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

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Abstract

Since 2010, crude oil production in the United States has surged over 100% leading to a dramatic increase in demand for pipeline transportation. However, the profitability of investing in oil pipelines is constrained as transportation rates are set subject to a price-ceiling. 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 total welfare under three separate regulatory environments: price-cap regulation, cost-plus regulation, and 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. However, 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 welfare relative to what could have been achieved under a fixed price-ceiling.

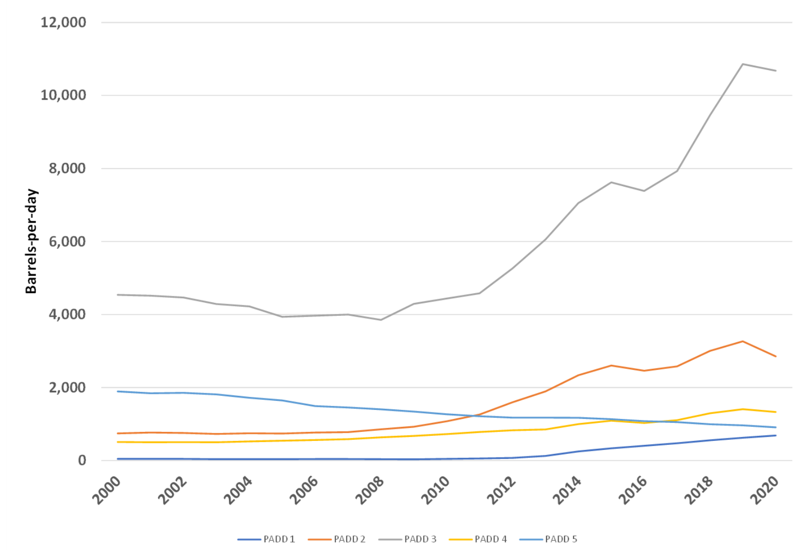
1 Introduction

The oil pipeline industry in the United States 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 production increasing by over 100%, from 5 million barrels per day (bpd) in 2000 to over 11 million bpd by 2020. Existing processing capacity was largely used to accommodate the increase in supply, as refining capacity only expanded 6% over the same period and total receipts by US refineries increased 11%. 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. This required new means of transportation to connect new wells to the existing processing infrastructure, generating a large increase in demand for additional pipeline construction.

The expected profitability of these investments was limited by the use of price-caps to regulate rates in the industry. Oil pipelines generate revenue by transporting barrels of petroleum and its derivatives, and transportation rates are subject to a price-ceiling determined by the Federal Energy Regulatory Commission (FERC). These price-ceilings limit the pipeline's ability to fully maximize the return-on-investment of a given project. As such, pipeline investment is weakly increasing in the level of the price-ceiling. 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 investments. In this paper, I examine the extent to which the use of price-cap regulation reduced the incentive for pipelines to invest in response to increased demand driven by the shale boom, and how their investment decisions would change under alternate forms of regulation.

In principal, initial price levels could be set to compensate firms for the sunk cost of investing. However, firms also had to anticipate whether the price-ceiling would rise fast

Figure 1: Growth in Oil and NGL Production by Region



Note: See Appendix Figure (23) for PADD definitions. Production figures include crude oil and natural gas liquids (NGLs).

enough to compensate them for exogenous increases in unit cost. Since 2000, firms saw capital and 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 regulatory requirements. In 2000, there were roughly 200 pipeline failures which led to the introduction of the Pipeline Safety Improvement Act of 2002 and the Pipeline Inspection, Protection, Enforcement and Safety Act of 2006. These acts, along with new rules from the Pipeline and Hazardous Material Safety Administration (PHMSA), required pipelines to invest in physical modifications to their system and repairs, as well as increased operational costs associated with more frequent maintenance and inspections. PHMSA testified in 2010 that these compliance costs were significant and "would continue to impose a significant financial burden".[2] And while PHMSA does not

[1]See Appendix Figures (21).

[2]See "Reply Comments of the U.S. Department of Transportation Pipeline and Hazardous Materials Safety Administration" in the 2010 Five-year Review of Oil Pipeline Pricing Index.

track the cost burden of their regulation, they noted that pipelines reported compliance costs between \$2.0 - \$2.5 billion. If firms anticipated that costs would grow faster than the price-ceiling, they would be further disinclined to undertake large capital investments.

To determine the impact of price-cap regulation on firm investment, I develop a model of pipeline production and investment where market participants are subject to a price-ceiling. Pipelines make optimal entry, exit, and investment decisions in response to an unanticipated demand shock that represents the shale boom. Pipelines are heterogeneous in their unit-cost and can invest to become more efficient, lowering their variable cost of service. However, a component of costs is changed exogenously to match the increase in average industry costs over the past two decades. Firms produce as local monopolists and set prices subject to a dynamic price ceiling.[3] A justification for price-cap regulation is that allowing firms to generate temporary rents provides them with the proper incentive to become lower their cost base. As long as the price-ceiling is slow to adjust, firms are able to capture any cost reduction as increased rents. I model this by allowing firms to invest to lower their unit-cost of production in each period. However, a slow-adjusting price-ceiling can reduce market entry and expansion when average costs are rising, which can be important determinants of total welfare. To capture this dynamic, I also allow firms to also invest in system expansion and in market entry. A low price-ceiling will decrease the profitability of these investments, especially if firms anticipate their costs will grow faster than the price-ceiling. In this case, a higher, faster-growing price-ceiling induces more entry and more expansion. This creates a trade-off when setting the price-ceiling; setting a high price-ceiling may induce more investment but it can increase rents and lessen the incentive to become increase productivity.

[3] The assumption that firms are local monopolists follows from the D.C. Circuit Court of Appeals ruling that there was a rebuttable presumption of market power. I discuss this in more depth in Section (4) below.

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 estimate an industry production function using data on physical units of output - total barrel-miles transported - and detailed cost accounting data. This recovers a measure of firm-level productivity and its evolution over time. The impact of environmental regulation manifests as a decline in average productivity over the sample period. Next, I maintain cost minimization to generate estimates of pipeline-time specific markups and use data on quantity and prices to generate pipeline-time specific estimates of marginal costs. The productivity and marginal costs estimates are then used as primary inputs when estimating a pipeline cost function that depends on the productivity-adjusted level of output and the size of the pipeline system. I further use instrumental variables to estimate demand and how it responded to the shale boom using product market outcomes. With estimates of the cost function and demand, I use the dynamic model to recover the industry fixed cost structure by matching predicted investment, entry and exit decisions to their empirical counterpart. I measure the welfare impact of price-cap regulation on the oil pipeline industry over the past two decades by exploring three effects of the price-cap index: how it changed incentives for firms to become more productive, how it constrained firms abilities to generate monopoly rents, and how it changed the incentives for firms to invest and enter/exit markets in response to rapidly changing regulatory costs and the shale boom. I use the estimated model to determine how welfare would have changed under three alternative regulatory regimes: cost-of-service (also known as cost-plus), a fixed price-cap, and deregulation.

Each alternate form of regulation impacts welfare in different way. Cost-plus regulation discourages firms from becoming more efficient as any cost reduction translates into lower prices. Additionally, having constrained profits limits the desire of pipelines to undertake investments, as cost-plus regulation effectively limits the upside potential of a risky investment while doing little to limit downside risk. Both of these effects serve to lower welfare. However, cost-plus regulation is effective at extracting rents, increasing consumer surplus through lower prices. Deregulation provides the greatest incentives for investment and efficiency gains, as firm can set prices to maximize returns when entering a new market and are the residual claimant on any cost reductions. Of course, deregulation increases dead-weight-loss as firms are allowed to charge their maximum sustainable price. As such, existing customers pay higher prices which decreases welfare, but customers in previously unserved markets generate consumer welfare from the introduction of a new good. Price-cap regulation strikes a balance between these two environments, constraining the firm's ability to charge monopoly prices while also allowing firms to generate rents that could stimulate efficiency gains and additional investment.

I find that the rate-index led to a significant increase in returns for oil pipelines relative to the cost-of-service mechanism, leading to 15% increase in market entry in response to the shale boom and 0.5% increase in total investment. Additionally, average firm productivity was 17% higher relative to the cost-of-service mechanism, as the rigidity of the price-ceiling led firms to improve productivity. However, there was a 15% decline in consumer surplus for existing customers as they paid considerably higher prices. Overall welfare increased 7% as these losses were offset by increased consumer surplus in new markets. As anticipated, deregulation led to the largest amount of market participation but welfare still declined by roughly 1.4% due to the much higher prices that existing customers had to pay. The rate index yielded better results than a traditional cost-of-service regime and deregulation, however welfare could have been further improved by not allowing the index to dynamically adjust. 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 ceiling.

This paper has several contributions. I use a new dataset to study entry and investment decisions by oil pipelines in the years encompassing the shale boom. 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. This paper provides one of the few structural models which have been used to determine the efficacy of incentive based regulation in general, and price-cap regulation in particular. Previous studies have largely utilized regression methods which use variation in the regulatory environment of firms to convincingly estimate the impact of different mechanisms. 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, while I find that costs increased by over 50% over the past two decades, the price-cap actually served to make firms more efficient relative to cost-plus regulation.

Additionally, rather than focus solely 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. 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. Section (5) provides an overview of my dynamic model of an oil pipeline and Section (6) gives and in-depth discussion of my empirical strategy. Readers interested in the empirical results can skip directly to Sections (7) and (8). Section (7) provides the estimates for the model primitives, including demand and cost functions, as well as the distribution of entry, exit, and investment costs. Section (8) 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. The uninterested reader can go directly to Section 3.

As of 2020, there was roughly 150,000 miles of oil pipeline installed in the United States. Of this, nearly 60% was dedicated to transporting crude oil and the rest was dedicated to transporting refined petroleum product.[4] Crude oil denotes unrefined petroleum that has been extracted from an underground reservoir and which must be further processed before being delivered to the end-user. Refined petroleum product is a broad term that covers any type of refined hydrocarbon, and includes gasoline, jet fuel, and diesel. Oil pipelines primarily generate revenue through the transportation of oil. Oil pipelines do not take ownership of the product during transportation and rarely sell pipeline capacity. Prices, as outlined in the pipeline's tariffs, are set based on the quantity shipped and vary based on the total distance transported. Oil pipelines are considered "common carrier", and as such have limited ability to provide dedicated, or "firm", transportation. If an oil

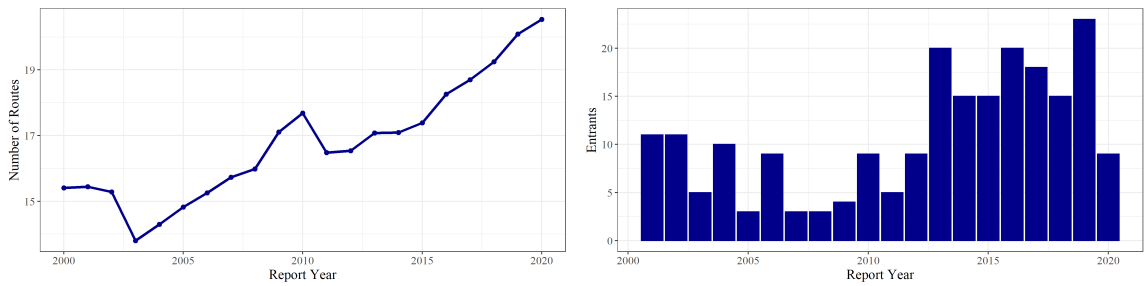
[4]See PHMSA "Annual Report Mileage for Hazardous Liquid or Carbon Dioxide Systems"

pipeline is oversubscribed then all shippers have capacity allocated to them proportionally. Oil pipelines have a diverse customer base, including upstream firms shipping crude oil to processing plants, downstream firms transporting refined product to regional markets, airports transporting fuel for flights, and large industrial customers.

Shale Boom The development of horizontal drilling, hydraulic fracturing, and seismic imagine made previously high-cost tight shale plays economically viable to drill. Starting around 2011, 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 pipeline footprint increased from 56,000 miles to 85,000 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 pipeline capacity was driven in part by the expansion of existing systems and by the construction of new pipeline systems. Panel (a) of Figure (2) shows the increase in average number of routes offered by pipelines from 2000 to 2020. The average number of routes increased 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. The shale boom is the principal confounding event in my analysis, as pipelines saw a large increase in the rate index during the past two decades but also saw a large increase in demand. A central question of this paper is whether a permissive rate index encouraged market expansion in response to this unprecedented demand shock.

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

Figure 2: Dynamics of Firm Entry and Route Expansion



(a) Average No. Routes

(b) Enterants per Year

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 rate 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.[5]

Pipelines saw their cost burden increase significantly over the past two decades, during a time when they were looking to make large capital investments to meet the increase in demand. This complicated the entry decision for many pipelines as they had to consider recovering their sunk entry costs as well as increased future operational costs. In an

[5] 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.

unregulated environment a portion of these costs would be passed-through to consumers. However, pipelines set prices subject to a price ceiling whose growth is exogenous, limiting their ability to adapt to sudden cost changes. I discuss the pipeline price regulation next.

3 Price-Cap Regulation

Most 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 rate of return. However, this mechanism distorts the firm's incentive to minimize their rate base 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 price-ceiling, 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.[6] Most important to this paper, FERC adopted price-caps as a form of price control when deregulating midstream oil services in 1996.

Price-cap regulation typically takes the form of

$$RPI + X$$

where RPI is a measure of inflation and X is a fixed "efficiency factor" determined by the regulator. In the online appendix, I provide an overview of how X is typically determined, both in theory and in practice. The efficiency factor is meant to reflect how industry costs

[6] 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.

and productivity are expected to change over a predetermined interval of time, called the review period. At the beginning of each review period the factor X is reset in order to pass any cost savings on to consumers. While the efficiency factor is a key component

3.1 Price-Cap Regulation in the Midstream Market

The Federal Energy Regulatory Commission (FERC) began regulating oil pipelines in 1977.[7] Initially, FERC proposed largely deregulating oil pipelines and letting market forces constrain their behavior. The D.C. Circuit Court of Appeals As with most natural monopolies at the time, oil pipelines were initially regulated under a "return-on-rate base" regime. The industry moved to incentive-based regulation in 1992, when FERC established the oil rate index to allow for the adjustment of oil pipeline tariffs without regulatory approval. The rate index is applicable to all pipelines in the industry, although there are exceptions for a select few pipelines to use cost-of-service filings or market-based rates.

Order-561 made clear FERC's goals when establishing the rate index. It was designed as a simple and generally applicable methodology that would ensure just and reasonable rates of return while putting a "greater emphasis [on] productive efficiency in noncompetitive markets than does traditional cost-of-service regulation." This, of course, depended in large part on how rate index was to be structured. If the rate index grows faster than costs, then pipelines would not be constrained in their ability to maximize rents. If the rate index grows too slower than costs, then the oil pipelines will not be able to generate a reasonable return on their capital and will be forced to exit the market. To avoid either scenario, FERC sought a rate index that would properly track the cost experience of a typical pipeline.

To this end, Professor Alfred Kahn proposed a simple method to calculate the efficiency factor (now known as the Kahn Methodology). He proposed calculating several measures

[7] 42 U.S.C. §7172(b)

of central tendency for the change in unit operating and capital expenditures over the preceding five year period and comparing how they changed relative to PPI-FG.[8] Professor Kahns defined the cost growth for each pipeline as

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

where OR_i represents the operating ratio of firm i, defined as the ratio of operating expenses to operating revenue. 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. For instance, MarketLink leases capacity from TransCanada and this lease is recorded as a rental expense. As such, MarketLink has few capital expenditures and it is proper to place more weight on the change in operating expenses. The Kahn Methodology then averages over the cost changes for all pipelines and calculates the efficiency factor as[9]

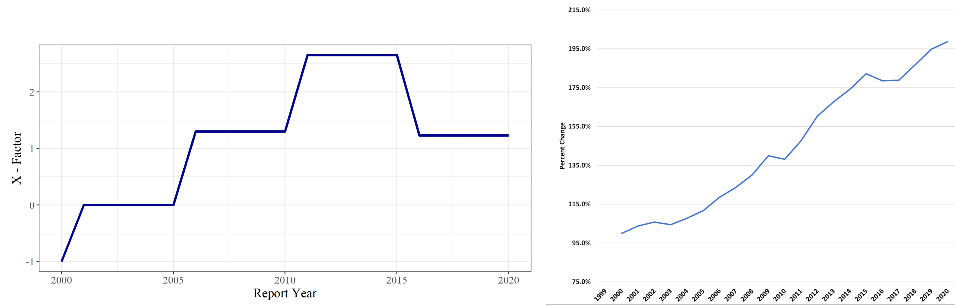
$$X = \left(\frac{1}{N} \sum_i \mathrm{CG}_{iT} \right)^{\frac{1}{T}} - \left(\frac{PPI_T}{PPI_0} \right)^{\frac{1}{T}}$$

Figure (3) shows the computed efficiency factor for each review period, along with the cumulative change in price ceilings since 1999. With the exception of the prior review, the efficiency factor has increased steadily in each review period and price levels have been

[8]The Kahn Methodology considers the median, mean, and weighted mean. Originally, the sample was limited to the middle 50% of cost changes, but was later expanded to include the middle 80%. These measures were calculated for the middle 50% of cost changes. The average of the three measures was taken, and then the average was taken across sub-samples. This method was developed out of a desire to reduce the influence of data errors that were frequently found in early filings, as well as better approximate the cost experience of a representative pipeline. The weighted mean was thought to put too much emphasis on large pipelines, the mean was not robust to outliers, and the median was too robust to outliers. The Kahn Methodology was a compromise across of these extremes.

[9]I focus on the mean cost growth here for simplicity. In practice, the mean, median, and weighted mean are all calculated and then an average is taken across these measures.

Figure 3: Efficiency Factor



(a) X-factor (b) Cumulative Change

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

allowed to increase over 100%.

One potential explanation for the steady rise in the efficiency 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. Of course, the Kahn methodology does not directly use the change in average total cost but instead a weighted average in the change of fixed and variable costs. So the extent to which this is an issue is an empirical question.

4 Data Sources

My primary data sources come from regulatory filings. For pipeline cost, revenue, and output data, I use the FERC Form 6, a mandatory, quarterly filing for all interstate oil pipeline that have at least \$500,000 in annual revenue. Pipelines that have annual revenues between \$350,000 and \$500,000 are not required to file the full Form 6, but must file and annual cost of service with FERC (called Page 700 data). I used data from pipeline responses to FERC Order 342.3, which requires all pipelines to file their current tariff sheet and provide and appendix justifying their routes for each service. The primary method of rate justification is the rate index. Finally, I use various datasets from the Bureau of Economic Analysis (BEA), the Energy Information Administration (EIA), the Pipeline and Hazardous Materials Safety Administration (PHMSA), and the Bureau of Labor Statistics (BLS). I discuss each data source in turn.

4.1 Form 6

The principal data source for this analysis is the FERC Form 6. Form 6 databases are provided annually by FERC for the years 2000 to 2020. These data include information on operational costs and revenues by productive activity, including the transportation of oil on gathering lines and on trunklines. Further, the data is often broken into interstate and intrastate transportation, as FERC's jurisdiction covers interstate movements. Operating expenses and capital expenses are a necessary input for my production function estimates, as I use them to approximate variable inputs and the capital stock.

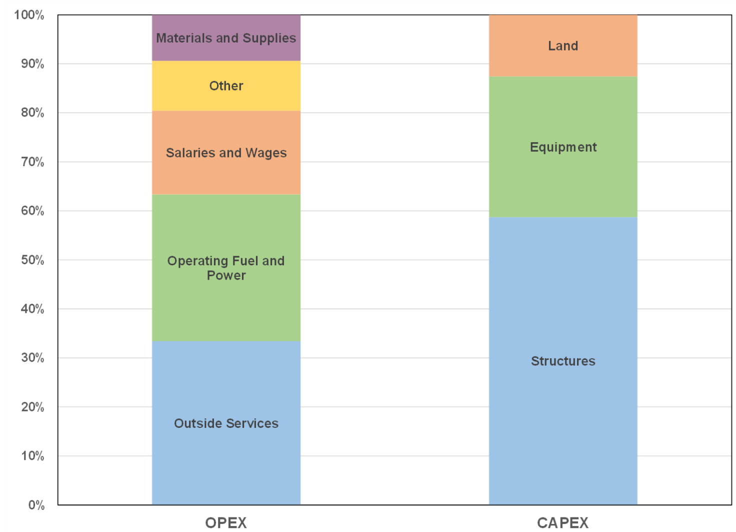
Operating expenses are broken out into two categories: general expenses and operating and maintenance expenses. I use operating and maintenance expenses (OPEX) as my measure of the variable inputs to production. Figure (4) shows the average share of each cost category in OPEX. The largest two shares 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, i.e. labor that is not directly employed by the firm. As such, 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[10] To convert operating expenses into variable inputs, I deflate these costs using the input price index for the pipeline transportation industry (NAICS code 486210) provided by the BEA.

Capital expenditures (CAPEX) are reported separately for gathering lines, trunk lines, and general expenditures. Additionally, CAPEX is reported by 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 construct a capital index using the perpetual inventory method. Capital is partitioned into three components: land, structures, and equipment. Figure (4) 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. 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. Several pipelines in my sample lease capacity on other pipeline systems. For instance, MarketLink leases capacity from TransCanada and includes the lease in their operating expense. I remove this rental expense from operating expenses and convert it to an equivalent capital stock. To convert to an equivalent capital stock, I take the rental expense and scale it by the firm's weighted average cost of capital. I deflate the capital

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

stock by the current periods nonresidential capital deflator. This process impacts fewer than 5% of firms and generates capital stocks that are similar to pipelines with comparable operating expenses and output.

Figure 4: Cost Category Components



I consider three measures of output: barrels, barrel-miles and deflated revenue. Small pipelines have a lower cost of operation, but can have a large volume of traffic when measured in barrels. Using barrel-miles captures the fact that large interstate pipelines "produce" more than small local pipelines. Further, tariffs are generally based on origin-destination pairs in addition to quantity shipped, reflecting the higher cost of transporting oil long distances. As such, I take barrel-miles to be the appropriate measure of output. However, I estimate a production function given each measure to see how they impact the results.

Pipelines must report all major changes in operations on pages 108 - 109 of the Form 6. This allows me to track major divestitures or ownership changes that happen during my sample which I need to correct for. 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.[11]

Market Definition Each pipeline system connects potentially several origin points to several destination points. These origin points can be either gathering fields, refineries, fractionators, or even other pipelines. Delivery points can be terminals, refineries, storage yards or even direct deliveries to consumers (such as airports). Pipelines rarely overlap in their product offerings, which I define as an origin-destination pair. That is not to say that pipelines cannot face competition, as several pipelines can contribute to the takeaway capacity of a production field or to the delivery capacity of a market. In fact, this is the position that FERC took when it initially determined a mechanism to regulate pipeline rates.

Oil pipelines came under the purview of FERC in the 1977. At the time, the D.C. Circuit Court of Appeals was hearing a challenge by shippers on the whether oil pipeline rates were just and reasonable. The court granted FERC a remand to determine a regulatory system by which it would regulate transportation rates. FERC ultimately decided to allow pipelines to set rate subject to a price ceiling in Order No. 154, arguing that market forces would constraint transportation rates. However, this ceiling was set so high that it would rarely bind in practice and the courts were unpersuaded by FERC's argument that pipelines lacked significant market power. As such, pipelines continued to be regulated under a cost-of-service regime. However, the D.C. Circuit Court of Appeals did allow for market-based rates if a pipeline could demonstrate that they lacked market power. The two main examples of this are Buckeye Pipeline in the Northeast and Explorer Pipeline, which moves between Texas and Illinois. Despite the existence of market-based rates, the

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

Figure 5: Example Midstream Company and Pipeline System

(a) Enterprise Product Partners, L.P.

(b) Dixie Pipeline

vast majority of pipelines operate under the price-cap mechanism.

5 Model

The fundamental unit of analysis is an interstate oil pipeline system.[12] 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 (5). These assets are comprised of several filing pipelines, including Enterprise TE Products (formerly TEPPCO), Mid-America Pipeline System, and Centennial Pipeline, to name a few. Panel (b) shows a typical pipeline system, in this case Dixie Pipeline.

Time is discrete with each period corresponding to a single year. 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. In each period, incumbent firms receive a scrap value and choose whether or not to exit the industry. Simultaneously, potential

[12] 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. This increases the coverage of my dataset.

entrants receive a fixed cost of entry and decide whether or not to enter. If they enter, then they must incur a cost to expand their system to a given size and only produce in the subsequent period. Note that the fixed costs incurred by the entrant are not necessarily monetary in nature and therefore won't be completely compensated for by FERC in their allowed price. These costs can include the cost of procuring right-of-way and regulatory risk. 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.[13] Note that an entrants decision does not impact existing firms due to the assumed non-overlapping nature of oil pipeline transportation services. After the entry and exit decisions are made, firms receive a productivity draw and a new price ceiling. Firms choose a prices, subject to the price ceiling, and supply the quantity demand at said price. Firms then choose how much to invest in productivity and how much to invest in the size of their system.

Each pipeline is indexed by an individual state, $s = \{\bar{p}_{it}, N_{it}, \omega_{it}, \lambda_i\}$. The state consists of their current price ceiling, the number of routes they serve, their productivity level, and their market specific demand shifter.[14] Of the individual states, only the demand shifter is time invariant. However, the demand shifter is subject to a one-time, unforecastable shock associated with the shale boom. In addition to the individual state, pipeline's also share an aggregate state $S = \{PPI, X, \bar{a}\}$. Here, PPI is the producer price index, X is the efficiency factor set in the prior review, and $\bar{a}$ is the current annualized five year change in average total cost. The aggregate states determine how the firm's price ceiling evolves as well as how the rate index is adjusted in subsequent reviews. I discuss this in more detail further below.

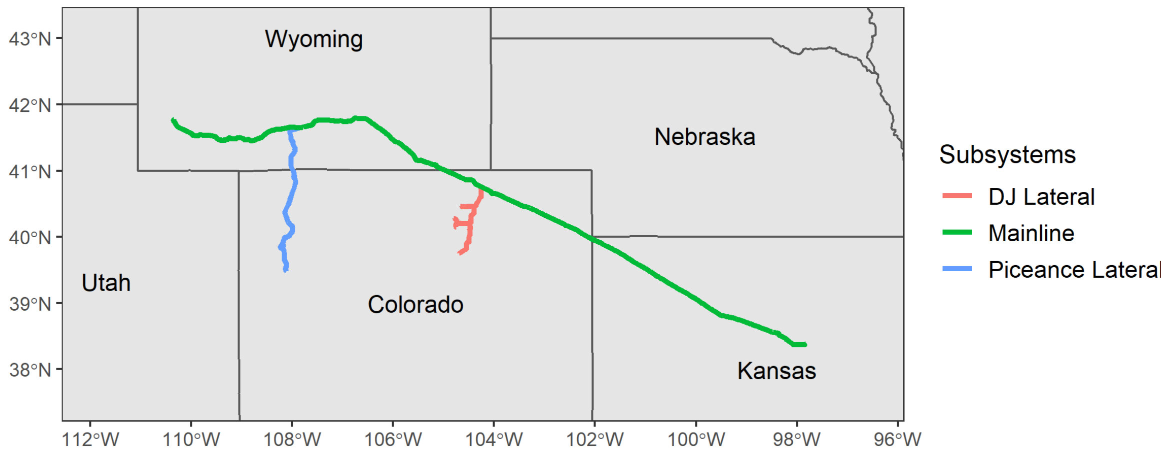
Demand is assumed to have the following functional form

$$\ln(Q_{it}) = \lambda_i + \beta_1 \ln(N_{it}) - \alpha \ln(\bar{p}_{it})$$

[13]See the TC Energy 2019 Annual Report.

[14]Because firms operate as monopolists, the market specific demand shifter is also firm specific.

Figure 6: Overland Pass Pipeline Subsystems



Total demand depends on the number of routes that a pipeline supplies. This is to capture the fact that demand does not depend solely on the size of the pipeline but also the markets that the pipeline serves. When a pipeline expands the footprint of its operations it will generate demand that did not exist before. This increases consumer welfare by introducing a product that did not exist before. Consider the addition of the Denver-Julesburg Lateral to the Overland Pass Pipeline system (see Figure (6)). This expansion added 55,000 BPD of capacity to the pipeline but more importantly accessed demand that was previously excluded from the pipeline system. This addition arguably increased total consumer surplus by giving customers in the Denver-Julesburg Basin access to the NGL market in Kansas.

Firm costs are assumed to have the following reduced form

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

where $\hat{Q} = \frac{Q}{e^{\omega}}$ 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. This flexibility allows me to avoid some of the more restrictive assumptions common in the literature and instead let the data inform the shape of the cost curve. An added benefit of this specification is that average variable cost has a closed form solution in Q. Marginal costs may increase with the total number of locations served by a pipeline, and this increase in cost can be either explicit or implicit. Explicit costs include those associated with the addition of new pumping stations or higher fuel costs. Implicit costs include those associated with the increased complexity of operations. Consider a pipeline that has a flow rate of 8 miles per day that connects to a new terminal with a flow rate of only 3 miles per day. If the pipeline has customers further downstream that demand the same product then it can siphon off flow to supply the new terminal. However, is no such consumer exists, then it would need to occasionally slow the flow of the entire system to service the new terminal, temporarily decreasing the pipeline's effective capacity.

Firms are also subject to quadratic adjustment costs when changing productivity. Adjustment costs therefore have the following functional form

$$\Phi_{\omega}(\xi) = (\gamma_{\xi 0} + \gamma_{\xi 1}\xi) \cdot \xi$$

I follow Ryan (2012) and assume that firms also face a random fixed cost when adjusting their number of routes. In this specification,

$$\Phi_N(\Delta) = (\gamma_{i0} + \gamma_{\Delta 0}\Delta + \gamma_{\Delta 1}\Delta^2)$$

and the fixed cost of adjustment is distributed normally, $\gamma_{i0} \sim N(\mu_{\gamma}, \sigma_{\gamma}^2)$. This specification helps explain the lumpiness of investment, as firm only invest if the benefit of doing so exceeds their fixed cost draw.

Finally, firms incur a fixed cost FC each period that depends on the total number of routes that they provide. This is meant to capture the capital costs of maintaining the pipeline system. Combining the relevant elements, the per-period profit function in a given state

$$\tilde{\pi}(s;\theta) = \bar{p} \cdot q(\bar{p}, N, \lambda) - c(q, N, \omega) - \Phi_\omega(\xi) - \Phi_N(\Delta_N) - FC * N$$

Finally, the incumbent firm draws a scrap value from a common distribution each period which is assumed to normally distributed

$$\kappa_{it} \sim N(\mu_\kappa, \sigma_\kappa)$$

and entrants draw a fixed cost of entry from a distribution as well

$$\phi_{it} \sim N(\mu_\phi, \sigma_\phi)$$

State Transition The size of the pipeline system evolves endogenously, with

$$N_{t+1} = N_t + \Delta_N \tag{1}$$

An investment at time t does not mature until the following period. Productivity evolves endogenously but is subject to a stochastic shock. Firms invest an amount ξ_t such that productivity in the following period is given by

$$\omega_{t+1} = \psi_0 + \psi_1 \omega_t + \xi_t + \eta_{t+1} \tag{2}$$

where $\eta_t \sim N(0, \sigma_\eta)$ is a productivity shock. This productivity shock could represent decreased output due to a spill, unanticipated pipeline maintenance, or cyberattacks. Price ceilings evolve according to a PPI + X rule, i.e.

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

All that remains is to specify the price-cap rule. During a review period, which I index to $\tau = 0$, the efficiency factor is set to match the difference in the growth in annualized average total cost less the change in the producer price index.[15] That is

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

Firms keep track of an aggregate state variable, $\bar{a}$ which represents the annualized change in average total cost.[16] This would normally require firms to keep track of the joint distribution of productivity, network size, and price ceilings 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

$$\Gamma(\bar{a}_{t+1}) = f(\bar{a}_t, PPI_t, X, P) + u \tag{4}$$

Here, f represents a reduced form approximation of the transition dynamics that depends

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

[16]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.

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.

Pipelines seek to maximize the real discounted sum of cash flows net investment given their information at time 0.

$$V_0(K_t) = \max_{\{N_t,\xi_t,P_t\}_{t\geq 0}} E\left[\sum_t \beta^t \tilde{\pi}(s;\theta) \Big| I_0\right] \tag{5}$$

$$\text{s.t. } P_t \leq \bar{P}_t, \forall t \tag{6}$$

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

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

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 rate index is reset before the period $\tau = 0$. The corresponding value function for an entrant is given by

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

5.1 Inflation

It is important to note that the producer price index is not meant to compensate firms for the effects of inflation, but change in their costs. When FERC sets initial rates they calculate a nominal rate of return on equity, which includes the real rate of return as well as an inflationary component. The inflationary component depends on the expected growth in the consumer price index (CPI) over the useful life of the asset. To account for the effect of inflation, I remove the amortized net deferred earnings that compensate pipelines for inflation from their operating revenue, leaving the "real" rate of return.

6 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 value for the "dynamic" 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 (7).

6.1 Stage 1 Estimates: Static Parameters

6.1.1 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

$$\ln(Q_{it}) = \beta_{i0} + \beta_1 \ln(N_{it}) + \beta_2 p_{it} + \beta_3 Shale_t - \alpha \ln(\bar{p}_{it}) + \epsilon_{it} \tag{7}$$

where β_{i0} represents a firm fixed effect that does not vary over time, p_{it} is the share of pipeline output dedicated to refined petroleum products, and $Shale_t$ is an indicator variable for the years 2011 and onward. I assume that the shale shock was unanticipated by oil pipelines, and so it does not factor into the firm's decision problem before the fact. Here, ϵ_{it} is assumed to be an i.i.d. residual that firms do not anticipate. However, they know the underlying distribution of these demand shocks. As such, the firms ex-ante demand function must be scaled by $E[e^{\epsilon_{it}}]$ which is estimated directly from the data.

6.1.2 Productivity and Marginal Costs

Two key inputs in my analysis are firm productivity and marginal costs. My approach is to estimate productivity by estimating an industry production function and then treating the residual as pipeline level total factor productivity. Then, I follow De Loecker and Warzynski (2012) and use cost minimization first-order conditions to recover marginal costs and markups. Two issues have recently been highlighted in the literature regarding the use of first-order conditions to recover marginal costs. 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 control function assumptions (specifically scalar unobservables and monotonicity) generally won't hold in imperfectly competitive or regulated markets. I control for this by using a new estimation routine proposed in Ponder (2021) which remains valid even when these assumptions are violated.

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

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

where ω_{it} is productivity known to the firm but unobserved by the researcher and ϵ_{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. It is common in the literature to assume that productivity follows a Markov process

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

where η_{it} is a productivity shock that is orthogonal to observations at time $k < t$. The Markov assumption is necessary for estimation, but it restricts the economic environment consistent with the results. To the extent that firms have a "productivity demand function", this function must depend solely on productivity at time $t-1$. We can expand this assumption to account for additional state variables. For instance, De Loecker and Warzynski (2012) include export status when estimating their production function, allowing firms to have greater (or worse) productivity gains after becoming an exporter. I use a similar approach by allowing the pipeline's state variables to enter the Markov process, where I assume that technology evolves according to the following Markov process

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

The commonly used control function approach assumes that input demand (either for investment or an intermediate input such as materials or operating fuel) is a monotonic function of ω_{it-1}. Then we can invert the conditional input demand and write

$$\omega_{it-1} = h(m_{it-1}, s_{it-1}, S_{it-1})$$

Combining with the previous equation gives

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

where m_{it-1}, the intermediate input, is observed. We can then substitute this equation into the production function to get

$$q_{it} = \beta_0 + v_{it}\beta_l + k_{it}\beta_k + v_{it}^2\beta_{ll} + k_{it}\beta_{kk} + k_{it}v_{it}\beta_{lk} + \tilde{g}(m_{it-1}, s_{it-1}, S_{it-1}) + \eta_{it} + \epsilon_{it}$$

and estimate using GMM, given a set of instruments Z_{it}, and with $\tilde{g}$ approximated by a complete polynomial series. Unfortunately, in a regulated environment, it will often be the case that m_{it} is not a monotonic function of ω_{it-1}.

Monotonicity Under Price-cap regulation To understand why monotonicity might fail, we can write intermediate demand as the solution to[17].

$$\max_{Q_{it}} \left\{ P_t(Q_{it})Q_{it} - P_{it}^M M(K_{it}, V_{it}, Q_{it}, \omega_{it}) \right\}$$

where P_{it} is the output price (which depends on Q_{it}), and P_{it}^M is the intermediate input price (which is assumed to be exogenously given). With a price ceiling, we need to add the following constraint

$$P_t(Q_{it}) \leq \bar{P}_{it}$$

which will introduce a Lagrange Multiplier, γ_{it}, into the first order conditions. The Karusch-Kuhn-Tucker conditions imply that

$$\gamma_{it} \geq 0$$

and

$$\gamma_{it}(\bar{P}_{it} - P_t(Q_{it})) = 0$$

[17] This follows the derivation in Bond et al. (2020).

So for firms with optimal Q_{it} such that $P_t(Q_{it}) < \bar{P}_{it}$, the first-order conditions hold exactly. And for firms where $\bar{P}_{it} = P_t(Q_{it})$, the first-order conditions must account for the presence of γ_{it}. The value of γ_{it} is a-priori unknownable and therefore will complicate the inversion of input demand. The value of γ_{it} depends on whether the firm is constrained and if so, the attributes of the heterogeneous demand curves. We therefore cannot control for γ_{it} even if we observed each firm's price ceiling. Given this, we must instead rely on a method of estimation that does not rely on scalar unobservables for estimation. A standard approach would be to use the dynamic panel method of Blundell and Bond (2000). However, this approach tends to remove significant variation in the data, and as mentioned, uses assumes that productivity follows and AR(1) process. This disallows relevant data generating process for ω_{it} and ultimately leads to unreasonable parameter estimates.

My approach is to assume that the transitory errors are independent of a set of our set of instruments. In Ponder (2021), I show that we can recover the parameters of the production function using semi-parameteric two-stage least squares. This avoids the need to use a control function and therefore does not rely on a monotonicity assumption. More broadly, firms are allowed to have additional unobserved state variables during estimation, which can aid in identification as has been pointed out in Gandhi et al. (2020) and Flynn et al. (2019). Additionally, unlike the standard Arellano-Bond estimator, productivity is allowed to follow a general Markov process, which is important in my context where firms are allowed to invest in their productivity given both their individual and aggregate state variables. For additional information, the reader is directed to Ponder (2021).

6.1.3 Approximating Marginal Cost and Markups

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

$$\min_{V_{it}} \; w_{it}V_{it} + r_{it}K_{it} \tag{8}$$

$$\text{s.t. } Q_{it} \geq \bar{Q}_{it} \tag{9}$$

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. 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 measure of markups that De Loecker and Warzynski (2012) use and is related to the traditional Lerner index by $L = 1 - \frac{1}{\mu_{it}}$. Importantly, this relationship holds for any flexible input that directly enters the production function. Following the literature, I use the aggregate expenditures on variable inputs (i.e. properly deflated operating expenses less depreciation charges) as the composite index during estimation. Operating expenses and revenue are reported in pipeline financial statements, so the left-hand side ratio is readily available in the data. To estimate markups, we only need an estimate of the input elasticity θ_{it} which comes from the production function estimates. Note that observing quantity data allows us to further recover marginal costs, as

$$\lambda_{it} = \frac{V_{itk}w_{itk}}{Q_{it}}\frac{1}{\theta_{itk}}$$

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.

6.1.4 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[18]

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

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 rate index and the spot price of West Texas Intermediate in Cushing, Oklahoma as demand shifters. The rate 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.

[18] This procedure is similar to that used in Dhyne et al. (2020). The authors directly estimate the change in variable cost with respect to quantity, 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.

6.2 Stage 2 Estimates: Dynamic Parameters

Given the parameter estimates that determine static profits, I estimate the dynamic 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 three residuals

$$\eta_{1it} = \omega_{it} - \psi_0 - \psi_1 \omega_{it-1} - \xi_{it}(X_{it-1}) \tag{10}$$

$$\eta_{2it} = \Delta_{it} - \Delta(X_{it}) \tag{11}$$

$$\eta_{3it} = I\left[exit_{it} = 1\right] - \Phi\left(\frac{EV(X_{it}) - \mu_\phi}{\sigma_\phi}\right) \tag{12}$$

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 residual represents the difference between the observed exit of firms and the models predicted probability of exit. 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, $\eta = \{\eta_1, \eta_2, \eta_3\}$, 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 (11). 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.

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.[19] 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

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

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

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 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.

7 Estimation Results

7.1 Demand Estimates

I estimate the demand side parameters following the log-linear specification in Equation (7). Several instruments were used to control for the potential of price endogeneity. These instruments include pipeline productivity, total pipeline miles and the rate index. Productivity and pipeline mileage are state variables for the firm, having a direct impact on their costs. As such, changes in these variables can be used as supply shifters to trace out the demand curve. Shifts in the rate index can also be used to identify the demand curve, as movements in the rate index can directly lead to essentially exogenous changes in prices.

In 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 2SLS. 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 * (t - 2008)					0.096^{***}	0.084^{***}
					(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 firm demand.

I consider two additional demand specifications. In column (5) I include a shifter for the Shale Boom, which I assume starts in 2008. This allows demand for pipeline transportation to shift out as oil and gas production began to explode in the late 2000s. The coefficient is statistically significant, and shows that demand increased by roughly 170% by 2020. However, this covariate explains little of the residual variation.[20] 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

[20]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.

ratio above 3. With the production function approach, the estimated ratio is 6 as of 2020, meaning that these demand estimates are not able to rationalize the markups in the second half of my sample. I turn now to the production function estimates.

7.2 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.[21] Researchers have often used deflated revenue when estimating production functions because financial data rarely provides information on physical output. However, I see several 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

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

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. However, 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 7 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-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.

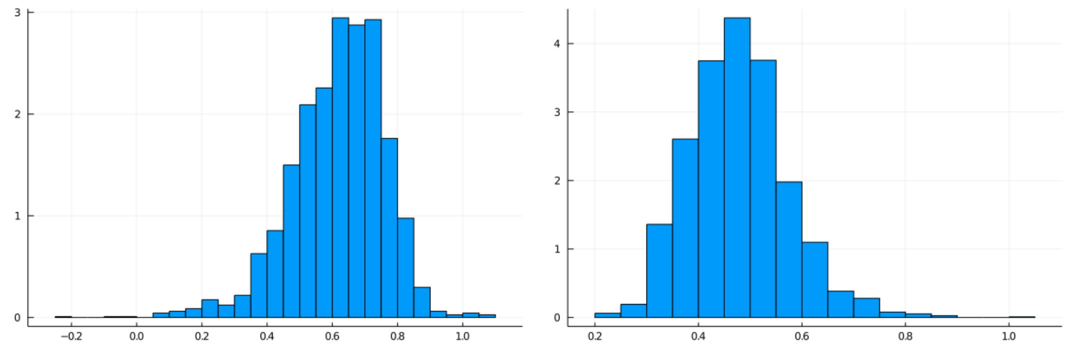
Figure 8 shows the distribution of input elasticities implied by my preferred estimator. It

Figure 7: 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

Figure 8: Distribution of Input Elasticities



(a) Variable Elasticity (b) Capital Elasticity

Note: Reported elasticities cover all years between 2001 and 2020 using .

has been claimed that transportation networks tend to exhibit constant marginal costs.[22] If this were the case, we would expect the distribution of input elasticities to be more concentrated around the mean value. The significant variation we see in the variable input elasticities indicates that the short-run marginal cost curve is not constant. In fact, estimates of the cost curve derived from the cost-minimization FOCs imply an increasing marginal costs over the relevant range of output. So while the mean input elasticity does not change much over time (see Appendix Figure 24 below), it is still appropriate to model short run marginal costs as an non-constant function.

Returns-to-Scale The estimates imply that the oil pipelines production function is, on average, increasing returns to scale (RTS). The textbook treatment of RTS typically uses pipelines as an example of an increasing RTS technology. If one doubles the radius of a pipeline, then the circumference increases by a factor of two. However, the cross-sectional area increases by a factor of four. If inputs demand is proportional to the pipeline circumference (as, for instance, construction costs would be), then doubling the inputs would yield four times the output and the technology is clearly increasing RTS. Of course,

[22]See Kahn (1988).

the RTS factor of 2 is significantly larger than the mean estimate of 1.25. One potential reason for this is that a significant portion of pipeline investment does not come in the form of expanding pipeline capacity, but in expanding pipeline length. If we double the length of an existing pipeline, then the input demand would roughly double as well. And on a barrel-mile basis, the output would double, not quadruple. Viewing investment in this way implies a constant RTS technology. In reality, the model fits a production function that is intermediate between these two extremes. It is worth noting that the implied RTS using deflated revenue is roughly constant. This may be due to a demand effect, where doubling inputs might generate more than double the output but this is offset by a reduction in rates. Then revenue will not increase at the same rate that output does, giving the impression that the RTS is in fact constant.

7.3 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. I provide two specifications, one with the quadratic terms on each co-variate and the other without. In each case, 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. In both specifications, we reject the hypothesis that the marginal cost of production is constant. This implies that papers which assume 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

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

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.

7.4 Dynamic Parameter Estimates

Table (3) shows the results of the dynamic parameter estimation. The average productivity level in my sample is roughly 3.0, meaning that the average pipeline would 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, such as weather or spills. 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 costs 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.[23] 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.

[23] 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: Dynamic 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 millions of dollars system investment and all distributions.

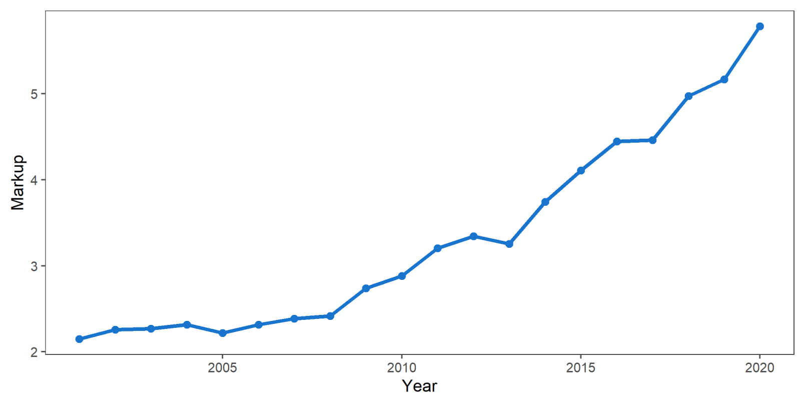
8 Oil Pipeline Industry Performance

Before turning to the results of my full model, I explore the estimated change in industry productivity and markups 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 efficiency factor X is set too high 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 more stringent safety regulations. 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-plus regulation.

8.1 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 (24) 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 (24) 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



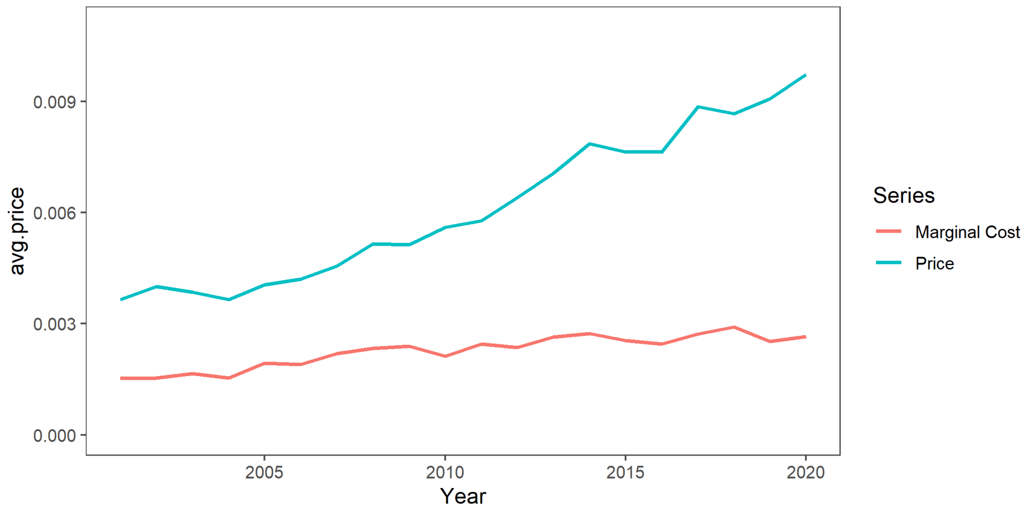
Recently, the literature has noted that markup and marginal cost estimates can be very sensitive to which flexible input is used to estimate their level. In my baseline results, I use a deflate measure of all operating and maintenance expenses, similar to the approach taken in De Loecker and Warzynski (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 the first-best price.

Figure 10: Markup by Flexible Input

Discussion 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. If an increase in markups is a result of decreasing marginal costs, then the rate index could actually be achieving its stated goal - limiting a firm's pricing power and encouraging firms to operate more efficiently. Of course, this explanation is somewhat at odds with the empirical record, as we do not see the rate index decreasing as these cost reduction as realized (save for the last index review). A straightforward test is to plot the average price and the average marginal cost, which I do in Figure (11). We can see that 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 increasing real marginal costs are not necessarily an indication of increasing inefficiency. The oil pipeline industry has seen substantial entry and investment since 2000. A dynamic investment model[24] would predict that low cost opportunities are chosen earlier on and high cost investments are delayed. Therefore, entering firms will

[24]See Hopenhayn (1992).

Figure 11: Evolution of Average Price and Marginal Cost



generally be higher cost than the established firm, increasing the industry average cost across time. Looking at the cost experience of individual pipelines helps substantiate this theory. For instance, Plains All American Pipeline saw a decrease in their marginal cost of 16% since 2004. Additionally, oil pipelines are subject to increasing environmental and regulatory costs which can lead to a higher per-unit cost of transportation.[25]

An alternative explanation is that fixed costs have increased over time and so markups have had to increase to allow firms to break even. In Appendix Figure (26) I plot the change in price to average total cost over the sample period. While this ratio has not increased as much as the price to marginal cost ratio, we can see that prices are also moving away from the second-best price. There is some evidence that firms have gotten more capital intensive over the past two decades, although we do see a slight decrease in the ratio of variable costs to capital since 2000. In fact, the cost of capital has also significantly decreased since 2004. Appendix Figure (25) plots the weighted average rate of return reported on Page 700 of the annual Form 6. This rate of return shows a steady decline from roughly 10.5% to 7.0%, meaning that capital has become cheaper over time. This rate of return represents the weighted average cost of debt and allowed return on equity. The cost of debt has

[25]See my discussion on increased regulation from PHMSA in Section 2.

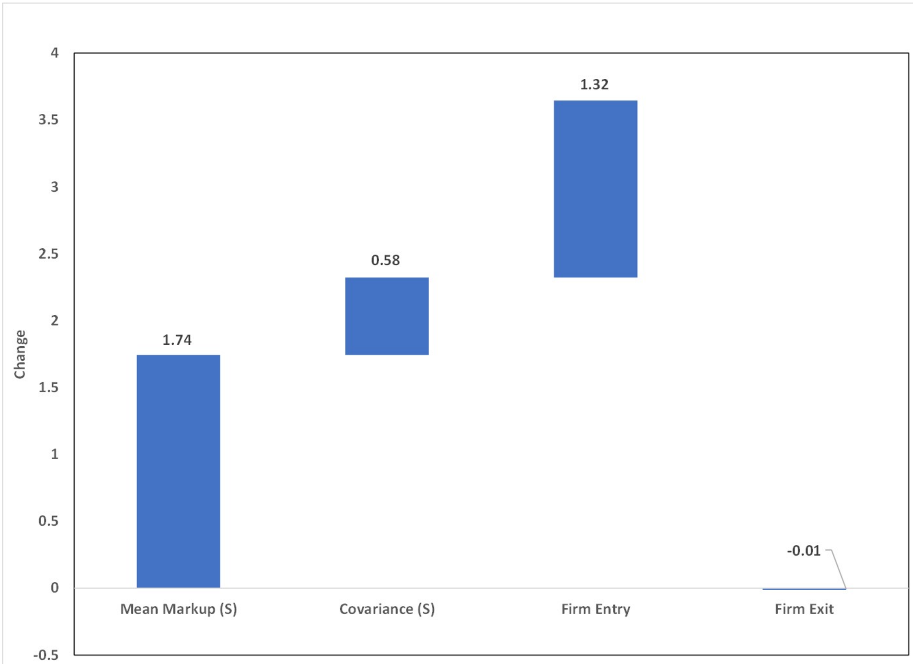
declined over the past two decades, reflecting historically low interest rates. As pipelines become increasingly leveraged, this has led to a decline in the cost of capital. Therefore, the slight decline in the labor-capital ratio could merely reflect the fact that capital costs are declining relative to variable costs. Cost minimization would therefore predict a higher capital utilization, even absent competitive conduct.

One thing to note is that markups increased more than the cumulative change in the rate index over this period. To understand why, I following Melitz and Polanec (2015) 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 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 level increasing across time and it is this share that is due changes in the rate index.

8.2 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 displays the decomposition of productivity into the unweighted average component and the sample covariance using the Olley and Pakes (1996)

Figure 12: Decomposition of the Change in Markups



decomposition

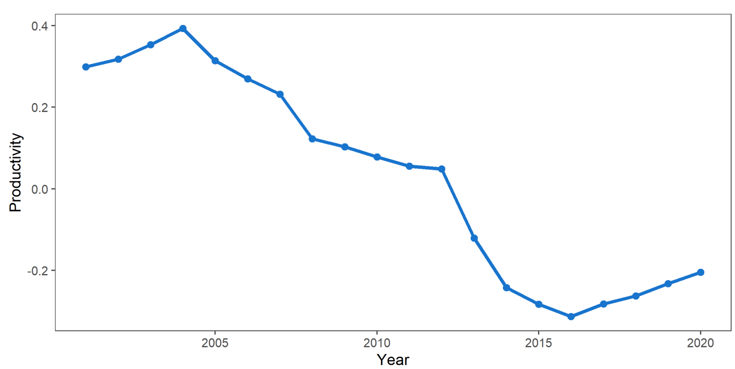
$$\mu_t = \bar{\mu}_t + \sum_j \Delta s_{jt} \Delta \mu_{jt}$$

where μ_t is the weighed mean, $\bar{\mu}_t$ is the average level, $\sum_j \Delta s_{jt} \Delta \mu_{jt}$ is the covariance between market share and deviations from mean productivity.[26] Larger pipelines were more productive on average at the start of the sample but this has declined over the past two decades. However, the mean level of productivity is what has decreased the most. Firms on average are half as productive today than they were in 2000. Figure (15) performs a similar decomposition, but includes the effect of entry and exit within the sample. We again see that, 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.

[26] This is the decomposition does not account for entry and exit of firms.

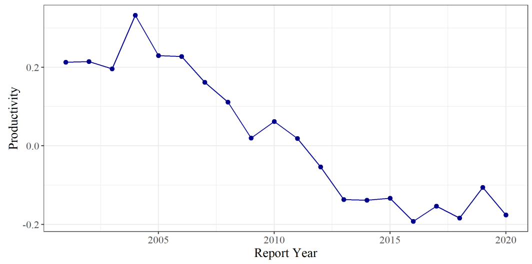
Of course, this decline in factor productivity is not necessarily caused by an ineffective price-cap as there have been several changes to the regulatory environment since 2000. For instance, in the 2010 index review, the Department of Transportation testified that it had adopted several safety regulations that would "impose significant obligations and costs on pipeline operators". Many of these regulations required pipelines to incur significant repair costs associated with excavating pipelines and replacing line segments. Therefore, this decrease in factor productivity might, in part, reflect a change in the quality of service. 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).[27] Figure (27) 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 rate index, we need the full theoretical model.

Figure 13: Change in Weighted Average Productivity

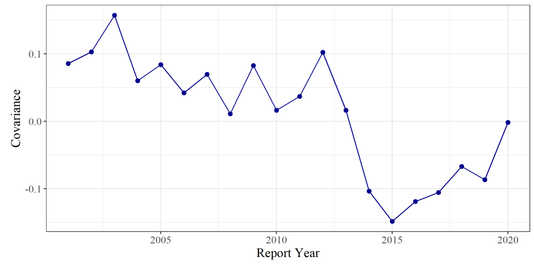


[27]See the discussion in 18 CFR Part 342, "Five-Year Review of Oil Pipeline Pricing Index".

Figure 14: Decomposition of Productivity

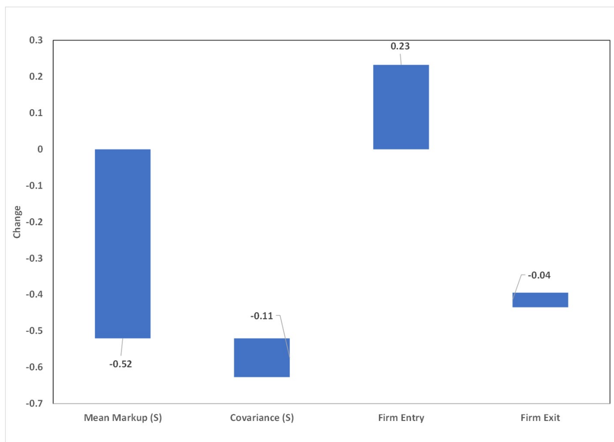


(a) $\bar{\omega}_t$



(b) $\Delta\omega_t \Delta s_t$

Figure 15: Change in Weighted Average Productivity



8.3 Impact of the Price-Cap on Industry Dynamics

Given the observed increase in markups, the rate index appears to have allowed firms to generate excessive rents during the sample period. Additionally, firms appear to be becoming less productive over the sample period as well. However, as I have discussed, these trends occurred during a period of significant change, in terms of cost changes, demand shifts, and increased regulation. The increase in rents were coupled with a stark increase in the number of pipelines operating in the United States and a large expansion in pipeline capacity. This large increase in pipeline capacity was largely in response to the shale boom, where demand for pipeline transportation increased by roughly 200% between 2011 and 2020. These pipelines entered with higher markup ratios and with higher productivity, confounding the impact of price-cap regulation on firm outcomes.

To untangle the impact of the price-cap on dead-weight-loss, productivity, and market entry and expansion, I rely on my theoretical model. The first counterfactual that I run assumes that FERC did not implement a price-cap in 1996, but instead deregulated the industry. Table (16) shows the results of this experiment for the year 2020. In the first set of results, I look at market outcomes for mature markets, defined as pipelines that have existed since the start of my sample. 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%. Total welfare would have decreased by 2.2%. There was considerable increase in system expansion, as pipelines added an additional 3.6 routes but this would have been offset in part by a decline in productivity. This decline would have been roughly 8%. The model implies that the majority of the decline in productivity since 2000 was due to exogenous forces, but that the price-cap did in-fact contribute to productivity gains. Additionally, as the price-cap constrained firms from charging their monopoly price, it results in a reduction in dead-weight-loss increasing welfare overall. After accounting for the reduction in exit rates, I see 5 more firms operating by 2020 absent the price-cap. [28] When considering all markets, total welfare would have only decreased by 1.4% if the price-cap was not put in place.

The next counterfactual that I consider is the impact of maintaining cost-of-service regulation in the industry. In this experiment, firms are allowed a maximum 12% return on their cost-base in each period. Table (17) presents the results. As predicted by theory, firm profits are greatly constrained leading to a significant decline in dead-weight-loss. Additionally, firms are considerably more productive under the price-cap, increasing their

[28] 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	Baseline	No Price Ceiling	Percent Difference
Mature Markets			
Producers Profit	24,616	26,665	8.3%
Net Consumer Surplus	298,019	289,024	-3.0%
Total Welfare	322,635	315,689	-2.2%
Avg. Routes	19.0	22.6	18.7%
Avg. Productivity	2.55	2.47	-3.3%
All Markets			
Producers Profit	53,179	55,737	4.8%
Net Consumer Surplus	630,368	618,002	-2.0%
Total Welfare	683,547	673,739	-1.4%

Note: Mature markets constitute markets active as of 2000.
Profits and welfare measures are in millions of dollars.
Results are based on simulating 50 samples.

productivity by roughly 17%. Firms produce more under cost-of-service regulation but opt not to expand the size of their system. Additionally, 22 fewer firms enter during this period, 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 consumer surplus in mature markets. Total welfare declined by 7.2% by 2020 driven largely by declines in producer surplus. Taken together, the price-cap appears to have performed better than either full 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.

That being said, the increase in observed markups since 2000 indicates that there may have been room for improvement. The final counterfactual I consider is the impact of fixing the price-cap. Firms enter with prices that are set equal to their average total cost of service and then are unable to adjust these prices during the sample period. Table (18) 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

Figure 17: Welfare Impact of Cost-of-Service

Measure	Baseline	Cost-of-Service	Percent Difference
Mature Markets			
Producers Profit	24,616	5,830	-76.3%
Net Consumer Surplus	298,019	366,875	23.1%
Total Welfare	322,635	372,705	15.5%
Avg. Routes	19.0	19.1	0.3%
Avg. Productivity	2.55	2.38	-6.7%
All Markets			
Producers Profit	53,179	8,553	-83.9%
Net Consumer Surplus	630,368	625,668	-0.7%
Total Welfare	683,547	634,221	-7.2%

Note: Mature markets constitute markets active as of 2000.
Profits and welfare measures are in millions of dollars.
Results are based on simulating 50 samples.

would have declined under a fixed price ceiling. This decline in investment happens gradually, as can be seen in Figure (20), and is a result of firms having lower expectations of future earnings.

Similar to the previous results, we see that 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 small reduction of a high price-ceiling increases the gain from investing in productivity. The lower price-ceiling 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.

Additionally, firms enter new markets at a much lower rate, and several firms exit markets that they otherwise would not have, under the fixed price cap. Figure (20) shows the

Figure 18: Welfare Impact of a Fixed Price Ceiling

Measure	Baseline	Fixed Price Ceiling	Percent Difference
Mature Markets			
Producers Profit	24,616	20,979	-14.8%
Net Consumer Surplus	298,019	313,082	5.1%
Total Welfare	322,635	334,061	3.5%
Avg. Routes	19.0	18.0	-5.3%
Avg. Productivity	2.55	2.57	0.9%
All Markets			
Producers Profit	53,179	48,565	-8.7%
Net Consumer Surplus	630,368	651,577	3.4%
Total Welfare	683,547	700,142	2.4%

Notes: Mature markets constitute markets active as of 2000.
Profits and welfare measures are in millions of dollars.
Results are based on simulating 50 samples.

Figure 19: Impact of a Fixed Price Ceiling on Investment

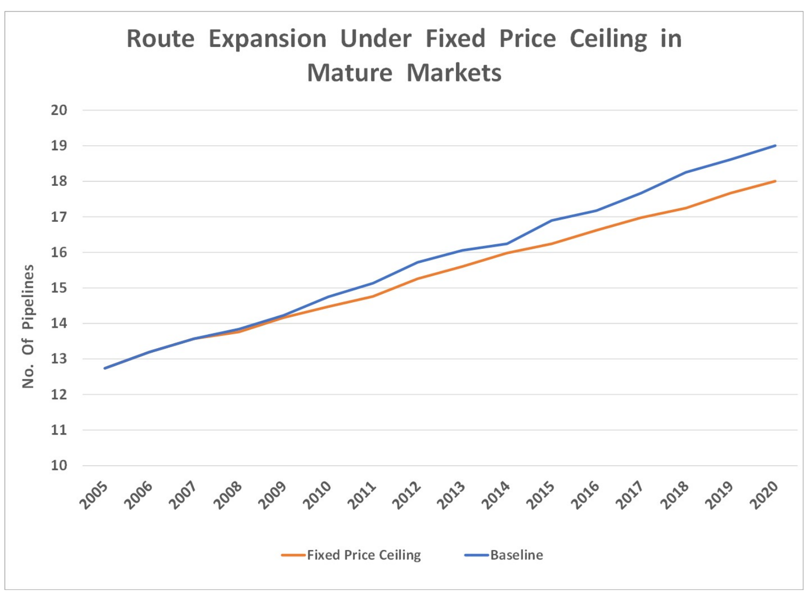
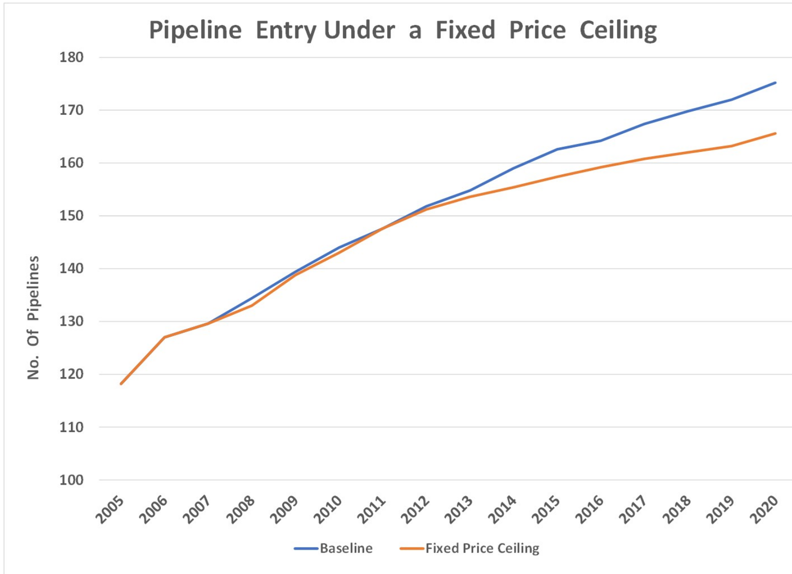


Figure 20: Impact of a Fixed Price Ceiling on Entry and Exit



difference in active firms under the fixed price-cap relative to baseline entry. There are 12 additional firms active under the baseline specification by 2020 than are active under a fixed cap. Four of these firms chose to exit under the fixed price-cap while 8 chose not to enter. The decline in firm entry, and the increase in firm exit, have a negative impact on total welfare as there is both a loss in consumer surplus as well as firm profit. 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 estimates that welfare would actually have been higher under a fixed price-ceiling by roughly 2.4%. By allowing the price ceiling 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 ceiling at the same time the market saw roughly 15% more entry.

9 Conclusion

In this paper, I examined the impact of price regulation on firm investment and total welfare in the oil pipeline industry in the years surrounding the shale revolution. I find that the existing price-cap regulation led to an increase in rents for firms over the past two decades relative to cost-plus regulation, but that the welfare loss from this increase was more than offset by increased firm productivity and investment. While price-cap regulation led to welfare gains relative to either cost-plus or deregulation, there was still considerable room for improvement. In fact, welfare could have been increased by an additional 2.4% had the efficiency 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 efficiency after the adoption of the price-cap, but I find this to be largely due to exogenous changes. Instead, the structural model predicts that firms actually did significantly decrease their unit-cost of production relative to cost-plus regulation.

The current analysis uses a structural 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-plus 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.[29] In 2010, rail transportation accounted for less than 1% of all crude movements but increased to over 7% by 2020.[30]. 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 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.

References

Ackerberg, D., K. Caves, and G. Frazer (2015). Identification properties of recent production function estimators. *Econometrica 83*(6), 2411–2451.

Ackerberg, D. and J. Hahn (2015). Some non-parametric identification results using timing and information set assumptions. *Unpublished manuscript*.

Blundell, R. and S. Bond (2000). Gmm estimation with persistent panel data: an application to production functions. *Econometric reviews 19*(3), 321–340.

Bond, S., A. Hashemi, G. Kaplan, and P. Zoch (2020). Some unpleasant markup arithmetic:

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

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

Production function elasticities and their estimation from production data. *National Bureau of Economic Research* (w27002).

Brumm, J. and S. Scheidegger (2017). Using adaptive sparse grids to solve high-dimensional dynamic models. *Econometrica 85*(5), 1575–1612.

Collard-Wexler, A. and J. De Loecker (2016). Production function estimation with measurement error in inputs. *National Bureau of Economic Research* (w22437).

Covert, T. and R. Kellog (2017). Crude by rail, option value, and pipeline investment. *NBER Working Paper Series* (23855).

De Loecker, J., J. Eeckhout, and G. Unger (2020). The rise of market power and the macroeonomic implications. *Quarterly Journal of Economics 135*(2), 561–644.

De Loecker, J. and F. Warzynski (2012). Markups and firm-level export status. *American Economic Review 102*(6), 2437–71.

Dhyne, E., A. Petrin, and F. Warzynski (2020). Deregulation and investment spillovers in multi-product production settings. *Working Paper*.

Flynn, Z., A. Gandhi, and J. Traina (2019). Identifying market power in production data. *SSRN* (3358472).

Gandhi, A., S. Navarro, and D. Rivers (2020). On the identification of gross output production functions. *Journal of Political Economy 128*(8).

Gowrisankaran, G. and M. Rysman (2012). Dynamics of consumer demand for new durable goods. *Journal of Political Economy 120*(6), 1173–1219.

Hopenhayn, H. (1992). Entry, exit, and firm dynamics in long run equilibrium. *Econometrica 60*(5), 1127–1150.

Kahn, A. (1988). *The economics of regulation: principles and institutions.* MIT press.

Krusell, P. and A. Smith (1998). Income and wealth heterogeneity in the macroeconomy. *Journal of Political Economy 106*(5), 867–896.

Littlechild, S. (1983). Regulation of british telecommunications' profitability. *Department of Industry, HMSO*.

Murarasu, A., J. Weidendorfer, G. Buse, D. Butnaru, and D. Pflüger (2011). Compact data structure and scalable algorithms for the sparse grid technique. *ACM SIGPLAN Notices 46*(8), 25–34.

Olley, S. and A. Pakes (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica 64*(6), 1263–1297.

Ponder, M. (2021). Estimating production functions when scalar unobservables does not hold. *Working Paper*.

Rust, J. (1987). Optimal replacement of gmc bus engines: An empirical model of harold zurcher. *Econometrica 55*(5), 999–1033.

Ryan, S. (2012). The costs of environmental regulation in a concentrated industry. *Econometrica 80*(3), 1019–1061.

Zhang, A. (2020). Estimation of high-dimensional dynamic games: Fintech lenders and bank branch closures. *Working Paper*.

A Appendix

A.1 Additional Figures

Figure 21: Average Unit Operating Cost

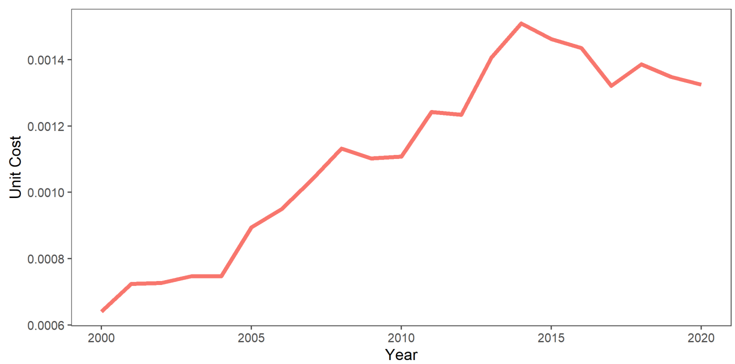


Figure 22: Petroleum Administration for Defense Districts (PADD)

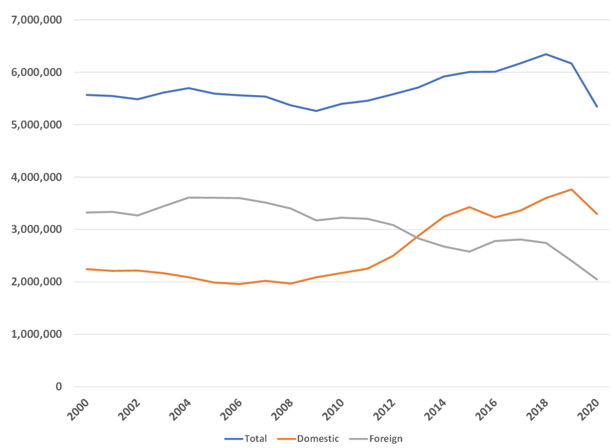


Figure 23: Petroleum Administration for Defense Districts (PADD)

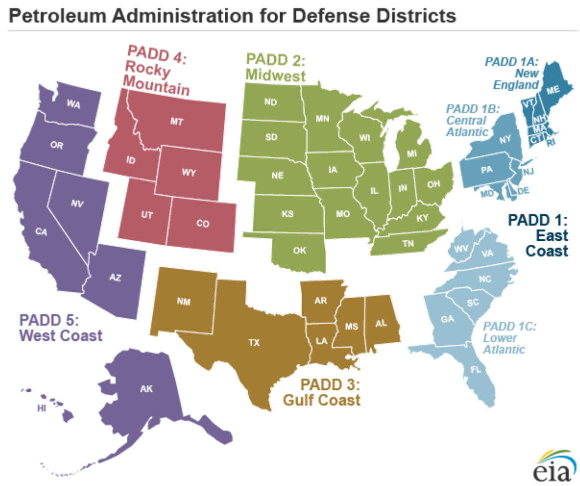


Figure 24: Variable Input Elasticity

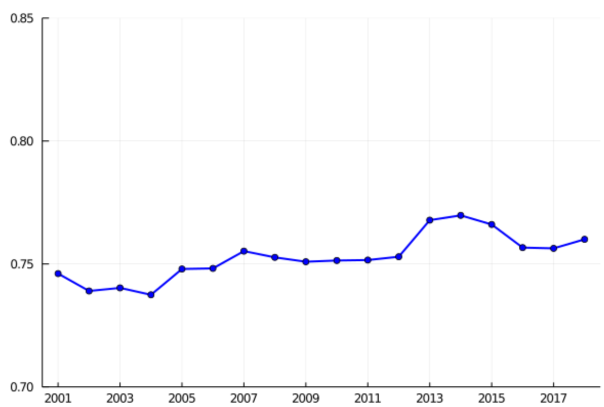


Figure 25: Weighted Average Cost of Capital

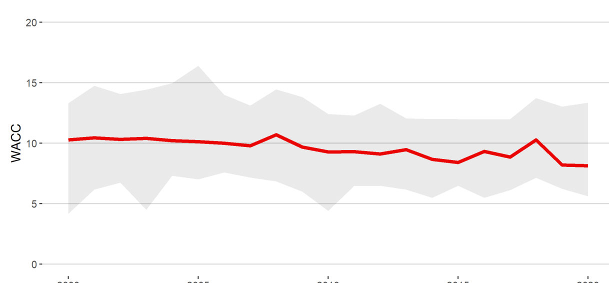


Figure 26: Change in Price to Average Total Cost

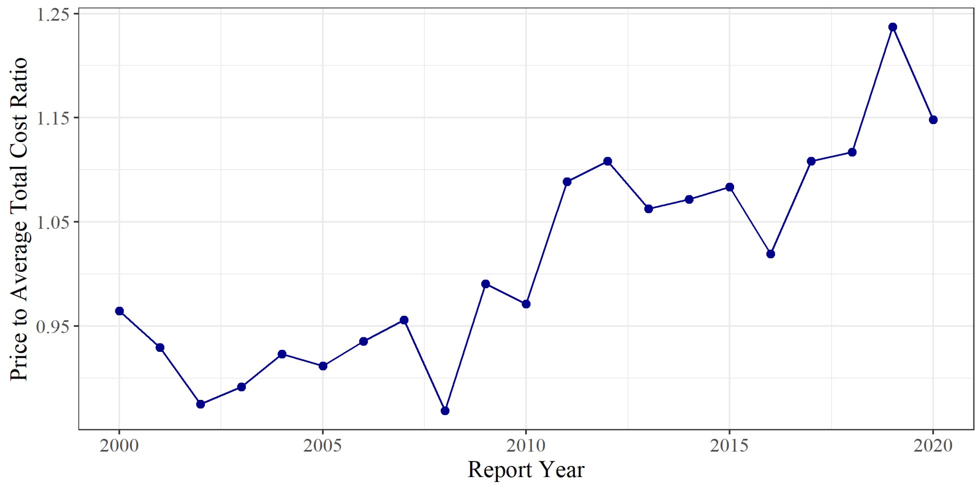
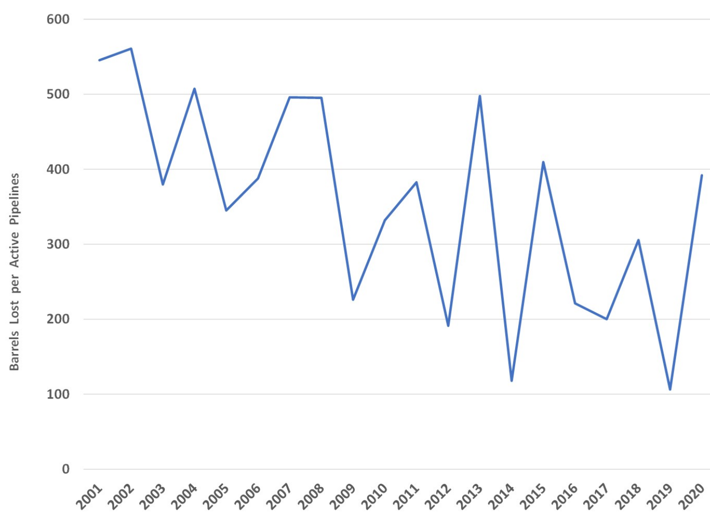


Figure 27: Barrels Lost per Active Pipelines



A.2 Alternative Efficiency Factor Calculation

The rate index 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 ceiling 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 ceiling 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

$$\begin{aligned}
\Delta &= ((P_1 - \mathrm{ATC}_1) - (P_0 - \mathrm{ATC}_0)) && (13)\\
&= \left(\epsilon_{ATC,P}^{-1} - 1\right) \Delta_{\mathrm{ATC}} && (14)
\end{aligned}$$

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 rate 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.

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

Table 4: Error-in-Capital Estimates

	Baseline (1)	Error-in-Capital (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

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