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Hotelling Under Injected Pressure

An empirical study on the price responsiveness of waterflooding in US oil production

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Master thesis, Business Analysis and Performance Management

NORWEGIAN SCHOOL OF ECONOMICS

Abstract

Harold Hotelling's (1931) canonical model of exhaustible resource extraction, featuring resource-owners that maximize profits by trading off extraction today versus extraction in the future, is widely cited in the literature. However, the mapping of Hotelling's logic to empirical work in the energy literature has been a limited success. To bridge this gap, Anderson, Kellogg & Salant (2018) aim to show that a Hotelling model for oil production and drilling can generate empirical predictions consistent with market observables. They find well-level oil production (the intensive margin) in Texas to be unresponsive to the oil price, while drilling activity (the extensive margin) responds strongly. Hence, they reformulate Hotelling's model as a drilling problem where resource-owners choose when to drill, but the oil flow is restricted by reservoir pressure. Our thesis aims to contribute to the literature by showing that resource-owners in fact do manipulate oil production on the intensive margin by injecting water to increase reservoir pressure.

We first graphically analyze how oil production and the drilling of new wells respond to crude oil prices in the US between 2000 and 2020. We find that production declines monotonically over time for a stock of existing wells and that firms respond to increasing crude oil prices by drilling new production- and water injection wells. These findings are in line with current literature. However, we also find that the oil production curves for wells that have injection wells nearby do not decline monotonically.

We then proceed to develop an expression for the marginal cost of water injection and a function for optimal water injection volumes. Using this function, we estimate a fixed-effect linear regression model and find that water injection volume responds to oil prices, adding to the current economic literature. Our findings indicate that firms leverage their ability to manipulate oil production on the intensive margin by injecting water in response to oil prices. The evidence contradicts a central assumption made in the model proposed by Anderson, Kellogg & Salant (2018).

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1. Introduction

The oil and gas industry is a vital component of the global economy, accounting for more than 55% of the energy resources consumed (BP, 2022). Major sectors like transportation, power generation, manufacturing, and agriculture rely on fossil fuels due to their cost-effectiveness and consistent availability. Recent global events, like the COVID-19 pandemic and Russia's invasion of Ukraine, have highlighted the crucial role played by the oil and gas sector in shaping global markets and geopolitics. The global economy's dependence on this sector is supported by forecasts; liquid fuel consumption is set to increase by 1,8 million barrels per day (bbl/d) to 102,7 million bbl/d in 2024 (EIA, 2023).

The (US) is the world's biggest oil producer[1], with an annual production of 11,2 million bbl/d in 2021, accounting for 14,4% of the global output (BP, 2022). This is mainly attributed to the technological advancement that made shale oil extraction profitable. As it becomes increasingly challenging to discover new conventional oil and gas reservoirs, the extraction dynamics of these fields change. To reach the less accessible petroleum, a production well undergoes several extraction stages, from natural flow to artificial pumping and waterflooding.

Hotelling's (1931) model of exhaustible resource extraction has been applied to a range of problems, including the extraction of crude oil. The model features resource-owners that maximize profits by trading off extraction today with extraction in the future. Anderson, Kellogg & Salant (2018) investigate the crude oil production in Texas between 1990 and 2007 and find that the production curves for a stock of existing wells exhibit monotonic decline and are unresponsive to the oil price. They modify Hotelling's (1931) model by investigating two levers available to resource-owners: the rate of drilling new wells and the rate of oil flow. They find the rate of oil flow to be unresponsive to the oil price, while the rate of drilling responds strongly. Hence, they focus their analysis on the drilling of new wells as the primary decision variable leveraged by firms to maximize profits.

Anderson, Kellogg & Salant (2018) leave water injection wells out of their analysis, which is arguably an important lever available to firms to increase reservoir pressure and enhance oil flow on the intensive margin. Therefore, we hypothesize that a model that includes water

[1] Includes crude oil, shale/tight oil, lease condensate or gas condensates that require further refining. Excludes liquid fuels from other sources such as biomass and synthetic derivatives of coal and natural gas.

injection is better able to capture the actual dynamics of oil production in the US. Our research question is:

How do oil production curves from wells with nearby water injection wells compare to those without, and to what extent do water injection volumes respond to oil prices?

The thesis aims to contribute to the literature on exhaustible resource extraction, with an emphasis on the dynamics of oil production on the intensive margin. We structure our analysis into multiple sections to comprehensively answer the research question.

In Section 2, we review the existing literature on the subject. Specifically, we focus on the *Hotelling Rule* for exhaustible resource extraction and how Hotelling's model is currently applied to oil extraction. We are particularly interested in the perspectives of Anderson, Kellogg & Salant (2018) as they have reformulated Hotelling's model to incorporate geological features of oil reservoirs.

In Section 3, we provide an overview of oil production in the US and describe the geological processes of oil extraction. Since we investigate the influence of waterflooding and reservoir pressure on oil production, we include a general outline of the geological nature of oil production. Specifically, to understand waterflooding, we need to understand how oil flows through the reservoir. Moreover, we describe the most common techniques used to extract oil to create a foundation for our discussion.

In Section 4, we describe our data sources and elaborate on the filtering choices we make. We use three primary datasets, two of which have been provided to us by Rystad Energy. They include oil production and water injection data for the US between 2000 and 2020. We filter our datasets to only include conventional oil production wells that do not produce heavy oil. We use West Texas Intermediate (WTI) front month crude oil prices, provided by the New York Mercantile Exchange (NYMEX), as the benchmark price in the analysis. Finally, we include descriptive statistics of the datasets to understand their structure and characteristics.

We use Section 5 to answer the first part of our research question. To ensure that we have the same empirical point of departure, we compare our US findings to those of Anderson, Kellogg & Salant (2018) from Texas. Next, to ascertain whether oil production curves from wells with water injection wells in close proximity decline monotonically, we bracket the oil production wells into groups. The separating factor is how many water injection wells are located nearby any given production well. Finally, we aggregate the oil production within the well groups and use the findings to formulate an appropriate hypothesis.

Using the hypothesis from Section 5, we derive a formal model in Section 6 of the firm's profit-maximizing problem. Moreover, we modify the reformulated Hotelling model proposed by Anderson, Kellogg & Salant (2018) to include water injection.

We test the model's applicability through econometric tests in Section 7. Using a fixed-effect linear regression model, we determine whether water injected by firms responds to prices, thus answering the latter part of our research question. Next, we discuss potential causal effects of our findings before testing the robustness and evaluating the implications of potential empirical misspecification. Finally, we summarize our findings, suggest topics for future research, and discuss the limitations of our thesis.

2. Literature review

Because of the global dependence on oil and gas (BP, 2022), there is a vast body of economic literature on the petroleum industry. In this thesis, we focus on the research pertaining to the optimal management of crude oil reserves, with emphasis on Hotelling (1931) and Anderson, Kellogg & Salant (2018).

2.1 The Hotelling Rule

Harold Hotelling's paper from 1931 on the economics of exhaustible resources established a foundational framework for the optimal extraction rate of finite resources. The model features forward-looking resource-owners that maximize profit by trading off extraction in the present with extraction in the future, considering the finite nature of the resource, the extraction costs, and the time value of money. Thus, when resource-owners operate according to the *Hotelling Rule*, they only extract the resource if it yields more profit than could be earned from other financial instruments (Hotelling, 1931).

Although Hotelling's model has been previously applied to crude oil reserves, the empirical literature has primarily focused on testing the *Hotelling Rule*, which posits that resource prices should rise at the rate of interest (Hotelling, 1931), often finding it fails to hold (Slade & Thille, 2009).

2.2 Hotelling Under Pressure

Anderson, Kellogg & Salant (2018) aim to bridge the gap between Hotelling's model and the current empirical energy literature. They show that with certain modifications, a Hotelling model of oil drilling and production can generate empirical predictions consistent with observables, like drilling activity, well-level production, and oil prices. They recast Hotelling's model as a decision problem where firms can affect oil production through adjustment on two margins: the rate of drilling new production wells (the extensive margin) and well-level oil flow (the intensive margin). However, their model incorporates a capacity constraint on oil flow that is directly proportional to the reservoir pressure. The reservoir pressure is, in turn, proportional to the amount of recoverable oil left in the reservoir. In practice, Anderson, Kellogg & Salant (2018) therefore treat adjustments on the intensive margin as a state variable.

Anderson, Kellogg & Salant (2018) find that the aggregate production curve from existing wells declines monotonically towards zero, unresponsive to the oil price. They attribute this to the oil flow capacity constraint and the absence of an incentive for resource owners to decrease production below the capacity constraint in Texas from 1990 through 2007. However, they find a strong and positive correlation between the oil price, the rate of drilling of new wells, and the cost of drilling.

A declining oil production curve from existing wells is supported in the economic literature, as demonstrated in Hamilton (2013), and further by the economic literature premised on a production constraint that declines with cumulative extraction (see Nystad, 1987; Adelman, 1990; Black & LaFrance, 1998; Davis & Cairns, 1998; Cairns & Davis, 2001; Thompson, 2001; Gao, Hartley & Sickles, 2009; Mason & van't Veld, 2013; Cairns, 2014; Okullo, Reynès & Hofkes, 2015). These papers are all founded on a constraint on oil flow that decreases with cumulative extraction due to a decrease in reservoir pressure. Furthermore, the finding of short-term price inelasticity of oil production is also supported in the literature, including Griffin (1985), Hogan (1989), Jones (1990), Dahl and Yucel (1991), and Günter (2014).

Based on their Texas findings, Anderson, Kellogg & Salant (2018) develop their reformulated Hotelling model with the rate of drilling new wells as the only central choice variable, disregarding the rate of oil flow. Thus, they only investigate how firms operate on the extensive margin of oil production and exclude manipulation on the intensive margin in their analysis.

While Anderson, Kellogg & Salant (2018) make a valuable contribution to the economic literature on the optimal management of finite resources, there is potential for improvement in their study. First, they disregard water injection from injection wells to increase reservoir pressure. Focusing their analysis on the extensive margin, the authors state that adjustment of the intensive margin does not play a significant role in determining oil output. Thus, the authors omit a key lever available to firms to adjust the oil extraction rate. Second, they conduct their analysis on the aggregate level, abstracting away from reservoir heterogeneity in their dataset. Accounting for this heterogeneity could increase the level of granularity in the paper and allow for a comparison of oil production curves between oil fields and regions. Third, the limited empirical evidence from Texas between 1990-2007 may not be sufficient to generalize inference from the study's findings.

3. Background on Oil Production in the US

The purpose of this section is to provide context and background on oil production in the US. We start by outlining the characteristics of oil production, refining capacity, and infrastructure. Next, we briefly elaborate on the fundamentals of petroleum extraction geology and reservoir dynamics. We round off the section by presenting the technologies used in primary- and secondary oil recovery in conventional oil-producing wells, including waterflooding.

3.1 Petroleum Production and Infrastructure

3.1.1 Crude Oil Production

Based on data from the US Energy Information Administration (EIA) (2023), the United States produced 4.34 billion barrels of crude oil in 2022. Barrels as a unit of measurement are widely used in oil markets, where one barrel of crude oil equals 158.98 liters. Over the past two decades, crude oil production has experienced a sharp increase, as depicted in Figure 1.

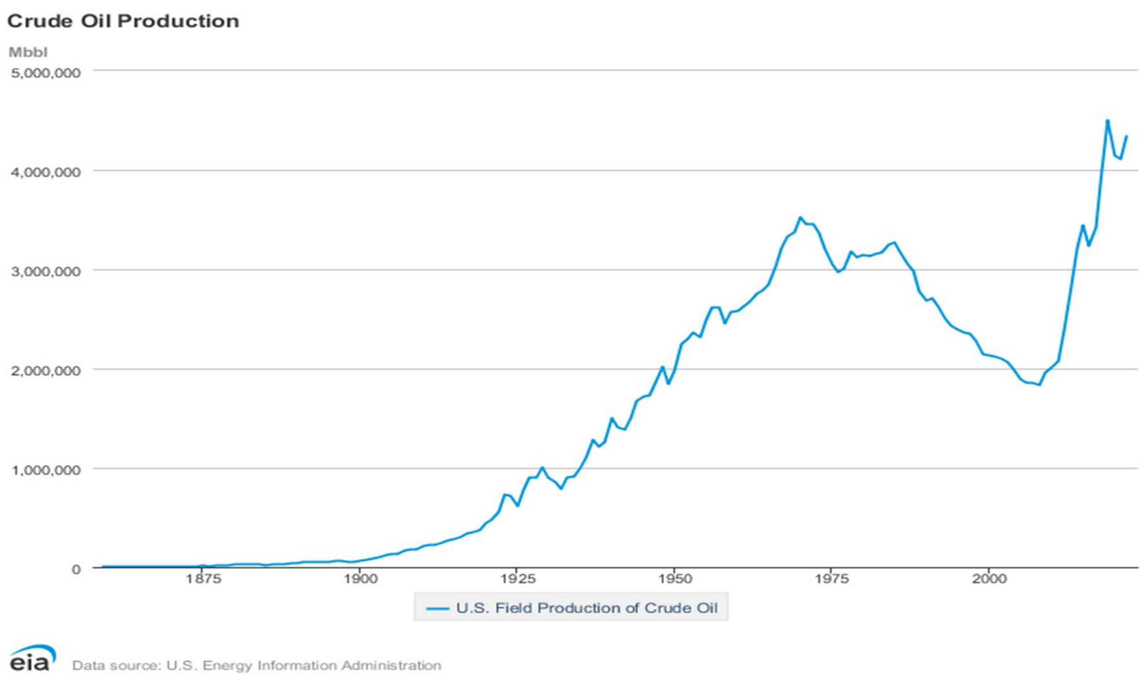

Figure 1 - Crude oil production in the US. Source: (U.S. EIA, 2023)

3.1.2 Oil Production Wells and Infrastructure

In the figure below, we observe the existing oil wells in the US. The US has a long history of producing oil, and geographical areas have gradually become mature for oil production when technology and techniques for both discovery and extraction have evolved. In 2021, the number of producing wells was 916,934. This is slightly down from 1,031,183 in 2014. Since 2013, approximately half of all oil that is extracted in the US comes from wells that produce between 100 bbl/d and 3,200 bbl/d. The share of wells that produce less than 15 bbl/d has remained steady at approximately 80% for the last two decades (U.S. EIA, 2022). The data therefore indicate that a substantial number of production wells are marginally productive.

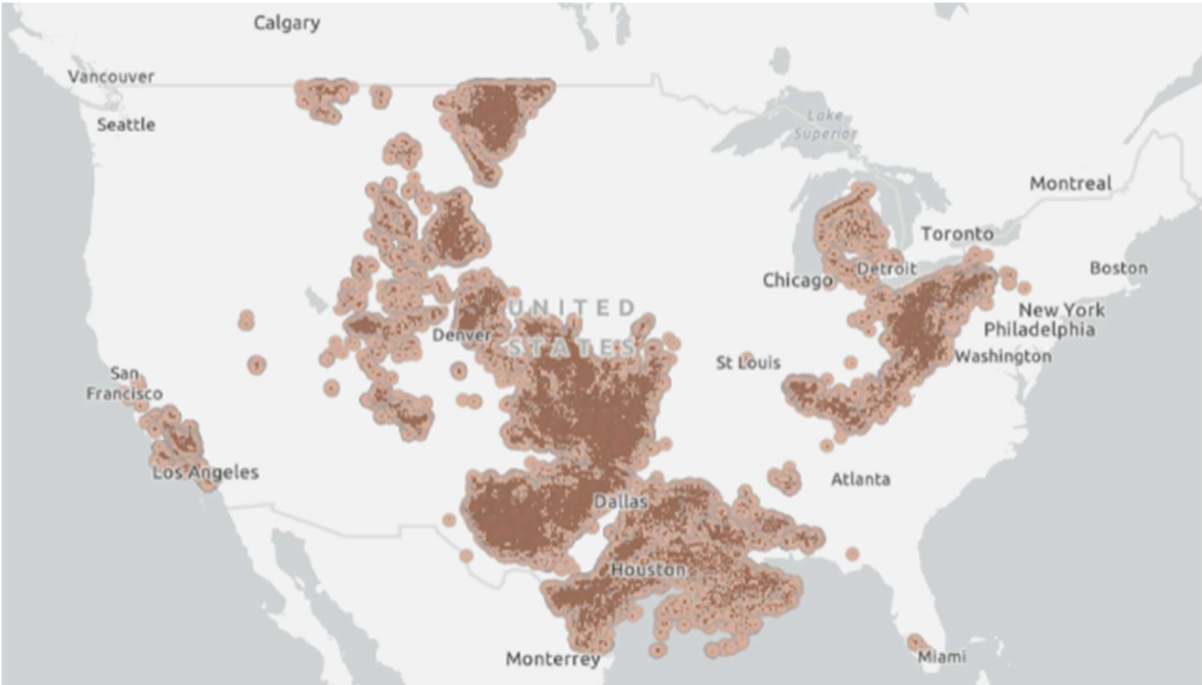

Figure 2 - Oil production wells in the US. Source: (U.S. EIA, 2023)

There is a notably higher density of refineries along the Gulf of Mexico coast. This is due to the fact that over 70% of all oil production occurs in the Petroleum Administration of Defense District (PADD) 3, which is also home to the majority of oil import and export terminals. In 2022, the US had a total refining capacity of 17,969 thousand bbl/d spread out across various locations throughout the country. The average capacity utilization in 2022 was 91.6%. A map of the refineries is included in Appendix 11.1. We note that the mid-west, including Texas, is extensively developed. Texas belongs to PADD 3 (U.S. EIA, 2012). A map of the PADDs is available in Appendix 11.4.

The US also has an elaborate network of crude oil and petroleum products pipelines that transport oil from the production oil wells, depicted in Figure 3, to terminals and refineries. The network also distributes petroleum products from terminals and refineries to areas where oil consumption occurs (U.S. EIA, 2023). We observe that multiple pipelines converge on Cushing, Oklahoma. The price of oil delivered at Cushing, OK is used as the benchmark price at the New York Mercantile Exchange (NYMEX), which we circle back to in Section 4.

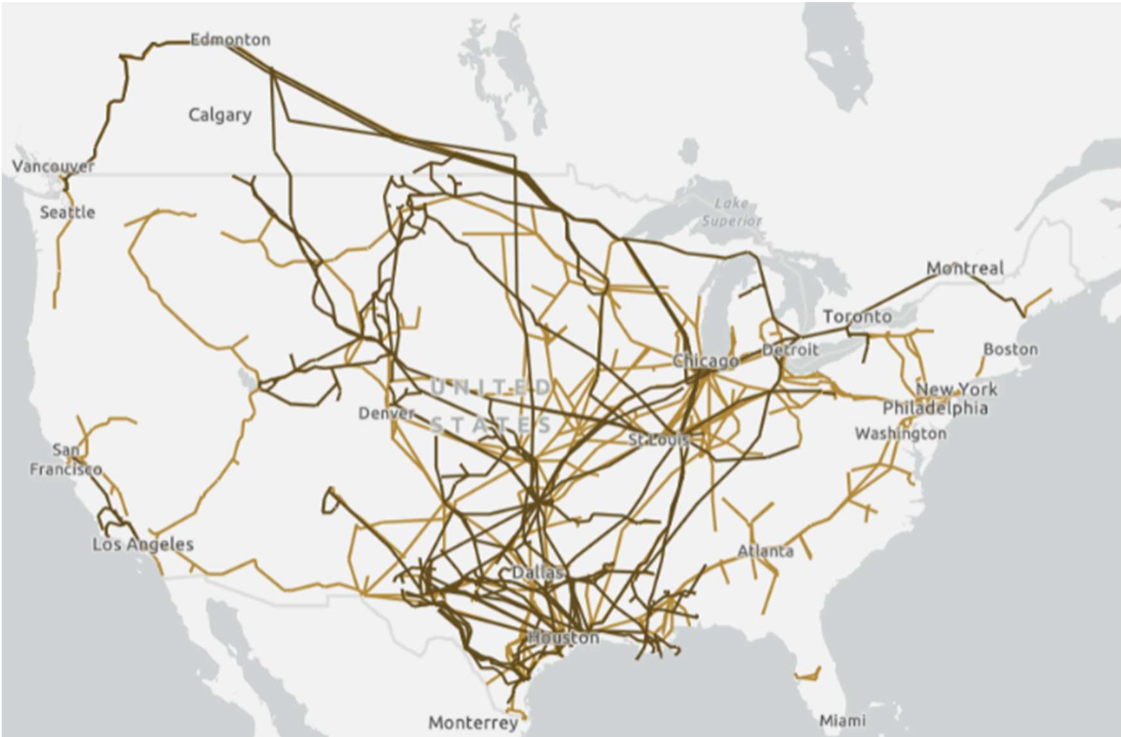

Figure 3 - Pipeline infrastructure in the US. Brown lines are crude oil pipelines, and yellow lines are petroleum products pipelines: Source: (U.S. EIA, 2023)

3.1.3 Consumption of Petroleum Products in the US

Crude oil is refined into a diverse range of products serving different purposes. These include heating oil, gasoline, diesel, jet fuel, lubricants, asphalt, ethane, propane, and butane. Petroleum products are integral to many aspects of modern Western society. It is used in transportation, manufacturing, energy production, and several other industries. The supply of petroleum products has remained relatively stable for the last two decades, with the two most notable decline periods during the 2008 financial crisis and a short drop during the COVID-

19 pandemic, as depicted in Figure 4. We observe that the supply of petroleum products[2] to the US was ~7.4bn barrels in 2022.

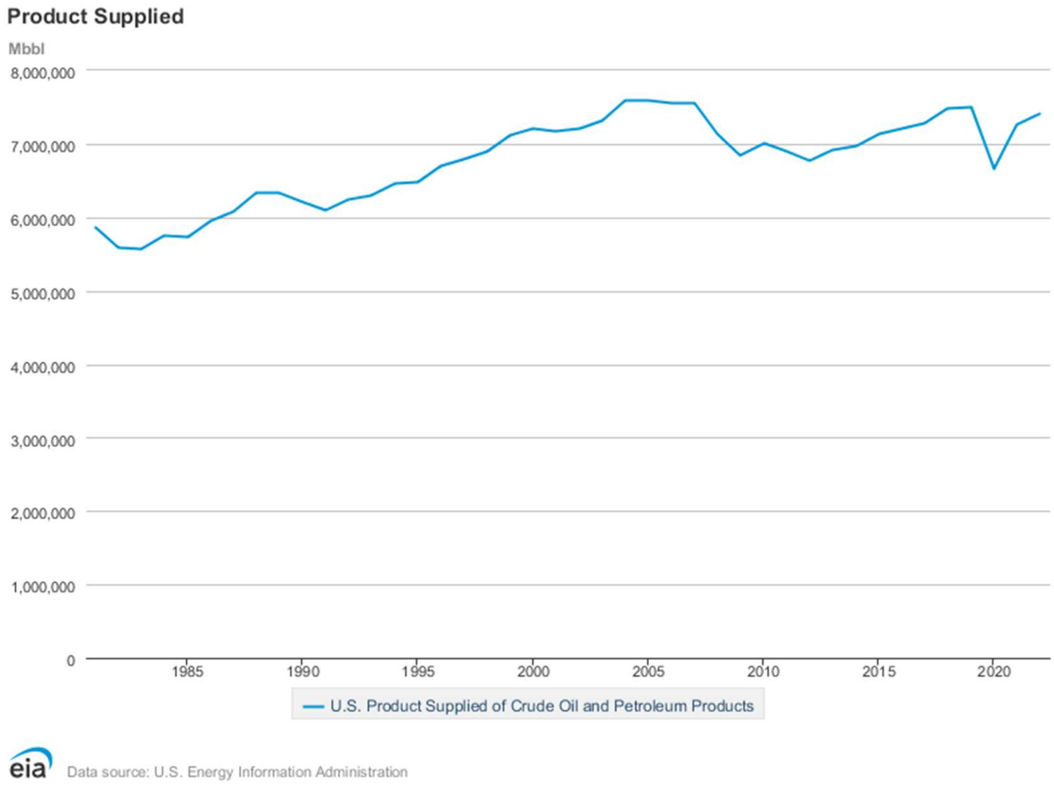

Figure 4 - Petroleum products supplied to the US trend.
Source: (U.S. EIA, 2023)

From Figure 5 below, we observe that motor gasoline is the largest category of supplied finished petroleum products, accounting for more than 53% in 2022. We also observe that the second largest supply group is Distilled Fuel Oil. Distilled Fuel Oil is widely used in the shipping industry. Generally, petroleum products used in transportation account for a large share of the consumption.

[2] The supply of petroleum products represents approximate consumption of petroleum products because it measures the disappearance of these products from primary sources like refineries. Source: (U.S. EIA, 2023)

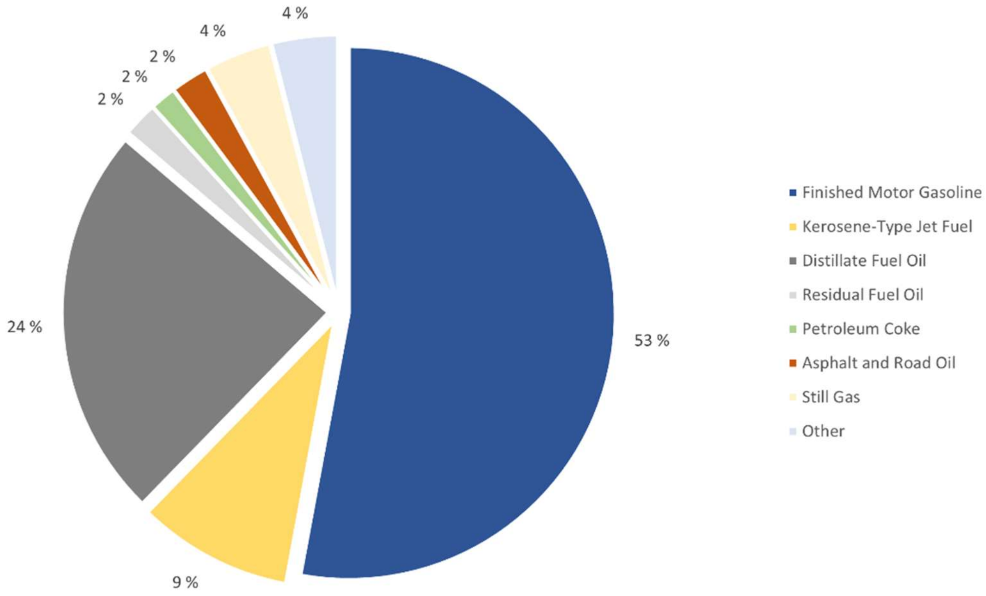

Figure 5 - Petroleum products supplied to the US in 2022 breakdown.
Source: (U.S. EIA, 2023)

3.2 The Geological Nature of Petroleum Reservoirs

Practically all petroleum occurrences are found in sedimentary rocks. In conventional reservoirs, the rock formations are mostly sandstones and carbonates that are sufficiently porous to hold large amounts of petroleum. In these types of reservoirs, the accumulation of hydrocarbons is present in rock formations that are both *porous* and *permeable*, the former signifying storage capability and the latter indicating the ease of petroleum flow through a rock formation (Dandekar, 2013). Other rock types like salt and shale also hold petroleum. Shale differs from conventional petroleum discoveries in that it often exhibits a layered or laminated structure due to the repeated deposition of sediment over millions of years. Shale, therefore, has both low porosity and permeability, meaning that oil does not flow easily through the reservoir without additional stimulation techniques like hydraulic fracturing (Bjørlykke, 2010).

3.2.1 Permeability and Pore Structure in Sandstone Reservoirs

Sandstones within reservoirs are, in general, oil-wet, meaning that they have a thin layer of water around the grains. A continuous phase of oil will flow easily if the permeability is high and the pore throats are wide, as can be seen in Figure 6. To traverse the restricted gaps between pores, oil droplets face the challenge of overcoming capillary forces. When the sediment consists of fine-grained particles with tiny pores, these forces serve as an impediment to the further migration of oil. As a result, oil cannot move as individual small droplets but instead forms a continuous oil phase where a majority of the pores are filled with oil, resulting in high oil saturation and minimal water presence (Bjørlykke, 2010).

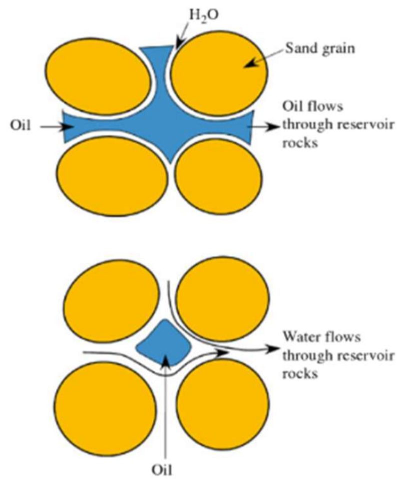

Figure 6 - Geology of liquid flow in reservoir rock. Source: (Bjørlykke, 2010)

3.2.2 Darcy's Law

According to Mason & van't Veld (2013), Darcy's law states that the flow from an oil well is proportional to the remaining size of the deposit from which extraction is taken. Let $q(t)$ be the rate of extraction, $R(t)$ as the remaining reserves, $\dot{R}(t)$ as the decline rate of remaining reserves, and δ as the factor of proportionality. We then get the constraint

$$(I)\ q(t) \leq \delta R(t).$$

As we extract resources from the reservoir, the remaining size of the reservoir declines at the rate of production

$$(II)\ \dot{R}(t) = -q(t),$$

which in turn implies

$$(III)\ \dot{R}(t) = -\delta R(t)$$

at any given moment where the upper bound of the extraction rate binds (Anderson, Kellogg, & Salant, 2018). The proportionality factor δ is referred to as the *decline rate* of production.

The value of the δ-coefficient depends on a multitude of geological factors, like the permeability and porosity of the reservoir rock, the viscosity of the crude oil, and the initial reservoir pressure, which vary with reservoir heterogeneity. δ implies that a given oil production well will experience high production volumes initially and decline at a relatively constant rate over time during the lifespan of the well.

3.2.3 Trap Types in Sandstone Reservoirs

A low permeability layer is needed to form a structure that is closed at the top to prevent medium/light oil and gas, which is lighter than water, from escaping. Bjørlykke (2010) poses the analogy that *"We can think of the oil trap as a barrel or bucket upside down."*. The point where oil may leak is called the *spill point.* The *closure* is the maximum oil column that the reservoir can hold before starting to leak through the spill point. We distinguish between *structural traps* and *stratigraphic traps*. Structural traps refer to traps that are formed by structural deformations like folding, doming, or faulting rocks. Stratigraphic traps, on the other hand, are related to the primary features in the sedimentary formations and do not rely on folding or faulting deformations (Bjørlykke, 2010). Examples of these trap types are depicted in Figure 7.

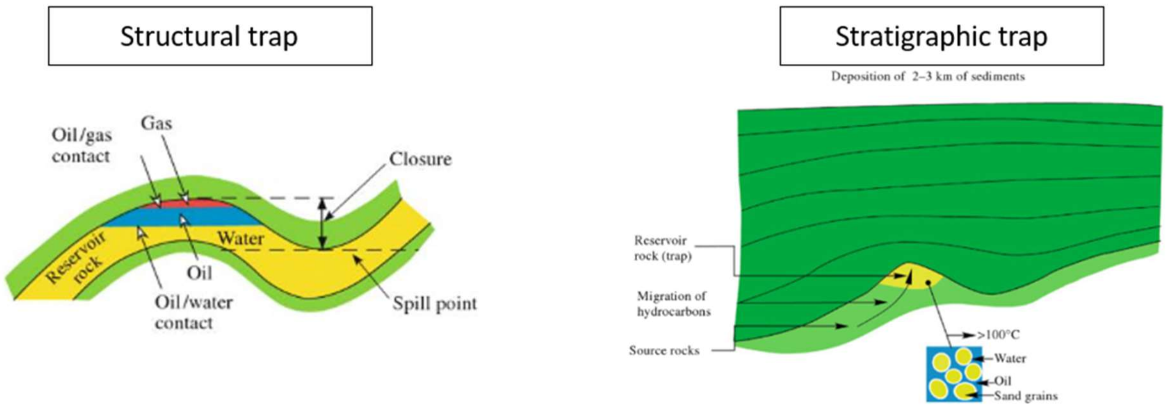

Figure 7 - Oil reservoir traps. Source: (Bjørlykke, 2010)

3.3 Oil Production Techniques and Technology

Having established a basic understanding of the geological composition of petroleum reservoirs, we investigate the techniques employed in the extraction of crude oil. In this section, we provide a brief presentation of the conventional oil production well type. We also elaborate on the use of water injection wells in oil production, as it directly ties into our analysis. We do not detail horizontally drilled wells as these extract oil by hydraulic fracturing.

3.3.1 Conventional oil production wells

Wells that are drilled vertically or moderately deviated are known as conventional wells. They are traditional in the sense that they are drilled directly above a reservoir. When drilling a conventional well, a drilling rig bores a hole through multiple layers of soil and rock until it reaches the oil reservoir. To cut through the rock, the drill bit is pushed down by the weight of the piping above. The piping is used to pump mud into the well, which is best described as a thick fluid that assists the drilling by maintaining the pressure below ground while also collecting debris created from the drill bit and bringing it to the surface (Cheatham, 1992).

In recent years, new technology for drilling deviated wells has been introduced. Deviated wells are usually drilled from a fixed drilling location, such as an offshore platform. One of the more recent techniques includes using a steerable rotary assembly. Signals from the operations control center can be sent to the drill bit to deflect in the appropriate direction whilst drilling (Downton et al., 2000).

Once a well has been drilled to its target depth, it is completed by sealing off the surrounding rock formations using cement. The cement is then perforated by creating small holes that allow oil and gas to flow into the wellbore. The oil and gas then flow either by natural pressure or by using a pump. This phase is referred to as the *primary recovery phase*. According to Thakur & Setter (1998), only 20% of the oil in the reservoir is extractable in the primary recovery phase of a conventional well.

3.3.2 Waterflooding

The term *waterflooding* refers to the use of water injection to increase the production output from oil reservoirs. Waterflooding is used during the *secondary recovery phase*, which typically follows the primary recovery phase. Waterflooding as a secondary recovery method is generally applied to sandstone and carbonate reservoirs. This contrasts with horizontally drilled wells, where firms generally use a hydraulic fracturing technique in the primary recovery phase, which renders the reservoir water-saturated (Dandekar, 2013). Increasing oil production through waterflooding is accomplished by *voidage replacement*. That is, water displaces the oil from the pore space in the rock formation. Through water injection, the well owners can regulate the pressure in the reservoir. Although the first waterflood occurred as an accidental water injection in the Pithole City area in Pennsylvania in 1865, the technique would later become popular for four main reasons: (i) The high availability of water, (ii) how easy it is to inject water, (iii) water's ability to spread through a petroleum-bearing formation, and (iv) the efficiency in which water displaces oil. The latter argument is specific to light/medium oil such as West Texas Intermediate (WTI) (Kamal, 1971).

The overall waterflood recovery efficiency is given by

$$(IV)\ E_{RW} \ = E_d \cdot E_V,$$

where

$$E_{RWF} = \text{Overall waterflood recovery efficiency, fraction}$$

$$E_D = \text{Displacement efficiency within the column swept by water, fraction}$$

$$E_V = \text{Volumetric sweep efficiency, fraction of the reservoir actually swept by water}$$

The dynamics that govern waterflooding efficiency imply that it is difficult to observe a linear relationship between water injection and oil production volume. The relationships vary with reservoir heterogeneity and change over time due to changing geological conditions. The factors affecting these efficiencies can be found in Appendix 11.2 (Thakur & Setter, 1998).

4. Data and descriptive statistics

In this section, we elaborate on the main datasets used in our analysis, as well as the techniques we use to organize and clean the data. This includes data on oil production wells, water injection wells, and crude oil prices. The two main datasets have been provided to us by Rystad Energy. The datasets are unbalanced panel data frames covering the years 2000-2020. We retrieve crude oil prices from NYMEX.

4.1 Oil Production

The first dataset contains onshore production wells in the US. Specifically, it includes the date, API number (well id), coordinates, oil production, water extraction, and completion date for every production well drilled in the US. The data is on a monthly level, and thus we have 252 individual months that are observed. The data has individual well-level granularity. The panel data on production wells include 81.8 million observations.

As we are only interested in observing oil-producing wells, we filter out Gas and Tight Gas wells. Moreover, we filter out wells drilled through shale formations. Firms utilize horizontal drilling techniques, like hydraulic fracturing (fracking), to extract oil from shale formations. Oil production wells that utilize fracking do not have adjacent water injection wells. Rather, the production wells themselves pump down water and chemicals. Since the horizontally drilled wells use significant amounts of fluids in the primary recovery phase, the secondary recovery phase is largely redundant as the rock formations become water-saturated (Raimi, 2016).

We drop observations from wells with an average API Gravity of less than 22.3, which would classify the oil as Heavy Oil (Demirbas, Alidrisi, & Balubaid, 2015). Heavy Oil extraction requires steam to be injected at a constant rate into the wells to prevent the collapse of the well (Pratama & Babadagli, 2022). Therefore, steam injection wells operate at a relatively constant rate, and steam injection cannot be considered a choice variable. Due to the nature of these wells, they are not interesting to our analysis.

Furthermore, we drop wells where no location data is disclosed as we need to know the geographical location of all the wells in order to correctly count nearby water injection wells. The original data provided by Rystad does not count how many water injection wells that surround a production well. Therefore, we use the geographical coordinates of both oil production wells and water injection wells to deduce whether production wells have injection wells nearby. We first create a polygon around each production well with radius r, using the *sf* package in R. We then proceed to count how many injection wells that intersect each individual polygon[3]. Based on the existing literature on waterflooding, we find that injection wells usually are drilled 50-750m away from production wells (Alizadeh & Salek, 2021). From the discussion in Tabatabaie, Haghighi & Kantzas (2015), we set a radius of 500m as the buffer in the analysis.

The data from Rystad contain a large number of observations where the oil production variable is NA. We filter out these observations as well. This leaves us with 4,929,054 observations from 33,423 individual production wells in our time period. There were 105,430 new conventional oil production wells drilled between 2000 and 2020.

n	mean	sd	median	trimmed	min	max	range	skew	kurtosis	se
4929054	1469	22367	156	284	0.001	4592455	4592455	85.4	11055	10.1

Table 1: Descriptive statistics on oil production

The 33,423 wells had a median oil production of 156 bbl/m and an average of 1,469 bbl/m. The standard deviation is 22,367 bbl/m. This indicates a right-skewed normal distribution, which is confirmed by the skewness score of 85.4 in Table 1. There are a few large outliers, while most observations are small and close to zero. We attribute the low median production rate to the fact that most conventional oil wells in the US drilled before the year 2000 were discovered a long time ago and became mature within our observable timespan, similar to the findings in Anderson, Kellogg & Salant (2018). The outliers may stem from a single well reporting the aggregate production of several wells nearby within a single field. That is, some wells may be geographically close together, and the oil production is measured at an above-ground storage facility that incapsulates all oil production from said wells. That would, in turn, yield an aggregated reporting that skews our data.

[3] The code was run on a virtual desktop cluster with 64 CPU cores and 256GB RAM provided by the IT-Department at NHH, by using a nested foreach loop to reduce time consumption for the code.

4.2 Water Injection

The second dataset contains data on water injection wells in the same timespan as the production well data. The data from these wells include liquid injection volume on a monthly basis. We impose two different data filters on this panel. First, we only include injection wells that are labeled as Secondary Recovery wells. Thus, we drop water injection wells that are labeled as Disposal Non-Productive. These types of wells do not tie into the oil production directly. Rather, they are a means of disposing of excess water and chemicals extracted from production wells. Second, we also filter on Average API Gravity equal to or greater than 22.3, as wells with lower Average API Gravity inject steam used to extract Heavy Oil (Demirbas, Alidrisi, & Balubaid, 2015). We also drop wells that have an undisclosed location in our data. After filtering, we are left with 6,058,629 observations. In addition, we observe that there were 19,948 new water injection wells drilled between 2000 and 2020.

n	mean	sd	median	trimmed	min	max	range	skew	kurtosis	se
6058629	12842.26	27837.91	6686	8544.63	0	15080000	15080000	91.59	32147.88	11.31

Table 2: Descriptive statistics on the volume of water injected (ibbl/m)

The remaining 40,502 water injection wells have a mean injection volume per month of 12,842 bbl/m. Similar to the data on oil production, we see clear evidence of a positive skewness. However, a skewed normal distribution does not violate the assumptions of Pooled OLS and thus does not hamper our analysis.

4.3 Crude Oil Prices

Similar to Anderson, Kellogg & Salant (2018), we use the WTI front month future price in the primary analysis. That is, the price of oil at time t that is delivered at time $t + 1$. This is known as the *front month future price*. Descriptive statistics of the WTI front month future price are depicted in Table 3.

n	mean	sd	median	trimmed	min	max	range	skew	kurtosis	se
252	73.6	30.5	66.2	71.5	17	168	151	0.581	-0.493	1.92

Table 3: Descriptive statistics on WTI front month prices

According to Kilian (2009), oil prices rose during the mid-2000s due to a series of unanticipated positive shocks to the demand for oil in the emerging Asian markets. Following this upward trend in crude oil prices, a substantial negative demand shock materialized in the midst of the financial crisis in 2008. The crude oil price recovered and remained relatively stable until 2014. In 2014, OPEC announced a strategic shift towards capturing market share. In an attempt to squeeze out high-cost producers of shale oil in the US, OPEC increased the production of crude oil. Consequently, crude oil prices dropped from a high of 106.7 USD in June 2014 to a low of 32.74 USD in February 2016 (Behar & Ritz, 2017). The price varied in the interval 32.74-74.13 USD until the COVID-19 pandemic delivered a substantial demand shock to the crude oil market, pushing the front month oil price to 19.23 USD.

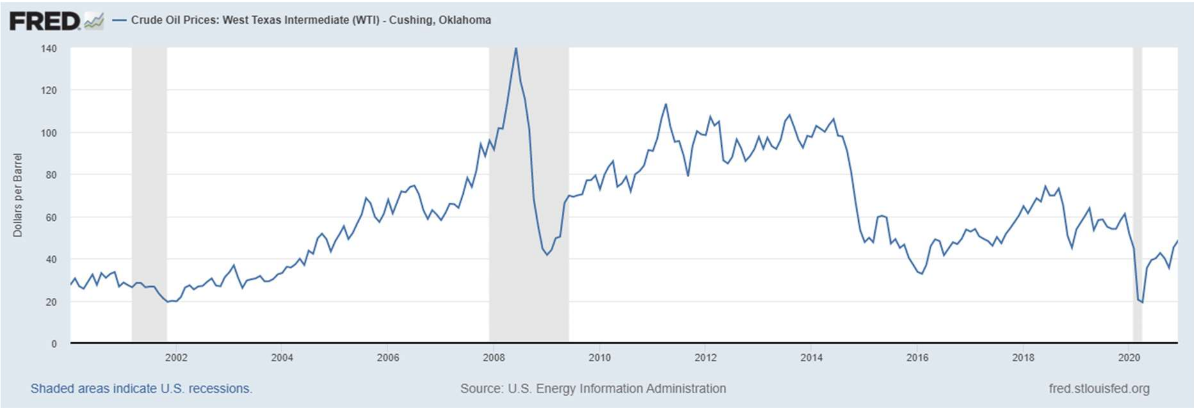

Figure 8 - West Texas Intermediate (WTI) front month price development.
Source: (U.S. EIA, 2023)

There are several reasons why we choose to use WTI front month future prices in our analysis. First, the market for WTI is highly liquid. It remains the second most actively traded futures contract in the world. The only futures contract more actively traded are futures contracts for Brent oil, which are used as a benchmark for two-thirds of the global market. Brent and WTI are both considered high-quality and sweet oils. As WTI has a sulfur content between 0.24% and 0.34%, it is most suitable for refining gasoline. Brent, on the other hand, has a slightly higher sulfur content that is generally between 0.35% and 0.40%. This makes it ideal for refining diesel. Oil with a sulfur content below 0.50% is considered sweet. Oil products with a lower sulfur content are generally traded at a premium, and the price of WTI should therefore be higher than the price of Brent. However, the two benchmarks operate in different markets. This implies differing market structures on the supply and demand side. As shale oil production gained traction in the US, the price of WTI declined to a bottom in April 2020. This is depicted in Figure 8, where the shaded areas indicate recessions in the US economy. Moreover, transporting WTI overseas comes at a cost, making it unlikely to be able to compete with Brent in terms of pricing. Therefore, the WTI prices now usually trade at a discount compared to Brent (FocusEconomics, 2016).

We use real prices in our analysis. Specifically, we discount the All Urban, All goods, Less Energy Consumer Price Index (CPI) of the Bureau of Labor Statistics to convert all prices to December 2020 US Dollars.. If we were to use nominal prices, we would only consider the market price of a commodity without accounting for inflation. In contrast, when we use real prices, we adjust the market price of a commodity to reflect the purchasing power of the currency at the time of the analysis. This adjustment considers the impact of inflation and provides a more accurate picture of the relative value of the commodity.

5. Preliminary Analysis

The purpose of this section is to answer the first part of our research question: "*How do oil production curves from wells with nearby water injection wells compare to those without?*". First, we analyze the oil production curves from wells that were drilled before 2000. We then proceed to analyze the drilling of production- and injection wells and compare our findings with those of Anderson, Kellogg & Salant (2018). Next, we group production wells based on the number of injection wells nearby and analyze whether the production curves of these wells decline monotonically over time. The findings in this section serve as the basis for further hypothesis development and empirical analysis.

While Anderson, Kellogg & Salant (2018) use data on the lease level from Texas, our dataset gives oil production and water injection on the well-level for the entire US. Anderson, Kellogg & Salant (2018) focus their analysis on leases on which there was no rig activity between 1990 and 2007, thus ensuring that all oil production comes from preexisting wells. To facilitate the comparison of our analyses, we only analyze conventional production wells that were drilled before 2000.

5.1 The Intensive Margin of Oil Production

Oil production on the intensive margin is determined by the rate of oil flow from each production well. Figure 9 presents the aggregate oil production from production wells without water injection wells nearby against front month prices. We confirm the findings of Anderson, Kellogg & Salant (2018) from Texas on our data for the entire US – a long-run downward trend of oil production that does not respond to the front month oil price. This indicates that the trend found by Anderson, Kellogg & Salant (2018) is not unique to Texas but instead describes a domestic trend in the US oil production from conventional wells. In early 2020 we observe a brief acceleration in the rate of production decline. We attribute this to the negative demand shock driven by the geopolitical and economic turmoil at the outset of the COVID-19 pandemic.

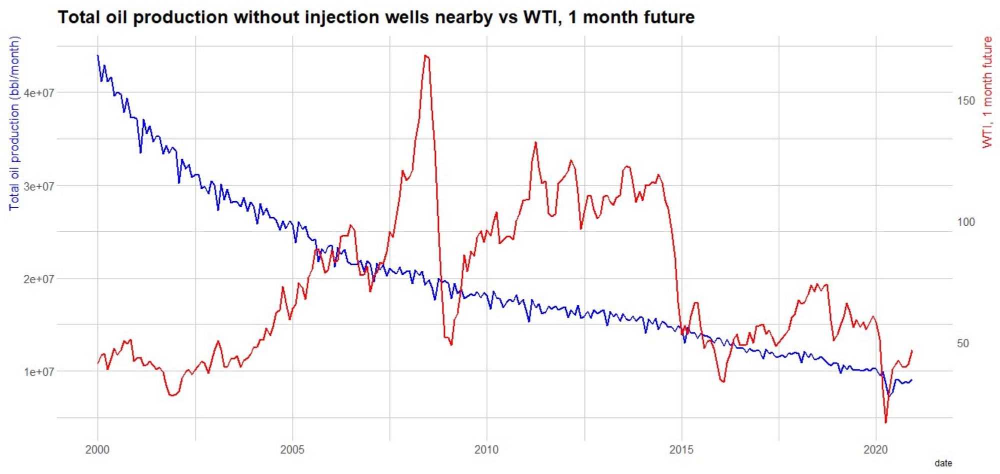

Figure 9 - Oil production from wells without water injection wells nearby. Oil price in real 2020 dollars.

It thus appears that an existing stock of conventional production wells without water injection wells nearby exhibits monotonic decline, similar to the findings in Anderson, Kellogg & Salant (2018).

5.2 The Extensive Margin of Oil Production

Oil production can be increased on the extensive margin by drilling new production wells, which Anderson, Kellogg & Salant (2018) find to be the main lever used by firms to manipulate oil production.

5.2.1 Drilling of production wells

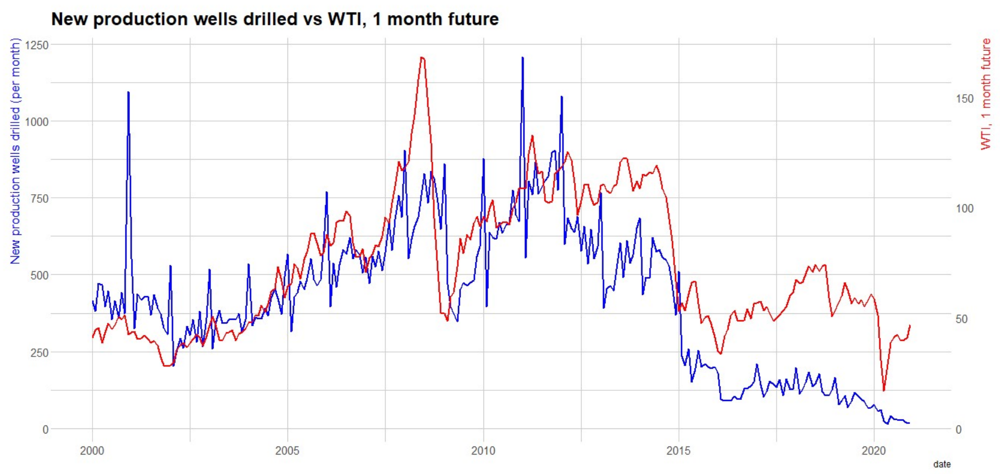

Figure 10 - Drilling activity of production wells. Oil price in real 2020 dollars.

We find a strong responsiveness to price on the drilling activity of new production wells in the US. This result mirrors the findings of Anderson, Kellogg & Salant (2018), solidifying the similarities in the trends found in our data. Figure 10 exhibits a strong correlation between new conventional production wells drilled per month and the front month oil price. Pearson's Product-Moment Correlation test yields a coefficient of 0.69. The drilling of conventional wells seems to subside after 2015. This coincides with the rise of the shale oil industry in the US, when it prevailed against the flood of supply from OPEC to push down oil prices and squeeze out high-cost US shale producers.

5.2.2 Drilling of injection wells

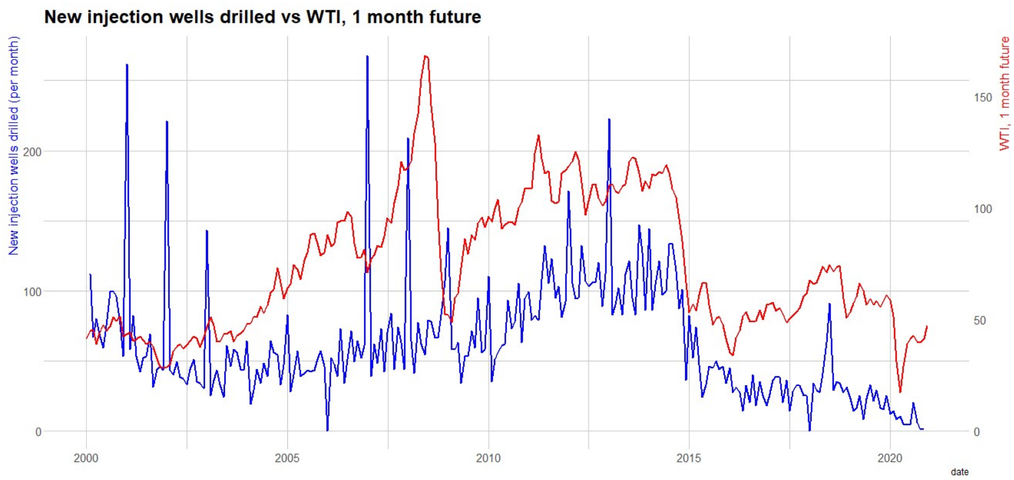

Figure 11 - Drilling of injection wells. Oil price in real 2020 dollars.

Next, we analyze how the drilling of new injection wells responds to the oil price. We find a correlation coefficient of 0.108 between the monthly number of injection wells drilled and the front month oil price, indicating some price responsiveness. In Figure 11, we observe several peaks in the number of wells drilled. These peaks are recurring in January of each year, and we attribute this to reporting practices, i.e., firms report their cumulative drilling numbers for the previous year in January of this year. As our analysis focuses on the trend in drilling over time, we retain these outliers.

5.2.3 The opportunity cost of drilling versus water injection

Firms typically drill wells by renting drilling rigs. According to Anderson, Kellogg & Salant (2018), the rig day rates have a positive and statistically significant correlation with the oil price. When the oil price increases, the demand for rigs and rig workers increases, which again drives prices up – particularly in the short term. This gives rise to an increase in the opportunity cost of drilling new wells. As the firm has two levers to manipulate the oil flow, the extensive and the intensive margin of the field, a change in the cost of increasing the extensive margin creates an incentive to increase the intensive margin of the field instead. This can be done by injecting a higher volume of water to increase reservoir pressure and oil flow.

5.3 Production at the Intensive Margin with Waterflooding

We extend the analysis of Anderson, Kellogg & Salant (2018) by analyzing the oil production curves of production wells that have water injection wells nearby. Including WTI front month prices in the plots allows for a graphical analysis of the price responsiveness of the production curves.

5.3.1 Hypothesis

We formulate the hypothesis that the oil production curves for production wells that have water injection wells nearby do not exhibit strictly monotonic decline. To test the hypothesis, we group production wells based on the number of water injection wells that are within a distance of 500m, as described in Section 4, and aggregate the group oil production by month.

To ensure consistency in the analysis, we only keep the production wells that have a constant number of injection wells in proximity for the entire 2000 to 2020 period. Thus, the effects of drilling new injection wells, shutting in, and reopening old injection wells are omitted. In other words, a production well will remain in one group for the entirety of the analysis, not allowing for inter-group shifts of oil production wells.

5.3.2 Production curves of wells with water injection wells nearby

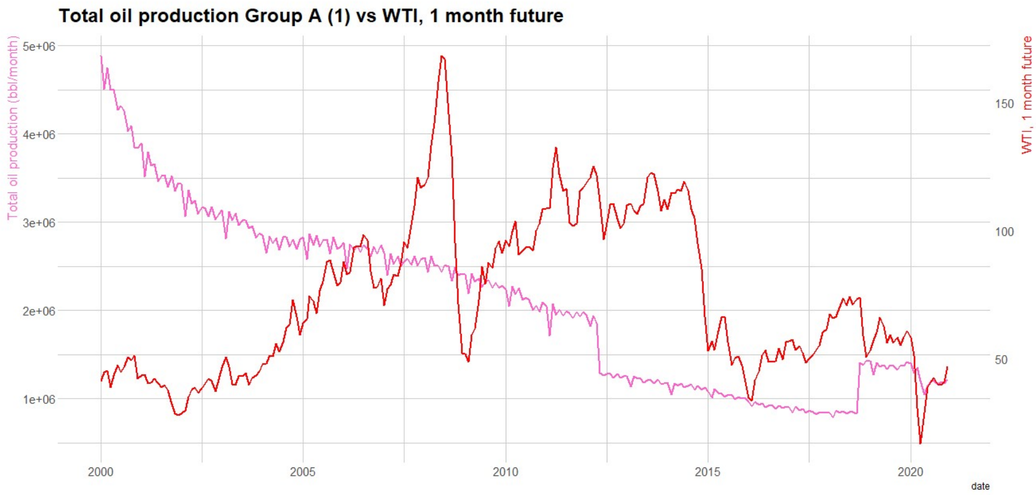

Figure 12 - Oil production from Group A, wells with one injection well in proximity. Oil price in real 2020 dollars.

Figure 12 shows that the aggregate oil production from wells with one injection well within the distance threshold (Group A) differs from the monotonic production decline curve presented by Anderson, Kellogg & Salant (2018). We observe a steep drop in production in 2012, with a corresponding upsurge in 2018. A production well operating at capacity cannot, by definition, increase oil flow beyond the capacity limit. Thus, the surge in oil production observed in 2018 implies that the production wells in Group A were (i) not operating at capacity in 2018 before the surge, and/or that (ii) the capacity of these wells was increased on the intensive margin.

In Figure 13, we observe oil production from wells in Group B that have between six and ten injection wells in proximity. Like in Group A, the production curve does not display a strictly monotonic decline. We observe accelerated declines in 2001, 2002, 2012, and most notably, a surge in 2018, corresponding to the surge in Group A.

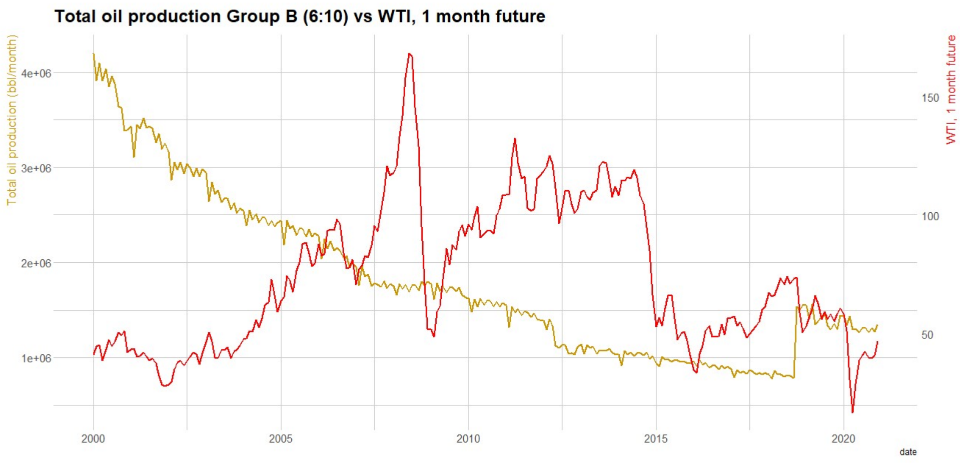

Figure 13 - Oil production from Group B, wells with six to ten injection wells in proximity. Oil price in real 2020 dollars.

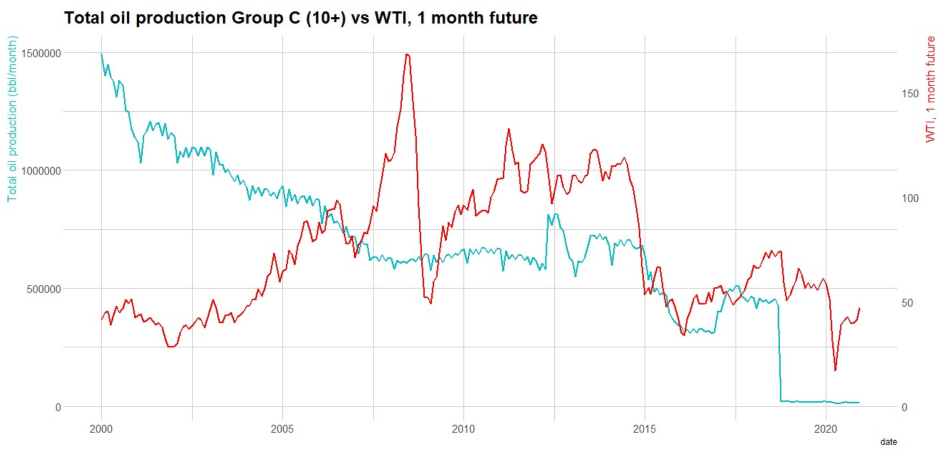

Figure 14 - Oil production from Group C, wells with more than ten injection wells in proximity. Oil prices in real 2020 dollars.

The production from Group C is plotted in Figure 14. The group consists of production wells with more than ten injection wells in proximity and illustrates the extent to which oil production can be manipulated on the intensive margin. Like in Group B, an accelerated decline rate of production is observed in 2001 and 2002. However, from 2012 onwards, we observe that oil production exhibits some price responsiveness, both increasing in times of higher oil prices and decreasing in times of lower oil prices. Notably, production *drops* from ~500,000 bbl/m to almost zero in 2018, corresponding to the sharp *increase* in production observed at the same time in Group A and B.

5.3.3 Discussion

Interestingly, we find that the production curves for all three groups deviate from the monotonic decline found in Section 5.1. The deviations from the monotonic decline curve seem to increase as the number of nearby water injection wells increases. Oil production from Group C exhibits the largest deviations from a monotonically declining production curve. In the period after 2012, the production seems to have a higher correlation with prices than in previous years.

By using waterflooding, firms may directly affect reservoir pressure through voidage replacement. Therefore, as the number of injection wells nearby a production well increases, the degree to which firms have the *ability* to manipulate reservoir pressure also increases. Using this lever on the intensive margin, firms may behave in a profit-maximizing manner and increase production in periods when prices are high and vice-versa.

If the firms manipulate the intensive margin by injecting water at a constant rate, the production curves still decline monotonically but at a less steep rate (Thakur & Setter, 1998). However, since all three groups deviate from a monotonic decline curve, it seems reasonable to assume that they do not inject water at a constant rate, but rather manipulate the injection rate dynamically over time. By this logic, the production curves for wells adjacent to water injection wells should display a relatively direct response to price fluctuations. However, we do not observe a direct price responsiveness in the production curves.

The subsequent question then becomes; why do we not observe this price responsiveness graphically? First, the extracted liquid from the reservoir contains oil, water, natural gas, and sediment. The fraction of produced fluid that is water, the water cut, can increase over time as more water is injected into the reservoir. Over time, this may cause a steeper decline in the oil production curves (Malakooti et al., 2015). At a certain point, it may become unprofitable to extract oil from these wells, and production drops. This may explain part of the steep drop in oil production observed in Group C in 2018. Second, the water cut development is heterogenous across wells and depends on both geological factors and production strategy decisions on the field level. Third, the injection of water into the reservoir can displace oil towards nearby production wells, leading to higher oil flow from these wells in the short- to medium term. However, over time water accumulates in the reservoir and displaces oil away from the production wells, resulting in lower oil production (Shuhong et al., 2012). The efficiency of waterflood recovery is dependent on the displacement efficiency and the volumetric sweep efficiency outlined in Section 3.3.2. Thus, a unit mass of water injected into the reservoir will increase oil flow by less than one unit (Ogbeiwi, Aladeitan, & Udebhulu, 2018).

Since water injection volume is the lever that is available to firms to manipulate oil production on the intensive margin, it follows that the price responsiveness of water injection volumes should be stronger than that of oil production. To investigate this possibility, we revise our hypothesis.

5.3.4 Revised Hypothesis

We formulate the hypothesis that firms manipulate the intensive margin of the field by increasing (decreasing) the volume of water injected when the oil price goes up (down). To test our revised hypothesis, we proceed in two steps. We first develop a reformulated Hotelling model that includes waterflooding in the firm's cost structure in Section 6. This model then allows us to empirically test whether the revised hypothesis holds.

6. Reformulating Hotelling with Water Injection

In this section, we formulate a theory of optimal oil extraction and water injection based on the modified model presented in Anderson, Kellogg & Salant (2018). We first formulate the firm's problem before deriving an expression for the marginal cost of water injection. We then proceed to develop the firm's cost structure and derive an expression for the profit-maximizing volume of water injection.

6.1 The Firm's Problem

The firm's problem describes the decision an oil well operator faces through time; how to maximize profits from the oil field given the price of oil and its cost structure. We formulate our model in a similar way to Anderson, Kellogg & Salant (2018), with a continuum of infinitely small wells that may be drilled. However, the novel feature of our model is that we allow for water injection to artificially increase reservoir pressure and enhance oil flow on the intensive margin. In other words, we distinguish between the extensive and the intensive margin of the field. Firms can increase the extensive margin by drilling one more production well. At the same time, firms can increase the intensive margin of the field by injecting one more barrel of water into an injection well.

The firm's intratemporal objective is to maximize its profits,

$$(1)\ \max \pi_t^i = P_t Oil_t^i - C_1\left(PW_t^i, Inj_t^i\right),$$

subject to the following constraints

$$(2)\ 0 \leq Oil_t^i \leq K_t^i,$$

$$(3)\ 0 \leq PW_t^i, 0 \leq Inj_t^i, 0 \leq TotW_t^i,$$

$$(4)\ K_t^i = K_{t-1}^i + \zeta_1 PW_{t-1}^i + \zeta_2 Oil_t^i + \zeta_3 Inj_t^i,$$

$$(5)\ TotW_t^i = TotW_{t-1} - PW_t^i,$$

where P_t is the price of oil at time t (a state variable), Oil_t^i is the rate of oil flow from field i at time t (a state variable), PW_t^i is the number[4] of new production wells drilled in field i at time t (a choice variable), Inj_t^i is the amount of water injected into the reservoir of field i at time t (a choice variable), K_t^i is the capacity constraint on oil flow (a state variable), and $TotW_t^i$ is the number of untapped wells in field i at time t (a state variable). The firm's cost of drilling wells and injecting water is given by $C_1(PW_t^i, Inj_t^i)$.

Condition (2) describes the limit of oil flow Oil_t^i. Oil flow can never be negative and is for all t constrained upward by the capacity constraint of oil flow K_t^i. (3) gives the non-negativity constraints for PW_t^i, Inj_t^i, and W_t^i. Condition (4) describes how the capacity constraint on oil flow K_t^i changes over time. At $t = 0$ the planning period begins with the stock K_0 inherited from previously drilled wells. The capacity constraint on the maximum oil flow rate from field i depends on the number of tapped production wells and reservoir pressure. Reservoir pressure decreases as oil is depleted, *ceteris paribus*. Thus, oil flow Oil_t^i reduces the capacity constraint at a factor of ζ_2 for all $\zeta_2 < 0$. However, the firm can increase capacity at time t by drilling new wells in period $t - 1$. Thus, the capacity constraint is relaxed by a factor of ζ_1 for each new unit mass of production wells PW drilled, where ζ_1 is interpreted as the maximum flow from a unit mass of newly drilled production wells. Likewise, the capacity constraint can be relaxed by injecting water to increase the reservoir pressure. This relaxes the capacity constraint by a factor of ζ_3. Condition (5) describes how the stock of untapped production wells $TotW_t^i$ in field i changes over time. In period $t = 0$ the planning period begins with a continuum of untapped wells and thereafter decreases by the rate of drilling of new wells.

Like Anderson, Kellogg & Salant (2018), we assume that there is no storage of oil above ground. This allows our analysis to focus on the dynamics of drilling, oil extraction, and water injection.

The resulting intertemporal problem can be solved using standard methods. For example, the Lagrangian writes

[4] As we assume that there is a continuum of infinitely small untapped wells, PW_t^i is strictly speaking the *unit mass* of newly drilled wells.

$$(6)\ \mathcal{L}_t^i = E_{t-1}\left\{\sum_{s=0}^{\infty}\beta^s\Big[P_{t+s}^i Oil_{t+s}^i - C_1\big(PW_{t+s}^i, Inj_{t+s}^i\big)\right.$$
$$+\ \sigma_{t+s}^i\big[K_{t-1+s}^i + \zeta_1 PW_{t+s-1}^i + \zeta_2 Oil_{t+s}^i + \zeta_3 Inj_{t+s}^i - K_{t+s}^i\big]$$
$$+\ \gamma_{t+s}^i\big[TotW_{t+s-1}^i - PW_{t+s}^i - TotW_{t+s}^i\big]$$
$$\left.+\ \phi_{t+s}^i\big[K_{t+s}^i - Oil_{t+s}^i\big]\Big] \mid \Omega_{\mathrm{t+s-1}}\right\}$$

where σ_{t+s}^i and γ_{t+s}^i are the costate variables on the two state variables K_t^i and $TotW_t^i$ respectively, and ϕ_{t+s}^i is the shadow cost of the oil flow capacity constraint. $\Omega_{\mathrm{t+s-1}}$ states that the realizations of the variables from $t = 1$ to $t - 1$ are known.

Taking the partial derivatives with respect to oil flow and capacity gives

$$\frac{\partial\mathcal{L}}{\partial Oil_t^i} = E_{t-1}\{P_t + \zeta_2\sigma_t^i - \phi_t^i\} = 0$$

$$(7)\ \phi_t^i = E_{t-1}[P_t] + \zeta_2\sigma_t^i$$

$$\frac{\partial\mathcal{L}}{\partial K_t^i} = E_{t-1}\{-\sigma_t^i + \beta\sigma_{t+1}^i + \phi_t^i\} = 0$$

$$(8)\ \phi_t^i = \sigma_t^i - \beta\sigma_{t+1}^i$$

Set (7) equal to (8)

$$E_{t-1}[P_t] + \zeta_2\sigma_t^i = \sigma_t^i - \beta\sigma_{t+1}^i$$

$$\beta\sigma_{t+1}^i + (\zeta_2 - 1)\sigma_t^i + E_{t-1}[P_t] = 0$$

$$(9)\ \sigma_{t+1}^i = \frac{(1-\zeta_2)}{\beta}\sigma_t^i - \frac{1}{\beta}E_{t-1}[P_t]$$

Where (9) gives the maximum amount of money the firm is willing to spend at time t to increase the production capacity by one bbl/m at time $t + 1$. Thus, (9) gives the law of motion of this quantity – the Euler equation.

We repeat the process with respect to the volume of water injected Inj_t^i, the number of new production wells PW_t^i, and the total amount of untapped wells $TotW_t^i$, which gives

$$\frac{\partial \mathcal{L}}{\partial Inj_t^i} = E_{t-1}\left\{-\frac{\partial C_1(\cdot)}{\partial Inj_t^i} + \zeta_3 \sigma_t^i\right\} = 0$$

$$(10)\ \sigma_t^i = \frac{1}{\zeta_3} E_{t-1}\left[\frac{\partial C_1(\cdot)}{\partial Inj_t^i}\right]$$

$$\frac{\partial \mathcal{L}}{\partial PW_t^i} = E_{t-1}\left\{-\frac{\partial C_1(\cdot)}{\partial PW_t^i} + \beta \zeta_1 \sigma_{t+1} - \gamma_t^i\right\} = 0$$

$$(11)\ \gamma_t^i = \zeta_1 \beta \sigma_{t+1}^i - E_{t-1}\left[\frac{\partial C_1(\cdot)}{\partial PW_t^i}\right]$$

$$\frac{\partial \mathcal{L}}{\partial TotW_t^i} = E_{t-1}\{\beta \gamma_{t+1}^i - \gamma_t^i\} = 0$$

$$(12)\ \gamma_{t+1}^i = \frac{1}{\beta}\gamma_t^i.$$

Substituting (11) in to (12) gives

$$\zeta_1 \beta \sigma_{t+2}^i - E_{t-1}\left[\frac{\partial C_1(\cdot)}{\partial PW_{t+1}^i}\right] = \frac{1}{\beta}\left[\zeta_1 \beta \sigma_{t+1}^i - E_{t-1}\left[\frac{\partial C_1(\cdot)}{\partial PW_t^i}\right]\right]$$

$$(13)\ \sigma_{t+1}^i = \frac{1}{\zeta_1 \beta} E_{t-1}\left[\frac{\partial C_1(\cdot)}{\partial PW_t^i}\right] + \frac{1}{\beta}\sigma_t^i - \frac{1}{\zeta_1 \beta^2} E_{t-1}\left[\frac{\partial C_1(\cdot)}{\partial PW_{t-1}^i}\right].$$

We now have one intratemporal and two intertemporal equations in (10), (9), and (13), respectively

$$(10)\ \sigma_t^i = \frac{1}{\zeta_3} E_{t-1}\left[\frac{\partial C_1(\cdot)}{\partial Inj_t^i}\right]$$

$$(9)\ \sigma_{t+1}^i = \frac{(1-\zeta_2)}{\beta}\sigma_t^i - \frac{1}{\beta} E_{t-1}[P_t]$$

$$(13)\ \sigma_{t+1}^i = \frac{1}{\zeta_1 \beta} E_{t-1}\left[\frac{\partial C_1(\cdot)}{\partial PW_t^i}\right] + \frac{1}{\beta}\ \sigma_t^i - \frac{1}{\zeta_1 \beta^2} E_{t-1}\left[\frac{\partial C_1(\cdot)}{\partial PW_{t-1}^i}\right].$$

Setting (9) equal to (13) gives

$$\frac{(1-\zeta_2)}{\beta}\sigma_t^i - \frac{1}{\beta}E_{t-1}[P_t] = \frac{1}{\zeta_1\beta}E_{t-1}\left[\frac{\partial C_1(\cdot)}{\partial PW_t^i}\right] + \frac{1}{\beta}\ \sigma_t^i - \frac{1}{\zeta_1\beta^2}E_{t-1}\left[\frac{\partial C_1(\cdot)}{\partial PW_{t-1}^i}\right]$$

$$\left(\frac{1-\zeta_2}{\beta} - \frac{1}{\beta}\right)\sigma_t^i = \frac{1}{\zeta_1\beta}E_{t-1}\left[\frac{\partial C_1(\cdot)}{\partial PW_t^i}\right] - \frac{1}{\zeta_1\beta^2}E_{t-1}\left[\frac{\partial C_1(\cdot)}{\partial PW_{t-1}^i}\right] + \frac{1}{\beta}E_{t-1}[P_t]$$

$$(14)\ \sigma_t^i = -\frac{1}{\zeta_1\zeta_2}E_{t-1}\left[\frac{\partial C_1(\cdot)}{\partial PW_t^i}\right] + \frac{1}{\zeta_1\zeta_2\beta}E_{t-1}\left[\frac{\partial C_1(\cdot)}{\partial PW_{t-1}^i}\right] - \frac{1}{\zeta_2}E_{t-1}[P_t].$$

Finally, substituting (10) into (14) gives (15)

$$\frac{1}{\zeta_3}E_{t-1}\left[\frac{\partial C_1(\cdot)}{\partial Inj_t^i}\right] = -\frac{1}{\zeta_1\zeta_2}E_{t-1}\left[\frac{\partial C_1(\cdot)}{\partial PW_t^i}\right] + \frac{1}{\zeta_1\zeta_2\beta}E_{t-1}\left[\frac{\partial C_1(\cdot)}{\partial PW_{t-1}^i}\right] - \frac{1}{\zeta_2}E_{t-1}[P_t]$$

$$(15)\ E_{t-1}\left[\frac{\partial C_1(\cdot)}{\partial Inj_t^i}\right] = -\frac{\zeta_3}{\zeta_1\zeta_2}E_{t-1}\left[\frac{\partial C_1(\cdot)}{\partial PW_t^i}\right] + \frac{\zeta_3}{\zeta_1\zeta_2\beta}E_{t-1}\left[\frac{\partial C_1(\cdot)}{\partial PW_{t-1}^i}\right] - \frac{\zeta_3}{\zeta_2}E_{t-1}[P_t].$$

The resulting equation (15) gives the *marginal cost of injecting one barrel of water*. The marginal cost is given by three terms on the right-hand side. The first fraction gives the marginal cost of drilling a unit mass of production wells at time t, the second fraction gives the marginal cost of drilling a unit mass of production wells at time $t-1$, and the third fraction gives the front month oil price at time t.

6.2 The Firm's Cost Structure

We proceed to describe the firm's cost structure. For simplicity, we ignore any fixed costs associated with operating, restarting, or shutting in wells to facilitate comparison to the findings of Anderson, Kellogg & Salant (2018). They argue that these costs are relevant only to wells that are marginally productive or when the oil price is very low.

We start with a simple cost structure

$$(16)\ C_1\left(PW_{t+s}^i, Inj_{t+s}^i\right) = \psi_0 + \psi_1 Inj_{t+s}^i + \frac{\psi_2}{2}{Inj_{t+s}^i}^2 + \psi_3 PW_{t+s}^i.$$

Taking the partial derivatives of (16) with respect to PW_{t+s}^i and Inj_{t+s}^i gives

$$(17)\ \frac{\partial C_1(\cdot)}{\partial PW_t^i} = \psi_3,\ \ and\ \ (18)\ \frac{\partial C_1(\cdot)}{\partial Inj_t^i} = \psi_1 + \psi_2 Inj_t^i.$$

We substitute the partial derivatives from (17) and (18) into (15), which gives

$$E_{t-1}\left[\psi_1 + \psi_2 Inj_t^i\right] = -\frac{\zeta_3}{\zeta_1\zeta_2}\psi_3 + \frac{\beta\zeta_3}{\zeta_2}\psi_3 - \frac{\zeta_3}{\zeta_2}E_{t-1}[P_t]$$

$$E_{t-1}\left[Inj_t^i\right] = -\frac{\psi_1}{\psi_2} - \frac{\zeta_3\psi_3}{\psi_2\zeta_1\zeta_2} + \frac{\beta\zeta_3\psi_3}{\psi_2\zeta_2} - \frac{\zeta_3}{\psi_2\zeta_2}E_{t-1}[P_t]$$

$$(19)\ E_{t-1}\left[Inj_t^i\right] = \lambda_0 + \lambda_1 E_{t-1}[P_t] + u_t^i$$

$$where\ u_t^i = \alpha^i + \epsilon_t^i.$$

Equation (19) gives an expression for the optimal quantity of water injection at time t as a function of the front month oil price. The error term u_t^i consists of the time-invariant individual effect α^i of each injection well, and ϵ_t^i, which can vary across both individual and time dimensions.

7. Main Analysis

In this section, we aim to answer the revised hypothesis from Section 5.3.4 empirically. By answering the revised hypothesis, we also address the latter part of the research question posed in Section 1: *"To what extent do water injection volumes respond to oil prices?"*. Using the mathematical model derived in Section 6, we develop an econometric specification that utilizes a fixed-effects linear regression model. After specifying the model, we review the results and discuss potential causal relationships. Finally, robustness testing is conducted as a means of verifying the validity of our model.

7.1 Econometric Specification

7.1.1 Stationarity

The volume of water (bbl/m) that any given water injection well injects at time t serves as our dependent variable. To decide on a suitable econometric specification, we perform an Augmented Dickey-Fuller test to determine whether the dependent variable in our panel is stationary. The null hypothesis is that the dependent variable has a unit root. We find that the ADF statistic is -661.71 with a p-value of 1e-04. We thus reject the null hypothesis that the dependent variable has a unit root. It is stationary at the 1% level of significance.

7.1.2 Model specification

We then proceed by estimating a level regression. We use

$$E_{t-1}\left[Inj_t^i\right] = \lambda_0 + \lambda_1 E_{t-1}[P_t] + \alpha^i + \epsilon_t^i.$$

as our model specification, as derived in Section 6. $E_{t-1}\left[Inj_t^i\right]$ is the optimal volume of water (bbl/m) that any given injection well should inject at time t to maximize profit. The front month price of WTI at the NYMEX exchange is denoted as $E_{t-1}[P_t]$ in real 2020 US Dollars. $E_{t-1}[P_t]$ is our explanatory variable of interest. We use these variables as they tie into our research question presented in Section 1, specifically that we want to know to what extent water injection volumes respond to crude oil prices. The model captures a level-difference.

7.1.3 Fixed Effects

We decompose the error term so that $\alpha^i + \epsilon_t^i. = u_t^i$. Pooled OLS may wrongfully estimate standard errors and, thereby, t-values. To address this issue, we utilize t-values that are computed with clustered standard errors on the well-level. This approach accounts for the correlation between error terms originating from the same injection well, as demonstrated in Wooldridge (2003). By including individual-specific and time-invariant factors that can affect the outcome variable in the model, we eliminate bias attributed to unobserved heterogeneity. We note that it is not obvious at what level standard errors should be clustered. Arguably, it is possible that we should cluster standard errors at the oil field-level. However, we do not have sufficient data to reliably cluster oil production wells into fields that are suitable for this purpose. Our empirical specification does not allow for time-fixed effects, as this would induce simultaneity bias into our model.

7.1.4 Heteroscedasticity

The presence of heteroscedasticity may ultimately yield incorrect inference results when using the standard methods. Heteroscedasticity is often a problem in large datasets such as ours. Therefore, we estimate our models with standard errors that are robust to heteroscedasticity. We then get

$$\widehat{var(\lambda_1|x_\iota)} = \frac{\sum_{i=1}^{n}(x_i - \overline{x})^2\,\hat{u}_i^2}{SST_x^2}.$$

The estimated standard deviation is found as the root of the equation above, and these provide the robust standard errors.

7.1.5 Measurement Errors

There could also be measurement errors on the LHS of our regression formula. That is, Rystad Energy's data collection may be faulty, or the data generation may be aggregated. The latter is more likely, as we have observed a few instances where the injected liquid volume for a specific well is precisely the same for all months within a year, but varies year to year, indicating yearly water gauge readout. From visual inspections of the dataset, this problem seems to be limited to a very small number of injection wells.

When we assume that $cov(\epsilon_t^i, E_{t-1}[P_t]) = 0$, we imply that measurement errors in the dependent variable do not yield bias in the OLS estimator. However, the variance of the error term will be larger than for models that do not suffer from measurement errors on the LHS, since

$$var(u_t^i) = var(\alpha^i + \epsilon_t^i) = \sigma_{\alpha^i}^2 + \sigma_{\epsilon_t^i}^2 > \sigma_{u_t^i}^2.$$

This may lead to higher variance and standard deviation for the OLS estimators. However, the estimator remains consistent and does not induce bias.

7.2 Main Results

The results from the regressions outlined in the previous section are presented in Table 4. Column (1) reports a simple Pooled OLS specification, with WTI front month price as the explanatory variable. The coefficient λ_1 comes out as positive, stating that if $E_{t-1}[P_t]$ increases by 1 USD, then the liquid volume injected by an injection well increases by 17.75 bbl/m. The coefficient is significant at the 1% level. The specification that is reported in column (2) includes well-level individual effects for the 40,502 production wells in the panel. We observe that the coefficient λ_1 is still positive and significant to the 1% level. However, the magnitude of the coefficient has decreased by 10.781 (60.73%). The results clearly show a positive correlation between the price of oil and the volume of water injected into a reservoir. We report the Pooled OLS model in column (1) to establish a benchmark while opting for the fixed-effect model in column (2) as our baseline model.

	Dependent variable:	
	Injection Liquid Volume	
	OLS	*Fixed Effects*
	(1)	(2)
WTI 1-month future price	17.775***	6.963***
	(0.371)	(0.816)
Constant	11,527.950***	
	(29.666)	
Observations	6,058,629	6,058,629
R^2	0.0004	0.0001
Adjusted R^2	0.0004	−0.007
Residual Std. Error	27,832.640 (df = 6058627)	
F Statistic	2,296.362*** (df = 1; 6058627)	713.349*** (df = 1; 6018126)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 4: Main regression results

7.2.1 Discussion

Anderson, Kellogg & Salant (2018) outline that the oil flow capacity constraint evolves over time at

$$\dot{K}(t) = a(t)X - \lambda F(t),$$

where $\dot{K}(t)$ is a state variable that binds at the upper boundary, $a(t)$ is the rate at which new wells are drilled (a choice variable), and $F(t)$ is the rate of oil flow at time t (a choice variable). The maximum rate of oil flow from a tapped well depends on the pressure in the well. This is proportional with factor λ, to the oil that remains in the reservoir. Therefore, the flow of oil $F(t)$ erodes capacity at the rate $\lambda F(t)$. While we concur with Anderson, Kellogg & Salant (2018) in that the capacity constraint on oil flow can be manipulated on the extensive margin, the assumption of monotonic decay of oil flow on the intensive margins is not supported by the evidence found in our model.

In fact, our findings suggest that firms leverage the ability to control water injection as the price of crude oil fluctuates. Doing so allows oil producers to effectively manipulate the flow of oil on the intensive margin. We observe that for every dollar the front month oil price rises, the volume of water injected increases by 6.963 bbl/m. This indicates that the water injection wells do not operate at a constant rate. There may be several reasons for firms to operate their secondary recovery dynamically in response to crude oil prices. We offer two possible explanations for this; the first being that water injection is a cost driver, and the second is that firms respond to future oil price expectations.

Water Injection is a Cost Driver

The first possible explanation for our findings is that water injection represents a marginal cost that is not zero or near zero. That is, firms may not inject water at capacity at a constant rate because of the cost of injection, and the price needs to be high enough to justify the added marginal cost of oil produced. The cost of injection can be broken down into two main components; (1) water as a commodity has a cost, and (2) the injection itself has a marginal cost.

Water as a commodity is an essential input in the context of secondary oil recovery, consequently exerting an influence on the costs incurred by firms. Thus, variations in water prices directly impact the overall cost structure of the firm.

The supply of water may be limited at certain geographical locations, driving the purchasing price up. Water scarcity is prevalent in parts of the US, as shown in Figure 15 (US Geological Survey National Water Information System, 2020). We observe that the western United States experienced high levels of water scarcity in 2020. Although we only observe a snapshot of the water scarcity situation in 2020, it seems reasonable to assume that this situation has developed gradually over time. As shown in Figure 2 in Section 3.1.2, these areas also contain a high density of oil production wells. This may have led to a negative shock in the local supply of water – increasing the firms' water costs.

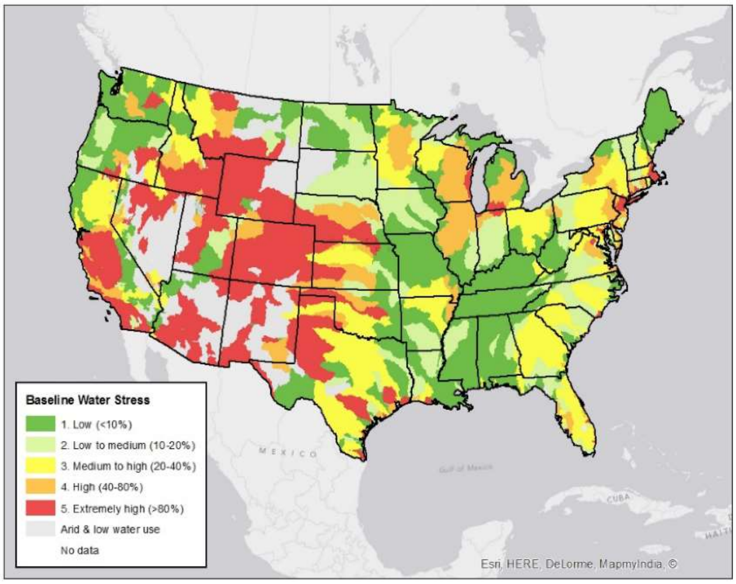

Figure 15 - Baseline water stress in the US in 2020. Source: (U.S. Geological Survey National Water Information System, 2020)

On the other side, the shale boom may have led to an increase in demand for fresh and non-fresh water used in oil production. In 2005, the estimated water requirements for conventional oil production in the US, weighted by primary, secondary, and tertiary recovery, had a Water-to-Oil Ratio (WOR) of 8. Primary recovery uses a minimal amount of water that is specifically related to drilling with a WOR of 0.2. However, secondary recovery, including waterflooding, had a WOR of 8.6 over the lifespan of the well. Tertiary recovery had a wide range of WOR between 1.9 and 13. Around 80% of the total water required for conventional oil production was attributed to secondary recovery. 70% of the water extracted from conventional oil production wells on a national basis was reinjected for use in oil production. Therefore, the average volume of non-produced water, or net Water-to-Oil ratio in conventional wells, was 3.6 (Scanlon, Reedy, & Nicot, 2014).

When comparing these ratios to shale oil production, the estimates of water use for fracking in the Eagle Ford Shale[5] play based on production to date generally fall within the lower range of WORs for conventional production. The increased water use in recent years is largely attributed to the expanded oil production using fracking and not because fracking itself is more water-intensive per barrel of oil produced (Scanlon, Reedy, & Nicot, 2014). As OPEC failed to squeeze out high-cost shale production after 2014, the positive shift in demand for water used in oil production may have driven up the cost of water. There might be a combination of shocks to both the supply and demand side of the market. Also, these shocks will inevitably vary across geographical locations as the water supply is highly local. Therefore, we cannot conclusively determine a causal relationship.

While the cost of acquiring water constitutes an important marginal cost of injection, so does the cost of pumping the water into the reservoir. According to Zhao et al. (2020), the marginal cost of injecting water depends on several factors, including the reservoir pressure. When the reservoir pressure is high, more energy is required to inject water through the injection pump. The energy that powers the pump, either electricity or diesel, may constitute a material marginal cost to the firms. This contradicts the assumption made by Anderson, Kellogg & Salant (2018) that the marginal cost of well-level production is zero or close to zero.

Future Crude Oil Price Expectations

The second possible explanation is that firms behave in accordance with the *Hotelling Rule* (Hotelling, 1931). Firms may choose to adjust the rate of oil production based on their expectations of future oil prices, which may be influenced by factors such as changes in global demand, geopolitical events, or the competitive landscape.

If firms expect a future increase in oil prices, they may opt to decrease the current rate of oil production. Firms can do this either by choking off the well or by decreasing the volume of water injected. The purpose is to conserve the resource and maximize profits by selling it at a higher price in the future. Conversely, if they expect a decrease in future oil prices, they may increase the rate of oil production to sell more oil at the current price before it decreases. Firms

[5] The Eagle Ford Shale play is a significant shale play located in South Texas, United States. The development of hydraulic fracturing and horizontal drilling techniques has enabled economic extraction of oil and gas from the Eagle Ford Shale (The Railroad Commission of Texas, 2014).

can do this by increasing water injection volumes to increase reservoir pressure and enhance oil flow.

In a simplified model that ignores extraction costs, firms would choose to invest their capital into interest-bearing securities (like U.S. Treasuries) if the expected increase in the oil price precedes the interest received on securities. For example, if a firm expects the oil price to increase by 10.0% in one year and the 1-year treasury rate is 5.0%, the firm is better off by conserving the oil in the reservoir and extracting it in the future when it can be sold for the higher price. Were the numbers switched, and the expected price increase of oil was 5.0% while the 1-year treasury rate was 10.0%, the firm would extract the oil, sell it, and invest the proceeds at a 10.0% yield. Thus, firms may operate in accordance with the *Hotelling Rule* to manage their resources efficiently and maximize profits over time.

In summary, our analysis reveals a positive and linear correlation between the injected water volume in water injection wells and the front month oil price. Diverging from the perspective presented in Anderson, Kellogg & Salant (2018) that oil production is adjusted only on the extensive margin, our model indicates that firms also manipulate oil flow on the intensive margin. We briefly explore two plausible explanations as to why firms manipulate their intensive margin using waterflooding. Firstly, the cost of water injection is not negligible and secondly, they behave in line with the *Hotelling Rule*. We confirm the revised hypothesis posed in Section 5.3.4, that the injected liquid volume has a positive and linear relationship with crude oil prices.

7.3 Robustness Analysis

We conduct our robustness analysis for the fixed-effect linear regression model in the previous section. We estimate a random effects model to determine whether our fixed effects model is indeed the preferred model. Thereafter, we exclude influential observations from our dataset and re-run the baseline model. Lastly, we discuss how the robustness test affects the interpretation of our main results and include an assessment validity of our findings.

7.3.1 Random Effects

First, we estimate a random effects (RE) model. The purpose of this estimation is to test whether a random effects estimator yields a more precise and consistent estimator than the fixed-effect estimator. RE models are only consistent if the individual specific components are uncorrelated with the x-variables while the fixed effect estimator is consistent regardless of this assumption. If the assumption is satisfied, random effects is the preferred model. We have estimated the RE model in Table 5.

	Dependent variable:
	Injection liquid volume
WTI 1-month future price	7.101***
	(0.816)
Constant	11,459.710***
	(104.070)
Observations	6,058,629
R^2	0.0002
Adjusted R^2	0.0002
F Statistic	738.687***
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 5: Random effects regression model

We use the *Hausman specification test* to determine which model is more efficient (Hausman, 1978). If both models are consistent, then we prefer to use RE. However, if only one model is consistent, we use our fixed-effect model and conclude that we have satisfying goodness-of-fit in the baseline model. We have the competing hypotheses

$$H_0: cov\left(\alpha^i \middle| E_{t-1}[P_t]\right) = 0$$

$$H_1: cov\left(\alpha^i \middle| E_{t-1}[P_t]\right) \neq 0$$

The test estimator yields a chisq equal to 64.537 and a p-value of 9.474e-16. We reject the null hypothesis. The baseline model we have estimated is preferred over a random effects model.

7.3.2 Influential Observations

In Section 4, we found the water injection data to be skewed with a long right tail. To test whether influential observations impact our result significantly, we remove large outliers. We conduct the test by calculating the z-score of all observations and then removing the observations that have a z-score of more than 3. If an observation has a z-score of 3, then it is 3 standard deviations larger than the mean. By using this threshold, we retain 99.25% of our observations but drop very large observations. We run our baseline model on the reduced dataset and get the estimated coefficients in Table 6, column (2). Column (1) depicts our original baseline model, including all observations.

	Dependent variable:	
	Injection Liquid Volume	
	(1)	(2)
WTI 1-month future price	6.963***	6.948***
	(0.816)	(0.819)
Observations	6,058,629	6,013,175
R^2	0.0001	0.0001
Adjusted R^2	−0.007	−0.007
F Statistic	713.349*** (df = 1; 6018126)	701.488*** (df = 1; 5972674)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 6: Baseline model with and without influential observations

λ_1 is still positive and significant when we exclude influential observations. The coefficient magnitude is marginally reduced. We can conclude that outliers do not significantly affect our model estimates. The model is robust to influential observations.

We performed a robustness check to evaluate the potential shortcomings of our model. In order to evaluate the goodness-of-fit for our fixed-effect linear regression model, we estimate a random effects model and perform a Hausman specification test. The test result indicates that the baseline model is preferable over the RE model. Finally, we remove influential observations and estimate the baseline model, finding a negligible change in the explanatory coefficient. In summary, the baseline model has sufficient empirical validity, and we retain the interpretation of the main findings.

8. Conclusion

The purpose of this thesis is to examine to what extent oil-producing firms manipulate water injection volumes on the intensive margin in response to crude oil prices. Specifically, we analyze oil production curves from tapped wells that have water injection wells in close proximity and observe whether the curves exhibit monotonic decline. Based on our preliminary findings, we propose a modified Hotelling model that accounts for waterflooding as a secondary recovery measure. Using the mathematical model, we empirically test whether water injection volumes exhibit responsiveness to crude oil prices. While earlier research on the subject has provided valuable insight into the price responsiveness of oil production on the extensive margin, none have provided evidence of price responsiveness on the intensive margin.

The preliminary analysis confirms the findings of Anderson, Kellogg & Salant (2018) that firms respond to crude oil prices on the extensive margin by drilling new production wells. The analysis further confirms the monotonic decline in the oil production curve from a stock of wells without water injection wells nearby. More interestingly, the analysis reveals that the oil production curves from wells with water injection wells in proximity do not decline monotonically. This implies that firms leverage their ability to manipulate the flow of oil on the intensive margin, contrary to the findings of Anderson, Kellogg & Salant (2018). We use this insight to formulate our hypothesis that firms manipulate the intensive margin through water injection in response to crude oil prices. We then proceed to modify their reformulated Hotelling model accordingly.

The following empirical analysis reveals that the injected liquid volumes have a clear linear and positive correlation with crude oil prices. That is, firms respond to fluctuating crude oil prices on the intensive margin by adjusting the volume of water they inject. The empirical evidence therefore reveals a potential weakness in the reformulated Hotelling model proposed by Anderson, Kellogg & Salant (2018). The findings are robust to potential empirical misspecification and exhibit sufficient validity.

We also discuss potential explanations for the adjustments in volume of water injected. Contrary to the assumptions made by Anderson, Kellogg & Salant (2018), we suggest that the marginal cost of oil production on the intensive margin is not zero or near-zero. Specifically, we discuss cost drivers of water injection. Another possible explanation is that oil producers behave in line with the *Hotelling Rule*. Although we discuss these potential explanations, determining causal relationships requires additional research that is out of scope for our thesis.

While our thesis uncovers a potential specification problem in the existing literature, it does not address the underlying cost structure of waterflooding. An interesting extension of the thesis would be to study the long-term effect of water scarcity on the marginal costs of oil extraction in the US. Secondly, it would be interesting to study whether firms manipulate the water injection volume in accordance with the *Hotelling Rule*. Thirdly, by assigning water injection volumes to nearby production wells, one could analyze the correlation between oil flow and water injection on a more granular level. We leave this for future research.

9. Limitations

Our thesis is subject to certain limitations that need to be accounted for. First, the cost function that we outline in Section 6 has a restrictive functional form. We could have included a more complex cost function that allows for a fixed ratio between the number of production wells drilled and the volume of water injection. This would yield an equilibrium variable of production wells drilled or future injected liquid volume. Therefore, the model we estimate could become more efficient if we were to include a more complex cost function.

Secondly, our empirical model does not allow for including time-fixed effects. By including time-fixed effects, we can increase the precision and validity of our estimates. Time-fixed effects address the concern of omitted variable bias by capturing time-varying shocks or trends that affect all individual injection wells simultaneously. However, including such effects or cointegrating our model would yield simultaneity bias. Simultaneity bias occurs when there is a reciprocal relationship between the dependent variable and one or more of the explanatory variables, leading to endogeneity in the model. Although the model could potentially prove richer if we were to include time-fixed effects, we choose not to include them to avoid said simultaneity problems.

Thirdly, we do not test whether firms act in accordance with the *Hotelling Rule*. To retest Hotelling exhaustively, we would need expressions for all the coefficients in equation (6), which are not derivable from our model. With a higher level of granularity, we could have analyzed whether firms acted in accordance with the *Hotelling Rule* through manipulation of water injection on the intensive margin.

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11. Appendices

11.1 Geographical locations of US refineries

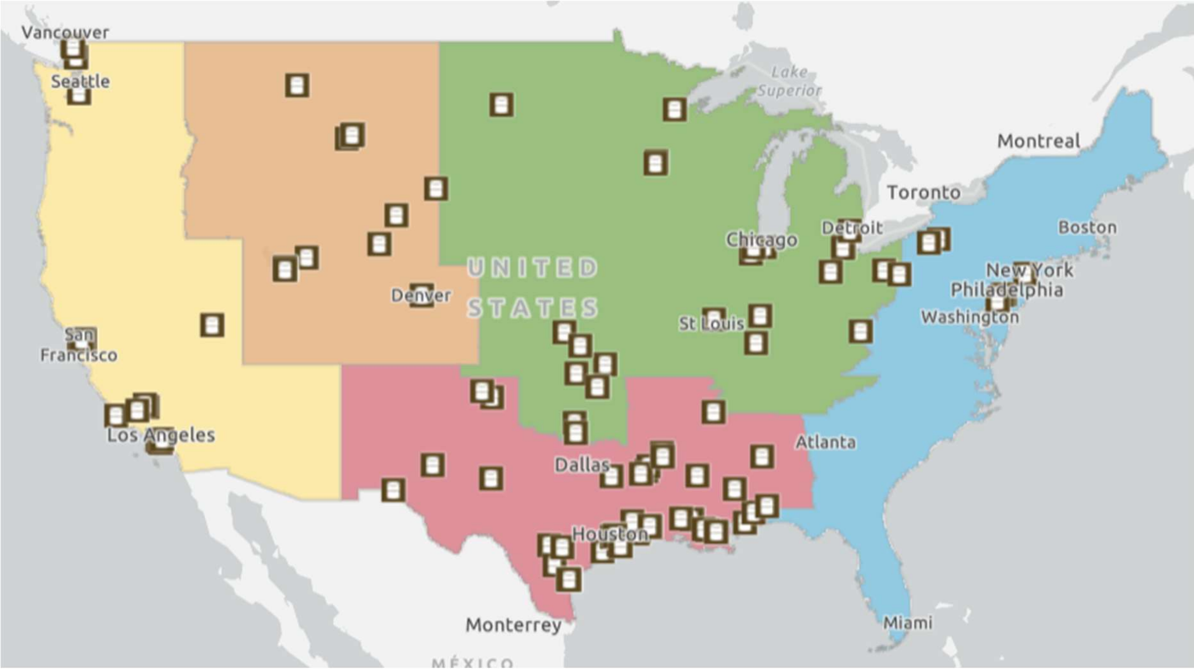

Figure 16 - Refinery locations in the US. Colorized areas represent the different PADDs. Source: (U.S. EIA, 2023)

11.2 Factors Affecting Waterflood Efficiencies

Factors Affecting Waterflood Efficiencies

Displacing Efficiency

Oil and Water Viscosities
Oil Formation Volume Factors at the start and end of flood
Oil Saturations at the start and end of flood
Relative Permeability Characteristics

Sweep Efficiencies

Reservoir Heterogeneity
(areal and vertical variations in porosity, permeability, and fluid Properties)

Directional Permeability

Formation Discontinuity/Faults

Horizontal and Vertical Fractures

Formation Deep

Flood Pattern Type

Cross-Flooding

Throughput

Oil/Water Mobility (effective permeability/viscosity) Ratio

Table 7: Factors that affect waterflooding efficiency. Source: (Thakur & Setter, 1998)

11.3 Pump Jack diagram

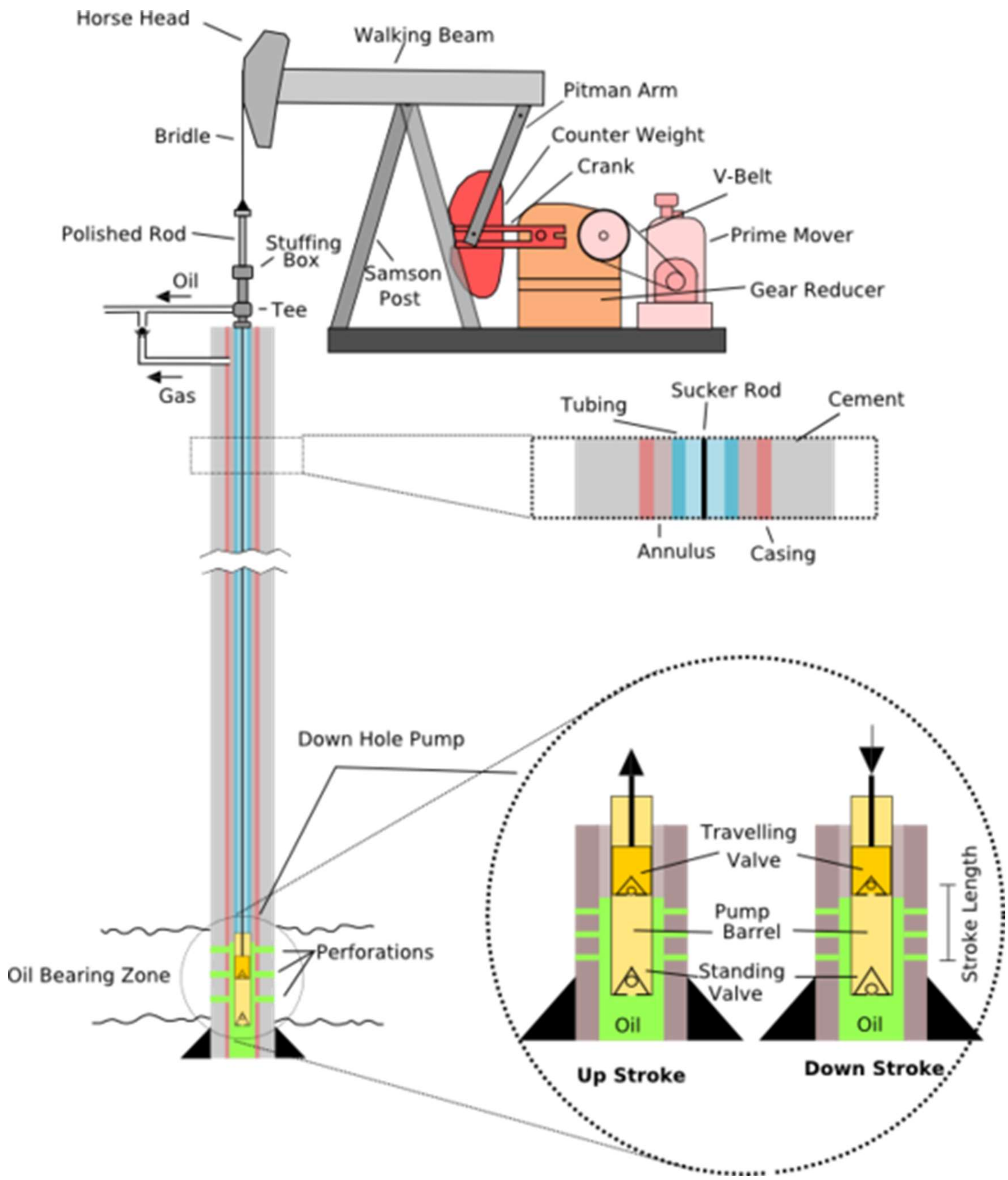

Figure 17 - Diagram of a pumpjack used in conventional oil production

11.4 US Petroleum Administration of Defense Districts

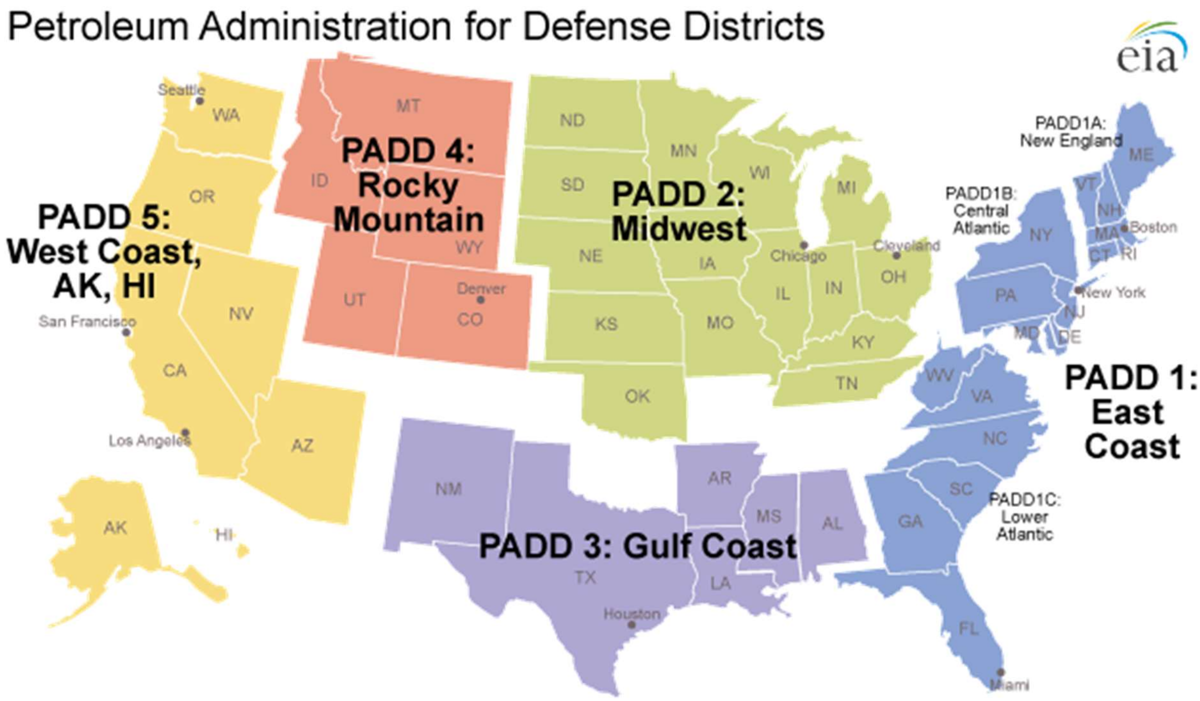

Figure 18 - Map of the Petroleum Administration of Defense Districts.
Source: (U.S. EIA, 2012)