Big Frack Attack: Learning-by-Doing in the U.S. Shale Sector

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Abstract The "Shale Revolution" has transformed world natural gas and oil markets in the past two decades. The revolution has been first and foremost a technological one. In this paper I analyze the contribution of learning-by-doing to this technical progress. Learning-by-doing affects both well productivity and the cost of drilling: the former effect leads to more output per well, and the latter effect results in an increase in the number of wells drilled. Basin-specific empirical estimates show that the median impact of LBD on production growth taking both intensive and extensive margins into account is 19 percent for gas and 38 percent for oil. Direct and indirect empirical evidence suggests that most of the learning effects are internalized, and that learning spillovers are modest. Furthermore, the empirical estimates imply that accumulated learning effects rendered attempts by Saudi Arabia to impede US oil production through predatory pricing strategies in 2014-2015 were futile.

1 Introduction

Natural gas and oil production in the United States has undergone a revolution since the mid-2000s. Specifically, the development of "unconventional" fossil fuel production in "tight" shale formations through the application of horizontal drilling techniques and hydraulic fracturing has resulted in a marked reversal in the long-term decline in United States oil and gas production. Furthermore, this increase in output has resulted not just on the extensive margin (drilling more wells using a new method) but on the intensive margin: wells have become more productive over time.

This dramatic transformation of gas and oil production in the United States naturally raises the question of its causes. Learning-by-doing–experiential or "passive" learning–has long been recognized as a source of productivity change. This article examines empirically the role of such learning on the productivity of gas and oil produced using horizontal drilling and hydraulic fracturing. The empirical results demonstrate that experiential learning has been an important source of productivity growth in this sector.

Using well-level data, I examine the impact of learning-by-doing on several measures of well productivity and on the cost of drilling wells. I study both firm-specific and production-basin-wide measures of experience.

For both gas and oil, I find that firm-specific learning (measured by the number of wells in a basin drilled by a particular firm) increases some measures of productivity–notably initial well production–but not others–such as drilling speed and well decline rates. The results for non-firm-specific learning are more equivocal: greater industry wide experience in a given basis does not uniformly result in greater productivity by any measure. However, it is necessary to be cautious in interpreting this last result as greater industry experience (*i.e.,* more total drilling in a given basin) also results in drilling in progressively less promising sites which would tend to reduce well productivity and thereby mask the effects of industry wide experience. The role of heterogeneous exogenous potential well productivity is further illustrated by the fact that productivity varies inversely with price, which can be explained by drillers choosing where to drill based on assessments of likely productivity, and are willng to drill relatively unproductive wells when prices are high.

The empirical results also provide strong evidence that learning reduces costs, especially fixed costs. Reductions in fixed costs result in an increase in the number of wells drilled at a given price, and the empirical results show that industry-wide experience in a particular basin result in a substantial shift out of supply curves, *i.e.,* an increase in the number of wells drilled at a given price. Firm-specific experience has a positive, but statistically weaker, impact on supply curves.

Thus, there is empirical evidence that firm-specific experience improves well productivity, and weakly reduces costs. In contrast, industry-wide experience in a basis reduces costs but does not demonstrably improve productivity, although the latter result could reflect the confounding effect of prioritizing exploitation of the most promising drilling sites.

The measured learning effects are an appreciable source of the growth in U.S. unconventional oil and gas production. The median share of increased production across basins attributable to learning effects (taking into account both impacts on per well productivity and the number of wells drilled) is 19 percent for natural gas and 38 percent for oil.

Learning-by-doing can also affect industry structure, and competitive interactions among firms. Industry-wide learning effects *can* lead to externalities. Such externalities would provide an incentive for firms to consolidate in order to internalize "spillovers." However, there was no tendency towards consolidation during the heyday of the shale revolution: indeed, if anything, the industry has become less consolidated. Moreover, although the existence of learning *can* provide incentives to engage in predatory strategies, I show that in at least one instance of alleged predation (Saudi oil output increases in 2014-2015) these efforts were futile: although these output increases and price cuts did cause reductions in United States oil output, the effect on experiential learning was too small to allow the putative predator to recoup the cost of predation.

The remainder of this article is organized as follows. Section 2 provides a brief overview of the "Shale Revolution." Section 3 summarizes the economic literature on learning-by-doing. Section 4 summarizes the empirical methods and the main empirical results regarding the contribution of experiential learning to well productivity and supply curves. Section 5 quantifies the effect of learning-by-doing on total United States gas and oil output. Section 6 examines how industry structure changed during the shale revolution, and in light of the lack of change of industry structure Section 7 briefly evaluates whether industry-wide experience effects imply the existence of externalities/spillovers. Section 8 examines the Saudi oil output increase episode of 2014-2015 to evaluate whether learning effects provide an incentive for predatory, raising rivals' cost strategies. Section 9 summarizes.

2 The Shale Revolution

What has rightly been called "The Shale Revolution" in the United States is the result of the application of two rather old technologies–horizontal drilling and hydraulic fracturing–to previously intractable "tight" hydrocarbon formations in which natural gas and/or oil are embedded in rock ("shale") rather than trapped in pools in cavities in the resource-bearing rock. Horizontal drilling is self-explanatory: it involves the drilling of wells with lateral arms running roughly parallel to the surface, in contrast to wells drilled vertically into pools of oil or gas. Hydraulic fracturing ("fracking") entails the injection of mixtures of proprietary drilling fluids and sand into the well laterals. The pressured injection of fluids and sand fractures ("fracks") the oil/gas-bearing rock thereby freeing these hydrocarbons to flow into the well for extraction.

Although the basic technologies date to the 1920s, they were applied to tight formations only in the 2000s. The first application was in gas, where George Mitchell and Mitchell Energy painstakingly experimented with their application to the Barnett Shale basin in north Texas. Somewhat later, Henry Hamm and Continental Energy applied the technology to oil production in the Bakken region of North Dakota and Montana.

After successes in these regions, the combination of horizontal drilling and fracturing (sometimes referred to as "unconventional" production) spread to other production basins. Figure 1 depicts gas production in several shale regions. Note the successive waves of production, first in the Barnett, then in Haynesville of eastern Texas and Louisiana, then in the Eagle Ford of South Texas and then in the Marcellus of Pennsylvania. Figure 2 portrays production in oil-bearing shale regions, with booms starting in the Bakken, proceeding to the Eagle Ford, and then culminating in the Permian region of west Texas and eastern New Mexico.

Production increases can occur for two reasons: an increase in the number of wells, and increases in the productivity of wells. Productivity gains have been marked. The United States Energy Information Agency periodically releases productivity reports that document these gains. Figure 3 depicts EIA data on output per drilling rig in gas for the Haynesville basin. Figure 4 depicts the production per drilling rig for the Permian region. The increases in productivity are evident.[1]

It should also be noted that expansions in output on the extensive margin can also reflect productivity gains: more efficient drilling techniques that lower costs of producing wells of a given level of productivity lead to the drilling of more wells and an expansion of output.

Thus, the unconventional hydrocarbon production sector of the United States underwent a profound shift beginning around 2005 in gas and somewhat later in oil. This shift, accurately characterized as a revolution, resulted in an increase in output and a secular increase in productive efficiency. This raises the question of the sources of these gains.

Experiential learning–"learning-by-doing"–has long been considered an important source of technological progress and productivity improvement. Thus, the question: has learning-by-doing been a material cause of productivity improvement in the United States shale sector, and if so, how much has it contributed to the documented increase in output? The remainder of this article attempts to answer those questions empirically.

3 The Economic Literature on Learning-by-Doing

The recognition that production experience could enhance productivity by generating "passive" learning dates from at least Wright's (1936) work on

[1]The EIA's measure of productivity has some problematic features which are evident in the graphs. Note for example the apparent decline in productivity in the Permian starting in February 2016. Due to low oil prices, many firms exercised the real option to drill but not complete wells. Thus, rigs were employed to drill wells that did not result in immediate increases in production, which depressed the EIA's productivity measure. In the empirical analysis that follows, I do not utilize the EIA's measure.

the impact of accumulated experience on the cost of airplane production that gave rise to the concept of "learning curves." World War II provided a plethora of empirical evidence of learning effects, especially in airframes and ships (Montgomery, 1943; Middleton, 1945; Alchian, 1950/1963; Lane, 1951; Searle, 1956; Asher, 1956; Rapping, 1965). Subsequent research in other industries provided further evidence of the ubiquity of learning-by-doing effects (Hirsch, 1952; Preston and Keachie, 1964; Baloff, 1966; Boston Consulting Group, 1972). Cliometrics provided yet further examples (David, 1973, 1975). Suffice it to say that the empirical basis for the importance of experience-based learning effects was well established by the last quarter of the 20th century, and indeed their importance had become a stylized fact.

The first seminal theoretical contribution was by Arrow (1962). The recognition that capital accumulation could not explain economic growth (Abramovitz, 1956; Solow, 1957) led economists to search for alternative explanations, and learning-by-doing has played a prominent role in this search. The literature is too massive to summarize, but Lucas (1988), Romer (1990), and Young (1991) are important contributions.

Economists have also explored the implications of learning for pricing strategies and strategic interactions between firms. Prominent examples include Rosen (1972), Spence (1981), Clarke, Darrough, and Heinecke (1982), Fudenberg and Tirole (1983), Dasgupta and Stiglitz (1981), Petrakis, Rasmusen, and Roy (1997), Cabral and Riordan, (1994, 1997) Hollis (2002), and Thompson (2010).

In sum, the prevalence and macro- and micro- importance of experiential learning are well-recognized. This recognition has extended to the oil industry, where Kellogg (2011) has documented some learning effects in the traditional oil sector (*i.e.,* vertical drilling). Given the substantial increase in the productivity in natural gas and oil drilling productivity since the mid-2000s, the extant empirical and theoretical literature emphasizing the importance of experiential learning raises the question of the extent of its importance in unconventionial fossilfuel production. The remainder of this article examines that question in detail, and answers to the affirmative.

4 Empirical Methodology

4.1 Potential Sources of Output Increases and Productivity Improvement

4.2 Well Productivity Analysis

Data on the well-level permits an analysis of productivity of wells over time and by basin. This data, provided by DrillingInfo, contains data on wells including *inter alia* the "spud date" (the date drilling commences), completion date, first production date, location (latitude/longitude), depth, type (vertical, horizontal, directional), horizontal length, and oil, gas, and water output by month. For the purposes of my analysis, I consider horizontal wells drilled in five major shale oil basins–Bakken, Permian, Eagle Ford, Niobrara, and StackScoop–and five major gas basins–Permian, Eagle Ford, Barnett, Haynesville and Marcellus. To be included in the analysis, a well must have twelve months of production experience. Thus, the analysis encompasses horizontal wells drilled in major shale plays through December, 2017.

For each basin, I estimate regressions of measures of productivity against learning and other variables:

$$q_{i,j,t} = g_q(\ln L_t, \ln \mathbf{E_{i,j,t}}, \delta_{i,j,t}, P_t, t) \tag{1}$$

where $q_{i,j,t}$ is a productivity variable for well i in basin j spudded in month

t, L_t is a measure of the length of the well, $\mathbf{E_{i,j,t}}$ is a vector of experience variables, $\delta_{i,j,t}$ is a measure of the density of wells around well i, P_t is the price of a one year futures "strip" three months prior to the spud date, and t is time.

I examine a variety of productivity variables, including:

- Initial well production, defined as output in the first full month of operation. Initial well production is number of barrels of oil for oil wells, and number of MMBTU of gas for gas wells.

- Maximum monthly well production in the first twelve months of operation, in number of barrels of oil for oil wells, and number of MMBTU of gas for gas wells.

- Twelve-month production, in number of barrels of oil for oil wells, and number of MMBTU of gas for gas wells.

- Geometric decline rate. Well output tends to decline monotonically over time. A standard measure of this decline rate is geometric. I estimate this decline rate as the slope coefficient β_1 in a regression $\ln Q_{i,j,\tau} = \beta_0 + \beta_1 \tau$ where $Q_{i,j,\tau}$ is the output of well i in basin j in month τ after first production, where $\tau = 1, \ldots, 12$.

- Output per unit of length, the ratio of the twelve-month production to a measure of well length/depth (discussed further below).

- Drilling speed, the number of feet of length drilled divided by the number of days from spudding to completion.

This represents a broader set of productivity variables than in prior studies (*e.g.,* Kellogg, which utilizes only drilling speed).

I utilize a variety of measures of L_t, including total measured depth, horizontal length, and lateral length: measured depth data is most complete, and the results are best, so I report the results from the regressions using this measure. A density variable is included because the productivity of a well may be impacted by other wells located in close proximity. Research suggests that wells located within 1500 feet of a well can reduce its productivity, but wells located further away have little or no impact. I therefore measure $\delta_{i,j,t}$ as the number of wells located within 1500 feet of well i that were spudded prior to the spudding of well i at time t.

The experience variables are the focus of interest. I measure experience at the level of the operator, which is disclosed in the DrillingInfo data. For well i in basin j at time t, one variable–"own-experience" E_t^{own}–measures the number of wells spudded by the operator of well i in basin j prior to t. For this well, the other variable–"other-experience" E_t^{other}–measures the number of wells drilled in basin j prior to t by operators other than the one associated with well i.

The own-experience variable measures production (drilling) experience by a particular operator. The other-experience variable quantifies the experience of other operators in the basin, and is intended to capture potential learning spillovers across firms, though as discussed later, the existence of other-experience effects does not imply the existence of externalities.

The analysis is performed at the basin level because geology differs substantially by basin, and by product (*i.e.,* oil vs. gas).

The experience variables are conventional, but the other-experience variable deserves some comment. Holding productivity and technology fixed, one expects well productivity to decline, the more wells that have been drilled in a particular basin. This can occur for several reasons. First, drillers may develop the most promising prospects first. Second, depletion of reservoirs by wells drilled early can reduce the productivity of wells drilled later.

This tendency for productivity to decline as a field is exploited more intensively over time is difficult to disentangle from other-experience learning effects. The other-experience variable captures the effects of both the tendency of productivity to decline due to more intensive exploitation, and cross-operator learning effects. Thus, it is likely that the coefficient on the other-experience variable understates cross-operator learning effects, and indeed, it is possible that the estimates of this coefficient could be negative if the exploitation effect dominates the learning effect.

The motivation for including price is that operators may choose to drill less promising wells when prices are high, and may focus only on promising ones when prices are low. This would tend to result in a negative relation between price and productivity.

The time index t is included to capture non-experience related technological progress: a time variable has been used to measure non-experience-related technical progress since David (1974). As with cumulative other-experience, the progressive exploitation of an oil or gas reservoir could offset technical progress in whole or in part, which would tend to cause the coefficient on t to underestimate the rate of exogenous technological advance. If depletion effects are sufficiently large, this coefficient could be negative even in the presence of non-learning-related productivity improvement.

In all the analyses the g_q functions are linear in the independent variables. All of the dependent variables, with the exception of the decline rate (which is a negative number) are in log form, *e.g.,* in the initial production regressions, the dependent variable is the natural logarithm of initial production by well i in basin j and time t. Due to the existence of outliers, I have used both

OLS and robust estimators.

The price variable is is the average price of a twelve-month strip of oil futures prices (for oil output equations) or a twelve-month strip of gas futures prices (for gas output equations): that is, P_t is the sum of 12 futures prices divided by 12. This reflects the fact that a well produces output over time, and hence forward as well as the spot price are relevant in determining the revenue from a well. Furthermore, I choose to use 12 months as the bulk of a well's output is produced within the first year of production. I lag this price variable by two months to reflect the fact that the decision to drill must be taken some time prior to the commencement of drilling.

4.3 Cost Analysis

Available data do not permit an analysis of costs on the well-level in the same way that they permit analysis of productivity. Although direct analysis of well costs analogous to direct analysis of well productivity is not feasible, it is possible to analyze costs indirectly, and thereby determine the contribution of learning-by-doing to cost reduction, and cost-driven output increases.

Specifically, technological changes that impact costs shift supply curves. Therefore, I explore the impact of learning-by-doing by estimating supply curves (on a basin-by-basin basis), and quantifying the impact of learning measures on the locations of the supply curves.

Supply curves can shift out due to increased output per well, or reduced costs per well, or both. With respect to the latter, standard price theory implies that technological improvements that reduce the (fixed) cost of a well shift out supply curves, and lead to the drilling of more wells at any given price. To isolate these effects, I estimate both a standard flow supply curve with output as a dependent variable, and a function with the number of wells drilled in a given month as a dependent variable.

The output equation is of the following form:

$$\ln Q_{12,j,t} = g_Q(\ln P_t, \ln \mathbf{X}, \ln \mathbf{E}^*_{\mathbf{j},\mathbf{t}}, \ln \sigma_P, t) \tag{2}$$

Here, $Q_{12,j,t}$ is the total amount of oil produced in the first twelve months of operation by all wells in basin j spudded in month t. This obviously depends on both the number of wells drilled, and the productivity of each well.

P_t is the average price of a twelve-month strip of oil futures prices (for oil output equations) or a twelve-month strip of gas futures prices (for gas output equations): that is, P_t is the sum of 12 futures prices divided by twelve.

The prices of Chicago Mercantile Exchange West Texas Intermediate futures are used in estimation of the oil output equations. During parts of the estimation period, transportation bottlenecks reduced oil prices at some locations (*e.g.,* the Bakken) relative to prices at the WTI delivery point of Cushing, Oklahoma. I therefore adjust the price of the WTI strip by the difference between the price of the front-month WTI price and the spot price in a particular basin. For example, to determine P_t for the Bakken, I subtract the difference between the front-month price of WTI and the spot month price of Bakken crude from the average price of the twelve-month WTI strip.[2]

For gas equation estimates, I utilize the prices I utilize CME Henry Hub natural gas futures. As with oil, transportation bottlenecks and patterns of

[2]This adjustment implicitly assumes that the differential between the price in any particular basin and the price in Cushing is expected to remain constant over the next twelve months. This is not necessarily true, and as a result differentials between, say, the Bakken price for delivery in six months and the WTI price for delivery in six months may differ from the spot differential. However, data on non-Cushing forward prices are not systematically available.

flow sometimes led to wide and varying divergences between gas prices in some basins (*e.g.,* Permian, Marcellus) and Henry Hub prices. I again adjust the Henry Hub strip price by the difference between the Henry Hub spot price and a spot price representative of gas prices in the basin of interest (*e.g.,* the Waha hub price for the Permian regressions).

Given that the amount of oil or gas supply added by wells drilled in a given month is small relative to total output, the prices are plausibly exogenous to shale producers. This is especially true for oil, for which the market is global in scope. The results presented below are based on the assumption that prices are exogenous. I have also estimated models that use instrumental variables to address potential endogeneity of prices. The results are effectively unchanged.[3]

Since a decision to drill a well must be made some time in advance of the actual spud date, I utilize the strip prices from the first day of the month two months prior to the first day of month t.[4]

The theory of investment under uncertainty motivates including the volatility variable. It is well known that there is optionality in the timing of drilling (Pindyck), and the theory of investment under uncertainty implies that in the presence of such optionality producers will defer some drilling when volatility is high (Dixit and Pindyck, 1994). Therefore, volatility changes should shift the supply curve: *ceteris paribus*, higher volatility should reduce supply. For

[3]For oil, I use lagged world oil liquids production, U.S. crude oil inventories on the last reporting date of the prior month, U.S. industrial production, and a time trend as instruments. For gas, I utilize lagged U.S. natural gas output, U.S. natural gas inventories on the last reporting date of the prior month, U.S. industrial production, and a time trend as instruments.

[4]I have estimated the models using different lag lengths, and find similar results to those reported here.

σ_P, I use the average implied volatility for twelve-month strips of at-the-money CME WTI futures options (for oil equations) and at-the-money CME Henry Hub futures options (for gas equations). As with P_t, the volatility average is calculated using options prices from the first day of the month two months prior to t.

For the input price vector $\mathbf{X_t}$, I utilize the Bureau of Labor Statistics producer price index for Drilling Oil and Gas Wells, and the BLS PPI for industrial sand.[5]

For the vector of learning variables, $\mathbf{E^*_{j,t}}$ as in the productivity analyses, I include both an own-experience and other-experience variable. The own-experience variable is the average of the own-experience variables used in the productivity analysis for each well spudded in month t. For example, if there were 120 wells spudded in basin j in month t, I calculate the average of the own-experience variables for these 120 wells. Similarly, for the other-experience variable, I calculate the average of the other-experience variable for each of the wells spudded in month t. Evaluation of the empirical results suggests some non-linearity in the learning effects. To capture this effect, I include two interaction terms, one for each learning variable. The first interaction term is the product of a dummy variable taking a value of one if the own learning variable is in the 70th percentile and the log of the own learning variable. Similarly, the second interaction term is the product of a dummy variable taking a value of one if the other learning variable is in the 70th percentile and the log of the other learning variable.

The analysis of the number of wells is similar. I estimate:

$$\ln N^w_{j,t} = g_N(\ln P_t, \ln \mathbf{X}, \ln \mathbf{E^*_{j,t}}, \ln \sigma_P, t) \tag{3}$$

[5] The BLS began releasing a PPI specifically for hydraulic fracturing sand in 2012. Its movements broadly track the PPI for industrial sand from 2012-2018.

where $N^w_{j,t}$ is the number of wells spudded in basin j in month t. The independent variables are the same as in the output equation.

Finally, I estimate:

$$\ln \frac{Q_{12,j,t}}{N^w_{j,t}} = g_{Q/N}(\ln P_t, \ln \mathbf{X}, \ln \mathbf{E^*_{j,t}}, \ln \sigma_P, t) \qquad (4)$$

The motivation here is that producers have drilling sites with varying levels of expected output. Less-promising wells may become economically viable when prices are high. One therefore expects that wells that average well output is negatively related to price.

4.4 Productivity

The results from some selected productivity analyses are shown in Tables I-III. Each panel presents the results for a different basin.

There is evidence of learning effects in output productivity measures. In particular, the own-experience variable in the twelve month output regressions is positive for 9 of 10 basins, and positive and significant for 8 of them.

The results for the other-experience variable are more equivocal. This variable's coefficient is negative for 5 of 10 basins, and negative and significant for 3 of them. As noted earlier, this may reflect the confounding effect of reservoir depletion on this coefficient. The phenomenon is most pronounced for gas, with negative other-experience coefficients on 4 of 5 gas basins.

A visual analysis of the relation between other-experience and 12 month productivity of gas wells suggests non-linearity: the relationship tends to have a positive slope for relatively high levels of other-experience. Estimates of a model including a term that interacts the other-learning variable with a dummy that is zero for other-experience values below a threshold and equal to one above the threshold for Permian gas and Eagle Ford gas produce coefficients on this interaction term that are positive and significant. The point estimates indicate that incremental learning effects are positive for other-experience levels slightly above the threshold for these gas basins.

There is not evidence of non-linearity in the other basins with negative other-experience coefficients. For the Haynesville basin, the positive coefficient appears to be an artifact of a jump in productivity across a threshold level of other-experience. For this basin, a specification that replaces the other-experience variable with a dummy equal to one for other-experience values above a threshold fits slightly better than the model that utilizes the log of other-experience as a regressor.

The coefficient on price is negative in most of the regressions, and usually significant. This indicates that well choice is affected by drilling decisions. Specifically, E&P firms drill wells that are expected to be less (more) productive when prices are high (low).

Turning to the decline rate regressions, interestingly most of the coefficients on the learning variables are negative, indicating that learning has it not taken the form of reducing decline rates. This can be reconciled with the results for 12 month well productivity by examining the results for initial well productivity. These are not shown, but are available in an online appendix, and are readily summarized. Learning coefficients tend to be positive for this variable.[6] Together, these results suggest that drillers have found ways to increase lifetime well output that trade-off initial (or maximum) production against decline rates.

The cost analysis presented below provides a potential explanation for this choice. The cost analysis provides strong evidence that learning has reduced

[6]Similar results hold for maximum well output, which are available in an on-line appendix.

the fixed cost of drilling a well. With lower fixed costs, it is cheap to replace wells that deplete more rapidly. Thus, the seemingly "negative learning" decline rate regressions may actually reflect optimization by drillers, and learning on other dimensions.

Perhaps the most surprising results obtain for the drilling speed regressions. Virtually all of the learning coefficients are negative. These results contrast with those of Kellogg, who utilizes drilling speed (for conventional non-horizontal wells) as his sole productivity measure, and finds that experience leads to increased drilling speeds. These results are also somewhat surprising in light of the cost analysis, which provides strong evidence that learning has reduced horizontal drilling costs: since *ceteris paribus* more rapid drilling should reduce costs, the speed productivity and cost analyses provide indirect evidence that (in contrast to Kellogg's findings for conventional wells), in horizontal drilling learning reduces costs on dimensions other than speed.

Drilling speeds have increased during the shale revolution (Council of Economic Advisors, 2019). However, the results of the regressions indicate that this improvement is not learning-driven. Instead, the improvement in speed (measured by drilling time, feet-drilled per day, and twelve month output per day of drilling time) are driven by the time trend variable. Since David (1970) the time trend variable in learning regressions has been interpreted as a measure of exogenous technical progress. The "incorrect" signs on the learning variables, and the strong and "correct" signs on the time trend variable strongly suggest that the widely-recognized improvements in drilling speed are not learning-driven, but are the result of exogenous technological improvements.

4.5 Horizontal Well Supply Curves

The data provide strong evidence of learning effects on both oil and gas supply curves, especially *via* the effect of learning on the number of wells. This indicates that learning has reduced costs, and specifically the fixed cost, of drilling.

Table IV reports the results for oil, and Table V reports the results for gas. In each table, Panel A reports the coefficients for learning and price elasticities for the 12 month supply of oil produced by wells spudded in a given month, Panel B reports these coefficients for the number of wells, and Panel C reports them for average output per well.

For oil, with one exception, the coefficients on average own experience in the 12 month output regressions are positive, although most are not statistically significant at the 10 percent level: those that are negative are not significant. For all basins, the coefficients on the average other experience variable is positive, and most are significant at very small $p-$values. Some are also quite large. For example, a one percent increase in other experience in Niobrara is associated with a 3.44 percent increase in 12 month oil output. In Bakken, a one percent increase in other experience is associated with a 1.44 percent rise in 12 month output.

The oil well number estimates are quite similar. Most of the average own experience coefficients are positive, and the negative ones are close to, and statistically indistinguishable from, zero. The average other experience variables are all positive, significant at extreme confidence levels, and often large. This provides strong evidence of learning effects on the fixed costs of drilling.

In all of these regressions, the coefficient on the price of the 12 month oil strip is positive, has a very low $p-$value, and is often quite large.

In these regressions, the oil volatility variable is never significant, and often positive (whereas the theory of investment under uncertainty implies it should be negative). The coefficients on the cost variable are of the correct sign (positive) in most of the regressions, and sometimes significant.

The explanatory power of these regressions is quite high.

The 12 month output per well regressions provide mixed evidence of learning effects. The own learning coefficients for three of the five basins are positive, but only two are statistically significant. Four of the five coefficients for the other experience variable are positive and significant: the negative one (Bakken) is not significant.

In all of output per well regressions, the coefficient on the oil price is negative. This suggests that producers drill less favorable prospects when prices are high.

The regressions for gas also provide strong evidence of learning. All of the own and other experience variables in the 12 month output regressions are positive, and eight of ten are statistically significant, usually at very high levels of significance. All of the experience coefficients in the well number equations are also positive, seven out of ten are significant at the 10 percent level, and six of ten at the 5 percent level.

All of the price coefficients in the well number regressions are positive, though only one is significant. The price coefficients in the 12 month output regressions are of the wrong sign in two of the basins, and none are significant. This reflects the fact that in the output per well regressions, the price coefficient tends to be strongly negative, and usually significant, indicating that gas producers expand output by drilling relatively unproductive wells when prices are are high. This behavior may also explain the fact that many of the learning coefficients in the output per well regressions are negative, and that only four (of ten) are positive and significant.

For the gas regressions, unlike the oil regressions, the coefficient on gas volatility is negative and significant at the five percent level (or better) for the 12 month output and well number regressions for all of the basins with the exception of Haynesville.

In sum, the empirical results are broadly supportive of the hypothesis that learning–especially learning from others–reduces drilling costs, and in particular, reduces the fixed cost of drilling. The impact of learning on the number of wells drilled (controlling for price and input prices) is the main evidence of the impact of learning on fixed costs.

These results are interesting in light of the earlier finding that learning does not reduce some cost-related variables, including most notably the speed of drilling. This suggests that learning affects costs on other dimensions, such as the cost of identifying promising drilling locations, depths, or directions, or the accuracy of these estimates.

5 The Contribution of Learning-by-Doing to U.S. Output Increases

The existence of statistically significant coefficients on experience variables in both productivity and cost regressions provides evidence of learning-by-doing, but begs the question of the economic significance of these effects. An analysis based on the estimated coefficients indicates that these effects are large.

The most straightforward measure of the economic contribution of learning effects is to use the estimated coefficients on the learning variables in the 12 month productivity regressions to estimate how much the drilling of a well at time t affects the cumulative production of wells drilled at $t' > t$.

Formally, a single well drilled by operator i at t increases log-own-experience for the firm drilling this well at $t' > t$ by $1/E_{t'}^{i,own}$ and log-other-experience by $1/E_{t'}^{j,other}$ for operator j. With own- and other-coefficients from the 12 month output regressions of β_{Q12}^{own} and β_{Q12}^{other}, respectively, the cumulative productivity gain resulting from operator i drilling a well at t is:

$$Q_t^{cum} \approx \sum_{t'>t} \sum_{j=1}^{N_o} \sum_{w=1}^{N_{w,j,t'}} [\beta_{Q12}^{own} \frac{\delta_i}{E_{t'}^{i,own}} + \beta_{Q12}^{other} \frac{1}{E_{t'}^{other}}] Q_{w,j,t'}$$

where $Q_{w,j,t'}$ is the 12 month output of well w drilled by operator j in month t', $\delta_i = 1$ if $j = i$ and $\delta_i = 0$ if $j \neq i$, and $N_{w,j}$ is the number of wells drilled by operator j in month t'.

This measure understates the impact of learning because it assumes that all wells drilled at t and at $t' > t$ would have been drilled regardless of learning effects. However, the cost regressions indicate that there are learning effects in cost, and that absent learning, fewer wells are drilled. Thus, full quantification of learning effects requires taking into account how much output would be affected had wells not been drilled in the absence of learning.

This effect is inherently dynamic. A well not drilled at t reduces future learning-induced cost reductions, which affects the number of wells drilled in the future. To quantify this effect, I make the conservative assumption that wells drilled prior to the beginning of the cost regression estimation period t_o contribute less learning-based capital than wells drilled during the estimation period. I therefore haircut the logs of own- and other-experience at t_0 by $-1 < h < 0$, and estimate that absent learning, the number of wells drilled in the first observation of the estimation period would have been reduced by:

$$\Delta N_w(t_0) = -h[\beta_{supply}^{own} + \beta_{supply}^{other}] N_w(t_0)$$

where β_{supply}^{own} (β_{supply}^{other}) is the coefficient on the own-experience (other-experience) variable in the supply curve regression.

If $h = -.025$, for instance, I assume that in the absence of learning effects 2.5 percent fewer wells would have been drilled prior to t_0. I then use the coefficients from the well-count regressions to estimate how many fewer wells would have been drilled at t_0 due to the elimination of learning effects.

For $t > t_0$,

$$\Delta N_w(t) \approx [\beta^{own}_{supply} \frac{\sum_{t'<t} \Delta N_w(t)}{N_o E^{own}_t} + \beta^{other}_{supply} \frac{\sum_{t'<t} \Delta N_w(t)}{E^{other}_t}] N_w(t)$$

In this expression $\sum_{t'<t} \Delta N_w(t)$ is the decline in total experience caused by previous declines in drilling due to elimination of learning effects. To calculate the impact on own-experience, I assume that this loss of experience is divided equally among the operators in a basin. The declines in experience are converted to percentages, multiplied by the coefficients on the log-experience variables, and then multiplied by the actual number of wells drilled at t to determine the decline in the number of wells drilled at t due to the assumed elimination of the effect of learning on the number of wells drilled.

This decline in wells has a direct impact on output. It is impossible to know which wells would not be drilled under this no-learning counterfactual, so to estimate the direct output effect I assume that each well drilled at t was equally likely not to be drilled under the counterfactual. Thus, if under the counterfactual 10 percent fewer wells are drilled at t, to calculate the direct impact at t I multiply the output of each well by -.1, and sum these products.[7]

To calculate the total impact of learning, taking into account both productivity effects and supply curve (cost) effects, I add the productivity impact

[7] This is arguably conservative because the least productive wells are most likely not to be drilled under the counterfactual.

and -1 times the direct output reduction effect. To avoid double counting (due to the fact that the productivity impact includes wells that would not be drilled under the counterfactual), I subtract the cumulative productivity gain attributable to the wells not drilled under the counterfactual.

Table VI presents the results by basin. To scale the results, I divide the impacts by the total 12 month output produced by all wells drilled in the sample period. The first column gives the productivity impact. The second column gives the combined impact, which takes into account the effect of learning on the supply curve, and hence the number of wells drilled.

These effects are economically large. The smallest total impact is .11 for Permian gas (a relatively small basin, with only 1100 wells in the sample), and the largest is .78 for Eagle Ford Gas. The median gas total impact is .19, and the median oil total impact is .38. The relative contributions of direct productivity effects and supply curve effects also varies by basin, with supply curve effects being 1 percentage point for Permian oil, and 78 percentage points for Eagle Ford gas. These results comport with the estimated impacts in the productivity and supply curve regressions.

These figures, though often large, likely understate the impact of learning due to the depletion effect discussed earlier. All else equal, drilling more wells tends to reduce productivity because of reservoir depletion and the tendency of operators to target more promising and lower-cost prospects first. This effect makes the coefficient on the other-experience variable in particular a downward biased estimate of learning effects. Despite this downward bias, learning contributes materially to output growth.

Learning-by-doing therefore is economically significant, as well as being statistically significant. Learning effects on productivity per well and the number of wells drilled account for a substantial fraction of the oil and gas produced from horizontal wells during the shale revolution.

6 Industry Structure

Learning-by-doing can affect dynamic pricing strategies (Rosen, 1972; Spence, 1981; Clarke, Darrough, and Heinecke, 1982). Furthermore, learning can also affect strategic interactions among firms, and these can lead to greater concentration and weaker competition (Fudenberg and Tirole, 1983; Dasgupta and Stiglitz, 1988; Petrakis, Rasmusen, and Roy, 1997). It can also incentivize predatory behavior (Cabral and Riordan, 1994, 1997; Hollis, 2002; Thompson, 2010).

To examine how industry structure has evolved over the period of the shale revolution, Figure 5 depicts monthly Hirshman-Herfindahl Indices for the oil basins, and Figure 6 depicts the HHIs for the gas basins. All basins exhibit similar behavior. Although concentration is moderately high early in each basin's history, it declines relatively rapidly, remains low, and exhibits no upward trend. Once basins are mature, after a few years of experience, drilling activity is very unconcentrated.

Indeed, the figures overstate the degree of concentration because they are based on monthly calculations. Many operators do not drill every month, meaning that over longer intervals (*e.g.,* over a year) market shares are smaller for those who do drill every month (or almost every month) and larger for those who drill less regularly. This makes lower-frequency HHIs smaller than depicted in the figures.

The absence of any trend towards greater concentration–and if anything, a trend in the opposite direction–suggests that learning-by-doing has little or no major effect on the nature of strategic interactions between firms. This plausibly reflects that even the biggest horizontal drillers in a particular basin are price takers, given the international scope of the oil market and the national scope of the natural gas market, and the existence of large legacy production.

7 Are Other-Experience Effects Evidence of Spillovers?

Although the absence of concentration trends suggests a lack of strategic interaction between drillers due to their lack of pricing power in the relevant global or national markets, it also provides evidence on the nature of the other-learning effects, which for some productivity measures for some basins, and for supply curves, are the dominant source of learning effects. The existence of such cross-firm effects is a necessary but not sufficient condition for learning externalities ("spillovers"): such measured cross-firm effects may be internalized through some mechanism.

If there is no mechanism to internalize cross-firm effects, their existence would provide a strong incentive for firms to merge in order to internalize them. Although there have been some mergers among shale operators, the HHIs presented in Figures 1 and 2 demonstrate that there has been no trend to consolidate in order to internalize learning effects. This provides indirect evidence that they have been internalized through some other mechanism.

One plausible mechanism is oil services firms who operate rigs, as hypothesized by Kellogg. Although data on rig-operator combinations analogous to Kellogg's is not available to me, service firm learning can explain both cross-operator learning effects and the absence of any increasing trend in concentration. Service firms that learn from their experience in drilling wells can incorporate their learning in their pricing. Learning that enhances well productivity allows them to charge higher prices for their services. Learning that reduces their costs allows them to sell at lower prices.

The oil services business is relatively concentrated. It interesting to note, however, that this industry became more concentrated during the shale revolution, with the merger of Halliburton and Brown & Root.

8 Learning and the Viability of Predatory Raising Rivals' Costs Strategies

Theoretical research suggests that learning-by-doing can make predatory, raising rivals' costs strategies profitable (Cabral and Riordan 1994, 1997; Hollis 2002; Thompson 2010). As Thompson (2012) notes, the specifics of the learning process affect the profitability of various strategies. For example, if learning effects are unbounded, an incumbent may have the incentive to lower prices to reduce the output of competitors that learn, but if learning effects are bounded, a large incumbent may prefer more entry because it fragments learning. But if there are cross-firm learning effects, this fragmentation may not benefit the incumbent. Though the theoretical predictions are diverse and often contradictory, based on modeling assumptions, it is nonetheless the case that there are circumstances in which a large incumbent might find it profitable to impede learning by competitors in order to raise their costs.

From the autumn of 2014 through April, 2016, a large incumbent oil producer–Saudi Arabia–raised output by approximately 9.6 percent in the face of declining demand. Oil prices fell dramatically during this period, from approximately $80/bbl on 31 October 2014 to $60/bbl on 1 June 2015. One rationale given for the Saudis' actions was that it was threatened by the rise of the U.S. shale oil sector, and wanted to force that sector to contract by lowering prices. Some explanations of Saudi behavior were more along the lines that they were trying to drive American producers into financial distress in order to induce them to exit the industry, but these explanations run into the standard objections to the rationality of predatory pricing.

A more subtle rationale is that by reducing prices, and thereby reducing U.S. drilling activity, the Saudis reduced the rate of learning-driven technological progress in the shale sector, and thereby caused the future supply curve for American oil to be higher than it would have been absent the Saudi output increases. This increase in shale drilling rivals' costs would have raised the derived future demand for Saudi oil, and permitted them to sell at higher prices in the future.

The results of the supply curve analysis make it possible to determine the profitability of this strategy. The results are readily summarized. Although the Saudi actions did cause a reduction in American drilling activity, the industry was already sufficiently advanced and so much learning had aready occurred that this reduction did not reduce learning sufficiently to have a material effect on the U.S. oil supply curve.

The details of the analysis are as follows. Given that learning is dynamic, I calculate dynamic supply effects. First, I posit that from November, 2014 through March, 2015, Saudi actions caused the price of crude oil to be 20 percent lower than it would have been absent the assumed predatory strategy. In November, 2014, for each oil basin (Permian, Eagle Ford, Bakken, Niobrara, and StackScoop), I use the estimated N^w equations to estimate how many more wells would have been drilled had the Saudis not driven down the price, *i.e.,* if the price had been 20 percent higher. Since the price elasticities in each basin are positive, this number is positive.

I then increase the beginning of December, 2014 learning variables to reflect this increase in activity in the but-for price scenario. I increment the average own-learning experience by the incremental number of wells divided by the number of firms that spudded wells in that month.[8] I increment the average other-experience variable by the incremental number of wells.[9] I use the estimated learning coefficients and these but-for experience variables to calculate a but-for supply curve for December, 2015. Given this but-for supply curve, I use the price elasticity coefficient to determine the additional number of wells that would have been drilled at the higher price. I then increment the learning variables for January, 2016, and repeat the process for that much and each subsequent month through March, 2016.

Given these but-for well number, learning, and price variables, and the coefficients from the $Q_{12,j,t}$ equations, I calculate but-for outputs for each month November, 2014-March, 2016. Finally, I calculate the difference between the estimated April, 2016 and but-for 2016 supply curves.

The analysis implies that the U.S. shale output would have been higher by approximately 750,000 barrels per day if prices had been 20 percent higher. This is actually a smaller amount than by which it is estimated that Saudi Arabia reduced output (approximately 980,000 barrels). Figure 7 illustrates the actual and but-for supply curves horizontally summed across all basins. The distances between these curves is small, on the order of 22,500 bpd at a price of \$70. Thus, the Saudi pricing strategy did not appreciably raise the post-predation-OPEC+ derived demand for Saudi (or OPEC+) oil.

This result reflects the logarithmic learning impact functions, and the fact that the Saudis implemented their strategy when the shale oil sector was relatively mature and had accumulated a substantial amount of experience.

[8] This assumption tends to exaggerate the learning impact, because in the but-for higher price world, more firms may have drilled than did in the actual, low price world.

[9] This also tends to exaggerate learning, because it effectively double counts, including each well in both the own-experience and other-experience variables.

Due to the logarithmic learning impact, the incremental effect of any learning foregone as a result of lower drilling activity in response to aggressive Saudi pricing was small.

9 Summary and Conclusions

The existence of a "shale revolution" is impossible to deny. But what are its causes? This article documents that learning-by-doing–experiential learning–has been an important driver of that revolution. Using conventional measures of experience I document that learning-by-doing has materially increased the productivity of unconventional wells on some dimensions–notably maximum production–but not others–notably decline rates. For well productivity, within-firm learning effects are pronounced, but cross-firm learning effects are more equivocal. However, interpretation of the latter result is complicated by confounding factors, namely that increases in industry-wide experience are accompanied by development of progressively less productive wells.

I show that measures of learning also reduce drilling costs, especially fixed costs. Holding prices constant, more experience results in an increase in the number of wells drilled, as would occur as the result in a decline in fixed costs.

The contributions of learning to output increases are large, around 20 percent for natural gas and 40 percent for oil. Thus, although learning is important, other factors are also at work in driving the output increases. The sources of these increases are a worthy subject of future research.

Table I.1
Permian Oil 12 Month Output

Variable	Coefficient	SE	$t-$stat	$p-$value
Constant	-6.1046	0.6863	-8.8948	0.0000
Density	-0.0142	0.0043	-3.2805	0.0005
Price	-0.0062	0.0004	-13.9066	0.0000
ln(Depth)	1.5542	0.0628	24.7373	0.0000
ln(Own)	0.0743	0.0050	14.7512	0.0000
ln(Other)	0.1521	0.0241	6.3122	0.0000
Time	0.0000	0.0000	2.1483	0.0158

Table I.2
Eagle Ford Oil 12 Month Output

Variable	Coefficient	SE	$t-$stat	$p-$value
Constant	-8.277	0.599	-13.811	0.000
Density	0.009	0.004	2.245	0.012
Price	-0.002	0.001	-3.383	0.000
ln(Depth)	1.989	0.060	33.113	0.000
ln(Own)	0.115	0.005	21.313	0.000
ln(Other)	-0.007	0.015	-0.452	0.325
Time	0.000	0.000	-0.097	0.461

Table I.3
Bakken Oil 12 Month Output

Variable	Coefficient	SE	$t-$stat	$p-$value
Constant	2.7233	0.4111	6.6242	0.0000
Density	-0.0031	0.0030	-1.0369	0.1499
Price	-0.0044	0.0005	-8.8677	0.0000
ln(Depth)	0.7057	0.0405	17.4426	0.0000
ln(Own)	0.0209	0.0058	3.6259	0.0001
ln(Other)	0.1146	0.0338	3.3932	0.0003
Time	0.0001	0.0000	2.5673	0.0051

Table I.4
Niobrara Oil 12 Month Output

Variable	Coefficient	SE	$t-$stat	$p-$value
Constant	2.3222	0.9590	2.4215	0.0077
Density	-0.0584	0.0307	-1.9022	0.0286
Price	-0.0023	0.0013	-1.7715	0.0382
ln(Depth)	0.2094	0.1050	1.9952	0.0230
ln(Own)	0.0758	0.0280	2.7035	0.0034
ln(Other)	0.2291	0.0566	4.0470	0.0000
Time	0.0001	0.0000	8.3121	0.0000

Table I.5
StackScoop Oil 12 Month Output

Variable	Coefficient	SE	$t-$stat	$p-$value
Constant	-2.5435	1.1876	-2.1417	0.0161
Density	-0.1675	0.0249	-6.7359	0.0000
Price	-0.0038	0.0018	-2.1888	0.0143
ln(Depth)	0.6053	0.1142	5.2984	0.0000
ln(Own)	0.0653	0.0157	4.1582	0.0000
ln(Other)	0.8918	0.1691	5.2731	0.0000
Time	0.00002	0.00008	0.3263	0.3721

Table I.6
Marcellus Gas 12 Month Output

Variable	Coefficient	SE	$t-$stat	$p-$value
Constant	-0.0673	2.3994	-0.0281	0.4888
Density	-0.0006	0.0078	-0.0705	0.4719
Price	-0.1251	0.0377	-3.3163	0.0005
ln(Depth)	1.5510	0.2556	6.0691	0.0000
ln(Own)	0.0528	0.0237	2.2265	0.0130
ln(Other)	-0.0965	0.0585	-1.6497	0.0495
Time	0.0002	0.0000	4.4187	0.0000

Table I.7				
Haynesville Gas 12 Month Output				
Variable	Coefficient	SE	$t-$stat	$p-$value
Constant	-16.1554	0.8952	-18.0471	0.0000
Density	0.0199	0.0094	2.1221	0.0169
Price	-0.0449	0.0100	-4.4775	0.0000
ln(Depth)	3.0183	0.0951	31.7302	0.0000
ln(Own)	-0.0068	0.0119	-0.5725	0.2835
ln(Other)	0.1569	0.0329	4.7640	0.0000
Time	0.0000	0.0000	0.0980	0.4610

Table I.8				
Barnett Gas 12 Month Output				
Variable	Coefficient	SE	$t-$stat	$p-$value
Constant	-0.5842	0.7394	-0.7901	0.2147
Density	0.0495	0.0034	14.5531	0.0000
Price	-0.0030	0.0042	-0.7193	0.2360
ln(Depth)	1.6999	0.0688	24.6919	0.0000
ln(Own)	0.1277	0.0054	23.5997	0.0000
ln(Other)	-0.1003	0.0172	-5.8235	0.0000
Time	-0.0001	0.0000	-3.6549	0.0001

Table I.9				
Eagle Ford Gas 12 Month Output				
Variable	Coefficient	SE	$t-$stat	$p-$value
Constant	-1.9458	0.6050	-3.2161	0.0006
Density	-0.0269	0.0068	-3.9429	0.0000
Price	0.0225	0.0144	1.5632	0.0590
ln(Depth)	1.6476	0.0587	28.0674	0.0000
ln(Own)	-0.0188	0.0090	-2.0786	0.0188
ln(Other)	-0.3338	0.0386	-8.6530	0.0000
Time	0.0004	0.0000	12.6305	0.0000

Table I.10 Permian Gas 12 Month Output				
Variable	Coefficient	SE	$t-$stat	$p-$value
Constant	-4.1475	1.4258	-2.9089	0.0018
Density	0.0092	0.0215	0.4278	0.3344
Price	0.0483	0.0208	2.3199	0.0102
ln(Depth)	1.6535	0.1429	11.5715	0.0000
ln(Own)	0.0738	0.0212	3.4827	0.0002
ln(Other)	-0.3567	0.0648	-5.5057	0.0000
Time	0.0003	0.0000	5.5115	0.0000

Table II.1 Permian Oil Decline Rate				
Variable	Coefficient	SE	$t-$stat	$p-$value
Constant	0.1967	0.0400	4.9173	0.0000
Decline	-0.0014	0.0006	-2.0931	0.0182
Price	0.0001	0.0000	3.6385	0.0001
ln(Depth)	-0.0087	0.0041	-2.1468	0.0159
ln(Own)	-0.0004	0.0006	-0.6627	0.2537
ln(Other)	-0.0141	0.0016	-8.6626	0.0000
Time	0.0000	0.0000	-2.8520	0.0022

Table II.2 Eagle Ford Oil Decline Rate				
Variable	Coefficient	SE	$t-$stat	$p-$value
Constant	0.2386	0.0589	4.0489	0.0000
Density	-0.0005	0.0004	-1.3090	0.0953
Price	0.0002	0.0000	4.6450	0.0000
ln(Depth)	-0.0251	0.0058	-4.3330	0.0000
ln(Own)	-0.0003	0.0006	-0.5081	0.3057
ln(Other)	0.0022	0.0016	1.3663	0.0859
Time	-0.00001	0.0000	-4.2686	0.0000

Table II.3 Bakken Oil Decline Rate				
Variable	Coefficient	SE	$t-$stat	$p-$value
Constant	0.0328	0.0426	0.7684	0.2211
Density	0.0004	0.0006	0.7314	0.2323
Price	0.0001	0.0001	1.6274	0.0518
ln(Depth)	0.0074	0.0035	2.1160	0.0172
ln(Own)	-0.0002	0.0005	-0.4959	0.3100
ln(Other)	0.0159	0.0056	2.8380	0.0023
Time	-0.00003	0.0000	-4.7618	0.0000

Table II.4 Niobrara Oil Decline Rate				
Variable	Coefficient	SE	$t-$stat	$p-$value
Constant	0.9610	0.7060	1.3612	0.0867
Density	-0.0029	0.0024	-1.2145	0.1123
Price	0.0000	0.0002	-0.1074	0.4572
ln(Depth)	-0.0026	0.0051	-0.5153	0.3032
ln(Own)	-0.0039	0.0025	-1.5202	0.0642
ln(Other)	0.0289	0.0333	0.8691	0.1924
Time	-0.00003	0.0000	-1.3206	0.0933

Table II.5 StackScoop Oil Decline Rate				
Variable	Coefficient	SE	$t-$stat	$p-$value
Constant	0.2989	0.3956	0.7556	0.2250
Density	0.0010	0.0026	0.3654	0.3574
Price	0.0001	0.0003	0.3614	0.3589
ln(Depth)	0.0469	0.0126	3.7312	0.0001
ln(Own)	0.0045	0.0032	1.4046	0.0801
ln(Other)	0.0571	0.0684	0.8346	0.2020
Time	-0.0001	0.0001	-1.5367	0.0622

Table II.6 Marcellus Gas Decline Rate				
Variable	Coefficient	SE	$t-$stat	$p-$value
Constant	-0.0652	0.0442	-1.4774	0.0698
Density	-0.00002	0.0009	-0.0199	0.4920
Price	0.0036	0.0016	2.2000	0.0139
ln(Depth)	-0.0044	0.0043	-1.0305	0.1514
ln(Own)	-0.0011	0.0011	-1.0257	0.1525
ln(Other)	0.0088	0.0037	2.3739	0.0088
Time	-0.00001	0.0000	-3.9371	0.0000

Table II.7
Haynesville Gas Decline Rate

Variable	Coefficient	SE	$t-$stat	$p-$value
Constant	0.269	0.075	3.607	0.000
Density	-0.001	0.001	-0.912	0.181
Price	-0.0001	0.001	-0.207	0.418
ln(Depth)	-0.042	0.007	-6.050	0.000
ln(Own)	0.002	0.001	2.225	0.013
ln(Other)	-0.009	0.003	-2.783	0.003
Time	0.00001	0.000	3.489	0.000

Table II.8
Barnett Gas Decline Rate

Variable	Coefficient	SE	$t-$stat	$p-$value
Constant	-0.1607	0.0694	-2.3156	0.0103
Density	-0.0004	0.0003	-1.4011	0.0806
Price	-0.0005	0.0004	-1.0736	0.1415
ln(Depth)	-0.0026	0.0067	-0.3851	0.3501
ln(Own)	-0.0006	0.0013	-0.4598	0.3228
ln(Other)	-0.0031	0.0019	-1.6017	0.0546
Time	0.00001	0.0000	3.1551	0.0008

Table II.9
Eagle Ford Gas Decline Rate

Variable	Coefficient	SE	$t-$stat	$p-$value
Constant	-0.1607	0.0694	-2.3156	0.0103
Density	-0.0004	0.0003	-1.4011	0.0806
Price	-0.0005	0.0004	-1.0736	0.1415
ln(Depth)	-0.0026	0.0067	-0.3851	0.3501
ln(Own)	-0.0006	0.0013	-0.4598	0.3228
ln(Other)	-0.0031	0.0019	-1.6017	0.0546
Time	0.00001	0.0000	3.1551	0.0008

Table II.10 Permian Gas Decline Rate				
Variable	Coefficient	SE	$t-$stat	$p-$value
Constant	0.0887	0.2041	0.4343	0.3320
Density	0.0005	0.0045	0.1158	0.4539
Price	-0.0054	0.0031	-1.7330	0.0415
ln(Depth)	0.0000	0.0194	-0.0022	0.4991
ln(Own)	-0.0034	0.0030	-1.1395	0.1272
ln(Other)	0.0303	0.0095	3.1997	0.0007
Time	-0.00003	0.0000	-3.0703	0.0011

Table III.1 Permian Oil Drilling Speed				
Variable	Coefficient	SE	$t-$stat	$p-$value
Constant	-15.9406	2.6463	-6.0238	0.0000
Density	-0.0369	0.0049	-7.6139	0.0000
Price	0.0061	0.0010	6.3312	0.0000
ln(Own)	0.0196	0.0052	-3.7260	0.0001
ln(Other)	-1.1905	0.1423	-8.3684	0.0000
Time	0.0012	0.0001	8.1068	0.0000

Table III.2 Eagle Ford Oil Drilling Speed				
Variable	Coefficient	SE	$t-$stat	$p-$value
Constant	-3.1926	0.7179	-4.4472	0.0000
Density	-0.0241	0.0058	-4.1206	0.0000
Price	0.0125	0.0010	12.3298	0.0000
ln(Own)	0.0000	0.0055	0.0015	0.4994
ln(Other)	-0.8405	0.0463	-18.1632	0.0000
Time	0.0011	0.0001	14.2231	0.0000

Table III.3 Bakken Oil Drilling Speed				
Variable	Coefficient	SE	$t-$stat	$p-$value
Constant	-1.3272	0.2786	4.7636	0.0000
Density	-0.0429	0.0032	-13.5361	0.0000
Price	0.7609	0.0278	27.3308	0.0000
ln(Own)	-0.0469	0.0048	-9.8194	0.0000
ln(Other)	-0.3332	0.0290	-11.4933	0.0000
Time	0.0002	0.0000	5.9807	0.0000

Table III.4 Niobrara Oil Drilling Speed				
Variable	Coefficient	SE	$t-$stat	$p-$value
Constant	-33.4000	18.9043	-1.7668	0.0386
Density	-0.1608	0.0359	-4.4770	0.0000
Price	0.8443	0.0764	11.0560	0.0000
ln(Own)	-0.1165	0.0483	-2.4112	0.0080
ln(Other)	-1.7922	0.9252	-1.9372	0.0264
Time	0.0012	0.0007	1.7305	0.0418

Table III.5 StackScoop Oil Drilling Speed				
Variable	Coefficient	SE	$t-$stat	$p-$value
Time	-5.0739	4.0370	-1.2568	0.1044
Density	-0.1054	0.0154	-6.8328	0.0000
Price	0.3157	0.1195	2.6409	0.0041
ln(Own)	-0.1490	0.0288	-5.1749	0.0000
ln(Other)	-1.5928	0.7830	-2.0341	0.0210
Time	0.0012	0.0006	2.1692	0.0150

Table III.6 Marcellus Gas Drilling Speed				
Variable	Coefficient	SE	$t-$stat	$p-$value
Constant	-0.0459	1.3980	-0.0329	0.4869
Density	-0.0089	0.0072	-1.2362	0.1082
Price	-0.1471	0.0387	3.7974	0.0001
ln(Own)	-0.0634	0.0172	-3.6926	0.0001
ln(Other)	-0.5695	0.0653	-8.7162	0.0000
Time	0.0006	0.0000	11.8808	0.0000

Table III.7 Haynesville Gas Drilling Speed				
Constant	8.8321	0.7944	11.1178	0.0000
Density	-0.0313	0.0103	-3.0475	0.0012
Price	0.0303	0.0111	2.7186	0.0033
ln(Own)	-0.0424	0.0080	-5.3115	0.0000
ln(Other)	-0.4167	0.0343	-12.1454	0.0000
Time	0.0003	0.0000	9.1583	0.0000

Table III.8
Barnett Gas Drilling Speed

Variable	Coefficient	SE	$t-$stat	$p-$value
Constant	-13.9012	2.3333	-5.9577	0.0000
Density	0.0970	0.0050	19.4245	0.0000
Price	-0.0167	0.0153	-1.0887	0.1381
ln(Own)	0.0500	0.0063	7.9760	0.0000
ln(Other)	-0.3147	0.0702	-4.4835	0.0000
Time	0.0006	0.0001	5.4299	0.0000

Table III.9
Eagle Ford Gas Drilling Speed

Variable	Coefficient	SE	$t-$stat	$p-$value
Constant	10.1904	0.3137	32.4823	0.0000
Density	-0.0525	0.0100	-5.2766	0.0000
ln(Own)	-0.0736	0.0087	-8.4780	0.0000
ln(Other)	-1.0644	0.0594	-17.9207	0.0000
Time	0.0009	0.0000	18.6742	0.0000

Table III.10
Permian Gas Drilling Speed

Variable	Coefficient	SE	$t-$stat	$p-$value
Constant	1.5582	0.7523	2.0713	0.0192
Density	-0.0745	0.0260	-2.8691	0.0021
Price	0.1480	0.0354	4.1842	0.0000
ln(Own)	-0.0458	0.0219	-2.0911	0.0183
ln(Other)	-1.0075	0.1700	-5.9258	0.0000
Time	0.0008	0.0001	6.6234	0.0000

Table IV.A Oil 12 Month Production					
Variable	Eagle Ford	Permian	Bakken	Niobrara	StackScoop
Time	0.001§	0.001†	-0.001‡	0.000	-0.002†
ln(Own)	0.249§	0.145†	0.082	-0.046	0.321†
ln(Other)	0.510‡	0.579‡	1.444‡	3.399‡	3.878‡
Volatility	-0.076	-0.158	-0.150	0.299	0.112
ln(POil)	2.945‡	1.191‡	0.558‡	2.472‡	0.401
ln(PGas)	-2.212‡	-0.389‡	0.319‡	-0.111	0.272
ln(RigPPI)	-10.155†	-6.591‡	0.212	-0.758	8.596§
InteractOwn	-0.058†	0.011	0.010	0.010	0.014
InteractOther	-0.040§	-0.132‡	-0.006	-0.065	-0.220‡
R^2	.93	.96	.86	.85	.91
‡Significant at 1 percent level †Significant at 5 percent level §Significant at 10 percent level					

Table IV.B Oil Number of Wells Drilled					
Variable	EagleFord	Permian	Bakken	Niobrara	StackScoop
Time	0.001	0.001‡	-0.001‡	0.000	0.000
ln(Own)	0.162	-0.040	0.054	-0.005	0.388†
ln(Other)	0.443‡	0.356†	1.650‡	2.364‡	0.939
Volatility	0.054	-0.185	-0.083	0.322	0.390§
ln(POil)	2.466‡	1.501‡	0.592‡	3.335‡	0.962‡
ln(PGas)	-1.502	-0.563	0.216‡	-0.539§	0.023
ln(RigPPI)	-7.867	-1.178	-1.987	-6.956	8.074‡
InteractOwn	-0.046	-0.018§	-0.006	-0.064†	-0.004
InteractOther	-0.068§	-0.108‡	-0.028	-0.001	-0.182‡
R^2	.91	.95	.86	.82	.90
‡Significant at 1 percent level †Significant at 5 percent level §Significant at 10 percent level					

Table IV.C Per Well 12 Month Output					
Variable	EagleFord	Permian	Bakken	Niobrara	StackScoop
Time	0.000	0.000‡	0.000†	0.000†	-0.001†
ln(Own)	0.087†	0.185‡	0.028	-0.040	-0.067
ln(Other)	0.067§	0.223‡	-0.206	1.035‡	2.940‡
Volatility	-0.130	0.027	-0.067	-0.024	-0.277†
ln(POil)	0.479†	-0.310†	-0.034	-0.863‡	-0.561§
ln(PGas)	-0.710‡	0.174§	0.103§	0.428	0.249
ln(RigPPI)	-2.288§	-5.414‡	2.199‡	6.197§	0.522
InteractOwn	-0.012§	0.029‡	0.016†	0.074‡	0.018
InteractOther	0.028†	-0.024‡	0.022‡	-0.063‡	-0.03†
R^2	.88	.89	.93	.60	.87
‡Significant at 1 percent level †Significant at 5 percent level §Significant at 10 percent level					

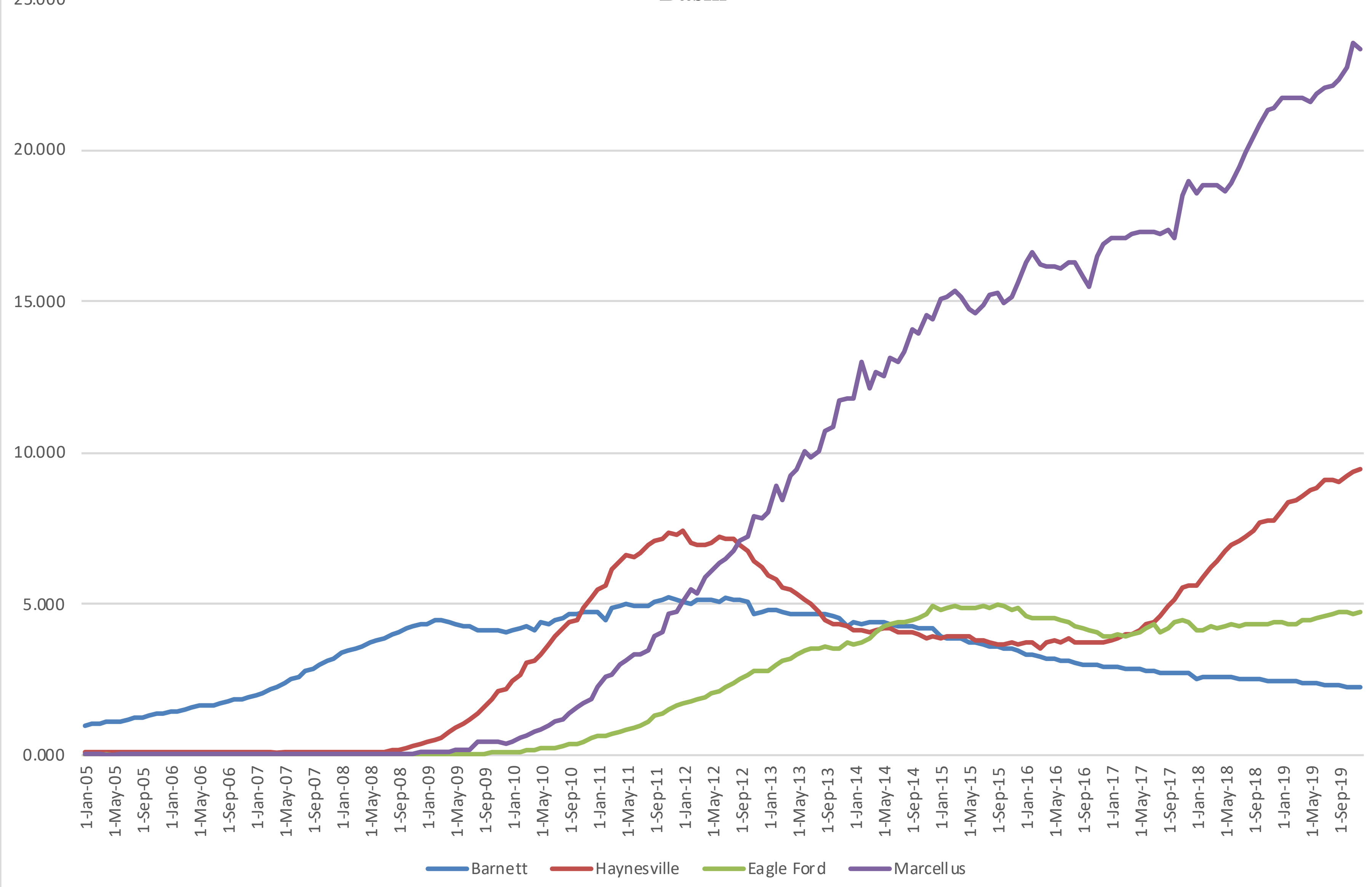
Table V.A Gas 12 Month Production					
Variable	Eagle Ford	Permian	Marcellus	Barnett	Haynesville
Time	-0.001‡	0.001‡	-0.001‡	-0.001‡	-0.001‡
ln(Own)	0.456‡	0.582‡	0.347†	0.589‡	0.339
ln(Other)	1.607‡	0.010	0.764‡	1.391‡	1.942‡
Volatility	-1.382‡	-0.287	-0.379	-0.990‡	-1.267‡
ln(RigPPI)	16.680‡	-6.251	30.485‡	-0.113	2.508
InteractOwn	-0.138	0.067	0.025	-0.044‡	-0.092†
InteractOther	0.006	-0.096‡	-0.080‡	-0.007	-0.108‡
ln(PGas)	-0.083	0.678	-0.979	0.624†	-1.821‡
R^2	.84	.68	.76	.87	.77
‡Significant at 1 percent level †Significant at 5 percent level §Significant at 10 percent level					

Table V.B Gas Number of Wells Drilled					
Variable	Eagle Ford	Permian	Marcellus	Barnett	Haynesville
Time	-0.002‡	0.001§	-0.001‡	-0.002‡	-0.001‡
ln(Own)	0.567‡	0.308‡	0.153	0.247‡	0.142
ln(Other)	1.817‡	1.016	0.815‡	1.712‡	1.756‡
Volatility	-1.284‡	-0.316	-0.291	-1.077‡	-0.799‡
ln(RigPPI)	17.403‡	-6.672	19.782‡	-0.408	1.070†
InteractOwn	-0.141	0.034	0.028	-0.012	-0.075†
InteractOther	-0.011	-0.091‡	-0.066	0.015	-0.085‡
ln(PGas)	0.281	0.908§	-0.524	0.848‡	-0.497
R^2	.84	.61	.68	.91	.66
‡Significant at 1 percent level †Significant at 5 percent level §Significant at 10 percent level					

Table V.C Per Well 12 Month Output					
Variable	Eagle Ford	Permian	Marcellus	Barnett	Haynesville
Time	0.000‡	0.000‡	0.000	0.000§	0.000§
ln(Own)	-0.110‡	0.274‡	0.194‡	0.342‡	0.196†
ln(Other)	-0.211†	-1.007†	-0.050	-0.321§	0.187
Volatility	-0.098	0.029	-0.088	0.088	-0.468‡
ln(RigPPI)	-0.722	0.421	10.70‡	0.296	1.439§
InteractOwn	0.003	0.033§	-0.003	-0.032†	-0.017§
InteractOther	0.017‡	-0.005	-0.014‡	-0.022‡	-0.023‡
ln(PGas)	-0.364‡	-0.230	-0.455‡	-0.224	-1.324‡
R^2	69	.50	.90	.37	.88
‡Significant at 1 percent level †Significant at 5 percent level §Significant at 10 percent level					

Table VI Learning Contribution to Output		
Basin	Productivity Ratio	Combined Ratio
Permian Oil	.30	.30
Eagle Ford Oil	.17	.17
Bakken	.11	.42
Niobrara	.29	.39
StackScoop	.72	.74
Permian Gas	.07	.12
Eagle Ford Gas	.01	.75
Marcellus	.11	.15
Barnett	.12	.61
Haynesville	.15	.19

Figure 1
United States Gas Production by Basin



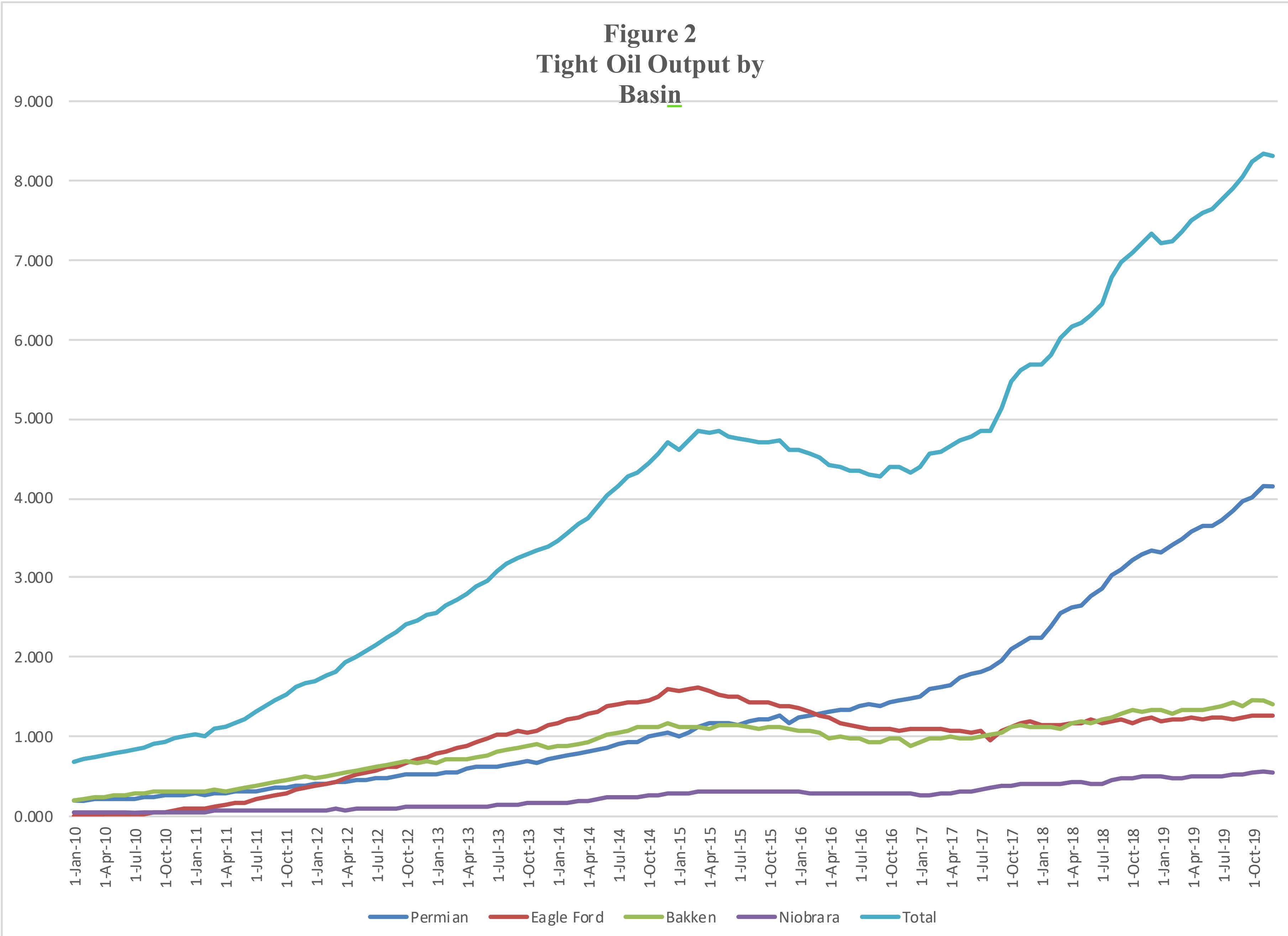


Figure 2
Tight Oil Output by
Basin
9.000
8.000
7.000
6.000
5.000
4.000
3.000
2.000
1.000
0.000
1-Jan-10
1-Apr-10
1-Jul-10
1-Oct-10
1-Jan-11
1-Apr-11
1-Jul-11
1-Oct-11
1-Jan-12
1-Apr-12
1-Jul-12
1-Oct-12
1-Jan-13
1-Apr-13
1-Jul-13
1-Oct-13
1-Jan-14
1-Apr-14
1-Jul-14
1-Oct-14
1-Jan-15
1-Apr-15
1-Jul-15
1-Oct-15
1-Jan-16
1-Apr-16
1-Jul-16
1-Oct-16
1-Jan-17
1-Apr-17
1-Jul-17
1-Oct-17
1-Jan-18
1-Apr-18
1-Jul-18
1-Oct-18
1-Jan-19
1-Apr-19
1-Jul-19
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Permian
Eagle Ford
Bakken
Niobrara
Total

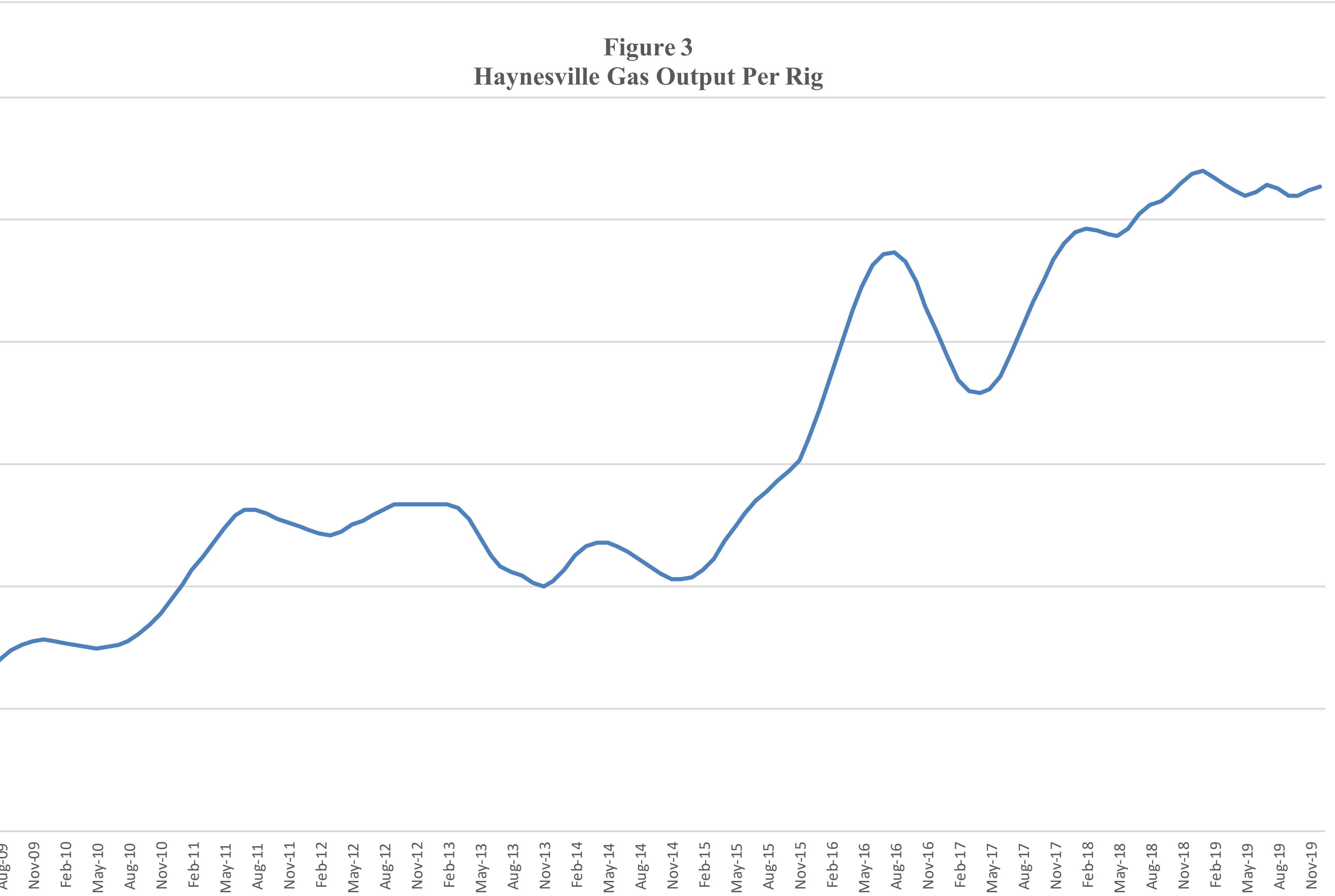


Figure 3
Haynesville Gas Output Per Rig
Aug-09
Nov-09
Feb-10
May-10
Aug-10
Nov-10
Feb-11
May-11
Aug-11
Nov-11
Feb-12
May-12
Aug-12
Nov-12
Feb-13
May-13
Aug-13
Nov-13
Feb-14
May-14
Aug-14
Nov-14
Feb-15
May-15
Aug-15
Nov-15
Feb-16
May-16
Aug-16
Nov-16
Feb-17
May-17
Aug-17
Nov-17
Feb-18
May-18
Aug-18
Nov-18
Feb-19
May-19
Aug-19
Nov-19

Figure 4
Permian Oil Output/Rig

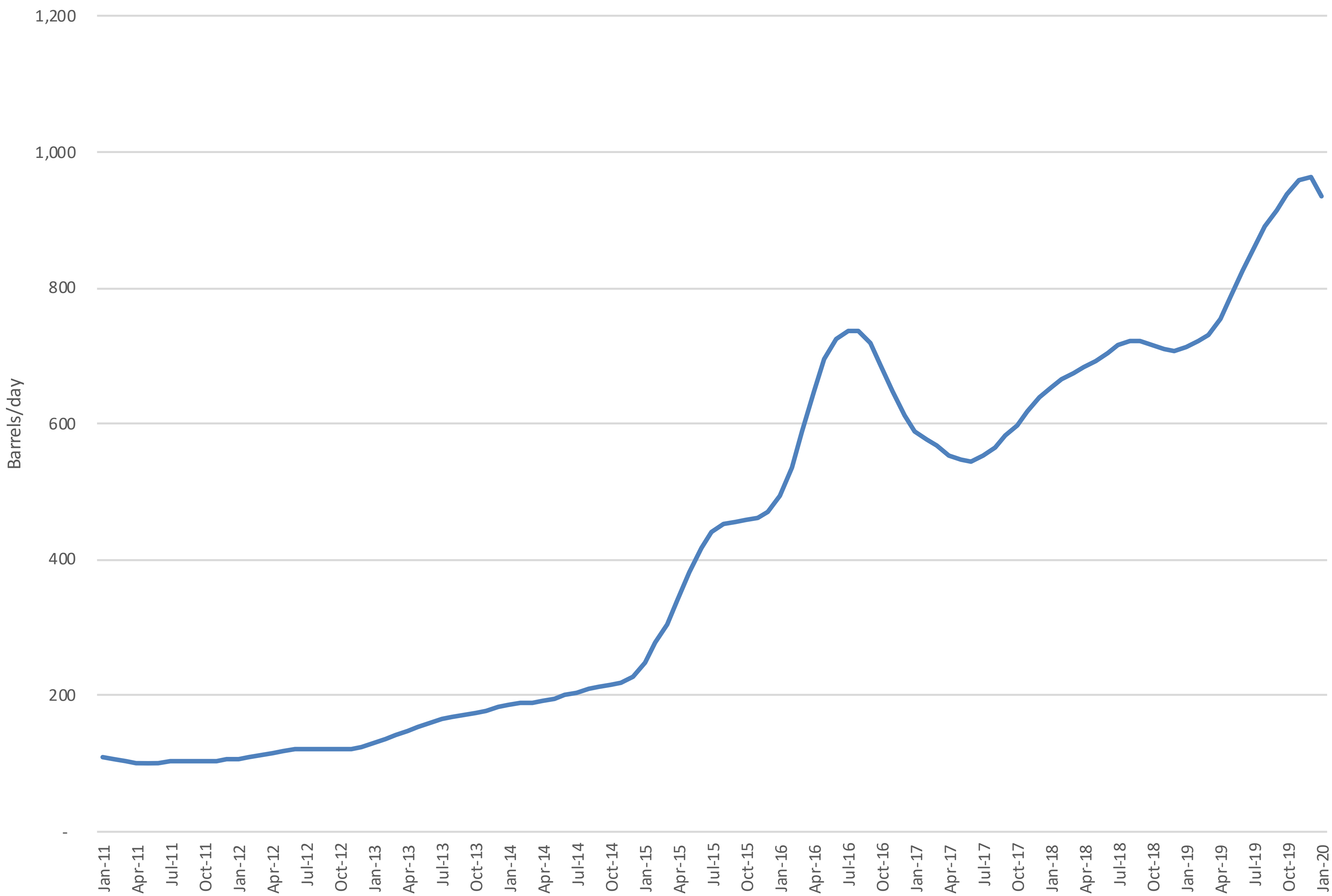


Figure 5
Gas Basin HHIs

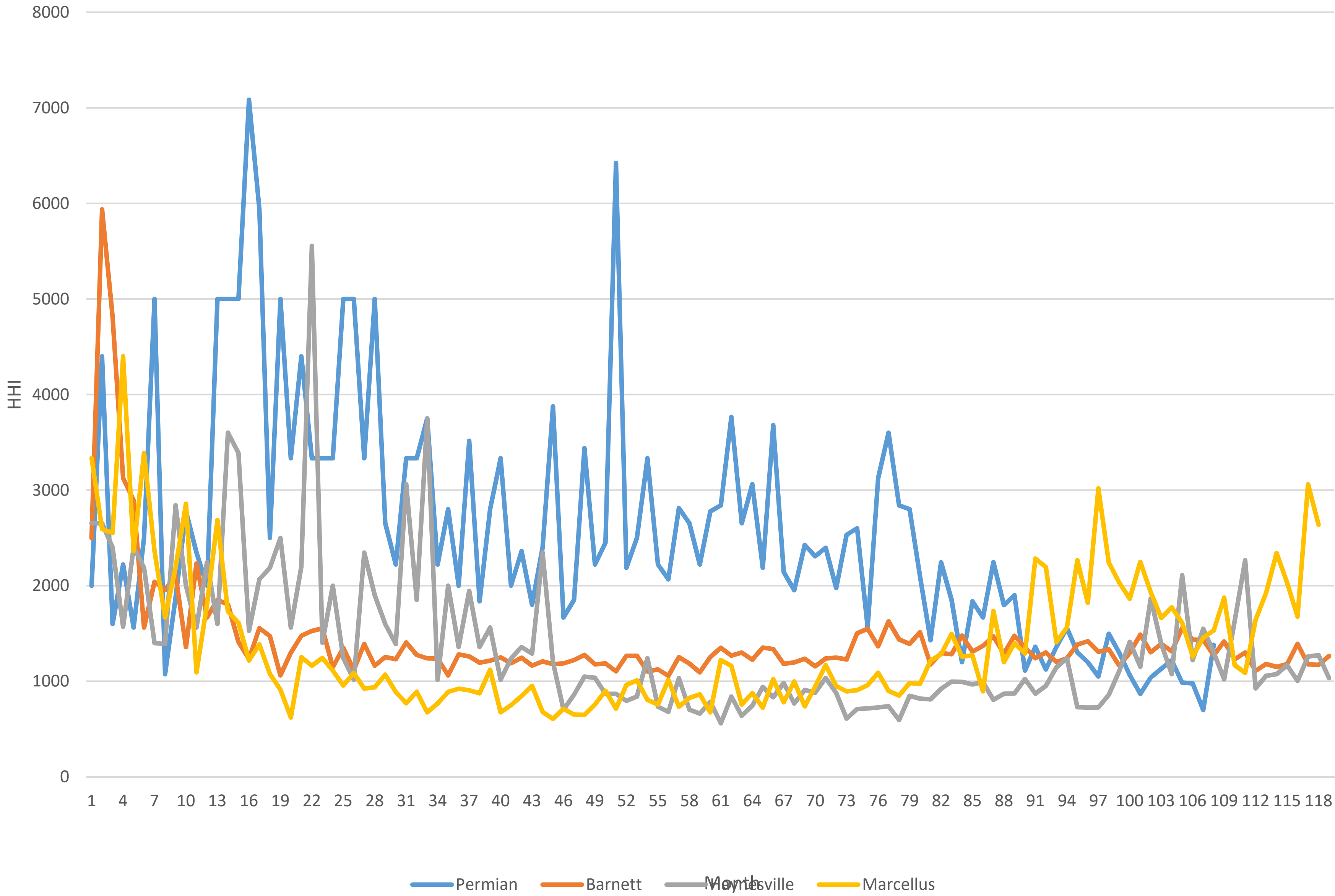
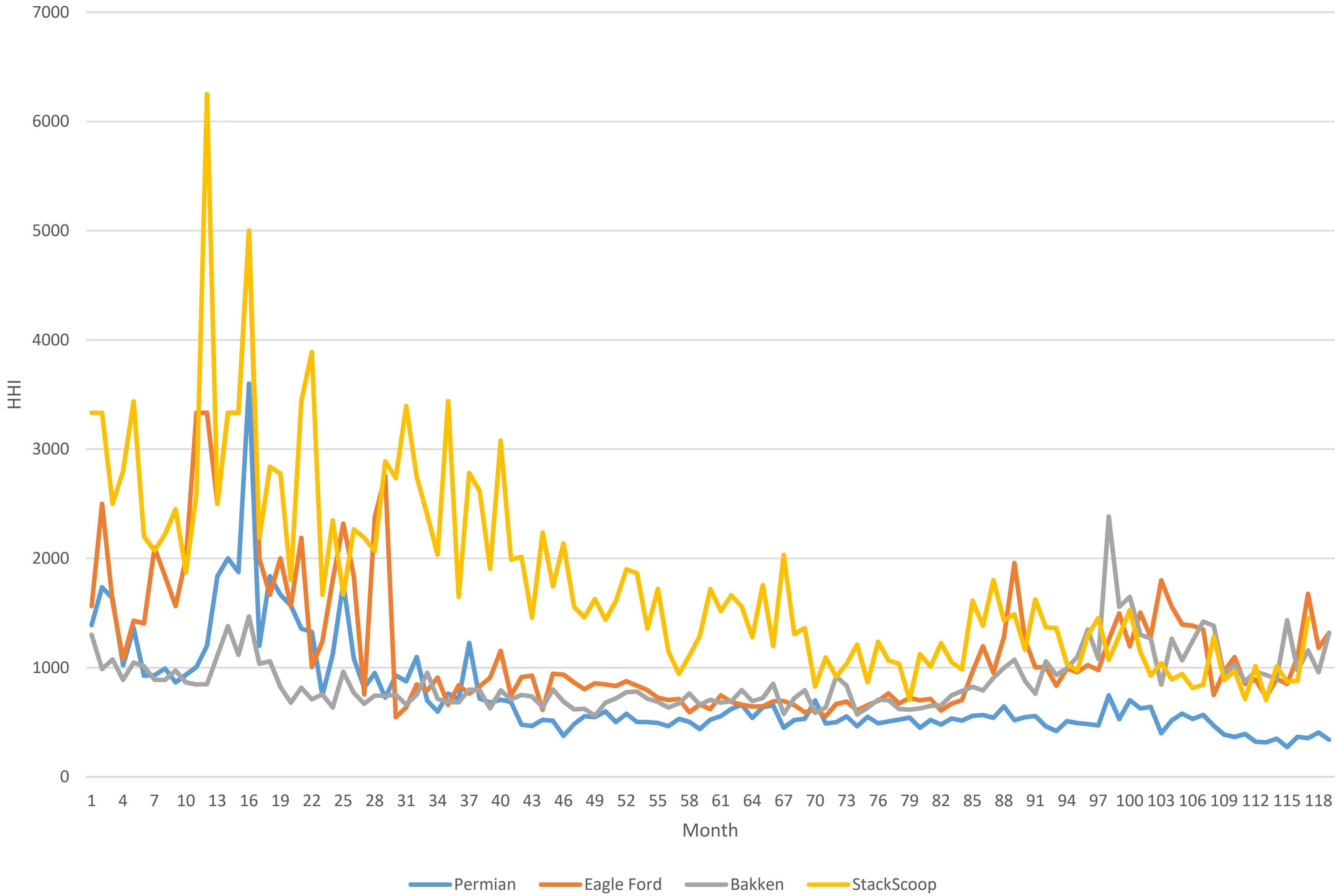


Figure 6
Oil Basin HHIs



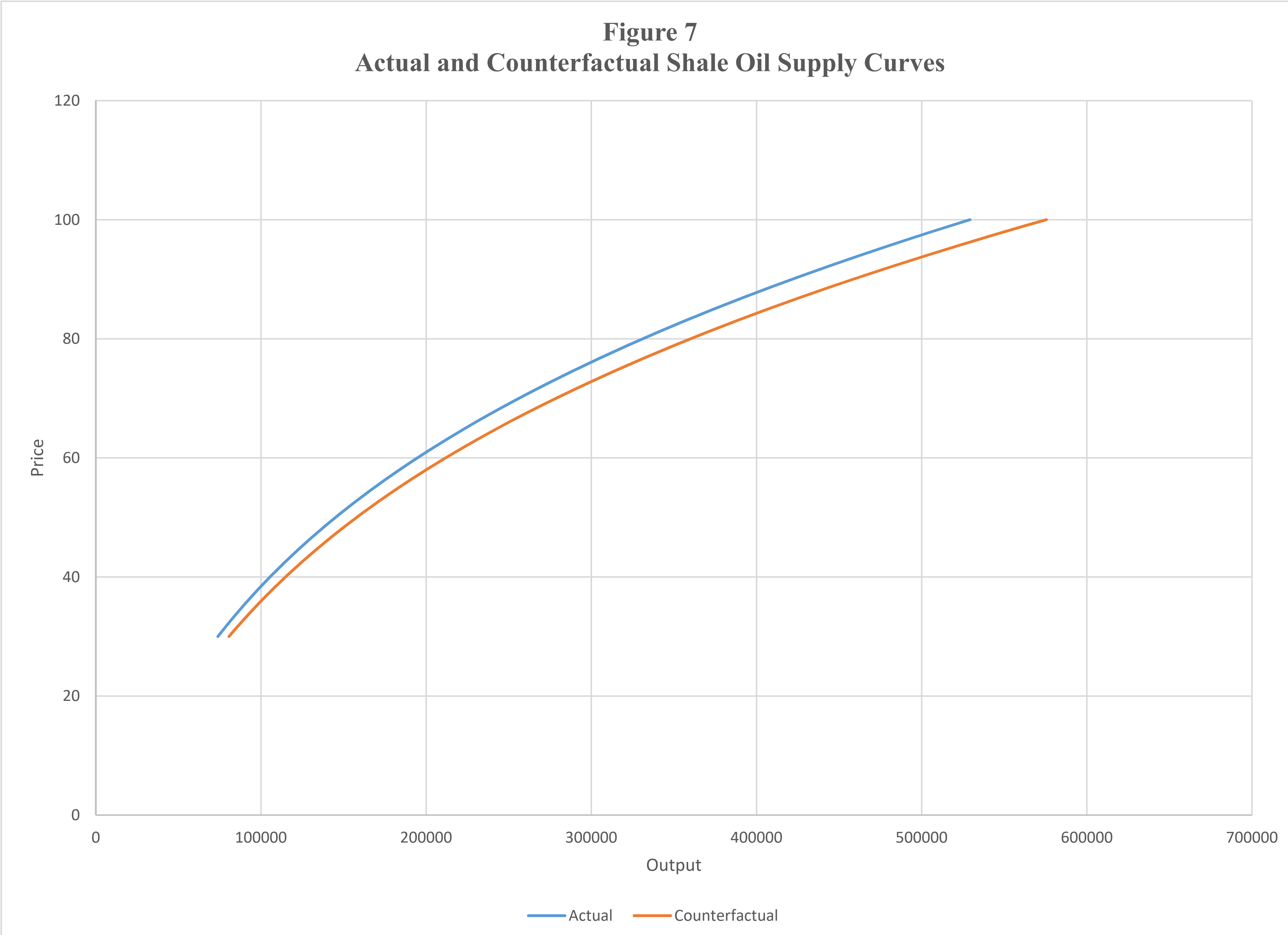


Figure 7
Actual and Counterfactual Shale Oil Supply Curves
120
100
80
60
40
20
0
Price
0
100000
200000
300000
400000
500000
600000
700000
Output
Actual
Counterfactual