Delaying the Coal Twilight
Local Mines, Regulators, and the Energy Transition*

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Coal is the first source of electricity worldwide, yet it is also the most polluting. Since 2008, the US has experienced a sharp reduction in natural gas prices, a close coal substitute. However, coal power plants invested 29 billion dollars in upgrades during the same period. This paper aims to reconcile these two seemingly contradictory facts through a novel mechanism: the protection of local mines by electricity regulators. Regulators from mining states encouraged coal plant upgrades that enabled the plants to keep procuring from the state's mines. Coal plant upgrades often translated into higher electricity prices, harming consumer welfare. Moreover, the upgrades extended the lifetime of the coal power plants, delaying their replacement and preventing substantial CO_2 emission reductions. This paper combines reduced-form and structural estimation methods to quantify this novel mechanism. Absent the coal protection channel, the total US coal plant capacity would have been 5% lower in 2019.

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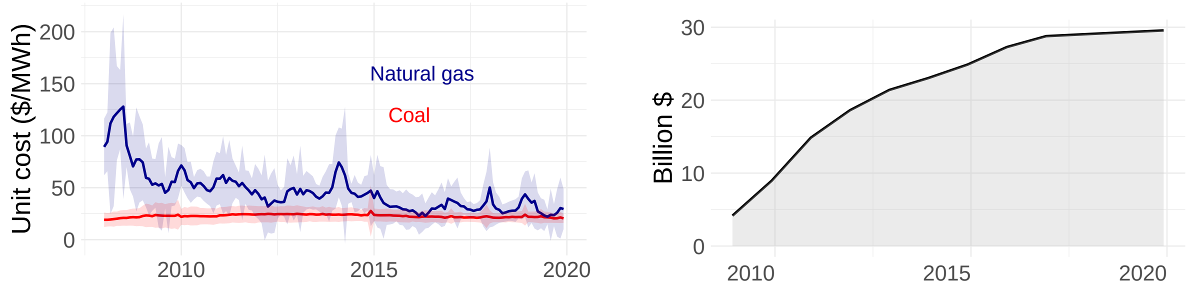
Figure 1: Coal and natural gas in the US



(a) Unit Cost of electricity

(b) Investment in sulfur filters, cumulative.

1 Introduction

Coal is the first source of electricity worldwide, yet it is also the most polluting. On the one hand, coal power plants issue many toxic pollutants to the atmosphere, among which sulfur is the most damaging. Sulfur emissions cause acid rain and, according to Holland et al. [2020], were responsible for environmental and health damages in the US worth 137.6 billion $ in 2010. These damages motivated the introduction of a federal sulfur emission threshold in 2016, which effectively forced coal plant owners to either adopt multi-million dollar sulfur filters or retire. Meanwhile, natural gas, a close substitute for coal, experienced a sharp cost reduction from 2010 and onward (Figure 1a). This drop was due to "hydraulic fracturing," a new natural gas extraction technique. Natural gas also happens to be cleaner than coal, as it generates half as much greenhouse gases and virtually no sulfur dioxide emissions.[1] However, the availability of cheap natural gas did not prevent coal plant owners from investing 29 billion $ in filters between 2008 and 2019, effectively extending the lifetime of these facilities for decades to come (Figure 1b).These lifetime extensions, in turn, delayed the replacement of coal by cleaner alternatives, contributing to climate change.

Two-thirds of US coal power plants are "regulated". These plants belong to investor-owned utility companies but charge a regulated electricity price to their consumers. The price is set by the "Public Utilities Commission", the state-level electricity regulatory body. The regulator may acknowledge the necessity for the filter by passing a regulated price that allows the plant owner to recover the investment. In Oklahoma, for instance, a 500 million $ sulfur filter installation was followed by a 15% increase of the state electricity price.[2] Traditionally, power plants procured coal ore from nearby mines to minimize freight costs. The introduction of a tight sulfur emission rule in 2016 altered this arrangement, as plants were required to adopt the most expensive filter type in order to keep burning local coal. Alternatively, plant owners could also comply with the standard by either combining a cheaper filter with a low-sulfur coal blend or retiring the facility.

This paper uncovers a novel mechanism driving sulfur filter adoption by US coal power plants: the local regulator's protection of local mines. I analyze this mechanism employing both reduced-form and structural estimation methods. I start by performing a series of reduced-form exercises to test the existence of the

[1] Find the EPA carbon dioxide emission coefficients here.
[2] Find news report here.

mechanism. According to these exercises, regulated plants are indeed more likely to adopt high-efficiency filters if these investments are to benefit the coal mines of their state. I complement the previous evidence with a model that formalizes the main tradeoffs involved in filter investment and plant retirement decisions. The model postulates a regulator utility function comprised of two elements: consumer surplus and revenue of local mines. I retrieve the importance of local mining revenue in the regulator utility function by estimating the model as a dynamic, discrete-choice problem. According to my result, regulators from mining states are eager to sacrifice 65 dollars of consumer surplus in exchange for a 100-dollar increase in mining revenue. Lastly, the structural model estimation enables me to quantify how much the mine protection channel delayed coal plant closures. Absent the coal protection channel, the US coal plant capacity would have been 5% lower in 2019.

The paper first shows that regulated plants from mining states are more likely to adopt expensive filters. The main empirical exercise consists of a proportional-hazards model on expensive filter adoption. Moreover, I complement this analysis with a multinomial logistic regression that comprises four possible decisions: retire the plant, install cheap filters, install expensive filters, or remain without a filter. These exercises rely on two sources of variation: the existence of in-state mines near the plant and the regulatory framework under which the plant operates.

The first source of variation consists of comparing regulated plants by whether they belong to a coal-mining state. I attune the effect of plants on the local mining industry through plant-specific covariates, such as the number of in-state miners working near each plant. This comparison assumes that regulators from non-mining states do not care about protecting this industry and, hence, encourage high-efficiency filter investments for other reasons. Still, the lack of a local mining industry does not imply regulated plants invest efficiently, as shown in Fowlie [2010].

The second source of variation tackles this concern by comparing "regulated" and "non-regulated" coal plants.[3] Non-regulated plants were initially regulated until some states forced their utilities to sell them to third-party investors. Consequently, regulated and non-regulated coal plants feature similar physical characteristics, such as age and size, yet operate under different incentive schemes. Unlike regulated plants, non-regulated facilities do not charge a regulated price, and consequently, local regulators cannot influence their filter investment decisions.

The interaction between the previous two sources of variation enables the identification the local coal protection mechanism. More specifically, I find that a hundred extra miners employed near a regulated plant increase its high-efficiency filter adoption probability by 9.5%. This effect is absent both for non-regulated plants and for adopting low-efficiency filters. The results are robust to several measures of local mining activity, such as the number of mines near the plant, the size of these mines, and their number of miners.

The previous evidence suggests that local coal protection drove expensive filter adoption. Still, previous reduced-form exercises do not inform about the tradeoffs involved in coal plant upgrade and retirement decisions.

[3] The empirical energy economics literature has extensively used non-regulated plants as a control group to identify regulatory distortions. See, for instance, Fowlie [2010], Jha [2020], Cicala [2015].

Start with the sulfur filter investment decision. The following tradeoff drives the choice between a high and a low-efficiency filter: On the one hand, high-efficiency filters are more expensive and, hence, may translate into a higher regulated electricity price. On the other hand, this filter type requires less low-sulfur coal to comply with the emission restriction. Consequently, high-efficiency filters decrease freight costs, especially for coal plants far from the low-sulfur mines. Lower transport costs, in turn, lead to a lower electricity price, benefiting consumers.

Consistent with the previous reasoning, a regulator that aims to maximize consumer surplus should only encourage expensive filter adoption if such investment reduces the electricity price. In contrast, a regulator from a mining state features an extra force pushing in favor of high-efficiency filter adoption: protecting the revenue of the state's mining industry. Consequently, these officials may prefer expensive filters, even when these investments translate into higher electricity prices.

Regarding the coal plant retirement decision, natural gas affordability played a key role, as documented in Linn and McCormack [2019]. Historically, a coal power plant contributed to consumer surplus by providing affordable electricity. Natural gas plants would have otherwise supplied this electricity at a significantly higher price. The drop in natural gas prices substantially reduced the coal plant's contribution to consumer surplus. This contraction featured two dimensions: On the one hand, coal plants supplied less electricity. On the other hand, the cost gap between natural gas and coal lessened, diminishing the consumer surplus contribution even when coal plants supplied electricity. In the face of future affordable natural gas, a consumer-friendly regulator would be keen on promoting coal plant retirement. Still, a regulator from a mining state internalizes the negative impact of plant retirement on the local mining industry and, hence, becomes less eager to retire.

On top of their respective tradeoffs, the filter investment and the plant retirement decisions are also deeply intertwined. This link is established by the 2016 sulfur emission standard, which effectively forced plant owners to adopt a filter or retire. Once a plant invests in a filter, its retirement probability significantly reduces, delaying its replacement by cleaner alternatives.

The previous considerations are integrated into a new model on coal procurement, sulfur filter investment, and plant retirement. I model the setup as a dynamic principal-agent model with full commitment and no asymmetric information. The regulator is the principal, and its utility function comprises two elements: the coal plant's contribution to consumer surplus and the revenue it provides to the state's mines. The regulator maximizes its utility by setting the stream of regulated prices that the coal plant charges to final consumers. These regulated prices should satisfy the plant participation constraint at every period. In other words, the regulated price should be high enough for the coal plant to recover both coal procurement expenses and the filter investment, which the plant owner pays in perpetual annuities.

Within each period, the price of natural gas electricity follows a random distribution. Power plants dispatch efficiently, and hence, the coal plant only supplies electricity if the regulated price is below the natural gas price realization. Consistent with the trend in 1a, natural gas cheapening reduces the coal plant's contribution to consumer surplus. A lower consumer surplus contribution, in turn, decreases the regulator's utility.

The plant owner is in charge of deciding the share of local coal in the coal blend. Local coal is more affordable but features a higher sulfur concentration, which ultimately translates into higher sulfur emissions. Regarding the filter investment and retirement decision, the plant owner must choose among four discrete options: Invest in a high-efficiency or low-efficiency filter, retire the plant, or postpone the decision to the next period. Consistent with the previous discussion, expensive filters are the most efficient, which increases in-state mining revenue and decreases coal freight costs. Assuming full commitment and absent asymmetric information, the regulator can make the plant owner choose its preferred option by promising a specific stream of regulated prices. Consequently, the regulator becomes the only relevant agent of the model.

At every period, the regulator decides over each coal generator under its control. When the generator features no filter, the regulator must choose among four options: install a cheap filter, install an expensive filter, retire the generator, or delay the decision to the next period. In case the generator already has a filter, the regulator's choice is between remaining open or retiring. The regulator is forward-looking and makes these discrete decisions to maximize its expected utility, comprised of consumer surplus and local mining revenue. In order to determine the importance of local mine revenue in the regulator utility function, I estimate the previous model as a dynamic discrete-choice problem following the procedure in Aguirregabiria and Mira [2007]. The model estimation relies on the dataset constructed for the reduced-form analysis. More specifically, I enrich this dataset by incorporating transaction-level data between mines and plants, generator-level production data, and natural gas electricity prices.

The estimation of the model requires imputing the effect of high and low-efficiency filters on coal blend unit costs and local mine revenue. This imputation exercise relies on several regressions that feature two sources of exogenous variation across plants: heterogeneous distance to the low-sulfur mines and different sulfur concentrations in the local mines. The aggregate state of the model consists of the natural gas price. Following Gowrisankaran et al. [2022], I discretize the natural gas price and assume it follows a Markov chain.

According to my estimate, regulators from mining states are willing to give up \$65 of consumer surplus in exchange for \$100 in local mine revenue. After estimating the model, the paper performs two counterfactuals. The first counterfactual eliminates local coal protection from the regulator utility function. Under this counterfactual, the regulators from mining states behave as their no-mining state equivalents. Absent the local coal protection channel, regulators from mining states are less likely to install a filter, which translates into more coal plant retirements. More specifically, the model predicts that by 2019, the US coal power capacity would have been 5% lower. This reduction is equivalent to the current coal capacity in Kentucky.[4]

The second counterfactual introduces a \$100/Ton carbon dioxide tax. A carbon tax is regarded as the first-best approach to address climate change, as it burdens the most polluting electricity generation technologies. A \$100/Ton tax would be over the benchmark of current European Union Emissions Trading Scheme permit prices, which nowadays oscillate around 90 €/Ton.Despite all the previous considerations, introducing such an ambitious tax does not translate into more regulated coal plant retirements. This result is because, in 2019, natural gas was already as affordable as coal. Hence, introducing a tax that made it comparatively cheaper had

[4]The model estimates a 9.19 GW reduction. Kentucky coal plant capacity in 2023 is 9.4 GW. Source: EIA energy profile.

no significant effect.

The two counterfactuals suggest market-based approaches to reducing carbon dioxide emissions may be ineffective in heavily regulated sectors. Place-based policies aimed at taming the local coal protection channel may be a more effective and feasible policy to accelerate coal plant closures. These policies may include subsidizing mine closures and miner re-training programs.

Related Literature

This paper relates to three strands of the energy economics literature: coal plant upgrades and closures, coal procurement, and regulatory distortions in electricity markets. The forthcoming section details my contribution to these areas, together with reviewing the existing research.

This paper studies the sulfur filter investment and closure decisions by US regulated coal power plants in the 2008-2019 period. In this regard, it complements Gowrisankaran et al. [2022], which studies the same decision for non-regulated coal plants. According to my paper, the regulator's desire to protect local mines motivated filter adoption by regulated plants. In this regard, my paper is closely related to Fowlie [2010], which studies nitrogen filter adoption. In this paper, the author found that regulated plants are more eager to comply with nitrogen oxide emission standards using capital-intensive methods such as filters. Non-regulated plants, in contrast, prefer the purchase of nitrogen emission allowances. This result aligns with the theoretical prediction of the seminal work of Averch and Johnson [1962].

My paper also relates to the early literature on sulfur emission allowance marketplaces: Ellerman and Montero [1998] studies the compliance strategies adopted by US coal power plants in response to the first sulfur permit program.[5] The authors find that coal plants responded to this new marketplace by switching to low-sulfur coal rather than purchasing emission allowances. Arimura [2002] analyses the overlap between the emissions marketplace and rate of return regulation. His results suggest that regulators from high-sulfur mining states prefer the emission allowance approach over fuel switching, as the former allows plants to keep burning high-sulfur local coal. This result aligns with my findings and hints that electricity regulators have consistently tried to protect their mining industry through different mechanisms.

This paper contributes to the literature on coal procurement by establishing the complementarity between high-efficiency filters on local coal in the context of a tight sulfur emission cap. In this regard, Cicala [2015] compares the coal procurement behavior of regulated and non-regulated plants between 1990 and 2009. Cicala finds that regulated coal plants were more likely to buy from in-state mines. The author attributes this distorted behavior to lobbying and regulatory capture. My paper builds on this finding by proposing a specific mechanism behind such distorted behavior: adopting expensive sulfur filters to protect local mines. In a more recent paper, Preonas [2023] studies the market power of coal freight companies. Coal is transported from mines to plants by train, and the author analyzes the markups of these freight companies. The paper finds that when coal plants struggle due to natural gas competition, freight companies reduce their markups to alleviate such

[5] The US Environmental Protection Agency introduced The Acid Rain Program (ARP) in 1995.

competitive pressure. Like my article, Preonas [2023] focuses on the US coal industry in the last decade. Still, Preonas focuses on freight companies as agents, while my paper analyzes utility regulators and their willingness to protect local mines.

Thirdly, this paper is related to the literature on "rate of return regulation" and its distortions. I contribute to this literature by uncovering a new source of distortion: the local regulator's protection of local mines through expensive filter adoption. Moreover, I find that this distortion has two dimensions: not only does it represent a capital over-investment, but it also delays coal plant retirement. In this regard, my paper is closely related to Gowrisankaran et al. [2020]. In this recent paper, the authors find that regulated coal plants have responded to cheap natural gas by supplying electricity at a loss. This excessive dispatch aims to make the plant look "used and useful" to delay its closure. Other papers of this literature include Lim and Yurukoglu [2018] on information asymmetries between the regulator and the utility and Besley and Coate [2003], which documents lower regulated electricity prices when the regulatory board is elected.

2 Institutional Context

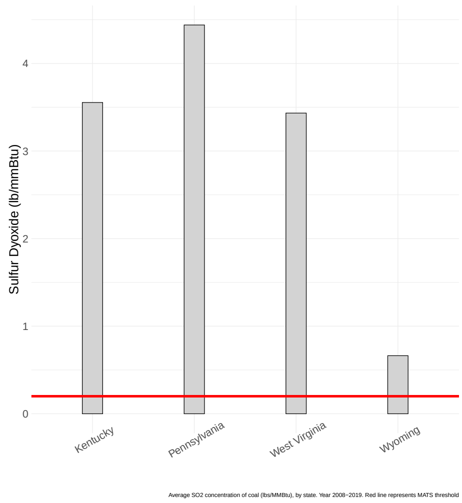
This section introduces the institutional features of my setup. Firstly, US coal power plants are broadly classified into two groups: on the one hand, "regulated" plants charge a price established by the electricity regulator of the state they belong to. "non regulated" or "merchant" plants, in contrast sell their output at a free price. Both plant types are subject to the Mercury Air Toxic Standards (MATS) rule, a new environmental regulation that mandates a drastic sulfur dioxide emission reduction. This new rule triggered two compliance strategies. On the one hand, coal plant have switched to low-sulfur coal blends. On the other hand, plants resorted to investing into "scrubbers", sulfur filters aimed at reducing emissions. Scrubbers are classified in two types: "dry" and "wet". Wet scrubbers are more expensive, but enable the use of high-sulfur coal blends, helping the mines that supply such coal. This paper focuses on the scrubber adoption by regulated plants, and only employs non-regulated facilities as a control group in the reduced-form exercise of Section 4. Readers interested in the scrubber adoption by non-regulated plants may refer to Gowrisankaran et al. [2022].

The following subsections address each of the aforementioned elements in detail: Firstly, Subsection 2.1 reviews the Mercury Air Toxic Standards (MATS). Secondly, Subsection 2.2 introduces the main coal basins in the US and their heterogeneity in sulfur concentration. Thirdly, the Subsection 2.3 is devoted to the "scrubbers". Fourthly, Subsection 2.4 describes the decision-making process behind scrubber investments, with a special focus on regulated plants.

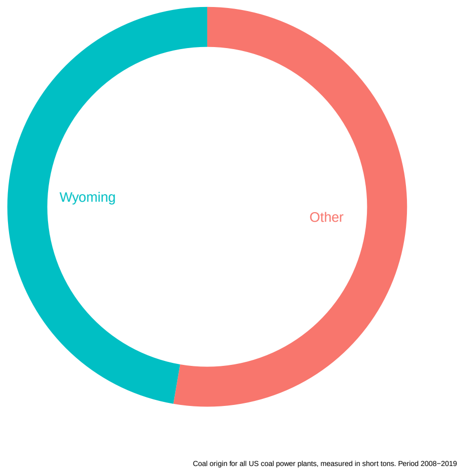
2.1 Sulfur Emission Regulation in the US

Sulfur emissions are a first-order environmental problem in the US. According to Holland et al. [2020], sulfur emission damages accounted for 137.6 billion $ on 2010 alone, and coal power plants were the main emitters of

Figure 2: Coal production in the US



(a) Sulfur content, by states



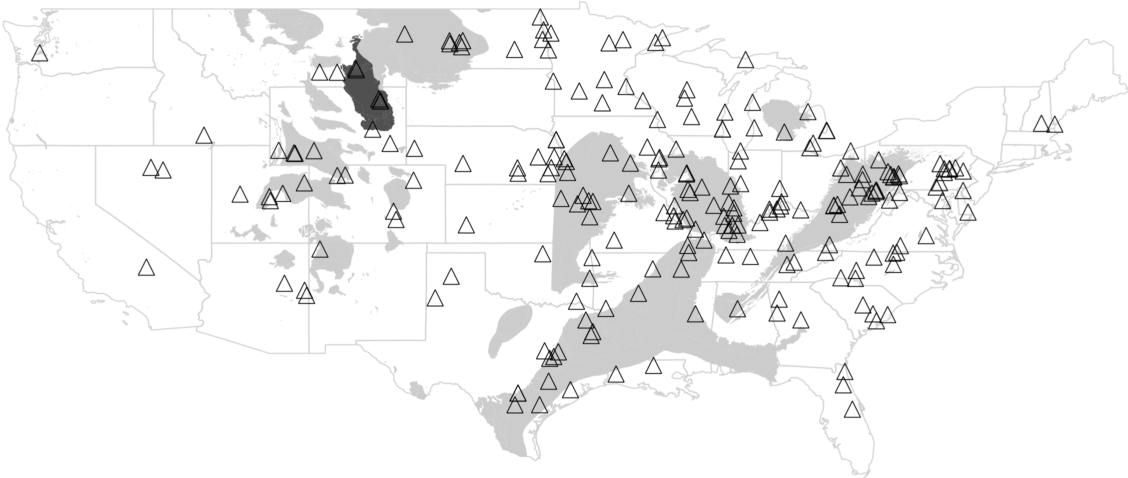
(b) Coal by origin 2008-2019

this pollutant.[6] This Subsection introduces the basic features of the Mercury Air Toxic Standard (MATS) rule, the main sulfur dioxide emission regulation of the last decade. Readers can find more details about this rule in Appendix A. Moreover, Appendix B provides a broad review of hazardous air pollution regulation in the US.

The MATS rule was promulgated in December 2011 by the US Environmental Protection Agency (EPA). The rule established that, by 2016, the sulfur emissions of all US coal plants should be below a per-unit threshold. More specifically, this threshold was established to be 0.2 sulfur dioxide pounds per million British Thermal input units (lb/mmBtu) or, alternatively, 1.5 sulfur dioxide pounds per each Megawatt-hour output unit (lb/MWh). Exceptionally, the EPA granted compliance extensions beyond 2016 on the grounds of supply reliability concerns.[7]

The MATS rule obliged US coal power plants to reduce their sulfur dioxide emissions. In this task, plants could resort to two complementary approaches: switching to a low-sulfur coal blend and investing in a sulfur filter, known as "scrubber". Forthcoming subsections 2.2 and 2.3 are each devoted to these two approaches.

Figure 3: Coal basins and coal power plants



Note: Dark gray area represents Wyoming coal basin. Light gray areas represent other coal basins. Triangles represent coal power plants.

2.2 US coal Basins

US coal is very heterogeneous in its sulfur content. Figure 2a takes the four largest coal producing US states and plots the sulfur content of the coal they extracted in the last decade. The Wyoming coal stands out as the one with lowest sulfur, featuring a 0.66 sulfur dioxide lbs/MMBtu concentration. West Virginia, in contrast, has an average content of 3.4 lbs/MMBtu, about five times more. Still, both concentrations are above the 0.2 lbs/MMBtu threshold mandated by MATS, represented by the horizontal line in Figure 2a.

The "coal blend" refers to the mix of different coal types that a power plant burns in order to produce electricity. This coal blend is a key determinant of sulfur dioxide emissions of the facility: when coal is burnt, the sulfur particles in the mineral react with oxygen, ultimately releasing sulfur dioxide to the atmosphere. Traditionally, the coal blend would be comprised of coal from nearby mines, in order to avoid the freight cost. A low-sulfur coal blend, in contrast, consists of a large fraction of Wyoming coal, so that the ultimate mix generates few sulfur dioxide emissions.[8] This compliance strategy has turned Wyoming into the first coal producing state in the US, as half of all the coal extracted in the country came from this state in the last decade (See Figure 2b)

Switching to a low-sulfur coal blend entails a major disadvantage: high transport costs. Figure 3 represents the Wyoming coal basin area in dark gray. Light gray areas represent other basins and triangles

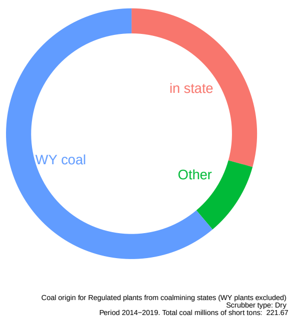
[6]Coal plants were responsible for 90% of the sulfur emissions in the electricity sector for the 1997-2007 period (EIA Today in Energy 2018, find link here).

[7]The rule established April 2015 as the original compliance deadline, but later offered a one-year extension. Regarding ad-hoc compliance extensions beyond 2016, find examples here and here.

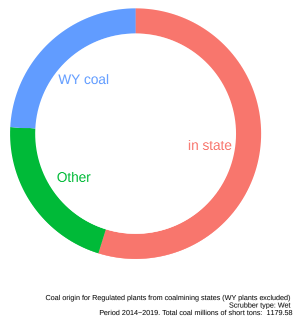
the MATS rule was challenged in court by several state attorney generals. These challenges forced the EPA to provide additional justification on the MATS necessity, but did not vacate the rule. Under the Trump administration, the EPA did not provide the requested justification, but the MATS rule remained enforced nevertheless.

[8]Piece of news here.

Figure 4: Coal blends by scrubber type.



(a) Dry Scrubbers



(b) Wet Scrubbers

identify coal power plants. The Wyoming coal basin is far away from most US coal power plants and, hence, low-sulfur coal blends translate into significant freight expenses. Moreover, even the sulfur concentration of Wyoming coal is still far above the MATS threshold of 0.2lbs/MMBtu. Switching to low sulfur coal is thus not enough to meet the MATS standard, forcing plants to adopt scrubbers. The following subsection introduces this technology and details how different scrubber technologies allow for different coal blends in order to ultimately comply with MATS.

2.3 Sulfur Filters: Scrubbers

The role of the scrubbers consists on filtering sulfur dioxide particles before they are released to the atmosphere. Scrubber types differ in their "efficiency", this is, in their ability to abate sulfur dioxide emissions. A scrubber of 90% efficiency, for instance, is able to prevent the release of nine out of ten sulfur dioxide particles.

Scrubbers are broadly classified into two categories: "dry" and "wet". Next, I briefly describe the advantages and disadvantages of each category. Wet scrubbers are the most expensive type of scrubbers. The median cost of a wet scrubber installed in the 2008-2019 period was approximately 200 million $. Still, wet scrubbers achieve sulfur oxyde filtering efficiencies up to 99%, allowing power plants to burn high-sulfur coal blends while complying with the MATS standard. Dry scrubbers on the contrary, are cheaper, with a median cost of approximately 100 million $. Still, the sulfur oxide removal efficiency of dry scrubbers does not exceed 95%. It is for this reason that, according to Sorrels [2021], dry scrubbers still require low-sulfur coal blends in order to comply with MATS. Appendix C provides more information about scrubber types and their characteristics.

The pie-charts of Figure 4 illustrate the positive spillovers of wet scrubbers on nearby mines, by comparing the sourcing behavior of power plants depending on their scrubber type. These two graphs focus only on the plants from coal-mining states[9] and classify their coal purchases in three categories: Firstly, "WY

[9]I define "Coalmine states" as all the states that supplied some coal to power plants in the 2008-2019 period. These states are: Alabama, Arkansas, Arizona, Colorado, Illinois, Indiana, Kansas, Kentucky, Louisiana, Maryland, Missouri, Mississippi, Montana, North Dakota, New Mexico, Ohio, Oklahoma, Tennessee, Texas, Utah, Virginia, Washington, West Virginia. Wyoming is excluded.

coal" corresponds to the coal bought to Wyoming. Coal purchases of an Indiana plant to a Wyoming mine, for instance, correspond to this category. Secondly, the "in state" label encompasses all the coal that plants purchase within their same state. Following with the previous example, a transaction between an Indiana plant and an Indiana mine would fall into this category. Thirdly, the "Other" category bundles the coal that corresponds to neither of the previous, for instance, when the Indiana plant buys coal to West Virginia mines.

2.4 Scrubber Investment and Regulatory Framework

In a context of cheap natural gas and MATS-rule enforcement, coal-power plants find themselves at a crossroads between investing in a scrubber or closing the facility. This section is devoted to the agent in charge of this decision. This agent is different depending on the type of regulation the plant operates under. In the case of "regulated" plants, the decision corresponds to the state electricity regulator, whereas, in the case of "non-regulated" plants, the choice is in the hands of the plant owner.[10]

Regulated coal power plants are the subject of this paper and represent about two-thirds of the total coal capacity in the US.[11] These plants operate under "cost of service" regulation and belong to investor-owned utilities (IOUs), privately owned companies that are granted a local monopoly over an area denominated "retail service territory". Utilities are the only electricity providers of their territory and consumers living within such area have no choice but to buy power from their utility. Customers, in turn, are protected from potential monopolistic abuses by the state Public Utilities Commission (PUC). Public utilities commissions are quasi-governmental agencies in charge of regulating the electricity sector of their state. The aim of PUCs is to guarantee state customers a reliable electricity supply at the lowest cost possible.[12] These commissions are usually comprised of 3 members or "commissioners' with 6 year-long staggered terms. In most states, PUC commissioners are appointed by the governor and ratified by the state legislature.[13]

Regulated plants require the PUC approval for investing in a scrubber. These decisions involve trial-like procedures in which the commissioners hear the testimony of all stakeholders involved. This procedure commences when the utility submits a proposal to install a scrubber into one of its power plants. Next, the Public Utilities Commission holds open hearings to collect feedback from all involved parties. These may include the state utility itself, consumer advocates, coal mine owners, labor unions, environmental groups, and other advocacy groups.[14] After gathering all this input, the PUC ultimately decides whether to approve the

[10] Following the standard approach of the literature, this paper classifies coal power plants into two regulatory categories: "non-regulated" and "regulated". See, for instance Fowlie [2010], Cicala [2015] and Gowrisankaran et al. [2020]

[11] Scrubber installation by non-regulated plants is addressed in Gowrisankaran et al. [2022].

[12] The West Virginia PUC mission, for instance, states that "The purpose of the Public Service Commission is to ensure fair and prompt regulation of public utilities; to provide for adequate, economical and reliable utility services throughout the state; and to appraise and balance the interests of current and future utility service customers with the general interest of the state's economy and the interests of the utilities".

[13] PUC commissioners are elected in 10 states: Arizona, Alabama, Georgia, Louisiana, Montana, Nebraska, North Dakota, Oklahoma. The state legislature appoints commissioners in 2 states: Virginia and South Carolina

[14] The Sierra Club Beyond Coal campaign, for instance, was very active in testifying against scrubber investments. See Drake and York [2021]. On the contrary, representatives of coal counties have expressed support for environmental upgrades, even at the expense of higher electricity prices (Read piece here). Moreover, the state of Wyoming funded a dark money group named the

scrubber investment. In case the investment is approved, the upfront cost is paid for by the utility that owns the plant. The regulator, in exchange, approves an increase of the electricity price so that the utility recovers the investment and obtains a "reasonable" return on capital.

3 Data

This section summarizes the datasets I employ in my effort of "taking the model to the data". More specifically, the "Empirical evidence" section will use this data to test the main predictions of my model, while the "Estimation" chapter estimates its structural parameters.

All the datasets employed in this paper are publicly available and encompass the 2008-2019 period. Still, coal plant data is available at three different levels of granularity and not all datasets report the same level: Firstly, "generators" are the most granular unit of observation and correspond to the furnaces in which coal is burnt to produce heat. Secondly, Boilers use this heat to convert water into steam, which laters moves a turbine that ultimately generates electricity. There are several generator-boiler configurations. Large generators may each have their boiler, but it is also feasible that many generators contribute to a single boiler. Thirdly, "plants" are the highest level of aggregation and represent whole facilities with several boilers.[15]

The EIA-860 dataset is an annual panel of the universe of electricity generators in the US by the Energy Information Administration (EIA). This dataset reports, among other covariates, the size of the generator, the type of fuel it uses -which allows to identify coal generators- and whether the generator remains open. Moreover, the EIA-860 also provides a complementary dataset of the universe of scrubbers installed at US power plants. These records are reported at the boiler level and include the scrubber type, total cost and installation date. This dataset allows me to classify coal generators into three scrubber categories: "Dry scrubbers", "wet scrubbers" and "none". The EIA-860 dataset serves as the foundation for building a comprehensive panel that incorporates information from other datasets.

Next, the EPA eGRID dataset is an annual panel of the universe of plants. Although offering a higher level of aggregation than the previous dataset, eGRID reports some crucial plant-level covariates, such as plant-level geolocation and whether the plant is regulated.

Thirdly, the EPA Continuous Emissions Monitoring System (CEMS) dataset offers hourly records of generator-level inputs and outputs. This dataset reports both the generator electricity output, in KWh, and the amount of input required to generate such output, in Btu heat units. These two variables allow for the calculation of the heat-rate at the generator level, this is, the amount of heat input needed to generate one output unit, in Btu/KWh units. Moreover, the CEMS also records generator-level sulfur oxide emissions, a crucial input to test whether the generator is complying with the MATS rule.

Energy Policy Network which advocated on the opposite direction.

[15] On top of these three different levels of aggregation, the EPA and the EIA differ in their generator and boiler coding system. I overcome this challenge by using the CAMD-EIA crosswalk dataset.

Fourthly, EIA 7A dataset is an annual panel of US coal mines. This panel reports annual output, labor input and records the US county the mine belongs to, which allows me to geolocate it in the centroid of the corresponding county. The panel also reports whether a mine remains operative, allowing to test the effect of scrubbers in the closure of closeby mines.

Fifthly, the EIA-923 reports transaction-level data between coal plants and the mines these plants source from. Crucially to my setting, these transactions report plant and mine identifiers, coal quantity, the total cost of the transaction -including freight cost- and the average sulfur content of the coal. The geolocation of both coal plants and mines enables me to proxy the travel distance of each transaction. Moreover, this dataset also enables me to compute both the sulfur content of the coal blends for each plant-year pair $\overline{s}_{it}$, and the share of coal bought in-state ρ_{it}. Finally, as EIA-923 also reports transactions of natural gas plants, It allows me to estimate an average unit cost of natural gas electricity production, for each state and year.

4 Suggestive Evidence

This section provides suggestive evidence on state regulators approving wet scrubbers in order to protect the coal mines of their state. The empirical exercises in this section rely on two main sources of variation: the regulatory framework and the geographical location of the plants.

Power plants operate under diverse regulatory frameworks. This variation allows me to infer the extent to which cost-of-service regulation distorted wet-scrubber investment decisions. Historically, all US coal plants were "regulated" and operated under cost-of-service arrangements. The 90's witnessed a significant push towards the liberalization of the US electricity market. In this context, some US states forced their investor-owned utilities to sell off the coal power plants they owned to third-parties. These divested plants were labeled as "non-regulated".

Today, a majority of US coal power plants still operates under cost of service regulation. These regulated plants belong to monopolistic, investor-owned utilities and charge a regulated price for their output. Moreover, the upgrades on these plants are decided by state utility regulators, as it is detailed in Subsection 2.4. In contrast, non-regulated plants do not operate under cost-of-service regulation and instead charge a market price for their output. Moreover, the state regulators have no agency over the scurbber installation in these plants, as the decision belongs to the new owners only. This section follows Fowlie [2010], Cicala [2015], Gowrisankaran et al. [2020] and others in employing "non-regulated" plants as a control. My identification strategy assumes that merchant plant-owners only install wet scrubbers in case they are profitable. The positive spillovers of wet scrubbers on state mines should, thus, play no role in the wet scrubber adoption by this subset of plants.

The second source of variation corresponds to the coal plant location, as only a subset of the plants belong to mining states.[16] The majority of US coal power plants were opened in the 70's and 80's, often nearby

[16]States with more than 1.000 miners in 2008 are considered "coal-mining states". These are: Alabama, Colorado, Illinois,

Figure 5: Share of open coal plants with wet scrubbers, classified by regulatory status. 2008-2019

(a) Mine States

(b) No-mine States

coal mines. This arrangement, labeled as "mine to mouth", minimized coal freight costs. The introduction of the MATS rule challenged this model, as procuring from local mines became incompatible with meeting the sulfur dioxide emission standard. High-efficiency wet scrubbers overcome this incompatibility, allowing coal plants to continue to source from nearby mines. Wet scrubbers, thus, both help local mines and minimize freight costs. My empirical strategy assumes that regulators from mine states care about these two forces, while the decision of regulators from no-mine states and non-regulated plant owners are solely driven by the latter.

Was the aforementioned assumption right, regulators from mine states are more likely to approve wet scrubbers. Figure 5 provides suggestive evidence pointing in such direction, by showcasing the share of open coal plants with wet scrubbers in the 2008-2019 period. In line with the two sources of variation mentioned at the beginning of the section, the figure classifies coal generators in four groups, depending on their regulation and by whether they belong to a mining state.

Figure 5 provides several insights on wet scrubber adoption. Firstly, plants from mine states (Figure 5a) feature a larger share of wet scrubbers at the beginning of the period, compared to their non mine state counterparts (Figures 5b). Still, wet scrubber adoption of non-regulated plants from mine states, Figure 5a, resembles that of non-regulated plants from no-mine states, in Figure 5b. Interestingly, the regulated plants from no-mine states in Figure 5b also follow a similar trend, reaching barely more than 50% of wet scrubber share by the end of the period. Regulated plants from mine-states instead pursue a more decisive adoption of wet scrubbers, ultimately reaching a share above 75%, as it is shown in Figure 5a.

The suggestive evidence from Figure 5 may be driven by covariates that correlate with the four-fold classification. Regulated plants from mine states, for instance, may be further from Wyoming than the rest and, hence, the transport cost savings enabled by wet scrubbers may also be larger. Table 1 tackles this concern

Indiana, Kentucky, Montana, North Dakota, New Mexico, Ohio, Texas, Utah, Virginia, West Virginia and Wyoming.

by providing mean values of key covariates. The table follows the approach in Figure 5 and classifies coal generators by their regulation and state. Non regulated plants are, on average, younger and smaller. Moreover, these plants also feature a lower heat rate, meaning there are able to produce more output per input unit. Table 10 presents the balance tests for each of the six covariates.

The geographical characteristics of the generators are summarized by three variables: distance to the closest mine, sulfur concentration of such closest mine and distance to the Wyoming mines. Unsurprisingly, generators from mine states are closer to their closest mine, for both regulatory frameworks. Regarding the sulfur concentration of the closest mine, regulated plants feature similar values, irrespective of state type. Non-regulated plants, in contrast, significantly vary, as those from mine-states feature high sulfur in nearby mines. This discrepancy is driven by the fact that Illinois, one of the states that implemented coal-plant divestitures, features singularly high-sulfur coal mines. Thirdly, the average distance to Wyoming is similar across groups, but for non-regulated plants from no-mine states. In this case, the discrepancy is mainly driven by the New England coal plants, which were also divested in the 90's and are the furthest from Wyoming.

Table 1: Characteristics of coal generators open in 2008, by regulation and state type. Mean values.

	Regulated		Non-regulated	
	Mine-state	Non-mine state	Mine-state	Non-mine state
Age	40.38	40.98	37.84	35.05
Size	326.71	303.77	311.52	222.19
Heat rate	10099.13	10401.98	10015.13	9972.16
Closest mine distance	0.89	2.94	0.87	2.15
Closest mine sulfur	1.83	1.87	2.30	1.29
Distance to Wyoming	18.09	19.31	19.18	26.12
N	357	432	154	187

Note: generators with more than 25MW. Age measured in years, size measured in MW, heat rate measured in Btu/KWh, Distance measures are Euclidean. Mine sulfur measured in % of weight.

Equation (1) presents the main specification of this section, consisting on a Cox-Proportional Hazard model for wet scrubber installation.

$$h_i(t) = h_0(t) \exp\left(\beta_1 \cdot Age_i + \beta_2 \cdot Size_i + \beta_3 \cdot HR_i + \beta_4 \cdot d_i^{wy} + \beta_5 \cdot m_i + \beta_6 \cdot Reg_i + \beta_7 \cdot m_i \times Reg_i\right). \quad (1)$$

In this specification, the dependent variable $h_i(t)$ represents the probability of generator i installing a wet scrubber at period t, conditional on not having installed such a scrubber in previous periods. Generators that already had a wet scrubber at the beginning of the period are excluded from the sample. The model includes five time-invariant controls: generator age at the beginning of the period Age_i, size $Size_i$, heat rate HR_i and distance to Wyoming d_i^{wy}. The specification in (1) assumes non-regulated plants from no-mine states as the baseline control group. The regression integrates the two sources of variation aforementioned: on the one hand, Reg_i is an indicator variable for regulated plants. On the other hand, $m_i \in [0, 1]$ represents the share of in-state mines close to generator i. Figure 6 provides intuition on how the m_i variable is constructed. The triangle represents the location of EW Bowen, a coal plant located in central Kentucky, while the circle dots identify

Figure 6: Illustration of the m_i treatment variable construction

Note: the triangle represents the EW Bowen coal power plant from Kentucky. The shaded circle around it represents a 138 mile radius centered on the plant. Dots represent coal mines. Gray dots are Kentucky mines within the radius. Black dots are non-Kentucky mines within the radius. The treatment variable m_i consists on dividing the number of Kentucky mines inside the radius (gray dots) over the total number of mines inside the same radius (gray and black dots).

coal mines. The gray circumference around the triangle encompasses a 138 mile radius.[17] Gray dots represent mines that belong to the state of Kentucky and fall within the circumference. Black dots, in contrast, are mines from states other than Kentucky which also belong to the circumference. Ultimately, $m_i \in [0, 1]$ is the ratio between the count of "gray" dots and the sum of "gray" and "black" dots. Note that $m_i = 0$ for all states with no mines. The interaction between the regulated indicator and the share of in-state mines $Reg_i \times m_i$ determines the importance of local coal mine protection by the regulator.

Table 2 presents the coefficient estimates of the empirical exercises. Columns 1-2 correspond to Cox Proportional-Hazard model estimates, for varying plant proximity radius-es. I complement the main specification with an equivalent Probit exercise, presented in Columns 3-6.

The coefficients that correspond to plant characteristics behave as expected: Age and Heat Rate coefficients are either non-significant or negative, meaning that older, less productive facilities are also less likely to get a wet scrubber. The coefficient regarding size, in contrast, is positive and significant, as wet scrubbers represent a fixed cost with notable economies of scale.

Regarding plant location, distance to Wyoming d_i^{wy} is a strong driver of wet scrubber installation in all specifications. This result is coherent with the transport cost reduction argument. Plants far from Wyoming are to pay higher freight costs for low-sulfur coal. Hence, installing a wet scrubber yields them more significant cost savings. Following the same cost-savings argument, I would expect m_i to be positive and significant, as power plants surrounded by many mines are the ones to benefit the most from substituting far Wyoming coal by nearby alternatives. Still, the coefficients for the share of close mines in state, m_i, are negative and non-significant. These results suggest that the cost-savings are mainly driven by the distance to Wyoming, and that

[17] 138 miles are median distance that coal travels from the mine to the plant.

Table 2: Scrubber installation and local coal protection

	Dependent variable:					
	Probability of installing a high-efficiency, wet scrubber					
	Cox-PH	Cox-PH	Probit	Probit	Probit	Probit
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept			−1.567*	−1.563	−1.263	−1.310
			(0.876)	(1.018)	(0.870)	(1.004)
Age	−0.018***	−0.018***	0.003	0.002	0.004	0.003
	(0.001)	(0.001)	(0.005)	(0.006)	(0.005)	(0.006)
Size (MW)	0.001***	0.001***	0.002***	0.002***	0.002***	0.002***
	(0.0001)	(0.0001)	(0.0003)	(0.0004)	(0.0003)	(0.0004)
Heat Rate (Btu/KWh)	−0.0001	−0.0001	−0.0001*	−0.0001*	−0.0001**	−0.0001*
	(0.00002)	(0.00002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Distance to Wyoming	0.057***	0.051***	0.047***	0.038***	0.043***	0.035***
	(0.003)	(0.003)	(0.010)	(0.012)	(0.010)	(0.012)
Close mines from the state	−0.060	−0.417	−0.158	−0.283	−0.950*	−1.084
	(0.105)	(0.189)	(0.289)	(0.390)	(0.547)	(0.785)
Regulated indicator	0.162	0.176	0.206	0.342	0.054	0.223
	(0.059)	(0.058)	(0.193)	(0.245)	(0.195)	(0.251)
Close of mines × Regulated	0.841**	1.235**	0.528	0.743*	1.574**	1.899**
	(0.113)	(0.200)	(0.330)	(0.428)	(0.626)	(0.840)
Periods	2008-2019	2008-2019	2008-2019	2010-2019	2008-2019	2008-2019
Close mines radius	138 miles	345 miles	138 miles	138 miles	345 miles	345 miles
Observations	9,000	9,000	760	686	760	686
R^2	0.104	0.093				

*p<0.1; **p<0.05; ***p<0.01

Regulated and non-regulated generators above 25MW.

Probit regressions drop generators that already had a wet scrubber at the beginning of the period.

the availability of local coal plays a second-order role.

The indicator for regulated plants Reg_i is positive, but non significant. The fact that this coefficient is positive falls in line with the Averch-Johnson effect, which states that regulated facilities are more likely to over-invest in capital. The result is also coherent with Fowlie [2010], which finds that regulated plants are more likely to resort to capital-intensive pollution abatement options.

Finally, the interaction term between regulated plants and the share of local mines $Reg_i \times m_i$ is positive for all specifications, suggesting that regulators from mine states approve wet scrubbers in order to protect the local mines. The significance of the coefficient, however, varies by specification. Column (1), for instance, encompasses the 2008-2019 period and, in this case, the interaction term is non-significant. Column (2) repeats the previous specification by focusing on latter periods, yielding a 10% significant coefficient. The fact that the coefficient increases its significance in latter periods is in line with the fact that, as time passed by and coal became less competitive against coal, protecting local mines became a more pressing issue. Lastly, the interaction coefficient is positive and significant for both Cox Proportional-Hazard specifications.

I complement the proportional-hazards model in Table 2 with a multinomial logit exercise. The multinomial logit abstracts from the dynamic nature of the problem, but enables me to study the scrubber choice and the closure decision together. In this exercise, the dependent variable may take four possible discrete values: remain without a scrubber, install a dry scrubber, install a wet scrubber, or retire. The coal generators that were open and without scrubber in 2008 are classified in one of the four groups as mentioned above, represented by subscript $j \in \{remain,\ install\ dry,\ install\ wet,\ retire\}$: the generators that installed no scrubber and remained open by 2019 belong to the first group. Generators that installed a dry scrubber and remained open by 2019 belong to the second group. Generators that installed a wet scrubber and remained open belong to the third group. Lastly, the generators that retired at some point in the 2008-2019 period belong to the fourth group.[18] Equation (2) details the multinomial logit specification. I set $J = remain$ as the baseline probability. Covariate vector X_i represents generator i's time-invariant covariates: opening year, size, heat rate, and distance to Wyoming. Indicator Reg_i turns on for regulated plants. Lastly, m_i represents the "treatment" to measure the importance of in-state mining near the plant.

$$\log\left(\frac{p_j(\mathbf{x})}{p_J(\mathbf{x})}\right) = \sum_j \beta_{0j} + \sum_j \beta_{1j} \times X_i + \sum_j \beta_{2j} \times Reg_i + \sum_j \beta_{3j} \times m_i + \sum_j \beta_{4j} \times Reg_i \times m_i \qquad (2)$$

I define four m_i treatments: The first treatment corresponds to an indicator that turns on when the generator belongs to mining states. The second treatment represents the share of mines close to the generator that belong to the same state, as illustrated in Figure 6. This variable always takes zero values for non-mining states, while it ranges between zero and one for mining states. The third treatment takes into account the size of nearby mines. This treatment consists of adding the output of all the in-state, close-by mines in 2008, measured in million tons of coal. The fourth treatment takes a similar approach and sums all the miners working at in-state, close-by mines in 2008, measured in thousands of miners. I define "close-by mines" as those within a

[18] The fourth group comprises all retired generators, regardless of whether they installed a scrubber.

138-mile distance from the generator. The choice of this distance is not arbitrary, as it represents the median mine-to-plant distance that coal travels.

Table 3 presents the coefficients of interest of specification (2). Each of the four columns corresponds to one of the four treatments defined before. The coefficients in the table represent how the covariate increases the probability of the corresponding choice. The "Retire, regulated" coefficient, for instance, represents how more likely it is that a regulated plant retires with respect to a non-regulated plant. In this regard, the coefficients in rows two and three are either positive or non-significant, suggesting that regulated generators are more likely to adopt both scrubber types. Rows six to nine present the point estimates of the interaction between the regulated indicator and the treatment. Consistent with my hypothesis, regulated plants surrounded by considerable local mining activity are more eager to adopt wet scrubbers. This effect is consistent throughout treatment types and remains robust when increasing the radius encompassing local mines, as reported in Table 15.

5 Model

This section introduces a principal-agent model on coal plant dispatch, procurement, and scrubber investment. The model consists of three agents: the state regulator, a coal plant owner and electricity consumers. The state regulator takes the role of the principal, while the plant owner is the agent. There is no asymmetric information between regulator and the plant owner and the former features full commitment.

The model is dynamic, infinite-horizon and with annual frequency, denoted by the subscript t. The model features a single, representative coal plant with the capacity to produce one unit of electricity every period t. Moreover, this plant requires a single unit of coal input to produce one unit of electricity output.[19] Lastly, the plant features a scrubber of efficiency ω_t. Scrubber efficiency can take three possible values $\omega_t \in \{h, l, 0\}$, ranked $1 > h > l > 0$.

Coal procurement is, together with scrubber efficiency ω, a key determinant of sulfur dioxide emissions. The procurement decision rests on the plant owner. The owner is in charge of choosing the share of local coal of the coal blend, denoted $\rho_t \in [0, 1]$. The optimal local blend is aimed at minimizing the unit cost of the coal blend, while complying with the mandatory sulfur emission cap $\overline{S}$. Consistent with the data, the model simplifies the available coal providers to two locations: local mines and Wyoming mines. Local mines are represented by subscript m, while subscript wy refers to Wyoming mines. These two mining locations represent a fundamental trade-off: local coal features lower unit cost $c_m < c_{wy}$ but higher sulfur concentration $s_m > s_{wy}$. I normalize $s_{wy} = 0$ for the sake of simplicity. The ultimate coal blend will feature sulfur concentration $\overline{s}_t(\rho_t) = \rho_t \cdot s_m$ and unit cost $\overline{c}_t(\rho_t) = \rho_t \cdot c_m + (1 - \rho_t) \cdot c_{wy}$. Note that a high ρ_t reduces unit costs, at the expense of a higher sulfur concentration. The sulfur dioxide emissions of the plant S_t are determined by the product between the scrubber efficiency and the sulfur concentration of the coal blend: $S(\rho_t, \omega_t) = (1 - \omega_t) \cdot \overline{s}_t(\rho_t)$. The plant owner should

[19]The plant heat rate indicates the amount of heat input a plant needs to produce a unit of output. Heat rate is the inverse of efficiency, as plants with lower heat rates require less input to produce a unit of output. The empirical estimation of the model in Section 6 accounts for plant heterogeneity in both nameplate capacity and heat rate.

Table 3: Scrubber adoption and local mines

	Dependent variable:			
	Four discrete choices: remain, retire, dry scrubber, wet scrubber			
	(1)	(2)	(3)	(4)
Retire, regulated	0.039	−0.787	0.243	0.221
	(0.484)	(0.509)	(0.349)	(0.341)
Dry scrubber, regulated	−0.176	−0.250	1.034*	1.207**
	(0.720)	(0.762)	(0.590)	(0.571)
Wet scrubber, regulated	1.058**	−0.218	1.122***	1.159***
	(0.531)	(0.545)	(0.372)	(0.363)
Retire, treatment	−0.010	−1.298**	0.024	0.542*
	(0.543)	(0.660)	(0.017)	(0.277)
Dry scrubber, treatment	−2.257**	−2.555**	0.008	0.443
	(0.947)	(1.082)	(0.027)	(0.407)
Wet scrubber, treatment	0.175	−2.326***	−0.004	0.183
	(0.586)	(0.744)	(0.020)	(0.293)
Retire, treatment × regulated	0.315	1.884**	0.044	0.733
	(0.601)	(0.758)	(0.030)	(0.469)
Dry scrubber, treatment × regulated	1.886*	2.041*	0.005	−0.113
	(1.015)	(1.207)	(0.045)	(0.671)
Wet scrubber, treatment × regulated	0.735	3.480***	0.075**	0.954**
	(0.651)	(0.837)	(0.033)	(0.482)
Treament: close mines from own state	State indicator	Mine share	Mine size	Employment
Close mines radius	-	138 miles	138 miles	138 miles
Observations	707	707	707	707
McFadden R^2	0.223	0.225	0.218	0.226
Log Likelihood	−661.354	−658.912	−664.773	−658.080
LR Test (df = 24)	378.562***	383.445***	371.724***	385.110***

*p<0.1; **p<0.05; ***p<0.01

Regulated generators, 2008-2019 period. All the specifications include generator age, size, heat-rate and distance to Wyoming as controls. I define close-by mines as those within a 138-mile radius around the generator. 138 miles is the median mine-to-plant distance that coal travels. Treatment of first specification consists on an indicator for generators that belong to mining states. Treatment of second specification is the share of close-by mines that belong to the same state as the plant. Treatment of the third specification is the millions of coal tones that close-by mines from the same state produced in 2008. Treatment of the fourth specification is the number of miners working in close by mines from the same state in 2008.

choose an optimal coal blend ρ_t^* that is below the sulfur emission cap $S(\rho_t, \omega_t) \leq \overline{S}$. The cost minimization objective drives the plant owner to increment ρ until the sulfur emission constraint is met with equality. Hence, the optimal share of local coal is

$$S(\rho_t^*, \omega_t) = \overline{S} \quad \rightarrow \quad \rho^*(\omega_t) = \frac{\overline{S}}{(1-\omega_t) \cdot s_m}. \tag{3}$$

Regarding the plant dispatch problem, consumers feature an annual electricity demand $Q_t > 1$ that is price-inelastic below a threshold price v.[20] Consumers can purchase their electricity from two sources: coal and natural gas plants. On the one hand, the representative coal power plant sells its output at a regulated price p_t, which remains constant within period t. On the other hand, a perfectly-competitive market comprised of uniform natural gas plants offers electricity at a price p^{gas}. Unlike p_t, p^{gas} is a random variable and follows a generic distribution Φ: $p^{gas} \sim \Phi(p^{gas}|\mu_t)$ within year t. This distribution is centered by parameter μ_t, which, as its subscript indicates, changes on a yearly basis. Consumers only purchase from the coal plant when the condition $p \leq p^{gas}$ is met. Henceforth, the the annual output of the coal plant is

$$q(\mu_t, p_t) = 1 - \Phi(p_t|\mu_t). \tag{4}$$

The outcomes of both coal procurement and plant dispatch problems yield an expression of plant per-period profits $\pi_t(\omega_t, \mu_t, p_t)$, where f_t represents a generic, per-period fixed cost. The discounted sum of π_t yields the an expression of present-value profits, at time $t = 0$:

$$\Pi = \sum_{t=0}^{\infty} \beta^t \cdot \pi_t(\omega_t, \mu_t, p_t), \tag{5}$$

where per-period profits are

$$\pi_t(\omega_t, \mu_t, p_t) = (p_t - \overline{c}_t(\omega_t)) \cdot q_t(\mu_t, p_t) - f_t. \tag{6}$$

Per-period profits depend on the stream of regulated prices $\{p_t, p_{t+1}, ...\}$ that the plant charges to electricity consumers. According to cost-of-service regulation, these prices are set by the regulator in order to guarantee non-negative present-value profits to the plant owner $\Pi \geq 0$.

Next, the scrubber investment decision corresponds to the plant owner. Consistent with the available technology, the model allows for two scrubber types, with varying efficiency and fixed costs: firstly, high-efficiency "wet" scrubbers feature an efficiency $\omega_t = h$ and a fixed cost F_h. Secondly, low-efficiency "dry" scrubbers are characterized by both a lower efficiency $\omega_t = l$ and a lower fixed cost $F_l < F_h$. Thirdly, a plant may have no scrubber at all, in which case scrubber efficiency is normalized to zero $\omega_t = 0$.

Regarding scrubber investment, the model makes the following three assumptions. Firstly, the scrubber investment decision is considered irreversible: if the plant owner decides to invest in a scrubber at period t, such scrubber can neither be removed nor replaced in future periods. Secondly, both scrubber types feature a one-period time-to-build. This means that, if the plant owner foregoes an investment $\omega^* \in \{l, h\}$ at time t, the scrubber efficiency for that period remains $\omega_t = 0$, and the effect of the new scrubber is realized from $t + 1$ and

[20] The assumption of price-inelasticity is in line with the empirical findings in Fabra et al. [2021]. The threshold price v can be interpreted as the value of loss load (VOLL) [Willis and Garrod, 1997].

onward: $\omega_{t+1} = \omega_{t+2} = \omega_{t+3} = ... = \omega^*$. Thirdly, the scrubber is paid for by the plant owner at time t, at the corresponding cost of F_{ω^*}.

Lastly, the plant-owner may decide to close the plant. In this case, the model establishes that the plant owner is to be compensated with a one-time transfer. This transfer may feature two values: if the closed plant had no scrubber, the transfer will be of amount Γ_0. In contrast, had the closed plant a scrubber, the transfer will be Γ. The model assumes that $\Gamma > \Gamma_0$, as upgraded plants are considered more valuable than non-upgraded plants.

In summary, the plant choice set over a plant with no scrubber is comprised of four options: remain without scrubber, invest in a dry scrubber, invest in a wet scrubber or close the plant. In contrast, the choice set for a plant with a scrubber is two-fold as it can either remain open or close.

The regulator can induce the plant to take its preferred decision through the stream of regulated prices. Take, for instance, a regulator that aims for the plant to install a wet scrubber. In the absence of asymmetric information and assuming full commitment, the regulator can offer a stream of prices that meet the $\Pi = 0$ condition only if the wet scrubber investment is realized. Consequently, this framework is equivalent to model in which the plant investment and exit decisions are taken by the regulator. The discrete choices of the regulator are driven by its per-period utility function U_t. The coming Subsection is devoted to explaining this object in detail.

5.1 Regulator Utility Function

The regulator utility function is comprised of two objects: the coal plant welfare contribution and the local coalmine revenue. These two objects comprise the per-period regulator utility function.

At every period t, the representative coal power plant contributes to total surplus TS_t in two dimensions: on the one hand, the coal plant improves consumer surplus CS_t by providing more affordable electricity. On the other hand, the plant generates profits π_t for its owner. It is immediate that, by satisfying the plant participation constraint with equality $\Pi = 0$, overall allocative efficiency is maximized. Under this assumption, the present-value of total welfare and the present-value consumer surplus are equivalent: $\sum_{t=0}^{\infty} \beta^t \cdot TS_t = \sum_{t=0}^{\infty} \beta^t \cdot CS_t$. This equivalence enables to measure per-period welfare as consumer surplus.

Coal plant improves welfare by supplying cheap electricity. When the regulated price of the coal plant is below that of natural gas plants $p \leq p^{gas}$, the coal plant produces at capacity. Was the plant closed, its output would have instead been supplied by natural gas facilities, at a higher price. In line with this intuition, I define the per-period "welfare contribution" of the coal plant, denoted $W(\mu_t, p_t)$.[21]

$$W(\mu_t, p_t) = \int_{p_t}^{\infty} (p^{gas} - p_t) \cdot \phi(p^{gas}|\mu_t) \cdot dp^{gas}. \tag{7}$$

The welfare contribution rests on the coal plant ability to replace natural gas. When natural gas electricity

[21] Appendix Subsection E.1 explains how $W(\mu_t, p_t)$ is constructed step by step.

price is below that of the coal plant, $p^{gas} \leq p_t$, there is no need for such replacement, and hence the coal plant does not contribute to welfare. In contrast, when natural gas price is above $p^{gas} > p_t$, the coal plant generates unit cost savings worth $p^{gas} - p_t$, improving total welfare.

Related to the previous explanation, Equation (7) provides intuition on how low natural gas electricity prices reduce the welfare contribution of the coal plant. Recall that μ_t represents the centering parameter of the natural gas price distribution. A low μ_t reduces the welfare contribution W_t through two channels: on the one hand, the support of the integral in Equation (7) diminishes, which means that the coal plant is dispatched less often. On the other hand, the unit cost savings at the periods at which the plant is dispatch shrink.

At this point, let us briefly discuss the effect of scrubbers on the welfare contribution expression of Equation (7). This effect is ambiguous and depends on two counteracting forces. Firstly, scrubber investments increase future regulated prices p_t. Recall that, although the scrubber fixed cost F_ω is disbursed by the plant owner, cost of service regulation establishes that present-value profits from Equation (5) need to be non-negative. Hence, this condition will translate the scrubber cost into higher regulated prices, ultimately harming electricity consumers. Secondly, the scrubber enables a higher share of local coal to be procured. As ρ_t increases, the unit cost of coal $\bar{c}_t$ is set to decrease, which ultimately translates into lower electricity prices through the cost-of-service regulation channel.

The second element of the regulator utility function is the local mine revenue, denoted $R(\mu_t, p_t, \omega_t)$. Local mine revenue consists of three elements: coal plant output (Equation (4)), local coal share (Equation (3)) and unit cost of coal c_m:

$$R(\mu_t, p_t, \omega_t) = q(\mu_t, p_t) \cdot \rho^*(\omega_t) \cdot c_m. \tag{8}$$

In line with Figure 4, high-efficiency wet scrubbers allow plants to buy a higher share of local coal: $\rho^*(\omega_t = h) > \rho^*(\omega_t = l)$. Higher local coal share translates into more revenue for local mines, a positive spillover that regulators take into account in their decision-making process.

$$R(\mu_t, p_t, h) > R(\mu_t, p_t, l) > R(\mu_t, p_t, 0) \geq 0. \tag{9}$$

The aforementioned two elements -welfare contribution and local mine revenue- come together in the regulator utility function $U(\mu_t, \omega_t, p_t)$, which is defined as

$$U(\mu_t, \omega_t, p_t) = W(\mu_t, p_t) + \alpha_1 \cdot R(\mu_t, p_t, \omega_t). \tag{10}$$

Structural parameter α_1 weights the importance of local mine revenues with respect to welfare contribution. The parameter α_1 is expected to be positive, as regulators internalize the spillover of coal-plants on nearby mines.

5.2 The Regulator Problem

Every period t, the regulator problem is comprised of two decisions: investing in a scrubber for all the forthcoming periods, ω_t, and setting the regulated price p_t. These two decisions are made in an uncertain context, in which prices of natural gas, represented by μ_t, evolve over time. Moreover, guaranteeing that the present-value profits from Equation (5) are non-negative depends on all past, present and future regulated prices $\{p_t\}_{t=0}^{\infty}$. The general version of the regulator problem, thus, involves a dynamic discrete choice bounded by a promise-keeping constraint.

As the previous two features make the general model intractable, this subsection introduces two particular cases of the model. These two cases introduce extra assumptions to the generic setup in order to reduce its complexity. The first case of the model imposes no natural gas price uncertainty $\mu_t = \mu$. Under this assumption, the dynamic discrete choice problem becomes a static decision. The static setup allows me to perform comparative static exercises, hence providing intuition on the regulator behavior. The second case reinstates uncertainty, but introduces further restrictions on the cost-of-service regulation condition. More specifically, the general present-value zero profit constraint $\Pi = 0$ is replaced by a more stringent per-period zero profit constraint $\pi_t(\mu_t, \omega_t, p_t) = 0$. This assumption yields a tractable regulator discrete-choice problem that is empirically estimated in Section 6.

5.2.1 The Static Discrete-Choice Case

The first case of the model assumes no aggregate uncertainty by imposing a constant natural gas cost for all t periods $\mu_t = \mu$. Absent uncertainty, a scrubber investment that is optimal at a period t is also the best choice at the previous period $t-1$. In other words, there is no upside in delaying the investment decision. Consequently, the regulator makes the optimal discrete choice ω^* at the first period $t = 0$ and remains committed to that same choice for all the subsequent periods.

I assume that the plant owner pays for the scrubber fixed cost F_ω in perpetual annuities. Moreover, as, the scrubber investment is always made in the first period, the generic per-period fixed cost f_t from Equation (6) is equal for all t periods. Thus, in this case, the per-period fixed cost only depends on the scrubber efficiency ω^*:

$$f_t = f(\omega^*) = \begin{cases} \frac{1-\beta}{\beta} \cdot F_{\omega^*} & \omega^* \in \{h, l\} \\ 0 & \omega^* = 0. \end{cases} \tag{11}$$

Next, the regulator is to choose a stream of prices $\{p_t\}_{t=1}^{\infty}$ that guarantees Equation (5) is equal to zero. Note that, due to the convexity of the welfare contribution expression $W(\mu_t, p_t)$ with respect to regulated prices and the lack of aggregate uncertainty, constant regulated prices over time $p_t = p^*$ are welfare maximizing.[22] Constant regulated prices, in turn, transform the generic output expression from Equation (4) into constant plant output $q^*(p^*) = q_t(\mu, p^*)$.

The regulated price p^* is comprised of two elements: the unit cost of coal $\overline{c}(\omega^*)$ and the remaining, fixed cost component. The perpetual annuity of the scrubber, $f(\omega^*)$, is divided by the coal plant output $q^*(p^*)$. Ultimately, the equilibrium regulated price $p^*(\omega^*)$ and plant output $q^*(\omega^*)$ are determined by the following two

[22] Welfare contribution convexity is proved at Appendix Subsection E.2. The optimality of constant prices is proved at Appendix Subsection E.3

expressions:

$$\begin{aligned} p^*(\omega^*) &= \bar{c}(\omega^*) + \frac{f(\omega^*)}{q^*(p^*(\omega^*))} \\ q^*(\omega^*) &= 1 - \Phi\left(p^*(\omega^*)\right). \end{aligned} \tag{12}$$

Equilibrium outcomes provide new welfare contribution $\widehat{W}(\omega^*)$, mine revenue $\widehat{R}(\omega^*)$ and regulator per-period utility $\widehat{U}(\omega^*)$ expressions. Note that the constant regulated price result allows me to replace p_t and achieve a regulator utility $\widehat{U}(\omega^*)$ that only depends on the scrubber efficiency ω^*:

$$\begin{aligned} \widehat{W}(\omega^*) &= \int_{p^*(\omega^*)}^{\infty} \left(p^{gas} - \bar{c}(\omega^*) - \frac{f(\omega^*)}{q^*(\omega^*)}\right) \cdot \phi(p^{gas}|\mu) \cdot dp^{gas} \\ \widehat{R}(\omega^*) &= q^*(\omega^*) \cdot \rho(\omega^*) \cdot c_m \\ \widehat{U}(\omega^*) &= \widehat{W}(\omega^*) + \alpha_1 \cdot \widehat{R}(\omega^*). \end{aligned} \tag{13}$$

The previous two considerations result in the following maximization problem for the regulator. Note that the lack of aggregate uncertainty transforms the dynamic discrete choice problem into a static comparison between the present value of each of the four discrete options. Moreover, the model assumes a one-year scrubber construction period. Taking these factors into consideration, the regulator discrete choice over a plant that has no scrubber $\omega_{t=0} = 0$ is as follows:

$$V(\omega) = \max \quad \left\{ \max_{\omega} \left\{ \frac{1}{1-\beta} \cdot \widehat{U}(\omega) \right\}, \quad \Gamma_0 \right\}. \tag{14}$$

In case the coal plant already features a scrubber at the first period, $\omega_{t=0} \in \{h, l\}$, the static discrete-choice problem of the regulator simplifies to the following problem:

$$V(\omega) = \max \quad \left\{ \frac{1}{1-\beta} \cdot \widehat{U}(\omega), \quad \Gamma \right\}. \tag{15}$$

Comparative Statics

The regulator decision rules in Equations (14) and (15), allow me to perform comparative static exercises that deliver three key findings: firstly, regulators that care about the revenue of the local mines are more likely to approve a scrubber. Secondly, these regulators are also more likely to approve a wet scrubber over a dry one. Thirdly, regulators are less likely to close coal plants that already have a scrubber. Together, these three results establish a link between scrubber investments and coal plant closures.

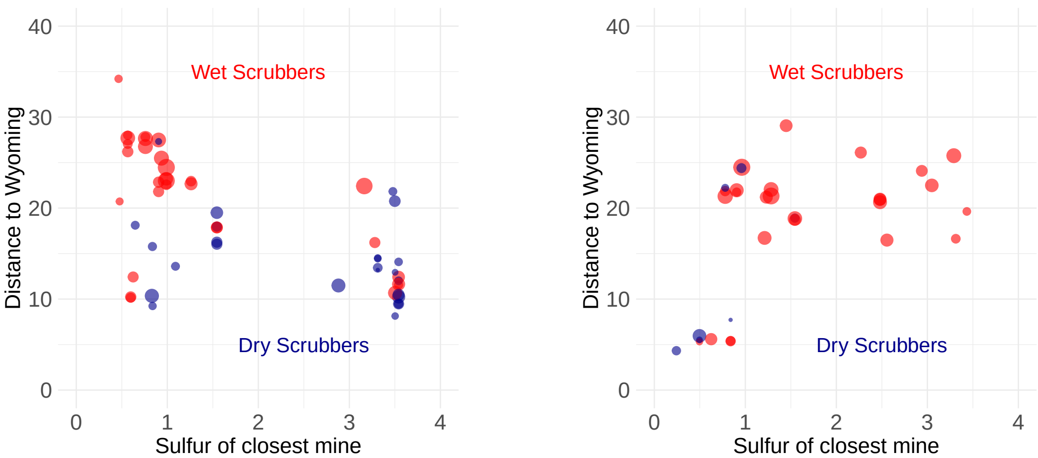
Starting from the first finding, a regulator that does not care about local mines $\alpha_1 = 0$ is to approve a scrubber if the following two conditions are met for some $\omega \in \{h, l\}$:

$$\begin{aligned} \frac{1}{1-\beta} \cdot \widehat{W}(\omega) &\geq -\Gamma_0 \\ \widehat{W}(\omega) &\geq \widehat{W}(0). \end{aligned} \tag{16}$$

The threshold conditions in Equation (16) become less stringent for regulators that do care about the local mines $\alpha_1 > 0$:

$$\begin{aligned} \frac{1}{1-\beta} \cdot \widehat{W}(\omega) + \frac{1}{1-\beta} \cdot \widehat{R}(\omega) &\geq -\Gamma_0 \\ \widehat{W}(\omega) + \alpha_1 \underbrace{\left(\widehat{R}(\omega) - \widehat{R}(0)\right)}_{>0} &\geq \widehat{W}(0). \end{aligned} \tag{17}$$

Figure 7: Scrubber adoption in the 2008-2019 period by regulated plants.



(a) No-mining states

(b) Mining states

Each dot represents a plant that installed a scrubber in the 2008-2019 period. Dot size represents plant size, in MW. Sulfur of closest mine is measured in % weight. Distance to Wyoming is euclidean.

Hence, regulators that care about protecting the revenue of the local mines are more likely to approve scrubbers in the first place.

Let us next study which type of scrubbers the regulators may prefer, depending on their utility function. Starting from the $\alpha_1 = 0$ case, this regulator will choose a wet scrubber over a dry one if the following condition is satisfied:

$$\widehat{W}(h) \geq \widehat{W}(l). \tag{18}$$

Regarding regulators that aim to protect local mines, the previous inequality is tilted in favour of the wet scrubber option:

$$\widehat{W}(h) + \alpha_1 \cdot \left(\widehat{R}(h) - \widehat{R}(l)\right) \geq \widehat{W}(l). \tag{19}$$

Thirdly, the static setup also allows me to study how the scrubber investment and plant closure decisions are intertwined. More specifically, regulators become less likely to retire coal power plants that have already undergone scrubber investments. Hence, scrubber over-investment not only inefficient by itself, but also forces states to stick to stranded assets intead of replacing them at due time. Take, for instance, a representative plant that already had a scrubber installed at the first period $\omega_{t=0} \in \{h, l\}$. The decision over this plant is going to be determined by the rule in Equation (15). According to such equation, the plant is to remain open if the following condition is satisfied:

$$\frac{1}{1-\beta} \cdot \widehat{U}(\omega \in \{h, l\}) \quad \geq \quad -\Gamma. \tag{20}$$

Still, the previous restriction is compatible with the following conditions, which would have triggered plant closure in the hypothetical case that the plant had no scrubber in the first place $\omega_{t=0} = 0$:

$$-\Gamma_0 \quad \geq \quad \underbrace{\frac{1}{1-\beta} \cdot \widehat{U}(\omega = 0)}_{Remain\ without\ scrubber\ \omega=0} \quad \geq \quad \underbrace{\frac{1}{1-\beta} \cdot \widehat{U}(\omega \in \{h, l\})}_{Remain\ with\ scrubber\ \omega \in \{h,l\}} \tag{21}$$

In case the Equations (20) and (21) hold simultaneously, the coal plant is a stranded asset: had the plant no scrubber in the first place, it would rather close it. Still, as the scrubber investment is already made, it is better to keep it open rather than closing it down.

5.2.2 The Dynamic Discrete-Choice Case

The second case of the generic regulator problem tackles the tractability problem by imposing $\pi_t = 0$ for all t periods, while allowing for a time-changing μ_t. Recall that, in the case of constant natural gas prices, postponing the scrubber investment was a sub-optimal decision. In contrast, under uncertain natural gas prices, delaying the investment may be the optimal choice, as it provides an option value to be executed in the next period. Hence, the per-period fixed cost expression for the dynamic model is slightly different to that of the static case:

$$f_t = f(\omega_t) = \begin{cases} \frac{1-\beta}{\beta} \cdot F_\omega & \omega_t = \{h, l\} \\ 0 & \omega_t = 0. \end{cases} \tag{22}$$

Under the previous two assumptions, the per-period regulated price $p_t^*(\mu_t, \omega_t)$ and coal plant output $q_t^*(\mu_t, \omega_t)$ are determined in equilibrium by the following system of equations:

$$\begin{aligned} p^*(\mu_t, \omega_t) &= \bar{c}_t(\omega_t) + \frac{f(\omega_t)}{q^*(\mu_t, p^*(\mu_t, \omega_t))} \\ q^*(\mu_t, \omega_t) &= 1 - \Phi(p^*(\mu_t, \omega_t)|\mu_t) \end{aligned} \tag{23}$$

Analogous to Equation (12), the equilibrium price and quantity ultimately determine the per-period welfare contribution $\widetilde{W}(\mu_t, \omega_t)$ and local mine revenue $\widetilde{R}_t(\mu_t, \omega_t)$. These two objects, in turn, pin down the regulator utility function $\widetilde{U}_t(\mu_t, \omega_t)$. Note that the, as it was the case in the static setup, the regulated price has been replaced as an argument in the ultimate regulator utility function. This result is essential for the empirical estimation of the model, as plant-level regulated prices $p^*(\mu_t, \omega_t)$ are not observed in the data.

$$\begin{aligned} \widetilde{W}(\omega_t|\mu_t) &= \int_{p_t^*(\mu_t, \omega_t)}^{\infty} (p^{gas} - \bar{c}_t(\omega_t)) \cdot \phi(p^{gas}|\mu_t) \cdot dp^{gas} - f_t \\ \widetilde{R}(\omega_t|\mu_t) &= q_t^*(\mu_t, \omega_t) \cdot \rho(\omega_t) \cdot c_m \\ \widetilde{U}(\omega_t|\mu_t) &= \widetilde{W}(\omega_t|\mu_t) + \alpha_1 \cdot \widetilde{R}(\omega_t|\mu_t). \end{aligned} \tag{24}$$

Regarding the construction period of scrubbers, the model assumes that it takes a period to install the device, regardless of the scrubber type. Hence, although the regulator may decide to invest in a scrubber in period t, the utility gains of such investment start to materialize at period $t+1$ and onward. Ultimately, the regulator investment decision over a plan with no scrubber $\omega_t = \omega_o$ is represented by the following Bellman equation

$$V(\omega = 0|\mu_t) = \max \left\{ \max_{\omega_t \in \{h,l,0\}} \{\widetilde{U}(0|\mu_t) + \beta E[V(\omega_t|\mu_t)]\}, \quad \widetilde{U}(0|\mu_t) + \beta \cdot \Gamma_0 \right\} \tag{25}$$

If the coal plant already has a dry scrubber, $\omega_t = \omega_l$, the regulator choice set is constrained to either keeping the plant open or closing it down

$$V(\omega = l|\mu_t) = \max \left\{ \widetilde{U}(l|\mu_t) + \beta E[V(l|\mu_t)], \quad \widetilde{U}(l|\mu_t) + \beta \cdot \Gamma \right\} \tag{26}$$

Equivalently, coal plants with wet scrubbers $\omega_t = h$ may remain open or close down. Similar to the scrubber construction, the model assumes that it takes one period to dismantle the plant. Hence, if the regulator decides to close the plant at time t, such closure is realized at $t+1$.

$$V(\omega = h|\mu_t) = \max\left\{\widetilde{U}(h|\mu_t) + \beta E\left[V(h|\mu_t)\right], \quad \widetilde{U}(h|\mu_t) + \beta \cdot \Gamma\right\} \tag{27}$$

5.3 Empirical predictions

The model introduced in the previous subsections provides several predictions on local coal procurement, coal blend unit costs, plant dispatch and scrubber fixed costs. This subsection tests the validity of such predictions through several reduced-form exercises.

5.3.1 Scrubbers and Local Coal Share

Equation (3) provides two testable predictions on local coal procurement: On the one hand, whether high-sulfur local coal reduces such share $\frac{\partial \rho^*(\omega)}{\partial s_m} < 0$. On the other hand, whether wet scrubbers increase the share of coal procured locally: $\rho^*(\omega_t = h) > \rho^*(\omega_t = l)$.

The Regressions in (28) outline the main specification of the test. Subscripts i and t indicate the coal plant and the year of the observation, respectively. The dependent variable $\rho_{it} \in [0,1]$ represents the share of coal that the plant bought to mines from its same state at the corresponding year. Regarding the regression covariates, d_i^m represents the distance between plant i and the closest mine location m, while s_i^m correspond to the sulfur concentration of such mine location. Lastly, h_{it} and l_{it} are indicators for wet and dry scrubbers, respectively.

$$\begin{aligned}
\rho_{it} =& \alpha + \beta_1 \cdot d_i^m + \beta_2 \cdot s_i^m + \beta_3 \cdot d_i^m \times s_i^m + \beta_4 \cdot h_{it} \times d_i^m + \beta_5 \cdot h_{it} \times s_i^m + \beta_6 \cdot h_{it} \times d_i^m \times s_i^m + \epsilon_{it} \\
\rho_{it} =& \alpha + \beta_1 \cdot d_i^m + \beta_2 \cdot s_i^m + \beta_3 \cdot d_i^m \times s_i^m + \beta_4 \cdot l_{it} \times d_i^m + \beta_5 \cdot l_{it} \times s_i^m + \beta_6 \cdot l_{it} \times d_i^m \times s_i^m + \epsilon_{it}
\end{aligned} \tag{28}$$

The decision of installing a scrubber is endogenous to the plant coal access, represented by covariates s_i^m and d_i^m. Plants nearby very high-sulfur locations, for instance, are expected to experience higher coal unit cost reductions from a wet scrubber and, hence, are also more likely to install it. I tackle this issue by estimating the aforementioned regressions in different subsamples. The first regression of (28), for instance, is only estimated using the subset of plants that installed a wet scrubber during the 2008-2019 period. Consequently, the parameter identification solely relies in the procurement behaviour change of this subset of plants. Equivalently, the second regression in (28) is estimated on the subset of plants that installed a dry scrubber. Lastly, both regressions are estimated using coal plants that belong to mining states, as the dependent variable ρ_{it} for non-mining states is always zero regardless of scrubber type.

Table 4 reports the estimated coefficients for the regressions in (28). Columns 1-3 correspond to the subset of coal plants that installed a dry scrubber in the 2008-2019 period. Equivalently, Columns 4-6 correspond to plants that installed a wet scrubber.

Table 4: The effect of scrubbers on local coal procurement.

	Dependent variable:					
	Share of Local Coal ρ_{it}					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.163***	0.550***	0.671***	0.279***	0.428***	0.964***
	(0.041)	(0.056)	(0.160)	(0.043)	(0.047)	(0.147)
Scrubber Indicator	0.137***	0.076*	0.088	0.234***	0.195***	−0.471***
	(0.047)	(0.044)	(0.169)	(0.045)	(0.042)	(0.150)
Distance to Closest Mine		−0.103***	−0.163**		−0.121***	−0.277***
		(0.016)	(0.074)		(0.009)	(0.078)
Closest Mine Sulfur		−0.122***	−0.176***		0.0001	−0.262***
		(0.017)	(0.065)		(0.011)	(0.064)
Distance × Sulfur			0.033			0.075
			(0.043)			(0.051)
Scrubbers × Distance			−0.034			0.283***
			(0.080)			(0.079)
Scrubbers × Closest Sulfur			−0.050			0.353***
			(0.072)			(0.066)
Scrubbers × Distance × Sulfur			0.039			−0.188***
			(0.046)			(0.053)
Installed scrubber type	Dry	Dry	Dry	Wet	Wet	Wet
Observations	443	443	443	1,144	1,144	1,144
R^2	0.019	0.180	0.213	0.023	0.158	0.236
Adjusted R^2	0.017	0.174	0.200	0.022	0.156	0.232

*p<0.1; **p<0.05; ***p<0.01

All coal plants, 2008-2019 period.

Coal mining states are: AL, AR, AZ, CO, IL, IN, KS, KY,

LA, MD, MO, MS, MT, ND, NM, OH, OK, TN, TX, UT, VA, WA, WV

The first model prediction stated that high-sulfur local coal translates into less in-state procurement. For this prediction to match the data, the regression coefficient β_2 in (28) is to be negative. The corresponding estimate in Table 4, labeled "Closest Mine Sulfur" is indeed negative and significant for all but for one specification.

The second model prediction stated that wet scrubbers should enable more local coal procurement than dry scrubbers. Starting from the specifications that correspond to dry scrubbers, reported in Columns 1-3 of Table 4, the effect of these devices on local coal procurement is weak. Unsurprisingly, longer distances to the closest mining location d_i^m and high-sulfur local coal s_i^m both decrease the share of coal bought in-state. Moreover, interacting these two variables with the dry scrubber indicator has no effect on the dependent variable.

Columns 4-6 report the specifications that correspond to plants that installed wet scrubbers. In line with the model prediction, The effect of wet scrubbers on local coal procurement is positive and significant (Columns 4 and 5). The interaction between the wet scrubber indicator with the local mine sulfur and distance variables, presented in Column 6, provides additional insights: wet scrubbers allow plants to procure from local mines that were not considering earlier, either because they were relatively far or featured high sulfur concentrations.

5.3.2 Scrubbers and Coal Blend Unit Cost

The model predicts that wet scrubbers enable the purchase of more local coal. A higher share of local coal, in turn, makes the coal blend more affordable. The regression in (29) aims to test this model prediction. The dependent variable $\bar{c}_{it}$ represents the coal blend cost for plant i at year t, in cent/MMBtu units. Covariates h_{it}, d_i^m and s_i^m represent high scrubber indicator, the distance to the closest mine and the sulfur concentration of the closest mine, respectively. Lastly, this regression also incorporates the distance between plant i and Wyoming mines, denoted d_i^{wy}. In order to tame the sample selection concerns discussed in 5.3.1, the regression in (29) is estimated separately on plants that installed either a dry or a wet scrubber in the 2008-2019 period.

$$\begin{aligned}\bar{c}_{it} =& \alpha + \beta_4 \cdot h_{it} + \beta_1 \cdot d_i^m + \beta_2 \cdot s_i^m + \beta_3 \cdot d_i^{wy} + \beta_4 \cdot (d_i^{wy})^2 + \beta_5 \cdot d_i^m \times s_i^m + \\ & \beta_6 \cdot h_{it} \times d_i^m + \beta_7 \cdot h_{it} \times s_i^m + \beta_8 \cdot h_{it} \times d_i^{wy} + \beta_9 \cdot h_{it} \times (d_i^{wy})^2 + \beta_{10} \cdot h_{it} \times d_i^m \times s_i^m + \epsilon_{it}\end{aligned} \tag{29}$$

Table 5 reports the regression results for coal blend unit costs. Note, firstly, that larger distances to both the closest mine and Wyoming mines translate into higher coal blend unit costs. These results are coherent with the fact that coal entails significant transport costs. Columns 1-3 estimate the specification on the plant sample that installed dry scrubbers in the period. According to the regression estimates, installing dry scrubbers does not translate into significant reductions of coal blend unit costs, as the estimates of "Scrubbers × Closest Distance" and "Scrubbers × Dist. to Wyoming" are non-negative. Columns 4-6 repeat the regression in (29) for the subset of plants that installed a wet scrubber. In this case, the estimate "Scrubbers × Dist. to Wyoming" is indeed negative and significant. This means that plants furthest from Wyoming are most to gain with wet scrubber installation, at this device enables them to replace remote Wyoming coal with local coal.

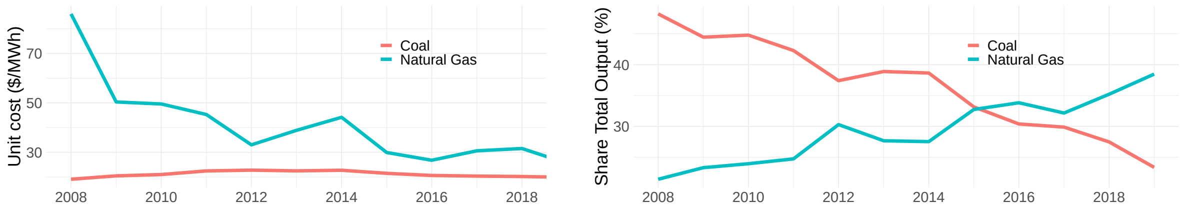
Table 5: The effect of scrubbers on coal blend unit cost.

	Dependent variable:					
	Coal blend unit cost $\bar{c}_{it}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	197.285***	92.918***	133.961***	261.291***	160.375***	71.488**
	(5.786)	(6.459)	(18.205)	(7.529)	(9.989)	(31.188)
Scrubber Indicator	5.442	14.677***	−28.859	−10.520	−9.048	89.664***
	(6.762)	(4.201)	(18.956)	(7.880)	(5.771)	(32.616)
Distance to Closest Mine		3.482***	3.180		3.079***	31.880***
		(1.014)	(3.640)		(0.972)	(8.236)
Closest Mine Sulfur		−8.577***	3.950		−27.031***	−26.858***
		(1.754)	(5.912)		(1.794)	(7.787)
Distance to Wyoming		8.482***	0.252		8.717***	19.506***
		(1.041)	(3.086)		(1.231)	(3.676)
Distance to Wyoming, squared		−0.021	0.257**		−0.062*	−0.418***
		(0.034)	(0.106)		(0.036)	(0.114)
Closest Distance × Sulfur			−2.612*			−8.786**
			(1.567)			(3.652)
Scrubbers × Closest Distance			1.344			−34.080***
			(4.181)			(8.452)
Scrubbers × Closest Sulfur			−16.405**			−2.738
			(7.101)			(8.129)
Scrubbers × Dist. to Wyoming			8.988***			−11.844***
			(3.320)			(3.903)
Scrubbers × Dist. to Wyoming, squared			−0.306***			0.397***
			(0.113)			(0.120)
Scrubbers × Closest Distance × Sulfur			3.210*			11.622***
			(1.851)			(3.781)
Installed scrubber type	Dry	Dry	Dry	Wet	Wet	Wet
Observations	702	684	684	1,344	1,301	1,301
R^2	0.001	0.626	0.638	0.001	0.473	0.484
Adjusted R^2	−0.001	0.623	0.632	0.001	0.471	0.480

*p<0.1; **p<0.05; ***p<0.01

All coal plants, 2008-2019 period.

Figure 8: Coal and natural gas in the US



(a) Unit Cost of electricity

(b) Share of total electricity output

5.3.3 Natural Gas and Coal Plant Dispatch

This subsection explores the effect of natural gas prices on coal plant dispatch. In line with the suggestive evidence displayed at Figure 8, my model predicts a negative correlation between these two variables $\frac{\partial q(\omega_t|\mu_t)}{\partial \mu_t} \leq 0$. Equation (30) introduces the specification for this test.

$$Q_{it} = \alpha + \beta_1 \cdot \mu_{st} + \beta_2 \cdot Age_{it} + \beta_3 \cdot Size_{it} + \beta_4 \cdot HR_i + \beta_5 \cdot h_{it} + \beta_6 \cdot X_i + \beta_7 \cdot h_{it} \times X_i + \epsilon_{it}. \tag{30}$$

The dependent variable of the specification $Q_{it} \in [0, 8760]$ represents the number of hours that plant i operated on year t. This variable slightly differs from its model equivalent $q_{it} \in [0, 1]$, as the latter stands for the share of hours that the coal plant i operates in year t instead. Regarding the regression covariates, μ_{it} is the average cost of producing one output unit of natural gas in state s and year t, measured in \$ cents per MWh. HR_i is the heat rate of the plant, this is the amount of input the plant needs to produce one unit of output. Heat rate is measured in Btu/MWh and is the inverse of productivity. Next, X_i is a vector that includes the time-invariant covariates d_i^m, s_i^m and d_i^{wy}. Lastly, h_{it} represents the wet scrubber indicator. As in previous exercises, the regression in (30) is estimated separately for plants that installed dry and wet scrubbers.

Table 6 presents the estimations of Equation (30) specification. Columns 1-3 correspond to generators that installed dry scrubbers, while Columns 4-6 report the regression results for generators that installed wet scrubbers. As expected, more expensive natural gas translates into more coal generator active hours. Plant age and heat rate, to the contrary, correlate with less dispatch.

5.3.4 Scrubber Fixed Cost

In the model, the tradeoffs between dry and wet scrubbers rely on the fact that the former are cheaper than the latter. The specification in (31) tests whether this assumption is valid. In this regression, the dependent variable F_{jt} represents the fixed cost of scrubber j, installed at plant i at period t. h_{jt} is an indicator for wet scrubbers and $Size_{it}$ represents the size of the plant that got the scrubber, measured in MW.

$$F_{jit} = \alpha + \beta_1 \cdot h_{jt} + \beta_2 \cdot h_{it} \times Size_{it} + \epsilon_{it}. \tag{31}$$

Table 6: Coal plant dispatch

	Dependent variable:					
	Number of active hours per year Q_{it}					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	6,492.710***	10,091.550***	9,872.666***	7,809.374***	10,471.750***	10,154.180***
	(685.458)	(634.330)	(647.005)	(423.555)	(414.862)	(436.881)
Natural gas cost (cent/MWh)	0.189***	0.231***	0.222***	0.154***	0.187***	0.186***
	(0.025)	(0.023)	(0.022)	(0.014)	(0.013)	(0.013)
Plant Age	−22.569***	−6.288*	−6.763**	−49.987***	−35.786***	−36.522***
	(3.806)	(3.370)	(3.346)	(2.661)	(2.578)	(2.587)
Plant Size (MW)	1.778***	1.644***	1.501***	0.534***	0.643***	0.625***
	(0.274)	(0.244)	(0.244)	(0.127)	(0.118)	(0.118)
Heat Rate (Btu/KWh)	−0.054	−0.364***	−0.364***	−0.022	−0.221***	−0.218***
	(0.060)	(0.054)	(0.054)	(0.034)	(0.033)	(0.033)
Scrubber Indicator	−82.658	−136.703	330.408	−115.805*	−34.753	366.443*
	(116.236)	(103.864)	(258.596)	(69.752)	(64.936)	(200.579)
Closest Mine Distance		217.875***	244.646***		100.937***	255.496***
		(39.449)	(51.330)		(26.669)	(48.818)
Closest Mine Sulfur		309.490***	307.439***		310.628***	385.704***
		(69.793)	(91.653)		(32.218)	(64.879)
Wyoming Distance		−129.004***	−103.052***		−103.837***	−99.502***
		(6.077)	(8.945)		(4.294)	(7.458)
Closest Distance × Sulfur		−83.723***	−106.434***		−51.983***	−108.866***
		(19.834)	(25.672)		(15.022)	(28.271)
Scrubber × Closest Dist.			−34.142			−214.364***
			(78.086)			(57.683)
Scrubber × Closest Sulfur			44.461			−104.461
			(132.442)			(74.821)
Scrubber × Wyoming Dist.			−48.375***			−3.459
			(11.858)			(8.720)
Scrubber × Closest Distance × Sulfur			44.920			80.560**
			(38.356)			(33.356)
Installed scrubber type	Dry	Dry	Dry	Wet	Wet	Wet
Observations	1,259	1,259	1,259	4,295	4,295	4,295
R^2	0.140	0.369	0.382	0.172	0.287	0.290
Adjusted R^2	0.136	0.365	0.376	0.171	0.286	0.288

*p<0.1; **p<0.05; ***p<0.01

Regulated plants, 2008-2019 period.

Table 7 reports the regression estimates of (31). As expected, the wet scrubber indicator is positive and significant throughout the different versions of the specification. Moreover, the coefficient for plant size is also positive, indicating that the fixed cost is increasing in plant size. Lastly, the negative coefficient for the wet scrubber and plant size interaction suggests a concave fixed cost function for wet scrubbers.

Table 7: The fixed cost of dry and wet scrubbers

	Dependent variable:		
	Scrubber fixed cost (million dollars)		
	(1)	(2)	(3)
Intercept	118.398***	96.072***	54.408**
	(15.743)	(17.843)	(25.798)
Wet Scrubber Indicator	81.613***	56.137***	116.842***
	(19.086)	(21.333)	(34.582)
Plant size (MW)		0.030**	0.085***
		(0.012)	(0.028)
Wet × Plant Size			−0.067**
			(0.030)
Observations	219	219	219
R^2	0.078	0.105	0.125
Adjusted R^2	0.073	0.096	0.112

*p<0.1; **p<0.05; ***p<0.01

All scrubber installation 2008-2019.

6 Estimation

This section explains the procedure to estimate the model described in Subsection 5.2.2 with the regulator utility function from Equation (24). The section starts by presenting the generic estimation problem. It next devotes one subsection to each of the two estimation challenges: the aggregate state space estimation and the value imputation. Lastly, the third subsection outlines the estimation algorithm. The estimation results are presented in section 7.

6.1 Empirical Model

The Model in section 5 focuses on a unique coal generator.The empirical model takes into account the heterogeneity of each generator i in the following time-invariant, observed dimensions: Opening year OY_i, size K_i, heat rate HR_i and location, summarized in vector X_i.[23] All the variables listed above are gathered in the covariate vector $\chi_i = (OY_i, K_i, HR_i, X_i)$. Thus, the empirical version of the regulator utility function from Equation (24) accommodates generator heterogeneity as follows:

$$U(\omega_{it}|\chi_i, \Omega_{it}) = W(\omega_{it}|\chi_i, \Omega_{it}) + \alpha_1 \cdot R(\omega_{it}|\chi_i, \Omega_{it}), \tag{32}$$

where $\Omega_{it} = \{\mu_{st}\}$ is the aggregate state comprised of the natural gas price μ_{st} at US state s and year t. Note that, the regulator utility expression from (32) depends on welfare $W(\omega_{it}|\chi_i, \Omega_{it})$ and local coal revenue $R(\omega_{it}|\chi_i, \Omega_{it})$. Subsection 6.3 explains how these two elements are approximated.

On top of the vector of observed covariates χ_i, the model also introduces unobserved heterogeneity across generators. This unobserved shocks follow the literature: at each period t and for each generator i, the regulator observes an eight-element vector ϵ_{it} of iid extreme value type 1 shocks ϵ_{it}, with one element for each transition: $\epsilon_{it} = \{\epsilon_{it}^{oo}, \epsilon_{it}^{ol}, \epsilon_{it}^{oh}, \epsilon_{it}^{ox}, \epsilon_{it}^{ll}, \epsilon_{it}^{lx}, \epsilon_{it}^{hh}, \epsilon_{it}^{hx}\}$. The model establishes a total of eight possible transitions. Generators with no scrubber have four options: remain without scrubber oo, invest in low-efficiency scrubber ol, invest in high-efficiency scrubber oh and exit ox. Generators with a low-efficiency scrubber have to options: remain ll or exit lx. Finally, generators with high-efficiency scrubbers also feature two options: remain hh or exit hx. The model also incorporates a scale parameter σ that tunes the dimension of the ϵ_{it} shock.

Adding both the observed and unobserved generator heterogeneity to the original Bellman expression for plants with no scrubbers, equation (25) transforms into the following expression:

$$\begin{aligned} V\left(\omega = 0|\chi_i, \Omega_{it}\right) = \max\{ \max_{\omega_{t+1} \in \{h,l,0\}} & \{U(0|\chi_i, \Omega_{it}) + \beta E\left[V\left(\omega_{t+1}|\chi_i, \Omega_{it}\right)\right] + \sigma \cdot \epsilon_{it}^{o\omega_{t+1}}\}, \\ & U(0|\chi_i, \Omega_{it}) + \sigma \cdot \epsilon_{it}^{ox} + \beta \cdot \Gamma_0\}. \end{aligned} \tag{33}$$

Regarding plants with either dry or wet scrubbers $\omega \in \{h, l\}$, their corresponding original Bellman Equations (26) and (27) transform into the following expression:

$$\begin{aligned} V\left(\omega|\chi_i, \Omega_{it}\right) = \max\{& U(\omega|\chi_i, \Omega_{it}) + \beta E\left[V\left(\omega|\chi_i, \Omega_{it}\right)\right] + \sigma \cdot \epsilon_{it}^{\omega\omega}, \\ & U(\omega|\chi_i, \Omega_{it}) + \sigma \cdot \epsilon_{it}^{\omega x} + \beta \cdot \Gamma\}. \end{aligned} \tag{34}$$

6.2 Aggregate State Space Estimation

This section tackles the estimation of the aggregate state space $\Omega_{it} = \{\mu_{st}\}$ and its law of motion. This model follows the procedure in Gowrisankaran et al. [2022] and discretizes the natural gas price continuous variable μ_{st} into discrete bins. The model further assumes that the discretized aggregate state space follows a Markov chain and, hence, estimates the transition probability matrix for the discretized space. This section provides a comprehensive intuition of the procedures employed, more details are available in Appendix G.1.

For each generator i period t pair, the aggregate state Ω_{it} consists of one variable: the price of natural gas μ_{st}. This variable is directly retrieved from the data and is computed at the US state s and year t level,

[23] Recall that X_i is comprised of three variables: closest mine distance, closest mine sulfur and distance to Wyoming.

which means that all the coal generators belonging to the same state s also face the same natural gas price at any period t. Next, continuous variable μ_{it} is discretized into equal size $B = 20$ bins.

The computational model solver relies on the aggregate-state discrete bins. This limitation requires that the two aggregate state variable μ_{st} to be recalculated at the bin level, yielding μ_b. For a given bin b, I take the subsample of aggregate state observations that belong to it, denoted Ω_{it}^b. Next, I compute mean natural gas price μ_b for each subsample, yielding a characterisation of each bin b:

$$\Omega_b = \{\mu_b\}.$$

I next proceed to compute the aggregate state transition matrix T. Aggregate state transition matrix T is a $B \times B$ transition matrix, and $T_{b,b'}$ refers to row b, column b' element of the matrix. Each row of the matrix corresponds to an aggregate state bin b. Matrix element $T_{b,b'}$ represents the likelihood of "arriving" to such bin b while coming from bin b' in the previous period.

6.3 Value Imputation

The regulator utility function in (32) is comprised of two elements: consumer welfare $W(\omega|\chi_i, \Omega_b)$ and local mine revenue $R(\omega|\chi_i, \Omega_b)$. The estimation of the model requires to impute values of these two components, for all i generators, b aggregate state bins and all scrubber types $\omega \in \{h, l, 0\}$. Observational data only provides a subset of all the feasible combinations. Take, for instance, a generator that installs a dry scrubber on 2015 and remains open until the last period. I do not observe the welfare contribution of such a plant had it installed a wet scrubber instead and, hence, this value needs to be imputed. For illustrative purposes, this section focuses on the imputation procedure for welfare $W(\omega|\chi_i, \Omega_b)$. The reader can find an exhaustive explanation of the imputation procedure at Appendix Section G.2.

The consumer welfare contribution expression in (24) is empirically approximated by the following expression

$$W(\omega|\chi_i, \Omega_b) = K_i \cdot Q(\omega|\chi_i, \Omega_b) \cdot (\mu_b - \bar{c}(\omega|X_i) \cdot HR_i).$$

The power plant nameplate capacity K_i, heat rate HR_i and natural gas cost centering parameter μ_b are observed. Coal generator active hours $Q(\omega|\chi_i, \Omega_b)$ and unit costs $\bar{c}(\omega|X_i)$, in contrast, need to be imputed.

Plant active hours are approximated using the empirical specification (30). More specifically, I use the significant point estimates of column 3 to estimate and 6 of Table 6 to predict the active hours for each generator i, aggregate state bin b and scrubber type ω combination. The active hours of a generator without scrubber are approximated using Column 3 estimates and setting the dry scrubber indicator to zero. In case that the predicted active hour figure falls outside the feasible value range $[0, 8760]$, such prediction is truncated. Unit costs of coal $\bar{c}(X_i, \omega)$ are imputed using an analogous procedure that employs the regression estimates in Table 5.

Natural gas cost centering parameter μ_b is also observed, which allows the simulation of 10,000 draws of natural gas prices within the year.[24] I next select the sample of natural gas price draws above $overlinec(\omega|X_i) \cdot HR_i$. I estimate the gas-to-coal price difference for this subset and compute the mean, which ultimately represents the markup $(\mu_b - \bar{c}(\omega|X_i) \cdot HR_i)$.

The resulting imputed vectors $\{Q_{ib\omega}\}$ and $\{\bar{c}_{ib\omega}\}$, allow to compute a complete vector of welfare contributions $\{W_{ib\omega}\}$. Repeating an equivalent procedure for both $\rho(\omega|X_i)$ and $c_m(\omega|X_i)$ allows to recover local coal revenues $\{R_{ib\omega}\}$. Moving forward, $\{W_{ib\omega}\}$ and $\{R_{ib\omega}\}$ are key inputs in the estimation procedure of Subsection 6.4.

Regarding the plant exit, the model parametrises closure transfers Γ_0 and Γ as a function of plant age OY_i and size K_i, weighted by structural parameters γ_2, γ_3. Moreover, the model allows for different intercepts depending on whether the plant has a scrubber:

$$\begin{aligned}\Gamma_0(\gamma|\chi_i) &= \gamma_1 + \gamma_2 \cdot OY_i + \gamma_3 \cdot K_i \\ \Gamma(\gamma|\chi_i) &= \gamma_2 \cdot OY_i + \gamma_3 \cdot K_i.\end{aligned} \tag{35}$$

Ultimately, the vector of structural parameters corresponding to closure transfers is defined as $\gamma = \{\gamma_1, \gamma_2, \gamma_3, \}$.

Lastly, the fixed cost of the scrubber F_ω for each generator i and scrubber type ω is approximated using the regressions in Table 7. Moreover, I incorporate an additional ϕ parameter to the dry scrubber fixed cost in order to capture expenses related to this type of scrubber.[25]

6.4 Estimation Algorithm

This subsection reviews the estimation procedure for retrieving the structural parameters of the model. Appendix G provides more details. The estimation procedure consists of two loops: an inner loop and an outer loop. The outer loop is initialized by defining a vector of candidate structural parameters θ^0. These candidate parameters are an input for estimating regulator utilities. Next, the inner loop consists on iterating the Bellman equations to obtain value function estimates. Once the inner loop procedure concludes, the resulting value functions are employed to compute the conditional choice probabilities for each of the transitions in the model. The log-likelihood function next compares the estimated conditional choice probabilities with the actual transitions observed in the data. Lastly, the discrepancy of the log-likelihood function provides a new set of candidate structural parameters, restarting the outer loop again.

The estimation procedure starts with defining some initial candidate parameters θ':

$$\theta^0 = \{\alpha^0, \phi^0, \gamma^0, \sigma^0\},$$

where $\alpha^0 = \{\alpha_1^0\}$ represents the weight of coal revenue in the regulator the utility function (Equation (32)). ϕ represents the unobserved fixed costs related to dry scrubbers and $\gamma^0 = \{\gamma_1^0, \gamma_2^0, \gamma_3^0\}$ encompasses the closure

[24]The simulation assumes a normal distribution of natural gas prices with a standard deviation of 6559 cent/MWh, consistent with the data.

[25]Installation of dry scrubbers may require de adoption of new coal stockpile management systems, as this article explains.

transfer parameters from (35). Combining the α_1 weight with the vectors of imputed values $\{W_{ib\omega}, R_{ib\omega}\}$ I obtain the corresponding vector of regulator per period utilities $U_{ib\omega}$. I next define matrixes

$$\underset{I\times B}{U^0}, \qquad \underset{I\times B}{U^l}, \qquad \underset{I\times B}{U^h},$$

which stack imputed utilities $U_{ib\omega}$, depending on the scrubber type $\omega \in \{h, l, 0\}$.

Next, I proceed with the inner loop of the algorithms, consisting on value function iteration. The iteration starts by initializing the integrated Value matrices to zero:

$$\underset{I\times B}{V^0} = 0 \qquad \underset{I\times B}{V^l} = 0 \qquad \underset{I\times B}{V^h} = 0$$

For generators without scrubbers $\omega = 0$, I compute four value functions, one for each of the four discrete choices:

$$\begin{aligned}
\underset{I\times B}{v^{00}} &= U^0 + \beta \cdot V^0 \times T' && \textit{Remaining without scurbber } \omega = 0\\
v^{0l} &= U^0 + \beta \cdot V^l \times T' && \textit{Investing in } \omega = l\\
v^{0h} &= U^0 + \beta \cdot V^h \times T' && \textit{Investing in } \omega = h\\
v^{0x} &= U^0 - \beta \cdot \Gamma_0(\gamma'|\chi_i) && \textit{Exiting without scurbber}
\end{aligned}$$

The value function for plants with scrubbers is analogous, but only entails two choices: remain or exit. For illustrative purposes, I next present the value function computation for a generator with a low-efficiency scrubber $\omega = l$.

$$\begin{aligned}
\underset{I\times B}{v^{ll}} &= U^l + \beta \cdot V^l \times T' && \textit{Remaining with scrubber } \omega = l\\
v^{lx} &= U^l - \beta \cdot \Gamma(\gamma'|\chi_i) && \textit{Exiting with scrubber } \omega = l
\end{aligned}$$

Next, the resulting value functions become an input for computing a new Emax Value function candidate. In the case of the Emax value function for generators with no scrubbers, the new candidate $V^{0'}$ is computed as

$$V^{0'} = \sigma \cdot ln\left[exp\left(\frac{v^{00}}{\sigma}\right) + exp\left(\frac{v^{0l}}{\sigma}\right) + exp\left(\frac{v^{0h}}{\sigma}\right) + exp\left(\frac{v^{0x}}{\sigma}\right)\right] + \sigma \cdot \gamma_{euler}$$

where γ_{euler} refers to the Euler constant.

The new integrated Value Function candidates $V^{0'}, V^{l'}, V^{h'}$, in turn, initialize the inner loop again, until the old and the new candidate converge. The value function iteration ultimately provides a vector of value functions. Each generator i, aggregate state bin b combination features eight value functions, one for each of the transitions that the model enables for:

$$\underbrace{v^{00}, v^{0l}, v^{0h}, v^{0x}}_{\omega=0}, \underbrace{v^{ll}, v^{lx}}_{\omega=l}, \underbrace{v^{hh}, v^{hx}}_{\omega=h}$$

Next, the value functions allow to compute the eight conditional choice probabilities. As an illustration, the following four conditional choice probabilities correspond to plants without scrubbers:

$$\underset{I\times G}{P^{00}} = \frac{exp\left(\frac{v^{00}}{\sigma}\right)}{exp\left(\frac{v^{00}}{\sigma}\right)+exp\left(\frac{v^{0l}}{\sigma}\right)+exp\left(\frac{v^{0h}}{\sigma}\right)+exp\left(\frac{v^{0x}}{\sigma}\right)} \qquad \textit{Probability of remaining without scrubber}$$

$$P^{0l} = \frac{exp\left(\frac{v^{0l}}{\sigma}\right)}{exp\left(\frac{v^{00}}{\sigma}\right)+exp\left(\frac{v^{0l}}{\sigma}\right)+exp\left(\frac{v^{0h}}{\sigma}\right)+exp\left(\frac{v^{0x}}{\sigma}\right)} \qquad \textit{Probability of investing in dry } \omega = l$$

$$P^{0h} = \frac{exp\left(\frac{v^{0h}}{\sigma}\right)}{exp\left(\frac{v^{00}}{\sigma}\right)+exp\left(\frac{v^{0l}}{\sigma}\right)+exp\left(\frac{v^{0h}}{\sigma}\right)+exp\left(\frac{v^{0x}}{\sigma}\right)} \qquad \textit{Probability of investing in wet } \omega = h$$

$$P^{0x} = \frac{exp\left(\frac{v^{0x}}{\sigma}\right)}{exp\left(\frac{v^{00}}{\sigma}\right)+exp\left(\frac{v^{0l}}{\sigma}\right)+exp\left(\frac{v^{0h}}{\sigma}\right)+exp\left(\frac{v^{0x}}{\sigma}\right)} \qquad \textit{Probability of Exiting}$$

Once the eight conditional choice probabilities are computed

$$\{P^{00}, P^{0l}, P^{0h}, P^{0x}, P^{ll}, P^{lx}, P^{hh}, P^{hx}\}$$

I test the discrepancy between such probabilities and the actual decisions observed in the data. The model contemplates eight possible transitions, each with its corresponding conditional choice probability. Computing the discrepancy between the model conditional choice probability and the actual decision first requires that the observed transition is determined. The decisions observed in the data are characterised by indicator functions. $\mathbb{1}\{\omega_{it} = 0\}$, for instance, is equal to one if generator i had no scrubber at time t. I use products of indicator functions to identify scrubber investment events. If, for instance, $\mathbb{1}\{\omega_{it} = 0\} \cdot \mathbb{1}\{\omega_{it+1} = h\} = 1$, it means that generator i got a wet scrubber $\omega = h$ installed at period t. Ultimately, the discrepancy $discrepancy_{it}$ between the model and the data, for generator i at period t, is computed as follows:

$$\begin{aligned} discrepancy_{it} = & \mathbb{1}\{\omega_{it} = 0\} \cdot \mathbb{1}\{\omega_{it+1} = 0\} \cdot P^{00}_{ig} + \\ & \mathbb{1}\{\omega_{it} = 0\} \cdot \mathbb{1}\{\omega_{it+1} = l\} \cdot P^{0l}_{ig} + \\ & \mathbb{1}\{\omega_{it} = 0\} \cdot \mathbb{1}\{\omega_{it+1} = h\} \cdot P^{0h}_{ig} + \\ & \mathbb{1}\{\omega_{it} = 0\} \cdot \mathbb{1}\{\omega_{it+1} = \emptyset\} \cdot P^{0x}_{ig} + \\ & \mathbb{1}\{\omega_{it} = l\} \cdot \mathbb{1}\{\omega_{it+1} = l\} \cdot P^{ll}_{ig} + \\ & \mathbb{1}\{\omega_{it} = l\} \cdot \mathbb{1}\{\omega_{it+1} = \emptyset\} \cdot P^{lx}_{ig} + \\ & \mathbb{1}\{\omega_{it} = h\} \cdot \mathbb{1}\{\omega_{it+1} = h\} \cdot P^{hh}_{ig} + \\ & \mathbb{1}\{\omega_{it} = h\} \cdot \mathbb{1}\{\omega_{it+1} = \emptyset\} \cdot P^{hx}_{ig} \end{aligned}$$

The ultimate Log-Likelihood function LL is minimized using a Nelder-Mead algorithm.

$$LL = \sum_{t}^{T}\sum_{i}^{I} log(discrepancy_{it}) \quad \leq \quad 0$$

7 Estimation Results and Model Fit

This section presents the parameter estimates obtained from the procedure described at Section 6.4. Recall that the model comprises six structural parameters: two regulator utility function parameters α, three scrap value

Table 8: Model Estimation Results. Estimated in regulated plants for the 2008-2019 period.

Parameter	Note	Point-estimates	Standard Errors
α_1	Coal Revenue R_{it}	0.65	0.29
ϕ	Dry Scrubber Fixed Cost	1339.75	1185.98
γ_1	Closure - no scrubber	4688.17	3358.14
γ_2	Closure - age	2.20	1.66
γ_3	Closure - size	13.59	1.01
σ	Scale Parameter	1050.55	741.19

parameters γ and the scale parameter σ. Table 8 presents the parameter point-estimates and standard errors. Point-estimates are obtained using the procedure described in 6.4. Standard errors are retrieved estimating the model over bootstrapped datasets. Appendix Section I describes this procedure in detail.

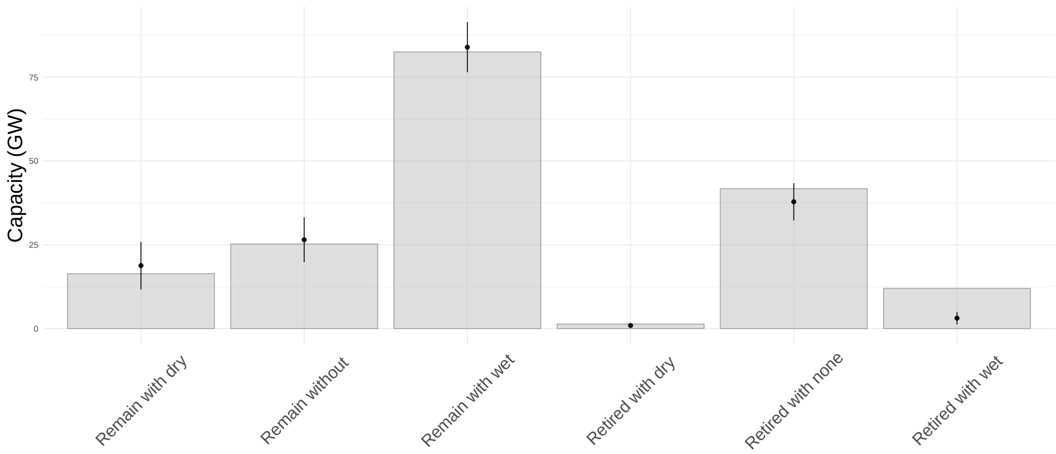
The identification of the model parameters heavily relies on plant location. In this regard, the model assumes that such a location was chosen without anticipating the future MATS sulfur regulation. This assumption is reasonable, as the US coal plants were built decades before the MATS approval. The introduction of this regulation acted as an exogenous "shock", and its impact was different depending on the plant location. The welfare gains of installing a wet scrubber, for instance, depend on the distance between the plant and Wyoming. Plants furthest from Wyoming are the most to gain from wet scrubber installation, as it allows to save significant freight costs from low-sulfur coal.

The identification of coal-mine revenue parameter α_1 relies on two sources of variation. On the one hand, the model assumes that regulators from states without mines do not care about local coal revenue. For this subset of generators, local coal revenue is truncated to zero $R_{it} = 0$. According to this assumption, regulators from no-mine states only install wet scrubbers if the consequent cost savings are significant. Coal-mine state regulators, in contrast, install wet scrubbers even when the cost savings are modest as long as such wet scrubbers help local mines. The second source of variation relies on the differences between coal-mine states, as mining states feature coal with very different sulfur concentrations. Colorado, for instance, extracts low-sulfur coal. Consequently, the consumption of local coal will remain high regardless of the scrubber type. Indiana, in contrast, features very high sulfur coal and, in this case, a high-efficiency wet scrubber to significantly benefit local mines.

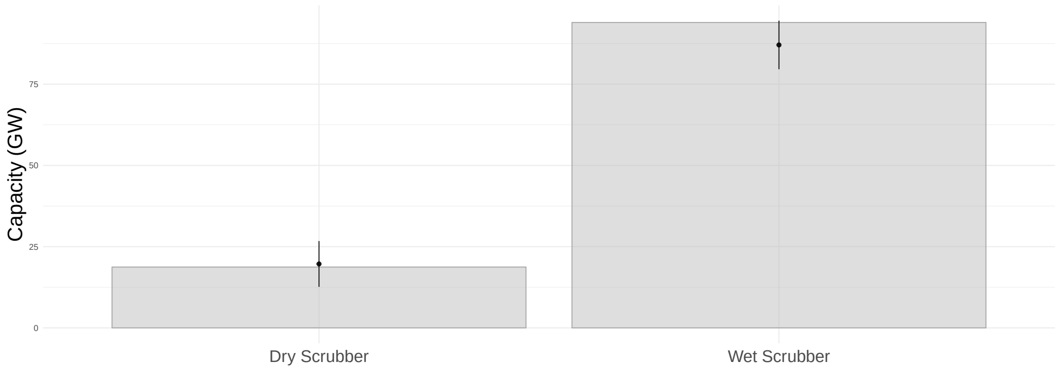
Parameter γ_1 represents the net payment that the regulator receives from the utility for closing down a generator with no scrubber, compared to an equivalent generator that has one. Note that the estimated parameter is positive, meaning that retiring a coal plant with no scrubber is less costly for the regulator. This parameter, thus, establishes a link between scrubber investment and energy transition delay. This result is in line with the stranded assets prediction presented in Subsection 5.2.1. Lastly, parameters γ_2 and γ_3 are also positive, meaning that older and bigger plants are less costly to retire.

The model's fit is tested by simulating coal plant behavior according to the original structural parameters. This simulation is repeated 50 times. At each repetition, The generator-level decisions are aggregated nationally and contrasted with the observed evolution. Figure 9 presents the results of the model fit exercise,

Figure 9: Model fit test, measured in generator capacity (GW)



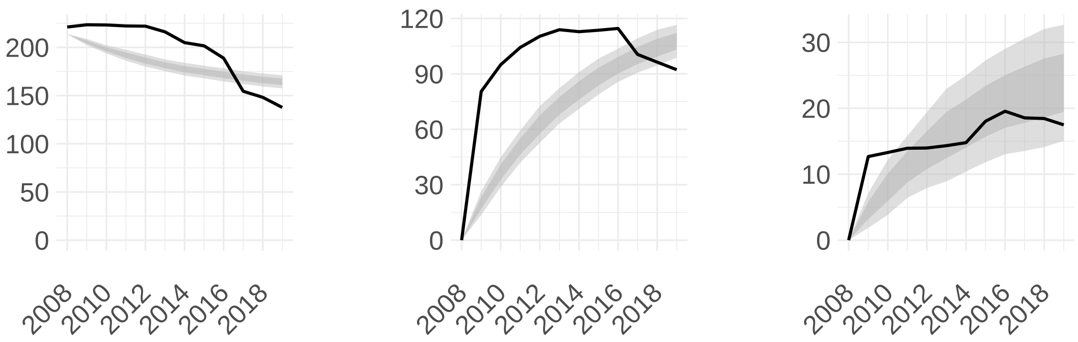
(a) Actual and predicted capacity by the end of the period (2019).



(b) Actual and predicted scrubber investment 2008-2019.

Gray bars represent actual behaviour of US regulated generators. Black points represent mean values obtained from simulating generator behaviour 50 times on original parameters. Confidence intervals around the black dots represents 2 s.d. obtained from the 50 simulations.

Figure 10: Actual and predicted regulated coal generator capacity, 2008-2019



(a) Total Capacity (GW) (b) Wet scrubber capacity (GW) (c) Dry scrubber capacity (GW)

Black line represents actual behaviour of US regulated generators. The gray confidence intervals represent simulated behaviour of regulated generators, obtained from 50 simulations. Light gray corresponds to 1 s.d. and light gray represents 2 s.d.

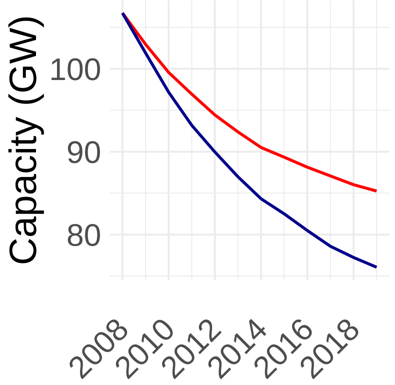
measured in generator capacity terms (GW).In these figures, gray bars represent actual regulated coal generator behavior. The black points represent the mean value for all simulations. The confidence intervals correspond to two standard deviations of the simulated behavior. Subfigure 9a classifies all the regulated coal generators into six groups, depending on their end-of-period situation. The model is able to mimic the behavior of the generators that remain open, regardless of their scrubber type (columns 1-3). Regarding generator retirement, the model also reproduces the exit of generators without scrubbers with accuracy. Lastly, the model performs the poorest in predicting the generator with scrubber exit. This fact is due to two reasons: On the one hand, the small sample of generators with scrubbers that close is small, and hence, the estimation of the structural parameters that govern this choice is noisy. In order to tame the small sample size concern, the scrap value of a generator with a scrubber is the same, regardless of scrubber type. This assumption fails to capture the fact that the retirement of generators with dry scrubbers is less likely than that of generators with wet scrubbers. Parameterizing the same payoff for the retirement of generators with scrubbers, regardless of scrubber type, ultimately leads to a non-optimal fit of the behavior of this subset of generators. Subfigure 9b reports cumulative scrubber investment in the 2008-2019 period. As with the previous graph, the gray bars correspond to actual dry and wet scrubber adoption, while black confidence intervals represent model accuracy.

I next test the period-by-period model fit, which is reported in Figure 10. In these figures, the solid black line represents the actual behavior of regulated generators, while the shaded area corresponds to the 50 generator behavior simulations. The dark gray interval represents one standard deviation, while the light gray band represents two standard deviations.

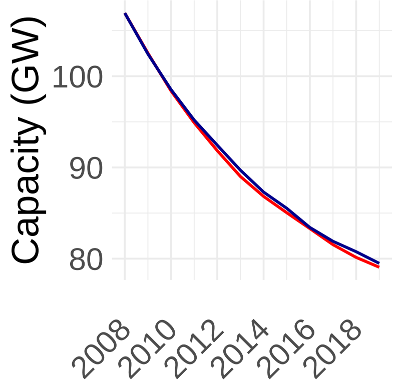
8 Counterfactuals

In this section, I employ model estimates of Section 6 to perform several counterfactual exercises. The first counterfactual exercise aims to estimate the US coal power capacity absent local coal protection by electricity regulators. I report this counterfactual exercise in Figure 11. The exercise starts by simulating the evolution of US regulated coal capacity under original model parameters 50 times, both in mining and no-mining states.

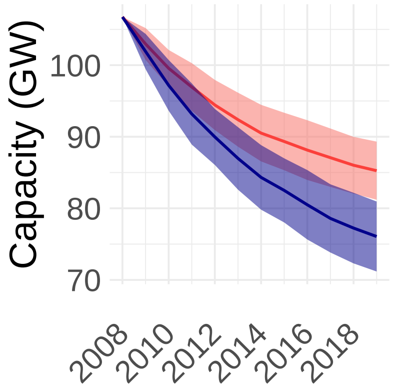
Figure 11: Regulated coal generator capacity, no local-mining protection counterfactual



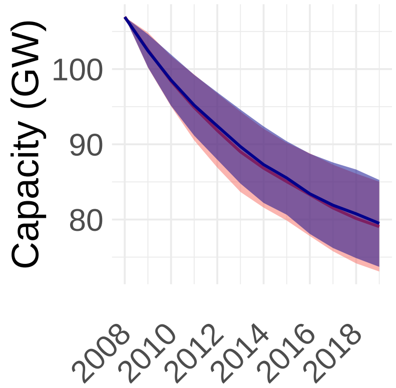
(a) Mining states, no confidence interval



(b) No-mining states, no confidence interval



(c) Mining states



(d) No-mining states

Red line represents regulated generator behaviour simulation with original parameters, computed as annual mean values of 50 simulations. Blue line represents regulated generator behaviour under $\alpha_1 = 0$. Confidence intervals represent 2 s.d., obtained from the 50 simulations.

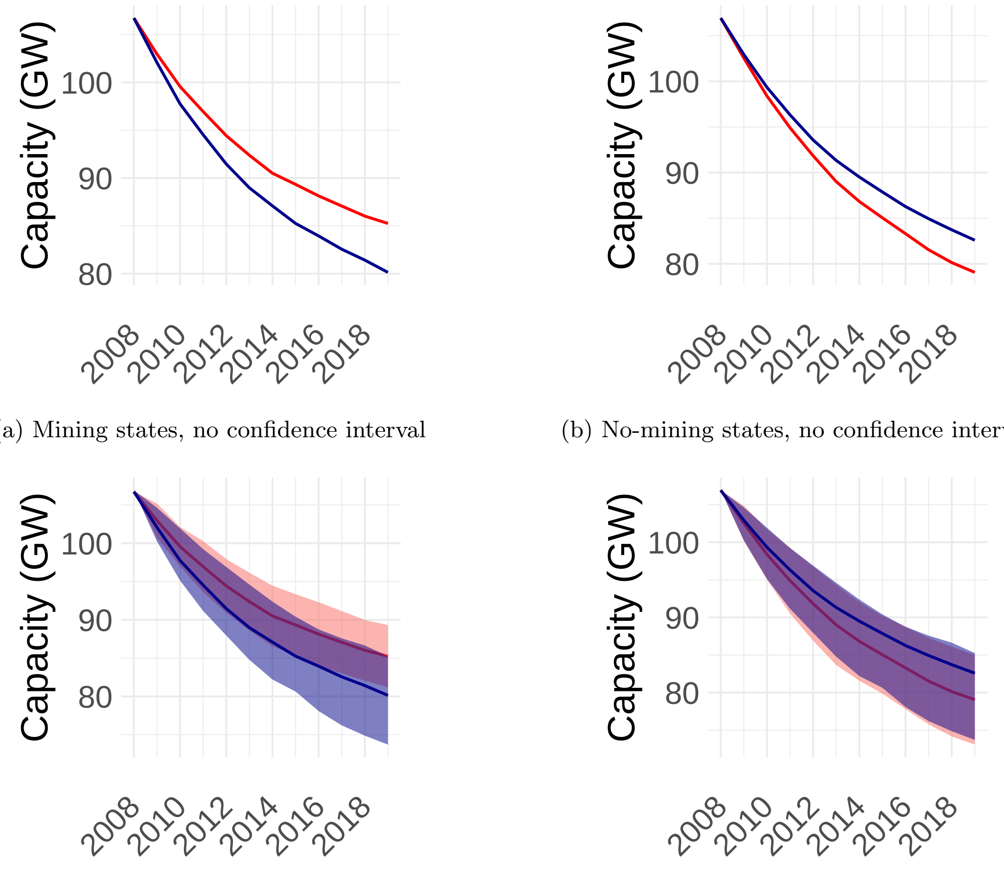
The red line plots annual mean values of the simulations, and the red area represents 2 standard deviation confidence intervals for the mean values. I next set the local coal protection parameter to zero $\alpha_1 = 0$ and perform another 50 simulations. The blue lines in Figure 11 represent the mean values of such simulations, with the corresponding confidence interval presented in shaded blue.[26]

Subfigures 11a and 11c present the counterfactual exercises for the US mining states. As expected, removing the local coal protection channel significantly reduces coal capacity in this subset of states. Specifically, the counterfactual estimates US coal capacity to be 9.194 GW lower without the local mine protection channel. I perform the same counterfactual exercise for the regulated plants from non-mining states, reported in Subfigures 11b and 11d. Recall that the local coal protection channel was already absent for this subset of plants in the baseline simulation. Consequently, removing such channel has no effect in accelerating plant closures for this subset of generators.

I complement the previous countefactual with a second exercise that introduces a carbon tax. The

[26] I provide more counterfactual estimation details in Appendix H.

Figure 12: Regulated coal generator capacity, 100$/CO2 ton tax.



(a) Mining states, no confidence interval

(b) No-mining states, no confidence interval

(c) Mining states

(d) No-mining states

Red line represents regulated generator behaviour simulation with original parameters, computed as annual mean values of 50 simulations. Blue line represents regulated generator behaviour under $\alpha_1 = 0$. Confidence intervals represent 2 s.d., obtained from the 50 simulations.

carbon tax is regarded as a first-best policy for tackling climate change. Still, introducing such a tax has so far been politically infeasible in the US.[27] In short, a carbon tax burdens the most carbon-intensive industries -such as coal power plants- and makes cleaner alternatives relatively more affordable. Natural gas electricity production, for instance, issues half as much carbon dioxide as coal; hence, introducing a carbon tax makes it comparatively cheaper to coal. Following this logic, I model the carbon tax as a reduction in natural gas prices, which in turn decreases the welfare contribution of coal power plants.[28]

I set an ambitious carbon tax of 100$/Ton of CO2. As a reference, the European Union Emission Trading System (EU-ETS) carbon allowance prices oscillated around 30€/Ton in 2019. Still, these allowance prices have steadily grown to about 90€/Ton in 2023.[29]

Figure 12 reports the countefactual exercise resulting from introducing a 100$/ton carbon tax. As in

[27] In his second term in office, President Obama acknowledged that, though “the most elegant solution”, a carbon tax was not feasible. Read article here.

[28] Counterfactual estimation details are in Appendix H.2.

[29] Find EU-ETS carbon permit pricing here.

the earlier exercise, the red line corresponds to the regulated coal generator capacity under realised natural gas prices. The blue line, in contrast, represents the regulated coal capacity, had natural gas become comparatively cheaper than coal due to the carbon tax. Interestingly, introducing a significant carbon tax seems to have a negligible impact in accelerating coal generator retirements. This result is driven by the fact that natural gas was already an affordable alternative to coal in the late periods of my sample. The introduction of a carbon tax thus, only reinforces this channel marginally, and does not translate into singficant plant closures.

9 Conclusion

Coal is the most polluting source of electricity, yet the most used worldwide. Between 2008 and 2019, the US experienced a sharp cost reduction of natural gas, a close coal substitute. Still, coal power plants invested 29 billion $ in upgrading their facilities during the same period. This paper reconciles the previous two seemingly contradictory facts through a novel mechanism: the local regulator's protection of local mines. I find that electricity regulators from mining states allow coal power plants to charge higher prices in exchange for them undertaking expensive upgrades. These upgrades, in turn, allow the plant to keep procuring coal from in-state mines.

This hypothesis is tested through several reduced-form exercises. The exercises rely on two sources of variation: On the one hand, they compare regulated and non-regulated plants. On the other hand, they also compare mining and non-mining state plants. These exercises find that regulated plants from mining states are more likely to undertake the expensive upgrades, in line with my hypothesis. The paper introduces a model for coal procurement, plant upgrade, and retirement. This model introduces a regulator utility function comprised of two elements: consumer surplus and local mining revenue. Estimating the model allows me to retrieve the relative importance of these two elements. According to my estimation, regulators from mining states are willing to give away 65 $ in consumer surplus if such waiver translates into a 100 $ increase in mining revenue.

The first counterfactual of my paper consists of turning off the local mine protection element in the regulator utility function. Absent this channel, the US coal capacity is reduced by 9.194 GW by the end of the period. The second counterfactual introduces an ambitious 100 $/Ton carbon tax. Still, the tax fails to accelerate coal plant closures significantly. The two counterfactual exercises suggest that subsidizing coal mine closures is a more effective policy to accelerate the energy transition.

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A Additional Details on the MATS Rule

The EPA introduced the MATS rule in December 2011 in order to target three air pollutants: acid gases[30], mercury, and non-mercury metals[31]. The MATS rule establishes a different standard for each of the three aforementioned categories, all of which have to be complied.[32]

Firstly, the acid gas category is regulated under a surrogate standard. Surrogate standards regulate a pollutant by establishing a cap on another pollutant that acts as a proxy for the original. In this case, the EPA established sulfur dioxide emissions as the surrogate for acid gas emissions. More specifically, coal power plants are are regarded as acid gas compliers if their sulfur dioxide emissions are below 0.2 lb/mmBtu or 1.5lb/MWh.[33]

Secondly, MATS mandates that coal plants cannot exceed the emission of is 1.2 pounds of mercury per trillion British thermal units of heat input (1.2 lb/TBtu).[34]

Thirdly, non mercury metal pollutants are also regulated through another surrogate standard. In this case, MATS establishes that filterable particulate matter (PM) emissions should be below the 0.03 lbs/mmBtu threshold for a coal plant to comply.

B Hazardous Air Pollutant Regulation in the US

The negative externalities of coal prompted the US government to take action, with uneven results. Starting with the global pollutants, the US Federal Government has not succeeded in introducing nor a carbon tax neither an emissions trading scheme. This void has been partially filled by state-level initiatives, such as the California cap-and-trade system.

In contrast with the inaction on global pollutants, the US Federal government has decisively addressed local pollutants by rolling out an array of regulations throughout the last decades. This subsection reviews these regulations, with a focus on those that affected coal power plants. For that aim, the section is divided in three parts: the first subsection reproduces the standard classification of environmental regulations. The second subsection reviews the timeline of coal-related environmental regulations starting in 1970 and to present day. The third subsection focuses on the Mercury Air Toxic Standards (MATS), a 2014 rule that established a sulfur emission constraint. This rule forced US coal power plants to install pollution control devices and, hence, is of first-order importance in this paper.

[30] like hydrochloric acid (HCI) and hydrofluoric acid (HF)

[31] such as like arsenic, chromium, and nickel

[32] Find surrogate standards here and here

[33] Pollutant emissions are measured in two ways: on the one hand, pounds per million British termal units (lb/mmBtu) is the per-input unit measure. On the other hand, pounds per Megawatt hour (lb/MWh) is the per-output unit measure.

[34] The equivalent, output-based standard establishes a maximum of of 0.013 mercury pounds per gigawatt-hour output (lbs/GWh).

B.1 The Negative Externalities of Coal

Coal power plants are responsible for major negative environmental externalities. The combustion of coal releases a myriad of pollutants to the atmosphere, which are classified into two categories: "global pollutants" and "local pollutants". This section reviews both global and local pollutants with a a special emphasis on sulfur, a local pollutant that is core to this paper.

Global pollutants generate a negative externality that affects the whole planet, regardless of where the pollutant issued. This category encompasses greenhouse gases (GHG), such as carbon dioxide. These gases, though not directly harmful to human health, accumulate in the atmosphere and exacerbate the greenhouse effect, causing the global warming. Coal is the most carbon intensive electricity production technology and emmits two times more carbon dioxide than natural gas, its closest substitute EPA [2019]. In 2022, US coal power plants represented 17% of all carbon dioxide emissions in the country[35].

In contrast with global pollutants, local pollutants feature negative externalities that concentrate in the areas nearby the pollution source. Local pollutants, such as sulfur dioxide, nitrogen oxides and lead, are toxic to the human body and pose inmediate health risks to the population that lives close to the source. More specifically, Holland et. al. Holland et al. [2020] estimate per-capita sulfur damages of 450$ in year 2010 alone. Coal plants play a big role in these damages, as they were responsible for 90% of the sulfur emissions in the electricity sector for the 1997-2007 period[36].

B.2 Regulation types

Environmental regulations can be broadly classified into three categories: emission allowances, performance standards and air quality standards. This Subsection briefly describes each category in order to provide a comprehensive framework before addressing the patchwork of US environmental regulations in Subsection **??**.

Emissions allowance standards represent the "market approach" to pollution reduction. Under this scheme, the regulator sets the total amount of pollutant to be emitted in a time period. Once this global target is established, the regulator issues emission allowances for that amount. Polluting facilities need to back their emissions with an equivalent amount of allowances, which are traded in a marketplace. The acid rain program (ARP) for sulfur, Clean Air Interstate Rule (CAIR) and the Cross State Air Pollution Rule (CSAPR) belong to this category.

In contrast with emission allowance standards, the remaining two categories feature a "command and control" approach to pollution reduction. Let us start with National emission standards for hazardous air pollutants (NESHAP), also known as "technology standards" or "performance standards". This type of rules establish a maximum amount of pollutant to be issued to the atmosphere, with no room for maneuver. In the case of coal power plants, performance standards establish an emissions threshold in either per input

[35] EIA Monthly Energy Review, April 2023, find link here.

[36] EIA Today in Energy 2018, find link here

(lbs/MMBtu) or per output (lbs/MWh) units. Emissions standards are often defined using the Maximum Achievable Control Technology (MACT) floor criteria[37]. This criteria establishes that all the power plants should achieve the average level of emissions of the top 12% best performing units.

Lastly, ambient standards establish a maximum concentration of the pollutant in open air. Unlike the previous two standards, air quality is measured in parts per million units (ppm). This measure of pollution is not easily traceable to specific coal power plants, as open air records bundle different pollution sources.

B.3 Timeline

This Section reviews the milestones of local pollutant regulations in the US. The aim of this tour is to provide a comprehensive view of the regulatory context before introducing the MATS rule. MATS is the main regulation of interest in this paper and is described in detail at Subsection **??**.

The 1970 Clean Air Act (CAA) is the main law regulating air quality in the US. This law empowered the Environmental Protection Agency (EPA) as the authority in charge of regulating 188 hazardous air pollutants (HAP).[38] The Clean Air Act created two standard types: the national ambient air quality standards (NAAQS) and the national emission standards for hazardous air pollutants (NESHAP).

The NAAQS is an ambient standard that focuses on six criteria pollutants: sulfur dioxide, carbon monoxide, lead, nitrogen oxides, ozone and particulate matters.[39] This standard establishes maximum concentrations of each pollutants in parts per million units (ppm), this is, for a certain air volume. Air quality is monitoried by the EPA air data monitors[40] but, as measures are taken on the open air, emissions cannot be traced back to individual coal power plants. The EPA employs the air data monitor measurements to classify the US counties as "attainment" or "nonattainment" areas. Being classified as a "nonattainment area" triggers a procedure by which the state and the EPA agree on a roadmap to reduce emmissios down to the NAAQS establihed threshold.[41] The NAAQS standards are routinely reviewed. In 2010, por instance, NAAQS primary sulfur indicator was tightened from a 0.03 parts per million (ppm) to 75 parts per billion (ppb). Three years later, 29 counties in 16 state were labeled as "nonattainment area" for the the new sulfur oxide standard.

The Clean Air Act also introduced National emission standards for hazardous air pollutants (NESHAP). The NESHAP aim to regulate the pollutants not covered by the NAAQS, such as mercury. In contrast with the NAAQS -an ambient standard- the NESHAP are technology standards. This means that, under the NESHAP, the pollutant emissions of each coal power plant cannot overcome a certain threshold. These

[37]Find more information about MACT floor criteria here
[38]Find the list of hazardous air pollutants here
[39]Find all NAAQS standards here
[40]The EPA air data monitor is different from the Continuous emission Monitoring System (CEMS).
[41]When an area is classified as nonattainment by the EPA, the state must draft States must draft a plan known as the state implementation plan (SIP). The SIP should include a list of measures to be taken in order to improve air quality in a nonattainment area. The EPA assists the SIP drafting process by offering a Menu of control measures (MCM), this is, a list of the feasible measures to achieve attainment status in the affected area. MCMs may include the installation of scrubbers in nearby coal power plants as a potential measure to meet the attainment status.

thresholds are usually established using the maximum achievable control technology (MACT) rule and are also routinely updated. The new source performance standards (NSPS) and the later, 1977 New Source Review (NSR) are examples of this periodical update.

The approval of the Clean Air Act was a groundbreaking milestone in hazardous air pollutant regulation. Two decades later, 1990 the Clean Air Act Amendment (CAAA) introduced the Acid Rain Program (ARP), the first emission allowance marketplace to tackle local pollutants. This program consisted on a US-wide permit trading scheme aimed at reducing sulfur dioxide emissions -causant of acid rain- to 50% of 1980 levels. Under the ARP, coal power plants were mandated a sulfur performance standard that could only be surpassed if the extra emissions were backed with an equivalent amount of allowances. The ARP required the roll-out of the continuous emission monitoring system (CEMS), a system that keeps and hourly track of hazardous pollutant emissions at the coal plant boiler level. This emissions marketplace was implemented in two phases. The first phase, comprising from 1995 to 1999, only affected the 110 dirtiest coal power plants. The second phase, from 2000 to 2011, was more comprehensive, as it included most generating units above 25KW. The ARP represented a significant shift towards market-based solutions to tackle local pollutants. Still, this shift was not absolute, a the "command and control" NAAQS and NESHAP standards remained enforced.

The 2005 Clear Air Interstate Rule (CAIR) complemented the original ARP emissions trading program with the introduction of new three new marketplaces. Each of the three marketplaces focused on a single pollutant: sulfur, nitrogen and ozone. Unlike the ARP, which remained as a nationwide program, the CAIR marketplaces only encompassed 28 US eastern states.[42] The aim of this regulation was to further restrict emissions of northeast and Appalachia states, which were often carried southwards by the wind, ultimately affecting the southern states. The CAIR, however, was short-lived, as courts vacated it in 2008.

In response to the CAIR invalidation, the EPA introduced the Cross State Air Pollution Rule introduced (CSAPR) in 2011. This rule was very similar to the original CAIR both in targeted pollutants and geographical scope.[43] Schmalensee and Stavins (2013) Schmalensee and Stavins [2013] offers a comprehensive study around CAIR and CSAPR marketplaces, including the evolution of the allowance prices from 1994 to 2012. CSAPR was also invalidated by the courts in 2015 and, since then, the EPA has returned to "command and control" approaches to tackle hazardous pollutants. The Mercury Air Toxic Standards (MATS) rule of 2011 was a milestone of the "command and control" comeback. This new rule tightened the emission standard of several pollutants, effectively forcing US coal power plants to either install scrubbers or shut down. As the MATS rule is a key ingredient of this paper, Section **??** is fully devoted to it.

[42] Alabama, Arkansas, Connecticut, Florida, Georgia, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Maryland, Massachusetts, Michigan, Minnesota, Mississippi, Missouri, Nebraska, New Jersey, New York, North Carolina, Ohio, Oklahoma, Pennsylvania, South Carolina, Tennessee, Texas, Virginia, West Virginia, Wisconsin

[43] the CSAPR included all CAIR states but Connecticut, Delaware, Florida and Massachusetts. It also added Oklahoma and Kansas.

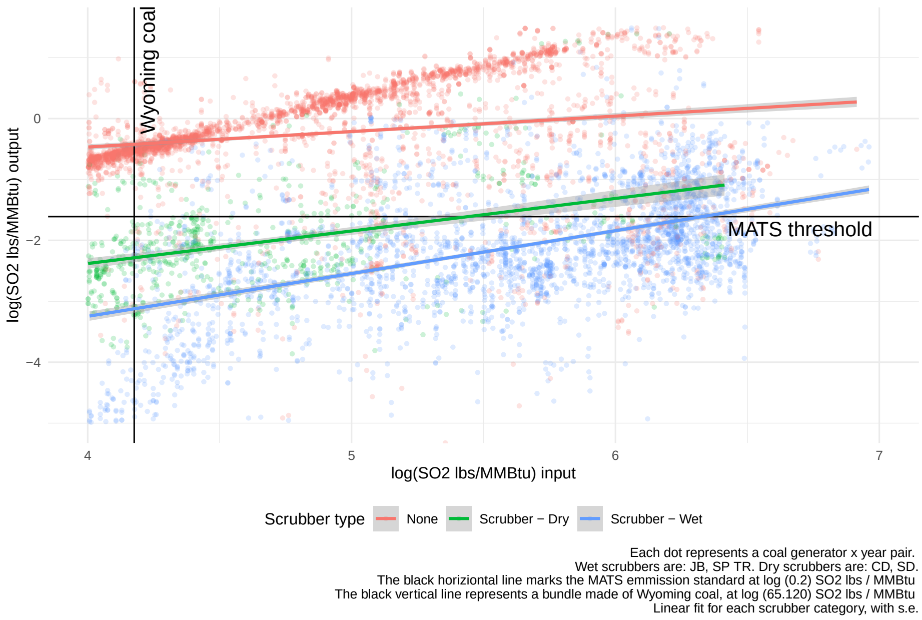
C Scrubbers

C.1 Scrubber Types

Table 9: Equipment code, description and classification. Based on EIA [2017]

Equipment type code	**Equipment type description**	**Wet**	**Dry**	**Big**	**N**	**Mean Unit Cost (Million \$/MW)**	**Mean Unit Cost (Million \$/MW)**	**Mean Cost (Million \$)**	**Median Cost (Million \$)**
JB	Jet bubbling reactor (wet) scrubber	1	0	1	18	0.169	0.126	279.27	276.256
MA	Mechanically aided type (wet) scrubber	0	0	0	0	-	-	-	-
PA	Packed type (wet) scrubber	0	0	0	0	-	-	-	-
SP	Spray type (wet) scrubber	1	0	1	137	0.159	0.126	186.00	189.558
TR	Tray type (wet) scrubber	1	0	1	66	0.140	0.105	227.17588	215.331
VE	Venturi type (wet) scrubber	0	0	0	0	-	-	-	-
CD	Circulating dry scrubber	0	1	1	34	0.161	0.108	103.54286	47.850
SD	Spray dryer type / dry FGD / semi-dry FGD	0	1	1	57	0.200	0.130	125.31842	88.000
DSI	Dry sorbent (powder) injection type	0	0	0	130	0.016	0.008	12.08743	5.300
OT	Other	0	0	0	0	-	-	-	-

Figure 13: Efficiency of each scrubber type, 2008-2019



C.2 Scrubber Efficiency

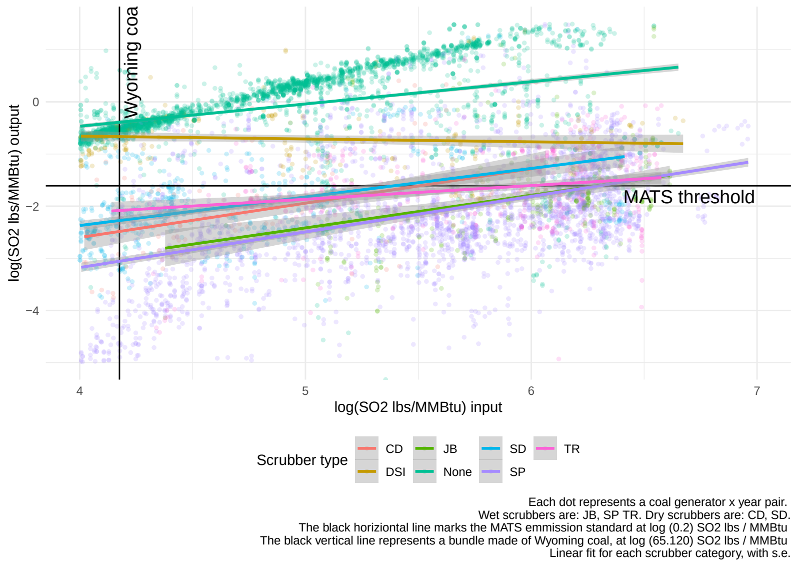
Figure 13 compares the efficiency of dry and wet scrubbers.[44] Each dot of the graph represents a generator-year pair for the 2008-2019 period. Hence, a single generator is represented by eleven dots, one per year. Each dot is characterized by two variables: The sulfur concentration of the coal blend input in the horizontal axis, and the sulfur dioxide issued to the atmosphere in the vertical axis.

Moreover, the dots are classified into three groups, depending on the type of scrubber that the generator features at the corresponding year. Note that, as power plants progressively install scrubbers in their facilities, generators transition from the “None” category to either the “Dry” or the “Wet” categories. Finally, The scatter-plot also fits a linear regression for each of the three categories.

The “MATS threshold” horizontal axis represents the unit sulfur cap established by this rule. Note that, while MATS was enforced from 2016 onward, the scatter-plot encompasses the 2008-2019 period. Hence, observations above the threshold do not correspond to non-compliers, but rather to the years prior to the compliance deadline. Moreover, virtually of the observations with “None” scrubber are situated above this horizontal line. This means that MATS rule compliance necessarily requires some sort of scrubber, which is in line with the “maximum available control technology” (MACT) nature of the rule. Lastly, the crossing between “MATS threshold” horizontal line with the “Scrubber-Dry” and “Scrubber-Wet” fitted lines determine the maximum sulfur concentration of the coal blend that is compatible with the MATS standard. The fact that the wet scrubber crossing point is located rightwards means that wet scrubbers allow for higher sulfur coal blends.

[44]Find a more disaggregated version of the scatterplot in Figure 14

Figure 14: Efficiency of each scrubber type



C.3 Scrubber Efficiency: a Rule of Thumb Calculation

This section provides the reader with three rule-of-thumb calculations on how different sulfur coal blends translate into sulfur dioxide emissions. The aim of the section is twofold: On the one hand, it provides intuition on how coal blends and scrubbers complement each other in meeting the MATS sulfur emission threshold. On the other hand, helps the reader understand the different accounting units and how they are equivalent.

Let us start with a hypothetical coal power plant that only burns Wyoming coal (0.2% of sulfur) and has no scrubber at all.

$$\frac{\text{1 ton of Wyoming coal}}{\text{22 mmBtu}} \times \frac{0,2 \cdot 1e^{-2} \text{ tons of sulfur}}{\text{1 ton of Wyoming coal}} \times \frac{\text{2 tons of } SO_2}{\text{1 ton of sulfur}} \times \frac{\text{2204 lb } SO_2}{\text{1 ton of } S0_2} = 0.4 \frac{\text{lb } SO_2}{mmBtu}$$

The resulting $0.4 \frac{\text{lb } SO_2}{mmBtu}$ sulfur emission level is twice the MATS threshold, set at $0.2 \frac{\text{lb } SO_2}{mmBtu}$. Hence, even plants with burning low sulfur coal blends are required to install an scrubber with minimum efficiency of about $\omega \approx 50\%$ in order to meet the MATS standard.

$$0.4 \frac{\text{lb } SO_2}{mmBtu} \cdot (1 - \omega) = 0.2 \frac{\text{lb } SO_2}{mmBtu}$$

Let us now repeat such calculation for a plant burning 1.5% sulfur coal blend:

$$\frac{\text{1 ton of coal}}{\text{22 mmBtu}} \times \frac{1.5 \cdot 1e^{-2} \text{ tons of sulfur}}{\text{1 ton of coal}} \times \frac{\text{2 tons of } S0_2}{\text{1 ton of sulfur}} \times \frac{\text{2204 lb } SO_2}{\text{1 ton of } S0_2} = 3 \frac{\text{lb } SO_2}{mmBtu}$$

For this latter case, the scrubber efficiency should be around $\omega \approx 93\%$ for the coal power plant to meet the MATS standard. Note that such a level of efficiency is in line with the dry scrubbers, which are deemed appropiate for coal blends up to 1.5% sulfur by the EPA Sorrels [2021].

$$3 \frac{\text{lb } SO_2}{mmBtu} \cdot (1-\omega) = 0.2 \frac{\text{lb } SO_2}{mmBtu}$$

Finally, let us repeat the same exercise one last time for plants burning high sulfur coal blend around 4%:

$$\frac{1 \text{ ton of coal}}{22 \text{ mmBtu}} \times \frac{4 \cdot 1e^{-2} \text{ tons of sulfur}}{1 \text{ ton of coal}} \times \frac{2 \text{ tons of } S0_2}{1 \text{ ton of sulfur}} \times \frac{2204 \text{ lb } SO_2}{1 \text{ ton of } S0_2} = 8 \frac{\text{lb } SO_2}{mmBtu}$$

In this extreme case, the power plant would require a scrubber with the efficiency of $\omega = 97.5\%$ in order to comply with the MATS requirement. Such efficiency can only be achieved with a wet scrubber (See Sorrels [2021]).

D Descriptives

D.1 Balance Table: Regulated and Non-Regulated Plants

Table 10: Balance test of generator covariates, by regulatory status and location

	Dependent variable:					
	Age	Size	Heat rate	Distance to closest mine	Sulfur of closest mine	Distance to Wyoming
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	35.022***	225.201***	9,972.162***	2.141***	1.304***	26.074***
	(0.978)	(19.455)	(117.083)	(0.124)	(0.085)	(0.492)
Regulated Indicator	5.648***	79.520***	429.820***	0.811***	0.572***	−6.785***
	(1.171)	(23.297)	(129.725)	(0.148)	(0.102)	(0.589)
Coal state indicator	2.634*	91.508***	42.967	−1.279***	0.989***	−6.871***
	(1.456)	(28.978)	(159.854)	(0.184)	(0.127)	(0.732)
Regulated × Coal state	−2.957*	−66.297*	−345.822*	−0.801***	−1.031***	5.706***
	(1.742)	(34.668)	(180.109)	(0.221)	(0.152)	(0.876)
Observations	1,111	1,111	907	1,111	1,111	1,111
R^2	0.025	0.018	0.024	0.245	0.054	0.145
Adjusted R^2	0.022	0.015	0.021	0.243	0.051	0.142

*p<0.1; **p<0.05; ***p<0.01

Coal genertors 2008-2019 period.

Coal mining states are: AL, CO, IL, IN, KY, MT, ND, NM, OH, TX, UT, VA, WV

D.2 Characteristics of Retired Generators

Table 11: Characteristics of Regulated coal generators that closed in the in 2008-2019 period - Mine States

		Size (MW)	Age (Years)	Heat Rate (Btu/MWh)	Coal Plants With Scrubbers	Coal Plants With Wet Scrubbers	Natural Gas Cost (cent/MWh)	Retirement Year	N Generators	N Plants
1	No scrubber	143.80	57.50	9970.44	0.22	0.21	2861.57	2015.00	148	56
2	Scrubber - Dry	138.35	43.50	10623.80	0.28	0.06	2945.36	2017.00	8	6
3	Scrubber - Wet	205.00	46.00	10009.57	0.27	0.18	2952.53	2017.00	29	15

Note: The table reports median values at the generator level. "Coal plants with scrubbers" refers to the share of regulated coal power plant capacity with either dry or wet scrubber in the state, over the total generation capacity of the state. "Coal plants with wet scrubbers" is equivalent, but only takes wet scrubbers into account. "Natural gas cost" refers to the cost of natural gas electricity production in the state on the year the generator was retired.

Table 12: Characteristics of Regulated coal generators that closed in the in 2008-2019 period - No-mine States

		Size (MW)	Age (Years)	Heat Rate (Btu/MWh)	Coal Plants With Scrubbers	Coal Plants With Wet Scrubbers	Natural Gas Cost (cent/MWh)	Retirement Year	N Generators	N Plants
1	No scrubber	90.00	56.00	10496.72	0.21	0.13	3158.68	2015.00	167	78
2	Scrubber - Dry	165.00	31.00	10742.80	0.22	0.14	3098.11	2015.00	5	5
3	Scrubber - Wet	125.00	47.50	10964.68	0.13	0.10	2776.94	2017.50	16	7

Table 13: Characteristics of Non-regulated coal generators that closed in the in 2008-2019 period - Mine States

		Size (MW)	Age (Years)	Heat Rate (Btu/MWh)	Coal Plants With Scrubbers	Coal Plants With Wet Scrubbers	Natural Gas Cost (cent/MWh)	Retirement Year	N Generators	N Plants
1	No scrubber	125.00	55.00	9876.74	0.03	0.03	3003.09	2013.00	102	47
2	Scrubber - Dry	57.40	29.00	9882.63	0.09	0.06	2449.82	2019.00	6	4
3	Scrubber - Wet	353.60	50.00	10015.47	0.03	0.03	2887.24	2013.00	11	8

E Derivations of the Model

E.1 Regulator Utility Function

$W^{coal}(\mu_t, p_t)$ expresses the consumer welfare when the coal plant is open. $W^{no\ coal}(\mu_t, p_t)$ reflects the consumer welfare, in case the coal plant were closed. The difference between the two expressions is regarded as the "consumer welfare contribution".

$$\begin{aligned}
W^{coal}(\mu_t, p_t) &= \underbrace{q_t \cdot (v - p_t) + (Q_t - q_t) \cdot \int_{p_t}^{\infty} (v - p^{gas}) \cdot \phi(p^{gas}) \cdot dp^{gas}}_{p_t < p^{gas}} + \underbrace{Q_t \cdot \int_{0}^{p_t} (v - p^{gas}) \cdot \phi(p^{gas}) \cdot dp^{gas}}_{p_t \geq p^{gas}} \\
W^{no\ coal}(\mu_t, p_t) &= Q_t \cdot \int_{0}^{\infty} (v - p_h^{gas}) \cdot \phi(p^{gas}) \cdot dp^{gas} \\
W(\mu_t, p_t) &= W^{coal}(\mu_t, p_t) - W^{no\ coal}(\mu_t, p_t)
\end{aligned} \tag{36}$$

Table 14: Characteristics of Non-regulated coal generators that closed in the in 2008-2019 period - No-mine States

		Size (MW)	Age (Years)	Heat Rate (Btu/MWh)	Coal Plants With Scrubbers	Coal Plants With Wet Scrubbers	Natural Gas Cost (cent/MWh)	Retirement Year	N Generators	N Plants
1	No scrubber	86.30	52.00	10337.44	0.00	0.00	3814.27	2014.00	48	31
2	Scrubber - Dry	93.50	47.00	10000.58	0.00	0.00	3505.18	2016.00	12	7
3	Scrubber - Wet	105.40	49.50	9471.42	0.00	0.00	4248.19	2015.50	6	4

E.2 Convexity of the Welfare Contribution

This subsection proves the convexity of the welfare function with respect to the regulated price p_t. Applying the Leibniz rule to the Equation **??**, the partial derivative of the welfare contribution expression is negative:

$$\begin{aligned} \frac{\partial W_t}{\partial p_t} &= (p_h^{gas} - p_t)\cdot \phi(p_h^{gas}|\mu_t)\cdot \cancelto{0}{\frac{\partial \infty}{\partial p_t}} + \\ &\cancelto{0}{(p_t - p_t)}\cdot \phi(p_t|\mu_t)\cdot \frac{\partial p_t}{\partial p_t} \\ &- \int_{p_t}^{p_h^{gas}} \phi(p_h^{gas}|\mu_t) \\ &= \Phi(p_t|\mu) - \Phi(\infty|\mu) \leq 0 \end{aligned} \tag{37}$$

Moreover, the second derivative with respect to the regulate price is.

$$\frac{\partial^2 W_t}{\partial^2 p_t} = \phi(p_t|\mu) \geq 0 \tag{38}$$

E.3 The Optimality of Uniform Pricing

This subsection proves that, in a context of cost of service regulation, charging a uniform regulated price over time is welfare improving. Take two periods, $t = 0$ and $t = 1$. Each period is characterized by a unit cost of coal $\bar{c}_0, \bar{c}_1$, a centering parameter of the natural gas price distribution μ_0, μ_1 and a regulated price p_0, p_1. Assume that the regulated price are different. Without loss of generality, I state that $p_0 = p_1 + \epsilon$. Consequently, the present-value profits of the plant owner are:

$$\Pi = (p_0 - \bar{c}_0)\cdot q(p_0, \mu_0) + \beta \cdot (p_1 - \bar{c}_1)\cdot q(p_1, \mu_1)$$

According to cost-of-service regulation, the regulator chooses a stream of regulated prices $\{p_0, p_1\}$ so that the plant owner reaches non-negative profits $\Pi = 0$.[45] Consequently, the regulated price p_1 is characterised by the following expression:

$$(p_1 + \epsilon - \bar{c}_0)\cdot q(p_0, \mu_0) + \beta \cdot (p_1 - \bar{c}_1)\cdot q(p_1, \mu_1) = 0$$

rearranging such expression provides the following equilibrium expression for $q(p_0, \mu_0) = \beta \cdot \frac{(\bar{c}_1 - p_1)\cdot q(p_1, \mu_1)}{p_1 + \epsilon - \bar{c}_0}$.

[45]Note that, for $\Pi = 0$ is incompatible with $p_0 > \bar{c}_0$ and $p_1 > \bar{c}_1$. I thus assume, without loss of generality, that $p_0 \geq \bar{c}_0$ and $p_1 \leq \bar{c}_1$.

Regarding consumer welfare, the discounted sum of per-period welfare contribution is

$$W = \underbrace{\int_{p_1+\epsilon}^{\infty} (p_h^{gas} - p_1 - \epsilon) \cdot \phi(p_h^{gas}|\mu_0) dp_h^{gas}}_{Period\ 0} + \beta \cdot \underbrace{\int_{p_1}^{\infty} (p_h^{gas} - p_1) \cdot \phi(p_h^{gas}|\mu_1) dp_h^{gas}}_{Period\ 1}$$

Rewriting the consumer welfare expression, I obtain,

$$W = \int_{p_1+\epsilon}^{\infty} p_h^{gas} \cdot \phi(p_h^{gas}|\mu_0) dp_h^{gas} - (p_1+\epsilon) \cdot \underbrace{\int_{p_1+\epsilon}^{\infty} \phi(p_h^{gas}|\mu_0) dp_h^{gas}}_{q(p_0,\mu_0)} + \beta \cdot \int_{p_1}^{\infty} p_h^{gas} \cdot \phi(p_h^{gas}|\mu_1) dp_h^{gas} - \beta \cdot p_1 \cdot \underbrace{\int_{p_1}^{\infty} \phi(p_h^{gas}|\mu_1) dp_h^{gas}}_{q(p_1,\mu_1)}$$

moreover, the previous expression is further simplified as,

$$W(\epsilon) = \int_{p_1+\epsilon}^{\infty} p_h^{gas} \cdot \phi(p_h^{gas}|\mu_0) dp_h^{gas} - (p_1+\epsilon) \cdot \beta \cdot \frac{(\overline{c}_1 - p_1) \cdot q(p_1, \mu_1)}{p_1 + \epsilon - \overline{c}_0} + \beta \cdot \int_{p_1}^{\infty} p_h^{gas} \cdot \phi(p_h^{gas}|\mu_1) dp_h^{gas} - \beta \cdot p_1 \cdot q(p_1, \mu_1)$$

As $\frac{\partial W(\epsilon)}{\partial \epsilon} \leq 0$, consumer welfare is maximized when $\epsilon = 0$. In other words, uniform pricing across time maximizes consumer welfare while satisfying the coal plant participation constraint.

F Additional Empirical Evidence

F.1 Multinomial logit

F.2 Coal Mine Closures

Plants with wet scrubbers increased their share of local coal. It is likely, thus, that such share translated into higher local coal mine revenue, preventing the closure of local mines. This section provides evidence that the installation of sulfur scrubbers by coal power plants prevented nearby coal mines from closing.

For such aim, I estimate several Cox-Proportional Hazard models.[46] In these models, the dependent variable $h_m(t)$ is the probability of a mine m closing at period t, conditional on that mine having remained open until $t-1$. The covariates of the regression include several mine-level controls X_m. Mine covariate vector X_m consists of the following variables: sulfur concentration of the coal extracted from the mine, distance from the mine to Wyoming $WyomingDist_{mt}$, distance from the mine to its closest plant $DistToClosest_{mt}$, mine labor productivity $Prodctivity_{mt}$ and and indicator on whether the plant that was originally the closest to the mine (as in 2008) still remains open, $ClosestIn2008isOpen_{mt}$. as well as two indicator variables for dry ω_{hmt} and wet ω_{lmt} scrubbers. ω_{hmt}, for instance, turns on if the closest plant to the mine m has a wet scrubber at time t. Finally, $MATS_t$ is an indicator that gathers all the years in which this regulation was enforced.

$$h(t) = h_0(t) \exp(\beta_1 X_m + \beta_1 \omega_{hmt} \times MATS_t + \beta_2 \omega_{lmt} \times MATS_t + \epsilon_{it}) \tag{39}$$

The result of specification 39 is presented in Table 16, which consists of three columns. The first two columns repeat the main specification over two different subsets: column 1 corresponds to the 2008-2013 period,

[46] Find all the estimated models in Subsection F

Table 15: Scrubber adoption and local mines

	Dependent variable:		
	Four choices: remain, retire, dry or wet scrubber		
	(1)	(2)	(3)
Retire, regulated	−0.746	0.652	0.540
	(0.543)	(0.435)	(0.402)
Dry scrubber, regulated	−0.668	0.874	1.167*
	(0.819)	(0.689)	(0.624)
Wet scrubber, regulated	−0.273	0.898**	1.044**
	(0.590)	(0.448)	(0.409)
Retire, treatment	−2.159*	0.040**	0.576**
	(1.232)	(0.017)	(0.225)
Dry scrubber, treatment	−5.811***	0.002	0.335
	(2.252)	(0.029)	(0.333)
Wet scrubber, treatment	−4.003***	−0.016	0.082
	(1.440)	(0.022)	(0.249)
Retire, treatment × regulated	2.914**	0.035	0.646*
	(1.453)	(0.026)	(0.365)
Dry scrubber, treatment × regulated	5.128**	0.050	0.471
	(2.486)	(0.038)	(0.485)
Wet scrubber, treatment × regulated	6.312***	0.091***	1.050***
	(1.617)	(0.030)	(0.382)
Treament: close mines from own state	Mine share	Mine size	Employment
Close mines radius	345 miles	345 miles	345 miles
Observations	707	707	707
McFadden R^2	0.226	0.229	0.236
Log Likelihood	−658.307	−656.207	−649.705
LR Test (df = 24)	384.656***	388.855***	401.859***

*p<0.1; **p<0.05; ***p<0.01

Regulated generators, 2008-2019 period. All the specifications include generator age, size, heat-rate and distance to Wyoming as controls. I define close-by mines as those within a 345-mile radius around the generator. Treatment of the first specification is the share of close-by mines that belong to the same state as the plant. Treatment of the second specification is the millions of coal tones that close-by mines from the same state produced in 2008. Treatment of the third specification is the number of miners working in close by mines from the same state in 2008.

in which the MATS regulation was still not enforced. Column 2, on the contrary, covers the 2014-2019 years, in which coal power plants were obliged to comply with the MATS sulfur emissions threshold. Finally, Column 3 specification is estimated over the whole dataset, and includes an indicator $MATS_i$ that activates for the periods in which the rule was enforced.

The results in 16 reinforce the link between coalmine survival and wet scrubber installation, as the indicator ω_{hmt} remains negative and significant throughout the four specifications. Moreover, the magnitude of such indicator more than doubles when estimated at the "Post MATS" years, in which coal plant sulfur emission standards were considerably tightened. Furthermore, the fact that the $\omega_{hmt} \times MATS_t$ interaction is negative and significant is consistent with the narrative.

Table 17 estimates specification **??** on three different datasets: The first column encompasses all coalmines, no matter how high the sulfur concentration of the coal they extract. The second column repeats the specification but focuses on "low sulfur mines", this is, mines whose coal contains less than 1.5% of weight in sulfur[47]. This threshold is not arbitrary, as the EPA establishes that dry scrubbers are only suitable for coal below it Sorrels [2021]. Finally, column 3 corresponds reproduces the specification by focusing on the mines above the aforementioned sulfur threshold. Finally, Column 4 in 17 estimates a modified varepsilon of the empirical specification, in which the wet and dry scrubber treatments are interacted with the indicator $HightSulfurCounty_i$, which turns on if mine i belongs to a county producing coal above the 1.5% threshold aforementioned.

The first five rows in Table 17 correspond to the mine-level covariate vector X_i. $WetScrubber_{it}$ stands as the only negative and significant coefficient of the table, meaning that installing a wet scrubber in a coal power plant significantly reduces the closure probability of the mines that have such coal plant as their closest client.

Table 18 repeats the previous empirical exercises over different data subsets. In this case, coal mines are classified as either "Small employers" or "Big employers", depending on whether they exceeded more than 50 workers at the early periods of the panel[48]. The results reported in 18 show that wet scrubbers are successful in deterring coal mine closures of both small and big coal mines. The effect of dry scrubbers, in contrast, is again more modest and concentrates in small mines only.

Finally, Table 19 combines all the previous dataset partitions in a single regression. For such aim, the main covariates of interest $WetScrubber_{it}$ and $DryScrubber_{it}$ are combined with the $MATS_t$ and $HighSulfurCounty_i$ indicators. The results in fall in line with the previous empirical exercises, as wet scrubbers emerge as the big deterrents of mine closures, specially after the MATS regulation enforcement.

[47]As reference point, Wyoming coal has a sulfur concentration around 0.2%

[48]Mines with more than 50 workers in either 2008, 2009 or 2010 are considered "Big employers"

Table 16: Cox Proportional Hazards model for Mine Closures

	Dependent variable:		
	Mine Closure		
	(1)	(2)	(3)
$Productivity_{mt}$	0.158	0.418	0.170
	(0.697)	(0.452)	(0.329)
$WyomingDist_m$	−0.103	0.046	−0.030
	(0.095)	(0.082)	(0.054)
$SulfurCounty_m$	0.161	1.711	0.544
	(2.169)	(1.633)	(1.149)
$ClosestIn2008isOpen_{mt}$	2.115	6.133	3.493*
	(3.135)	(6.302)	(2.174)
$DistToClosest_{mt}$	−1.724	5.674	1.110
	(7.407)	(5.415)	(3.402)
ω_{hmt}	−0.514**	−1.275***	−0.477**
	(0.185)	(0.230)	(0.177)
ω_{hmt}	−0.140	0.063	0.016
	(0.182)	(0.177)	(0.171)
$MATS_t$			−19.505***
			(811.062)
$\omega_{hit} \times MATS_t$			−0.798***
			(0.271)
$\omega_{lit} \times MATS_t$			−0.105
			(0.228)
Observations	10,033	6,016	16,049
Sample	Pre MATS	Post MATS	All
R^2	0.018	0.022	0.061
Max. Possible R^2	0.506	0.491	0.523
Log Likelihood	−3,450.914	−1,967.612	−5,431.909
Wald Test	2,872.080*** (df = 34)	311.320*** (df = 34)	85,440.210*** (df = 38)
LR Test	179.797*** (df = 34)	131.035*** (df = 34)	1,001.909*** (df = 38)
Score (Logrank) Test	175.793*** (df = 34)	140.216*** (df = 34)	857.210*** (df = 38)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 17: Cox Proportional Hazards model for Mine Closures. Low and high sulfur mines

	Dependent variable:			
	Mine closure			
	(1)	(2)	(3)	(4)
$Productivity_{it}$	0.138	−0.417	−3.389	0.171
	(0.317)	(1.182)	(4.585)	(0.340)
$WyomingDist_i$	−0.025	−0.058	−0.492	−0.002
	(0.054)	(0.152)	(0.639)	(0.060)
$SulfurCounty_i$	0.407	−1.320	−2.760	1.071
	(1.157)	(4.717)	(6.429)	(1.310)
$ClosestIn2008isOpen_{it}$	2.339	1.311	−14.461	2.085
	(2.232)	(6.564)	(23.070)	(2.510)
$DistToClosest_{it}$	1.283	−0.353	15.042	1.810
	(3.603)	(7.600)	(40.367)	(4.171)
$WetScrubber_{it}$	−1.270***	−1.452***	−0.894***	−1.352***
	(0.145)	(0.198)	(0.263)	(0.181)
$DryScrubber_{it}$	−0.357***	−0.699***	−0.721	−0.508***
	(0.118)	(0.140)	(0.371)	(0.132)
$HighSulfurCounty_i$				−1.534***
				(0.241)
$WetScrubber_{it} \times HighSulfurCounty_i$				0.197
				(0.292)
$DryScrubber_{it} \times HighSulfurCounty_i$				0.358
				(0.326)
Observations	16,049	11,357	4,692	16,049
Sample	All	Low sulfur	High sulfur	All
R^2	0.027	0.041	0.019	0.030
Max. Possible R^2	0.523	0.545	0.373	0.523
Log Likelihood	−5,711.797	−4,233.291	−1,049.075	−5,685.711
Wald Test	462.420*** (df = 34)	2,991.750*** (df = 34)	296.910*** (df = 34)	2,803.350*** (df = 38)
LR Test	442.134*** (df = 34)	478.915*** (df = 34)	88.914*** (df = 34)	494.305*** (df = 38)
Score (Logrank) Test	494.279*** (df = 34)	520.219*** (df = 34)	112.737*** (df = 34)	553.877*** (df = 38)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 18: Cox Proportional Hazards model for Mine Closures. Small and big employers.

	Dependent variable:		
	Mine Closure		
	(1)	(2)	(3)
$Productivity_{it}$	-6.317^{***}	0.414	0.128
	(2.745)	(0.459)	(0.316)
$WyomingDist_i$	-0.921^{**}	-0.040	-0.027
	(0.403)	(0.062)	(0.054)
$SulfurCounty_i$	-11.491^{**}	-0.399	0.355
	(6.147)	(1.362)	(1.148)
$ClosestIn2008isOpen_{it}$	-26.934^{*}	2.296	2.230
	(12.943)	(2.485)	(2.208)
$DistToClosest_{it}$	-75.180^{**}	1.998	1.522
	(30.639)	(4.213)	(3.668)
$WetScrubber_{it}$	-1.671^{***}	-1.184^{***}	-1.169^{***}
	(0.382)	(0.159)	(0.155)
$DryScrubber_{it}$	-0.063	-0.450^{***}	-0.457^{***}
	(0.371)	(0.125)	(0.123)
$BigEmployer_i$			-0.641^{***}
			(0.157)
$WetScrubber_{it} \times BigEmployer_i$			-0.255
			(0.352)
$DryScrubber_{it} \times BigEmployer_i$			0.633^{*}
			(0.291)
Observations	3,912	12,137	16,049
Sample	Big Employers	Small Employers	All
R^2	0.024	0.031	0.029
Max. Possible R^2	0.279	0.562	0.523
Log Likelihood	-592.356	$-4{,}816.376$	$-5{,}694.947$
Wald Test	956.170^{***} (df = 34)	399.220^{***} (df = 34)	$1{,}281.490^{***}$ (df = 38)
LR Test	96.119^{***} (df = 34)	385.422^{***} (df = 34)	475.833^{***} (df = 38)
Score (Logrank) Test	82.765^{***} (df = 34)	435.899^{***} (df = 34)	532.181^{***} (df = 38)

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

Table 19: Cox Proportional Hazards model for Mine Closures. Interactions.

	Dependent variable:	
	Mine Closure	
	(1)	(2)
$Productivity_{it}$		-0.142
		(0.148)
$WyomingDist_i$		-0.032
		(0.032)
$SulfurCounty_i$		0.520
		(0.623)
$ClosestIn2008isOpen_{it}$		2.063^{*}
		(1.181)
$WetScrubber_{it}$	-0.545^{**}	-0.409^{*}
	(0.206)	(0.218)
$DryScrubber_{it}$	-0.369^{**}	0.075
	(0.172)	(0.191)
$HighSulfurCounty_i$	-0.655^{***}	-1.412^{***}
	(0.169)	(0.270)
$MATS_t$	-19.677^{***}	-19.610^{***}
	(798.562)	(883.967)
$WetScrubber_{it} \times HighSulfurCounty_i$	0.119	-0.146
	(0.363)	(0.372)
$DryScrubber_{it} \times HighSulfurCounty_i$	0.374	-0.035
	(0.427)	(0.446)
$WetScrubber_{it} \times MATS_t$	-1.129^{***}	-1.173^{***}
	(0.342)	(0.344)
$DryScrubber_{it} \times MATS_t$	-0.105	-0.322
	(0.246)	(0.252)
$HighSulfurCounty_i \times MATS_t$	0.425	0.150
	(0.279)	(0.300)
$WetScrubber_{it} \times SulfurCounty_i \times MATS_t$	0.823	0.664
	(0.550)	(0.558)
$DryScrubber_{it} \times SulfurCounty_i \times MATS_t$	0.594	0.819
	(0.588)	(0.605)
Observations	16,049	16,049
Sample	All	All
R^2	0.051	0.060
Max. Possible R^2	0.523	0.523
Log Likelihood	$-5{,}513.729$	$-5{,}436.976$
Wald Test	$90{,}179.070^{***}$ (df = 15)	$89{,}553.180^{***}$ (df = 30)
LR Test	838.269^{***} (df = 15)	991.775^{***} (df = 30)
Score (Logrank) Test	669.265^{***} (df = 15)	826.382^{***} (df = 30)
Note:		*p<0.1; **p<0.05; ***p<0.01

G Estimation

G.1 The Aggregate State Space

The aggregate state space Ω_{it} consists of two variables, for each generator i and period t: the cost of natural gas μ_{st} and the share of scrubbed coal plant in the state κ_{it}.

$$\Omega_{it} = \{\mu_{st}, K_{it}\}$$

The model assumes that Ω_{it} follows a Markov chain, as in Gowrisankaran et al. [2022]

The estimation of the natural gas price μ_{st} benefits from the fact that the EIA-923 dataset reports transaction level data for natural gas power plants. Moreover, following the analogous procedure employed for coal plants, I retrieved heat rates of natural gas plants from the CEMS dataset. The previous two variables enable the computation of plant-level the cost of electricity in \$/kWh. Such plant-level annual costs are then weighted by the total output of the plant at the corresponding period, ultimately yielding μ_{st}.

The estimation for the κ_{it} parameter is as follows: For each period t and plant i, I identify all the coal power generators with either dry or wet scrubber that belong to the same state as generator i. Next, I add up all the capacity of these coal plants (in MW), excluding plant i itself.[49] Moreover, I also add up the capacity of all power plants within the state i belongs to. These include not only coal but also natural gas, solar, hydropower and other generation technologies. Dividing the two numbers provides the share of scrubbed coal plants in the state K_{it}, which is between zero and one.

G.1.1 Aggregate State Discretization

Each of the two variables in Ω_{it} is discretized in Q quantiles (See **??** for intuition). The combination between the two arrays of segments yields a total of B bins.[50]

$$Q \times Q = B$$

The previous procedure discretizes the aggregate state space Ω_{it} into $1, 2, ...b...B$ bins. Consequently, all Ω_{it} observations belong to some b bin. Once all aggregate state observations Ω_{it} belong to some bin b, I next proceed to characterise each bin. For such task I compute, for all the $\Omega_{it} \in b$, the average natural gas cost and the average coal capacity:

$$K_b = \frac{1}{n_b} \sum_{\Omega_{it} \in b} K_{it} \qquad \mu_b = \frac{1}{n_b} \sum_{\Omega_{it} \in b} \mu_{it}$$

This procedure ultimately yields a vector of discretized aggregate states

$$\Omega_b = (\mu_b, K_b)$$

[49] Because of the exclusion of the own plant, K_{it} takes different values for different generators, even at the same state and year.
[50] The paper uses $S = 20$, $B = 400$

G.1.2 The Transition Matrix

The transition matrix $\underset{B\times B}{T}$ is a square matrix that determines how the aggregate state evolves over time. Notationwise, $T_{b,b'}$ denotes the row b, column b' element of the transition matrix. $T_{b,b'}$ represents the probability of "landing into" bin b when "coming from" bin b' in the previous period.

The following procedure details how the transition matrix T is constructed, for each row b:

1. Find all aggregate state observations that belong to bin b and exclude those from the first period $t = 1$.

$$\Omega_{it} \in b \qquad t \in 2, 3, 4, ...$$

2. Compute the sample size of each bin:

$$n_b = \sum 1\{\Omega_{it} \in b \quad \& \quad t \in 2, 3, 4, ...\}$$

3. For each of the resulting observations Ω_{it}, find $\Omega_{i,t-1}$, this is, the aggregate state observation for same generator i at the previous period $t-1$.

4. Next, find the bin b' to which $\Omega_{i,t-1}$ belongs To

$$b' \quad s.t. \quad \Omega_{i,t-1} \in b'$$

5. For a row b, column b' represents the probability there is of landing in b coming from b'.

6. The resulting element of the transition matrix will be:

$$T_{b,b'} = \frac{\sum 1\{\Omega_{it-1} \in b'\}}{n_b} \leq 1$$

G.2 Value imputation

This section explains how to compute the per-period utility of the regulator, for each generator i, aggregate state bin b and scrubber type ω.

$$U_{ib\omega} = W_{ib\omega}(\omega_t, X_i, \lambda_{it}) + \alpha_1 \cdot R_{ib\omega}(\omega_t, X_i, \lambda_{it}) - \alpha_2 \cdot S_{ib\omega}(\omega_t, X_i) - \alpha_3 \cdot K_{ib\omega}$$

The estimation of the per-period utility function requires the imputation of each of the four elements of the function: $\{W_{ib\omega}, R_{ib\omega}, S_{ib\omega}, K_{ib\omega}\}$. Out of the four elements, $K_{ib\omega}$ is directly imputed as K_b. The remaining three elements, however, require a more complex procedure. Henceforth, the following three subsections describe the imputation procedure for each of the elements in detail.

G.2.1 Consumer Welfare Contribution

Consumer welfare contribution expression is empirically approximated by the following expression:

$$W_{ib\omega} = K_i \cdot q_{ib\omega}(X_i, \mu_b, \omega) \cdot (\mu_b - HR_i \cdot \bar{c}_{ib\omega}(X_i, \omega))$$

Generator nameplate capacity K_i, generator heat rate HR_i and natural gas cost μ_b are observed and, hence, directly retrieved from the data. Generator active hours $q_{ib\omega}$ and coal unit costs $\overline{c}(X_i, \omega)$, in contrast, are to be imputed.

The imputation procedure is as follows: I regress generator active hours as a function of generator covariates X_i and the aggregate state variables $\{\mu_{st}, K_{it}\}$. Such regression is repeated three times, one for each of the scrubber types:

$$q_{it}^{\omega_h} = \alpha^h + \beta_1^h X_i + \beta_2^h \mu_{st} + \beta_3^h K_{it} + \epsilon_{it} \qquad High\ efficiency\ scrubbers\ \omega_h \tag{40}$$

$$q_{it}^{\omega_l} = \alpha^l + \beta_1^l X_i + \beta_2^l \mu_{st} + \beta_3^l K_{it} + \epsilon_{it} \qquad Low\ efficiency\ \omega_h\ scrubbers\ \omega_l \tag{41}$$

$$q_{it}^{\omega_0} = \alpha^0 + \beta_1^0 X_i + \beta_2^0 \mu_{st} + \beta_3^0 K_{it} + \epsilon_{it} \qquad No\ scrubbers\ \omega_0 \tag{42}$$

Next, I employ the point estimates of the previous regressions to predict generator active hours at all $i \times b \times \omega$ combinations:

$$q_{ib\omega_h} = \alpha^h + \beta_1^h X_i + \beta_2^h \mu_b + \beta_3^h K_b \qquad High\ efficiency\ scrubbers\ \omega_h \tag{43}$$

$$q_{ib\omega_l} = \alpha^l + \beta_1^l X_i + \beta_2^l \mu_b + \beta_3^l K_b \qquad Low\ efficiency\ \omega_h\ scrubbers\ \omega_l \tag{44}$$

$$q_{ib\omega_0} = \alpha^0 + \beta_1^0 X_i + \beta_2^0 \mu_b + \beta_3^0 K_b \qquad No\ scrubbers\ \omega_0 \tag{45}$$

The procedure for imputing coal unit costs $\overline{c}_{ib\omega}$ is analogous to the previously described.[51] In short, coal unit cost is regressed against plant covariates X_i, for each of the three scrubber types. The regression point estimates are later employed to predict coal unit costs at every $i \times b \times \omega$ triplet.

Once $q_{ib\omega_h}$ and $\overline{c}_{ib\omega}$ are imputed, computing the welfare contribution at each gridpoint becomes a straightforward task:

$$W_{ib\omega} = K_i \cdot q_{ib\omega} \cdot (\mu_b - HR_i \cdot \overline{c}_{ib\omega})$$

G.2.2 Local Coal Revenue

The empricial expression of local coal revenue $R_{ib\omega}$ is a direct translation of the Model formula:

$$R_{ib\omega} = K_i \cdot HR_i \cdot q_{ib\omega} \cdot c_{ib\omega} \cdot \rho_{ib\omega}$$

Out of the five elements that comprise the local coal revenue expression, generator capacity K_i and generator heat rate HR_i are directly retrieved from the data. Moreover, plant active hours $q_{ib\omega}$ is estimated as described in Subsection G.2.1.

In consequence, this subsection focuses on imputing the remaining two elements: cost of local coal $c(X_i, \omega)$ and share of local coal $\rho(X_i, \omega)$. Starting with the cost of local coal, the procedure is analogous to that of Section G.2.1.[52] I start by running the following regression, where the dependent variable $c_{it}^{\omega_h}$ is the unit

[51] $\overline{c}_{ib\omega}$ units are in \$/Btu

[52] c_m units are in \$/Btu

cost of the non-Wyoming coal bought by generator i at period t:

$$c_{it}^{\omega_h} = \alpha + \beta_1 X_i + \epsilon_{it} \quad High\ Efficiency\ Scrubbers\ \omega_h$$

The regression above is run for generators with ω_h scrubbers only, and the procedure is repeated for each of the remaining two scrubber categories.

Next, the point estimates of the previous regression are used for imputing local coal unit costs to all gridpoints. In the case below, the regression of high-efficiency scrubbers is used to impute local coal unit costs.

$$c_{ib\omega_h} = \alpha^h + \beta_1^h X_i$$

The imputation of local coal shares $\rho_{ib\omega}$ follows an analogous procedure. Firstly, local coal shares ρ_{it} are regressed on generator covariates X_i. Such regression is performed three times, one for each scrubber type. The regression estimates are later used to impute local coal shares at all grid points $\rho_{ib\omega}$.

After imputing generator active hours $q_{ib\omega}$, local coal unit costs $c_{ib\omega}$ and local coal share $\rho_{ib\omega}$, I proceed to estimate the local coal revenue figure:

$$R_{ib\omega} = K_i \cdot HR_i \cdot q_{ib\omega} \cdot c_{ib\omega} \cdot \rho_{ib\omega}$$

Note that, that the model assumes that the regulators from states without mines do not care about the local coal revenue. Hence, I impute $R_{ib\omega} = 0$ to those plants belonging to no-coalmine states.

G.2.3 Unit Sulfur Emissions

Thirdly, I need to impute unit sulfur emissions $S_{ib\omega}$ for all generator i, aggregate state bin b and scrubber type ω triplets. In doing so, I once again resort to the previous procedure: S_{it} generator-level sulfur emissions are regressed on plant covariates X_i. Such regression is performed three times, once for each scrubber type. The estimated coefficients are later used to impute sulfur emissions at all grid points, yielding a $S_{ib\omega}$ vector.

Once $W_{ib\omega}$, $R_{ib\omega}$, $S_{ib\omega}$ and $K_{ib\omega}$ are imputed for all generator i, aggregate state bins b and ω combinations, computing the regulator utility is a straightforward task:

$$U_{ib\omega} = W_{ib\omega} + \alpha_1 \cdot R_{ib\omega} + \alpha_2 \cdot S_{ib\omega} + \alpha_3 \cdot K_{ib\omega}$$

Moving forward, I introduce the following matrix notation for regulator utility functions. For intuitive purposes, row i of U_{ω_h} represents the utility of plant i, with high efficiency scrubber ω_h, for all b aggregate state bins.

$$\underset{I\times B}{U_{\omega_h}} \qquad \underset{I\times B}{U_{\omega_l}} \qquad \underset{I\times B}{U_{\omega_0}}$$

G.3 Candidate structural parameters

The estimation procedure will start by defining a set of candidate structural parameters:

$$\theta = (\alpha, X, \sigma)$$

Recall the meaning of each parameter:

- α is the vector of weights in the regulator utility function.
- X is the scrap value of the generator.
- σ is the scale parameter of the unobserved iid EV-T1 shocks ϵ.

G.4 Bellman Iteration

The bellman iteration starts by combining candidate structural parameters α and imputed values $(W_{ib\omega}, K_{ib\omega}, S_{ib\omega}, R_{ib\omega})$ to compute per-period regulator utility, for each generator i, aggregate state bin b and scrubber type ω triplet:

$$U_{ib\omega} = W_{ib\omega} + \alpha_1 \cdot R_{ib\omega} + \alpha_2 \cdot S_{ib\omega} + \alpha_3 \cdot K_{ib\omega}$$

Plants that already have a wet scrubber ω_h are to choose between remaining open or exiting. Hence, the discretized version of their Bellman equation is as follows:

$$\begin{aligned} V_{ib\omega_h} = \max\{&U_{ib\omega_h} + \beta E\left[V_{ib\omega_h}\right] + \sigma \cdot \epsilon_{hit}, \\ &U_{ib\omega_h} + X + \sigma \cdot \epsilon_{xit}\} \end{aligned} \tag{46}$$

Plants with dry scrubber ω_l face a similar situation, as they are to choose between remaining open or closing:

$$\begin{aligned} V_{ib\omega_l} = \max\{&U_{ib\omega_l} + \beta E\left[V_{ib\omega_l}\right] + \sigma \cdot \epsilon_{lit}, \\ &U_{ib\omega_l} + X + \sigma \cdot \epsilon_{xit}\} \end{aligned} \tag{47}$$

On the contrary, the plants that do not yet have a scrubber are to choose between four discrete options:

$$\begin{aligned} V_{ib\omega_0} = \max\{&U_{ib\omega_h} + \beta E\left[V_{ib\omega_0}\right] + \sigma \cdot \epsilon_{oit}, \\ &U_{ib\omega_h} + \beta E\left[V_{ib\omega_l}\right] + \sigma \cdot \epsilon_{lit}, , \\ &U_{ib\omega_h} + \beta E\left[V_{ib\omega_h}\right] + \sigma \cdot \epsilon_{hit}, , \\ &U_{ib\omega_h} + X + \sigma \cdot \epsilon_{xit}\} \end{aligned} \tag{48}$$

From this point onwards, I employ matrix notation.

G.4.1 Value Function Iteration

1. The value function iteration starts by initializing the Emax Value function matrixes to zero:

$$\underset{I \times B}{V_{\omega_h}} = 0 \qquad \underset{I \times B}{V_{\omega_l}} = 0 \qquad \underset{I \times B}{V_{\omega_0}} = 0$$

2. Next I calculate the two value functions for generators that have a wet scrubber:

$$\underset{I\times B}{v^r_{\omega_h}} = \underset{I\times B}{U_{\omega_h}} + \beta \cdot \underset{I\times B}{V_{\omega_h}} \times \underset{B\times B}{T'} \qquad \textit{Remaining}$$

$$\underset{I\times B}{v^x_{\omega_h}} = \underset{I\times B}{U_{\omega_h}} + X \qquad \textit{Exiting}$$

3. The previous procedure also applies for generators with dry scrubbers:

$$\underset{I\times B}{v^r_{\omega_l}} = U_{\omega_l} + \beta \cdot V_{\omega_l} \times T' \qquad \textit{Remaining}$$

$$v^x_{\omega_l} = U_{\omega_l} + X \qquad \textit{Exiting}$$

4. Thirdly, the value functions of generators without scrubbers are computed as follows:

$$\underset{I\times B}{v^r_{\omega_0}} = U_{\omega_0} + \beta \cdot V_{\omega_0} \times T' \qquad \textit{Remaining}$$

$$v^{\omega_l}_{\omega_0} = U_{\omega_0} + \beta \cdot V_{\omega_l} \times T' \qquad \textit{Investing in } \omega_l$$

$$v^{\omega_h}_{\omega_0} = U_{\omega_0} + \beta \cdot V_{\omega_h} \times T' \qquad \textit{Investing in } \omega_h$$

$$v^x_{\omega_0} = U_{\omega_0} + X \qquad \textit{Exiting}$$

5. Integrate-out the action space, obtaining three new candidates for the Emax function: $V^{'}_{\omega_h}, V^{'}_{\omega_l}, V^{'}_{\omega_0}$. Recall that the EV-T1 distribution with standard deviation σ enables the closed-form expression for the Emax function. γ is the Euler constant. The resulting new Emax functions are the following three:

$$\underset{I\times G}{V^{'}_{\omega_h}} = \sigma \cdot ln\left[exp\left(\frac{v^r_{\omega_h}}{\sigma}\right) + exp\left(\frac{v^x_{\omega_h}}{\sigma}\right)\right] + \sigma \cdot \gamma$$
$$V^{'}_{\omega_l} = \sigma \cdot ln\left[exp\left(\frac{v^r_{\omega_l}}{\sigma}\right) + exp\left(\frac{v^x_{\omega_l}}{\sigma}\right)\right] + \sigma \cdot \gamma$$
$$V^{'}_{\omega_0} = \sigma \cdot ln\left[exp\left(\frac{v^r_{\omega_0}}{\sigma}\right) + exp\left(\frac{v^{\omega_l}_{\omega_0}}{\sigma}\right) + exp\left(\frac{v^{\omega_h}_{\omega_0}}{\sigma}\right) + exp\left(\frac{v^x_{\omega_0}}{\sigma}\right)\right] + \sigma \cdot \gamma$$

6. Compare the discrepancy between the two versions of the Emax function. Such discrepancy is to be below ϵ.[53]

$$max\left(|V^{'}_{\omega_h} - V_{\omega_h}|\right) < \epsilon \quad \& \quad max\left(|V^{'}_{\omega_l} - V_{\omega_l}|\right) < \epsilon \quad \& \quad max\left(|V^{'}_{\omega_0} - V_{\omega_0}|\right) < \epsilon$$

7. If the previous condition is met, save the value functions and move forward to Section G.5.

8. If the previous condition is not met, iterate the loop starting with the new Emax value function candidates:

$$V_{\omega_h} = V^{'}_{\omega_h} \qquad V_{\omega_l} = V^{'}_{\omega_l} \qquad V_{\omega_0} = V^{'}_{\omega_0}$$

G.5 Conditional Choice Probabilities

The Extreme Value Type 1 distribution of ϵ_{it} allows to compute closed-form conditional choice probabilities. Plants with either dry or wet scrubbers will have two conditional choice probabilities each. Plants without scrubbers, to the contrary, face four choices and hence have four conditional choice probabilities.

[53] $\epsilon = 1e^{-6}$

1. Starting from generators with high-efficiency wet scrubbers, $P^r_{\omega_h}$ denotes the probability of remaining, while $P^x_{\omega_h}$ refers to the probability of exiting.

$$\underset{I\times G}{P^r_{\omega_h}} = \frac{exp\left(\frac{v^r_{\omega_h}}{\sigma}\right)}{exp\left(\frac{v^r_{\omega_h}}{\sigma}\right) + exp\left(\frac{v^x_{\omega_h}}{\sigma}\right)} \qquad Probability\ of\ remaining$$

$$\underset{I\times G}{P^x_{\omega_h}} = \frac{exp\left(\frac{v^x_{\omega_h}}{\sigma}\right)}{exp\left(\frac{v^r_{\omega_h}}{\sigma}\right) + exp\left(\frac{v^x_{\omega_h}}{\sigma}\right)} \qquad Probability\ of\ exiting$$

2. The procedure for generators with low-efficiency dry scrubber is analogous:

$$\underset{I\times G}{P^r_{\omega_l}} = \frac{exp\left(\frac{v^r_{\omega_l}}{\sigma}\right)}{exp\left(\frac{v^r_{\omega_l}}{\sigma}\right) + exp\left(\frac{v^x_{\omega_l}}{\sigma}\right)} \qquad Probability\ of\ remaining$$

$$P^x_{\omega_l} = \frac{exp\left(\frac{v^x_{\omega_l}}{\sigma}\right)}{exp\left(\frac{v^r_{\omega_l}}{\sigma}\right) + exp\left(\frac{v^x_{\omega_l}}{\sigma}\right)} \qquad Probability\ of\ exiting$$

3. Thirdly, the computation of conditional choice probabilities for gererators without scrubbers follows the same logic as before.

$$\underset{I\times G}{P^r_{\omega_0}} = \frac{exp\left(\frac{v^r_{\omega_0}}{\sigma}\right)}{exp\left(\frac{v^r_{\omega_0}}{\sigma}\right) + exp\left(\frac{v^{\omega_l}_{\omega_0}}{\sigma}\right) + exp\left(\frac{v^{\omega_h}_{\omega_0}}{\sigma}\right) + exp\left(\frac{v^x_{\omega_0}}{\sigma}\right)} \qquad Probability\ of\ remaining$$

$$P^{\omega_l}_{\omega_0} = \frac{exp\left(\frac{v^{\omega_l}_{\omega_0}}{\sigma}\right)}{exp\left(\frac{v^r_{\omega_0}}{\sigma}\right) + exp\left(\frac{v^{\omega_l}_{\omega_0}}{\sigma}\right) + exp\left(\frac{v^{\omega_h}_{\omega_0}}{\sigma}\right) + exp\left(\frac{v^x_{\omega_0}}{\sigma}\right)} \qquad Probability\ of\ investing\ in\ \omega_l$$

$$P^{\omega_h}_{\omega_0} = \frac{exp\left(\frac{v^{\omega_h}_{\omega_0}}{\sigma}\right)}{exp\left(\frac{v^r_{\omega_0}}{\sigma}\right) + exp\left(\frac{v^{\omega_l}_{\omega_0}}{\sigma}\right) + exp\left(\frac{v^{\omega_h}_{\omega_0}}{\sigma}\right) + exp\left(\frac{v^x_{\omega_0}}{\sigma}\right)} \qquad Probability\ of\ investing\ in\ \omega_h$$

$$P^x_{\omega_0} = \frac{exp\left(\frac{v^x_{\omega_0}}{\sigma}\right)}{exp\left(\frac{v^r_{\omega_0}}{\sigma}\right) + exp\left(\frac{v^{\omega_l}_{\omega_0}}{\sigma}\right) + exp\left(\frac{v^{\omega_h}_{\omega_0}}{\sigma}\right) + exp\left(\frac{v^x_{\omega_0}}{\sigma}\right)} \qquad Probability\ of\ Exiting$$

4. Ultimately, the eight conditional choice probabilities are stacked in a threee dymension matrix:

$$\underset{I\times G\times 8}{P}$$

G.6 Matching the Model to the Data

Once the conditional choice probabilities are calculated, the next step consist on comparing with the actual choices observed in the data. Take the observation of generator i at period t.

1. The procedure starts by selecting the row of the conditional choice probability matrix that belongs to generator i:

$$\underset{1\times G\times 8}{P_i}$$

2. Recall that the aggregate state of the observation Ω_{it} belongs in between the mean values of four aggregate state bins.

$$\underset{1\times 4\times 8}{P_{it}}$$

3. The ultimate conditional choice probabilities are thus a weighted average of the four closest bins, yielding a vector of eight conditional choice probabilities.

$$\underset{1\times 1\times 8}{P_{it}}$$

4. The model contemplates eight possible transitions, each with its corresponding conditional choice probability. Computing the discrepancy between the model conditional choice prediction and the actual data first requires that the observed transition is determined. $\mathbb{1}\{\omega_h \wedge \omega_{it} = \omega_0\}$, for instance, is an indicator that turns on if the plant, having no scrubber $\omega_{it} = \omega_0$, invests into a wet srubber ω_h at period t. Out of the eight indicator variables, all are to be zero but one of them. Next, the nonzero indicator is multiplied by the probability that the model assigned to such transition: $\left(\mathbb{1}\{\omega_h \wedge \omega_{it} = \omega_0\} \cdot [P_{it}]^r_{\omega_0}\right)$. Ultimately, the discrepancy between the model and the observation it is computed as follows:

$$\begin{aligned}
discrepancy_{it} =& \mathbb{1}\{r \wedge \omega_{it} = \omega_0\} \cdot \left(\mathbb{1}\{r \wedge \omega_{it} = \omega_0\} \cdot [P_{it}]^r_{\omega_0}\right) + \\
& \mathbb{1}\{\omega_l \wedge \omega_{it} = \omega_0\} \cdot \left(\mathbb{1}\{\omega_l \wedge \omega_{it} = \omega_0\} \cdot [P_{it}]^r_{\omega_0}\right) + \\
& \mathbb{1}\{\omega_h \wedge \omega_{it} = \omega_0\} \cdot \left(\mathbb{1}\{\omega_h \wedge \omega_{it} = \omega_0\} \cdot [P_{it}]^r_{\omega_0}\right) + \\
& \mathbb{1}\{x \wedge \omega_{it} = \omega_0\} \cdot \left(\mathbb{1}\{x \wedge \omega_{it} = \omega_0\} \cdot [P_{it}]^r_{\omega_0}\right) + \\
& \mathbb{1}\{r \wedge \omega_{it} = \omega_l\} \cdot \left(\mathbb{1}\{r \wedge \omega_{it} = \omega_l\} \cdot [P_{it}]^r_{\omega_0}\right) + \\
& \mathbb{1}\{x \wedge \omega_{it} = \omega_l\} \cdot \left(\mathbb{1}\{x \wedge \omega_{it} = \omega_l\} \cdot [P_{it}]^r_{\omega_0}\right) + \\
& \mathbb{1}\{r \wedge \omega_{it} = \omega_h\} \cdot \left(\mathbb{1}\{r \wedge \omega_{it} = \omega_h\} \cdot [P_{it}]^r_{\omega_0}\right) + \\
& \mathbb{1}\{x \wedge \omega_{it} = \omega_h\} \cdot \left(\mathbb{1}\{x \wedge \omega_{it} = \omega_h\} \cdot [P_{it}]^r_{\omega_0}\right)
\end{aligned}$$

5. The ultimate Log-Likelihood function will thus be:

$$LL = \sum_{t}^{T} \sum_{i}^{I} log(discrepancy_{it}) \quad \leq \quad 0$$

6. The Log likelihood function LL is minimized using an Nelder-Mead algorithm.

H Counterfactual Estimations

H.1 The importance of coal plant protection

This section outlines the procedure to estimate the counterfactual estimation of the model. I will focus on the case of $\theta_{\Delta R=0} = 0$.

1. Take the vector of original structural parameters θ^* and set all the "coal protectionism" parameters to zero:

$$\theta_{\Delta R=0} = 0$$

2. Compute a single bellman iteration for $\theta^*_{\Delta R=0}$.

3. Use the continuation values V from the previous bellman iteration to find new CCPs for each generator and period pair.

4. For each generator and year pair, find the highest CCP and assign its corresponding discrete choice as the decision that would have been taken in the counterfactual world.

5. ISSUE: all original and counterfactual CCPs are about 85% remain.

6. Prediction is that no plant invests or exits.

7. Need to define a different cutoff.

8. This procedure ultimately generates a panel of generator, year pairs in which decisions over coal plants were not influenced by the "coal protectionism" factor.

Now, to the interesting policy counterfactuals, one can compute:

- Utility per-period revenue with and without "coal protectionism":

$$\Delta\Pi_{\Delta R=0} = \Pi_{\theta^*} - \Pi_{\Delta R=0}$$

- Coal mine per-period revenue with and without "coal protectionism":

$$\Delta R_{\Delta R=0} = R_{\theta^*} - R_{\Delta R=0}$$

- In case we found out,

$$\Delta\Pi_{\Delta R=0} > \Delta R_{\Delta R=0}$$

a policymaker could rather raise a tax, transfer it to the coal mining industry, and divest in coal, rather than bail out the mines through delayed divestiture.

H.2 Carbon tax

This subsection explains how I estimate a counterfactual scenario of a carbon tax. The carbon tax, denoted $t\left(\frac{\$}{CO_2\ Ton}\right)$, is paid by both natural gas and coal power plants. Still, as natural gas is less carbon-intensive than coal, the tax will ultimately damage coal and benefit natural gas. I assume all natural gas power plants emit 976 $\left(\frac{lbs\ CO_2}{MWh}\right)$ and coal plants 2,257 $\left(\frac{lbs\ CO_2}{MWh}\right)$.[54]

The carbon tax, thus, makes natural gas comparatively cheaper. More specifically, I recalculate the natural gas price of each aggregate state bin b under a carbon tax t as:

$$\mu_b^t = \mu_b - (2,257 - 976)\left(\frac{lbs\ CO_2}{MWh}\right) \cdot \frac{1}{2,000}\left(\frac{Ton\ CO_2}{lbs\ CO_2}\right) \cdot t\left(\frac{\$}{Ton\ CO_2}\right)$$

I Standard Errors of Structural Parameters θ

Once the vector of structural parameters θ^* is found,

- Simulate a population of coal generators, each with its own time-invariant characteristics (heat rate, distance to Wyoming, state, wet scrubber equipment at the beginning of the period etc.).
- For each generator, simulate an aggregate state for a total of 10 periods. Take the observed natural gas price of the state at 2008 and simulate future draws based on an AR-1 process.
- The previous procedure will create a simulated panel of generator x year observations.
- Solve the bellman iteration of the simulated generators, for the original structural parameters θ^*. This procedure will return continuation values V for each generator, aggregate state and discrete decision.
- Use the aforementioned continuation values to compute the CCPs from each of the generator, gridpoint pairs.
- Find, for each observation of the simulated panel, the CCP corresponding to that generator and aggregate state. Assign the highest of the CCPs as the actual decision of the generator at the period.
- Now, we have a panel of generators with discrete decisions in it, so one can run the estimation procedure from scratch.
- Rerunning the estimation procedure on the simulated data will generate a new vector of structural parameters $\theta^*_{s=1}$.

By re-running the previous sequence S repeated times -say, 25- we get a vector of optimal structural parameters:

[54]The emission estimates are by the EIA 2019. Find the report here.

$$\theta^*_{s=1}, \quad \theta^*_{s=2}, \quad \theta^*_{s=3}, \quad ..., \quad \theta^*_S$$

Standard errors of the original structural parameters θ^* are computed using such vector. For a structural parameter α, the sample standard deviation sd_α and standard errors se_α are:

$$\sigma_\alpha = \sqrt{\frac{\sum_{s=1}^{S} \left(\alpha^*_s - \alpha^*\right)^2}{S-1}} \qquad se_\alpha = \frac{\sigma_\alpha}{\sqrt{S}}$$