

FIRM SIZE'S IMPACT ON ORGANIZATIONAL LEARNING:
A CASE STUDY OF WASTE AND PRODUCTION EFFICIENCY
IN PENNSYLVANIA'S OIL AND GAS INDUSTRY

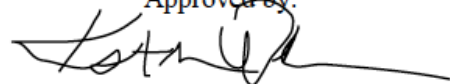
**FIRM SIZE'S IMPACT ON ORGANIZATIONAL LEARNING: A CASE STUDY
OF WASTE AND PRODUCTION EFFICIENCY IN PENNSYLVANIA'S OIL
AND GAS INDUSTRY**

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of the Kenan-Flagler Business School at the
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Approved by:

A handwritten signature in black ink, appearing to read 'Kristin Wilson', written over a horizontal line.

(Dr. Kristin Wilson)

ABSTRACT

Tara Christine Nath

Firm Size's Impact on Organizational Learning: A Case Study of Waste and Production Efficiency in Pennsylvania's Oil and Gas Industry

(Under the direction of Dr. Kristin Wilson)

An understanding of organizational learning provides insights into how companies evolve and remain competitive in an ever-changing environment. Companies in the Oil Field Services & Equipment (OFSE) sector have to operate under constantly squeezing profit margins while handling environmental concerns from local communities where they operate. Companies who are able to learn effectively will likely have greater financial success in the competitive landscape and bring about less of an environmental impact, thus satisfying many key stakeholders. My research explores two hypotheses in the context of Pennsylvania's oil and gas industry, the second largest natural gas producer in the United States. First, are large operators are less agile and slower learners due to size factors like bureaucracy in decision making? Or, second, are small operators less agile and slower learners because of a lack of economies of scale? This study was conducted using both multivariate analyses and data charting of raw waste and production data from 1990 to 2018.

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LITERATURE REVIEW

What is Organizational Learning

Understanding organizational learning has provided insights into how companies evolve and remain competitive in an ever-changing environment. Learning, specifically the learning curve, was first discovered and understood by psychologists regarding the behavior of individuals (Argote, 2013, p. 3). Learning is exhibited when time taken to complete a task decreases, the number of errors made when doing said task decreases, or the cost per unit decreases over time; the graphical representation of these metrics are displayed in what is called a learning curve (Argote, 2013). Researchers have since identified learning patterns across a wide range of industries at the individual, firm, and industry levels. Some methodologies and learning trends have also been identified. As early as 1936, Theodore Wright analyzed the factors affecting the cost of airplanes in his famous study of organizational learning. This study was one of the first of its kind to provide evidence that the cost of production declined as cumulative output increased (Wright, 1936). Additionally, a 1964 study by Winfred Hirschmann found that the petroleum refining industry followed a learning curve (1964). This was an important discovery because it showed that labor does not have to be the sole driver of learning and that it can instead come from modifications in the organization or technology. These findings are only some amongst a plethora of research into organizational learning and learning curve patterns; researchers are continuously attempting to discover learning trends and

Understanding the determinants of organizational learning and learning curves is valuable for internal decision makers, policymakers, and investors associated with almost any industry. Argot points out that internal decision makers can use learning curves and planning and forecasting tools to make strategic decisions in relation to other firms (2013, p. 23). She adds that internal uses include creating production schedules, budgeting, making delivery commitments, and monitoring performance. Externally, uses include predicting competitor's costs, how to price products, and whether or not to enter a new market. Understanding learning curves is also valuable for policymakers as the learning rate and the ability of firms to transfer knowledge are important considerations for antitrust and trade policies. Investors can also find value in learning curves as these graphical representations can give insights into market structure and performance (Argote, 2013, p, 23).

Organizational Learning in the Oil and Gas Industry

Companies in the Oil Field Services & Equipment (OFSE) sector have to operate under constantly squeezing profit margins while handling environmental concerns from local communities where they operate. If any of these companies are able to realize the benefits of organizational learning, such as improved efficiency, budgeting, and performance monitoring regarding waste outputs, they will likely have greater financial success in the competitive landscape and bring about less of an environmental impact, thus satisfying many key stakeholders.

Financial Pressures of the Oil and Gas Industry

OFSE companies must be able to withstand fluctuating oil prices and the complexities associated with international competition and trade. For example, in 2018, a year in which Wall Street predicted oil would surpass \$100, the market was plagued with ongoing U.S.-China trade disputes, Iranian sanctions, and disagreements within OPEC (Organization of Petroleum Exporting Countries). U.S. crude dropped 25% from the beginning of the year with Brent crude (the international oil benchmark) down 19.5% (DiChristopher, 2018). Concurrently, an increased fuel economy was leading to lower gasoline consumption, thus forcing the industry to operate under extremely tight margins (Ati, Brinkman, Peacock, & Wood, 2016). Given the constant potential for oil price volatility, it is absolutely vital that OFSE companies cut costs whenever and wherever possible.

Environmental Pressures of the Oil and Gas Industry and Fracking

Oil and gas well operators' cost-cutting measures, particularly in the area of waste disposal, have piqued the concern of environmentalists and citizens alike. These concerns have resulted in negative publicity, law suits, and increased oversight from regulatory bodies. Many existing environmental concerns have been compounded by the recent boom of fracking in the United States. Fracking, derived from the term "hydraulic fracturing," is the process of drilling into the land to release and extract the gas inside. The Independent Petroleum Association of America (n.d.) elaborates that fracking is "the process of injecting liquid and materials at high pressure to create small fractures within tight shale formations to stimulate the production and safely extract energy from an

underground well...” (para. 1). This unconventional process has transformed the natural gas industry in terms of increased production quantity. However, the actual fracking process has caused environmental uproar in geographic areas with active wells throughout the United States.

One of the main environmental complaints about fracking is the impact it has on local water sources. Depending on the rock formation, well operator, and well configuration, among other factors, each fractured well requires between 1.5 and 16 million gallons of water (American Geosciences Institute, 2014). This water is often extracted from the surrounding area, effectively reducing the amount of clean water available to local residents. A 2014 article published in the Energy Policy Journal conducted a public opinion poll and identified a series of externalities that a majority of Americans had associated with fracking, including strains on water and sewage infrastructure (Boudet et al., 2014). However, more threatening is the potential for this waste water to contaminate local water sources. Historically, between 20% and 40% of frack water returned to the ground is toxically contaminated with waste from the fracking process. This water, often injected into wastewater injection wells or drained into open air impoundment pits (frack ponds), has a tendency to leak into local water supplies (Horton, 2018). While operators have the technology to recycle frack water, disposal methods currently have lower direct costs.

Growth of the Natural Gas Industry

The economics of the oil and gas industry currently have a positive outlook. Authors Zajicek, Karagiannis, and Wiljoit (2016) claim that technological development

in the United States along with the discovery of new oil and gas resources are shifting supply dynamics of the energy sector. They claim that this shift can be seen particularly in shale production where suppliers are looking to increase liquefied gas exports and decrease imports. Their research determined that between December 2007 and June 2015, domestic natural gas production increased 186% and domestic oil production increased 342%; both of these increases have been primarily attributed to the fracking boom. While the share of natural gas growth is expected to decrease from 29% to 27%, given the extraordinary scale of this energy output measurement, I assume there is still ample opportunity for growth of US natural gas production and the industry will continue to prosper.

How Organizational Learning Can Help

Given financial and environmental pressures present in the oil and gas industry, compounded with tremendous growth potential, this is a good opportunity to study organizational learning. Through previous studies of organizational learning, it is apparent that increased efficiency is a common outcome, and one that would greatly benefit this industry. IPIECA, the global oil and gas industry association responsible for promoting environmental and social performance, explains how all stakeholders have a role to play to ensure that energy is produced and used in a clean and efficient manner. Specifically, the organization reports that improved efficiency has a “central role to play in reconciling the goals of economic development, energy security and environmental protection” (IPIECA, 2013, p. 3).

Across the industry, well operators are aware of the tremendous business opportunities and widespread economic benefits associated with fracking and are financially incentivized, both internally and by investors, to be efficient, cut costs, and maximize the potential benefits. As BP's former CEO John Browne stated,

Learning is at the heart of a company's ability to adapt to a rapidly changing environment. It is the key to being able both to identify opportunities that others might not see and to exploit those opportunities rapidly and fully. This means that in order to generate extraordinary value for shareholders, a company has to learn better than its competitors and apply that knowledge throughout its businesses faster and more widely than they do (Prokesch, 1997).

Browne's message underlines the essentiality of organizational learning for financial success in the oil and gas industry. Mr. Browne elaborated that important and effective types of learning include tracking employee expertise, promoting a learning culture, collecting and sharing explicit knowledge, and utilizing technological systems to share captured knowledge (Prokesch, 1997).

Unfortunately, as discussed previously, these financial benefits are currently accompanied by wasteful processes and potentially negative impacts on local communities. Across Pennsylvania, well operators face external pressures from communities to manage waste and frack responsibly. A recent 2018 public opinion study discovered that residents have a growing concern about the industry. In August 2011, only 35% of survey respondents believed that the environmental risks of fracking outweighed its potential economic benefits. As of March 2018, 55% reported that the potential environmental risks outweighed the potential economic benefits of the fracking industry in Pennsylvania (Frazier, 2018). This growing concern must be given attention

as communities historically have been shown to push back against the industry by implementing fracking bans, well limits, traffic and road use restrictions, and high impact fees (Squillace, 2016, p. 554). Each of these pushbacks from local communities would negatively impact a well's operation and consequently the company's bottom line, thus demonstrating the financial incentive to be efficient and environmentally responsible. By harnessing the knowledge gained from organizational learning through investment in methods such as energy efficient technology, benchmarking indices for well performance, and eliminating unnecessary waste, it is possible to develop greater community relationships and decrease the risk of negative community pushback (IPIECA, 2013).

Conclusion

It has been found that learning does not automatically improve with experience alone, but instead is a function of a wide variety of factors that work together to impact a firm's organizational learning rates. Researchers speculate that some of these variables include individual learning, organizational structure improvements, and more effective new employees, leadership, and equipment. As Argote states in her book, "for organizations to compete effectively, we need to understand why some organizations show rapid rates of learning and others fail to learn. A greater understanding of factors responsible for the variation observed in organizational learning rates is needed" (2013, p. 2).

One factor that is under-researched in the organizational learning space is the relationship between firm size and learning. It is widely understood that differences between small and large firms can be seen in organizational structure and management, growth and productivity, and innovation (Schiersch, 2013). Firm size can also be understood as a proxy for operational scope; as a firm's size increases, their scope also increases since they have more resources to conduct more business in a more efficient manner. Schiersch explained that previous empirical research on size-efficiency relationships yielded ambiguous results with both positive and negative relationships. Further, a majority of size-efficiency studies are set in developing countries, with a minority analyzing successful industries in developed countries (2013). At this point, no known study analyzes size-efficiency or size-learning relationships in the oil and gas industry.

Given the lack of previous research and knowledge on the impact of increased operational scope on learning in the oil and gas industry, especially in terms of environmental responsibility, research is needed to understand whether operational scope is a driver of organizational learning. This study will analyze whether the size of the operator, measured by the firm's average number of wells in operation over the firm's total operating period, is a driver of organizational learning (quantified by a waste efficiency ratio) in the oil and gas industry.

Understanding this differentiation would be valuable for multiple stakeholders. First, understanding their company's learning curve will help internal decision makers' when formulating long-term plans and potentially provide insight into the types of plans they should make moving forward. Additionally, it could provide an important metric for

investors to understand which companies have lean, efficient processes. Moreover, this information would be valuable for policymakers in the energy sector. An understanding of organizational learning abilities of operators of different sizes would shed light onto different firm's abilities to meet target objectives as well as the potential differential impacts of regulations.

One hypothesis tested in this study is that larger operators are less agile and slower learners because it is more challenging for larger companies to have "timely responses that span organizational, product and geographic boundaries (Harraf, Wanasika, Tate, & Talbott, 2015, p. 676). Similarly, as size increases, the costs of errors increases resulting in more risk-averse decision making. As Harraf et al. explain, these growth factors make agility more challenging and therefore less likely to be incorporated into organizational processes (2015, p. 676).

On the other hand, another hypothesis to be tested is that smaller operators are less agile and slower learners because they do not have benefits of economies of scale ("The keys to organizational agility," 2015). Similarly, it is possible that they have lesser capacity for knowledge sharing, given that they have fewer active wells from which to learn.

Given the lack of existing research on the size-learning relationship and competing theories behind this relationship, specifically in the oil and gas industry, research is needed to identify what relationship, if any, exists between operational scope and organizational learning in this context.

METHODOLOGY

Selection of the Fracking Industry

In the 1980s, George Mitchell pioneered fracking for the extraction of shale gas (Gertner, 2013). Since then, the industry has boomed and continues to have positive growth prospects. Given the highly politicized rhetoric around the environment, fracking has also proven to be a frequently debated industry as of late. According to ABI inform, limited to the search of frack as a root (thus encompassing fracking, fracker, frackers, etc.), the Wall Street Journal alone published 295 articles in the past two years (December 6, 2016 to December 6, 2018) that mention fracking. Considering the relatively new nature of the industry paired with the excitement of contemporary debates, it is both an interesting time to research this industry and valuable to provide insights into how it can function more efficiently.

Fracking in Pennsylvania

Pennsylvania was selected as the location for this study due to geographic policy differences and the scope of the industry across the state. Fracking regulations differ by geographic area; some states have full fracking bans, some localities have bans or moratoria, and other areas are currently debating the issue (Hirji & Song, 2015). I opted to study a single state to control for some of these dramatic policy differences.

Pennsylvania is consistently identified as one of the top natural gas producers in the country and, as a Pennsylvania native, these conversations and debates are particularly interesting and hit close to home. Fracking in Pennsylvania is made possible because of the Marcellus Shale Formation. The Marcellus Shale is a stretch of sedimentary rock reaching from Upstate New York down through Pennsylvania, West Virginia, and Ohio. Buried thousands of feet below the surface, this formation created a large volume of natural gas over millions of years. Now, this shale formation gives life to the Pennsylvania fracking industry. As of August 2018, Pennsylvania is home to almost 9,000 active wells (“The Marcellus Shale, Explained,” n.d.). The Pennsylvania Department of Community and Economic Development also listed natural gas as one of the top industries in the state (n.d). In 2016 alone, gross natural gas production in Pennsylvania exceeded 5 trillion cubic feet and consequently, as the nation’s second largest natural gas producer, has been ranked among the top three energy exporters in the country. Further, the Global Energy Institute, an arm of the U.S. Chamber of Commerce, issued a report on the economic impact of fracking regulation across the country. Pennsylvania was highlighted as one of the states whose economy relies the most on the fracking industry; the study reported that a ban on fracking in Pennsylvania could lose the state \$50 billion a year in state GDP (2016). Due to the scope of the industry and its integral nature on Pennsylvania’s economy, it is sufficiently representative of other fracking geographies across the United States.

Frack Wastewater

Large amounts of fracking wastewater provide a financial burden to well operators and serve as the basis for many environmental concerns. In fact, one of the largest frack waste components is water, with each well requiring approximately 350,000 barrels or more of water input (one barrel is equal to 42 gallons). For a typical Marcellus well in Washington County, Pennsylvania (one of the largest producing counties in the state), per well water costs are estimated to be \$1.4 million (Haines, 2018). Well operators are financially motivated to increase production efficiency and decrease the total amount of water used on each well.

Additionally, in 2011, the U.S. Environmental Protection Agency formally banned the disposal of frack waste water at public sewage plants. This regulation was preceded by former Pennsylvania Governor Tom Corbett's directive to oil and gas companies to end the practice. While disposal at public treatment facilities was never the most popular method of disposal, it has indefinitely ruled out the option for operators and forces them to come up with independent disposal processes (Hurdle, 2016). Some of these other processes include "spreading" (releasing waste water on unpaved roads to control dust), impoundment pits, and injection wells. Each of these methods involves the risk of toxic water contaminating local water sources. This contamination, or even the *idea* of contamination, has resulted in many lawsuits being filed against well operators. According to the Westlaw database limited to Pennsylvania courts and related federal cases, Range Resources (one of the most prominent Pennsylvania oil and gas companies) alone has been implicated in approximately 80 cases in the past 10 years (2008 to 2018). These cases are costly, time consuming, and reflect poorly on the firm's public opinion.

Range Resources is one of thousands of operators in the state, meaning that industry-wide across Pennsylvania, lawsuits hinder financial performance.

Well Selection

Both conventional and unconventional wells from 1990 to 2018 were selected for this study. This time frame was selected because the process of fracking Shale gas was first pioneered in the late 1980s by George Mitchell (Gertner, 2013). Given that the Marcellus Shale Formation underlies approximately 60% of Pennsylvania's total landmass (see Figure 1) and is the principal source of oil and gas in the state, it follows that 1990 is when fracking could first be considered viable in Pennsylvania.

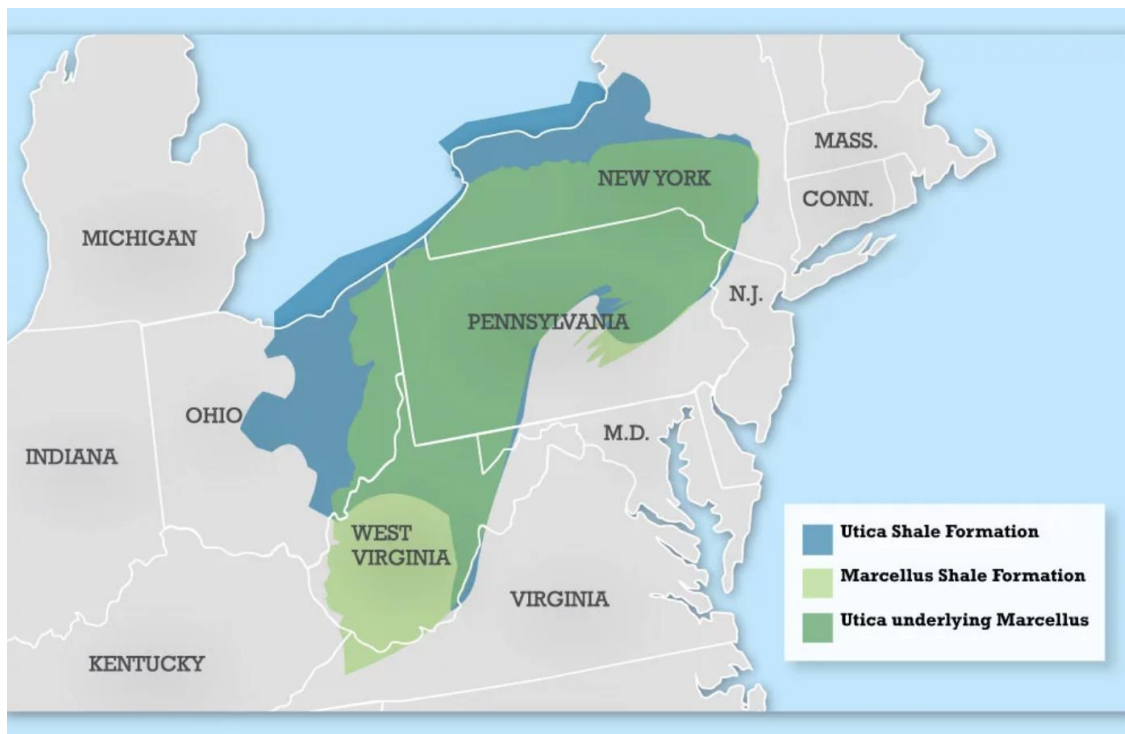


Figure 1. Map of shale formations in the northeast. From “Marcellus and Utica Shale Formation Map,” by Marcellus Shale Coalition, <http://marcelluscoalition.org/pa-map/>.

Conventional and unconventional wells are the two methods of oil extraction utilized in Pennsylvania. Conventional wells are vertical configurations used when oil is

already flowing beneath the ground. Unconventional wells are typically horizontal wells used to extract oil from rock with low permeability (e.g. coal, shale, sandstone).

Unconventional wells are typically recognized as extracting oil through the fracking process. However, conventional and unconventional wells can be at work contemporaneously to maximize oil extraction from a single geographic location. In addition, a single well could switch from extracting oil by conventional methods to later, once most free flowing oil has been extracted, extracting oil through unconventional methods. Considering many well operators own both conventional and unconventional wells, operate them within the same geographic regions, and utilize much of the same labor and technology for operation, it follows that they should both be included in this efficiency study.

Data Selection

Data was collected from the Pennsylvania Department of Environmental Protection's Oil & Gas Production Reports and Waste Reports ("PA DEP Oil & Gas Reporting Website - Production / Waste Reports," n.d.). The Production Reports included data related to oil, gas, and concentrate output per well. The Waste Reports reported types and quantities of wastes per well. All data collected from both reports is self-reported by well operators pursuant to directives included in the Oil and Gas Act of 1984. The Act requires that "...every well operator shall file with the department, on a form provided by the department, an annual report specifying the amount of production on the most well-specific basis available. Annual reports shall also specify the status of each well..." (Oil and Gas Act of 1984). This act was updated and replaced by the Oil and Gas

Act of 2012 which required that operators instead report data on a monthly basis.

However, since data prior to 2012 could not be identified on monthly levels, annual data was used throughout this study.

Data Explanation

After cleaning and merging Production and Waste Reports, the final data set consisted of sixteen variables, eleven of which were descriptive. These data provided insights into well operators, well operating years, and well types (conventional or unconventional) along with production and waste quantities. See Appendix A for a list of variables included in the final data set. The raw data was reported by well for each year it was in operation and will be henceforth referred to as “well/year measurements.”

Data Operationalization

In order to determine if operator size is a driver of organizational learning in the oil and gas industry, I tracked operator’s waste output per unit of production over cumulative production output. Prior research identified an increase in efficiency over increased cumulative output to be an indicator of organizational learning. In the context of this analysis, an increase in efficiency is explained as a reduction in the amount of waste being generated per unit of production output. In order to ultimately track these measurements, I operationalized key measures including operator size, total waste and production outputs, and waste ratios. All data operationalization and analysis was conducted using STATA.

Learning Model

Learning was measured as a function of waste output per unit of production output and is subsequently referred to as “waste ratio.” The waste ratio was generated using the following formula:

$$\text{Waste Ratio} = (\text{Total Waste} \div \text{Total Production})$$

This ratio for a certain group (industry, quartile, individual operators) was tracked and plotted on graphs. These graphs used cumulative output as the independent variable and the waste ratio as the dependent variable. I first gathered summary statistics and ran simple regressions on those data. An indication of the *potential for* organizational learning would be if the waste ratio had a negative correlation with cumulative quantity at a significant level ($\alpha = 0.05$). I then graphed linear and quadratic functions on the data to visualize the learning curve for the group and to compare it with other groups. Organizational learning was exhibited in learning curves that had a significant, negative geometric relationship. This model was replicated at the industry level (by quartiles identified by firm size), and by individual operators. Measuring the waste ratio over cumulative output to ultimately generate graphical representations of industry level efficiency trends required the construction of several key variables.

Dependent Variable: Waste Ratio

Production and waste variables were converted to their most basic form for analysis. Conventional and unconventional wells produce three types of outputs: oil, gas,

and concentrate. For the purpose of this research, there is little value in viewing them as individual outputs, so I combined them into one “total production” value for each well/year measurement. Similarly, many different types of fracking wastes were reported in the waste reports, so I combined them into a single “total waste” well/year measurement. Using these two total measurements, I created the waste ratio. By creating this waste ratio, rather than looking at total waste output, I controlled for increased waste levels due to increased production levels, and vice versa.

Preliminary Analysis: Time

Given the nature of learning curves, the first independent variable in this analysis is time. In this case, time serves as a proxy for experience as a well operator. Per the directive of the Oil and Gas Act of 1984, annual data from wells was collected and starting in 2012, monthly data was collected. However, all monthly data was transformed to yearly quantities to maintain consistency throughout the analysis.

The graphs created by this preliminary analysis represent an eyeball test of the diffusion of practices across industry. While this analysis is confounded by external influences such as international conflict or gas prices, it is still important to understand what is happening over time.

Primary Analysis: Cumulative Quantity

In the primary set of regressions, cumulative production quantity was used as the independent variable as a measurement of operational scope. This measure was constructed in order to compare well operators waste ratios at a certain period in their

production timeline, rather than at a certain year. By running the analysis in this manner, it controlled for the fact that not all firms begin and end operation during the same years, i.e. an operator who began operation in 2002 and an operator who began in 2009 will have their waste ratios compared at a certain production level (Q) rather than in a certain year when the older operator had more experience than the newer one.

Measuring Learning

Previous research shows that learning occurs at the industry, organizational, and individual levels. Individual level learning is not particularly applicable to the research question posed, so it is not included in the analysis. However, it is necessary to control for industry level learning and knowledge sharing, other technological improvements, or external shocks, before concluding that any learning being observed is solely at the organization level based on operator size. While many learning curve analyses today consist of multivariate regressions, early concepts of learning curves began as simple graphical representations of cumulative output on unit costs or efficiency ratios. This first part of this analysis follows a similar model of looking for patterns in raw data based on graphical evidence visualized through learning curves. The second part of this analysis uses a multivariate analysis to determine the impact of firm size and operational scope on the waste ratio.

Industry Level Learning by Quartile

To determine the upper and lower quartiles of operators (by size), I generated a measurement (well per year) averaging the number of wells an operator had in operation over the time they were active across the state using the formula below:

$$\text{well per year} = \text{well number} \div \text{year counter}$$

given:

well number = How many wells each operator operated over their time in PA

year counter = How many years each operator was operating in PA

By determining upper and lower quartiles based on this well-per-year measurement, rather than the total number of wells an operator had in total, I was able to limit survivorship bias in the quartile selection process. Additionally, the middle 50 percent of measurements were separated and used as the control and as the metric of comparison between the upper and lower quartiles. The middle 50% is subsequently referred to as the “interquartile range” or “IQR.”

In order to control for knowledge sharing and organizational learning at the industry level, I totaled the waste ratio values of every well held by every operator each year, effectively ignoring individual wells and operators, and looking at the yearly waste ratios across the industry (separated by the previously explained quartiles). By analyzing data at the industry level, rather than operator or individual well level, it is possible to see trends in the industry’s waste ratio. In order to control for intertemporal variation, a second version of this graphical analysis was conducted using a 95% confidence interval

difference in means graph. The following two new ratios were generated and graphed for each year between 1990 and 2018:

$$\text{New Bottom Ratio} = \text{Annual Bottom Quartile Average Waste Ratio} - \text{Annual IQR Average Waste Ratio}$$

$$\text{New Upper Ratio} = \text{Annual Upper Quartile Average Waste Ratio} - \text{Annual IQR Average Waste Ratio}$$

If either the original or new waste ratio was seen decreasing as cumulative output was increasing in either facet of the study, it was interpreted to mean that that knowledge sharing and learning were occurring within the specified quartiles across the industry.

Organizational Level Learning by [Quartile](#) Operational Scope

In order to determine if operational scope is a driver of organizational learning in the oil and gas industry, I totaled the waste ratio values of every well for each year an operator was in service, effectively ignoring individual wells and looking at the yearly waste ratios at an operator level. By analyzing data at the operator level rather than the industry or individual well level, it was possible to track the variation in the firm's waste ratio over time. To conduct this analysis, the cumulative production quantity was used as the independent variable and waste ratio as the dependent. If learning was occurring, the waste ratio would be seen decreasing as cumulative quantity was increasing. By conducting a regression of the logged values of firm size (as previously determined by upper and lower quartile of wells per year), cumulative quantity, and an interaction term of the two on the logged waste ratio, it was possible to determine the average learning

trend, the effect of being either large or small on efficiency, and the difference in learning between small and large operators.

RESEARCH FINDINGS

Throughout this section, my analysis focuses on the incidence of organizational learning in the Pennsylvania oil and gas industry. Operationalized by running regressions on and graphing the waste ratio for 1,199 well operators between 1990 and 2018, this study determined that decreases in the waste ratio over time were not significantly determined by operational scope. My study first looked at trends within Pennsylvania's oil and gas industry over time. I then controlled for learning at the industry level and determined that there is no evidence of organizational learning across small operators or large operators, compared to learning of the IQR. Further multivariate analysis controlling for the fixed effects of individual firms was conducted to determine if organizational learning was occurring within operators. It was found that on average all firms, regardless of operational scope, decreased their waste ratio as their cumulative output increased. I later went into detail regarding how these findings aligned with prior research and my original hypotheses.

Industry Level Trends Over Time

I began by comparing both the upper and lower quartile average annual waste ratios to the IQR's waste ratio to determine if they were statistically different. After closer analysis of the annual difference in waste ratio means between the bottom quartile and IQR, I in fact rejected with 95% confidence that the average means of the bottom

quartile and IQR were the same. This piece of the analysis provided basis for proving a difference between the bottom quartile's and IQR's efficiency trends over time. The graphical representation of this relationship is seen in Figure 2.

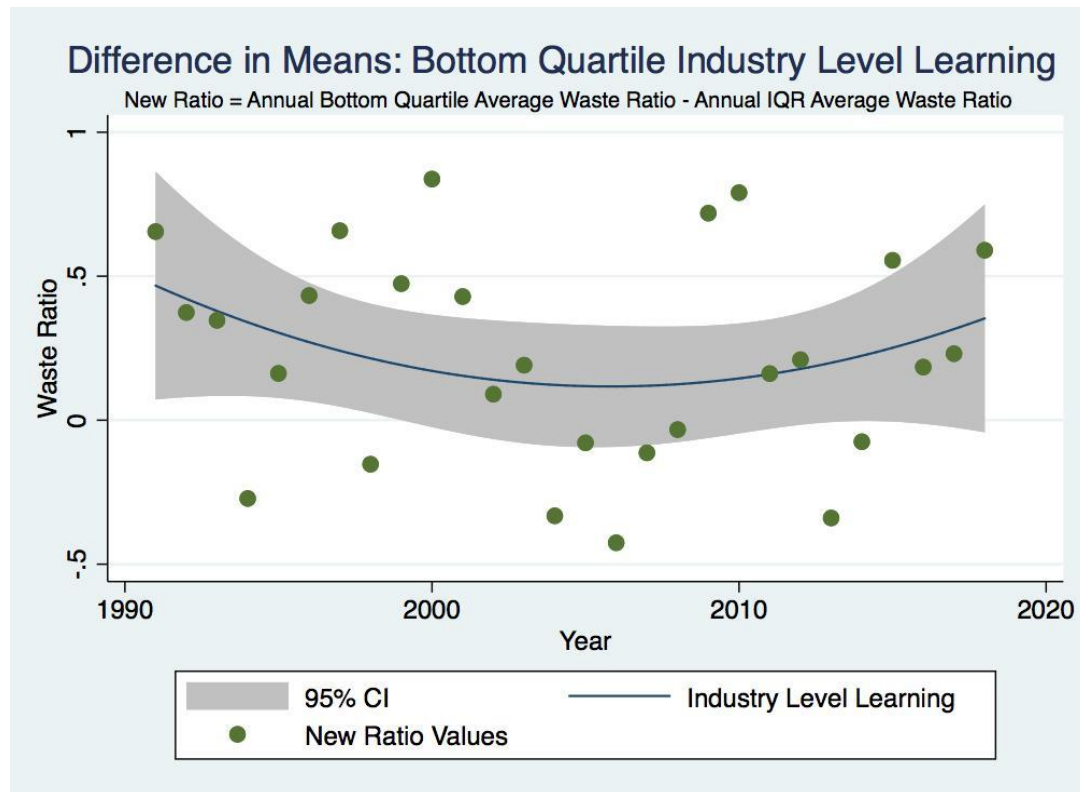


Figure 2. Industry level bottom quartile difference in means.

See Appendix E for summary statistics and the graphical comparison between the difference in mean waste ratios at the industry level.

Through an analysis of the difference in annual means between the upper quartile and IQR, industry wide shocks were taken into consideration. Ultimately the regression explains 32% of the variation in waste ratio between 1990 and 2018. A graphical representation of this relationship can be seen in Figure 3.

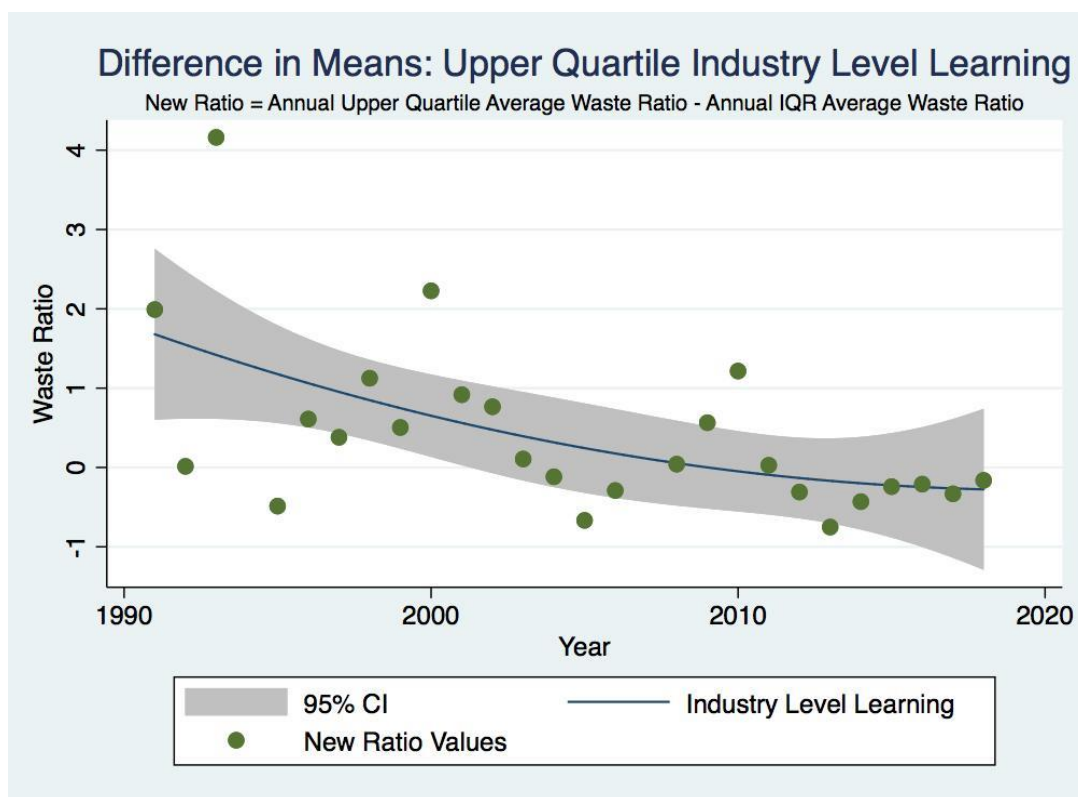


Figure 3. Industry level upper quartile difference in means

This analysis reveals evidence declining difference in waste ratios between the upper quartile of Pennsylvania’s oil and gas industry and the IQR. Upon further evaluation, Appendix F shows that the upper quartile’s waste ratio was consistently much higher than that of the interquartile range until 2010, when it dropped below and followed closer to the ratios of the IQR. The primary driver of this change was a large growth in production output starting in 2010, during which time waste output remained consistent with the IQR level. Lastly, the growth of the industry in terms of number of wells in the state was positive from 1990 to 2018. This trend can be seen below in Figure 4.

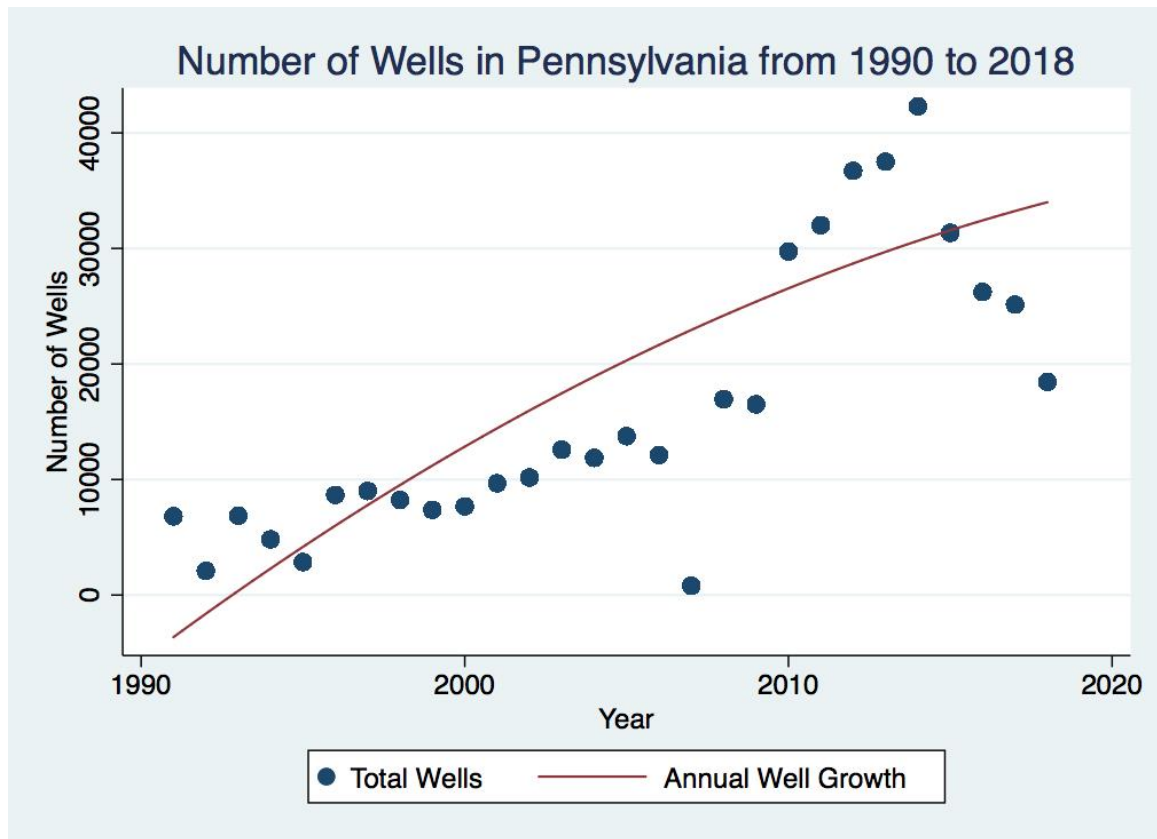


Figure 4. Number of wells per year in Pennsylvania from 1990 to 2018.

In conclusion, the effects of time on waste ratio are inconclusive, likely due to confounding effects such as technological advancement, pricing and market conditions, and regulatory shocks. Therefore, the next stage of the analysis will look into the effects of organizational learning in Pennsylvania's oil and gas industry by analyzing the effect of increasing cumulative output on firms' waste ratios.

Industry Level Learning by Quartile

This analysis sought to understand industry level efficiency trends over time across the oil and gas industry before exploring whether organizational learning was

occurring at the industry level. Tables detailing the summary statistics of data utilized in this analysis can be found in Appendices C and D (Appendix C details all data and Appendix D details data without outliers in the 99th percentile). Through simple regressions and data charting by quartile, I examined the effect of firm size on organizational learning at the industry level.

Bottom Quartile

For the bottom quartile, there is a .0347818 weak positive linear correlation between the waste ratio and cumulative quantity. With a p-value of 0.000, this relationship can be viewed as significant. Likewise, it is unlikely that learning was exhibited at the industry level, but further analysis was necessary to substantiate this assumption. Upon initial observation of the raw data trends, it was determined that the bottom quartile's waste ratio was generally higher than that of the IQR as cumulative quantity increased. In conjunction, these observations demonstrated that smaller firms were generally less efficient than average firms. This trend can be seen in Figure 5.

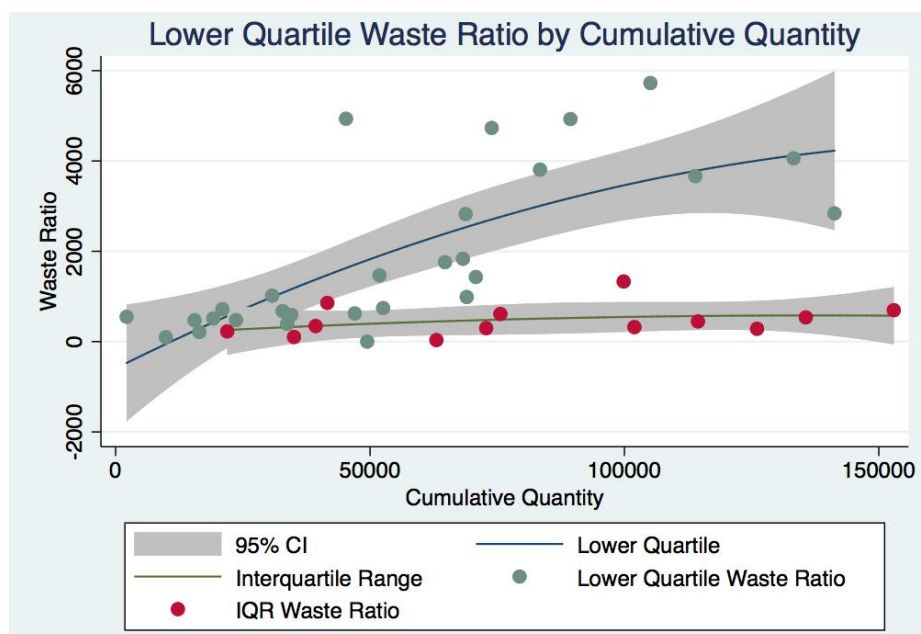


Figure 5. Lower quartile waste ratio by cumulative quantity

Upper Quartile

For the upper quartile, there is a .0005858 positive linear correlation between the waste ratio and cumulative quantity. However, this relationship is not significant. Based on the insignificance of this relationship, it is unknown whether learning is occurring on the industry level within the upper quartile, so further analysis is required. A graphical representation of the waste ratio by cumulative quantity, as seen in Figure 6.

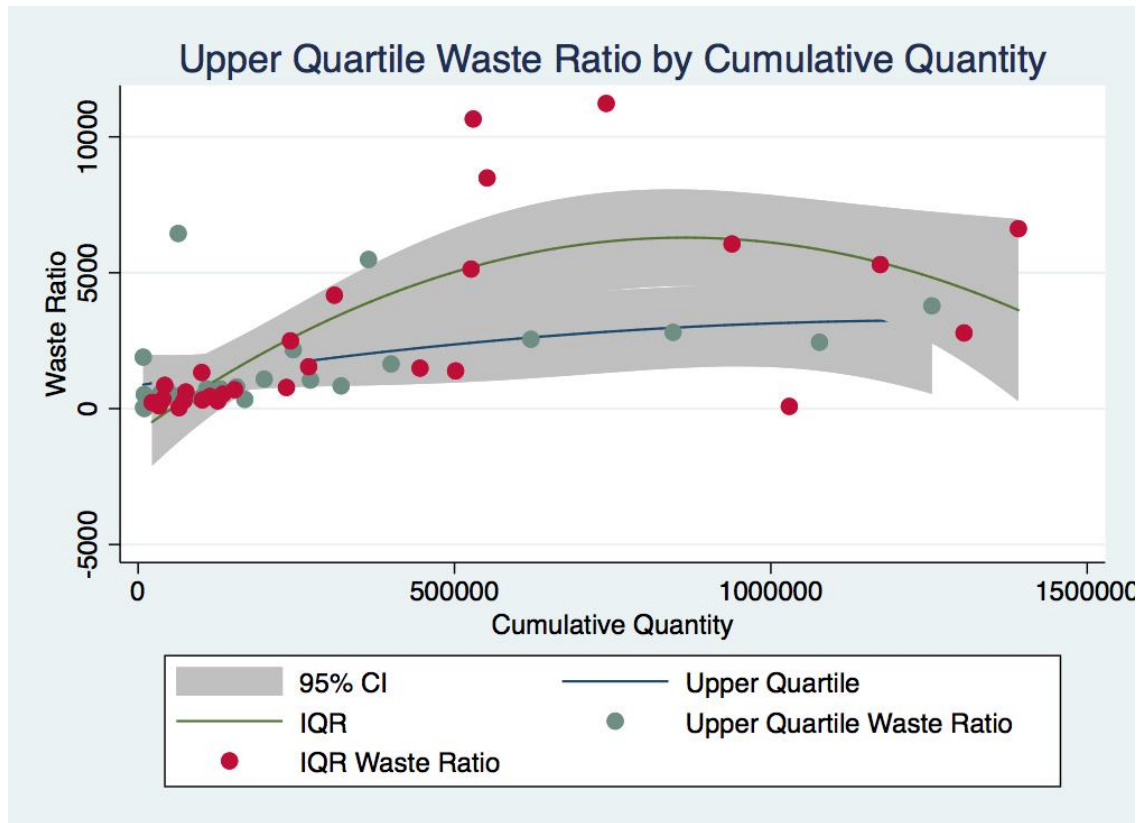


Figure 6. Upper quartile waste ratio by cumulative quantity.

The conclusion made by analyzing these graphs revealed that there was no significant, consistent learning mechanism at place at the industry level. This result was a necessary conclusion to isolate organizational level learning for the next step of the

analysis. The drivers of internal differences seen in the graphs will be further investigated in the next analysis when controlling for fixed effects of individual firms.

Organizational Level Learning by [Quartile Firm Size](#)

The second part of this analysis sought to identify organizational learning by small and large individual operators within the oil and gas industry. Through multivariate regressions and data charting, I examined the effect of operational scope and firm size on learning at the organization level.

The Impact of Increased Operational Scope

By running a regression on the logged relationship between waste ratio and the operational scope, it was found that on average, as cumulative output was increasing, waste ratio was decreasing, thus providing evidence for learning across all firms of all sizes. In fact, a 1% increase in the cumulative output was associated with a significant decrease in the corresponding waste ratio by 0.43%. See Figure 7 for a graphical representation of this trend.

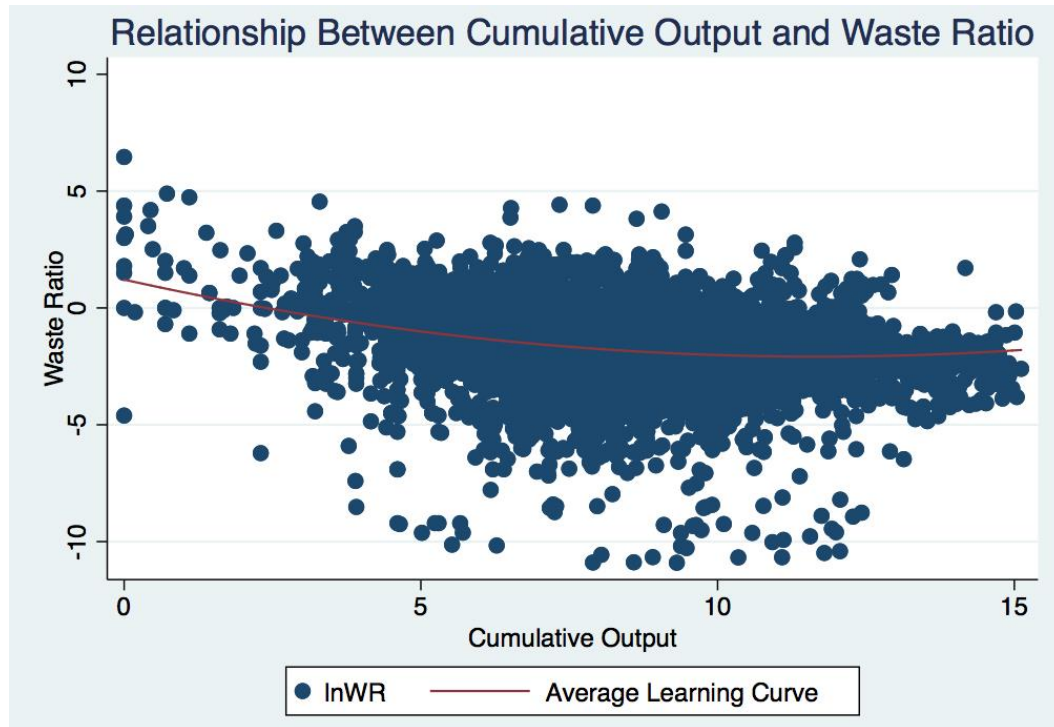


Figure 7. Relationship between cumulative output and waste ratio.

The primary goal of this analysis was to determine if a large firm's waste ratios were decreasing at a different rate over time than those of not-large firms. Similarly, a second analysis was run to determine if a small firm's waste ratios was decreasing at a different rate over time than those of not-small firms. If the waste ratio was seen decreasing as the operator's cumulative output was increasing, it was interpreted that knowledge sharing and learning were occurring within the firm.

For large firms, an analysis of the regression of logged cumulative quantity and an interaction variable (the combination of size and cumulative quantity) on logged waste ratio showed no significant change in the coefficient for the logged cumulative quantity from the basic regression of the logged cumulative quantity on logged waste ratio. Further, the interaction term's coefficient of 0.0385 had a p-value greater than 0.05 and therefore could not be considered significant. Similarly, the same regression for small firms again showed no significant change in the coefficient for the logged cumulative

quantity and had an insignificant p-value for the interaction coefficient. Please see Figure 5 below for a breakdown of these numbers.

Impact of Being a Large or Small Operator	
<i>Regression 1:</i> Cumulative quantity (logged) on waste ratio (logged) <i>Regression 2:</i> Cumulative quantity (logged) and interaction (logged cumulative quantity and firm size) on waste ratio (logged) *all regressions were run with the <i>xtreg</i> command in Stata. All regressions also controlled for fixed effects and robustness.	
<i>Regression 1:</i>	
Logged cumulative quantity coefficient	-0.4305
Logged cumulative quantity p-value	0.000
<i>Large Operators Regression 2:</i>	
Logged cumulative quantity coefficient	-0.4344
Logged cumulative quantity p-value	0.000
Logged interaction coefficient	0.0385
Logged interaction p-value	0.594
<i>Small Operators Regression 2:</i>	
Logged cumulative quantity coefficient	-0.3968
Logged cumulative quantity p-value	0.000
Logged interaction coefficient	-0.0599
Logged interaction p-value	0.282

Figure 8. Quantitative impact of being a small or large firm.

In conclusion, this analysis found that neither being a large or small firm impacts learning more than the other. There was no significant difference between firms of any size and their ability to be more efficient and learn over time. Therefore, this analysis shows that firm size is not a driver of organizational learning in Pennsylvania's oil and gas industry.

Stakeholder Takeaways

The findings of this research can provide value for key stakeholders including investors, policy makers, and internal decision makers.

Investors

From the investor perspective, a firm's ability to practice organizational learning within the oil and gas industry could be used as a metric of interest for investment decisions. Given that the industry trend is a decrease in waste ratio associated with an increase in cumulative output, if a firm is not meeting industry standards it is likely not a worthwhile investment. Similarly, investors should recognize that firm size was not an indicator of increased efficiency over an increase in cumulative output. Likewise, firm size alone should not be a key decision point for investors. Future research of interest to investors would include relationships between learning rates (or lack thereof) discovered in this research and firm profitability measurements.

Policy Makers

While there is evidence across firms of all sizes within Pennsylvania's oil and gas industry of declining waste ratios with increases in cumulative quantity, it would be valuable to understand what enables some firms to be more efficient than others. With future research, policy makers could understand which firms need extra incentives to be efficient and create policy as such. Further, even though firms in general are becoming more efficient, it would be beneficial to communities if firms generated less waste. In 2018, Ross Craft, chairman and CEO of Approach Resources Inc, explained that

environmentally friendly, efficient technologies exists that are capable of cleaning water to a point where it can be put into local water sources, used for farming, or even consumption (Haines, 2018). Unfortunately, he admits that the technology is expensive, an obvious deterrent for oil and gas operators already operating in tight margins. Accordingly, well developed policies and regulation enforcement could incentivize oil and gas companies to take the next step to invest in technology that help protect the environment.

Internal Decision Makers

Considering the overwhelming direct and indirect costs of waste and waste handling, it is vital for firm's financial interests to efficiently manage and reduce their respective waste ratios. Likewise, it is important that individual firms research and understand their respective abilities to decrease their waste ratio as their cumulative output increases. By capitalizing on internal strengths and learning opportunities, firms would reap significant cost savings. As John Browne, former CEO of BP, explained, knowledge "is relatively inexpensive to replicate if you can capture it"(Prokesch, 1997). He expands to discuss that working activities in the oil and gas industry are not one-time events and, that if each repetition can be more efficient than the last, a lot more money can be made (1997).

DISCUSSION

A number of limitations from this study are noteworthy and the resulting opportunities for future research warrant additional discussion.

Limitations

While a majority of data limitations were consciously avoided through this study's methodology, others were ineludible. First, data utilized in this study was self-reported by well operators. Due to the nature of this collection process, data is not likely to be completely accurate, either by accident or because of adverse reporting incentives and a lack of institutional oversight. While notice was taken to clean the data and avoid glaring misrepresentations of truth, it is possible that some data utilized in this study was not true to reality. Further, inconsistent reporting guidelines, while anticipated due to the nature of the newly developing and rapidly growing industry, forced the simplification of analysis. For example, when the Oil and Gas Act of 2012 was implemented, waste and production metrics were subsequently reported monthly rather than annually, and there were more specific descriptions of waste types and waste disposal methods. All of these increasingly specific data measures would have made for a richer study and analysis.

Future Research Opportunities

Future research on organizational learning's impact on energy efficiency, specifically within the setting of Pennsylvania's oil and gas industry, would shed light on some of the questions left behind from this study. One of the largest questions I had at the completion of my research was: "How have energy operators managed, both financially and legally, to not decrease their waste ratios over time?" I believe an avenue of future research that could shed light on this question would be to measure and track the rate of waste being recycled. A possible hypothesis is that while overall waste ratios might not be decreasing, the amount of waste being recycled is increasing, effectively decreasing the environmental impact of waste being created and disposed of.

An additional element that could be valuable to incorporate in future research would be to control for well geography. While it was beyond the scope of this project, I hypothesize that regardless of the identity of the well operator, certain geographies have varying access to resources and disposal methods based on proximity to bodies of water, the necessity to navigate mountainous terrain, and even varying levels of precipitation. Additionally, the existence of local regulations or restrictions could impact a well operator's ability to operate at optimal efficiency levels.

Similarly, it would be interesting to conduct this same or similar research in other states or on a national scale. Perhaps companies with operations in multiple states have efficiency bottlenecks in certain states but are able to make headway in others. By only analyzing a single state, it is difficult to truly put operator performance in perspective. While I concluded that waste ratio had not significantly decreased over time in Pennsylvania, maybe Pennsylvania operators have efficiency figured out and have no

room for improvement. Likewise, having a comparison to other states or a national basis would provide valuable insights and basis of comparison for this research question and subsequent findings.

Lastly, supplementary research into well-level, individual learning rates would provide valuable insights for internal decision makers. By analyzing individual wells' waste ratios, underperforming wells could be identified and remedying steps could be taken to improve the well as needed. This research would also provide insight into whether or not firm leadership needs to invest in and facilitate more knowledge sharing within the company. By understanding which wells are performing exceptionally, explanatory metrics (technological innovation, organizational structure, leadership, etc.) can be identified and shared across the company.

APPENDIX

Appendix A

Final Data Set Variables

FINAL DATA	
Production Variables	Waste Variables
Operator Operator Number Period ID Reporting Period Unconventional Well County Well Latitude Well Longitude Well Permit Number Well Status Well Type Condensate Quantity Gas Quantity Oil Quantity	Operator Operator Number Period ID Reporting Period Unconventional Well County Well Latitude Well Longitude Well Permit Number Well Status Well Type Units Waste Quantity
* Bolded terms indicate variables present in both lists prior to merging data	

Appendix B

Bottom and Top Quartile Operator Selection Methodology

OPERATOR SELECTION METHODOLOGY	
Bottom Quartile	Top Quartile
<ol style="list-style-type: none"> 1. Sort firms by average number of wells per year 2. Determine firms in 25th percentile of average number of wells per year and label them as BOTTOM 3. Determine 75th percentile of wells per year of BOTTOM operators (operators with 16+ wells per year) 4. Determine 75th percentile of years in operation of BOTTOM operators (operators in service for over 17+ years) 5. Identify BOTTOM operators with 16+ wells per year and 17+ years of service) <ol style="list-style-type: none"> a. 7 operators were identified 6. Identify BOTTOM operators with 15+ wells per year and 17+ years of service) <ol style="list-style-type: none"> a. 0 additional operators were identified 7. Identify BOTTOM operators with 14+ wells per year and 17+ years of service) <ol style="list-style-type: none"> a. 3 additional operators were identified 8. Select remaining 10 operators for further analysis 	<ol style="list-style-type: none"> 1. Sort firms by total number of years in operation 2. Determine firms in 75th percentile of average number of wells per year and label them as TOP 3. Determine 75th percentile of wells per year of TOP operators (operators with 270+ wells per year) 4. Determine 75th percentile of years in operation of TOP operators (operators in service for over 18+ years) 5. Identify TOP operators with 270+ wells per year and 18+ years of service) <ol style="list-style-type: none"> a. 1 operator was identified 6. Identify TOP operators with 18+ years of service) <ol style="list-style-type: none"> a. 4 additional operators were identified 7. Identify TOP operators with 14+ years of service) <ol style="list-style-type: none"> a. 5 additional operators were identified 8. Select remaining 10 operators for further analysis
<p>Notes:</p> <ul style="list-style-type: none"> ● Selection of firms operating in the upper percentiles of operating years in their respective quartiles was necessitated by the overarching research methodology. Without sufficient years to track the waste ratio, conclusions could not be determined. ● While there could be inherent differences in firms selected because of falling in the upper percentile of operating years, prior research has determined that there is no direct correlation between experience and learning rates (Argote, 2013). ● This methodology controls for years in operation and allows the key differentiating factor to be operator size (as measured by average number of wells held over time) 	

Appendix C

Summary Statistics for Industry Level Learning - With Outliers

Industry Level Summary Statistics - With Outliers		
Well per Year:	Mean	95.78
	25th Percentile	22.62
	50th Percentile	41.60
	75th Percentile	99.53
	Standard Deviation	124.60
Waste Quantity:	Mean	165.81
	50th Percentile	23.62
	Standard Deviation	14966.99
Production Quantity:	Mean	348.27
	50th Percentile	252.90
	Standard Deviation	322.4296
Waste Ratio	Mean	1.53
	50th Percentile	0.09
	Standard Deviation	93.54091
Notes: <ul style="list-style-type: none"> ● Statistics based on 207,520 well/year measurements <ul style="list-style-type: none"> ○ Originally had 448,302 well/year measurements <ul style="list-style-type: none"> ■ Observations were dropped if the waste ratio was missing or equal to 0 ■ Observations were dropped if total production was less than 1 		

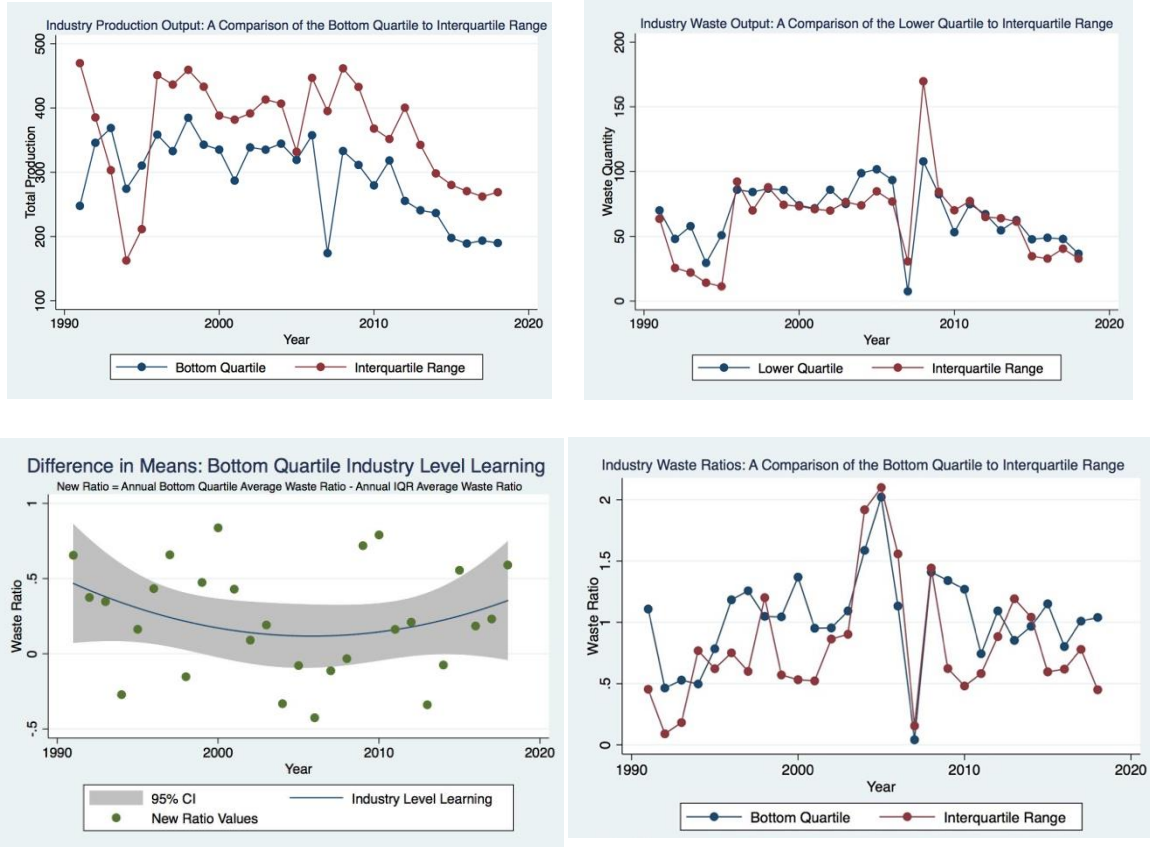
Appendix D

Summary Statistics for Industry Level Learning - Without Outliers

Industry Level Summary Statistics - Without Outliers		
Well per Year:	Mean	92.02
	25th Percentile	22.48
	50th Percentile	41.28
	75th Percentile	99.53
	Standard Deviation	116.27
Waste Quantity:	Mean	61.25
	50th Percentile	21.97
	Standard Deviation	102.88
Production Quantity:	Mean	346.05
	50th Percentile	250
	Standard Deviation	321.47
Waste Ratio	Mean	0.86
	50th Percentile	0.09
	Standard Deviation	5.00
Notes: <ul style="list-style-type: none"> ● Statistics based on 200,717 well/year measurements <ul style="list-style-type: none"> ○ Observations were dropped if total waste, production, or waste ratio exceeded the 99th percentile 		

Appendix E

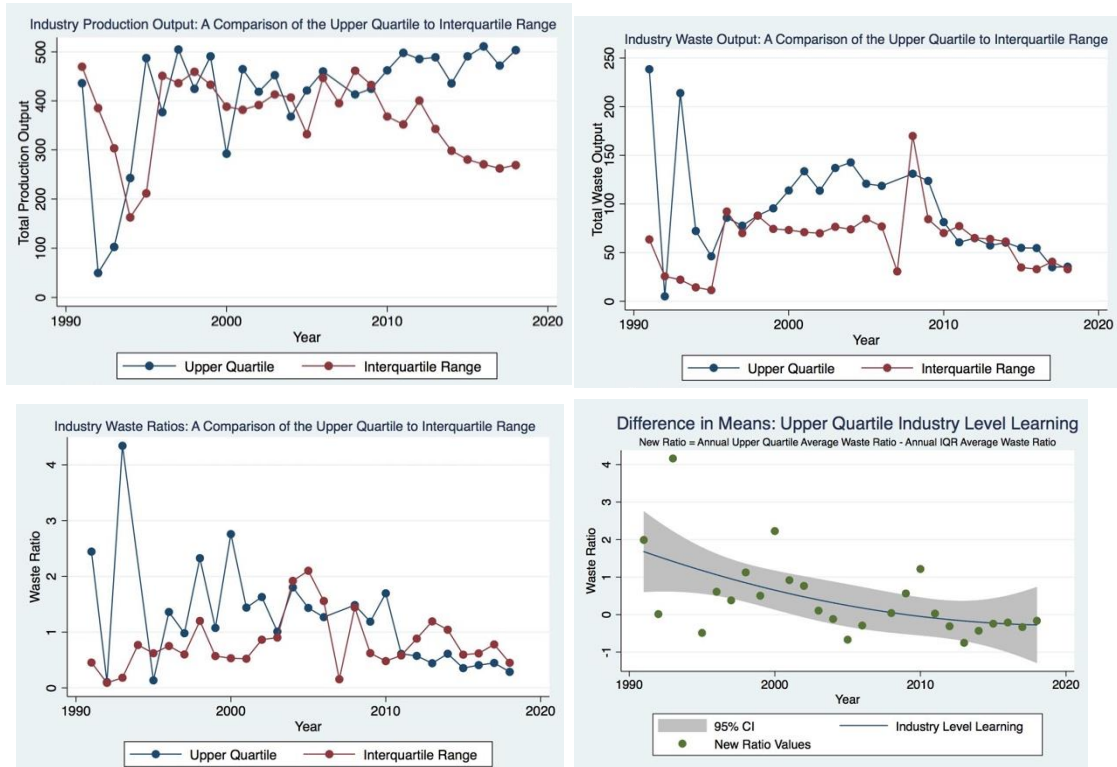
Summary Statistics and Graphical Representation of Bottom Quartile and IQR Industry Level Waste Ratios



Summary Statistics of Industry Level Waste Ratios: Bottom Quartile vs IQR	
Ho: mean = 0 Ha: mean = 0 *mean = bottom quartile average annual waste ratio - IQR average annual waste ratio	
Statistic	Value
t-statistic	3.259
df	27
obs	28
95% confidence interval	0.083 to 0.365

Appendix F

Summary Statistics and Graphical Representation of Upper Quartile and IQR Industry Level Waste Ratios



Summary Statistics of Industry Level Waste Ratios: Upper Quartile vs IQR

H₀: mean = 0 H_a: mean = 0

*mean = upper quartile average annual waste ratio - IQR average annual waste ratio

Statistic	Value
t-statistic	1.4017
df	26
obs	27
95% confidence interval	-0.6320 to 3.342

Notes:

- One outlier, the single observation in the 99th percentile, was removed for the difference in means regression

REFERENCES CITED

- American Geosciences Institute. (2014, June 17). How much water does the typical hydraulically fractured well require? Retrieved March 24, 2019, from <https://www.americangeosciences.org/critical-issues/faq/how-much-water-does-typical-hydraulically-fractured-well-require>
- Argote, L. (2013). *Organizational Learning: Creating, Retaining and Transferring Knowledge* (2nd ed.). New York, NY: Springer Science+Business Media.
- Ati, N., Brinkman, M., Peacock, R., & Wood, C. (2016, March). Margins under pressure as market falls further | McKinsey. Retrieved March 17, 2019, from <https://www.mckinsey.com/industries/oil-and-gas/our-insights/margins-under-pressure-as-market-falls-further>
- Boudet, H., Clarke, C., Bugden, D., Maibach, E., Roser-Renouf, C., & Leiserowitz, A. (2014). “Fracking” controversy and communication: Using national survey data to understand public perceptions of hydraulic fracturing. *Energy Policy*, 65, 57–67. <https://doi.org/10.1016/j.enpol.2013.10.017>
- DiChristopher, T. (2018, December 31). Oil prices had their worst year since 2015 — here’s what went wrong. Retrieved March 24, 2019, from <https://www.cnbc.com/2018/12/31/oil-prices-are-set-for-their-worst-year-since-2015.html>
- Frazier, R. (2018, April 3). Poll: Public concern grows over natural gas industry’s environmental impact. Retrieved March 31, 2019, from StateImpact Pennsylvania website: <https://stateimpact.npr.org/pennsylvania/2018/04/03/poll-public-concern-grows-over-natural-gas-industrys-environmental-impact/>
- Gertner, J. (2013, December 21). George Mitchell, father of fracking. *The New York Times*. Retrieved from <https://www.nytimes.com/news/the-lives-they-lived/2013/12/21/george-mitchell/>

- Global Energy Institute. (2016, November 4). New Energy Institute Report Finds that U.S. Could Lose Nearly 15 Million Jobs If Hydraulic Fracturing is Banned. Retrieved December 6, 2018, from <https://www.globalenergyinstitute.org/energy-accountability-fracking-press-release>
- Haines, L. (2018). Shaving Water Costs. Oil and Gas Investor. Retrieved from <https://www.approachresources.com/approach/files/d6/d6f702b6-07e5-4b26-b297-6b744dc8cb3b.PDF>
- Harraf, A., Wanasika, I., Tate, K., & Talbott, K. (2015). Organizational Agility. *Journal of Applied Business Research; Laramie*, 31(2), 675.
- Hirji, Z., Song, L. (2015, January 20). Map: The Fracking Boom, State by State. Retrieved September 17, 2018, from <http://insideclimatenews.org/news/20150120/map-fracking-boom-state-state>
- Hirschmann, W. (1964). Profit from the learning curve. *Harvard Business Review*, 42(1), 125–139.
- Horton, M. (2018, July 16). What are the effects of fracking on the environment? Retrieved March 24, 2019, from <https://www.investopedia.com/ask/answers/011915/what-are-effects-fracking-environment.asp>
- Hurdle, J. (2016, June 14). EPA bans disposal of fracking waste water at public treatment plants. Retrieved March 26, 2019, from <https://stateimpact.npr.org/pennsylvania/2016/06/14/epa-bans-disposal-of-fracking-waste-water-at-public-treatment-plants/>
- Independent Petroleum Association of America. (n.d.). Retrieved December 5, 2018, from <https://www.ipaa.org/fracking/>
- IPIECA. (2013). Saving energy in the oil and gas industry. London, United Kingdom.
- Marcellus Shale Coalition. (n.d.). Marcellus and Utica Shale Formation Map. Retrieved March 26, 2019, from <http://marcelluscoalition.org/pa-map/>
- Oil and Gas Act, Penn. Assemb. 223 (1983-2984), Chapter 11 (Penn. Stat. 1984)

- PA DEP Oil & Gas Reporting Website - Production / Waste Reports. (n.d.). Retrieved April 2, 2019, from Pennsylvania Department of Environmental Protection website:
<https://www.paoilandgasreporting.state.pa.us/publicreports/Modules/Welcome/ProdWasteReports.aspx>
- Pennsylvania Department of Community and Economic Development. (n.d.). Retrieved December 6, 2018, from <https://dced.pa.gov/key-industries/naturalgas/>
- Prokesch, S. (1997, September 1). Unleashing the Power of Learning: An Interview with British Petroleum's John Browne. *Harvard Business Review*, (September–October 1997). Retrieved from <https://hbr.org/1997/09/unleashing-the-power-of-learning-an-interview-with-british-petroleums-john-browne>
- Schiersch, A. (2013). Firm size and efficiency in the German mechanical engineering industry. *Small Business Economics*, 40(2), 335–350.
<https://doi.org/10.1007/s11187-012-9438-8>
- Squillace, M. (2016). Managing unconventional oil and gas development as if communities mattered. *Vermont Law Review* 40(3), 525-560.
- The keys to organizational agility. (2015). Retrieved March 31, 2019, from <https://www.mckinsey.com/business-functions/organization/our-insights/the-keys-to-organizational-agility>
- The Marcellus Shale, Explained. (n.d.). Retrieved December 6, 2018, from <https://stateimpact.npr.org/pennsylvania/tag/marcellus-shale/>
- T. P. Wright. (1936). Factors Affecting the Cost of Airplanes. *Journal of the Aeronautical Sciences*, 3(4), 122-128.