The Impact of Price Regulation on U.S. Pipeline Investment During the Shale Revolution

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Abstract

Since the shale boom began in 2010, crude oil production in the United States has surged over 100% leading to a dramatic increase in demand for pipeline transportation. The profitability of investing in oil pipelines is constrained as transportation rates are set subject to a price cap. In this paper, I examine the impact of price regulation on pipeline investment in response to the shale boom. I develop a theoretical model of the pipeline industry, where firms make production and investment decisions while being subject to a dynamically changing price ceiling. I estimate the model using detailed operational data derived from regulatory filings and compare welfare under three separate regulatory environments: price cap regulation, cost-of-service regulation, and price deregulation. I find that price cap regulation was superior to the alternative mechanisms considered, as it increased market entry by 15% and incentivized firms to operate 17% more efficiently. I find evidence suggesting that prices were allowed to increase too quickly. While this led to an increased rate of entry into new markets it came at the expense of higher prices in existing markets. This ultimately resulted in a transfer in consumer surplus from existing customers to new customers and a slight decrease in total relative to what could have been achieved under a fixed price ceiling.

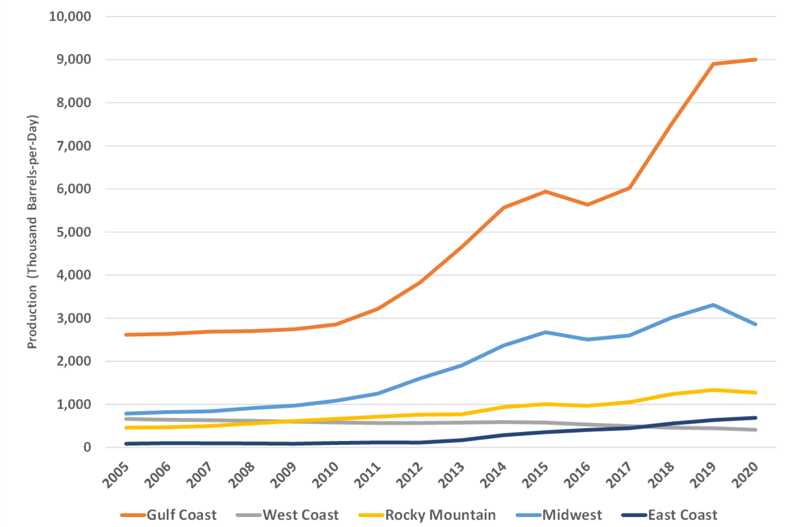
1 Introduction

The United States oil pipeline industry has experienced significant change over the past two decades due to an unprecedented demand shock and increased regulatory scrutiny. Innovations in hydraulic fracturing, horizontal drilling, and seismic imaging led to a boom in oil production with domestic supply increasing by over 100%, from 5 million barrels per day (bpd) in 2000 to over 11 million bpd by 2020. As shown in Figure (1), the impact of the shale boom was felt across the United States as previously marginally productive fields greatly increased their supply. However, the surge in production was largely accommodated using the existing processing infrastructure, as refining capacity only expanded 6% over the same period. This required new means of transportation to connect new wells to the processing infrastructure, generating a large increase in demand for additional crude oil pipeline construction.

The profitability of constructing new pipelines is constrained by the use of price caps to regulate transportation prices in the industry. Oil pipelines primarily generate revenue through the provision of transportation services, charging a fixed price to transport a barrel of oil. These prices are set subject to a price cap that is determined by the Federal Energy Regulatory Commission (FERC). The initial price cap depends on the pipeline's average total cost while the evolution of the price cap depends on movements in the producer price index plus the difference between the mean industry average total cost and the change in the producer price index. The price cap mechanism was implemented to prevent pipelines from generating excessive rents, but this created a trade-off as it also disincentivizes firms from undertaking potentially welfare improving investment. In this paper, I examine the extent to which the use of price cap regulation impacted the incentive for pipelines to invest in response to the shale boom, and how their investment decisions would have changed under alternate forms of regulation.

Price cap regulation can impact investment decisions through two channels: the initial

Figure 1: Growth in Oil and NGL Production by Region



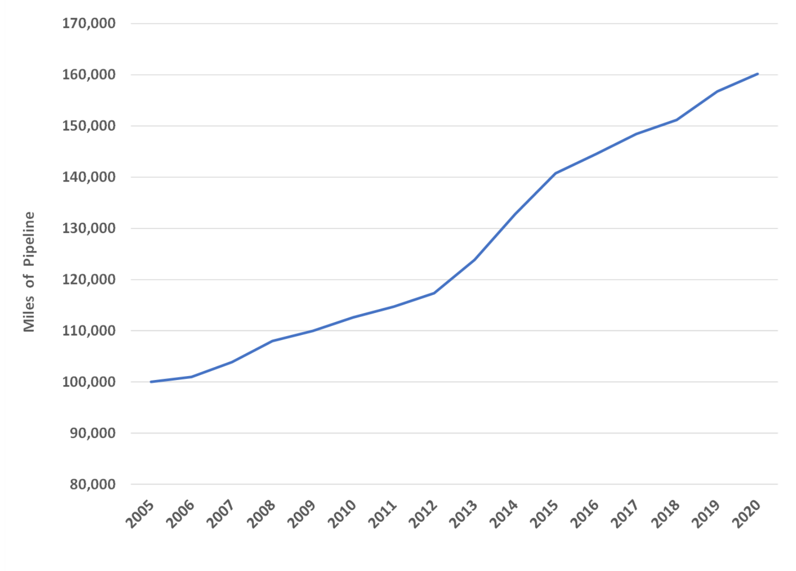
Note: Production figures include crude oil and natural gas liquids (NGLs). Data are from the EIA and include production of crude oil and plant condensate.

price ceiling level and how the ceiling trends over time. In principle, the regulator can set initial price levels to compensate firms for sunk investment costs in order to incentivize construction. However, when making entry decisions, firms also have to anticipate whether the price ceiling will rise fast enough to compensate them for exogenous increases in unit cost. Since 2000, firms saw operational costs grow by roughly 65%.[1] The exact cause of this increase is difficult to determine, however, the regulatory record shows that it was in part due to expanded environmental and safety requirements which increased operational and capital costs for pipelines. If pipelines anticipated that costs would grow faster than the price cap, they could be further deterred from undertaking additional capital expansion.

To determine the impact of price cap regulation on investment, I develop a model of pipeline production and investment where pipelines are subject to price regulation. Pipelines supply oil transportation services to shippers, which include oil producers, refineries, and industrial

[1]See Appendix Figures (21).

Figure 2: Growth in Crude Oil and Natural Gas Liquids Pipelines



Note: Data are from the PHMSA and include mileage for crude oil and highly volatile liquids pipelines.

manufacturers. Pipelines are modeled as local monopolist that choose the optimal timing of market entry to maximize their expected profit and face a sunk cost of entry. After entering a market, pipelines can further invest to lower their unit cost and to expand their system. Pipelines must set prices subject to a price cap, which limits the expected return to pipeline construction. The price cap evolves over time, so pipelines must predict how the price cap will change in response to changing industry costs and demand. Pipelines can then exit if the price cap falls below the cost of production.

Pipeline decisions impact welfare in three ways. First, to the extent that the price cap is above the marginal cost of production, pipelines generate dead-weight-loss and lower total welfare. Second, firms are able to invest to lower their unit-cost of production and lower production costs are potentially eventually passed on to shippers in the form of lower prices. Finally, pipelines may expand their system in response to higher expected returns, potentially increasing welfare.

To determine the relative importance of these various effects, I estimate the model using a rich dataset gathered from regulatory filings made to FERC. I begin by estimating a demand curve for pipeline transportation, regressing data on the total quantity transported (in barrel-miles) on the transportation price and additional covariates. These covariates include the number of routes a pipeline provides, market-specific fixed-effects, and an indicator variable for the shale boom. I estimate that the shale boom increased demand for pipeline transportation by roughly 90% on average.

Next, I estimate the variable cost of production in a two-step process. First, I estimate an industry production function using data on physical units of output - total barrel-miles transported - and detailed data on variable and capital costs. Data on variable costs include wages, materials and supplies, operating fuel, and outside services. My capital series is construct following Olley and Pakes (1996), using capital expenditures on land, equipment, and structures. The production function estimates recover a measure of firm-level productivity and how it evolved over time. Average productivity is estimated to decline by 50% over the sample period, suggesting that increased safety regulation led to higher costs.

Following Dhyne et al. (2020), I then maintain cost-minimization to recover firm-level marginal costs. These marginal costs are then regressed on observed output levels and pipeline routes to recover a marginal cost function in a manner analogous to Dhyne et al. (2020). Integrating the marginal cost function yields the variable cost of production. The marginal cost of transportation is estimated to be U-shaped and is relatively flat over the relevant range of output.

With estimates of the variable cost function and demand, I use the model to recover the industry fixed cost structure by matching predicted investment, entry, and exit decisions to their empirical counterpart. I estimate large sunk costs of market entry of roughly \$1.3 billion, with 95% of sunk costs falling between \$700 million and \$1.9 billion. The fixed cost of system expansion is similarly large but has a higher variance. Together, these large costs suggest that pipelines need reasonably large expected returns in order to either build new systems or expand an existing system.

I use the estimated model to determine how welfare would have changed under three alternative regulatory scenarios: cost-of-service, price deregulation, and a non-adjusting price cap. I find that the price cap led to a significant increase in returns for oil pipelines relative to the cost-of-service mechanism, leading to 15% increase in market participation after the shale boom. System expansion is marginally impacted, increasing by only 0.5%, as both forms of regulation encourage pipelines to operate on a larger scale. Average pipeline productivity is estimated to be 17% higher under the price cap. However, welfare gains from entry and productivity investment are somewhat offset by the higher prices charged to existing customers, who see their consumer surplus decline by 15%.

Price deregulation leads to the highest level of market participation among regulatory scenarios I consider and pipelines undertake roughly 18% more system expansion. However, this is more than offset by an 8% decline in average productivity and much higher prices for customers so that welfare declines by roughly 1.4%.

The price cap yielded better results than a traditional cost-of-service regime and price deregulation, however welfare could have been further improved by not allowing the index to adjust dynamically. Under the fixed price cap, entry would have been 6% lower after the shale boom. However, the lower prices that existing customers would have faced leads to an increase in consumer surplus of 5%. The ultimate impact is that welfare would have been 2.4% higher given a fixed price cap.

Related Literature and Contribution A few papers have analyzed oil pipeline investment after the shale boom. Covert and Kellog (2017) studies the impact of rail transportation on pipeline investment in the Bakken and finds that railroads can provide an important alternative to pipelines due to their flexibility. McRae (2017) studies how the expansion of pipeline capacity in the Permian impacted oil price differentials. In this paper, I use a new dataset to study entry and investment decisions by oil pipelines across the United Sates over the same time period. Detailed data on pipeline operations allows me to take a comprehensive look at how the industry was impacted by increased regulatory scrutiny and significant changes in demand. Additionally, this paper focuses on how price regulation changed investment decisions.

I build on the literature studying the impact of incentive-based regulatory mechanisms. Several papers have used regressions techniques, exploiting variation in firm regulatory environments, to estimate the impact of price caps, including Ai and Sappington (2002), Ai et al. (2004), Majumdar (2016), and Sappington (2003). Domah and Pollitt (2001) and Bottasso and Conti (2009) use a structural approach where they estimate cost functions. This paper provides one of the few dynamic structural models which have been used to determine the efficacy of incentive-based regulation. Pint (1992) also develops a structural model to compare price cap vs cost-of-service regulation, however the author does not estimate the model parameters. By using a structural model, I am able to explore different regulatory environments and decompose the impact of price cap regulation through different channels. This decomposition is important, especially when the industry of interest experiences significant changes after the regulation is introduced. For instance, several paper haves found that productivity falls after the implementation of price cap regulation, for instance Jenkins (2004). I find a similar results with unit-costs increasing by over 50% over the past two decades. However, the structural model implies that most of this increase was exogenous and that the price cap actually served to make firms more efficient relative to cost-of-service regulation.

Additionally, rather than focus on the trade-off between achieving the optimal price structure and incentivizing productivity gains, I allow firms to make optimal investment and market participation decisions. This adds an additional margin, of particular importance for the oil pipeline industry after 2008, through which the price cap regulation can impact market outcomes. Evans and Guthrie (2012) also study the impact of price cap regulation on investment using a continuous time model but do not consider entry or exit. Complementing the theoretical literature on price cap regulation, I find that productivity was substantially improved compared to traditional cost-of-service regulation. However, I also find that price cap regulation was important for encouraging firm entry into markets that were previously not served. These markets can provide significant gains in consumer surplus, and so constitute an important margin for regulators to consider when implementing a price cap mechanism.

My paper proceeds as follows. In Section (2), I give a high level look at the oil pipeline industry and discuss my primary confounding event, the shale boom. Next, in Section (3) I provide an overview of price cap regulation and specifically how it is implemented in the oil pipeline industry. Section (4) discusses the various datasets that I use during my analysis, with a particular emphasis on the FERC Form 6, the primary oil pipeline regulatory filing. Sections (5) and (6) provides an overview of my model of an oil pipeline production and investment. Section (7) provides an in-depth discussion of my empirical strategy. Readers interested in the empirical results can skip directly to Sections (8) and (9). Section (8) provides the estimates for the model primitives, including demand and cost functions, as well as the distribution of entry, exit, and investment costs. Section (9) shows the evolution of markups and productivity over the past two decades in the industry and provides my main counterfactuals, namely how investment and entry would have changed as we alter the price cap.

2 Industry Overview

In this section I provide a high-level overview of the oil pipeline industry and how it was impacted by the shale boom and increased governmental oversight. I provide a more detailed description of the industry in my online appendix. Readers not interested in industry details can go directly to Section 7.

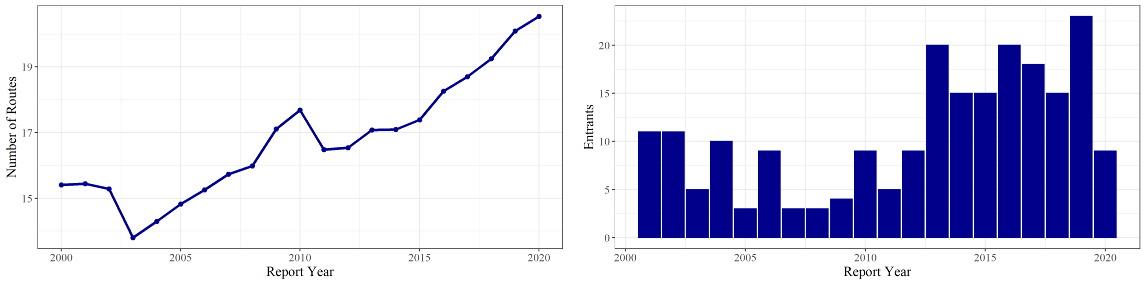
Oil pipelines primarily generate revenue through the transportation of oil, charging prices that vary based on the total distance the oil is shipped. Oil pipelines are limited in their ability to provide dedicated transportation and must reasonably accommodate all shippers that that demand transportation at the posted price. Broadly speaking, pipelines can be classified by whether they transport crude oil or refined petroleum product. Shippers on crude pipelines are generally oil producers and refineries while shippers on refined product pipelines including terminaling companies, airports, and large industrial customers. As of 2020, there was roughly 225,000 miles of oil pipeline installed in the United States. Of this, nearly 70% was dedicated to transporting crude oil and highly volatile liquids (HVL)[2], with the rest dedicated to transporting refined petroleum product.[3]

Shale Boom The development of horizontal drilling, hydraulic fracturing, and seismic imagine made previously high-cost oil fields economically viable to drill. Starting around 2010, low interest rates and a high price-per-barrel for crude oil led upstream oil companies to invest heavily in shale exploration and production. The results were striking as oil production rose over 100% in less than a decade. This massive increase in oil supply led to a similar increase in demand for pipeline transportation. The total crude/HVL pipeline footprint increased from roughly 100,000 to 160,000 miles by 2020, while existing pipelines delivering product into Northeast were reversed and started moving petroleum from the Marcellus/Utica to processing plants along the Gulf Coast. The increase in

[2]Highly volatile liquids include propane, butane, and other condensates.

[3]See PHMSA "Annual Report Mileage for Hazardous Liquid or Carbon Dioxide Systems"

Figure 3: Dynamics of Firm Entry and Route Expansion



(a) Average No. Routes

(b) Enterants per Year

pipeline capacity was driven in part by the expansion of existing systems and by the construction of new pipeline systems. Panel (a) of Figure (3) shows the increase in average number of routes offered by pipelines from 2000 to 2020, increasing from 15 to 20. Panel (b) shows the introduction of new pipeline systems. Following a similar pattern, there was an average of 5 entrants per year prior to 2011, but this increased to over 15 in the subsequent decade.

Increased Safety Regulation The pipeline industry saw an increase in environmental and safety regulation over this time period, starting with the passing of the Pipeline Safety Improvement Act of 2002 and the Pipeline Inspection, Protection, Enforcement and Safety Act of 2006. The Pipeline and Hazardous Materials Safety Administration (PHMSA) imposed new integrity management regulations that required pipelines to invest in physical modifications to their pipelines and repairs, as well as increased operational costs associated with more frequent inspections. While PHMSA does not collect quantitative data on the cost of this regulation, they did provide anecdotal evidence in the 2010 price cap index review noting that pipelines have reported compliance costs between \$2.0 - \$2.5 billion. The Deepwater Horizon Spill and the Kalamazoo River oil spill put further scrutiny on the pipeline industry, leading to additional regulation under the Pipeline Safety, Regulatory Control, and Job Creation Act of 2011 and reviews of pipeline safety by the National Transportation Safety Board and the Government Accounting Office. These reviews recommended further measures to ensure the integrity of pipeline systems, culminating in the Protecting our Infrastructure of Pipelines and Enhancing Safety Act of 2016. Each of these acts, along with new rules adopted by PHMSA, appear to have contributed to increased in costs for oil pipelines over the past two decades.[4] The price cap potentially limited the ability of pipelines to raise prices in response to these costs. I discuss the mechanics of price regulation in the oil pipeline industry next.

3 Price Cap Regulation

Many regulated industries have historically operated under a cost-of-service mechanism. Under this scheme, the regulator compensates firms for all costs accrued during operations and provides them with a pre-determined return on their unit-cost. However, this mechanism distorts the firm's incentive to minimize their costs because they are compensated for all incurred costs. Littlechild (1983) proposed a different method of regulating British Telecom after its privatization in the 1980s based on a dynamically changing price cap, called price cap regulation. Firms set prices subject to a ceiling and become the residual claimant on any reduction in their cost base, providing the proper incentives to operate efficiently. Since then, price cap regulation has been applied extensively to utilites around the world.[5] Most important to this paper, FERC adopted price caps as a form of price control when deregulating midstream oil services in 1996.

The initial level of each firm's price cap is determined using a standard cost-of-service filing, such that the ceiling is set equal to average total cost. Firms report their cost of pro-

[4]Pipeline also face increased regulatory uncertainty as concerns over pipeline spills, climate change, and social justice have increase. The Keystone XL pipeline incurred over $1.5 billion of development costs before TC Energy was forced to abandoned the project.

[5]Ofwat adopted price caps to regulate water and sewage services at its inception in 1989 and Ofgem adopted price caps for the downstream natural gas market after it formation in 2000. In 1989, the FCC adopted price caps to regulate interstate telecommunication services, and was followed by several states soon after.

duction and the regulator sets the maximum price level based on the allowed rate of return. Firms can then improve their profit margin by reducing their unit-cost. The evolution of the price cap is based on the movement of a price index (FERC uses the producer price index) and average industry performance. This typically takes the form of $PPI+X$, where PPI is a measure of inflation and X is a term determined by the regulator. Firm-specific price cap then evolves according to

$$\bar{P}_{t+1} = \bar{P}_t \left(\frac{PPI_{t+1}}{PPI_t} + X \right)$$

The term X is meant to reflect how industry costs and productivity are expected to change relative to PPI over a predetermined interval of time, called the review period. At the beginning of each review period the term X is reset in order to pass any cost savings on to consumers. Every 5 years, FERC sets this term equal to

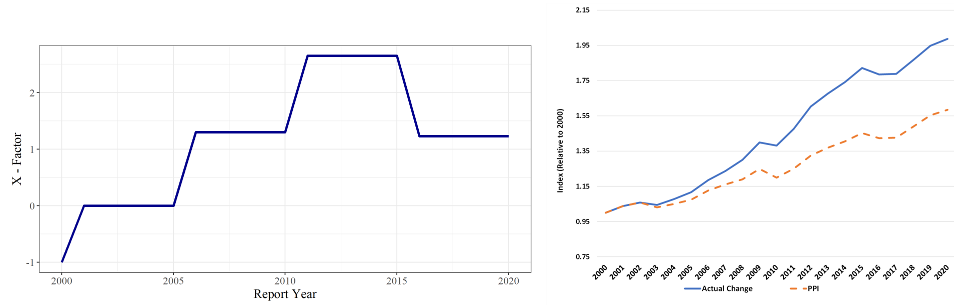
$$X = \left(\frac{1}{N} \sum_i \mathrm{CG}_{i \in I} \right)^{\frac{1}{5}} - \left(\frac{PPI_5}{PPI_0} \right)^{\frac{1}{5}}$$

where

$$\mathrm{CG}_{iT} = \left((1 - OR_i) \frac{\mathrm{AFC}_{iT}}{\mathrm{AFC}_{i0}} + OR_i \frac{\mathrm{AVC}_T}{\mathrm{AVC}_0} \right)$$

Here, OR_i is the operating ratio of firm i, defined as the ratio of operating expenses to operating revenue. AFC_i is the average fixed cost, defined as the average capital net of depreciation, and AVC_i is the average variable cost, defined as the the average operating and maintenance expense. The use of the operating ratio when calculating the cost growth index is meant to capture the relative importance of operating expenses for certain pipelines. Figure (4) shows the realized value of X for each review period, along with the cumulative change in price cap since 1999. With the exception of the prior review, the adjustment factor has increased steadily in each review period and price levels have been allowed to

Figure 4: Adjustment Factor



(a) Adjustment factor (b) Cumulative Change

Note: Panel (a) shows the adjustment factor established after each review period. Panel (b) shows the cumulative change in price caps since 2000.

increase over 100%.

One potential explanation for the steady rise in the adjustment factor is that increases in market power can lead to an increase in unit operational cost. In the online appendix, I show that when marginal costs are constant the change in average total cost to a change in price is roughly equal to

$$\frac{\partial \text{ATC}}{\partial p}\frac{P}{\text{ATC}} = \frac{\text{FC}}{\text{TC}} \cdot |\epsilon_D|$$

When firms restrict output to increase price their average total cost increases as well. In the pipeline industry, capital expenses are on the order of 60% and I estimate the elasticity of demand to be roughly 1.2 to 1.5, so a 10% increase in price would translate to an 7.2% - 9.0% increase in average total cost. This has the potential to create a feedback loop, where increased prices contribute to increased unit costs, which in turn leads to a higher rate index and therefore prices. The extent to which this is an issue is an empirical question.

4 Data Sources

My primary data sources on pipeline operations come from regulatory filings made to FERC, including the Form 6 and responses to FERC Order 342.3. These sources provide information on prices, physical output, and costs, which I discuss them in the following section.

Form 6 The principal data source for this analysis is the FERC Form 6, a mandatory, quarterly filing for all interstate oil pipeline that have at least $500,000 in annual revenue.[6] Form 6 databases are provided annually by FERC for the years 2000 to 2020. These data include information on firm revenue by interstate and intrastate transportation. Data is provided on transportation quantities by product type, type of transportation, and region. Output is reported in both barrels and in barrel-miles, where the latter reflects the total distance the oil was transported. The Form 6 also contains detailed data on pipeline operating and capital costs.

Operating expenses are broken out into two categories: general expenses and operating and maintenance expenses. I use operating and maintenance expenses (OPEX) as my measure of the variable inputs to production. Figure (5) shows the average share of each cost category in OPEX. The largest two shares include Outside Services and Operating Fuel and Power. Together, they account for 63% of the pipelines variable cost. A significant component of outside services is the use of outside contractors so I include Outside Services in the labor expense. Salaries and Wages directly payed by the firm account for roughly 15% of pipeline variable costs. Materials and Supplies account for roughly 10% and the remainder is Other Expenses[7] To convert operating expenses into variable inputs,

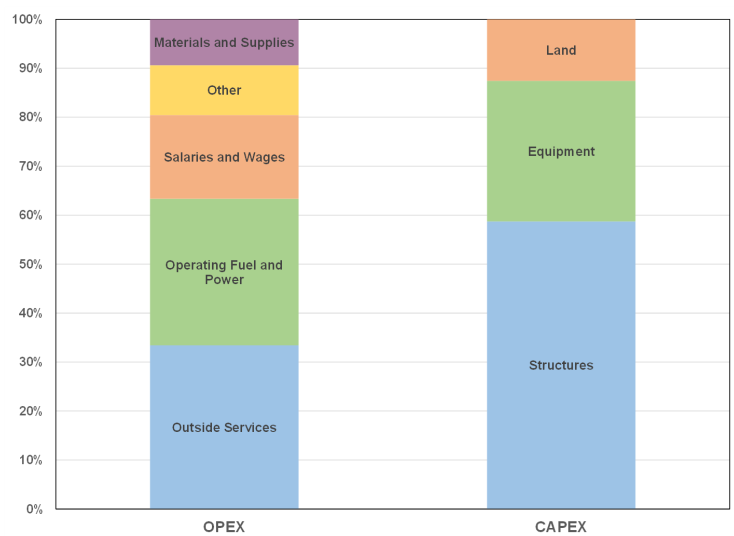
[6] Interstate pipelines are pipelines that transport product that has crossed state lines. Importantly, it is not the pipeline which needs to cross state lines. So pipelines that are entirely contained within a single state may still show up as interstate pipelines and therefore report to FERC. This increases the coverage of my dataset.

[7] Other expenses include oil losses and shortages, where companies incur the cost of spilled oil.

I deflate these costs using the input price index for the pipeline transportation industry (NAICS code 486210) provided by the BEA.

Capital expenditures (CAPEX) recorded separately for carrier property (capital that is used to directly transport petroleum) and non-carrier property (capital that is not used in the transportation of petroleum). I limit my data series to carrier property, as this is the capital stock most directly tied to production. These data are then further broken out into line items, including land, right of way, pipe, and machines and tools. I partition capital into three components: land, structures, and equipment. Figure (5) shows the average share of each component in CAPEX. The largest component is structures, which include line pipe and oil tanks, at almost 60%. The next largest component is equipment at roughly 25%. Finally, land accounts for roughly 15% of pipeline CAPEX.

Figure 5: Cost Category Components



I construct a capital index using the perpetual inventory method, analogously to Olley and Pakes (1996). Capital at time t is equal to the depreciated stock at time t plus deflated investment. I use a separate depreciation rate for each CAPEX category. Following FERC, land is not depreciated and is deflated using the price index for nonresidential investment from the BEA. Pipeline companies are required to report line item depreciation rates, which I aggregate to generate a weighted average depreciation rate for each of the three components. Structures and equipment are deflated by their analogous nonresidential price indices, also provided by the BEA.[8]

Pipelines must report all major changes in operations when submitting the Form 6. This allows me to track major divestitures or changes in ownership that happen during the sample period for which the data need to be adjusted. A fairly common occurrence is that a pipeline will change change its legal status, generating a new FERC identifier. For instance, "Minnesota Pipe Line Company" became an LLC in 2006 and changed its name to "Minnesota Pipe Line Company, LLC". Observations such as these are combined into a single reporting unit for my analysis.[9]

Tariffs and Responses to Order 342.3 Pipeline tariffs provide system prices, terms of service, and a list of pipeline routes. Pipelines report the evolution of their price cap and their current rate in their annual response to Order 342.3. Both of these sources further help me identify which pipelines operate under the price cap mechanism and which pipelines operate under a different regulatory regime. For example, pipelines in the the Trans-Alaskan Pipeline System still use cost-of-service filings to set rates which Explorer Pipeline may charge market base rates. These pipelines are excluded from my analysis when necessary.

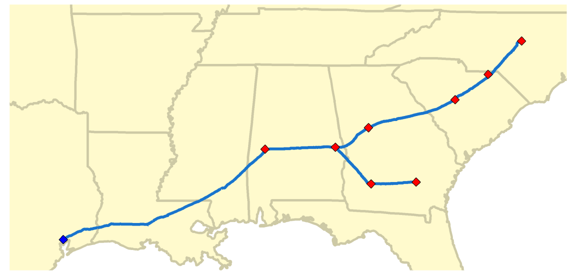
Unit of Analysis The unit of analysis is an interstate oil pipeline system. Pipeline systems are often controlled by a larger holding company, however they generally operate

[8] Several pipelines in my sample lease capacity on other pipeline systems. To convert to an equivalent capital stock, I take the rental expense and scale it by the firm's weighted average cost of capital and then deflate this measure. This impacts fewer than 5% of firms.

[9] See the online appendix for other sample adjustments and how costs were categorized.

Figure 6: Example Midstream Company and Pipeline System

(a) Enterprise Product Partners, L.P.



(b) Dixie Pipeline

autonomously. Consider the case of Enterprise Product Partners, LP, which a master limited partnership (MLP) that owns and operates several midstream oil assets. The full collection of interstate assets have been plotted in Panel (a) of Figure (6). These assets are comprised of several pipeline systems, including Enterprise TE Products (formerly TEPPCO), Mid-America Pipeline System, and Centennial Pipeline, to name a few. Panel (b) shows a typical pipeline system, Dixie Pipeline. Dixie Pipeline transports propane from Mont Belvieu, TX to locations in the south and southeast. Because it shares a limited geographic footprint with the MLP's other assets, its operations are not generally impacted by the operations of the other pipeline systems.

5 Demand

In this section, I describe demand for pipeline transportation and how I derive a firm-specific demand curve.

Several pipelines can service the same oil field or the same downstream market, but pipelines infrequently overlap in a given origin-destination pair, generating a degree of product differentiation. In principle, pipelines may compete with other modes of transportation such as railroads and trucks between within a given origin and destination. However, these other modes tend to have much higher prices for transporting oil than pipelines. For instance, a Congressional Research Service report estimated an average per-barrel cost of pipeline transportation of \$5 and an average cost of \$10 to \$15 for equivalent transportation by rail.[10] As such, I assume that each transportation demand can be approximated by an pipeline-specific demand curves.

I model transportation demand as shippers choosing among their various transportation alternatives. I assume that there is a continuum of oil shippers, each wanting to transport a fixed amount of output each period. These producers choose the lowest cost of transportation to deliver their product to a destination market and sell their output at a uniform price. Let i index the pipelines serving a basin, t the period, and j the oil producers. Following Eaton and Kortum (2002), let the cost of transportation be given by the pipeline's transportation rate divided by a Frechet distributed idiosyncratic shock, $\tau_i(j)$.[11] As such, the shipper solves

$$\min_i \left\{ \frac{P_i}{\tau_i(j)} \right\}$$

Integrating over shipper gives the following standard demand functional form

$$Q_{it} = M_t \frac{T_{it} p_i^{-\theta}}{\sum_k^N T_{kt} p_k^{-\theta}}$$

where Q_{it} represents demand for pipeline i and M_t is the basins potential level of production in period t. The distribution of cost shocks τ_{it} is governed by the parameters T_{it} and θ. T_{it} governs the absolute cost advantage of pipeline i in period t and θ determines the dispersion of the shocks. Taking logarithms, demand has the following functional form

[10] See Frittelli et al. (2014).

[11] These shocks represent exogenous factors that change the cost of transportation for a given mode for a specific shipper. For instance, an oil well might be situated in a geological formation not readily accessible by a pipeline.

$$\ln(Q_{it}) = \ln(M_t) + \ln(T_{it}) - \theta \ln(P_i) - \ln(\Phi_t)$$

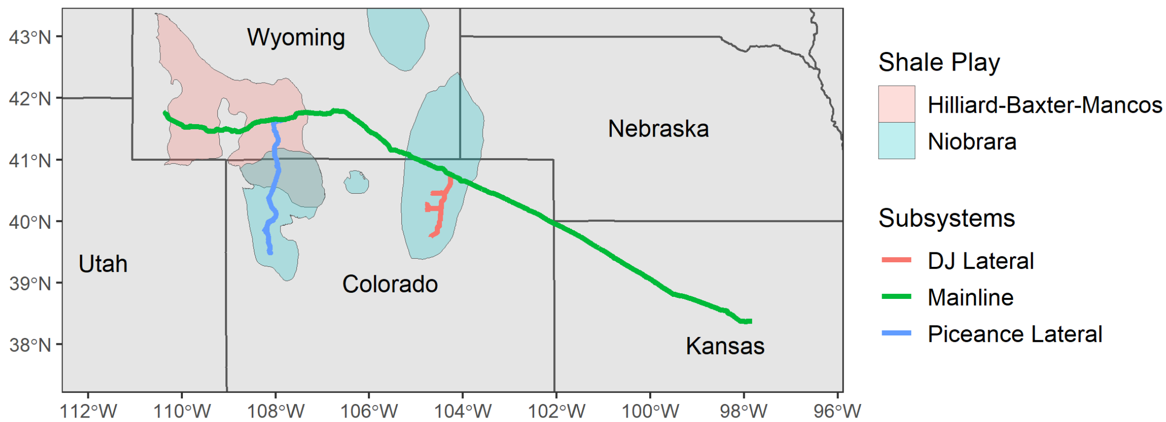
where $\Phi_t = \sum_k^N T_{kt} p_k^{-\theta}$ is common to all pipelines serving an oil field. Note that $\gamma \Phi_t^{\frac{1}{\theta}}$ is the expected transportation cost for oil producers and it is through this term that potential competitive effects can arise. I abstract away from these competitive effects and assume that firms treat Φ_t as fixed in a given period. Collecting terms, this results in the following constant elasticity demand function for pipeline transportation for firm i

$$\ln(Q_{it}) = \lambda_{it} - \theta \ln(P_{it}) + \epsilon_{it}$$

where $\lambda_{it} = \ln(M_t) + \ln(T_{it}) - \ln(\Phi_t)$. I assume that $\ln(T_{it}) = \delta_1 Prod_i + \beta \ln(N_{it})$ where $Prod_i$ indicates that a pipeline transports refined petroleum product instead of crude oil and N_{it} is the number of routes the pipeline serves. The term $Prod_i$ is accounts for the fact that product pipelines tend to have lower rates than crude pipelines. I include the number of routes in demand as a pipeline with more routes will be closer to more wells and therefore will more frequently be the lowest cost option for transportation. Consider the addition of the Denver-Julesburg Lateral to the Overland Pass Pipeline system (see Figure (7)). This expansion increased demand for the pipeline system by connecting the pipeline to a new region of the Niobrara shale in the Denver Basin. Adding this route is analogous to the introduction of a new product, as the addition gave customers in the Denver Basin access to the NGL market in Kansas. As such, increasing the number of routes shifts out demand and increases consumer surplus at a given price point.

I model the potential level of production as $\ln(M_t) = \ln(M) + \delta_2 \cdot Shale_t$. $Shale_t$ is an indicator variable for the years after 2010 which reflects the increase in cost-effective reserves after the shale boom. The term ϵ_{it} is a mean-zero i.i.d. shock to T_{it} that is unanticipated by the firm. However, they know the underlying distribution of these demand shocks.

Figure 7: Overland Pass Pipeline Subsystems



Combining the various components, the firm's demand curve is given by

$$\ln(Q_{it}) = \ln(\Phi_t) + \delta_1 Prod_i + \beta \ln(N_{it}) + \ln(M) + \delta_2 \cdot Shale_t - \theta \ln(P_{it}) + \epsilon_{it}$$

In my baseline specification, I assume that $\Phi_t = \Phi$. I turn now to the pipelines production and investment decisions.

6 Supply

My model of pipeline investment and market participation builds off of the model proposed in Ryan (2012). In my model I abstract away from oligpolistic competition and instead incorporate price regulation.

6.1 Markets and Timing

There are N markets which are defined as regional origin-destination pairs and are assumed to be served by a single pipeline.[12] There is an infinite number of periods, with each period corresponding to a year. In each period, the sequence of events is as follows

1. Operating pipelines receive a random scrap value, a random fixed cost of expansion, and an i.i.d. productivity shock. Pipelines observe the evolution of their price cap and the state of the industry. The state of the industry includes the level of the producer price index, the average cost change for operating pipelines from the previous period, and the current term X. They then decide whether or not to exit.

2. Pipelines that continue to operate choose their level of investment in productivity and system expansion. Investments mature in the subsequent period.

3. Operating pipelines choose a price level subject to the price cap and shippers demand transportation at the posted price. Pipelines incur both a variable and fixed cost of production.

4. Pipelines that are potential entrants receive a random sunk cost of entry and a productivity draw. They then decide whether to enter and, if so, how large of a system to build. Entrants do not produce in the period they enter.

In the following section, I discuss the firm's per-period profit function and my functional form assumptions. I then discuss the state-evolution of each pipeline and conclude with the Bellman equations for operating pipelines and potential entrants.

6.2 Per-Period Profits

The pipeline's per-period profits are determined by the revenue generated from providing transportation services less the costs associated with providing the service and any investment costs incurred during the period. Letting i index the pipeline system and t the period,

[12] I assume further that pipelines do not operate in multiple markets.

the per-period profit in state $s_{it} = \{\bar{P}_{it}, N_{it}, \omega_{it}, \lambda_{it}\}$ is given by

$$\pi(P_{it}, \xi_{it}, \Delta_{N,it}, s_{it}) = P_{it} \cdot Q(P_{it}, N_{it}, \lambda_{it}) - c(Q_{it}, N_{it}, \omega_{it}) - i_{it} - \Gamma_N(\Delta_{N,it}, \gamma_0) - FC * N_{it}$$

where price must satisfy $P_{it} \leq \bar{P}_{it}$. The variable i_{it} represents the pipeline's level of productive investment and $\Delta_{N,it}$ the pipeline's investment in system expansion. The variable cost of production is $c(Q_{it}, N_{it}, \omega_{it})$, which depends on the level of production Q_{it}, the number of routes N_{it}, and the productivity of the pipeline ω_{it}. I allow variable costs to increase with the size of a pipeline as increasing the geographic footprint of a pipeline may come with additional costs.

Pipelines are subject to convex adjustment costs when changing their number of routes, given by $\Gamma_N(\Delta_{N,it}, \gamma_{0,it})$. Additionally, I assume that pipelines draw a random fixed cost in each period associate with expanding their system, given by $\gamma_{0,it}$. Pipelines incur a fixed cost FC each period that depends on the total number of routes that they provide.

Potential entrants draw a random sunk cost each period, given by κ_{it}, which they must pay in order to start producing. These costs can include the development costs and regulatory risk.[13] Operating pipelines draw a random scrap value ϕ_{it} each period that they receive if they exit. I summarize these costs in the following function, where a is the pipelines action

$$\Phi(a; \kappa_{it}, \phi_{it}) = \begin{cases} -\kappa_{it}, & \text{if the firm is an entrant} \\ \phi_{it}, & \text{if the firm exits} \end{cases}$$

The per-period profits including entry and exit costs are given by

[13] A prime example comes from the proposed Keystone XL Pipeline, which incurred \$1.5 billion in development costs before ultimately being canceled after its permit was revoked by the Biden Administration. See the TC Energy 2019 Annual Report.

$$\tilde{\pi}(P_{it}, \xi_{it}, \Delta_{N,it}, a_{it}, s_{it}) = \pi(P_{it}, \xi_{it}, \Delta_{N,it}, s_{it}; \theta) + \Phi(a_{it}; \kappa_{it}, \phi_{it})$$

I next discuss my parameterization of the firm's variable and adjustment cost functions, as well as the distributional assumptions for the various fixed costs.

6.2.1 Cost Functions

Firm marginal costs are assumed to have the following functional form

$$\ln \mathrm{mc}_{it} = \gamma_1 + \gamma_2 \ln(\hat{Q}_{it}) + \gamma_3 \ln(\hat{Q}_{it})^2 + \gamma_4 \ln(N_{it}) + \gamma_4 \ln(N_{it})^2$$

where $\hat{Q}_{it} = \frac{Q_{it}}{e^{\omega_{it}}}$ is the productivity adjusted output. This functional form nests the commonly assumed case where marginal cost is constant in the quantity produced, i.e. $\gamma_2 = \gamma_3 = 0$. However, it also allows for the case of U-shaped marginal costs as well as monotonically increasing or decreasing costs.

I assume that the convex cost of adjusting routes is given by

$$\Gamma_N(\Delta_{N,it}, \gamma_{0,it}) = \gamma_{0,it} \cdot I(\Delta_{N,it} \neq 0) + \gamma_{\Delta 0}\Delta_{N,it} + \gamma_{\Delta 1}\Delta_{N,it}^2$$

I assume that the fixed cost of investing $\gamma_{0,it}$, the sunk cost of entry κ_{it}, and the scrap value upon exit ϕ_{it} are all normally distributed and independent of one another.

6.3 State Transition

The size of the pipeline system evolves endogenously, with

$$N_{it+1} = N_{it} + \Delta_{N,it} \tag{1}$$

An investments at time t does not mature until the following period. Productivity evolves endogenously but is subject to a stochastic shock. Following Ericson and Pakes (1994), pipelines invest an amount i_{it} to improve their distribution of productivity draws in the subsequent period. That is, the distribution of productivity at $t+1$ is given by $p(\omega_{it+1}|\omega_{it}, i_{it})$. The authors specify a productivity process where productivity can be decomposed as $\omega_{it+1} = \omega_{it} + \xi_{it}(\omega_{it}, i_{it}) + \eta_{it}$, where τ_{it} represents the deterministic change in productivity from investing i_{it} and η_{it} is a stochastic component. I make three modifications. First, I assume ω_{it} is an AR(1) process, absent investment. Second, I assume that $\xi_{it}(\omega_{it}, i_{it}) = \xi_{it}(i_{it})$. Finally, I assume that ξ_{it} is continuous instead of discrete. This yields the following process

$$\omega_{it+1} = \psi_0 + \psi_1\omega_{it} + \xi_{it}(i_{it}) + \eta_{it+1} \tag{2}$$

where $\eta_{it} \sim N(0, \sigma_\eta)$ is a productivity shock. I implicitly define $\xi(i_{it})$ by the equation $i_{it} = \gamma_{\xi,0}\xi_{it} + \gamma_{\xi,1}\xi_{it}^2$. The productivity shock η_{it} can represent decreased output due to a spill, unanticipated pipeline maintenance, or cyber-attacks. I assume that the firm's demand shifter λ evolves according to

$$\lambda_{it+1} = \lambda_{it} + \ln(N_{it+1}) - \ln(N_{it})$$

This assumes that firms do not anticipate the shale boom or the potential entry that may occur after a pipelines has entered the market. This assumption is made to simplify the problem for estimation. An alternative assumption would be that firms use a reduced-form rule that predicts the evolution of λ_{it} and that this rule would account for changes in production and changes in the competitive environment.

The price caps evolve according to a PPI + X rule, i.e.

$$\bar{P}_{it+1} = \bar{P}_{it}\left(\frac{PPI_{t+1}}{PPI_t} + X\right)$$

All that remains is to specify the price cap rule. During a review period, which I index to $\tau = 0$, the adjustment factor is set to match the difference in the growth in annualized average total cost less the change in the producer price index.[14] That is

$$X_{t+1} = \begin{cases} \bar{a}_t - E\left[\left(\frac{PPI_{t+5}}{PPI_t}\right)^{\frac{1}{5}}\right] & \text{if mod(t,5)} = 4 \\ X_t & \text{otherwise} \end{cases} \tag{3}$$

Firms keep track of an aggregate state variable, $\bar{a}$ which represents the annualized change in average total cost.[15] This would normally require firms to keep track of the joint distribution of productivity, network size, and price caps to determine the likely evolution of this state variable. As this would be intractable, I following Krusell and Smith (1998) and Gowrisankaran and Rysman (2012) and assume that the firms approximate the evolution of the aggregate state of the economy according to

$$\bar{a}_{t+1} = f(S_t) + u \tag{4}$$

where $S_t = \{PPI_t, X_t, \bar{a}_t\}$ is the aggregate state. Here, f represents a reduced form approximation of the transition dynamics that depends only on the aggregate state variables. In equilibrium, the firm's approximation must be consistent with the actual evolution of the aggregate state. I include the residual u to represent the fact that f is only an approximation.

[14] See my comment on the Kahn Methodology and the adjustments that are necessary to better reflect this process.

[15] In my counterfactuals this aggregate state can represent different measures of cost or productivity. For instance, this measure can represent the evolution of total factor productivity or of marginal costs.

6.4 Value Function

Pipelines seek to maximize the real discounted sum of cash flows net investment given their information at time 0. Firms discount the future at a rate $\beta = 0.87$, which I chose to coincide with the mean weighted average cost of capital (WACC), using quantities as weights.

$$V_0(s_{i0}) = \max_{\{N_{it},\xi_{it},P_{it}\}_{t\geq 0}} E\left[\sum_t \beta^t \tilde{\pi}(s_{it};\theta) \middle| I_0\right] \tag{5}$$

$$\text{s.t. } P_{it} \leq \bar{P}_{it}, \forall t \tag{6}$$

and subject to the transition laws in (1), (2), (3) and the perceived law of motion in (4). The value function for an incumbent incumbent is given by

$$V_\tau(s;\theta,\epsilon) = \max_{\{P,\xi,\Delta\}} \left\{ \tilde{\pi}(s;\theta) + \int \max\left\{\phi, \max_{\Delta,\xi}\left[\beta \int E_\epsilon V_{\tau'}(s';\theta,\epsilon) dP(s'|s)\right]\right\} dF(\phi)\right\} \tag{7}$$

with $\epsilon = \{\phi, \kappa, \gamma\}$. Here, τ indexes the time that has elapsed since a review period, and evolves according to $\tau' = \tau + 1 \mod T$. I assume that the price cap is reset before the period $\tau = 0$. The corresponding value function for an entrant is given by

$$V_\tau^e(s;\theta,\epsilon) = \int \max\left\{0, \max_{\xi,\Delta}\left[-\Phi_N(\Delta_N;\gamma) + \beta \int E_\epsilon V_{\tau'}(s';\theta,\epsilon) dP(s'|s)\right] - \kappa\right\} dF(\kappa) \tag{8}$$

Equilibrium An equilibrium in this model is a set of policy functions and a law of motion for the aggregate states $\{PPI, X, \bar{a}\}_t$ such that, given the evolution of the aggregate state, the policy functions solve (7) for operating firms and (8) for potential entrants, the policy functions generate the law of motion (4), and the policy functions are consistent with evolution of X.

Now that I have described the theoretical model, I will explain how I map the model to the data.

7 Empirical Strategy

Estimation proceeds in two stages. In the first stage, I recover the determinants of firm profitability in each period, including the demand curve, the cost curve, and firm level productivity. In the second stage, I use a nested fixed point (NFXP) estimation routine where I guess a value for the parameters, solve the firm's dynamic programming problem, and minimize a Generalized Method of Moments (GMM) criterion. I describe the details of each stage in turn. The reader who is uninterested in the estimation details may proceed directly to Section (8).

7.1 Demand Estimates

Demand parameters are recovered using two-stage least squares. I estimate several versions of demand, with the most comprehensive having the following form

$$\ln(Q_{it}) = \beta_{i0} + \beta_1 \ln(N_{it}) + \beta_2 Prod_{it} + \beta_3 Shale_t - \alpha \ln(P_{it}) + \epsilon_{it} \tag{9}$$

where β_{i0} represents a market fixed effect that does not vary over time, $Prod_{it}$ classifies a pipeline as either carrying refined petroleum product or crude oil and controls for changes in the product type, and $Shale_t$ is an indicator variable for the years 2010 and onward. Here, ϵ_{it} is estimated as the residual of this regression. The market-specific intercept control for variations in the level of demand along specific routes. The shale indicator captures the change in demand for oil transportation that resulted from the shale boom. I allow all pipelines to be equally impacted by the shale boom as most oil producing regions have shale deposits. Finally, I control for the type of pipeline as product pipelines generally charge lower rates than crude oil pipelines.

The exogenous movement of the price cap helps trace out the demand curve. However, while the large majority of pipelines have prices regulated using the price cap there are still several that are regulated under different regulatory mechanisms. For instance, pipelines in the Trans-Alaskan Pipeline System (TAPS) are regulated using a cost-of-service scheme because their costs increase fast enough that they are unlikely to recover their cost of capital under the price cap mechanism. I exclude these pipelines when estimating the full model but include them when estimating demand as they still provide useful variation for recovering price elasticities. Including these pipelines can reintroduce an endogeneity problem as prices are now jointly determined with output. To account for this, I use several different instruments. First, I include lags of the firm state variables, including productivity, system size, and the producer price index. These variable directly impact firm costs and therefore provide valid instruments to identify the demand curve.

7.2 Supply Estimates

Two key inputs in my analysis are firm productivity and marginal costs. My approach is to recover productivity by estimating an industry production function and then treating the residual as pipeline level total factor productivity. Then, I follow Dhyne et al. (2020) and use cost minimization first-order conditions to recover marginal costs. I then regress the marginal cost on productivity-adjusted output and system routes to recover the cost function. I discuss each step in turn.

Production Function Estimation I assume that the production technology is translog during estimation. The translog production function is given by

$$q_{it} = \beta_0 + v_{it}\beta_l + k_{it}\beta_k + v_{it}^2\beta_{ll} + k_{it}\beta_{kk} + k_{it}v_{it}\beta_{lk} + \omega_{it} + u_{it}$$

where v_{it} and k_{it} are logged variable and fixed inputs, respectively, ω_{it} is productivity known to the firm but unobserved by the researcher, and u_{it} is an i.i.d. error that can be thought of as an unanticipated productivity shock or approximation error. Here, ω_{it} is the researchers problem as firms know their productivity when optimally choosing the level of variable input, v_{it}. As such, we need to control for the endogeneity of v_{it} and ω_{it} during estimation. I follow the literature and assume that ω_{it} follows a Markov process. Since the policy function for productivity investment depends on the pipeline's information set at time $t-1$, I assume that technology evolves according to the following Markov process

$$\omega_{it} = g(\omega_{it-1}, s_{it-1}, S_{it-1}) + \eta_{it}$$

where s_{it-1} is the pipeline's individual state variables and S_{it-1} are aggregate state variables.

Two issues have recently been highlighted in the literature regarding when estimating production functions. First, it is common to use deflated revenue in place of physical output when estimating production functions as output is generally not observed in accounting data. However, if firm's are heterogeneous in their markups then using deflated revenue will bias the parameter estimates. I observe output directly, so this issue does not impact my results. Second, the assumptions underlying the most popular method for production function estimation, the control function approach, often do not hold in imperfectly competitive or regulated markets. I account for this by using the estimation routine proposed in Ponder (2021) which remains valid even when these assumptions are violated. The author shows that the parameters of the production function can be recovered using semi-parameteric two-stage least squares if u_{it} is independent of a set of instruments. This avoids the need to use a control function and therefore does not rely on a monotonicity assumption.

Estimating Markups and Marginal Costs To estimate firm level markups, I follow the insight of Hall (1988) and De Loecker and Warzynski (2012) and use a cost minimization approach to approximates markups. In order to produce a given quantity $\bar{Q}_{it}$, they solve the following cost minimization problem

$$\min_{V_{it}} \; w_{it}V_{it} + r_{it}K_{it} \tag{10}$$

$$\text{s.t. } Q_{it} \geq \bar{Q}_{it} \tag{11}$$

where w_{it} is the price of the variable input. The cost minimization first order conditions require that

$$w_{it} = \lambda_{it}\frac{\partial Q_{it}}{\partial V_{it}}$$

where λ is the Lagrange multiplier on the production constraint. Because this describes the increase in costs associated with a unit increase in output, the multiplier is exactly equal to the pipeline's marginal cost, mc_{it}. Multiplying both sides by V_{itk} and dividing by $Q_{it}P_{it}$ yields

$$\frac{V_{itk}w_{itk}}{P_{it}Q_{it}} = \frac{\lambda_{it}}{P_{it}}\frac{\partial Q_{it}}{\partial V_{itk}}\frac{V_{itk}}{Q_{it}} = \frac{\theta_{itk}}{\mu_{it}}$$

The term μ_{it} is the markup. Importantly, this relationship holds for any flexible input that directly enters the production function. Operating expenses and revenue are reported in pipeline financial statements. To estimate markups, wI only need an estimate of the input elasticity θ_{it} which comes from the production function estimates. Dhyne et al. (2020) extend this procedure to the multi-product setting and show that observing quantity data allows us to consistently estimate marginal costs using

$$\text{mc}_{it} = \frac{V_{itk} w_{itk}}{Q_{it}} \frac{1}{\theta_{itk}}$$

Given estimates of marginal costs we can determine whether markup changes were driven by changes in price, marginal cost, or both. Additionally, the marginal cost estimates allow us to test whether marginal costs are constant, as is commonly assumed in the regulatory literature, or depend on the level of output.

Cost Function Given estimates of firm productivity, I generate a productivity adjusted output level, $\hat{q} = q_t - \hat{\omega}_t$. I then estimate the marginal cost function using the marginal costs recovered from the cost-minimization FOCs. This procedure follows that used in Dhyne et al. (2020). The authors directly estimate the variable cost function, controlling for firm productivity, capital, and input prices. I do not directly observe input prices, so I assume they are common across the industry and control for them using annual fixed effects. Additionally, I directly regress marginal costs on productivity adjusted quantities, rather than variable costs. The marginal cost function is given by

$$\ln \hat{\text{mc}} = \gamma_{1t} + \gamma_2 \ln(\hat{Q}) + \gamma_3 \ln(\hat{Q})^2 + \gamma_4 \ln(N) + \gamma_4 \ln(N)^2 + u_{it}$$

Here, u_{it} is assumed to be a residual that is due to either measurement error or misspecification error. In order to control for the potential endogeneity between u_{it} and the covariates, I use two-stage least squares to estimate $\{\gamma_k\}$. Specifically, I use the price cap index and the spot price of West Texas Intermediate in Cushing, Oklahoma as demand shifters. The price cap index is exogenous to firm decisions (by design) and moves around the price of transportation. The spot price of oil is largely driven by movements in global supply, which oil pipeline rates play a de minimis role in determining. As such, the spot price of oil is assumed to be exogenous and therefore a valid instrument. Further, the spot price of oil determines the level at which fields produce, making it a relevant instrument. Finally, I include individual firm dummies as instruments, imposing the u_{it} is mean zero for each pipeline. I estimate models with and without the quadratic terms.

7.2.1 Adjustment and Fixed Costs

Given the parameter estimates that determine per-period profits, I estimate the remaining model parameters using a nested-fixed point algorithm following Rust (1987). In the inner loop, I solve for the firm's value function and optimal policy functions given a guess of the parameter coefficients. Then, I form four residuals

$$\eta_{1it} = \omega_{it} - \psi_0 - \psi_1 \omega_{it-1} - \xi_{it}(X_{it-1}) \tag{12}$$

$$\eta_{2it} = \Delta_{it} - \Delta(X_{it}) \tag{13}$$

$$\eta_{3it} = I\left[exit_{it} = 1\right] - \Phi\left(\frac{EV(X_{it}) - \mu_\phi}{\sigma_\phi}\right) \tag{14}$$

$$\eta_{4it} = I\left[enter_{it} = 1\right] - \Phi\left(\frac{EV^e(X_{it}) - \mu_\kappa}{\sigma_\kappa}\right) \tag{15}$$

The first residual represents is the stochastic shock to productivity. The second residual is the difference between observed investment and the models predication. I assume that this is specification error and that the residual is mean zero, conditional on a set of instruments. Finally, the third and fourth residuals represents the difference between the observed exit and entry of firms and the models predicted probabilities. As the sample size grows, the sample frequency of exit and the predicted probability of exit should converge. I then interact these residuals with a set of instruments, Z_{kit}. Valid instruments include the state variables of firms at $t-1$, as these should be correlated with their decision at time t but should be orthogonal to expectational errors at time t.

Letting Z be a block diagonal matrix of Z_k, $\eta = \{\eta_1, \eta_2, \eta_3, \eta_4\}$, and θ the vector of parameters, we can form the following residual

$$g(\theta) = Z'\eta(\theta)$$

such that in expectation

$$E[g(\theta)|Z] = 0$$

The GMM objective function is then

$$GMM(\theta) = g(\theta)'Wg(\theta)$$

and the outer loop searches over θ to minimize this quantity. Note that the size of the residuals can be quite different, which leads the objective function to place more weight on residual (13). To remedy this, I take a two-step approach. First, I use an initial guess of θ_0 and calculate the implied residual $\hat{\eta}_0$. I generate

$$g_{it}(\theta_0) = Z_{it} \cdot \hat{\eta}_0$$

and approximate the optimal weight matrix

$$\hat{W}_0 = \frac{1}{NT} \sum_{it} g_{it}(\theta_0) \cdot g_{it}(\theta_0)'$$

I estimate the model parameters using the nested-fixed point algorithm to generate the first set of consistent estimates. I recalculate the optimal weighted matrix using these estimates and then re-run the estimation routine.

8 Estimation Results

8.1 Demand

Table (1) I present several different specifications for demand. The simplest is presented in column (1), where I only use price as an independent variable and estimate the equation using OLS. The coefficient implies a relatively low elasticity of -1.35. Interestingly, the R^2 for this regression is 0.512, meaning that a constant term and price have a significant amount of explanatory power. Column (2) presents the same regression, but this time uses two-stage least squares. The estimated elasticity decreases marginally to -1.43. This modest change is likely due to the fact that prices are almost set exogenously. When firms price at the ceiling, then price changes are driven entirely by movements in PPI and this exogenous changes serves to trace out the demand curve.

Table 1

	Dependent variable: ln(Q)					
	OLS	*Instrumental Variable*				
	(1)	(2)	(3)	(4)	(5)	(6)
ln(P)	-1.346^{***}	-1.432^{***}	-1.440^{***}	-1.351^{***}	-1.488^{***}	-1.522^{***}
	(0.024)	(0.027)	(0.027)	(0.024)	(0.025)	(0.066)
Prod. Pipeline			-0.159^{***}	-0.471^{***}	-0.445^{***}	-0.239^{***}
			(0.058)	(0.054)	(0.053)	(0.059)
ln(N)				0.493^{***}	0.479^{***}	0.178^{***}
				(0.019)	(0.019)	(0.034)
Shale Boom					0.72^{***}	0.64^{***}
					(0.006)	(0.006)
Constant	21.116^{***}	22.079^{***}	22.237^{***}	20.537^{***}	21.637^{***}	25.324^{***}
	(0.270)	(0.300)	(0.305)	(0.284)	(0.285)	(0.731)
Observations	3,005	3,005	3,005	3,005	3,005	3,005
R^2	0.512	0.510	0.511	0.601	0.624	0.877
Adjusted R^2	0.512	0.510	0.510	0.601	0.624	0.864
Residual Std. Error	1.590 (df = 3003)	1.593 (df = 3003)	1.592 (df = 3002)	1.438 (df = 3001)	1.396 (df = 3000)	0.839 (df = 2730)
F Statistic	$3{,}151.042^{***}$ (df = 1; 3003)					

Note: *p<0.1; **p<0.05; ***p<0.01

Pipelines move different types of product and these products might have different demand shifters. To account for this difference, column (3) adds a dummy variable to describe whether or not the pipeline ships crude oil or refined petroleum product. The estimates imply that demand for transporting refined petroleum product is lower by roughly 15% at any price point. Column (4) includes the log number of routes that a pipeline provides. Ideally, we would be able to estimate demand at the individual route level. However, data are not available at this level of granularity. Including the total number of routes provided captures the fact that demand shifts out as pipeline enter additional markets. Including the log number of routes increases the R^2 by almost 0.1, showing the importance of this variable in explaining transportation demand.

I consider two additional demand specifications. In column (5) I include a shifter for the Shale Boom, which I assume starts in 2010. The coefficient is statistically significant, and shows that demand increased by roughly 100% by 2020. However, this covariate explains little of the residual variation.[16] Finally, I include a pipeline fixed effect, reported in column (6). This increases the R^2 from 0.624 to 0.877, implying that market specific demand shifters are important component in describing demand.

Notably, the estimated demand elasticities all fall within a range of -1.52 to -1.35. The specification with the most covariates also has the most elastic demand. One potential problem with these estimates is that they place a limit on the maximum markup that a monopolist will charge. Specifically, the ratio of a monopolist's marginal revenue to demand is given by $\left(1 - \frac{1}{|\epsilon|}\right)^{-1}$. An estimated elasticity of -1.5 implies a ratio of 3, so a monopolist pricing at the profit maximizing price will never have a price to marginal cost ratio above 3. With the production function approach, the estimated ratio is 6 as of 2020,

[16] One could allow this coefficient to have a time trend, reflecting the fact that production did not increase instantaneously. However, this leads to very similar results and does not improve the fit of the estimating equation.

meaning that these demand estimates are not able to rationalize the markups in the second half of my sample. I turn now to the supply side estimates.

8.2 Supply

I begin with the results from the first stage of estimation, including the production function estimation results and implied marginal cost function. Then, I discuss the results from the second stage of estimation, which includes the parameters associated with the exogenous part of productivity, the convex adjustment costs, and the distributional costs associated with entry, exit, and investment.

8.2.1 Production Function Estimates

I estimate the production function parameters using several different specifications. The benchmark estimates are recovered using OLS, ignoring the endogeneity between ω_{it} and the inputs. To the extent that the covariance between the variable inputs and productivity is low, this would tend to give a reasonable approximation to the truth and does not depend on the other modeling assumptions. For my first specification, I use a Cobb-Douglas production function and for the second I use a translog production function. Next, I assume that productivity follows a Markov process and use the semi-parametric estimator from Ponder (2021) to control for endogeneity. Cross-validation is used to determine the number of terms included in the polynomial approximation to the productivity process. As with the OLS estimates, I estimate both a Cobb-Douglas and a translog production function.

Before presenting the results, a quick comment on my measure of output is in order.[17] Researchers have often used deflated revenue when estimating production functions because financial data rarely provides information on physical output. However, I see several

[17] I provide a detailed description of the various variables I use and how I construct each input time series in the appendix.

measures of pipeline output in my dataset, which I use to bring the estimation routine closer to economic theory. My preferred measure of output is barrel-miles, i.e. the number of barrels times the total distance each barrel traveled. However, these data are only reported on an annual basis, which limits the size of my dataset. Alternatively, I can use barrels or deflated operating revenue, which are reported quarterly. The disadvantage of using barrels is that it does not take into account the distance traveled. As such, a long-haul pipeline and a short-haul pipeline might have the same reported barrels in a year, but the long-haul pipeline has considerably higher input costs. This ultimately leads to estimates that imply significant decreasing returns to scale. Operating revenue circumvents this issue, as the long-haul shipments yield a significantly higher revenue than short-haul movements. However, operating revenue potentially biases the estimates because an increase in revenue can come from increasing prices or increasing output. Using barrel-miles comes with the cost that my sample size is reduced to a quarter of the full sample. I present the results using annual data here, and then provide results using other measures of output in the appendix. As an additional robustness check, I estimate the production function assuming that there are errors in the measurement of capital. These estimates are also discussed in the appendix.

Table 8 shows the results of the various estimators. Column (1) shows the Cobb-Douglas estimates using OLS. The mean variable input elasticity of 0.87 is the largest of all my estimates, roughly 20% greater than my preferred estimates. Column (2) shows the translog estimates, again using OLS. None of the second-order terms are statistically significantly and a F-test fails to rejected the hypothesis that these terms are zero. The mean variable elasticity is then estimated to be roughly 0.83 and the mean capital elasticity 0.4, implying a returns-to-scale of roughly 1.23. Column (3) shows the results for the semi-parametric estimator using the Cobb-Douglas specification. The mean variable input elasticity decreases by roughly 20% while the capital elasticity remains relatively unchanged. Column (4) shows my preferred estimator. Production is assumed to be translog and I use the semi-

Figure 8: Production Function Estimates

	Dependent variable: q_t			
	OLS		Semi-Parametric	
	CD	Translog	CD	Translog
k_t	0.362***	0.348***	0.381***	0.242***
	(0.026)	(0.118)	(0.017)	(0.029)
k_t^2		0.007		0.031***
		(0.021)		(0.007)
v_t	0.873***	0.907***	0.728***	0.470 ***
	(0.028)	(0.102)	(0.017)	(0.070)
v_t^2		-0.018		0.024
		(0.024)		(0.015)
$v_t k_t$		-0.001		0.023***
		(0.041)		(0.004)
Constant	2.535***	2.471***		
	(0.081)	(0.185)		
Observations	2,863	2,863	2,863	2,863
OPEX Elast.	0.873	0.836	0.728	0.730
CAPEX Elast.	0.362	0.403	0.381	0.528
Note:				*p<0.1; **p<0.05; ***p<0.01

parametric estimator. The second-order terms are now statistically significant, save for v_{it}^2, and the mean capital elasticity increases from 0.38 to 0.53. The implied returns-to-scale are comparable to those implied by the OLS estimates. The principal difference is that the variable elasticity is much lower and the capital elasticity is higher, which we would expect if variable inputs were correlated with unobserved productivity.

8.2.2 Cost Function

The results of the marginal cost regression are presented in Table (2). The dependent variable is the estimate log marginal cost of production for each pipeline, in each period. The independent variables include the productivity-adjusted measure of output, $\hat{q} = q_t - \omega_t$ and the number of routes. All coefficients are statistically significant at $\alpha = 0.1$. The model with quadratic terms has a slightly better fit, with an adjusted-R^2 of 0.867 compared to an adjusted-R^2 of 0.8 for the log-log specification.

A model with constant marginal costs would estimate the coefficient on output to be 0. The null hypothesis that marginal costs are constant is rejected at $\alpha = 0.01$. This implies that assuming a constant marginal cost may be missing an important dimension of the regulated firm's environment. Marginal costs are shown to U-shapes in that they increase significantly as production approaches zero and increase gradually as output increases. Increasing the number of routes has a positive impact on the marginal cost of production, reflecting the fact that increasing the size of a system requires additional pumping stations and adds complexity to the scheduling process. However, the quadratic term implies that, over the range of the data, adding additional routes increases marginal cost but at a decreasing rate.

8.2.3 Productivity, Adjustment Costs, and Distributional Parameters

Table (3) shows the results of the nonlinear GMM estimation. The first set of parameters determine the exogenous changes to productivity and productive investment. The average productivity level in my sample is roughly 3.0, meaning that the average pipeline would

Table 2: Marginal Cost Function Estimates

	Dependent variable:
	ln(mc)
$\ln(\hat{q})$	-0.296^{***}
	(0.097)
$\ln(\hat{q})^2$	0.037^{***}
	(0.007)
$\ln(N)$	0.134^{**}
	(0.065)
$\ln(N)^2$	-0.023^{*}
	(0.012)
Constant	10.001^{***}
	(0.366)
Observations	2,122
R^2	0.882
Adjusted R^2	0.867
Residual Std. Error	0.454 (df = 1893)
F Statistic	61.867^{***} (df = 228; 1893)
Note:	*p<0.1; **p<0.05; ***p<0.01

expected their efficiency to decline exogenously by 30% over the sample period. Shocks to productivity are quite large relative to the mean level reflecting the significant role of outside forces. Productivity investment costs are quite large so that most firms only invest to improve efficiency by 3% - 10% annually and a large number of firms make no investment at all.

Each additional route is estimated to cost roughly \$74 million and this cost increases as more routes are added. However, the main cost of construction appears to be the fixed cost of investment, which the model estimates to be \$1.1 billion. Interestingly, the mean fixed cost of expanding an existing system is comparable to the mean entry cost of creating a new system, which is \$1.3 billion.[18] The principal difference is that the variance of the investment fixed cost is almost three times are large. This likely reflects the fact that system expansions can be relatively minor or can be comparable to building an entirely new system. The mean scrap value of a pipeline system is estimated to be fairly small at roughly $\$10,000,000$. However, unlike the other distributional parameters, the variance is substantially larger than the mean value. This likely accounts for the fact that pipelines exit under a variety of circumstances. For instance, existing can incur substantial costs related to pipeline abandonment or generate revenue from the selling of assets.

9 Oil Pipeline Industry Performance

Before turning to the results of my full model, I explore the estimated change in industry markups and productivity derived from the production function estimation and cost-minimization FOCs. price caps are in principal meant to ensure that prices cannot diverge substantially from the first-best (price equal to marginal cost) or second-best (price equal to average total cost) price level. However, if the adjustment factor X is set too high

[18] For reference, the Oil and Gas Journal estimated pipeline construction costs of \$6.57 million per mile in 2014. Since 2010, the average length of new pipeline construction was 260 miles so the average construction cost was \$1.7 billion, slightly higher than what I estimate here.

Table 3: Parameter Estimates

Parameter	Mean	SE
Exogenous Productivity		
ψ_0	0.183	0.006
ψ_1	0.931	0.005
σ_η	0.527	0.001
Productivity Investment		
$\gamma_{\xi 0}$	178	2.1
$\gamma_{\xi 1}$	10,889	256.9
System Investment		
$\gamma_{\Delta 0}$	74,035	2,172
$\gamma_{\Delta 1}$	985	49
Fixed Cost (FC)	17,269	2,091
Scrap Value		
μ_ϕ	9,995	1,660
σ_ϕ	89,670	16,155
Entry Cost		
μ_κ	1,292,410	975,756
σ_κ	312,315	160,852
Investment Fixed Cost		
μ_γ	1,102,962	152,708
σ_γ	861,524	25,286

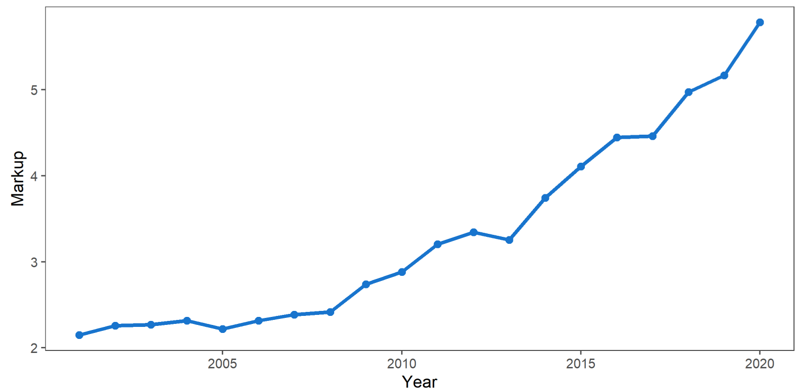
Note: Units are in millions of dollars for productivity investment. Units are in thousands of dollars for system investment and all distributions.

then firms may generate excessive rents. A simple test is to use the markups from the cost-minimization FOCs determine how markups evolved over the past two decades. An increase in the markup ratio implies that either prices have increased faster than costs or that cost have declines but these gains have not been passed on to customers. I find that both average price and the average marginal cost have increased over my sample period but that prices increased much faster. The price cap is also meant to encourage productivity gains and several papers in the regulatory literature have documented the evolution of productivity after the introduction of a price cap. While I find that firm productivity declined over the same period, this was likely due to exogenous factors. As I show in the final section, my model implies that the higher price cap led to considerable gains in both productivity and entry than we would have seen under a the traditional cost-of-service regulation.

9.1 Evolution of Markups

Using the estimated production function and the observed variable cost-revenue shares, I used cost-minimization FOCs to recover the average industry markup. The evolution of the markups since 2000 are shown in Figure (9). The rise in markups has been substantial since 2000, increasing from roughly 2 to 6. In terms of price-cost margins, this is an increase from 50% to 80%. There are two principal terms in the first-order conditions: the revenue-to-operating expense ratio and the input elasticity. We have already seen that the first term increased significantly over the past two decades. It is worth asking to what extent did the second term change. Appendix Figure (23) plots the weighted average input elasticity over the same time period. The average level of the input elasticity has increased slightly over this period, meaning that most of the increase in markups has been driven by the first term. I do not report the decomposition of Figure (23) here, but each component has been stable as well. Firms appear to be producing roughly the same level of output using the same mixture of inputs, but have been given a higher price, in real terms, for each unit of output.

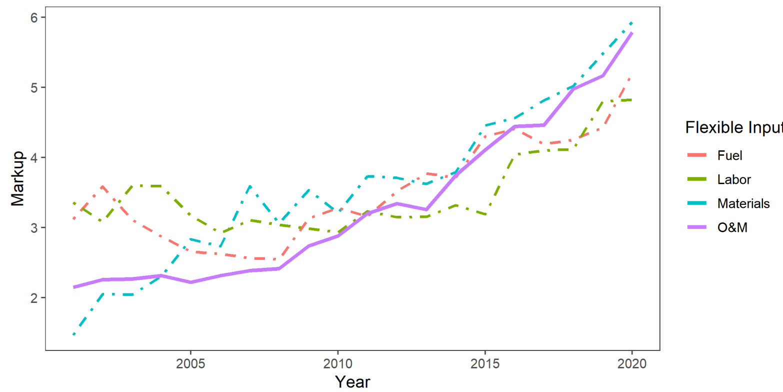
Figure 9: Evolution of Markups



Recently, the literature has noted that markup and marginal cost estimates can be very sensitive to which flexible input is used to estimate their level. In my baseline results, I use a deflate measure of all operating and maintenance expenses, similar to the approach taken in De Loecker and Warzynski (2012) and De Loecker et al. (2020). An alternative approach would be to estimate production function with a separate term for each cost category and estimate the change in markups using different measures of flexible inputs. Figure (10) shows the results of this analysis. Using "Materials and Supplies" shows an evolution in markups highly similar to my baseline approach. Markups start at comparable levels in 2000 and increase by roughly the same amount. However, markups increase more uniformly over time, as opposed to baseline results where markups are flat before 2007. Using "Operating Fuel" or "Labor" results in less of an increase in markups, largely due to the higher level that they start at. While the baseline estimates have an average markup of roughly 2 in 2000, using either "Operating Fuel" or "Labor" results in a markup of 3 in the same year. Ultimately, we can bound the increase in markups between 160% and 300%, which represents a substantial divergence from marginal cost pricing.

A rise in markups does not necessitate that firms are acting anti-competitively. It has long been noted that high markups can be explained by low marginal costs, high prices, or a combination of the two. As noted in Dhyne et al. (2020), observing physical output allows us to separate out changes in price from changes in marginal cost. Figure (11) plots

Figure 10: Markup by Flexible Input

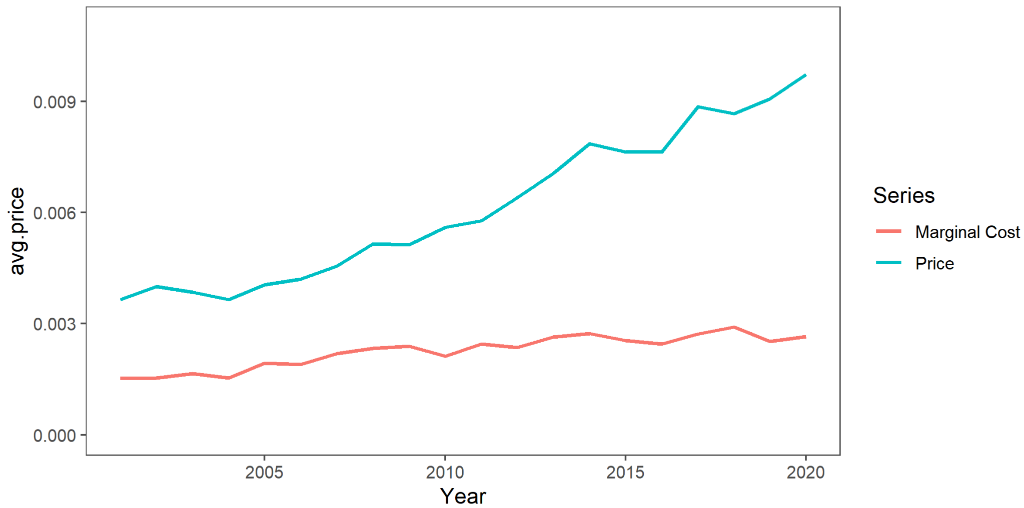


the average price and the average marginal cost over my sample period. Real prices have increased at a faster rate than real marginal costs since 2004, implying that decreasing marginal costs are not driving the change in estimated markups. Note that an increasing average marginal cost is not necessarily an indication of increasing inefficiency. The oil pipeline industry has seen substantial entry and investment since 2000. Many dynamic investment models[19] predict that low cost opportunities are chosen first and high cost investments are delayed. Therefore, new construction will generally be higher cost than the established firm, increasing the industry average cost across time.

Markups increased more than the cumulative change in the average price cap over this period. To understand why, I follow Melitz and Polanec (2015) and decompose the change in the weighted average markup into four components: the unweighted mean change in markups, the change in the covariance between market share and markups, the impact of firm entry, and the impact of firm exit. Figure (12) shows this decomposition. The first thing to note is that markups increased significantly due to firm entry. Entrants on average had a higher initial markup than existing firms and this difference contributed to roughly a third of the increase in markups. Firm exit had minimal impact on the change in markups, as firms that exited tended to have markups similar to surviving firms. Surviving

[19]For instance, see Hopenhayn (1992).

Figure 11: Evolution of Average Price and Marginal Cost

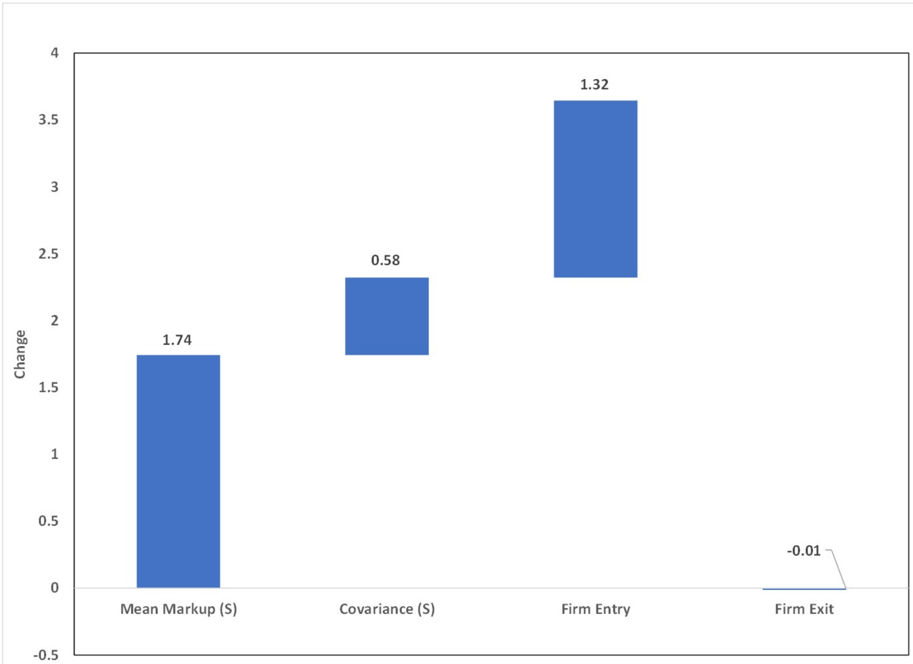


firms saw the covariance between their market share and their markups increase by 0.58, accounting for 16% of the markup increase. Finally, the average markup ratio increased by 1.74, accounting for roughly 50% of the overall increase. As such, a significantly portion of the increase in markups is due to firm entry and reallocation of markups to firms with higher output. Of the overall increase, 50% is due to the average price level increasing across time and it is this share that could be attributable to changes in the price cap index.

9.2 Evolution of Productivity

Figure 13 displays the change in (demeaned) weighted average productivity over the sample period. The log change of roughly -0.45 between 2001 and 2020 is consistent across all specifications and estimation routines, and corresponds to a roughly 50% decrease in total factor productivity. Figure (14) performs the same Melitz and Polanec (2015) decomposition described in the section on markups. On average, surviving pipelines were considerably less productive at the end of the sample and that the covariance between size and productivity declined. However some of this decline was offset by firm entry, where new firms entered with a higher average level of productivity than the existing firms.

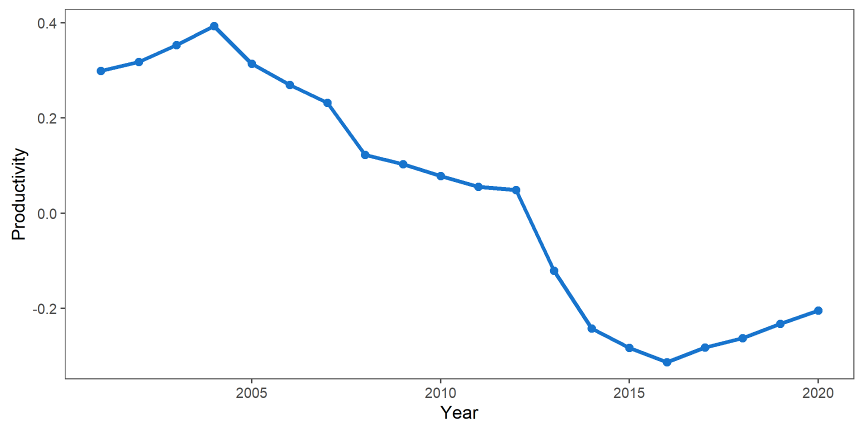
Figure 12: Decomposition of the Change in Markups



This decline in factor productivity is not necessarily caused by an ineffective price cap as there have been several changes to the regulatory environment since 2000. The decrease in factor productivity might, in part, reflect a change in the quality of service through increased safety and environmental regulation. Pipeline repairs lead to a decrease in the likelihood of spillage and the associated loss of service, which is arguably good for both shippers and households (who would experience a significant externality if a pipeline ruptured).[20] Figure (26) in the appendix shows that total pipeline incidents have declined over time, after accounting for the number of active pipelines, reflecting an increase in the quality of transportation. Therefore, in order to disentangle the impact of exgoneous changes in productivity and changes in response to the price cap index, it is necessary to analyze the full theoretical model.

[20]See the discussion in 18 CFR Part 342, "Five-Year Review of Oil Pipeline Pricing Index".

Figure 13: Change in Weighted Average Productivity

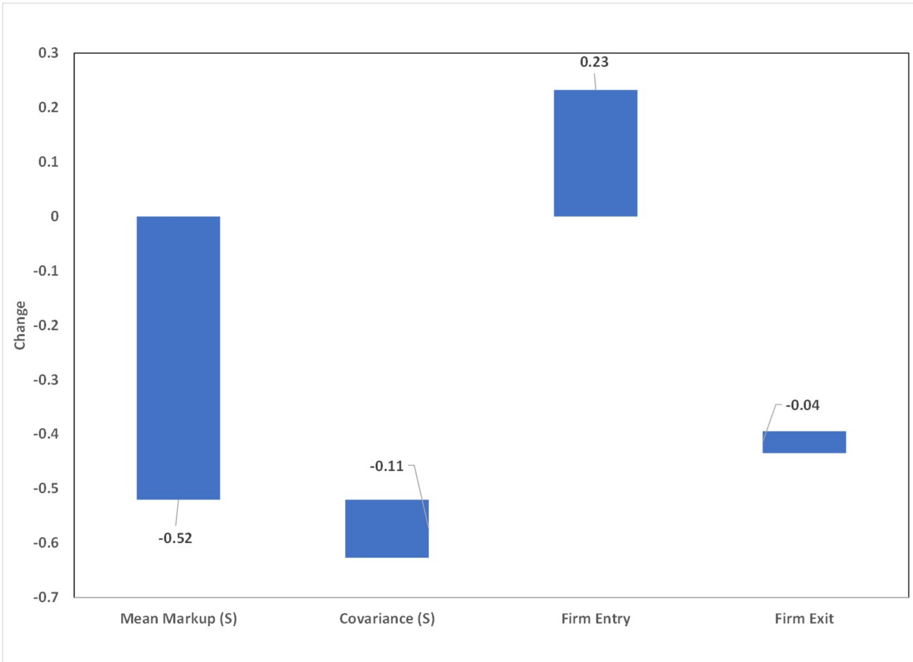


9.3 Impact of the price cap on Industry Dynamics

To assess the impact of the price cap regulation on industry performance, I rely on my theoretical model. The first counterfactual that I run assumes that FERC maintained cost-of-service regulation in the industry. In this experiment, firms are allowed a maximum 13% return on their cost-base in each period, where 13% was chosen to match the observed average weighted average cost of capital. I estimate the impact of the regulation change on two sets of firms: those that have operated continuously since 2000, which I call mature markets, and all firms. Table (15) presents the results. As predicted by theory, firm profits are greatly constrained leading to a significant decline in producer profits. Customers in mature markets would have seen a substantial increase in their consumer surplus due to the lower prices. Some of this welfare gain for existing customers was offset by a roughly 19% decline in average productivity and the lower producer profits, however welfare would have been roughly 15% higher in mature markets.

After accounting for the impact on firm entry, total welfare across all markets declines by 7%. Entry is roughly 15% lower, showing that fewer firms found it profitable to enter given the constraint on profits. Interestingly, there was little impact on consumer surplus, as the reduction in consumer surplus from entry was almost exactly offset by increases in

Figure 14: Change in Weighted Average Productivity



consumer surplus in mature markets. Total welfare declined by 7.2% by 2020 driven largely by declines in producer surplus.

The previous results imply that entry plays an important role in determining total welfare. Deregulating prices would have yields the greatest incentive to undertake market expansion, so next counterfactual considers what would have happened if the price cap was removed. Table (16) shows the results of this experiment. I again consider the impact on mature markets and all markets. Absent a price cap, firms in mature markets would have seen their profits increase by 8.3% while consumer surplus would have decreased by 3.0%, ultimately resulting in a total welfare decline of 2.2%. There was considerable increase in system expansion, as pipelines added an additional 3.6 routes. The welfare gains from system expansion would have been offset by a decline in productivity and higher prices. This decline would have been roughly 8%.

Figure 15: Welfare Impact of Cost-of-Service

Measure	Price-cap	Cost-of-Service	Percent Difference
Markets with a pipeline operating since 2000			
Producers Profit	25	6	-76.3%
Net Consumer Surplus	298	367	23.1%
Total Welfare	323	373	15.5%
Avg. Routes	19.0	19.1	0.3%
Avg. Productivity	2.55	2.38	-15.7%
All Markets			
Producers Profit	53	9	-83.9%
Net Consumer Surplus	630	626	-0.7%
Total Welfare	684	634	-7.2%
Operating Firms	177	151	-14.7%

Note: Profits and welfare measures are in billions of dollars.
Results are based on simulating 50 samples.

Price deregulation did lead to additional firms operating as of 2020. After accounting for the reduction in exit rates, I see 3% more firms operating under price deregulation. [21] However, these gains were offset by the higher prices that existing customers would have ended up paying. When considering all markets, total welfare would have decreased by 1.4% if the price cap was not put in place.

Taken together, the price cap appears to have performed better than either price deregulation or maintaining a cost-of-service mechanism, as it struck a balance between allowing high enough returns to stimulate entry but constraining profits sufficiently that the increase in dead-weight-loss in mature markets did not offset these gains.

[21] I fix the number of markets in the data to those that I observe. The shale boom led to an over-expansion in capacity meaning that it is unlikely additional markets would have been entered, event absent the price cap. As such, the difference in observed operating firms and predicted operating firms in this experiment is due to exit.

Figure 16: Welfare Impact of Deregulation

Measure	Price-cap	Price Deregulation	Percent Difference
Markets with a pipeline operating since 2000			
Producers Profit	25	27	8.3%
Net Consumer Surplus	298	289	-3.0%
Total Welfare	323	316	-2.2%
Avg. Routes	19.0	22.6	18.7%
Avg. Productivity	2.55	2.47	-8.2%
All Markets			
Producers Profit	53	56	4.8%
Net Consumer Surplus	630	618	-2.0%
Total Welfare	684	674	-1.4%
Operating Firms	177	182	2.8%

Note: Profits and welfare measures are in billions of dollars.
Results are based on simulating 50 samples.

The observed increase in markups since 2000 indicates that there may have been room for improvement. The final counterfactual I consider is to only let price caps rise according to the change in PPI, which is equivalent to removing the adjustment factor X. I call this experiment the “fixed price cap”, reflecting that X does not adjust. Table (17) shows the impact of fixing the price cap in perpetuity. In mature markets, firm profits would have declined significantly, by roughly 15%. Consumer surplus would have increased by roughly 5.1% by 2020 leading to an overall welfare gain of 3.5%. As expected, firm investment would have declined under a fixed price cap. This decline in investment happens gradually, as can be seen in Figure (18), and is a result of firms having lower expectations of future earnings.

Similar to the previous results, productivity would have increased. However, the gains are substantially less than we saw going from no price cap to the current mechanism. The reason for this is that the productivity investment policy function is non-monotonic. A

Figure 17: Welfare Impact of a price cap without the Factor X

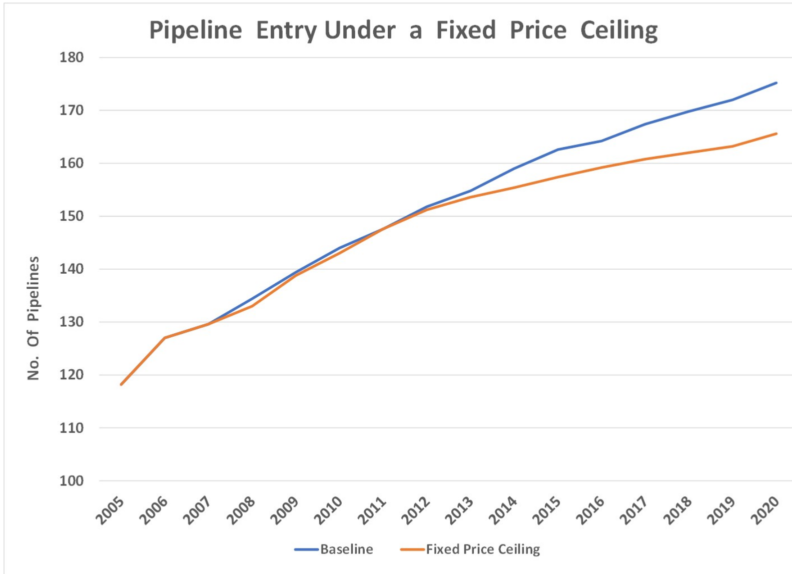
Measure	Price-Cap	PPI Price Ceiling	Percent Difference
Markets with a pipeline operating since 2000			
Producers Profit	25	21	-14.8%
Net Consumer Surplus	298	313	5.1%
Total Welfare	323	334	3.5%
Avg. Routes	19.0	18.0	-5.3%
Avg. Productivity	2.55	2.57	2.4%
All Markets			
Producers Profit	53	49	-8.7%
Net Consumer Surplus	630	652	3.4%
Total Welfare	684	700	2.4%
Operating Firms	177	167	-5.6%

Notes: Profits and welfare measures are in billions of dollars.
Results are based on simulating 50 samples.

small reduction of a high price cap increases the gain from investing in productivity. The lower price cap results in firms producing more, and since productivity gains lower the cost of infra-marginal production firms will see more of a benefit from making investments in productivity gains. However, as the price cap continues to decrease, firms eventually see the returns to productivity investment decrease as well. Prices being to fall below the cost of production and firms anticipate that they may have to exit from the market. This results in them decreasing their efforts at reducing costs. For precisely this reason, we see only modest gain in productivity under a fixed price cap.

Firms enter new markets at a lower rate, and several firms exit markets that they otherwise would not have, under the fixed price cap. Figure (18) shows the difference in active firms under the fixed price cap relative to baseline entry. The decline in firm entry and increase in firm exit have a negative impact on total welfare. However, most of this entry and exit occurs in smaller markets. The larger markets are also the mature markets, which would have seen a large increase in consumer surplus under a fixed price cap. Therefore, the model

Figure 18: Impact of a Fixed Price cap on Entry and Exit



estimates that welfare would actually have been higher under a fixed price cap by roughly 2.4%. By allowing the price cap to dynamically adjust, FERC essentially incentivized firms to enter new markets by reducing consumer surplus in established markets. Customers of firms in mature markets saw their consumer surplus decrease by 5.1% relative to a fixed-price cap at the same time the industry saw roughly 5% more entry.

10 Conclusion

In this paper, I examined the impact of price regulation on firm investment and welfare in the oil pipeline industry during the years surrounding the shale revolution. I find that the existing price cap regulation led to an increase in returns for firms over the past two decades relative to cost-of-service regulation, but that the welfare loss from higher prices was more than offset by increased firm productivity and investment. While price cap regulation led to welfare gains relative to either cost-of-service or price deregulation, there was still room for improvement. In fact, welfare could have been increased by an additional 2.4% had the adjustment factor been held fixed over the 20 year period. While this would have led to less investment in response to the shale boom, existing customers would have paid considerably lower prices, increasing their consumer surplus. I find that using a structural model is important when assessing the impact of different forms of regulation. Standard methods of estimating firm level productivity would have found a large decline in productivity after the adoption of the price cap, but I find this to be largely due to exogenous changes in firm costs. Instead, the full model predicts that firms actually did significantly decrease their unit-cost of production relative to cost-of-service regulation.

The current analysis uses a theoretical model to determine the impact of different regulatory regimes on investment and welfare. However, direct evidence of the regulatory impact is more difficult to find. One potential area for future research is to compare the experience of oil pipelines to that of natural gas pipelines, which operate under cost-of-service regulation. Despite natural gas production seeing an increase comparable to that of oil production, natural gas pipelines added less than a quarter of the total mileage that oil pipelines did. A similar analysis would need to be taken to determine if the difference in investment was due to higher sunk investment costs, lower transportation demand, or lower expected returns.

This analysis has abstracted away from competitive effects, both between pipelines and other forms of transportation. While I have argued that this is a reasonable approximation, recent papers have documented that this margin may be important in determining pipeline investment.[22] In 2010, rail transportation accounted for less than 1% of all crude movements but increased to over 7% by 2020.[23]. Future analyses can extend the current framework to account for the impact of competition, where it exists, and substitution to other forms of transportation. The current analysis also abstracts away from the impact of foreign production on domestic supply and transportation demand. The increased domestic

[22] For instance, see Covert and Kellog (2017).

[23] "Crude Oil and Petroleum Products Transported in the United States by Mode", Department of Transportation

production largely served to displace foreign imports so that existing processing capacity only expanded 6% in response to the shale revolution. Future analyses can study the impact of foreign oil supply on pipeline investment and vice versa. Finally, an important caveat to the welfare analysis in this paper is that it fails to account for the environmental impacts of oil pipelines, both in terms of oil spills and more broadly to facilitating the consumption of fossil fuels. These externalities can be important determinants of welfare and estimating their significance would constitute an important extension of the current work.

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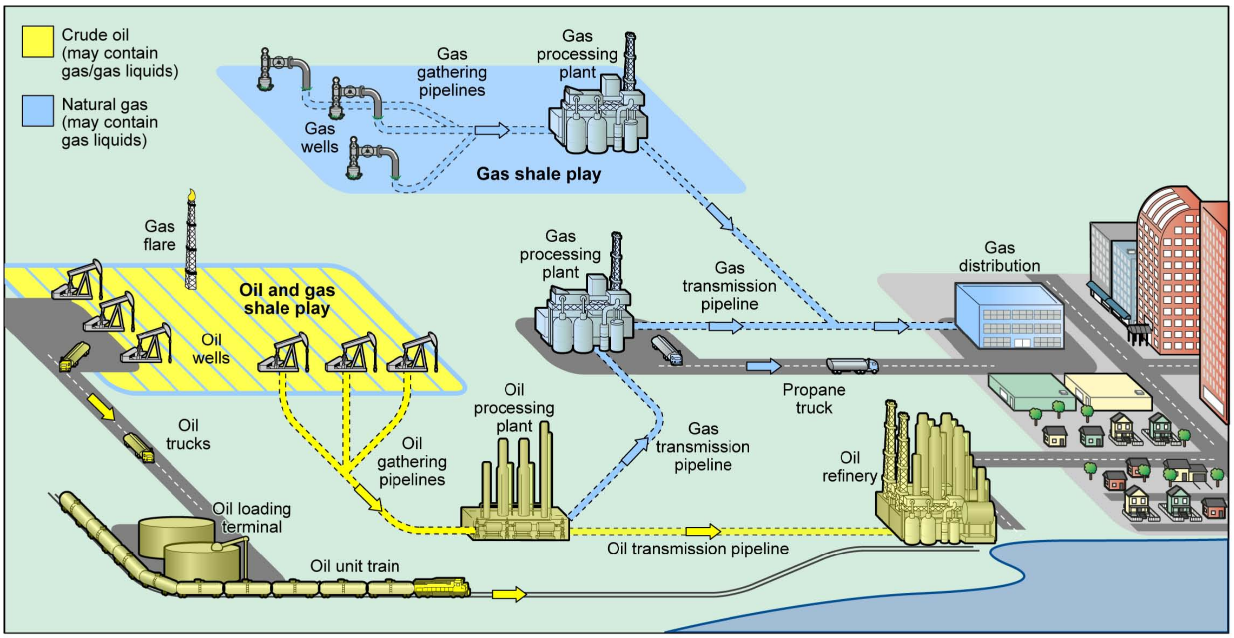
A Appendix

A.1 Additional Figures

Figure 19: Modes of Oil Transportation



Source: GAO. | GAO-14-667

Figure 20: Sample Market

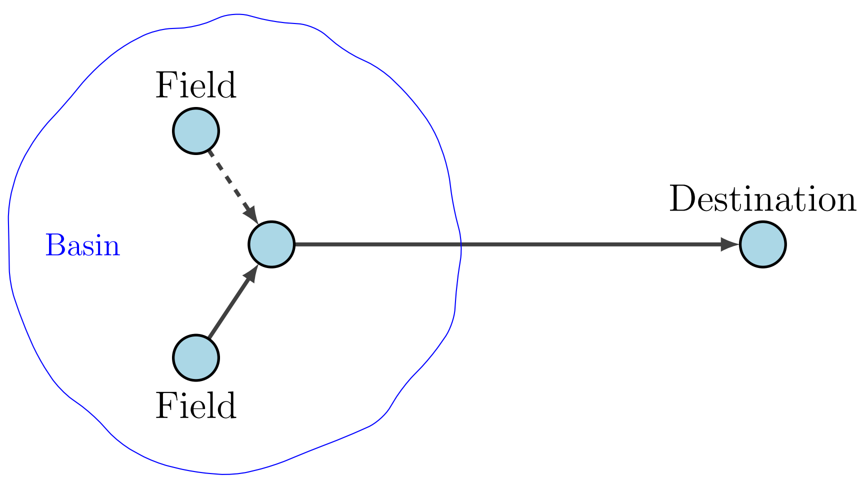


Figure 21: Average Unit Operating Cost

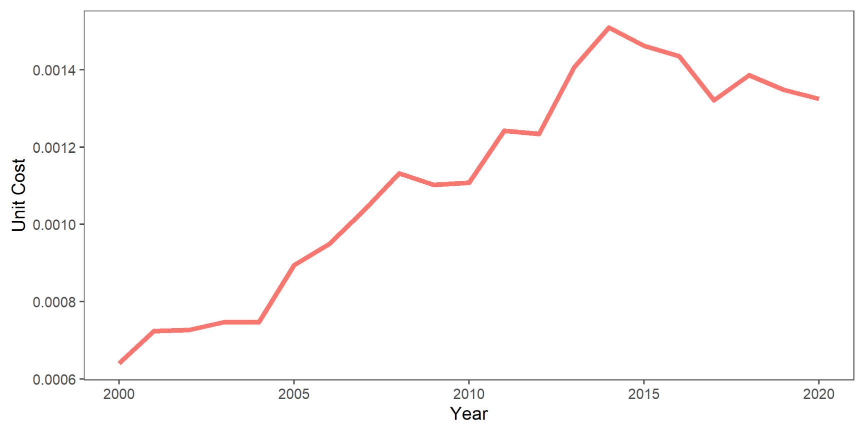


Figure 22: Petroleum Administration for Defense Districts (PADD)

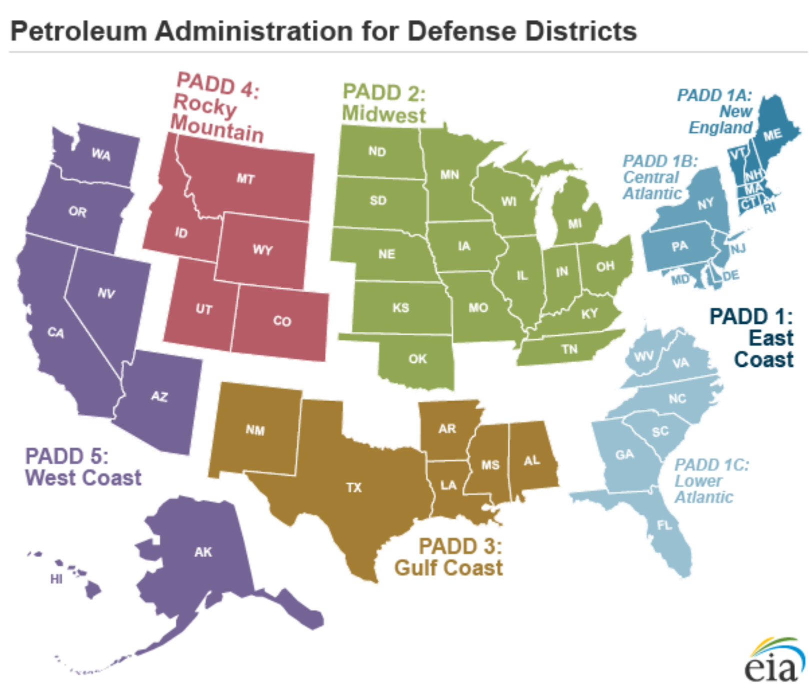


Figure 23: Variable Input Elasticity

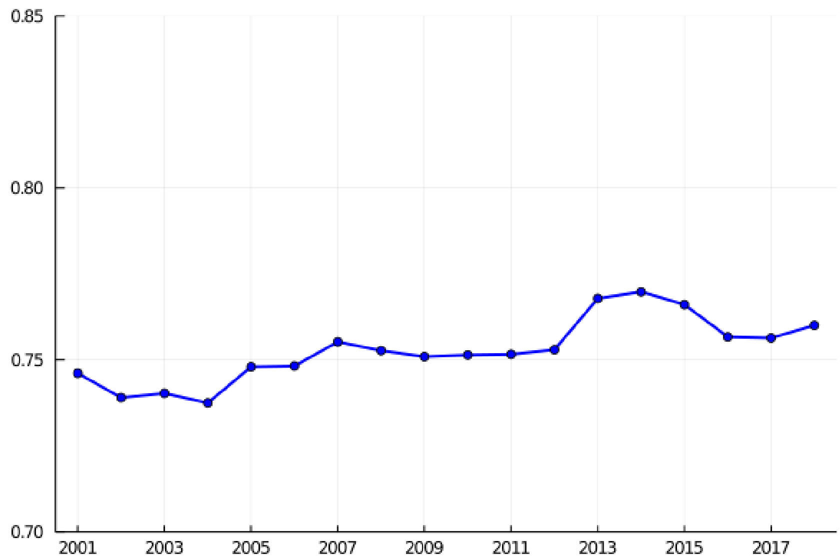


Figure 24: Weighted Average Cost of Capital

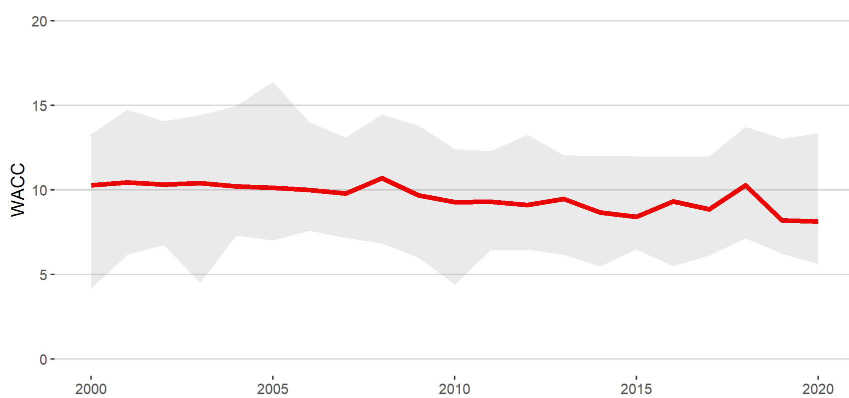


Figure 25: Change in Price to Average Total Cost

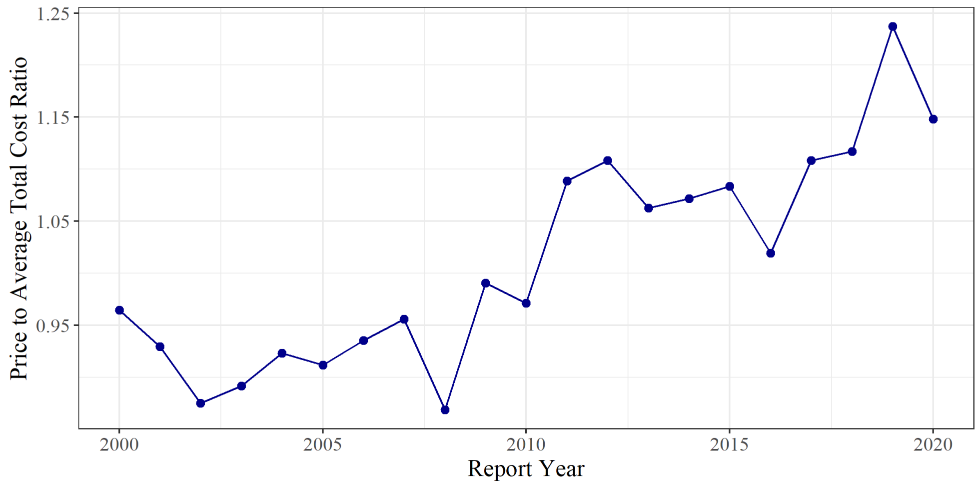
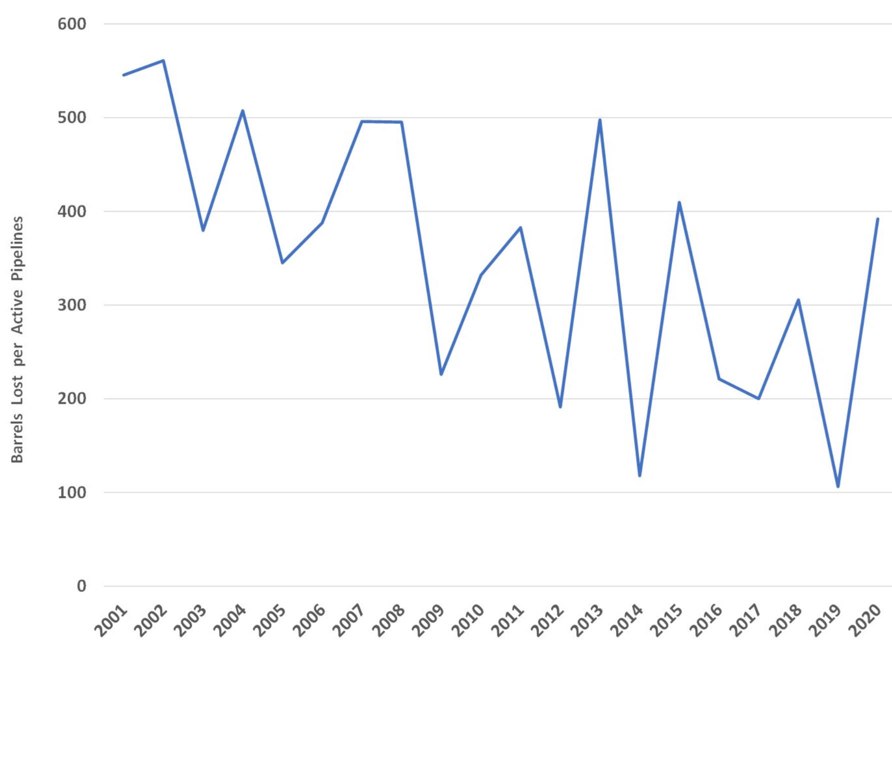


Figure 26: Barrels Lost per Active Pipelines



A.2 Alternative X Factor Calculation

The price cap is intended to compensate pipelines for industry-wide changes in cost, whether these changes come from different factor prices or changes to the aggregate productivity. Ideally, it would reflect shifts in the supply curve, representing changes in costs at every level of output. The Kahn Methodology proxies for shifts in the supply curve by considering changes in the average unit cost. However, changes in unit costs can arise from both a shift in the supply curve as well as a movement along the supply curve. While not directly comparable, the above calculation shows that the Kahn Methodology is most closely related to the change in average total cost. Average total cost can change due to a technological progress as well as a changes in the competitive environment. Consider the case of constant marginal costs and positive fixed costs of production. Taken together, these assumptions imply that the average cost curve is everywhere decreasing. Assume further that the price cap currently achieves the first-best solution of price equal to marginal cost. With downward sloping demand, the profit maximizing firm wants to set marginal revenue equal to marginal cost, so any increase in the price cap will result in the firm charging a higher price and restricting output. Because average total cost is everywhere decreasing, this implies that the average variable cost increases *even if* fixed costs and marginal costs remain unchanged.

We don't want to focus just on the change in price or the change in average total cost, as we conflate three things: shifts in demand, shifts in cost, and movements along a demand curve. It is this last category that we seek to exclude from the calculation of the price index as it captures competitive effects, rather than changes in the industry primitives. We can solve for the change in average total cost due to movement along the demand curve by focusing on deviations of price from the average total cost curve. Changes in average total cost are given by

$$\Delta = ((P_1 - \text{ATC}_1) - (P_0 - \text{ATC}_0)) \tag{16}$$

$$= \left(\epsilon_{ATC,P}^{-1} - 1\right) \Delta_{\text{ATC}} \tag{17}$$

So that the change in average total cost due to movement along the demand curve is given by

$$\Delta_{\text{ATC}} = \frac{\Delta}{\left(\epsilon_{ATC,P}^{-1} - 1\right)} = \Delta \frac{\epsilon_{ATC,P}}{1 - \epsilon_{ATC,P}}$$

A.3 Robustness

A.3.1 Error in Capital

We can extend this method to handle measurement error in the capital stock in a manner similar to that of Collard-Wexler and De Loecker (2016). They assume that the measurement error is uncorrelated with the true capital stock and that we see

$$k_{jt} = k_{jt}^* + u_{jt}$$

If we strengthen this to statistically independent, then we can follow an approach analogous to before, this time instrumenting for capital with investment, lags of capital, or other macro-indicators that are uncorrelated with the error term. Note that this relies on the production function being linear in parameters. In this way, $E[k_{jt}|Z]$ and $E[k_{jt}^*|Z]$ span the same space (when including a constant), so we consistently recover the parameter β_k. Additional restrictions must be placed on u_{jt} to consistently estimate a translog production function. The most natural would be to assume that u_{jt} is mean zero. Then following the previous logic

$$
\begin{aligned}
E[k_{jt}^2|Z] &= E[k_{jt}^{*2}|Z] + E[k_{jt}u_{ij}|Z] + E[u_{jt}^2|Z] \\
&= E[k_{jt}^{*2}|Z] + 2E[k_{jt}^*|Z]E[u_{ij}] + E[u_{jt}^2|Z] \\
&= E[k_{jt}^{*2}|Z] + E[u_{jt}^2]
\end{aligned}
$$

Note that the variation in $E[k_{jt}^2|Z]$ is driven entirely by the term $E[k_{jt}^{*2}|Z]$, meaning that after conditioning on a constant we will get consistent estimates for all model parameters.

This result is interesting in that we can consistently estimate the parameters of the Cobb-Douglas and translog production functions under some natural assumptions on the measurement error. However, these assumptions are still strong. For instance, the measurement error in the capital stock arises from how we calculate the proxy. Therefore, it is unlikely that the measurement error will truly be independent of the true stock. Further, even if the measurement error is independent of the capital stock, there is little reason to believe it will be mean zero. In most regression models, the mean zero assumption is innocuous because we can always add a constant to control for a non-zero mean. Here, however, this assumption is used to separate out the variation of $E[k_{jt}^2|Z]$ and $E[k_{jt}|Z]$, and is therefore necessary for identification.

While this approach appears to be more general than what I use in the text, it has one serious drawback. There is no way to separate out u_{it} from k_{jt}^*. This means that all of the elasticity estimates will also be measured with error. As such, I do not use the results as a starting point in the analysis. However, Table 4 presents the results for a translog assuming that capital has been measured with error. I no longer use k_t as an instrument for itself, but instead using k_{t-1}. Additionally, I add in the price cap index as an instrument. Column (1) reproduces the baseline estimates from the text, while column (2) presents the results of this alternative procedure. Both input elasticities are estimated to be higher on average in the baseline specification, and the returns-to-scale is also larger. Most significantly, the estimated elasticities are all positive. In the baseline model (and for the other methods that I used), a few pipelines were estimated to have negative input elasticities. This problem disappeared when instrumenting for capital.

Table 4: Error-in-Capital Estimates

	Baseline	Error-in-Capital
	(1)	(2)
β_v	0.470	0.752
	(0.070)	(0.147)
β_k	0.242	0.415
	(0.029)	(0.07)
β_{v^2}	0.024	0.045
	(0.015)	(0.011)
β_{k^2}	0.031	0.023
	(0.007)	(0.011)
β_{vk}	0.023	-0.064
	(0.004)	(0.029)
Avg. Capex Elast.	0.730	0.642
Avg. Opex Elast.	0.528	0.492
Local RTS	1.258	1.134
Observations	2,863	2,863

A.3.2 Different Measures of Output

As mentioned in the main text, barrel-miles is not the only potential dependent variable. We can instead use either barrels or deflated revenue. Using barrels runs the risk of using outputs with a different "quality", by which I mean two barrels of oil traveling different distances have a different inherent value. Deflated revenue is consistently used in the literature when measures of physical output are not available. To check the robustness of my results and to have a point of comparison with the literature, I estimate the model using each measure separately. Because I have quarterly data available for revenue and barrels, I use this for estimation. Unfortunately, I do not have the line item data for capital at the quarterly basis, so I use Net Carrier Property as a proxy. Estimation using annual data generates similar results.

Column (2) shows the results using barrels rather than barrel-miles. The most striking difference is the implied returns to scale when using barrels. Rather than being increasing returns to scale, the estimated input elasticities imply a decreasing returns to scale technology. This makes intuitive sense in that larger pipelines tend not to produce more barrels but instead transport barrels over a greater distance. Therefore, we see that increases in capital tend to lead to marginal changes in output, measured in barrels. This has the effect of making the capital elasticity very nearly zero. The variable input responds more readily to changes in throughput, but it is still significantly attenuated. This demonstrates the importance of using quality adjusted output during estimation.

Column (3) shows the results using deflated revenue. The model predicts that the input elasticity is declining in capital at low levels and then increasing in capital at higher levels. The variable elasticity is strongly decreasing in the level of capital. Combined, these results imply that the standard deviation of the input elasticities are over twice as large. Additionally, 19% of the observations have a negative capital elasticity. The production function is estimated to have constant returns to scale. The lower estimated returns to scale makes sense as firms with higher throughput tend to charge lower prices. So doubling output will increase revenue by less than a factor of two.

Table 5: Estimates for Alternative Dependent Variables

	Barrel-Miles	Barrels	Deflated Revenue
	(1)	(2)	(3)
β_v	0.470	0.176	1.673
	(0.070)	(0.404)	(0.134)
β_k	0.242	-0.233	-0.724
	(0.029)	(0.157)	(0.059)
β_{v^2}	0.024	0.016	0.061
	(0.015)	(0.03)	(0.007)
β_{k^2}	0.014	0.032	0.137
	(0.013)	(0.03)	(0.007)
β_{vk}	0.023	0.048	-0.233
	(0.004)	(0.063)	(0.023)
Avg. Opex Elast.	0.730	0.407	0.761
Avg. Capex Elast.	0.528	0.074	0.242
Local RTS	1.258	0.481	1.003
Observations	2,863	7,404	6,999

A.4 Approximating the Value Function

The nested-fixed point problem involves solving an eight dimensional value function iteration problem at each step. To reduce the computational burden, I rely on adaptive sparse grids to endogenously choose the interpolation grid for the value and policy functions. Several recent papers have employed adaptive sparse grid interpolation to solve high dimensional economic models including Brumm and Scheidegger (2017) and Zhang (2020). Tensor product grids grow exponentially in the dimension of the firm's state space. For instance, if we use N points in each dimension then we would need to evaluate the value function (or policy functions) at N^d points. Even for small N, this becomes infeasible for moderate to high dimensional problems. Sparse grids ameliorate this problem by dropping grid points that contribute little to reducing the approximation error and focus on grid points. The number of grid points for a regular sparse grid increases at a rate $O(2^n n^{d-1})$, where n denotes the level of refinement. For functions with bounded second-order derivatives, the approximation error decays rapidly in n, so we can generate equivalent approximations to the underlying function using orders of magnitude fewer points.[24] However, this result depends on the function being sufficiently smooth, a criteria that is often violated in economic models. For instance, in my model, firms often have policy functions with kinks in them. Without further refinement, a regular sparse grid misses these non-linearities and can provide a poor approximation to the underlying function.

Adaptive sparse grids seek to remedy this issue by selectively building out points where the approximation error is the highest. We further trim points in regions where the approximation error is small and only add points where it is high. This further reduces the number of points necessary for an accurate approximation, but has the added benefit adapting to the specifics of the function to be approximated. In the case of a kinked policy function, additional points are added around the kink to capture the sudden change in function value. The key problem in using adaptive sparse grids is in defining the pruning criteria.

A pipeline's Euler Equation residual for productivity investment is given by

$$
\begin{aligned}
r_\xi = \frac{\partial \tilde{\pi}}{\partial \xi} + \beta \Bigg(& \Phi(EV(s');\mu,\sigma)\frac{\partial EV(s')}{\partial \omega} + \Phi'(EV(s');\mu,\sigma)\frac{\partial EV(s')}{\partial \omega}\left(EV(s)-\mu\right) - \\
& \sigma\Phi'(EV(s');\mu,\sigma)\frac{\partial EV(s')}{\partial \omega}\frac{EV(s)-\mu}{\sigma}\Bigg)
\end{aligned}
$$

with an analogous expression for route investment. These equations can be used to adaptively refine the sparse grid by only adding points where the error in the pipelines Euler

[24] For a more detailed discussion, see Brumm and Scheidegger (2017).

Equation is large. As we have two Euler Equations, I re-scale the residuals so that they have the same average magnitude and then only add points when the maximum absolute residual is above a certain threshold. That is, I add points when the following condition is met

$$\max\{|r_\xi|, |r_\Delta|\} \geq \gamma$$

where $\gamma = 0.01$ for the policy function and 0.001 for the value function. One minor contribution of this work is that I extend the results of Murarasu et al. (2011) to account for non-regular sparse grids. The authors provide a compact data structure for regular sparse grids that relies on a bijection between sparse grid level indices and the integers. With this bijection, they avoid storing hierarchical coefficients with their associated level and point multi-indices. This reduces the storage requirement significantly for moderate to high dimensional problems. I derive a similar bijection for Curtis-Clenshaw type grids, which allow me to use a similarly compact structure when solving my model. The interested reader can find the full details in my online appendix.