Delaying the Energy Transition: Local Regulators, Mines, and Coal Plant Closure Resistance*

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I document how electricity regulators protect local coal mines at the expense of higher electricity prices. I focus on the U.S. electricity generation sector over 2008-2019, when new environmental standards and stiff competition forced coal plants to either upgrade or close. Exploiting geographical and institutional variation, I show that regulators approved upgrades primarily to support local mines. Using a dynamic discrete choice model, I evaluate the political feasibility of welfare-improving policies. I show that consumer-to-mine transfers neutralize this distortion, enabling faster coal plant closures and thereby reducing both electricity prices and emissions.

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1 Introduction

Coal is the most polluting source of electricity. In 2024, coal power plants accounted for 34% of the worldwide electricity output (OWD [2026a]) and were responsible for 40% of all CO_2 emissions (OWD [2026b]). On top of their significant contribution to global warming, coal plants also issue many toxic pollutants, among which sulfur is one of the most hazardous.[1] These damages motivated the tightening of the U.S. nationwide sulfur emission limit in 2016.

The new standard forced coal plant owners to choose among three compliance paths: First, install an expensive, yet efficient sulfur filter and combine it with high-sulfur local coal. Second, invest in a less costly, less efficient "standard" filter and use low-sulfur, out-of-state coal.[2] Third, close the coal plant and replace it with a natural gas facility, an less polluting and increasingly affordable alternative. Coal plant owners' compliance strategy was determined by the regulatory framework that they are subject to.[3] Two-thirds of U.S. coal power plants are "regulated", meaning that their filter investments should be approved by the electricity regulator of their state. The remaining "non-regulated" plants operate outside the purview of state regulators, and hence their choice is not influenced by them.

Previous literature studied coal plant owners' incentives to upgrade their facilities (Fowlie [2010], Gowrisankaran et al. [2022]). This is the first paper that adresses upgrades from the regulators' point of view. Doing so, I uncover a novel distortion in regulated monopoly setups: regulators' willingness to protect the sector that supplies the monopoly. According to this mechanism, several state electricity regulators approved expensive filter investments so that coal plants could keep burning local coal, thus protecting the revenue of their state's coal mining sector.

I document this distortion employing both reduced-form and structural estimation methods. First, I show that regulated coal plants are more likely to adopt expensive filters, but only if these investments are to benefit the coal mines of their state. Then, I estimate a dynamic principal-agent model that formalizes the main tradeoffs involved in coal procurement, filter investment, and plant retirement decisions. Based on the reduced-form evidence, the model features a regulator utility function with two elements: the total surplus in the electricity sector and the revenue of the state's mining sector. Parameter estimates show that two-thirds of the mining-state regulators take into account local mining revenue in their decisionmaknig process.

I simulate a counterfactual scenario where regulator utility only depends on total surplus.

[1] In the U.S., sulfur emissions accounted for $137.6 billion worth of environmental and health damages in 2010 alone (Holland et al. [2020]).

[2] Note that sulfur filters do not reduce coal power plant CO_2 emissions.

[3] 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. [2023]

This simulation yields larger total surplus, lower local mining revenue and faster coal plant closures. Interestingly, the resulting surplus *increase* is often larger than the revenue *decrease*. Thus, there is room for a "politically feasible" transfer that uses a fraction of the total surplu increase to compensate local mine revenue losses. In short, the transfer protects local mining revenue, increases surplus, and decreases pollution. More specifically, it is as effective as a 60$/Ton CO_2 carbon tax in accelerating coal plant closures.

The paper starts by documenting three key empirical facts about the U.S. coal electricity generation sector in the 2008-2019 period. First, coal features high transport costs. Second, local coal requires expensive filters to meet the new sulfur emissions standard. Third, the availability of affordable natural gas reduces coal power plants' output.

Next, I exploit institutional and geographical variation to test whether regulated plants from mining states are more likely to invest in expensive filters. The main empirical exercise consists of a multinomial logistic regression with four possible outcomes: Retire the plant, install a standard or expensive filter, or remain without one. First, I compare "regulated" and "non-regulated" coal plants, as investment decisions of the latter group are not determined by local electricity regulators.[4] Second, I exploit whether regulated plants belong to coal mining states, as regulators from non-mining states have no local mines to protect and may encourage expensive filter investments for reasons other than mining protection.[5] The interaction between the two sources of variation identifies the local coal protection mechanism. More specifically, a hundred extra miners employed near a regulated plant increase its probability of adopting an expensive filter by 9.5%. This effect is absent both for non-regulated plants and for the adoption of standard filters. The results are robust to several measures of local mining activity, such as the number of mines near the plant and the size of these mines.

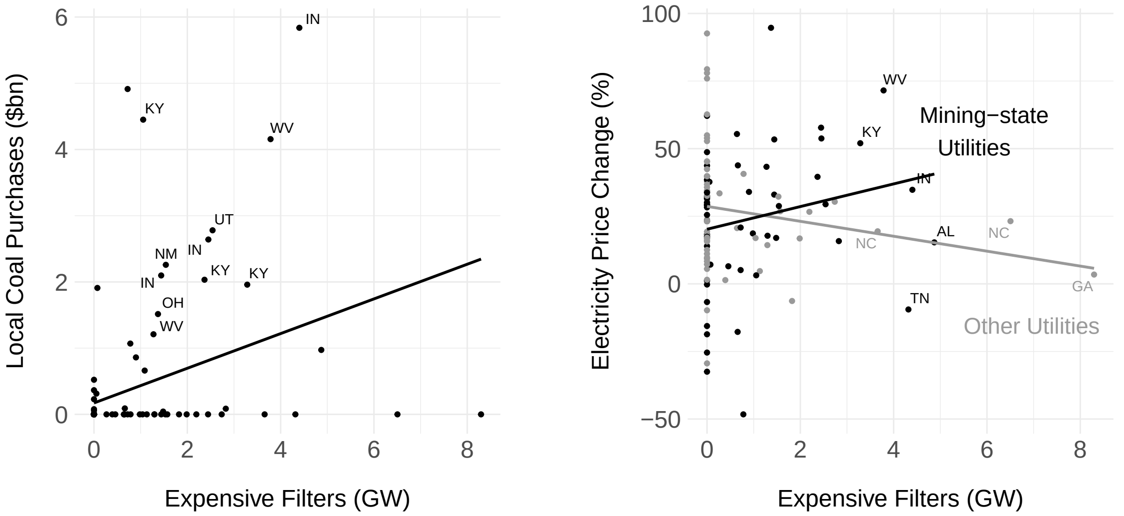
After documenting the local mine protection channel, I estimate a dynamic principal-agent model where the state electricity regulator features the principal role, while the plant-owner is the agent (Lim and Yurukoglu [2018], Gowrisankaran et al. [2023]). The regulator offers the plant owner a menu of the regulated prices it may charge to final electricity customers. Such a menu is conditional on the investment and closure decisions undertaken by the plant owner.[6] Next, the plant owner observes the menu of prices offered by the regulator and subsequently chooses among four discrete options: Invest in either an expensive or an standard filter, retire the plant, or postpone

[4]The empirical energy economics literature has extensively used non-regulated plants as a control group to identify regulatory distortions (Fowlie [2010], Jha [2020] and Cicala [2015]).

[5]In this regard, the lack of in-state mines does not necessarily mean that regulated plants are immune to other distortions, such as the Averch-Johnson effect (Averch and Johnson [1962]). Hence, the investment behavior of regulated plants from non-mining states may still differ from that of non-regulated plants, as in Fowlie [2010].

[6]These regulated prices should satisfy the plant's 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.

Figure 1: Sulfur Filter Investment, Electricity Prices, and Local Coal Procurement



(a) Filter Capacity and Local Mine Revenue

(b) Filter Investment and Electricity Price Changes

Notes: Each dot represents a U.S. regulated utility × state pair. Black dots represent utilities from mining states, while gray dots represents utilities from non-mining states. Wyoming utilities are excluded from the sample. Horizontal axes represent utility-owned coal plants equipped with expensive filters, averaged-out over the 2008–2019 period. Panel (a): The vertical axis represents the total coal purchases from the utility to its state's mines in the 2008–2019 period. Panel (b): The vertical axis shows the percent change in residential electricity prices.

the decision to the next period. If the plant already has a filter, the plant owner chooses between remaining open or being retired. The forward-looking regulator offers a menu of prices to induce the utility into the choice that maximizes its own expected utility. The regulator's utility function is comprised of two elements: The coal plant's contribution to the electricity sector's total surplus and the revenue the plant provides to the state's coal mines.[7]

The filter choice represents a tradeoff between fixed and variable costs: On the one hand, high-efficiency filters are more expensive. This fixed cost is common to all plants, regardless of their location. On the other hand, expensive filters can be paired with local coal. Local coal entails less transport costs than low-sulfur coal, which can only be imported from Wyoming mines, and thus often entails high transport costs. Transport costs savings are heterogeneous across coal plants, as they depend on each plant's distance to Wyoming. For regulated utilities, both fixed and variable costs pass-through into the regulated electricity price that final consumers pay, ultimately determining the plant's contribution to total surplus. Additionally, installing expensive filters enables the use of local coal, thus increasing local mine revenue. Figure 1a correlates expensive filter adoption

[7] Assuming full commitment and the absence of asymmetric information, my model collapses into a single-agent dynamic discrete-choice model where the regulator directly takes the investment and exit decisions on behalf of the plant owner.

and purchases to in-state mines, at utility level.[8]

A regulator aiming to maximize total surplus should only approve an expensive filter when the resulting transport cost savings make up for the additional fixed cost. In contrast, a regulator from a mining state features an extra force pushing in favor of the expensive filter: protecting the revenue of the state's mines. Consequently, these officials may prefer expensive filters, even when these investments increase electricity prices. Figure 1b correlates expensive filter adoption and electricity price changes, for major U.S. utilities over the 2008–2019 period. The Figure suggests a slightly negative correlation for the utilites from non-mining states, labeled "Other Utilities". This trend is consistent with regulators that only advocate for expensive filters when these investments increase total surplus. In contrast, the correlation turns positive for "Mining-state Utilities". This correlation matches a regulator utility function that aims to protect local coal mining revenue, even at the expense of reducing total surplus in the electricity sector. Anecdotically, the correlation is especially acute for the main utility in West Virginia, the US state with the most miners.

Regulators decided on filters as natural gas prices plummeted (Linn and McCormack [2019]). Natural gas, coal's closest substitute in electricity generation, is cleaner: it emits half as much carbon and virtually no sulfur. In consequence, several state regulators rejeceted filter investments, and instead advocated for the replacement of coal plants by natural gas powered facilities. In the model, the forward-looking regulator expects the forthcoming natural gas price drop and factors-in this information when deciding whether to upgrade or close the coal power plant, as in Gowrisankaran et al. [2022]. The prospect of affordable natural gas makes consumer-friendly regulators more keen on coal plant retirement. In contrast, regulators from mining states internalize the negative impact of plant retirement on the local mining industry and, hence, are less eager to plant closures.

To retrieve the importance of local mine revenue in each state regulator's utility function, I estimate the previous model as a single-agent, dynamic discrete-choice problem following the procedure in Rust [1987]. The model estimation relies on the dataset constructed for the reduced-form analysis, enriched by incorporating transaction-level data between mines and plants, generator-level production data, and natural gas electricity prices. According to the model estimates, two-thirds of the mining-state regulators put some positive weight to local mining revenues in their investment decisionmaking. This mechanism reduced surplus, and delayed the replacement of coal power plants by cleaner generation technologies.

I simulate a counterfactual scenario where the regulator utility funcion is only comprised of total surplus, hence turning off the local mine protection mechanism. This simulation results into higher surplus, lower local mining revenue, and faster coal plant closures. I study the feasibility

[8]A state may feature several utilities, each serving a different territory within the state.

of transitioning from the baseline to the counterfactual scenario through a "politically feasible" transfer. Such a transfer requires that the surplus *increase* from baseline to counterfactual scenarios exceeds the local mining revenue *decrease*. Under this condition, the transfer would consist on taxing a portion of the surplus increase and handing it to the local mining sector, to compensate for the revenue decrease. As a result, surplus weakly increases, local mining sector remains indifferent, and coal plant closures accelerate. I find that these transfers are as effective as a 60$/Ton carbon tax in accelerating coal power plant retirements by 2040.

Related Literature

This paper constributes to the empirical industrial organization literature by uncovering a new distortion in regulated markets: the willigness of local regulators to protect the sector that supplies to the regulated monopoly, in the context of the energy transition. Other empirical papers studying distortions in energy markets include Besley and Coate [2003], Davis and Wolfram [2012], Lim and Yurukoglu [2018], Eisenberg [2019], Abito [2019], MacKay and Mercadal [2023], Dunkle Werner and Jarvis [2023], and Safavi. My work focuses on U.S. coal power plants in the 2008–2019 period, thus sharing the same setup as in Gowrisankaran et al. [2023] Gowrisankaran et al. [2022]. These two papers study the behaviour of coal power plant owners.[9] In contrast, my paper focuses on the behaviour of electricity regulators. In this regard, the paper contributes to emerging literature estimating the preferences of regulators (Bodéré et al. [2025], Seim and Waldfogel [2013]). More broadly, this paper also relates to the literature on lobbying and regulatory capture Kang [2015], i Vidal et al. [2012] , and Cowgill et al. [2021].

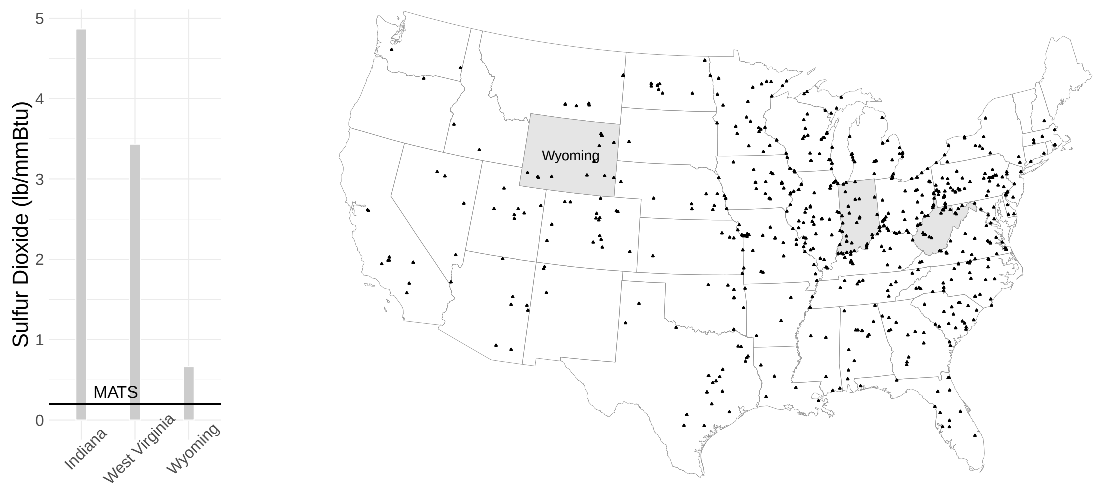
Furthermore, I contribute to the empirical literature on pollution abatement strategies. Early work on this topic includes Ellerman and Montero [1998] and Arimura [2002], focused on studying the first U.S. emission allowance marketplaces. Fowlie [2010] studies nitrogen oxide filter adoption and finds that regulated plants are more willing to abate emissions using capital-intensive methods, backing the theoretical prediction in Averch and Johnson [1962].

Finally, my work also relates to the literature on resource extraction. Papers in this literature includeCicala [2015], Preonas [2023] Joskow [1987] and Joskow [1990].

The remaining of the paper is sctructured as follows: Section 2 details the sulfur emission regulation that motivated filter adoption, and the crucial role of state electricity regulators in this decision. Section 3 presents the data sources. Section 4 documents key empirical facts of my setup. Section 5 presents the causal inference exercises testing the existence of the local mine protection

[9]The first paper found that regulated utilities dispatch their coal plants at a loss, to make them look "used and useful" in front of the regulators, and keep them in the rate base. The second paper studies the regulatory uncertainty surrounding the MATS adoption, from the point of view of non-regulated coal plants

Figure 2: Coal Mine and Coal Power Plant Location in the U.S.



(a) Sulfur, Mining States

(b) Coal Plant Location

Note: (a) Average SO2 concentration of the extracted coal (lbs/MMBtu), for selected states. Year 2008-2019. Black line represents MATS threshold (b) Each dot represents an operating coal power plant in 2008. Indiana, West Virginia, and Wyoming are highlighted in gray.

channel. Section 6 introduces the model. Section 7 outlines the model estimation strategy and test the estimation fit. Section 8 dicusses the main policy counterfactual of the paper. Section 9 concludes.

2 Institutional Context

This section introduces the institutional features of my setup. First, Subsection 2.1 reviews the Mercury Air Toxic Standards (MATS) and explains the main paths to comply with this regulation. Then, Subsection 2.2 explains the role of state electricity regulators in determining coal plant owners' compliance path choice.

2.1 Sulfur Emission Regulation and Compliance Paths

The Mercury and Air Toxics Standards rule (MATS) obliged U.S. coal power plants to significantly reduce their sulfur dioxide emissions. 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 this pollutant.[10] The MATS rule

[10] Coal plants were responsible for 90% of the sulfur emissions in the electricity sector for the 1997-2007 period (EIA [2018]).

was promulgated in December 2011 by the Obama-era 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: 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).[11] Coal plant operations have two complementary ways to reduce sulfur emissions. Burn coal with low sulfur content, reducing the release of sulfur dioxide, and install filters that capture the released sulfur dioxide.

Wyoming mines are the only source of low-sulfur coal in the U.S., and transporting it to distant plants is often expensive. Traditionally, U.S. coal plants procured coal from nearby local mines to minimize transport costs. However, the sulfur concentration of "local" coal is much higher than that from Wyoming. Figure 2a takes some of the largest coal producing U.S. states and plots the sulfur content of the coal they extracted in the last decade. As mentioned, Wyoming "Powder River Basin" coal stands out as the one with lowest sulfur, featuring a 0.66 sulfur dioxide lbs/MMBtu concentration. West Virginia and Indiana, in contrast, have an average content above 3 lbs/MMBtu. Consequently, many plants switched to burning Wyoming coal, turning this state into the first producer in the U.S.[12] Switching from "local" to Wyoming coal usually entailed a major disadvantage: higher transport costs. Figure 2b represents the geographical distribution of U.S. active coal power plants in 2008. The states of Wyoming, West Virginia and Indiana are highlighted in gray. It is immediate that Wyoming is far from most US coal power plants and, hence, adopting low-sulfur coal translates into significant freight expenses. Moreover, even the sulfur concentration of Wyoming coal is 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 filters.

Plants burning "local" coal require an expensive filter to meet the MATS standard. Filters are technically known as "scrubbers", and "catch" sulfur dioxide molecules before they are released to the atmosphere. These devices are classified into two categories: "dry scrubbers" and "wet scrubbers". For the sake of clarity, I refer to "dry scrubbers" as "standard filters", and to "wet scrubbers" as "expensive filters". The median cost of an expensive filter installed in the 2008-2019 period was approximately $200 million. Expensive filters achieve filtering efficiencies up to 99%, allowing power plants to burn local coal while complying with the MATS limit. Standard filters are cheaper, with a median cost of approximately $100 million. Still, the sulfur dioxide removal

[11] The rule established April 2015 as the original compliance deadline, but later offered a one-year extension. Moreover, EPA granted exceptional extensions beyond 2016 based on electricity supply reliability concerns (Walton [2016], Pow [2015]). 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.

[12] 40% of all the coal extracted in the U.S. in the last decade came from Wyoming. Source: EIA. Anecdotal evidence from Propp [2017]

efficiency of these devices does not exceed 95%. It is for this reason that, according to Sorrels [2021], standard filters still require low-sulfur coal to to comply with MATS. Importantly, none of these filters reduce coal power plant CO_2 emissions, and hence, upgraded coal power plants remain significant contributors to global warming.

2.2 The Role of State Regulators in Filter Investment Decisions

U.S. state-level authorities play a significant role in regulating coal power plants. About two-thirds of U.S. coal power plants are "regulated", meaning that they belong to investor-owned utilities (IOUs). These utilities are vertically integrated local monopolies, as they are the only suppliers of electricity within their "retail service territory". In other words, the consumers living in a service territory are forced to buy their power from their corresponding utility. Utilities charge a regulated electricity price to their captive consumers. This price is set by the "Public Utilities Commission" (PUC), the state-level electricity regulator. PUCs are quasi-governmental agencies in charge of overseing the electricity utilities of their state, and hold the authority to set the electricity price that IOUs charge to their captive consumers. The mission of PUCs is to guarantee state customers a reliable electricity supply at the lowest cost possible, while ensuring that utility owners earn a "reasonable" rate of return, in line with "cost of service" regulation.[13] PUCs are usually comprised of three to six commissioners with 6 year-long staggered terms. In most states, PUC commissioners are appointed by the governor and ratified by the state legislature.[14]

State electricity regulators ultimately decide whether a coal plant installs a filter, or closes. Cost of service regulation requires utilities to regularly submit "Integrated Resource Plans" (IRPs) to their respective state regulators. These plans outline future capital investments, including, among others, sulfur filter installations, coal power plant closures, and new gas power plant constructions. The IRPs are assessed by the regulators in trial-like procedures where the commissioners hear the testimonies from stakeholders. These may include the utility itself, consumer advocates, coal mine owners, labor unions, environmental groups, and other advocacy groups.[15] After gathering stake-

[13]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".

[14]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

[15]The Sierra Club Beyond Coal campaign, for instance, was very active in testifying against filter investments. See Drake and York [2021]. On the contrary, representatives of coal mining counties have expressed support for power plant upgrades, even at the expense of higher electricity prices. Anecdotically, a state representative from West Virginia's Marshall County advocated for a coal power plant upgrade stating that "We need to keep that plant open, and if it means raising our utility bills a little bit, so be it." (Ohi [2021], Van Voorhis [2021]). Moreover, the state of Wyoming funded a dark money group named the Energy Policy Network which advocated on the opposite direction.

holder input, the PUC decides which of the proposed investments are "prudent". Once the regulator approves the investment, 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.

The remaining third of U.S. coal plants are labeled as "non-regulated", and do not operate under "cost of service" regulation. In consequence, state regulators cannot influence their filter investment decisions. "Non-regulated" plants were originally "regulated", as they belonged to vertically-integrated utilities. Starting in the mid-1990s, some states forced their utilities to sell their coal power plants to third-party investors, hence turning these facilities into "non-regulated". This wave of divestitures abruptly ended after the 2000-2001 California electricity crisis, resulting in a mixed landscape that simultaneously features "regulated" and "non regulated" plants (Cicala [2015]). Consequently, regulated and non-regulated coal plants have similar physical characteristics, such as age and size. Still, state regulators only influence the investment and exit decisions of the regulated coal plants.

3 Data

I combine multiple publicly available datasets to build a panel of the universe of U.S. coal plants from 2008 to 2019. The panel includes information on each unit's coal source, output, filter type, regulatory status, as well as time-invariant covariates such as location. Coal plant data is available at three different levels of granularity and not all datasets report the same level: Firstly, "generators" 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.[16] Thirdly, "plants" represent the highest level of aggregation and represent whole facilities that may encompass several generators and boilers.[17]

The EIA-860 dataset is an annual panel of the universe of electricity generators in the U.S. and serves as the foundation of my data construction process. 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 filters installed at U.S. power plants. These records are reported at the boiler level and include the filter type, total cost and installation date. This dataset allows me to classify coal generators into three filter categories: "standard filters", "expensive filters" and "none".

[16]There are several generator–boiler configurations. Large generators may each have their own boiler, but in some cases multiple generators can share a single boiler. Although less common, a large generator may also supply steam to several smaller boilers.

[17]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.

Next, I use the EPA eGRID dataset to enrich my original panel. eGRID is a biannual panel of U.S. power plants providing some crucial plant-level covariates, such as geolocation and regulatory status.

Thirdly, I use the EPA Continuous Emissions Monitoring System (CEMS) dataset to obtain output, heat-rate, and sulfur emissions. CEMS reports hourly, generator-level heat input and electricity output. 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. Moreover, the CEMS also records generator-level sulfur oxide emissions, a crucial input to test whether the generator is complying with the MATS rule.

Fourthly, the EIA-923 reports coal power plant procurement behaviour. The dataset reports transactions 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 transport cost entailed in each transaction.[18] Lastly, EIA-923 also reports transactions of natural gas plants, which allows me to estimate an average unit cost of natural gas electricity production, for each state and year.

4 Empirical Facts

This section introduces three empirical facts relevant to my setup: first, transport represents a large fraction of coal unit cost. Second, local coal requires expensive filters to meet the MATS sulfur emission standard. Third, the availability of affordable natural gas has significantly reduced the output of coal power plants, and prompted their closure. These empirical facts, together with the causal evidence laid in Section 5, motivate the introduction of the model in Section 6.

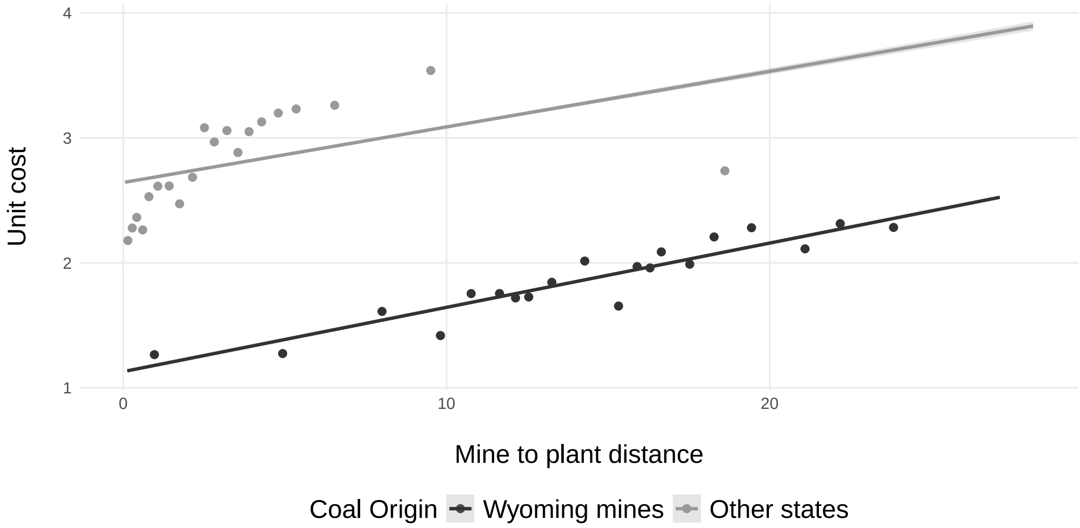
4.1 Coal Transport Costs are Significant

Coal is extracted from mines and transported to power plants, where it serves as an input for electricity generation. The high transportation costs associated with coal have historically encouraged power plant owners to source locally. In some cases, power plants were even located alongside mines in so-called "mine-to-mouth" operations to minimize these costs. However, recent sulfur emission regulations pushed plant owners to switch to low-sulfur coal from far-away Wyoming mines.

Procuring distant coal entails significant unit cost incrases. Figure 3 illustrates the rela-

[18] Coal plants are geolocated using eGRID dataset, while coal mines are assigned the centroid of their county using the EIA 7A dataset.

Figure 3: Coal Origin and Transport Costs



Binscatter of 20 bins for each coal origin. The linear fit line is estimated using the underlying dataset. Each observation of the underlying dataset represents a transaction between a mine and a regulated plant, between 2008 and 2019. Each observation includes the unit price of coal, including the mine-to-plant transportation cost. The horizontal axis represents the euclidean distance between the mine and the plant measured in degrees on earth. One degree earth is equivalent to 69 miles, which is approximately 111,319 km. The Vertical axis represents the unit cost of the coal ($/MMBtu). Transactions are classified by whether the coal origin is the state of Wyoming.

tionship between the transportation distance of coal purchases and their unit costs, distinguishing transactions by whether the mine of origin is in Wyoming. The plot reveals three patterns. First, Wyoming coal has a lower base price compared with coal from other U.S. basins. Second, Wyoming coal travels longer distances, likely reflecting its appeal as a low-sulfur fuel source. Third, despite its lower origin price, the high transportation costs associated with Wyoming coal often make its delivered cost higher than that of coal from closer mines.

The previous binscatter is formalized through a regression framework, the results of which are presented in Table 1. The dependent variable is the unit cost of coal for each mine-to-plant transaction. State and county fixed effects are included to account for unobserved characteristics of coal-producing regions that influence coal prices at the origin, such as mining productivity and the sulfur content of the extracted coal. The key explanatory variable, Mine–plant distance, measures the Euclidean distance between the origin mine and the destination power plant for each transaction.

4.2 Local Coal Requires Expensive Filters

Plants that burn coal with more sulfur produce more sulfur dioxide, but their ultimate sulfur dioxide emissions depend on their type of filter. Subfigure 4a represents this correlation, for different filter types. Each observation in the underlying dataset corresponds to a generator–year pair for the 2008–2019 period. The horizontal axis represents the logarithm of the sulfur concentration of the

Table 1: Coal transportation costs

	Dep. Var.: Unit Cost of Coal	
	(1)	(2)
Intercept	3.515***	3.184***
	(0.020)	(0.084)
Mine–plant distance	0.067***	0.066***
	(0.0004)	(0.0004)
Fixed Effects	State	County
Observations	140,695	140,695
R^2	0.432	0.554
Adj. R^2	0.432	0.553

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$

Note: Mine to plant coal transactions for regulated plants and between 2008 and 2019. The dependent variable is measured in \$/MMBtu. The "Mine-plant distance" covariate represents the euclidean distance between the mine and the plant, measured in degrees on earth. One degree earth is equivalent to 69 miles, which is approximately 111,319 km.

coal purchased by the plant in that year, while the vertical axis represents the logarithm of the generator's sulfur dioxide emission rate. Each generator–year observation is classified into one of three categories based on the type of sulfur filter installed in that year and the figure also includes fitted linear regressions for each category.[19]

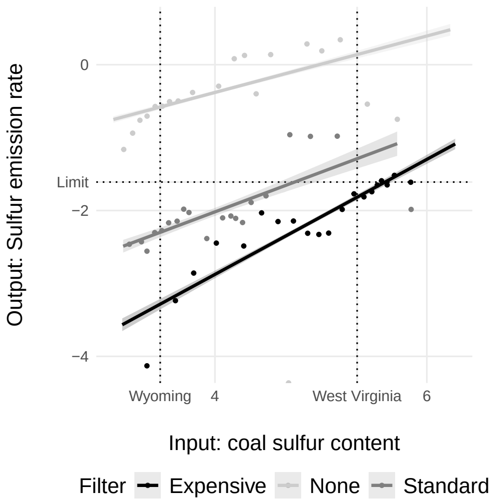
Subfigure 4a's horizontal "Limit" line represents the unit sulfur dioxide emission cap established under the MATS rule. Although MATS took effect in 2016, the scatterplot covers the 2008–2019 period. Consequently, observations appearing above the threshold do not necessarily indicate noncompliance, but rather reflect plant–year observations that predate the enforcement deadline.[20] The vertical lines labeled "Wyoming" and "West Virginia" indicate the average sulfur content of coal extracted from these respective states.

Subfigure 4a conveys four insights. First, the correlation between the sulfur content of coal and sulfur dioxide emissions is, as expected, positive. Second, the fitted line corresponding to generators equipped with expensive filters lies uniformly below that of standard filters, indicating that they achieve greater reductions in sulfur dioxide emissions for any given sulfur content. Third,

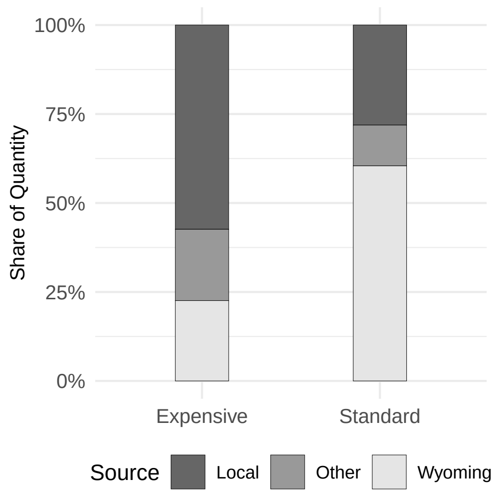
[19] As plants install a filter over the years, they transition from the "None" category to either the "Standard" or "Expensive" categories.

[20] Moreover, nearly all observations corresponding to generators without scrubbers ("None") lie above this threshold. This implies that compliance with the MATS rule effectively requires the installation of some form of sulfur removal technology, consistent with the "maximum achievable control technology" (MACT) standard embodied in the regulation.

Figure 4: Filter Types and Coal Procurement Patterns



(a) Efficiency of each filter type



(b) Coal Sources, by Filter Type

Note: (a) Binscatter of 20 bins for each filter type. The linear fit line is estimated using the underlying dataset. The underlying dataset aggregates plants' coal purchases and sulfur dioxide emissions annualy, between 2008 and 2019. The horizontal axis represents the logarithm of the average sulfur concentration of the coal purchased by the plant, measured in sulfur pounds per million british termal units (sulfur lbs/MMBtu). The Vertical axis represents the logarithm of the sulfur emission intensity of the plant, measured in sulfur dioxide emissions per unit of input (SO2 lbs/MMBtu). Plant-year observations are assigned a filter type every year. The horizontal line "Limit" represents the sulfur emission threshold established by MATS, enforce from 2016 and onwards. The vertical lines "Wyoming" and "West Virginia" are the average sulfur concentrations of the coal extracted in those states and serve illustrative purpose. (b) Coal sources of U.S. plants from mining states, after MATS enforcement. Wyoming coal plants are excluded. "Local" refers to transactions involving plants and mines sitting in the same state. "Wyoming" refers to coal imported from Wyoming mines. "Other" groups transactions that fail to meet any of the previous categories.

Table 2: Filter Efficiency, by Filter Type

	Dep. Var.: log(Sulfur emission rate)		
	No filter	Standard	Expensive
Intercept	-1.966^{***}	-3.372^{***}	-6.032^{***}
	(0.078)	(0.167)	(0.116)
log(Input sulfur content)	0.404^{***}	0.420^{***}	0.789^{***}
	(0.019)	(0.042)	(0.023)
Observations	4,390	1,047	3,047
R^2	0.095	0.088	0.271
Adjusted R^2	0.095	0.087	0.271

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$

Note: The underlying dataset aggregates plants' coal purchases and sulfur dioxide emissions annualy, between 2008 and 2019. The covariate represents the logarithm of the average sulfur concentration of the coal purchased by the plant in the year, measured in sulfur pounds per million british termal units (sulfur lbs/MMBtu). The dependent variable represents logarithm of the sulfur emission intensity of the plant, measured in sulfur dioxide emissions per unit of input (SO2 lbs/MMBtu). Plant-year observations are assigned a filter type every year. The specification is estimated separately for each type of filter

a coal plant burning Wyoming coal will always comply with the MATS rule, regardless of its filter type. Forth, a coal plant burning West Virginia coal would only meet the MATS emission cap if it were equipped with an expensive filter, as the intersection between the "West Virginia" vertical line and the standard filter fitted line lies above the regulatory threshold.

Subfigure 4a implies that plants willing to use local coal must install an expensive filter to comply with the MATS rule. Subfigure 4b confirms this implication by showing the coal sources of plants, by filter type. As expected, plants with expensive filters purchase a higher share of local coal, while Wyoming coal is prevalent for plants with standard filters.

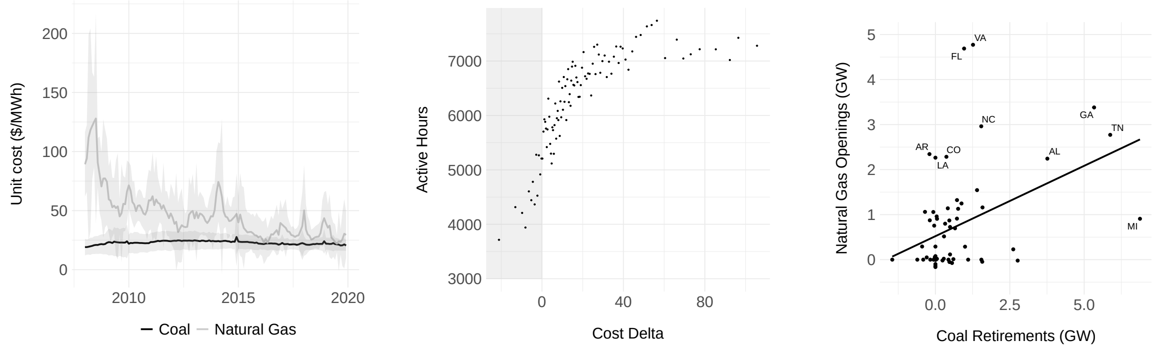
Table 2 formalizes the Subfigure 4a correlations, by estimating the sulfur dioxide emission intensity of each plant-year pair as a function of the sulfur intensity of the input coal.

4.3 Affordable Natural Gas Reduces Coal Plant Output

Natural gas is coal's closest substitute in electricity generation. This fuel became significantly cheaper in the U.S.during the 2008-2019 period thanks to "hydraulic fracturing" a new extraction technique that untapped previously inaccessible underground reserves (See Subfigure 5a).

Subfigure 5b displays how coal power plant output reacts to its relative unit cost with respect to natural gas. The horizontal axis "Cost Delta" variable is computed by substracting the

Figure 5: Coal and Natural Gas, 2008-2019 Period



(a) Unit Costs (b) Coal Plant Output (c) Retirements and Openings

Notes: (a) Average montly costs across states. Bandwidth represents 1 standard deviation. (b) Binscatter of 100 bins. Each observation of the underlying dataset is a plant-year pair, between 2008 and 2019. The horizontal axis "Cost Delta" represents the difference between the unit cost of producing electricity using natural gas at the plant's own state (in $/MWh units) and the coal plan's input unit costs (also in $/MWh). This is, the higher the "Cost Delta", the more affordable coal is with respect to natural gas. In contrast, The shaded area corresponds to events when "Cost Delta"< 0, thus representing instances in which natural gas was more affordable than coal for electricity production. The vertical line "Active Hours" represt the number of hours that the coal plant was producing electricity, for a given year. (c) Each dot represents a utility. Coal Plant Retirements represent the net decrease in coal capacity over 2008–2019. Natural Gas Plant Openings represent the net increase in natural gas capacity over the same period.

plants' unit cost of coal to that of natural gas plants in their same state. Negative "Cost Delta"-s mean coal was more expensive than gas for electricity production, and are represented by the gray area. The vertical axis "Active Hours" variable counts the number of hours a coal plant was active in a year.

Subfigure 5b provides three intuitions. Firstly, there is an unsurprising positive correlation between coal plants' relative affordability -represented by higher "Cost Delta" values- and coal power plant outcome. Second, the positive correlation is not linear: as the "Cost Delta" increases, coal plants move towards producing at all the hours of the year. Still, once plants hit this capacity constraint, further cost ratio increases cannot translate into more coal plant output. Third, when natural gas is cheaper, coal plants still supply a significant amount of output. The shaded area in Figure 5b represents the instances when natural gas is more affordable than coal. When facing this situations, coal power plants reduce their output, but remain active for a significant amount of hours. This supply behaviour may be due to grid reliability concerns, transmission constraints, or the need for regulated utilities to justify the "usefulness" of their facilities to earn a rate of return on them (Gowrisankaran et al. [2023]).

The natural gas cost reduction significantly influenced utilities' investment decisions, as many of them replaced their coal power plants with natural gas facilities (Gowrisankaran et al. [2023]). This fact is illustrated by Subfigure 5c, which plots the net change in coal and natural gas

Table 3: Linear Regression for Coal Plant Dispatch

	Dep. Var.: Number of Active Hours h_{it}		
	(1)	(2)	(3)
Constant	5,711.928***	5,622.624***	6,041.395***
	(32.690)	(111.967)	(362.350)
Cost Difference "Delta"	28.125***	26.639***	26.859***
	(1.009)	(1.047)	(0.858)
Fixed effects	No	State	Plant
Observations	6,737	6,737	6,737
R^2	0.103	0.236	0.535

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$

capacity for each utility between 2008 and 2019. The figure reveals a clear correlation between coal plant retirements and natural gas plant openings, suggesting that utilities that retired more coal capacity also invested more in natural gas generation.

I next formalize the previous discussion into a linear regression specification. The dependent variable of the specification $h_{it} \in [0, 8760]$ represents the number of hours that plant i operated on year t. Regarding the main covariate of interest "Delta", is the difference between average cost of producing one electricity output unit using natural gas in state s and year t, measured in \$ cents per MWh, and coal plant i's unit cost of coal, for same year t. Table 3 presents the estimations of the specification, for different fixed effects. As expected, more expensive natural gas translates into more coal generator active hours.

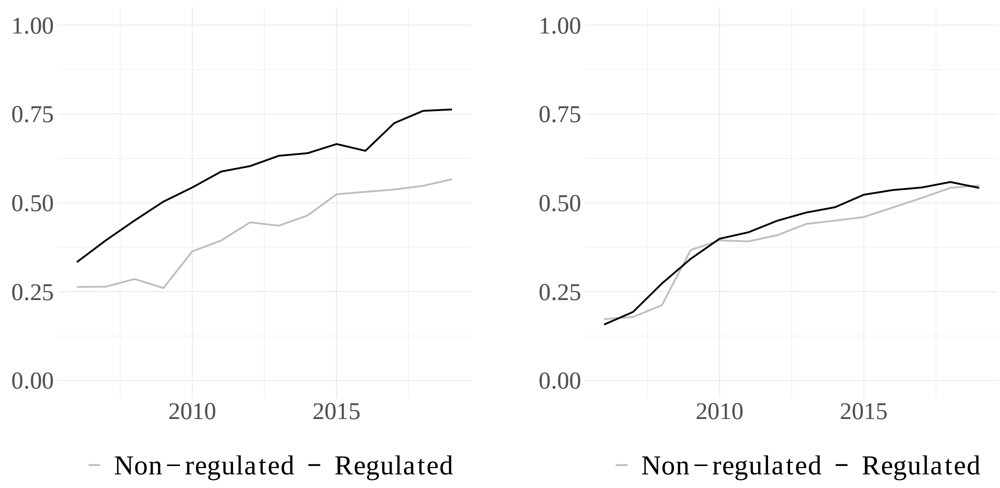
5 Causal Evidence

This section provides causal evidence on state regulators approving expensive filters to protect the coal mines of their state. The empirical exercises in this section rely on the interaction between institutional and geographical variation.

Historically, all U.S. coal plants were "regulated", as they belonged to vertically integrated utilities operating under the supervision of state electricity regulators. This means that state electricity regulators effectively decide whether regulated plants install a filter —and of which type— or close.[21] The 90's witnessed a significant push towards the liberalization of the U.S. electricity generation market. In this context, some U.S. states forced some of their vertically-integrated util-

[21] See Subsection 2.2 for more institutional details.

Figure 6: Share of Coal Plants with Expensive Filters, Classified by Regulatory Status. 2008-2019



(a) Mine States (b) No-mine States

ities to divest their coal power plants. These divested plants became known as “non-regulated” or “merchant”. State regulators have no oversight power over the filter installation in these plants, as the decision belongs to the new owners only. Still, regulated and non-regulated coal plants are subject to the federal sulfur emission constraint set by MATS, effectively forcing them to either install a filter or shut down. This section follows Fowlie [2010], Cicala [2015], Gowrisankaran et al. [2023] and others in leveraging “non-regulated” plants as a control to identify regulatory distortions. My identification strategy assumes that merchant plant-owners are private profit maximizers that only install expensive filters when they are the most lucrative option. For instance, an expensive filter may be the most economical MATS compliance option when a plant is far from Wyoming, as it allows the owner to skip low-sulfur coal transport costs. In contrast, expensive filter investments in regulated plants may be driven by regulatory distortions, such as the Averch-Johnson effect (Averch and Johnson [1962], Fowlie [2010]), or by the desire of state regulators to protect local coal mines.

I disentangle regulatory distortions by exploiting coal power plant location: mining state regulators only oversee a subset of the regulated plants. The remaining facilities are managed by regulators with no local mines to protect.[22] My empirical strategy assumes that regulators from mining states are equivalent to those in other states in all aspects but for the fact that the former internalize their local coal mines’ interests when choosing a filter.

According to the previous assumption, we should observe more expensive filter investment in regulated plants from mining states, as shown in Figure 6. The figure classifies coal power plants into four categories, according to their regulatory status and by whether they belong to mining

[22] States with more than 1.000 miners in 2008 are considered “coal-mining states”. These are: Alabama, Colorado, Illinois, Indiana, Kentucky, Montana, North Dakota, New Mexico, Ohio, Texas, Utah, West Virginia and Wyoming.

Table 4: 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	10,099.13	10,401.98	10,015.13	9,972.16
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.

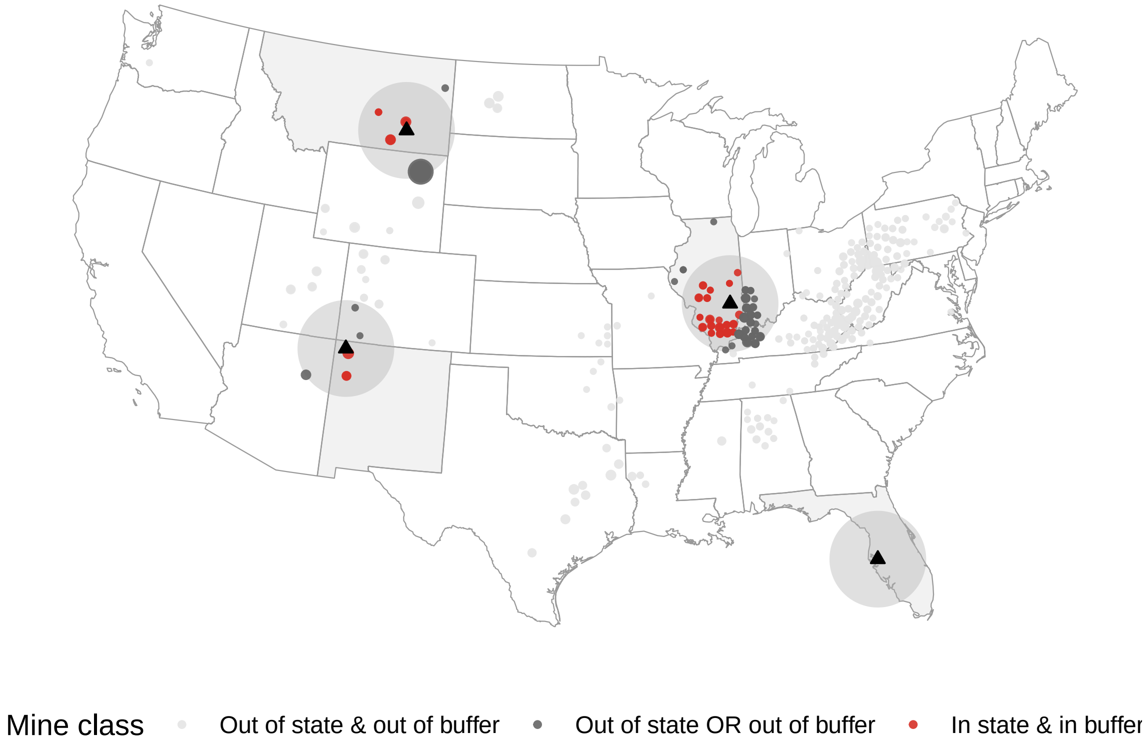
states. By plotting the share of coal power plants with expensive filters over time, regulated plants from mining states stand out. This suggestive evidence may be driven by covariates that correlate with the four-fold classification. Regulated plants from mine states, for instance, may be further from Wyoming than the rest and, hence, the transport cost savings enabled by expensive filters may also be larger. Table 4 adresses this concern by providing mean values of key covariates. The table follows the approach in Figure 6 and classifies coal generators by their regulation and state. Non regulated plants are, on average, younger, smaller, and more productive.

Power plant location is represented by three time-invariant covariates: 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, regardless of regulatory status. 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. 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.

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

Equation (1) presents the first specification of this section, consisting on a Cox-Proportional Hazard model for expensive filter installation. In this specification, the dependent variable $h_i(t)$ represents the probability of generator i installing an expensive filter at period t, conditional on not having installed such a filter in previous periods. Generators that already had an expensive filter at

Figure 7: Illustration of the m_i local mining variable construction



Note: black triangles represent coal power plants from Montana, New Mexico, Illinois and Florida. The shaded catchment area around them represents a 138 mile radius around them. Dots represent coal mines. Dark gray dots represent mines that either belong to the same state as the plant, or fall within the plant's catchment area. Red dotted mines fall within both the catchment area and the state. The treatment variable m_i consists on the share of in-state mines within the catchment area of each plant. $m_i = 0$ for the plants with no mines in the catchment area.

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}. Equation (1) assumes non-regulated plants from no-mine states as the baseline group. The regression interacts institutional and geographical variation: on the one hand, Reg_i is an indicator variable for regulated plants. On the other hand, $m_i \in [0, 1]$ represents the local mining sector around generator i.

Figure 7 provides intuition on how the $m_i \in [0, 1]$ variable is constructed. Triangles represent the location of selected coal power plants, while the dots identify coal mines. The gray catchment area around each triangle encompasses a 138 mile radius.[23] Coal mines are classified into three groups, for each plant. Light gray dots represent mines that fall ouside the plant's catchment area and do not belong to the plant's same state. Dark gray dots represent mines that either belong to the catchment area or the plant's same state. Lastly, "red" mines belong to both the plant's catchment area and its same state. The treatment variable m_i is computed as the share of in-state

[23] 138 miles are median distance that coal travels from the mine to the plant.

Table 5: Proportional Hazards Model - Expensive Filter Installation

	Dep. var.: Probability of expensive filter	
	(1)	(2)
Age	-0.018^{***}	-0.018^{***}
	(0.001)	(0.001)
Size (MW)	0.001^{***}	0.001^{***}
	(0.0001)	(0.0001)
Heat Rate (Btu/KWh)	-0.0001	-0.0001
	(0.00002)	(0.00002)
Distance to Wyoming	0.057^{***}	0.051^{***}
	(0.003)	(0.003)
Local mining m_i	-0.060	-0.417
	(0.105)	(0.189)
Regulated	0.162^{***}	0.176^{***}
	(0.059)	(0.058)
Local mining m_i × Regulated	0.841^{***}	1.235^{***}
	(0.113)	(0.200)
Periods	2008-2019	2008-2019
Close mines radius	138 miles	345 miles
Observations	9,000	9,000
R^2	0.104	0.093

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

mines (red mines) within the catchment area of each plant (sum of red and dark gray mines). I assign $m_i = 0$ to the plants with no mines in their catchment area.

Table 5 presents the coefficient estimates of the empirical exercises. Each column corresponds to a different catchment area radius. The coefficient estimates that correspond to plant characteristics behave as expected: Age and Heat Rate are either non-significant or negative, meaning that older, less productive facilities are also less likely to get an expensive filter. The coefficient regarding size, in contrast, is positive and significant, as expensive filters represent a fixed cost with notable economies of scale.

Regarding plant location, distance to Wyoming d_i^{wy} is a strong driver of expensive filter installation in all specifications. This result is coherent with the transport cost reduction argument. Plants far from Wyoming are to pay higher transport costs for low-sulfur coal. Hence, installing a expensive filter 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 the availability of local coal plays a second-order role.

The indicator for regulated plants Reg_i is positive and significant, in line with the theoretical prediction in Averch and Johnson [1962]. The result is also coherent with the empirical findings in Fowlie [2010]. Finally, the interaction term between regulated plants and the share of local mines $Reg_i \times m_i$ is also positive and significant for both specifications, showing that regulators from mine states consider protecting local mines when approving expensive filters investments.

$$\log \frac{p_j(x_i)}{p_J(x_i)} = \beta_{0j} + \beta_{1j}^{\top} X_i + \beta_{2j} Reg_i + \beta_{3j} m_i + \beta_{4j} Reg_i \times m_i, \tag{2}$$

I complement the Cox proportional-hazards model with a multinomial logit exercise outlined in Equation (2). The multinomial logit abstracts from the dynamic nature of the problem, but enables me to study the filter choice and the closure in the same specification. I take the subset of coal generators that were open without a filter in 2008, and classify them into four groups, represented by subscript $j \in \{remain,\ std,\ exp,\ ret\}$: the generators that installed no filters and remained open by 2019 belong to the first group $j = remain$. Generators that installed an standard filter and remained open by 2019 belong to the second group $j = std$. Generators that installed a expensive filter and remained open belong to the third group $j = exp$. Lastly, the generators that retired at some point in the 2008-2019 period belong to the fourth group $j = ret$.[24] 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 variable Reg_i is positive for regulated plants. Lastly, m_i measures the importance of in-state mining around the plant, as previously defined. The mining state regulators' willigness to protect local mines by installing expensive filters is represented by coefficient $\beta_{4j=exp}$.

Table 6 presents the parameter estimates of the specification. In line with the paper's main hypothesis, the "Regulated × Mine Size" interaction coefficient is positive and significant for expensive filters. I assess the sensitivity of the Equation 2 specification by estimating it with alternative definitions for the m_i treatment variable. I define the following three additional m_i treatments: The first treatment corresponds to an indicator that turns on when the generator belongs to mining states. The second treatment consists of adding the output of all the in-state, close-by mines in 2008, measured in million tons of coal. The third treatment takes a similar approach and sums all the miners working at in-state, close-by mines in 2008, measured in thousands of miners. The resulting specifications are presented in Appendix A and are consistent with the main results of this section.

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

Table 6: Multinomial Logit - Mine Share Specification

	Dependent variable		
	j = retire	j = standard	j = expensive
Regulated	-0.787	-0.250	-0.218
	(0.509)	(0.762)	(0.545)
Mine Share	-1.298^{**}	-2.555^{**}	-2.326^{***}
	(0.660)	(1.082)	(0.744)
Regulated x Mine Share	1.884^{**}	2.041^{*}	3.480^{***}
	(0.758)	(1.207)	(0.837)
		McFadden R2	0.225
	*p<0.1	**p<0.05	***p<0.01

Note: One observation per coal generator. Specification includes 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. The treatment consists on the share of close-by mines that belong to the same state as the plant, which can take a range of values between zero and one.

6 Model

This section introduces a dynamic principal-agent model on coal procurement, plant dispatch, electricity price setting, filter investment, and plant decomissioning. The model consists of two agents: the state electricity regulator as the principal, and a representative utility as the agent.

The model features a static and a dynamic stage. In the static stage, the utility takes the the regulated electricity price, electricity import prices and the filter of its coal plant as given, and makes coal procurement and plant dispatch decisions to maximize its profits, while meeting sulfur emission standards. These intratemporal decisions are short-lived, as they can be reconsidered every period. In the dynamic stage, the state regulator offers the utility a menu of regulated electricity prices depending on the filter investment or decommissioning decisions, and the utility takes such decisions accordingly. These intertemporal decisions are long-lived and lock the utility into an electricity generation mix.

6.1 Static Stage: Local Coal Demand and Plant Dispatch

For any fixed year $t \geq 2008, 2009, \ldots, \infty$, a representative utility u obtains its revenue by charging a regulated electricity price p_{ut} to its captive consumers, who feature an inelastic electricity demand

Q_u with indifference threshold price $\hat{p}$.[25] The representative utility owns a single coal plant, indexed by subscript i. The utility can meet its electricity demand by either producing it with its own coal plant i, or by importing it from other suppliers, at price p_{ut}^{imp}.

Power plant i uses coal as its input to produce electricity. Plant i chooses a coal source $m_{it} \in \{l, wy\}$: either its local mine $m_{it} = l$, or the Wyoming coal basin $m_{it} = wy$. Each coal type is characterised by three time-invariant characteristics: its sulfur concentration s_i^m, the mine-to-plant distance d_i^m and unit price p_i^m. The coal unit price has two elements $p_i^m = p_m + \tau \cdot d_i^m$, where p_m is the price of coal type m at its origin, and τ represents the transportation cost per distance unit. Lastly, q_{it}^m represents the amount of coal procured by the plant i, from coal source m.

Coal power plant i is characterised by its capacity KW_i, which determines the maximum amount of electricity the plant can supply in an hour. $h_{it} \in [0, 8760]$ represents the number of active hours of plant i, at year t. To account for the plant's capacity constraint, I define a plant level optimal number of active hours h_{0i}. Supplying above that level of optimal hours entails a quadratic penalty $\mathbb{1}\{h_{it} > h_{0i}\} \cdot \xi \cdot (h_{0i} - h_{it})^2$, where $\xi > 0$. I assume that, during active hours, coal plant supplies at full capacity, hence, the coal power plants annual electricity output Q_{it} is a linear function of its active hours $Q_{it} = KW_i \cdot h_{it}$. The production function of the plant is $Q_{it}(q_{it}^m) = \frac{1}{HR_i} \cdot q_{it}^m$, where HR_i represents the coal plant's heat rate.[26] At this stage, I gather all the time-invariant characteristics of coal plant i into vector χ_i.[27]

$$\chi_i = \left\{d_i^{wy}, d_i^m, s_i^m, KW_i, HR_i, h_{0i}, Age_i^{t=2008}\right\}$$

At a given year t, the coal plant features a sulfur emission filter ω_{it}, which can take three discrete values: none $\emptyset$, standard $\underline{\omega}$, or expensive $\bar{\omega}$: $\omega_{it} \in \{\emptyset, \underline{\omega}, \bar{\omega}\}$. As empirical evidence suggested, expensive filters are better than standard ones in reducing sulfur emission instensity. The utility's capital investment on the fiter is represented by a one-time payment $F_\omega(\omega_{it})$, where $F_\omega(\omega_{it} = \emptyset) = 0$, and $F_\omega(\omega_{it} = \underline{\omega}) < F_\omega(\omega_{it} = \bar{\omega})$. I also define equivalent perpetual annuities of the filter fixed costs: $f_\omega(\omega_i) = \frac{1-\beta}{\beta} \cdot F_\omega(\omega_i)$.

The utility combines coal plant electricity generation and electricity imports to meet its downstream demand. Both electricity sources feature capacity constraints: Firstly, recall the coal plant's capacity constraint is modeled through a quadratic penalty of the deviation between optimal active hours h_{oi} and actual active hours h_{it}, denoted $\mathbb{1}\{h_{it} > h_{0i}\} \cdot \xi \cdot (h_{0i} - h_{it})^2$. Secondly, replacing coal electricity generation by imports becomes increasingly costly, due to transmission and availability constraints, among others. I model this constraint as an quadratic penalty on downward

[25] The assumption of price-inelasticity is in line with the empirical findings in Fabra et al. [2021], [Willis and Garrod, 1997].

[26] Heat rate is the amount of heat (in BTUs) required to produce one unit of electricity (usually 1 kilowatt-hour, kWh). A lower heat rate means the plant needs less fuel per kWh, hence, it is more efficient.

[27] $Age_i^{t=2008}$ represents the age of plant i at the beginning of the sample period, year 2008.

deviations of the coal plant's optimal active hours: $\mathbb{1}\{h_{it} < h_{0i}\} \cdot \xi \cdot (h_{0i} - h_{it})^2$. The symmetric nature of the capacity and import constraint penalties allow for a tractable representation of the coal plant dispatch decision that captures the empirical facts outlined in Section 4.3.

Coal combustion generates sulfur emissions. The sulfur emission intensity of plant i at period t, denoted S_{it} is determined by two factors: the sulfur concentration of the procured coal s_i^m, and plant i's filter type ω_{it}.[28] The resulting sulfur emission intensity of plant i that sources from mine m is: $S(m_{it}|\chi_i, \omega_{it}) = \alpha_\omega \cdot (s_i^{m_{it}})^{\beta_\omega}$ (See Section 4.2 for empirical analogue).

The Mercury Air Toxic Standard requires for the coal power plant unit sulfur emission intensity to remain below threshold $\bar{S}$. The standard enforcement begins at year $t = 2016$ and remains active for all subsequent periods. To account for this institutional feature, I define count-down variable T_t, which indicates how many periods are left for reaching the first enforcement year $t = 2016$.

$$T_t = \begin{cases} 2016 - t & \text{if } t \leq 2016 \\ 0 & \text{if } t > 2016 \end{cases} \tag{3}$$

I next introduce a sulfur emissions penalty parameter $\gamma(T_t) = \mathbb{1}\{T_t = 0\} \cdot \gamma$ that only activates in the MATS enforcement periods $T_t = 0$. Moreover, I also assume that violating the standard entails a per input unit penalty that is linear to the extent of the deviation: $\gamma(T_t) \cdot \left(S(m_{it}|\chi_i, \omega_{it}) - \bar{S}\right)^+$. At this stage, I define the aggregate state space Ω_{it} as a vector that gathers four time-variant elements. Note that, at any period t, the future path of variables T_t, γ_t and $\bar{S}$ is certain. In contrast, future realizations of electricity import prices p_{ut}^{imp} are uncertain.

$$\Omega_{it} = \left\{p_{ut}^{imp}, T_t, \gamma_t, \bar{S}\right\} \tag{4}$$

The new notation allows me to define coal unit costs as a function of mine choice m_{it}, conditional on plant time-invariant characteristics, the aggregate state space, and filter type:

$$c(m_{it}|\chi_i, \Omega_{it}, \omega_{it}) = p_i^m(m_{it}|\chi_i) + \gamma(\Omega_{it}) \cdot \left(S(m_{it}|\chi_i, \omega_{it}) - \bar{S}\right)^+ \tag{5}$$

By bringing all the previous assumptions together, the utility's profit function for year t can be expressed as a function of mine choice $m_{it} \in \{l, wy\}$ and coal plant active hours h_{it}, conditional on plant characteristics χ_i, the aggregate state space Ω_{it}, and filter type $\omega_{it} \in \{\emptyset, \underline{\omega}, \bar{\omega}\}$:

$$\begin{aligned} \pi_{ut}(m_{it}, h_{it}) &= \underbrace{p_{ut} \cdot Q_u}_{\text{Revenue}} - \underbrace{c(m_{it}) \cdot q_{it}^m}_{\text{Coal Cost}} - \underbrace{\xi\,(h_{0i} - h_{it})^2}_{\text{Constraints}} - \underbrace{f_\omega(\omega_{it})}_{\text{Fixed Cost}} - \underbrace{p_{ut}^{imp} \cdot (Q_u - Q_{it}(q_{it}^m))}_{\text{Import Costs}} \\ \text{s.t.} \quad Q_{it}(q_{it}^m) &= \frac{1}{HR_i} \cdot q_{it}^m = h_{it} \cdot KW_i \end{aligned} \tag{6}$$

The utility sequentially chooses the coal source m_{it} and coal plant active hours h_{it} to maximize its per-period profits.[29] The coal procurement decision rule often consists on a balancing act

[28] Sulfur emission intensity is measured as emitted pounds of SO2 per input unit (measured in mmBtu)

[29] Coal plant active hours, in turn, determines coal plant annual output Q_{it}.

beetween coal unit costs and sulfur emission penalties. Local coal will feature lower transportation costs, which are a key determinant of the fuel's unit price p_i^m. However, local coal is also more sulfur-intensive, which may lead to higher emission penalties. This tradeoff is mediated by the plant's filter type ω_i, as expensive filters further reduce sulfur emissions and, consequently, the emission penalty. Equation 7 presents the optimal mine choice decision $m^*(\chi_i, \Omega_{it}, \omega_{it})$:

$$m^*(\chi_i, \Omega_{it}, \omega_{it}) = \begin{cases} wy & \text{if } p_i^{m=l} + \gamma(\Omega_{it}) \cdot \left(S(l|\chi_i, \omega_{it}) - \bar{S}\right)^+ > p_i^{m=wy} + \gamma(\Omega_{it}) \cdot \left(S(wy|\chi_i, \omega_{it}) - \bar{S}\right)^+ \\ m & \text{otherwise} \end{cases} \tag{7}$$

The optimal mine choice determines the difference between electricity import prices and coal mine unit costs: $\Delta(m^*|\chi_i, \Omega_{it}, \omega_{it}) = p_{ut}^{imp} - c(m_{it}|\xi_i, \Omega_{it}, \omega_{it}) \cdot HR_i$. This cost delta is a key determinant of the coal power plant dispatch decision. I next take first-order conditions of the utility profit function (Equation 6) with respect to active hours h_{it}. The resulting optimal coal plant dispatch hours h^* as a function of plant covariates are characterised by the following expression:

$$h^*(m^*|\chi_i, \Omega_{it}, \omega_{it}) = h_{0i} + \frac{1}{2 \cdot \xi} \cdot \Delta(m^*|\chi_i, \Omega_{it}, \omega_{it}) \cdot KW_i \tag{8}$$

The decision rules for coal procurement and plant dispatch allow to estimate the total welfare generated by the utility $W_{ut}(m_{it}^*, h_{it}^*|\chi_i, \Omega_{it}, \omega_{it})$, which I assume is comprised by equally weighted consumer surplus CS_{ut} and utility profits π_{ut}.

$$\begin{aligned} W_{ut}(m_{it}^*, h_{it}^* \mid \chi_i, \Omega_{it}, \omega_{it}) = &\underbrace{(\hat{p} - p_{ut}) \cdot Q_u}_{CS_{ut}} + p_{ut} \cdot Q_u - c(m_{it}|\xi_i, \Omega_{it}, \omega_{it}) \cdot \underbrace{h_{it}^* \cdot HR_i \cdot KW_i}_{q_{it}^{m^*}} + \\ &- \xi \left(h_{0i} - h_{it}^*\right)^2 - f_\omega(\omega_{it}) - p_{ut}^{imp} \cdot (Q_u - \underbrace{h_{it}^* \cdot KW_i}_{Q_{it}^*}) \end{aligned} \tag{9}$$

6.2 Dynamic Stage: Filter Investment and Plant Closure

The dynamic stage of the model consists of a discrete-choice, infinite-horizon principal-agent model. At each year t, the forward looking utility and its corresponding state-level regulator engage in a principal-agent relationship that ultimately determines filter investment or plant closure decisions. More specifically, the regulator (principal) offers the utility (agent) a menu of the retail prices it can charge to the final consumer depending on investment or closure decision that decides to tackle. The utility observes this menu of prices and makes the investment or closure decision that maximizes its expected sum of discounted profits.

The Agent: The Electric Utility

Every period t the utility faces two subsequent decision regarding its coal plant i. Firstly, whether to retire the plant, or rather keep it open for the next period $\delta_{ut} \in \{0, 1\}$. In the event that the utility decides to retire its coal plant i $\delta^*_{ut} = 0$, the utility has to build a natural-gas power plant to replace it.

Consistent with the positive correlation between coal plant retirements and natural gas buildups (See Subfigure 5c), the new natural gas plant size should be proportional to the retired coal capacity KW_i. The fixed cost of building the new natural gas plant is represented by a perpetual annuity $f_{ng}(KW_i)$. The newly built natural gas plant produces electricity at unit cost p^{imp}. The resulting per-period profit function for the utility that retires its coal plant at time t, together with the per-period welfare generated by the electricity sector are:

$$\begin{aligned} \pi_{ut}(\delta^*_{ut} = 0|\omega_{it}) &= \left(p_u - p^{imp}_{ut}\right) \cdot Q_u \ - f_\omega(\omega_{it}) \ - f_{ng}(KW_i) \\ W_{ut}(\delta^*_{ut} = 0|\omega_{it}) &= \left(\hat{p}_u - p^{imp}_{ut}\right) \cdot Q_u \ - f_\omega(\omega_{it}) \ - f_{ng}(KW_i) \end{aligned} \tag{10}$$

Note that, in the event that utility u has previously invested in a filter $\omega_{it} \in \{\underline{\omega}, \bar{\omega}\}$ and decides to retire coal plant i, the utility still keeps paying the perpetual annuities corresponding to that filter, even when the plant it was installed on is no longer operative.

In the event that the utility decides to keep its coal plant open $\delta^*_{ut} = 1$, the utility has to make a subsequent decision on filter investment. The filter investment decision features three assumptions: firstly, I assume that filter installation is irreversible, this is, once the utility invests into a filter type, such filter cannot be removed nor replaced in future periods. Secondly, I assume that plants cannot have more than one filter. Thirdly, both filter types feature a one-period time-to-build. This means that, at time t, the utility decides on the optimal investment for the forthcoming period $\omega^*_{i,t+1}$, all while the filter efficiency for the present period remains $\omega_t = \emptyset$. Thus, in case that the utility decides to invest on a filter at time t, the effect of the new filter is thus realized from $t+1$ and onward, and sticks forever: $\omega^*_{t+1} = \omega_{t+2} = \omega_{t+3} = ...$ In consequence, the filter investment decision only entails to open coal plants with no filter at time t: $\omega_{it} = \emptyset$. The resulting threefold decision choice is $\omega_{it} \in \{\emptyset, \underline{\omega}, \bar{\omega}\}$.

In summary, the utility's choice set over a plant with no filter is comprised of four options: remain without any filter, invest in a standard filter, invest in an expensive filter or close the plant. In contrast, the choice set for a plant with a filter is two-fold as it can either remain open or close.

Equation 11 defines the welfare *contribution* of coal plant i at period t as $W(\omega_{it}|\chi_i, \Omega_{it})$, this is, how much welfare the the coal plant generates relative to a scenario in which it is decomissioned and replaced by a natural gas unit. Intuitively, the coal plant improves welfare by replacing relatively expensive imports. However, the coal plant can also harm welfare by blocking its replacement for affordable natural gas. The welfare contribution figure can thus be either positive or negative: If the coal plant's unit cost of generation is below that of the imports, the plant unambiguously contributes to welfare. In contrast, if natural gas-generated unit cost of electricity is cheaper than that of coal, keekping the coal plant open may harm welfare.

$$W(\omega_{it} \mid \chi_i, \Omega_{it}) = W_{ut}(\delta^*_{ut} = 1 \mid \omega_{it}) - W_{ut}(\delta^*_{ut} = 0 \mid \omega_{it}) =$$
$$= \underbrace{h^*(m^*|\chi_i, \Omega_{it}, \omega_{it}) \cdot KW_i}_{Q^*_{it}} \cdot \Delta(m^*|\chi_i, \Omega_{it}, \omega_{it}) - \xi\big(h^*(m^*|\chi_i, \Omega_{it}, \omega_{it}) - h_{0i}\big)^2 + f_{ng}(KW_i). \tag{11}$$

Following the previous logic, $R(\omega_{it} \mid \chi_i, \Omega_{it})$ represents the revenue *contribution* that coal plant i makes to its own state's mining sector. For this contribution to be strictly positive, two conditions must hold: Firstly, that coal plant i belongs to a coal mining state $\mathbb{1}\{i \in CoalState\}$. Secondly, that the plant decides to procure local coal $\mathbb{1}\{m^* = l\}$. Note that, in the event that the coal plant is closed, the utility ceases to provide any revenue to the local mines.

$$R(\omega_{it} \mid \chi_i, \Omega_{it}) = \mathbb{1}\{i \in CoalState\} \cdot \mathbb{1}\{m^* = l\} \cdot p^l_i \cdot HR_i \cdot h^*(m^*|\chi_i, \Omega_{it}, \omega_{it}) \cdot KW_i \tag{12}$$

The Principal: The Utility Regulator

In line with the causal evidence of Section 5, the state regulator's per-period utility function is comprised of two objects: the coal plant's welfare contribution and the in-state mining revenue. Parameter α_s weights the importance of local mine revenues with respect to welfare contribution and is state s specific. The parameter α_s is expected to be positive, as regulators internalize the revenues that coal plants provide to nearby mines.

$$U(\omega_{it}|\chi_i, \Omega_{it}) = W(\omega_{it}|\chi_i, \Omega_{it}) + \alpha_s \cdot R(\omega_{it}|\chi_i, \Omega_{it}) \tag{13}$$

Every period t, the regulator offers the utility a menu of retail prices the utility may charge to the final electricity consumers. This menu of prices is a function of the utility's filter invesmtent and exit decisions $p_{ut}(\delta_{ut}, \omega_{it})$. The regulator tweaks the price menu offering to induce the utility to take its preferred investment or closure decision. Take, for instance, a regulator that aims for the utility to install an expensive filter. In the absence of asymmetric information and assuming full commitment, the regulator can offer a stream of prices that meet the participation constraint of the utility $\pi_{u\tau} = 0 \forall \tau \geq t$ only if the $\omega^*_{i,t+1} = \bar{\omega}$ expensive investment is realized, $\pi_{u\tau} < 0$ otherwise. Note that such a stream of regulated prices should always satisfy the consumer's participation constraint: $p_{u\tau} \leq \hat{p}$. Consequently, this framework is equivalent to model in which the plant investment and exit decisions are directly taken by the regulator to maximize the expected sum of discounted per-period utility $U(\omega_{it}|\chi_i, \Omega_{it})$.

The model assumes that it takes a period to install the filter, regardless of type. Likewise, it also takes a year to decomission a coal plant and build its natural gas replacement. Hence, although the utility may decide to invest in a filter or close the plant in period t, the effect of such decision materializes at period $t+1$ and onward. Ultimately, the investment or closure decision over a plant with no filter $\omega_{it} = \emptyset$ is represented by the following Bellman equation:

$$V(\omega_{it} = \emptyset) = \max\left\{ \max_{\omega_{i,t+1} \in \{\emptyset, \underline{\omega}, \bar{\omega}\}} \{U(\omega_{it} = \emptyset) - F_{\omega}(\omega_{i,t+1}) + \beta E\left[V(\omega_{i,t+1})\right]\}, \quad U(\omega_{it} = \emptyset) \right\} \tag{14}$$

If the coal plant already has a standard filter, $\omega_{it} = \underline{\omega}$, the regulator choice set is constrained to either keeping the plant open or closing it down

$$V(\omega_{it} = \underline{\omega}) = \max\left\{U(\omega_{it} = \underline{\omega}) + \beta E\left[V(\omega = \underline{\omega})\right], \quad U(\omega_{it} = \underline{\omega})\right\} \tag{15}$$

Equivalently, coal plants with expensive filters $\omega_t = h$ may remain open or close down. Similar to the filter construction, the model assumes that it takes one period to dismantle the coal plant and build its natural gas replacement. Hence, if the regulator decides to close the plant at time t, such closure is realized at $t+1$.

$$V(\omega_{it} = \bar{\omega}) = \max\left\{U(\omega_{it} = \bar{\omega}) + \beta E\left[V(\omega_{it} = \bar{\omega})\right], \quad U(\omega_{it} = \bar{\omega})\right\} \tag{16}$$

6.3 Comparative Statics on the Filter Choice Decision

This section discusses how plants' distance to Wyoming d_i^{wy}, local coal sulfur intensity s_i^l, and regulator's willingness to protect local mine revenue $\alpha_s > 0$ determine filter investment decisions.

For tractability, I collapse the dynamic dimension of the model by assuming a time-invariant electricity import price, p_{ut}^{imp}, and by imposing the sulfur standard from the first period onward ($T_t = 0\ \forall t$), which renders the aggregate state space Ω_{it} time-invariant.[30] I further assume the absence of capacity and transmission constraints ($\xi = 0$), implying that the coal plant operates at full capacity whenever import prices exceed coal unit costs—an condition I take to always hold—so that $h^*(\underline{\omega}) = h^*(\bar{\omega}) = \bar{h}$.[31] I also set local coal transport costs to zero ($d_i^l = 0$) and assume that plants burning Wyoming coal always comply with the emissions standard regardless of filter type, consistent with Figure 4a. Finally, for notational convenience, I normalize plant heat rate HR_i and capacity KW_i to the unit.

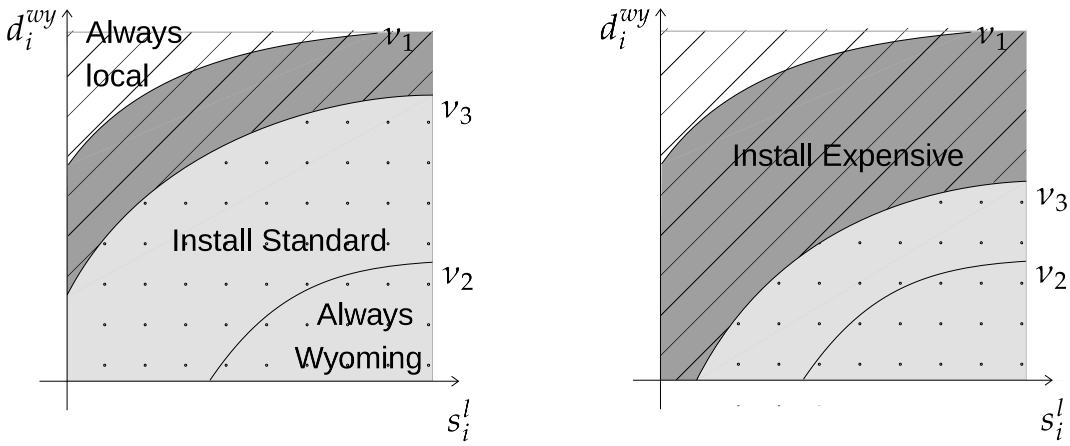
Starting from the utility's mine choice decision, the inequality in Equation 7 can be rearranged as a generic indifferent curve that classifies plants depending on whether they purchase locally, in the d_i^{wy}, s_i^l two-dymensional space displayed in Figure 8.[32] Solving this generic indifference curve for both standard and expensive filters yields two indifferent curves, one for each filter

[30] Under uncertain future import prices, the regulator may delay the filter investment decision to preserve its option value. In contrast, in this perfect-foresight scenario the regulator computes its per-period utility for each filter type in the first period, and then chooses the option that yields higher utility. In this scenario, postponing the filter decision is never optimal.

[31] This assumption substantially simplifies the algebra, as dispatch no longer depends on coal unit costs.

[32] See Appendix C for more details.

Figure 8: Coal Procurement and Filter Investment in Static Setup



(a) Filter Investment for $\alpha_s = 0$.

(b) Filter Investment for $\alpha_s > 0$.

Stripes represent local-coal purchases. Dotted area represent Wyoming-coal purchases. "Always Wyoming" region plants always purchase Wyoming coal, regardless of their filter. "Always local" plants always purchase local coal, regardless of their filter. Light gray area represents instances when the regulator installs a standard filter. Dark gray area represents instances when the regulator installs an expensive filter.

type:

$$\nu_1(s_i^l \mid \underline{\omega}) = d_i^{wy} = \frac{p_l - p_{wy} + \gamma\left[\left(\alpha_{\underline{\omega}}(s_i^l)^{\beta_{\underline{\omega}}} - \bar{S}\right)^+\right]}{\tau}$$

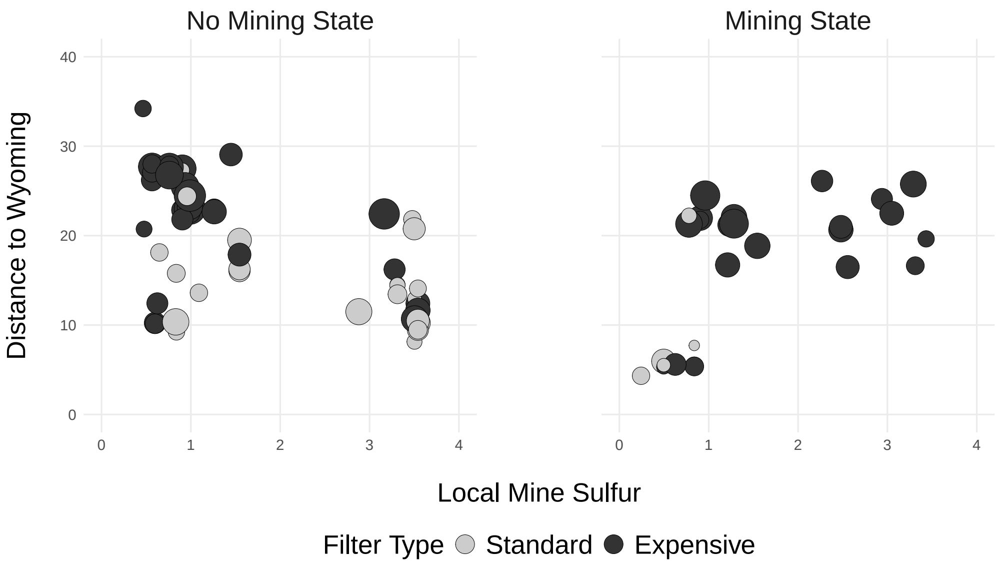
$$\nu_2(s_i^l \mid \bar{\omega}) = d_i^{wy} = \frac{p_l - p_{wy} + \gamma\left[\left(\alpha_{\bar{\omega}}(s_i^l)^{\beta_{\bar{\omega}}} - \bar{S}\right)^+\right]}{\tau}$$

These indifference curves are weakly increasing in s_i^l and delimit three regions (See Figure 8a). Firstly, plants leftward of the ν_1 indifference curve belong to the "Always local" region. This region consists of plants located far from Wyoming, with relatively low sulfur local coal. The significant transport costs of Wyoming coal, paired with the moderate sulfur content of the local coal, makes these plants always pick the latter source, regardless of their filter type. Inversely, the ν_2 curve delimits the "Always Wyoming" region. This area is characterised by plants that are close to the Wyomig basin, and feature very high sulfur local coal. The closedness to Wyoming, coupled with the likely breach of the sulfur standard when using local coal, forces these plants to always purchase from Wyoming, regardless of their filter type. Lastly, plants "between" ν_1 and ν_2 indifference curves belong to the intermediate region, where utilities choose their coal source depending on the filter of their plant.

When the regulator finds itself in the "Always Wyoming" region, the utility's coal choice will not depend on the filter type. As the fixed cost of expensive filters is superior to that of standard ones $f_{\bar{\omega}}(KW_i = 1) > f_{\underline{\omega}}(KW_i = 1)$, the regulator always installs standard filters.[33]

[33] The condition for the regulator to install an expensive filter $W(\bar{\omega}) - f_{\bar{\omega}}(KW_i = 1) \geq W(\underline{\omega}) - f_{\underline{\omega}}(KW_i = 1)$ is

Figure 9: Filter Investment by Regulated Plants.



Each dot represents a regulated coal power plant that installed a filter 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.

In the intermediate region, the filter determines the utility's procurement behaviour: if the regulator chooses an expensive filter, the utility procures locally. If the regulator chooses an standard filter, the utility buys from Wyoming. Aware of this fact, the utility will pick an expensive filter if the following condition is satisfied: $W(\bar{\omega})+\alpha_s \cdot R(\bar{\omega})-f_{\bar{\omega}}(KW_i=1) \geq W(\underline{\omega})-f_{\underline{\omega}}(KW_i=1)$. Solving for the corresponding curve yields the following expression, represented in Figure 8a.[34]

$$\nu_3(\alpha_s) = \nu_2(s_i^l) - \frac{\alpha_s \cdot p_i^l}{\tau} + \frac{\Delta f}{\bar{h}\,\tau}$$

Indifference curve ν_3 partitions the intermediate space into two regions. The stripped region with the dark gray background in Figure 8a, corresponds to plants that receive an expensive filter. These plants are far from Wyoming but feature high sulfur coal, and hence expensive filters are the most economical option to meet the sulfur emission standard. The dotted light gray region corresponds to plants that will receive the standard filter. These plants are relatively close to Wyoming and hence the standard filter is the preferred solution.

Crucially, indifference curve ν_3 is negative with respect to the mine protection parameter α_s. In consequence, larger mine protection parameters displace ν_3 rigthward, widening the expensive filters region (See Figure 8b). Intuitively, regulators aiming to protect local mines will install expensive filters in the 2008-2019 period, even when the alternative approach of combining Wyoming coal with an standard filter is more affordable.

never satisfied.

[34] Where $\Delta f = f_{\bar{\omega}}(KW_i = 1) - f_{\underline{\omega}}(KW_i = 1)$

Figure 9 represents the empirical analogue of Figure 8. The horizontal axis is the sulfur concentration of each plant's closest mine. The verticla axis represents the distance between the plant and the Wyoming coal basin. Each dot represents a regulated coal plant. Black dots correspond to plants that installed expensive filters, while gray dots corresponds to plants that invested in standard filters.

The left caption in 9 corresponds to plants that do not belong to mining states. In this case, the filter adoption pattern resembles that of Figure 8a. In contrast, the right Subfigure represents plants from mining states. The adoption of expensive filters was much more prevalent in this case and follows the distribution described in Subfigure 8b.

7 Estimation and Model Fit

This section explains the procedure to estimate the model described in Section 6 with the regulator utility function from Equation (13). The section is divided into four parts: I start by explaining the procedure to estimate the model parameters of the model's static stage. Next, I outline the procedure for the aggragate state space estimation. I build on the previous two subsections to then estimate the structural parameters of the dynamic model. Lastly I test the model's fit.

7.1 Static Stage Parameters

This subsection presents the estimation procedure for the parameters that determine the mine choice and coal power plant dispatch decisions: coal transport cost parameter τ, filter efficiency parameters $\alpha_{\bar{\omega}}, \alpha_{\underline{\omega}}, \beta_{\bar{\omega}}, \beta_{\underline{\omega}}$, sulfur emission penalty parameter γ, each plant's optimal operating hours h_{0i}, and the plants' operating constraint ξ.

The procedure starts by estimating transport cost parameter τ through OLS (See Table 1, Column 2). This estimation allows me to find $\tau(d_i^{wy} - d_i^l)$ for all plants. I next estimate filter efficiency parameters for standard and expensive filters $\alpha_{\bar{\omega}}, \alpha_{\underline{\omega}}, \beta_{\bar{\omega}}, \beta_{\underline{\omega}}$. These four parameters are estimated through OLS and estimates are reported in the second and third columns of Table 2. I then use these parameters to predict the unit sulfur emissions of each plant, for all coal types, given their filter type $\hat{S}(m_{it} \mid \omega_{it})$. For predicting sulfur emissions of the local coal choice, the average sulfur content of the closest mining county is used. For predicting sulfur emissions of the Wyoming coal choice, the Wyoming statewide average sulfur content is used.

From the coal purchase decision rule defined in Equation 7, I estimate its empirical analogue

Table 7: Probit Model for Wyoming Coal Choice

	Dep. var.: $Pr(m_{it} = wy)$	
	(1)	(2)
Emissions rate penalty γ_t	2.895*	16.213***
	(1.524)	(4.058)
Fixed effects	Local mine	Local mine
Sample	2008-2015	2016-2019
Observations	1,459	665

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

for the enforcement period $T_t = 0$ to retrieve sulfur emission penalty γ.

$$Pr(m_{it} = wy \mid \chi_i, \Omega_{it}, \omega_{it}) = \Phi\Big(FE_l - \tau(d_i^{wy} - d_i^l) + \gamma\left(\hat{S}(m = l \mid \omega_{it}) - \bar{S}\right)^+ \\ - \gamma\left(\hat{S}(m = wy \mid \omega_{it}) - \bar{S}\right)^+\Big) \quad (17)$$

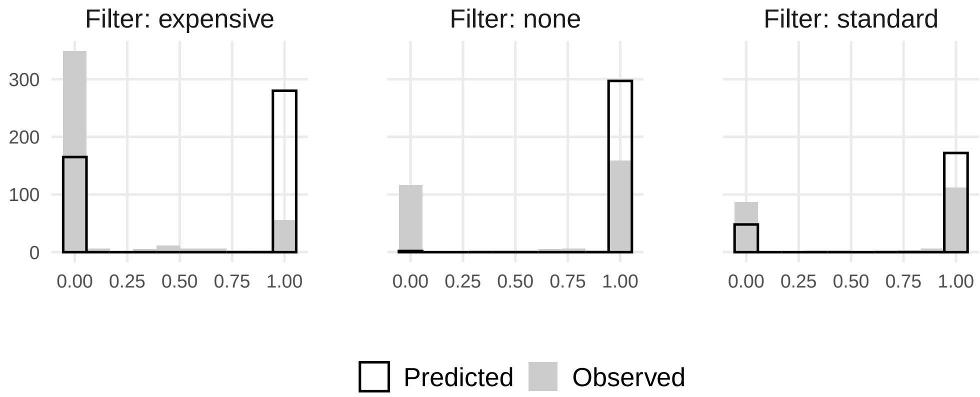
The dependent variable $m_{it} = wy$ takes value 1 if the plant i has bought more than half of its coal from Wyoming mines t. Plants that have Wyoming as their closest mining states are purposefully excluded from the estimating sample. The price gap between local coal and wyoming coal -excluding transport costs- is represented by the "closest mine" fixed effects FE_l. I assume that, when purchasing coal from their closest mining state, plants buy from the closest county, which allows me to impute the fixed effect of that county and the plant to county distance as covariates of the regression.[35] Recall that $\bar{S}$ represents the MATS threshold, set at 0.2 lb SO2/mmBtu since 2016. The model is estimated using coal plants that had some type of filter, during the 2016-2019 period. I also report the results for the 2008-2015 period subsample. Table 7 reports the parameter estimates. There is a negative and significant penalty for sulfur emissions, representing the sulfur-related regulations prior to hte MATS cap enforcement. As expected, the penalty parameter increases after the MATS enforcement date.

After estimating the sulfur emission rate penalty parameter, I test the accuracy of the model by predicting the local coal choice for each plant-year observation in the 2016-2019 period. Figure 10 compares the actual and predicted share of local coal procurement, by filter type.

The estimation of the γ parameter enables me to estimate the unit cost of coal for any source and filter combination $c(m_{it}|\chi_i, \Omega_{it}, \omega_{it}) = p_i^m(m_{it}|\chi_i) + \gamma(\Omega_{it}) \cdot \left(S(m_{it}|\chi_i, \omega_{it}) - \bar{S}\right)^+$. Firstly, $p_i^m(m_{it}|\chi_i)$ is imputed using the OLS regression from Table 1, Column 2. Second, sulfur emission parameter takes value $\gamma_t = 16.213$ if $t > 2015$, zero otherwise (See Table 7, Column 2). The previous step allows me to impute $\Delta_{it}(p_{it}^{m^*}, \omega_{it}, p_{it}^{imp}) = p_{it}^{imp} - c(m_{it}|\chi_i, \Omega_{it}, \omega_{it}) \cdot HR_i$, for each coal plant i.

[35] When predicting Wyoming coal price, I assume that all plants buy from Campbell County and impute the corresponding fixed effect. Campbell is the county with the largest coal production in Wyoming.

Figure 10: Actual and predicted Wyoming coal procurement share



The share of coal that each power plant purchased from Wyoming mines, data on annual frequency. The model was estimated using compliant MATS power plants (plants with some type of filter) during the 2016-2019 period, when MATS was already enforced. Actual share also correspond to 2016-2019 period.

Table 8: Linear Regression for Coal Plant Dispatch

	Dep. var.: Active Hours
Cost difference × capacity ($KW_i \cdot \Delta_{it}$)	0.008***
	(0.0004)
Fixed effects	Plant-level
Observations	6,737
R^2	0.947

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

I assume that import prices p_{ut}^{imp} are equal to the average natural gas price in the plant's state at year t.

Regarding coal power plant dispatch hours, Equation 18 presents the empirical analogue of the optimal dispatch rule (Equation 8). Plant-level fixed effects correspond to the optimal dispatch hours of each unit $FE_i = h_{0i}$. Regression slope parameter is inversely related to the import and dispatch constraints parameter: $\beta = \frac{1}{2 \cdot \xi}$.

$$h_{it}^{*} = FE_i + \beta \cdot (KW_i \cdot \Delta_{it}) + \epsilon_{it} \tag{18}$$

7.2 Aggregate State Space Estimation

The time-varying elements aggregate state space $\Omega_{it} = \{p_{it}^{imp}, T_t\}$ and its law of motion, are estimated as in Gowrisankaran et al. [2022].[36] The procedure starts by merging the natural gas transaction data from EIA-923 and natural gas plant-level heat rates HR_i to obtain a state $\times$ year dataset reporting each state s's average cost of natural gas-generated electricity at year t, which is assumed to be import price p_{st}^{imp}. The resulting dataset also records the stage of the regulatory countdown at year t as $T_t \in \{8, 7, 6, \cdots, 0\}$. Note that import prices are equal for all coal plants in the same state s, and year t. Moreover, the countdown variable T_t is common to all US coal power plants. In consequence, all the plants belonging to the same state s feature the same aggregate state at period t.

I then discretize the continuous variable p_{st}^{imp} into five bins.[37] Countdown variable T_t is discrete by nature, featuring 9 bins. The resulting discretized aggregate state space is comprised of $B = 5 \times 9 = 45$ bins, indexed by $b \in \{1, 2, \cdots B\}$. The combination of each bin's assigned import price p_b^{imp} and the corresponding countdown stage, denoted T_b, fully characterises each bin: $\Omega_b = \{p_b^{imp}, T_b\}$.

I assume that the discretized aggregate state space Ω_b follows a Markov chain. I estimate the corresponding transition probability matrix T of $B \times B$ dimensions. Each row of the matrix corresponds to an aggregate state bin b. $T_{b,b'}$ refers to row b, column b' element of the T matrix, and represents the probability of moving from present bin b to bin b' in the next period. This probability is estimated using the state $\times$ year dataset.

7.3 Value Imputation

The regulator utility function is comprised of two elements: 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 filter types ω. Observational data only provides a subset of all the feasible combinations. Take, for instance, a generator that installs a standard filter on 2015 and remains open until the last period. I do not observe the welfare contribution of such a plant had it installed an expensive scrubber instead and, hence, this value needs to be imputed.

For any coal plant i, filter type ω and bin b, the imputation procedure starts with predicting the local coal and Wyoming coal costs, by plugging the time-invariant plant covariates χ_i into Equation 1. Next, I determine the unit sulfur emissions for each plant, filter type, and coal source

[36] The remaining elements of Ω_{it}: γ_t and $\bar{S}$, are directly imputed.

[37] I take all the p_{st}^{imp} that belong to the same bin and I compute the mean value, assigning it to the corresponding bin.

combination by using the Equation (2).

Plugging in coal costs, sulfur emissions, and the bin's regulation enforcement status into the plant's Wyoming coal procurement decision rule (Equation (7)) I retrieve the probability that the plant i, filter type ω at aggregate state bin b would procure Wyoming coal. If this probability is above the 0.5 threshold, I assume that the plant procures Wyoming coal, otherwise it procures local coal. After determining the coal source choice, I proceed to estimate the chosen source's unit cost, as defined in Equation (5). The difference between this unit cost and the bin's import price, multiplied by the plant's heat rate HR_i yields the coal plant's cost delta $\Delta_{ib\omega}$.

This procedure ultimately yields vectors for coal source choice $\{m^*_{ib\omega}\}$, coal plant dispatch hours $\{h^*_{ib\omega}\}$, unit costs $\{c^*_{ib\omega}\}$, and cost deltas $\{\Delta_{ib\omega}\}$, for all i generators, b aggregate state bins and filter types ω. Moreover, I parametrize natural gas plant constuction cost $f_{ng}(\chi_i)$ as a linear function of plant size KW_i and age in 2008 $Age_i^{t=2008}$: $f_{ng}(\chi_i) = N_0 + N_1 \cdot KW_i + N_2 \cdot Age_i^{t=2008}$. The aforementioned vectors are plugged into the welfare contribution and local mining revenue definitions (Equations (11) and (12)) to retrieve vectors $\{W_{ib\omega}\}$ and $\{R_{ib\omega}\}$. Lastly, the filter fixed cost F_ω for each plant i and type ω is approximated using the regressions in Table 13. Moreover, I incorporate an additional linear parameter ϕ_ω for each filter type to capture expenses related to that type of filter.[38]

7.4 Dynamic Stage Parameter Estimation

This subsection reviews the single-agent, dynamic discrete choice model estimation procedure from Rust [1987] in the context of my setup. The estimation procedure starts by defining a vector of candidate structural parameters $\theta^0 = \{\alpha_s^0, \phi^0, N^0, \sigma^0\}$.[39] Combining the candidate parameters with the vectors of imputed welfare contribution and local mine revenue values $\{W_{ib\omega}, R_{ib\omega}\}$ I obtain the regulator's per period utilities $U_{ib\omega}$.

The model specifies eight possible transitions, from current period filter type ω to next period ω'. Generators with no filter have four options: remain without filter, invest in standard filter, invest in expensive filter, or decomission the plant and replace it by a natural gas facility: $\omega' \mid \omega = 0 \in \{0, \underline{\omega}, \bar{\omega}, \emptyset\}$. Generators with a filter have two options: remain open with the current filter or decomission: $\omega' \mid \omega \neq 0 \in \{\omega, \emptyset\}$. Each transition can thus be denoted as $\omega\omega'$. Each plant i period t pair features an eight-element vector $\epsilon_{it}^{\omega\omega'}$ of of iid extreme value type 1 shocks. As is standard in the literature, the shocks are observed by the regulator but unobserved by the econometrician. The model also incorporates a scale parameter σ that tunes the dimension of the

[38] For example, the installation of standard filters (dry scrubbers) may require de adoption of new coal stockpile management systems (McCartney [2006]).

[39] α_0^0 is comprised of 15 values, ϕ^0 of 2 values, and N^0 of 3 values. σ^0 is a scalar.

$\epsilon_{it}^{\omega\omega'}$ shock.

Next, I proceed with the inner loop of the estimation algorithm, consisting on value function iteration. The iteration starts by initializing the integrated Value matrices to zero: $V_{ib\omega} = 0$. For transitions that involve no decomissioning $\omega' \neq \emptyset$, the generic expression for computing the value function is $v_{ib\omega}^{\omega\omega'} = U_{ib\omega} + \beta \cdot V_{ib\omega'} \times T'$. In contrast, for transitions that involve decomissioning $\omega' = \emptyset$, the value function is computed as $v_{ib\omega}^{\omega'} = U_{ib\omega}$. The resulting value functions become an input for computing a new Emax value function candidate.[40]

$$V_{ib\omega}^{0'} = \sigma \cdot ln \left[\sum_{\omega'|\omega} exp \left(\frac{v_{iib\omega}^{\omega'}}{\sigma} \right) \right] + \sigma \cdot \gamma_{euler}$$

The new integrated Value Function candidates $V_{ib\omega}^{'}$, 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, filter type ω combination features eight value functions, one for each of the transitions that the model enables for: $v_{ib\omega}^{\omega'}$. The resulting value functions allow to compute the eight conditional choice probabilities, one for each transition:

$$P_{ib\omega}^{\omega'} = \frac{exp\left(\frac{v_{iib\omega}^{\omega'}}{\sigma}\right)}{\sum_{\tilde{\omega}'|\omega} exp\left(\frac{v_{iib\omega}^{\tilde{\omega}'}}{\sigma}\right)}$$

Once the eight conditional choice probabilities are computed, I test the discrepancy between such probabilities and the actual decisions observed in the data. For each observation it, I find its corresponding transition as the pair ω_{it}, ω_{it+1}. Then, I retrieve its aggregate state $\Omega_{it} = \{p_{st}^{imp}, T_t\}$ and find the bins b and b' such that $p_b^{imp} \leq p_{it}^{imp} < p_{b'}^{imp}$ and $T_t = T_b = T_{b'}$. I compute bin b's weight as

$$w_b = \frac{\left| p_{b'}^{\text{imp}} - p_{it}^{\text{imp}} \right|}{\left| p_{b'}^{\text{imp}} - p_{b}^{\text{imp}} \right|}.$$

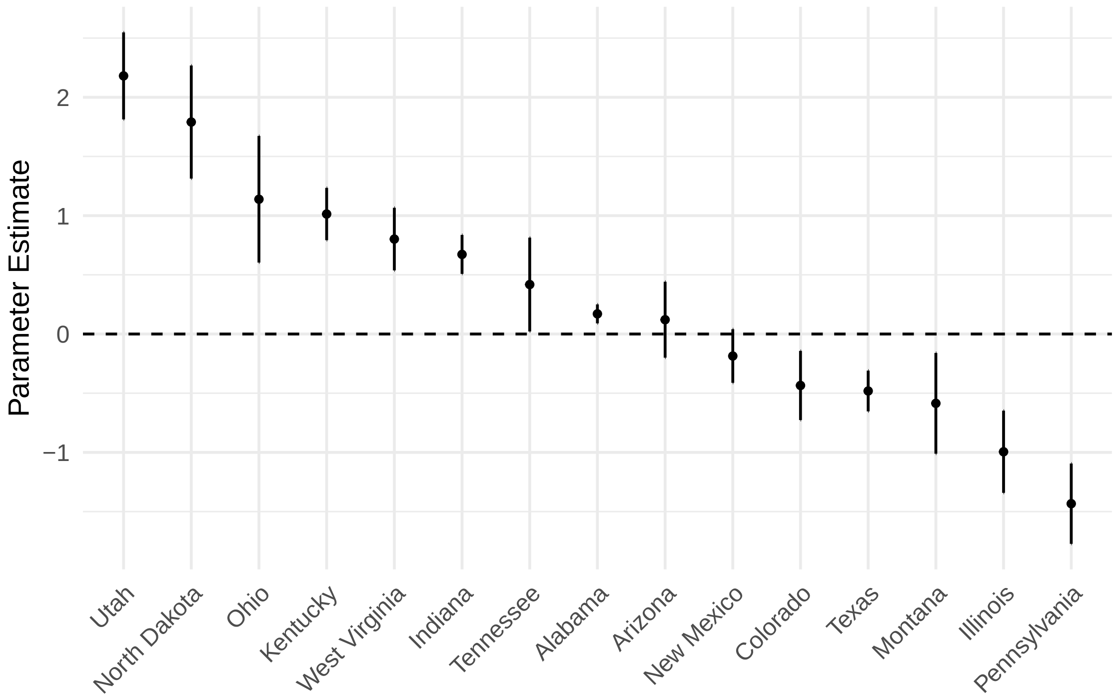
The decisions observed in the data are characterised by indicator functions. $\mathbb{1}\{\omega_{it} = 0\}$, for instance, is equal to one if generator i had no filter at time t. I use products of indicator functions to identify filter investment events. If, for instance, $\mathbb{1}\{\omega_{it} = 0\} \cdot \mathbb{1}\{\omega_{it+1} = \bar{\omega}\} = 1$, it means that generator i got an expensive filter installed at period t. Ultimately, the discrepancy $D_{it}(\theta^0)$ between the model and the data, for generator i at period t, and candidate parameters θ^0 is computed as follows:

$$D_{it}(\theta^0) = \sum_{\omega} \sum_{\omega'|\omega} \mathbb{1}\{\omega_{it} = \omega\} \cdot \mathbb{1}\{\omega_{i,t+1} = \omega'\} \cdot \left(P_{ib\omega}^{\omega'} \cdot w_b + P_{ib'\omega}^{\omega'} \cdot (1 - w_b) \right).$$

The ultimate Log-Likelihood function $LL = \sum_t^T \sum_i^I log(D_{it}(\theta^0)) \leq 0$ is minimized with respect to θ^0 using a Nelder-Mead algorithm, resulting into a vector of optimal parameters θ^*. Figure 11 presents each mining state regulator's mine protection parameter α_s estimates. Table 9 presents the remaining parameter estimates. In both cases, standard errors are retrieved estimating the model over bootstrapped datasets.

[40] γ_{euler} refers to the Euler constant.

Figure 11: Regulator Local Coal Protection α_s parameter estimates



Note: Each state reflects the α_s parameter of its utility regulator. Positive values imply regulators are accounting for in-state coal mining revenue in their decisionmaking process. Ranges represent 95% confidence intervals, obtained throught non-paremetric bootstrap method for $N = 20$.

The identification of the model parameters heavily relies on power 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 an expensive filter, for instance, depend on the distance between the plant and Wyoming. Expensive filter installation on the plants furthest from Wyoming contribute to welfare the most, as they save significant freight costs of Wyoming coal.

The identification of the local coal protection parameters α_s 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 always truncated to zero $R_{ib\omega} = 0$. According to this assumption, regulators from no-mine states only install expensive filters if the consequent welfare gains are significant. Coal-mine state regulators, in contrast, may install expensive filters even when the welfare gains are modest, as long as such expensive filters 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 filter type. Indiana, in contrast, features very high sulfur coal and, in this case, an expensive filter is a

Table 9: Model Estimation Results. Estimated in regulated plants for the 2008-2019 period.

Parameter	**Note**	**Point Estimate**	**Standard Errors**
α_s	Mine Protection	See Fig 11	See Fig 11
$\phi_{\underline{\omega}}$	Unobserved Cost - Standard Filter	2461.80	103.17
$\phi_{\bar{\omega}}$	Unobserved Cost - Expensive Filter	1548.81	52.90
N_0	Natural Gas - Baseline Parameter	-0.81	0.19
N_{size}	Natural Gas - Capacity Parameter	0.00	0.00
N_{age}	Natural Gas - Age Parameter	-6.77	0.39
σ	Scale Parameter	574.93	31.79

Note: Mine protection parameters α_s are reported in Figure 11. Standard Errors are obtained throught non-parametric bootstrap method $N = 20$.

prerequisite for the plant to use local coal.

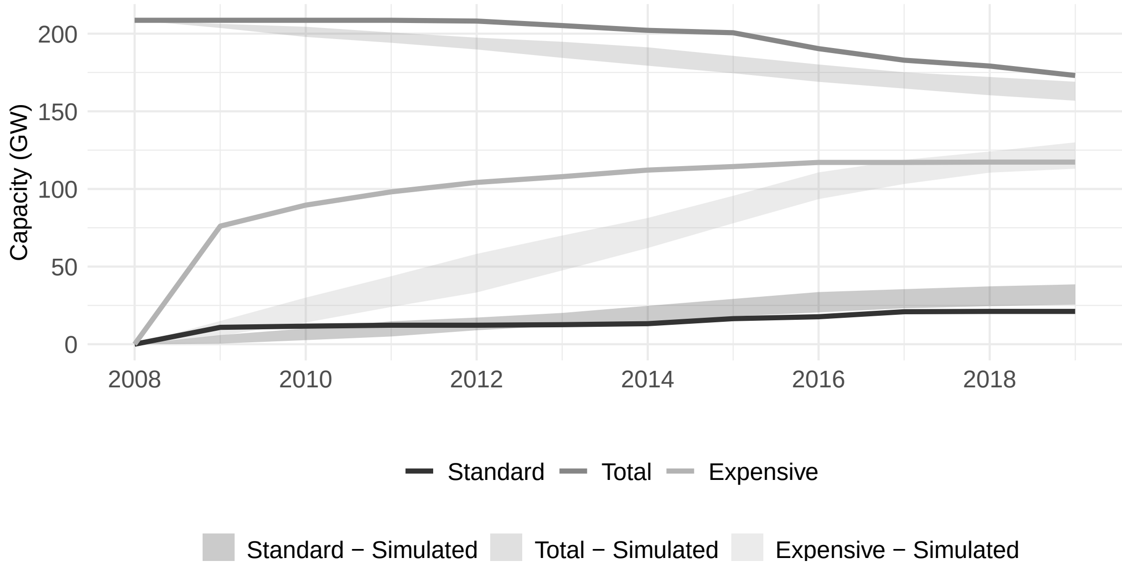
7.5 Model Fit

The model's fit is tested by simulating regulator decisonmaking under original parameter estimates θ^*. Simulation starts by identifying the population of coal power plants without any type of filter in 2008. I also identify the two bins that characterize the plant's aggregate state. I then use conditional choice probabilities to simulate the regulator's discrete choice for the forthcoming period. Moreover, I employ the transition probability matrix T to find the bins that characterize next period's aggregate state. This procedure is repeated for eleven periods, until reaching 2019.

The previous simulation is repeated 50 times. I contrast the outcomes of the simulated decisionmaking with the actual evolution of the regulated coal fleet between 2008 and 2019. Figure 12 presents the evolution of the U.S. regulated coal capacity. Capacity is grouped into three categories: total regulated coal capacity, capacity with standard filters, and capacity with expensive filters. The solid lines represent the actual capacity, while the shaded intervals represent the simulated capacity.

Figure 13 presents each state's actual and predicted regulated coal capacity in 2019. The dots represent each state's actual regulated coal power plant capacity by 2019. The ranges represents the two standard deviation interval from the 50 simulations. Gray shade highlights the states where the interval does not include the actual capacity.

Figure 12: Actual and predicted regulated coal capacity, 2008-2019



Solid lines represent the realized trend. Shaded intervals represent two standard-deviation intervals of 50 simulations using original parameter estimates. Label "Total" represets the total regulated coal capacity in GW in the US. "Standard" represents the cummulative investment in standard filters. "Expensive" represents the cummulative investment in expensive filters.

8 Counterfactuals

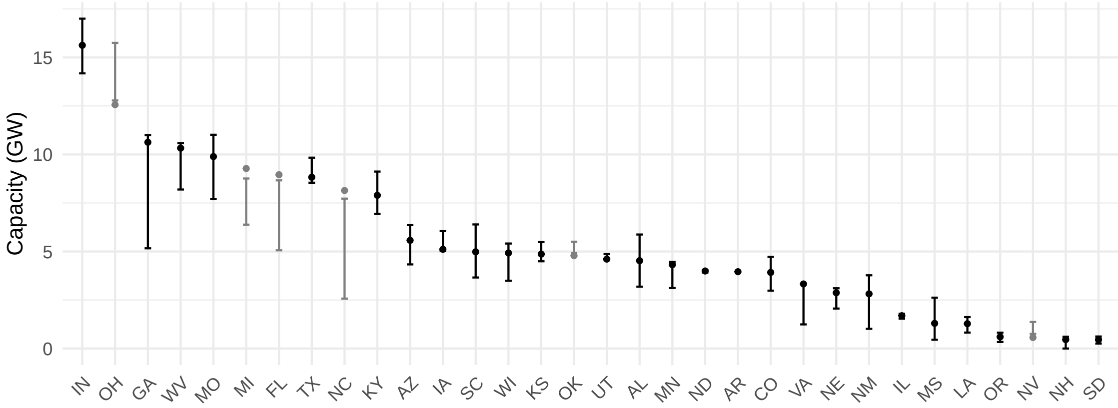
This section performs counterfactual exercises to assess the feasibility of welfare-improving policies. More specifically, I study if a direct transfer from electricity consumers to the local coal mining sector can simultaneously increase consumer welfare and accelerate coal power plant closures, all while keeping local coal mining revenue constant.

To test the feasibility of such a transfer, I simulate regulators' decisions under baseline parameters $\alpha_s > 0$ from 2008 to 2040.[41] The simulation generates, for each plant i and year $t = 2008, \dots, 2040$, per-period welfare contribution W_{it} and local mining revenue R_{it} figures. I then compute the present value of the welfare contribution and local mining revenue for each plant i as $W_i = \sum_{t=2008}^{2040} \beta^{t-2008} W_{it}$ and $R_i = \sum_{t=2008}^{2040} \beta^{t-2008} R_{it}$. Moreover, I find each plant i's baseline retirement year ret_i.

I next propose a counterfactual scenario where the local coal mines get a transfer that guarantees them baseline revenue R_{it} at every period, regardless of the amount of coal they sell. In other words, if the local mine fails to obtain revenue R_{it} from plant i in period t, the transfer makes up for the difference. In this scenario, the regulators' filter investment decisions do not affect local mining revenue, as the transfer guarantees the mining sector's income. I thus set the regulators'

[41] I focus on the states where the local coal mine protection parameter α_s estimate is indeed positive.

Figure 13: Actual and Predicted Regulated Coal Plant Capacity by State, 2019



Note: Dots represent each state's actual regulated coal power plant capacity by 2019, in GW. The range represents the 2 standard deviation interval of capacity out of 50 simulations using original parameter estimates. Gray shade highlights the instances where the 2 standard deviation interval does not include the actual capacity.

local protection parameters to zero, i.e., $\alpha_s = 0$ and simulate their choices. This simulation yields counterfactual present values W_i^{CF}, R_i^{CF}, and retirement years ret_i^{CF}.

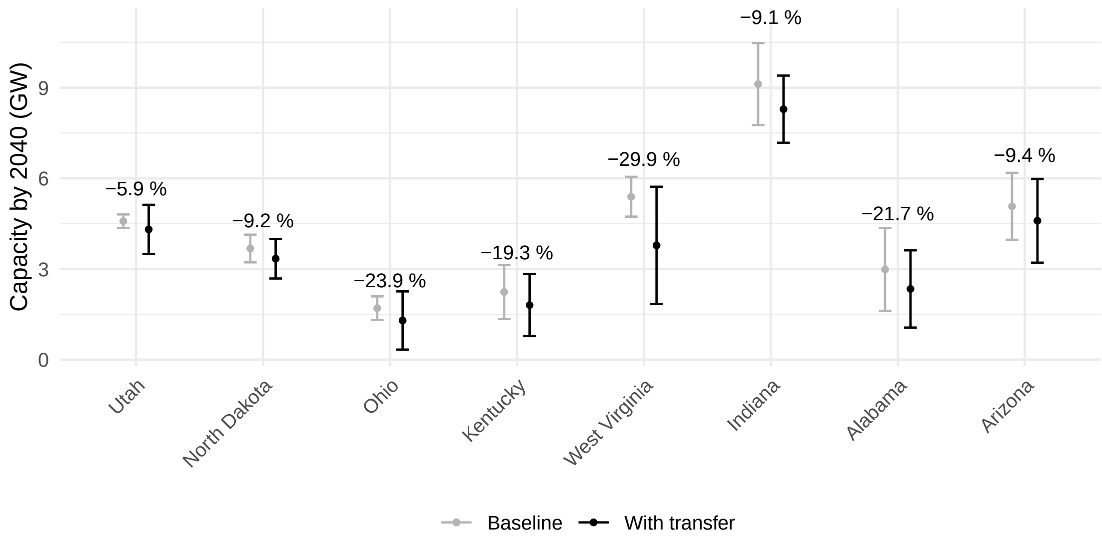
For the transfer to be politically feasible, it should improve the standing of both consumers and miners. In other words the consumer welfare gains must outweigh the local mining revenue losses. I search for such feasible instances by calculating transfer-driven welfare gains $\Delta W_i = W_i^{CF} - W_i$ and mining revenue losses $\Delta R_i = R_i^{CF} - R_i$ for each plant i. A transfer is politically feasible if conditions $\Delta W_i > 0$ and $\Delta W_i + \Delta R_i > 0$ are simultaneously satisfied. Lastly, I define the ultimate counterfactual retirement year $ret_i^{CF'}$: plants that feature feasible transfers keep their counterfactual retirement year $ret_i^{CF'} = ret_i^{CF}$; otherwise, they retain their original retirement year $ret_i^{CF'} = ret_i$.

By repeating the above procedure 50 times, I obtain baseline and counterfactual estimates of active coal power plant capacity by 2040. Figure 14 reports the results state-by-state. The gray confidence intervals represent the baseline simulations, while the black confidence intervals correspond to the consumer-to-mining-sector transfer counterfactual. Percentage point figures show the average decrease in coal plant capacity. On aggregate, such a transfer would reduce U.S. coal power plant capacity by 2040 in approximate 5 GW. Reductions are concentrated in Kentucky, Indiana and West Virginia, states with a sizable local mining sector.

I benchmark the politically feasible transfer against carbon taxes. The 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.[42] I simulate $\alpha_s > 0$ regulators' decisions under different carbon

[42] In his second term in office, President Obama acknowledged that, though "the most elegant solution", a carbon tax was not feasible Lehmann [2015].

Figure 14: Remaining Coal Power Plants by 2040



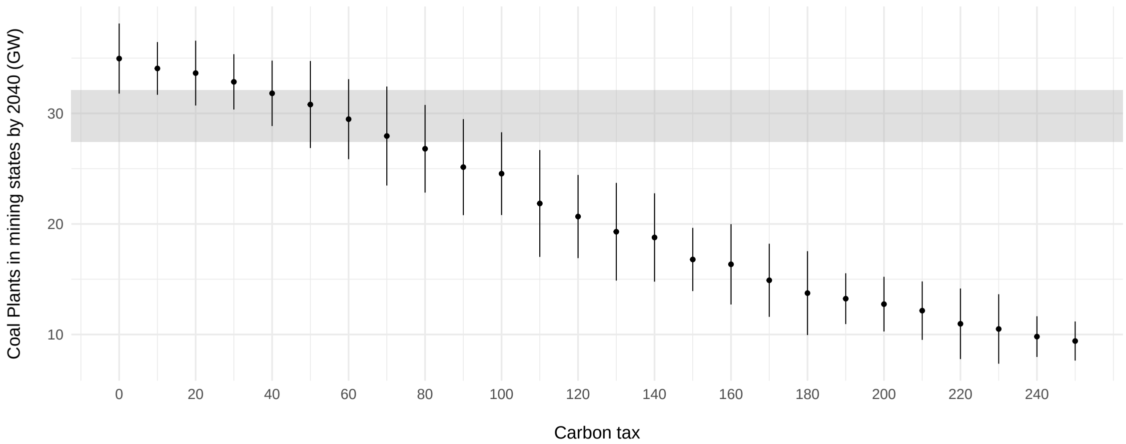
Note: Number of active coal power plants by 2040. The gray confidence intervals correspond to simulations under original parameters. The black confidence intervals correspond to simulations under a consumer-to-mining-sector transfer counterfactual.

tax levels ranging from 0 to 250\$/Ton of CO2.[43] Coal power plants are the most carbon intensive source of electricity; hence, carbon taxes disproportionately increase their unit costs with respect to natural gas power plants. As before, I simulate regulators' decisions 50 times for each carbon tax level, obtaining estimates of total coal power plant capacity by 2040.

Figure 15 reports the results of these simulations. The horizontal axis represents the carbon tax level, while the vertical axis shows aggregated active regulated coal power plant capacity by 2040 in mining states with $\alpha_s > 0$. Points represent mean values across the 50 simulations, while error bars represent 1 s.d. The horizontal gray interval represents the active capacity range in such states with the politically feasible transfer, absent any carbon tax. The figure shows that even a high carbon tax of 50\$/Ton of CO2 fails to reduce coal power plant capacity as much as the proposed consumer-to-mining-sector transfer. This result suggests that granting a constant income to the coal mining sector, regardless of its activity, may be both a more effective and politically feasible policy to accelerate the energy transition.

[43] 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. Find EU-ETS carbon permit pricing, visit TradingEconomics.com [2026].

Figure 15: Regulated coal generator capacity in mining states, carbon tax counterfactuals



Horizontal axis represents carbon tax level (in $/Ton). Vertical axis represents active regulated coal plants in mining states by 2040, measured in Gigawats. I simulate the regulator decisionmaking process five times for each carbon tax level. Points represent mean values, and error bars represent 1 s.d. Horizontal gray band represents the counterfactual coal capacity with no carbon taxes, but implementing the "politically feasible" transfer.

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 more than $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, two thirds of the regulators from mining states considered the protection of local mines in their decisionmaking. The paper proposes to overcome this distortion through a politically feasible transfer that protects the local mining sector by ensuring its revenue regardless of output. This transfers "liberates" electricity regulators from having to protect local mines, as their decisions no longer determine their revenue. in consequence, regulators focus on reducing electricity prices for ratepayers. This price reductions are often more than enough to pay for the transfer, making it politically feasible. I find that this "politically feasible" transfer is as effective as a significant carbon tax in accelerating coal plant closures.

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A Additional Multinomial Logit Specifications

Table 10: Multinomial Logit - Mining State Indicator Specification

	Dependent variable		
	j = retire	j = standard	j = expensive
Regulated	0.039	-0.176	1.058**
	(0.484)	(0.720)	(0.531)
Mine state	-0.010	-2.257**	0.175
	(0.543)	(0.947)	(0.586)
Regulated x Mine state	0.315	1.886*	0.735
	(0.601)	(1.015)	(0.651)
		McFadden R2	0.223
	*p<0.1	**p<0.05	***p<0.01

One observation per coal generator. Specification includes 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. The treatment consists on an indicator for generators that belong to mining states.

Table 11: Multinomial Logit - Mine Size Specification

	Dependent variable		
	j = retire	j = standard	j = expensive
Regulated	0.243	1.034*	1.122***
	(0.349)	(0.590)	(0.372)
Mine Size	0.024	0.008	-0.004
	(0.017)	(0.027)	(0.020)
Regulated x Mine Size	0.044	0.005	0.075**
	(0.030)	(0.045)	(0.033)
		McFadden R2	0.218
		N	707

One observation per coal generator. Specification includes 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. The "Mining Size" treatment consists on the millions of coal tones that close-by mines from the same state produced in 2008.

Table 12: Multinomial Logit - Miner Count Specification

	Dependent variable		
	j = retire	j = standard	j = expensive
Regulated	0.221	1.207**	1.159***
	(0.341)	(0.571)	(0.363)
Miners	0.542*	0.443	0.183
	(0.277)	(0.407)	(0.293)
Regulated x Miners	0.733	-0.113	0.954**
	(0.469)	(0.671)	(0.482)
		McFadden R2	0.226
	*p<0.1	**p<0.05	***p<0.01

One observation per coal generator. Specification includes 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. The treatment consists on the number of miners working in close by mines from the same state in 2008, measured in thousand workers.

B Filter Fixed Cost

In the model, the tradeoffs between standard and expensive filters rely on the fact that the former are cheaper than the latter. The specification in (19) tests whether this assumption is valid. In this regression, the dependent variable $F_{\omega,i}$ represents the fixed cost of filter type ω, installed at plant i, in million dollars. $\mathbb{1}\{\omega = \bar{\omega}\}$ is an indicator for expensive filters and $Size_i$ represents the size of the plant that got the filter, in MW.

$$F_{ijt} = \alpha + \beta_1 \cdot \mathbb{1}\{\omega = \bar{\omega}\} + \beta_2 \cdot Size_{it} + \beta_3 \cdot \mathbb{1}\{\omega = \bar{\omega}\} \times Size_{it} + \epsilon_{it}. \tag{19}$$

Table 13 reports the regression estimates of (19). As expected, the expensive filter 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 expensive filter and plant size interaction suggests a concave fixed cost function for expensive filters.

Table 13: The fixed cost of standard and expensive filters

	Dep. var.: Filter cost		
	(1)	(2)	(3)
Intercept	118.398***	96.072***	54.408**
	(15.743)	(17.843)	(25.798)
Expensive Filter Indicator	81.613***	56.137***	116.842***
	(19.086)	(21.333)	(34.582)
Plant size (MW)		0.030**	0.085***
		(0.012)	(0.028)
Expensive × 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

Note: Each observation represents the adoption of a filter in a power plant. The dependent variable is measured in millions of dollars.

Table 14: Filter type code, description and classification

Code	Description	Wet	Dry	Big	N	Mean Unit Cost (M$/MW)	Median Unit Cost (M$/MW)	Mean Cost (M$)	Median Cost (M$)
JB	Jet bubbling reactor (wet) scrubber	1	0	1	18	0.169	0.126	279.27	276.26
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	189.56
TR	Tray type (wet) scrubber	1	0	1	66	0.140	0.105	227.18	215.33
VE	Venturi type (wet) scrubber	0	0	0	0	—	—	—	—
CD	Circulating dry scrubber	0	1	1	34	0.161	0.108	103.54	47.85
SD	Spray dryer type/dry FGD/semi-dry FGD	0	1	1	57	0.200	0.130	125.32	88.00
DSI	Dry sorbent (powder) injection type	0	0	0	130	0.016	0.008	12.09	5.30
OT	Other	0	0	0	0	—	—	—	—

Note: Each observation represents the adoption of a filter in a power plant. Cost variables are measured in millions of dollars. Based on EIA [2017].

C Derivations of the Comparative Statics

In a time-invariant setup where the sulfur emission restriction is enforced for all periods, the coal power plant i with filter type ω_i is indifferent between procuring local or wyoming coal when the following equation is satisfied.[44]

$$p_i^{m=l} + \gamma \cdot \left(S(l|\chi_i, \omega_i) - \bar{S}\right)^+ = p_i^{m=wy} + \gamma \cdot \left(S(wy|\chi_i, \omega_i) - \bar{S}\right)^+ \tag{20}$$

Replacing the expressions for coal price and unit sulfur emissions in the previous equation, I solve for an indifference curve in the local coal sulfur inensity and distance differences two-dimensional space.[45] The resulting indifference curve is weakly increasing in local sulfur intensity s_i^l (See figure **??**):

$$\Delta d_i(s_i^l, \omega_i) = d_i^{wy} - d_i^l = \frac{p_l - p_{wy} + \gamma\left[\left(\alpha_{\omega_i}(s_i^l)^{\beta_{\omega_i}} - \bar{S}\right)^+ - \left(\alpha_{\omega_i}(s_i^{wy})^{\beta_{\omega_i}} - \bar{S}\right)^+\right]}{\tau}.$$

I assume that coal plants burning Wyoming coal always comply with the standard, regardless of whether they have a standard or an expensive filter (See Figure **??**), and that local coal transport costs are negligible $d_i^l = 0$. By further writing it for the standard and expensive filter cases, I obtain two indifference curves:

$$\nu_1(s_i^l) = d_i^{wy} = \frac{p_l - p_{wy} + \gamma \cdot \left(\alpha_{\underline{\omega}}(s_i^l)^{\beta_{\underline{\omega}}} - \bar{S}\right)^+}{\tau}$$

$$\nu_2(s_i^l) = d_i^{wy} = \frac{p_l - p_{wy} + \gamma \cdot \left(\alpha_{\bar{\omega}}(s_i^l)^{\beta_{\bar{\omega}}} - \bar{S}\right)^+}{\tau}$$

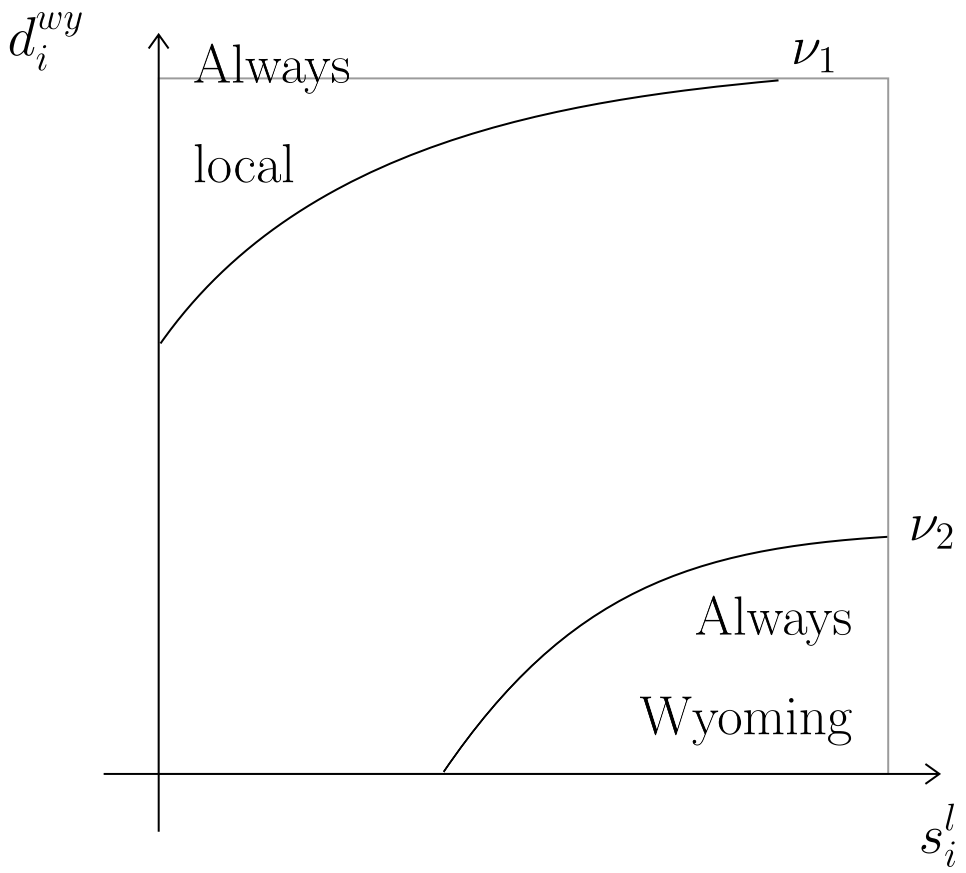
Note that the previous indifferent curves are weakly increasing in filter efficiency parameter α_ω, and that $\alpha_{\underline{\omega}} > \alpha_{\bar{\omega}}$. In consequence, installing an expensive filter is analogous to an rightward "jump" of the indifference curve (See Figure 16). This indifferent curve partitions the two dymensional space in three groups: plants that will always procure locally, regardless of filter type ("Always local" region); plants that will always procure from Wyoming, regardless of filter type ("Always Wyoming" region); and an intermediate region where plants that only procure locally when having an expensive filter, otherwise procure from wyoming:

When deciding which filter to install, the regulator will behave differently depending on the category the subject plant belongs to: firstly, if the plant is an "Always Wyoming" facility, it will always satisfy the emission standard, regardless of filter. Moreover, installing the expensive filter will not increase local mining revenue. In consequence, the regulator will always choose the standard filter option. Secondly, in the case of "Always local" plants, the regulation faces a tradeoff between filter cost and compliance breach, as standard filters paired with local coal are likely to overcome

[44] Derivation is straightforward from Equation 7

[45] Recall that coal unit price has two elements $p_i^m = p_m + \tau \cdot d_i^m$, where p_m is the price of coal type m at its origin, and τ represents the transportation cost per distance unit. Unit sulfur emissions are $S(m_i|\chi_i, \omega_i) = \alpha_\omega \cdot \left(s_i^{m_i}\right)^{\beta_\omega}$

Figure 16: Indifference Curves in Coal Procurement



Coal power plants that fall into the "Always local" category will always source locally, regardless they have a standard or an expensive filter. Coal power plants in the "Always Wyoming" area also purchase coal from wyoming, regardless of filter type. Lastly, the intermediate region between the two indifference curves gathers a subset of plants that procure locally with an expensive filter, but otherwise from Wyoming.

the emissions threshold. Still, the filter choice is not going to be determined by the local mining revenue channel, as it will remain constant regardless of the investment type. Lastly, the plants in the intermediate region are the most interesting case, as in these facilities the filter type determines the coal source. It is for this subset of plants that regulators have an incentive to install expensive filters to help the local mines. I will next focus on the investment decision of this intermediate group. In these cases, the previous expression for cost differences between imports an coal can be rewriten as a function of the filter type ω_i:

$$\Delta(\underline{\omega}) = p_u^{imp} - \Big(p_{wy} + \tau \cdot d_i^{wy}\Big)$$
$$\Delta(\bar{\omega}) = p_u^{imp} - \Big(p_l + \gamma\big(\alpha_{\bar{\omega}}(s_i^l)^{\beta_{\bar{\omega}}} - \bar{S}\big)^+\Big)$$

Regarding coal power plant dispatch, I assume no capacity neither transmission constraints $\xi = 0$ and that import price is high enough so that the utility dispatches the plant at capacity regardless of filter type $h^*(\underline{\omega}) = h^*(\bar{\omega}) = \bar{h}$. Previous two expressions determine coal plant welfare contribution (Equation 11) and local mine revenue (Equation 12) as a function of filter type:

$$\begin{aligned}
W(\bar{\omega}) &= \bar{h} \cdot \Delta(\bar{\omega}) + f_{ng}(KW_i = 1).\\
W(\underline{\omega}) &= \bar{h} \cdot \Delta(\underline{\omega}) + f_{ng}(KW_i = 1).\\
R(\bar{\omega}) &= p_i^l \cdot \bar{h}\\
R(\underline{\omega}) &= 0
\end{aligned} \tag{21}$$

Regulators choose an expensive filter if $W(\bar{\omega}) + \alpha_s \cdot R(\bar{\omega}) - f_{\bar{\omega}}(KW_i = 1) \geq W(\underline{\omega}) - f_{\underline{\omega}}(KW_i = 1)$. This inequality characterizes an indifference curve in the d_i^{wy}, s_i^l two-dimensional space. The resulting indifferent curve $\nu_3(s_i^l, \alpha_s)$ is weakly increasing in s_i^l, strictly decreasing in α_s, and characterised by the following indifference curve:

$$\begin{aligned}
\nu_3(\alpha_s) = d_i^{wy} &= \frac{p_i^l - p_{wy} + \gamma\left(\alpha_{\bar{\omega}}(s_i^l)^{\beta_{\bar{\omega}}} - \bar{S}\right)^+}{\tau} - \frac{\alpha_s \cdot p_i^l}{\tau} + \frac{\Delta f}{\bar{h}\,\tau},\\
\Delta f \;&=\; f_{\bar{\omega}}(KW_i = 1) - f_{\underline{\omega}}(KW_i = 1).
\end{aligned} \tag{22}$$

Rewriting the expression for $\nu_3(\alpha_s)$ as a function of $\nu_2(s_i^l)$ yields the following equation:

$$\nu_3(\alpha_s) = \nu_2(s_i^l) - \frac{\alpha_s \cdot p_i^l}{\tau} + \frac{\Delta f}{\bar{h}\,\tau}$$

In order to completely characterize the distance delta, local sulfur intensity space, I lastly address the regulator's filter investment decision in the "Always Local" region. However, repeating the previous procedure for this region is not feasible, as the equation that would characterize the indifference curve does not feature d_i^{wy}. It is for this reason that this area of the space remains undetermined.