59]	[3.60]	[2.58]	[2.27]
Firm Fixed Effect$_i$	Yes	Yes	Yes	Yes	No	No
Year Fixed Effect$_t$	Yes	Yes	Yes	Yes	No	No
Firm-Year Fixed Effect$_{i,t}$	No	No	No	No	Yes	Yes
Portfolio Fixed Effect$_k$	No	No	No	No	No	Yes
R-Squared	0.704	0.704	0.704	0.704	0.873	0.874
F-Statistic	9.393	7.847	7.843	7.298	10.567	6.266
Observations	3,946	3,946	3,946	3,946	3,946	3,946

Table 19: Arp Model Estimation

This table reports coefficient estimates from an OLS regression, and t-statistics robust to heteroskedasticity and within-firm dependence in bracket. The period of the sample is from 1983 to 2010. The unit of observation in the underlying table is at the well j and well's age m (in month) level. Subscript p denotes specific township, and subscript t indicates the year well j was drilled. The *Age* variable corresponds to the well age m (in month) raise to the power of the superscript. For example, Age^2 denotes the well's age in month raised to the power of 2. The variable $Depth_j$ denotes the natural logarithm of the well's total vertical depth in foot. The variable Local $Information_j$ corresponds to the natural log of the number of wells drilled in well j's township at the moment of drilling well j. The variable Firm's Local $Experience_j$ denotes the natural log of the total number of wells drilled by firm i in well j's township, at the moment of drilling well j. Firm Total $Experience_j$ represent the natural log of the total number of wells drilled by firm i, at the time of drilling well j. The precision of those coefficient is important to properly match the realized production data. For this reason, I allow for 21 digits. See appendix B for a complete description of the model derivation. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Ln(Gas Well Monthly $Production_{j,m}$)
(β_1) Age^1	-0.046123952293677099312230***
	[-205.33]
(β_2) Age^2	0.000802229619753800043784***
	[73.52]
(β_3) Age^3	-0.000011060405281200000582***
	[-46.35]
(β_4) Age^4	0.000000095973699714300002***
	[35.72]
(β_5) Age^5	-0.000000000484147915426000***
	[-29.96]
(β_6) Age^6	0.000000000001290652064010***
	[26.20]
(β_7) Age^7	-0.000000000000001402168849***
	[-23.46]
(β_8) $Ramp_0$	-0.508063974623592096158120***
	[-184.07]
(β_9) $Ramp_1$	0.032797358221284100832094***
	[12.40]
(β_{10}) $Depth_j$	0.260683920294977111709045***
	[189.55]
(β_{11}) Local $Information_j$	-0.004502789277263300089793***
	[-4.53]
(β_{12}) Firm Local $Experience_j$	0.038126923544065098592437***
	[31.90]
(β_{13}) Firm Total $Experience_j$	0.015990787856916301168386***
	[38.76]
Firm-Year Fixed $Effect_{i,t}$	Yes
Tonwship-Year Fixed $Effect_{p,t}$	Yes
R-Squared	0.686
Observations	30,420,544

Table 20: Idiosyncratic Shocks and The Stochastic Discount Factor

This table reports coefficient estimates from an OLS regression for the relation between wells' idiosyncratic shocks and the stochastic discount factor of the CAPM model (i.e., a function of the *Market Excess Return*), and t-statistics robust to heteroskedasticity and within-firm dependence in bracket. The period of the sample is from 1983 to 2010. The unit of observation in the underlying table is at the year *t* level. The market excess return corresponds to the market earning-to-price ratio net of the 10-year risk-free rate. The *Idiosyncratic shock* is measured at the individual well level and corresponds to the well's idiosyncratic productivity shocks. See appendix A.1. and A.2 for the full methodological details. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Market Excess Return (%)$_t$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(β_1) Idiosyncratic Shocks$_j$	-0.472	0.330	0.186	0.318	-0.529	0.179	0.114	0.170
	[-1.17]	[1.25]	[0.78]	[1.07]	[-1.18]	[1.21]	[0.55]	[0.89]
(β_2) Assets$_{i,t}$					-0.000***	-0.001***	-0.000***	-0.001***
					[-3.14]	[-3.68]	[-3.66]	[-3.13]
Township Fixed Effect$_p$	No	No	Yes	No	No	No	Yes	No
Firm Fixed Effect$_i$	No	Yes	No	No	No	Yes	No	No
Township-Firm Fixed Effect$_{p,i}$	No	No	No	Yes	No	No	No	Yes
R-Squared	0.001	0.240	0.112	0.264	0.009	0.264	0.120	0.280
F-Statistic	1.369	1.569	0.603	1.141	5.470	9.251	7.082	6.381
Observations	114,696	114,696	114,696	114,696	114,696	114,696	114,696	114,696

Table 21: Projects' Idiosyncratic Risk and Probability of Dry Hole

This table reports the incidence rate ratio estimates of a Poisson regression, and t-statistics robust to heteroskedasticity and within-township dependence in bracket. A coefficient value greater that 1 indicate a positive relation between the variable of interest and the outcome variable, while a value smaller than 1 indicate a negative relation. The unit of observation is at the township p, and year t level. The dependent variable, *Number of Dry Hole*, is a count variable that corresponds to the number of dry wells drilled in a given township-year. For example, a value of 2 indicates that there were 2 dry holes drilled in the township during that given year. *Project's Idiosyncratic Risk*$_{p,t}$ denotes the cross-sectional dispersion of the well's idiosyncratic productivity shock, computed at the township p and year t level. The variable *Project's Idiosyncratic Risk* is scaled by its standard deviation to simplify the lecture of the table and facilitate its comparison with the other regression tables. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Number of Dry Holes$_{p,t}$			
	(1)	(2)	(3)	(4)
(β_1) Project's Idiosyncratic Risk$_{p,t}$	1.476***	1.425***	1.377***	1.532***
	[9.56]	[7.54]	[2.66]	[2.86]
(β_2) Township Average Production$_{p,t}$	0.999***	0.999***	0.999***	0.999***
	[-4.40]	[-4.71]	[-3.31]	[-2.72]
Year Fixed Effect$_t$	No	Yes	No	Yes
Township Fixed Effect$_p$	No	No	Yes	Yes
Pseudo R-Squared	0.128	0.170	0.278	0.295
Observations	12,386	12,386	12,386	12,386

Table 22: Managers' Project's Idiosyncratic Risk Pricing and Hadlock-Pierce Index

This table reports coefficient estimates from an OLS regression and a 2SLS regression for the effect of projects' idiosyncratic risk on firms' discount rate, and t-statistics robust to heteroskedasticity and within firm dependence in bracket. The time period of the sample is from 1983 to 2010. The unit of observation in the underlying table is at the firm i, year t, and portfolio k level. Projects' Average Idiosyncratic Risk denotes the projects' average idiosyncratic risk measure for each firm-year portfolio (i.e., the high or low idiosyncratic risk portfolio). The *Hadlock-Pierce Index* is used as a costly external financing proxy. Its calculation details are available in appendix A.3. The instrumented regression contains two instrumented variables, the *Projects' Average Idiosyncratic Risk* and the *Projects' Average Idiosyncratic Risk * Hadlock-Pierce Index*. The analysis is restricted to the set of firms available in Compustat for which the necessary variables for each indexes was available. The variable Project's Average Idiosyncratic Risk is scaled by its standard deviation to simplify the lecture of the table and facilitate its comparison with the other regression tables. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Discount Rate (%)$_{i,t,k}$							
	Reduced Form Regression				Instrumented Regression			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(β_1) Projects' Average Idiosyncratic Risk$_{i,t,k}$	7.101***	7.110***	10.024***	9.242***	7.730***	7.714***	12.094***	11.557***
	[4.44]	[4.44]	[3.87]	[3.56]	[3.94]	[3.93]	[4.43]	[4.10]
(β_3) Projects' Average Idiosyncratic Risk$_{i,t,k}$ * HP$_{i,t}$	1.504***	1.509***	2.291***	2.177***	1.667***	1.665***	2.714***	2.634***
	[3.44]	[3.43]	[3.26]	[3.11]	[3.18]	[3.17]	[3.79]	[3.63]
(β_3) HP$_{i,t}$	7.195***	7.083***			7.104***	6.998***		
	[6.03]	[6.04]			[5.93]	[5.95]		
(β_4) Assets$_{i,t}$		0.002				0.002		
		[0.63]				[0.64]		
(β_5) Budget$_{i,t}$		-0.004				-0.004		
		[-1.01]				[-1.00]		
(β_6) Average Natural Gas Production Level$_{i,t,k}$	0.777***	0.779***	0.759***	0.668***	0.767***	0.769***	0.688***	0.636***
	[7.08]	[7.13]	[5.81]	[5.07]	[6.34]	[6.39]	[4.82]	[4.62]
Firm Fixed Effect$_i$	Yes	Yes	No	No	Yes	Yes	No	No
Year Fixed Effect$_t$	Yes	Yes	No	No	Yes	Yes	No	No
Firm-Year Fixed Effect$_{i,t}$	No	No	Yes	Yes	No	No	Yes	Yes
Portfolio Fixed Effect$_k$	No	No	No	Yes	No	No	No	Yes
R-Squared	0.735	0.735	0.884	0.884	0.735	0.735	0.883	0.884
F-Statistics	31.379	26.100	37.816	24.057	30.577	25.693	40.172	26.604
Kleibergen-Paap First Stage F-Statistics	N.A.	N.A.	N.A.	N.A.	69.810	69.964	81.939	95.983
Observations	3,946	3,946	3,946	3,946	3,946	3,946	3,946	3,946

Table 23: Managers' Project's Idiosyncratic Risk Pricing and Firms' Private/Public Status

This table reports coefficient estimates from an OLS regression and a 2SLS regression for the effect of firms' average projects' idiosyncratic risk on firms' discount rate, and t-statistics robust to heteroskedasticity and within-firm dependence in bracket. The time period of the sample is from 1983 to 2010. The unit of observation in the underlying table is at the firm i, year t, and portfolio k level. *Project's Average Idiosyncratic Risk* denotes the average projects' idiosyncratic risk measure for each firm-year portfolio (i.e., the high or low idiosyncratic risk portfolio). The variable *Private Dummy* is equal to 1 if the firm is private and 0 otherwise. The instrumented regression contains two instrumented variables, the *Projects' Average Idiosyncratic Risk* and the *Projects' Average Idiosyncratic Risk * Dummy*. The variable *Project's Average Idiosyncratic Risk* is scaled by its standard deviation to simplify the lecture of the table and facilitate its comparison with the other regression tables. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Discount Rate (%)$_{i,t,k}$							
	Reduced Form Regression				Instrumented Regression			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(β_1) Projects' Average Idiosyncratic Risk$_{i,t,k}$	5.810***	5.595***	5.926***	4.633***	6.998***	6.593***	6.938***	6.199***
	[4.32]	[4.28]	[4.42]	[3.53]	[4.87]	[4.64]	[4.79]	[3.53]
(β_3) Projects' Average Idiosyncratic Risk$_{i,t,k}$ * Private Dummy$_i$	1.568	1.666	1.495	-3.033**	0.776	1.108	1.009	-3.645*
	[0.73]	[0.78]	[0.70]	[-2.10]	[0.34]	[0.50]	[0.45]	[-1.97]
(β_3) Private Dummy$_i$	2.570*	1.775	1.554		3.175*	2.221	1.956	
	[1.68]	[1.21]	[1.04]		[1.91]	[1.37]	[1.21]	
(β_4) Assets$_{i,t}$		-0.015***	-0.011***			-0.015***	-0.011***	
		[-5.00]	[-3.24]			[-4.93]	[-3.18]	
(β_5) Budget$_{i,t}$			-0.010				-0.010	
			[-1.60]				[-1.61]	
(β_6) Average Natural Gas Production Level$_{i,t,k}$	1.234***	1.326***	1.351***	0.556***	1.188***	1.282***	1.308***	0.477**
	[5.36]	[5.89]	[5.93]	[3.19]	[5.10]	[5.57]	[5.63]	[2.47]
Year Fixed Effect$_t$	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Firm-Year Fixed Effect$_{i,t}$	No	No	No	Yes	No	No	No	Yes
Portfolio Fixed Effect$_k$	No	No	Yes	Yes	No	No	Yes	Yes
R-Squared	0.313	0.329	0.331	0.880	0.312	0.328	0.330	0.879
F-Statistics	22.551	19.846	15.397	17.706	23.647	21.054	16.528	19.574
Kleibergen-Paap First Stage F-Statistics	N.A.	N.A.	N.A.	N.A.	42.024	41.382	38.73	89.187
Observations	3,946	3,946	3,946	3,946	3,946	3,946	3,946	3,946

Table 24: Managers' Project's Idiosyncratic Risk Pricing and the Cleary Index

This table reports coefficient estimates from an OLS regression and a 2SLS regression for the effect of projects' idiosyncratic risk on firms' discount rate, and t-statistics robust to heteroskedasticity and within-firm dependence in bracket. The time period of the sample is from 1983 to 2010. The unit of observation in the underlying table is at the firm i, year t, and portfolio k level. Projects' Average Idiosyncratic Risk denotes the projects' average idiosyncratic risk measure for each firm-year portfolio (i.e., the high or low idiosyncratic risk portfolio). The *Cleary Index* is used as a costly external financing proxy. Its calculation details are available in appendix A.3. The instrumented regression contains two instrumented variables, the *Projects' Average Idiosyncratic Risk* and the *Projects' Average Idiosyncratic Risk * Cleary Index*. The analysis is restricted to the set of firms available in Compustat for which the necessary variables for each indexes was available. The variable Project's Average Idiosyncratic Risk is scaled by its standard deviation to simplify the lecture of the table and facilitate its comparison with the other regression tables. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Discount Rate (%)$_{i,t,k}$							
	Reduced Form Regression				Instrumented Regression			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(β_1) Projects' Average Idiosyncratic Risk$_{i,t,k}$	7.437***	7.428***	8.016***	7.389***	8.932***	8.964***	10.447***	10.558***
	[3.78]	[3.76]	[3.95]	[3.49]	[3.21]	[3.24]	[3.54]	[3.16]
(β_2) Projects' Average Idiosyncratic Risk$_{i,t,k}$ * Cleary Index$_{i,t}$	0.029*	0.029**	0.035*	0.036*	0.032	0.033	0.048	0.048
	[1.97]	[2.02]	[1.73]	[1.80]	[1.24]	[1.30]	[1.40]	[1.40]
(β_3) Cleary Index$_{i,t}$	-0.029*	-0.029*			-0.032	-0.031		
	[-1.91]	[-1.88]			[-1.43]	[-1.41]		
(β_4) Assets$_{i,t}$	0.010	0.009			0.010	0.009		
	[1.23]	[1.23]			[1.27]	[1.28]		
(β_5) Budget$_{i,t}$	-0.011	-0.009			-0.011	-0.009		
	[-1.43]	[-1.40]			[-1.45]	[-1.42]		
(β_6) Leverage$_{i,t}$		-13.148				-12.877		
		[-1.23]				[-1.20]		
(β_7) Average Natural Gas Production Level$_{i,t,k}$	0.362	0.385	0.175	0.044	0.243	0.264	-0.060	-0.045
	[1.43]	[1.54]	[0.72]	[0.16]	[0.83]	[0.91]	[-0.20]	[-0.15]
Firm Fixed Effect$_i$	Yes	Yes	No	No	Yes	Yes	No	No
Year Fixed Effect$_t$	Yes	Yes	No	No	Yes	Yes	No	No
Firm-Year Fixed Effect$_{i,t}$	No	No	Yes	Yes	No	No	Yes	Yes
Portfolio Fixed Effect$_k$	No	No	No	Yes	No	No	No	Yes
R-Squared	0.647	0.649	0.841	0.842	0.644	0.646	0.837	0.837
F-Statistic	4.554	4.276	8.076	4.343	4.353	4.136	8.242	4.473
Kleibergen-Paap First Stage F-Statistic	N.A.	N.A.	N.A.	N.A.	26.081	25.885	48.554	37.115
Observations	792	792	792	792	792	792	792	792

Table 25: Managers' Project's Idiosyncratic Risk Pricing and the Whited-Wu Index

This table reports coefficient estimates from an OLS regression and a 2SLS regression for the effect of projects' idiosyncratic risk on firms' discount rate, and t-statistics robust to heteroskedasticity and within-firm dependence in bracket. The time period of the sample is from 1983 to 2010. The unit of observation in the underlying table is at the firm i, year t, and portfolio k level. *Projects' Average Idiosyncratic Risk* denotes the average projects' idiosyncratic risk measure for each firm-year portfolio (i.e., the high or low idiosyncratic risk portfolio). The Whited-Wu Index is used as a costly external financing proxy. Its calculation detail is available in appendix A.3. The instrumented regression contains two instrumented variables, the *Projects' Average Idiosyncratic Risk* and the *Projects' Average Idiosyncratic Risk * Whited-Wu Index*. The analysis is restricted to the set of firms available in Compustat for which the necessary variables for each indexes was available. The variable *Project's Average Idiosyncratic Risk* is scaled by its standard deviation to simplify the lecture of the table and facilitate its comparison with the other regression tables. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Discount Rate (%)$_{i,t,k}$							
	Reduced Form Regression				Instrumented Regression			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(β_1) Projects' Average Idiosyncratic Risk$_{i,t,k}$	6.264***	6.240***	6.590***	5.961***	7.553***	7.541***	8.354***	8.474***
	[3.54]	[3.49]	[3.95]	[3.31]	[3.42]	[3.39]	[3.90]	[3.24]
(β_2) Projects' Average Idiosyncratic Risk$_{i,t,k}$ * WW Index$_{i,t}$	0.353	0.343	0.533	0.565	0.190	0.193	0.346	0.336
	[0.67]	[0.65]	[0.85]	[0.95]	[0.23]	[0.23]	[0.33]	[0.33]
(β_3) WW Index$_{i,t}$	-0.752	-0.731			-0.639	-0.629		
	[-1.24]	[-1.23]			[-0.86]	[-0.86]		
(β_4) Assets$_{i,t}$	0.009	0.008			0.010	0.009		
	[1.14]	[1.13]			[1.18]	[1.18]		
(β_5) Budget$_{i,t}$	-0.010	-0.009			-0.011	-0.009		
	[-1.40]	[-1.38]			[-1.41]	[-1.39]		
(β_6) Leverage$_{i,t}$		-12.551				-12.301		
		[-1.19]				[-1.16]		
(β_7) Average Natural Gas Production Level$_{i,t,k}$	0.371	0.393	0.169	0.044	0.258	0.278	-0.060	-0.043
	[1.42]	[1.50]	[0.64]	[0.15]	[0.84]	[0.91]	[-0.17]	[-0.13]
Firm Fixed Effect$_i$	Yes	Yes	No	No	Yes	Yes	No	No
Year Fixed Effect$_t$	Yes	Yes	No	No	Yes	Yes	No	No
Firm-Year Fixed Effect$_{i,t}$	No	No	Yes	Yes	No	No	Yes	Yes
Portfolio Fixed Effect$_k$	No	No	No	Yes	No	No	No	Yes
R-Squared	0.642	0.644	0.838	0.839	0.640	0.642	0.835	0.835
F-Statistic	4.495	4.063	7.433	3.759	5.016	4.583	8.260	4.379
Kleibergen-Paap First-Stage F-Statistic	N.A.	N.A.	N.A.	N.A.	20.496	20.477	64.180	39.036
Observations	792	792	792	792	792	792	792	792

Table 26: Managers' Project's Idiosyncratic Risk Pricing and the Kaplan-Zingales Index

This table reports coefficient estimates from an OLS regression and a 2SLS regression for the effect of projects' idiosyncratic risk on firms' discount rate, and t-statistics robust to heteroskedasticity and within-firm dependence in bracket. The time period of the sample is from 1983 to 2010. The unit of observation in the underlying table is at the firm i, year t and portfolio k level. *Projects' Average Idiosyncratic Risk* denotes the average projects' idiosyncratic risk measure for each firm-year portfolio (i.e., the high or low idiosyncratic risk portfolio). The Kaplan-Zingales Index is used as a costly external financing proxy. Its calculation details are available in appendix A.3. The instrumented regression contains two instrumented variables, the *Projects' Average Idiosyncratic Risk* and the *Projects' Average Idiosyncratic Risk * Kaplan-Zingales Index*. The analysis is restricted to the set of firms available in Compustat for which the necessary variables for each indexes was available. The variable *Project's Average Idiosyncratic Risk* is scaled by its standard deviation to simplify the lecture of the table and facilitate its comparison with the other regression tables. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Discount Rate (%)$_{i,t,k}$							
	Reduced Form Regression				Instrumented Regression			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(β_1) Projects' Average Idiosyncratic Risk$_{i,t,k}$	6.086***	6.085***	6.219***	5.876***	7.164**	7.185**	7.972***	8.219**
	[3.19]	[3.15]	[3.57]	[3.19]	[2.61]	[2.59]	[3.00]	[2.66]
(β_2) Projects' Average Idiosyncratic Risk$_{i,t,k}$ * KZ Index$_{i,t}$	0.928	0.898	0.979	0.850	0.658	0.621	0.456	0.507
	[0.69]	[0.66]	[0.85]	[0.75]	[0.38]	[0.35]	[0.26]	[0.29]
(β_3) KZ Index$_{i,t}$	-1.569	-0.219			-1.320	0.030		
	[-0.82]	[-0.13]			[-0.63]	[0.02]		
(β_4) Assets$_{i,t}$	0.011	0.010			0.011	0.011		
	[1.50]	[1.53]			[1.53]	[1.57]		
(β_5) Budget$_{i,t}$	-0.013*	-0.011*			-0.013*	-0.012*		
	[-1.74]	[-1.84]			[-1.75]	[-1.84]		
(β_6) Leverage$_{i,t}$		-14.100				-14.027		
		[-1.05]				[-1.04]		
(β_7) Average Natural Gas Production Level$_{i,t,k}$	0.300	0.320	0.131	0.054	0.213	0.231	-0.061	-0.021
	[1.16]	[1.24]	[0.48]	[0.18]	[0.70]	[0.75]	[-0.18]	[-0.06]
Firm Fixed Effect$_i$	Yes	Yes	No	No	Yes	Yes	No	No
Year Fixed Effect$_t$	Yes	Yes	No	No	Yes	Yes	No	No
Firm-Year Fixed Effect$_{i,t}$	No	No	Yes	Yes	No	No	Yes	Yes
Portfolio Fixed Effect$_k$	No	No	No	Yes	No	No	No	Yes
R-Squared	0.375	0.376	0.376	0.645	0.636	0.637	0.826	0.825
F-Statistic	2.172	2.458	2.237	4.263	5.138	4.623	9.574	5.084
Kleibergen-Paap First Stage F-Statistic	N.A.	N.A.	N.A.	N.A.	7.550	7.529	14.908	12.808
Observations	792	792	792	792	792	792	792	792

Table 27: Managers' Project's Idiosyncratic Risk Pricing and Managers' Budget - States

This table reports coefficient estimates from an OLS regression for the effect of projects' idiosyncratic risk on firms' discount rate, and t-statistics robust to heteroskedasticity and within-firm dependence in bracket. The time period of the sample is from 1983 to 2010. The unit of observation in the underlying table is at the firm i, year t, and portfolio k level. Project's Average Idiosyncratic Risk denotes the average projects' idiosyncratic risk measure for each firm-year portfolio (i.e., the high or low idiosyncratic risk portfolio). The variable Managers' Average Budget corresponds to the managers budget size averaged at the firm-year level, when assuming that managers are assigned to distinct states. The instrumented regression contains two instrumented variables, the *Projects' Average Idiosyncratic Risk* and the *Projects' Average Idiosyncratic Risk * Managers' Average Budget*. The variable *Project's Average Idiosyncratic Risk* is scaled by its standard deviation to simplify the lecture of the table and facilitate its comparison with the other regression tables. Detailed calculation of the regression variables is available in appendix A.1. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Discount Rate (%)$_{i,t,k}$							
	Reduced Form Regression				Instrumented Regression			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(β_1) Projects' Average Idiosyncratic Risk$_{i,t,k}$	6.723***	6.725***	7.323***	6.768***	6.721***	6.724***	8.193***	7.747***
	[3.47]	[3.46]	[3.53]	[3.25]	[3.80]	[3.80]	[4.64]	[4.18]
(β_2) Projects' Average Idiosyncratic Risk$_{i,t,k}$ * Managers' Average Budget$_{i,t}$	-0.054**	-0.054**	-0.069**	-0.069**	-0.048***	-0.048***	-0.065***	-0.064***
	[-2.50]	[-2.48]	[-2.52]	[-2.50]	[-2.94]	[-2.94]	[-3.32]	[-3.21]
(β_3) Assets$_{i,t}$	0.005	0.004			0.004	0.004		
	[1.40]	[1.34]			[1.38]	[1.36]		
(β_4) Budget$_{i,t}$		0.002				0.001		
		[0.22]				[0.21]		
(β_5) Managers' Average Budget$_{i,t}$	0.017	0.015			0.013	0.011		
	[0.89]	[0.73]			[0.72]	[0.52]		
(β_6) Average Natural Gas Production Level$_{i,t,k}$	1.282***	1.283***	0.746**	0.587*	1.268***	1.269***	0.607*	0.511
	[5.63]	[5.56]	[2.24]	[1.73]	[4.45]	[4.41]	[1.90]	[1.58]
Firm Fixed Effect$_i$	Yes	Yes	No	No	Yes	Yes	No	No
Year Fixed Effect$_t$	Yes	Yes	No	No	Yes	Yes	No	No
Firm-Year Fixed Effect$_{i,t}$	No	No	Yes	Yes	No	No	Yes	Yes
Portfolio Fixed Effect$_k$	No	No	No	Yes	No	No	No	Yes
R-Squared	0.616	0.616	0.835	0.836	0.616	0.616	0.835	0.836
F-Statistic	9.243	11.160	17.771	10.927	10.127	10.888	20.810	12.182
Kleibergen-Paap First Stage F-Statistic	N.A.	N.A.	N.A.	N.A.	63.901	63.822	111.074	88.060
Observations	3,946	3,946	3,946	3,946	3,946	3,946	3,946	3,946

Table 28: Firms Characteristics and Projects' Risk

This table reports the effects of firm characteristics on the chosen projects' risk level, and t-statistics robust to heteroskedasticity and within-firm dependence in bracket. The time period of the sample is from 1983 to 2010. The unit of observation in the underlying table is at the township p, and year t level. The dependent variable *Project's Idiosyncratic Risk*$_{p,t}$ denotes the cross-sectional dispersion of the well's *Idiosyncratic Productivity Shock*, computed at the township p and year t level (see appendix A.1. for the detailed calculation). *Managers' Average Budget* corresponds to the firm-year average manager's budget when managers are assumed to be assignment to specific fields in columns (1) to (3), or to specific states level in columns (4) to (6). The variable *Manager's Average Budget* is scaled by its standard deviation.* indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Project's Idiosyncratic Risk$_{p,t}$					
	Managers' Budget (Region = Field)			Managers' Budget (Region = State)		
	(1)	(2)	(3)	(4)	(5)	(6)
(β_1) Managers' Average Budget$_{i,t}$	0.439**	0.645*	0.700*	0.507***	0.669***	0.685***
	[2.35]	[1.96]	[1.74]	[3.55]	[3.21]	[3.36]
(β_2) Assets$_{i,t}$		-0.001	-0.001		-0.001	-0.002
		[-1.15]	[-1.07]		[-1.27]	[-1.18]
(β_3) Budget$_{i,t}$			-0.000			0.000
			[-0.13]			[0.16]
(β_4) Township-Year Average Well's Cost$_{p,t}$			-2.002			-2.062
			[-0.85]			[-0.87]
Firm Fixed Effect$_i$	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect$_t$	Yes	Yes	Yes	Yes	Yes	Yes
Township Fixed Effect$_p$	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.474	0.475	0.475	0.475	0.475	0.475
F-Statistic	5.520	2.087	1.337	12.568	6.002	3.756
Observations	20,725	20,725	20,725	20,725	20,725	20,725

Table 29: Managers' Project's Idiosyncratic Risk Pricing - Real Option Effect (2)

This table reports coefficient estimates from an OLS regression for the effect of projects' idiosyncratic risk on firms' discount rate, and t-statistics robust to heteroskedasticity and within-firm dependence in bracket. The time period of the sample is from 1983 to 2010. The unit of observation in the underlying table is at the firm i, year t, and portfolio k level. For this specification, the projects' internal rate of return used to estimate the firms' discount rate are obtained using a real option value decision rule. Instead of assuming that managers find it optimal to investment whenever the projects discounted value of cash flow is greater than the cost of investment, I assume that the optimal investment trigger is the real option optimal threshold. See appendix C for a detailed discussion of the estimation strategy. For the Kill test, the goal is to find the level at which the real option calibration eliminate the results of the paper (column 6). To implement that, in the real option calibration, I multiplied the idiosyncratic risk variable by 28.8%, such that the coefficient for the idiosyncratic risk variable (β_1) is no longer statistically significant. The variable *Project's Average Idiosyncratic Risk* is scaled by its standard deviation to simplify the lecture of the table and facilitate its comparison with the other regression tables. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Discount Rate (%)$_{i,t,k}$					
	+0%					Kill test
	(1)	(2)	(3)	(4)	(5)	(6)
(β_1) Projects' Average Idiosyncratic Risk$_{i,t,k}$	2.868***	0.530	0.515	1.040**	0.745*	0.542
	[4.12]	[1.19]	[1.16]	[2.52]	[1.90]	[1.64]
(β_2) Budget$_{i,t}$			-0.007			
			[-1.49]			
(β_3) Assets$_{i,t}$			0.002			
			[1.40]			
(β_4) Average Natural Gas Production Level$_{i,t,k}$	4.918***	4.301***	4.351***	2.363**	1.924*	
	[6.58]	[4.16]	[4.37]	[2.48]	[1.87]	
Firm Fixed Effect$_i$	No	Yes	Yes	No	No	No
Year Fixed Effect$_t$	No	Yes	Yes	No	No	No
Firm-Year Fixed Effect$_{i,t}$	No	No	No	Yes	Yes	Yes
Portfolio Fixed Effect$_k$	No	No	No	No	Yes	No
R-Squared	0.572	0.610	0.610	0.828	0.829	0.835
F-Statistic	3.275	5.425	3.144	11.964	5.438	2.696
Observations	2,716	2,716	2,716	2,716	2,716	2,716

CHAPTER 2 : Real Option Exercise: Empirical Evidence

Every investment decision made by a firm is both a decision about which capital project to pursue as well as when to pursue it. The flexibility associated with the timing of investment decisions has value to the firm; this value is commonly referred to as real option value (Myers and Turnbull 1977). Real options are a central component of models of the macroeconomy (Bernanke 1983), and their exercise has received ample attention in the corporate finance theory literature (e.g., Dixit and Pindyck 1994; Kellogg 2014). Moreover, existing corporate finance theories hypothesize the importance of peer exercise decisions and information revelation in determining exercise behavior.[1] However, despite the importance of real options, micro-level empirical evidence on exercise behavior remains limited.[2] In this study, we provide novel evidence on the real option exercise behavior of firms and directly assess the role that peer effects and information externalities can have on exercise decisions.

Characterizing firms' real option exercise behavior is empirically challenging. First, detailed data on the timing flexibility associated with capital projects is typically unavailable. Second, to understand a firm's exercise behavior, one would need data on both the projects that a firm decides to undertake, as well as those it decides *not* to pursue. This level of disclosure is often not available. Third, being able to observe key inputs that might drive option exercise decisions is necessary in order to characterize exercise behavior; these would include expected project cash flows, costs, and volatility of project cash flows. Fourth, in a competitive setting where peer firms' exercise behavior can have an influence, one needs to be able to precisely measure the actions taken on peer firm projects in order to gauge their potential impact. Fourth, one needs to develop an empirical framework to appropriately identify the effect of peer behavior and mitigate potential endogeneity concerns.

[1]See Grenadier 1996, Grenadier 1999, Grenadier 2002, Novy-Marx 2007, Grenadier and Wang 2005, Grenadier and Malenko 2011, and Scharfstein and Stein 1990.

[2]Kellogg 2014 studies oil drilling activity and finds that oil price volatility affects investment decisions in a manner consistent with real option models. However, the study, which focuses on fields operated by a single firm, does not assess the importance of information externalities across firms. Moel and Tufano 2002 study mine opening and closing decisions relative to what real option theories would imply; however, their setting is also not conducive to assessing the importance of peer effects and information externalities.

This study focuses on a setting which allows us to make significant progress on each of these challenges. We analyze $107.9 billion in capital projects composed of exercised and unexercised natural gas shale infill well drilling projects in major shale developments in North America. First, the institutional structure of this setting allows us to have clear visibility into the timing flexibility firms have in making drilling decisions. Second, because of the institutional structure of lease contract terms we are also able to observe both exercised and unexercised options at any given point in time. Third, because the key determinant of project cash flow is the price of natural gas, a commodity whose expected price and implied volatility are readily observable to the econometrician from financial derivatives, we have the inputs necessary to characterize investment behavior. Fourth, due to the regulatory environment of the shale fields in our setting, we are able to observe and precisely measure neighboring activity from peers.[3] Third, and finally, we develop an empirical framework which uses novel quasi-exogenous variation in peer activity to mitigate some of the challenges in identifying peer effects.

Our empirical design to assess the exercise behavior of firms is based on a duration analysis using a hazard model. The objective of using this empirical framework is to compute how different factors affect the probability of exercising an option at time t, conditional on the option having not been exercised up to time t. The data in our sample is conducive to this type of analysis because each option has a well-defined starting point, we can clearly observe when an option is exercised, and we have detailed data on how covariates vary during and up to the time of exercise. This empirical specification is consistent with others that have modeled drilling decisions (Kellogg 2014).

We find that the likelihood that a firm exercises its real option is strongly related to peer exercise behavior. Specifically, a 1-standard-deviation increase in adjacent peer project exercise activity is linked with between a 10.9% and 38.2% increase in exercise likelihood. These magnitudes imply that peer behavior can be as economically important as baseline

[3]This is a key distinction from Kellogg 2014, who focuses on single operated fields, where only one firm operates in each area.

real option inputs, such as commodity prices and volatility, in determining exercise decisions.[4] We show that our baseline peer effect result holds after mitigating endogeneity concerns linked with peer exercise decisions as well as across a series of robustness tests.

Corporate finance theory provides a rich set of extensions to baseline real option models highlighting the importance of peer behavior and information revelation for exercise decisions (e.g., Grenadier 1999; Grenadier and Wang 2007; Grenadier and Malenko 2011; Novy-Marx 2007). Our empirical framework is well suited to assess these theories. In most other settings, even the task of defining the set of peers can be a challenge.[5] In our setting, geographical proximity of *real options* to one another provides a natural way to define peer sets. Specifically, we precisely observe how firms respond to adjacent competitor project exercise decisions, because our data are granular enough that we can observe the specific drilling units (real options) a firm has, as well as the adjacent drilling units operated by competitors. The grid pattern of drilling units in the shale fields in our setting are such that every 6-sq. mi. township is divided in thirty-six sections and for each section in our sample, we have eight adjacent sections to it. We can take advantage of the significant variation in neighboring activity to evaluate two possible channels through which peer exercise could affect exercise decisions.

First, as Grenadier 1996 highlights, firms may face a common pool problem, in which case they may decide to exercise early because the common pool of resources could be drained by neighboring competitors and hence unravel any option value to wait. However, this phenomenon is unlikely to explain exercise behavior because shale rock lies deep underground and traps hydrocarbons tightly. It is only under very intense pressure (hydraulic fracturing or "fracking") that the highly nonpermeable rock releases hydrocarbons, with minimal impact on neighboring nonfracked shale rock. If shale gas were a significant common pool,

[4]Like Kellogg 2014, we find that commodity price and implied volatility are linked with exercise decisions in our setting.

[5]In a broad cross-section of firms, defining peer sets, often through industry classification, can be challenging (see Hoberg and Phillips 2016). Defining geographic proximity at the firm level represents another challenge; for instance, headquarter location (easily observable) might act as a poor proxy for the location of firm operations.

one would likely see only a few wells being drilled to extract natural gas, which is in sharp contrast to the dense drilling that one actually observes in shale gas extraction. Because Kellogg 2014 focuses on the exercise behavior of conventional nonshale oil wells, that study focuses on single operated fields to avoid the common pool problem. Given our focus on shale wells, we are able to analyze the exercise behavior of infill wells with adjacent activity without confounding issues related to common pools.

Second, we evaluate the role that competitor exercise behavior has in providing potentially important information externalities. As Grenadier 1999 points out, information revelation through real option exercise decisions is a key dimension through which real option exercise behavior differs from financial option exercise behavior. However, micro-level empirical evidence attempting to quantify the potential importance of information revelation remains limited. We find direct evidence that information externalities linked with peer behavior are important. Specifically, we find that firm exercise activity is most strongly linked to peer exercise decisions when peers have more experience in drilling natural gas shale infill projects. Firms with the most experience in a field are higher up the learning curve in terms of how to extract natural gas, so the information revealed from their exercise is likely more valuable.

What is the nature of the information firms obtain from adjacent exercise activity? Adjacent exercise activity could inform a firm on how to better extract reserves from its own project. Specifically, adjacent exercised projects reveal detailed information on the "target" depths at which the formation was drilled, which helps firms target their own drilling prospects better. Further, public disclosures require information to be disclosed on the mix of fracking chemicals and techniques applied to drill and complete a well; this information then can be used by peer firms to determine which approach will allow them to extract natural gas most efficiently from their own reservoir (e.g., Covert 2015).[6] Lastly, adjacent exercise activity by peer firms also could be a reflection of some private information about rock quality a

[6]See fracfocus.org for examples of public disclosures.

firm has which is not yet publicly known, so that observing a peer firm exercise could cause a firm to update positively on the rock quality of a project. All these reasons highlight how neighboring peer exercise activity can lead to economically important information externalities that can result in upward revisions in project value.

A central concern when evaluating the effect of peer exercise decisions is endogeneity. For example, common characteristics (e.g., shared geology or technology) may be driving the exercise behavior of both the firm and its neighboring competitors. This common unobserved factor is a well-established source of endogeneity that leads to the reflection problem (Manski 1993). To mitigate this endogeneity concern we develop novel quasi-exogenous variation in peer firm exercise activity.

Our primary identification strategy relies on the idea that beyond the net present value (NPV) of a project, the relative rank of a given project in a firm's portfolio of capital projects may also matter for investment exercise decisions.[7] Therefore, two peer firms with adjacent projects of similar NPVs could undertake exercise decisions differently due to the relative rank of their project within each firm's portfolio of projects. For each real option in our sample, we construct the average relative rank percentile of adjacent projects within the peer firms' portfolio of projects at each point in time. We use this variable to instrument for adjacent peer project exercise activity. We find evidence, using both instrumented and reduced-form versions of this measure of quasi-exogenous variation in peer exercise activity, that the adjacent exercise behavior of peer firms affects the exercise behavior of a firm.

The identification assumption of our empirical design is that the relative rank of the NPV of an adjacent real option in a peer firm's portfolio affects a firm's own exercise decision only through its effect on the likelihood that the peer firm will exercise that adjacent option, and not through another channel. While this assumption is not directly testable, we can provide several pieces of evidence that support it. First, if a common characteristic affected

[7] It is well established that firms cannot pursue all positive NPV projects at the same time because of operational, labor, or capital constraints. Hence, project ranking is a commonly used tool to select only the most profitable projects (see Berk and DeMarzo 2016 as an example).

both the relative rank of a peer firm's real option as well as the exercise of a firm's own real option, then the exclusion restriction would be violated. In such circumstances, one might expect highly ranked projects by different firms would tend to cluster in the same area, and we show this is not the case. Specifically, we show that after controlling for local geography fixed effects, which essentially controls for the absolute NPV of a project, the relative rank of adjacent projects owned by peer firms is uncorrelated with the relative rank of a given project within a firm's own portfolio.[8] Second, we show that our results hold when we limit our sample only to the real options with low relative rank within a firm's portfolio, while its peer firms' adjacent projects' relative rank is high. Third, we find that firms still respond to peer exercise decisions on units that are directly adjacent to theirs, even after controlling for peer exercise decisions on projects elsewhere. Fourth, we find that firms' response to adjacent peer exercise decisions is concentrated around the activity from peers with substantial experience in extracting shale in the area of interest. Taken together, these tests make significant progress in addressing the primary endogeneity concerns in measuring responses to peer real option exercise decisions, and set a high bar for alternative explanations. Specifically, an alternative explanation would need to reconcile why the relative NPV rank of a given project in a peer firm portfolio would have a direct effect on a firm's exercise decision for a reason other than peer exercise activity, when that relative rank is uncorrelated with any metric that is linked with the absolute NPV of a project ex ante.

Ideally one would want to have visibility into all real options a firm has to have a complete rank ordering of projects. Despite the focused geographical scope of our study, we still obtain strong statistical power from using the rankings of real options in explaining infill option exercise decisions. This is consistent with the notion that drilling decisions are typically made at the shale play/regional level, and, as such, the portfolio ranking within our geographic area of focus, shale natural gas in Oklahoma, still results in a strong instrument.

[8]The relationship is not statistically significant. Further, throughout all specifications, we directly control for the absolute quality of peer firm projects by using the production from the first well of each adjacent peer units as a proxy for the NPV of the peers' adjacent infill wells.

That is, so long as the real option exercise decisions we study are made within the same capital allocation category, the rank orderings we compute will give us enough statistical power. A further concern could be that firms might have shale oil infill projects, which are not included in our analysis, that could alter the interpretation of our tests. However, shale oil infill options are much rarer in the data than shale gas infill options, largely because of the much later adoption of fracking technology to oil. Specifically, for the median observation during our sample period a firm's infill option portfolio is composed of 7.8% shale oil infill options and 92.2% shale gas infill options. Moreover, we find that shale oil and shale gas infill options exist in geographically distinct areas, and, consistent with the view that these projects are in distinct capital allocation categories, we find that there are no cross-sectional differences in the explanatory power of our shale gas rank ordering on shale gas infill decisions between firms with above-median shale oil infill options and firms with below-median shale oil infill options.[9]

As a final set of analysis, we estimate the optimal stopping (exercise) time based on standard real option models (e.g., Paddock et al. 1988; Dixit and Pindyck 1994). After incorporating all the detailed granular inputs our setting affords into these baseline models, we find that differences exist between actual exercise behavior and predicted exercise behavior. However, we find that the baseline model's predictions are closer to actual observed behavior once we account for information externalities due to adjacent peer exercise decisions. Specifically, if we model beliefs about the value of unexercised infill options to be a function of both the production of the first well on a drilling unit and the adjacent peer exercise activity, we find that exercise decisions are significantly closer to those predicted by theory.

By analyzing peer effects and social learning in the context of real option exercise behavior, our study contributes to two important strands of the literature. First, we contribute to the real option literature by empirically evaluating the importance of a broad set of theories,

[9]Given the limited amount of activity for shale oil infill projects in our sample there is much lower statistical power to comprehensively study option exercise activity among these types of projects, so we exclude these well types from our study. However, we undertake a series of tests in Sections 3.2.4 and 3.3, to ensure that the presence of shale oil infill projects does not alter the interpretation of our main results.

which hypothesize that information revelation and externalities may be an important component of exercise decisions (Grenadier 1996; Grenadier 1999; Grenadier 2002; Novy-Marx 2007; Grenadier and Wang 2005; Grenadier and Malenko 2011). In particular, we show that peer exercise is important relative to the predictions from standard real option models (e.g., Dixit and Pindyck 1994; Kellogg 2014). To understand why this may be the case, we focus on a setting where we can directly identify peer effects and the role of information externalities in option exercise behavior (Grenadier 1999). Using a hazard model framework, we show that information externalities from peer effects can have economic effects on the same order of magnitude as natural gas prices and volatility. Second, our novel micro-level evidence of the effect of peer activity on option exercise helps us contribute to the literature on learning from peers. That literature documents that peer effects are important for a variety of corporate decisions, such as those on investment policy (Foucault and Fresard 2014; Bustamante and Fresard 2017), capital structure policy (Leary and Roberts 2014), and dividend policy (Greenan 2019). The economics literature provides evidence on social learning and the adoption of new technologies (e.g., Foster and Rosenzweig 1995; Thompson and Thompson 2001; Conley and Hudry 2010; Covert 2015). Covert 2015, in particular, relates to this study, because he documents social learning on decisions related to what technology to use to drill and complete wells. The evidence Covert 2015 provides is precisely the type of information externality that can make social learning important for real option exercise decisions. However, much of the existing literature related to social learning is focused on how firms learn and invest (see Conley and Hudry 2010; Covert 2015). Our contribution is to show that this peer learning also has an important impact on the *timing* of investment decisions, that is within a real options context, peer learning affects *when* firms invest.

2.1 Real Options in the Context of Shale Drilling

2.1.1 Project overview: Natural gas shale drilling

Our setting exploits the institutional features of natural gas shale development to study the real option exercise behavior of firms. To extract shale natural gas, firms must first drill a well with a horizontal leg into shale rock (typically more than a mile below the surface), then complete the well by hydraulically fracturing ("fracking") it. Drilling a well may take a few days to a few weeks, whereas fracking is a separate process performed after drilling. Both drilling and fracking entail substantial upfront capital costs of $4.7 million per well on average in our sample. Once a well is completed, it produces natural gas and declines over time. The critical features determining the cash flows are natural gas prices and the volume extracted. Costs include lease operating costs and royalty costs, and typically comprise less than 40% of a well's revenues after the well is drilled. Cash flows are at their highest level at the beginning of a well's life and then decline over time as pressure from the well declines. Once a well starts producing a firm can do little to cause the production to go up or down outside of a well's natural decline without risking damage to a well. Figure 10 plots the cash flows and capital expenditures associated with drilling a well (see Gilje and Taillard 2016b for more details).

2.1.2 Infill drilling

One of the key features of our setting is the unique ability to observe the flexibility and maturity that firms have on their investment options. Like Kellogg 2014, we focus on "infill" drilling projects in order to have well-defined maturity assumptions. An "infill" project corresponds to the decision to drill additional wells on a drilling unit (section) that a firm already operates. The first (or existing well) on a unit contractually holds the operatorship of the acreage as long as the first well produces; in this case the lease is said to be "held by production" or HBP. A firm has the option to drill additional wells at any point in the future so long as the initial well is still producing. This provides firms with options that have very long maturities as the life of the first well can range anywhere from 20 to 40 years. In all the natural gas shale developments that we study in Oklahoma, a single drilling unit (section) of 640 acres can support up to 8 shale wells (or roughly up to $37.8 million in capital expenditures). With 2,853 units representing up to $107.9 billion in potential capital commitments, the infill options in this study represent capital investments that are economically meaningful, with a significant degree of flexibility on when to exercise these options. Figure 11 plots a timeline of the infill drilling decision.

A key advantage of focusing on infill drilling is that, unlike most studies of investment decisions, we can observe both exercised *and* unexercised options. Indeed, drilling units with only one existing well effectively contain many unexercised options as no additional (infill) wells have been drilled in the unit yet. Our study focuses on the timing of the first infill well in a unit. It is important to note that a firm could delay the exercise of the second, third, and follow-up infill wells. However, we find that 90.2% of all infill wells are drilled concurrently to the first infill well. As such, infill drilling does not seem to be exploratory by nature but, rather, is a decision to extract significantly more resources from a unit that has been held by production with the first well up to that point.

2.1.3 Measuring peer activity

The ability to analyze firm's investment responses to competitors' actions is a key novelty of our study. We focus on the development of major natural gas fields across multiple operators, a setting where information and other externalities may be more relevant. This is a key distinction from Kellogg (2014), who focuses on single operated fields, where only one firm drills a field.

The regulatory and land environment in Oklahoma lends itself well to further our understanding of how firms might react to adjacent drilling activity. Specifically, every drilling unit in our setting conforms to Jeffersonian survey, and lies on a grid system with squares that are one mile by one mile. Every 6 by 6 group of squares (thiry-six "units" in total) rolls up to a township survey (township level). This is attractive for several reasons. Every drilling unit, by construction, has eight clearly delineated adjacent units. We observe every natural gas well drilled in Oklahoma so we can observe the exact timing and nature of all adjacent activity throughout our sample period. Second, we can use the township survey information to control for potential geography or area specific effects in our econometric specifications. Figure 12 plots the shale drilling activity in a township. The lines represent the horizontal wellbores of shale wells. Sections in the grid are the drilling units; sections with one wellbore have not yet been infill drilled; and sections with multiple wellbores have been infill drilled.

2.1.4 Real option framework

The firm's option to infill drill corresponds to the choice it has to spend capital to further develop its proven natural gas reserves. As noted in the introduction, the timing flexibility related to the investment decision to drill a well on proved reserves can be viewed as an American call option (e.g., Paddock et al. 1988). Infill drilling maps nicely into the real option framework: the capital needed to develop the reserves can be viewed as the strike price of the option. The value of the reserves after capital has been expended, that is, the producing proved developed reserves, corresponds to the underlying asset. The timing flexibility a firm has to infill drill can be viewed as the time to maturity. Because the first well on the section holds by production (HBP) the section as long as it is economically viable, the option to infill drill has a long maturity attached to it; at least 20 years on average. And as the decision to infill drill (exercise the option) can be made at any time over this period, it can be viewed as an American call option. The cash flow volatility of infill wells corresponds to the volatility of the underlying asset used in standard option pricing model. Firms in our setting all produce the same commodity, natural gas, and the market provides indicators of expected futures prices and volatility, both of which can be used as inputs for an option pricing model, along with other inputs described in more details in Section 4.

2.1.5 Optimal exercise time and peer effects

It is well established that American call options on dividend paying underlying assets have an optimal exercise time that can occur prior to maturity. As Dixit and Pindyck 1994 point out dividends can be viewed as either explicit or implicit in the context of real options, and broadly speaking can be viewed as the benefit a firm obtains from exercising an option sooner rather than later. In our setting, a straightforward way of viewing the cost a firm incurs by waiting is that future cash flows get discounted by a firm's cost of capital. The longer a firm waits to exercise, the more discounting will be applied to the underlying cash flows generated by the well. Conversely, waiting (delaying drilling) confers the ability to drill in future states of the world that exhibit higher natural gas prices. Therefore, one can view early exercise as the result of a tradeoff between the value of early exercise from having to discount cash flows less and delaying the exercise to get better natural gas pricing in the future.[10]

All else equal, higher cash flow volatility tends to result in delayed investment, due to the increased prospects of higher cash flows, while a higher cost of capital tends to result in investment occurring sooner. The classic derivations of the optimal stopping time (see Section 4 for more details) lead to a trigger rule, whereby a trigger value can be computed such that it is optimal to exercise the option when the value of the underlying asset (natural gas reserves) exceeds the trigger value from below for the first time. When natural gas prices rise, it is more likely that the value of the underlying asset will exceed the trigger value. Hence, commodity price increases will lead to earlier exercise of the real option all else equal.

Natural gas prices and natural gas price volatility have clear predictions as to how they might affect exercise based on a standard options framework, with volatility being negatively correlated with exercise (more valuable to delay when volatility is high) and natural gas prices being positively correlated with likelihood of exercise. We also include information on

[10] As we will see in Section 4, in our context, a firm's cost of capital will correspond to the dividend rate of a stock.

nominal interest rates in our initial tests. Typically, a decrease in interest rates decreases the discount rate and hence makes projects more valuable and hence more likely to be undertaken. However, in the context of real options, the effect of interest rates is more ambiguous because a decrease in interest rates makes waiting more appealing, as cash flows in the future are valued more today.[11]

Assessing how peer effects alter option exercise behavior is the central focus of this study. A broad set of theoretical papers claim that informational spillovers from peer activity can be of first- order importance in understanding real option exercise behavior. The mechanism underpinning these peer effects relate to the information content that is revealed by the exercise of infill drill options on the eight adjacent drilling units (see Figure 13). Specifically, the more infill wells being drilled nearby, the more information there is on the depths and porosity of the formation, which will in turn inform a firm on how to most efficiently extract natural gas from its own infill wells. Additionally, public disclosures require information to be disclosed on particular chemical mixes and techniques of hydraulic fracturing of "fracking" a well (see Covert 2015). This reveals information on techniques that might work well for fracking a particular reservoir as well as those that might not work as well. It is important to note that, even seeing a negative outcome in terms of production in an adjacent section, that is knowing which "fracking" techniques do not work, will allow a firm to learn how to better extract from its own section. Lastly, adjacent exercise activity by peer firms also could be a reflection of some private information about rock quality a peer firm has which is not yet publicly known; as such, observing adjacent exercise may lead a firm to update positively on the rock quality of a project. Grenadier 1999's develops a theoretical framework of real option exercise to assess the potential impact of information externalities from peer exercise activity. All of the reasons listed above justify why we could see positive information externalities from neighboring activity in our setting and thus validate the use of our setting to empirically assess Grenadier 1999's main prediction

[11] The effect depends somewhat on whether a movement in interest rates (r) will have a commensurate impact on the firm's cost of capital (δ). See section 5.4 of Dixit and Pindyck 1994 for a more detailed discussion of the topic.

that peer exercise activity will lead firms to exercise early. Within the context of a classic Dixit and Pindyck 1994 framework, the information externalities from peer effects result in an upward revision of the underlying asset value, pushing firms closer to the optimal "trigger" rule, all else equal.

2.2 Data

2.2.1 Construction of panel for hazard model

Our sample period begins in January 2005 and ends in December 2016. We construct a panel of all units (sections) in Oklahoma with one horizontal natural gas shale well in production.[12] This first well confers the operator the option to infill drill the unit with additional wells as described above. The number of these outstanding available options gradually increases over the sample period. By the end of our sample in 2016, there is a total of 2,853 infill drilling options, 680 of which have been exercised (˜24%). The number of firms (operators) corresponds to 159. Table 30 reports the summary statistics for the panel we use in the hazard model. In total our data is composed of wells in 442 townships across every natural gas shale development in Oklahoma.

Our empirical analysis is based on the panel data of exercise decisions to infill drill on sections held by production with the existing well (first drilled) on the section. The unit of observation in this panel is at the drilling unit-month level. In total, our sample comprises 162,905 drilling unit-monthly observations prior to exercise. To test some of the key predictions of the real option framework outlined in the previous section, we include the 18-month natural gas futures price from Bloomberg L.P. and 18-month implied volatility of natural gas prices like in Kellogg 2014. We also include the 5-year nominal risk-free rate on U.S. Treasury bond to capture the impact of interest rate movements. All these variables are computed at the monthly frequency.

[12]Oklahoma contains both shale oil and shale gas. We only focus on wells designated as natural gas shale wells on their drilling and completion reports, meaning the primary economic rationale for drilling the well is the recovery of natural gas, not oil. Therefore, natural gas prices and natural gas price volatility are directly related to the investment decision to drill a well in our sample.

To proxy for the expected value of the reserves that will be unlocked by exercising the option to infill drill, we compute the present value of future cash flows generated by the infill well using the futures curve for pricing, and an expected production profile based off the unit's first horizontal well's production in its first year.[13] Production data are reported by the Oklahoma Corporation Commission and Oklahoma Tax Commission at the well level. Finally, we estimate drilling costs in our sample. Drilling costs vary substantially over time due to the supply and demand for drilling and completion services; however, they vary little across operators and geography within a shale basin at any given point in time (Gilje and Taillard 2016b). As such, we compute a single time-series for the average drilling costs at the monthly frequency by collecting data on 996 wells from the Oklahoma Corporation Commission (OCC) regulatory pooling documents over our sample period. These data provide us with expected drilling costs by all firms who initiate the drilling of the first well in a given drilling unit.[14]

The final set of variables relate to adjacent activity from the firm itself (own) and its peers (competitors). Recall that each section can have up to eight neighboring infill options exercised. We find that on average, over the entire sample period, there are 0.34 adjacent options exercised by its peers and 0.40 by itself. Throughout our regression specifications, to aid the economic interpretations in the tables, we standardize all variables related to adjacent activity (adjacent peer exercise, adjacent firm exercise, and associated relative ranking variables) to have a mean of zero and standard deviation of one. This scaling does not affect the statistical significance of any variables, but does provide an attractive economic interpretation of these variables such that the Hazard Impact factors relate to a 1-standard-deviation change relative to the mean. Table 30, also highlights that the medians are at zero reflecting the fact that many units do not have any infill wells during our sample

[13]The expected production of a well can be potentially modeled in many ways. We settled on the simplest specification based on the first well in the drilling unit. Our results are robust to modeling different types of technological improvements over time. Using the simple approach, we find that using the first well's production explains (R-squared) 64% of the variation in the second well's production in the drilling unit (i.e., the first infill well exercised).

[14]These data are used by other firms with ownership stakes in the drilling unit to decide whether they want to participate in the well and pay their share of the drilling costs.

period, the standard deviations do signal heterogeneity in neighboring activity. We exploit this heterogeneity in our main econometric specifications. To address potential endogeneity concerns, we also compute the ranking of each infill well based on the portfolio of options an operator has at any given point in time. This variable can only be computed on a subset of observations (103,451) and is defined as the relative rank of an infill option based on the quality of the first horizontal well drilled on a drilling unit at a given point in time (see Section 3 for details).

The key event that we use to determine whether an option is exercised is the "spud date" of the first infill well. This is the date when drilling capital expenditure is initiated and the drilling of a second well in the section begins and is directly observable from regulatory filings from the Oklahoma Corporation Commission. From these data we know the precise date, time, firm, and location (drilling unit) of the infill exercise decision. Figure 14A plots the number of options exercised over time, while Figure 14B plots the amount of time firms wait to exercise an option for the subset of options that are exercised. Because an option only becomes available to exercise after the first well has been drilled on a drilling unit, the number of options during the sample period is not the same over time. Figure 14C plots the number of options over time, as well as the number of options exercised at any given point in time.

2.3 Results

2.3.1 Peer effects and option exercise

To assess the factors that might affect real option exercise behavior, we perform a duration analysis based on hazard functions. The objective of using a hazard function is that it allows us to compute the probability of exercising an option, within an interval, conditional on having not exercised the option up to the time of the interval. Specifically, the hazard function is defined as:

$$h(t) = \lim_{s \to 0} \frac{Pr(t \leq T < t + s | T \geq t)}{s}$$

We parametrize the hazard function using a commonly-used semi-parametric approach:

$$h(t) = h_0(t)\exp(\beta_1 NGPrice_t + \beta_2 NGVol_t + \beta_3 DrillCosts_t + \beta_4 IntRate_t$$

$$+\beta_5 FirstWellProd_i + \beta_6 AdjExerOwn_{i,t} + \beta_7 AdjExerPeer_{i,t})$$

This parametrization corresponds to the well-established Cox Proportional Hazard Model, whereby the unit of observation is at the drilling unit-month level. This empirical design determines the factors that make it more (or less) likely that the option to drill the first infill well on a unit (section) is exercised. Once an option is exercised on a drilling unit it is dropped from our sample. Specifically, our duration model specification models the infill drilling decision as a "single-spell" data set, whereby each individual unit (section) enters the data set when the first well in the section is drilled and exits either when the first infill well is exercised (drilled) or is (right) censored if no infill wells are exercised prior to the end of our sample period.[15]

We cluster standard errors at the township level in every specification, the appendix provides further robustness tests of the econometric specifications. A useful baseline when conducting hazard analysis is to plot the survival function; this allows us to observe the rate at which options are being exercised in the sample, we do this in Figure 15. The plot begins at 1 and then declines as time passes (in months) and options are exercised (and no longer survive). By the end of the sample period, 23.8% of all options are exercised. Having established this baseline hazard rate, we can then assess which covariates may cause a shift up or down in the curve in Figure 15, that is, what are the factors that might lead firms to exercise options sooner or later.

The focus of our study is on how neighboring peer project activity affects the baseline

[15]Most infill wells (90.2%) are exercised (drilled) concurrently with the first infill well. That is, when firms exercise their first real option to do infill drilling, they typically exercise many infill options at once. Because infill options tend to get exercised together, modeling the time to exercise of the first infill well is capturing the main economic decision for reserve extraction in the unit; this modeling also allows us to maintain a tractable modeling framework.

hazard rate. To do this, we test the effect of neighboring peer activity on the decision to exercise by calculating the number of adjacent drilling sections (as many as eight) that have infill options exercised by peer firms at each point in time. We include this new variable as well as a measure of the firm's own adjacent activity in the parametrization of the hazard function. To provide context for this peer effect, we include in our baseline specifications the same set of variables as those found in Kellogg 2014. These include natural gas prices, natural gas volatility, drilling costs and interest rates. Recall from Section 1 that standard option theory makes prediction on these variables. For instance, as higher volatility makes the option to delay more valuable, hence all else equal an increase in volatility should push firms to delay investment. By including volatility of natural gas as a covariate ($NGVol_t$), we can assess whether this theoretical relationship holds in the data.

Table 2 shows the results. We find a strong positive relationship between the likelihood of exercising and peer real option exercise activity. To facilitate the interpretation of the adjacent real option exercise variables, we standardize the variables to have mean of zero and standard deviation of one, so that each coefficient/Hazard Impact factor can be interpreted as a 1-standard-deviation change relative to the mean. Specifically, a 1-standard-deviation increase in adjacent peer infill exercise activity increases the likelihood that a firm will exercise its infill option by between 10.9% and 38.2% depending on the specification. This result is supportive of Grenadier 1999's main prediction that information externalities play an important role in the exercise decisions of firms.

Like Kellogg 2014, we find that natural gas prices and natural gas volatility affect real option exercise decisions. Namely, we find that higher volatility reduces the hazard rate (the rate at which options are exercised). Conversely, natural gas prices ($NGPrice_t$) have a positive effect on the hazard rate, as an increase in the natural gas price increases the value (NPV) of the project and makes the option to delay less valuable. In economic terms, based on the Hazard Impact percentage in specification (1) of Table 31, we find that a one standard deviation increase in natural gas price volatility decreases the likelihood of exercising an option by 14.0% (-3.23*4.32) relative to the baseline hazard rate. Alternatively, a 1-standard-deviation increase in the price of natural gas increases the likelihood of exercise by 26.1% (14.77*1.77) relative to the baseline hazard rate. These results hold across the three specifications of Table 31. They suggest that firms' behavior is directionally consistent with these key predictors of option exercise activity. Furthermore, these magnitudes provide important context for our peer effect results. Specifically, peer effects have an economic impact on the same order of magnitude as some of the baseline real option model inputs such as natural gas price and volatility.

Lastly, we also control for the quality of the first horizontal well drilled in the unit as well as the estimated cost of the infill well in specifications (2) and (3) of Table 31. The intuition behind the first of these controls is that the first well is an indicator of the quality of the geology in an area: the more it produces, the higher the value of the additional infill projects, and hence the more likely the option to infill drill will be exercised. Results in Table 31 support this hypothesis. Specifically, a 1-standard-deviation increase in the quality of the first well results in an 88.5% (51.48*1.72) increase in the likelihood of exercise. Drilling costs will vary over time; for instance, wages for qualified workers were rising over our sample period (e.g., Bartik et al. 2018). These time-varying costs could affect option exercise behavior by changing the strike price over time, so controlling for time-varying drilling costs is also important. Results from Table 31 show no significant impact of drilling costs on the likelihood of exercising early, similar to Kellogg 2014's finding.

2.3.2 Endogeneity: Peer effects and option exercise

A potential concern with the interpretation of Table 31 is that the correlation between a firm's exercise behavior and its competitors' adjacent exercise activity cannot necessarily be attributed to a *reaction* to adjacent activity (Manski 1993). For example, a common factor, such as shared technology or similar reserve quality, could affect both the adjacent competitors' decisions to exercise as well as a firm's own decision to exercise. To address this concern, we need to identify the exogenous component of adjacent exercise activity.

Defining the instrument for peer activity

For the construction of our measure of exogenous variation in peer activity, we start from the observation that firms typically face operational, labor, or capital constraints and thus are unlikely to undertake all positive NPV projects at once. As such, they make decisions to invest not only based on the absolute NPV of a project but also the relative NPV or the rank of a project in a firm's portfolio of capital projects.

The measure we construct can best be illustrated with an example. Figure 16 shows the real options of three firms. Firm A has two separate drilling units, each of which is adjacent to drilling units owned by firms B and C. Now assume that the NPV of firm A's infill projects and the infill project adjacent to it, owned by its peers, is $1 million. However, let's also assume that firm B has a portfolio of four additional real options with NPVs, if exercised today, of $2 million, $3 million, $4 million, and $5 million, respectively. Alternatively, firm C has a portfolio of real options with an NPV, if exercised today, of $0.90 million, $0.50 million, $0.30 million, and $0.20 million. All firms have positive NPV projects, but for firm B the project adjacent to firm A is ranked fifth among its portfolio of projects, whereas for firm C it is ranked first. Now assuming that these firms face some operational, labor, or capital constraints, and firms can only undertake one project at a given point in time.[16] Based on the rankings of these projects, we would expect firm B to be more likely than firm C to exercise its project next to firm A, even though the projects have the same absolute NPV. When firm C exercises, firm A benefits from the information on how to complete the well, and information on the depths of the zone to target, while it has no new information for its project next to firm B. Therefore, firm A benefits from an information externality not due to any shared or common characteristic of the specific real option in question, but due to the ranking within the existing portfolio of the other real options that firm C has. The identification assumption is that the rankings of the projects in firm B and firm C's portfolios is exogenous relative to the investment opportunities that firm A has. We offer

[16] Our analysis assumes all projects have the same investment cost at a given point in time, a reasonable assumption in our sample as Gilje and Taillard 2016b provide evidence that investment cost does not significantly vary across firms in a given region for shale gas development.

several tests in the next section to document that the project value of a given firm's option is unrelated to the relative ranking of the adjacent options owned by peer firms.

Table 3 reports whether rank ordering matters in option exercise decisions. The variable we construct is the relative percentile of each infill project in a firm's portfolio. Our rank ordering is based on the production of the first horizontal well on a drilling unit.[17] For every month in the sample, for every firm, we rank the total number of natural gas shale infill real options the firm has across the entire state of Oklahoma as of that point in time, and then map that rank ordering to percentiles. So, for example, if a firm has 20 real options in its portfolio, the number one well would be in the 95th percentile (1–1/20). As can be seen in Table 32, the higher the percentile rank in a firm's portfolio, the more likely it is that the project is exercised. To ease the interpretation of the relative rank percentile coefficients, the data has been normalized to have mean of 0 and standard deviation of 1. Therefore, based on the different specifications found in Table 32, for a 1-standard-deviation increase in percentile, a firm is between 65.8% and 84.9% more likely to exercise an option.

Instrumental variable approach

Table 33, panel A, reports the two-stage estimation, where Adjacent Peer Exercise Activity, defined as the number of infill options exercised by peers adjacent to the drilling unit i at month t, is the variable that is instrumented.[18] The instrument we construct is the average relative percentile of all adjacent drilling units owned by peer firms as of month t based on the relative rank of each adjacent infill project in a peer's portfolio of projects. The relative ranking of each infill project will fluctuate over time; for example, if a peer firm adds real options with strong first wells elsewhere, then the relative percentile will go down. If it

[17] We assessed the potential of several alternative measures for project ranking, including adjusting the production of the first well by its vintage. We found that the unadjusted first well production had the highest explanatory power over infill production, relative to any alternatives. Additionally, we find no variation in the explanatory power of the first well production for infill productivity based on whether the well was drilled early on or later in the shale development.

[18] Table 33 has fewer observations than Table 32, because we can only use our instrument once some adjacent peer infill options exist: if a firm's real option to infill has no adjacent infill options then there is no relative rank from an adjacent peer that can be used to construct the instrument.

adds real options with relatively poor first wells elsewhere, then the relative percentile will improve. We include all control variables from the second stage of our model in the first stage. The first-stage regression is given by

$$\begin{aligned}\#AdjExercisedOptPeer_{i,t} = \\ & \beta_1 AvgRelRankPercAdjPeerProj_{i,t} \\ & +Controls + TownshipFE + \varepsilon_{i,t}\end{aligned}$$

The second stage is given by the Cox proportional hazard model whereby the covariates are comprised of our instrumented variable for neighboring peer activity from the first stage, as well as a series of additional control variables. We correct for the estimation error in the first stage in our Cox two-stage IV model by bootstrapping the standard errors (MacKinnon 2002). The appropriateness of this approach has been supported in recent literature (see Tchetgen et al. 2015).[19]

Table 39 reports the full first-stage estimations with control variables. As can be seen across the different first-stage specifications, our instrument, the average relative rank of the adjacent real option peer projects, has high predictive power for the adjacent peer exercise activity. In addition to the reported regression coefficients, we compute an F-test statistic for our instruments in specifications (1), (2), and (3) and obtain values of 12.14, 11.01, and 10.79 respectively, suggesting an appropriate instrument in our setting.[20] In our second-stage estimations, we directly control for the absolute NPV of adjacent peer infill projects by including the average production from the first (pre-infill) well of adjacent infill peer options as a control. The underlying assumption of this instrument is that the only dimension through which it affects our key dependent variable of interest, the exercise decision of a firm, is through the exercise behavior of peers. We provide a number of tests

[19]We document the robustness of our main two-stage models by estimating both IV probit and IV 2SLS models on our data and obtain similar results to our main Cox model tests, see Tables 41, 42, 43, and 44 and our related discussion in Section 3.2.3.

[20]We also report the first-stage regression in Table 39 without the instrument, including the instrument has minimal effect on the sign, magnitude, and statistical significance of the other control variables.

supporting this assumption in Section 3.2.4. Among the control variables, the only one that loses significance in the instrumental approach (relative to Table 31) is the implied volatility of natural gas prices. We directly test whether our instrument is correlated with implied volatility. The correlation between implied volatility and our instrument is slightly negative, -0.0245, but not statistically different from zero. Further, while the coefficient does lose its statistical significance, it remains firmly in the general range of the baseline estimates. Given the economic channel through which the instrument affects peer activity, this evidence does not suggest that our instrument is operating through any effect on the implied volatility. We also report a regression specification relating volatility to adjacent peer ranking and a firm's own project ranking, along with controls in Table 40, and find no statistically meaningful relationship between these variables and implied volatility.

Overall, the results from Table 33 suggest that the economic interpretation from Table 31 still holds when we use an exogenous source of variation in adjacent peer exercise activity driven by the relative rank of projects in peers' portfolios. For ease of economic interpretation for our key variable of interest, we report the coefficient on the standardized variable, so each coefficient/Hazard Impact factor can be interpreted as a 1-standard-deviation change relative to the mean. As such, a 1-standard-deviation increase in our instrumented adjacent peer options exercised leads to between a 79.1% and 94.0% increase in the likelihood of exercising the option to infill drill. We should be careful to note, as with any instrumental variable estimates, these economic magnitudes should be viewed as local average treatment effects. That is, these are effects on outcomes (exercise behavior) that could conceivably be influenced by the instrument, as opposed to outcomes on real options that are too far out of the money to be exercised, or too deep in the money they would be exercised regardless of adjacent peer activity.

Robustness tests

We first report the reduced-form results in Table 33, panel B, for robustness. This regression is still subject to the exclusion restriction, which in our case means that the relative ranks of adjacent projects only affect a firm's decision to exercise via the relative rank's effect on adjacent peer project exercise decisions. By not instrumenting we lose the economic interpretation of the coefficient on the number of adjacent peer exercised options, but maintain the overall intuition of the result reported in Table 33, panel A: firms' exercise decisions are affected when a project has plausibly exogenous exposure to a variable that affects adjacent exercise behavior (relative rank percentile of adjacent peer projects (β_6)).

We retain the Cox model as the primary specification in the paper because we are studying the motivation behind the decision to exercise real options, and this decision is dynamic by nature: firms have to decide in each period whether to exercise or not, conditional on not having exercised until then. A natural econometric specification for this is the duration model (like in Kellogg 2014). The hazard function allows us to approximate the probability of exercising the option, conditional on having not exercised until then. This modeling has been used in other contexts in corporate finance (e.g., Leary and Roberts 2014) and has several advantages. One of the main advantages in the context of our study being that the hazard function can easily be made to depend on time-varying variables and has a natural interpretation.

Linear probability models and probit specifications both face several drawbacks. First, even though the decision to exercise is binary, a linear specification implicitly assumes that the outcome variable can be nonbinary and even negative. This is one drawback of using the linear probability model. Second, both the linear and probit models are not well suited to capture the dynamic nature of the decision to exercise. Even for probit (or logit) models that accommodate for the binary nature of the left-hand-side variable, these modeling approaches aim to explain the proportion of exercised options across the entire sample at any given point in time, which is different from what the hazard models capture in terms of the variables that influence the probability of exercise at time t, conditional on not having been exercised up to that time. Third, censoring the data is another impediment to implementing traditional methods such as linear probability models or probit regressions.

In our setting, the censoring bias is caused by the fact that we only observe the data until the end of the sample (right censoring); for firms that do not exercise prior to the end of the sample period, we only know that they did not exercise their option until that point in time. Although the linear and probit specifications do not have a natural way of handling this right censoring issue, the maximum likelihood estimations (MLE) of Cox hazard models are well suited to handle this specific type of right censoring (see section 20.3.2 of Wooldridge 2002).

That being said, estimating models using the IV 2SLS (two-stage least squares) and IV probit frameworks is informative in assessing the robustness of our estimates to the choice of estimation model. As such, we perform two other specifications for the IV approach based on an IV probit and IV 2SLS specification for which the statistical properties are well established. Namely, in Table 41, we run an IV probit specification, where the second stage is a probit modeling of the exercise decision instead of a duration model. The coefficient on the instrumented adjacent drilling activity of peers is positive and significant. Table 42 provides the results for the IV 2SLS specification. Again, we find a positive and significant loading on the instrumented adjacent peer activity variable.[21]

Throughout all our main specifications, we have clustered the standard errors at the township level. In Tables 45 and 46, we rerun Table 33, panels A and B, but this time we allow for clustering at the township and year levels (double clustering). Our results remain robust to the double-clustering approach.[22] The double-clustering results typically yield smaller standard errors (i.e., higher t/z-statistics) than one-way clustering by township, hence to be conservative we report township clustering for our main results.[23] Taken together, the evidence in this section suggests that our primary findings are robust across several different

[21]In terms of economic magnitudes, an increase in adjacent peer activity by 1-standard-deviation, relative to the mean, is associated with an increased proportion of infill options exercised of between 94% and 145%. This effect is the same order of magnitude as that in our main tests in Table 33.

[22]Tables 43 and 44 also provide further support for the results found in the context of the IV probit and IV 2SLS specification when clustering of standard errors at the township and year levels (double clustering).

[23]Table 47 documents that our main results are robust to including a control for the first well being drilled ("purchasing an infill option), and Table 48 documents that our main results are robust to including operator fixed effects.

econometric specifications.

Internal validity

In this subsection, we undertake several falsification tests to assess the validity of the instrument we outline above. While the exclusion restriction cannot be tested directly, we can assess the plausibility of some potential explanations that would invalidate our instrument.

One potential explanation which might be problematic for our instrument would be if all firms had similar locations for their high percentile wells. For example, if all firms had their 90th percentile wells in one township, and their 80th percentile wells in another, such clustering would render inference problematic. Although our main tests include specifications with township fixed effects and township level clustering, which would control for an overall township effect, if there is clustering within townships of high percentile groups in some areas and low percentile groups in other areas, it would be problematic as one could argue the instrument might proxy for the absolute value of the NPV of a project and not just the relative NPV of a project. We also directly control for production from adjacent peer wells, which should alleviate this concern to some extent. Nonetheless, we can also directly assess the impact of this possibility when we regress the relative rank of a real option in a firm's portfolio on the relative rank of the real options owned by peers that are adjacent to it at a given point in time, like in the regression below:

$$\begin{aligned} RelRankPercOwnProj_{i,t} &= \\ & \beta_1 AvgRelRankPercAdjPeerProj_{i,t} \\ & + TownshipFE + \varepsilon_{i,t}. \end{aligned}$$

The unit of observation is at the drilling unit i, month t level, and Table 34 estimates the ordinary least squares (OLS) regression. As can be seen the coefficient β_1 is neither statistically nor economically significant, suggesting that once township fixed effects are controlled for (as they are in our main specifications in Table 33), there is no correlation between the percentile rank of a given real option and the average percentile ranks from adjacent peer firms' surrounding real options. This test provides evidence against the idea that all firms have their 90th percentile wells clustered together somewhere, and their 80th percentile wells clustered somewhere else in a way that would confound our tests.

Conceptually, this makes sense as prior to any wells being drilled firms go out and lease drilling acreage when not much information is known about the natural gas resource. Firms thus end up with different portfolios which can be quite dispersed in terms of their potential (see Figure 17); this is the variation that is being exploited with our instrument.

An alternative way to test whether the clustering of relative project quality is driving our results is to look at situations where a real option is ranked low in a given firm's relative percentile rank (below median), whereas the adjacent real options are ranked highly based on peer relative rank (above median). Specifications (1) and (2) of Table 35 report results on this subsample of real options with highly dispersed relative rankings, and as can be seen from the table, our main result holds.[24] Overall, we find magnitudes higher in these tests than our baseline regressions, which is consistent with the idea that information externalities become more important when relative ranks are more dispersed.

Another potential concern with our identification is whether a firm exercises its real option because of the action of a competitor (adjacent exercise) or a characteristic of an adjacent competitor as described in Manski 1993.[25] For example, one might imagine that a competitor exercising their option on an adjacent drilling unit also might be pursuing significant drilling activity (exercising other real options) elsewhere in the region, which might signal, for instance, an overall improvement in extraction technology going forward. In this case, a firm and its competitor are both deciding to exercise options that are adjacent to each other, but it is not because the firm is responding to information externalities from the competitor's actions taken on the neighboring drilling unit, but rather, due to the general

[24]Township fixed effects for this model are not well identified because of the dramatically reduced sample size, and much of the sample is absorbed by township fixed effects.

[25]Leary and Roberts 2014 articulate this issue in detail as it relates to their capital structure analysis.

activity of the competitor taking place both nearby and elsewhere.

To assess empirically whether our main coefficient of interest for peer effects is affected by such characteristics, we look at competitors with adjacent drilling units and test whether their drilling activity *outside* of the township also bears an influence on a firm's decision to exercise. Our hazard regression in Table 36 includes this measure as an additional explanatory variable ("Regional" activity). We find that our main coefficient of interest for peer exercise activity is unaffected by the inclusion of this control variable. Furthermore, we also find no consistent direction in the effect of the "Regional" activity variable across model specifications. Overall, this evidence supports the view that firms are influenced by peers' activity when it occurs on the drilling units directly adjacent to them, consistent with the information channel hypothesized.

Lastly, while we exclude any oil infill projects from our main analysis, we still assess the potential impact of their exclusion from the analysis on our instrument. It is important to note that shale oil infill options are much rarer in the data than shale gas infill options, largely due to the much later adoption of fracking technology to oil shale. Specifically, for the median observation during our sample period a firm's infill option portfolio is composed of 7.8% shale oil infill options and 92.2% shale gas infill options. A concern would be that for firms with different oil exposures the rank ordering variable we compute among natural gas projects would have a different impact on natural gas infill drilling decisions. To assess this concern, we split our sample by above- and below-median oil-infill option exposure and rerun Table 32 across the three sets of specifications for both subgroups separately. As we report in Table 49, above- and below-median oil exposure firms have the same relationship between their natural gas shale project rank ordering and shale gas infill exercise decisions. As we show at the bottom of the table, none of the coefficients across these subgroups are economically or statistically different from one another. Overall, these results are consistent with the idea that firms allocate capital separately across shale oil and shale natural gas projects and provide no support for oil infill options confounding the use of the shale gas relative rank measure we rely on for identification.

2.3.3 Information content of adjacent exercise activity

After having established that firms react to neighboring exercise activity when making their own exercise decisions, we set out to investigate the possible channels behind this result. To do so, we reestimate the hazard model from Table 31 with adjacent exercise activity as an explanatory variable, but this time, we decompose the adjacent exercise activity by competitor type. In particular, we define experienced and inexperienced competitors as those with above- (respectively below-) median drilling activity in Oklahoma at the time of exercise.

In an information transmission framework where agents do not have perfect information on the value of their drilling prospects, operators will look for informational cues from more experienced operators about the drilling opportunities in and around their own prospects (e.g., Grenadier 1999). Moreover, the type of information disclosed via well completion and fracking reports is likely more useful when performed by more experienced firms that are higher up the learning curve in a given resource development. Under this hypothesis, we would expect firms to react more strongly to adjacent exercise behavior from experienced operators.

Table 8 shows the results of our empirical decomposition of neighboring activity. We standardize both of our inexperienced and experienced adjacent activity variables so that we can more readily make a direct comparison between the two coefficients. Specifically we normalize these variables to have a mean of zero and a standard deviation of one. We find that firms exhibit a strong reaction to the adjacent exercise activity of experienced competitors. The economic magnitudes are similar to Table 31's results. These results support Grenadier 1999, whereby operators make specific inferences from their competitors' exercise of real options. In particular, their exercise behavior is influenced by the exercise activity of experienced operators, and thus experienced operators seem to be creating positive informational spillovers when exercising their real options.

Finally, while we mentioned in the previous section that oil infill options comprise only a small fraction of the portfolio of infill options our sample firms hold, we still assess how adjacent oil infill option exercise could confound the interpretation of the main informational effect we identify. First, it is important to highlight that shale oil and shale gas infill options exist in geographically distinct areas. Two-thirds of the townships in the study do not have any oil-related infill options. Further, even in the townships with oil infill options, the median number of sections with an oil infill option is less than 10% of the total (3 of 36). To empirically assess whether learning from adjacent nearby oil infill options could confound our main tests, we replicate the main panels in Table 33 focusing on only the townships that have natural gas shale. Table 50 (panels A and B) reports these tests. The idea is to test whether limiting our data set to areas where learning from oil drilling cannot occur alters our main coefficients. The coefficients we identify on this subset are nearly identical (and remain statistically significant) to the main tests of the paper. This result provides evidence that potential information externalities from shale oil are not meaningfully altering the main interpretation of our findings.

2.4 Real Option Framework and Optimal Exercise Time

In this section, we aim to relate the observed exercise behavior to the optimal exercise behavior predicted by real options models. Our data provides us with the unique ability to compute the inputs a firm would have if it were to follow real option decision rules following the classic real options models of Paddock et al. 1988 and Dixit and Pindyck 1994. We calibrate these models to our data to derive optimal exercise thresholds, that is, conditions to be satisfied if firms are to exercise in an optimal manner. We then adjust the framework to take into account information externalities from adjacent peer real option exercise activity and compare both calibrations to the actual exercise behavior observed in the data. The appendix extends these results by calibrating the dynamic discrete choice model of Rust 1987 that was first applied to the oil and gas industry in Kellogg 2014.[26]

2.4.1 Value of underlying asset

To apply a real option framework, a first necessary step is to ascertain the value of the real option's underlying asset. In our context, the underlying asset corresponds to the natural gas reserves that are being developed when the real option to infill drill is exercised. To obtain the expected value of a well's developed reserves (V), we rely on a set of commonly used assumptions to estimate (1) the expected production volume out of the reserves (in mcf), and (2) the expected net profit per mcf produced. Production volumes are estimated assuming that the well reserves deplete following an exponential decline rate model (Fetkovich et al. 1996). More precisely, we rely on the exponential Arps model properties to estimate the production out of the reserves.[27] Second, we make the simplifying assumption that the 18-month futures price of natural gas can be used to compute the price per mcf obtained over the life of the well (P), and that firms discount their cash flows at a flat discount rate (μ). Third, the net profit per mcf is obtained by taking into account the operational cost (ϕ), the royalty rate (ρ), the accounting depreciation rate (θ) and the corporate tax rate (τ) such that $\Pi = P\left[(1-\phi-\rho) - \tau\left(1-\phi-\rho-\theta\right)\right]$.

The expected value of a well's developed reserves (at time of exercise) is given by:

$$V = E[\int_{t=0}^{\infty} \underbrace{Qe^{-\omega t}}_{(1)} * \underbrace{\Pi e^{-\mu t}}_{(2)} dt]$$

The first term of the value equation, $E[Q]e^{-\omega t}$, corresponds to the Arps model estimates of monthly production at time t where $E[Q]$ is the well's expected production baseline (i.e., its initial production level), ω is the reserve annual depletion rate, and t is the well's age, with $t = 0$ corresponding to the time of exercise. The second term of the equation, $\Pi e^{-\mu t}$,

[26] This extension does not alter our conclusions of this section.

[27] Several recent papers have referred to the Arps model to obtain oil or gas well's reserves estimates (See Kellogg 2014 and Covert 2015).

corresponds to the (discounted) price obtained for the well's natural gas at time t. Solving for the integral, we get a simplified expression for V:

$$V = E[Q]\frac{\Pi}{\mu + \omega}.$$

Thus, the value of the developed reserves is a function of the well's expected production baseline ($E[Q]$), profit per mcf (Π), discount rate (μ), reserves depletion rate (ω).

In terms of comparative statics, the expected reserve value (V) increases with price (P), and expected production baseline ($E[Q]$).[28] Conversely, the expected reserve value (V) decreases when the discount rate (μ), the operational cost (ϕ), the royalty rate (ρ), the accounting depreciation rate (θ), the corporate tax rate (τ), or depletion rate (ω) increases.

2.4.2 Optimal exercise time

The option to expend capital in order to develop shale natural gas reserves through infill drilling corresponds to a real option. Firms in our sample can decide when to exercise these real options and a large body of work has been developed to establish both the pricing of these real options as well as their optimal exercise (stopping) time.[29]

Given that the real option in our study can be viewed as an American call option on the underlying reserves, the optimal exercise time for the real option is derived similarly to the optimal exercise time for an American call option. It is given by a "trigger" rule whereby the option should be exercised, or "triggered," when the expected value of the underlying reserves (V) crosses from below the optimal threshold value (V^*) for the first time. Defining I as the drilling costs of the well, the threshold value is given by

$$V^* = \frac{\beta_1}{\beta_1 - 1}I$$

[28] $V = E[Q]\frac{\Pi}{(\mu+\omega)}$. Thus, $\frac{\partial V}{\partial \omega} = -E[Q]\frac{\Pi}{(\mu+\omega)^2} < 0$.

[29] Detailed derivations can be found in Paddock et al. 1988 and chapters 5.2 (pp. 140–43) and 12.1 (pp. 396–403) in Dixit and Pindyck 1994.

where

$$\beta_1 = \frac{1}{2} - \frac{(r-\delta)}{\sigma_P^2} - \sqrt{\left[\frac{(r-\delta)}{\sigma_P^2} - \frac{1}{2}\right]^2 + \frac{2r}{\sigma_P^2}}$$

Thus, the optimal threshold value (V^*) depends on the drilling costs (I), the risk-free rate (r), the dividend rate of the project (δ), and the volatility of the underlying project value (σ_P). From a simple comparative static analysis, the optimal threshold value increases with drilling costs (I), the risk-free rate (r), and the volatility of the underlying project value (σ_P). Conversely, when the dividend rate of the project (δ) increases, the optimal threshold value (V^*) goes down.[30]

2.4.3 Estimates for real option input variables

An attractive feature of our setting is that we are able to obtain all of the inputs needed to compute both V and V^* defined above and thus empirically test whether the predictions of the real option framework are reflected in the exercise behavior observed in our sample.

Estimating the underlying asset value

To compute the V of each wells at any time period, we need estimates for the following parameters: Π, μ, $E[Q]$, ω and for Π, we need estimates of: P, ϕ, ρ, τ, θ. We provide both the data source and the necessary computations (if necessary) for each one of these inputs below.

Recall that the net profit per mcf is given by: $\Pi = P\left[(1-\phi-\rho) - \tau\left(1-\phi-\rho-\theta\right)\right]$. For the price per mcf over the life of the well (P), we use natural gas price data from Bloomberg. Specifically, like in our main hazard model specifications and consistent with Kellogg 2014, we use the 18-month futures price of natural gas to proxy for the overall natural gas prices over the life of the well.

Lease operating costs (ϕ) are the costs incurred after initial drilling and completion to maintain production during the life of the well. To estimate these costs, we collected data

[30] Refer to chapter 5.2a (pp. 142–4) in Dixit and Pindyck 1994 for more details.

on lease operating costs from the public firms in our sample (10-K filings), and found that on average during our sample time period lease operating costs were 21.6% of well revenues. Lease operating costs are the labor and equipment costs incurred by the well operator to maintain and produce from the well after drilling; these costs would include well pumper costs, company engineering expense, repairs and maintenance. Royalty rates (ρ) correspond to a separate expense computed as a percentage of the well's revenue that goes directly to the mineral rights owners, the individuals who the natural gas company leased the land from for a given well. The royalty rate estimates are based on royalty percentages obtained from DrillingInfo on 322,340 natural gas leases signed in Oklahoma, the median (and mode) royalty rates are equal to 18.75%.[31] For the final elements needed for Π, we set the depreciation rate (θ) to 40% and the effective tax rate (τ) at 0%.[32]

Recall that $V = E[Q]\frac{\Pi}{\mu+\omega}$. Following the computation of Π, we need estimates for the discount rate (μ), the expected production baseline ($E[Q]$) and the annual depletion rate (ω). The discount rate (μ) is set at 10% throughout the sample period, in line with the SEC guidelines in valuing reserves and recent empirical work estimates (e.g., see Kellogg 2014).[33]

Production data at a monthly frequency on every well in our sample is available from the Oklahoma Corporation Commission and Oklahoma Tax Commission. From these data, we estimate both the well's expected production baseline ($E[Q]$), as well as the reserves' depletion rate (ω). From the exponential depletion rate formula of the reserves, we have that the production at a given point in time t is equal to $E[Q]e^{-\omega t}$. For each well we empirically estimate the annual depletion rate ω from the ratio of second year production to the first year production: $\frac{Prod_{t=2}}{Prod_{t=1}} = e^{-\omega}$. We find an average well has an annual depletion rate of

[31] In our sample, the average royalty rate is 19.05%, but the industry standard is 18.75%, and 79% of the lease data has a royalty rate of 18.75%. The sensitivities we report encompass a range that is covered by 87.7% of the royalty terms in the sample.

[32] During the covered period, natural gas exploration firms benefited from multiple generous deductions and tax credits, which enabled them to pay virtually no cash taxes.

[33] In the sensitivity section, we run the calculations using annual discount rate ranging from 7.5% to 12.5%.

27%.[34] Finally, the well's expected production baseline ($E[Q]$) is estimated in two different ways depending on how firms form expectations. In particular, the modeling of expected well productivity depends on whether firms incorporate adjacent peer activity into their updating. Given the centrality of this parameter, a separate section below is devoted to it (see Section 4.3.3).

Estimating the optimal exercise threshold

To compute the optimal trigger value V^* of each wells at any time period, we need estimates for the following parameters: I, and β_1 and for β_1, we need estimates of: r, δ, and σ_P. We provide both the data source and the necessary computations (if necessary) for each one of these inputs below.

We first need an estimate of a well's drilling costs (I). We take the same time-series of drilling costs estimated over our sample period as the one we use in our survival analysis. The detailed description of this time series is given in Section 2.1. We proxy the volatility of the project's underlying asset value (σ_P) with the 18-month implied volatility of natural gas futures prices. For the risk-free rate, like in Section 2, we use the 5-year nominal yield on U.S. Treasury bond to capture the impact of interest rate movements.

Finally, the computation of V^* depends on δ, the implicit dividend a firm generates from a project. Dixit and Pindyck 1994 show that δ equals a firms risk-adjusted cost of capital (m) minus the expected appreciation of the project (a), $\delta = \mu - \alpha$. The intuition behind this result is that the effect of discounting can be offset by the expected appreciation of the underlying asset. For the purpose of our study we assume that expected appreciation of the asset (its drift) is zero. This baseline assumption is reasonable given that the natural gas futures curve is relatively flat throughout our sample. In this case δ simplifies to a firm's cost of capital. From the definition of V^*, the higher the cost of capital, the smaller the wedge between the NPV rule and the optimal trigger rule. We explore a wide range for δ

[34] In the sensitivity section, we vary ω from 25% to 29%, covering approximately 90% of the empirical depletion rate distribution.

in the next section.

Incorporating updating from peer activity

We take a first step at incorporating updating from peer activity by making the expected value of the developed reserves a function of peer activity. It is important to note that the only mechanism through which we are updating the inputs in our real option framework is through the forecast of the productivity of the well.[35]

We derive the expected value of the developed reserves under two scenarios: (1) when firms do not include any additional information from adjacent exercise of peers ($V^{NoUpdating}$), and (2) when firms augment their expectations using additional information from adjacent peer activity ($V^{Updating}$). Under the Arps decline model, to obtain the expected value of the total reserves accessible by the infill well, we need an estimate of the infill well's expected initial production: ($E\left[Q^{NoUpdating}\right]$) and ($E\left[Q^{Updating}\right]$).

In the "No Updating" case, we first use the realized data from all past infill wells drilled in Oklahoma and regress the first year of production of the second well (infill well) on the first year of production of the first well for each section. Second, we take the estimated regression coefficient and combine it with the first year of production of the first well in the section of interest to obtain a *prediction* of the infill well's first year of production ($\widehat{Q}^{NoUpdating}$). Finally, we compute the expected value of the undeveloped reserve ($V^{NoUpdating}$) using the equation introduced in Section 4.1 and the calibrated parameters of Section 4.3.1.

To obtain the expected value of the developed reserves in the "Updating" case, we proceed similarly. First, using data from all past natural gas shale infill wells drilled in Oklahoma, we perform a regression of the first year of production of the second well (infill well) on the first year of production of the first well *and* an indicator variable for adjacent peer exercise activity for each section. The indicator variable is equal to one if there is existing adjacent peer activity when the infill well is being drilled, and zero otherwise. Second, we take the

[35]For instance, our estimates of V^* do not depend on any updating from adjacent peer exercise behavior.

estimated regression coefficients and combine them with the first year of production of the first well in the section of interest as well as the indicator of adjacent peer activity for that section to obtain a *prediction* of the infill well's first year of production ($\widehat{Q}^{Updating}$). Finally, we compute the expected value of the undeveloped reserve ($V^{Updating}$) using the equation introduce in Section 4.1 and the calibrated parameters of Section 4.3.1.

2.4.4 Exercise behavior: Actual versus predicted

In this section we compute the real option decision rules that firms would have if they followed the behavior predicted by real option theory and compare this predicted exercise behavior with their actual exercise behavior. Over the period of interest, there are a total of 2,853 potential infill well real options available. Of these infill well options, 680 are exercised. The objective of this section is to assess whether firms behave in a way that is consistent with the real option framework and whether the information obtained from adjacent peers activity has an effect on their timing decision.

According to the optimal stopping time rule, firms should exercise their drilling option when the value of the developed reserves (V) is equal to the optimal threshold value (V^*), such that $V - V^* = 0$. From a real option perspective, systematic deviations from the optimal decision rule correspond to suboptimal exercise behavior. For instance, if firms were to systematically apply the NPV rule ($NPV = V - I \geq 0$) instead of the optimal trigger rule, we would find them exercising relatively too early (i.e., firms would exercise their drilling option when $V < V^*$) as the NPV rule would lead firms to invest at the margin when $V = I$ and $I < \frac{\beta_1}{\beta_1 - 1} I = V^*$ (since $\beta_1 > 1$). Given the option value to delay, the value of the underlying asset needs to exceed the investment cost (and in some cases by a large margin) before it becomes optimal to exercise. Thus we would expect a positive wedge between the real option trigger rule and the NPV rule.

Full sample

In our baseline case shown in panel A of Table 38, we find that infill projects have an average NPV of \$1.92 million at the time of exercise. The distribution of NPVs at exercise is shown in Figure 18 and clearly shows that a majority of infill wells are positive NPV projects at the time they are exercised. However, the estimated optimal threshold value (V^*) at time of exercise is higher than the estimated expected present value of the well (V). By defining $V^* - V$ as forgone value at exercise, Table 38 shows that firms forgo on average \$0.42 million (\$0.42 = \$7.08 - \$6.66) in our baseline case, with a median forgone value standing at more than twice that number.[36] Figure 19 plots the distribution of forgone value at exercise time. The histogram clearly shows that the majority of the wells are exercised when V minus V^* is negative (i.e., $V < V^*$), reflecting the fact that most wells are exercised prior to reaching their optimal threshold (V^*). This conclusion is only reinforced by running a similar exercise with a more advanced model in the appendix, whereby we estimate a dynamic discrete choice model (see Rust 1987) that also allows for both volatility and drilling costs to be stochastic (see Kellogg 2014).

To assess how robust our conclusions are to changes in model parameters, Table 9, panel B, reports sensitivities across every major parameter in the model. As expected, the NPV of the average (and median) well goes down as the (1) discount rate, (2) operational costs, (3) tax rate, (4) depletion rate, and (5) royalty rate increase. More importantly, this sensitivity exercise informs us on how the forgone value ($V^* - V$) changes due to changes in underlying parameters of the model. In each case, both the average and median forgone values in our sample point to early exercise as they remain positive and statistically different from zero throughout. However, so far, these computations do not incorporate any updating from adjacent peer exercise behavior.

[36] In the figures, we compute histograms of $V - V^*$, in which case values below zero represent forgone values.

Conditioning on adjacent peer activity

The previous sections did not consider the potential information externalities generated by adjacent peer exercise activity. Specifically, the infill well's expected production was simply a function of the unit's first well's realized production (see 4.3.2). In this section, our goal is to identify the role that adjacent peer exercise decisions may play in forming expectations on second well recoveries. To do so, we compare firms' second well (infill well) expectations with their actual realizations with and without conditioning on adjacent peer activity.

To identify the role of adjacent peer exercise activity, we break the sample into two groups: (1) the wells with no adjacent peer activity and (2) the wells with adjacent peer activity.[37] For both groups, we first compute the deviations between the realization of the second well and the expectation of the second well based only on information conferred from the first well's production. We find that for second wells with no adjacent activity, forming the expectation based solely on the first well's production does not lead to any statistically significant deviations from realized production on average. However, for the second wells with adjacent activity, we find that the first well's production realizations do not adequately predict the second well realization. The deviations are positive and statistically different from zero (p-value of 0.066). In other words, adjacent peer activity is associated with significantly higher well productivity, after conditioning for the first well's realized productivity.

Under the assumption that firms form appropriate expectations for their infill wells, such evidence suggests that updating from operators does take into account the information conveyed by peer activity. To incorporate updating of expectations based on adjacent peer activity, expectations now stem from (1) the unit's first well's realized production and (2) the adjacent units' peer exercise activity. We operationalize this updating by using an indicator variable that takes the value of one if there is one or more adjacent infill real options that have been exercised by peer firms. When doing so, we find a statistically

[37] Of a total of 680 exercised options, we have 635 infill wells (second well in unit) with at least 1 year of realized production. Of those 635 infill wells, 214 have adjacent peer exercise activity and 421 have no adjacent peer activity.

and economically significant positive loading on adjacent peer activity when explaining the realized production of second wells based on this augmented set of two variables. The coefficient on the adjacent activity dummy variable is 119,323, which can be interpreted as firms revising up production on the second well by 14.4% relative to the average forecasted production based only on the first well's production if adjacent peer activity occurs. This effect is statistically significant at the 1.9% level.

This result is consistent with one of Grenadier 1999's main assertion that real option exercising from peers conveys an informative signal. Namely, units with more adjacent real options activity are more likely to hold greater reserves. It is also consistent with the findings from the broader literature that documents the importance of peers and "social learning" in technological adoption (see, for instance, Griliches 1957; Foster and Rosenzweig 1995; Thompson and Thompson 2001; Conley and Hudry 2010; Stoyanov and Zubanov 2012). Specific to the oil and gas industry, Covert 2015 shows that there is some degree of technological sharing across peers in shale drilling techniques (e.g., optimal mix of sand and water used in fracking). This finding also could be at work in our context as firms learn how to improve extraction from reserves by observing how peers drill wells in leases adjacent to theirs.

Reconciling realized versus predicted with adjacent activity

The next logical step in our analysis is to assess whether incorporating information from adjacent peer activity makes the decisions to exercise closer to those predicted by theory. To do so, we compute V minus V^* under the two different information sets, one information set that relies on the first well's production exclusively and one information set which incorporates both the first well's production and an indicator for adjacent peer exercise activity. Recall that the optimal trigger threshold V^* is invariant to productivity expectations of the infill well. However, the expected discounted value of the developed reserves of the infill well, V, depends on its expected productivity. Figure 11, panel A (panel B), plots the histogram of V minus V^* for the subset of infill wells with (respectively without) adjacent peer exercise activity.[38]

Panel A of Figure 11 reveals significant differences between the distributions of V minus V^* across the two different information sets used to form expectations. This difference can be explained by the fact that V is revised upward under the information set that takes into account adjacent peer activity. Comparing the proportions of options exercised too early (i.e., $V < V^*$ at the time of exercise), we find that 57% of infill wells are exercised too early under the first information set, relative to only 44% when the information set is augmented to take into account adjacent peer exercise activity. These differences are statistically significant at the 1% level. This evidence suggests that updating expectations for the productivity of the infill well based on adjacent peer activity leads to an approximate 20% reduction in the likelihood of exercising too early.[39]

The results in this section allow us to show that through a basic updating framework, incorporating information on adjacent peer exercise decisions helps to explain a portion of the gap between V and V^* using a baseline Dixit and Pindyck 1994 framework. We do not observe the full model that firms use for either updating beliefs or making real option decisions, and there may be important additional components to such models, which we do not include here. However, the objective of our exercise is to demonstrate that under a basic set of assumptions on real option modeling and a plausible framework for updating, adjacent peer exercise activity could play a first order role in explaining the gap between actual and predicted behavior for real option exercise. Overall, this exercise provides useful context for our empirical results in Section 3.

[38] Each bin represents a $1M interval.

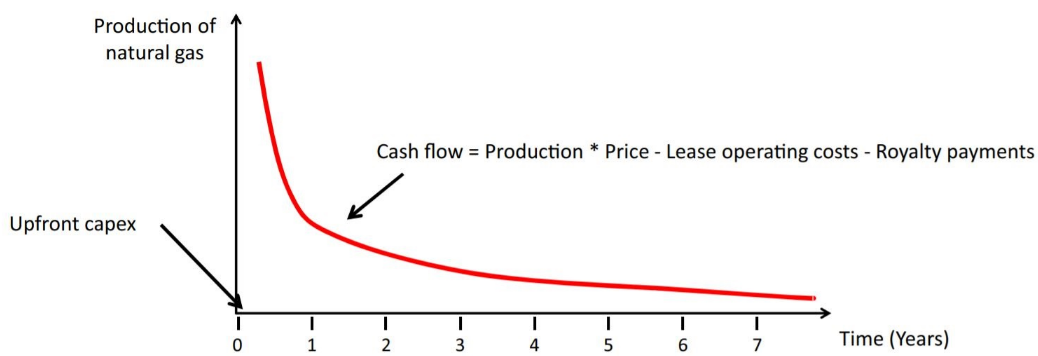
[39] For completeness, and as a falsification, we show Figure 11, panel B reveals no meaningful differences between the distributions of V minus V^* across the two different information sets used to form expectations when looking at the subset of wells without adjacent peer exercise activity. This result should not come as a surprise as we know from above that the big difference in expected productivity comes from observing adjacent activity.

2.5 Conclusion

In this paper we exploit detailed data on a large set of real options to empirically characterize the option exercise strategies employed by firms. We find that peer exercise behavior via an information revelation channel is as important in explaining exercise activity as standard real option inputs such as commodity prices and volatility. To date, the empirical real options literature has been limited, largely by data constraints. Our paper provides important micro-level evidence on both how real options are exercised, and which channels are important in explaining exercise behavior. Our results provide novel empirical support for the importance of information revelation from competitor exercise behavior in explaining how firms exercise real options.

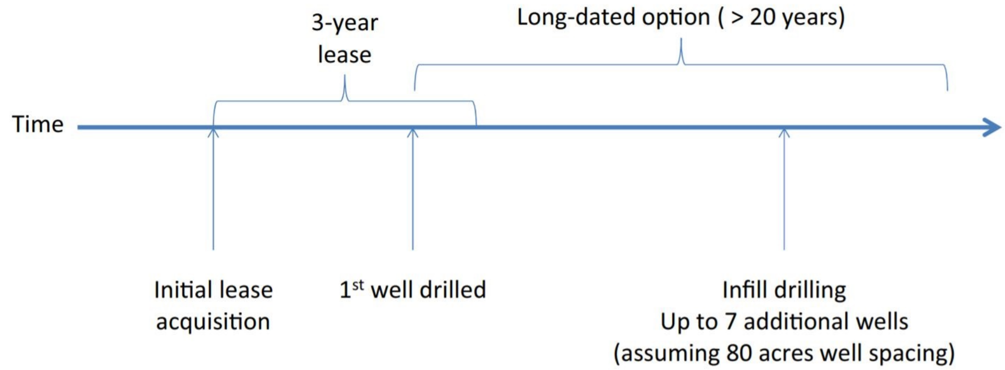
2.5.1 Figures

Figure 10: Project time line



Project time line
This figure plots a typical production curve over time for a natural gas well, once production begins. It is based on similar figures found in Lake et al. (2012) and company investor presentations.

Figure 11: Infill drilling option exercise timeline



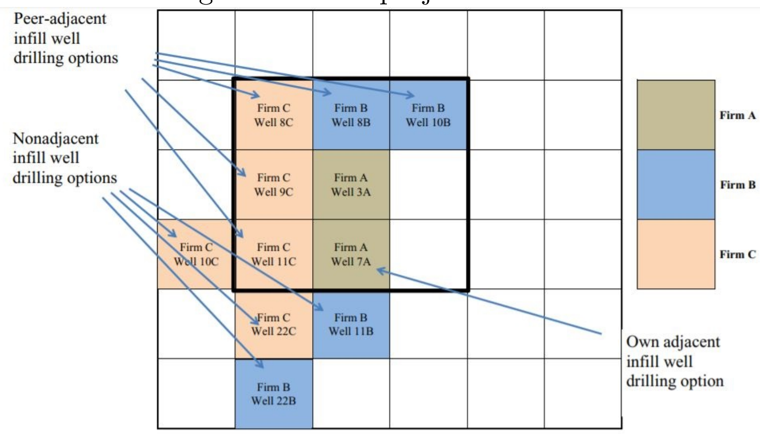
Infill drilling option exercise timeline
This figure plots the time line associate with the option to infill drill.

Figure 12: Map of real option exercise activity

Map of real option exercise activity

This figure provides a map of drilling activity in one township in the Arkoma Woodford shale. The area covers approximately thirty-six individual drilling units. The blue lines represent the horizontal wellbores of the wells in the drilling units and the multiple horizontal lines in a drilling unit correspond to the real option to "infill" drill having been exercised. In some instances the wellhead (top of the well) may be in a different drilling unit than the horizontal wellbore. In this instance, the well will only drain the reservoir in the drilling unit with the horizontal wellbore. The colors of the wellhead correspond to different companies.

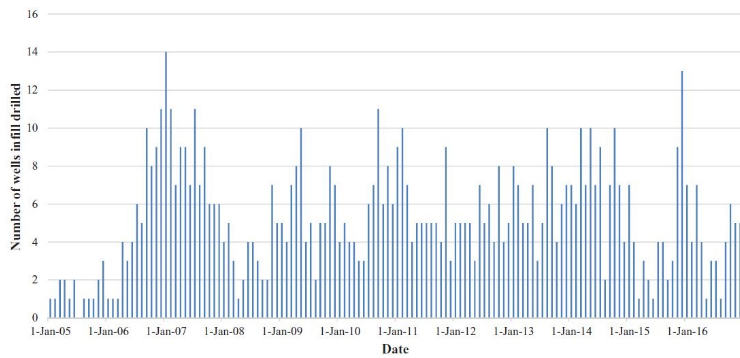
Figure 13: Peer project definition



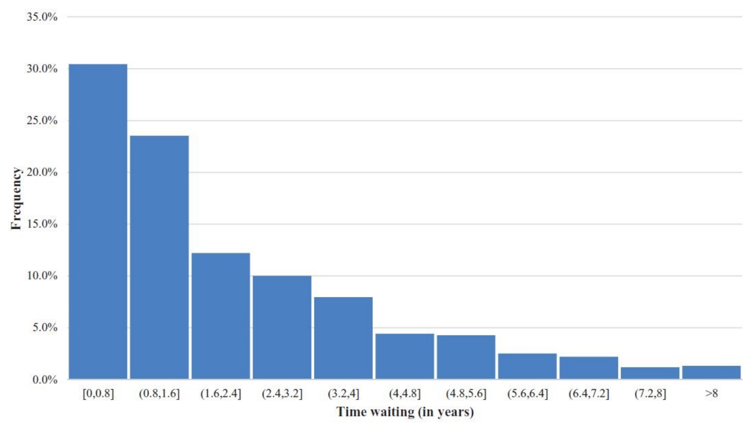
Peer project definition

This figure provides an illustrative example of the definition used for adjacent peer exercise activity. Specifically, the figure plots a 6×6 township that has thirty-six one mile by one mile drilling tracts. Because of institutional features of the land survey in our empirical setting, all infill drilling options conform to the above grid layout, and each infill drilling option is linked to a one mile by one mile drilling tract. We compute adjacent activity as the number of adjacent infill options that have been drilled by firms on the 8 adjacent drilling tracts, we further subdivide this activity by whether peer firms or a firm itself has exercised. For example, for the infill option on well 3A, if firm C exercised option 8C and 9C and no other options were exercised, the number of adjacent peer options exercised would be 2. If firm A exercised option 7A, then its own adjacent options exercised would increase to 1, while peer adjacent exercise would remain at 2.

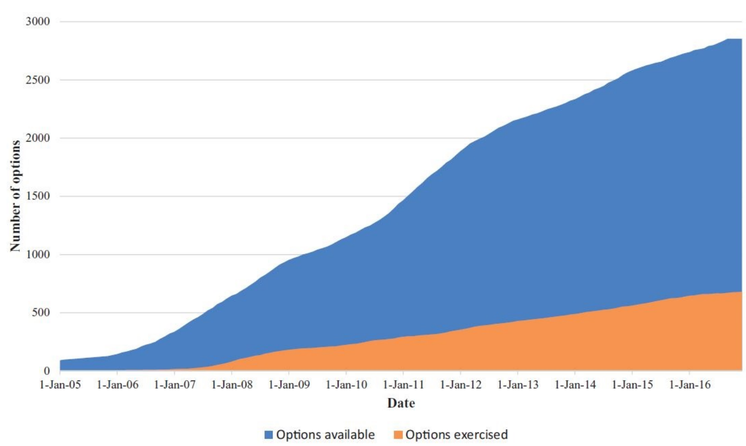
Figure 14: Panel of 3 Figures



Number of infill wells exercised over time
This figure plots the infill drilling exercise activity, measured by the number of infill wells drilled in a given month over our sample period from 2005 through 2016.



Time to exercise the infill drilling option
This figure plots the frequency distribution of the time that firms wait before exercising an infill drilling option over our sample period from 2005 through 2016.



Infill well options and exercise over time
This figure plots the number of infill drilling options available and the number of options that have been exercised, measured by the number of infill wells drilled over our sample period from 2005 through 2016.

2.5.2 Tables

Table 30: Summary statistics

A. Sample statistics

Time period	2005–2016
Total number of real options	2,853
Number of exercised options over sample period	680
Number of townships	442
Number of firms	159

B. Panel data summary statistics

Baseline variables	N	Mean	Median	SD
Natural gas price	162,905	4.56	4.05	1.77
Implied volatility of natural gas	162,905	26.58	25.44	4.32
Interest rates	162,905	1.63	1.51	0.85
log(first well production)	162,905	12.40	12.68	1.72
Peer effect variables				
Adjacent competitor options exercised	162,905	0.34	0.00	0.86
Adjacent own firm options exercised	162,905	0.40	0.00	0.88
Relative rank percentile (own infill option)	103,451	0.46	0.45	0.29
Relative rank percentile (adjacent peer infill options)	103,451	0.57	0.58	0.29

This table contains summary statistics for the data in our study. Panel A presents an overview of the sample of options on natural gas infill shale drilling opportunities in Oklahoma, including how many real options there are, how many have been exercised, over how many townships, and the number of firms (operators) in the sample. Panel B presents summary statistics on the panel data we estimate our hazard models on. The unit of observation in this panel is at the infill option-month level, that is, there is an observation for every infill option available for exercise every month. The baseline variables are all variables used in the hazard model to assess whether exercise is directionally correlated with factors that standard real option theories suggest are important; log(first well production) is a proxy for the underlying reserves in the unit where the infill well can be exercised. The number of adjacent infill options exercised by competitors (peers) corresponds to the variable used to assess whether peer-related real option exercise activity in adjacent drilling units can affect option exercise decisions. We compute a similar measure of adjacent exercise activity for the firm itself (own). The relative rank percentile measures are used to instrument real option exercise activity.

Table 31: Peer effects and real option exercise

Hazard model for infill option exercise

	(1)		(2)		(3)	
	Estimates	HI (%)	Estimates	HI (%)	Estimates	HI (%)
(β_1) Implied volatility of natural gas (percent)$_t$	−0.0328**	−3.23	−0.0337***	−3.31	−0.0282**	−2.79
	[−2.47]		[−2.58]		[−2.22]	
(β_2) Natural gas price ($/mcf)$_t$	0.1378***	14.77	0.1412***	15.17	0.1839***	20.19
	[3.68]		[2.98]		[4.10]	
(β_3) log drilling cost$_t$			−0.0079	−0.79	0.0667	6.90
			[−0.03]		[0.24]	
(β_4) 5-year risk-free interest rate$_t$			0.1382	14.82	0.0749	7.77
			[1.50]		[0.78]	
(β_5) log first well production$_i$			0.4153***	51.48	0.3302***	39.13
			[5.74]		[3.08]	
(β_6) Number of adjacent exercised options (own)$_{i,t}$	0.546***	72.63	0.5263***	69.26	0.3781***	45.95
	[15.22]		[14.24]		[8.83]	
(β_7) Number of adjacent exercised options (peer)$_{i,t}$	0.3233***	38.17	0.2821***	32.59	0.1038*	10.94
	[8.75]		[7.58]		[1.96]	
Township FE	No		No		Yes	
N	162,905		162,905		162,905	

This table reports coefficient estimates from a Cox hazard model of real option exercise. The time period of the sample is from 2005 to 2016. The unit of observation in the underlying panel is at the "infill drill option" i, month t level. The spell in the hazard model is defined as the time period from which an infill option becomes available (first well gets drilled in section) to when the infill option is exercised (second well gets drilled in section) or the end of our sample period if no exercise until that point (right censored). The number of adjacent exercised options (competitor) for an unexercised option i at time t is the number of adjacent drilling units owned by competitors in which the "infill drill option" has been exercised by time t. The number of "own" adjacent options exercised for an unexercised option i at time t is the number of adjacent drilling units owned by the firm itself in which the "infill drill option" has been exercised. The implied volatility of natural gas is the implied volatility based on option prices 18 months in the future, and the natural gas price is the price of the natural gas futures contract 18 months out into the future. The 5-year risk-free rate is the 5-year nominal risk-free rate on U.S. Treasury bonds. The log of drilling costs is a time-varying estimate of drilling costs for an infill well (analogous to the strike price of the real option). The log first well production variable is fixed for a given option and is the logarithm of the first year of production of the first well on the drilling unit, which corresponds to production prior to the exercise of the infill option. The following variables have been scaled to have mean 0 and standard deviation of 1, to facilitate economic interpretations: Number of adjacent exercised options (own) and Number of adjacent exercised options (peer). The hazard impact percentage (HI), which is the percentage change in the hazard rate per unit change of the covariate, is reported next to the coefficient. z-statistics are reported in brackets below the coefficients. Standard errors are clustered by township. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 32: Project relative rank percentile and option exercise

Hazard model for infill option exercise

	(1)		(2)		(3)	
	Estimate	HI (%)	Estimate	HI (%)	Estimate	HI (%)
(β_1) Implied volatility of natural gas (percent)$_t$	−0.0252*	−2.49	−0.028**	−2.76	−0.0245*	−2.42
	[−1.92]		[−2.07]		[−1.77]	
(β_2) Natural gas price (\$/mcf)$_t$	0.1751***	19.14	0.1692***	18.44	0.1631***	17.71
	[4.21]		[3.28]		[3.38]	
(β_3) log drilling cost$_t$			0.1772	19.39	−0.0141	−1.40
			[0.62]		[−0.05]	
(β_4) 5-year risk-free interest rate$_t$			0.0533	5.47	−0.0093	−0.93
			[0.60]		[−0.10]	
(β_5) log first well production$_i$			0.1273	13.57	−0.0974	−9.28
			[1.29]		[−1.44]	
(β_6) Relative rank percentile (own project)$_{i,t}$	0.6147***	84.91	0.5059***	65.84	0.6014***	82.47
	[10.24]		[4.70]		[5.69]	
Township FE	No		No		Yes	
N	162,905		162,905		162,905	

This table reports the effect of the relative project rank percentile within the portfolio of a firm's infill drilling options on the decision to exercise the real option to infill drill. The time period of the sample is from 2005 to 2016. The unit of observation in the underlying panel is at the "infill drill option" i, month t level. The relative project rank percentiles are based on the quality of the project, as measured by the production from the first well on a drilling tract within a firm's portfolio. The percentile is computed as the rank of the project divided by the total number of infill options a firm has, higher percentile projects can be viewed as having a higher relative NPV rank within a firm's portfolio. The variable "Relative rank percentile (own project) has been scaled to have mean 0 and standard deviation of 1, to facilitate economic interpretations. The hazard impact percentage (HI), which is the percentage change in the hazard rate per unit change of the covariate, is reported next to the coefficient. z-statistics are reported in brackets below the coefficients. Standard errors are clustered by township. $^{*}p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 33: Real option exercise and exogenous peer effects

A. Instrumented - Number of adjacent exercised options (peer)

	Hazard model					
	(1)		(2)		(3)	
	Estimate	HI (%)	Estimate	HI (%)	Estimate	HI (%)
(β_1) Implied volatility of natural gas (percent)$_t$	−0.0245 [−1.45]	−2.42	−0.0281 [−1.62]	−2.77	−0.0166 [−0.98]	−1.64
(β_2) Natural gas price (\$/mcf)$_t$	0.2062*** [2.86]	22.90	0.1546*** [2.62]	16.72	0.2801*** [2.70]	32.33
(β_3) log drilling cost$_t$	0.0494 [0.17]	5.06	−0.0319 [−0.10]	−3.14	0.4462 [1.07]	56.24
(β_4) 5-year risk-free interest rate$_t$	0.1325 [1.07]	14.17	0.1564 [1.50]	16.93	0.2168 [1.29]	24.21
(β_5) log first well production$_i$	0.2432*** [2.61]	27.54	−0.0064 [−0.07]	−0.64	−0.0565 [−0.68]	−5.50
(β_6) Instrumented - Number of adjacent exercised options (peer)$_{i,t}$	0.595*** [2.72]	81.31	0.5825*** [2.82]	79.06	0.6623** [2.16]	93.93
(β_7) Average log first well production adjacent options (peer)$_{i,t}$	−0.0671 [−1.63]	−6.49	−0.0746** [−2.15]	−7.18	−0.0236 [−0.75]	−2.33
(β_8) Number of adjacent exercised options (own)$_{i,t}$			0.3731*** [3.35]	45.22	0.7649*** [4.25]	114.88
(β_9) Relative rank percentile (own project)$_{i,t}$			0.311** [2.05]	36.48	0.2563 [1.63]	29.21
Township FE	No		No		Yes	
N	103,451		103,451		103,451	

	First-stage F-test statistics for Average relative rank percentile (adjacent peer projects)$_{i,t}$		
	(1)	(2)	(3)
F-test statistic	12.14	11.01	10.79

B. Reduced form - Relative rank percentile (adjacent peer projects)

	Hazard model					
	(1)		(2)		(3)	
	Estimate	HI (%)	Estimate	HI (%)	Estimate	HI (%)
(β_1) Implied volatility of natural gas (percent)$_t$	−0.0242 [−1.55]	−2.39	−0.028* [−1.84]	−2.76	−0.0211 [−1.43]	−2.09
(β_2) Natural gas price (\$/mcf)$_t$	0.1838*** [3.64]	20.18	0.1301*** [2.71]	13.90	0.1588*** [3.12]	17.21
(β_3) log drilling cost$_t$	0.1768 [0.55]	19.34	0.0805 [0.26]	8.39	0.2025 [0.55]	22.45
(β_4) 5-year risk-free interest rate$_t$	0.0704 [0.75]	7.30	0.1022 [1.11]	10.76	0.0441 [0.45]	4.51
(β_5) log first well production$_i$	0.295*** [3.40]	34.31	0.0045 [0.06]	0.45	−0.0446 [−0.60]	−4.36
(β_6) Relative rank percentile (adjacent peer projects)$_{i,t}$	0.3043*** [3.31]	35.57	0.2676*** [3.65]	30.69	0.2417*** [2.90]	27.34
(β_7) Average log first well production adjacent options (peer)$_{i,t}$	0.0567*** [3.46]	5.84	0.0365** [2.31]	3.72	0.0566*** [3.06]	5.82
(β_8) Number of adjacent exercised options (own)$_{i,t}$			0.5002*** [11.01]	64.90	0.3985*** [7.67]	48.96
(β_9) Relative rank percentile (own project)$_{i,t}$			0.4146*** [3.86]	51.37	0.4256*** [3.67]	53.05
Township FE	No		No		Yes	
N	103,451		103,451		103,451	

Table 34: Internal validity: Correlation of project relative rank percentiles

	Dependent variable = Relative rank percentile (own project)	
	(1)	(2)
(β_1) Relative rank percentile (adjacent peer projects)$_{i,t}$	−0.0359	0.0316
	[−1.11]	[1.12]
(β_2) Implied volatility of natural gas (percent)$_t$		0.0001
		[0.13]
(β_3) Natural gas price ($/mcf)$_t$		0.0367***
		[5.42]
(β_4) log drilling cost$_t$		0.0908***
		[3.37]
(β_5) 5-year risk-free interest rate$_t$		−0.0138
		[−1.11]
(β_6) log first well production$_i$		0.4205***
		[7.40]
(β_7) Average log first well production adjacent options (peer)$_{i,t}$		0.0121***
		[2.68]
(β_8) Number of adjacent exercised options (own)$_{i,t}$		0.0258
		[0.99]
Township FE	Yes	Yes
N	103,451	103,451

This table reports the coefficient estimates of an ordinary least squares (OLS) regression of the relative rank percentile of a firm's own project on the relative rank percentiles of adjacent infill options owned by peer firms. The unit of observation in the underlying panel is at the "infill drill option" i, month t level. t-statistics are reported in brackets below the coefficients. Standard errors are clustered by township. $^{*}p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 35: Internal validity: Subsample analysis

	Hazard model			
	Low own project rank vs. high adjacent peer project rank			
	Reduced-form peer effects (1)		Instrumented peer effects (2)	
	Estimates	HI (%)	Estimates	HI (%)
(β_1) Implied volatility of natural gas (percent)$_t$	−0.0107	−1.06	−0.0157	−1.56
	[−0.38]		[−0.56]	
(β_2) Natural gas price (\$/mcf)$_t$	0.0584	6.02	0.1579**	17.11
	[0.66]		[2.03]	
(β_3) log drilling cost$_t$	−0.0701	−6.77	−0.0328	−3.23
	[−0.15]		[−0.06]	
(β_4) 5-year risk-free interest rate$_t$	0.1505	16.25	0.1107	11.71
	[1.01]		[0.78]	
(β_5) log first well production$_i$	0.0241	2.44	0.0308	3.12
	[0.27]		[0.29]	
(β_6) Relative rank percentile (adjacent peer projects)$_{i,t}$	0.4345***	54.42		
	[3.46]			
(β_7) Average log first well production adjacent options (peer)$_{i,t}$	0.0793***	8.26	−0.0936	−8.93
	[3.02]		[−1.17]	
(β_8) Number of adjacent exercised options (own)$_{i,t}$	0.399***	49.03	0.0166	1.67
	[5.27]		[0.04]	
(β_9) Relative rank percentile (own project)$_{i,t}$	0.1793	19.64	−0.2562	−22.60
	[0.83]		[−0.85]	
(β_{10}) Instrumented - Number of adjacent exercised options (peer)$_{i,t}$			1.1038**	201.57
			[2.21]	
Township FE	No		No	
N	43,686		43,686	

This table reports coefficient estimates from a Cox hazard model of real option exercise on a specific subsample to test instrument validity. The time period of the samples are from 2005 to 2016. The unit of observation in the underlying panel is at the "infill drill option" i, month t level. Specifications (1) and (2) report exercise behavior for the subsample of real options where a project's relative rank percentile within a given firm's portfolio is below median for that firm, but adjacent projects owned by peers have project relative rank percentiles in peer project portfolios that are above median. The following variables have been scaled to have mean 0 and standard deviation of 1, to facilitate economic interpretations: Number of adjacent exercised options (own), Number of adjacent exercised options (peer), Relative rank percentile (own project), and Relative rank percentile (adjacent peer projects). The hazard impact percentage (HI), which is the percentage change in the hazard rate per unit change of the covariate, is reported next to the coefficient. z-statistics are reported in brackets below the coefficients. Standard errors are clustered by township. $*p<0.10$; $**p<0.05$; $***p<0.01$.

Table 36: Actions versus characteristics

	Reduced-form peer effects				Instrumented peer effects			
	(1)		(2)		(3)		(4)	
	Estimates	HI (%)	Estimates	HI (%)	Estimates	HI (%)	Estimates	HI (%)
(β_1) Implied volatility of natural gas (percent)$_t$	−0.0272*	−2.69	−0.0203	−2.01	−0.0289*	−2.85	−0.0168	−1.67
	[−1.80]		[−1.38]		[−1.67]		[−0.93]	
(β_2) Natural gas price ($/mcf)$_t$	0.1205**	12.81	0.1548***	16.75	0.1665***	18.12	0.2767***	31.88
	[2.54]		[3.08]		[2.81]		[2.96]	
(β_3) log drilling cost$_t$	0.0536	5.51	0.2035	22.57	0.0145	1.46	0.4603	58.45
	[0.17]		[0.55]		[0.04]		[1.30]	
(β_4) 5-year risk-free interest rate$_t$	0.1052	11.09	0.0501	5.13	0.1471	15.85	0.2193	24.52
	[1.13]		[0.51]		[1.39]		[1.08]	
(β_5) log first well production$_i$	0.0048	0.48	−0.0413	−4.05	−0.0033	−0.33	−0.0564	−5.49
	[0.06]		[−0.55]		[−0.04]		[−0.56]	
(β_6) Relative rank percentile (adjacent peer projects)$_{i,t}$	0.2689***	30.85	0.2448***	27.74				
	[3.65]		[2.94]					
(β_7) Average log first well production adjacent options (peer)$_{i,t}$	0.0307**	3.12	0.0535***	5.50	−0.0665**	−6.43	−0.0200	−1.98
	[1.96]		[2.91]		[−2.17]		[−0.57]	
(β_8) Number of adjacent exercised options (own)$_{i,t}$	0.5106***	66.62	0.4066***	50.18	0.355***	42.62	0.7553***	112.83
	[11.11]		[7.93]		[3.01]		[4.07]	
(β_9) Relative rank percentile (own project)$_{i,t}$	0.4107***	50.79	0.4207***	52.30	0.3062**	35.82	0.2527	28.75
	[3.84]		[3.63]		[2.02]		[1.26]	
(β_{10}) Regional activity peer)$_{i,t}$	0.0916***	9.60	0.0575**	5.92	−0.2544**	−22.46	−0.1165	−11.00
	[4.24]		[2.26]		[−1.96]		[−1.00]	
(β_{11}) Instrumented - Number of adjacent exercised options (peer)$_{i,t}$					0.7351***	108.58	0.6926*	99.89
					[2.79]		[1.76]	
Township FE	No		Yes		No		Yes	
N	103,451		103,451		103,451		103,451	

This table reports coefficient estimates from a Cox hazard model of real option exercise. The time period of the sample is from 2005 to 2016. The unit of observation in the underlying panel is at the "infill drill option" i, month t level. The variable "Regional activity" is computed in two steps. First, we compute the drilling activity intensity across the entire region for each adjacent competitor at a given point in time t, while excluding the wells they drilled in the township of infill option i. Then, for each infill drill option in our sample, we define the variable "Regional activity" as the sum of the adjacent competitor activity outside the township of the infill drill option at each point in time. The following variables have been scaled to have mean 0 and standard deviation of 1, to facilitate economic interpretations: Number of adjacent exercised options (own), Number of adjacent exercised options (peer), Relative rank percentile (own project), Regional activity (peer), and Relative rank percentile (adjacent peer projects). The hazard impact percentage (HI), which is the percentage change in the hazard rate per unit change of the covariate, is reported next to the coefficient. z-statistics are reported in brackets below the coefficients. Standard errors are clustered by township. *$p<0.10$; **$p<0.05$; ***$p<0.01$.

Table 37: Real option exercise and experienced peers

	Hazard model			
	(1)		(2)	
	Estimates	HI (%)	Estimates	HI (%)
(β_1) Implied volatility of natural gas (percent)$_t$	−0.0339***	−3.33	−0.0282**	−2.78
	[−2.59]		[−2.22]	
(β_2) Natural gas price ($/mcf)$_t$	0.1407***	15.10	0.1842***	20.23
	[2.96]		[4.09]	
(β_3) log drilling cost$_t$	0.0009	0.09	0.0669	6.91
	[0.00]		[0.24]	
(β_4) 5-year risk-free interest rate$_t$	0.1398	15.00	0.0746	7.74
	[1.51]		[0.77]	
(β_5) log first well production$_i$	0.4144***	51.35	0.3309***	39.22
	[5.72]		[3.08]	
(β_6) Number of adjacent exercised options (own)$_{i,t}$	0.525***	69.04	0.3786***	46.03
	[14.32]		[8.89]	
(β_7) Number of adjacent exercised options (experienced peer)$_{i,t}$	0.2658***	30.45	0.1022**	10.76
	[7.54]		[2.14]	
(β_8) Number of adjacent exercised options (inexperienced peer)$_{i,t}$	0.0871***	9.10	0.0152	1.53
	[3.03]		[0.30]	
Township FE	No		Yes	
N	162,905		162,905	

This table reports coefficient estimates from a Cox hazard model of real option exercise. The time period of the sample is from 2005 to 2016. The unit of observation in the underlying panel is at the "infill drill option" i, month t level. The signal quality variables (Adjacent Experienced / Adjacent Inexperienced) are constructed in two steps. First, we identify if the adjacent firms exercising their drilling option are more (less) experienced than the median firm in the sample based on the number of wells drilled and, accordingly, we define them as Experienced (Inexperienced). In the second step, we aggregate the wells that are drilled by experienced firms into the variable adjacent experienced options (experienced peer) and those drilled by unexperienced firms into adjacent exercised options (inexperienced peer). The following variables have been scaled to have mean 0 and standard deviation of 1, to facilitate economic interpretations: Number of adjacent exercised options (own), Number of adjacent exercised options (experienced peer), and Number of adjacent exercised options (inexperienced peer). The hazard impact percentage (HI), which is the percentage change in the hazard rate per unit change of the covariate, is reported next to the coefficient. z-statistics are reported in brackets below the coefficients. Standard errors are clustered by township. $^{*}p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 38: Real option value estimates and sensitivity analysis

A: Summary statistics

Well-level statistics at time of exercise	N	Mean	Median	SD
Well costs (I)	680	\$4,740,347	\$4,798,365	\$651,954
Present value of well cash flow (V)	680	\$6,656,654	\$6,146,015	\$3,390,738
Optimal Trigger Value (V*)	680	\$7,079,647	\$7,307,629	\$1,407,007
Net Present Value (V-I)	680	\$1,916,307	\$1,374,095	\$3,414,682

B. Sensitivity analysis

Depletion rate sensitivity	Mean	Pr(Mean = 0)	Median	Pr(Median = 0)
Net present value (V-I at exercise)				
Depletion rate ($\omega = 25\%$)	\$2,101,214	0.00	\$1,540,539	0.00
Depletion rate ($\omega = 27\%$)	\$1,916,307	0.00	\$1,374,095	0.00
Depletion rate ($\omega = 29\%$)	\$1,574,940	0.00	\$1,078,187	0.00
Forgone value (V*-V at exercise)				
Depletion rate ($\omega = 25\%$)	\$238,086	0.07	\$702,787	0.00
Depletion rate ($\omega = 27\%$)	\$422,993	0.00	\$866,943	0.00
Depletion rate ($\omega = 29\%$)	\$764,360	0.00	\$1,144,138	0.00
Operational cost sensitivity	Mean	Pr(Mean = 0)	Median	Pr(Median = 0)
Net present value (V-I at exercise)				
Operational cost ($\phi=15\%$)	\$2,459,708	0.00	\$1,864,696	0.00
Operational cost ($\phi=20\%$)	\$1,916,307	0.00	\$1,374,095	0.00
Operational cost ($\phi=25\%$)	\$1,372,907	0.00	\$903,057	0.00
Forgone value (V*-V at exercise)				
Operational cost ($\phi=15\%$)	\$259,973	0.05	\$721,624	0.00
Operational cost ($\phi=20\%$)	\$422,993	0.00	\$866,943	0.00
Operational cost ($\phi=25\%$)	\$694,693	0.00	\$1,078,926	0.00
Discount rate sensitivity	Mean	Pr(Mean = 0)	Median	Pr(Median = 0)
Net present value (V-I at exercise)				
Discount rate ($\mu=7.5\%$)	\$2,398,674	0.00	\$1,811,878	0.00
Discount rate ($\mu=10\%$)	\$1,916,307	0.00	\$1,374,095	0.00
Discount rate ($\mu=12.5\%$)	\$1,495,000	0.00	\$1,008,892	0.00
Forgone value (V*-V at exercise)				
Discount rate ($\mu=7.5\%$)	\$857,331	0.00	\$1,346,908	0.00
Discount rate ($\mu=10\%$)	\$422,993	0.00	\$866,943	0.00
Discount rate ($\mu=12.5\%$)	\$318,536	0.01	\$760,092	0.00
Tax rate sensitivity	Mean	Pr(Mean = 0)	Median	Pr(Median = 0)
Net present value (V-I at exercise)				
Tax rate ($\tau=0\%$)	\$1,916,307	0.00	\$1,374,095	0.00
Tax rate ($\tau=15\%$)	\$1,569,890	0.00	\$1,073,808	0.00
Tax rate ($\tau=30\%$)	\$1,223,472	0.00	\$772,849	0.00
Forgone value (V*-V at exercise)				
Tax rate ($\tau=0\%$)	\$422,993	0.00	\$866,943	0.00
Tax rate ($\tau=15\%$)	\$769,411	0.00	\$1,148,941	0.00
Tax rate ($\tau=30\%$)	\$1,115,829	0.00	\$1,470,295	0.00
Royalty rate sensitivity	Mean	Pr(Mean = 0)	Median	Pr(Median = 0)
Net present value (V-I at exercise)				
Royalty rate ($\rho=13.75\%$)	\$2,459,708	0.00	\$1,864,696	0.00
Royalty rate ($\rho=18.75\%$)	\$1,916,307	0.00	\$1,374,095	0.00
Royalty rate ($\rho=23.75\%$)	\$1,372,907	0.00	\$903,057	0.00
Forgone value (V*-V at exercise)				
Royalty rate ($\rho=13.75\%$)	\$259,973	0.05	\$721,624	0.00
Royalty rate ($\rho=18.75\%$)	\$422,993	0.00	\$866,943	0.00
Royalty rate ($\rho=23.75\%$)	\$694,693	0.00	\$1,078,926	0.00

This table first reports in panel A summary statistics on well costs (I), present value of cash flows (V), the optimal trigger value (V*), and the net present value (NPV=V−I) at the time of exercise, as generated by a baseline real options model (see Paddock et al. 1988; and Dixit Pindyck 1994). Panel B reports a sensitivity analysis for the net present value (NPV=V−I) and forgone value (V*−V) at time of exercise. The sensitivity analysis is performed on the different assumptions for several model parameters.

Table 39: First-stage regression and coefficient comparison

	First-stage regression with instrument			First-stage regression without instrument		
	(1)	(2)	(3)	(4)	(5)	(6)
(β_1) Implied volatility of natural gas (percent)$_t$	0.0001	0.0000	−0.0064**	0.0003	0.0002	−0.0062**
	[0.07]	[0.01]	[−2.59]	[0.15]	[0.08]	[−2.55]
(β_2) Natural gas price ($/mcf)$_t$	−0.0096	−0.0111	−0.0838***	−0.0019	−0.0047	−0.0756***
	[−0.55]	[−0.65]	[−5.75]	[−0.11]	[−0.28]	[−5.51]
(β_3) log drilling cost$_t$	0.0547	0.0508	−0.0648	0.0683	0.0619	−0.0509
	[1.05]	[1.00]	[−1.43]	[1.31]	[1.22]	[−1.15]
(β_4) 5-year risk-free interest rate$_t$	−0.0266	−0.0245	−0.0832**	−0.0235	−0.0214	−0.0818**
	[−1.18]	[−1.09]	[−2.26]	[−1.06]	[−0.97]	[−2.23]
(β_5) log first well production$_i$	0.0222	0.0049	0.0075	0.0377*	0.0089	−0.0005
	[1.29]	[0.30]	[0.57]	[1.90]	[0.54]	[−0.04]
(β_6) Relative rank percentile (adjacent peer projects)$_{i,t}$	0.1306***	0.1210***	0.1117***			
	[3.28]	[3.14]	[2.93]			
(β_7) Average log first well production adjacent options (peer)$_{i,t}$	0.0532***	0.0502***	0.0429***	0.0428***	0.0402**	0.0336***
	[5.38]	[5.02]	[6.25]	[5.32]	[4.88]	[6.24]
(β_8) Number of adjacent exercised options (own)$_{i,t}$		0.0574	−0.1657***		0.0607	−0.1644***
		[1.52]	[−4.17]		[1.59]	[−4.13]
(β_9) Relative rank percentile (own project)$_{i,t}$		0.0468	0.0608**		0.0738*	0.0652***
		[1.18]	[2.47]		[1.76]	[2.66]
Township FE	No	No	Yes	No	No	Yes
N	103,451	103,451	103,451	103,451	103,451	103,451

This table reports the first-stage estimation of the two stage model of Table 4, panel A. The first stage runs an OLS regression of adjacent peer activity on the instrument used in the study (relative rank percentile of peer projects) and the set of controls from the second-stage estimation. Columns (1)—(3) map to the three specifications of Table 4, panel A. Columns (4)—(6) run OLS specifications of adjacent peer activity on the same set of controls, but without the instrument. Standard errors are clustered by township. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

Table 40: Instrument and implied volatility

	Dependent variable = Implied volatility		
	(1)	(2)	(3)
(β_1) Relative rank percentile (adjacent peer projects)$_{i,t}$	0.0396		0.0394
	[1.21]		[1.22]
(β_2) Relative rank percentile (own project)$_{i,t}$		0.0060	0.0045
		[0.17]	[0.13]
(β_3) Natural gas price (\$/mcf)$_t$	1.0038***	1.0066***	1.0036***
	[55.94]	[58.00]	[55.80]
(β_4) log drilling cost$_t$	4.4830***	4.4877***	4.4825***
	[40.52]	[40.73]	[40.92]
(β_5) 5-year risk-free interest rate$_t$	0.5493***	0.5499***	0.5494***
	[12.27]	[12.34]	[12.31]
(β_6) log first well production$_i$	0.0195	0.0148	0.0176
	[1.41]	[0.77]	[0.95]
(β_7) Average log first well production adjacent options (peer)$_{i,t}$	−0.0091	−0.0125	−0.0092
	[−0.76]	[−1.01]	[−0.77]
(β_8) Number of adjacent exercised options (own)$_{i,t}$	−0.0401	−0.0398	−0.0402
	[−1.37]	[−1.35]	[−1.37]
Township FE	Yes	Yes	Yes
N	103,451	103,451	103,451

This table reports regressions of implied volatility on the instrument used in the study (relative rank percentile of peer projects) and the set of controls from the second-stage estimation in Table 4, panel A. Standard errors are clustered by township. $*p<0.10$; $**p<0.05$; $***p<0.01$.

Table 41: Real option exercise and exogenous peer effects: IV probit model, clustered by township

	IV probit model Instrumented - Number of adjacent exercised options (peer)		
	(1)	(2)	(3)
	Estimate	Estimate	Estimate
(β_1) Implied volatility of natural gas (percent)$_t$	−0.0088*	−0.0097*	−0.0046
	[−1.79]	[−1.94]	[−0.76]
(β_2) Natural gas price ($/mcf)$_t$	0.0241	0.0093	0.0867***
	[1.05]	[0.42]	[3.51]
(β_3) log drilling cost$_t$	−0.0373	−0.0592	0.1389
	[−0.35]	[−0.57]	[1.13]
(β_4) 5-year risk-free interest rate$_t$	0.0581*	0.07*	0.0958**
	[1.65]	[1.92]	[1.97]
(β_5) log first well production$_i$	0.0436	−0.0103	−0.0099
	[1.34]	[−0.48]	[−0.39]
(β_6) Instrumented - Number of adjacent exercised options (peer)$_{i,t}$	0.5688***	0.5697***	0.5476***
	[4.14]	[4.22]	[2.69]
(β_7) Average log first well production adjacent options (peer)$_{i,t}$	−0.014*	−0.0182***	−0.0154
	[−1.86]	[−2.68]	[−1.25]
(β_8) Number of adjacent exercised options (own)$_{i,t}$		0.15***	0.2567***
		[3.91]	[7.95]
(β_9) Relative rank percentile (own project)$_{i,t}$		0.0707	0.0686
		[1.39]	[1.01]
Township FE	No	No	Yes
N	103,451	103,451	103,451

This table reports results of the main instrumental variable tests reported in Table 4, panel A, using IV probit as the estimation model. Variable definitions and panel structure match what is used in Table 4. Standard errors are clustered by township.

Table 42: Real option exercise and exogenous peer effects: IV-2SLS model, clustered by township

	IV probit model Instrumented - Number of adjacent exercised options (peer)		
	(1)	(2)	(3)
	Estimate	Estimate	Estimate
(β_1) Implied volatility of natural gas (percent)$_t$	−0.0001	−0.0001*	−0.0001
	[−1.63]	[−1.70]	[−1.04]
(β_2) Natural gas price ($/mcf)$_t$	0.0009**	0.0008*	0.0017***
	[2.04]	[1.85]	[3.04]
(β_3) log drilling cost$_t$	−0.0007	−0.0008	0.0013
	[−0.44]	[−0.49]	[0.86]
(β_4) 5-year risk-free interest rate$_t$	0.0006	0.0007	0.0007
	[0.92]	[1.03]	[0.98]
(β_5) log first well production$_i$	0.0003	−0.0002	−0.0002
	[1.54]	[−1.13]	[−0.79]
(β_6) Instrumented - Number of adjacent exercised options (peer)$_{i,t}$	0.0071***	0.0046**	0.0052*
	[2.97]	[2.10]	[1.65]
(β_7) Average log first well production adjacent options (peer)$_{i,t}$	−0.0001	−0.0001	0.0000
	[−0.75]	[−0.71]	[0.17]
(β_8) Number of adjacent exercised options (own)$_{i,t}$		0.0032***	0.0039***
		[4.89]	[4.04]
(β_9) Relative rank percentile (own project)$_{i,t}$		0.0018***	0.0019***
		[3.13]	[2.71]
Township FE	No	No	Yes
N	103,451	103,451	103,451

This table reports results of the main instrumental variable tests reported in Table 4, panel A, using IV-2SLS as the estimation model. Variable definitions and panel structure match what is used in Table 4. Standard errors are clustered by township.

Table 43: Real option exercise and exogenous peer effects: IV probit model (clustered by township and by year)

	IV probit model Instrumented - Number of adjacent exercised options (peer)		
	Estimate	Estimate	Estimate
(β_1) Implied volatility of natural gas (percent)$_t$	−0.0088*	−0.0097**	−0.0046
	[−1.80]	[−2.05]	[−0.51]
(β_2) Natural gas price ($/mcf)$_t$	0.0241	0.0093	0.0867***
	[1.04]	[0.38]	[3.19]
(β_3) log drilling cost$_t$	−0.0373	−0.0592	0.1389
	[−0.29]	[−0.44]	[1.16]
(β_4) 5-year risk-free interest rate$_t$	0.0581*	0.07*	0.0958**
	[1.68]	[1.91]	[2.30]
(β_5) log first well production$_i$	0.0436	−0.0103	−0.0099
	[1.61]	[−0.47]	[−0.44]
(β_6) Instrumented - Number of adjacent exercised options (peer)$_{i,t}$	0.5688***	0.5697***	0.5476***
	[4.88]	[4.66]	[2.79]
(β_7) Average log first well production adjacent options (peer)$_{i,t}$	−0.014*	−0.0182***	−0.0154
	[−1.90]	[−2.64]	[−1.15]
(β_8) Number of adjacent exercised options (own)$_{i,t}$		0.15***	0.2567***
		[3.95]	[7.55]
(β_9) Relative rank percentile (own project)$_{i,t}$		0.0707	0.0686
		[1.31]	[0.97]
Township FE	No	No	Yes
N	103,451	103,451	103,451

This table reports results of the main instrumental variable tests reported in Table 4, panel A, using IV probit as the estimation model. Variable definitions and panel structure match what is used in Table 4. Standard errors are clustered by township and by year.

Table 44: Real option exercise and exogenous peer effects: IV 2SLS regression model (clustered by township and by year)

	IV probit model Instrumented - Number of adjacent exercised options (peer)		
	(1) Estimate	(2) Estimate	(3) Estimate
(β_1) Implied volatility of natural gas (percent)$_t$	−0.0001	−0.0001	−0.0001
	[−1.38]	[−1.38]	[−0.74]
(β_2) Natural gas price ($/mcf)$_t$	0.0009	0.0008	0.0017***
	[1.49]	[1.32]	[4.19]
(β_3) log drilling cost$_t$	−0.0007	−0.0008	0.0013
	[−0.32]	[−0.34]	[0.77]
(β_4) 5-year risk-free interest rate$_t$	0.0006	0.0007	0.0007
	[0.88]	[0.98]	[1.01]
(β_5) log first well production$_i$	0.0003*	−0.0002	−0.0002
	[1.71]	[−1.09]	[−0.90]
(β_6) Instrumented - Number of adjacent exercised options (peer)$_{i,t}$	0.0071***	0.0046***	0.0052**
	[3.49]	[2.82]	[1.96]
(β_7) Average log first well production adjacent options (peer)$_{i,t}$	−0.0001	−0.0001	0.0000
	[−0.84]	[−0.79]	[0.16]
(β_8) Number of adjacent exercised options (own)$_{i,t}$		0.0032***	0.0039***
		[3.65]	[3.74]
(β_9) Relative rank percentile (own project)$_{i,t}$		0.0018**	0.0019**
		[2.39]	[2.15]
Township FE	No	No	Yes
N	103,451	103,451	103,451

This table reports results of the main instrumental variable tests reported in Table 4, panel A, using IV 2SLS as the estimation model. Variable definitions and panel structure match what is used in Table 4. Standard errors are clustered by township and by year.

Table 45: Real option exercise and exogenous peer effects: IV Cox model (clustered by township and by year)

	Hazard model Instrumented - Number of adjacent exercised options (peer)					
	(1)		(2)		(3)	
	Estimate	HI (%)	Estimate	HI (%)	Estimate	HI (%)
(β_1) Implied volatility of natural gas (percent)$_t$	−0.0245 [−1.39]	−2.42	−0.0281 [−1.55]	−2.77	−0.0166 [−0.61]	−1.64
(β_2) Natural gas price (\$/mcf)$_t$	0.2062** [2.23]	22.90	0.1546 [1.63]	16.72	0.2801** [2.45]	32.33
(β_3) log drilling cost$_t$	0.0494 [0.15]	5.06	−0.0319 [−0.08]	−3.14	0.4462 [0.96]	56.24
(β_4) 5-year risk-free interest rate$_t$	0.1325 [1.11]	14.17	0.1564 [1.19]	16.93	0.2168 [1.15]	24.21
(β_5) log first well production$_i$	0.2432*** [3.10]	27.54	−0.0064 [−0.08]	−0.64	−0.0565** [−2.44]	−5.50
(β_6) Instrumented - Number of adjacent exercised options (peer)$_{i,t}$	0.595*** [3.65]	81.31	0.5825*** [3.11]	79.06	0.6623*** [2.79]	93.93
(β_7) Average log first well production adjacent options (peer)$_{i,t}$	−0.0671* [−1.82]	−6.49	−0.0746** [−2.00]	−7.18	−0.0236 [−0.96]	−2.33
(β_8) Number of adjacent exercised options (own)$_{i,t}$			0.3731*** [3.41]	45.22	0.7649*** [5.03]	114.88
(β_9) Relative rank percentile (own project)$_{i,t}$			0.311** [2.04]	36.48	0.2563* [1.68]	29.21
Township FE	No		No		Yes	
N	103,451		103,451		103,451	

This table reports results of the main instrumental variable tests reported in Table 4, panel A, with standard errors double clustered by township and by year. Variable definitions and panel structure match what is used in Table 4.

Table 46: Reduced-form model (clustered by township and by year)

	Hazard model					
	Reduced form - Relative rank percentile (adjacent peer projects)					
	(1)		(2)		(3)	
	Estimate	HI (%)	Estimate	HI (%)	Estimate	HI (%)
(β_1) Implied volatility of natural gas (percent)$_t$	−0.0242 [−1.33]	−2.39	−0.028* [−1.67]	−2.76	−0.0211 [−1.09]	−2.09
(β_2) Natural gas price ($/mcf)$_t$	0.1838*** [3.95]	20.18	0.1301** [2.54]	13.90	0.1588*** [4.11]	17.21
(β_3) log drilling cost$_t$	0.1768 [0.50]	19.34	0.0805 [0.22]	8.39	0.2025 [0.58]	22.45
(β_4) 5-year risk-free interest rate$_t$	0.0704 [1.02]	7.30	0.1022 [1.34]	10.76	0.0441 [0.44]	4.51
(β_5) log first well production$_i$	0.295*** [3.45]	34.31	0.0045 [0.05]	0.45	−0.0446 [−0.81]	−4.36
(β_6) Relative rank percentile (adjacent peer projects)$_{i,t}$	0.3043*** [4.38]	35.57	0.2676*** [4.42]	30.69	0.2417*** [2.96]	27.34
(β_7) Average log first well production adjacent options (peer)$_{i,t}$	0.0567*** [3.51]	5.84	0.0365** [2.24]	3.72	0.0566*** [3.13]	5.82
(β_8) Number of adjacent exercised options (own)$_{i,t}$			0.5002*** [11.93]	64.90	0.3985*** [7.60]	48.96
(β_9) Relative rank percentile (own project)$_{i,t}$			0.4146*** [3.55]	51.37	0.4256*** [3.77]	53.05
Township FE	No		No		Yes	
N	103,451		103,451		103,451	

This table reports results of the main reduced-form tests reported in Table 4, panel B, with standard errors double clustered by township and by year. Variable definitions and panel structure match what is used in Table 4.

Table 47: Effect of adjacent first wells

	Reduced-form peer effects (1)		Instrumented peer effects (2)	
	Estimate	HI (%)	Estimate	HI (%)
(β_1) Implied volatility of natural gas (percent)$_t$	−0.0200	−1.98	−0.0179	−1.77
	[−1.34]		[−1.09]	
(β_2) Natural gas price ($/mcf)$_t$	0.1621***	17.60	0.249**	28.27
	[3.28]		[2.41]	
(β_3) log drilling cost$_t$	0.1969	21.76	0.4256	53.05
	[0.54]		[1.00]	
(β_4) 5-year risk-free interest rate$_t$	0.0782	8.13	0.1981	21.90
	[0.78]		[1.20]	
(β_5) log first well production$_i$	−0.0436	−4.27	−0.0520	−5.07
	[−0.61]		[−0.65]	
(β_6) Relative rank percentile (adjacent peer projects)$_{i,t}$	0.2633***	30.12		
	[3.18]			
(β_7) Average log first well production adjacent options (peer)$_{i,t}$	0.0270	2.74	0.0261	2.64
	[1.44]		[1.40]	
(β_8) Number of adjacent exercised options (own)$_{i,t}$	0.4724***	60.39	0.5556***	74.30
	[9.52]		[6.22]	
(β_9) Relative rank percentile (own project)$_{i,t}$	0.4157***	51.55	0.2627*	30.04
	[3.73]		[1.83]	
(β_{10}) Number of adjacent first wells drilled (peer)$_{i,t}$	0.312***	36.61	−0.7108*	−50.88
	[5.82]		[−1.66]	
(β_{11}) Instrumented - Number of adjacent exercised options (peer)$_{i,t}$			1.1168**	205.50
			[2.29]	
Township FE	Yes		Yes	
N	103,451		103,451	

This table reports results of the main instrumental variable and reduced-form tests reported in Table 4, panel A (specification (3)), and Table 4, Panel B (specification (3)), with the inclusion of an additional control variable to capture the number of unexercised infill real options from peers (Number of adjacent first wells drilled (peer)). Other variable definitions and panel structure match what is used in Table 4. Standard errors are clustered by township.

Table 48: Operator fixed effects

	Reduced-form peer effects		Instrumented peer effects	
	(1)		(2)	
	Estimate	HI (%)	Estimate	HI (%)
(β_1) Implied volatility of natural gas (percent)$_t$	−0.0229	−2.26	−0.013*	−1.29
	[−1.43]		[−1.72]	
(β_2) Natural gas price (\$/mcf)$_t$	0.1636***	17.77	0.0906***	9.48
	[2.80]		[2.43]	
(β_3) log drilling cost$_t$	0.2906	33.72	0.3216	37.93
	[0.74]		[1.63]	
(β_4) 5-year risk-free interest rate$_t$	−0.0543	−5.29	0.0670	6.93
	[−0.56]		[0.34]	
(β_5) log first well production$_i$	−0.0509	−4.96	−0.0885	−8.42
	[−0.48]		[−0.32]	
(β_6) Relative rank percentile (adjacent peer projects)$_{i,t}$	0.1619*	17.58		
	[1.87]			
(β_7) Average log first well production adjacent options (peer)$_{i,t}$	0.0524***	5.38	0.0171	1.72
	[2.76]		[0.14]	
(β_8) Number of adjacent exercised options (own)$_{i,t}$	0.3205***	37.78	0.1894***	20.85
	[6.15]		[2.58]	
(β_9) Relative rank percentile (own project)$_{i,t}$	0.5406***	71.70	0.1664***	18.11
	[4.15]		[2.52]	
(β_{10}) Instrumented - Number of adjacent exercised options (peer)$_{i,t}$			0.1466***	15.78
			[2.39]	
Township FE	Yes		Yes	
Operator FE	Yes		Yes	
N	103,451		103,451	

This table reports results of the main instrumental variable and reduced-form tests reported in Table 4, panel A (specification (3)), and Table 4, panel B (specification (3)), with the inclusion of operator fixed effects. Other variable definitions and panel structure match what is used in Table 4. Standard errors are clustered by township.

Table 49: Project relative rank percentile and option exercise: Above-median oil exposure versus below-median oil exposure

Hazard model for infill option exercise

	Below-median oil		Above-median oil		Below-median oil		Above-median oil		Below-median oil		Above-median oil	
	(1)		(2)		(3)		(4)		(5)		(6)	
	Estimate	HI (%)	Estimate	HI (%)	Estimate	HI (%)	Estimate	HI (%)	Estimate	HI (%)	Estimate	HI (%)
(β_1) Implied volatility of natural gas (percent)$_t$	−0.0244	−2.41	−0.0245	−2.42	−0.0275	−2.71	−0.0285	−2.81	−0.0251	−2.48	−0.0234	−2.32
	[−1.36]		[−1.19]		[−1.44]		[−1.39]		[−1.20]		[−1.11]	
(β_2) Natural gas price (\$/mcf)$_t$	0.2317***	26.07	0.134**	14.33	0.2227***	24.94	0.1443*	15.52	0.2207***	24.70	0.1181	12.53
	[4.42]		[2.18]		[4.01]		[1.76]		[3.88]		[1.35]	
(β_3) log drilling cost$_t$					0.2707	31.09	0.3200	37.72	0.2758	31.75	0.0035	0.35
					[0.76]		[0.82]		[0.68]		[0.01]	
(β_4) 5-year risk-free interest rate$_t$					0.1058	11.16	−0.0068	−0.67	0.0316	3.21	−0.0933	−8.91
					[0.95]		[−0.06]		[0.24]		[−0.71]	
(β_5) log first well production$_i$					0.2171	24.25	0.0920	9.64	0.1470	15.83	−0.0313	−3.08
					[1.30]		[0.73]		[0.43]		[−0.30]	
(β_6) Relative rank percentile (own project)$_{i,t}$	0.6239***	86.62	0.6158***	85.11	0.4608***	58.53	0.5282***	69.58	0.5046**	65.64	0.5232***	68.75
	[7.94]		[7.47]		[3.19]		[3.46]		[2.03]		[3.71]	
Township FE	No		No		No		No		Yes		Yes	
N	82,265		80,640		82,265		80,640		82,265		80,640	
	Below-median β_6 - Above-median β_6				Below-median β_6 - Above-median β_6				Below-median β_6 - Above-median β_6			
	0.0081				−0.0674				−0.0192			
p-value testing whether difference ≠ 0	p-value = 0.91				p-value = 0.75				p-value = 0.57			

This table is based on the same specification as Table 3, but estimates the specification across two different subsamples, firms with above-median oil exposure versus firms with below-median oil exposure. Oil exposure is based on the percentage of oil infill options a firm has in its infill option portfolio.

Table 50: Real option exercise and exogenous peer effects: Shale gas townships only

A. Instrumented - Number of adjacent exercised options (peer)

	Hazard model					
	(1)		(2)		(3)	
	Estimate	HI (%)	Estimate	HI (%)	Estimate	HI (%)
(β_1) Implied volatility of natural gas (percent)$_t$	−0.0200	−1.98	−0.0247	−2.44	−0.0134	−1.33
	[−1.01]		[−1.07]		[−0.62]	
(β_2) Natural gas price ($/mcf)$_t$	0.233***	26.24	0.1683**	18.33	0.2411**	27.26
	[3.32]		[2.13]		[2.48]	
(β_3) log drilling cost$_t$	−0.2426	−21.54	−0.3335	−28.36	0.0202	2.04
	[−0.60]		[−0.94]		[0.05]	
(β_4) 5-year risk-free interest rate$_t$	0.1713	18.68	0.1947	21.49	0.2227	24.95
	[1.30]		[1.35]		[1.18]	
(β_5) log first well production$_i$	0.4146***	51.37	0.0353	3.59	−0.0690	−6.67
	[3.30]		[0.26]		[−0.53]	
(β_6) Instrumented - Number of adjacent exercised options (peer)$_{i,t}$	0.6129**	84.57	0.6362**	88.93	0.6561**	92.72
	[2.17]		[2.04]		[2.14]	
(β_7) Average log first well production adjacent options (peer)$_{i,t}$	−0.0818	−7.85	−0.1005**	−9.56	−0.0218	−2.16
	[−1.35]		[−2.02]		[−0.59]	
(β_8) Number of adjacent exercised options (own)$_{i,t}$			0.4976***	64.47	0.8055***	123.78
			[3.49]		[4.26]	
(β_9) Relative rank percentile (own project)$_{i,t}$			0.3456	41.29	0.3109*	36.47
			[1.46]		[1.82]	
Township FE	No		No		Yes	
N	67,868		67,868		67,868	

B. Reduced form: Relative rank percentile (adjacent peer projects)

	(1) Estimate	(1) HI (%)	(2) Estimate	(2) HI (%)	(3) Estimate	(3) HI (%)
(β_1) Implied volatility of natural gas (percent)$_t$	−0.0165	−1.63	−0.0210	−2.08	−0.0166	−1.65
	[−0.83]		[−1.10]		[−0.82]	
(β_2) Natural gas price ($/mcf)$_t$	0.2151***	24.00	0.148**	15.95	0.1273*	13.57
	[3.55]		[2.54]		[1.93]	
(β_3) log drilling cost$_t$	−0.2081	−18.79	−0.3001	−25.93	−0.2183	−19.62
	[−0.62]		[−0.93]		[−0.64]	
(β_4) 5-year risk-free interest rate$_t$	0.1112	11.76	0.1339	14.33	0.0642	6.63
	[0.93]		[1.15]		[0.53]	
(β_5) log first well production$_i$	0.475***	60.81	0.0667	6.89	−0.0538	−5.24
	[4.46]		[0.60]		[−0.62]	
(β_6) Relative rank percentile (adjacent peer projects)$_{i,t}$	0.2791**	32.19	0.2781***	32.06	0.2253**	25.27
	[2.33]		[2.80]		[2.16]	
(β_7) Average log first well production adjacent options (peer)$_{i,t}$	0.0481**	4.93	0.0321	3.26	0.0549**	5.65
	[2.00]		[1.37]		[2.16]	
(β_8) Number of adjacent exercised options (own)$_{i,t}$			0.5029***	65.36	0.4527***	57.26
			[9.89]		[7.27]	
(β_9) Relative rank percentile (own project)$_{i,t}$			0.4204***	52.26	0.4637***	59.00
			[2.96]		[3.24]	
Township FE	No		No		Yes	
N	67,868		67,868		67,868	

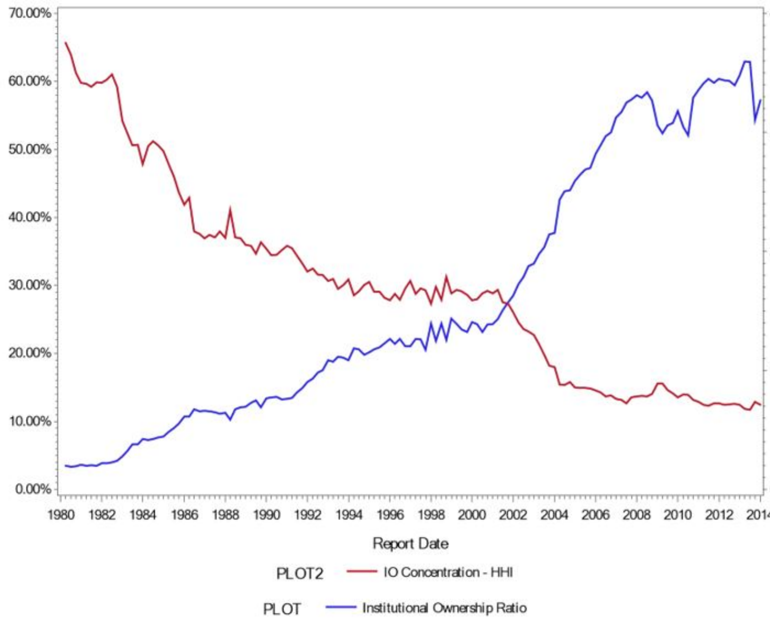
This table reports the same specifications as panels A and B of Table 4 in the main paper, but limits the sample to townships that have shale natural gas only (and no shale oil).

CHAPTER 3 : Ownership Concentration and Firm Risk-Taking Behavior

The undertaking of profitable but risky business opportunities lies at the center of long-term economic growth Acemoglu and Zilibotti 1997; Obstfeld 1994. However, without the proper incentives and institutional environment, managers naturally dislike risk and tend to opt for safer and less growth enhancing projects Smith and Stulz 1985; Amihud and Lev 1981, potentially leading to suboptimal resource allocation. Therefore, it is imperative to identify which channels support the adoption of risk-taking behavior that improve economic welfare and resource allocation.

In this sense, economic theory and recent empirical results support the idea that resourceful and committed large institutional investors are potentially well-suited partners for firms that aim to develop a competitive hedge such as the implementation of riskier projects (i.e. research and development, new technology adoption) Porter and Parker 1992; Aghion et al. 2013. It is then reassuring to note that over the past 30 years the proportion held by institutional shareholders of a representative firms has grown from 5% in the 1980's to approximately 50% in the 2010's. However, a large theoretical literature also posits that the ability of such owners to affect resource allocation depends on ownership concentration. Indeed, ownership concentration affects owners' ability to coordinate their choice of corporate policies, willingness to produce information, and capacity to optimally monitor managers Edmands 2017. Given the steady decline in ownership concentration observed for the same period, from 40% in 1980 to 10% in 2014, identifying whether ownership concentration is a relevant corporate governance lever on firms' behavior is of prime importance.

Figure 15: Firm-Year Portfolio's Projects' Expected IRR Distribution



Time Series of Institutional Ownership Statistics For US Common Stocks (Median Statistics in %)

Specifically, this paper investigates the relationship between ownership concentration and firms' risk-taking behavior. While, there has been ample coverage in the theoretical literature on the relationship between ownership concentration and firms' risk-taking behavior, providing compelling evidence of a causal relationship has been challenging. Indeed, past research has provided mixed results and failed to provide a causal statement. For example Tufano 1996 found that firms' dominated by highly concentrated insider ownership were less likely to have managers' adopting riskier business strategy while Paligorova 2010 found that blockholders are positively correlated with corporate risk-taking. Indeed, from an empirical perspective there are two main limitations to clearly identifying the relationship. First, risk-taking behavior and ownership concentration are simultaneously determined, thus making it difficult to obtain a causal interpretation of ownership concentration on firms' risk- taking decisions. Second, there exists no perfect measure of corporate risk-taking behavior, with each available proxy facing potential limitations.

To overcome the identification challenge, I use the merger of financial holdings to construct an instrumental variable capturing an exogenous shock to ownership concentration. I construct the instrument variable using a natural experiment that was first used in a difference-in-difference setup to measure the effect of competition on bias in the context of analyst earnings forecasts Hong and Kacperczyk 2010. More closely related to this paper, some researchers used this natural experiment to investigate the relation between cross-ownership structure and product market competition Huang and Jie 2017; Azar et al. 2017, and the effects of blockholders' diversity on firms performance Volkova 2017. However, to the best of my knowledge, this is the first empirical paper to investigate a causal relationship between firms' risk-taking behavior and ownership concentration.

To overcome the difficulty of correctly measuring firms' risk-taking behavior, I introduce three proxies to capture the risk component in firms' behavior. Using accounting data, I derive two operational risk measures of risk: the volatility of returns on assets and the volatility of the returns on sales. From the stock market data, I derive the third measure of risk using the volatility of market returns.

This paper relates to several literatures. First, it complements the literature that identifies channels affecting corporate risk-taking. Investigating the relation of CEO remuneration package structure on risk-taking behavior, Hayes et al. 2012 found a weak economic relationship while Gormley et al. 2013 found that the effect of CEO remuneration on firms' risk-taking was slow to impact the risk decisions of the firms. Also, Gilje 2016 showed that firms' distance-to-default affects firms' risk appetite. Finally, John et al. 2008 identified that the quality of ownership legal protection was positively related to corporate risk-taking and firms' growth rate. Perhaps the paper most similar to mine is Gormley and Matsa 2016 who found that a reduction in the risk of take-over treat would reduce the firms' risk incentive, leading to 7.5% of a standard deviation decrease in stocks volatility while I found that a one standard deviation change in ownership concentration lead to a 17.1% increase in stocks volatility.

Finally, it is related to the developing literature on institutional ownership impact on firms' outcomes. Research papers have shown that the quantity of institutional shareholders positively impacts firms' research and development policies Aghion et al. 2013, firms' performance and governance quality Appel et al. 2016, payout policies Gaspara et al. 2005, and investment horizons Bena 2017. More recently, a burgeoning literature started to focus on the structure of institutional ownership on firms' performance. Huang and Jie 2017; Azar et al. 2017 found that firms' cross-ownership positively impact firms' product-market performance and Volkova 2017 showed that owners' diversity negatively impact firms' return on asset and investment opportunity.

3.1 Motivation and Theoretical Predictions

To understand the potential relation between ownership structure and risk taking, it is first enlightening to look at how the firms' ownership concentration impact the quantity of information production and monitoring intensity of the shareholders and then look at how monitoring effort from the shareholders impacts managers' project decisions and risk-taking behavior.

Regarding the ownership issue, the ownership structure impacts the inner dynamic among shareholders, and ultimately affects their willingness to exert efforts monitoring the manager. Because, large shareholder better internalizes the benefits from their monitoring efforts, a more concentrated ownership should alleviate the free-riders issue present in more diffuse ownership structure and stimulate the monitoring intensity Grossman and Hart 1980; Shleifer and Vishny 1986. Additionally, the recent theoretical results posit the numbers of larges investors and their relative size is likely to determine the owners intervention incentives and the effects of their actions Edmans and Manso 2011; Noe 2002.

Regarding the effect of monitoring effect and information production of the shareholders on managers risk taking behavior, firms with more concentrated ownership should experience increasing monitoring efforts and information production. Therefore, it should reduce the informational frictions between the owners and the manager. There are three theoretical results support the idea that a reduction of information asymmetry between firms' owners and the manager should foster risk taking.

1) Then the career concern hypothesis Kaplan and Minton 2006 assumes that managers might be reluctant to take on risky projects because of the risk of being fired should the project fail. Indeed, engaging in risky projects has the potential to yield greater payoffs, but if the project fails for purely stochastic reasons, the owners might assume that the manager is bad and fire her. If contracting technologies cannot resolve entirely the issues, having owners with better monitoring ability can alleviate part of the problem. In this sense, the capacity of large institutional investors to reduce the information asymmetry problem connected to firms' strategies is widely understood in the literature Hall and Lerner 2010. Indeed, by allocating substantial resources to support and monitor managers in designing their corporate strategies Appel et al. 2016, and by reducing the level of information asymmetry Edmans 2009, institutional investors can help firms' management team to take on more unconventional projects. Indeed, Edmans 2009 showed that blockholders can encourage the manager to invest in riskier and more demanding projects (i.e. long-term projects). In his proposed model, if the firm announces low earnings, the blockholder receives a signal about the cause of low earnings. If the signal is not related to managers' lack of effort or low firm quality, the blockholder retains his stake, supporting the stock price. This expected support fostered by the blockholder's ability to access superior information on the firm's outcome encourages the manager to invest in projects that would be career-threatening in situations where ownership was more disperse.

2) Additionally, the quiet life hypothesis postulate that if managers are not closely monitored, they might choose to take projects that require less efforts and avoid projects that are riskier Bertrand and Schoar 2003; Hart 1983. In this case, the improved monitoring capacity of a more concentrated ownership would incentivize the manager to pursue corporate policies that require more efforts and that potentially have a riskier payoff structure.

3) Finally, from the asset substitution problem side Jensen and Meckling 1976, equity holders are the residual owners of firms' proceeds, which incentivize them to favor riskier projects. Thus, an increase in owners' coordination ability resulting from a more concentrated ownership is likely to improve the capacity of equity holders to impact managers' decisions, potentially at the expense of debt holders. Also, even if large shareholders cannot exercise intervene easily, they can still impact the manager policy choices through the alternative channel of exit Edmans 2009; Admati and Pfleiderer 2009 (i.e. they can sell their shares and drive down the stock price to punish the manager ex-post and induce him to act in their interest ex-ante). Then, the assumption is that by having the equity holders to increase their ability to coordinate and communicate with the management team, firms would yield more easily to large shareholders preferences and increase their risk exposure.

These theoretical results support the hypothesis that ownership concentration should play a role in firms' risk-taking behavior.

3.2 Data

To conduct my analysis, I used the 13f Thomson ownership dataset to identify institutional investors' ownership and the SDC dataset to identify the institutional investors that merged between 1980 and 2013. I restricted the sample for that date range, since the Thomson 13f dataset is notorious for having issues in the subsequent period. Since there exists no unique identifier common to the 13f dataset and the SDC dataset, I manually merged the two datasets. I restricted my investigation to the mergers that were completed in less than 2 years after the announcement date. Thus, the final set of transactions in the experiment includes 202 MA transactions over the 33-year sample.

When working with the Thomson 13f and SDC datasets, one potential issue is that financial holdings sometimes complete their merger before portfolios are consolidated. It is possible to schematize the development of a problematic deal in the following graph.

Figure 16: Timeline of a deal development

In such a case, even if the deal is identified as completed in the SDC dataset, it is possible that I do not observe a transfer of share ownership between the target and the acquirer on the day the deal is completed. As a consequence of this asynchrony, I would then incorrectly measure the effect of the merger on the ownership concentration level around the time of the merger. Indeed, since I am interested in measuring the control level of ownership, I can expect that, even if the two merged holdings have not consolidated their portfolios right after completing the deal, they would now vote in a complementary fashion. To circumvent this challenge, I manually consolidated the holdings' portfolios at the time of the deal completion.

Finally, to obtain the stock market data and accounting data, I used an annually updated monthly CRSP dataset and the annually updated quarterly Compustat dataset, respectively. In the appendix, I explain the variable construction used in the regression and how I transformed the Compustat data from quarterly to yearly frequency. I removed all observations with saleq¡ 0 and atq¡ 0. I winsorized the investment dependent variables to the 1st and 99th percentile and the risk variables to the 2.5st and 97.5th percentile. Finally, I did not include the firms in the utilities industry, sic contained between 4900 and 4999, or in the financial industry, sic between 6000 and 6999.

3.2.1 Choice of Proxy Measure

The existing theory on ownership structure on the role of large shareholders has mostly. However, to empirically investigate the dynamic between the role of large shareholders and corporate risk-taking we need a measure to capture the nature of the ownership structure. Most of the academic work conducted on the role of ownership structure focused on the role of blockholders (i.e. generally defined as the shareholders with more than 5% of the total outstanding shares). However, there are no theoretical results that justify setting the threshold at that level Edmands 2017. To avoid restricting my analysis to any arbitrary threshold I consider the ownership of all available institutional shareholders. Instead, I plan on capturing the nature of the ownership structure by using the firms' ownership concentration, measured by the Herfindalh index of the institutional owners ($HHI_{i,t} = \sum_i s_{i,t,j}^2$, where $s_{i,t,j}$ is the fraction of firm j held by owner i). The Herfindalh index appears to be a well-suited proxy for ownership structure as it does not restrict the analysis to a subgroup of the owners, it takes into account the number of shareholders and the size of their position.

3.3 Identification Strategy

The main regression of this paper identifies the relationship between risk taking and ownership concentration such that: $Risk_{i,t+1} = \beta HHI_{i,t} + \theta X_{i,t} + f_i + m_t + \epsilon_{i,t+1}$ where $Risk_{i,t}$ is a risk proxy, $HHI_{i,t}$ is the ownership concentration level, $X_{i,t}$ is a set of control variables, f_i and m_t are respectively the firms' and quarter-year fixed effects, and $\epsilon_{i,t}$ is the error term. However, there are strong reasons to believe that the variable of interest, $HHI_{i,t}$, is endogenously determined with the level of risk taking ($Risk_{i,t}$), precisely $cov(HHI_{i,t}; \epsilon_{i,t}) \neq 0q$. Thus, to identify the causal relationship between risk taking and ownership structure, I must have some exogenous variation in the ownership structure. Using an instrument variable design, the regression setup becomes:

First Stage: $HHI_{i,t} = \theta Z_{i,t} + \omega X_{i,t} + f_i + m_t + \epsilon_{i,t}$

Second Stage: $Risk_{i,t+1} = \beta H\hat{H}I_{i,t} + \phi X_{i,t} + f_i + m_t + \epsilon_{i,t}$

Where $Z_{i,t}$ is the instrumental variable and $H\hat{H}I_{i,t}$ is the instrumented level of ownership concentration.

The instrument captures the exogenous change in ownership concentration due to the merger of financial holdings, and filters out all the potential variation coming from the endogenous responses of other market participants or financial holdings involved in the merger event. To achieve this objective, I designed the instrument such that it measures the change

Figure 17: Example of the ownership structure of a representative firm

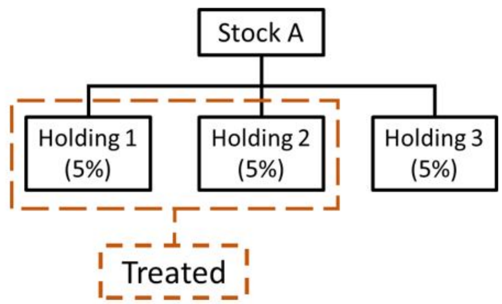
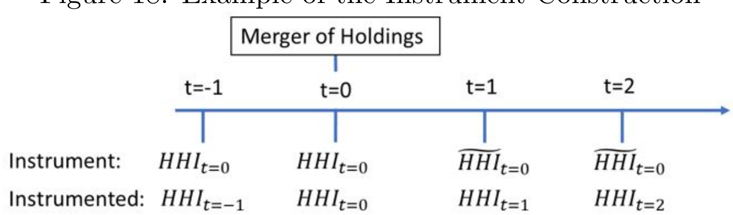


Figure 17 presents the hypothetical ownership structure for firm A that has 3 institutional shareholders, each owning 5% of the outstanding shares before holding 1 and holding 2 merge. Then the quarter prior to the merger, the effective HHI value, $HHI_t = 0$ would be 75. Under the alternative scenario that the merger would have already happened at that point in time, the implicit HHI value, $HHI_t = 0$, would be 125. I instrumented the Herfindalh index with the implicit level of Herfindalh index.

Figure 18: Example of the Instrument Construction



For this instrument to be valid, it needs to satisfy the relevance condition and the exclusion restriction.

3.3.1 Relevance Condition

To satisfy the relevance condition, the instrument must be correlated with the instrumented variable. Consistent with this hypothesis, the first stage regression shows that the instrument is significant to the 1% significance level. Additionally, when looking at the first stage Wald F-test of the risk-taking regression, the statistic ranges from 905 to 1245, strongly rejecting the null hypothesis of a weak instrument.

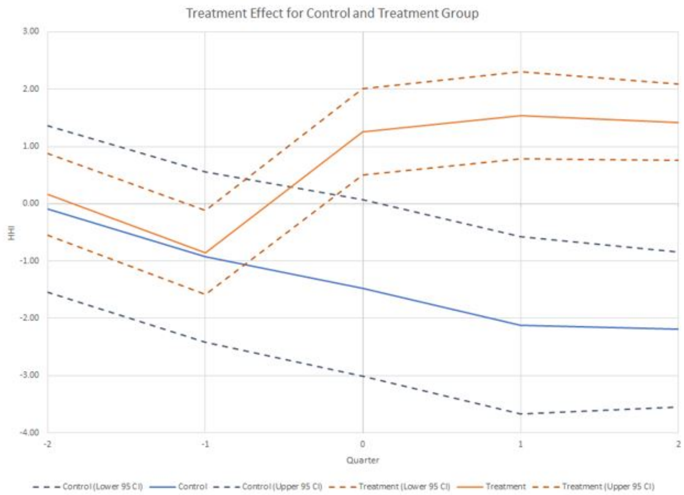
Table 51: First Stage Regression

	(1) HHI	(2) HHI
Instrument	0.5635***	0.5918***
	[4.55]	[5.19]
Market size		-0.0146***
		[-7.58]
Market Leverage		-0.0120
		[-1.01]
Tobin's Q		0.0007
		[0.34]
Institutional Ownership		-0.0670***
		[-6.98]
Firm Fixed Effect	YES	YES
Quarter-Year Fixed Effect	YES	YES
Observations	37549	37493
R^2	0.7030	0.7227

t statistics in brackets, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Errors are doubled clustered at the firm and quarter-year level.

Additionally, looking at the treatment effect around the merger event of the institutional shareholders, we observe a clear treatment effect. The HHI index of the treated firms jumps at the moment of the merger.

Figure 19: Treatment Effect for Control and Treatment Group



3.3.2 Exclusion Restriction

For the exclusion restriction to hold, financial holdings must not have merged to increase their position in the treated firms. Considering that acquisition of financial holdings is a complicated and risky process that is heavily regulated, it is hard to believe that financial holdings chose to merge for this reason. Additionally, there exist simpler ways to increase one's position in a firm such as direct purchase on the open market.

Given the design of the instrument, I need to add extra control to ensure that the exclusion restriction is satisfied. After adding a firm fixed effect, the instrument virtually becomes a measure of the exogenous variation between the effective and implicit level of HHI. Since the difference between the real HHI and the implied HHI is purely exogenous, the instrument variable should satisfy the exclusion restriction.

3.3.3 Sample Construction

For each merger events, I restricted the analysis to a 3-year window around the events. Also, to better identify the time trend, I matched the treated firms based on their market capitalization size and their total institutional level of ownership with a potential control.

Firms with larger market capitalization or a greater level of institutional ownership are mechanically more likely to become a treatment given the context of my experiment. Indeed, the probability that a stock held by virtually every holding be treated is greater than if the stock is held by fewer holdings. Additionally, since the effect of ownership structure in large firms might be different from that in small firms, using the matching technique enabled me to properly identify the effect of ownership structure in firms of similar characteristics.

I defined the set of available stocks in the following way. For a given merger event, I first identified the set of treated stocks. Then, looking at all the remaining available stocks in the compustat universe, I removed those that had been treated in a 5-year window around the event. The stocks I was left with became part of the pool of potential matches for the treatment stocks of that event. Using a propensity score, I identified in the potential match dataset the stocks more closely related to our treated stocks. I repeated the same technique for all the merger events and stacked the matched stocks together in the final dataset.

3.4 Results

There does not exist a perfect proxy of the firms' operational risk level. To provide a convincing picture of firms' risk-taking behavior, I introduced three potential measures of firms' risk taking. In the first section, I considered the prediction of ownership structure on the variance of return on assets (ROA) and the variance of return on sales (ROS). I measured the variance of those metrics over 8 quarters. Using accounting data enabled me to avoid working with financial market data, which might capture factors other than firms' operating policies. In addition to those accounting measures of risk, I used the variance of the trailing 12-month stock returns.

Table 52: Operational Risk Regression

	(1) Vol. of ROS	(2) Vol. of ROS	(3) Vol. of ROA	(4) Vol. of ROA
$\widetilde{HHI}$	0.2876***	0.2836***	0.1029**	0.1014**
	[3.69]	[3.69]	[2.14]	[2.22]
Market Size		0.0006		0.0020
		[0.36]		[1.47]
Market Leverage		0.0153		0.0290***
		[1.39]		[3.46]
Tobin's Q		0.0057**		0.0092***
		[2.31]		[4.22]
Inst. Ownership		0.0049		-0.0123*
		[0.55]		[-1.89]
Firm Fixed Effect	YES	YES	YES	YES
Quarter-Year Fixed Effect	YES	YES	YES	YES
Observations	28668	28640	29811	29763
R^2	0.6706	0.6730	0.7527	0.7603
First Stage Wald F-test	1054.502	1245.832	905.649	1077.444

t statistics in brackets, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Errors are doubled clustered at the firm and quarter-year level.

The dependent variable is winsorized at the 2.5% and 97.5% percentile level.

In columns (1) and (2) I regress the ROS with the instrumented HHI (HHI) and the controls. I obtain a coefficient of 0.2836 significant at the 1% level, which means that on average the ownership concentration level is responsible for (0.2836 * 0.113) 3.2% of the risk level. Also, for a one standard deviation increase in HHI I obtain a (0.2836 * 0.119/0.197) 17,1% of a standard deviation increase of the volatility of ROS.

In columns (3) and (4), I use the same regression on the ROA. I obtain a coefficient of 0.1014 significant at the 5% level, such that on average the ownership concentration is responsible for 1.3% of the volatility of ROA. In addition, a one standard deviation in ownership concentration leads to a (0.68 * 0.119) 42.15% of a standard deviation increase of the volatility of market returns.

3.4.1 Market Proxy for Operational Risk

In this section, I used the volatility of equity returns to proxy for operational risk.

Table 53: Market Risk Regression

	(1) Vol. of Returns	(2) Vol. of Returns
$\widetilde{HHI}$	0.6806***	0.6505***
	[2.66]	[2.80]
Market Size		-0.0007
		[-0.16]
Market Leverage		0.0785***
		[3.26]
Tobin's Q		0.0068
		[1.19]
Inst. Ownership		-0.0077
		[-0.39]
Firm Fixed Effect	YES	YES
Quarter-Year Fixed Effect	YES	YES
Observations	35861	35837
R^2	0.6779	0.6806
First Stage Wald F-test	823.628	954.364

t statistics in brackets, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Errors are doubled clustered at the firm and quarter-year level.

The dependent variable is winsorized at the 1% and 99% percentile level.

I obtain a coefficient of 0.6505 significant at the 1% level, which means that on average the ownership concentration level is responsible for (0.6505 * 0.113) 7.35% of the risk level, when measured using market returns. Also, for a one standard deviation increase in HHI I obtain a (0.2836 * 0.119/0.197) 17,1% of a standard deviation increase of the volatility of the monthly returns.

3.5 Investment Policies

Although investment policies do not perfectly capture firms' risk-taking decision, risk-taking behavior of firms can partially translate into the investment policy of firms. One must be careful about relating risk-taking behavior with investment policies because of risk-shifting behavior. Indeed, firms could simultaneously increase their level of investment while changing the nature of their investment portfolio by replacing risky projects by safer ones. For the analysis, I proxy the investment decisions with the ratio of $\frac{Capex+RD}{TotalAsset}$.

Table 54: Investment Behavior

	(1)	(2)
	(Capex+RD) / Asset	(Capex+RD) / Asset
HHI	0.6103**	0.6377***
	[2.23]	[2.94]
Market size		-0.0070
		[-1.55]
Market Leverage		-0.0226
		[-1.12]
Tobin's Q		0.0267***
		[4.31]
Institutional Ownership		0.0219
		[1.06]
Firm Fixed Effect	YES	YES
Quarter-Year Fixed Effect	YES	YES
Observations	30055	30011
R^2	0.8620	0.8750
First Stage F-test	745.828	927.691

t statistics in brackets, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The dependent variable is winsorized at the 1% and 99% percentile level.
Errors are doubled clustered at the firm and quarter-year level.

I obtain a coefficient of 0.6377 significant at the 1% level, which means that on average the ownership concentration level leads to a ratio of (0.6377 * 0.363) 0.231%. Also, for a one standard deviation increase in HHI I obtain a (0.6377 * 0.119/0.377) 20.1% of a standard deviation increase in investment.

3.6 Robustness Analysis

One key concern about the results, is that the merger might have been motivated by positions that represent a large portion of the merging institutional shareholders. It is indeed plausible that when those funds merge together they consider the effect of the merger on their most important positions. To control for this potential problem, the analysis has been rerun including only the stocks that are among the smallest quartile of their portfolio size. After implementing this additional specification, I found that the results presented in the above section are robust to this additional specification.

Table 55: Robustness: Investment Behavior

	(1) (Capex+RD) / Asset	(2) (Capex+RD) / Asset
HHI	0.5762***	0.5615**
	[2.64]	[2.07]
Mkt Size	-0.0083*	
	[-1.75]	
Mkt Leverage	-0.0287	
	[-1.38]	
Tobin'Q	0.0265***	
	[4.13]	
Inst. Ownership	0.0156	
	[0.77]	
Firm FE	YES	YES
Quarter-Year FE	YES	YES
Observations	29670	29714
R^2	0.8761	0.8623
First Stage F-test	927.691	745.828

t statistics in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Errors are doubled clustered at the firm and quarter-year level.

Table 56: Risk and Volatility

	(1) Vol. ROS	(2) Vol. ROS	(3) Vol. ROA	(4) Vol. ROA	(5) Vol. Returns	(6) Vol. Returns
HHI	0.3138***	0.3121***	0.1127**	0.1124**	0.7062**	0.6792***
	[3.70]	[3.69]	[2.29]	[2.43]	[2.53]	[2.62]
Mkt Size		0.0002		0.0017		-0.0006
		[0.10]		[1.17]		[-0.11]
Mkt Leverage		0.0264*		0.0315***		0.0738***
		[1.93]		[3.69]		[2.95]
Tobin'Q		0.0119***		0.0112***		0.0070
		[3.02]		[4.90]		[1.20]
Inst. Ownership		0.0065		-0.0090		-0.0075
		[0.59]		[-1.39]		[-0.36]
Firm FE	YES	YES	YES	YES	YES	YES
Quarter-Year FE	YES	YES	YES	YES	YES	YES
Observations	28253	28225	29451	29403	35692	35668
R^2	0.6900	0.6925	0.7525	0.7617	0.6711	0.6737
First Stage F-test	1051.163	1202.469	888.954	1023.132	833.486	931.757

t statistics in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Errors are doubled clustered at the firm and quarter-year level.

Table 57: Robustness: Issuance

	(1) Equity Issuance	(2) Equity Issuance	(3) New Debt Issuance	(4) New Debt Issuance
HHI	-0.0971**	-0.1212***	0.0733	0.0797
	[-2.03]	[-3.02]	[0.98]	[1.03]
Mkt Size		0.0099***		0.0037*
		[8.51]		[1.97]
Mkt Leverage		0.0649***		-0.0195**
		[10.59]		[-2.18]
Tobin'Q		0.0017		0.0032*
		[1.39]		[1.69]
Inst. Ownership		-0.0300***		0.0116
		[-5.33]		[1.44]
Firm FE	YES	YES	YES	YES
Quarter-Year FE	YES	YES	YES	YES
Observations	36864	36809	36736	36684
R^2	0.0687	0.0736	0.1468	0.1520
First Stage F-test	755.404	874.688	766.467	881.690

t statistics in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Errors are doubled clustered at the firm and quarter-year level.

3.7 Conclusion

The merger of financial holdings provides a plausible natural experiment to obtain exogenous variation in ownership concentration. Using the implicit level of ownership concentration before the merger is effectively implemented, I obtain the exogenous variation of the HHI, enabling me to assess the causal relationship between ownership structure and firms' risk-taking behavior.

The research results indicate that ownership concentration is related to firms' risk-taking behavior when considering three different proxies of risk taking (i.e. standard deviation of ROA, standard deviation of ROS, and standard deviation of monthly equity returns). In addition, ownership concentration has a strong and significant effect on firms' investment policies. In support of existing theoretical results, ownership structure appears to be of first importance to understand the nature of risk behavior in firms.

This research does not identify the nature of the policies leading to an increase in risk taking. A natural extension to this work should investigate through which channels managers increase their risk exposure.

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