THREE ESSAYS IN ENERGY
AND ENVIRONMENTAL
ECONOMICS

by

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ABSTRACT

This thesis exploits the boom in U.S. oil and gas production to explore several empirical questions in environmental and energy economics. In the first essay, statistical techniques are employed to evaluate learning-by-doing in the Bakken Shale Play. Furthermore, the essay demonstrates organizational forgetting and knowledge spillovers among firms. The results show rates of learning in an important sector the U.S. economy and may have broader lessons for productivity gains and losses. The second essay investigates interfirm learning economies in oil well drilling in terms of productivity improvements and increases in environmental safety. The empirical results improve our understanding of how interfirm relationships influence productivity as well as the drivers of environmental incidents. Lastly, the third essay analyzes the impacts of stricter environmental regulations on oil production and well drilling in North Dakota. The results have particular relevance for policymakers seeking to understand the trade-offs between resource development and environmental quality. These three essays ultimately expand our knowledge of how learning economies occur and the effects of environmental regulations on economic activity.

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To my wife Elisabeth,

for all the things you are.

CHAPTER 1
INTRODUCTION

This thesis consists of three essay that explore different questions in energy and environmental economics. The chapter provides a brief summary of each chapter. The third essay, chapter 4, is co-authored with Professor Ian Lange.

1.1 Summary of Chapter 2

Improvements in horizontal drilling and hydraulic fracturing have helped unlock U.S. “tight oil” resources and reverse the decades-long decline in domestic onshore oil production. Whether low oil prices will turn the shale boom into a bust depends in part on how companies have reduced the cost of drilling wells. This paper investigates learning-by-doing in drilling horizontal wells within the Bakken Shale Play. Using a large set of data on oil wells drilled in North Dakota between 2005 and 2014, I measure the extent to which firms increase drilling productivity and drill longer horizontal wells as they gain experience. Additionally, I investigate organizational forgetting associated with the rigs that undertake drilling and learning spillovers across firms. The empirical results show evidence of learning in terms of reducing drilling costs and extending the horizontal length of wells. However, the cost reductions from learning are relatively small, with the first year of experience yielding a per-well cost reduction that is just 1% of total well cost. There is evidence of organizational forgetting, which arises from breaks between drilling wells. Lastly, I find evidence consistent with learning spillovers across firms drilling within the same oilfield. These results help explain how shale plays are expanding the role of learning economies in oil and gas extraction and have implications for how U.S. drilling activity will be affected by recent oil price declines.

1.2 Summary of Chapter 3

This paper examines interfirm learning economies in improving productivity and environmental safety. Regression analysis is conducted with well-level data for the Bakken Shale Play. I estimate the extent to which the joint experience of companies involved in drilling oil wells increases productivity. Moreover, I evaluate whether interfirm learning occurs in reducing the number of environmental incidents during the drilling process. There is some evidence of relationship-specific learning between well operators and contractors that results in greater productivity. There is little evidence of firm or interfirm learning in improving environmental safety; however, characteristics of the pair of firms engaged in drilling appear to influence environmental safety. This analysis provides insights into interfirm learning and the factors that contribute to environmental damages.

1.3 Summary of Chapter 4

As technology and our ability to alter the natural world expand, it may lead to changes in the level or type of externalities that economic activity places on society. This may prompt changes in the laws and regulations governing activity to limit the new externalities. While new regulations will change the distribution of rents around, welfare is impacted if the regulations alter the pace of economic activity. This analysis seeks to understand whether changes in oil and gas regulation brought about by the shale revolution have restricted the pace of drilling and production. This hypothesis is tested using data on North Dakota and Montana both before and after North Dakota increased the level of bonding required to operate in the state as well as stricter rules on waste disposal. Using regression discontinuity and difference-in-differences methods, results generally find that the new regulations had no statistical impact on the pace of drilling and production. While the average impact of the regulations on production was statistically indistinguishable from zero, it is found that production shifted from smaller to larger companies. These results are relevant for policymakers weighing the loss of economic welfare against improved environmental quality in deciding on new regulations.

CHAPTER 2

DRILLING DOWN THE BAKKEN LEARNING CURVE

There is empirical evidence of learning-by-doing in manufacturing a variety of goods, such as aircraft (Benkard, 2000), semiconductors (Irwin and Klenow, 1994), and automobiles (Levitt et al., 2013). The repetitive and structured production processes often observed in manufacturing accommodate learning-by-doing. In contrast, the extractive resource sectors typically involve investments in unique projects (e.g., development of an offshore oilfield), where the opportunities for learning appear more limited. The U.S. "tight oil" and "shale gas" resource plays, however, are transforming this traditional view of oil and gas extraction: "the nature of fracking is far more akin to a standardised, repeated, manufacturing-like process, rather than the one-off, large-scale engineering projects that characterise many conventional oil projects"—Spencer Dale, BP Chief Economist (Dale, 2015).

The economics literature has recently taken notice of the potential for learning economies in fracking wells within shale plays (Covert, 2014; Fitzgerald, 2015).[1] This paper adds to the literature by examining learning-by-doing in the process of drilling oil wells within the Bakken. Prior to fracking, a borehole must be drilled, and drilling often makes up around 40%–60% of a well's total cost (Apaydin, 2014; Lipps, 2013). Using data on individual wells drilled in the Bakken from 2005 to 2014, I estimate the extent to which firms improve drilling productivity as they gain experience. Additionally, I examine how firm-level experience increases the horizontal length of wells. Nearly all wells in the Bakken are drilled so that a section of the borehole (called the "lateral") runs horizontally through the oil reservoir. Drilling longer laterals is challenging but enhances a well's hydrocarbon production (Sorenson and Terneus, 2008). Lastly, I investigate organizational forgetting and learning spillovers across firms.

[1] Hydraulic fracturing (a.k.a. "fraccing" or "fracking") is the process of pumping fluid,"proppant" (e.g., sand), and chemicals into a well to create fractures in the rock that allow hydrocarbons to flow.

Learning economies in oil and gas extraction are relevant for three primary reasons. First, learning-by-doing has several implications for microeconomic theory, such as optimal pricing and output decisions by firms, strategic behavior of incumbents, and the evolution industry concentration (Thompson, 2010). To the extent that shale plays provide greater opportunities for learning, relative to conventional oil and gas production, this may alter firm behavior and the market structure of the drilling industry. Second, a recurring topic in non-renewable resource extraction is the potential for productivity gains to counteract depletion and reduce resource scarcity (Simpson, 1999). Empirical evidence of learning-by-doing can help identify the mechanisms behind productivity improvements in resource extraction. Third, learning in the Bakken has implications for how U.S. drilling activity will be affected by declines in oil prices, such as the price drop that occurred in 2014. That is, the ability of oil companies to "weather the storm" partly depends on the degree to which learning has reduced costs. This has ramifications for job growth in the oil and gas sector and the future of U.S. oil production.

This paper makes three main contributions to the literature. First, it provides evidence of learning in drilling horizontal wells in a shale play. Kellogg (2011) shows the existence of relationship-specific learning in drilling vertical wells in Texas between 1991 and 2005. He finds evidence of learning associated with the joint experience of an operating company, which owns and designs wells, and the rig contracted to undertake the drilling. Osmundsen et al. (2012) find mixed evidence for learning when analyzing drilling in the Norwegian Continental Shelf. In their study, learning is associated with the experience of the operating company but not the facility that performs the drilling. It may not be possible to extrapolate the findings in these articles to the Bakken. Horizontal wells involve different techniques and technologies than wells drilled only vertically. Moreover, due to the geologic characteristics of shale plays, wells are typically spaced closer together to fully exploit a deposit (Khanal et al., 2015), and because hydrocarbon production declines more rapidly compared to conventional deposits, wells must be drilled more frequently (Maugeri, 2013). This suggests there may be greater learning in drilling within shale plays. Furthermore, by estimating learning in drilling longer laterals, this study explores a second dimension of learning that is not possible with vertical wells.

Second, it provides evidence of organizational forgetting in oil and gas drilling. Organizational forgetting is a depreciation in a firm's stock of knowledge that causes productivity to decrease. The volatility of oil and gas prices, as well as the seasonality of drilling in North Dakota, creates interruptions in drilling activity that can be exploited to examine forgetting. The prevalence and magnitude of forgetting is especially relevant for understanding how drilling productivity is affected by oil price crashes.

Third, this paper analyzes learning spillovers among firms drilling in the Bakken. Existing literature on learning in drilling has not found evidence of spillovers (Kellogg, 2011; Osmundsen et al., 2012). The boom in activity within the Bakken, along with the high geographic concentration of drilling, may give rise to opportunities for spillovers that have not been observed in other basins. One might anticipate the spillover mechanisms in oilfields are similar to the hypotheses noted by Glaeser and Resseger (2010) in explaining the positive relationship observed between metropolitan size and productivity: in denser cities, knowledge transfers occur more easily among workers and ideas spread faster to boost productivity.

There are three principal findings on the role of learning-by-doing in drilling horizontal wells in the Bakken. First, learning is associated with rigs, which are large machines staffed by a crew that undertakes the drilling. The magnitude of these cost savings are relatively small. Cost reductions through learning over a typical rig's first year of drilling are only about 1% of a well's total cost. There is also evidence that as firms gain experience, they are able to drill longer laterals. Second, organizational forgetting arises from breaks in a rig's drilling activity, although the economic magnitude of this forgetting is relatively small on a per well basis. A doubling of the duration of a rig's break increases the cost of drilling a well by less than 1%. Third, and finally, there is evidence of learning spillovers among firms drilling within the same oilfield.

Section 2.1 provides an overview of drilling operations in the Bakken. Section 2.2 discusses the data sample summary statistics and sources. Section 2.3 describes the estimation methods, and Section 2.4 details potential identification issues. Section 2.5 presents the empirical results of the base learning-by-doing models, and Sections 2.6 and 2.7 investigate organizational forgetting and learning spillovers, respectively. Lastly, Section 2.8 concludes on the findings and implications of the results.

2.1 Bakken Overview

Drilling in North Dakota is concentrated in the Williston Basin, a hydrocarbon-rich depression spanning 150,000 square miles and stretching into Canada, Montana, and South Dakota (NDGS, nd). Nearly all wells drilled in North Dakota target oil in the Bakken and Three Forks formations, which are about 10,000 feet below the surface. Oil was discovered in the Bakken in 1951 (Heck, 1998). Due to the Bakken's low permeability (i.e., fluids cannot easily flow through the rock) and low porosity (i.e., there is limited void space within the rock), much of the oil in place could not be economically extracted until the recent advances in hydraulic fracturing.

In July 2005, EOG Resources drilled the "Nelson Farms 1-24H" well into the Bakken. This well is considered to be a turning point in that it showed how combining horizontal drilling and hydraulic fracturing could unlock the Bakken's once uneconomic hydrocarbons (EERC, 2014; LeFever and Nordeng, 2015). Figure 2.1 shows the number of active oil wells in the Bakken remained constant through the early 2000s and began to climb in 2005.

Several firms are involved in drilling an oil or gas well, and learning may occur by each firm. The operating company or "operator" owns the right to drill the well and produce oil and gas. The operator typically creates the drilling program, which is a detailed plan for how the well will be constructed (Fraser et al., 1991). Several decisions made in planning a well can influence the speed in which it is drilled: the well's path, drilling mud selected, and types of drill bits used. Operators can adjust a well's path to avoid geologic features (e.g., faults) that may cause problems while drilling. Mud serves many purposes in drilling, such as counteracting the pressures from underground geologic formations. The properties of a mud (e.g., its density) affect the speed of drilling, and different types of muds and additives are selected depending on the characteristics of the formations encountered. Drill bits are used to cut and crush rock and make the hole, and

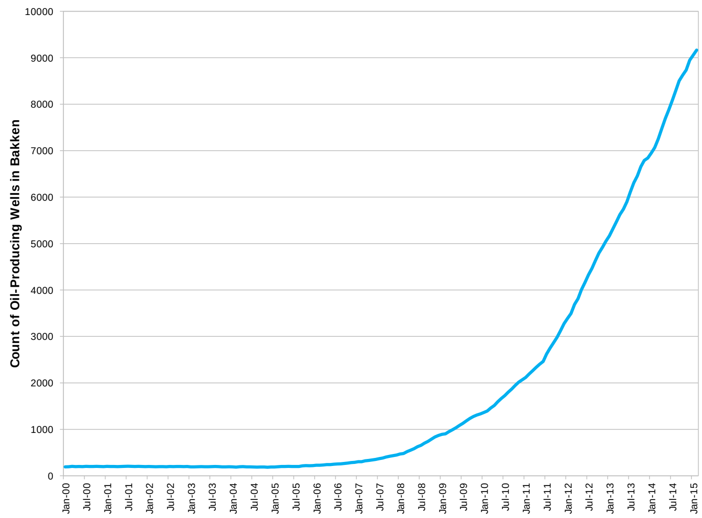

Figure 2.1: Oil-producing wells in the Bakken (January 2000–January 2015)

various bits can be used for different formations; formations have varying degrees of "drillability" and experiences in nearby wells can be useful in selecting bit types (Fraser et al., 1991). Much of an operator's potential learning appears to come from acquiring experience with drilling wells through specific geologic formations, and thus their learning may be oilfield specific.[2]

The operator contracts with a "drilling contractor" that provides the rig and crew to drill the well. Rigs contain several components, most prominently the derrick or mast, which is a tower that supports the pulley system, motor, and drillstring (a series of large steel pipes). The motor rotates the drillstring, and a drill bit attached to the end of the drillstring cuts and crushes the rock to make the wellbore. As drilling progresses, the well's depth increases and crews connect additional drill pipes to the drillstring. Baker (2001) describes several key personnel on a rig. The rig manager or "toolpusher" oversees drilling operations and coordinates with the operator's representative on the rig. The "driller" operates the controls and oversees the drilling crew. "Roughnecks" handle the drill pipe as it is lowered into the hole and connected to the drillstring. Learning may result, for example, from crews increasing their proficiency at operating equipment or toolpushers more

[2] A field consists of one or more accumulations of oil or gas that share a common "geological structural feature and/or stratigraphic condition" (EIA, 2015).

effectively managing rig operations.

A second contractor referred to as the "directional company" or "directional driller" is hired by the operator to work with the rig and drill the horizontal section (or lateral) of the well. In drilling a horizontal well, the wellbore is first drilled straight down, and at the "kickoff point" it begins to deviate from its vertical path. The directional company controls specialized tools attached to the drillstring to steer the drill bit and change the direction of the wellbore. Although there are different types of directional drilling tools, a system with a steerable mud motor is most commonly used in the Bakken (Han et al., 2013). In a steerable mud motor system, a bent housing allows the bit to point in a particular direction while a motor uses mud to rotate the bit and create the hole (Mantle, 2014).

There are multiple difficulties encountered in horizontal drilling in the Bakken (Djurisic et al., 2010; Halliburton, 2012). For example, it is more difficult to rotate the tools and drillstring (referred to as "excess torque"). There is greater friction between the drillstring and the walls of the wellbore (known as "drag"); this makes it more challenging to remove the drillstring from the well, which is necessary for switching out the drill bit or directional tools during drilling (Short, 1993). Learning by directional companies may arise from improving their abilities to mitigate these and other issues. Moreover, learning in drilling lateral sections of wells in the Bakken is reported to occur in part from "understanding the formation drilled" (Djurisic et al., 2010). This suggests that, as with operators, learning by directional companies may be specific to an oilfield.

In addition to reducing well costs, learning by directional companies may allow for drilling longer horizontal sections. While wells with longer laterals are more challenging to drill (Halliburton, 2012), these wells have more exposer to the reservoir rock containing hydrocarbons and in turn, higher levels of oil production (Sorenson and Terneus, 2008). Over time, the horizontal length of wells drilled in the Bakken is reported to have increased (Rankin et al., 2010); this motivates studying whether firms have learned how to drill wells with greater horizontal length.

When an operator contracts with a drilling contractor and directional company, a dayrate (or daywork) contract is most often used (Fraser et al., 1991; King, 2007). This type of contract is structured so that the contractor is paid by the operator for the number of days spent drilling. This suggests that the speed in which a well is drilled is related to the cost of drilling, and it supports using the rate of drilling as a measure of drilling productivity. Moreover, the speed in which a well is drilled is considered a key measure of drilling efficiency (Cochener, 2010). The adage "time is money" is often heard in the oil and gas sector (Baker Hughes, 2013; Schlumberger, 2005); this point is perhaps best articulated by Halliburton (2015a), "In the drilling industry, everyone knows that time is money." Accordingly, I use the speed in which a well is drilled to measure the productivity of drilling, which is consistent with the related literature on learning in drilling (Kellogg, 2011; Osmundsen et al., 2012).

A potential concern is that the dayrate contract structure may not create an incentive for contractors to improve drilling speeds. This issues is mitigated by the presence of the operator's representative (known as the "company man") on the drill site. This person oversees operations and ensures that drilling is carried out efficiently. Additionally, contractors may be motivated to drill more efficiently to maintain their reputation and secure future contracts. A contractor's reputation for drilling quickly is reported to factor into whether it is hired by an operator (Anderson, 1989).

2.2 Data

The data used in this analysis include 4,625 horizontal wells drilled in either the Bakken or Three Forks formation from 2005 to 2014. Summary statistics are presented in Table 2.1. The mean rate in which a well is drilled is 818 feet per day with a minimum of 123ft/day and a maximum of 4,853ft/day. The mean number of days spent drilling a well is twenty-seven with a minimum of four days and a maximum of 157 days. Table 2.1 shows two measures of a well's depth: measured depth (MD), which refers to the length of the wellbore, and true vertical depth (TVD), which is the vertical distance from the surface to the end of the well. MD measures the footage drilled and is used to calculate the rate of drilling each well. The mean MD in the sample is 19,089 feet with a minimum of 9,289 feet and a maximum of 26,908 feet. The mean TVD of 10,213 feet and standard deviation of 802 indicate there is not a substantial amount of variation in the vertical depth of wells in the sample. The horizontal length of a well measures the distance of the well's lateral. The mean horizontal length is 9,065 feet with a minimum of 1,340 feet and a maximum of 16,022 feet.

Information on a well's spud date (i.e., when the drill bit hits the earth and drilling begins), total depth date (i.e., when total depth is reached and drilling ceases), MD, TVD, horizontal length, operator, and field are sourced from Drillinginfo, an online provider of oil and gas data and analytics tools (Drillinginfo, 2015). The name of the rig used to drill the well and the directional drilling company hired are from information reported by well operators to the North Dakota Industrial Commission (NDIC) Oil and Gas Division (NDIC, 2015). Temperature and wind data are sourced from the National Oceanic and Atmospheric Administration (NOAA) (NOAA, 2015).[3] The experience of a firm is measured as the cumulative number of wells it has drilled. Section 2.3 discusses in detail the rationale for using wells drilled as the proxy variable for experience.

The number of days spent drilling is calculated as the difference between the total depth date (the date drilling ended) and the spud date (the date drilling began). There are three issues that complicate using this difference as a measure of the days spent drilling. The first is that wells may have multiple laterals. In these cases, a single vertical wellbore is first drilled. Then several horizontal "legs" are drilled in different directions from the vertical section. For these observations, the well's drilling time and MD are set equal to the days required to drill the first lateral and the first lateral's MD. The practice is seldom used in the Bakken with only 83 wells (1.8% of the sample) having multiple laterals.

A second issue arises when a small rig is used to start a well and a larger rig is hired to finish drilling. These smaller rigs, called "spud rigs", are used to drill the vertical "surface hole", which is typically about 2,000 feet deep. Using the difference between the total depth date and spud date will include any break in time between the spud rig finishing the surface hole and the larger rig

[3]NOAA temperature and wind data are used to calculate the average of the daily minimum ambient temperature and average daily wind speed over the period of drilling a well. There are six weather stations in western North Dakota that report daily temperature and wind speed: Bismark Municipal Airport, Dickinson Theodore Roosevelt Regional Airport, Garrison, Hettinger Municipal Airport, Minot International Airport, and Williston Sloulin Field International Airport. Weather data from the station nearest the well is used to calculate the average temperature and wind speed.

Table 2.1: Well drilling summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max	P50
Rate (feet/day)	4625	818	303	123	4853	786
Drilling Time (days)	4625	27	11	4	157	24
Measured Depth (feet)	4625	19089	2301	9289	26908	20020
True Vertical Depth (feet)	4625	10213	802	5272	14945	10428
Horizontal Length (feet)	4110	9065	2013	1340	16022	9899
Temperature (°C)	4625	-1	11	-25	18	0
Wind Speed (m/s)	4625	4	1	2	8	4
Operator Experience	4625	129	131	1	563	79
Rig Experience	4625	14	12	1	66	11
Directional Co. Experience	4625	339	367	1	1730	206
Operator-Field Experience	4625	25	53	1	329	6
Rig-Field Experience	4625	4	6	1	47	2
Dir. Co.-Field Experience	4625	14	27	1	189	4
Field Experience	4625	45	75	1	424	15

Sample includes wells drilled between 2005 and 2014. Experience is measured as the number of wells previously drilled by the respective firm. Operator-field experience is the number of wells drilled by an operator within a field. Dir. Co.-Field experience is the number of wells drilled by a directional company within a field. There are a total of 326 rigs, 85 operators, 48 directional companies, and 327 fields.

beginning to drill. For wells that use a spud rig, the rate is measured as the days spent drilling by the larger rig divided by the well's MD. This inflates the apparent drilling speed by the larger rig, so the estimation model accounts for whether a spud rig is used to start a well. Spud rigs are used in 1,190 wells, which comprise about 26% of the sample.

Third and finally, some operators in the Bakken use a procedure called "batch drilling" to simultaneously construct multiple wells on the same drill site. In batch drilling, a rig is used to first drill the surface hole for each well. That same rig then drills the vertical section of each well followed by the horizontal section. For these wells, the data often do not allow for distinguishing how much time was spent drilling each well, so these observations are excluded from the estimation but are included in calculating the experience variables.

The spud and total depth dates are available from Drillinginfo for 6,025 wells drilled in Bakken between 2005 and 2014, and 4,625 wells are ultimately included in the estimation. Of the 1,400 observations excluded, 1,225 were excluded because these wells were drilled simultaneously with another well and the days spent drilling could not be determined. The 175 other excluded observations were dropped because at least one of the following variables was not reported: well measured depth, field, rig, or directional company.

2.3 Estimation

The first learning-by-doing model is presented in equation 2.1. Consistent with much of the existing learning-by-doing literature, a log-log functional form is used. The dependent variable is the natural log of the rate in which a well is drilled, where the rate is the measured depth of a well (in thousands of feet) divided by the number of days spent drilling. As discussed in Section 2.1, the time required to drill a well is expected to be highly correlated with drilling costs. Using the rate of drilling as the dependent variable is also consistent with the existing empirical literature on learning-by-doing in drilling (Kellogg, 2011; Osmundsen et al., 2012).

$$\begin{aligned} LnRate_{rodft} = \alpha_0 LnE_{rt} + \alpha_1 LnE_{oft} + \alpha_2 LnE_{dft} + \\ \beta \mathbf{x}_{rodft} + \phi_r + \psi_o + \zeta_d + \kappa_f + \boldsymbol{\lambda}_t + \epsilon_{rodft} \end{aligned} \quad (2.1)$$

The variable $LnRate_{rodft}$ is the natural log of the rate of drilling a well (i.e., well depth divided by drilling days). Each well has a rig r, operator o, and directional company d and is drilled in a field f at a time t. The vector of control variables ($\mathbf{x}_{rodft}$) is described later in this section. The parameters ϕ_r, ψ_o, ζ_d, and κ_f, are rig, operator, directional company, and oilfield fixed effects. The vector $\boldsymbol{\lambda}_t$ encompasses a year-quarter fixed effect (2005Q1, 2005Q2, etc.) and month-of-year fixed effect (January, February, etc.), and ϵ_{rodft} is the idiosyncratic error term.

The variable E_{rt} is the experience of rig r within the Bakken and measured as the cumulative number of wells drilled by rig r prior to time t. The experience variables E_{oft} and E_{dft} correspond to the experience of operator o in field f and directional company d in field f, respectively. As described in Section 2.1, operators and directional companies are expected to learn by acquiring knowledge of a field's geologic characteristics and thus their learning is oilfield specific. Table A.1 of Appendix A presents specifications with additional experience variables and the results are fairly similar.

There are two alternative potential measures of experience: cumulative number of feet drilled and cumulative number of days spent drilling. Using either the number of wells drilled or feet drilled is consistent with the vast majority of the learning-by-doing literature, which measures experience based on cumulative output. But these different measures highlight that any variable is merely a proxy for true experience. Consequently, studies on drilling efficiency in petroleum engineering literature may provide guidance on the appropriate measure of experience. This literature consistently uses the number of wells previously drilled (Jablonowski et al., 2011; Li et al., 2010; Perry et al., 1992; Rampersad et al., 1994; Studer et al., 2007). Table A.2 of Appendix A shows the overall results are similar when measuring experience as cumulative number of feet drilled.

The control variables in equation 2.1 include the well's true vertical depth (TVD), measured depth (MD), MD squared, and MD cubed to allow the rate of drilling be non-linear in well depth. Varying the degree of the polynomial has no effect on the estimation results. Additionally, the average daily minimum ambient temperature and average daily wind speed over the drilling period are included to account for the effects of weather. Sufficiently high winds or low temperatures can slow down or halt drilling operations (Spiess, 2014). All wells in the sample are drilled into either the Bakken or Three Forks formation, and a dummy variable for the targeted formation is also included. Lastly, a final control variable is a dummy for whether a spud rig was used to start the well divided by the well's MD. As discussed in Section 2.1, a spud rig may be used to drill a well's surface hole, which is about 2,000 feet deep, and a larger rig is hired to finish drilling. The use of a spud rig has the effect of saving the larger rig about two days of drilling regardless of the well's eventual depth. Thus, if not accounted for, a spud rig will inflate the apparent rate of drilling by the larger rig, since the rate is calculated using the well's total depth and not just the depth drilled by the larger rig. The effect of using a spud rig on drilling speed will also decline as the well depth increases. That is, for shallower wells, a spud rig will have a relatively large impact on the apparent speed in which a well is drilled; for deeper wells, the effect will be smaller.

In addition to drilling faster, firms may be learning to drill longer laterals. As discussed earlier, the average horizontal length of wells drilled in the Bakken has been increased over time and helped boost oil production (Sorenson and Terneus, 2008). In equation 2.2, the dependent variable is the length of a well's horizontal section (in thousand feet).

$$LnHorz_{rodft} = \delta_0 LnE_{dft} + \delta_1 LnE_{rt} + \beta \mathbf{x}_{rodft} + \eta_r + \theta_o + \xi_d + \upsilon_f + \boldsymbol{\omega}_t + \nu_{rodft} \quad (2.2)$$

The variable $LnHorz_{rodft}$ is the natural log of the well's horizontal length, measured in thousand feet. The explanatory variables include the experience of the firms that undertake drilling the lateral of a well: directional driller within a field (LnE_{dft}), and the rig (LnE_{rt}). The control variables for equation 2.2 are a dummy variable for the geological formation the well is drilled into (i.e., Bakken or Three Forks) and the number of days spent drilling the well. The amount of time spent drilling may be an important control, since wells with longer laterals likely require more time to drill. While information on the time spent drilling the lateral section of each well is not available, drilling time for entire well likely serves as an appropriate proxy variable. Horizontal drilling is considered the most challenging part of a well (Schlumberger, 1995), and the lateral section usually takes the longest to drill (Djurisic et al., 2010).

2.4 Identification

This section discusses the potential identification problems and sources of variation that allow for identifying learning. First, several fixed effects are included in the estimation equations to account for firm-level and oilfield-level time-invariant unobservables. In the case of operators and directional companies, management quality or technology may vary across firms, and these unobservables may be correlated with experience. Including operator and directional company fixed effects implies that experience is identified by within firm variation, and this controls for potential unobservables specific to a firm. As for rigs, there are differences in physical and human capital. For example, a rig has a rated depth and horsepower, which determine how deep and fast it can drill (Varhaug, 2011). Rig-level fixed effects control for these time-invariant unobservables.

While I do not observe the rig crew, a brief—and by no means comprehensive—review of well reports submitted to the State of North Dakota show that rig managers (toolpushers) tend to stay on the same rig for a couple years. To account for turnover, I modify the experience variables to include only wells drilled by a rig in the prior two years. Using experience within the last two years, which is done in Kellogg (2011), has little impact on the results (see Table A.2 of Appendix A). The geologic formations of an oilfield can influence drilling speed, and fields that are easy to drill in may have more wells. Including the field-level fixed effects accounts for different geology across fields in the Bakken. Lastly, the year-quarter fixed effects control for Bakken-wide changes that influence drilling speeds, such as technological advances, as well as other unobservable effects specific to a particular quarter.

A second identification issue is measurement error. There may be measurement errors resulting from inaccuracies in the data, yet there are reasons to have a high degree of confidence in the quality of the datasets used in this analysis. As mentioned in Section 2.2, the data sources are the NDIC, which is the regulatory body overseeing drilling operations, and Drillinginfo, which sources the data relevant to this analysis from the NDIC. Drillinginfo is a subscription-based service and likely has a strong interest in maintaining the integrity of its data. Another measurement error results from the fact that the experience regressors are proxy variables for actual experience. Although Section 2.3 provides justifications for using the number of wells previously drilled as the measure of experience, there is unavoidable measurement error that creates an attenuation bias. A final source of measurement error is that the data set includes only wells drilled within North Dakota. Firm experience in other oil-producing regions is not accounted for in the estimation equation. While many of the companies in the data set operate outside of North Dakota, it is unclear if this experience is actually relevant for operations in the Bakken. Companies in the oil and gas industry report that in terms of geology, "no two shale plays are alike" (Halliburton, 2015b; King, 2010; Schlumberger, 2010). Furthermore, in a related study of learning in hydraulic fracturing operations in the Bakken, Covert (2014) finds there is limited evidence that experience outside of the Bakken is relevant. Nevertheless, excluding experience is expected to bias the coefficient estimates downward, away from evidence of learning. The level of a firm's experience in the Bakken may be negatively correlated with its experience outside the Bakken. For example, if a rig drills a well in the Bakken it forgoes the ability to drill a well elsewhere. This implies that, if experience outside of North Dakota increases productivity in the Bakken, this unobserved experience biases the coefficient estimates downward (toward zero).

Third, endogeneity can occur in learning-by-doing models from serial correlation in the error terms, since cumulative output is used to measure experience (Benkard, 2000; Kellogg, 2011). In typical learning models, output is observed over set time periods (months or years). A serial correlated shock in the current period affects the dependent variable (e.g., labor-input requirement) and in turn the cumulative level of output (experience) in the next period. This creates a correlation between the experience variable (cumulative output) and the error term. This analysis is slightly different in that I do not observe output per period but rather the unit of observation is an oil well. For this reason, and because I use total cumulative experience, serial correlated shocks are not expected to create an endogeneity issue. As wells are drilled sequentially, if there is a serial correlated shock that increases the number of days it takes to drill one well, it does not change the number of wells finished by the time the next well is started.

Fourth, there is the potential for attrition bias. In the sample, a single rig drilled as few as one well and as many as sixty-six wells (Section 2.2, Table 2.1). It is possible that over time in North Dakota, smaller rigs have been replaced by larger rigs that can drill faster and deeper. Including rig-level fixed effects, however, accounts for unobserved variation in rig-level capital that influences drilling speeds and horizontal length.

Several sources of variation exist for identifying the effects of experience on the rate of drilling and a well's horizontal length. Breakthroughs in hydraulic fracturing that allowed extraction of known but previously uneconomic resources and fluctuations in oil prices are likely to be the primary drivers of variation in drilling over time. Firm learning within a field is identified by variation in firm-level experience across fields that occurs from new fields being discovered and companies drilling wells in multiple oilfields simultaneously. Rigs also contract with multiple operators, and directional drillers are usually employed by several operators, which allows for determining the firm associated with learning (see Table 3.2).

2.5 Results

The estimation results for equation 2.1 are presented in Table 2.2. Column 1 shows the results with all fixed effects and controls and serves as the base model. The coefficient estimate for logged rig experience is 0.091 and statistically significantly different from zero at the 1% level. This estimate implies that doubling experience increases the rate in which a rig drills a well by about 9.1%. The coefficient for logged operator experience within a field is 0.021 (significant at the 1% level). This is consistent with the idea that learning by operators is field-specific, potentially as a result of gaining knowledge about a field's geology. Note that the other firms (i.e., the rig and directional company) may be involved in transferring knowledge acquired through drilling to the operator. The coefficient estimate for the experience of a directional company within a field is not significant at any reasonable level (p=0.77). This does not necessarily imply that no learning occurs in the process of drilling the lateral section of a well. A potential explanation for this result is that learning by directional companies occurs through drilling longer laterals rather than drilling faster.

The remaining columns in Table 2.2 provide robustness checks. In column 2, the estimation results for equation 2.1 are presented without including the control variables. The coefficient estimates are generally similar to column 1, suggesting that the results are not driven by the group of control variables selected. In columns 3 and 4, the coefficient estimates for the experience variables are similar when different experience variables are excluded.

Table A.3 of Appendix A shows the results for equation 2.1 with the coefficient estimates for the control variables. The magnitudes and signs for the control variables appear to be reasonable and consistent with expectation. The coefficients for the measured depth variables are significant at the 1% level. The coefficients for the temperature and wind variables indicate that, as expected, lower temperatures or higher winds speeds reduce the rate of drilling. Lastly, the coefficient estimate for the spud rig control variable is positive and statistically significantly different from zero ($p<0.01$), which is expected because use of a spud rig reduces the time the larger rig must spend drilling.

The results in Table 2.2 show evidence of learning associated with rigs and operators within a field. To demonstrate the economic significance of this learning, consider the following learning curve for a hypothetical rig. In the sample, a rig drills about eight wells per year in the Bakken, and the mean number of days required to drill a well is twenty-seven (Table 2.1). Assume a rig takes twenty-seven days to drill its first well. If over the course of the first year it drills 8 wells, then by the eighth well the drilling time has fallen to about 22.3 days.[4] The so called "rig day rate", which is the amount the operator pays the drilling contractor for the rig's service, may range around $24,000 in the Bakken (RigData, 2012). This implies that the estimated time savings of 4.7 days translates to a $112,000 cost reduction on the eighth well compared to the first well. A typical well in the Bakken is estimated to cost around $7–$8 million, which consists of both drilling and completion costs. Completion costs include the amount spent on hydraulic fracturing and often amount to 40%–60% of a Bakken well's total cost (Apaydin, 2014; Lipps, 2013). Thus the time savings over the first year amounts to about 1% of the well's total cost. It is likely, however, this estimate is a lower bound on the total cost savings from learning. For example, this estimate does not take into account that fewer days spent drilling means less labor input is required from the operator (i.e., the company man supervising drilling) and less money may be paid to the directional company, which are also hired on a day rate contract.

The estimation results for equation 2.2 are presented in Table 2.3 with column 1 as the preferred specification. The coefficient estimates for experience of the directional company within a field (LnE_{dft}) and the experience of the rig (LnE_{rt}) are both positive and statistically significantly different from zero at the 1% level. These results imply that a doubling of a directional driller's experience in a field results in a 1.4% increase in the length of the horizontal section of the well.

[4]Drilling rate (y) can be written as function of experience (x): $y(x) = Ax^{0.091}$. By increasing experience from 1 well to 8 wells, the rate increases by about 21%: $y(8)/y(1) = (8/1)^{0.091} = 1.21$. Holding well depth constant and assuming 27 days were required to drill the first well, yields a drilling time of 22.3 days for the eight well.

Table 2.2: Regression results for drilling productivity

	(1) LnRate	(2) LnRate	(3) LnRate	(4) LnRate
LnE_{rt}	0.091***	0.093***	0.095***	0.091***
	(0.014)	(0.015)	(0.015)	(0.014)
LnE_{oft}	0.022**	0.028***		0.022***
	(0.008)	(0.008)		(0.006)
LnE_{dft}	-0.001	-0.001		
	(0.007)	(0.007)		
MD	0.449***		0.465***	0.449***
	(0.129)		(0.126)	(0.129)
MD^2	-0.022**		-0.023**	-0.022**
	(0.008)		(0.008)	(0.008)
MD^3	0.0003*		0.0003*	0.0003*
	(0.0001)		(0.0001)	(0.0001)
Controls	Yes	No	Yes	Yes
Rig FE	Yes	Yes	Yes	Yes
Operator FE	Yes	Yes	No	Yes
Dir. Co. FE	Yes	Yes	No	No
Field FE	Yes	Yes	Yes	Yes
Year-Qtr FE	Yes	Yes	Yes	Yes
N	4625	4633	4625	4625

Dependent variable in all specifications is the log rate of drilling. Standard errors clustered on field in parentheses. MD is the measured depth of the well. Additional control variables include the well true vertical depth, average min temperature, average min temperature squared, average wind speed, average wind speed squared, month of year dummies, a dummy variable for whether a spud rig was used divided by the well's depth, and a dummy indicating if the well was drilled into the Bakken or Three Forks formation.

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

Similarly, a doubling of a rig's experience increases the length of the horizontal section of the well by 3.5%. This results suggest that as directional companies and rigs gain experience, they are able to drill longer laterals and as a result increase oil production.

Table 2.3: Regression results for horizontal length

	(1) LnHorz	(2) LnHorz	(3) LnHorz	(4) LnHorz
LnE_{dft}	0.014***	0.012**	0.017***	0.013***
	(0.005)	(0.005)	(0.005)	(0.005)
LnE_{rt}	0.035***	0.018*		0.035***
	(0.009)	(0.010)		(0.009)
LnDrillDays	0.191***		0.183***	0.191***
	(0.023)		(0.023)	(0.023)
ThreeForks	0.082***		0.087***	0.082***
	(0.027)		(0.027)	(0.027)
LnE_{dt}				0.015
				(0.011)
Rig FE	Yes	Yes	Yes	Yes
Operator FE	Yes	Yes	Yes	Yes
Dir. Co. FE	Yes	Yes	Yes	Yes
Field FE	Yes	Yes	Yes	Yes
Year-Qtr FE	Yes	Yes	Yes	Yes
N	4110	4114	4110	4110

Dependent variable in all specifications is the log horizontal length. Standard errors clustered on field in parentheses. ThreeForks is an indicator variable equal to 1 if the well was drilled into the Three Forks formation and 0 if drilled into the Bakken. LnDrillDays is the logged number of days taken to drill the well. Additional control variables include month of year dummies

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

2.6 Learning and Forgetting

Existing literature has shown that when there is learning, there is the potential for organizational forgetting (Argote et al., 1990; Benkard, 2000). As firms learn, their stock of knowledge about a production process grows and productivity increases. Organizational forgetting occurs when a firm's stock of knowledge depreciates and productivity decreases. Forgetting may occur because of employee turnover, layoffs, literal forgetting by workers, or production interruptions. Benkard (2000) notes that the term "forgetting" is not quite appropriate because it encompasses several mechanisms, such as layoffs, where no one is actually forgetting. It may be more accurate to characterize it as "depreciation of experience."

The boom and bust nature of the oil and gas industry lends itself to studying the effects of organizational forgetting. Gyrations in oil prices and discoveries of new reserves cause drilling activity to ebb and flow. Moreover, in North Dakota, drilling activity follows a seasonal pattern that peaks in the summer and falls in the cold winter months. Fluctuations in drilling create variability in the duration of the length of time in which a rig finishes drilling one well and begins the next. To determine the effect of interruptions, equation 2.3 supplements equation 2.1 with a variable measuring the natural log of the number of days a rig was inactive prior to drilling a well. Note that when a rig finishes drilling one well, it must be disassembled, transported to another site, and reassembled before drilling another well. Thus, a rig will always have a break between wells.

$$LnRate_{rodft} = \gamma LnBreak_{rt} + \alpha_0 LnE_{rt} + \alpha_1 LnE_{oft} + \alpha_2 LnE_{dft} + \beta X_{rodft} + \phi_r + \psi_o + \zeta_d + \kappa_f + \lambda_t + \epsilon_{rodft} \quad (2.3)$$

$Rate_{rodft}$ is the depth (in thousand feet) divided by days spent drilling the well drilled by rig r, operator o, and directional company d in field f at time t. $LnBreak_{rt}$ is the natural log of the days between the date the rig finished the last well and the date it began the current well. If the sign of the coefficient γ is negative it suggests that longer breaks diminish the benefits of learning.

There are reasons to suspect that a rig's break in drilling is potentially endogenous. This endogeneity may arise if there is a serially correlated shock to drilling productivity that also affects the duration of a rig's break. For example, there may be time-varying quality of rig management. A rig with poor management may take longer to drill wells, and it also may be in less demand and have longer breaks; if rig management quality is time-varying, it cannot be accounted for by including the rig fixed effect. This will bias the coefficient estimate for the $LnBreak_{rt}$ variable downward (away from zero).

To deal with this issue, I exploit the cyclical and seasonal nature of drilling activity within the Bakken. Oil prices are likely a major determinant of the level of rig demand and thus how long a rig waits to drill the next well. Rigs in the Bakken can also be used to drill wells outside of North Dakota. Greater drilling activity outside of North Dakota may pull rigs away and increase the duration of the break between finishing one Bakken well and drilling the next one.[5] A final source of variation in breaks is the seasonal pattern of drilling in North Dakota, which peaks in the summer months and declines in the winter months (see Figure A.2 of Appendix A).

The variable $LnBreak_{rt}$ is instrumented with the average West Texas Intermediate (WTI) oil price, the average continental U.S. rig count (excluding North Dakota) observed during the quarter in which a rig last finished drilling, and the interaction of these two variables. Additionally, I include the year-month in which the rig last finished drilling to capture seasonality and allow the effects of seasonality to vary over the sample period. Given the boom in activity observed over 2005 to 2014, it is not unreasonable to expect that the seasonal pattern of drilling varies over time. Note that equation 2.3 accounts for seasonal factors influencing drilling speeds by including the month of year in which a well was spud, the average minimum ambient temperature, and the average wind speed during drilling.

The strong correlation between the price of oil and the North Dakota rig count (Figure A.1) and the seasonality of drilling activity (Figure A.2) suggest these instruments are not likely to be weak. The first stage of the IV shows no evidence of underidentification or weak instruments: the Kleibergen-Paap LM statistic is 407.48 (p-value$<$0.000), the Cragg-Donald Wald F statistic for weak identification is 41.35, and the Kleibergen-Paap Wald rk F statistic is 18.40. There is no reason to expect that these instruments are endogenous. Unobservables that influence drilling speed (e.g., time-varying quality of rig management) should not have an influence on the price of oil or the total U.S. rig count (outside of North Dakota). Additionally, the year-month in which a rig

[5] This analysis of forgetting does not account for the number of wells drilled by rigs outside of the Bakken. Learning is assumed to be Bakken specific, so that experience acquired in other basins is not transferable to wells drilled in the Bakken.

last finished drilling is not expected to be correlated with unobservables influencing drilling speed. For example, there no reason to anticipate that all poorly-managed rigs would finish drilling in one particular month while the well-managed rigs would finish in a different month. Accordingly, the first stage of the IV show no evidence of overidentification (p=0.29 for Hansen J-statistic).

The regression results for equation 2.3, with and without the variable $LnBreak_{rt}$ instrumented, are presented in columns 2 and 3 of Table 2.4. The results of equation 2.1 are shown in column 1 for reference. The coefficient for the logged break in drilling by the rig is -0.020 and significant at the 1% level. When instrumenting for a rig's break, the coefficient for the logged break in drilling by the rig is -0.025 and significant at the 1% level, implying that a doubling of the break leads to a 2.5% decrease in the speed of drilling a well. While the coefficient estimate in the IV is less than the non-IV estimate, the difference is within the standard error of the non-IV estimate.

2.7 Learning Spillovers

Learning spillovers are observed in several industries (Benkard, 2000; Conley and Udry, 2010; Irwin and Klenow, 1994). Often in empirical literature, aggregate experience of all firms is used to estimate spillovers. If aggregate experience influences a single firm's productivity, when controlling for firm-level experience, this suggests knowledge spreads among firms.

Each well potentially generates new knowledge that may be useful in drilling subsequent wells. For example, as discussed in Section 2.1, operators can varying their drilling plans based on the geologic characteristics of an oilfield. Operators typically use "offset wells", which are nearby a proposed well, to serve as a guide in planning and designing (Fraser et al., 1991; Schlumberger, 2015). The boom in drilling within the Bakken, along with the close proximity of wells, may facilitate the spread of knowledge across firms. This may be analogous to the mechanisms mentioned in urban agglomeration literature, where knowledge diffuses among workers employed in a dense area or ideas spread among firm management (Glaeser and Resseger, 2010). That is, multiple wells being drilled within the same oilfield around the same time may promote the transfer of knowledge among firms.

Table 2.4: Regression results for learning-by-doing and forgetting

	(1) Base LnRate	(2) Forget LnRate	(3) Forget IV LnRate
LnE_{rt}	0.091***	0.057***	0.055***
	(0.014)	(0.017)	(0.014)
LnE_{oft}	0.022***	0.018**	0.018**
	(0.008)	(0.008)	(0.007)
LnE_{dft}	-0.001	0.002	0.001
	(0.007)	(0.008)	(0.007)
LnBreak_{rt}		-0.020***	-0.025***
		(0.006)	(0.007)
Controls	Yes	Yes	Yes
Rig FE	Yes	Yes	Yes
Operator FE	Yes	Yes	Yes
Dir. Co. FE	Yes	Yes	Yes
Field FE	Yes	Yes	Yes
Year-Qtr FE	Yes	Yes	Yes
N	4625	4328	4328

Dependent variable in all specifications is the log rate of drilling. Standard errors clustered on field in parentheses. Column 1 is the estimation results from equation 2.1. Columns 2 and 3 show the results of estimating equation 2.3 without and with instrumenting for LnBreak_{rt}. The instruments are the oil price, U.S. rig count (excluding North Dakota), and the interaction of oil price and rig count for the quarter in which the rig last finished drilling, as well as dummy variables for the year-month dummies in which the rig last drilled a well. Control variables include MD, MD squared, MD cubed, TVD, average min temperature, average min temperature squared, average wind speed, average wind speed squared, month of year dummies, a dummy variable for whether a spud rig was used divided by the well's depth, and a dummy indicating if the well was drilled into the Bakken or Three Forks formation.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Although the existing literature on learning in drilling has not demonstrated spillovers, the density of drilling activity in the Bakken may help create spillovers that are not observed in conventional oil and gas deposits. Kellogg (2011) finds no evidence of spillovers in studying the drilling of vertical wells in Texas between 1991 and 2005. Drilling in Texas, however, began in the 19th century. It is conceivable that learning spillovers may have occurred during the rise of drilling activity in Texas but dried up by the 1990s. In contrast, the sample period in this analysis covers the beginning and boom of drilling in the Bakken (Figure 2.1). Osmundsen et al. (2012), who study learning in the Norwegian Continental Shelf between 1968 and 2008, also find no evidence of learning spillovers. This may be a result of the distance between offshore wells. In comparison, drilling activity in the Bakken is relatively geographically concentrated. The low permeability and porosity of the Bakken reservoir rock requires wells to be drilled closer to one another compared to conventional plays (Khanal et al., 2015), and steep rates of production decline require new wells to be drilled frequently (Maugeri, 2013). This density of drilling, in both spatial and temporal dimensions, may facilitate greater learning spillovers.

To examine learning spillovers, the forgetting model (equation 2.3) is supplemented with a variable for the aggregated experience within an oilfield. Spillovers within a field are examined for two reasons. First, because fields share a common "geological structural feature and/or stratigraphic condition" (EIA, 2015), knowledge acquired in one field may be most useful in drilling subsequent wells within that same field. Second, wells drilled within the same field tend to be close proximity to one another. Knowledge may spread more easily among firms drilling near one another compared to firms in entirely different areas of the Bakken.

$$\begin{aligned} LnRate_{rodft} = \gamma LnBreak_{rt} + \alpha_0 LnE_{rt} + \alpha_1 LnE_{oft} + \alpha_2 LnE_{dft} + \alpha_3 LnE_{ft} + \\ \beta X_{rodft} + \phi_r + \psi_o + \zeta_d + \kappa_f + \lambda_t + \epsilon_{rodft} \end{aligned} \tag{2.4}$$

The variable for aggregate experience in a field (LnE_{ft}) is first measured as the cumulative number of wells drilled within a field f prior to time t.

In subsequent specifications, this experience variable is replaced with the variable LnERec_{ft}, which measures experience as the number of wells drilled within given period (e.g., 6 months) prior to time t. This allows for testing whether more recent experience has a different effect on drilling productivity. While knowledge may be generated with each well drilled, information from older wells may not spread to firms currently drilling in a field. For example, the firms that drilled older wells may no longer be active in a field, and there may be no opportunity for knowledge to transfer to other firms currently drilling. To account for the possibility that the variable LnERec_{ft} is picking up a firm's own recent experience in a field, as opposed to aggregate experience, the recent experience of the operator in the field is also included in the model (LnERec_{oft}).

As in the prior equations, $Rate_{rodft}$ is the depth (in thousand feet) divided by days spent drilling the well drilled by rig r, operator o, and directional company d in field f at time t. Fixed effects are included for the firms, year-quarter, month-of-year, and field, the later of which accounts for the possibility that some fields may be easier to drill in and as a result have greater number of wells (i.e., more aggregate experience).

The results are shown in Table 2.5. In column 1, the results of the forgetting IV model from Section 2.6 are presented for reference. In column 2, aggregate experience in a field is measured as the cumulative number of well drilled. The coefficient estimate for the variable LnE_{ft} is not statistically indistinguishable from zero at any reasonable level. In columns 3 through 6, the aggregate experience is measured as the cumulative wells drilled in the prior three, six, nine, and twelve months, respectively. In column 3, using the three month experience window, the coefficient estimate is 0.018 and statistically significant at the 10% level. In columns 4 and 5, using with experience measured as the number of wells drilled in the last six and nine months, respectively, the coefficient estimate is 0.016 and also significant at the 10%. In column 6, with the twelve month experience window, the coefficient estimate is 0.008 and no longer statistically significantly different from zero. When excluding the forgetting variable, the results remain similar (Table A.4 of Appendix A).

Table 2.5: Regression results for learning-by-doing spillovers

	(1) Base LnRate	(2) Spillover LnRate	(3) Spill-3mnth LnRate	(4) Spill-6mnth LnRate	(5) Spill-9mnth LnRate	(6) Spill-12mnth LnRate
LnE$_{rt}$	0.055***	0.055***	0.055***	0.055***	0.055***	0.054***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
LnE$_{oft}$	0.018**	0.017**	0.018***	0.024**	0.020**	0.011
	(0.008)	(0.007)	(0.008)	(0.009)	(0.010)	(0.012)
LnE$_{dft}$	0.001	0.001	-0.001	-0.000	-0.001	-0.001
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
LnBreak$_{rt}$	-0.025***	-0.024***	-0.024***	-0.025***	-0.024***	-0.024***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
LnE$_{ft}$		0.005				
		(0.011)				
LnERec$_{ft}$			0.018*	0.016*	0.016*	0.011
			(0.010)	(0.009)	(0.009)	(0.009)
LnERec$_{oft}$			-0.006	-0.014	-0.007	0.005
			(0.012)	(0.011)	(0.011)	(0.013)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Rig FE	Yes	Yes	Yes	Yes	Yes	Yes
Operator FE	Yes	Yes	Yes	Yes	Yes	Yes
Dir. Co. FE	Yes	Yes	Yes	Yes	Yes	Yes
Field FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4261	4261	4261	4261	4261	4261

Dependent variable in all specifications is the log rate of drilling. Standard errors clustered on field in parentheses. Column 1 presents the forgetting IV specification. In column 2, aggregate experience is logged cumulative number of wells drilled in a field, In columns 3–6, aggregate experience is logged cumulative number of wells drilled in the field in the prior 3, 6, 9, and 12 months, respectively. Control variables include well depth, well depth squared, well depth cubed, average min temperature, average min temperature squared, average wind speed, average wind speed squared, month of year dummies, a dummy variable for whether a spud rig was used divided by the well's depth, and a dummy indicating if the well was drilled into the Bakken or Three Forks formation.

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

These results suggest that firms externalize information acquired through drilling. Spillovers appear to result from wells recently drilled in a field, rather than the cumulative number of wells drilled since a field's discovery. This may be driven by knowledge transfers more easily as firms drill in close proximity and around the same time as one another.

2.8 Conclusion

Shale plays are an increasingly important source of global oil and gas production and are believed to contain sizable hydrocarbon resources (EIA, 2013). Recent literature has evaluated learning economies in the process of fracking oil wells in shale deposits. This paper has sought to complement the existing studies on learning in fracking and contribute to the wider body of empirical literature on learning-by-doing. To do this, two dimensions of learning-by-doing in drilling oil wells within the Bakken were analyzed: increases in drilling speeds and increases in lateral length of wells. Moreover, this paper explores organizational forgetting associated with rigs and learning spillovers among firms drilling within the same oilfield.

There are three primary findings of this work. First, there is evidence of learning-by-doing in terms of greater drilling productivity and drilling wells with longer laterals. There is learning associated with rigs, although the economic magnitude of this learning is relatively small on a per well basis. For example, over the course of a rig's first year of drilling in the Bakken, learning reduces the cost of drilling a well by only about 1% of total well cost. This finding suggest that learning economies through drilling alone are unlikely to allow firms in the Bakken to weather a significant downturn in oil prices. In addition to cost reductions, there is evidence that directional companies are able to drill longer laterals as they increase their experience in an oilfield. Longer horizontal sections allow for greater oil production, although it is not feasible in this analysis to estimate of the impact of this learning on ultimate oil recovery.

A second finding is that organizational forgetting is associated with rigs, wherein a longer break in between drilling wells results in diminishes productivity. As drilling activity in the U.S. slows, rigs have been idled. This work suggests that, if drilling rebounds, the interruptions in activity will negatively affect drilling productivity. Third and lastly, learning appears to spillover across firms drilling within the same oilfield. Although these spillovers are small relative to total well costs, they are similar in magnitude to the rates of learning through a firm's own experience.

CHAPTER 3

INTERFIRM LEARNING ECONOMIES IN DRILLING AND ENVIRONMENTAL SAFETY

Although there is evidence of learning-by-doing in a variety of industries, the mechanisms that translate experience into productivity gains are not well understood. Much of the existing empirical work has set out to identify and estimate rates of learning economies. As noted by Levitt et al. (2013), the literature is currently seeking to "move beyond a progress function that simply relates reductions in unit costs to cumulative production." One aspect of learning-by-doing that has received little attention in the literature is interfirm learning, wherein productivity increases result from the joint experience of two firms working together rather than each firm's individual experience.

This paper investigates interfirm learning in improving the productivity and environmental safety of oil and gas operations. Using data on individual wells constructed in the Bakken Shale Play from 2005 to 2014, I apply regression analysis to estimate the effect of interfirm experience on drilling productivity and the number of environmental incidents that occur. Operations in the Bakken are ideal for studying interfirm learning because there are multiple contractors involved in drilling horizontal wells. Companies called "operators" own and design wells and supervise contractors hired for the construction stage.

Additionally, this paper explores whether interfirm learning leads companies to maintain relationships and reap further productivity increases. Duration analysis is used to show that the likelihood of severing a relationship declines as companies drill more wells together. Although this is consistent with relationship-specific learning, it may also be explained by firms learning about their match quality (Nagypál, 2007).[6] Accordingly, I perform additional statistical tests to strengthen the evidence that it is interfirm learning that influences contracting choices. This in-

[6]In learning about match quality, over time two firms gain information about the underlying productivity of working together; relatively good and more stable matches are maintained, so the likelihood of severing a relationship declines as its duration increases. Nagypál (2007) discusses distinguishing between learning-by-doing and learning about match quality in the context of employer-employee relationships.

volves estimating how the shared experience of two firms affects the likelihood they continue their relationship in response to a negative oil price shock.

There are three main findings of this work. First, there is some evidence of interfirm learning that increases drilling productivity. Second, there is limited evidence of interfirm learning in improving environmental safety. One obstacle to identification is the potential for endogenous matching among firms. For example, two firms that share similar safety protocols or risk preferences may be more effective at preventing environmental disasters when drilling together and thus be more inclined to contract with one another. When controlling for potential endogenous matching, there is no evidence that firms improve their environmental safety as their experience increases. Hence, the characteristics of a pair of two firms working together, not just each firm's own attributes, appear to be important determinants of environmental performance. This may have relevance for companies and policymakers seeking to understand the factors the cause environmental disasters. Third, and finally, firms make contracting decisions that are consistent with interfirm learning. The probability of two companies severing a relationship is shown to decline as their joint experience increases. Moreover, in response to a negative shock, firms are less likely to terminate longer relationships than shorter ones.

There are three primary contributions of this paper. First, it studies interfirm learning in a production process that involves multiple contractors. Kellogg (2011) evaluates learning by two firms (operators and rigs) in drilling vertical wells in Texas and finds evidence of learning that is specific to the operator-rig relationship. In horizontal wells, which are the focus of this paper, operators contract with a rig but also hire another firm (called a directional drilling company) to drill the horizontal section of a well. It is possible to test whether relationship-specific learning occurs between 1) the principal firm and contractors (operator-rig and operator-directional driller), 2) contractors hired by the same principal (rig-directional driller), and 3) all three firms involved in the production process (operator-rig-directional driller). This provides information on which types of interfirm relationships bring about learning economies and may give insights into its mechanisms. Moreover, the results may have relevance for understanding the prevalence of relationship-specific learning in large-scale, complex projects that require collaboration of multiple firms.

Second, while there is extensive literature on learning-by-doing, the relationship between experience and environmental safety has received little attention. Although not evaluating learning-by-doing, Sider (1983) studies the relationship between worker safety and mine productivity and finds that the decrease in productivity of U.S. coal mines in the 1970s was not a result of improved safety conditions. In explaining the effects of firm size on safety violations in natural gas operations, Eyer (2015) finds that an operator's experience, which is included as a control variable, has no effect on the number of violations it receives—this study does not observe well contractors. Interfirm experience may be important for reducing environmental incidents in hazardous industries. The interactions between two firms, in particular the effectiveness of their communication, is thought to play a critical role in preventing environmental disasters. For example, inadequate communication between well operator and contractors has been cited as one contributor to the 2010 Macondo well disaster in the U.S. Gulf of Mexico (Deepwater Horizon Study Group, 2011; National Commission on the BP Deepwater Horizon Oil Spill and Offshore Drilling, 2011).

Third, although existing literature shows that two firms with a longer history together tend to continue contracting with one another (Kellogg, 2011), this persistence could be explained by firms learning about the underlying productivity their relationship (i.e., learning about match quality). Therefore this paper applies techniques to distinguish between firm behavior driven by learning-by-doing and learning about match quality. This provides more definitive evidence that companies seek to preserve relationship in order to take advantage of the productivity gains that accrue through interfirm learning-by-doing.

There are few studies of interfirm or relationship-specific learning. Huckman and Pisano (2006) investigates how surgeon experience reduces patient mortalities and finds learning associated with a surgeon's experience at a particular hospital, but this learning does not transfer to surgeries carried out by the same surgeon at different facilities. Fitzgerald (2015) analyzes learning in hydraulic fracturing and finds little evidence of productivity gains in oil production resulting from the joint experience of the well operator and the contractor hired to perform the hydraulic fracturing. There is also literature on learning by employees that is job-specific (Mortensen, 1988; Parsons, 1972), yet it unclear how applicable these results are to interfirm relationships.

Section 3.1 provides a brief conceptual framework for learning economies in improving environmental performance, and Section 3.2 summarizes the data used in this analysis. Section 3.3 describes the empirical strategies and identification issues, and Section 3.4 presents the results. Section 3.5 explores whether operator contracting decisions are driven by relationship-specific learning-by-doing. Lastly, Section 3.6 concludes on the findings and opportunities for future work.

3.1 Conceptual Framework

Existing literature discusses theoretical and conceptual models of learning economies. Thompson (2010), provides a thorough review of the theory on learning-by-doing (e.g., bounded and unbounded learning). This section focuses on a conceptual framework for only the effect of experience on environmental incidents.

Assume firms incur a cost for undertaking environmental safety effort (e.g., preventing oil spills). This cost (C) is linear and strictly increasing in safety effort (z): $C(z) = \gamma z$, where $\gamma > 0$. Environmental incidents are a function of experience (E) and safety effort: $S = S(z, E) = \alpha z^{-1} + \beta E$, where $\alpha > 0$ and $\beta < 0$. Note this function requires the values of α, β, z, and E are sufficiently well-behaved so that S is always non-negative. The implications of modifying this specific functional form are discussed below. Incidents are then strictly decreasing in both safety effort and experience. That is, greater experience reduces environmental incidents for a given level of safety effort. This is consistent with the notion of passive learning that is an "incidental and costless byproduct of a firm's production activities." (Thompson, 2010). This functional form implies that the marginal effect of safety effort on incidents is independent of the level of experience (i.e., $S_z = -\alpha z^{-2}$).

Firms incur a cost for incidents, which may include clean-up expenses and fines, and this cost is linear in the level of incidents: $h(S) = \delta S$, where $\delta > 0$. Note that this cost may not reflect the full social cost of environmental damages. By substituting in $S(z, E)$ from above,

$h(S) = \delta(\alpha z^{-1} + \beta E)$.

There are drilling costs, which are unrelated to safety effort, and defined by the function $g(x)$, where x is a vector of production inputs (e.g., labor and capital). For simplicity, the costs of safety, environmental incidents, and other production costs are additively separable. The firm's problem is to choose inputs (x) and safety effort (z) to minimize the cost of drilling a well subject to a production function $F(x)$:

$$\underset{x,z}{\text{minimize}}\ g(x) + C(z) + h(z, E), \quad s.t.\ F(x) = 1$$

The firm's cost minimizing level of environmental safety effort (z^*) is chosen such that

$$C_{z^*} = \gamma = \delta\alpha z^{-2} = -h_{z^*}$$

Hence, firms choose a level of safety effort ($z^* = \alpha^{1/2}\beta^{1/2}\gamma^{-1/2}$) such that the marginal cost of additional effort (C_{z^*}) is equal to the marginal benefit of avoiding incidents ($-h_{z^*}$).

This result shows that, under the assumptions thus far, the level of experience E does not affect the firm's optimal choice of safety effort. An increase in experience clearly reduces environmental incidents since $S_E = \beta < 0$ and z^* is unaffected. This setup motivates an empirical model that estimates the effect of firm experience on environmental spills. In the empirical section, experience is measured as the natural log of the number of wells previously drilled by a firm. This captures the stock of knowledge acquired by a firm as it engages in the production process.

In this setup, there is not expected to be a correlation between experience and safety effort, which is desirable in the empirical estimation because safety effort is unobserved. This is the case because, by assumption, the marginal effect of safety effort on incidents (S_z) is not a function of E. If this assumption were relaxed, the effect of experience on incidents would be more nuanced. An increase in experience has the direct effect of reducing incidents through $S(z, E)$ but also has the indirect effect through altering safety effort. These effects can be seen by taking the derivative of S with respect to E: $\frac{dS}{dE} = \frac{\partial S}{\partial E} + \frac{\partial S}{\partial z^*}\frac{\partial z^*}{\partial E}$. The direct effect ($\frac{\partial S}{\partial E}$) is negative; the sign of second term (the indirect effect) is negative as long as $\frac{\partial z^*}{\partial E} \geq 0$.[7]

[7] To see when $\frac{\partial z^*}{\partial E} \geq 0$, let $C_{zz} \geq 0$ and $h_{zE} \leq 0$; an increase in E causes the RHS of the FOC $C_z = -h_z$ to increase, and the level of safety effort must rise for the LHS to increase and maintain the condition.

Thus, when allowing for experience to alter the marginal effect of safety effort on incidents ($S_{zE} \neq 0$), the firm's optimal choice of safety effort increases, and there is then a positive correlation between experience and safety effort, which presents empirical issues that are discussed in the Section 3.3.2. The purpose of this section is not to make a case for a particular functional form for the cost of safety and environmental incidents but rather discuss the assumptions necessary for identifying learning in environmental safety given that safety effort in unobserved.

Learning may occur through both within-firm and interfirm experience. Firms may increase their knowledge of efficient safety protocols and individuals may become more proficient at preventing accidents. Just as the joint experience of two firms has been shown to affect productivity (Kellogg, 2011), interfirm experience may also influence environmental safety. One potential mechanisms is better communication with other firms engaged in the production process. As noted in earlier, miscommunication among firms has been cited as a cause of environmental disasters. The National Commission on the BP Deepwater Horizon Oil Spill and Offshore Drilling, for example, reported that "poor communication" between the well operator and its contractors was a contributing factor to the incident. This has also been noted as in other oilfield accidents and near misses (BSEE, 2013, 2015).

3.2 Data

Summary statistics for wells in North Dakota are shown in Table 3.1. There are 4,625 observations, which are horizontal wells that were drilled in North Dakota from 2005 to 2014. The mean amount of time spent drilling a well is 27 days, and the mean length of a well is 19,089 feet. There are 326 drilling rigs, 85 operators, and 48 directional drilling companies in the dataset. Note that for each well, there is an operator, rig, and directional drilling company involved in drilling.

Table 3.2 summaries the distribution of different interfirm relationships as well as the number of companies drilling within an oilfield. For example, the first row (# of Fields per Dir. Co.) shows the that the typical directional drilling company is active in twenty-four different oilfields. That is, the mean number of different oilfields each directional company has drilled a well in is twenty-

Table 3.1: Data summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max	P50
Rate (feet/day)	4625	818	303	123	4853	786
Drilling Time (days)	4625	27	11	4	157	24
Measured Depth (feet)	4625	19089	2301	9289	26908	20020
True Vertical Depth (feet)	4625	10213	802	5272	14945	10428
Horizontal Length (feet)	4110	9065	2013	1340	16022	9899
Temperature (°C)	4625	-1	11	-25	18	0
Wind Speed (m/s)	4625	4	1	2	8	4
Experience						
Operator	4625	129	131	1	563	79
Rig	4625	14	12	1	66	11
Directional Co.	4625	339	367	1	1730	206
Operator-Field	4625	25	53	1	329	6
Rig-Field	4625	4	6	1	47	2
Dir. Co.-Field	4625	14	27	1	189	4
Field	4625	45	75	1	424	15
Operator-Rig	4625	11	10	1	65	8
Operator-Dir. Co.	4625	50	65	1	464	26
Dir. Co.-Rig	4625	9	9	1	58	6

Sample includes wells drilled between 2005 and 2014. Experience is measured as the number of wells previously drilled by the respective firm. Operator-rig, operator-directional, and directional-rig experience are the cumulative number of wells drilled by operator-rig, operator-directional, and directional-rig pairs, respectively.

four. This table highlights that firms usually contract with multiple companies and drill wells in several different fields. The average operator hires seven different rigs and four directional drilling companies. This variation in firm contracting is necessary for identifying the effects of interfirm learning. For instance, if an operator and rig drill wells with only each other, it would not be possible to attribute productivity gains to a particular firm.

Table 3.2: Summary statistics for interfirm relationships

Variable	Obs	Mean	Std. Dev.	Min	Max	P50
# of Fields per Dir. Co.	48	24.208	41.033	1	176	5
# of Operators per Dir. Co.	48	7.229	10.022	1	42	2.5
# of Rigs per Dir. Co.	48	16.563	29.827	1	130	3
# of Dir. Cos. per Field	327	3.554	2.667	1	13	3
# of Operators per Field	327	2.642	2.019	1	14	2
# of Rigs per Field	327	5.798	6.426	1	44	3
# of Dir. Cos. per Operator	85	4.082	3.626	1	21	3
# of Fields per Operator	85	10.165	13.644	1	84	5
# of Rigs per Operator	85	7.082	8.771	1	45	4
# of Dir. Cos. per Rig	326	2.439	1.48	1	9	2
# of Fields per Rig	326	5.816	4.502	1	20	5
# of Operators per Rig	326	1.847	1.148	1	6	1

This table summarizes the firm-firm pairings and the number of firms operating in different oilfields. For example, the last row, labeled "# of Operators per Rig", shows that among the 326 rigs in the dataset, the mean number of unique operators that a rig worked with was 1.8.

Table 3.3 presents data on environmental incidents, which are sourced from the North Dakota Department of Health (North Dakota Department of Health, 2015). These incidents include oil or saltwater leaks from tanks and valves, well blowouts, and equipment failures. For 172 wells, at least one incident was reported to have occurred while drilling. This represents about 3.5% of all wells in the sample. A total of 192 incidents occurred, of which 172 were reported to be contained (e.g., oil does not spill outside of the drill site) and 20 were not contained. The volume of oil and brine spilled during an incident are often reported to be zero. For these incidents, no volumes may have been spilled or it is possible that the exact volume was unknown. The average quantity of oil spilled per incident is 60 gallons with a minimum of zero and a maximum of 4,032 gallons.

Table 3.3: Summary statistics for environmental incidents

Variable	Obs	Mean	Std. Dev.	Min	Max	P50
Incidents per Well						
All Incidents	4967	.039	.215	0	3	0
Non-Contained Incidents	4967	.004	.069	0	2	0
Contained Incidents	4967	.035	.203	0	3	0
Volumes Spilled						
Oil Spilled (US gallons)	192	59.7	393.2	0	4032	0
Brine Spilled (US gallons)	192	210.9	994.1	0	9240	0
Days until Reported	192	2.0	7.3	0	69	1

Incidents per Well is the number of environmental incidents that occur per well drilled. There are 342 additional observations in the empirical analysis for environmental incidents because fewer covariates are required and fewer observations are lost due to missing values. Volumes spilled is the amount of oil and brine spilled in reported incidents. 192 incidents are reported to have occurred while drilling 172 different wells. Data on oilfield environmental incidents are sourced from the North Dakota Department of Health. Non-contained/contained refers to whether an incident was limited to the boundaries of a facility, drill site, etc.

3.3 Empirical Strategy

This section presents the empirical methods used to estimate interfirm learning economies in well drilling. Section 3.3.1 details the estimation model for leaning-by-doing in improving the productivity of drilling, and Section 3.3.2 describes the model for learning in environmental safety.

3.3.1 Drilling Productivity

Drilling productivity is measured as the natural log of the total depth of the well (in thousand feet) divided by the days spent drilling (i.e., Ln(feet/day)). Ideally, information on drilling costs or production inputs would be observed for each well. However, cost information is limited to indices of average costs of Bakken wells, such as Spears & Associates Drilling & Completion Cost Service (Spears and Associates, 2016), and sparse reporting of information by companies. Detailed data on labor and capital inputs used in drilling are not likely tracked by companies operating in North Dakota and if it were, it would not be publicly available.

Despite these data limitations, the rate of drilling likely serves as an accurate proxy for productivity due to the nature of the drilling process. Capital is fixed by the rig, which has certain specifications (e.g., motor size) that determine the speed and depth to which it can drill. Labor use per unit of time is largely set by the long-established positions on a rig (e.g., roughneck, driller, toolpusher). Thus, productivity improvements are expected to occur by reducing the time required to drill a well rather than reducing inputs per unit of time spent drilling. Moreover, drilling time is well correlated with costs and input requirements because drilling contractors are typically compensated by operators based on the number of days spent drilling in so called “day rate” contracts. The speed of drilling is also used in petroleum engineering studies of drilling efficiency (Perry et al., 1992; Studer et al., 2007). Lastly, the conventional view of companies involved in drilling oil and gas wells is that drilling time and costs are correlated (Halliburton, 2015a).

Equation 3.1 presents the first learning-by-doing specification. The unit of observation is a well, where each well has an associated operator o, rig r, directional company d, field f, and date t. The dependent variable (LnRate$_{ordft}$) is the natural log of the well's depth (in thousand feet) divided by the number of days spent drilling.

$$LnRate_{ordft} = \alpha_0 LnE_{ot} + \alpha_1 LnE_{oft} + \alpha_2 LnE_{ft} + \beta \mathbf{x}_{ordft} + \phi_o + \kappa_f + \boldsymbol{\lambda}_t + \epsilon_{ordft} \quad (3.1)$$

The variable E_{ot} is the experience of operator o within the Bakken and measured as the cumulative number of wells drilled by the operator prior to date t. The variable E_{oft} is the number of wells drilled by operator o in field f, which allows for quantifying learning by the operator within an oilfield. The final experience variable (E_{ft}) measures aggregate experience within a field as the cumulative number of wells drilled by all operators within field f.

The vector $\mathbf{x}_{ordft}$ contains several control variables. These include the well's true vertical depth (TVD), measured depth (MD), average ambient temperature and maximum wind speed during the drilling period, and a variable indicating whether the well was drilled in the Bakken or Three Forks formation. The final control consists of an indicator variable for whether a spud rig was used to start the well divided by the well's MD.[8] The parameters ϕ_o and κ_f are operator and field fixed

[8]Spud rigs are sometimes used to drill the first one to two thousand feet of a well, and a larger rig drills the remaining portion. Allowing the effect of using a spud rig to vary with well depth accounts for the fact that using a spud rig reduces the larger rig's drilling time by a fixed number of days irrespective of its depth.

effects, respectively. The parameter $\boldsymbol{\lambda}_t$ encompasses a year-quarter fixed effect (2005Q1, 2005Q2, etc.) and month-of-year fixed effect (January, February, etc.), and the final term (ϵ_{ordft}) is the idiosyncratic error.

Equation 3.1 includes the experience of only the well operator and omits the experience of the contractors involved. Learning-by-doing studies often do not account for contractor experience (Argote et al., 1990; Benkard, 2000; Irwin and Klenow, 1994), and failing to do so may lead to incorrectly attributing learning to principal firms or concluding that learning does not occur. Two contractors employed in drilling that have considerable influence on the speed in which a well is drilled are the drilling contractor and directional drilling company. Drilling contractors supply the rig and crew that operate the rig's equipment and create the wellbore. Learning associated with rigs may result from crews increasing their proficiency with equipment or improving the management of rig operations. The directional company drills the horizontal section of a well, although the rig is still involved. Learning by directional companies may occur as they gain knowledge of geologic formations in field or increase their proficiency with tools and equipment.

In equation 3.2, rig and directional driller experience variables are included. The variables E_{rt} and E_{dt} are the cumulative number of wells drilled by rig r and directional driller d, respectively, prior to date t. Learning by contractors that is oilfield specific is captured through the variables E_{rft} and E_{dft}, which measure the number of wells previously drilled by rig r and directional driller d in field f, respectively.

$$\begin{aligned} LnRate_{ordft} = \alpha_0 LnE_{ot} + \alpha_1 LnE_{oft} + \alpha_2 LnE_{ft} + \\ \alpha_3 LnE_{rt} + \alpha_4 LnE_{dt} + \alpha_5 LnE_{rft} + \alpha_6 LnE_{dft} + \\ \beta \mathbf{x}_{ordft} + \phi_o + \psi_r + \zeta_d + \kappa_f + \boldsymbol{\lambda}_t + \epsilon_{ordft} \end{aligned} \tag{3.2}$$

In interfirm learning, productivity gain arise from the shared experience of two (or more) firms. That is, the cumulative number of wells drilled by a pair of firms may affect the speed in which they drill future wells. There are four relationships that may give rise to interfirm learning: 1) operator-rig, 2) operator-directional driller, 3) rig-directional driller, and 4) operator-rig-directional driller.

Equation 3.3 includes experience variables for each of these relationships to test for the presence of interfirm learning.

$$\begin{aligned} LnRate_{ordft} = \alpha_0 LnE_{ot} + \alpha_1 LnE_{oft} + \alpha_2 LnE_{ft} + \\ \alpha_3 LnE_{rt} + \alpha_4 LnE_{dt} + \alpha_5 LnE_{rft} + \alpha_6 LnE_{dft} + \\ \alpha_7 LnE_{ort} + \alpha_8 LnE_{odt} + \alpha_9 LnE_{rdt} + \alpha_{10} LnE_{ordt} + \\ \beta \mathbf{x}_{ordft} + \phi_o + \psi_r + \zeta_d + \kappa_f + \boldsymbol{\lambda}_t + \epsilon_{ordft} \end{aligned} \quad (3.3)$$

The variable E_{ort} is the number of wells operator o and rig r drilled together prior to date t. Similarly, the variables E_{odt} and E_{rdt} are number of wells the drilled by the operator-directional driller and rig-directional driller pairs, respectively. The final experience variable E_{ordt} measures the joint experience of all three firms.

A potential obstacle to identifying interfirm learning is endogenous matching among firms. Firm-specific, time-invariant unobservables that influence drilling productivity are captured in equation 3.3 by the firm-level fixed effects (ϕ_o, ψ_r, and ζ_d). However, there may be unobservables that are specific to a pair of firms (e.g., an operator and rig). This creates endogeneity if these pair-level unobservables affect drilling productivity and are correlated with the pair's experience (i.e., the number of wells the two firms have drilled together). For example, two firms that share similar characteristics in management style or workflows may be more productive together than two firms that are dissimilar. If companies tend to contract with companies they are more productive with, then these pair-level characteristics may be correlated with the experience of the pair.

Failing to account for endogenous matching among firms may misattribute productivity improvements to interfirm learning rather than the pair-level unobservables. This paper follows the approach by Kellogg (2011) by including specifications with fixed effects for firm pairs, which is essentially interacting firm-level fixed effects. Interfirm learning is thus identified through variation in experience within a pair of firms.

3.3.2 Environmental Incidents

Equation 3.4 estimates learning economies in environmental safety. The unit of observation is a well drilled, and the dependent variable (Env_{ort}) is the number of environmental incidents that occurred while drilling.

$$Env_{ort} = \alpha_0 LnE_{ot} + \alpha_1 LnE_{rt} + \alpha_2 LnE_{ort} + \beta Days_{ort} + \phi_o + \psi_r + \boldsymbol{\lambda}_t + \epsilon_{ort} \quad (3.4)$$

Each well has an operator o, rig r, and is drilled at time t. This analysis considers only environmental incidents that occur during drilling and not while a well is in production. Drilling contractors are released once a well has been drilled, and thus it is not possible to study interfirm learning in the production stage.

As in the previous section, the experience of each firm is measured as the natural log of the number of wells it previously drilled. The experience of the operator, rig, and the shared experience of the operator-rig pair are regressors. Note that the experience of the directional drilling company is not an explanatory variable. The directional drilling company's scope of work is limited to operating specialized tools that drill the lateral section of the well, and it is not expected to influence the number environmental incidents that occur. Table B.2 of Appendix B considers specifications with alternative experience variables, and the overall results are unchanged.

Through experience companies may gain knowledge on when accidents are most likely to occur while drilling and be more adept at preventing them. Operator and rigs may develop a better understanding of when it is and is not necessary to perform a test of safety equipment (e.g., valves and pumps that can leak). Interfirm learning may occur primarily through improved communication on safety issues that develops between operators and rigs as their experience working together increases. As noted earlier, miscommunication among firms has been cited as a cause of environmental disasters. The Bureau of Environmental Safety and Enforcement (BSEE), which regulates and enforces environmental safety in U.S. offshore oil operations, states that among operators and contractors, "inadequate, incomplete communications remains one of the most common causes of major accidents" (BSEE, 2013).

The number of days spent drilling a well ($Days_{ort}$) is included as a control variable. As a well takes longer to drill, the opportunities for incidents (e.g., spills, fires, blowouts) increases. Operator and rig fixed effects are included to account for time-invariant unobservables that may cause environmental incidents (e.g., management quality or safety culture). The time fixed effect term ($\boldsymbol{\lambda}_t$) encompasses month-of-year and year-quarter fixed effects.

In equation 3.4, the control variable for days spent drilling a well ($Days_{ort}$) is potentially endogenous. This may be the case if there is feedback between the time required to drill a well and the number of environmental incidents that occur. Environmental incidents may prolong the time it takes to drill a well by temporarily stopping operations. While the coefficient estimate for the regressor $Days_{ort}$ is not of primary interest in this analysis, its endogeneity may bias the coefficient estimates for the experience variables. This occurs if there is a correlation between the days spent drilling and experience, which is expected if firms are becoming more productive (i.e., drilling faster) with greater experience.

To correct for this possible endogeneity, a valid instrumental variable (IV) is required: it must be correlated with the amount of time spent drilling and uncorrelated with unobservables that influence environmental incidents. The depth of a well is a potential instrument. It is correlated with the drilling time since deeper and longer wells take more time to complete, and it is unlikely that well depth is correlated with factors that cause incidents. Results presented in Section 3.4.2 show depth is well correlated with drilling time and not a weak instrument. The model is exactly identified because there is only one instrumental variable, so it not possible to test for overidentification. However, it appears unlikely that a well's depth would be correlated with the occurrence of environmental incidents (e.g., a spill occurring at the surface).

A second identification issue is that safety effort is not observed. Company level expenditures on environment, health, and safety are not publicly available, and information would not likely be broken down by individual oil well. Section 3.1 provided a conceptual framework where experience did not influence a firm's optimal choice of safety effort. Under this assumption, while safety effort is omitted from equation 3.4, it is not correlated with experience and thus does not bias the coefficient estimates. If this assumption is relaxed, so that experience affects a firm's optimal choice of safety effort, the coefficient estimate for the experience variables will be biased. As long as greater experience improves the marginal effect that safety effort has on incidents (i.e., more experience causes the incremental safety effort to go farther in reducing incidents), this will lead to a positive correlation between experience and safety effort. Failing to include safety effort in the estimation models will thus bias the coefficient estimates for experience downward (toward evidence of learning).

3.4 Results

Section 3.4.1 presents the empirical results for drilling productivity, and section 3.4.2 shows results for environmental safety estimation models.

3.4.1 Drilling Productivity

Table 3.4 provides estimation results for equations 3.1-3.3. This section gives a detailed description of the full results, but the table suggests one overall finding. That is, there is evidence of interfirm learning, but it is not definitive. In specifications that account for endogenous matching among firms by including firm-pair fixed effects (columns 5 and 6), there is evidence of learning among operators and rigs. Alternatively, in specifications that do not include firm-pair fixed effects, there is evidence of interfirm learning among rigs and directional companies (column 3) but not between operators and rigs (column 4).

The results for equation 3.1, where only operator experience is included, are shown in column 1 of Table 3.4. The coefficient estimate for the experience of an operator within a field (LnE_{oft}) is 0.031 and statistically significantly different from zero at the 1% level. When the experience of the contractors are included (column 2), the coefficient estimate for operator experience within a field becomes 0.012 (p=0.227). This highlights that failing to account for the experience of contractors may attribute learning to the principal firm. Indeed, there is evidence of learning by contractors. The coefficient estimates for rig experience (LnE_{rt}) and rig experience within a field (LnE_{rft}) are

0.086 ($p<0.01$) and 0.020 ($p=0.083$), respectively. There is no evidence for learning by directional drillers, but rather the coefficient estimate for the experience of the directional driller is -0.037 ($p=0.036$). This could result if, as directional drillers increase their experience, they are hired for more difficult wells that take longer to drill. Control variables are used to account for factors that may influence the time required to drill a well (depth, geologic formation, and oilfield). However, if these do not fully control for the inherent difficulty of drilling a well, and if directional drillers with greater experience are hired for more time-consuming wells, this may cause the coefficient estimate for experience variable of the directional driller to be negative.

Columns 3 and 4 of Table 3.4 introduce experience variables for each pair of firms involved in drilling: operator-rig, operator-directional company, and rig-directional company. In column 3, there is evidence of learning specific to the rig and directional driller (i.e., the two contractors) but not the operator-rig pair. The coefficient estimate for joint experience of the rig and directional driller is 0.016 ($p=0.081$), and the coefficient for operator-rig experience is 0.010 ($p=0.473$).

As noted in Section 3.3.1, there is a potential for endogenous matching among firms. There may be unobservables that are specific to a pair of two firms that 1) influence the productivity of drilling and 2) are correlated with their joint experience. For example, if two firms are highly compatible in terms of management style or risk preferences, these unobserved factors may increase their joint productivity (two compatible firms drill faster together) and may be correlated with their joint experience (two compatible firms are more likely to drill together).

To deal with this issue, columns 5 and 6 include pair fixed effects for each of the interfirm relationships. In column 5, the coefficient estimate for joint operator-rig experience is 0.046 and nearly significant at the 10% level ($p=0.100$). In column 6, with all experience variables included, the coefficient estimate for the joint operator-rig experience is significant ($p=0.064$). When including firm-pair fixed effects, the coefficient estimate for the operator-rig experience increases in magnitude, which is counterintuitive. Under endogenous matching, without the pair fixed effect, the coefficient estimate is biased upward and its inclusion should correct the bias to bring the coefficient estimate downward. This would suggest that firms are more likely to drill with companies

Table 3.4: Regression results for interfirm learning in drilling productivity

	(1) No Contractors	(2) Contractors	(3) Firm Pairs	(4) Firm Triad	(5) Firm Pairs FE	(6) Firm Triad FE
Operator	0.025	0.007	-0.002	-0.003	-0.025	-0.026
LnE$_{ot}$	(0.019)	(0.017)	(0.018)	(0.018)	(0.035)	(0.035)
Operator-Field	0.031***	0.012	0.015	0.015	0.006	0.006
LnE$_{oft}$	(0.008)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Field	-0.000	0.010	0.014	0.013	0.004	0.004
LnE$_{ft}$	(0.013)	(0.012)	(0.013)	(0.012)	(0.013)	(0.013)
Rig		0.086***	0.066***	0.062***	0.023	0.018
LnE$_{rt}$		(0.014)	(0.017)	(0.018)	(0.024)	(0.025)
Directional		-0.037**	-0.045**	-0.046**	-0.074***	-0.076**
LnE$_{dt}$		(0.018)	(0.018)	(0.018)	(0.037)	(0.037)
Rig-Field		0.020*	0.016	0.016	0.010	0.010
LnE$_{rft}$		(0.012)	(0.010)	(0.011)	(0.011)	(0.011)
Directional-Field		-0.005	-0.011	-0.011	0.002	0.002
LnE$_{dft}$		(0.008)	(0.008)	(0.008)	(0.010)	(0.010)
Operator-Rig			0.010	0.017	0.046	0.056*
LnE$_{ort}$			(0.014)	(0.017)	(0.028)	(0.030)
Operator-Dir			0.006	0.007	0.015	0.017
LnE$_{odt}$			(0.009)	(0.009)	(0.026)	(0.026)
Rig-Dir			0.016*	0.030	0.037	0.059
LnE$_{rdt}$			(0.009)	(0.021)	(0.026)	(0.054)
Op-Rig-Dir				-0.018		-0.027
LnE$_{ordt}$				(0.024)		(0.052)
Firm X Firm FE	No	No	No	No	Yes	Yes
N	4642	4625	4625	4625	4625	4625

Dependent variable in all specifications is the log rate of drilling a well. Firm, oilfield, and time fixed effects and controls included in all specifications. Standard errors clustered on field in parentheses. Firm fixed effects include operator fixed effects for column 1 and operator, rig, and directional drilling level effects for columns 2–6. Firm X Firm fixed effects are interacted firm-level effects; Column 5 includes operator-rig, operator-directional driller, rig-directional driller FEs. Column 6 includes all interacted effects in column 5 and operator-rig-directional driller level effect. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

that they are less productive with (negative correlation between unobservables and joint experience).[9] A potential explanation is that if rigs are sufficiently scarce, operators may have to settle for rigs they are less compatible with in order to get wells drilled.

Table 3.4 suggest some evidence of interfirm learning but it not conclusive in all specifications. Without including firm pair fixed effects, there is evidence of learning specific to rigs and directional companies (column 3). When including firm pair fixed effects (columns 5 and 6), there is some evidence of interfirm learning among operators and rigs.

While not definitive, these results can provide some insights on interfirm learning. First, interfirm learning appears more likely to occur in relationships where there is more interaction among personnel of the two companies. Operators and rigs likely have significant interactions because the operator's representative on the drill site (referred to as the "company man" or "well site manager") supervises operations. This person has typically worked many different roles on a rig and has extensive experience in drilling (Baker, 2001). Directional drilling companies are hired to use specialized tools to drill the lateral section of a well, and while engaged with the rig crew that is also involved in drilling the well's lateral, there may be less interaction with the operator. This may also explain why there is some evidence of interfirm learning among rigs and directional drillers (column 3) but not operators and directional drillers.

A second insight pertains to the prevalence of relationship-specific learning in production process that involve several firms. There is solid evidence of interfirm learning in vertical wells drilled by two firm (operators and rigs) (Kellogg, 2011), yet learning appears less significant among the three firms involved in drilling horizontal wells. A potential explanation is that the additional complexity and coordination required in operations that involve the specialties of several firms may hinder interfirm learning. Production processes that require three companies may reduce the interaction between any two firms. Instead of robust learning among two different firms, there may be modest (or no) interfirm learning among all three firms.

[9]It is also possible for unobservables that lead two firms to work together to be correlated with slower drilling speeds (negative correlation between unobservable and productivity). However, it is difficult to construct an explanation for why this would occur.

3.4.2 Environmental Incidents

Table 3.5 presents the estimation results for equation 3.4 where the dependent variable is the number of environmental incidents that occur while drilling a well. Columns 1 and 2 show evidence of interfirm learning among operators and rigs. In column 1, the coefficient estimate for the joint experience of the operator and rig is -0.013 (p=0.089). In column 2, when instrumenting for the days spent drilling a well ($Days$) with the well's depth, the coefficient estimate slightly smaller in magnitude but still statistically significant (p=0.098). The first-stage results show no evidence of a weak instrument (F-stat=353.71). Operator-rig fixed effects are included in column 3 (without the IV) and in column 4 (with the IV), and the coefficient estimates for the joint experience of the operator and rig become statistically indistinguishable from zero.

These results highlight that operator-rig pair unobservables may be an important determinant of environmental incidents. Including operator-rig fixed effects causes the coefficient estimates for the shared experience variable (LnE_{ort}) to become smaller in magnitude and lose statistical significance. This is consistent with the presence of unobservables specific to an operator-rig pair that are 1) positively correlated with the joint experience of an operator-rig pair and 2) negatively correlated with the occurrence of environmental incidents. Firms with similar safety protocols or preferences for risk may be more adept at preventing incidents when drilling with each other and as a result more likely to work together. Thus, not only do firm-level attributes affect environmental safety, but it appears the characteristics of the pair of firms engaged in drilling matter.

Table 3.6 shows results for equation 3.4 for only non-contained environmental incidents. These are incidents that were not contained within the boundary of the well site. The results generally mirror the previous table. When operator-rig fixed effects are excluded, there is evidence of interfirm learning in environmental performance. However, when including operator-rig fixed effects, the coefficients estimates become statistically indistinguishable from zero at any reasonable level.

Table 3.7 present the results when considering only incidents that were contained within the well site. There is no evidence of relationship-specific learning, nor of learning by individual firms, in reducing the occurrence of contained incidents. The coefficient estimate for joint operator-rig

Table 3.5: Regression results for environmental incidents

	(1) Env Non-IV	(2) Env IV	(3) Env Non-IV	(4) Env IV
LnE_{ot}	0.003	0.003	0.016	0.014
	(0.010)	(0.009)	(0.012)	(0.011)
LnE_{rt}	0.003	0.005	-0.003	-0.002
	(0.011)	(0.009)	(0.013)	(0.012)
LnE_{ort}	-0.013*	-0.012*	-0.012	-0.008
	(0.008)	(0.007)	(0.014)	(0.013)
Days	0.001**	0.003**	0.001*	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Operator-Rig FE	No	No	Yes	Yes
1st Stage F-stat	N/A	353.71	N/A	331.43
N	4967	4967	4967	4967

The dependent variable is the number of environmental incidents reported to occur while drilling a well. Standard errors clustered on rig are shown in parentheses. Clustering on rig generally yields similar but slightly larger standard error estimates compared to clustering on operator or year-qtr. First stage F-statistics are from the first stage regression results of the IV, where the well's total depth instruments for Days.

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

Table 3.6: Regression results for non-contained environmental incidents

	(1) Env Non-IV	(2) Env IV	(3) Env Non-IV	(4) Env IV
LnE_{ot}	0.003	0.003	0.004	0.004
	(0.003)	(0.003)	(0.005)	(0.005)
LnE_{rt}	0.003	0.004	0.005	0.006
	(0.003)	(0.003)	(0.005)	(0.004)
LnE_{ort}	-0.004*	-0.004	-0.007	-0.006
	(0.002)	(0.003)	(0.005)	(0.005)
Days	0.000	0.000	0.000	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Firm FE	Yes	Yes	Yes	Yes
Year-Qtr FE	Yes	Yes	Yes	Yes
Month-of-Year FE	Yes	Yes	Yes	Yes
Operator-Rig FE	No	No	Yes	Yes
1st Stage F-stat	N/A	353.71	N/A	331.43
N	4967	4967	4967	4967

The dependent variable is the number of non-contained environmental incidents reported to occur while drilling a well. Standard errors clustered on rig are shown in parentheses. Clustering on rig generally yields similar but slightly larger standard error estimates compared to clustering on operator or year-qtr. First stage F-statistics are from the first stage regression results of the IV, where the well's total depth instruments for Days.

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

experience is negative but statistically indistinguishable from zero across the four specifications.

A potential explanation of the difference in results for contained and non-contained incidents may be that non-contained incidents are more costly to firms. In non-contained incidents, oil or brine may spill onto areas near a drilling site and require the firm to compensate landowners affected. Non-contained incidents may trigger a follow-up by the State of North Dakota (North Dakota Department of Health, 2015), and these incidents may be more costly to clean up. Thus firms may have a greater incentive to prevent non-contained incidents relative to contained ones.

Table 3.7: Regression results for contained environmental incidents

	(1) Env Non-IV	(2) Env IV	(3) Env Non-IV	(4) Env IV
LnE$_{ot}$	-0.000	0.000	0.012	0.011
	(0.010)	(0.009)	(0.011)	(0.010)
LnE$_{rt}$	-0.001	0.001	-0.009	-0.008
	(0.010)	(0.009)	(0.012)	(0.011)
LnE$_{ort}$	-0.009	-0.008	-0.005	-0.002
	(0.007)	(0.007)	(0.013)	(0.011)
Days	0.001**	0.002**	0.001	0.002*
	(0.000)	(0.001)	(0.001)	(0.001)
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Operator-Rig FE	No	No	Yes	Yes
1st Stage F-stat	N/A	353.71	N/A	331.43
N	4967	4967	4967	4967

The dependent variable is the number of contained environmental incidents reported to occur while drilling a well. Standard errors clustered on rig are shown in parentheses. Clustering on rig generally yields similar but slightly larger standard error estimates compared to clustering on operator or year-qtr. First stage F-statistics are from the first stage regression results of the IV, where the well's total depth instruments for Days.

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

3.5 Contracting Choices

This section explores whether firm contracting behavior is consistent with interfirm learning. Given that the previous sections suggest there is mixed evidence of interfirm learning, this section serves two functions. First, it can be viewed as providing some, albeit circumstantial, evidence of interfirm learning. Second, it evaluates whether companies appear to take interfirm learning into account by maintaining relationships to accrue further productivity gains.

A duration analysis of operator-rig relationships is first conducted. The unit of observation is an operator-rig relationship, where an operator and rig drill at least one well together. The duration is measured as the number of wells drilled before the relationship is terminated. A relationship is considered to end if an operator and rig pair do not drill at least one well together for twelve or more months. Defining a relationship as ending if inactive for twelve months allows for some relationships in the sample to have ended—otherwise there would be no failures in the dataset. Furthermore, using twelve months accounts for situations where an operator temporarily releases a rig when they do not have a well to drill, such as if drilling slows down for the winter months, but soon rehires the rig. There are a total of 736 operator-rig relationships observed, and of these, 423 are considered to have terminated.[10] The average duration of a relationship is 8.5 wells with a standard deviation of 10.4 and a minimum and maximum of 1 and 68, respectively.

A Cox proportional hazard model is used to estimate the hazard rate for operator-rig relationships. This model has the advantage that is non-parametric and thus does not force a particular functional form to the data. The hazard function, which represents the instantaneous rate of failure, can provide evidence that firms consider interfirm learning when deciding to continue a relationship. If the hazard function is generally sloping downward, this suggests that as an operator's experience with a rig increases, it is less likely to release the rig. Indeed, Figure 3.1 shows the smoothed hazard function estimated by the Cox proportional hazard regression.

[10]A relationship is not considered to have ended if the date of the last well drilled by an operator-rig pair was within one year of the end of the sample period (June 2014) or if the operator drilled no other wells.

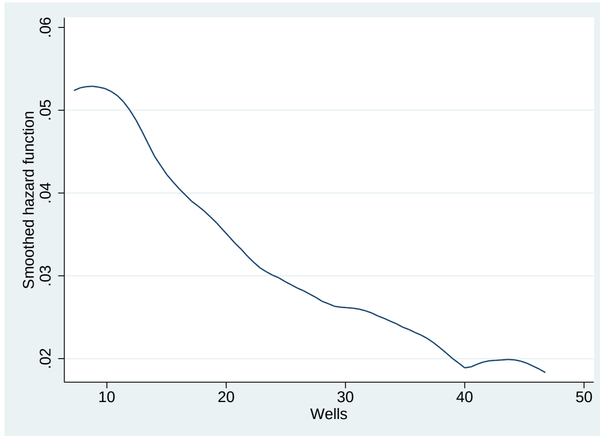

Figure 3.1: Estimated hazard function for operator-rig relationships

While the results of the duration analysis can be explained by interfirm learning, learning about match quality could cause the downward sloping hazard function. Nagypál (2007) notes that in employer-employee relationships, it can be difficult to distinguish between learning-by-doing and learning about match quality.[11] Learning-by-doing occurs as an employee gains knowledge that is specific to the employer. In contrast, learning about match quality arises when agents learn about the productivity of the employer-employee pair. In drilling, learning-by-doing may result from rigs and operators increasing their shared experience; learning about match quality may occur as firm gain knowledge about the underlying productivity of their relationship (i.e., how good of a match the two firms are).

With learning-by-doing, match-specific capital grows as the joint experience of two firms increases, and operators are less likely to release rigs they have more experience with because the pair is more productive. For learning about match quality, operators gain knowledge over time about which rigs are a good match. Rigs that are relatively poor matches are released early on, which leaves higher quality matches that are less likely to be released. Hence, the hazard function shown in Figure 3.1 does not necessarily imply that interfirm learning causes operators and rigs to sustain relationships, since it could be explained by firms learning about match quality.

[11]There are several articles relating to on the job learning-by-doing and learning about match quality (Farber, 1993; Flinn, 1986; Jovanovic, 1979; Mortensen, 1988).

Nagypál (2007) notes that exogenous shocks can help distinguish learning-by-doing from learning about match quality. Under learning-by-doing, when a negative shock occurs, operators are less likely to release a rig that it has more experience with because the two firms are relatively more productive. That is, there is match-specific capital that has accrued and will be destroyed if the relationship ends. Under learning about match quality, match-specific capital does not necessarily increase as firms drill more wells together, so in response to a negative shock, operators may be willing to terminate the more experienced rigs.[12]

To determine whether learning-by-doing or learning about match quality is driving the duration of operator-rig relationships, I evaluate contracting decisions in response to an exogenous oil price shock that occurred in 2008. If relationship-specific learning-by-doing is occurring, operators should retain rigs that they have drilled more with in the past. Alternatively, if firms are only learning about match quality, a rig's experience with an operator should not influence whether it is released.

Oil prices dropped 80% from $145 per barrel in July 2008 to $30 per barrel in December 2008 (Figure 3.2). Prices slowly rebounded in the following years, reaching $80 per barrel in October 2009 and eventually $100 per barrel in 2011. Drilling activity in North Dakota fell, although with a lagged response to the price decline. The number of wells spud (i.e., wells that started drilling) in North Dakota peaked in September 2008 at sixty-seven, fell by more than 50% to twenty-nine spuds in April 2009, and steadily increased back to sixty-seven by January 2010.

The observations are limited to operator-rig pairs that drilled wells together from October 2006 to September 2008. The shock is assumed to start at the end of September 2008 because that is the month that well drilling peaked in North Dakota; however I run specifications where the sample period is varied. An issue with selecting this time period is that there are fewer operator-rig pairs than in the total dataset. There are only forty-four operator-rig pair observed in the dataset that

[12] Nagypál (2007) offers an concise summary of this point in the context of employee-employer relationships. Briefly, in learning about match quality, employers become more selective over time and drop low quality matches, which causes match-specific capital to increase with tenure; however, the option value of keeping an employee (and learning more about their match quality) declines over time as more information is acquired, which in turn reduces match-specific capital.

drilled wells between October 2006–September 2008. A rig is considered to be released and a relationship terminated if an operator-rig pair drilled together during October 2006–September 2008 but did not drill in the subsequent two years (October 2008–September 2010). Of the forty-four operator-rig relationships, twenty-nine were continued after the shock and fifteen were terminated.

Figure 3.2: Oil prices and wells spud in North Dakota

Equation 3.5 presents a logit model used to estimate the effect of joint operator-rig experience on the probability a relationship is terminated. In this model, that probability that an operator-rig relationship is terminated follows the cumulative logistic function $F(\cdot)$. The variable $RelExp_{or}$ is the relative experience of rig r with operator o; it is calculated as the number of wells rig r has drilled with operator o relative to the rig that has the least experience with operator o. For example, if operator employs only two rigs (A and B), and rig A has drilled four wells with the operator and rig B has drilled two wells with the same operator, then the relative experiences of rigs A and B are two and one, respectively. This allows for estimating how a rig's experience with an operator, relative to all other rigs employed by that operator, affects whether it is retained.

$$Pr(Terminate_{or} = 1) = F(\beta_0 + \beta_1 RelExp_{or}) \tag{3.5}$$

The results for equation 3.5 are provided in Table 3.8 with coefficient estimates, as opposed to exponentiated coefficients. The coefficient estimate for a rig's relative experience with an operator ($RelExp_{or}$) is -0.68 and statistically significantly different from zero at the 5% level. This suggests that an increase in a rig's relative experience with an operator reduces the probability that it is released. Specifically, a one unit increase in its relative experience reduces the probability of being released by about 10% (calculated at the mean). Column 2 shows an alternative specification where operator-rig experience is replaced with a rigs total experience. The coefficient estimate for rig experience is not statistically significant, which demonstrates that a rig's overall experience does not appear to drive termination decisions. Column 3, which includes both operator-rig experience and rig experience, also shows that operators are less likely to terminate rigs that they have accrued greater experience. Columns 4–6 present the results of an OLS estimation model, and the coefficient estimates are still negative and statistically significant. Appendix B presents the estimation results for equation 3.5 when the sample period is varied. Generally the results remain consistent when varying the time period.

The results in this section demonstrate that in response to negative shocks, companies are less likely to end relatively long relationships. This strengthens the case that learning-by-doing, as opposed to learning about match quality, explains firm contracting choices.

Table 3.8: Logit and OLS estimation results for relationship termination

	(1)	(2)	(3)	(4)	(5)	(6)
	Logit	Logit	Logit	OLS	OLS	OLS
	Terminate	Terminate	Terminate	Terminate	Terminate	Terminate
$RelExp_{or}$	-0.68**		-1.06**	-0.04***		-0.09**
	(0.31)		(0.47)	(0.01)		(0.01)
$RelExp_{r}$		-0.11	0.46		-0.02	0.05***
		(0.10)	(0.39)		(0.01)	(0.01)
Constant	0.75	-0.26	0.38	0.48***	0.42***	0.44***
	(0.60)	(0.46)	(0.57)	(0.10)	(0.10)	(0.10)
N	44	44	44	44	44	44

Robust standard errors in parentheses. The variable $Terminate$ indicates if an operator-rig relationship ends; the variable is equal to 0/1 for 29/15 of 44 observations.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

3.6 Conclusion

This paper has investigated the role of interfirm learning economies in increasing drilling productivity and environmental safety. The analysis demonstrates some evidence that relationship-specific learning occurs between operators and rigs engaged in drilling oil wells in the Bakken Shale Play. Yet the evidence is not robust across all empirical specifications. This contrasts with the strong evidence for relationship-specific learning in drilling of vertical wells in Texas (Kellogg, 2011). A possible explanation for these differential results is that as the number of firms engaged in a production process grows, cultivation of interfirm relationships that lead to learning becomes more difficult. Future work may explore how the nature of firm-to-firm relationships and production processes influence interfirm learning.

Despite the somewhat mixed evidence for relationship-specific learning, companies appear to account for it by maintaining relationships. This strengthens the evidence for relationship-specific learning and demonstrates that firm behavior is consistent with awareness of this learning and its associated benefits to productivity.

There is little evidence of within-firm or interfirm learning in improving environmental safety. However, this paper shows that the characteristics of a pair of two firms working together appear to influence environmental safety. This is particularly relevant for understanding the underlying causes of environmental disasters. There is opportunity for further work on refining the empirical estimation of firm learning in environmental safety by including controls for firm-level safety effort as well as identifying other contributors to environmental incidents.

CHAPTER 4

EFFECTS OF STRICTER ENVIRONMENTAL REGULATIONS ON RESOURCE DEVELOPMENT

Technical progress in hydraulic fracturing and horizontal drilling have helped spur a renaissance in U.S. energy production. Productivity improvements, when considered in isolation, may lead to greater economic growth and enhanced economic welfare. Demsetz (1967) argued that technological advance alters the net benefits of property right specification, generally so that property rights will be further specified to internalize new externalities that arise. The impact these newly specified property rights, or regulations, have on overall economic welfare will depend upon whether the regulated firms decide to forgo previously productive activities.

In the case of the shale revolution, there are numerous potential negative externalities associated with oil and gas production that can lead to changes in regulation. These include polluting surface water and groundwater, degrading air quality, and spilling oil and waste (EPA, 2015; NETL, 2014). To mitigate these environmental externalities, many state and local governments in the U.S. are considering or have implemented stricter regulations on oil and gas drilling and production operations. Proponents of stronger regulations consider them necessary to protect the environment. Opponents claim regulations can be overly burdensome and hinder resource extraction. Policymakers in state governments are faced with balancing the often competing goals of resource development and environmental quality. Compounding the difficulty of this task is uncertainty over the extent to which tighter regulations ultimately reduce drilling and production.

This paper exploits a quasi-natural experiment to assesses the effects of stricter regulations on oil and gas well drilling and production in North Dakota (ND) using regression discontinuity (RD) and difference-in-differences methodology. In 2012, ND tightened regulations that effectively increased the cost of drilling for and producing oil and gas. The regulation change, which is detailed in Section 4.1, included higher well bonding requirements and stricter rules on drilling waste disposal.[13] The boundary between ND and Montana (MT) divides several oil and gas deposits, and many wells have been drilled near the border. MT did not implement the same regulations and serves as a control group in the analysis. We restrict the geographic area of study to a narrow window around the MT-ND boundary to ensure the treatment and control groups share many characteristics that influence drilling and production, such as geology, infrastructure, and geography. The outcomes analyzed here are drilling, production, and firm exit.

Valid estimation of an RD requires that the outcome is continuous around the treatment discontinuity point and that the discontinuity point is exogenously set. A number of different functional forms, both parametric and non-parametric, and bandwidths are used to ensure that any discontinuity in the outcome found at the MT-ND border is not due to misspecification of the data around the border. Given that the MT-ND border was set in 1863, when the U.S. acquired the Idaho Territories and established the end of the Dakota Territory at the 27th meridian west of Washington D.C., there is little concern that the border was set based on concerns for oil and gas drilling. To further ensure that any discontinuity found at the MT-ND border is attributable to the regulation, this analysis utilizes data on drilling before the change in regulation for both ND and MT.

Results find no statistical change in the pace of drilling wells after the ND regulations came into effect. This result is consistent across multiple specifications, including different bandwidths and functional forms of the data. Production of oil did not on average decline with the imposition of the ND regulations; however the distribution of production amongst firms did change. Results consistently find reduced production from operators in the first quartile of production in the year previous to the regulation and increased production from operators in the fourth quartile. The reduction in production for small operators in ND after the regulation went in effect, relative to production in MT, is about 0.5%. The reduction in production from small operators seems to be coming from operator exit. Regression and duration models show an increase propensity for small operators to leave the area of analysis while no statistical change is found for larger operators.

[13] States require companies to submit bonds in order to cover the cost of environmental damage in the event the company is unable to pay. Davis (2015) provides an overview of the policy issues surrounding well bonding requirements and alternative regulatory approaches.

Taken together, these results imply that while the regulation had little, if any, impact on drilling and production, it did redistribute rents within the industry. In this light, the regulations look like larger operators were able to raise the costs of smaller competitors in order improve their profitability, a la Salop and Scheffman (1983). A final component of the analysis estimates if the regulation had an effect on the occurrence of environmental incidents (e.g., oil spills). Data on incidents are only available for North Dakota, so an OLS regression with operator fixed effects and a time trend is performed; the results suggest an relationship between the regulation change and fewer incidents.

The bulk of previous literature estimating the impact of regulation on industry behavior comes from the manufacturing industry. Henderson (1996), Greenstone (2002), and Becker and Henderson (2000) all use air pollution policy to determine how the manufacturing industry altered its activity when environmental regulations increased. While manufacturing and oil and gas drilling have some similarities, oil and gas drilling has very mobile capital (rigs), which can move much quicker than a manufacturing plant.

The part of the literature similar to the analysis undertaken here is Boomhower (2014), which examines the effects well bond requirements implemented in Texas in 2002 on oil and gas production, firm exit, and environmental quality. A principal difference of this paper is that it evaluates the effects of well bonding on new investment decisions (i.e., the drilling of new wells). Moreover, wells drilled in Montana and North Dakota are much deeper ($\sim$20,000 feet) than many wells in Texas ($\sim$3,000 feet) and thus more expensive. Bonding makes up less of the total well cost, and the effects of higher bond requirements may be limited.

These results here are helpful to policymakers weighing the benefits and costs of further regulation in the oil and gas industry. It is quite common for industry associations to sponsor research that estimates the impacts regulation will have on the state or national economy. These estimates, by their nature, are prospective in that they predict how a proposed regulation will alter an industry and how that industry's change in behavior ripples through the economy. An analysis such as the one undertaken here provides a post-regulation evaluation of how the industry changed its behavior.

4.1 Background

This section provides a brief background on oilfield regulations and describes the 2012 rule changes in North Dakota. Although all levels of government (federal, state, and local) have some role in regulating oil and gas operations, state governments serve as primary regulators of drilling and production.[14] In North Dakota and Montana, as well as many other states, a state agency sets regulations for all stages of well operations: drilling, production, and abandonment. Drilling regulations consist of rules for well spacing, waste disposal, cement and casing standards, blowout prevent, hydraulic fracturing, and well bonding requirements. In the production stage, states regulate the venting and flaring of natural gas, handling and treatment of produced water, and reporting of production volumes. Lastly, rules are set rules on shutting down well production, decommissioning equipment, and reclaiming sites.

On April 1, 2012, the North Dakota Industrial Commission (NDIC) adopted several revised rules on oil and gas drilling practices. Although twenty-six different sections of the North Dakota Administrative Code were altered, there were four primary policy changes: higher well bond requirements, new restrictions on waste disposal, disclosure of chemicals used in hydraulic fracturing, and formal standards for hydraulic fracturing (NDIC, 2012b, 2016).

To bond a well, operators must submit a cash bond (e.g., a certificate of deposit) or a surety bond to the state regulatory agency prior to drilling. In the case of surety bonds, a surety company issues a bond that the well operator submits to the regulator. If an environmental incident occurs or the well is abandoned, and the operator cannot pay for the associated costs of cleanup or reclamation, the surety company is liable up to the face value of the bond. The 2012 regulation change in North Dakota increased the required face value for all new and existing wells from $20,000 to $50,000. In comparison, Montana requires a bond face value of $10,000 for a single well that is deeper than 3,500 feet (MBOGC, 2016), which applicable to all Bakken wells in the state.

[14]The federal government, for example, has certain authorities under the Clean Water Act and Clean Air Act to regulate water and air qualities. The power of local governments to implement rules on oilfield practices is often limited and varies across states (Richardson et al., 2013).

Raising bonding requirements has the effect of increasing the cost of producing oil and gas. Operators pay premiums to surety companies for issuance of the bond, and higher bond values increase premiums. The annual payments by operators to the surety company can be 1%–5% of the bond's face value or up to 15%–20% for relatively small firms (Boomhower, 2014; Gerard, 2000). Operators with relatively poor environmental histories or weak financial positions face higher premiums (Davis, 2015), and these companies are likely to be impacted most by the higher bond requirements.

The second key component of the regulation change dealt with waste disposal. Drilling operations generate two primary types of waste: drill cuttings and mud. Drill cuttings are ground rock that result from creating the wellbore. Water or oil-based fluids, commonly referred to as mud, are used in drilling to remove cutting from the hole and prevent hydrocarbons in underground formations from rising to the surface and creating a "blowout." Following drilling operations, mud may be disposed of at the drill site in open pits, referred to as reserve pits or earthen pits. A report by the U.S. Fish and Wildlife Service states that these pits can contain diesel, oil, caustic soda, glycols, and potentially chromium, zinc, polypropylene, and lead, and may pose a risk to groundwater, surface water, and soils (Ramirez Jr, 2009). In the spring of 2011, flooding in North Dakota led to some of these pits overflowing and polluting nearby lands (Kusnetz, 2012; MacPherson, 2012). Birds and other wildlife may also be attracted to the pits, become entrapped, and killed (Ramirez Jr, 2009).

Prior to 2012, oil and gas companies in North Dakota could dispose of mud waste in earthen pits or open receptacles. The 2012 regulation change revised rules so that, with limited exceptions, "no saltwater, drilling mud, crude oil, waste oil, or other waste shall be stored in earthen pits or open receptacles except in an emergency and upon approval by the director."[15] Operators thus have to store drilling mud in tanks or dispose of it at other locations. In comparison, Montana regulations (Rule 36.22.1005) specify that waste must be disposed off-site for wells using brine or

[15]The exceptions allowed include shallow wells with a total depth less than 5,000 feet and temporary pits used in well completions, servicing, or plugging and to flare casinghead gas. All wells in the Bakken, and nearly every other formation, are deeper than 5,000 feet.

oil-based muds only when located in floodplains or irrigated croplands (MBOGC, 2016).

The revisions to the well bonding and waste disposal regulations were viewed as significant when enacted. The Assistant Director of the NDIC, the state's oil and gas regulatory agency, stated "These rule changes are the most significant changes we have made in the 31 years I've been with the Commission." (NDIC, 2012a). In discussing the rule changes, the president of the North Dakota Petroleum Council[16] stated "They are the most onerous regulatory changes we've ever seen," and considered North Dakota's regulations "now overly burdensome and among the most stringent and costly in the nation." (MacPherson, 2012). Taken together the well bonding requirements and disposal regulations were estimated to increase the cost of drilling a single well by up to $400,000 (MacPherson, 2012). This represents about 5%–6% of the $7–$8 million total cost of a typical Bakken well.

The third major component of the regulation change required companies to disclose information on the chemicals used in fracking fluids through the FracFocus.org website. The fourth and final element of the rule change outlined requirements for the hydraulic fracturing process that were not previously addressed by the NDIC. These included guidelines on testing the well casing before fracking and installing pressure relief vales. This analysis, however, cannot assess the effects of the changes to rules on fracking because Montana implemented similar changes around the same time. On August 27, 2011, about seven months before the effective date of the new North Dakota regulations, Montana adopted five new rules (MBOGC, 2011). Two of the new rules were relatively minor and involved notifying and submitting information to the state's regulator agency. The other three rules dealt with disclosure of chemicals used in frack fluids and the fracking procedures. As in North Dakota, companies were required to start reporting information on chemicals to the FracFocus.org website. The new fracking procedures were very similar to those passed in North Dakota in requiring testing of well casing before fracking and installing relief valves.

In Montana and North Dakota, the Bureau of Land Management (BLM) manages oil and gas resources on public lands and Indian trust lands, such as leases on the Dakota Prairie Grasslands

[16] This organization describes itself as "the primary voice of the oil and gas industry in North Dakota since 1952." (NDPC, 2012)

in North Dakota and the Fort Peck Indian Reservation in Montana. Companies operating on lands managed by BLM must comply with federal regulations on drilling and production. Operators are still subject to state laws and regulations regarding oilfield practices, including well bonding requirements and waste disposal rules (MBOGC, 2016; NDIC, 2016). Moreover, the BLM requires proof of a bond in the amount of $10,000 per well and allows reserve pits for drilling waste. Thus, the change in North Dakota's regulations to increase bond requirements to $50,000 per well and eliminate pits affected operations on BLM-managed lands.

4.2 Conceptual Framework

The oil and gas industry generally use a net present value (NPV) calculation to determine which deposit to access by drilling a well. Society of Petroleum Engineers (2011) defines the standard method for determining revenues and costs in the evaluation of a drilling project. Projects whose return is higher than the minimum acceptable rate of return are generally undertaken. The new regulations outlined in Section 4.1 will raise the operating costs of a project. Raising the bonding requirement and restricting how drilling waste can be disposed of will increase operating expenses. This lowers the NPV of a given project, relative to before the regulation changes. If these increased operating expenses lowers the rate of return of a project below that of the minimum acceptable rate of return it will cause a project to be abandoned. This would lead to a reduction in economic welfare. If the increased operating expenses lowers that project's rate of return but the return is still above the minimum acceptable rate of return, the project will still be undertaken but the operator either earns less of a profit or it bargains with its input suppliers to reduce costs elsewhere so that the operator's profits remain constant. This would not change economic welfare but shift the distribution of rents. One manner in which operators can alter their input costs is through the payments made to landowners for access rights to subsurface resources. These leases are generally private but a selection of Texas gas leases were made publicly available and analyzed by Timmins and Vissing (2014). They find that the average length of a lease is 40 months, implying that operators cannot immediately alter their payments landowners. Another manner in which rents can be redistributed is discussed in Davis (2015) and Boomhower (2014). Bonding costs can disproportionately affect small operators as they are more likely to be credit constrained. In this case, an increase in bonding requirements might imply that it is more likely that a project becomes unprofitable for a small operator than for a large operator.

4.3 Data

Data on well location (latitude and longitude) and the drilling date are available from Drillinginfo (2015), which is a subscription-based source of oil and gas statistics and information. Table 4.1 summarizes the number of oil and gas wells drilled within two windows (twenty miles and thirty miles) around the MT-ND border and their distances from the boundary. The RD approach uses twenty-and thirty-mile windows on each side of the MT-ND boundary, but additional results are provided in Appendix C. In the two-year period prior to the regulation change (April 2010–March 2012), 156 wells were drilled in Montana within 20 miles of its eastern border with North Dakota—the closest well being just 100 feet from the boundary. In the twenty-mile window on the North Dakota side, 332 wells were drilled over the same time period with one well as close as 500 feet from Montana. In the two year period following the regulation change (April 2012–March 2014), 158 and 425 wells were drilled in the Montana and North Dakota twenty-mile windows, respectively.

Figure 4.1 presents a histogram of wells drilled within fifty miles of the MT-ND border in the two years leading up the regulation revisions (April 2010–March 2012). There is no obvious discontinuity in the density of drilling activity at the border before the regulation change. This figure also shows that drilling becomes more prevalent in North Dakota as distance from the border increases. The flexible functional forms used in an RD design will allow for drilling to vary nonlinearly in distance from the cutoff.

Table 4.2 presents summary statistics for oil production near the Montana and North Dakota boundary from 2010 to 2013. The table shows the average daily production (barrels per day) in each state within ten miles of the border. Production is broken down by company size, where

Table 4.1: Summary statistics of wells drilled within 20-and 30-mile windows

	Well	Well Distance from MT-ND Border						
	Count	Mean	Std. Dev.	Min	P25	P50	P75	Max
20-Mile Window								
April 2010–March 2012								
Montana	156	7.8	5.42	0.02	3.35	6.86	12.29	19.79
North Dakota	332	10.52	5.62	0.09	5.83	10.29	15.76	19.96
April 2012–March 2014								
Montana	158	7.83	5.08	0.1	3.56	7.14	11.1	19.82
North Dakota	425	12.43	5.54	0.12	9.12	13.45	17.04	19.99
30-Mile Window								
April 2010–March 2012								
Montana	180	10.13	7.86	0.02	4.17	8.04	15.02	29.79
North Dakota	578	16.78	8.64	0.09	8.84	17.39	24.43	29.97
April 2012–March 2014								
Montana	212	12.37	8.99	0.1	5.24	9.18	21.25	29.61
North Dakota	883	19.12	7.78	0.12	13.85	20.33	25.53	30

The windows include wells drilled in Montana and North Dakota that are within 20/30 miles of their shared border.

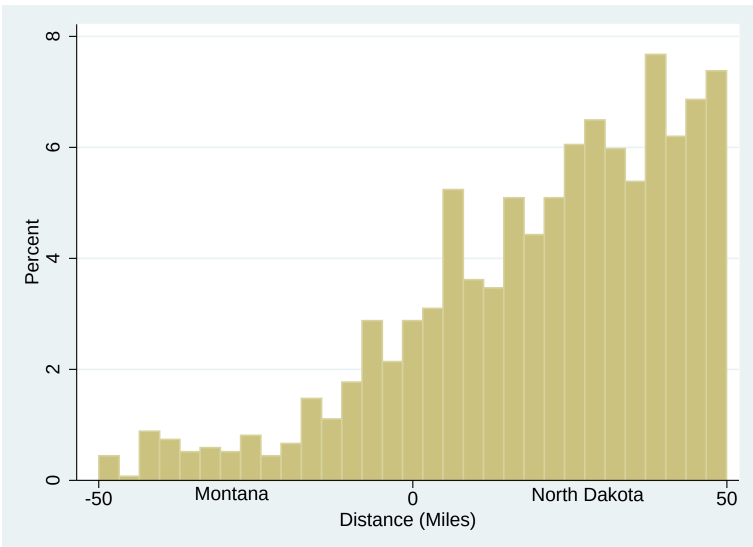

Figure 4.1: Histogram of wells drilled near MT-ND border (April 2010–March 2012)

he first quartile (Qrt 1) refers to the smallest firms and the fourth quartile contains the largest firms. Operators are partitioned into quartiles based on their size, which is measured as total oil production in 2011 (prior to the regulation change). Oil production varies greatly across firms, with some of the smallest firms having less than ten barrels per day and the larger operators producing 3,000 barrels or more a day.

Table 4.2: Oil production summary statistics

	Oil Production (Barrels per Day)				
	2010	2011	2012	2013	Operators
Montana					
Qrt 1	295	244	304	246	15
Qrt 2	723	880	1103	1544	12
Qrt 3	2183	2844	4726	6149	10
Qrt 4	6085	9305	12072	12909	10
Total	9286	13273	18205	20847	47
North Dakota					
Qrt 1	57	70	72	38	7
Qrt 2	369	754	758	4320	10
Qrt 3	1749	4305	8666	9747	11
Qrt 4	29655	31742	33264	28465	10
Total	31830	36871	42760	42571	38

Oil production is the average number of barrels produced per day within ten miles of MT-ND border for all companies in a quartile. Quartiles are constructed based each operator's total oil production in MT and ND in 2011, so the number of operators within a quartile may not be the same in both states. Production data shown are for only operators that were active in the year 2011 and included in the analysis

4.4 Empirical Strategy

This paper employs two empirical strategies. The RD design used to evaluate the effect of the regulations on drilling activity is described in Sections 4.4.1 and 4.4.2. Sections 4.4.3 and 4.4.4 discuss a difference-in-differences approach to assess the effects on operator oil production and exit.

4.4.1 Drilling Activity

An RD design is well suited to evaluate the effects of the regulation change on drilling activity for three reasons.[17] First, the border between Montana and North Dakota intersects several hydrocarbon-bearing rock layers (i.e., geologic formations), such as the Bakken, Three Forks, Madison, Red River, and others (NDGS, nd). This creates a cutoff that is necessary in a sharp RD, where observations on only one side of the threshold receive the treatment. Second, an area's hydrocarbon potential is a function of the geologic characteristics of the underlying oil or gas reservoirs. "Location, location, location" are sometimes said to be the three factors that make a "good well" because geology has such influence on oil and gas production potential (Gold, 2015; Hume, 2015). Thus, wells drilled near one another, but on other sides of the border, may be similar in their oil or gas production and economic attractiveness. Third, an RD can flexibly model drilling activity over space. Figure 4.2 shows there are substantially more wells were drilled in North Dakota (4,815 wells from April 2012–October 2015) than Montana (498 wells). Drilling in North Dakota is concentrated about fifty to seventy-five miles away from the border with Montana. This is largely explained by the existence of a fold in the subsurface rock formations called the "Nesson Anticline" that creates a so called "sweet spot" because natural fractures in the rock enhance oil production. The RD analysis focuses on a narrow window around the border (20/30 miles on each side) to prevent the relatively oil-rich areas of North Dakota from influencing the results, but RD estimation with various windows are presented in Appendix C.

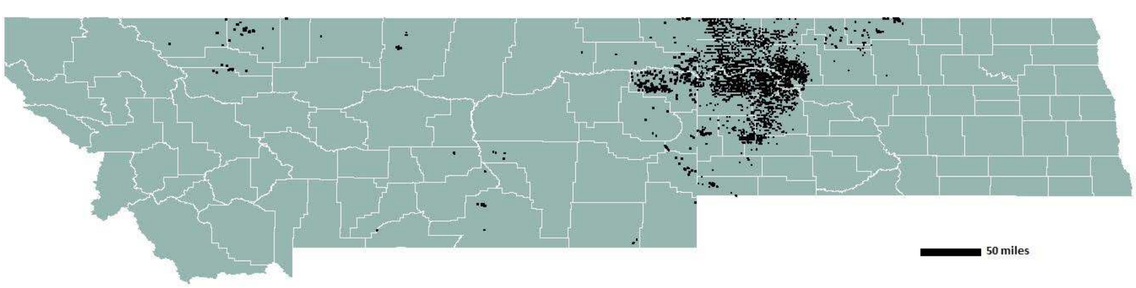

Figure 4.2: Oil and gas wells drilled in MT and ND (April 2012–October 2015)

[17]This is similar to the approach taken by Cust and Harding (2014), who exploit country boundaries to evaluate the effects of institutions on oil and gas exploration.

The units of observation are geographically-defined cells near the MT-ND border. The cells are identical in size, equal in length and width, and each cell is located in either Montana or North Dakota. The nearly straight line that creates the Montana–North Dakota boundary, as well as the border with Canada (the 49th parallel north), make constructing the cells straightforward. Wells in the Bakken were initially spaced so that one well occupied a square mile (referred to as 640-acre spacing), but they have become closer so that spacing typically range from 40-acre to 160-acre (4–16 wells per square mile). Cell dimensions of 1x1 mile are thus a natural starting point, although robustness checks are performed where the cell dimensions are modified to 5x5 miles.

Equation 4.1 presents a regression model for a parametric RD design.

$$LnWells_i = \alpha + \beta D_i + f(x_i) + \gamma_i + \epsilon_i \tag{4.1}$$

The variable $LnWells_i$ is the natural log of the number of wells drilled in cell i after the regulation change, where each cell is a one-square-mile block of land. The sample period is limited to wells drilled from April 2012 to March 2014, and robustness checks show that varying the start or end of the sample period does not influence the results (Table C.7 of Appendix C).[18]

The assignment variable (D_i) is equal to one for cells in ND and zero for cells in MT. The force variable (x_i) is the distance from the border to the midpoint of cell i, and the distances for MT cells are negative. The polynomial function $f(x_i)$ maps distance from the border to drilling in a flexible manner. The function is defined as follows: $f(x_i) = f_L(x_i) + D_i(f_R(x_i) - f_L(x_i))$, where $f_L(x_i)$ is a polynomial function of x for the left side of the cutoff (MT) and $f_R(x_i)$ is polynomial function for the right side (ND).

The force variable measures only a cell's east-west distance from the border, and thus captures one dimension of spatial variation in drilling. The term γ_i is included to account for north-south variation in drilling activity. This is accomplished in the estimation by including dummy variables for cell distance from the intersection of the MT-ND border with Canada (i.e., its north-south distance). Note that this is feasible because by construction, each cell's distance from the Canadian

[18]North Dakota revised oil and gas regulations on spill reporting, pipelines, and waste treatment plants in April 2014. April 2012–March 2014 thus serves as a natural post-treatment time period.

border is discrete.[19] Lastly, the error term is denoted by ϵ_i.

Estimation of Equation 4.1 may not identify effects of the regulation change if there is a pre-existing discontinuity in drilling at the MT-ND border. This may arise from several factors, such as differences in oil and gas severance tax rates, state corporate income tax rates, or regulatory requirements. Hence it is necessary to estimate the how the discontinuity at the border changes following the stricter regulations.

In equation 4.2, the pre-and post-treatment sample periods are pooled to estimate the difference in the discontinuity before and after the revision to the regulations. This is similar to the "pretest RD" method introduced by Wing and Cook (2013) (see Appendix C). The pretest RD improves identification of the standard RD design by including pre-treatment observations, which contain information on the underlying relationship between the force variable and outcome variable. In this paper, not only do pre-treatment observations help establish the relationship between distance from the border and drilling activity, but they are also necessary to account for a potential pre-existing discontinuity at the border.

$$LnWells_{it} = \rho D_{it} + \zeta S_i + h_0(x_i) + T_{it}(h_1(x_i) - h_0(x_i)) + \gamma_i + \epsilon_{it} \tag{4.2}$$

where $h_0(x_i) = h_{0L}(x_i) + S_i(h_{0R}(x_i) - h_{0L}(x_i))$,
and $h_1(x_i) = h_{1L}(x_i) + S_i(h_{1R}(x_i) - h_{1L}(x_i))$

The dependent variable ($LnWells_{it}$) is the natural log of the number of wells drilled in cell i in period t. There are two periods: $t = 0$ is the pre-treatment period (April 2010–March 2012) and $t = 1$ is the post-treatment period (April 2012–March 2014). Note that Table C.6 and Table C.7 of Appendix C show that varying the sample period does not alter conclusions drawn from the results. The variable S_i indicates whether the cell is in North Dakota ($S_i = 1$) or Montana ($S_i = 0$). The polynomial functions allow drilling activity to vary across time periods (pre-and post-treatment) and the cutoff. The functions $h_0(x_i)$ and $h_1(x_i)$ are polynomials for the pre-treatment and post-treatment periods, respectively. The variable T_t is equal to zero for cells in the pre-treatment

[19] Results are presented without this fixed effect in Table C.8. Including this term does not have an effect on the overall results.

($T_0 = 0$) period and equal one for cells in the post-treatment ($T_1 = 1$) period. For example, for $t = 0$, drilling activity follows the polynomial $h_0(x_i)$, which in turn differs for the Montana side ($h_{0L}(x_i)$) and North Dakota side ($h_{0R}(x_i)$). The term γ_i is the fixed effect for the north-south position of cell i, and ϵ_{it} is the error term.

A parametric RD is applied, as opposed to a nonparametric RD, because the force variable is discrete. Distance is measured from the border to the midpoint of each cell (0.5, 1.5, 2.5 miles, etc.). Lee and Card (2008) note that the non-parametric and semi-parametric RD methods rely on comparing outcomes in arbitrary small neighborhoods around the threshold. In cases with discrete force variables, it is not possible to be arbitrarily close the threshold even as the sample size grows. The approach recommended by Lee and Card (2008), which is followed in this analysis, is to use parametric functional form and cluster the standard errors on the force variable. Non-parametric RD yields similar results though (Table C.5 of Appendix C).

The polynomial order is selected based on the specification's Akaike information criterion (AIC) value. Based on the findings by Gelman and Imbens (2014), who caution against using high order polynomials, only models with zero through second-order polynomials are considered. In choosing the width of the window around the border, there is a trade-off between observations and potential bias. Results for twenty-mile and thirty-mile windows are presented in Section 4.5, but results for additional windows in give similar findings (Appendix C).

4.4.2 RD Design Identification

This section discusses five issues that threaten identification through the RD design. First, a necessary assumption is that the conditional regression functions are continuous at the cutoff. That is, there is no discontinuity in the outcome variable at the cutoff— that is unrelated to the treatment. As discussed in Section 4.4.1, this assumption may be violated because of pre-existing differences between Montana and North Dakota. This is resolved by pooling pre-treatment and post-treatment data into a single RD (Equation 4.2) and estimating the difference in this discontinuity following the regulation revisions.

The second identification issue is whether there is a discontinuity in the density of the force variable near the cutoff. In this paper, the unit of observation is a geographically-defined cell, and firm decisions on where to drill are the outcomes of interest. Thus, if drilling is relatively sparse on the North Dakota side following the regulation change, this would not necessarily imply that the identification strategy is invalid but rather that the new regulations has an effect. Figure 4.3 in Section 4.5.1 shows there is no apparent discontinuity in the density of drilling activity at the boundary (i.e., firms do not avoid the places near the border) in the two years leading up to the regulation change (April 2010–March 2012).

Third, identifying the treatment effect requires the stable unit treatment value assumption (SUTVA) to hold. The Montana observations must not be affected by the treatment applied to North Dakota. This assumption is violated if stricter regulations in North Dakota cause firms to relocate to Montana, making drilling activity in Montana to be higher than it would be otherwise. Since the validity of this assumption is unknown here, we consider the estimation results to be an upper bound of the average treatment effect at the threshold.

Fourth, the enactment of regulation revisions may coincide with temporal shifts in drilling from one state to the other. A possible scenario is that drilling was concentrated in one state in the years leading up to the regulation change; that state became saturated with wells near the time of regulation change, and activity then shifted to other state. Such a situation may give the incorrectly attribute shift in drilling to the regulations. To deal with this issue, a control variable for the number of previously wells drilled within a cell is added to equation 4.1. The number of wells previously drilled is specified in both linear and quadratic forms, which allows for drilling within a cell to become saturated and decline over time. There is no meaningful difference in the estimation results when including this control (see Table C.10 of Appendix C).

Fifth and finally, a common identification issue with in applications of RD is endogeneity of the cutoff's placement. It is highly unlikely that oil and gas deposits had any influence over location of the Montana-North Dakota border and that such placement would be correlated with the 2012 regulation change. The current MT-ND border was originally the eastern border of the

Idaho territory created by Congress in 1863 (State Historical Society of North Dakota, 2016). This later become the border between Montana and North Dakota when the two states where formed in 1889. The first oil wells were drilled in Montana and North Dakota in 1901 and 1929, respectively (Erdmann, nd; NDGS, nd). Moreover, the border is reported to have been chosen “out of the blue”, and “The line does not coincide with any particular section or half-section line, or anything else of local or regional significance.” (Bluemle, 2007).

4.4.3 Oil Production and Exit

Higher bond requirements may increase the marginal cost of oil production and cause firms to reduce output. For example, operators could shut in wells that are no longer profitable or drill fewer wells. The stricter drilling waste disposal rules are not expected to affect production at existing wells, but these rules can reduce production by discouraging the drilling of new wells.

Equation 4.3 estimates the effects of the revised regulations on operator-level oil production.

$$LnProd_{ijt} = \tau D_{jt} + \theta_i + \kappa_j + \lambda_t + \eta_{ijt} \tag{4.3}$$

The dependent variable ($LnProd_{ijt}$) is the natural log of oil produced by operator i in state j during month t. Production is limited to oil produced from wells within ten miles of the MT-ND boundary to ensure the treatment and control groups are similar. The treatment variable (D_{jt}) is equal to one for observations in North Dakota after the regulation change (April 2012 and onward) and zero otherwise. Time-invariant unobservables are controlled for with fixed effects for the operator (θ_i), state (κ_j) and month (λ_t). The last term (η_{ijt}) is the idiosyncratic error.

In the estimation of Equation 4.3, operators that shut down production completely leave the sample and are no longer observed. If firms shut down production or sell off wells and exit, there will be an attrition bias that causes the effects of the regulation on oil production to be underestimated. The final regression model is shown in Equation 4.4, which estimates the effect on operator exit from the ten-mile window in North Dakota.[20]

$$Exit_{ijt} = \mu D_{jt} + \phi_i + \psi_j + \omega_t + \upsilon_{ijt} \tag{4.4}$$

[20] A duration analysis performed in Appendix C provides similar findings.

The dependent variable ($Exit_{ijt}$) is equal to one if operator i exits state j in month t and zero otherwise. Note that this measures if an operator exits the area within the ten miles of the border and not whether it ceases operations in the entire state. An exit is considered to occur if an operator's production falls to zero and remains shutdown throughout the sample period. The treatment variable (D_{jt}) is equal to one for observations in North Dakota after the regulation change (April 2012 and onward) and zero otherwise. Fixed effects are included to account for time-invariant effects specific to the operator (ϕ_i), state (ψ_j), and month of production (ω_t). The final term, υ_{ijt}, is the idiosyncratic error.

Equations 4.3 and 4.4 estimate the average effect across all operators, but firms may respond differently depending on their size. Section 4.5.2 provides estimation results where the coefficient estimate for the treatment variable is allowed differ by firm size. Each operator's total oil production in all of Montana and North Dakota in 2011 (prior to the regulation change) is the proxy used for firm size.

It is usually more costly for smaller firms to meet well bond requirements. Operators, especially small companies, often post a surety bond. As discussed in Section 4.1, a surety company issues a bond to the operator, which submits the bond to the state regulator. The operator pays the surety company a premium that is typically a percentage of the face value of the bond. Firms with relatively limited assets, poor environmental or safety records, or in precarious financial positions, often pay higher premiums. Smaller operators may pay larger premiums to surety companies because these companies are potentially judgment proof, which occurs when a firm is unable to pay its full legal liabilities. That is, in bankruptcy, a company is liable up to the value of its assets and can have the obligations that exceed their assets eliminated. Bonding requirements could require operators to invest in safety and set output at levels that are socially optimal if operator behavior were perfectly observable by surety companies. Surety companies, however, recognize that because behavior is not perfectly observable and that smaller operators have less of an incentive to undertake safety measures because they will not be fully liable for potential damages. Thus, these smaller operators face higher premiums, and increasing the well bonding requirement has a larger financial impact on smaller (and potentially judgment proof) firms.

A final outcome variable studied is environmental incidents (e.g., oil spills) that occur in drilling. Data on incidents are only available for North Dakota, so it is not possible to use a diff-in-diff approach. The effect of the regulation change on the rate of environmental incidents that occur in drilling a well is estimated for only wells in Norther Dakota through an OLS with well operator fixed effects and a time trend.

4.4.4 Diff-in-Diff Identification

There are three primary identification issues to address with the estimation equations 4.3 and 4.4. First, there is the potential for policy endogeneity. That is, there may be unobserved factors that influence production (or firm exit) and North Dakota's adoption of the revised regulations. Inclusion of the state fixed effect controls for time-invariant unobservables specific to each state. These unobservables may be differences in existing tax structures, general friendliness to resource development, or geographic features within the window. Time-varying, state-level unobservables, however, are not accounted for with a state fixed effect. One potential time-varying factor is the Bakken Shale Play boom that began in 2008. The breakthroughs in horizontal drilling and hydraulic fracturing may have had different effects on oil activity in Montana and North Dakota. North Dakota encompasses more of the Bakken and the so called "sweet spots" that offer higher oil production rates. As the Bakken boom was occurring, it is conceivable that policy-makers in North Dakota judged that passing stricter regulations would have a limited effect on oil activity because evolving technology was unlocking the state's rich hydrocarbon potential. To deal with this issue, the sample is restricted to oil production in each state that is within ten miles of the MT-ND border. This ensures that the resource potential is very similar across the treatment and control groups, and the regulation change should not be endogenous.

The second identification issue is the appropriateness of the control group. To accurately estimate the treatment effect, the control group must serve as an appropriate counterfactural to North Dakota. Including oil production from only wells within a ten-mile window on each side of the border allows for wells in the sample to share similar geology and production potential. Figure 4.3 depicts Montana and North Dakota oil production within the ten-mile window and shows that pre-treatment, production in the two states generally follows a similar trend. Formal tests show no difference in pre-treatment trends between the two states (Table 4.6).

Third and finally, as discussed in Section 4.4.2, the stable unit treatment value assumption is required to identify the average treatment effect. The control group may be contaminated if firms shift production activities to Montana in response to the regulation change. This is an issue in many studies that attempt to estimate the effects of environmental regulations on firm investment decisions (Millimet et al., 2009). Thus, as in the RD design, the diff-in-diff estimation results can be interpreted as an upper bound of the treatment effect.

4.5 Results

Section 4.5.1 presents the results for the RD design, and section 4.5.2 shows the results of the diff-in-diff analysis.

4.5.1 RD Results

Figure 4.3 shows well drilling near the MT-ND border in the two-year period prior to the regulation change (April 2010–March 2012). The log number of wells drilled within a cell is on the vertical axis, and the cell's distance from the border is shown on the horizontal axis. The cutoff is at distance zero with Montana on the left side and North Dakota to the right. The left panel of Figure 4.3 captures a twenty-mile window on each side the border with a fitted quadratic. Estimation of equation 4.1 with the function $f(x_i)$ as a second-order polynomial yields the lowest AIC score for all models with zero to second-degree polynomials. The right panel presents a thirty-mile window with a quadratic polynomial (selected by lowest AIC value). Figure 4.3 suggests there is not a discontinuity in drilling activity at the border prior to the regulation change, and this is confirmed in Table 4.3.

Table 4.3 presents the estimation results of equation 4.1 for well drilling during the two-year period prior to the regulation change. Results for a twenty-mile window with zero, first, and

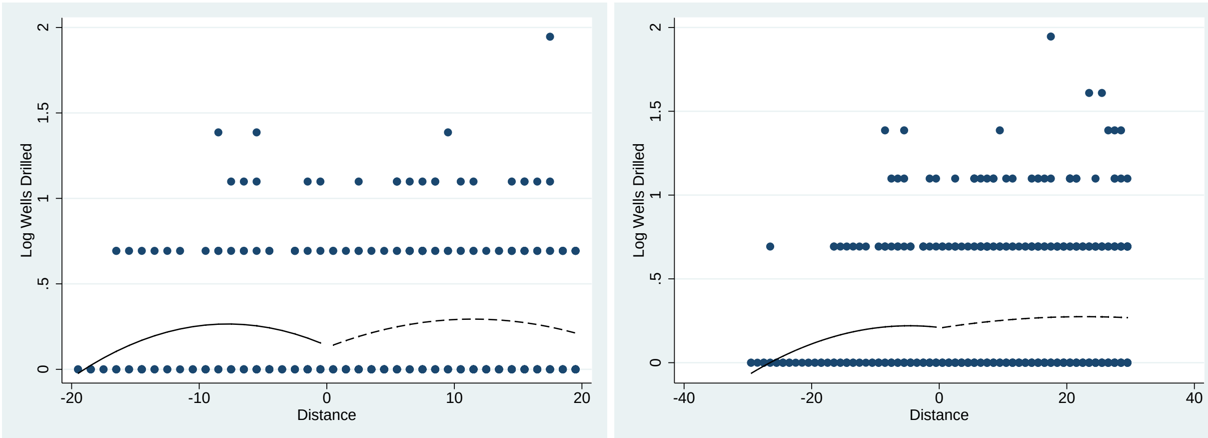

Figure 4.3: Drilling activity at MT-ND border (April 2010–March 2012)

second-order polynomials are shown in columns 1–3. The coefficient estimates for the assignment variable (D_i) are not statistically indistinguishable from zero at any reasonable level across the different specifications. For a thirty-mile window (columns 4–6), the estimate of the coefficient for the assignment variable is statistically significant at the 5% level in only the zero-order polynomial model. The specification with a quadratic polynomial is preferred (based on lowest AIC value) for both the twenty-mile and thirty-mile windows. Table C.1 of Appendix C shows the coefficient estimate for several windows and polynomial of orders zero through six.

Table 4.3: RD results for well drilling (April 2010–March 2012)

	20-Mile Window			30-Mile Window		
	(1)	(2)	(3)	(4)	(5)	(6)
	LnWells	LnWells	LnWells	LnWells	LnWells	LnWells
Assign. Var. D_i	0.052	0.015	-0.033	0.088**	0.020	0.024
	(0.041)	(0.120)	(0.154)	(0.034)	(0.085)	(0.123)
Poly. Order	Zero	1st	2nd	Zero	1st	2nd
AIC	330.0	251.5	248.1	526.0	470.3	468.2
R^2	0.004	0.353	0.355	0.010	0.274	0.274
Clusters	40	40	40	60	60	60
N	354	354	354	546	546	546

Standard errors clustered on force variable (x_i) in parentheses. Specification with lowest AIC is preferred. Constant only models do not include the latitude fixed effect term γ_i

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 4.4 displays drilling activity in the two years following the regulation change (April 2012–March 2014). Twenty-and thirty-mile windows are shown in the left and right panels, respectively, with fitted second-order polynomials, which are selected based on AIC values. Small, yet statistically insignificant, discontinuities at the MT-ND border are apparent in both panels.

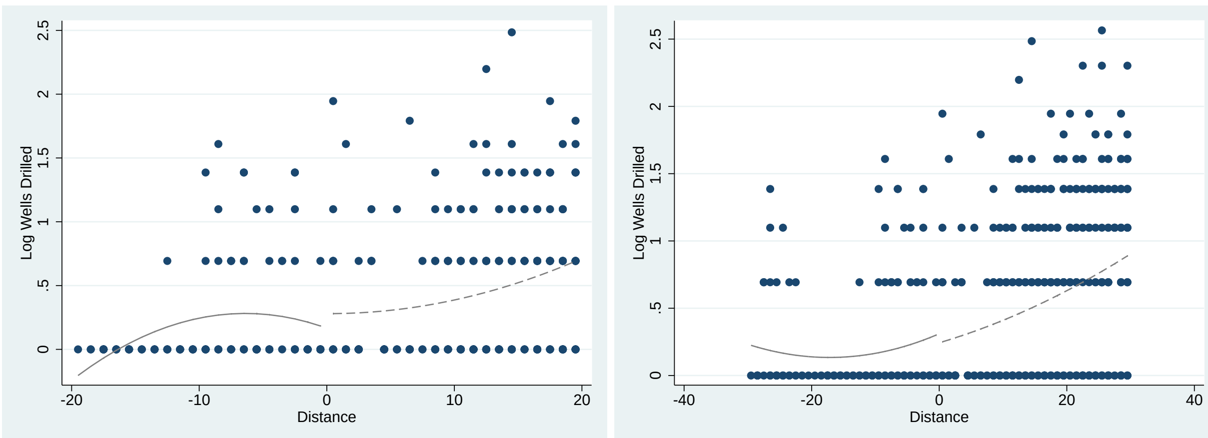

Figure 4.4: Drilling activity at MT-ND border (April 2012–March 2014)

Table 4.4 provides the estimation results of equation 4.1 for well drilling after the regulation change (April 2012–March 2014). Overall, there is little evidence of a discontinuity in drilling activity at the border. The coefficient estimates for the assignment variable (D_i) are positive and statistically significantly different from zero at the 1% level in only the models with a polynomial of order zero (columns 1 and 4). In the specifications with a second-order polynomial, the coefficient estimates for the assignment variable are not statistically indistinguishable from zero (columns 3 and 6).

Figure 4.5 contains wells drilled in both the pre-treatment period (April 2010–March 2012) and post-treatment period (April 2012–March 2014) for twenty-and thirty-mile windows. The fitted polynomials are allowed to vary across the threshold and time (pre-and post-treatment periods). The difference at the cutoff (distance zero) between the fitted curves labeled “MT Pre-Treat” and “ND Pre-Treat” depict the discontinuity existing prior to the regulation change. The discontinuity following the regulation change is shown by the difference in the curves labeled “MT Post-Treat” and “ND Post-Treat.” The estimated effect is measured by change in the discontinuity following

Table 4.4: RD results for well drilling (April 2012–March 2014)

	20-Mile Window			30-Mile Window		
	(1)	(2)	(3)	(4)	(5)	(6)
	LnWells	LnWells	LnWells	LnWells	LnWells	LnWells
Assign. Var. D_i	0.275***	-0.138	0.025	0.396***	-0.063	-0.097
	(0.073)	(0.202)	(0.309)	(0.061)	(0.146)	(0.238)
Poly. Order	Zero	1st	2nd	Zero	1st	2nd
AIC	517.7	462.1	460.2	961.0	823.8	820.7
R^2	0.061	0.359	0.362	0.088	0.422	0.425
Clusters	40	40	40	60	60	60
N	340	340	340	550	550	550

Standard errors clustered on force variable (x_i) in parentheses. Specification with lowest AIC is preferred. Constant only models do not include the latitude fixed effect term γ_i

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

the regulation revisions. Table 4.5, which presents the estimation results for Equation 4.2, shows there is little evidence of a shift in the discontinuity. For both the twenty-mile and thirty-mile windows, the coefficient estimate for the treatment variable (D_{it}) is not statistically significant in the specifications with a first-order or second-order polynomial, the latter of which has the lowest AIC value. Robustness checks that vary the window widths and polynomial orders offer no evidence that the regulation change had an effect on drilling activity (Appendix C, Table C.2).

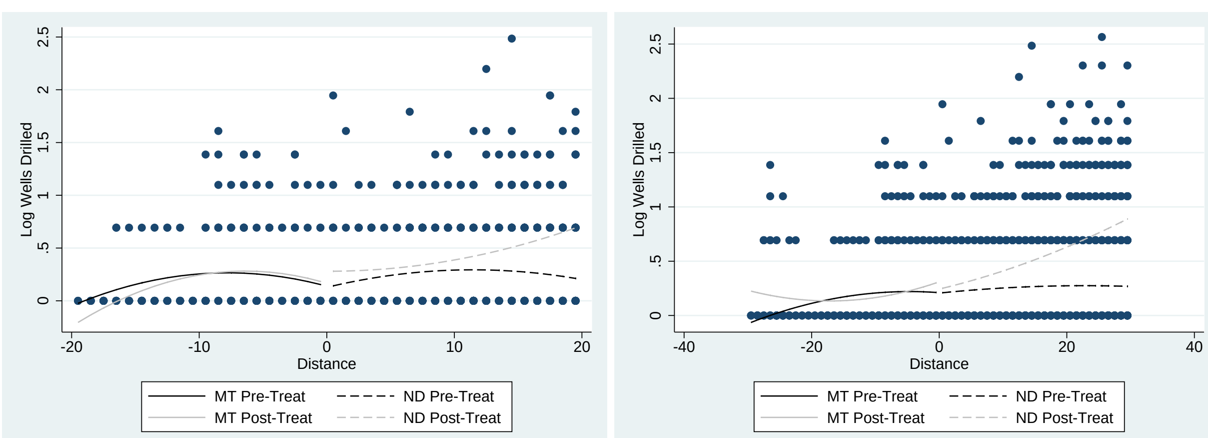

Figure 4.5: Drilling activity at MT-ND border (April 2010–March 2014)

Table 4.5: RD results for well drilling (April 2010–March 2014)

	20-Mile Window			30-Mile Window		
	(1)	(2)	(3)	(4)	(5)	(6)
	LnWells	LnWells	LnWells	LnWells	LnWells	LnWells
Treatment D_{it}	0.223***	-0.098	0.035	0.308***	-0.020	-0.151
	(0.073)	(0.182)	(0.282)	(0.060)	(0.137)	(0.206)
Poly. Order	Zero	1st	2nd	Zero	1st	2nd
AIC	877.6	759.2	756.4	1569.0	1368.7	1366.3
R^2	0.060	0.285	0.288	0.113	0.332	0.334
Clusters	40	40	40	60	60	60
N	694	694	694	1096	1096	1096

Standard errors clustered on force variable (x_i) in parentheses. Specification with lowest AIC is preferred. Constant only models do not include the latitude fixed effect term γ_i.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

One may be concerned that the results shown thus far do not account for the fact that landowner leases are not completely flexible and this is the cause for the null results related to drilling activity. As discussed in Timmins and Vissing (2014), landowner leases are generally about forty months long. Table C.6 re-runs equation 4.2 but removes the year immediately before and after the regulation was implemented to determine whether previous results are influenced by the inability to terminate or change lease terms. Results generally find no statistical change in drilling activity when comparing discontinuous time periods that allow for the unwinding of landowner leases.

4.5.2 Diff-in-Diff Results

Figure 4.6 shows oil production in each state—within ten miles of their shared border—from April 2009 to March 2014. Prior to the treatment, oil production in the two states (within the window) appears to follow similar trends, and this is confirmed in Table 4.6. Oil production drifts downward from April 2009 to early 2011 and trends upward from 2011 through mid-2013. There is no apparent change in North Dakota oil production relative to Montana after the regulation change occurs, and this is confirmed in Table 4.7.

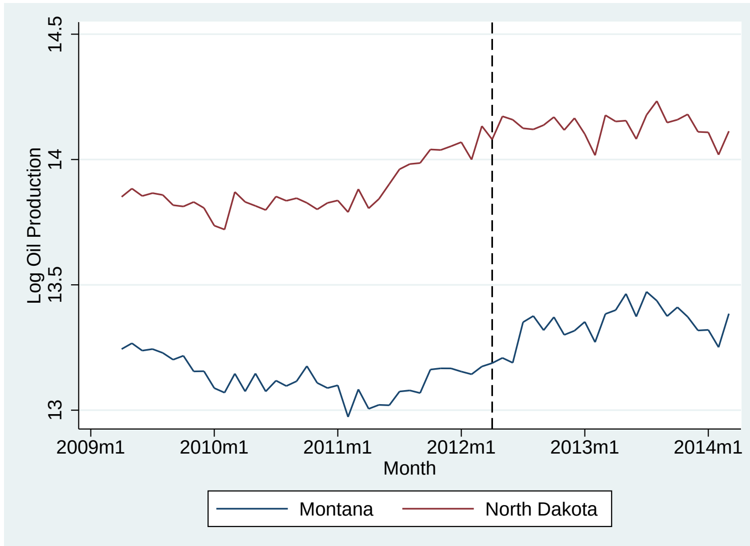

Figure 4.6: Oil production within 10-mile window of MT-ND border (April 2009–March 2014)

Table 4.6: Oil production pre-treatment trends (April 2011–March 2012)

	(1) LnProd	(2) LnProd
$Time$	0.02*	2.31
	(0.01)	(3.27)
$ND \times Time$	0.03	-0.37
	(0.02)	(6.68)
$Time^2$		-0.00
		(0.00)
$ND \times Time^2$		0.00
		(0.01)
Operator FE	Yes	Yes
N	942	942
R^2	0.045	0.045

Standard errors clustered on operator in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The estimation results for equation 4.3 are presented in Table 4.7. The sample period starts one year prior to the regulation change and ends two years after its implementation (April 2011–March 2014). This time period is selected because of the change in production trends beginning in early 2011 (Figure 4.6) and the implementation of new regulations in April 2014. In the first two columns, which include different time fixed effects, the coefficient estimates for the treatment variable are positive but not statistically indistinguishable from zero at any reasonable level. In column 3, the time fixed effects are replaced with a linear time trend, which is restricted to be the same for Montana and North Dakota oil production. The coefficient estimate for the treatment variable becomes positive and significant, which is counter to the expectation that stricter environmental regulations and bond requirements would discourage production. When the linear time trend is allowed to differ across the two states (column 4), the coefficient estimate is no longer significant.

Table 4.7: Oil production diff-in-diff results

	(1) LnProd	(2) LnProd	(3) LnProd	(4) LnProd
$Treat$	0.126	0.133	0.214*	0.162
	(0.153)	(0.125)	(0.125)	(0.123)
ND	0.375	0.368	0.316	-2.072
	(0.330)	(0.327)	(0.323)	(6.494)
$Time$			-0.002	-0.003
			(0.007)	(0.007)
$ND \times Time$				0.004
				(0.010)
Time FE	Month	Year	None	None
Operator FE	Yes	Yes	Yes	Yes
N	2667	2667	2667	2667
R^2	0.051	0.044	0.038	0.038

Standard errors clustered on operator in parentheses. Estimation results for equation 4.3.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.8 presents the results for Equation 4.3 when the treatment effect is allowed to vary with firm size. Each operator's total oil production in Montana and North Dakota in the year prior to the regulation change (2011) serves as a proxy for its size. Operators are partitioned into quartiles based on their 2011 oil production levels: quartile one representing the smallest firms and quartile four containing the largest ones. In columns 1–4, the coefficient estimate for the treatment variable interacted with the quartile 1 indicator variable is negative and significant at either the 1% or 5% levels. The results are similar when varying the sample period (Table C.12 and Table C.13 of C). The coefficient estimate in column 1, for example, implies that the regulation change reduced monthly oil production for the smallest firms by 0.46%. This translates to a output reduction of about seventeen barrels per year for a typical small producer in North Dakota.[21] The results also suggest that the regulation change had a positive and statistically significant effect on oil production for the largest firms. This can be explained by production shifting from smaller to larger firms. Small operators may exit and sell existing wells to larger companies, or as smaller firms reduce drilling, larger firms drill in their place. Note that the results do not account for operators that shut down production entirely and are no longer observed in the sample. Thus the estimates in Table 4.8 can be interpreted as the effect of the regulation change on oil production for companies that remained in operation throughout the sample period.

Figure 4.7 depicts operator exits within ten-mile windows around the Montana and North Dakota border from April 2009 to March 2014. The vertical axis is the number of firms that exit during a month, where an exit is defined as permanently ceasing oil production for the remainder of the sample period. Operator exits appear to have considerable noise and the number of exits per month are typically zero or one. It is unclear how closely the pre-treatment trends in Montana and North Dakota match up given the level of noise in both series. For example, a jump in exits occur in Montana in August 2010 but no similar increase happens in North Dakota. The results for equation 4.4 is presented with this caveat noted.

[21] Operators in quartile 1 in ND averaged ten barrel per day of oil production in 2011: 3,650$\times$0.046%= 17.

Table 4.8: Oil production diff-in-diff results with effects by firm size

	(1)	(2)	(3)	(4)
	LnProd	LnProd	LnProd	LnProd
$Treat \times Q1$	-0.461***	-0.485***	-0.370**	-0.414**
	(0.136)	(0.156)	(0.148)	(0.197)
$Treat \times Q2$	-0.521	-0.538	-0.457	-0.508
	(0.456)	(0.468)	(0.463)	(0.480)
$Treat \times Q3$	0.209	0.192	0.287	0.239
	(0.416)	(0.439)	(0.417)	(0.396)
$Treat \times Q4$	0.753**	0.737**	0.829**	0.781**
	(0.334)	(0.338)	(0.335)	(0.370)
ND	0.326	0.338	0.278	-1.920
	(0.325)	(0.328)	(0.321)	(6.959)
$Time$			-0.001	-0.001
			(0.007)	(0.008)
$ND \times Time$				0.004
				(0.011)
Time FE	Month	Year	None	None
Operator FE	Yes	Yes	Yes	Yes
N	2494	2494	2494	2494
R^2	0.087	0.094	0.081	0.081

Standard errors clustered on operator in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

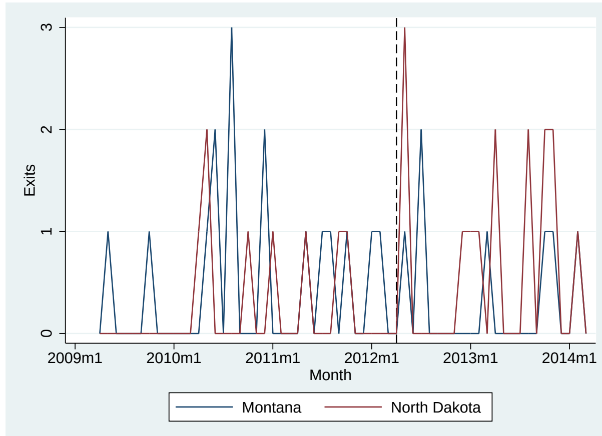

Figure 4.7: Operator exits in 10-mile window of MT-ND border (April 2009–March 2014)

In Table 4.9, the estimation results show mixed evidence for whether the regulation change had an effect on the rate of operator exit. In columns 1 and 2, the coefficient estimate for the treatment variable is almost always positive and significant at the 10% level, which implies that the regulation change increased the rate of firm exits. The estimation results are carried out with linear time trends for sake of completeness and despite the clear lack of a linear trend in exits prior to the regulation change. In columns 3 and 4, the coefficient estimates for the treatment variable remain positive but are no longer statistically indistinguishable from zero any reasonable significance level.

In Table 4.10, where the treatment effect is allowed to vary across firm size, the results are generally consistent with Table 4.9. The coefficient estimates for the treatment variable interacted with the quartile 1 indicator variable are positive and statistically significantly different from zero at the 10% level. For the remaining quartiles, the coefficient estimates are positive but not significantly different from zero at a significance level of 10% or less. These results suggest the regulation change led to an exit by relatively smaller firms but had no impact on the rate of exit by larger firms. There are two important caveats for these results. First, it is unclear that the ten-mile window along the border in Montana serves as a suitable counterfactual to North Dakota (Figure 4.7). Second, the results are somewhat sensitive to changes in the sample period. When varying the sample period to April 2011–March 2013 (Table C.14 of Appendix C), the coefficient estimates are marginally significant (p-values$\approx$ 0.11), yet the coefficient estimates are fairly stable; the coef-

Table 4.9: Firm exit diff-in-diff results

	(1)	(2)	(3)	(4)
	Exit	Exit	Exit	Exit
$Treatment$	0.0087*	0.0085*	0.0067	0.0053
	(0.0051)	(0.0048)	(0.0048)	(0.0081)
ND	-0.0014	-0.0013	-0.0005	-0.0437
	(0.0033)	(0.0031)	(0.0030)	(0.2033)
$Time$			0.0004***	0.0004***
			(0.0001)	(0.0001)
$ND \times Time$				0.0001
				(0.0003)
Time FE	Month	Year	None	None
Operator FE	Yes	Yes	Yes	Yes
N	4874	4874	4874	4874
R^2	0.020	0.006	0.007	0.007

Standard errors clustered on operator in parentheses. Estimation results for equation 4.4.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

ficient estimates remain significant when the sample period is changed to April 2009–March 2013 (Table C.15).

Table 4.10: Firm exit diff-in-diff results by firm size

	(1) Exit	(2) Exit	(3) Exit	(4) Exit
$Treat \times Q1$	0.0399*	0.0410*	0.0410*	0.0402
	(0.0223)	(0.0229)	(0.0231)	(0.0250)
$Treat \times Q2$	0.0072	0.0084	0.0083	0.0074
	(0.0120)	(0.0125)	(0.0127)	(0.0177)
$Treat \times Q3$	0.0050	0.0057	0.0056	0.0047
	(0.0089)	(0.0081)	(0.0082)	(0.0107)
$Treat \times Q4$	0.0099	0.0109	0.0109	0.0100
	(0.0086)	(0.0081)	(0.0080)	(0.0102)
ND	-0.0033	-0.0037	-0.0037	-0.0313
	(0.0034)	(0.0032)	(0.0030)	(0.2282)
$Time$			0.0003**	0.0003**
			(0.0001)	(0.0001)
$ND \times Time$				0.0000
				(0.0004)
Time FE	Month	Year	None	None
Operator FE	Yes	Yes	Yes	Yes
N	3644	3644	3644	3644
R^2	0.029	0.012	0.012	0.012

Standard errors clustered on operator in parentheses. $Q1 - Q4$ are indicator variables for firm's quartile.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.11 shows the results for estimating the effect of the regulation change on environmental incidents. The regulation is associated with a level shift down in the number of incidents that occur while drilling, which is consistent with higher bond requirements encouraging better safety and exit of relatively unsafe operators.

Table 4.11: North Dakota environmental incidents

	(1) Incident	(2) Incident
$Treat$	-0.030**	-0.030**
	(0.015)	(0.013)
$Time$	0.009***	0.009***
	(0.004)	(0.003)
Month FE	Yes	Yes
Operator FE	Yes	Yes
Rig FE	Yes	Yes
Clustering	Operator	Rig
N	4960	4960

The dependent variable is the number of incidents that occur during drilling a well. Robust standard errors in parentheses. The variable $Treat$ is equal to 1 for April 2012 and onward and zero otherwise.

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

4.6 Conclusion

Technological expansion will always force a re-evaluation in the specification of property rights, as explained in the seminal work by Demsetz (1967). A determinant in whether and how to change property right specification is how these changes effect economic welfare. The recent shale revolution has significantly altered our ability to extract oil and gas. This has resulted in a change in the way that oil and gas operations are regulated. This analysis asks what impact those new regulations have on firms production, drilling, and exit decisions. ND changed its oil and gas regulations to require a higher level of bonding and restrict how firms dispose of waste. The main oil basin, the Bakken, is under ND and MT thus we use a RD and difference-in-differences methodology to determine how these new regulations altered firm's decisions in ND with MT as a control. Since the ND-MT border was set long before an oil industry emerged, the border acts as an exogenous discontinuity in treatment. Additionally, restricting the analysis to a short distance around the border helps ensure that other unobservables, like geology, is constant.

Results find no change in the pace of drilling nor the level of oil production in ND after the regulations passed relative to MT. However, this average effect masks a change in organization in the oil industry in ND. Small operators are statistically more likely to exit the area of analysis and to reduce the level of production. This effect is countered by an increase in production from large operators. The results imply that larger firms may have benefited from the regulation through reduction competition by raising their rivals costs, an outcome predicted by Salop and Scheffman (1983).

This analysis also provides useful information for policymakers weighing the costs and benefits of increased environmental regulation. The potentially regulated firms usually argue that proposed regulations will threaten their activities in the relative jurisdiction and argue that this will cost jobs and tax revenue. However, it is difficult for policymakers to find rigorous, objective information on how firms have responded to previous environmental regulations. In this case, the increase bonding requirements and restrictions on drilling waste disposals did not change the pace of economic activity. Unfortunately, this analysis can not reveal whether the change in industrial composition will have long-run consequences for the oil industry in ND. The short-run consequences have been small, if any.

CHAPTER 5

CONCLUSION

This thesis has investigated several aspects of the U.S. tight oil boom. Chapter 2 demonstrated learning economies associated with oil rigs, but the magnitude of the cost savings from learning were relatively small. This chapter also shows evidence of organizational forgetting created from interruptions in drilling activity and knowledge spillovers among firms. These findings help in understanding learning economies in oil well drilling and potentially other sectors.

Chapter 3 shows evidence of interfirm learning that increases drilling productivity. Additionally, it finds limited evidence of interfirm learning in improving environmental safety. Lastly, multiple statistical analyses find evidence that firms make contracting decisions that are consistent with interfirm learning. These findings help explain the mechanisms behind productivity gains and improve our understanding of the factors behind environmental incidents.

Lastly, the results of chapter 4 show no evidence that enactment of stricter environmental regulations in North Dakota altered the level of well drilling or oil production. Smaller operators were statistically more likely to exit and reduce production, but this was mitigated by an increase in production from larger operators. This analysis provides important empirical evidence for policymakers seeking to assess the benefits and costs of greater environmental regulation.

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APPENDIX A

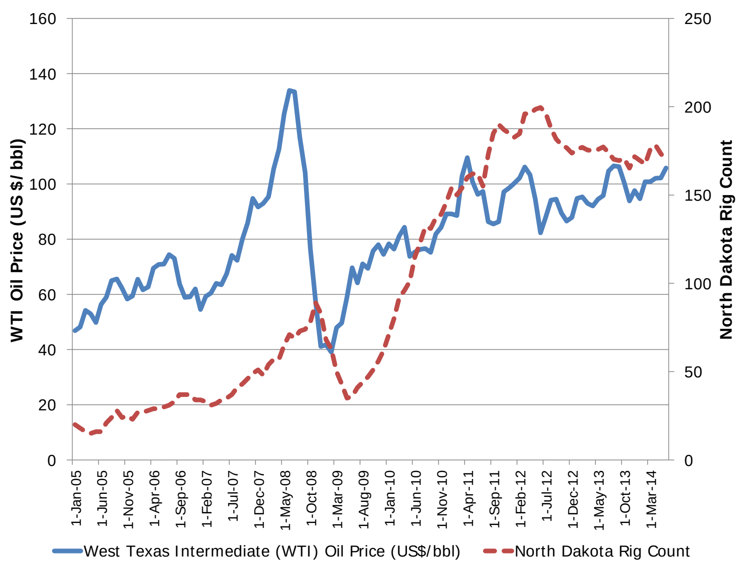

Figure A.1: WTI oil price and North Dakota rig count (January 2005–June 2014)

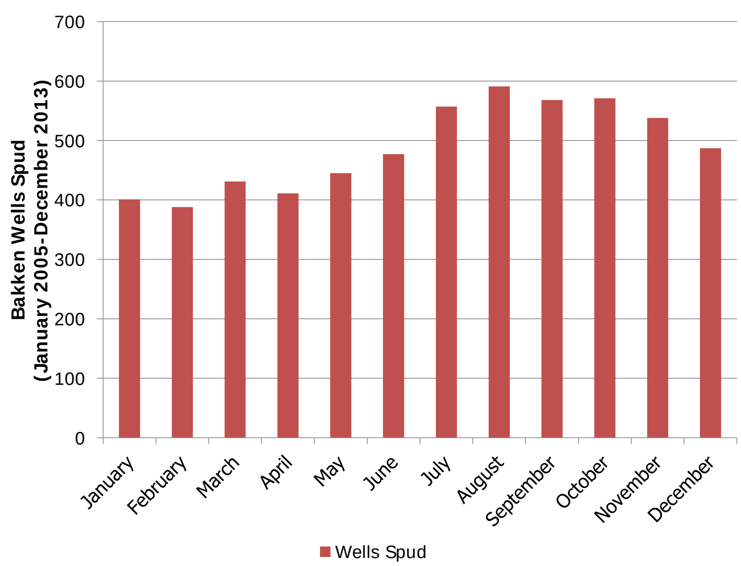

Figure A.2: North Dakota wells spud (January 2005–December 2013)

Table A.1: Regression results for alternative specifications

	(1) LnRate	(2) LnRate	(3) LnRate	(4) LnRate	(5) LnRate
LnE$_{rt}$	0.091***	0.085***	0.085***	0.086***	0.072***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.017)
LnE$_{oft}$	0.022***	0.014	0.014	0.013	0.014
	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
LnE$_{dft}$	-0.001	-0.006	-0.006	-0.004	-0.003
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
LnE$_{rft}$		0.021*	0.021*	0.020*	0.015
		(0.011)	(0.011)	(0.012)	(0.011)
LnE$_{ot}$			0.005	0.009	0.003
			(0.017)	(0.017)	(0.017)
LnE$_{dt}$				-0.036**	-0.038**
				(0.018)	(0.017)
LnE$_{rot}$					0.019
					(0.012)
Controls	Yes	Yes	Yes	Yes	Yes
Rig FE	Yes	Yes	Yes	Yes	Yes
Operator FE	Yes	Yes	Yes	Yes	Yes
Dir. Co. FE	Yes	Yes	Yes	Yes	Yes
Field FE	Yes	Yes	Yes	Yes	Yes
Year-Qtr FE	Yes	Yes	Yes	Yes	Yes
N	4625	4625	4625	4625	4625

Estimation results for equation 2.1 with alternative specifications. Dependent variable in all specifications is the log rate of drilling. Standard errors clustered on field in parentheses. Control variables include well depth, well depth squared, well depth cubed, average min temperature, average min temperature squared, average wind speed, average wind speed squared, month of year dummies, a dummy variable for whether a spud rig was used divided by the well's depth, and a dummy indicating if the well was drilled into the Bakken or Three Forks formation.

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

Table A.2: Regression results with alternative measures of experience

	(1) Experience: Cumulative Wells LnRate	(2) Experience: Cumulative Feet LnRate	(3) Experience: Wells in Prior 2 Years LnRate
LnE_{rt}	0.091***	0.084***	0.094***
	(0.014)	(0.012)	(0.014)
LnE_{oft}	0.022***	0.020**	0.022***
	(0.008)	(0.008)	(0.008)
LnE_{dft}	-0.001	-0.001	-0.001
	(0.007)	(0.008)	(0.007)
MD	0.449***	0.436***	0.448***
	(0.129)	(0.129)	(0.130)
MD^2	-0.022***	-0.021***	-0.022***
	(0.008)	(0.008)	(0.008)
MD^3	0.0003**	0.0003**	0.0003**
	(0.0001)	(0.0002)	(0.0002)
Controls	Yes	Yes	Yes
Rig FE	Yes	Yes	Yes
Operator FE	Yes	Yes	Yes
Dir. Co. FE	Yes	Yes	Yes
Field FE	Yes	Yes	Yes
Year-Qtr FE	Yes	Yes	Yes
N	4328	4328	4328

Estimation results for equation 2.1 with alternative measures of experience. Dependent variable in all specifications is the log rate of drilling. Standard errors clustered on field in parentheses. Control variables include well depth, well depth squared, well depth cubed, average min temperature, average min temperature squared, average wind speed, average wind speed squared, month of year dummies, a dummy variable for whether a spud rig was used divided by the well's depth, and a dummy indicating if the well was drilled into the Bakken or Three Forks formation.

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

Table A.3: Regression results with control variables

	(1)	(2)	(3)	(4)
	LnRate	LnRate	LnRate	LnRate
LnE_{rt}	0.091***	0.093***	0.095***	0.091***
	(0.014)	(0.015)	(0.015)	(0.014)
LnE_{oft}	0.022***	0.028***		0.022***
	(0.008)	(0.008)		(0.006)
LnE_{dft}	-0.001	-0.001		
	(0.007)	(0.007)		
MD	0.449***		0.465***	0.449***
	(0.129)		(0.126)	(0.129)
MD^2	-0.022***		-0.023***	-0.022***
	(0.008)		(0.008)	(0.008)
MD^3	0.0003*		0.0003*	0.0003*
	(0.0001)		(0.0001)	(0.0001)
TVD	0.003		0.005	0.003
	(0.018)		(0.017)	(0.018)
SpudRig/MD	3.221***		3.288***	3.220***
	(0.358)		(0.348)	(0.358)
Temp	0.006***		0.006***	0.006***
	(0.002)		(0.002)	(0.002)
Temp^2	0.000**		0.000**	0.000**
	(0.000)		(0.000)	(0.000)
Wind	-0.130***		-0.126***	-0.130***
	(0.037)		(0.038)	(0.037)
Wind^2	0.015***		0.015***	0.015***
	(0.004)		(0.005)	(0.004)
ThreeForks	-0.027		-0.028	-0.027
	(0.024)		(0.024)	(0.024)
N	4625	4633	4625	4625

Estimation results for equation 2.1 with controls presented. Standard errors clustered on field in parentheses

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

Table A.4: Regression results for spillovers

	(1) Base LnRate	(2) Spillover LnRate	(3) Spill-3mnth LnRate	(4) Spill-6mnth LnRate	(5) Spill-9mnth LnRate	(6) Spill-12mnth LnRate
LnE$_{rt}$	0.091***	0.091***	0.091***	0.091***	0.090***	0.090***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
LnE$_{oft}$	0.022***	0.021***	0.022**	0.017*	0.016	0.004
	(0.008)	(0.008)	(0.010)	(0.009)	(0.011)	(0.013)
LnE$_{dft}$	-0.001	-0.002	-0.004	-0.004	-0.004	-0.004
	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)
LnE$_{ft}$		0.007				
		(0.013)				
LnERec$_{ft}$			0.018*	0.018*	0.016	0.008
			(0.010)	(0.010)	(0.010)	(0.011)
LnERec$_{oft}$			-0.005	0.007	0.005	0.021
			(0.013)	(0.012)	(0.014)	(0.014)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Rig FE	Yes	Yes	Yes	Yes	Yes	Yes
Operator FE	Yes	Yes	Yes	Yes	Yes	Yes
Dir. Co. FE	Yes	Yes	Yes	Yes	Yes	Yes
Field FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4625	4625	4625	4625	4625	4625

Estimation results for equation 2.4 with the $LnBreak$ variable excluded. Standard errors clustered on field in parentheses

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

APPENDIX B

This appendix provides additional analysis on interfirm learning economies. First, it attempts to provide a better understanding of what drives interfirm learning. Second, it examines whether relationship-specific learning occurs at the level of the operator and drilling contractor, which owns the rig. No two wells are identical, but wells drilled in the same field by the same operator may have similar characteristics (e.g. depth and design of curve and lateral section). The relationship-specific learning observed between operators and rigs may result from rigs becoming more proficient at drilling particular types of wells drilled for an operator. This is analogous to employees of a firm becoming more efficient as they learn the practices and processes specific to their employer. Similarly, in the case of rig-directional driller learning, the contractors may learn together as they drill a particular type of well for an operator, but this learning may not transfer when drilling potentially different kinds of wells for other operators.

Drilling contractors typically own many rigs. Relationship-specific learning may occur at the level of the rig or the drilling contractor. Learning that occurs at the operator-rig level may result as a rig's crew and operator's representative work together. This learning may transfer to other rigs employed by the same operator. Drilling contractors with multiple rigs may actively work to diffuse knowledge among rigs working for the same operator, or crew members may be transferred to other rigs drilling wells for the same operator. Similar mechanisms may be at work for learning specific to rigs and directional drillers.

Table B.1 presents several results relating to operator-rig learning. Columns 1 and 2 show the estimation results when operator-rig experience is included with and without operator-rig fixed effects. In column 1, without operator-rig effects, the coefficient estimate for logged operator-rig experience is 0.020 (p=0.110). When operator-rig fixed effects are included in column 2, the coefficient becomes 0.070 ($p<0.001$). The variable for logged operator-rig experience within a field (LnE_{orft}) is included in column 3 (without operator-rig effects) and column 4 (with operator-rig fixed effects), and the coefficient estimates are -0.091 (p=0.003) and -0.096 (p=0.006), respectively. These coefficient estimates are likely a result of the high collinearity (0.98 correlation coefficient) between the experience of an operator-rig pair within a field (LnE_{orft}) and the experience of a rig in a field (LnE_{rft}). Wells drilled by a rig within a field are almost always drilled for the same operator; note that the coefficient estimate for rig experience within a field increases and becomes highly significant once the variable LnE_{orft} is included. These results suggest that it is not possible to distinguish the importance of rig experience within a field and operator-rig experience within a field. In columns 5 and 6, variables are included for the logged experience of the drilling contractor (LnE_{ct}) and joint experience of the drilling contractor and operator (LnE_{oct}). The coefficient estimate for the operator-drilling contractor joint experience variable is insignificant at any reasonable level in column 5 (without operator-rig fixed effects) and in column 6 (with operator-rig fixed effects).

Table B.1: Regression results for extended models

	(1) LnRate	(2) LnRate	(3) LnRate	(4) LnRate	(5) LnRate	(6) LnRate
Operator	0.001	-0.029	0.002	-0.030	-0.006	-0.046*
LnE$_{ot}$	(0.017)	(0.022)	(0.017)	(0.023)	(0.017)	(0.025)
Operator-Field	0.013	0.003	0.018*	0.007	0.013	0.003
LnE$_{oft}$	(0.009)	(0.010)	(0.010)	(0.010)	(0.009)	(0.010)
Field	0.011	0.010	0.010	0.009	0.013	0.011
LnE$_{ft}$	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Rig	0.071***	0.044**	0.065***	0.040*	0.090***	0.060***
LnE$_{rt}$	(0.017)	(0.021)	(0.016)	(0.021)	(0.018)	(0.022)
Directional	-0.039**	-0.053***	-0.039**	-0.053***	-0.040**	-0.053**
LnE$_{dt}$	(0.017)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Rig-Field	0.015	0.008	0.099***	0.100***	0.014	0.008
LnE$_{rft}$	(0.011)	(0.011)	(0.030)	(0.035)	(0.011)	(0.011)
Directional-Field	-0.005	0.004	-0.005	0.004	-0.004	0.005
LnE$_{dft}$	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)
Operator-Rig	0.020	0.070***	0.028**	0.076***	0.012	0.058*
LnE$_{ort}$	(0.012)	(0.021)	(0.012)	(0.020)	(0.014)	(0.023)
Op-Rig-Field			-0.091***	-0.096***		
LnE$_{orft}$			(0.031)	(0.035)		
Drill Contractor					-0.058***	-0.063***
LnE$_{ct}$					(0.018)	(0.024)
Op-Drilling Contractor					0.010	0.027
LnE$_{oct}$					(0.011)	(0.018)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Operator-Rig FE	No	Yes	No	Yes	No	Yes
Year-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Field FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	4625	4625	4625	4625	4625	4625

The dependent variable is the log rate of drilling. Standard errors clustered on field in parentheses. LnE$_{ct}$ and LnE$_{oct}$ are logged drilling contractor and operator-drilling contractor experience, respectively. Firm fixed effects include operator, rig, and directional drilling level effects.

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

Table B.2 presents alternative specifications for the learning in environmental safety model in equation 3.4. Columns 1 and 2 include the experience of only the operator and only the rig, respectively. Column 3 includes the experience of the operator, rig, and the operator-rig pair, and column 4 adds the experience of the directional drilling company.

Table B.3, Table B.4, and Table B.5 show estimation results for equation 3.4 where the dependent variable is changed to the spilled volumes of oil, brine, and total oil and brine, respectively. While there is some evidence of reduction in spilled volumes of brine (Table B.4) and total oil and brine (Table B.5), the accuracy of data on reported spill volumes is unknown. In the 192 incidents reported, 146 incidents reported zero volumes of oil and brine had spilled. It is unclear if no volumes of oil and brine were spilled, the amount spilled was unknown, or left unreported.

Table B.6 displays the types of environmental incidents reported during drilling operations. The data source is North Dakota Department of Health (2015).

Table B.2: Regression results for environmental incidents alternative specifications

	(1) Env	(2) Env	(3) Env	(4) Env
LnE_{ot}	-0.009		0.003	-0.002
	(0.013)		(0.010)	(0.011)
LnE_{rt}		-0.004	0.003	-0.000
		(0.008)	(0.011)	(0.012)
LnE_{ort}			-0.013*	-0.015*
			(0.008)	(0.009)
LnE_{dt}				0.017
				(0.011)
Days	0.002***	0.001**	0.001**	0.001**
	(0.001)	(0.000)	(0.001)	(0.001)
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Operator-Rig FE	No	No	No	No
N	4967	4967	4967	4641

The dependent variable is the number of environmental incidents reported to occur while drilling a well. Standard errors clustered on rig are shown in parentheses.

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

Table B.3: Regression results for oil volumes spilled

	(1) Non-IV Oil	(2) IV Oil	(3) Non-IV Oil	(4) IV Oil
LnE_{ot}	-114.165*	-109.684*	-99.209	-108.173
	(66.435)	(62.848)	(73.597)	(69.723)
LnE_{rt}	-18.107	0.192	-136.536	-132.431
	(42.563)	(39.726)	(88.950)	(84.748)
LnE_{ort}	17.484	31.737	134.972	158.869*
	(25.649)	(24.046)	(96.262)	(94.026)
Days	2.252	17.250**	1.946	12.219*
	(1.575)	(7.187)	(1.719)	(6.587)
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Operator-Rig FE	No	No	Yes	Yes
1st Stage F-stat	N/A	343.05	N/A	320.69
N	4892	4857	4892	4857

The dependent variable is the gallons of oil reportedly spilled while drilling. Standard errors clustered on rig are shown in parentheses.

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

Table B.4: Regression results for brine volumes spilled

	(1) Non-IV Brine	(2) IV Brine	(3) Non-IV Brine	(4) IV Brine
LnE_{ot}	-601.777	-591.733	-267.964***	-282.754***
	(476.022)	(428.812)	(102.342)	(95.584)
LnE_{rt}	173.997	233.117	-59.462	-51.747
	(179.640)	(186.108)	(129.092)	(104.962)
LnE_{ort}	-75.788	-46.752	57.997	86.902
	(92.158)	(80.014)	(127.967)	(108.147)
Days	-0.760	39.009^{+}	-0.431	12.921
	(3.005)	(22.802)	(3.102)	(11.005)
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Operator-Rig FE	No	No	Yes	Yes
1st Stage F-stat	N/A	316.64	N/A	304.32
N	4767	4733	4767	4733

The dependent variable is the gallons of brine reportedly spilled while drilling. Standard errors clustered on rig are shown in parentheses.

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

Table B.5: Regression results for oil and brine volumes spilled

	(1) Non-IV Spill	(2) IV Spill	(3) Non-IV Spill	(4) IV Spill
LnE_{ot}	-751.129	-732.013	-394.600**	-422.160***
	(556.754)	(500.754)	(152.451)	(142.648)
LnE_{rt}	171.890	252.128	-207.168	-196.739
	(207.888)	(211.373)	(188.568)	(167.258)
LnE_{ort}	-74.899	-29.832	202.027	261.307
	(98.803)	(89.245)	(200.666)	(185.961)
$Days$	2.257	59.430**	3.245	28.940**
	(3.775)	(26.606)	(3.871)	(13.975)
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Operator-Rig FE	No	No	Yes	Yes
1st Stage F-stat	N/A	309.07	N/A	295.70
N	4720	4686	4720	4686

The dependent variable is the gallons of oil and brine reportedly spilled while drilling. Standard errors clustered on rig are shown in parentheses.

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

Table B.6: Types of environmental incidents

Incident Type	Count	Percent
Blowout	3	1.56
Fire	7	3.65
Pipeline Leak	10	5.21
Pump Leak	12	6.25
Tank Leak	8	4.17
Tank Overflow	46	23.96
Truck Overflow	2	1.04
Valve/Piping Connection Leak	56	29.17
Other	48	25
Total	192	100

Source: North Dakota Department of Health (2015). Reported Incidents include both contained and non-contained environmental incidents that occurred during well drilling.

Table B.7 and Table B.8 present estimation results for equation 3.5 when the sample period is varied. In Table B.7, the sample is limited to operators and rigs that drilled wells during October 2007–September 2008. The dependent variable ($Terminate_{or}$) in equation 3.5 is equal to 1 if the operator-rig pair did not drill another well over the next 12 months (October 2008–September 2009) and equal to 0 if the pair drilled at least one well together.

Table B.8 modifies the sample period to September 2006–August 2010. An operator-rig pair relationship that existed during September 2006–August 2008 is considered to terminate if the pair did not drill a well in the subsequent 24 months (September 2008–August 2010). Lastly, when the sample period is changed to November 2006–October 2010, the coefficient estimates for the relative experience variable ($RelExp_{or}$) become insignificant. Although this is largely driven by one relationship with relatively high experience that terminates. When omitting this observation, the coefficient estimate for the relative experience variable is significant at the 5% level (column 1 specification) and 1% level (column 4 specification).

Table B.7: Logit and OLS results for relationship termination (October 2007–September 2009)

	(1) Logit Terminate	(2) Logit Terminate	(3) Logit Terminate	(4) OLS Terminate	(5) OLS Terminate	(6) OLS Terminate
$RelExp_{or}$	-0.53**		-0.86*	-0.06***		-0.11***
	(0.22)		(0.51)	(0.02)		(0.02)
$RelExp_{r}$		-0.01	0.38		-0.00	0.05***
		(0.13)	(0.44)		(0.03)	(0.01)
Constant	0.24	-0.81	-0.06	0.45***	0.31**	0.42***
	(0.57)	(0.57)	(0.57)	(0.11)	(0.12)	(0.11)
N	37	37	37	37	37	37

Robust standard errors in parentheses. The $Terminate$ indicates if an operator-rig relationships ends; the variable is equal to 0/1 for 26/11 of 37 observations. $Terminate = 1$ if a operator-rig drilled a well between October 2007 and September 2008 and did not drill at least one well between October 2008 and September 2009.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.8: Logit and OLS results for relationship termination (September 2006–August 2010)

	(1) Logit Terminate	(2) Logit Terminate	(3) Logit Terminate	(4) OLS Terminate	(5) OLS Terminate	(6) OLS Terminate
$RelExp_{or}$	-2.11*		-2.18**	-0.05***		-0.09***
	(1.10)		(1.08)	(0.01)		(0.01)
$RelExp_{r}$		-0.15	0.22		-0.02	0.04***
		(0.16)	(0.15)		(0.02)	(0.01)
Constant	2.65*	-0.19	2.34*	0.48***	0.43***	0.45***
	(1.41)	(0.56)	(1.41)	(0.11)	(0.11)	(0.11)
N	37	37	37	37	37	37

Robust standard errors in parentheses. The $Terminate$ indicates if an operator-rig relationships ends; the variable is equal to 0/1 for 25/12 of 37 observations. $Terminate = 1$ if a operator-rig drilled a well between September 2006 and August 2008 and did not drill at least one well between September 2008 and August 2010.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

APPENDIX C

This appendix provides several variations of the RD design discussed in Section 4.4.1. In general, modifications to the sample period, functional forms, and windows do not change the overall conclusion that there is no evidence the regulation change affect drilling activity.

Table C.1 and Table C.2 present expanded results for the RD estimation in equation 4.1. In Table C.1, the coefficient and standard errors estimates for the assignment variable are shown for well drilling in the two-year period prior to the regulation revisions (April 2010–March 2012). Additionally, the AIC values for each model are included below the standard error estimates. Table C.2 presents the coefficient estimates for the sample period following the regulation change (April 2012–March 2014). The window around the Montana-North Dakota border is varied across the columns, and the rows reflect different polynomial orders for the function $f(x_i)$ in equation 4.1.

Table C.3 shows the estimation results for equation 4.2. The coefficient estimates for the treatment variable (D_{jt}) are presented along with the standard error estimates and AIC values. The sample period for well drilling is April 2010 to March 2014. The columns are different windows around the Montana-North Dakota border, and the rows are specifications with varying polynomial orders.

Table C.4 and Table C.5 contain non-parametric RD results for well drilling in the two years before and two years following the regulation change. The results are generally consistent with Table C.1 and Table C.2 in showing no discontinuity in drilling at the border either prior to or after the regulation revisions.

Table C.6 presents the estimation results for equation 4.2 when the pre-treatment and post-treatment sample periods are limited to April 2010–March 2011 and April 2013–March 2014, respectively. This restricts the sample to drilling activity that occurred 12-24 months before and 12–24 months after the regulation change. It allows for testing whether the regulation had a delayed effect on well drilling. The results are fairly similar to Table 4.5: there are more coefficient estimates that are negative but none are statistically significant.

Table C.7 shows the results are largely unchanged when the sample period is changed to April 2009–March 2015. Table C.8 shows that the estimation results for equation 4.2, when the latitude fixed effect (γ_i) is excluded, are fairly similar to the results with the fixed effects included.

Table C.9 contains the estimation results for equation 4.2 when the cell size is modified from 1x1 miles to 5x5 miles. The results show little evidence that the regulation revisions had an effect on drilling. For only one window width (50 miles) and one polynomial function (cubic) is the coefficient estimate for the treatment variable negative and statistically indistinguishable from zero.

Table C.10 presents the estimation results for equation 4.1 with the number of wells drilled within the cell in the prior two years (April 2010–March 2012) included as a control. This allows for the possibility that the level of drilling activity within a cell before the regulation change may affect subsequent drilling levels. Cells may have an existing well because they are more economically attractive, and in turn experience more drilling in the following two years. Additionally a cell may become saturated with wells and drilling within the cell may decline. The number of wells previously drilled, and the squared number of wells previously drilled are included as controls. The results consistent with other specifications that show no evidence that the regulation influenced drilling.

Table C.1: RD results with alternative specifications and windows (April 2010–March 2012)

	(1)	(2)	(3)	(4)	(5)	(6)
	LnWells	LnWells	LnWells	LnWells	LnWells	LnWells
Window (Miles)	10	20	30	50	75	100
Polynomial Order						
Zero	0.032	0.052	0.088**	0.123***	0.196***	0.187***
	(0.064)	(0.041)	(0.034)	(0.028)	(0.029)	(0.028)
	192.9	330.0	526.0	951.8	1865.7	2130.2
First	-0.046	0.015	0.020	0.101	0.003	0.063
	(0.157)	(0.120)	(0.085)	(0.064)	(0.062)	(0.061)
	105.8	251.5	470.3	949.0	1840.3	2174.9
Second	-0.152	-0.033	0.024	0.030	0.033	-0.071
	(0.201)	(0.154)	(0.123)	(0.098)	(0.098)	(0.087)
	103.1	250.1	468.2	947.5	1836.0	2164.9
Third	0.142	-0.060	-0.057	0.023	-0.010	0.092
	(0.392)	(0.158)	(0.137)	(0.127)	(0.138)	(0.118)
	100.7	247.6	463.4	949.5	1833.7	2151.1
Fourth	0.377	-0.155	0.005	-0.034	-0.040	-0.066
	(0.375)	(0.219)	(0.138)	(0.140)	(0.150)	(0.149)
	87.6	243.1	462.8	950.2	1834.0	2139.0
Fifth	-0.224	0.156	-0.139	-0.080	0.004	-0.075
	(0.499)	(0.345)	(0.193)	(0.142)	(0.155)	(0.147)
	85.6	238.3	460.5	944.8	1839.2	2132.9
Sixth	0.239	0.424	0.005	-0.151	0.024	0.014
	(0.451)	(0.319)	(0.213)	(0.164)	(0.159)	(0.157)
	81.4	241.8	467.5	952.0	1833.1	2137.2
Clusters	20	40	60	97	124	145
N	192	354	546	964	1519	1724

Estimation includes data on well drilling from April 2010 to March 2012. Coefficient estimates for the assignment variable (D_j) in equation 4.1. Standard errors clustered on cell distance in parentheses; AIC values shown below standard errors.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.2: RD results with alternative specifications and windows (April 2012–March 2014)

	(1)	(2)	(3)	(4)	(5)	(6)
	LnWells	LnWells	LnWells	LnWells	LnWells	LnWells
Window (Miles)	10	20	30	50	75	100
Polynomial Order						
Zero	-0.093	0.222*	0.269***	0.506***	0.584***	0.560***
	(0.192)	(0.128)	(0.098)	(0.065)	(0.054)	(0.052)
	140.4	472.4	845.7	1622.3	2799.1	3049.4
First	0.003	-0.138	-0.063	0.023	0.184*	0.269**
	(0.332)	(0.202)	(0.146)	(0.109)	(0.103)	(0.106)
	139.7	462.1	823.8	1581.1	2759.5	3056.0
Second	0.379	0.025	-0.097	-0.101	-0.112	-0.121
	(0.333)	(0.309)	(0.238)	(0.170)	(0.148)	(0.137)
	133.1	460.2	820.7	1579.8	2743.4	3004.3
Third	0.674*	0.402	0.096	-0.104	-0.000	-0.040
	(0.337)	(0.262)	(0.293)	(0.235)	(0.194)	(0.188)
	129.4	452.9	817.7	1579.8	2743.8	3005.7
Fourth	1.016**	0.650**	0.427*	0.062	-0.154	-0.037
	(0.464)	(0.243)	(0.233)	(0.275)	(0.253)	(0.232)
	216.3	504.8	923.3	1719.2	2890.8	3123.8
Fifth	1.562	0.825***	0.597***	0.278	0.106	-0.159
	(1.016)	(0.272)	(0.206)	(0.254)	(0.268)	(0.288)
	124.6	450.4	810.8	1578.9	2743.6	3007.0
Sixth	0.128	1.096***	0.902***	0.422*	0.254	0.246
	(1.386)	(0.331)	(0.187)	(0.239)	(0.270)	(0.258)
	119.7	451.6	810.8	1576.8	2743.7	3001.7
Clusters	20	40	60	99	131	147
N	150	340	550	964	1513	1648

Estimation includes data on well drilling from April 2012 to March 2014. Coefficient estimates for the assignment variable (D_j) in equation 4.1. Standard errors clustered on cell distance in parentheses; AIC values shown below standard errors

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.3: RD results with alternative specifications and windows (April 2010–March 2014)

	(1)	(2)	(3)	(4)	(5)	(6)
	LnWells	LnWells	LnWells	LnWells	LnWells	LnWells
Window (Miles)	10	20	30	50	75	100
Polynomial Order						
Zero	-0.021	0.223***	0.308***	0.348***	0.333***	0.330***
	(0.109)	(0.073)	(0.060)	(0.045)	(0.039)	(0.038)
	409.5	877.6	1569.0	2866.1	4983.1	5487.7
First	0.098	-0.098	-0.020	0.072	0.322***	0.308***
	(0.266)	(0.182)	(0.137)	(0.103)	(0.090)	(0.088)
	308.9	759.2	1368.7	2666.8	4752.6	5365.4
Second	0.407	0.035	-0.151	-0.117	0.001	0.093
	(0.238)	(0.282)	(0.206)	(0.170)	(0.135)	(0.128)
	303.0	756.4	1366.3	2653.1	4727.2	5293.6
Third	0.513*	0.478*	0.026	-0.199	-0.029	-0.105
	(0.271)	(0.260)	(0.264)	(0.236)	(0.191)	(0.179)
	289.0	744.1	1358.1	2652.2	4725.9	5273.0
Clusters	20	40	60	100	133	155
N	342	694	1096	1928	3032	3372

Estimation includes data on well drilling from April 2010 to March 2014. Coefficient estimates for the treatment variable (D_{jt}) in equation 4.2. Standard errors clustered on cell distance in parentheses; AIC values below standard errors

$^{*} p < 0.1$, $^{**} p < 0.05$, $^{***} p < 0.01$

Table C.4: Non-parametric RD results (April 2010–March 2012)

	(1)	(2)	(3)	(4)	(5)	(6)
	LnWells	LnWells	LnWells	LnWells	LnWells	LnWells
Window (Miles)	10	20	30	50	75	100
Bandwidth						
lwald	-0.016	-0.015	-0.015	-0.015	-0.015	-0.015
	(0.212)	(0.203)	(0.194)	(0.190)	(0.187)	(0.188)
lwald50	0.078	0.078	0.078	0.078	0.078	0.078
	(0.271)	(0.271)	(0.271)	(0.271)	(0.271)	(0.271)
lwald200	-0.046	-0.051	-0.058	-0.065	-0.068	-0.068
	(0.130)	(0.129)	(0.127)	(0.124)	(0.122)	(0.122)
N	192	354	546	964	1519	1724

Estimation includes data on well drilling from April 2010 to March 2012. Coefficient estimates for the assignment variable (D_j) for non-parametric RD. lwald is the optimal bandwidth based on minimizing MSE. Standard errors clustered on cell distance in parentheses

$^{*}\, p < 0.1$, $^{**}\, p < 0.05$, $^{***}\, p < 0.01$

Table C.5: Non-parametric RD results (April 2012–March 2014)

	(1)	(2)	(3)	(4)	(5)	(6)
	LnWells	LnWells	LnWells	LnWells	LnWells	LnWells
Window (Miles)	10	20	30	50	75	100
Bandwidth						
lwald	0.738***	0.604	0.604	0.604	0.604	0.604
	(0.279)	(0.377)	(0.377)	(0.377)	(0.377)	(0.377)
lwald50	0.604	0.492**	0.492**	0.492**	0.492**	0.492**
	(0.377)	(0.234)	(0.234)	(0.234)	(0.234)	(0.234)
lwald200	0.386**	0.645**	0.627**	0.655**	0.638**	0.647**
	(0.196)	(0.258)	(0.250)	(0.263)	(0.255)	(0.259)
N	150	340	550	964	1513	1648

Estimation includes data on well drilling from April 2012 to March 2014. Coefficient estimates for the assignment variable (D_j) for non-parametric RD. lwald is the optimal bandwidth based on minimizing MSE. Standard errors clustered on cell distance in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.6: RD results of well drilling for April 2010–March 2011 and April 2013–March 2014

	(1)	(2)	(3)	(4)	(5)	(6)
	LnWells	LnWells	LnWells	LnWells	LnWells	LnWells
Window (Miles)	10	20	30	50	75	100
Polynomial Order						
Zero	-0.073	0.213^{*}	0.296^{***}	0.371^{***}	0.418^{***}	0.409^{***}
	(0.150)	(0.113)	(0.088)	(0.066)	(0.060)	(0.060)
	191.8	412.3	742.7	1381.3	2468.8	2722.9
First	-0.315	-0.177	0.107	0.132	0.258^{*}	0.301^{**}
	(0.404)	(0.398)	(0.263)	(0.156)	(0.134)	(0.130)
	64.3	292.1	614.6	1260.5	2363.1	2686.1
Second	-1.251	-0.560	-0.442	-0.109	0.023	-0.043
	(0.780)	(0.556)	(0.435)	(0.288)	(0.222)	(0.205)
	56.5	288.9	605.5	1256.7	2345.9	2634.2
Third	0.820	-0.183	-0.573	-0.271	-0.094	-0.202
	(0.960)	(0.691)	(0.622)	(0.434)	(0.314)	(0.294)
	35.4	276.5	600.2	1253.7	2343.9	2633.1
Clusters	20	40	60	98	126	142
N	172	365	566	1030	1659	1872

Estimation includes data on wells drilled for April 2010–March 2011 and April 2013–March 2014. Coefficient estimates for the treatment variable (D_{jt}) in equation 4.2. Standard errors clustered on cell distance in parentheses; AIC values below standard errors.

$^{*}\, p < 0.1$, $^{**}\, p < 0.05$, $^{***}\, p < 0.01$

Table C.7: RD results with alternative specifications and windows (April 2009–March 2015)

	(1) LnWells	(2) LnWells	(3) LnWells	(4) LnWells	(5) LnWells	(6) LnWells
Window (Miles)	10	20	30	50	75	100
Polynomial Order						
Zero	-0.021	0.229***	0.319***	0.358***	0.336***	0.327***
	(0.103)	(0.073)	(0.063)	(0.045)	(0.039)	(0.038)
	479.2	987.9	1694.7	3073.2	5451.7	6090.0
First	0.115	-0.059	0.012	0.073	0.309***	0.316***
	(0.259)	(0.186)	(0.141)	(0.104)	(0.090)	(0.088)
	381.9	873.0	1492.3	2862.7	5195.2	5952.1
Second	0.425	0.112	-0.092	-0.103	-0.018	0.085
	(0.259)	(0.273)	(0.207)	(0.178)	(0.136)	(0.128)
	377.9	869.2	1488.4	2851.4	5165.7	5883.2
Third	0.753***	0.617***	0.102	-0.155	-0.051	-0.114
	(0.255)	(0.220)	(0.249)	(0.240)	(0.188)	(0.179)
	367.6	855.1	1479.0	2850.6	5164.3	5854.0
Clusters	20	40	60	100	134	157
N	374	745	1168	2053	3306	3721

Estimation includes data on well drilling from April 2009 to March 2015. Coefficient estimates for the treatment variable (D_{jt}) in equation 4.2. Standard errors clustered on cell distance in parentheses; AIC values below standard errors.

$^{*}\, p < 0.1$, $^{**}\, p < 0.05$, $^{***}\, p < 0.01$

Table C.8: RD results without latitude fixed effects (April 2010–March 2014)

	(1)	(2)	(3)	(4)	(5)	(6)
	LnWells	LnWells	LnWells	LnWells	LnWells	LnWells
Window (Miles)	10	20	30	50	75	100
Polynomial Order						
Zero	-0.021	0.223***	0.308***	0.348***	0.333***	0.330***
	(0.109)	(0.073)	(0.060)	(0.045)	(0.039)	(0.038)
	409.5	877.6	1569.0	2866.1	4983.1	5487.7
First	0.230	-0.097	-0.010	0.175*	0.339***	0.338***
	(0.208)	(0.168)	(0.124)	(0.090)	(0.081)	(0.080)
	407.0	862.6	1518.4	2829.9	4908.2	5457.7
Second	0.492***	0.125	-0.063	-0.055	0.029	0.118
	(0.168)	(0.226)	(0.206)	(0.152)	(0.118)	(0.113)
	410.3	862.1	1524.1	2816.1	4895.9	5415.1
Third	0.756***	0.573***	0.164	-0.126	-0.104	-0.126
	(0.198)	(0.175)	(0.233)	(0.220)	(0.172)	(0.163)
	412.0	861.1	1524.4	2823.0	4897.3	5410.8
Clusters	20	40	60	100	133	155
N	342	694	1096	1928	3032	3372

Coefficient estimates for the treatment variable (D_{jt}) in equation 4.2 when the fixed. Standard errors clustered on cell distance in parentheses; AIC values below standard errors.

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table C.9: RD results with 5x5 mile cell dimensions (April 2010–March 2014)

	(1)	(2)	(3)	(4)	(5)	(6)
	LnWells	LnWells	LnWells	LnWells	LnWells	LnWells
Window (Miles)	50	75	100	125	150	200
Polynomial Order						
Zero	0.163	0.211*	0.199*	0.205*	0.188*	0.173*
	(0.122)	(0.111)	(0.108)	(0.109)	(0.108)	(0.099)
	1581.8	2373.6	2690.6	2761.8	2819.0	2915.6
First	0.073	0.155	0.143	0.180	0.098	0.075
	(0.240)	(0.200)	(0.189)	(0.187)	(0.187)	(0.156)
	1386.4	2147.3	2500.6	2594.1	2666.2	2757.6
Second	-0.254	0.108	0.166	0.258	0.166	0.121
	(0.328)	(0.288)	(0.268)	(0.262)	(0.245)	(0.222)
	1354.3	2129.2	2422.3	2484.4	2568.3	2703.9
Third	-1.004***	-0.256	-0.228	0.016	-0.065	-0.026
	(0.343)	(0.373)	(0.306)	(0.321)	(0.295)	(0.242)
	1350.2	2118.1	2414.3	2481.0	2545.9	2648.1
Clusters	20	29	36	41	50	63
N	596	872	980	1000	1020	1062

Coefficient estimates for the treatment variable (D_{jt}) in equation 4.2 when the cell size is modified to 5x5 miles. Standard errors clustered on cell distance in parentheses; AIC values below standard errors.

$^{*}\, p < 0.1$, $^{**}\, p < 0.05$, $^{***}\, p < 0.01$

Table C.10: RD results with pre-treatment drilling controls (April 2012–March 2014)

	(1) Wells Linear LnWells	(2) Wells Quadratic LnWells	(3) Wells Linear LnWells	(4) Wells Quadratic LnWells
Polynomial Order				
Zero	0.269***	0.271***	0.269***	0.271***
	(0.072)	(0.072)	(0.072)	(0.072)
	517.2	517.3	517.2	517.3
First	-0.122	-0.113	-0.139	-0.131
	(0.161)	(0.162)	(0.203)	(0.202)
	504.7	505.5	461.3	460.9
Second	0.100	0.096	0.026	0.027
	(0.222)	(0.225)	(0.308)	(0.313)
	505.3	506.4	459.4	458.9
Third	0.463**	0.459**	0.407	0.407
	(0.189)	(0.191)	(0.258)	(0.265)
	503.0	504.1	452.0	451.6
Latitude FE	No	No	Yes	Yes
Clusters	40	40	40	40
N	340	340	340	340

Coefficient estimates for the treatment variable (D_j) in equation 4.1 with 20-mile window. The number of wells drilled during the prior 2 years are included as controls in either linear or quadratic forms. Standard errors clustered on cell distance in parentheses; AIC values below standard errors.

$^{*}\, p < 0.1$, $^{**}\, p < 0.05$, $^{***}\, p < 0.01$

This appendix also describes the results of a slightly different RD method to estimating the effect of the regulation change on drilling activity. Wing and Cook (2013) introduce a modified RD approach, which they call "pretest RDD", that incorporates pre-treatment observations. The authors note that if the underlying functional relationship between the outcome and force variables is stable, the pretest RDD can improve identification relative to the standard RD design. This occurs because pre-treatment observations may contain information on the underlying relationship between the force variable and outcome variable.

This method requires a pre-treatment period, where no observations received the treatment, and a post-treatment period, where only observations above a cutoff receive the treatment. For a parametric RD, the first step involves estimating a polynomial function for all untreated observations, which includes drilling activity in cells observed in Montana and North Dakota prior to the treatment (April 2010–March 2012). This estimation equation is shown in Equation C.1 and includes an indicator variable for the State (S_i=0 if MT; S_i=1 if ND) and an indicator variable for the time period ($t = 0$ if pre-treatment;$t = 1$ if post-treatment). The function $f(x)$ denotes a polynomial function, which varies from a zero degree to quadratic polynomial in different specifications.

$$LnWells_{it}(0) = \beta S_i + \gamma T_t + f(x_i) + \epsilon_{it} \tag{C.1}$$

The second step is to estimate a polynomial function for the treated observations, which includes only drilling in ND cells following the regulation change. This is carried out in Equation C.2, where $g(x_i)$ is a polynomial function. The third and final step is to estimate the treatment at the cutoff. This is done by calculating the difference between the fitted value at the cutoff from the polynomial regression in Equation C.2 and the fitted value at the cutoff from the polynomial regression Equation C.1.

$$LnWells_{it}(1) = g(x_i) + \epsilon_{it} \tag{C.2}$$

Table C.11 presents the pretest RDD results for three polynomial regressions (zero degree to quadratic) for a 20-mile window and 30-mile window on each side of the MT-ND boundary. The first and second columns presents the fitted values at the cutoff from the untreated and treated sample polynomial regressions, respectively. The third column shows the difference in the fitted values and the corresponding Z-statistic for the difference in the fitted values. The fourth, fifth, and sixth columns display results for a 30-mile window. Overall, the results are very similar to in Table 4.5 and show no evidence of an effect on drilling activity.

Table C.11: Cook and Wing Pretest RDD results

	20-Mile Window			30-Mile Window		
	Treated: Fitted Value at Cutoff	Untreated: Fitted Value at Cutoff	Difference	Treated: Fitted Value at Cutoff	Untreated: Fitted Value at Cutoff	Difference
Zero Order	0.238***	0.461***	0.223***	0.28***	0.588***	0.308***
	(0.057)	(0.048)	(0.075)	(0.044)	(0.044)	(0.062)
1st Order	0.295**	0.198*	-0.097	0.203**	0.193**	-0.01
	(0.138)	(0.112)	(0.178)	(0.099)	(0.081)	(0.127)
2nd Order	0.155	0.28**	0.125	0.306*	0.243	-0.063
	(0.257)	(0.137)	(0.291)	(0.178)	(0.151)	(0.233)
N	694	694	694	1096	1096	1096

Bootstrapped standard errors in parentheses. Standard errors are clustered on cell distance and estimated through 500 replications.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.12: Oil production diff-in-diff results with effects by firm size (April 2010–March 2013)

	(1) LnProd	(2) LnProd	(3) LnProd	(4) LnProd	(5) LnProd
$Treat \times Q1$	-0.400***	-0.374**	-0.347**	-0.671***	-0.672***
	(0.138)	(0.158)	(0.141)	(0.195)	(0.197)
$Treat \times Q2$	-0.354	-0.332	-0.335	-0.700	-0.659
	(0.414)	(0.426)	(0.415)	(0.428)	(0.433)
$Treat \times Q3$	0.525	0.546	0.562	0.219	0.236
	(0.412)	(0.433)	(0.409)	(0.364)	(0.364)
$Treat \times Q4$	1.012***	1.035***	1.046***	0.697*	0.714*
	(0.351)	(0.358)	(0.349)	(0.357)	(0.359)
ND	0.116	0.106	0.101	-11.242**	-207.974
	(0.307)	(0.310)	(0.305)	(5.476)	(169.255)
$Time$			0.003	-0.000	0.255
			(0.006)	(0.006)	(0.301)
$ND \times Time$				0.018**	0.648
				(0.009)	(0.541)
$Time^2$					-0.000
					(0.000)
$ND \times Time^2$					-0.001
					(0.000)
Time FE	Month	Year	None	None	None
Operator FE	Yes	Yes	Yes	Yes	Yes
N	3306	3306	3306	3306	3306
R^2	0.085	0.095	0.080	0.085	0.091

Table shows results for equation 4.3 with the sample period varied. Standard errors clustered on operator are shown in parentheses. The dependent variable is the natural log of monthly oil production. The sample period is April 2010 to March 2013. Q1, Q2, Q3, and Q4 are indicator variables for firm size quartiles.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.13: Oil production diff-in-diff results with effects by firm size (April 2009–March 2013)

	(1) LnProd	(2) LnProd	(3) LnProd	(4) LnProd	(5) LnProd
$Treat \times Q1$	-0.364**	-0.326*	-0.322*	-0.725***	-0.672***
	(0.170)	(0.190)	(0.163)	(0.214)	(0.197)
$Treat \times Q2$	-0.294	-0.262	-0.284	-0.730*	-0.659
	(0.395)	(0.407)	(0.394)	(0.419)	(0.433)
$Treat \times Q3$	0.696	0.730	0.725*	0.313	0.236
	(0.426)	(0.447)	(0.416)	(0.369)	(0.364)
$Treat \times Q4$	1.142***	1.175***	1.166***	0.740**	0.714*
	(0.374)	(0.382)	(0.374)	(0.364)	(0.359)
ND	0.029	0.017	0.020	-11.411**	-207.974
	(0.298)	(0.301)	(0.297)	(4.820)	(169.255)
$Time$			0.002	-0.001	0.255
			(0.005)	(0.005)	(0.301)
$ND \times Time$				0.019**	0.648
				(0.008)	(0.541)
$Time^2$					-0.000
					(0.000)
$ND \times Time^2$					-0.001
					(0.000)
Time FE	Month	Year	None	None	None
Operator FE	Yes	Yes	Yes	Yes	Yes
N	4021	4021	4021	4021	3306
R^2	0.085	0.094	0.081	0.090	0.091

Table shows results for equation 4.3 with the sample period varied. Standard errors clustered on operator are shown in parentheses. The dependent variable is the natural log of monthly oil production. The sample period is April 2009 to March 2013. Q1, Q2, Q3, and Q4 are indicator variables for firm size quartiles.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.14: Firm exit diff-in-diff results with effects by firm size (April 2011–March 2013)

	(1) Exit	(2) Exit	(3) Exit	(4) Exit
$Treat \times Q1$	0.0404	0.0430	0.0429	0.0428
	(0.0253)	(0.0261)	(0.0265)	(0.0290)
$Treat \times Q2$	0.0052	0.0078	0.0075	0.0074
	(0.0141)	(0.0145)	(0.0147)	(0.0217)
$Treat \times Q3$	0.0044	0.0066	0.0063	0.0061
	(0.0106)	(0.0093)	(0.0095)	(0.0130)
$Treat \times Q4$	0.0087	0.0111	0.0109	0.0108
	(0.0100)	(0.0090)	(0.0087)	(0.0124)
ND	-0.0013	-0.0028	-0.0026	-0.0088
	(0.0057)	(0.0051)	(0.0049)	(0.4128)
$Time$			0.0005**	0.0005**
			(0.0002)	(0.0002)
$ND \times Time$				0.0000
				(0.0007)
Time FE	Month	Year	None	None
Operator FE	Yes	Yes	Yes	Yes
N	2639	2639	2639	2639
R^2	0.029	0.011	0.011	0.011

Table shows results for equation 4.4 with the sample period varied. Standard errors clustered on operator are shown in parentheses. The dependent variable is an indicator variable for operator exit from state. The sample period is April 2011 to March 2013. Q1, Q2, Q3, and Q4 are indicator variables for firm size quartiles.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.15: Firm exit diff-in-diff results with effects by firm size (April 2009–March 2013)

	(1) Exit	(2) Exit	(3) Exit	(4) Exit
$Treat \times Q1$	0.0384*	0.0392*	0.0399*	0.0408*
	(0.0212)	(0.0217)	(0.0219)	(0.0228)
$Treat \times Q2$	0.0063	0.0072	0.0078	0.0088
	(0.0110)	(0.0115)	(0.0117)	(0.0144)
$Treat \times Q3$	0.0054	0.0059	0.0065	0.0074
	(0.0086)	(0.0080)	(0.0079)	(0.0087)
$Treat \times Q4$	0.0088	0.0095	0.0102	0.0111
	(0.0082)	(0.0078)	(0.0077)	(0.0086)
ND	-0.0023	-0.0026	-0.0028	0.0225
	(0.0022)	(0.0021)	(0.0020)	(0.1103)
$Time$			0.0002***	0.0003***
			(0.0001)	(0.0001)
$ND \times Time$				-0.0000
				(0.0002)
Time FE	Month	Year	None	None
Operator FE	Yes	Yes	Yes	Yes
N	4652	4652	4652	4652
R^2	0.030	0.013	0.012	0.012

Table shows results for equation 4.4 with the sample period varied. Standard errors clustered on operator are shown in parentheses. The dependent variable is an indicator variable for operator exit from state. The sample period is April 2009 to March 2013. Q1, Q2, Q3, and Q4 are indicator variables for firm size quartiles.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Additionally, this appendix provides the results of a duration analysis approach to estimating the effects of the regulation change on firm exit. Duration analysis (or hazard modeling) is well suited for evaluating firm exit because it allows the rate of exit to be time dependent and can account for censored data. Equation C.3 is a Cox proportional hazard model for an operator's exit from a state. An operator is considered to exit a state when they shutdown production within the 10-mile window of the MT-ND boundary and do not restart production for the remainder of the sample period. The hazard function and baseline hazard function are denoted by $h(t)$ and $h_0(t)$, respectively. The variable D is the treatment variable, which is equal to one for operator production in North Dakota and equal to zero for operator production in Montana.

$$h(t) = h_0(t)exp(\beta D) \tag{C.3}$$

Table C.16 presents the results of four variations of the Cox proportional hazard model in Equation C.3. This table shows exponentiated coefficient estimates, where a value greater than one in suggests there is a positive correlation between the regulation change and the probability of firm exit; conversely, a coefficient estimate less than one implies the a negative correlation with the probability of exit (i.e., prolongs the survival of the firm). Column 1, which presents the hazard model results with the treatment dummy as the sole explanatory variable, shows the regulation change is associated with a higher rate of firm exit. In column 2, where the baseline hazard function ($h_0(t)$) is allowed to vary by operator, the coefficient estimate for the treatment variable is similar and statistically significant at the 10% level.

Columns 3 and 4 show the effects of the regulation on firm exit differ across firm size. Firm size is measured as the operator's total oil production in 2011, which is prior to the regulation change. Operators are partitioned into quartiles based on their total oil production in Montana and North Dakota in 2011. The 1st quartile contains the smallest firms, and the 4th quartile contains the largest ones. The treatment variable is interacted with the four indicators variables corresponding to the quartiles. The exponentiated coefficient estimates suggest the effect of the regulation change on firm exit was higher for firms in quartile one but lower for firms in quartile two.

Table C.16: Firm exit hazard model analysis

	(1) Basic Cox Proportional	(2) Stratified by Operator	(3) Firm Size Treatment	(4) Stratified by Size
$Treat$	2.487**	3.000*		
	(1.130)	(1.685)		
$Treat \times Q1$			3.607*	3.901*
			(2.490)	(2.819)
$Treat \times Q2$			0.000***	0.000***
			(0.000)	(0.000)
$Treat \times Q3$			1.823	1.883
			(1.467)	(1.570)
$Treat \times Q4$			4.249	4.187
			(4.478)	(4.497)
$Q2$				0.398
				(0.479)
$Q3$				0.678
				(0.601)
$Q4$				0.306
				(0.347)
Log Likelihood	-97.1	-4.5	-56.4	-80.1
N	101	101	89	89

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$