Supporting Information:

Funding a just transition away from coal in the U.S. considering avoided damage from air pollution.

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Appendix A: Estimating Marginal Damages.

AP3 INTEGRATED ASSESSMENT MODEL

The AP3 integrated assessment model (IAM) [1]–[3] connects emissions to monetized damages in the United States (U.S.) for the following five criteria air pollutants: ammonia (NH_3), nitrogen oxides (NO_x), primary particulate matter (primary $PM_{2.5}$), sulfur dioxide (SO_2), and volatile organic compounds (VOCs). AP3 is the third installment of the Air Pollution Emissions Experiments and Policy analysis (APEEP) model [4]. For information on APEEP, see its technical appendix [5].[1]

AP3 operates by first estimating an ambient $PM_{2.5}$ concentration, mortality risk, and damage baseline for every contiguous U.S. (CONUS) county. Then, it computes impacts *on the margin* from one additional ton of a pollutant from a specific source. The changes from the baseline with the additional ton give us the marginal impacts and, specifically, the marginal damages (MDs) of source- and pollutant-specific emissions.[2]

Ambient $PM_{2.5}$ Concentration Baseline

AP3's Input Emissions

AP3 uses all emissions provided by the Environmental Protection Agency's (EPA's) National Emissions Inventory (NEI) to estimate baseline concentrations of ambient $PM_{2.5}$ in every CONUS county [7]–[9]. We use the 2014 NEI and the 2017 NEI to compute unique baselines against which we assess marginal emissions. Tschofen et al. (2019) [1] was the first study to employ the 2014 NEI for AP3 modeling. This is the first study to employ the 2017 NEI for AP3 modeling. For 2014 and 2015, we use the 2014 NEI-derived baseline. For 2016, 2017, 2018, and 2019, we use the 2017 NEI-derived baseline. These baselines account for ambient pollution levels resulting from nationwide emissions.[3]

AP3's Binning Structure

Atmospheric dispersion behaves differently based on the height of pollutant discharge. Therefore, AP3 divides emission sources into bins that treat ground-level sources differently than point sources and divides point sources by effective height—i.e., stack height plus the plume rise. When APEEP was developed, point sources with effective heights $>$ 500 meters were identified and uniquely modeled in the tall stacks bin. Other facilities are placed in the medium stacks bin if they have an effective height $\geq$ 250 meters or the low stacks bin if they have an effective height $<$ 250 meters. We calculate effective heights according to Turner (1994) [10]. Stack and discharge parameters are retrieved from Sparse Matrix Operator Kerner Emissions flat files, available through the EPA [11]. Weather parameters are from National Centers for Environmental

[1] APEEP's air quality module was built using the Climatological Region Dispersion Model from Latimer (1996) [6].
[2] AP3 only assesses damages within CONUS. Other local air pollution damages (e.g., those experienced across national borders in Canada and Mexico) from U.S. emissions of NH_3, NO_x, primary $PM_{2.5}$, SO_2, and VOCs are not modeled by AP3 nor are they included in the totals reported in this study.
[3] The 2020 NEI released in 2023 [9]. Typically, modelers may select a baseline that is closest to their year of interest (e.g., 2016, 2017, and 2018 are closest to 2017 as compared to 2014 or 2020). However, with the drastic changes to economic activity during the COVID-19 pandemic, 2020 may be a less adequate as a proxy for 2019 conditions.

Prediction (NCEP) reanalysis data provided by the Physical Sciences Laboratory of National Oceanic and Atmospheric Administration (NOAA) [12].

We calculate the annual average of surface-level temperatures and horizontal wind speeds (from daily average data) spatially resolved in a 2.5-degree latitude by 2.5-degree longitude gridded format. Each county is assigned the weather data of the cell in which it resides. If a county intersects multiple cells, the area-weighted average of the data is used. Our process assumes stable conditions, an average lapse rate of -0.0065 K/m, and that, for each facility, the dominant mechanism between the buoyant rise and momentum rise is the one producing the higher rise.

Point sources in the tall stacks bin are modeled from the coordinates of the facility and the effective height of the stack(s). Those in the low and medium stacks bins are modeled from their county's population-weighted centroid and the average effective height of all facilities within their respective bins. Ground-level sources, including those reported by the NEI as nonpoint, onroad, nonroad, and events/fires, are also modeled from their county's population-weighted centroid.

We include fire emissions to AP3's baseline composition for both the 2014 NEI-derived and 2017 NEI-derived baselines, which were previously excluded because of their highly seasonal influences. However, with the recent decreases in emissions from major economic sectors [1] and the increasing importance of wildfire emissions on air quality in the West [13], including them now improves model performance [14]. Since 2002, the NEI has been published for national emissions every three years (i.e., 2002, 2005, 2008, 2011, 2014, 2017). Childs et al. (2022) showed that 2017 was the first of these years to have substantial wildfire activity. This helps to explain why excluding them from the model previously did not affect modeling performance while doing so for 2017 did. We also add tribal land emissions to both baselines.

Table A1 shows total emissions by pollutant and AP3 bin contributing to AP3's 2014 and 2017 baseline against which we assess marginal emissions. Table A1 also reports the count of facilities by AP3 bin.

Table A1. National emissions contributing to AP3's baseline concentrations.

Year	AP3 Bin	Facilities	Emissions (Short Tons)				
			NH_3	NO_x	$PM_{2.5}$	SO_2	VOC
2014	Ground	0	3.46e+06	9.91e+06	4.68e+06	4.20e+05	5.39e+07
	Low	80,206	6.36e+04	1.49e+06	2.61e+05	7.66e+05	8.95e+05
	Medium	994	1.82e+04	5.94e+05	8.16e+04	9.15e+05	8.06e+04
	Tall	258	9.28e+03	1.25e+06	1.38e+05	2.50e+06	2.15e+04
	Total	**81,458**	**3.55e+06**	**1.32e+07**	**5.16e+06**	**4.60e+06**	**5.49e+07**
2017	Ground	0	4.18e+06	8.44e+06	5.00e+06	4.46e+05	3.92e+07
	Low	79,486	5.95e+04	1.27e+06	2.34e+05	5.05e+05	8.49e+05
	Medium	977	1.83e+04	4.51e+05	7.03e+04	4.64e+05	8.59e+04
	Tall	244	7.85e+03	7.88e+05	7.12e+04	1.07e+06	1.70e+04
	Total	**80,707**	**4.27e+06**	**1.10e+07**	**5.38e+06**	**2.49e+06**	**4.02e+07**

Sources: Emissions data are from EPA's NEI [7], [8].
Notes: Ground are nonpoint, onroad, nonroad, and events/fires. Tall facilities are hardwired into AP3. Low and medium facilities are determined considering effective heights.

AP3's Atmospheric Transport

AP3 uses source-receptor (SR) matrices to estimate resolved concentrations of speciated pollution in every CONUS county from all sources of emissions. The SR matrices use Gaussian plumes, which model three-dimensional atmospheric dispersion or pollutant transport from the discharge point [15]–[17].

The following equations demonstrate the SR matrix modeling process of AP3. First, emissions (e) from each source county or tall stacks bin facility (s) are loaded in as vectors (E) by pollutant (p) and bin height (h), as shown in Equation A1:

Equation A1. AP3's Emissions Inventories.

$$E_{p,h} = \begin{bmatrix} e_1 \\ \vdots \\ e_s \end{bmatrix}$$

AP3's SR matrices, depicted in Equation A2, model the transport (χ) of a ton of pollution from each source to each receptor county (r), again by pollutant and bin height.[4] The SR matrices represent an average of atmospheric conditions relevant to pollutant transport from the source:

Equation A2. AP3's Source-Receptor Matrices.

$$SR_{p,h} = \begin{bmatrix} \chi_{1,1} & \cdots & \chi_{1,r} \\ \vdots & \ddots & \vdots \\ \chi_{s,1} & \cdots & \chi_{s,r} \end{bmatrix}$$

Multiplying the emissions vectors by the corresponding SR matrices, shown in Equation A3, provides annual average speciated concentrations (C) of ambient pollution, by pollutant and bin height, in each CONUS county resulting from all sources' emissions:

Equation A3. AP3's Speciated Concentration Estimates.

$$C_{p,h} = (E_{p,h})^T \times (SR_{p,h})$$

The concentrations are subsequently aggregated across the different bin heights for total annual average speciated ambient pollution in every county resulting from emissions of NH_3, NO_x, primary $PM_{2.5}$, SO_2, and VOCs.

AP3's Interpollutant Atmospheric Chemistry

The total ambient $PM_{2.5}$ modeled by AP3 combines directly emitted $PM_{2.5}$, organic aerosols from VOCs, ammonium sulfate ($(NH_4)_2SO_4$) from NH_3 and SO_2, sulfate (SO_4^{2-}) from just SO_2, and ammonium nitrate (NH_4NO_3) from NH_3 and NO_x. Critically, the formation of each $(NH_4)_2SO_4$, SO_4^{2-}, and NH_4NO_3 is dependent on the equilibrium between total ammonia (NH_3 plus NH_4^+), particulate sulfate (SO_4^{2-}), and total nitrate (gaseous nitric acid and particulate nitrate) in the ambient air (note: "total" includes both gas and particulate components). Specifically, AP3 models the chemical reactions between NH_3, sulfuric acid (H_2SO_4 from SO_2), and nitric acid (HNO_3 from

[4] For more details on Equation A2's χ term, representing three-dimensional transport of one short ton of emissions from each source to annual concentrations of $PM_{2.5}$ in each downwind receptor considering a representation of average atmospheric conditions, see the APEEP technical appendix [5] or Turner (1994) [18].

NO_x) as they form particulates [19]–[21].[5] AP3 then aggregates all subspecies of ambient $PM_{2.5}$ to determine total concentrations in each county.

NH_3 preferentially reacts with H_2SO_4 to form $(NH_4)_2SO_4$.[6] Then, what NH_3 remains is free to react with HNO_3, forming NH_4NO_3.[7] This results in two possible regimes: (1) nitrate-limited, where NH_3 is in surplus, and (2) ammonium-limited, where HNO_3 is in surplus. The regime in which a receptor county resides affects the efficiency with which marginal emissions of NH_3 and NO_x form NH_4NO_3 because neither free NH_3 (i.e., not reacting with H_2SO_4) nor HNO_3 act as secondary $PM_{2.5}$ without reacting—i.e., they occur in the gas phase. Emissions of SO_2, on the other hand, form ambient $PM_{2.5}$ with or without NH_3 because SO_4^{2-} is in the particulate phase.[8]

AP3's Calibration

AP3 is calibrated using EPA Air Quality System (AQS) monitoring data [23]. The process involves comparing AP3-modeled ambient $PM_{2.5}$ concentrations to those measured at monitors and conducting several calibration steps to improve the prediction-observation fit.

Table A2. Performance metrics for AP3 following calibration.

Year	Ambient Pollutant	Performance Metrics			
		MFE	MFB	r	n
2014	**Total $PM_{2.5}$**	**0.304**	**-0.011**	**0.530**	**592**
	Sulfate	0.400	-0.016	0.864	302
	Nitrate	0.540	-0.016	0.547	299
	Organic Aerosols	0.392	0.021	0.620	146
	Ammonium	0.462	0.253	0.297	177
2017	**Total $PM_{2.5}$**	**0.292**	**0.012**	**0.523**	**603**
	Sulfate	0.329	-0.105	0.699	255
	Nitrate	0.492	0.070	0.624	251
	Organic Aerosols	0.398	-0.043	0.450	247
	Ammonium	0.996	0.995	0.546	132

Sources: Monitored data are from EPA's AQS [23].
Notes: Summarizes calibration efforts conducted by Tschofen et al. (2023) [14]. r is Pearson's correlation coefficient. n is the number of AQS-monitored counties for each pollutant.

The primary calibration step is an iterative process that reduces the mean fractional error (MFE) and the mean fractional bias (MFB) by adjusting calibration coefficients applied alongside the SR matrices. Equation A4 and Equation A5 depict these two performance metrics [24]:

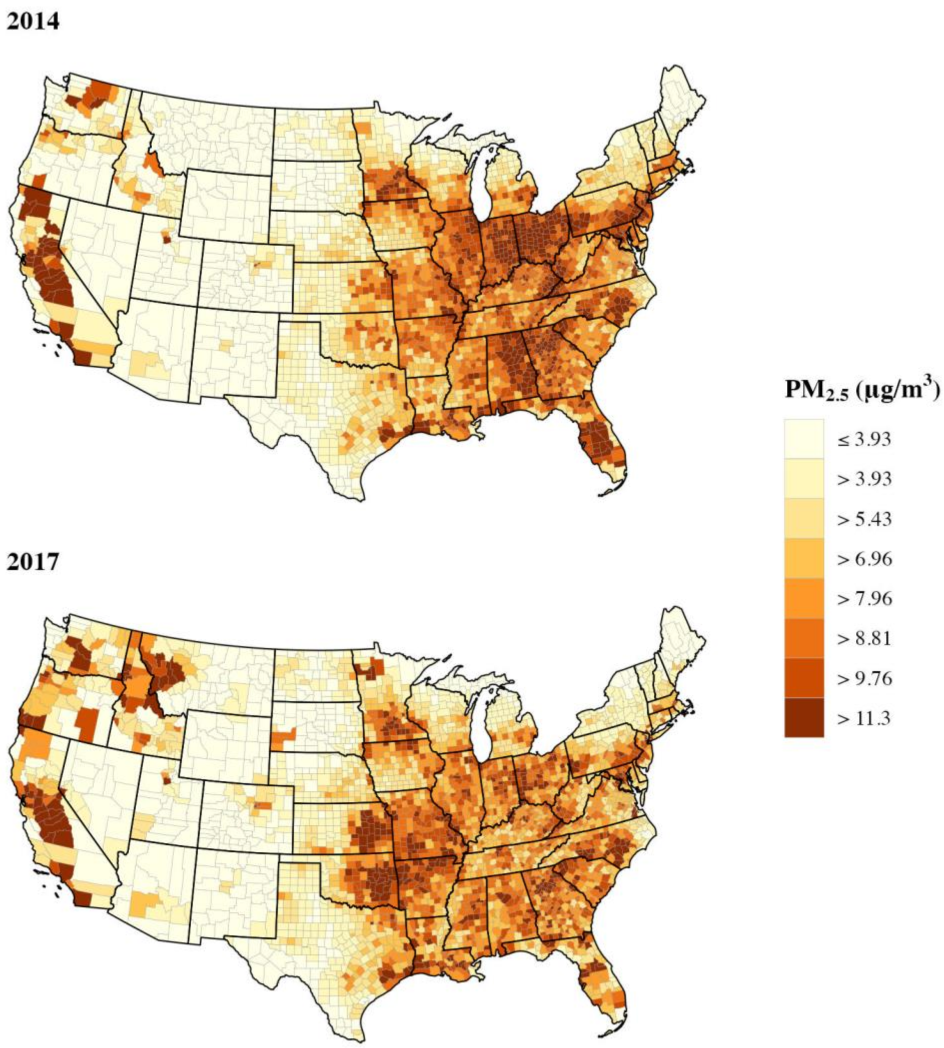
[5] SO_2 and NO_x form H_2SO_4 and HNO_3 when they react with oxygen (O_2) and water (H_2O). For example, $2SO_2 + O_2 + 2H_2O \rightarrow 2H_2SO_4$. For more information on the atmospheric behavior of the family of NO_x compounds, see [22].
[6] $H_2SO_4 + 2NH_3 \rightarrow (NH_4)_2SO_4$.
[7] $NH_3 + HNO_3 \rightarrow NH_4NO_3$.
[8] As discussed by Tsimpidi et al. (2007) [21], particulate SO_4^{2-} exists in the form of ammonium bisulfate ($(NH_4)HSO_4$) or even as H_2SO_4 in extreme cases when concentrations of NH_3 are low.

Equation A4. Mean Fractional Error.

$$MFE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|c_{m,i} - c_{o,i}\right|}{\left(\frac{c_{m,i} + c_{o,i}}{2}\right)}$$

Equation A5. Mean Fractional Bias.

$$MFB = \frac{1}{n}\sum_{i=1}^{n}\frac{c_{m,i} - c_{o,i}}{\left(\frac{c_{m,i} + c_{o,i}}{2}\right)}$$



Sources: Concentrations are modeled with AP3 [1]–[3]. Mapping uses the *usmap* R package [25].
Notes: Color scale divides county-year concentrations into equally sized groups.

Figure A1. Annual Average $PM_{2.5}$ Concentration by County Modeled in AP3.

In Equation A4 and Equation A5, model predictions of ambient concentrations ($C_{m,i}$) are compared to observed levels of ambient concentrations ($C_{o,i}$) for receptor county locations with AQS pollution data (i).

A secondary calibration step is also conducted to adjust the portion of ambient $PM_{2.5}$ sourced from primary $PM_{2.5}$ emissions for the 2.5th percentile of counties with the greatest absolute difference between modeled and monitored pollution levels. Subsequently, in a tertiary calibration step, neighboring counties surrounding the counties adjusted via the secondary calibration step are also considered for adjustment, where monitoring data and modeling estimates support such decisions.

Calibration efforts were conducted as part of the 2017 NEI update to AP3. We attribute calibration work to Tschofen et al. (2023) [14] and Tschofen (2023) [26]. The calibration procedure was based on previous work [27]–[29].

Table A2 summarizes the performance metrics for AP3 following calibration for the 2014 and 2017 baseline. The maps in Figure A1 show AP3-modeled annual average $PM_{2.5}$ concentrations in every CONUS county in 2014 and 2017.

Mortality Risk

Concentration-Response

We use peer-reviewed dose-response (DR) functions from the epidemiological literature to associate premature mortality risk with exposure to ambient $PM_{2.5}$. This study's default DR function for adult mortality is from the 2009 American Cancer Society (ACS) cohort study [30]. The study's findings match a more recent follow-up [31].[9] The ACS study identified the at-risk population to be anyone who is 30 or older. It reported relative risk (i.e., the chances of an event occurring in an exposed group vs. the chances of it happening in a control group) of all-cause mortality associated with a 10 $\mu g/m^3$ increase in ambient $PM_{2.5}$ exposure.

The most recent reanalysis of the Harvard Six Cities (H6C) study found a more substantial effect of $PM_{2.5}$ exposure and an at-risk age of 25 and older, which we consider for our high damage estimate [32]. Both adult DR functions are log-linear. Infant mortality is assessed using a distinct DR function [33]. This DR function, from Woodruff et al. (2006), is of the logistic form because the study worked with odds ratios (i.e., the odds of an event occurring in an exposed group vs. the odds of it happening in a control group).

Concentration response information is summarized in Table A3.

Table A3. Dose-response information from the epidemiological literature.

Epidemiological Study	Dose-Response Information			
	Age Group At-Risk	**Beta Coefficient**	**Standard Error**	**Functional Form**
ACS: Krewski et al. (2009)	30 & Older	0.00583	0.000963	Log-Linear
H6C: Lepeule et al. (2012)	25 & Older	0.0131	0.00335	Log-Linear
Woodruff et al. (2006)	Infants	0.00677	0.00734	Logistic

Source: Dose-response information are from Krewski et al. (2009) [30], Lepeule et al. (2012) [32], and Woodruff et al. (2006) [33].

[9] Turner et al. (2016) evaluated ACS Cancer Prevention Study-II participants [31].

The DR functions calculate the expected change in mortality rates across populations given a change in $PM_{2.5}$ exposure. The inputs are the β coefficient, the background mortality rate of the exposed population (y_0), and the change in ambient $PM_{2.5}$ pollution (ΔPM). The log-linear DR function for adult mortality is shown in Equation A6:

Equation A6. DR Function: Change in Mortality Rate.

$$\Delta y = y_0\left(1 - \frac{1}{exp(\beta \times \Delta PM)}\right)$$

The β coefficient is further defined in Equation A7. β is the natural log of the relative risk (RR) given a change in ambient $PM_{2.5}$ pollution—a 10 μg/m^3 increase in $PM_{2.5}$ for the ACS and the H6C studies [30], [32]:

Equation A7. DR Function: Beta Coefficient.

$$\beta = \frac{ln(RR)}{\Delta PM}$$

We then multiply the expected change in mortality rate (Δy) by the corresponding population to get the expected premature mortality associated with the change in $PM_{2.5}$:

Equation A8. DR Function: Change in Mortality.

$$\Delta Mortality = \Delta y \times Population$$

The logistic DR function for infant mortality and its corresponding β coefficient are as follows in Equation A9:

Equation A9. DR Function: Infant Mortality.

$$\Delta y = y_0\left(1 - \frac{1}{(1 - y_0) \times exp(\beta \times \Delta PM) + y_0}\right)$$

$$\beta = \frac{ln(OR)}{\Delta PM}$$

The β coefficient here is calculated with the natural log of the odds ratio (OR) given a change in ambient $PM_{2.5}$ pollution—a 10 μg/m^3 increase in $PM_{2.5}$ [33].

Population and Mortality Rate Data

To model pollution exposure, AP3 uses county-level population inventories by five-year age groups from the Centers for Disease Control and Prevention's (CDC's) WONDER database [34]. Age differentiation is essential for two reasons. First, anyone under 30 who is not an infant (i.e., less than one-year-old) is considered not to be at risk of premature mortality from long-term ambient $PM_{2.5}$ exposure [30]. Second, the effects of $PM_{2.5}$ are highest among older populations [35], [36].

Mortality rates for every age group in every county are determined using data also from the CDC [37]. The data are mortality counts by age group in every county, and mortality rates are calculated by dividing deaths by corresponding population counts. Where mortality data are unavailable (for privacy and confidentiality purposes or due to a lack of information), first state average mortality rates, then U.S. Health and Human Services region average mortality rates, then the national average mortality rate are substituted in, as needed. We employ CDC population and mortality rate data specific for 2014 through 2019.

Valuation

Monetizing Mortality Risk with the Value of a Statical Life (VSL)

This study uses the value of a statistical life (VSL) approach for mortality risk monetization [38]. Critically, the VSL does not place a value on life itself but instead represents the amount a person is willing to pay (or willing to accept) to reduce (or take on additional) mortality risk. It is the marginal rate of substitution between money and mortality risk [39]. The VSL, approximately $10 million per statistical life, is better communicated as an individual being willing to pay $10 for a mortality risk reduction equal to one in a million (or that individual being willing to accept $10 for a mortality risk increase of the same magnitude). The VSL can also be considered what a group of individuals is willing to pay for risk reductions that sum to a 100% chance (i.e., one statistical life). The VSL is often misunderstood, leading some authors to suggest changing its name [40]. The damages of $PM_{2.5}$ exposure are estimated using expected premature deaths times the VSL.

The EPA's 2010 meta-analysis considered various revealed and stated preference studies to determine the VSL [41]. This study uses the EPA's recommended central VSL estimate of $7.4 million (2006 USD). We apply the VSL uniformly across all ages and county populations per EPA guidelines. Another study also conducted a meta-analysis to determine the VSL [42]. The study's central estimate is much lower than the EPA's, at $2 million (1998 USD), which we consider for our low damage estimate.

Inflation and Wealth Adjustments to the VSL

As instructed by the EPA [41], we account for inflation and wealth effects over time to get the VSL to 2020 USD each year from 2014 to 2019. We adjust for inflation using July-to-July estimates from the U.S. Bureau of Labor Statistics' (BLS's) consumer price index inflation calculator [43].[10] The degree to which the VSL increases as income increases is characterized by income elasticity. This study uses an income elasticity of 0.7, the EPA's central estimate consistent with the balanced approach to VSL estimation [44].

The following equation is used to adjust the VSL considering real income growth from 2006 and 1998 to our years of study [45]:

[10] We adjust for inflation using this procedure wherever needed henceforth.

Equation A10. VSL Wealth Adjustments

$$VSL_B = VSL_A * \left(\frac{Income_B}{Income_A}\right)^{Elasticity}$$

Equation A10, we use the VSL from the reference year (*A*), an income ratio of the year of analysis (*B*) over the reference year, and the income elasticity to determine the VSL for the year of study. For income ratios, we use real gross domestic product (GDP) per capita data from 1998 to 2019 (2012 USD) from Federal Reserve Economic Data (FRED) provided by the Federal Reserve Bank of St. Louis [46].

The following is a step-by-step process for VSL adjustment in this study as informed by the mortality risk valuation literature and economic analysis guidelines:

1. Adjust VSL from reference years' (1998 and 2006) nominal values to 2012 USD.[11]
2. Determine the income ratio of years of analysis (2014 through 2019) to reference years.
3. Equation A10 to adjust the VSL to the year of analysis for wealth/income effects.
4. Adjust the VSL once again for inflation from 2012 USD to 2020 USD.

Table A4 shows the resulting VSLs by year used for this paper.

Table A4. VSL for mortality risk monetization in AP3.

Mortality Risk Valuation Study	Reference Year	Reference Year VSL (Million $)	Analysis Year	Analysis Year VSL (Million $)
EPA Meta-Analysis (2010)	2006	7.40 (2006 USD)	2014	9.66
			2015	9.80
			2016	9.86
			2017	9.97
			2018	10.1
			2019	10.3
Mrozek and Taylor (2002)	1998	2.00 (1998 USD)	2014	3.65
			2015	3.70
			2016	3.72
			2017	3.76
			2018	3.83
			2019	3.87

Sources: Original VSL data are from the EPA [41] and Mrozek & Taylor (2002).
Notes: Final VSL values for each year are in 2020 USD.

Marginal Damages

We estimate MDs by source, pollutant, and year. The following algorithm computes MDs:

1. Add 1 ton of emissions to the baseline for a source, a pollutant, and a year.

[11] This step is not entirely necessary. It is included to keep nominal values consistent at each stage of the adjustment process. However, Steps 2 and 3 plus 4 but adjusting for inflation from 1998 USD or 2006 USD works the same.

2. Estimate marginal impacts by subtracting baseline impacts from the new impacts with the marginal ton added.
3. Reset the model to its baseline.
4. Repeat for each source, pollutant, and year combination.

Again, the 2014 $PM_{2.5}$ concentration baseline is used for 2014 and 2015. The 2017 $PM_{2.5}$ concentration baseline is used for 2016 through 2019. Population and mortality rate data and valuation information are unique for each year.

MDs are the output of AP3. Then, we multiply total (avoided) emissions by their respective MDs for total (avoided) damages. This is an approach based on that conducted in previous work—e.g., [1], [27], [47]. (See emissions-weighted MDs from the U.S. coal fleet in Table A7.)

SOCIAL COST OF CARBON

Putting a Price on Carbon

Carbon dioxide (CO_2) is a greenhouse gas (GHG). GHGs behave differently than criteria air pollutants, making their impacts more straightforward to assess in some ways and more complex in others. CO_2 is a well-mixed pollutant, so unlike criteria air pollution, which remains "local," it is distributed uniformly throughout the atmosphere. This simplifies impact valuation for CO_2 emissions because it does not matter where the pollution is released. In other words, a ton of CO_2 released from one geographic location has the same impact on the global climate system as a ton of CO_2 released from any other geographic location.

On the other hand, the impacts of climate change are vast and complex, resulting in uncertain yet substantial costs for many human and environmental systems worldwide. These impacts include but are not limited to the following [48], [49]:

- Changes to agricultural systems.
- Impacts on human health.
- Sea level rise and ocean acidification.
- Extreme weather and flooding.
- Dryer conditions and more wildfires.
- Wildlife and species losses.

These impacts are particularly challenging to deal with for several reasons.[12] While there is little scientific doubt that anthropogenic emissions of GHGs are driving temperature increases, the pace at and extent to which global warming is occurring and driving impacts are highly uncertain. In other words, there are layers of uncertainty regarding the damage caused by an additional ton of CO_2. Moreover, "tipping points" may result in unexpected, potentially catastrophic consequences.

Then, there is the challenge of impact valuation. The idea is to measure the total economic damage resulting from the impacts of climate change. However, these depend not only on the trajectory of climate change but also on societal progress and adaptation. Additionally, we must again navigate non-market valuation—e.g., what is the cost of species extinction?

[12] The following paragraphs provide a summary, but see William Nordhaus's *Climate Casino: Risk, Uncertainty, and Economics for a Warming World* for an in-depth discussion on the environmental economics of climate change [48].

Lastly, the impacts of climate change are complexly distributed across space and time. Consequences can be local (e.g., flooding), regional (e.g., heat waves), or global (e.g., ocean acidification). Furthermore, emissions released today result in a stream of damages extending far into the future. Therefore, we must account for the time value of money and discount future costs and benefits [50]. To what extent we discount the future depends on methodology, mainly whether we employ a prescriptive (normative) or descriptive (opportunity-cost) approach. In short, many factors make "putting a price on carbon" difficult.

Estimates from the U.S. Government's Interagency Working Group

Several IAMs evaluate the climate damages associated with CO_2 emissions—e.g., the Dice Integrated Climate-Economy, or DICE, model [51]. This study employs the social cost of carbon (SCC), as provided by the Interagency Working Group on Social Cost of Greenhouse Gases (IWG) under the Obama Administration, which derives SCC estimates using three IAMs [52]. The SCC from the IWG estimates the discounted present value of the globally incurred stream of total damages due to one additional (marginal) ton of CO_2. In other words, the SCC is an MD. The IWG reports the SCC for each year from 2010 to 2050; the different SCCs for each year account for additional units of warming having more significant incremental damages as the climate system becomes more stressed.

Table A5. SCC for climate impact monetization.

Description	Year	3% SDR Average	5% SDR Average	3% SDR 95th Percentile
2007 USD Per Metric Ton	2014	35.0	11.0	101
	2015	36.0	11.0	105
	2016	38.0	11.0	108
	2017	39.0	11.0	112
	2018	40.0	12.0	116
	2019	41.0	12.0	120
2020 USD Per Short Ton	2014	39.5	12.4	114
	2015	40.6	12.4	118
	2016	42.9	12.4	122
	2017	44.0	12.4	126
	2018	45.1	13.5	131
	2019	46.3	13.5	135

Sources: Original SCC data are from the IWG [52]..
Notes: Final SCC values for each year are in 2020 USD.

To address the time value of money, we must select a social discount rate (SDR). The IWG reports the average modeled SCC for three SDRs: 2.5%, 3%, and 5%. For our central damage estimates, we choose 3%.[13] For our low damage estimate, we choose 5%, further discounting future generations' benefits and costs. The IWG also provides a higher SCC considering the

[13] More than two-thirds of experts recommend an SDR between 1% and 3% [50]. For our study, 3% is on the conservative end of the recommended interval, as we are demonstrating the extent to which benefits of avoided CO_2 exceed a variety of policy-related costs.

potential for a less probable but more damaging scenario. This is characterized by the 95th percentile of modeling estimates for the SCC using the 3% SDR. We use this 95th percentile SCC for our high damage estimate.

We adjust the SCCs for inflation from the IWG's reported values in 2007 USD to 2020 USD [43]. Table A5 summarizes the SCC values. Like with MDs from AP3, we multiply total (avoided) emissions by their respective MDs for total (avoided) damages.

Because this study focuses on benefits and costs within the U.S., we consider CO_2-induced damages incurred domestically separately from those incurred internationally. While we contend that properly putting a price on carbon emissions should include total damages experienced globally, the policies discussed herein center around coal communities and the coal industry within the U.S. If we consider avoided damages as justification for funding just transition solutions within the U.S., it is reasonable to consider those damages avoided within the U.S. distinctly.

A recent study provided country-level SCC estimates [53]. The study reports that the U.S. incurs about 11% of the global SCC, which we employ for this study. It also reports a lower bound of 0% and an upper bound of 15%, which we employ for our lower and upper damage estimates. We note that the study finds a much higher global SCC than the IWG—at more than $400 per metric ton of CO_2; however, the authors report that the relative distribution of damages among countries is robust to uncertainties surrounding the global SCC estimate.

We also note that a recent study led by authors from Resources for the Future reports a substantially greater global SCC as well—at $185 per metric ton of CO_2 [54]. The study used "updated scientific understanding throughout all components of the [SCC] estimation" per recent National Academy of Sciences recommendations. While we choose to use SCC values close to those currently recommended by the U.S. government, given the goals of this study (i.e., U.S. federal policy analysis), future work should consider using a greater estimate based on this evidence.

MARGINAL DAMAGE UNCERTAINTY

Discussion of Uncertain Inputs

There are several sources of uncertainty for our damage modeling. Some of these we do not explore in this study, including but not limited to uncertainty with our atmospheric modeling, emissions data, population and mortality rate data, and economic data. For some of these, we are limited by data availability. For example, NEI data, used to construct AP3's baseline, have no comprehensive alternative. Others are only slightly influential compared to other related factors—e.g., income elasticity's effect on the VSL vs. the alternative value from Mrozek & Taylor (2002) or choosing an SCC with an SDR of 1% vs. the 95th percentile with an SDR of 3%.

Future work may use comparable reduced-complexity air quality models to further the work herein and/or verify findings. Two examples of these are the Estimating Air pollution Social Impact Using Regression (EASIUR) [55] and Intervention Model for Air Pollution (InMAP) [56]. For an inter-comparison of AP3, EASIUR, and InMAP, see Gilmore et al. (2019) [57]. In general, Gilmore et al. (2019) finds that the models are in good agreement.

The following section reviews the uncertain inputs we evaluate herein related to the DR function, the VSL, and the SCC.

Variable Substitutions for Uncertainty Assessments & Marginal Damages Summary

Table A6 summarizes the variable substitutions for this paper's lower and upper bound uncertainty analyses. For each scenario, all variables are adjusted simultaneously unless otherwise specified. The bounds are created from a U.S. perspective. For example, the lower bound considers a 5% SDR and 0% domestic incurrence; international damages are the difference between global and domestic incurrence.

Central, lower bound, and upper bound emissions-weighted marginal damages from the U.S. coal fleet are reported in Table A7.

Table A6. Summary of variable substitutions for sensitivity analysis of damages.

Variable	Lower Bound	Central	Upper Bound
Dose-Response	Krewski et al. (2009)	Krewski et al. (2009)	Lepeuele et al. (2012)
Value of a Statistical Life	Mrozek & Taylor (2002) $2.0 Million (1998 USD)	EPA Meta-Analysis $7.4 Million (2006 USD)	EPA Meta-Analysis $7.4 Million (2006 USD)
Global Social Cost of Carbon	5% SDR	3% SDR	95th Percentile SCC (Catastrophic Outcomes)
Domestic vs. International Social Costs of Carbon	0% vs. 100%	11% vs. 89%	15% vs. 85%

Sources: DR [30], [32]; VSL [41], [42]; SCC [52]; Domestic vs. International [53].
Notes: Gray wording shows where inputs are the same as the central estimate.

Table A7. Emissions-weighted marginal damages from the U.S. coal fleet.

Units	Pollutant	Estimate	Emissions-Weighted Marginal Damages					
			2014	2015	2016	2017	2018	2019
Thousand $ Per Short Ton	SO_2	**Central**	**40.8**	**42.0**	**41.9**	**41.9**	**44.2**	**45.0**
		Lower	15.4	15.8	15.8	15.8	16.7	17.0
		Upper	85.2	87.8	88.5	88.4	93.4	95.1
	NO_x	**Central**	**10.6**	**11.1**	**9.66**	**9.85**	**10.1**	**10.3**
		Lower	4.01	4.17	3.64	3.72	3.82	3.87
		Upper	22.2	23.1	20.4	20.8	21.4	21.6
	Primary $PM_{2.5}$	**Central**	**52.0**	**53.2**	**54.2**	**55.7**	**58.0**	**58.0**
		Lower	19.6	20.1	20.4	21.0	21.9	21.9
		Upper	108	111	114	118	122	122
Dollars Per Short Ton	CO_2: Domestic	**Central**	**4.34**	**4.47**	**4.72**	**4.84**	**4.97**	**5.09**
		Lower	0	0	0	0	0	0
		Upper	17.1	17.8	18.3	19	19.6	20.3
	CO_2: International	**Central**	**35.2**	**36.2**	**38.2**	**39.2**	**40.2**	**41.2**
		Lower	12.4	12.4	12.4	12.4	13.5	13.5
		Upper	96.9	101	104	107	111	115

Notes: Damages are in 2020 U.S. dollars. SO_2, NO_x, and primary $PM_{2.5}$ damages are modeled with AP3. CO_2 damages are modeled with the SCC. Domestic and international CO_2 damages are differentiated considering country-level SCC estimates from Ricke et al. (2018) [53]. Uncertainty bounds use the variable substitutions from Table A6.

Appendix B: Retrospective Damages & Wage Replacement.

EMISSIONS DATA & DECOMPOSITION

Emissions from Coal

SO_2, NO_x, and CO_2 Emissions from Coal

U.S. coal electric generating unit (EGU) emissions of SO_2, NO_x, and CO_2 are from the EPA's Clean Air Markets Program Data (CAMPD) [58]. These data are reported at the unit and power plant level, with a unit identification number and an Office of Regulatory Information Systems Plant Location (ORISPL) identification number (i.e., power plant identification number). We consider only EGUs with a primary fuel source of coal, including coal, coal refuse, petroleum coke, and any combination of fuels including at least one of these. Further, we only consider CONUS EGUs. We also collect data at the plant level, inclusive of emissions from units powered by other fuel sources. These plants cover any facility with at least one EGU with coal as a primary fuel source. In other words, the data include any power plant with an EGU in the filtered unit-level dataset.

Interpolating Primary $PM_{2.5}$ Emissions from Coal

CAMPD does not report primary $PM_{2.5}$ emissions. Instead, we interpolate the emissions using data from CAMPD and the NEI [7], [8], [58]. This is a multi-step process considering three $PM_{2.5}$-to-variable ratios at the emissions inventory system (EIS) level, which the NEI uses for annual emissions tracking for point sources. We use an EIS-to-ORISPL crosswalk provided to us by the EPA [7], [8] to connect CAMPD-tracked power plants (ORISPL) to the proper NEI-tracked emissions sources (EIS).[14]

NEI data are only available for 2014 and 2017, so we use ratios computed with data only from these two years. As with the AP3 $PM_{2.5}$ concentration baselines, 2014 data are used for 2014 and 2015, and 2017 data are used for 2016, 2017, 2018, and 2019. Besides being limited to 2014 and 2017, the NEI's EIS identification scheme differs from unit and plant identification as follows:

1. Emissions are tracked at the plant level, considering all activities and sources. Coal-fired power plants frequently have multiple EGUs, some primarily powered by other fuel sources (e.g., natural gas).
2. Some EIS identifiers cover multiple ORISPL identifiers (typically, neighboring power plants run by the same operator and tracked as one facility—presumably, for reporting simplicity). On the other hand, in some instances, multiple EIS identifiers cover just one ORISPL identifier; however, this is only the case with the EGUs fueled by sources other than coal.

[14] At the time this paper was written, the contact at the EPA covering point sources of the NEI who provided the EIS-to-ORISPL crosswalk was Ron Ryan. Relevant points of contact can be found here: https://www.epa.gov/air-emissions-inventories/air-emissions-points-contact.

Hence, we aggregate our variables included in the interpolation ratios to the EIS level. Our ratios are as follows: $PM_{2.5}$-to-SO_2, $PM_{2.5}$-to-NO_x, and $PM_{2.5}$-to-heat input.[15] EIS-level SO_2 and NO_x are from the NEI, and EIS-level heat input is derived from CAMPD.

We compute our ratios where data are available and then conduct a simple outlier analysis using z-scores to "clean" our data. We find this a necessary step because some sources have very high ratios of $PM_{2.5}$-to-SO_2, $PM_{2.5}$-to-NO_x, and $PM_{2.5}$-to-heat input, leading to unreasonably high estimates of unit-level $PM_{2.5}$. While we refrain from an in-depth analysis of this phenomenon, some investigating suggests that this occurs for facilities with minimal SO_2, NO_x, or heat input. Any ratio with a z-score > 3 (as compared to the rest of the fleet) is excluded from the interpolation process. Then, heat input-weighted fleet averages of the ratios are computed for each year and used to populate the excluded and otherwise missing observations.

Lastly, we use our ratios to compute three separate estimates of $PM_{2.5}$ emissions by unit. Then, we take the median estimate among the three for each to serve as our unit-level interpolated value. This is, again, to limit the impact of outliers on the interpolation process. We also conduct this process at the plant level, including all units' emissions and heat input.

A Summary of Emissions from Coal

Table B1 shows annual emissions from 2014 to 2019 from EGUs with coal as a primary fuel source at CONUS facilities. We note that coal EGUs account for most emissions from power plants with at least one EGU with coal as a primary fuel source.

Table B1. Emissions, heat input, and emission rates from U.S. coal EGUs.

Coal EGU Variable		2014	2015	2016	2017	2018	2019
Emissions (Short tons)	SO_2	3.13e+06	2.19e+06	1.47e+06	1.32e+06	1.24e+06	9.56e+05
	NO_x	1.55e+06	1.24e+06	1.05e+06	9.33e+05	8.64e+05	7.18e+05
	Primary $PM_{2.5}$	1.31e+05	1.07e+05	9.03e+04	8.37e+04	7.61e+04	6.22e+04
	CO_2	1.73e+09	1.50e+09	1.39e+09	1.35e+09	1.28e+09	1.09e+09
Heat Input (MMBtu)		1.68E+10	1.46E+10	1.35E+10	1.31E+10	1.25E+10	1.06E+10
Emission Rates (lb/MMBtu)	SO_2	0.372	0.299	0.217	0.201	0.198	0.181
	NO_x	0.184	0.169	0.155	0.142	0.138	0.136
	Primary $PM_{2.5}$	0.0156	0.0146	0.0133	0.0128	0.0122	0.0118
	CO_2	206	205	205	206	205	207

Sources: Emissions and heat input data are from the EPA [7], [8], [58].
Notes: Emission rates are emissions divided by heat input. Data are only emissions and heat input from EGUs with a primary fuel source of coal.

A comparison of our totals from Table B1 to data for Fossil Fuel Electric Power Generation (NAICS Code 221112) facilities reported by the NEI suggests that our $PM_{2.5}$ are within the expected margin of error; for both 2014 and 2017, the discrepancies between total SO_2 reported by the two sources are greater than those between NEI-reported and interpolated $PM_{2.5}$. Notably,

[15] Heat input is the amount of heat, in million British thermal units (MMBtu), produced during the combustion of fuel within a steam-powered unit. It is the first step in the electric power generation process and that most directly tied to emissions. The creation of heat releases SO_2, NO_x, $PM_{2.5}$, CO_2, and several other pollutants. That heat is then used to create steam at high temperatures and pressures in a boiler. The steam then flows through a turbine and creates mechanical energy. Lastly, the mechanical energy is converted into electric power via a generator.

the NEI data in this first-order assessment are not limited to coal plants (i.e., they are for all electric power generation from fossil fuels). Several other factors may also systematically drive differences between CAMPD and the NEI (e.g., data collection and/or management procedures).

Decline and Improvement Decomposition

We differentiate emission changes by decline and improvement because we want to evaluate the effects of moving away from coal rather than of coal-fired generation occurring at lower emission rates. These drivers, and the resulting benefits, are critical to distinguish from one another when we consider associated costs.

An example of analogous costs to benefits from decline would be those from employment cuts resulting from less economic activity, and we precisely assess these costs in this study. An example of analogous costs to the benefits from improvement would be installing pollution abatement technology (e.g., SO_2 scrubbers), which can cost millions of dollars to own and operate [59]. We do not assess these costs in this study.

Comparison to Holland et al. (2020)

Like the recent study by Holland et al. (2020) [60], we conduct a decomposition analysis to quantify the effects of drivers of change in the U.S. power sector. Our analysis, however, differs in a few crucial ways:

- First, we focus on emissions, whereas Holland et al. (2020) decomposed damages.[16]
- Second, we look at only coal-fired EGUs, whereas Holland et al. (2020) looked at plants across the entire power sector.
- Third, we conduct a two-variable decomposition, focusing only on decline and improvement, whereas Holland et al. (2020) conducted a multi-variable decomposition focusing on scale, composition, technique, and valuation (see explanations below).
- Fourth, we consider a slightly later time frame. Holland et al. (2020) covered 2010-2017; we cover 2014-2019.

In Holland et al. (2020), *scale* represented renewable penetration, *composition* represented a shift in generation shares, *technique* represented emission rate improvements, and *valuation* represented increases in marginal damages.[17] Our decline and improvement variables are some combination of Holland et al. (2020)'s scale, composition, and technique variables. We do not consider valuation because we only look at emission changes.

Decline will include some scale, some composition, and even some technique. Considering the first two, we capture where coal is presumably (we do not specifically explore) replaced by other fuel sources. We treat this occurrence the same regardless of what fuels those replacements comprise. Holland et al. (2020)'s decomposition was at the plant level, so switching to cleaner fuels within a power plant is captured as part of the technique effect. Contrarily, our decomposition is at the unit level, so switching to cleaner fuels within a power plant is captured as part of the decline effect.

[16] Holland et al. (2020) decomposed emissions rather than damages as a supplementary analysis in their Appendix.
[17] This results from trends such as population and wealth growth over time, for example. It also accounts for baseline pollution changes over time.

On the other hand, *improvement* will include some (but not all) of the technique effect. We note that about 25% of the technique effect observed by Holland et al. (2020) was driven by fuel switching from coal. For this study, those changes are attributed to the decline rather than the improvement effect.

In summary, decline is unique to our study because it incorporates changes in emissions driven by decreased production, including facilities going offline or converting to another fuel source. We assess production using heat input (MMBtu), the direct result of combustion and the variable most directly associated with emissions. Heat input converts water into pressurized steam that moves through the plant and eventually powers its generator(s).[18] Herein, we do not account for what a facility does when it stops producing heat input with coal; we simply account for the fact that it does, indeed, stop. Hence, any changes not attributed to coal's improvement, where coal itself generates cleaner electricity at lower emission rates (lb/MMBtu), are attributed to coal's decline.

Comparing our results to those of Holland et al. (2020) is challenging based on methodological differences, but we conduct a first-order assessment to compare findings. Holland et al. (2020) found that the decrease in annual damages from "cleaner coal" (i.e., new SO_2 controls and improvements without new technology in the technique effect) amounted to 35% of those obviously attributable to changes to do with coal. The other obviously coal-related effects considered for this first-order assessment are less coal (25%), switching from coal (4%), and coal's exit (23%) in the composition effect and switching from coal (13%) in the technique effect. Notably, no renewable penetration via the scale effect is considered, which would decrease the relative shares of each effect. We discuss this first-order assessment further when looking at our decomposition results.

Decomposition Methodology

Table B1 also shows the total heat input and the fleetwide emission rates across EGUs with coal as a primary fuel source each year from 2014 to 2019. Heat input data are from CAMPD [58]. Importantly our decomposition is at the unit level, meaning a decomposition of Table B1's values would not return identical results to those for this study. Simply put, emission rates in Table B1 decreased over the years because coal EGUs improved and EGUs with higher-than-average emission rates went offline over time—a trend associated with the decline effect.

The online appendices of Holland et al. (2020) discuss several decomposition methods for discrete data over time. Following suit, we begin with the product rule from differential calculus:

Equation B1. Decomposition: Product rule.

$$\frac{de}{dt} = \frac{dh}{dt}r + \frac{dr}{dt}h$$

The left-hand side of Equation B1 is the change in emissions over time. The first term of the right-hand side is the effect of changing h (e.g., output from coal via heat input) while keeping

[18] A main reason we use heat input rather than generation as our production variable is the relationship between boilers and generators at power plants. Some power plants have one-to-one boiler-to-generator connections whereas some have some combination of boilers connecting to some combination of generators [58]. Disentangling which emissions are associated with what generation can be challenging for some facilities where, for example, multiple generators, each producing generation, are connected to one boiler releasing the plant's emissions. Using heat input allows us to evade this challenge while also providing a sound measure of production.

r (e.g., emission rate) fixed. Conversely, the second term of the right-hand side is the effect of changing r while keeping h fixed. Assumptions about the fixed or reference quantities (i.e., r and h) affect the ratios and the error term of the decomposition, called the "index number problem" by Oaxaca (1973) [61].

A two-variable decomposition using the Marshall-Edgeworth method [62], [63] for defining the reference results in an error term of zero. This method involves taking the average between the new time and the base time to define the fixed/reference quantities:

Equation B2. Decomposition: Marshall-Edgeworth.

$$\Delta e = \Delta h \bar{r} + \bar{h} \Delta r$$

Practically speaking, Equation B2 leads to the following procedure to decompose our emission changes into the decline effect and the improvement effect:

- Decline Effect
  - Hold emission rates constant as the average between the new time (e.g., 2017) and the base time (e.g., 2014).
  - Compute *proxy emissions* for the new time and the base time using the fixed emission rates (e.g., the average between 2014 and 2017) and actual heat input.
  - Calculate the difference between the *proxy emissions* in the new time vs. the base time to find the emissions changes attributable to the decline effect.
- Improvement Effect
  - Hold heat input constant as the average between the new time and the base time.
  - Compute *proxy emissions* for the new time and the base time using the fixed heat input and actual emission rates.
  - Calculate the difference between the *proxy emissions* in the new time vs. the base time to find the emissions changes attributable to the improvement effect.

While the changes are computed using *proxy emissions*, the changes between them characterize (and add up to) the changes between the *actual emissions*. Critically, only coal EGUs operating in both the new and base times are subject to decomposition. If an EGU explicitly retires or no longer reports heat input from coal and associated emissions, all emission changes are attributed to the decline effect.

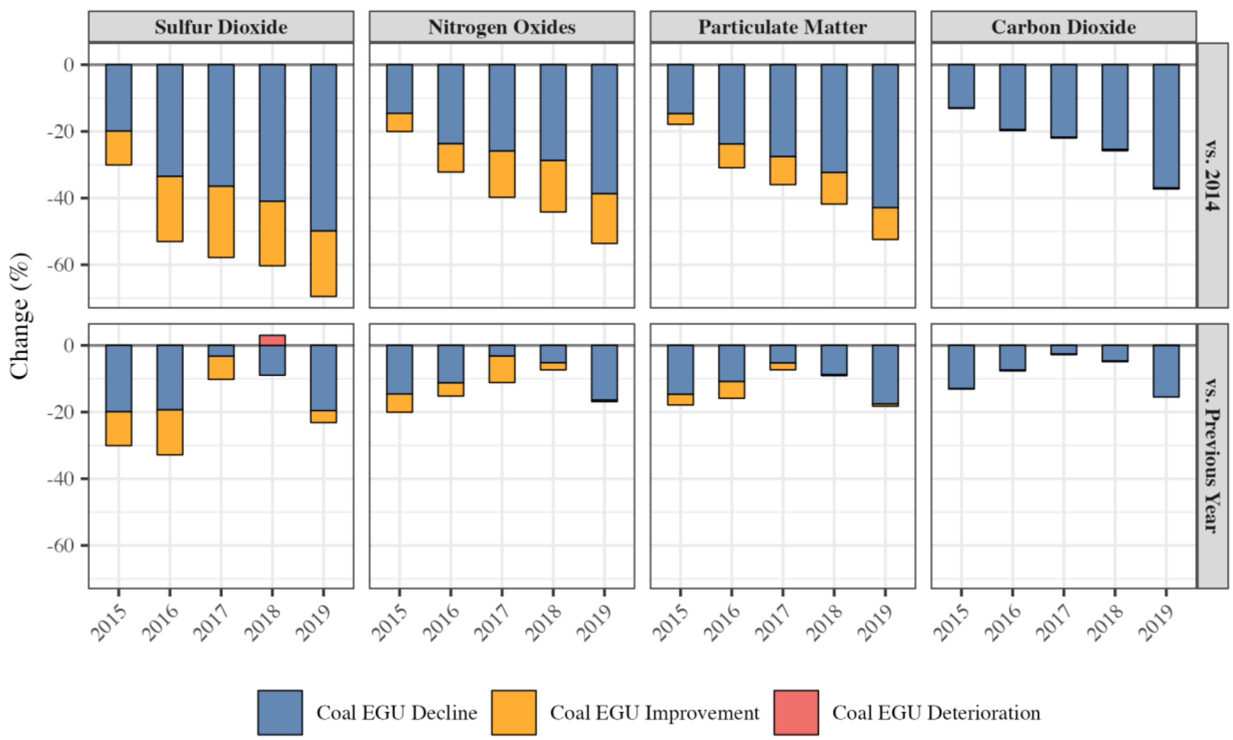
Other methods for defining the reference/fixed variable include using the initial value, averaging across all years in the analysis, and using the final value [61], [64], [65]. However, each of these results in an error term, where the aggregate change across effects differs from the actual change.

Emission Changes by Effect

Figure B1 shows percentage changes in emissions each year decomposed by the decline (blue) and improvement (yellow) effects vs. a baseline of 2014 (top) and the previous year (bottom). Deterioration—additional emissions from increased emission rates—is shown in red. This is only relevant for SO_2 emissions from 2017 to 2018 and CO_2 emissions from 2018 to 2019; the latter data are so small that the bar cannot be seen. Damages differ from emissions in that it matters where the pollution is released. Still, the two are, of course, correlated. Hence, we will discuss the data in more detail when looking at benefits over time, but much of that discussion is also relevant here.

That said, we will mention here that one of the more striking takeaways here is that CO_2 changes were nearly all due to less (decline) rather than better (improvement) coal. Looking at the data by EGU, there is substantial variability among SO_2, NO_x, and primary $PM_{2.5}$ emission rates (both within and across years), but CO_2 is nearly perfectly correlated with heat input.

We offer two explanations. First, criteria air pollution abatement technology is largely developed and widely commercialized, whereas that for CO_2, namely carbon capture, utilization, and sequestration, is currently not. Second, there are significant environmental regulations for criteria air pollution from coal-fired power plants, incentivizing air pollution abatement at coal plants, but not for CO_2.



Sources: Emissions data are from the EPA [7], [8], [58].
Notes: Decline represents fewer emissions from less output. Improvement represents fewer emissions from lower emission rates. Deterioration represents additional emissions from increased emission rates. Emissions are from EGUs with coal as a primary fuel source. Decomposition considers either 2014 (top panel) or the previous year (bottom panel) as the counterfactual for each year.

Figure B1. Percentage Changes in U.S. Coal Emissions Decomposed by Decline and Improvement.

RETROSPECTIVE DAMAGES & BENEFITS

Damages of Coal Emissions

Table B2 summarizes damages from coal emissions from 2014 to 2019. Damages are broken down by pollutant (source) and whether the damage is experienced domestically or internationally (receptor).

We note a few interesting points on annual damage accounting. First, among the four pollutants, SO_2 accounted for 85% of the 2014-to-2019 decrease within the U.S. Inclusive of international climate damages, this contribution remains very large at 74%. This finding aligns with that of Holland et al. (2020), showing that 88% of the 2010-to-2017 annual damage decrease from U.S. power plants was due to SO_2. This dominating influence of SO_2 on total local air pollution damages from coal has long been recognized in the literature—e.g., [66], [67].

Second, the U.S. incurred 73% of its coal emission damages in 2014. However, that share decreased to 57% in 2019 because the relative contribution of SO_2 to total damages decreased while that of CO_2 increased.

Table B2. Damages from U.S. coal emissions.

Source/Receptor of Damage	Estimate	Damages (Billion $)					
		2014	2015	2016	2017	2018	2019
SO_2	**Central**	**128**	**91.9**	**61.7**	**55.3**	**55.0**	**43.0**
	Lower	48.2	34.7	23.3	20.9	20.7	16.2
	Upper	267	192	130	117	116	90.9
NO_x	**Central**	**16.4**	**13.7**	**10.1**	**9.19**	**8.75**	**7.36**
	Lower	6.20	5.17	3.83	3.47	3.30	2.78
	Upper	34.3	28.6	21.4	19.4	18.5	15.6
Primary $PM_{2.5}$	**Central**	**6.79**	**5.71**	**4.89**	**4.66**	**4.41**	**3.61**
	Lower	2.56	2.15	1.85	1.76	1.66	1.36
	Upper	14.2	11.9	10.3	9.84	9.31	7.61
Criteria Air Pollutant Total	**Central**	**151**	**111**	**76.7**	**69.2**	**68.1**	**54.0**
	Lower	57.0	42.0	28.9	26.1	25.7	20.4
	Upper	316	233	162	146	144	114
CO_2: Domestic	**Central**	**7.52**	**6.72**	**6.55**	**6.53**	**6.37**	**5.52**
	Lower	0.00	0.00	0.00	0.00	0.00	0.00
	Upper	29.6	26.7	25.4	25.6	25.2	22.0
CO_2: International	**Central**	**60.8**	**54.4**	**53.0**	**52.9**	**51.6**	**44.7**
	Lower	21.5	18.7	17.2	16.8	17.4	14.7
	Upper	168	151	144	145	143	125
Greenhouse Gas Total	**Central**	**68.3**	**61.1**	**59.5**	**59.4**	**57.9**	**50.2**
	Lower	21.5	18.7	17.2	16.8	17.4	14.7
	Upper	197	178	169	171	168	147
Domestic Total	**Central**	**159**	**118**	**83.3**	**75.7**	**74.5**	**59.5**
	Lower	57.0	42.0	28.9	26.1	25.7	20.4
	Upper	346	260	187	172	169	136
Emissions Total	**Central**	**219**	**172**	**136**	**129**	**126**	**104**
	Lower	78.5	60.7	46.1	42.9	43.1	35.1
	Upper	514	411	331	317	312	261

Notes: Damages are in 2020 U.S. dollars. Criteria air pollutant total includes SO_2, NO_x, and primary $PM_{2.5}$. Greenhouse gas total includes both domestic and international CO_2 damages. Domestic total includes criteria air pollutant and domestically incurred CO_2 damage. Uncertainty bounds use the variable substitutions from Table A6.

Third, there was a decrease in annual damages incurred within the U.S. each year from 2014 to 2019, but more than three-fourths of the total change occurred from 2014 to 2016. Less than 10% of the total change occurred from 2016 to 2018, and 15% occurred from 2018 to 2019.

Interestingly, 43% of the total decrease in internationally incurred damages occurred from 2018 to 2019 (and 40% occurred from 2014 to 2015).

Benefits from Avoided Coal Emissions

Benefits are estimated by computing the damages of emissions each year that are avoided compared to a 2014 baseline. In other words, it is the difference between damages that were and damages that would have been given a 2014 counterfactual emissions scenario (i.e., without the changes due to decline and improvement). For example, if a coal unit emitted 100 short tons of SO_2 in 2014 and 30 short tons of SO_2 in 2017, the avoided emissions in 2017 were 70 short tons. Avoided damages are then 70 short tons times the MD of one ton of SO_2 from that coal unit in 2017.

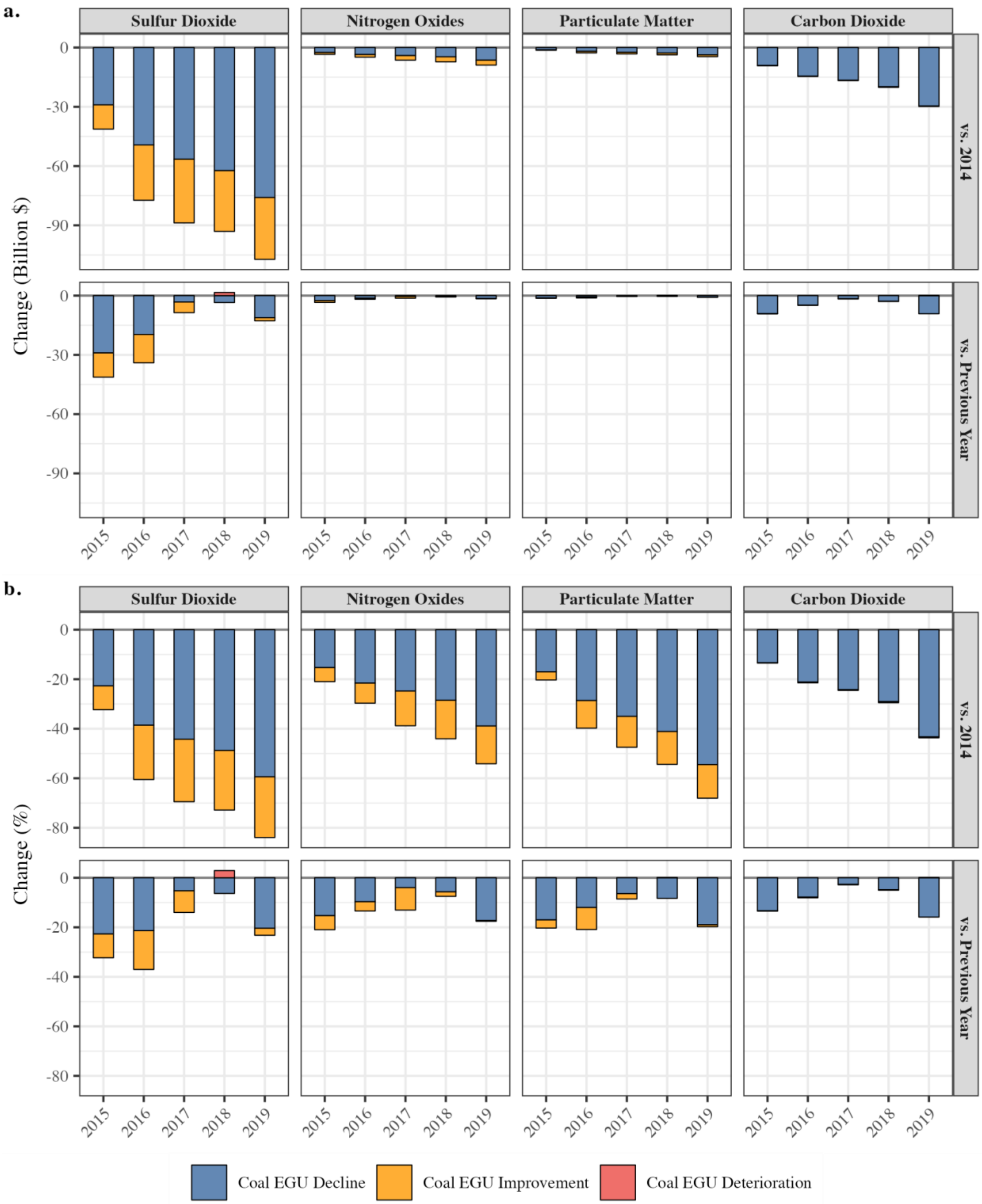
Figure B2 shows the change in damages from coal emissions decomposed by the decline (blue) and improvement (yellow) effects vs. a baseline of 2014 (top panels) and the previous year (bottom panels). Deterioration—additional damages from additional emissions driven by increased emission rates—is shown in red. The top plot shows the absolute avoided damages in billions of dollars, and the bottom plot shows the relative avoided damages in percentages. Table B3 summarizes the benefits of avoided coal emissions from 2014 to 2019. Benefits are broken down by pollutant (source), whether the damage is experienced domestically or internationally (receptor), and the effect driving the change relative to 2014.

Overall, we find that decline played a more prominent role than improvement, both domestically and especially globally, as anticipated based on the emission changes decomposition results (Figure B1).[19] Circling back to the results from Holland et al. (2020), that coal's explicit improvement accounted for 35% of clearly coal-related changes, we see somewhat expected results—especially for SO_2, where decline accounted for 67% of the five-year benefits and improvement accounted for 33%. Decline is more influential for the other pollutants—especially CO_2, where decline accounted for 99% of the five-year benefits. Our previous discussion of the differences between our study and their study qualitatively supports what we see here, but again, further comparisons are limited by methodological differences.

Overall, we note the greatest benefits resulted from SO_2 (among pollutants), the decline effect (rather than improvement), and during 2019 (compared to other years). The last point is intuitive as it is the year with the greatest compounded gains from coal output decreasing over time. Domestically, SO_2 was the primary driver of gains (88%). The decline effect's SO_2 reduction accounted for 59% of domestic benefits, and the improvement effect's SO_2 reduction accounted for 29%. The other pollutants were less influential. Considering all (global) damage, SO_2 still accounted for 75% of benefits (50% attributable to decline and 25% attributable to improvement). International benefits from CO_2 were next most influential at 15%—nearly all from decline.

Including international avoided CO_2 damages matters when determining the relative influence of the different pollutants on decline benefits. For example, globally, SO_2 accounted for 69% of decline benefits, and just domestically, SO_2 accounted for 86% of decline benefits. This, however, is not the case for improvement benefits, nearly all of which were experienced within the U.S. (SO_2 emission rate reductions drove 91%).

[19] Decline is even more influential considering global damages because benefits from CO_2 (the only pollutant driving international damages) are nearly all driven by coal's decline. The criteria air pollutants (causing damage only domestically) saw more changes due to improvement.



Notes: (a) Top plot shows damage changes. (b) Bottom plot shows percentage changes. Decline represents fewer emissions from less output. Improvement represents fewer emissions from lower emission rates. Deterioration represents additional emissions from increased emission rates. Emissions are from EGUs with coal as a primary fuel source. Decomposition considers either 2014 (top panels of the plots) or the previous year (bottom panels of the plots) as the counterfactual for each year. CO_2 damages are both domestic and international.

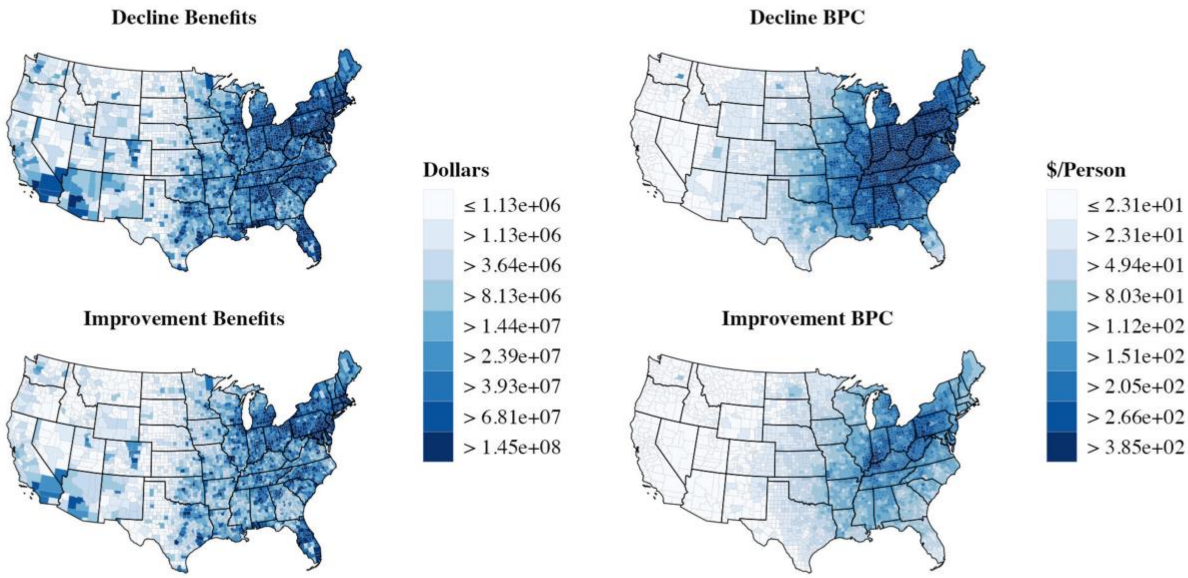
Figure B2. Changes in U.S. Coal Air Pollution Damages Decomposed by Decline and Improvement.

Table B3. Central estimate of benefits from avoided U.S. coal emissions.

Source/Receptor of Benefits	Effect (vs. 2014)	Benefits (Billion $) 2015	2016	2017	2018	2019	Five-Year Total
SO_2	**Total**	**41.3**	**77.3**	**88.8**	**93.1**	**107**	**408**
	Decline	29	49.3	56.5	62.3	75.9	273
	Improvement	12.3	28	32.3	30.7	31.3	135
NO_x	**Total**	**3.45**	**4.88**	**6.38**	**7.24**	**8.9**	**30.8**
	Decline	2.52	3.55	4.07	4.68	6.39	21.2
	Improvement	0.933	1.33	2.31	2.56	2.51	9.63
Primary $PM_{2.5}$	**Total**	**1.38**	**2.7**	**3.22**	**3.69**	**4.62**	**15.6**
	Decline	1.16	1.94	2.38	2.79	3.7	12
	Improvement	0.223	0.757	0.848	0.9	0.922	3.65
Criteria Air Pollutant Total	**Total**	**46.1**	**84.9**	**98.4**	**104**	**121**	**454**
	Decline	32.7	54.8	63.0	69.8	86.0	306
	Improvement	13.5	30.1	35.5	34.2	34.7	148
CO_2: Domestic	**Total**	**1.01**	**1.61**	**1.84**	**2.22**	**3.28**	**9.96**
	Decline	1.00	1.59	1.82	2.18	3.25	9.85
	Improvement	0.0106	0.0229	0.0212	0.0342	0.0269	0.116
CO_2: International	**Total**	**8.19**	**13.0**	**14.9**	**17.9**	**26.5**	**80.6**
	Decline	8.11	12.9	14.7	17.7	26.3	79.7
	Improvement	0.0857	0.186	0.172	0.277	0.218	0.937
Greenhouse Gas Total	**Total**	**9.21**	**14.7**	**16.7**	**20.2**	**29.8**	**90.6**
	Decline	9.11	14.4	16.6	19.8	29.6	89.5
	Improvement	0.0963	0.208	0.193	0.311	0.245	1.05
Domestic Total	**Total**	**47.1**	**86.5**	**100**	**106**	**124**	**464**
	Decline	33.7	56.4	64.8	72.0	89.2	316
	Improvement	13.5	30.1	35.5	34.2	34.8	148
Emissions Total	**Total**	**55.3**	**99.5**	**115**	**124**	**151**	**545**
	Decline	41.8	69.2	79.5	89.6	116	396
	Improvement	13.5	30.3	35.6	34.5	35	149

Notes: Benefits are in 2020 U.S. dollars. Criteria air pollutant total includes SO_2, NO_x, and primary $PM_{2.5}$. Greenhouse gas total includes both domestic and international CO_2 damages. Domestic total includes criteria air pollutant and domestically incurred CO_2 damage. Decomposition considers 2014 as the counterfactual for each year and includes the decline (fewer emissions from less output) and improvement (fewer emissions from lower emission rates) effects. Reported benefits do not consider offsets from natural gas substitution.

Pivoting to year-over-year benefits (the bottom panels of the plots in Figure B2), we see that the most substantial decline and improvement benefits occurred early in the timeline (i.e., 2014 to 2015 and 2015 to 2016). This aligns with when several effective environmental policies emerged and SO_2 control technology installations surged [60], [68]. Notably, coal's improvement resulted in more benefits than coal's decline for both SO_2 and NO_x from 2016 to 2017, but overall, coal's decline drove more year-over-year benefits most of the time. This allows us to see that it is not just simply coal's accumulating production decreases (compounding each year vs. 2014) that leads to the decline effect's dominance.



Sources: Population data for benefits per capita calculations are from the CDC [34]. Mapping uses the *usmap* R package [25].
Notes: Benefits are five-year cumulative totals (2015 to 2019 vs. 2014) in 2020 U.S. dollars. Left maps shows benefits. Right maps shows benefits per capita (labeled BPC). Benefits are from criteria air pollutants only (i.e., SO_2, NO_x, and primary $PM_{2.5}$). Color scales divide county-effect benefits and benefits per capita into equally sized groups. Decomposition considers 2014 as the counterfactual for each year and includes the decline (fewer emissions from less output) and improvement (fewer emissions from lower emission rates) effects. In contrast to Figure 1 of the manuscript, benefits do not consider offsets from natural gas substitution, which are relatively minimal (see Table B7).

Figure B3. Five-Year Benefits and Benefits Per Capita from Avoided Coal Emissions in the U.S. by County.

Figure B3 looks at the spatial distribution of five-year benefits and benefits per capita from 2015 to 2019 vs. a 2014 counterfactual.[20] Population data are from the CDC [34]. Benefits evaluated spatially are only those from criteria air pollution (i.e., SO_2, NO_x, and primary $PM_{2.5}$). It is possible to distribute climate impact damages to the county level—e.g., Hsiang et al. (2017) [69]. However, we refrain from doing so herein because (1) criteria air pollution drives most damages incurred within the U.S. and (2) climate damages have a substantially delayed effect. Benefits were greatest where the majority of coal's damages have been incurred, historically—e.g., [27], [70], [71].

The most significant absolute gains from coal's decline were in highly populated urban centers in the Midwest and Ohio Valley. As shown in Table B4, the counties home to Chicago (Cook), Detroit (Wayne), Pittsburgh (Allegheny), and Cleveland (Cuyahoga) saw gains exceeding $3 billion. Next in line was Philadelphia County (Philadelphia), with just less than $2.5 billion in five-year benefits. Not shown are counties home to Brooklyn, Columbus, Queens, and Indianapolis, which all saw benefits of $2 billion or more. These counties all have millions of residents. (Note: Table B4, unlike Figure B3, accounts for offsets from natural gas substitution—see Table B7 and the associated discussion.)[21]

Table B4 also shows the top five counties for maximum benefits per capita from coal's decline. Here, we see a shift from highly populated cities towards less populated counties in

[20] Damages and damages per capita follow similar geographic patterns.
[21] Herein, the term "offsets" is used to concisely refer to damages from additional natural gas that takeaway from benefits driven by coal's decline, not to be confused with "carbon offsets" (i.e., reductions in GHGs to compensate for GHGs occurring elsewhere).

Mississippi, West Virginia, and Indiana, all with more than $1,000 in five-year benefits per capita. A Virginia county (Portsmouth) also exceeds this amount. Without in-depth analysis, we can hypothesize a few facts about these counties. First, we can safely assume they have (or had) exceptionally high levels of criteria air pollution from coal and saw substantial air quality gains over the timeframe assessed herein. Specifically, we could guess that a few large facilities nearby retired or substantially cut operations. This, however, may be only part of the story. These counties could have populations with higher baseline mortality rates, an input to the DR function (see Equation A6), resulting in greater premature mortality risk (and risk reductions) from additional (or decreased) pollution.

Table B4. Counties with the most benefits and benefits per capita from coal's decline in the U.S.

Measure	County	State	Benefits (Billion $)	Population (Thousand)	Benefits Per Capita ($/Person)
Highest Benefits	Cook	IL	4.58	5,200	176
	Wayne	MI	3.77	1,760	429
	Allegheny	PA	3.27	1,220	535
	Cuyahoga	OH	3.13	1,250	501
	Philadelphia	PA	2.47	1,580	312
Highest Benefits Per Capita	Stone	MS	0.142	18.3	1,560
	Harrison	MS	1.47	205	1,440
	Lincoln	WV	0.113	20.9	1,080
	Clay	WV	0.0471	8.71	1,080
	Morgan	IN	0.376	69.9	1,070

Sources: Population data for benefits per capita calculations are from the CDC [34].
Notes: Benefits are five-year cumulative totals (2015 to 2019 vs. 2014) in 2020 U.S. dollars. Benefits are from criteria air pollutants only (i.e., SO_2, NO_x, and primary $PM_{2.5}$). Data are reported to three significant figures. Reported benefits do consider offsets from natural gas substitution (see Table B7).

The largest absolute gains from coal's improvement aligned mainly with those from its decline (e.g., Chicago, Detroit, Pittsburgh, and Cleveland). Interestingly, Indiana has 10 of the top 20 counties for benefits per capita from the improvement effect. We could guess that one or more big coal EGUs nearby took substantial measures to reduce their emission rates (e.g., installed SO_2 scrubber technology). Benefits and those per capita were all lowest in the West. Again, referring to the literature [27], [70], [71], this is explained by the fact that these areas have been far away from the air quality repercussions of combusting coal to source electricity.

Uncertainty with Benefits

Table B5 reports the lower estimate for benefits of avoided damages from coal emissions vs. a 2014 counterfactual. See Table A6 for variable changes resulting in these estimates. Using the VSL from Mrozek & Taylor (2002) [42] lowers the benefits from the criteria air pollutants by about 62% from the central estimate. For domestic climate damages, we see a 100% decrease (i.e., to $0), as the U.S. incurs (very nearly) 0% of the global SCC for this lower estimate [53]. Instead, the lower bound scenario results in all climate damages occurring internationally. However, discounting at a 5% SDR for the SCC [52] lowers the international benefits by 67% and global benefits from CO_2 by 71%. Overall, we conclude that, on the lower end, climate damages (and the resulting benefits) are more sensitive to the evaluated uncertain input variables than health damages (and the resulting benefits), but both are more than halved from the central estimate.

Table B5. Lower estimate of benefits from avoided U.S. coal emissions.

Source/Receptor of Benefits	Effect (vs. 2014)	Lower Estimate of Benefits (Billion $)					
		2015	**2016**	**2017**	**2018**	**2019**	**Five-Year Total**
SO_2	**Total**	**15.6**	**29.2**	**33.5**	**35.1**	**40.5**	**154**
	Decline	10.9	18.6	21.3	23.5	28.6	103
	Improvement	4.63	10.6	12.2	11.6	11.8	50.8
NO_x	**Total**	**1.30**	**1.84**	**2.41**	**2.73**	**3.36**	**11.6**
	Decline	0.949	1.34	1.54	1.77	2.41	8.00
	Improvement	0.352	0.502	0.870	0.965	0.946	3.64
Primary $PM_{2.5}$	**Total**	**0.520**	**1.02**	**1.22**	**1.39**	**1.74**	**5.89**
	Decline	0.436	0.733	0.897	1.05	1.40	4.52
	Improvement	0.0842	0.286	0.320	0.339	0.348	1.38
CO_2: Domestic	**Total**	**0**	**0**	**0**	**0**	**0**	**0**
	Decline	0	0	0	0	0	0
	Improvement	0	0	0	0	0	0
CO_2: International / Greenhouse Gas Total	**Total**	**2.81**	**4.24**	**4.72**	**6.05**	**8.73**	**26.6**
	Decline	2.78	4.18	4.67	5.95	8.66	26.2
	Improvement	0.0294	0.0604	0.0544	0.0933	0.0716	0.309
Criteria Air Pollutant / Domestic Total	**Total**	**17.4**	**32.1**	**37.1**	**39.2**	**45.6**	**172**
	Decline	12.3	20.7	23.7	26.3	32.4	116
	Improvement	5.07	11.4	13.4	12.9	13.1	55.8
Emissions Total	**Total**	**20.2**	**36.3**	**41.8**	**45.3**	**54.3**	**198**
	Decline	15.1	24.9	28.4	32.3	41.1	142
	Improvement	5.10	11.4	13.4	13.0	13.2	56.1

Notes: Benefits are in 2020 U.S. dollars. Criteria air pollutant total includes SO_2, NO_x, and primary $PM_{2.5}$. Greenhouse gas damages all occur internationally, and the domestic total is just from the criteria air pollutants. Decomposition considers 2014 as the counterfactual for each year and includes the decline (fewer emissions from less output) and improvement (fewer emissions from lower emission rates) effects. See Table A6 for variable changes resulting in the lower estimates. Reported benefits do not consider offsets from natural gas substitution.

Table B6 reports the upper estimate for benefits of avoided damages from coal emissions vs. a 2014 counterfactual. See Table A6 for variable changes resulting in these estimates. Using the DR function from Lepeule et al. (2012) [32] increases the benefits from the criteria air pollutants by about 110% from the central estimate. We see a nearly 300% increase in domestic climate damages as the U.S. incurs a greater percentage of the global SCC [53], representing catastrophic climate outcomes via the 95th percentile SCC estimate [52]. The upper bound scenario results in a lower share of climate damages from U.S. coal occurring internationally, but the greater SCC still increases benefits by approximately 180% from the central estimate. Again, we conclude that climate damages (and the resulting benefits) are more sensitive to the evaluated uncertain input variables than health damages (and the resulting benefits), but on the upper end, both are more than doubled vs. the central estimate.

Table B6. Upper estimate of benefits from avoided U.S. coal emissions.

Source/Receptor of Benefits	Effect (vs. 2014)	Upper Estimate of Benefits (Billion $) 2015	2016	2017	2018	2019	Five-Year Total
SO_2	**Total**	**86.3**	**163**	**188**	**197**	**226**	**860**
	Decline	61.6	104	119	132	160	576
	Improvement	25.7	59.2	68.2	65.0	66.2	284
NO_x	**Total**	**7.20**	**10.3**	**13.5**	**15.3**	**18.8**	**65.1**
	Decline	5.25	7.49	8.60	9.89	13.5	44.7
	Improvement	1.95	2.81	4.87	5.41	5.30	20.3
Primary $PM_{2.5}$	**Total**	**2.88**	**5.69**	**6.80**	**7.79**	**9.75**	**32.9**
	Decline	2.41	4.10	5.02	5.89	7.81	25.2
	Improvement	0.467	1.59	1.79	1.89	1.94	7.68
Criteria Air Pollutant Total	**Total**	**96.4**	**179**	**208**	**220**	**255**	**958**
	Decline	69.3	116	133	148	181	646
	Improvement	28.1	63.6	74.9	72.3	73.4	312
CO_2: Domestic	**Total**	**4.03**	**6.25**	**7.21**	**8.77**	**13.1**	**39.4**
	Decline	3.99	6.16	7.13	8.63	13.0	38.9
	Improvement	0.0421	0.0889	0.0831	0.135	0.107	0.457
CO_2: International	**Total**	**22.8**	**35.4**	**40.9**	**49.7**	**74.2**	**223**
	Decline	22.6	34.9	40.4	48.9	73.6	220
	Improvement	0.239	0.504	0.471	0.767	0.608	2.59
Greenhouse Gas Total	**Total**	**26.8**	**41.7**	**48.1**	**58.5**	**87.3**	**262**
	Decline	26.6	41.1	47.5	57.5	86.6	259
	Improvement	0.281	0.593	0.554	0.902	0.715	3.05
Domestic Total	**Total**	**100**	**185**	**216**	**229**	**268**	**997**
	Decline	73.3	122	140	156	194	685
	Improvement	28.2	63.7	74.9	72.4	73.5	312
Emissions Total	**Total**	**123**	**221**	**256**	**278**	**342**	**1220**
	Decline	94.8	157	180	205	268	905
	Improvement	28.4	64.1	75.4	73.2	74.1	315

Notes: Benefits are in 2020 U.S. dollars. Criteria air pollutant total includes SO_2, NO_x, and primary $PM_{2.5}$. Greenhouse gas total includes both domestic and international CO_2 damages. Domestic total includes criteria air pollutant and domestically incurred CO_2 damage. Decomposition considers 2014 as the counterfactual for each year and includes the decline (fewer emissions from less output) and improvement (fewer emissions from lower emission rates) effects. See Table A6 for variable changes resulting in the upper estimates. Reported benefits do not consider offsets from natural gas substitution.

Retrospective Damages from Natural Gas Substitution

If we assume that emissions-free renewables replaced coal, our benefit calculations reported in Table B3, Table B5, and Table B6 hold. However, natural gas, which accounted for both the greatest share as well as an increasing share (33% to 41%) of U.S. electricity generation from 2015 to 2020 [72], is most likely to have replaced coal in any location, although that may not be the case everywhere (e.g., renewables could have been more likely if natural resources and/or local policy landscapes were favorable for wind or solar).

For this research, we assume that natural gas replaced coal. This assumption accounts for the potential for additional emissions from natural gas offset avoided damages from coal's decline, attenuating benefits. Given the findings herein (i.e., that the evaluated benefits far exceed the evaluated costs), this is an analytically conservative approach.

Table B7. Additional damages from retrospective natural gas substitution.

Natural Gas EGU Variable		2015	2016	2017	2018	2019	Five-Year Total
Lost Heat Input (MMbtu)		2.17E+09	3.28E+09	3.68E+09	4.30E+09	6.25E+09	1.97E+10
Natural Gas Emission Rates (lb/MMbtu)	SO_2	0.00194	0.00206	0.00197	0.00206	0.00143	0.00189[A]
	NO_x	0.0313	0.0324	0.0304	0.0316	0.0308	0.0313
	Primary $PM_{2.5}$	0.00270	0.00278	0.00274	0.00279	0.00267	0.00274
	CO_2	120	120	121	119	119	120
Central Estimate Damages (Billion $)	SO_2	0.0903	0.147	0.169	0.208	0.213	0.828
	NO_x	0.379	0.516	0.569	0.722	1.03	3.22
	Primary $PM_{2.5}$	0.172	0.277	0.321	0.390	0.545	1.71
	CO_2: Domestic	0.581	0.927	1.08	1.27	1.89	5.75
	CO_2: International	4.70	7.50	8.72	10.28	15.3	46.5
	Air Pollution	**0.641**	**0.941**	**1.06**	**1.32**	**1.79**	**5.75**
	Domestic	**1.22**	**1.87**	**2.14**	**2.59**	**3.68**	**11.5**
	Total	**5.92**	**9.37**	**10.9**	**12.9**	**19.0**	**58.0**
Lower Estimate Damages (Billion $)	SO_2	0.0341	0.0555	0.0639	0.0784	0.0805	0.312
	NO_x	0.143	0.195	0.215	0.272	0.389	1.21
	Primary $PM_{2.5}$	0.0649	0.105	0.121	0.147	0.206	0.644
	CO_2: Domestic	0	0	0	0	0	0
	CO_2: International	1.61	2.44	2.76	3.46	5.04	15.3
	Air Pollution	**0.242**	**0.355**	**0.400**	**0.498**	**0.675**	**2.17**
	Domestic	**0.242**	**0.355**	**0.400**	**0.498**	**0.675**	**2.17**
	Total	**1.86**	**2.80**	**3.16**	**3.96**	**5.71**	**17.5**
Upper Estimate Damages (Billion $)	SO_2	0.189	0.311	0.358	0.439	0.451	1.75
	NO_x	0.791	1.09	1.20	1.52	2.17	6.78
	Primary $PM_{2.5}$	0.360	0.586	0.678	0.824	1.152	3.60
	CO_2: Domestic	2.31	3.59	4.22	5.02	7.56	22.7
	CO_2: International	13.1	20.4	23.9	28.5	42.8	129
	Air Pollution	**1.34**	**1.99**	**2.24**	**2.79**	**3.78**	**12.1**
	Domestic	**4.53**	**6.88**	**7.92**	**9.63**	**13.8**	**42.8**
	Total	**17.6**	**27.2**	**31.8**	**38.1**	**56.6**	**171**

Sources: SO_2, NO_x, and CO_2 emission rates are derived using emissions and heat input data from the EPA [58].
Notes: A = five-year average (rather than five-year total). Damages are in 2020 U.S. dollars. Assumes natural gas makes up for all lost heat input from EGUs with a primary fuel source of coal. Calculations consider the fleetwide emission rates from EGUs with a primary fuel source of gas. Primary $PM_{2.5}$ emission rates are derived using the gas-to-coal emission rate ratios for NO_x. Computed emissions are from combustion only. MDs for estimating damages from emissions are EGU specific. Because natural gas has a higher thermal efficiency than coal [73], MMBtu needing replaced (in the case of electricity production) is overestimated. Uncertainty bounds use the variable substitutions from Table A6.

The computations for natural gas offsets (here and henceforth meaning additional natural gas damages that takeaway from coal benefits) are summarized in Table B7, which begins by showing the lost heat input from coal needing to be made up for every year. We subtract heat input each year from a 2014 counterfactual, to stay parallel to benefits from avoided damages (these data can be replicated using heat input from Table B1—i.e., 2014 data minus year-specific data). These calculations are conducted at the EGU level so that MMBtu needing to be replaced is location-specific.

Then, we pull fleetwide natural gas emission rates each year from CAMPD [58]. For these emission rates, we consider all EGUs reported by CAMPD with a primary fuel source of gas, including liquified petroleum gas, natural gas, other gas, pipeline natural gas, and process gas. We drop any EGU with a primary fuel source including both gas and coal. As previously discussed, $PM_{2.5}$ data are not reported by CAMPD. Using data in Table B1, we simply assume that the gas-to-coal emission rate ratio is the same for NO_x and $PM_{2.5}$ each year (19% to 23% over the years). This is a conservative assumption, as the ratio for SO_2 is much lower (about 1%). Notably, the ratio for CO_2 is higher (57% to 59%), but we stick with the criteria air pollutants for this interpolation procedure. Multiplying lost heat input (location-specific) by emission rates (fleet average) gives us spatially distributed emission in short tons from an all-gas substitution.

The last step is to use coal EGU-specific MDs for emissions coming from natural gas-replaced MMBtu. There are three caveats to note:

- We assume that new natural gas emissions were released from the same coordinates from which the coal EGU emissions are modeled. For tall stack facilities, this is the exact location of the plant. For lower stack facilities, this is the population-weighted centroid of the county where the plant resides. MDs would be slightly incorrect if heat input were being replaced from a natural gas facility in a different location (either different coordinates or a different county). However, we contend that the replacement natural gas generation likely (1) would be relatively close by and (2) would have similar MDs due to local/regional meteorological conditions and population profiles.
- Related to the first point, we assume the height of pollution discharge is the same for the coal EGU and the replacement natural gas EGU. Again, this may not be the exact case, but it is a reasonable assumption—natural gas emissions, like those from coal, are typically released from tall smokestacks. The pollutants would then be subject to similar atmospheric conditions and have a similar fate.
- Natural gas power plants have a higher thermal efficiency than coal-fired power plants [73]. According to the National Academy of Sciences, a typical coal-fired power plant has a thermal efficiency of about 33%. Contrarily, a typical gas-fired power plant has a thermal efficiency of about 42%. Moreover, a typical combined-cycle natural gas power plant has a thermal efficiency of approximately 60%. Simply put, heat input from natural gas typically generates more power than heat input from coal. As such, MMBtu needing to be replaced due to coal's decline (at least in the case of electricity production) is less than a 1:1 ratio. Hence, we overestimate natural gas substitution emissions and associated benefit offsets.

Methane Leakage Offsets

A more complicated issue to address is upstream methane leakage from natural gas. Depending on leakage rates, these emissions can greatly offset the GHG-related benefits of using natural gas in place of coal to generate electricity. As shown in Table B1 and Table B7, gas emits about one-half the CO_2 emissions per MMbtu as coal [58]. These data, however, only account for emissions released during combustion.

Both coal and natural gas release methane during earlier stages of their life cycles. For coal, this happens during the mining stage [74]. For natural gas, methane leakage occurs throughout various stages of the supply chain (e.g., drilling, processing, distribution) [75]. A recent study by Gordon et al. (2023) found that by incorporating these processes when comparing coal vs. natural gas life cycle GHG intensities, natural gas can be on par with coal under certain scenarios [76]. Specifically, the study found that a leakage rate of 4.7% results in the same GHG emissions (i.e., CO_2-equivalent) for natural gas and coal considering a 20-year timeframe.[22] This finding is similar to other research in the field [79]–[81].

Methane leakage rates are highly uncertain. That said, life cycle GHG estimates provided by the National Renewable Energy Laboratory (NREL) suggest that natural gas is still better than coal [82]. For this paper, however, we consider the "worst-case scenario" where natural gas is as bad as coal for life cycle GHG intensities when incorporating upstream methane leakage (note: "worst-case scenario" is in quotes because there is a feasible scenario where natural gas is worse than coal for GHG emissions). In this "worst-case scenario," CO_2 benefits are completely offset, leaving just those from local air pollution that are not offset by added natural gas local air pollution. Consulting Table B3 and Table B7, this offsets $37.3 in global GHG benefits ($4.10 in domestic GHG benefits) accrued when only considering combustion.

This results in our base case benefits of $300 billion (central estimate). The lower and upper estimates in the base case are $113 billion and $634 billion, respectively, in this base case.

LABOR MARKET MODELING

Utility and Mining Sector Panel Datasets

Utility Sector and Mining Sector Jobs

We construct two datasets for our labor market regression modeling: a utility sector dataset and a mining sector dataset. The first represents the coal industry's power sector, and the other represents the coal industry's mining sector. Our dependent variable is jobs by CONUS county and by year from 2014 to 2019. We use the BLS's Quarterly Census of Employment and Wages (QCEW) datasets, which provide county-level job estimates by North American Industry Classification System (NAICS) code [83].

NAICS codes cover general sectors (e.g., 22 Utilities) and more specific economic activities (e.g., 221112 Fossil Fuel Electric Power Generation). The benefit of using a more detailed NAICS code is that it can limit omitted variable bias concerns. However, more counties disclose employment information for more general NAICS codes—i.e., there is more (and more complete) data. This paper uses more general NAICS classifications but controls for factors that may otherwise lead to omitted variable bias. We choose the following NAICS codes for each dataset:

- NAICS 22: Utilities
    - Dataset includes 8,064 observations across 1,671 counties (1,464 observations across 290 counties with coal activity).

[22] Because methane has a shorter lifetime than CO_2 [77], [78], this increases to 9% for a 100-year timeframe [76].

    - Includes 2211 Electric Power Generation, Transmission, and Distribution, 2212 Natural Gas Distribution, and 2213 Water, Sewage, and Other Systems employment.
- NAICS 21: Mining, Quarrying, and Oil and Gas Extraction
    - Dataset includes 7,025 observations across 1,453 counties (765 observations across 148 counties with coal activity).
    - Includes 2111 Oil and Gas Extraction, 2121 Coal Mining, 2122 Metal Ore Mining, 2123 Nonmetallic Mineral Mining and Quarrying, and 2131 Support Activities for Mining employment.

Any county-year that does not disclose employment data for the private sector is excluded from the datasets. We do not exclude counties that do not disclose employment data for the public sector. While roughly one-third of establishments in 22 Utilities are part of the local, state, or federal government, the private sector accounts for nearly 90% of establishments in 221112 Fossil Fuel Electric Power Generation. Moreover, over 99% of 21 Mining, Quarrying, and Oil and Gas Extraction establishments are private. Therefore, we can assume that most jobs we are attempting to assess (i.e., those directly impacted by declining coal industry activity and plants and mines) are within the private sector.

We filter our datasets to include only coal counties, defined as having at least one year of data signifying coal activity—represented by our coal variables, which will be discussed shortly. Therefore, our final utility sector dataset includes 1,464 observations across 290 counties, and our final mining sector dataset includes 765 observations across 148 counties with coal activity.

Coal Variables

Our utility and mining sector employment models each assess the effects of two coal variables on the number of jobs in counties from 2014 to 2019. Those for the utility sector are as follows:

- Coal capacity (GW)
    - Source: U.S. Energy Information Administration's (EIA's) Form EIA-860 for 2014 through 2019 [68].
    - Description: Nameplate capacity of operating generators, as well as those that retired during the year for which the data are collected, with a primary fuel source of bituminous coal (BIT), sub-bituminous coal (SUB), lignite coal (LIG), waste coal (WC), coal-derived synthetic gas (SGC), refined coal (RC), coal-based synfuel (SC), coke oven gas (COG), and anthracite coal (ANT).
- Coal generation (TWh)
    - Source: Form EIA-923 for 2014 through 2019 [84].
    - Description: Electricity sourced from BIT, SUB, LIG, WC, SGC, RC, SC, COG, and ANT.

Any county-year that does not have a power plant with at least one generator with coal as a primary fuel source is given a zero for the coal capacity variable. Any county-year that does not have a power plant producing electricity with coal is given a zero for the coal generation variable. The two coal-related variables for the mining sector are as follows:

- Mining contracts (#)

- Source: Form EIA-923 for 2014 through 2019 [84].
  - Description: Unique annual transactions between coal mines/suppliers and domestic power plants designated as being under contract aggregated to the county in which the supplying mine is located. Mining contracts not attributed to a specific contiguous county in the U.S. are excluded.
- Coal sales (million short tons)
  - Source: Form EIA-923 for 2014 through 2019 [84].
  - Description: Coal quantity sold to domestic power plants aggregated to the county in which the supplying mine is located for each year. Coal sales not attributed to a specific contiguous state are excluded. Coal sales attributed to a state but not to a specific county are partitioned to the state's counties based on the percentage of known coal quantity sold each county within the state accounted for.

Any county-year without coal sales designated as being under contract is given a zero for mining contracts, and any county-year without coal transactions reported is given a zero for coal sales.

Control Variables

We control for other factors likely affecting utility and mining sector employment—and potentially associated with our variables of interest, to isolate the effects of our coal variables and avoid omitted variable bias. For the utility sector, we add:

- Power variables for natural gas, nuclear, renewables, and other fuel sources
  - Source: Capacity (GW) [68] and generation (TWh) [84] for 2014 through 2019.
  - Description: Variables are analogous to those for coal. The different categories include the following fuel types:
    - Natural Gas: Natural gas
    - Nuclear: Nuclear
    - Renewables: Solar, wind, hydro, geothermal, and biomass
    - Other fuel: Anything not covered by the first four fuel categories
- Fuel prices ($/MMBtu)
  - Source: Form EIA-923 for 2014 through 2019 [84].
  - Description: Price of coal and natural gas for power plants by county, weighted by fuel quantity. Includes purchase and delivery costs incurred by the plant buying the fuel. Where county data are not available, we use state quantity-weighted averages. If state data are unavailable, we use the quantity-weighted averages across the U.S. Nominal values are adjusted to 2020 USD [43].
- Other utility sector establishments (#)
  - Source: QCEW for 2014 through 2019 [83].
  - Description: Number of business establishments in 2212 Natural Gas Distribution and 2213 Water, Sewage, and Other Systems.

Any county-year that does not have a power plant with at least one generator primarily power by a fuel is given a zero for that fuel category's capacity variable. Any county-year that does not have a power plant producing electricity with a fuel category is given a zero for that fuel category's generation variable. Any county-year without reported business establishments for other economic activity under 22 Utilities is given a zero. For the mining sector, we add:

- Percentage of coal mined underground (%)
    - Source: Form EIA-923 for 2014 through 2019 [84].
    - Description: Mine type by county, weighted by coal quantity. Where county data are not available, we use state quantity-weighted averages. If state data are unavailable, we use the quantity-weighted average across the U.S.
- Coal prices ($/MMBtu)
    - Source: Form EIA-923 for 2014 through 2019 [84].
    - Description: Price of coal from mines by county, weighted by coal quantity. Includes purchase and delivery costs incurred by the plant buying the fuel. Where county data are not available, we use state quantity-weighted averages. If state data are unavailable, we use the quantity-weighted average across the U.S. Nominal values are adjusted to 2020 USD [43].
- Other mining sector establishments (#)
    - Source: QCEW for 2014 through 2019 [83].
    - Description: Number of business establishments in 2111 Oil and Gas Extraction, 2121 Coal Mining, 2122 Metal Ore Mining, 2123 Nonmetallic Mineral Mining and Quarrying, and 2131 Support Activities for Mining.
- Coal mining region[23]
    - Source: EIA [85].
    - Description: Appalachian, Interior, or Western coal region designation by state. Kentucky is part of both the Appalachian and Interior coal regions. We assign Kentucky to the Appalachian coal region, considering its land area within each coal region.

Any county-year without reported business establishments for other economic activity under 21 Mining, Quarrying, and Oil and Gas Extraction is given a zero. For both sectors, we add:

- Population (thousand people)
    - Source: CDC WONDER [34].
- Population density (million people per square mile)
    - Source: CDC WONDER [34] and U.S. Census Bureau [86].
    - Description: Population divided by county land area.
- GDP (million $)
    - Source: U.S. Bureau of Economic Analysis (BEA) [87].
    - Description: Chained 2012 USD are adjusted to 2020 USD [43].
- Percentage of GDP in respective sector (%)
    - Source: U.S. BEA [87].
    - Description: 22 Utilities and 21 Mining, Quarrying, and Oil and Gas Extraction GDP, adjusted for inflation [43], as a percentage of total GDP.

[23] This control variable is not relevant when using a fixed effects modeling framework, which conducts the within transformation. It is only relevant for the explored alternative models that are not used for the main paper.

Two-Way Fixed Effects Modeling

The Problem with Pooled Ordinary Least Squares

This section discusses our reasoning for using a two-way fixed effects model (FEM) specification for this study. We begin by emphasizing that this paper aims to identify the relationships between our chosen coal variables and employment in the utility and mining sectors (i.e., their magnitudes and whether they are significant).

We first introduce pooled ordinary least squares (OLS) modeling, which is the most standard form of regression and uses the following functional form:

Equation B3. Regression Modeling: Standard Form.

$$y_i = \beta X_i + \varepsilon_i$$

In Equation B3, y_i are observations of the dependent variable, in our case, sectoral jobs differentiated by county and year. X_i represents a vector of regressors (e.g., coal variables) for each observation. β is a vector of model coefficients optimized to minimize the sum of the squared residuals—i.e., observed vs. predicted jobs—and representing the associations between jobs and the regressors. ε_i is the error term.

It is essential, however, to acknowledge the structure of our data. Our datasets contain observations from the same groups (i.e., counties and years). We want to capture the associations between job changes and changes in our regressors. However, we may be confounding our coefficient estimates if we do not account for this structure, which we do not do with a pooled OLS model. Are job changes from one observation to the next due to changes in our regressors or because they belong to different counties and/or years with distinct characteristics (i.e., due to variability between groups)?

Importantly, ε_i from Equation B4 is a composite error term [88], which includes the sum of unobserved effects and idiosyncratic errors:

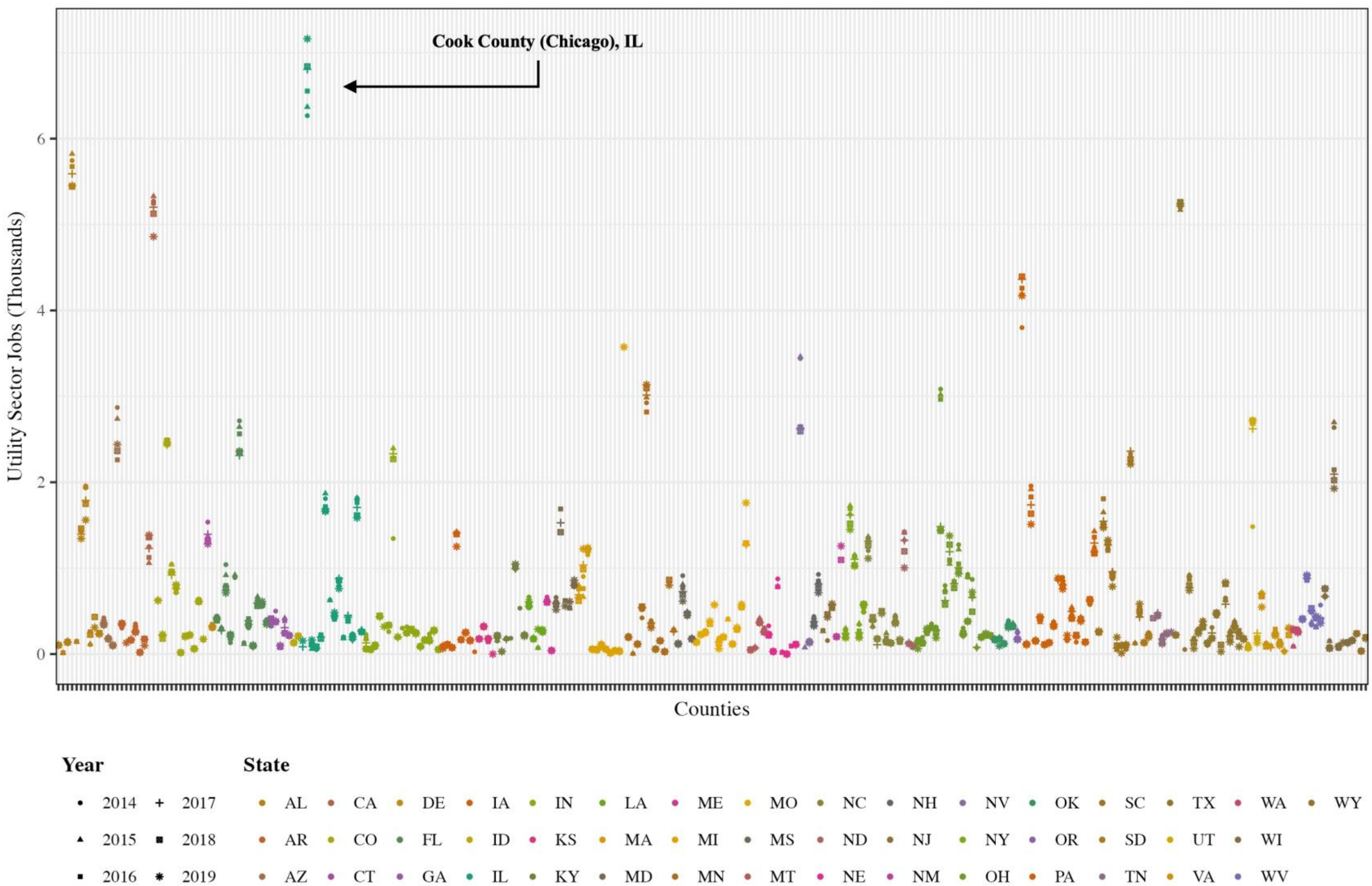
Equation B4. Regression Modeling: Composite Error Term.

$$\varepsilon_i = \mu_c + \lambda_t + \varepsilon_{ct}$$

In Equation B4, μ_c is the county error component, and λ_t is the year error component. These two components represent errors driven by unobserved time-invariant heterogeneity between counties and unobserved county-invariant heterogeneity between years, respectively [88]. These factors may result in omitted variable bias, as county-specific or year-specific characteristics affecting employment may be falsely attributed to the independent variables included in the model.

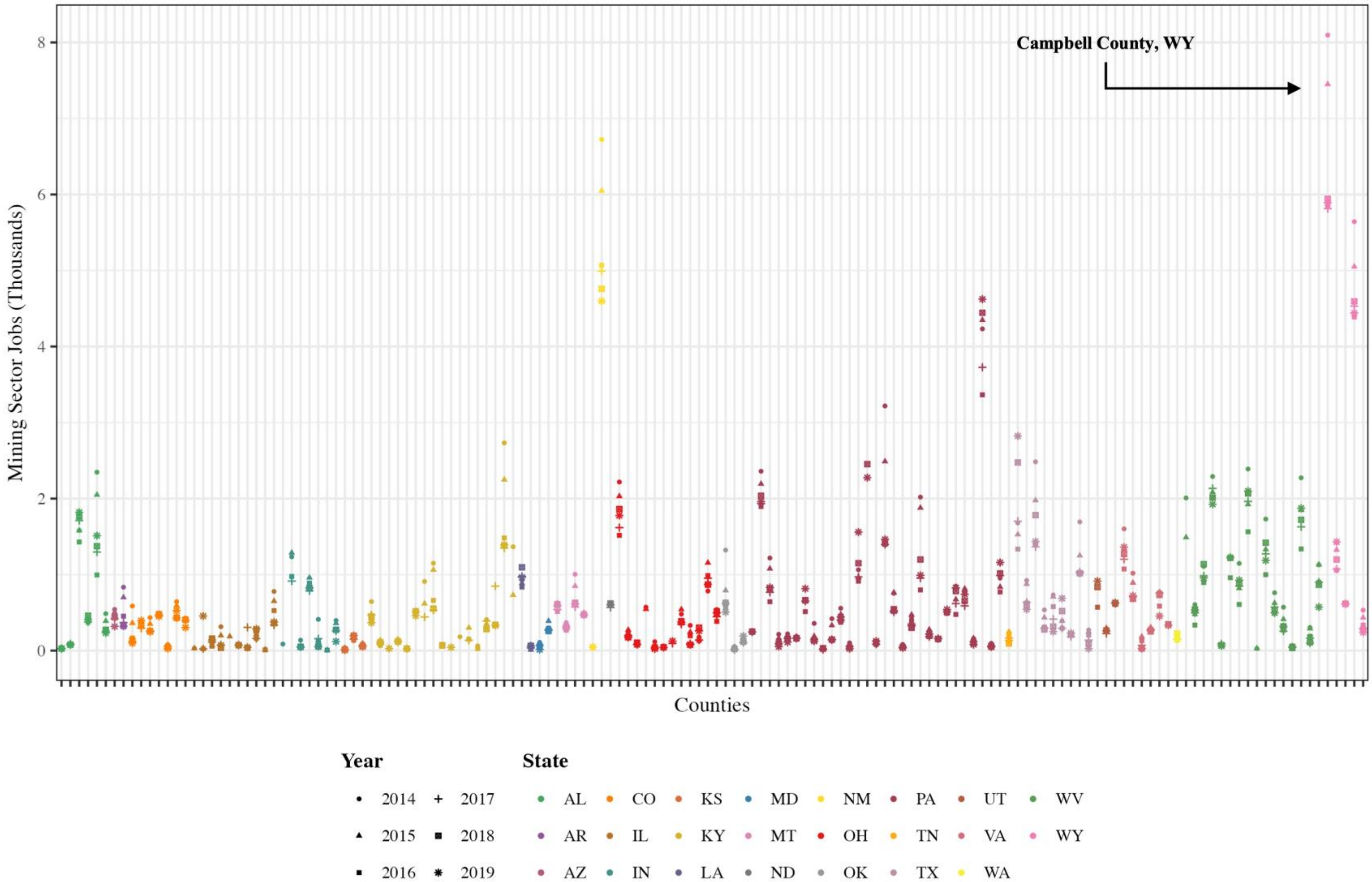
County and Year Data Structure

We evaluate the data structure (by county and year) for utility and mining sector employment in Figure B4 and Figure B5, respectively. Due to the large number of counties in our datasets, we exclude county identification in the visuals; however, we identify the state within which each county resides. We specifically identify only the counties with the greatest number of jobs for each sector—Cook County, IL, for the utility sector and Campbell County, WY, for the mining sector, which are discussed below.



Sources: Utility sector employment data are from the BLS [83].
Notes: Employment is on the y-axis. Counties are on the x-axis. Years are represented by shape. States are represented by color.

Figure B4. Utility Sector Employment in the U.S. by County and Year.



Sources: Mining sector employment data are from the BLS [83].
Notes: Employment is on the y-axis. Counties are on the x-axis. Years are represented by shape. States are represented by color.

Figure B5: Mining Sector Employment in the U.S. by County and Year.

The figures show evident heterogeneity in the number of jobs by county. We see some heterogeneity in the number of jobs by year, particularly in the mining sector, but the variability is considerably less pronounced than that across counties. This makes sense, as we expect counties with specific characteristics to have more of these jobs than others:

- Example 1: Cook County, IL, is home to the city of Chicago and has more than double the number of people than the next most populous county included in our utility sector dataset (Clark County, NV [Las Vegas]).[24] This helps to explain why Cook County has so many utility sector jobs. However, population size is not the only driver of utility sector jobs in Cook County. To demonstrate, if we normalize by population, Cook County's 1.28 jobs per thousand people falls below the dataset's first quartile of 1.40 jobs per thousand people.
- Example 2: Shifting the focus to mining sector jobs, Campbell County, WY, does not have a notably high population count compared to other counties in the dataset. Instead, we find that it has a vast mining industry. Its average number of mining contracts (344 per year) is more than five times greater than the next highest (Converse County, WY, with 65). Its average coal sales (285 million short tons per year) was nearly ten times greater than the next highest (again, Converse County, WY, with 28.8 million short tons).

National economic conditions over time are a good example of county-invariant heterogeneity between years. There may be more jobs in one year versus another because the economy is doing better overall.

Testing for Unobserved Effects

Heterogeneity between groups is not a problem if we control for it (i.e., "observe it" in the model). We can do our best with this, but controlling for every factor that drives group heterogeneity is difficult. Unobserved heterogeneity between groups is also not a problem if it is not associated with the regressors included in the model.

We can test for significant unobserved effects (i.e., for when they are a problem) in our pooled OLS models, presented in the "Alternative Models" subsection (Table B16). Like a similar study on natural gas labor markets [89], we assess the significance of county, year, and two-way (county and year) unobserved effects. We run the King/Wu and Breusch/Pagan tests for unbalanced panel data [90] using the *plm* R package [91]. We find that county unobserved effects are significant for both the utility and mining sector pooled OLS model specification ($p \leq 0.01$). We also find that year unobserved effects are not significant but that two-way unobserved effects are. Overall, the results demonstrate that we need to control for county unobserved effects, but it is likely best to control for any time unobserved effects as well because of the two-way unobserved effects testing.

Two-way Fixed Effects Modeling Specification

Panel data (i.e., cross-sectional time-series data) models can be specified to control for the unobserved effects from Equation B4. One way to do this is by introducing fixed effects into the model, resulting in a FEM [88].

Equation B5 represents our base case model for this study:

[24] We consider the 2014 to 2019 average population. Notably, county averages across years act as time-invariant heterogeneity and year averages across counties work as county-invariant heterogeneity (see Equation B6).

Equation B5. Regression Modeling: Two-Way Fixed Effects.

$$y_{ct} = \beta_1 x_{1,ct} + \beta_2 x_{2,ct} + Z_{ct}\theta + \alpha_c + \gamma_t + \varepsilon_{ct}$$

In Equation B5, y_{ct} is the utility or mining sector employment for each county (c) during each year (t). $x_{1,ct}$ and $x_{2,ct}$ represent our coal variables. Z_{ct} is a vector representing all our control variables. β_1 is the average job change with an additional unit of $x_{1,ct}$. β_2 is the average job change with an additional unit of $x_{2,ct}$. θ is a vector representing the β coefficients for the control variables. ε_{ct} is the error term.

α_c are county fixed effects, and γ_t are year fixed effects. Here, ε_{ct} is just the idiosyncratic error term. As written, Equation B5 represents a two-way fixed effects model that accounts for unobserved county and year characteristics. We can remove γ_t for a county fixed effects model (which we will look at in the "Alternative Models" subsection), or we can remove α_c for a year fixed effects model (which we will not explicitly look at because we know county effects matter).

These models, in effect, add dummy variables for each county and/or year that adjust the constant coefficient for each observation depending on which group(s) the observation belongs to. We can also perform the within transformation to estimate fixed effects models, which alters the modeled data as follows:

Equation B6. Regression Modeling: Within Transformation.

$$(y_{ct} - \bar{y}_c - \bar{y}_t + \bar{y}) = \beta_1\left(x_{1,ct} - \bar{x}_{1,c} - \bar{x}_{1,t} + \bar{x}_1\right) + \cdots + (\varepsilon_{ct} - \bar{\varepsilon}_c - \bar{\varepsilon}_t + \bar{\varepsilon})$$

Equation B6 is the within transformation for two-way fixed effects, adding the overall population mean back in after subtracting both the mean of the county and the mean of the year the observation is a part of.

We point out that this process removes the unobserved effects (i.e., μ_c and λ_t from Equation B4). It does so by adding unobserved group effects into the model via dummy variables (i.e., Equation B5) or by subtracting them out using the within transformation (i.e., Equation B6). It also controls for/removes observed group effects similarly—factors included in the model that drive variability between groups (e.g., average population). This leaves us with an assessment examining the relationships between jobs and our regressors within groups. This is particularly advantageous because it allows us to isolate the effects of our regressors on jobs across the entire population while controlling for group heterogeneity.

Interaction Term for Influential Outlier

On the other hand, if we critically consider the final statement of the previous paragraph—we may ask, is there a single effect for each of our regressors across the entire population after controlling for group heterogeneity? Are changes in the independent variables associated with the same changes in the dependent variables across heterogeneous groups? In the "Alternative Models" subsection, we will explore an alternative to FEMs that addresses this question. However, we bring attention to the concept here because our model evaluation analyses discover an influential outlier in the mining sector dataset, which leads us to adjust our FEMs.

Campbell County, WY's huge coal mining labor market (see Figure B5) initially raised concerns about leverage, a measure of how far observations of independent variables are from other observations. This did not necessarily indicate that Campbell County, WY, was destined to be an influential outlier county for our analysis—consider the following:

- *First*, we moved to fixed effects modeling, so it is no longer jobs that drive leverage but rather how far jobs within Campbell County, WY, each year are from its average number of jobs from 2014 to 2019. In other words, leverage does not result from many coal mining jobs compared to other counties—leverage results from big within-county changes in coal mining jobs compared to other counties. Figure B5 shows leverage concerns via wide ranges of jobs from 2014 to 2019.
- *Second*, its observations must also have high discrepancy, which can be thought of as large residuals if we constructed the mining sector models without Campbell County, WY's data and then used that model to predict Campbell County, WY's data (i.e., large studentized residuals).

Campbell County, WY, indeed demonstrates both high leverage and discrepancy and influences the observed relationships between mining sector jobs and coal sales. Hence, we include an interaction term that accounts for this unique effect. See the "Confidence Intervals" subsection for further justification for adding this interaction term to our mining sector model.

Base Case Regression Tables

Table B8 shows our base case two-way fixed effects utility sector model. Table B9 shows our base case two-way fixed effects mining sector model.

For this study, our critical value is $p \leq 0.10$—a conventional threshold for statistical significance. In plain English, we reject the null hypothesis when the probability of the tested event occurring under the null hypothesis is less than or equal to 10%. In regression, the null hypotheses are that the β coefficient estimates are equal to zero (i.e., no association exists between the dependent variable and the tested regressor).

Table B8 and Table B9 are constructed using the *plm* R package [91]. The reported standard errors are robust with regard to heteroskedasticity and serial correlation of county data over time [92]. The β coefficient estimates from Table B8 can be interpreted as follows. The average change in utility sector jobs associated with a one unit (GW) increase in coal capacity is 37.2. The average change in utility sector jobs associated with a one unit (TWh) increase in coal generation is 9.61.

Similarly, the β coefficient estimates from Table B9 can be interpreted as follows. The average change in mining sector jobs associated with a one unit (contract) increase in mining contracts is 8.38. The average change in mining sector jobs associated with a one unit (million short ton) increase in coal sales is 38.9. The adjustment from the population effect of a one unit increase in coal sales in Campbell County, WY, is -31.1 jobs, making its association 7.79 jobs per million short ton of coal sales.

Again, these models' coefficients represent within-county effects. In other words, we are not observing the effect of the variables between counties during one (or more) time period(s) but rather within the same counties over time. Therefore, the β coefficients provide us with estimates for marginal employment effects from changes in coal economic activity.

Table B8. Utility sector employment two-way fixed effects model.

Coefficients	**Estimate**	**Std. error**	**t value**	**Pr(>|t|)**	**Signif. code**
Coal Capacity	37.2	18.9	1.97	4.92E-02	**
Coal Generation	9.61	5.05	1.90	5.73E-02	*
Natural Gas Capacity	-33.2	28.5	-1.16	2.45E-01	
Natural Gas Generation	4.12	6.33	0.651	5.15E-01	
Nuclear Capacity	-459	354	-1.30	1.95E-01	
Nuclear Generation	18.2	27.5	0.663	5.08E-01	
Renewables Capacity	13.6	97.6	0.139	8.89E-01	
Renewables Generation	19.5	30.3	0.642	5.21E-01	
Other Capacity	11.8	26.4	0.447	6.55E-01	
Other Generation	55.3	46.7	1.18	2.37E-01	
Coal Cost	2.10	12.8	0.164	8.70E-01	
Gas Cost	-1.36	1.12	-1.21	2.25E-01	
Natural Gas Distribution Establishments	12.8	12.0	1.07	2.86E-01	
Water, Sewage, And Other Systems Establishments	23.4	5.59	4.19	3.00E-05	***
Population	-5.21	1.33	-3.92	9.42E-05	***
Population Density	4.61	1.74	2.65	8.12E-03	***
Gross Domestic Product (GDP)	6.85	8.42	0.814	4.16E-01	
Percent of GDP in Utility Sector	-2.04	1.84	-1.11	2.68E-01	
Observations	1464				
Panel Groups	290				
Time Groups	6				
RMSE	81.1				
R^2	0.181				
Adjusted R^2	0.171				

Notes: Signif. codes: *** ≤ 0.01; ** ≤ 0.05; * ≤ 0.1. Sample is limited to counties with coal activity for at least one year. Timeframe is 2014 though 2019. Dependent variable is jobs. Select notes for independent variables (see “Utility and Mining Sector Panel Datasets” subsection for more information): Capacity variables are in GW; Generation variables are in TWh; Fuel cost variables are in $/MMBtu; Population is in thousands of people; Population density is in millions of people per square mile; GDP is in millions of dollars. Standard errors are heteroskedasticity and serial-correlation robust [92].

Table B9. Mining sector employment two-way fixed effects model.

Coefficients	Estimate	Std. error	t value	Pr(>|t|)	Signif. code
Contracts	8.38	2.55	3.29	1.07E-03	***
Sales	38.9	11.4	3.41	6.89E-04	***
Campbell County, WY x Sales	-31.1	11.4	-2.74	6.39E-03	***
Percent Mined Underground	0.210	0.266	0.788	4.31E-01	
Coal Price	11.1	15.2	0.734	4.63E-01	
Oil and Gas Extraction Establishments	20.8	7.12	2.93	3.55E-03	***
Support Activities for Mining Establishments	26.8	5.28	5.07	5.21E-07	***
Metal Ore Mining Establishments	-90.9	69.1	-1.32	1.89E-01	
Nonmetallic Mineral Mining Establishments	-3.21	16.7	-0.192	8.48E-01	
Population	17.9	23.7	0.756	4.50E-01	
Population Density	-3.22	13.2	-0.243	8.08E-01	
Gross Domestic Product (GDP)	-5.16	22.8	-0.226	8.21E-01	
Percent of GDP in Mining Sector	6.62	2.73	2.42	1.57E-02	**
Observations	765				
Panel Groups	148				
Time Groups	6				
RMSE	125				
R^2	0.498				
Adjusted R^2	0.489				

Notes: Signif. codes: *** ≤ 0.01; ** ≤ 0.05; * ≤ 0.1. Sample is limited to counties with coal activity for at least one year. Time frame is 2014 though 2019. Dependent variable is jobs. Select notes for independent variables (see "Utility and Mining Sector Panel Datasets" subsection for more information): Sales are in million short tons; Campbell County, WY x sales is an interaction term; Coal price is in $/MMBtu; Population is in thousands of people; Population density is in millions of people per square mile; GDP is in millions of dollars. Standard errors are heteroskedasticity and serial-correlation robust [92].

Model Performance Statistics & Residual Plots

In Table B8 and Table B9, we report the root mean squared error (RMSE), the R^2 value, and the adjusted R^2 value. The equations for these three metrics are included below:

Equation B7. Regression Modeling: Root Mean Squared Error.

$$RMSE = \sqrt{\frac{\sum(y_i - \hat{y}_i)^2}{n-k}}$$

Equation B8. Regression Modeling: R^2.

$$R^2 = 1 - \frac{SS_{Resdiuals}}{SS_{Total}} = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y}_i)^2}$$

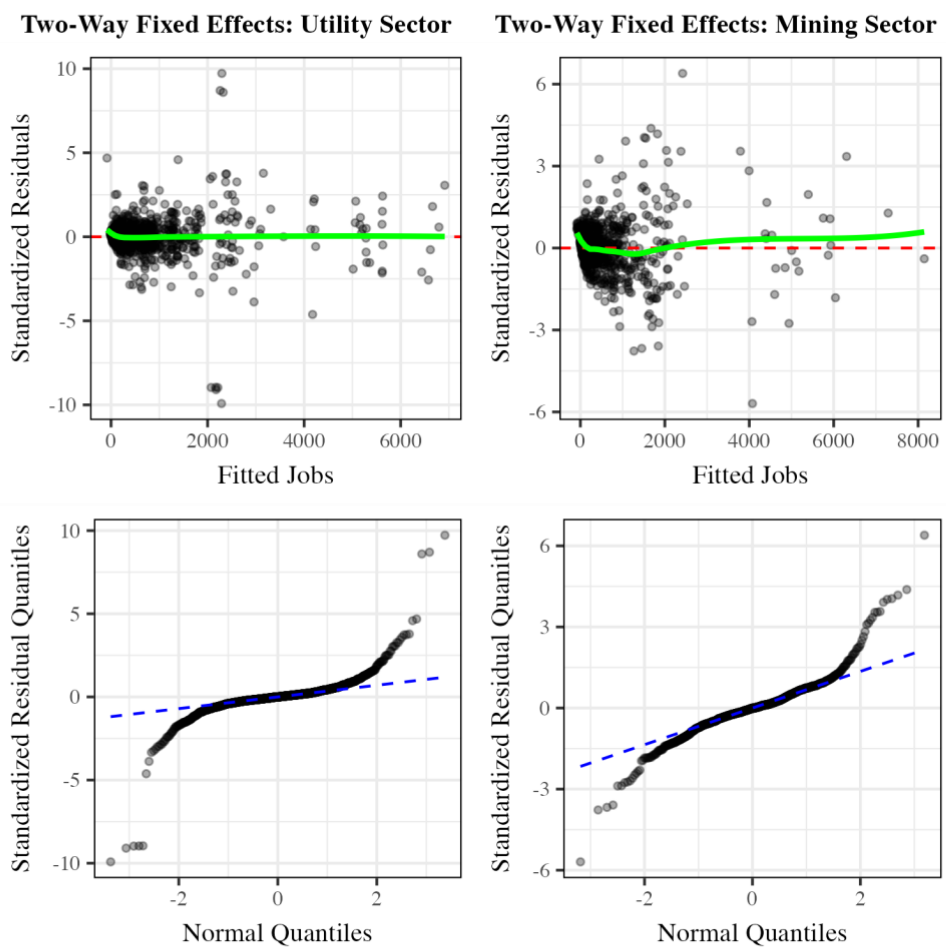
Equation B9. Regression Modeling: Adjusted R^2.

$$Adj. R^2 = 1 - \left[\frac{(1-R^2)(n-1)}{n-k-1}\right]$$

In Equation B7 through Equation B9, y_i are the observed values of the dependent variable, and $\hat{y}_i$ are the model-fitted values of the dependent variable. n is the number of observations, and k is the number of predictors. $SS_{Resdiuals}$ is the residual sum of squares (i.e., unexplained variation), and SS_{Total} is the total sum of squares (i.e., total variation). $\bar{y}_i$ is the mean value of the dependent variable.

The statistics computed in Table B8 and Table B9 consider the within-transformed versions of the models. In other words, k is chosen to be the number of β coefficients in the tables rather than that count plus the number of counties and years, which would be k for the least squares dummy variable (LSDV) equivalent. Notably, the LSDV equivalent models have much higher R^2 and adjusted R^2 values (all are > 0.98) because they represent the variation explained both within and between counties. Those reported in Table B8 and Table B9 exclude the latter.

A lower RMSE indicates stronger model performance via smaller residuals across the observations. Contrarily, an R^2 value closer to one indicates that variation in the regressors explains more variation in the dependent variable. While these statistics help us to understand the models' performances, they are not necessarily indicative of a "good model" for the sake of our goals—i.e., to identify the β coefficients for our coal variables. We will revisit this in the "Alternative Models" and "Model Evaluation Summary" subsections.



Notes: Top plots are standardized residuals versus fitted jobs. Bottom plots are quantiles of standardized residuals versus quantiles of a normal distribution with matched moments. Left plots are for the utility sector. Right plots are for the mining sector.

Figure B6. Two-Way Fixed Effects Modeling Residual Plots.

Residual plots are a better way to determine a "good model." Well-performing models have residuals normally distributed around zero, with no noticeable patterns. Figure B6 shows residual plots for the two base case models. The green lines on the upper panels follow the trends of the standardized residuals as model-fitted jobs increase. The blue dashed lines on the lower panels represent the quantiles of a simulated normal distribution sharing moments (i.e., mean and standard deviation) with the standardized residual data.

In the upper panel, we prefer models with relatively straight green lines at or around zero and no abnormal patterns with the standardized residuals (e.g., more variance with increasing model-fitted jobs, a case of heteroskedasticity). These residual plots for the two-way fixed effects models indicate that we are achieving desired performance.

In the lower panel, we prefer standardized residual quantiles aligning with the dashed blue lines, which would signify a normal distribution. These residual plots for the two-way fixed effects models have standardized residual quantiles aligning with the dashed blue lines but with deviations at higher and lower quantiles in a manner that suggests they may better follow the t-distribution (i.e., like a normal distribution but with heavier tails). This is no cause for concern.

Simultaneous Equation Bias

One potential concern for our labor market modeling for this research is simultaneous equation bias. One problem here is that, while we are testing hypotheses regarding the influence of the "coal variables" (capacity, generation, mining contracts, and sale quantity) on employment, we may be partially picking up the effect that labor supply has on the coal variables. Another aspect of this concern is that the "coal variables" and labor supply may be jointly determined.

We first note that our FEMs control for time-invariant characteristics or attributes of counties covered by the analysis. This is inclusive of persistent aspects of county-level labor markets such as the relative size of the workforce, human capital (as that pertains to coal sector labor), and proximity of the counties to mines and power plants. We argue that these characteristics (captured by the county fixed effects) are the primary drivers of labor market outcomes in these sectors. The identifying variation exploited in our regression models is within-county variation.

We next discuss simultaneity as it pertains to the mining sector regressions. Coal seams are a naturally occurring phenomenon and, hence, are exogenous relative to labor supply. We argue that changes in mining activity are driven by demand for coal at power plants. These relationships have far more to do with the existing spatial arrangement of mines, transportation networks, and plants rather than the prevalence of workers at the mines. Further, given large, short-run job losses in the sector nationally, and hence, excess labor supply, it seems unlikely that short-run changes in output from the mines (the focus of this study) are constrained by labor supply.

Next, we discuss the utility sector. Given the (advanced) age of the coal-fired power plants in this study, location and sizing decisions were made decades ago. Admittedly, these decisions were likely based in part on access to coal *and* labor. Specifically, power plants are likely to locate according to several key criteria, including access to fuel (via barge, rail, or a mine itself), regional demand for power, regional compliance with air quality restrictions, and access to labor, so that there are personnel to run the plant. However, these decisions are not directly relevant to the present study, which explores a relatively short period at or near the end of the plants' effective lifetimes. If this analysis focused on where power plants were adding coal capacity (the last of which occurred in 2014 [68]), simultaneity of the sort under discussion might be an issue. In this study, however, we mostly observe reductions in power generation and retirements. These decisions are largely due to low natural gas prices (and, to a lesser extent, environmental policy constraints) [60], [93]–[95], not wages or other labor market-related factors.

Confidence Intervals

To address uncertainty for our coal variables' marginal employment effects (i.e., β coefficient estimates from Table B8 and Table B9), we construct a 90% confidence interval (CI) for each to serve as our lower and upper bound marginal employment effect estimates. A CI can equally be thought of as (1) the set of values for which a hypothesis test with a critical value of p ≤ 0.10 does not reject and (2) having a 90% chance of containing the true coefficient value [96]. Equation B10, which utilizes the β coefficients and robust standard errors (RSE) from Table B8 and Table B9, computes the 90% CIs:

Equation B10. Regression Modeling: Confidence Intervals via Robust Standard Errors.

$$90\%\ CI = [\beta \pm 1.645 * RSE]$$

We also use bootstrapping to compute 90% CIs. Bootstrapping is a method that samples our datasets with replacement many times and reconstructs the model each time to see how it varies with the different resamples [97].

Table B10. 90% confidence intervals for coal variable coefficients.

Sector	Coal Variable	β Coefficient	90% Confidence Intervals		
			Robust Standard Errors	**Random Sampling Bootstrap**	**Block Sampling Bootstrap**
Utility	Coal Capacity	37.2**	[6.11, 68.2]	[7.06, 66.3]	[1.06, 68.9]
	Coal Generation	9.61*	[1.30, 17.9]	[2.56, 16.0]	[0.420, 17.4]
Mining	Contracts	8.38**	[4.19, 12.6]	[4.09, 13.8]	[3.44, 13.2]
	Sales	38.9***	[20.1, 57.6]	[20.2, 56.7]	[17.2, 58.2]
	Interaction Term	-31.1**	[-49.8, -12.4]	[-50.4, -9.29]	[-47.3, 0]

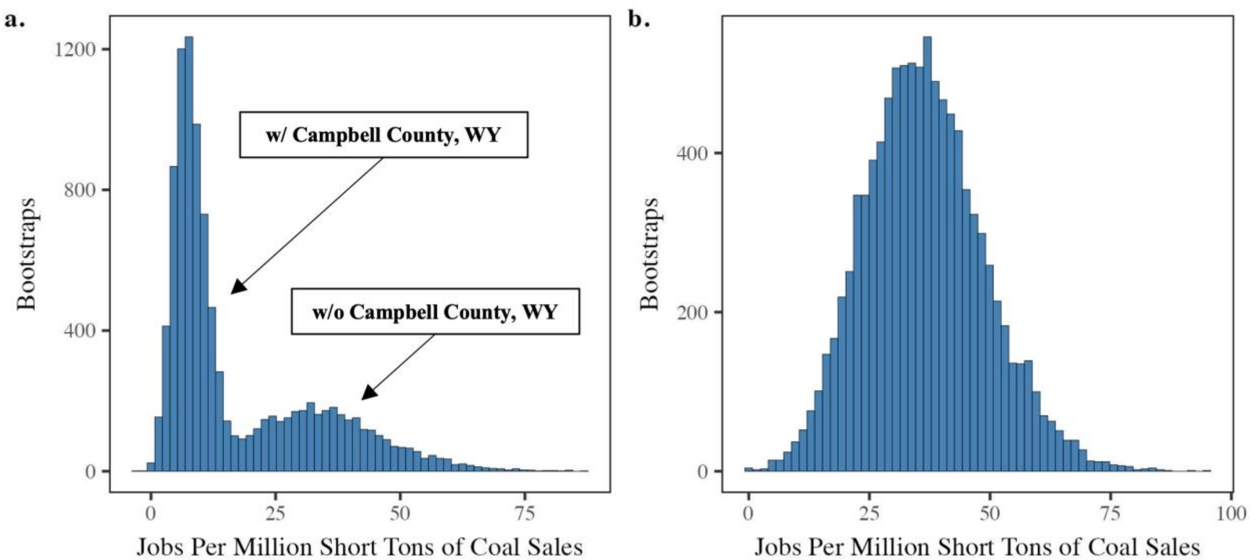
Notes: Signif. codes: *** ≤ 0.01; ** ≤ 0.05; * ≤ 0.1. Interaction term is Campbell County, WY x sales from Table B9. For utility sector model, see Table B8. For mining sector model, see Table B9.

We conduct 10,000 iterations. We both randomly sample observations and block sample by county (i.e., sample counties with replacement, then include all their observations rather than sampling them themselves). Block sampling by county allows us to maintain counties' dependence structures between years [89]. The results of both methods are distributions of model estimations—for this study, we are interested in the distributions of the estimated coal variable coefficients. The 90% CIs are built considering the 5th and 95th percentiles of the bootstrapped distribution.

Table B10 shows our 90% CI results for each coal variable. In the main paper, we report the 90% CIs computed via robust standard errors (Equation B10); however, the CIs across the different methods are relatively similar. The most notable differences are with block sample bootstrapping, which (1) generally results in larger CIs, especially on the lower end for the utility sector and (2) has an upper-end estimate for the interaction term between Campbell County, WY, and sales of zero. It is inherently zero if we do not explicitly model the interaction term (for this county or any other). Hence, we assume the interaction term is zero without Campbell County in the sample.[25]

Besides acting as a sensitivity check, the bootstrapped results also account for correlation in coefficient variation (e.g., when a sample's coefficient for coal capacity's coefficient goes up, that for coal's generation tends to go down). We will return to this concept when estimating uncertainty intervals for total employment impacts (see the "Employment Changes Associated with Coal Variables" subsection).

There are several ways to identify influential outliers in regression; however, our block sample bootstrapping results in a strong visual demonstrating Campbell County, WY's leverage and discrepancy influencing the β coefficient for sales. Figure B7 shows a histogram of the β coefficient for sales across 10,000 iterations of a bootstrapped model without the interaction term between Campbell County and sales (Table B12).



Notes: 10,000 block-sampled bootstraps of the β coefficient for coal sales. (a) Left plot's model does not have the interaction term for Campbell County, WY, and coal sales (i.e., it uses Table B12's right-side model). (b) Right plot's model has the interaction term for Campbell County, WY, and coal sales (i.e., it uses Table B9's model).

Figure B7. Bootstrapped Coefficient Distribution for Coal Sales in the Mining Sector.

Figure B7 shows a striking difference between bootstrap iterations that include Campbell County and others that do not. The outlier's leverage and discrepancy strongly influence the β coefficient for the population. Including the interaction term allows us to control for this influence and get a stronger estimate of β for coal sales across the country for counties other than Campbell County, WY (Figure B7's bottom plot).

[25] This is phenomenon limited to block sample bootstrapping because random sampling is more likely to have at least two observations from Campbell County—at least enough so that the 90th percentile estimate is not zero.

Alternative Models

This section explores several alternative modeling specification options and assesses their details compared to the base case. Throughout this section, we will use several abbreviations as outlined below:

- 2212 Est. = Number of 2212 Natural Gas Distribution business establishments
- 2213 Est. = Number of 2213 Water, Sewage, and Other Systems business establishments
- 2111 Est. = Number of 2111 Oil and Gas Extraction business establishments
- 2131 Est. = Number of 2131 Support Activities for Mining business establishments
- 2122 Est. = Number of 2122 Metal Ore Mining business establishments
- 2123 Est. = Number of 2123 Nonmetallic Mineral Mining and Quarrying business establishments
- Cap. = Capacity; Gen. = Generation; Cont.= Contracts
- Nat. Gas = Natural Gas; Nuc. = Nuclear; Ren. = Renewables
- CCWY = Campbell County, WY

One Coal Variable Models

The first set of alternative models assesses variations of the base case models looking at only one of the two coal variables. For the utility sector, we build a two-way FEM considering only coal's (and other fuels') capacity and another considering only coal's (and other fuels') generation. For the mining sector, one model has only contracts, and the other has only sales. Both mining sector models include an interaction variable for our influential outlier county, Campbell County, WY.

Table B11 shows that the coefficients for coal capacity and generation both increase when evaluated separately. This suggests possible omitted variable bias when excluding one coal variable or the other—i.e., we falsely associate lost jobs resulting from less generation with less capacity or vice versa. We conclude that including both coal variables for the utility sector model is essential, as both are positive and significant when included together.

Similarly, Table B11 shows that the coefficients for contracts and sales both increase when evaluated separately. Again, omitted variable bias may be a concern when excluding one coal variable or the other. We conclude that including both coal variables for the mining sector model is important. Another observation regarding the interaction term applied for Campbell County, WY. We see that the interaction term is significant for sales but not for contracts. We will revisit this point with our next mining sector alternative model evaluation.

For both sets of these one coal variable models, the RMSE statistics are greater, and the R^2 statistics are lower than for the base case models. While not always the reason we may choose one model over another, these comparisons help validate that we prefer the two coal variable variations of the two-way FEMs.

Table B11. One coal variable alternative models.

Utility sector employment two-way fixed effects model: Only capacity.

Coefficients	*Beta*	*SE*	*t value*	*Pr(>|t|)*	
Coal	49.8	17.2	2.9	3.79E-03	***
Natural Gas	-32.1	17.5	-1.84	6.66E-02	*
Nuclear	-321	366	-0.877	3.81E-01	
Renewables	53.3	40.2	1.33	1.85E-01	
Other	20.3	34.5	0.587	5.57E-01	
Coal Cost	-0.129	11.8	-0.0109	9.91E-01	
Gas Cost	-1.3	1.3	-0.998	3.19E-01	
2212 Est.	12.4	4.94	2.5	1.24E-02	**
2213 Est.	23	3.36	6.83	1.36E-11	***
Population	-5.17	0.493	-10.5	1.30E-24	***
Density	4.46	0.408	10.9	1.61E-26	***
GDP	6.95	2.33	2.99	2.87E-03	***
% GDP Util.	0.706	1.32	0.536	5.92E-01	
Observations	1464				
Sample	Coal Counties				
Panel Groups	290				
Time Groups	6				
RMSE	81.4				
R^2	0.173				
Adjusted R^2	0.166				

Signif. codes: *** ≤ 0.01; ** ≤ 0.05; * ≤ 0.1.

Utility sector employment two-way fixed effects model: Only generation.

Coefficients	*Beta*	*SE*	*t value*	*Pr(>|t|)*	
Coal	12.5	3.31	3.77	1.72E-04	***
Natural Gas	-0.925	3.74	-0.247	8.05E-01	
Nuclear	-9.62	22.3	-0.431	6.66E-01	
Renewables	17.9	13.2	1.36	1.76E-01	
Other	67.5	41.9	1.61	1.08E-01	
Coal Cost	7.63	11.8	0.648	5.17E-01	
Gas Cost	-1.43	1.31	-1.09	2.75E-01	
2212 Est.	12	4.93	2.42	1.56E-02	**
2213 Est.	22.2	3.34	6.65	4.49E-11	***
Population	-5.07	0.492	-10.3	7.62E-24	***
Density	4.51	0.411	11	9.59E-27	***
GDP	6.8	2.33	2.92	3.56E-03	***
% GDP Util.	-1.68	1.61	-1.04	2.98E-01	
Observations	1464				
Sample	Coal Counties				
Panel Groups	290				
Time Groups	6				
RMSE	81.5				
R^2	0.171				
Adjusted R^2	0.164				

Signif. codes: *** ≤ 0.01; ** ≤ 0.05; * ≤ 0.1.

Mining sector employment two-way fixed effects model: Only contracts.

Coefficients	*Beta*	*SE*	*t value*	*Pr(>|t|)*	
Contracts	14.1	2.02	7	6.79E-12	***
CCWY:Cont.	-0.0777	2.4	-0.0323	9.74E-01	
% Underground	0.262	0.264	0.993	3.21E-01	
Coal Price	4.1	14.2	0.288	7.73E-01	
2111 Est.	24.5	4.43	5.53	4.73E-08	***
2131 Est.	26.3	2.3	11.4	1.87E-27	***
2122 Est.	-79.4	37.7	-2.11	3.54E-02	**
2123 Est.	-1.75	10.5	-0.167	8.67E-01	
Population	19.7	13.1	1.5	1.33E-01	
Density	-5.15	9.43	-0.546	5.85E-01	
GDP	0.435	14.7	0.0297	9.76E-01	
% GDP Min.	7.74	1.63	4.75	2.59E-06	***
Observations	765				
Sample	Coal Counties				
Panel Groups	148				
Time Groups	6				
RMSE	128				
R^2	0.471				
Adjusted R^2	0.463				

Signif. codes: *** ≤ 0.01; ** ≤ 0.05; * ≤ 0.1.

Mining sector employment two-way fixed effects model: Only sales.

Coefficients	*Beta*	*SE*	*t value*	*Pr(>|t|)*	
Sales	50.7	6.83	7.43	3.88E-13	***
CCWY:Sales	-34.5	6.92	-4.98	8.18E-07	***
% Underground	0.19	0.262	0.725	4.69E-01	
Coal Price	11.6	14.2	0.822	4.11E-01	
2111 Est.	18.4	4.4	4.17	3.51E-05	***
2131 Est.	26.6	2.29	11.6	2.88E-28	***
2122 Est.	-94.2	37.6	-2.51	1.24E-02	**
2123 Est.	-7.35	10.4	-0.709	4.78E-01	
Population	20.4	13	1.57	1.17E-01	
Density	-2.44	9.36	-0.26	7.95E-01	
GDP	-1.24	14.6	-0.085	9.32E-01	
% GDP Min.	6.92	1.63	4.24	2.59E-05	***
Observations	765				
Sample	Coal Counties				
Panel Groups	148				
Time Groups	6				
RMSE	127				
R^2	0.480				
Adjusted R^2	0.472				

Signif. codes: *** ≤ 0.01; ** ≤ 0.05; * ≤ 0.1.

Outlier Interaction Exploration

Next, we look at the inclusion (and exclusion) of interaction variables for our influential outlier county Campbell County, WY. Our base case mining sector model, including an interaction term between Campbell County and sales, effectively adjusts the slope—or marginal employment effect—of sales for Campbell County away from that of the rest of the population. Our first alternative here also includes an interaction term between Campbell County and contracts, and our second alternative does not include any interaction terms (this is the model resulting in the bootstrapped coefficient distribution shown in Figure B7).

Table B12. Interaction variable alternative mining sector models.

Mining sector employment two-way fixed effects model: Both coal variable interactions.

Coefficients	*Beta*	*SE*	*t value*	*Pr(>|t|)*	
Contracts	9.60	2.17	4.43	1.11E-05	***
CCWY:Cont.	-4.22	3.97	-1.06	2.88E-01	
Sales	37.1	7.39	5.02	6.72E-07	***
CCWY:Sales	-26.2	8.22	-3.19	1.48E-03	***
% Underground	0.213	0.258	0.828	4.08E-01	
Coal Price	11.0	13.9	0.79	4.30E-01	
2111 Est.	210	4.37	4.80	2.01E-06	***
2131 Est.	26.8	2.25	11.9	1.64E-29	***
2122 Est.	-88.9	37	-2.4	1.66E-02	**
2123 Est.	-3.11	10.2	-0.303	7.62E-01	
Population	17.1	12.8	1.33	1.83E-01	
Density	-3.00	9.21	-0.326	7.45E-01	
GDP	-5.71	14.4	-0.398	6.91E-01	
% GDP Min.	6.59	1.61	4.1	4.70E-05	***
Observations	765				
Sample	Coal Counties				
Panel Groups	148				
Time Groups	6				
RMSE	125				
R^2	0.499				
Adjusted R^2	0.489				

Signif. codes: *** ≤ 0.01; ** ≤ 0.05; * ≤ 0.1.

Mining sector employment two-way fixed effects model: No interactions.

Coefficients	*Beta*	*SE*	*t value*	*Pr(>|t|)*	
Contracts	9.29	1.86	5.00	7.42E-07	***
Sales	8.05	2.43	3.31	9.76E-04	***
% Underground	0.251	0.262	0.958	3.38E-01	
Coal Price	5.50	14.1	0.39	6.97E-01	
2111 Est.	22.4	4.42	5.06	5.46E-07	***
2131 Est.	25.9	2.28	11.4	2.96E-27	***
2122 Est.	-72.3	37.3	-1.94	5.33E-02	*
2123 Est.	-4.61	10.4	-0.444	6.57E-01	
Population	17.8	13	1.37	1.71E-01	
Density	-2.76	9.36	-0.295	7.68E-01	
GDP	-1.25	14.6	-0.0858	9.32E-01	
% GDP Min.	7.89	1.61	4.91	1.20E-06	***
Observations	765				
Sample	Coal Counties				
Panel Groups	148				
Time Groups	6				
RMSE	127				
R^2	0.481				
Adjusted R^2	0.472				

Signif. codes: *** ≤ 0.01; ** ≤ 0.05; * ≤ 0.1.

Table B12 shows us a few things. First, including an additional interaction term between Campbell County and contracts results in a relatively high adjustment for the outlier (-4.22 jobs per contract), but the effect is insignificant. Moreover, the population estimate for the marginal employment effect of contracts only increases slightly (from 8.38 to 9.60) when controlling for the unique effect in Campbell County. Including this interaction term is deemed unnecessary.

On the other hand, not including any interaction terms substantially changes our coefficient for coal sales. The population effect in the base case model is 38.9 jobs per million short tons, and without an interaction term controlling for the unique effect in Campbell County, this decreases to 8.05 jobs per million short tons. The outlier's leverage and discrepancy greatly influence the coefficient estimate for the rest of the population.

The summary statistics suggest that the models in Table B12 perform no better than our base case mining sector model. That, plus the coefficient analysis above, indicates that including the interaction term for Campbell County and sales but not for Campbell County and contracts is our preferred specification.

Expanded Sample

Our base case models include only coal counties in the sample (i.e., counties with at least one year of positive coal variable economic activity). In this section, we check how the results change considering all counties where we have sectoral jobs data. The datasets for these models simply assign zeros to our coal variables where the data are not reported. The resulting utility sector dataset includes 8,064 observations across 1,671 counties, and the resulting mining sector dataset includes 7,025 observations across 1,453 counties.

Table B13 shows the expanded sample models. Our coal variables' coefficients remain positive and significant, and their magnitudes are relatively similar to those in the base case models. Most coal variables' coefficients see a slight increase, but that for sales sees a decrease.

Table B13. Expanded sample alternative models.

Utility sector employment two-way fixed effects model: All counties.

Coefficients	*Beta*	*SE*	*t value*	*Pr(>|t|)*	
Coal Cap.	42.7	18.2	2.35	1.87E-02	**
Coal Gen.	10.6	3.20	3.3	9.65E-04	***
Nat. Gas Cap.	-25.9	13.5	-1.91	5.56E-02	*
Nat. Gas Gen.	1.97	2.85	0.694	4.88E-01	
Nuc. Cap.	449	207	2.17	3.03E-02	**
Nuc. Gen.	5.64	12.4	0.455	6.49E-01	
Ren. Cap.	-60.1	34.1	-1.76	7.79E-02	*
Ren. Gen.	14.5	8.44	1.72	8.55E-02	*
Other Cap.	2.43	32.1	0.0756	9.40E-01	
Other Gen.	83.2	38.2	2.18	2.93E-02	**
Coal Cost	-4.52	7.55	-0.599	5.49E-01	
Gas Cost	-0.191	1.12	-0.171	8.64E-01	
2212 Est.	12.5	2.65	4.73	2.28E-06	***
2213 Est.	8.59	1.7	5.06	4.21E-07	***
Population	0.900	0.18	4.99	6.24E-07	***
Density	0.63	0.0862	7.31	2.92E-13	***
GDP	-9.7	0.577	-16.8	4.60E-62	***
% GDP Util.	0.0504	1.17	0.0431	9.66E-01	
Observations	8064				
Sample	All Counties				
Panel Groups	1671				
Time Groups	6				
RMSE	89				
R^2	0.0635				
Adjusted R^2	0.0614				

Signif. codes: *** ≤ 0.01; ** ≤ 0.05; * ≤ 0.1.

Mining sector employment two-way fixed effects model: All counties.

Coefficients	*Beta*	*SE*	*t value*	*Pr(>|t|)*	
Contracts	11.8	3.93	2.99	2.82E-03	***
Sales	25.4	14.8	1.71	8.68E-02	*
CCWY:Sales	-24.1	14	-1.72	8.50E-02	*
% Underground	-0.533	0.431	-1.24	2.17E-01	
Coal Price	-12.0	8.64	-1.39	1.66E-01	
2111 Est.	60.8	0.896	67.9	0.00E+00	***
2131 Est.	43.5	1.14	38.1	2.45E-282	***
2122 Est.	7.20	16.8	0.428	6.69E-01	
2123 Est.	8.10	6.27	1.29	1.96E-01	
Population	-3.78	0.589	-6.42	1.45E-10	***
Density	1.49	0.363	4.12	3.84E-05	***
GDP	5.62	1.65	3.4	6.70E-04	***
% GDP Min.	9.41	1.4	6.73	1.87E-11	***
Observations	7025				
Sample	Coal Counties				
Panel Groups	1453				
Time Groups	6				
RMSE	278				
R^2	0.503				
Adjusted R^2	0.502				

Signif. codes: *** ≤ 0.01; ** ≤ 0.05; * ≤ 0.1.

The more notable changes are for the control variables' coefficients. For the mining sector model, we see a big increase for the Oil and Gas Extraction (NAICS 2111) establishments coefficient—from 20.8 jobs per establishment to 60.8 jobs per establishment—and for the Support Activities for Mining (NAICS 2131) establishments variable—from 26.8 jobs per establishment to 43.5 jobs per establishment. We can hypothesize that this is the influence of the oil and gas sector in counties with no coal activity and that the larger effects are because the establishments in non-coal counties support more jobs on average.

The utility sector model is more challenging to interpret. Perhaps most perplexing is the marginal employment effect of natural gas activity. We see a negative coefficient for capacity and a very small, yet insignificant, coefficient for generation. We refrain from doing so herein, but a closer assessment may be necessary to fully understand what these results suggest (e.g., we could observe a model for just natural gas counties).

Nuclear, renewables, and other fuel source variables make more sense. A unit of nuclear capacity is associated with many jobs, which makes sense as nuclear activity occurs at labor-intensive facilities. Renewable generation is associated with positive jobs, but renewable capacity is associated with negative jobs. This is explainable because once solar farms or wind turbines are installed, the associated labor is maintenance rather than facility operations. Other fuel source generation has a positive effect.[26]

[26] We note that the commentary here is speculative, and further investigation on these specific topics is needed to substantiate and build upon the discussion.

Simple Model

The risk of overfitting a model always exists, which can lead to various undesirable outcomes. To check to ensure that none of our control variables greatly confound our β coefficient estimates, we create a simple model with no control variables. The FEM specification will control for unobserved heterogeneity across counties and years, so this evaluation looks to see whether the observed coefficients for the coal variables within groups substantially change when including the control variables, which also focus on changes within groups.

Table B14. Simple alternative models.

Utility sector employment two-way fixed effects model: Simplified version.

Coefficients	*Beta*	*SE*	*t value*	*Pr(>|t|)*	
Coal Cap.	44.5	17.3	2.58	1.01E-02	**
Coal Gen.	7.04	2.96	2.38	1.76E-02	**
Observations	1464				
Sample	Coal Counties				
Panel Groups	290				
Time Groups	6				
RMSE	88.4				
R^2	0.0178				
Adjusted R^2	0.0165				

Signif. codes: *** ≤ 0.01; ** ≤ 0.05; * ≤ 0.1.

Mining sector employment two-way fixed effects model: Simplified version.

Coefficients	*Beta*	*SE*	*t value*	*Pr(>|t|)*	
Contracts	7.37	2.19	3.37	8.12E-04	***
Sales	47.3	8.42	5.62	2.87E-08	***
CCWY:Sales	-33.8	8.02	-4.22	2.87E-05	***
Observations	765				
Sample	Coal Counties				
Panel Groups	148				
Time Groups	6				
RMSE	152				
R^2	0.245				
Adjusted R^2	0.242				

Signif. codes: *** ≤ 0.01; ** ≤ 0.05; * ≤ 0.1.

Table B14 shows relatively similar results with the simple alternatives compared to our base case models. There are slight changes (i.e., up for capacity and sales and down for generation and contracts) but not to the extent that raises concerns. The RMSEs go up, and, as expected, the R^2 values go down, as the model explains less variation in the dependent variables. Overall, we decide that controlling for omitted variable bias using carefully selected additional regressors is important.

County Fixed Effects

Recall that county unobserved effects, rather than year unobserved effects, are most concerning when using a pooled OLS model. In this section, we look at a county FEM alternative:

Equation B11. Regression Modeling: County Fixed Effects.

$$y_{ct} = \beta_1 x_{1,ct} + \beta_2 x_{2,ct} + Z_{ct}\theta + \alpha_c + \varepsilon_{ct}$$

$$(y_{ct} - \bar{y}_c) = \beta_1\left(x_{1,ct} - \bar{x}_{1,c}\right) + \cdots + (\varepsilon_{ct} - \bar{\varepsilon}_c)$$

Equation B11 represents this model. It is the same as for the two-way FEM specification (Equation B5 and Equation B6) but without the year fixed effects (γ_t). The within transformation for county fixed effects subtracts the mean of the county that the observation is a part of.

Table B15 shows the county FEMs for the utility and mining sectors. We see very similar coefficient estimates as with the two-way FEMs. Therefore, we can assume that λ_t, the year component in the pooled OLS composite error term from Equation B4, is not a substantial driver of omitted variable bias. Overall, these models are likely sufficient to identify our coal variables' marginal employment effects, but the two-way FEMs are a more comprehensive selection as the jobs data characterize distinct years.

Table B15. County fixed effects alternative models.

Utility sector employment county fixed effects model.

Coefficients	*Beta*	*SE*	*t value*	*Pr(>|t|)*	
Coal Cap.	38.7	17.8	2.17	2.98E-02	**
Coal Gen.	11.2	3.34	3.35	8.39E-04	***
Nat. Gas Cap.	-38	19.7	-1.93	5.41E-02	*
Nat. Gas Gen.	3.39	4.2	0.807	4.20E-01	
Nuc. Cap.	-462	500	-0.923	3.56E-01	
Nuc. Gen.	17	30.5	0.558	5.77E-01	
Ren. Cap.	9.47	63.8	0.148	8.82E-01	
Ren. Gen.	11.6	19.7	0.587	5.57E-01	
Other Cap.	12	35.2	0.341	7.33E-01	
Other Gen.	65.6	42.7	1.54	1.25E-01	
Coal Cost	23.3	10.3	2.26	2.43E-02	**
Gas Cost	-0.729	1.23	-0.593	5.53E-01	
2212 Est.	12	4.96	2.41	1.61E-02	**
2213 Est.	23.8	3.38	7.05	3.05E-12	***
Population	-5.05	0.507	-9.97	1.61E-22	***
Density	4.39	0.415	10.6	4.55E-25	***
GDP	4.8	2.27	2.11	3.47E-02	**
% GDP Util.	-1.7	1.63	-1.04	2.97E-01	
Observations	1464				
Sample	Coal Counties				
Panel Groups	290				
RMSE	81.8				
R^2	0.184				
Adjusted R^2	0.174				

Signif. codes: *** ≤ 0.01; ** ≤ 0.05; * ≤ 0.1.

Mining sector employment county fixed effects model.

Coefficients	*Beta*	*SE*	*t value*	*Pr(>|t|)*	
Contracts	9.84	1.91	5.14	3.71E-07	***
Sales	41.2	7.45	5.52	4.92E-08	***
CCWY:Sales	-34.5	7.03	-4.91	1.18E-06	***
% Underground	0.323	0.275	1.17	2.40E-01	
Coal Price	28.7	13.9	2.07	3.90E-02	**
2111 Est.	19.8	4.38	4.51	7.62E-06	***
2131 Est.	27.3	2.39	11.4	1.59E-27	***
2122 Est.	-115	39.4	-2.91	3.76E-03	***
2123 Est.	2.05	10.9	0.187	8.51E-01	
Population	19.1	13.3	1.44	1.51E-01	
Density	-5.22	9.43	-0.553	5.80E-01	
GDP	-2.09	15.3	-0.137	8.91E-01	
% GDP Min.	6.37	1.71	3.72	2.19E-04	***
Observations	765				
Sample	Coal Counties				
Panel Groups	148				
RMSE	134				
R^2	0.539				
Adjusted R^2	0.531				

Signif. codes: *** ≤ 0.01; ** ≤ 0.05; * ≤ 0.1.

A Return to Pooled OLS

For a complete analysis, we explore the pooled OLS models for our data. The pooled OLS specification is represented by Equation B12:

Equation B12. Regression Modeling: Pooled Ordinary Least Squares.

$$y_{ct} = \beta_1 x_{1,ct} + \beta_2 x_{2,ct} + Z_{ct}\theta + \alpha + \varepsilon_{ct}$$

In Equation B12, all variables are the same as in Equation B5, with the following exceptions. It excludes county fixed effects (α_c) and year fixed effects (γ_t). It includes a constant coefficient (intercept) for all county-year observations (α). Also, ε_{ct} is the composite error term from Equation B4.

Table B16 shows the pooled OLS models. We see vastly different β coefficient estimates compared to our two-way FEM base case specification. Clearly, μ_c, the county component in the pooled OLS composite error term from Equation B4, is a substantial driver omitted variable bias. While not shown herein, the models' residuals exhibit some problems via patterns and deviations from normality.

We conduct F tests comparing the county FEMs (Table B15) and the base case two-way FEMs (Table B8 and Table B9) to these pooled OLS models using the *plm* R package [91]. We also compare year FEMs to the pooled OLS models.[27] We find that the county and two-way FEMs outperform the pooled OLS models ubiquitously ($p \leq 0.01$). We find that the time FEMs are not better than the pooled OLS specification for the utility sector ($p > 0.1$) but that they are for the mining sector ($p \leq 0.1$). Overall, we verify that we prefer the models incorporating county fixed effects and that two-way fixed effects ensure we capture any unobserved time effects, especially with the mining sector model.

Table B16. Pooled ordinary least squares alternative models.

Utility sector employment pooled ordinary least squares model.

Coefficients	*Beta*	*SE*	*t value*	*Pr(>|t|)*	
(Intercept)	-243	53	-4.58	5.06E-06	***
Coal Cap.	-6.25	36.5	-0.171	8.64E-01	
Coal Gen.	40.0	7.71	5.19	2.37E-07	***
Nat. Gas Cap.	-20.9	32.7	-0.638	5.24E-01	
Nat. Gas Gen.	-2.78	8.48	-0.327	7.44E-01	
Nuc. Cap.	1510	775	1.94	5.20E-02	*
Nuc. Gen.	-150	99.3	-1.51	1.31E-01	
Ren. Cap.	-34.3	69	-0.497	6.19E-01	
Ren. Gen.	-6.86	20.1	-0.34	7.34E-01	
Other Cap.	49.2	77	0.639	5.23E-01	
Other Gen.	-250	47.5	-5.26	1.63E-07	***
Coal Cost	63.3	19.3	3.28	1.05E-03	***
Gas Cost	0.889	3.45	0.257	7.97E-01	
2212 Est.	80.1	5.8	13.8	7.57E-41	***
2213 Est.	10.6	1.7	6.24	5.73E-10	***
Population	1.72	0.126	13.7	4.25E-40	***
Density	-0.106	0.0276	-3.85	1.22E-04	***
GDP	-6.32	1.67	-3.78	1.61E-04	***
% GDP Util.	-1.27	1.67	-0.761	4.46E-01	
Observations	1464				
Sample	Coal Counties				
RMSE	438				
R^2	0.767				
Adjusted R^2	0.764				

Signif. codes: *** ≤ 0.01; ** ≤ 0.05; * ≤ 0.1.

Mining sector employment pooled ordinary least squares model.

Coefficients	*Beta*	*SE*	*t value*	*Pr(>|t|)*	
(Intercept)	-112	74.7	-1.5	1.34E-01	
Contracts	14.1	2.44	5.77	1.15E-08	***
Sales	19.2	5.81	3.31	9.95E-04	***
CCWY	-3110	1180	-2.63	8.66E-03	***
CCWY:Sales	-16.7	6.07	-2.75	6.13E-03	***
% Underground	0.866	0.368	2.35	1.88E-02	**
Coal Price	80.5	22	3.66	2.72E-04	***
2111 Est.	10.3	3.2	3.21	1.40E-03	***
2131 Est.	27.7	1.16	23.9	2.88E-94	***
2122 Est.	-251	52.4	-4.78	2.07E-06	***
2123 Est.	-2.4	2.89	-0.829	4.07E-01	
Interior Region	-259	37.8	-6.85	1.59E-11	***
Western Region	-333	51.6	-6.46	1.84E-10	***
Population	4.02	0.644	6.25	6.84E-10	***
Density	-2.26	0.28	-8.07	2.72E-15	***
GDP	-5.65	7.51	-0.752	4.52E-01	
% GDP Min.	6.21	0.893	6.95	7.90E-12	***
Observations	765				
Sample	Coal Counties				
RMSE	388				
R^2	0.853				
Adjusted R^2	0.849				

Signif. codes: *** ≤ 0.01; ** ≤ 0.05; * ≤ 0.1.

First-Differenced

Like FEMs, first-differenced models (FDMs) account for unobserved heterogeneity between unique individuals (i.e., counties) in panel data [88]. However, they do so differently by subtracting the previous year's data from each observation and regressing the dependent variable's year-to-year differences on the regressors' corresponding year-to-year differences. This is depicted in Equation B13:

Equation B13. Regression Modeling: First-Differenced.

$$\Delta y_{ct} = \beta_1 \Delta x_{1,ct} + \beta_2 \Delta x_{2,ct} + \Delta Z_{ct}\theta + \Delta\varepsilon_{ct}$$

In Equation B13, the variables are the same as in Equation B5, but the county fixed effects (α_c) and year fixed effects (γ_t) are excluded. Instead, we have the differences (Δ) in jobs between consecutive years regressed on the differences in the regressors between consecutive years.

[27] We do not show these models because we know that our pooled OLS models contain at least county effects.

Table B17 includes FDM alternatives for our utility sector and mining sector models. We see that the β coefficient estimates for our coal variables are all lower in magnitude than those from the base case two-way FEMs. Additionally, we see that the coefficients for coal generation in the utility sector and for the interaction term between Campbell County, WY, and sales in the mining sector are not significant.

FDMs are more efficient than FEMs when the idiosyncratic errors are not serially uncorrelated but rather follow a random walk, such that the first differences of the idiosyncratic errors are serially uncorrelated [88]. We look at our FEMs to see whether their idiosyncratic errors are serially correlated. We assess the significance of serial correlation in the idiosyncratic errors using Wooldridge's first-difference-based test [88] using the *plm* R package [91]. Using this test, we also test for serial correlation in the differenced errors. The null hypothesis is that the idiosyncratic errors (or their differences) are not serially correlated, and not rejecting one of the two tests provides support for using that specification.

Table B17. First-differenced alternative models.

Utility sector employment first-differenced model.

Coefficients	*Beta*	*SE*	*t value*	*Pr(>|t|)*	
(Intercept)	-3.89	3.1	-1.26	2.09E-01	
Coal Cap.	35.4	15.1	2.35	1.89E-02	**
Coal Gen.	4.27	3.15	1.36	1.75E-01	
Nat. Gas Cap.	-26.3	17	-1.55	1.22E-01	
Nat. Gas Gen.	1.89	3.75	0.505	6.14E-01	
Nuc. Cap.	-624	495	-1.26	2.08E-01	
Nuc. Gen.	6.76	19.1	0.354	7.23E-01	
Ren. Cap.	-156	62.3	-2.5	1.27E-02	**
Ren. Gen.	31.5	19.7	1.6	1.11E-01	
Other Cap.	9.29	31.7	0.293	7.70E-01	
Other Gen.	-9.91	36.6	-0.271	7.87E-01	
Coal Cost	4.07	10.7	0.381	7.03E-01	
Gas Cost	-0.725	0.778	-0.931	3.52E-01	
2212 Est.	7.5	4.34	1.73	8.43E-02	*
2213 Est.	22.2	2.98	7.46	1.73E-13	***
Population	-3.02	0.754	-4.01	6.47E-05	***
Density	2.65	0.603	4.39	1.24E-05	***
GDP	0.66	3.04	0.218	8.28E-01	
% GDP Util.	-0.342	1.68	-0.204	8.39E-01	
Observations	1174				
Sample	Coal Counties				
Panel Groups	276				
Time Groups	5				
RMSE	86.2				
R^2	0.0861				
Adjusted R^2	0.0711				

Signif. codes: *** ≤ 0.01; ** ≤ 0.05; * ≤ 0.1.

Mining sector employment first-differenced model.

Coefficients	*Beta*	*SE*	*t value*	*Pr(>|t|)*	
(Intercept)	-17.8	7.34	-2.43	1.56E-02	**
Contracts	6.54	1.68	3.9	1.09E-04	***
Sales	20.9	7.91	2.65	8.37E-03	***
CCWY:Sales	-9.88	7.95	-1.24	2.15E-01	
% Underground	0.132	0.242	0.546	5.85E-01	
Coal Price	21.1	12.5	1.68	9.28E-02	*
2111 Est.	9.73	5.38	1.81	7.13E-02	*
2131 Est.	19.5	2.91	6.71	4.54E-11	***
2122 Est.	-79	41.6	-1.9	5.77E-02	*
2123 Est.	5.79	11.4	0.508	6.12E-01	
Population	50.1	21.9	2.29	2.26E-02	**
Density	-20.2	15.6	-1.29	1.97E-01	
GDP	57.6	23.1	2.5	1.27E-02	**
% GDP Min.	9.58	1.97	4.85	1.56E-06	***
Observations	617				
Sample	Coal Counties				
Panel Groups	142				
Time Groups	5				
RMSE	156				
R^2	0.302				
Adjusted R^2	0.286				

Signif. codes: *** ≤ 0.01; ** ≤ 0.05; * ≤ 0.1.

We find that the idiosyncratic errors are serially correlated for both the utility and mining sector models ($p \leq 0.01$). On the other hand, we find that the differenced errors are not serially correlated for the utility sector models ($p > 0.1$) but are for the mining sector models ($p \leq 0.01$). This suggests that the FDM specification could be better suited for the utility sector modeling conducted herein.

FEMs provide consistent but not efficient estimates for our β coefficients if the residuals are serially correlated [89]. In its presence, we can control for serial correlation (and heteroskedasticity) by computing robust standard errors clustered by group [92]. This helps to alleviate the concerns with serial correlation when evaluating statistical significance associated with our modeled β coefficients.

Mixed Effects

With FEMs, the assumption is that the county-specific and year-specific effects are correlated with our regressors. However, if this is not the case, we may want to use a mixed effects model (MEM) [90], [98], [99].[28] With these models, the assumption is that group effects are uncorrelated with our regressors. MEMs allow us to address and assess the data's hierarchical nature, where the overall population's effect (i.e., the fixed effect) varies from group to group (i.e., the random effects).[29] With MEMs, we do not remove group heterogeneity as we do with fixed effects and first-differenced specifications; instead, we model it via random effects.

MEMs allow for partial pooling, a compromise between complete pooling (i.e., pooled OLS) and no pooling (i.e., FEMs). The amount of pooling is optimally determined considering group sample size and within- and between-group variance. The resulting models provide overall effects for the population (i.e., the fixed effects) from which groups deviate via random effects; these make up the mixed effects. Equation B14 show the MEM framework where random effects are introduced for counties:

Equation B14. Regression Modeling: Mixed Effects.

$$y_{ct} = \beta_{1,c}x_{1,ct} + \beta_{2,c}x_{2,ct} + Z_{ct}\theta + \alpha_c + \varepsilon_{ct}$$

$$\alpha_c = \lambda_0 + r_{0,c}$$

$$\beta_{1,c} = \lambda_1 + r_{1,c}$$

$$\beta_{2,c} = \lambda_2 + r_{2,c}$$

The difference between Equation B14 and Equation B12, depicting the pooled OLS model, are the three terms further broken down. α_c represents the mixed effects term for the intercept. $\beta_{1,c}$ represents the mixed effects term for the average change in jobs with an additional unit of $x_{1,ct}$. $\beta_{2,c}$ represents the mixed effects term for the average change in jobs with an additional unit of $x_{2,ct}$. Each mixed effects term has two components: a fixed/population effect, λ, and random effects by county, r. For this study, we care about λ.

Keeping in mind our influential outlier (Campbell County, WY) in the mining sector, this method is particularly advantageous because we can introduce random effects to the associations between the dependent variables and independent variables (i.e., to the β coefficients). This could be important if the associations between the variables significantly vary from group to group. This acts similarly to the interaction terms introduced for the FEMs but applies to every county. We estimate two groups of MEMs for the utility and mining sectors:

[28] Mixed effects models, multi-level models, hierarchical models, and random effects models all generally refer to the same concept. There are nuances, but they are based in the same mathematics and theory.

[29] Fixed effects modeling is different than the fixed effects in the context of mixed effects modeling. Fixed effects in the context of mixed effects modeling refers to the overall “population effect.”

- Varying Intercepts: partial pooling intercepts (i.e., α constants) by county. In other words, we introduce random effects instead of fixed effects. With these models for the mining sector, we keep the interaction terms for Campbell County, WY.
- Varying Slopes: partial pooling of both intercepts and only the coal variables' slopes by county. We introduce random effects in place of fixed effects and also introduce random effects for our coefficients of interest. We assess random effects on the first coal variable and then the second coal variable independently from one another. Then, we assess random effects on both coal variables at the same time.

Table B18 shows the mixed effects models for the utility sector. Table B19 shows the mixed effects models for the mining sector. These models are constructed using the *lme4* R package [100].[30] Looking at the utility sector models, we see that the coefficients increase when using mixed effects rather than fixed effects for counties (i.e., varying intercepts). When also introducing random effects for the coal capacity variable (i.e., varying slopes), we see an even greater increase in the population effect of coal capacity. Contrarily, when introducing random effects for the coal generation variable, we see a decrease in the population effect of coal generation. These coefficient trends also exist when random effects are introduced for both coal variables. Overall, this suggests that the coal capacity marginal employment effect could be much higher than in our base case two-way FEM.

The mining sector models show that the coefficients remain relatively consistent when using mixed effects rather than fixed effects for counties. When also introducing random effects for the contracts variable, its coefficient increases while that for sales decreases. Contrarily, when introducing random effects for the sales variable (and notably removing the interaction term between Campbell County, WY, and sales), we see an increase in the population effect of sales and a decrease in that of contracts. When random effects are introduced for both coal variables, the coefficient for contracts is nearly equivalent to that in the base case two-way FEM, while that for sales is notably higher. This suggests that the sales marginal employment effect could be much higher than in our base case two-way FEM.

We evaluate whether fixed or random effects are better for our modeling using the Hausman test via the *plm* R package [91], [102]. This analysis effectively assesses the county FEMs and the varying intercepts MEMs. As previously discussed, the assumption with FEMs is that the group-specific effects are correlated with our regressors, whereas the assumption with MEMs is that they are not. The null hypothesis of the Hausman test is that the group-specific effects are not correlated with the regressors, indicating exogeneity.

We find that the group-specific effects are indeed correlated with the regressors for both sectors ($p \leq 0.01$). Hence, introducing random rather than fixed effects increases the risk of omitted variable bias, which may confound the parameter estimates we care about. Still, by choosing a FEM over a MEM specification, we may be misrepresenting the population effects of our coal variables due to the influence of individual counties' unique effects (e.g., Campbell County, WY, on sales without an interaction term).

[30] The R^2 statistics presented for the mixed-effects models are the marginal R^2 statistics, or the variance explained by the fixed/population effects [101]. The adjusted R^2 statistics presented for the mixed-effects models take the number of population/fixed effects predictors into account.

Table B18. Mixed effects alternative utility sector models.

Utility sector employment mixed effects model: Intercept random effects.

Coefficients	*Beta*	*SE*	*t value*	*Pr(>|t|)*	
(Intercept)	-52.6	43.5	-1.21	2.27E-01	
Coal Cap.	61.6	17.3	3.55	3.92E-04	***
Coal Gen.	13.6	3.33	4.09	4.55E-05	***
Nat. Gas Cap.	-2.48	18.9	-0.131	8.96E-01	
Nat. Gas Gen.	-5.12	4.17	-1.23	2.20E-01	
Nuc. Cap.	318	265	1.2	2.30E-01	
Nuc. Gen.	-2.5	31.4	-0.0798	9.36E-01	
Ren. Cap.	-142	61.3	-2.32	2.03E-02	**
Ren. Gen.	-14.5	19.1	-0.759	4.48E-01	
Other Cap.	-1.16	36.6	-0.0317	9.75E-01	
Other Gen.	23.9	41.5	0.575	5.66E-01	
Coal Cost	8.58	10.5	0.817	4.14E-01	
Gas Cost	-0.569	1.3	-0.438	6.61E-01	
2212 Est.	17.7	4.76	3.71	2.13E-04	***
2213 Est.	25.5	2.4	10.6	6.67E-25	***
Population	1.11	0.153	7.25	8.16E-13	***
Density	-0.0414	0.0561	-0.738	4.61E-01	
GDP	0.677	1.95	0.348	7.28E-01	
% GDP Util.	-1.79	1.56	-1.14	2.53E-01	
Observations	1464				
Sample	Coal Counties				
Panel Groups	290				
Time Groups	6				
RMSE	87.8				
R^2	0.734				
Adjusted R^2	0.731				

Signif. codes: *** ≤ 0.01; ** ≤ 0.05; * ≤ 0.1.

Mining sector employment mixed effects model: Intercept & capacity random effects.

Coefficients	*Beta*	*SE*	*t value*	*Pr(>|t|)*	
(Intercept)	-58.1	39.2	-1.48	1.39E-01	
Coal Cap.	83.0	44.3	1.87	6.28E-02	*
Coal Gen.	12.3	3.09	3.99	6.99E-05	***
Nat. Gas Cap.	-25.3	19.1	-1.32	1.86E-01	
Nat. Gas Gen.	-2.88	3.97	-0.727	4.67E-01	
Nuc. Cap.	273	225	1.21	2.26E-01	
Nuc. Gen.	5.54	27	0.205	8.38E-01	
Ren. Cap.	-61.2	54.2	-1.13	2.58E-01	
Ren. Gen.	-14.9	16.8	-0.884	3.77E-01	
Other Cap.	-4.46	32.9	-0.136	8.92E-01	
Other Gen.	52.7	41.6	1.27	2.06E-01	
Coal Cost	18.8	9.68	1.94	5.23E-02	*
Gas Cost	-0.729	1.11	-0.659	5.10E-01	
2212 Est.	14.1	4.22	3.35	8.21E-04	***
2213 Est.	25.1	2.06	12.2	2.29E-31	***
Population	0.801	0.132	6.08	1.77E-09	***
Density	-0.116	0.0466	-2.48	1.37E-02	**
GDP	5.34	1.69	3.15	1.67E-03	***
% GDP Util.	0.431	1.73	0.249	8.04E-01	
Observations	1464				
Sample	Coal Counties				
Panel Groups	290				
Time Groups	6				
RMSE	72.5				
R^2	0.591				
Adjusted R^2	0.585				

Signif. codes: *** ≤ 0.01; ** ≤ 0.05; * ≤ 0.1.

Mining sector employment mixed effects model: Intercept & generation random effects.

Coefficients	*Beta*	*SE*	*t value*	*Pr(>|t|)*	
(Intercept)	-80.7	40	-2.02	4.40E-02	**
Coal Cap.	71.0	17.9	3.96	7.95E-05	***
Coal Gen.	4.50	5.69	0.792	4.30E-01	
Nat. Gas Cap.	-11.9	19.4	-0.616	5.38E-01	
Nat. Gas Gen.	-5.69	4.22	-1.35	1.77E-01	
Nuc. Cap.	229	260	0.882	3.78E-01	
Nuc. Gen.	7.04	31.6	0.223	8.24E-01	
Ren. Cap.	-90.3	59.1	-1.53	1.26E-01	
Ren. Gen.	-22	18.3	-1.2	2.30E-01	
Other Cap.	9.13	37.6	0.243	8.08E-01	
Other Gen.	8.77	42.1	0.208	8.35E-01	
Coal Cost	9.77	10.4	0.935	3.50E-01	
Gas Cost	-0.097	1.26	-0.0772	9.38E-01	
2212 Est.	19.2	4.58	4.2	2.85E-05	***
2213 Est.	24.2	2.18	11.1	1.94E-26	***
Population	1.12	0.14	8.05	2.68E-15	***
Density	-0.0501	0.0484	-1.04	3.01E-01	
GDP	1.13	1.83	0.615	5.39E-01	
% GDP Util.	4.15	2.17	1.91	5.62E-02	*
Observations	1464				
Sample	Coal Counties				
Panel Groups	290				
Time Groups	6				
RMSE	83				
R^2	0.758				
Adjusted R^2	0.755				

Signif. codes: *** ≤ 0.01; ** ≤ 0.05; * ≤ 0.1.

Mining sector employment mixed effects model: Intercept & both coal variable random effects.

Coefficients	*Beta*	*SE*	*t value*	*Pr(>|t|)*	
(Intercept)	-62	39.1	-1.58	1.14E-01	
Coal Cap.	97.2	45.5	2.14	3.44E-02	**
Coal Gen.	6.93	3.95	1.76	8.41E-02	*
Nat. Gas Cap.	-28.5	19.2	-1.48	1.38E-01	
Nat. Gas Gen.	-3.46	3.97	-0.871	3.84E-01	
Nuc. Cap.	237	226	1.05	2.94E-01	
Nuc. Gen.	10.6	27.1	0.391	6.96E-01	
Ren. Cap.	-49.9	54.1	-0.923	3.56E-01	
Ren. Gen.	-18.7	16.9	-1.11	2.68E-01	
Other Cap.	2.54	33.2	0.0765	9.39E-01	
Other Gen.	40.6	41.4	0.981	3.27E-01	
Coal Cost	17.9	9.72	1.85	6.49E-02	*
Gas Cost	-0.557	1.1	-0.508	6.11E-01	
2212 Est.	14.5	4.22	3.45	5.85E-04	***
2213 Est.	25	2.05	12.2	3.54E-31	***
Population	0.798	0.131	6.09	1.67E-09	***
Density	-0.112	0.0462	-2.43	1.59E-02	**
GDP	5.51	1.69	3.26	1.16E-03	***
% GDP Util.	2.05	1.88	1.09	2.76E-01	
Observations	1464				
Sample	Coal Counties				
Panel Groups	290				
Time Groups	6				
RMSE	71				
R^2	0.595				
Adjusted R^2	0.590				

Signif. codes: *** ≤ 0.01; ** ≤ 0.05; * ≤ 0.1.

Table B19. Mixed effects alternative mining sector models.

Mining sector employment mixed effects model: Intercept random effects.

Coefficients	*Beta*	*SE*	*t value*	*Pr(>|t|)*	
(Intercept)	-214	61.4	-3.48	5.51E-04	***
Contracts	9.76	1.8	5.41	8.47E-08	***
Sales	35.6	6.16	5.78	1.16E-08	***
CCWY:Sales	-33.9	5.54	-6.11	1.75E-09	***
% Underground	0.383	0.266	1.44	1.51E-01	
Coal Price	48.7	13.1	3.71	2.21E-04	***
2111 Est.	21.3	3.71	5.75	1.28E-08	***
2131 Est.	23.7	1.63	14.5	3.73E-40	***
2122 Est.	-150	37.4	-4.02	6.59E-05	***
2123 Est.	2.97	6.04	0.492	6.23E-01	
Population	3.67	1.14	3.21	1.48E-03	***
Density	-1.25	0.634	-1.96	5.17E-02	*
GDP	-16.2	10.5	-1.54	1.24E-01	
% GDP Min.	5.93	1.31	4.53	7.36E-06	***
Observations	765				
Sample	Coal Counties				
Panel Groups	148				
Time Groups	6				
RMSE	137				
R^2	0.840				
Adjusted R^2	0.837				

Signif. codes: *** ≤ 0.01; ** ≤ 0.05; * ≤ 0.1.

Mining sector employment mixed effects model: Intercept & contracts random effects.

Coefficients	*Beta*	*SE*	*t value*	*Pr(>|t|)*	
(Intercept)	-191	58.1	-3.28	1.12E-03	***
Contracts	12.8	4.6	2.78	7.45E-03	***
Sales	31.9	6.86	4.66	3.82E-06	***
CCWY:Sales	-20.4	7.71	-2.65	8.33E-03	***
% Underground	0.224	0.254	0.883	3.78E-01	
Coal Price	42.6	12.3	3.45	5.97E-04	***
2111 Est.	17.8	3.58	4.96	8.95E-07	***
2131 Est.	24.9	1.55	16.1	9.95E-47	***
2122 Est.	-108	38.7	-2.8	5.30E-03	***
2123 Est.	3.27	5.63	0.58	5.63E-01	
Population	3.89	1.06	3.67	2.99E-04	***
Density	-1.41	0.592	-2.39	1.83E-02	**
GDP	-16.2	9.72	-1.67	9.62E-02	*
% GDP Min.	5.77	1.25	4.59	5.50E-06	***
Observations	765				
Sample	Coal Counties				
Panel Groups	148				
Time Groups	6				
RMSE	122				
R^2	0.634				
Adjusted R^2	0.627				

Signif. codes: *** ≤ 0.01; ** ≤ 0.05; * ≤ 0.1.

Mining sector employment mixed effects model: Intercept & sales random effects.

Coefficients	*Beta*	*SE*	*t value*	*Pr(>|t|)*	
(Intercept)	-149	55.7	-2.68	7.71E-03	***
Contracts	5.18	2	2.58	9.95E-03	***
Sales	63.8	15.2	4.19	8.81E-05	***
% Underground	0.373	0.242	1.55	1.23E-01	
Coal Price	48.9	11.9	4.1	4.65E-05	***
2111 Est.	11.7	3.66	3.19	1.50E-03	***
2131 Est.	18.4	1.67	11	1.00E-25	***
2122 Est.	-59.4	39.4	-1.51	1.32E-01	
2123 Est.	2.6	5.25	0.495	6.21E-01	
Population	4.02	1.01	3.97	9.74E-05	***
Density	-1.41	0.558	-2.53	1.26E-02	**
GDP	-14.5	9.26	-1.56	1.18E-01	
% GDP Min.	6.06	1.21	5.01	7.73E-07	***
Observations	765				
Sample	Coal Counties				
Panel Groups	148				
Time Groups	6				
RMSE	118				
R^2	0.386				
Adjusted R^2	0.376				

Signif. codes: *** ≤ 0.01; ** ≤ 0.05; * ≤ 0.1.

Mining sector employment mixed effects model: Intercept & both coal variable random effects.

Coefficients	*Beta*	*SE*	*t value*	*Pr(>|t|)*	
(Intercept)	-156	55.8	-2.8	5.38E-03	***
Contracts	9.46	4.05	2.34	2.42E-02	**
Sales	57.2	15	3.82	5.07E-04	***
% Underground	0.288	0.239	1.2	2.30E-01	
Coal Price	46.2	11.7	3.95	8.58E-05	***
2111 Est.	11.5	3.6	3.19	1.48E-03	***
2131 Est.	19.1	1.67	11.4	1.86E-27	***
2122 Est.	-67.4	39.2	-1.72	8.63E-02	*
2123 Est.	3.96	5.29	0.749	4.55E-01	
Population	3.9	1.01	3.88	1.38E-04	***
Density	-1.35	0.559	-2.42	1.73E-02	**
GDP	-14.2	9.15	-1.56	1.20E-01	
% GDP Min.	6.17	1.21	5.11	4.74E-07	***
Observations	765				
Sample	Coal Counties				
Panel Groups	148				
Time Groups	6				
RMSE	112				
R^2	0.426				
Adjusted R^2	0.417				

Signif. codes: *** ≤ 0.01; ** ≤ 0.05; * ≤ 0.1.

Model Evaluation Summary

We conclude modeling evaluation efforts by comparing the evaluated utility and mining sector models discussed herein. We begin by noting that the R^2 values should be interpreted carefully as they characterize different things for different models: within-group variation explained for FEMs, within- and between-group variation explained for pooled OLS, and variation explained by the population effects (rather than random effects or the entire model) for MEMs.[31] The RMSEs can be evaluated across the different models without interpretation caveats.

Overall, the RMSEs for our base case two-way FEMs are only outperformed by certain MEM alternatives that use varying slopes (i.e., random effects on the coal variables). This makes some sense, as we are introducing further complexity to the models without further penalizing the performance metric. (Herein, we only compute the RMSEs considering k as the number of coefficients—see Equation B7.) Either way, our Hausman tests advise us against using random effects due to endogeneity, which may result in omitted variable bias that confounds our β coefficient estimates.

Our statistical testing for serial correlation within the original and differenced errors suggests that the first-differenced specification may be preferred, at least for the utility sector. Here, however, we examine the resulting coefficients from our various models. First, we can ignore the pooled OLS estimates, as the data's structure makes it a poor option. Otherwise, we see that the FDMs suggest lower coefficients and the MEMs suggest much higher coefficients for capacity and sales (when random effects are introduced).

Base Case Model Selection

We choose the two-way FEM specification as our preferred option, as it offers a middle-ground option for the coefficients (between FDMs and MEMs). We compute robust standard errors according to [92] to curtail concerns of serial correlation and any heteroskedasticity. We identify and control for the unique effect of Campbell County, WY's sales on jobs to better estimate the population effect rather than that influenced by a group with high leverage and discrepancy. Lastly, the calculated CIs (Table B10) cover most of the coefficients computed in the alternative models (i.e., Table B11 through Table B19).

ESTIMATING LOST JOBS & WAGES

Recall that for retrospective avoided damage benefits, we compute the difference between damages that were and damages that would have been given a 2014 counterfactual emissions scenario (i.e., without the changes due to decline and improvement). We do this by multiplying the difference in emissions, say SO_2 in 2017 versus SO_2 in 2014, times the associated MDs (dollars per ton) for the year that the emissions are "missing."

Here, our methodology is similar. We estimate changes in jobs considering coal variables that were and coal variables that would have been given a 2014 counterfactual economic activity scenario (i.e., without the decline of the coal industry). We do this by multiplying the difference in the coal variables, say TWh from coal in 2017 versus TWh from coal in 2014, times the associated marginal employment effect (jobs per TWh) for the year that the coal activity is "missing."

Employment Changes Associated with Coal Variables

Changes in Coal's Utility and Mining Variables

Table B20 summarizes our coal variables each year from 2014 to 2019. Capacity data are from [68], generation data are from [84], contracts data are from [84], and sales data are from [84]. The

[31] For FDMs, it is the variation in the year-to-year differences of the dependent variable explained by the variation in the year-to-year differences of the independent variables.

data cover all CONUS counties. For more details, see “Coal Variables” located in the “Utility and Mining Sector Panel Datasets” subsection.

In Table B20, coal sales are reported nationally but are also divided depending on whether they were from Campbell County, WY, or somewhere else in the U.S. This is an essential step due to the adjustment we apply to the marginal employment effect of coal sales in Campbell County via the coefficient of the interaction term (Table B9). Notably, Campbell County accounts for a very large amount of national coal sales.

Table B20. Coal capacity, generation, contracts, and sales in the U.S.

Sector	Coal Variable	Coal Industry Activity					
		2014	2015	2016	2017	2018	2019
Utility	Capacity (GW)	331	321	299	286	279	263
	Generation (TWh)	1,581	1,347	1,239	1,204	1,148	961
Mining	Contracts (#)	1,712	1,313	1,185	1,038	1,016	1,022
	Total Sales (Million Short Tons)	846	776	644	637	593	556
	Sales Not from Campbell County, WY	499 (59%)[A]	448 (58%)	387 (60%)	360 (57%)	334 (56%)	316 (57%)
	Sales from Campbell County, WY	347 (41%)[B]	327 (42%)	257 (40%)	277 (43%)	260 (44%)	240 (43%)

Sources: Data are from the EIA [68], [84].
Notes: A = percent of total coal sales not from Campbell County, WY. B = percent of total coal sales from Campbell County, WY. All coal sales variables are in million short tons of coal.

Using Marginal Employment Effects to Estimate Job Losses

We now employ our marginal employment effects (i.e., the coefficients from Table B8 and Table B9) to estimate job changes associated with the coal variable changes seen in Table B20. Multiplying the marginal employment effects by coal variable changes versus a 2014 counterfactual provides job-year changes. As opposed to annual job changes (i.e., year over year), this measure accounts for the same job being gone over time—assuming decreased activity that drives the job loss is the continued driver of that job not existing in the years after. Table B21 reports changes in job-years and annual jobs each year from 2015 to 2019 relative to a 2014 counterfactual. It also aggregates for a five-year total.

As discussed in the main paper, this methodology very likely overestimates unemployment. Using concepts from the trade literature, namely *adjustment*—i.e., employment contractions—and *efficiency*—i.e., displaced workers finding other jobs—a related study estimated county-level employment losses and foregone earnings due to the reduction in U.S. coal mining [103]. We only capture the former of the trade literature concepts (adjustment) and not the latter (efficiency). In other words, we ignore that some workers will quickly find new work. In fact, some may seamlessly transition from working with a coal EGU to a natural gas EGU at the same facility; however, this would be a phenomenon limited to the utility sector. Still, understanding the gross job losses in the industry is helpful for understanding the changing economic landscape in coal communities, which tend to depend strongly on coal [104], [105].

Table B21. Lost employment by associated coal variable.

Employment Variable	Sector	Associated Coal Variable	Change in Coal Employment 2015	2016	2017	2018	2019	Five-Year Total
Job-Years (Thousands)	Utility	**Sector Total**	**-2.60**	**-4.46**	**-5.28**	**-6.10**	**-8.49**	**-26.9**
		Capacity	-0.355	-1.18	-1.66	-1.94	-2.54	-7.68
		Generation	-2.25	-3.28	-3.62	-4.16	-5.95	-19.3
	Mining	**Sector Total**	**-5.47**	**-9.47**	**-11.6**	**-13.0**	**-13.7**	**-53.2**
		Contracts	-3.34	-4.42	-5.65	-5.83	-5.78	-25.0
		Sales	-2.12	-5.06	-5.96	-7.12	-7.94	-28.2
		Not from Campbell County	-1.97	-4.36	-5.41	-6.44	-7.11	-25.3
		From Campbell County	-0.156	-0.701	-0.550	-0.684	-0.838	-2.93
Annual Jobs (Thousands)	Utility	**Sector Total**	**-2.60**	**-1.86**	**-0.816**	**-0.819**	**-2.39**	**-8.49**
		Capacity	-0.355	-0.827	-0.481	-0.278	-0.596	-2.54
		Generation	-2.25	-1.03	-0.334	-0.541	-1.80	-5.95
	Mining	**Sector Total**	**-5.47**	**-4.01**	**-2.13**	**-1.35**	**-0.773**	**-13.7**
		Contracts	-3.34	-1.07	-1.23	-0.184	0.0500	-5.78
		Sales	-2.12	-2.94	-0.900	-1.16	-0.823	-7.94
		Not from Campbell County	-1.97	-2.39	-1.05	-1.03	-0.669	-7.11
		From Campbell County	-0.156	-0.546	0.151	-0.133	-0.154	-0.838

Notes: Job-years are cumulative lost working years compared to 2014, assuming no reemployment. Annual jobs are job changes compared to the previous year. Data are computed using changes from Table B20 and coefficients from Table B8 for the utility sector and Table B9 for the mining sector. Sales from Campbell County, WY, are subject to the interaction term in Table B9.

Uncertainty with Job Changes—w/ Coefficient Correlation

We evaluate uncertainty in two ways. The first accounts for the correlation between coefficient estimates. The process employs the block sample bootstrapping procedure (discussed in the "Confidence Intervals" subsection).[32] This provides coefficient "pairings" for each resample, which are used to estimate job-year losses—resulting in one distribution of utility sector job-year losses and another distribution of mining sector job-year losses. We identify the 5th and 95th percentile of job-year loss estimates, with an associated coefficient pairing that differs from the 90% CIs of the coefficients. Put simply, here, we use lower- and upper-bound models rather than lower- and upper-bound individual coefficients. The lower and upper bound correlated coefficients are as follows:

- Lower Bound Job-Year Losses
  - Utility Sector: 42.0 jobs per GW & -0.814 jobs per TWh.
  - Mining Sector: 4.91 jobs per contract, 23.8 jobs per million short tons of coal sales, and an adjustment of -9.95 jobs per million short tons of coal in Campbell County, WY.
- Upper Bound Job-Year Losses
  - Utility Sector: 34.9 jobs per GW & 17.9 jobs per TWh.

[32] We prefer block sample bootstrapping versus random sample bootstrapping so as to maintain counties' dependence structures between years [89].

- Mining Sector: 6.43 jobs per contract, 58.4 jobs per million short tons of coal sales, and no adjustment for sales from Campbell County, WY.

Notice that not every coefficient making up the models does what we would expect. For example, the coefficient for jobs per GW increases from 37.2 to 42.0 in the lower bound model. This is because the correlated change in jobs per TWh goes from 9.61 to less than zero. This makes sense as, from Table B21, coal generation is a more significant driver of job losses (72%) than coal capacity (28%) in the base case scenario.

For the mining sector's lower-bound model, both principal coefficients decrease, but Campbell County, WY's adjustment interacts with sales such that we estimate more lost job-years there than in the base case model.

We see similar occurrences for the upper-bound job-year loss estimates, where the coefficients for both coal capacity in the utility sector and mining contracts in the mining sector go down to make way for large increases for coal generation in the utility sector and sales in the mining sector. Moreover, in the mining sector, we now see no adjustment factor for Campbell County, WY, indicating that the upper bound model results from a block resample that excludes Campbell County.

We emphasize that these employment loss estimates are associated with changes in the evaluated coal variables. Therefore, we do not expect to capture all job losses, including those driven by other factors. This is helpful to remember when we evaluate our estimates against national coal mining data after reviewing the next way to address uncertainty with our labor modeling.

Uncertainty with Job Changes—w/o Coefficient Correlation

The second way of dealing with uncertainty ignores the correlation between coefficient estimates. The process employs the block sample bootstrapped 90% CI for each coefficient. The exception to this rule is the adjustment for Campbell County, WY. We do not take the lower end 90% CI estimate (-47.3 jobs per million short tons of sales) for the lower bound estimate but rather compute an estimate considering the ratio of the base case adjustment from the population coefficient for sales (-31.1) and the base case population coefficient of sales itself (38.9). The ratio is about -80%. Hence, we use that to get a reasonable adjustment for the lower bound.[33]

We again note that if we do not explicitly model the interaction term for Campbell County, WY, which we do not for many block sample bootstrapping resamples, it is inherently zero. Therefore, without Campbell County in the sample, we assume its adjustment for the coal sales coefficient is zero.

Uncertainty with Job Changes Discussion

There are arguments for either using the correlated coefficient approach or the independent coefficient approach for assessing uncertainty with job changes. Given our goals for this study, we are more concerned with the upper bound estimates (i.e., to compare benefits to costs and show how substantially the former outweigh the latter). Two follow-up, first-order assessments help guide our decision to use the correlated coefficient approach.

[33] Without this methodology, the coefficient for Campbell County employment associated with sales would be -30.1 jobs per million short tons of coal sales, which is unreasonable. We do not expect that Campbell County would add about 30 more jobs for every one million short ton loss of coal sales.

First, considering the 97.5th percentile of lost jobs from the block sample bootstrapped pairings, we still achieve lower job-year losses than the independent coefficient approach estimates. With the 99th percentile, we only just surpass the estimate for utility sector lost job-years but still do not for the mining sector. In other words, nearly no correlated pairings result in the employment losses estimated by the uncorrelated coefficient approach.

Second, we investigate national coal mining job changes from 2014 to 2019 from FRED [106]. We find that 73.2 thousand employees in 2014 decreased to 50.5 thousand in 2019, a difference of 22.7 thousand. Our lost mining job estimates using the correlated coefficient approach are 21.4 thousand, while those determined using the independent coefficient approach are 26.0 thousand. Circling back to the fact that we are only identifying job losses driven by the industry's decline, our base case estimate of 13.7 thousand makes sense.[34] Nevertheless, an upper bound estimate exceeding the total lost jobs associated with every driving factor does not.

Table B22 shows the lower and upper estimates for lost employment each year by coal industry sector using the correlated coefficient approach.

Table B22. Lower and upper estimates for lost employment by associated U.S. coal sector.

Employment Variable	Estimate	Coal Sector	Change in Coal Employment 2015	2016	2017	2018	2019	Five-Year Total
Job-Years (Thousands)	Lower	Utility	-0.210	-1.06	-1.57	-1.84	-2.36	-7.04
		Mining	-3.44	-6.51	-7.61	-8.58	-9.24	-35.4
	Upper	Utility	-4.53	-7.23	-8.31	-9.57	-13.5	-43.1
		Mining	-6.69	-15.2	-16.6	-19.3	-21.4	-79.1
Annual Jobs (Thousands)	Lower	Utility	-0.210	-0.846	-0.515	-0.268	-0.521	-2.36
		Mining	-3.44	-3.07	-1.10	-0.976	-0.656	-9.24
	Upper	Utility	-4.53	-2.70	-1.08	-1.27	-3.91	-13.5
		Mining	-6.69	-8.51	-1.39	-2.68	-2.12	-21.4

Notes: Lower and upper bounds are selected as the 5th and 95th percentile of job-year loss estimates from correlated pairing of coefficients using block sample bootstrapping. Job-years are cumulative lost working years compared to 2014, assuming no reemployment. Annual jobs are job changes compared to the previous year.

Costs from Lost Wages

Annual Compensation Per Worker

We obtain annual compensation information for coal industry employees each year from the BLS's QCEW data [83]. The data are reported for each year regionally and by economic activity via NAICS classification. For utility sector jobs, we use wage data for Fossil Fuel Electric Power Generation (NAICS code 221112). For mining sector jobs, we use wage data for Coal Mining (NAICS code 2121). We assume that most job losses within the utility and mining sectors driven by our coal variables are experienced by coal plant and coal mine workers, respectively.

At the state level, we divide the total wages paid by the number of employees reported yearly to get regional compensation per worker estimates. QCEW wage data include base pay and other forms of compensation such as bonuses, investment options, severance pay, and, for some states, employer contributions to specific retirement plans [83]. Where state data are unavailable, first, census division averages, then census region averages, then the national average are

[34] We isolate for the effects of coal's decline versus other factors like technological advancements (e.g., automation).

substituted as necessary to capture regional wage differences best. We adjust nominal values for inflation to 2020 USD [43].

The average wage lost by utility sector workers was $117 thousand per year. The average wage lost by mining sector workers was $88.5 thousand per year.

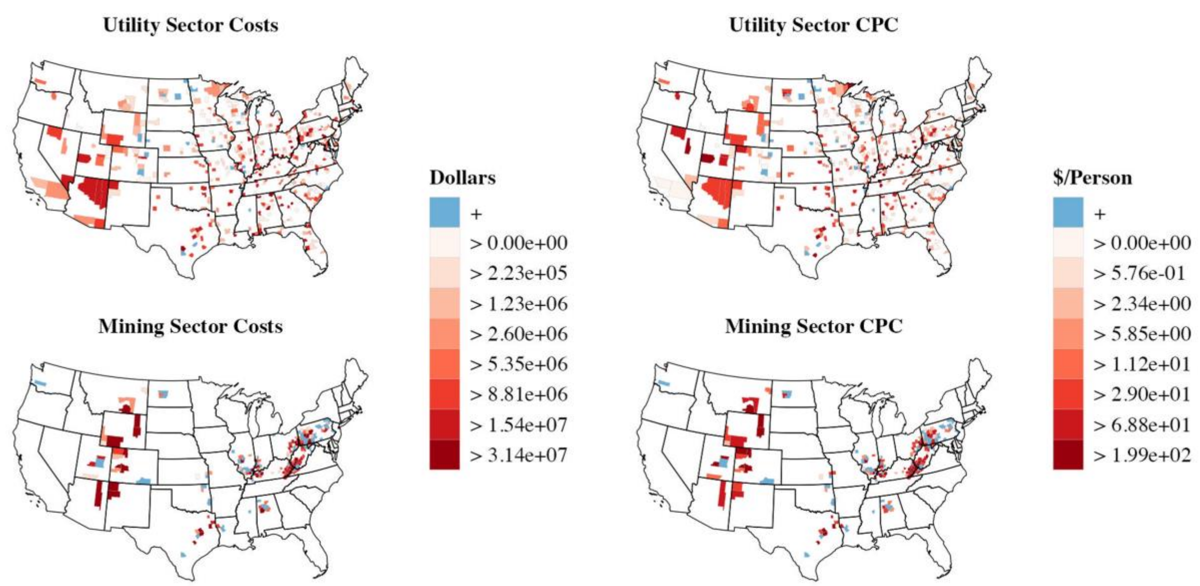
Estimating Lost Wages

To estimate lost wages (Table B23), we multiply job-year losses comprising the aggregate totals shown in Table B21 by state- and year-specific wages for each economic activity.

Table B23. Lost wages by associated coal variable.

Sector	Associated Coal Variable	Costs from Lost Coal Wages (Billion $)					
		2015	2016	2017	2018	2019	Five-Year Total
Utility	**Sector Total**	**-0.301**	**-0.509**	**-0.614**	**-0.714**	**-1.00**	**-3.14**
	Capacity	-0.0425	-0.135	-0.194	-0.227	-0.298	-0.896
	Generation	-0.259	-0.374	-0.420	-0.487	-0.699	-2.24
Mining	**Sector Total**	**-0.482**	**-0.821**	**-1.034**	**-1.15**	**-1.22**	**-4.71**
	Contracts	-0.295	-0.378	-0.499	-0.515	-0.506	-2.19
	Sales	-0.187	-0.444	-0.535	-0.634	-0.715	-2.51
Industry Total		**-0.783**	**-1.33**	**-1.65**	**-1.86**	**-2.22**	**-7.84**

Sources: Wage data are from the BLS [83].
Notes: Costs consider job-year losses from Table B21 and are in 2020 U.S. dollars. Wages are state- and year-specific.



Sources: Population data for costs per capita calculations are from the CDC [34]. Mapping uses the *usmap* R package [25].
Notes: Costs are five-year cumulative totals (2015 to 2019 vs. 2014) in 2020 U.S. dollars. Left map shows costs. Right map shows costs per capita (labeled CPC). Utility sector costs are foregone wages from lost jobs associated with changes in coal generation and capacity. Mining sector costs are foregone wages from lost jobs associated with changes in mining contracts and quantity of coal sales. Color scales divide county-sector costs and costs per capita into equally sized groups. Blue represents added wages.

Figure B8. Five-Year Costs and Costs Per Capita from Lost Coal Wages in the U.S. by County.

Figure B8 looks at the spatial distribution of five-year costs and costs per capita from 2015 to 2019 versus a 2014 counterfactual. Population data are from the CDC [34]. Costs are foregone wages from lost jobs associated with the change in coal generation and capacity in the utility sector and mining contracts and coal sales in the mining sector.

Utility sector costs were sparsely distributed in a manner that intuitively follows the location of coal plants. Table B24 shows the top five counties for most utility sector costs and costs per capita from foregone wages associated with coal's decline. Notably, these counties each lost at least one coal-fired power plant—via retirement or fuel conversion—over the timeline considered [68], [84]. We note that there is no overlap of counties with the greatest costs and the greatest costs per capita.

Mining sector costs were more regionally concentrated in counties with the Appalachian, Interior, and Western coal regions. Table B24 also shows the top five counties for most mining sector costs and costs per capita from foregone wages associated with coal's decline. Unlike the utility sector, there is a substantial overlap of counties with the greatest costs and the greatest costs per capita (four counties make both lists). The counties shown for the top five costs account for one-third of the total mining sector costs throughout CONUS. This contrasts with the utility sector, where the top five counties account for less than 10% of the total.

Table B24. Counties with the most costs and costs per capita from coal's decline in the U.S.

Measure	Sector	County	State	Costs (Million $)	Cumulative Percentage	Population (Thousand)	Costs Per Capita ($/Person)
Highest Costs	Utility	Beaver	PA	70.3	2.2%	830	84.7
		Will	IL	60.8	4.1%	3,450	17.6
		Muhlenberg	KY	50.7	5.7%	155	327
		Jackson	AL	49.8	7.2%	259	192
		Adams	OH	48.3	8.8%	139	348
	Mining	Campbell	WY	691	14%	237	2,910
		Greene	PA	460	23%	184	2,500
		Pike	KY	215	27%	298	724
		Union	KY	127	30%	73	1,730
		Converse	WY	125	32%	70	1,790
Highest Costs Per Capita	Utility	Morgan	OH	42.8	*NA*	73.2	584
		Jasper	IL	25.6	*NA*	47.9	535
		Greene	AL	21.9	*NA*	41.6	526
		Lawrence	KY	35.2	*NA*	78.4	449
		Pointe Coupee	LA	45.1	*NA*	110	409
	Mining	Campbell	WY	691	*NA*	237	2,910
		Greene	PA	460	*NA*	184	2,500
		Big Horn	MT	124	*NA*	67	1,850
		Converse	WY	125	*NA*	70	1,790
		Union	KY	127	*NA*	73	1,730

Sources: Population data for costs per capita calculations are from the CDC [34].
Notes: Costs are five-year cumulative totals (2015 to 2019 vs. 2014) in 2020 U.S. dollars. Utility sector costs are foregone wages from lost jobs associated with changes in coal generation and capacity. Mining sector costs are foregone wages from lost jobs associated with changes in mining contracts and quantity of coal sales. Data are reported to three significant figures.

Comparing values per capita in Table B24 vs. those from Table B4, we see that costs per capita in the utility sector were generally lower than benefits per capita of improved air quality from coal's decline, considering the most affected counties for both categories. On the other hand, costs per capita in the mining sector are notably higher for the most affected counties. Importantly, these costs per capita are normalized by the total county population, not the total coal worker count. Overall, Table B24 suggests that mining sector impacts may be more detrimental to coal communities. Knowing that more people not affected by coal's decline live where utility sector costs are incurred (i.e., lower costs per capita) indicates that those areas may be more economically diverse. That said, more research is required to confirm this hypothesis.

Lastly, we point out that Campbell County, WY, has both the greatest overall costs and costs per capita for foregone wages in the mining sector. The former is not all that surprising, given our observations in "County and Year Data Structure" located in the "Two-Way Fixed Effects Modeling" subsection (e.g., Figure B5). The latter is further evidence of the county's enormous coal mining economy. As a reminder, Campbell County is assigned a lower marginal employment effect for coal quantity sold changes than the rest of the country by quite some margin (80% lower). If we ignored Campbell County's interaction term and used the rest-of-the-country coefficient, these costs would be markedly higher. This, however, is not advisable. As outlined in the "Labor Market Modeling" section, Campbell County, WY, has a much lower coefficient for the quantity of coal sold than the rest of the country.

Uncertainty with Lost Wages

To evaluate uncertainty with lost wages (Table B25), we multiply job-year losses comprising the lower- and upper-bound totals shown in Table B22 by state- and year-specific wages for each economic activity.

Table B25. Lower and upper estimates for lost wages by associated U.S. coal sector.

Estimate	Coal Sector	Costs From Lost Coal Wages (Billion $)					
		2015	**2016**	**2017**	**2018**	**2019**	**Five-Year Total**
Lower	Utility	-0.0261	-0.120	-0.183	-0.216	-0.277	-0.822
	Mining	-0.304	-0.569	-0.682	-0.765	-0.828	-3.15
	Industry Total	**-0.330**	**-0.69**	**-0.86**	**-0.98**	**-1.11**	**-3.97**
Upper	Utility	-0.523	-0.824	-0.965	-1.12	-1.58	-5.02
	Mining	-0.594	-1.34	-1.50	-1.73	-1.94	-7.11
	Industry Total	**-1.12**	**-2.17**	**-2.46**	**-2.85**	**-3.52**	**-12.1**

Sources: Wage data are from the BLS [83].
Notes: Costs consider job-year losses from Table B22 and are in 2020 U.S. dollars. Wages are state- and year-specific.

We keep wage data constant for each scenario but acknowledge that lost jobs could tend to be compensated at lower or higher rates. For example, power plants and/or mines may let go of younger workers at lower pay scales, protecting their longer-term employees. On the other hand, firms may let go of older workers—who are likely paid more if they have worked at the firm for a long time—as a strategy to manage costs.

Net Benefits & Wage Replacement Policy Analysis

Table B26 shows the net benefit calculations comparing the five-year cumulative (2015 to 2019 vs. a 2014 counterfactual) avoided air pollution damages and lost wages from coal's decline. Table B26 shows three damage categories. The first is the manuscript's base case, which incorporates natural gas offsets (see the "Retrospective Damages from Natural Gas Substitution" subsection). This category excludes CO_2 benefits (due to the potential for methane leakage to offset GHG-derived benefits completely [76]) and offsets some criteria air pollution benefits (see Table B7). The other two damage categories do not consider natural gas offsets and incorporate either domestic or global CO_2 avoided damages. These damage categories either (1) ignore additional natural gas damages or (2) assume emissions-free alternatives substitute in for coal.

Net benefit uncertainty considers lower and upper estimates of net benefits themselves—i.e., the lower estimate has higher costs and lower benefits, and the upper estimate has lower costs and higher benefits. The ultimate result of the Table B26 is the last two columns: benefits minus costs and the ratio of costs to benefits. Each damage category includes central, lower, and upper benefit estimates (considering variable substations from Table A6), aligning with the central, lower, and upper net benefits estimates. Employment costs consider the base case, upper, and lower labor market impacts (see Table B23 and Table B25), aligning with the central, lower, and upper net benefits estimates.

Table B26. Five-year net benefits from avoided damages and lost wages from coal's decline in the U.S.

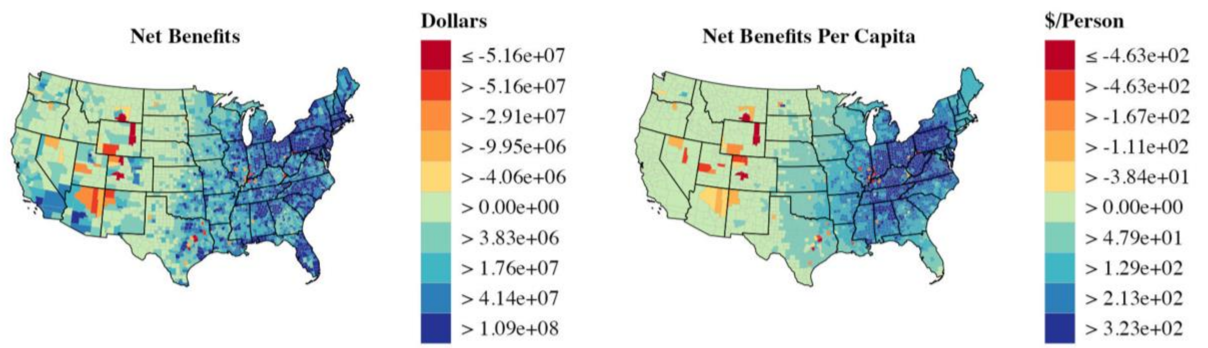
Labor Impacts	Damage Category	Estimate	Air Pollution Benefits (and Source)		Employment Costs (and Source)		Net Benefits	Costs / Benefits
Associated w/ Coal Variables	Base Case	Central	300	(Table B3) & (Table B7)	7.84	(Table B23)	293	2.6
		Lower	113	(Table B5) & (Table B7)	12.1	(Table B25)	101	11%
		Upper	634	(Table B6) & (Table B7)	3.97	(Table B25)	630	0.6%
	Domestic	Central	316	(Table B3)	7.84	(Table B23)	308	2.5%
		Lower	116	(Table B5)	12.1	(Table B25)	104	10%
		Upper	685	(Table B6)	3.97	(Table B25)	681	0.6%
	Global	Central	396	(Table B3)	7.84	(Table B23)	388	2.0%
		Lower	142	(Table B5)	12.1	(Table B25)	130	8.5%
		Upper	905	(Table B6)	3.97	(Table B25)	901	0.4%
Extrapolated Total	Base Case	Central	300	(Table B3) & (Table B7)	14.4	(via FRED)	286	4.8%
	Domestic	Central	316	(Table B3)	14.4	(via FRED)	302	4.5%
	Global	Central	396	(Table B3)	14.4	(via FRED)	382	3.6%

Sources: Extrapolated employment costs are derived using jobs data from FRED [106].

Notes: Benefits and costs are five-year cumulative totals (2015 to 2019 vs. 2014) in 2020 U.S. dollars. Uncertainty for net benefits takes lower benefits and upper costs for lower estimates and vice versa for upper estimates. Base case avoided damages models natural gas offsets for criteria air pollutants and assumes no CO_2 benefits. Domestic avoided damages exclude natural gas offsets and includes domestic CO_2 benefits. Global avoided damages exclude natural gas offsets and includes global CO_2 benefits. Uncertainty bounds for estimates use the variable substitutions from Table A6. Extrapolated totals consider that our modeling observes 55% of the total lost job-years in the mining sector when compared to FRED jobs data; both utility sector and mining sector wages are extrapolated. Sources for air pollution benefits and employment costs data are provided in parentheses.

Table B26 shows the labor impacts determined via the analysis conducted herein (i.e., associated with the assessed coal variables) but also extrapolates a “total” impact estimate for employment costs. This is a first-order assessment using data from FRED [106]. National coal mining lost job-years from 2015 to 2019 relative to a 2014 counterfactual amounted to 97.5 thousand. Our base case estimate for coal mining job-year losses, 53.2 thousand, is 55% of this. Recall that we isolate for losses associated with the industry’s decline via our coal variables to exclude job losses driven by other factors (e.g., automation). However, we can extrapolate total wage losses using this 55% ratio to get roughly $14.4 billion in lost wages—across both the utility and mining sectors.

Figure B9 looks at the spatial distribution of five-year net benefits and net benefits per capita from 2015 to 2019 versus a 2014 counterfactual. Population data are from the CDC [34]. Benefits are those from Figure B3, and costs are those from Figure B8.



Sources: Population data for net benefits per capita calculations are from the CDC [34]. Mapping uses the *usmap* R package [25].
Notes: Net benefits are five-year cumulative totals (2015 to 2019 vs. 2014) in 2020 U.S. dollars. Left map shows net benefits. Right map shows net benefits per capita. Benefits are from Figure B3. Costs are from Figure B8. Color scales divide counties with net benefits (and net benefits per capita) and net costs (and net costs per capita) each into equally sized groups. In contrast to Figure 3(C) of the manuscript, net benefits do not consider offsets from natural gas substitution, which are relatively minimal (see Table B7).

Figure B9. Five-Year Net Benefits and Net Benefits Per Capita from Coal’s Decline in the U.S. by County.

Table B27. Counties with the most net costs from coal’s decline in the U.S.

Measure	County	State	Benefits (Million $)	Costs (Million $)	Mining Sector Costs	Net Costs (Million $)	Net Costs Per Capita ($/Person)
Highest Net Costs	Campbell	WY	3.79	695	99%	691	2,910
	Greene	PA	120	460	100%	340	1,840
	Converse	WY	1.93	127	99%	125	1,790
	Big Horn	MT	1.70	126	98%	124	1,860
	Union	KY	34.9	127	100%	91.6	1,250
	Delta	CO	7.99	95.3	100%	87.4	572
	Gunnison	CO	1.76	84.6	100%	82.9	985
	Leon	TX	10.5	80.8	100%	70.2	815
	Lee	TX	7.70	74.6	100%	66.9	785
	Freestone	TX	11.7	65.7	67%	54.0	548

Sources: Population data for net costs per capita calculations are from the CDC [34].
Notes: Benefits and costs are five-year cumulative totals (2015 to 2019 vs. 2014) in 2020 U.S. dollars. Benefits are from avoided SO_2, NO_x, and primary $PM_{2.5}$. Utility sector costs are foregone wages from lost jobs associated with changes in coal generation and capacity. Mining sector costs are foregone wages from lost jobs associated with changes in mining contracts and quantity of coal sales. Data are reported to three significant figures. Reported benefits do consider offsets from natural gas substitution (see Table B7).

Counties with the greatest net benefits align closely with those with the greatest benefits (e.g., those home to Chicago, Detroit, Pittsburgh, and Cleveland). Counties with the greatest net costs are more interesting to look at. Table B27 shows the top ten. The takeaway is twofold. First, these counties (mostly) tend to be far removed from the historically coal-polluted East. The exceptions are Greene County, PA, and Union County, KY, which both had substantial five-year avoided air pollution benefits compared to the others on the list. Second, these counties are coal mining counties. Only one of the top 10 (Freestone County, TX) had utility sector losses exceeding 2% of the county total.

Eight of the 10 counties in Table B27 also have the greatest net costs per capita. The additional two are Pike County, IN, and Webster County, KY, which had \$808 per capita and \$617 per capita in net costs, respectively. (Note: Table B27, unlike Figure B9, accounts for offsets from natural gas substitution—see Table B7 and the associated discussion.)

Wage Replacement Policy Analysis

Table B28 summarizes a succinct wage replacement policy analysis. We multiply annual job losses each year (i.e., versus the previous year) by state- and year-specific compensation for x number of years. Wages are assumed to all be paid out instantaneously. x is a policy design variable that, in Table B28, we set to be 3, 5, 10, 15, or 20 years. The costs to replace wages, net benefits, and benefits-to-costs ratios are depicted.

The damages category used for the net benefits calculations is the manuscript's base case, which incorporates natural gas offsets (see the "Retrospective Damages from Natural Gas Substitution" subsection). This category excludes CO_2 benefits (due to the potential for methane leakage to offset GHG-derived benefits completely [76]) and offsets some criteria air pollution benefits (see Table B7).

Net benefit and benefits-to-costs ratio uncertainty consider lower and upper estimates of net benefits and benefits-to-costs ratios themselves—i.e., the lower estimates have higher costs and lower benefits, and the upper estimates have lower costs and higher benefits. The base case damages category includes benefit estimates of \$300 billion (central), \$113 billion (lower), and \$634 billion (upper)—uncertainty considering variable substations from Table A6—aligning with the central, lower, and upper net benefits and benefits-to-costs ratio estimates. Payments consider the base case, upper, and lower labor market models (those yielding results in Table B23 and Table B25), aligning with the central, lower, and upper net benefits and benefits-to-costs ratio estimates.

Table B28. Costs of wage replacement for lost U.S. coal jobs and net benefits considering avoided damages.

Number of Years	Wage Replacement Payment (Billion \$)			Net Benefits (Billion \$)			Benefits / Costs		
	Lower	**Central**	**Upper**	**Lower**	**Central**	**Upper**	**Lower**	**Central**	**Upper**
3	3.28	6.59	10.4	103	294	631	10.9	45.6	193
5	5.47	11	17.4	96.0	289	628	6.52	27.3	116
10	10.9	22	34.8	78.6	278	623	3.26	13.7	58.1
15	16.4	32.9	52.1	61.3	268	617	2.18	9.13	38.6
20	21.9	43.9	69.5	43.9	257	612	1.63	6.84	28.9

Notes: Dollar values are in billions of 2020 U.S. dollars. Wage replacement payments are paid out the year of job termination. Wages are state- and year-specific. Rows show select number of years of wage replacement payments. Net benefits consider the base case damage category.

We finalize this section by noting that, in the base case scenario with $300 billion in avoided damages from the decline of coal, the government could have replaced 136 years of wages for every job lost from 2014 to 2019 without incurring net costs.

Tax Revenue Replacement

Raimi et al. (2022) reported annual average downstream power government revenue from all fossil power plants of $2.1 billion in 2019 USD (or $2.12 billion in 2020 USD) nationally from 2015 to 2019 [107]. The study also reported annual average upstream government revenue from coal adding up to $3.1 billion in 2019 USD (or $3.13 billion in 2020 USD) in 21 states from 2015 to 2019, which accounted for 97.3% of U.S. coal production [107]. This normalizes to $3.22 billion in 2020 USD across 100% of coal production. This tax revenue has a variety of sources (e.g., severance, production, property, income, and sales) and primary recipients (e.g., local, state, tribal, and federal) [107].

Table B29. Downstream power government revenue from all fossil power plants.

Year	Electricity Generation (TWh)						Annual Revenue (Billion $)			Revenue Per Unit ($/GWh)
	Coal		Natural Gas		Petroleum & Other		Coal	Natural Gas	Petroleum & Other	
2015	1,352	49%	1,335	49%	50	1.8%	1.05	1.03	0.0387	775
2016	1,239	47%	1,379	52%	44	1.7%	0.987	1.10	0.0350	796
2017	1,206	47%	1,298	51%	40	1.6%	1.01	1.08	0.0333	833
2018	1,149	43%	1,472	55%	46	1.7%	0.913	1.17	0.0366	795
2019	965	37%	1,589	61%	39	1.5%	0.789	1.30	0.0319	818
Average	**1,182**	**45%**	**1,414**	**54%**	**43.8**	**1.7%**	**0.948**	**1.137**	**0.0351**	**803**

Sources: Tax revenue data are from Raimi et al. (2022) [107]. Electricity generation data are from [72].
Notes: Dollar values are in 2020 U.S. dollars. Computations assumes equal tax revenue per unit of electricity generation.

Table B30. Upstream government revenue from coal.

Year	Coal Mined (Million Short Tons)				Annual Revenue (Billion $)		Revenue Per Unit ($/Short Ton)
	Underground Mining		Surface Mining		Underground Mining	Surface Mining	
2015	394	34%	771	66%	1.09	2.13	2.76
2016	339	32%	729	68%	1.02	2.19	3.01
2017	344	32%	715	68%	1.04	2.17	3.04
2018	348	34%	673	66%	1.10	2.12	3.15
2019	354	35%	656	65%	1.13	2.09	3.19
Average	**356**	**33%**	**709**	**67%**	**1.08**	**2.14**	**3.03**

Sources: Tax revenue data are from Raimi et al. (2022) [107]. Coal mining data are from [108].
Notes: Dollar values are in 2020 U.S. dollars. Computations assumes equal tax revenue per unit of coal mined.

Table B29 uses the data from Raimi et al. (2022) and national electricity generation data by source from the EIA [72] to estimate revenue per unit of production. We assume equal tax revenue per GWh across coal, natural gas, and petroleum and other products. Table B29 suggests that coal accounted for $789 million to $1.05 billion in tax revenue each year from 2015 to 2019 and that the revenue per GWh of fossil fuel generation was approximately $800. Multiplying this by the 2.07 thousand TWh decrease from Table 2 of the manuscript yields lost tax revenue of about $1.6 billion.

Table B30 uses the data from Raimi et al. (2022) and national coal mining data from the EIA [108] to estimate revenue per unit of production. We assume equal tax revenue per short ton of coal for both underground and surface mining. Table B30 suggests that the revenue per short ton of coal mined was approximately $3. Multiplying this by the 1.03 billion short ton decrease from Table 2 of the manuscript yields lost tax revenue of about $3.1 billion.

Indirect Job Multipliers & Spillover Wage Losses

Bivens (2019) reported 957.7 total indirect jobs per 100 direct utility sector jobs and 390.0 total indirect jobs per 100 direct mining sector jobs [109]. Total indirect jobs include both (1) supplier jobs, those linked to inputs and materials going toward the direct jobs, and (2) induced jobs, those reliant on the wages paid to the direct and supplier jobs [109].

Table B31 uses job multipliers from [109] alongside direct coal employment change estimates from Table B21 to estimate supplier, induced, and total indirect job-year losses. Table B32 uses national average wage data across all sectors from the BLS's QCEW to monetize lost employment [83]. The resulting spillover wage losses were $27.4 billion.

Table B31. Spillover employment losses from the decline of coal.

Category	Sector	Indirect Job Multiplier	Change in Employment (Thousand Job-Years)					
			2015	2016	2017	2018	2019	Five-Year Total
Direct	Utility	*NA*	-2.61	-4.46	-5.28	-6.10	-8.49	-27.0
	Mining	*NA*	-5.46	-9.48	-11.6	-13.0	-13.7	-53.2
Supplier	Utility	5.15	-13.4	-23.0	-27.2	-31.4	-43.8	-139
	Mining	2.24	-12.2	-21.2	-26.0	-29.0	-30.7	-119
Induced	Utility	4.42	-11.5	-19.7	-23.3	-27.0	-37.5	-119
	Mining	1.66	-9.06	-15.7	-19.3	-21.5	-22.8	-88.3
Total Indirect	Utility	9.58	-24.9	-42.7	-50.6	-58.4	-81.3	-258
	Mining	3.90	-21.3	-37.0	-45.3	-50.5	-53.5	-207

Sources: Employment multipliers are from EPI [109].
Notes: Job-years are cumulative lost working years compared to 2014, assuming no reemployment. Direct data are computed using changes from Table B20 and coefficients from Table B8 for the utility sector and Table B9 for the mining sector (this information is also reported in Table B21). Supplier, induced, and total indirect data are computed using indirect job multipliers from Bivens (2019) [109].

Table B32. Spillover wages losses from the decline of coal.

Category	Sector	Change in Spillover Wages (Billion $)					
		2015	2016	2017	2018	2019	Five-Year Total
Supplier	Utility	-0.770	-1.33	-1.59	-1.85	-2.62	-8.16
	Mining	-0.701	-1.22	-1.52	-1.71	-1.84	-6.99
Induced	Utility	-0.661	-1.14	-1.37	-1.59	-2.24	-7.00
	Mining	-0.521	-0.906	-1.13	-1.27	-1.36	-5.19
Total Indirect	Utility	-1.43	-2.47	-2.97	-3.44	-4.86	-15.2
	Mining	-1.22	-2.14	-2.66	-2.97	-3.20	-12.2

Sources: Employment multipliers are from EPI [109]. Wage data are from the BLS [83].
Notes: Costs consider job-year losses from Table B31 and are in 2020 U.S. dollars. Wages are the national average across all sectors.

There are a few points to note. To begin, Table B31 and Table B32 overestimate spillover impacts because of utility and mining sector interdependencies. A substantial portion of utility sector supplier jobs are in the mining sector, losses of which we already capture directly in our labor market modeling. As such, utility sector induced jobs are a function of both utility sector (direct) jobs and mining sector (supplier jobs) [109]. There are also relationships (albeit less obvious) in the other direction—i.e., mining uses electricity and other utility sector products as inputs. On the other hand, not all utility sector supplier jobs are in the mining sector, and, obviously, not all mining sector supplier jobs are in the utility sector.

For a lower bound estimate, we could assume that all utility sector supplier jobs are coal mining jobs and exclude the associated $8.16 billion in lost wages. We could proceed to then include just a portion of the utility sector induced jobs. It may make sense to include just 16% of the utility sector induced jobs, which is the portion of "inducing jobs" accounted for by direct rather than supplier jobs (i.e., 1 direct per 5.15 supplier). (Note: this approach ignores indirect job multiplier variability by sector). This process decreases total spillover wage losses to $13.3 billion, a little less than half the original $27.4 billion. Excluding utility sector indirect jobs completely decreases spillover wage losses to $12.2 billion, 45% of the estimate from Table B32.

Additionally, like with coal jobs, these spillover wage losses also do not account for re-employment. To illustrate this point, let us say a utility sector employee loses their job working at a retiring coal plant, but, shortly after, they are re-employed at a new natural gas plant. This would, effectively, offset utility sector spillover losses because both the old job and new job are in the utility sector. Table B31 and Table B32 model the scenario where no new job arrives to offset spillover impacts associated with either sector.

Regarding both points, we prefer to err on the side of caution and highlight the potential for higher rather than lower costs. Hence, the summary in the manuscript quotes tens of billions of dollars for spillover wage losses, mostly in reference to the $27.4 billion in spillover wage losses computed in Table B32. This is the analytically conservative approach for research finding that benefits far exceed costs. Future work could further assess utility and mining sector interdependencies to derive a narrower range for these costs.

Appendix C: Prospective Damages & Buyouts.

FORECASTING DAMAGES FROM THE U.S. COAL FLEET

Remaining Coal Fleet

The Remaining Coal Fleet in 2020

We use six years of historical data (2014 through 2019) to forecast emissions and MDs, distinctly, for SO_2, NO_x, $PM_{2.5}$, and CO_2 from 250 power plants in the coal fleet as of 2020, accounting for 271 GW of capacity. Coal plant data are forecasted individually (i.e., for each variable, every coal plant has a separate forecast).

In 2020, CAMPD tracked 280 facilities with at least one unit with coal as a primary fuel source [58]. 261 of 280 had at least one generator with coal as a primary fuel source [68]. 250 of 261 had net positive generation powered by coal [84]. All emissions from these power plants (regardless of fuel source) are considered for the forecasting analysis. This contrasts with the retrospective emissions analysis, which focused on EGUs with coal as a primary fuel source. That said, at these 250 power plants, 89% of capacity and 91% of generation were powered by coal [68], [84]. Also, most emissions from the coal fleet (i.e., at least one coal EGU) are accounted for by EGUs with coal as a primary fuel source rather than another fuel source [58].

Forecasting Methodology

Forecasting emissions separately from MDs allows us to capture the mainly decreasing emissions trends, as plants decline and improve, separately from the increasing trends of MDs, linked to population and wealth growth over time. We forecast out to 2035 for damage accounting, choosing a timeline that aligns with the Biden Administration's pledge to create a carbon pollution-free power sector [110]. However, this is a relatively arbitrary choice, and future damages could be lower or higher depending on this selection, which we will quantify as part of the "Sensitivity Analysis of Forecasts" subsection (Table C5).

We also forecast net generation and heat input (for natural gas substitution forecasting) using data from 2014 to 2019. Data are from Form EIA-923 [84] and CAMPD [58], respectively.

Exponential Smoothing State Space Model

We employ an exponential smoothing state space modeling framework to conduct forecasting in this study [111]. With *exponential smoothing*, forecasts are based on past observations, with the influence of the points exponentially decreasing as they get older. *State space* models allow for flexibility in the specification of the parametric structure of the system, whose development over time is influenced by associated but unobserved variables. The state space model represents the relationship between these unobserved variables and the realized observations, driving the level, trend, seasonality, and error components of the time series. *Level* is simply the average value of the data at a specific time. *Trend* refers to a long-term "direction"—i.e., whether the data increase or decrease, by how much, and in what way. *Seasonality* is a somewhat regular pattern that repeats periodically at known intervals. *Error* refers to the unpredictable components of the data.[35]

[35] Another element of time series data is a cycle. A cycle is like seasonality, but it has unknown and/or changing periods [111]. Cyclic components can be assumed to fit into the trend component for many applications.

Equation C1 depicts the general innovations formulation of the exponential smoothing state space model. This pair of equations can be used to represent any combination of modeling specifications[36]:

Equation C1. Exponential Smoothing State Space Model.

$$y_t = w(x_{t-1}) + r(x_{t-1})\varepsilon_t$$

$$x_t = f(x_{t-1}) + g(x_{t-1})\varepsilon_t$$

Equation C1's first line is the measurement equation and gives us the observation (y) for each observation at time (t). It characterizes the relationship between the observation and the unobserved states (x_{t-1}). Equation C1's second line is the transition (or state) equation and gives us the "state vector" (x) each time (t). It describes the evolution of the states over time and contains the level, trend, and seasonality components of the time series data. w, r, f, and g are coefficients determined by maximizing the likelihood function (i.e., the probability that the sample data come from the specified model).

We estimate our models using the *forecast* R package [111]. The parametric structure of the model is ultimately selected via an iterative process conducted to find the best option with the lowest Akaike's information criterion (AIC). This value decreases as likelihood increases but penalizes for the number of parameters in the model.

An alternative to exponential smoothing state space modeling is autoregressive integrated moving average (ARIMA) modeling [112]. However, exponential smoothing methods are more appropriate for non-stationary time series (i.e., with a trend). We know that MDs increase with time and that coal emissions will likely decrease; hence, it is the more appropriate method for our application. However, we explore how our results change using an ARIMA modeling alternative in the "Sensitivity Analysis of Forecasts" subsection (Table C5).

Custom Forecasting Adjustments

Dealing with Negative Projections

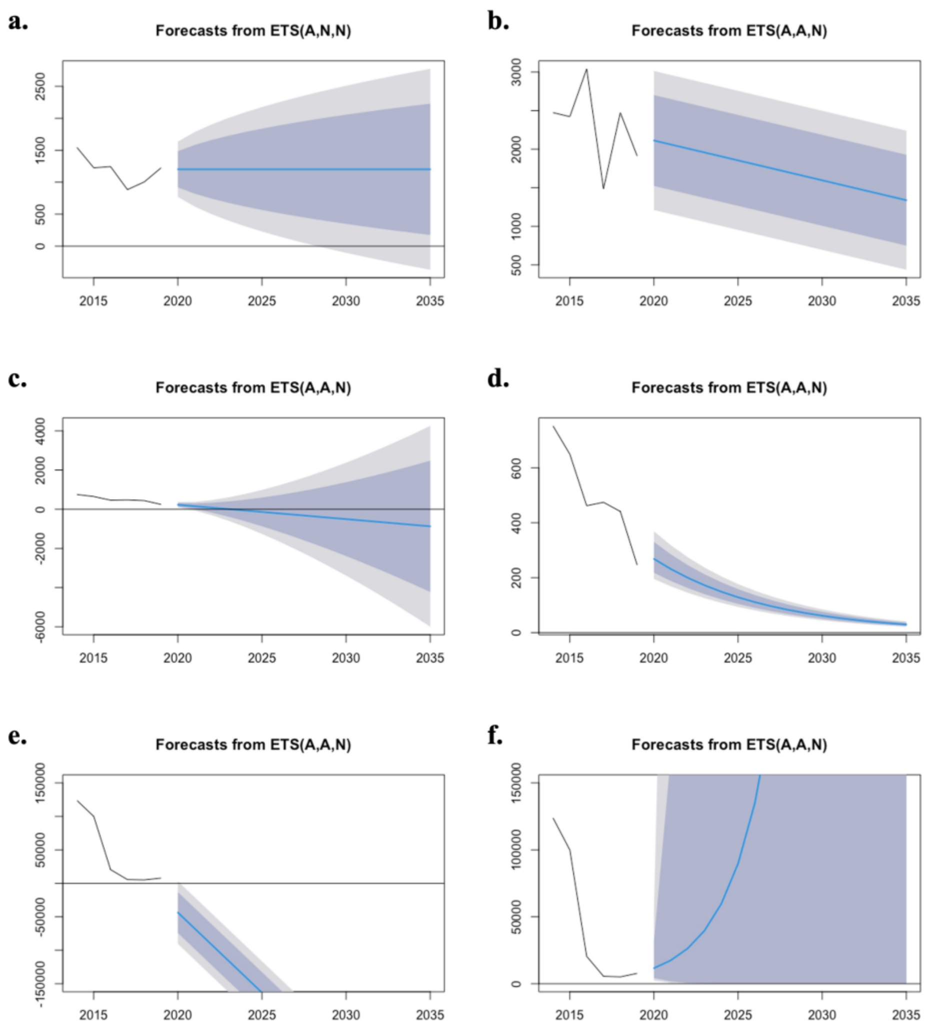
MD forecasting invariably results in a steady increase over time. However, emissions, net generation, and heat input forecasting—collectively discussed here as *operations* forecasting—is more volatile, requiring several custom adjustment steps in some instances. Our procedure, including these steps, is outlined below. Critically, each plant's variables (e.g., SO_2, CO_2, or net generation) are subject to these steps independently of one another:

- Step 1 (Zero): If a coal plant had zero operations in 2019, forecast zero operations forward.
- Step 2 (Base): Otherwise, generate an exponential smoothing state space model [111].
    - Step 2.1 (Log-Transform): If the forecast results in negative operations projections at any point through 2035, log-transform the forecast via the Box-Cox transformation parameter—an approach that ensures operations approach rather than cross zero.

[36] Exponential smoothing state space models can employ a variety of methods. Key to this conversation are the concepts of *additive* versus *multiplicative* specifications for the trend, seasonality, and error components of the times series. See Hyndman et al. (2008) [111] for a further explanation.

- Step 2.2 (Last): If the log-transform from Step 2.1 results in operations increasing (when the initial modeling results in operations decreasing and crossing zero), forecast operations data for 2019 forward.

Step 1 only applies to a small number of the 1,250 (250 plants x 5 operations variables) forecasts. On the other hand, most of the forecasts are subject to just the exponential smoothing state space model (i.e., that selected to minimize the AIC) with no data transformation (Step 2). A decent number of forecasts are subject to log transformation via Step 2.1 (21% to 28%, depending on the operations variable). Finally, just three forecasts have their 2019 values specifically projected forward via Step 2.2.



Sources: Models use the *forecast* R package [111].
Notes: Plots show examples of exponential smoothing state space modeled forecasts of SO_2 emissions through 2035 from select coal-fired power plants. (a) and (b) show randomly selected forecasts subject to no custom adjustments. (c) & (d) show a forecast originally resulting in negative projections (c) log-transformed via Adjustment Step 2.1 to instead approach, rather than cross, zero (d). (e) and (f) show a forecast originally resulting in negative projections (e) log-transformed via adjustment Step 2.1 but resulting in increasing emissions (f)—prompting adjustment Step 2.2 for a 2019 value forecasted forward. Dark and light grey represent the 80% and 95% confidence intervals of forecasting results, respectively. The notation's triplet within the paraeneses refers to the three components of the model: (Error, Trend, Seasonality) [111].

Figure C1. Examples of Exponential Smoothing State Space Modeling Forecasts.

Figure C1 shows examples of the exponential smoothing state space modeling for SO_2 emissions from select coal-fired power plants. The notation's triplet within the paraeneses refers to the three components of the model: (Error, Trend, Seasonality) [111]. Figure C1(a) shows an example of how an ETS(A,N,N) model is selected when there is no clear trend in the data (i.e., additive error, no trend, and no seasonality); the model projects a weighted average forward. Figure C1(b) shows an example of how an ETS(A,A,N) model is selected when there is a clear (decreasing) trend in the data (i.e., additive error, additive trend, and no seasonality).

Figure C1(c) shows an example where a model identifies a clear decreasing trend that projects negative SO_2 emissions before 2035. We do not know, however, that the represented coal plant's SO_2 emissions will stop (e.g., it will go offline) when the projection shows it to. Hence, we employ adjustment Step 2.1, which log-transforms the forecast so that it approaches rather than crosses zero (Figure C1d).

Figure C1(e) and Figure C1(f) exemplifies the rare cases needing adjustment Step 2.2. The model identifies a decreasing trend in the data and projects negative SO_2 emissions (Figure C1e). We again do not know if the coal plant's coal plant's emissions will cease at this time. However, when we employ the log transformation instructed by adjustment Step 2.1, the emissions shoot upward (Figure C1f). Clearly, this is not what we expect will happen to the coal plant's emissions; in fact, it is far less likely than the emissions going to zero as suggested by Figure C1(e). Our solution is to forecast 2019's emissions forward.

Coal Plant Retirement Schedule

To account for when coal plant emissions will stop (i.e., because the plant does go offline), we adapt the operations forecasts considering the coal fleet retirement schedule as of 2021 [68], setting subsequent years' operations estimates to zero. The planned retirement schedule for coal-fired generators as of 2021 showed that 83 GW of capacity at coal-fired power plants were scheduled to go offline through 2035. 7 GW more were to retire through 2040. 79 GW (95%) and 86 GW (96%) of these totals, respectively, are with coal as a primary fuel source (rather than another fuel source). As a reminder, we consider any facility with at least one unit with coal as a primary fuel source, at least one generator with coal as a primary fuel source, and net positive generation powered by coal as a coal plant. Hence, not all capacity at these facilities is power by coal.

We make an interesting observation regarding the differences between the planned retirement schedule in 2020 and 2021. Quite a few plants delayed their plans, either to a later date or indefinitely [68]. This suggests that setting operations forecasts to zero when a plant is expected to retire (based on the schedule) may underestimate future damage, net generation, and heat input if the plant does not go offline, as the data indicate. On the other hand, coal plants may also retire unexpectedly for various reasons. In summary, the retirement schedule is a best guess at how the coal fleet may change in the future but should not be taken as the schedule that coal plants will definitely follow. We test the sensitivity of forecasts to adapting based on the retirement schedule from the EIA in the "Sensitivity Analysis of Forecasts" subsection (Table C5).

Computing Prospective Damages

To compute prospective damages each year from each pollutant coming from each coal plant, we multiply total forecasted emissions by their respective forecasted MDs. This is analogous to computing damages (or those avoided) as discussed for the retrospective work conducted for this study (Appendix B's "Retrospective Damages & Benefits" section).

Discounting Future Damages

Like with climate damages from CO_2 (discussed in the "Social Cost of Carbon" section of Appendix A), we discount future damages to account for the time value of money [50]. The idea, further divulged in the next paragraph, is that a dollar today is worth more than a dollar in the future. Discounting can either be prescriptive (normative) or descriptive (opportunity-cost).

The prescriptive approach considers pure rate of time preference and wealth effects components. The former discounts the future simply because it is the future and not the present. The latter discounts the future because a dollar on the margin today is worth more than a dollar on the margin in the future, assuming that populations become more wealthy as trends suggest they will [46]. The descriptive approach discounts future values because of opportunity cost. Investing billions of dollars to avoid future damages takes away from investments in other public goods (e.g., education, infrastructure, or health care). We can discount future values because today's dollar can accumulate wealth elsewhere (e.g., the stock market) over time.

We employ a 3% discount rate for future damages to get a 2020 present value. More than two-thirds of experts recommend an SDR between 1% and 3% [50], and our selection of the upper bound is conservative for benefits estimation (i.e., they would be higher at a lower discount rate). However, we explore how sensitive our damage projections are to this decision in the "Sensitivity Analysis of Forecasts" section (Table C5).

Limitations of Forecasting

There are a few critical limitations to this forecasting analysis. Our forecasts are generated with six years of historical data from 2014 to 2019 and are ignorant to happenings afterward—except for planned retirements. Without a more detailed plant-by-plant investigation, we cannot know planned fuel switching, emissions control technologies or strategies, or declines in operations not already captured in 2014-to-2019 trends. In other words, there are bound to be dynamics with time that will shift what is expected from the coal fleet's emissions, net generation, and heat input variables.

EMISSION, MARGINAL DAMAGE, & NET GENERATION PROJECTIONS

Forecasts

Table C1 shows forecasted emissions from all coal-fired power plants making up the coal fleet each year through 2035. As expected, fleetwide emissions are projected to decrease each year.

Table C2 shows emissions-weighted average MDs annually through 2035 for the coal fleet. Both undiscounted (future) and discounted (present) values are shown. As anticipated, the future values of MDs increase with time. However, the effects of discounting are strong enough to more than offset this trend, such that MDs decrease with time.

We note that there is one exception to the increasing MD trend when looking at future values. MDs for NO_x are instead projected to remain constant (or slightly decrease). This is indicative of shifts in baseline pollution levels throughout the CONUS. Emissions of NO_x rely on the reaction with free ammonia to form ammonium nitrate—a subspecies of $PM_{2.5}$. Without free ammonia, NO_x will not result in ambient $PM_{2.5}$. Therefore, as emissions from anthropogenic sources continue to fall—like NH_3 from agriculture [1]—MDs from NO_x could decrease due to it resulting in lower marginal concentrations of $PM_{2.5}$. See the "Ambient $PM_{2.5}$ Concentration

Baseline" subsection of Appendix A for a description of AP3's atmospheric chemistry modeling, which further explains the phenomenon discussed here.

Figure C2 and Table C3 show forecasted damages from all coal-fired power plants making up the coal fleet yearly through 2035 by pollutant and where CO_2 damages occur. Table C3 also reports forecasted net generation and heat input. A PWh is the equivalent of a thousand TWh, the units discussed in the main paper.

Table C1. Forecasted U.S. coal fleet emissions through 2035.

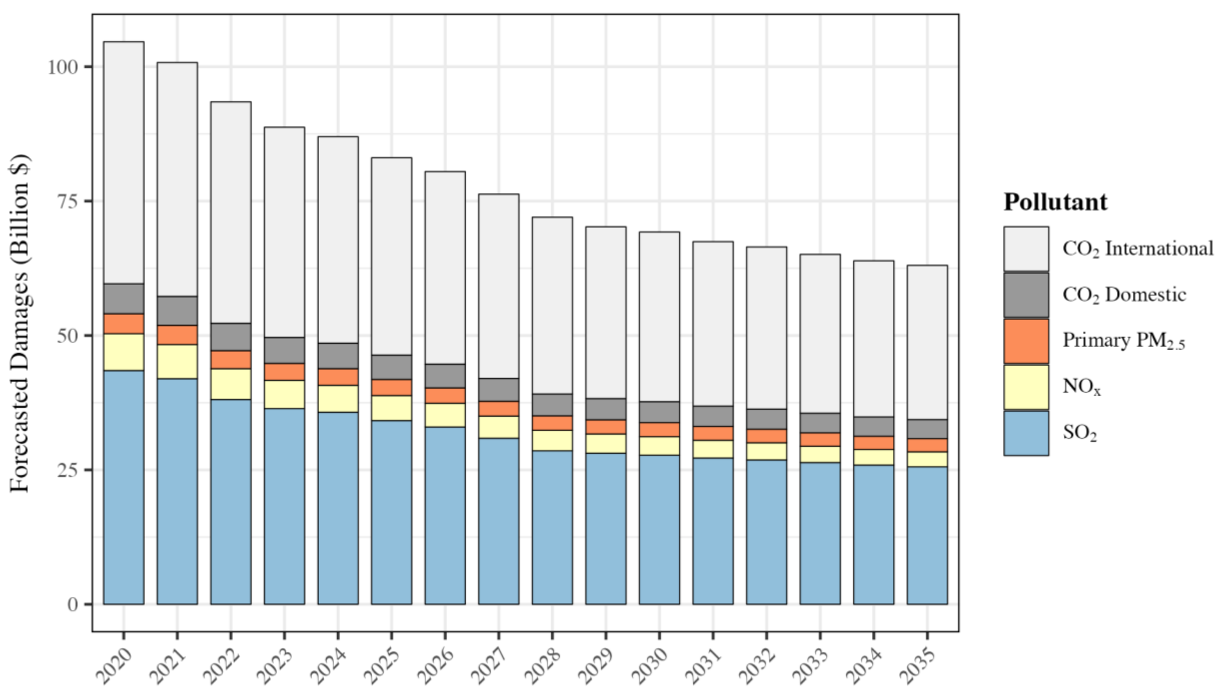
Year	Emissions (Short Tons)			
	SO_2	NO_x	Primary $PM_{2.5}$	CO_2
2020	9.35E+05	6.77E+05	6.09E+04	1.07E+09
2021	9.03E+05	6.48E+05	5.90E+04	1.04E+09
2022	8.34E+05	6.06E+05	5.54E+04	9.92E+08
2023	8.01E+05	5.74E+05	5.26E+04	9.48E+08
2024	7.90E+05	5.64E+05	5.20E+04	9.38E+08
2025	7.61E+05	5.38E+05	5.03E+04	9.04E+08
2026	7.43E+05	5.28E+05	4.91E+04	8.89E+08
2027	7.02E+05	5.03E+05	4.78E+04	8.59E+08
2028	6.55E+05	4.81E+05	4.70E+04	8.32E+08
2029	6.49E+05	4.68E+05	4.62E+04	8.16E+08
2030	6.46E+05	4.64E+05	4.62E+04	8.14E+08
2031	6.39E+05	4.58E+05	4.56E+04	7.97E+08
2032	6.36E+05	4.55E+05	4.52E+04	7.95E+08
2033	6.31E+05	4.45E+05	4.52E+04	7.87E+08
2034	6.27E+05	4.39E+05	4.52E+04	7.83E+08
2035	6.26E+05	4.36E+05	4.53E+04	7.83E+08
Total	**1.16E+07**	**8.28E+06**	**7.93E+05**	**1.40E+10**

Sources: Historical emissions data for forecasting are from the EPA [7], [8], [58]. Forecasted emissions are adapted considering the retirement schedule as of 2021 from the EIA [68].
Notes: Forecasted emissions are for 250 coal-fired power plants comprising 271 GW of capacity. In contrast to Table B1 of Appendix B, emissions are for all EGUs at coal plants (defined as any power plant with at least one EGU with coal as a primary fuel source).

Table C2. Forecasted average U.S. coal fleet marginal damages through 2035.

Year	Criteria Air Pollutant MDs (Thousand $)						Greenhouse Gas MDs ($)			
	SO_2		NO_x		Primary $PM_{2.5}$		CO_2: Domestic		CO_2: International	
	Future	Present	Future	Present	Future	Present	Future	Present	Future	Present
2020	46.5	46.5	10.1	10.1	61.1	61.1	5.20	5.20	42.1	42.1
2021	47.9	46.5	10.1	9.80	62.6	60.8	5.32	5.17	43.1	41.8
2022	48.4	45.7	10.0	9.47	64.3	60.6	5.45	5.13	44.1	41.5
2023	49.7	45.4	10.0	9.17	65.4	59.8	5.57	5.10	45.1	41.2
2024	50.9	45.2	10.0	8.90	66.9	59.4	5.69	5.06	46.1	40.9
2025	52.1	44.9	10.0	8.65	69.1	59.6	5.82	5.02	47.1	40.6
2026	53.0	44.4	10.0	8.38	69.4	58.1	5.94	4.98	48.1	40.3
2027	54.1	44.0	10.1	8.19	71.2	57.9	6.07	4.93	49.1	39.9
2028	55.2	43.6	10.0	7.92	72.7	57.4	6.19	4.89	50.1	39.5
2029	56.5	43.3	10.0	7.66	74.4	57.0	6.31	4.84	51.1	39.2
2030	57.7	42.9	10.0	7.44	76.0	56.5	6.44	4.79	52.1	38.8
2031	58.9	42.6	10.0	7.22	77.8	56.2	6.56	4.74	53.1	38.4
2032	60.2	42.2	10.0	7.01	79.7	55.9	6.69	4.69	54.1	37.9
2033	61.4	41.8	10.0	6.81	81.3	55.4	6.81	4.64	55.1	37.5
2034	62.5	41.3	9.96	6.58	82.9	54.8	6.94	4.58	56.1	37.1
2035	63.7	40.9	9.96	6.39	84.5	54.2	7.06	4.53	57.1	36.7

Notes: Forecasted marginal damages are in 2020 U.S. dollars. Averages are weighted by forecasted coal-fired power plant emissions (Table C1). Future values are not discounted. Present values are discounted (by 3%) to 2020 present values.



Notes: Forecasted damages are discounted (by 3%) to 2020 present values and are in 2020 U.S. dollars. Forecasted damage calculations multiply forecasted emissions by their respective forecasted marginal damage. Forecasted damages are for 250 coal-fired power plants comprising 271 GW of capacity. Damages are for all EGUs at coal plants (defined as any power plant with at least one EGU with coal as a primary fuel source).

Figure C2. Forecasted Damages from U.S. Coal Fleet Emissions by Pollutant through 2035.

Table C3. Forecasted U.S. coal fleet damages, net generation, and heat input through 2035.

Year	Damages (Billion $)								Net Generation (PWh)	Heat Input (Billion MMBtu)
	SO_2	NO_x	Primary $PM_{2.5}$	CAP Total	CO_2		Total			
					USA	Int.	USA	Global		
2020	43.5	6.85	3.72	54.1	5.56	45.0	59.6	105	1.00	10.5
2021	42.0	6.35	3.58	51.9	5.38	43.5	57.3	101	0.979	10.2
2022	38.1	5.74	3.36	47.2	5.09	41.2	52.3	93.5	0.938	9.77
2023	36.4	5.26	3.15	44.8	4.83	39.1	49.7	88.7	0.904	9.35
2024	35.7	5.01	3.09	43.8	4.75	38.4	48.6	87.0	0.899	9.26
2025	34.2	4.66	3.00	41.8	4.53	36.7	46.4	83.1	0.871	8.92
2026	33.0	4.43	2.85	40.3	4.43	35.8	44.7	80.5	0.859	8.77
2027	30.9	4.12	2.77	37.8	4.24	34.3	42.0	76.3	0.830	8.47
2028	28.6	3.81	2.70	35.1	4.06	32.9	39.1	72.0	0.804	8.21
2029	28.1	3.58	2.64	34.3	3.95	31.9	38.3	70.2	0.791	8.06
2030	27.7	3.45	2.61	33.8	3.90	31.5	37.7	69.2	0.792	8.04
2031	27.2	3.31	2.56	33.1	3.78	30.6	36.9	67.5	0.779	7.88
2032	26.9	3.19	2.53	32.6	3.73	30.2	36.3	66.5	0.779	7.86
2033	26.4	3.03	2.50	31.9	3.65	29.5	35.6	65.1	0.775	7.79
2034	25.9	2.89	2.48	31.3	3.59	29.0	34.9	63.9	0.773	7.75
2035	25.6	2.79	2.46	30.8	3.55	28.7	34.4	63.1	0.774	7.75
Total	**510**	**68.5**	**46.0**	**625**	**69.0**	**558**	**694**	**1,252**	**13.6**	**139**

Notes: Forecasted damages are discounted (by 3%) to 2020 present values and are in 2020 U.S. dollars. Forecasted damage calculations multiply forecasted emissions by their respective forecasted marginal damage. Forecasted damages are for 250 coal-fired power plants comprising 271 GW of capacity. Unlike in Table B2, damages are for all EGUs at coal plants (defined as any power plant with at least one EGU with coal as a primary fuel source). CAP stands for criteria air pollutants, including SO_2, NO_x, and primary $PM_{2.5}$. USA stands for domestic. Int. stands for international. USA (domestic) total includes criteria air pollutant and domestically incurred CO_2 damage. Global total includes USA (domestic) total plus internationally incurred CO_2 damage. Net generation is in PWh (or thousand TWh—the units in the main paper).

Prospective Damages from Natural Gas Substitution

Like retrospective damage accounting (see Appendix B), if we assume that emissions-free renewables replace coal, our prospective calculations herein hold as they are. However, natural gas, which accounts for the greatest share of U.S. electricity generation [72], is currently the most likely to replace coal in any location, although that may not be the case everywhere or otherwise into the future (e.g., renewables could be more likely if natural resources and/or local policy landscapes are or become favorable for wind or solar). That said, we assume natural gas substitution. This assumption accounts for the potential for additional emissions from natural gas to offset avoided damages from coal's decline, attenuating benefits. Given the findings herein (i.e., that the benefits far exceed the costs), this is an analytically conservative approach. In the prospective scenario, it is also the more cautious approach given the potential for adverse impacts to the grid; natural gas is a dispatchable energy resource not subject to intermittency challenges. Emissions-free alternatives provide the benefit of no avoided damage offsets but potential costs associated with grid impacts, an assessment of which we relegate to future work.

The computations for natural gas offsets are summarized in Table C4. The emissions are calculated considering lost heat input from coal needing to be made up for every year (from Table C3) and five-year average natural gas emission rates (from Table B7 and sourced from [58]). These calculations are conducted at the plant level so that the heat input needing replaced by natural gas and the resulting emissions are location-specific.

The last step is to use coal plant-specific forecasted MDs for emissions coming from natural gas-replaced MMBtu. The caveats discussed in the "Retrospective Damages from Natural Gas Substitution" subsection of Appendix B are also applicable here. Namely, (1) assume that future natural gas emissions are released from the same coordinates from which future coal plant emissions are modeled, (2) we assume the height of pollution discharge is the same for the original coal plant and the replacement natural gas plant, and (3) natural gas power plants have a higher thermal efficiency than coal-fired power plants [73], so we overestimate natural gas substitution emissions and associated benefit offsets.

Table C4. Forecasted natural gas substitution emissions and damages offsetting avoided coal damages.

Year	Emissions (Short Tons)				Damages (Billion $)		
	SO_2	NO_x	Primary $PM_{2.5}$	CO_2	Air Pollution	Domestic (USA)	Total (Global)
2020	9.97E+03	1.65E+05	1.44E+04	6.31E+08	2.99	6.27	32.8
2021	9.69E+03	1.60E+05	1.40E+04	6.14E+08	2.86	6.03	31.7
2022	9.24E+03	1.53E+05	1.34E+04	5.85E+08	2.68	5.68	30.0
2023	8.84E+03	1.46E+05	1.28E+04	5.60E+08	2.52	5.37	28.5
2024	8.76E+03	1.45E+05	1.27E+04	5.54E+08	2.45	5.26	27.9
2025	8.44E+03	1.40E+05	1.22E+04	5.34E+08	2.34	5.02	26.7
2026	8.30E+03	1.37E+05	1.20E+04	5.25E+08	2.24	4.86	26.0
2027	8.01E+03	1.33E+05	1.16E+04	5.07E+08	2.14	4.65	24.9
2028	7.76E+03	1.28E+05	1.12E+04	4.91E+08	2.04	4.44	23.9
2029	7.62E+03	1.26E+05	1.10E+04	4.83E+08	1.97	4.30	23.2
2030	7.61E+03	1.26E+05	1.10E+04	4.82E+08	1.93	4.24	22.9
2031	7.46E+03	1.23E+05	1.08E+04	4.72E+08	1.87	4.10	22.2
2032	7.43E+03	1.23E+05	1.08E+04	4.71E+08	1.83	4.04	21.9
2033	7.37E+03	1.22E+05	1.07E+04	4.66E+08	1.78	3.95	21.4
2034	7.33E+03	1.21E+05	1.06E+04	4.64E+08	1.74	3.86	21.1
2035	7.33E+03	1.21E+05	1.06E+04	4.64E+08	1.71	3.81	20.8
Total	**1.31E+05**	**2.17E+06**	**1.90E+05**	**8.30E+09**	**35.1**	**75.9**	**406**

Notes: Forecasted damages are discounted (by 3%) to 2020 present values and are in 2020 U.S. dollars. Forecasted emission calculations multiply forecasted heat input by five-year average emission rates (see Table B7). Forecasted emissions are from combustion only. Forecasted damage calculations multiply forecasted emissions by their respective forecasted marginal damage. Forecasted damages are for natural gas substitution needed to replace lost forecasted heat input associated with 250 coal-fired power plants comprising 271 GW of capacity (see Table C3). Air pollution damages comprise those from the criteria air pollutants (labeled CAP in Table C3), including SO_2, NO_x, and primary $PM_{2.5}$. Domestic (USA) includes criteria air pollutant and domestically incurred CO_2 damage. Total (global) includes domestic plus internationally incurred CO_2 damage.

Methane Leakage Offsets

As in the retrospective case, upstream methane leakage could greatly offset the climate benefits of moving from coal to natural gas (i.e., those from less CO_2 during combustion). See Appendix B's "Retrospective Damages from Natural Gas Substitution" subsection for a more detailed discussion.

While natural gas is typically still better than coal when incorporating life cycle GHG intensity [82], we consider the "worst-case scenario" where natural gas is as bad as coal. (Note: "worst-case scenario" is in quotes because there is a feasible scenario where natural gas is worse than coal for GHG emissions.) Gordon et al. (2023) find this to be the case with natural gas methane leakage rates of just less than 5% considering a 20-year timeframe and approximately 9%

considering a 100-year timeframe [76]. In this scenario, CO_2 benefits are completely offset, leaving just the benefits from local air pollution that are not offset by added natural gas emissions.

Consulting Table C3 and Table C4, benefits further decrease from $694 billion domestically or $1.25 trillion globally to $589 billion for the base case category of damages—all driven by criteria air pollution damages within the U.S. Natural gas offsets benefits by 53% considering global impacts and 15% considering domestic impacts.

Sensitivity Analysis of Forecasts

Table C5 shows the sensitivity analysis results on forecasted domestic damages, global damages, and net generation from the coal fleet through 2035. Table C5 explores changes to the forecasting procedure, uncertainty with forecasting, alternative discount rates, the lower and upper MD estimates, and the forecasting timeline.

Sensitivity Scenarios for Future Coal Damages and Net Generation

In Table C5, Scenario 1 is the central estimate—i.e., the results shown in Table C3.

Scenarios 2 to 6 look at forecasting procedures. Scenario 2 ignores the 2021 coal plant retirement schedule. Scenario 3 does not conduct any transformations when there are negative projections (Step 2.1 and Step 2.2 from the "Custom Forecasting Adjustments" subsection) and instead just substitutes zeros. Scenario 4 instructs the exponential smoothing state space modeling to automatically find the best data transformation (e.g., natural log) for the data rather than not transforming the data unless there are negatives. Scenario 5 uses an ARIMA modeling specification. Scenario 6 only considers three years of historical data (2017 to 2019) for forecasting.

Scenarios 7 to 12 look at forecasting uncertainty. The scenarios consider either an 80% CI or a 95% CI, the default uncertainty bounds in the *forecast* R package [111]. Forecasting uncertainty is relevant for both emissions and MD projections. For the lower bound emissions estimates, we consider all adjustment steps from the "Custom Forecasting Adjustments" subsection as well as just Step 1 and Step 2 (i.e., no transformations). We only consider the latter for the upper bound emissions estimate, as the log transformation (Step 2.1) results in extraordinarily high upper bounds.[37]

Scenarios 13 to 16 look at discounting. Scenarios 13 and 14 discount future damages less. Scenarios 15 and 16 discount future damages more.

Scenarios 17 to 22 look at MDs. See Table A6 for variable changes comprising the lower and upper bound estimates. Scenarios 17 and 18 adjust all MDs down and up, respectively. Scenarios 19 and 20 adjust only criteria air pollutant MDs. Scenarios 21 and 22 adjust only GHG MDs.

Scenarios 23 to 24 look at the timeline. Scenario 23 has a shorter timeline, stopping at 2030. Scenario 24 has a longer timeline, stopping at 2040.

Scenarios 25 to 26 look at compounded uncertainty. Scenario 25 considers the lower bound 80% CI without transformations and the lower bound MDs for all pollutants. Scenario 26 considers the upper bound 80% CI without transformations and the upper bound MDs for all pollutants.

[37] As discussed in the "Custom Forecasting Adjustments" subsection, these adjustment steps are only relevant for emissions forecasting, not MD forecasting.

Table C5. Sensitivity of forecasted U.S. coal fleet damages and net generation through 2035.

Scenario	Topic	Explanation	Domestic Damages (Billion $)		Global Damages (Billion $)		Net Generation (PWh)	
			Estimate	Change	Estimate	Change	Estimate	Change
1	Forecasting Methodology	Central estimate	694	0%	1,252	0%	13.6	0%
2		Forego accounting for 2021 retirement schedule	833	20%	1,484	19%	15.7	16%
3		Forego any transformations (Adj. Steps 2.1 and 2.2)	654	-6%	1,196	-4%	13.2	-2%
4		Apply automatic data transformation	706	2%	1,335	7%	14.3	5%
5		ARIMA alternative	814	17%	1,451	16%	14.5	7%
6		Use 3 years of historical data	711	2%	1,282	2%	13.5	-1%
7	Forecasting Uncertainty	Lower bound 80% CIs: All adj. steps	298	-57%	663	-47%	8.88	-34%
8		Lower bound 80% CIs: Forego transformations	279	-60%	636	-49%	8.62	-36%
9		Upper bound 80% CIs: Forego transformations	1,889	172%	2,855	128%	23.2	71%
10		Lower bound 95% CIs: All adj. steps	218	-69%	523	-58%	7.42	-45%
11		Lower bound 95% CIs: Forego transformations	202	-71%	500	-60%	7.18	-47%
12		Upper bound 95% CIs: Forego transformations	2,751	297%	3,987	218%	29.3	116%
13	Discounting	No Discounting	853	23%	1,543	23%	13.6	*NA*
14		Discount at 1%	794	14%	1,435	15%	13.6	*NA*
15		Discount at 5%	612	-12%	1,104	-12%	13.6	*NA*
16		Discount at 10%	467	-33%	840	-33%	13.6	*NA*
17	Damage Valuation	Lower bound all MDs	236	-66%	392	-69%	13.6	*NA*
18		Upper bound all MDs	1,619	133%	3,253	160%	13.6	*NA*
19		Lower bound criteria air pollution MDs	305	-56%	863	-31%	13.6	*NA*
20		Upper bound criteria air pollution MDs	1,399	102%	1,958	56%	13.6	*NA*
21		Lower bound greenhouse gas MDs	625	-10%	780	-38%	13.6	*NA*
22		Upper bound greenhouse gas MDs	913	32%	2,547	103%	13.6	*NA*
23	Timeline	Forecast to 2030	512	-26%	920	-26%	9.62	-29%
24		Forecast to 2040	858	24%	1,552	24%	17.5	29%
25	Compounded Uncertainty	Scenarios 8 and 17	89.4	-87%	181	-86%	8.62	-36%
26		Scenarios 9 and 18	4,329	524%	7,264	480%	23.2	71%

Notes: Change variables are percentage changes compared to the central estimates—i.e., Scenario 1 (see Table C3). For damages, yellow indicates more and green indicates less. For net generation, blue indicates more and red indicates less.

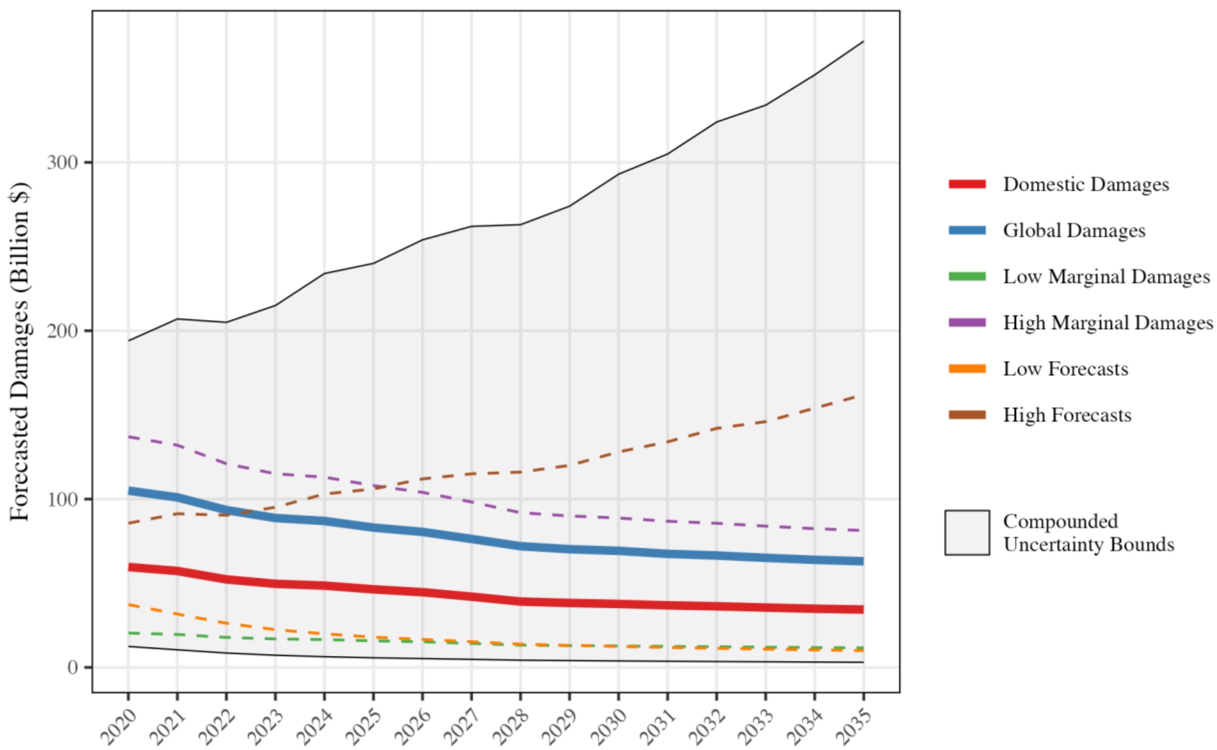
Uncertainty with Forecasting Discussion

Table C5 shows that the projections are relatively insensitive to our forecasting procedure. The most significant influence on estimates comes from ignoring the 2021 coal plant retirement schedule, increasing domestic damages by 20% and net generation by 16%. We also see that the ARIMA specification gives us higher estimates, and no custom transformations gives us lower estimates.

The next least influential categories are discounting and timeline. Importantly, these are both subjective inputs.

We see that MD uncertainty has a greater influence on forecasting. As expected, domestic damages are susceptible to the criteria air pollutant MDs, but global damages are more sensitive to GHG MDs. Notably, net generation is not subject to MD (nor discounting) uncertainty.

Ultimately, projections are most sensitive to forecasting uncertainty. We see that damages and net generation could be much higher or lower based on the uncertainty associated with using exponential smoothing state space modeling to project future data.



Notes: Data are annual. Forecasted damages are discounted (by 3%) to 2020 present values and are in 2020 U.S. dollars. Domestic damages (red) exclude internationally incurred CO_2 damage. Global damages (blue) include internationally incurred CO_2 damage. Low and high MDs employ the variable changes from Table A6 and characterize domestic damage uncertainty. Low and high forecasts employ the 80% CI estimates for both emissions and MD projections and characterize domestic damage uncertainty. Compounded uncertainty bounds consider both MD and forecasting uncertainty for domestic damages.

Figure C3. Uncertainty of Forecasted Damages from U.S. Coal Fleet Emissions through 2035.

For the main paper, we report uncertainty using the compounded effects of both the 80% CIs of forecasting (no custom transformations) and all MDs. We find it essential to capture both the vast uncertainty with estimating damages and projecting future data. All other scenarios explored in Table C5 are well within the resulting intervals.

Figure C3 shows forecasted damages each year from 2020 to 2035 under select scenarios. Both domestic and global damages (bold) are those for the central estimates. MD and forecasting uncertainty characterize domestic damages and are shown via the dashed lines. The compounded uncertainty bounds consider both MD and forecasting uncertainty for domestic future damage modeling.

Figure C3 shows that forecasting uncertainty increases with time while that for MDs remains relatively consistent. This makes sense, as our future predictions become less confident the further we get away from the historical data. Compounded uncertainty shows how considering MD and forecasting uncertainty together creates a sizeable upper bound. We see a situation where the uncertainty, quite literally, is greater than the sum of its parts. This is because forecasting uncertainty also affects MD projections.

Uncertainty with Natural Gas Benefit Offsets

Considering the compounded effects of both the 80% CIs of forecasting (no custom transformations) and all MDs, we adjust our lower and upper bound estimates for natural gas substitution damages. Future natural gas substitution modeling uses forecasts of heat input and MDs and fleetwide average emission rates to estimate future emissions and damages (see Table C3 and Table C4).

This decreases the lower bound benefits from $181 billion (global) or $89.4 billion (domestic) to $81.8 billion for the base case damage category. This decreases the upper bound benefits from $7.26 trillion (global) or $4.33 trillion (domestic) to $3.67 trillion for the base case category.

BUYING OUT COAL-FIRED POWER PLANTS

The social value flow of a hypothetical coal-fired power plant buyout in 2020 is as follows. In 2020, the government buys out a coal plant, and benefits accrue every year in the future through 2035 from avoided damage. Two effects drive the changes in the social value of future damages. First, there are real changes—e.g., lower damages due to fewer emissions. Second, there is the discounting of future values, which is discussed in the "Computing Prospective Damages" subsection. Net benefits of a buyout are simply the present value of total avoided damage benefits minus buyout or replacement costs.

Purchase Price

Value of Coal Assets

We define the purchase price of coal-fired power plant assets at $650,000 per MW, aligning with the fleetwide net book value per unit of capacity reported by the Rocky Mountain Institute (RMI) [113]. This value normalizes asset value data reported via the Federal Energy Regulatory Commission [114] by capacity. The value represents "steam" technologies, mainly coal and some natural gas steam turbine plants [113].

Across 271 GW of coal capacity, the value of the coal fleet is determined as $176 billion.

Costs of Capacity Replacement

In the scenario where the U.S. government does not just buy out coal plants but funds replacement natural gas generators, costs would amount to about $1.12 million per MW. This is determined using the average cost of installing new natural gas, as reported by the EIA [115]. Therefore, across 271 GW of coal capacity, the cost of replacing the coal fleet with new natural gas capacity is $304 billion.

If we were to replace coal with wind or solar generators instead, the costs would increase to $1.50 or $1.66 million per MW, respectively [115]. Hence, the cost of replacing the coal fleet with new wind capacity is $407 billion, and the cost of replacing the coal fleet with new solar capacity is $450 billion. However, this becomes more complicated when considering grid operations as these resources depend on geographically variable natural resources and are non-dispatchable without complementary storage solutions. Assessing natural gas replacement is a more cautious approach because it is a dispatchable energy resource not subject to intermittency challenges. Emissions-free alternatives provide the benefit of no avoided damage offsets but potential costs associated with grid impacts, an assessment of which we relegate to future work. Notably, natural gas is less damaging than coal [58], [82]. Still, natural gas emits both criteria air pollution and GHGs, so our analytically conservative approach should not be mistaken for an endorsement. In the "worst-case scenario," natural gas emits GHG emissions at the same rate as coal [76], and installing substantial new natural gas capacity would prevent the U.S. from achieving climate goals [110].

Differentiating Damage Categories

Analogous to Appendix B's "Net Benefits & Wage Replacement Policy Analysis" subsection, this policy analysis considers three damage categories. The first is the manuscript's base case, which incorporates natural gas offsets (see the "Prospective Damages from Natural Gas Substitution" subsection). This category excludes CO_2 benefits (due to the potential for methane leakage to offset GHG-derived benefits completely [76]) and offsets some criteria air pollution benefits (see Table C4). The other two damage categories do not consider natural gas offsets and incorporate either domestic or global CO_2 avoided damages. These damage categories either (1) ignore additional natural gas damages or (2) assume emissions-free alternatives substitute in for coal.

The following analyses refer to these categories as base case, domestic, and global damages, benefits, or avoided damages. We note that for domestic or global damages where we assume (2) instead of (1) above, our generator replacement costs should be higher. However, we disregard this truth in these sensitivity analyses for simplicity.

Complete, Efficient, & Partial Buyouts

Fleetwide Buyout

Table C6 shows the benefits, costs, net benefits, and return on investment (ROI)—i.e., the ratio of net benefits to costs—of a complete coal fleet buyout in 2020. Benefits are from avoided future base case, domestic, or global damages. Costs are from buying out or replacing coal capacity with natural gas.

Notably, buyout and replacement costs do exceed benefits given lower estimate damages in the base case ($81.8 billion). Under several scenarios evaluated in Table C5, replacement costs exceed avoided domestic damages. (Note: Base case forecasted damages are necessarily lower than domestic forecasted damages.) With central estimate forecasting, net benefits and the ROI are still positive and extensive. That said, if future damages end up being lower due to various drivers of uncertainty, a fleetwide replacement (or buyout) could result in net costs.

Table C6. Benefits and costs of buying out or replacing the U.S. coal fleet in 2020.

Required Funding	Considered Damages	Benefits (Billion $)	Costs (Billion $)	Net Benefits (Billion $)	Return On Investment
Buyout ($650 Thousand Per MW)	Base Case	589	176	413	2.34
	Domestic	694	176	517	2.93
	Global	1252	176	1076	6.10
Replacement ($1.12 Million Per MW)	Base Case	589	304	286	0.940
	Domestic	694	304	390	1.28
	Global	1252	304	948	3.12

Sources: Buyout considers net book value per MW from RMI [113]. Replacement considers natural gas generator construction costs per MW from the EIA [115].

Notes: Buyout or replacement considers 271 GW of coal capacity projected to generate 13.6 thousand TWh of power through 2035. Forecasted base case benefits are avoided criteria air pollution damages from removed coal (Table C3) minus added natural gas criteria air pollution damages (Table C4); all avoided CO_2 damages are assumed to be offset by additional natural gas combustion and methane leakage. Forecasted domestic and global damages are from Table C3.

Efficient Buyout: Equating Marginal Benefits & Marginal Costs

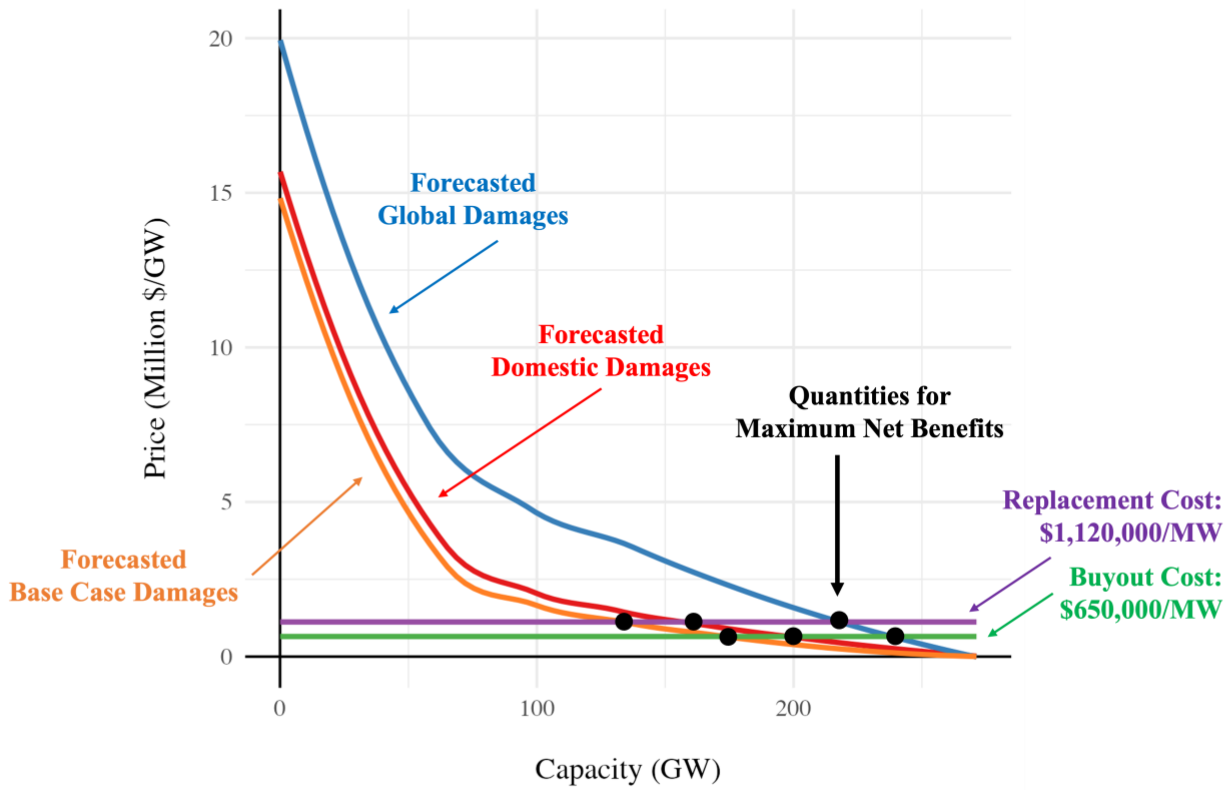
Economic principles dictate that efficient quantities are where marginal benefits (MBs) equal marginal costs (MCs). We determine the efficient quantity of coal capacity to buy out or replace by considering MBs as avoided future damage per MW and MCs as the buyout price per MW. Where MBs exceed MCs, the coal capacity should be bought or replaced; where MCs exceed MBs, it should not. This maximizes net benefits.

Typically, MBs decrease as quantities increase due to the law of diminishing marginal utility. In that case, each unit is identical; however, each additional unit's value to the consumer decreases as that consumer accumulates more units. Here, we can think about MBs "decreasing" for a different reason. The units of coal capacity are not identical but have varying values aligning with their forecasted future damages. Therefore, if we arrange the coal capacity from most to least damaging through 2035, we can mimic a typical decreasing MB curve. This is shown in Figure C4, where the orange, red, and blue lines show base case, domestic, and global MBs of removing coal capacity when strategically ordering units from most to least damaging.

MCs are the uniform price to buy out or replace a MW of coal capacity for our purposes. They are represented by the green and purple lines in Figure C4.

The six black points—i.e., where the curves intersect—in Figure C4 show the quantities to maximize net benefits, considering a combination of either base case, domestic, or global future damages of coal capacity and the cost to buy it out or replace it. The areas between the MB and MC curves give us our net benefits. Net benefits increase as the quantity bought out increases, so long as MBs exceed MCs. Once MCs exceed MBs, additional buyouts decrease net benefits.

Table C7 shows the benefits, costs, net benefits, and ROI of efficient coal fleet buyouts in 2020. The quantities are determined by equating MBs and MCs (or, specifically, only buying out each coal plant if the MBs of doing so exceed the MCs). Compared to Table C6, there are two added variables: lost capacity and lost generation, representing capacity bought out (out of 271 GW) and generation through 2035 forgone due to removal (out of 13.6 thousand TWh), respectively. Moreover, benefits and costs decrease while net benefits and ROIs increase compared to Table C6.



Sources: Buyout considers net book value per MW from RMI [113]. Replacement considers natural gas generator construction costs per MW from the EIA [115].
Notes: Capacity is sorted from greatest to least forecasted base case (orange), domestic (red), and global (blue) damages—making the marginal benefits curve. Marginal costs are set at $650 thousand per MW for buyouts (green) and $1.12 million per MW for replacements (purple). Maximum net benefits are where marginal benefits equal marginal costs (black points).

Figure C4. Marginal Benefits vs. Marginal Costs of 2020 U.S. Coal-Fired Power Plant Buyouts.

Table C7. Benefits and costs of buying out or replacing an efficient quantity of U.S. coal capacity in 2020.

Required Funding	**Considered Damages**	**Lost Capacity (GW)**	**Lost Generation (PWh)**	**Benefits (Billion $)**	**Costs (Billion $)**	**Net Benefits (Billion $)**	**Return on Investment**
Buyout	Base Case	168	9.85	562	109	452	4.14
	Domestic	199	11.5	671	129	542	4.19
	Global	238	13.4	1,243	155	1,088	7.03
Replacement	Base Case	141	8.92	537	158	379	2.40
	Domestic	163	10.3	640	182	457	2.51
	Global	225	13.3	1,231	252	980	3.90

Sources: Buyout considers net book value per MW from RMI [113]. Replacement considers natural gas generator construction costs per MW from the EIA [115].
Notes: Buyout costs are $650 thousand per MW. Replacement costs are $1.12 million per MW. Capacity is that which is bought out, where marginal benefits exceed marginal costs. Generation is that forecasted through 2035 but lost via the 2020 efficient buyout.

REVERSE AUCTION POLICY ANALYSIS

Germany's Coal Phase-Out

Coal Exit Act Policy Summary

Our analysis of reverse auctions to buy out coal in the U.S. mimics Germany's 2020 Coal Exit Act, passed to gradually phase out German coal by 2038 at the latest. A report provided by the think tank *Agora Energiewende* provides an in-depth overview of the policy design and initial playout [116].[38] Here, we will review some of the essential points from the report.

The German Coal Commission was created in 2018 to develop a plan to accelerate coal's phase-out to achieve its decarbonization goals. The group set forth a proposal to address German coal, focusing on five points of action: (1) phase out coal, (2) support the transition, (3) modernize the power system, (4) alleviate hardship, and (5) monitor and adjust measures.

The proposal ultimately led to the passing of the Coal Exit Act in July 2020, which included a budget to fund reverse auctions for coal-fired power plants. In a standard auction, bidders offer a willingness to pay for a contested good or service, and the sale goes to the highest bidder for the offered price. A reverse auction is the reverse, where bidders (here, power plants) offer a willingness to accept to decommission sooner than planned, and the assets are purchased from the lowest bidder for the offered price. The points below summarize relevant details of the Coal Exit Act's reverse auctions in Germany:

- Auctions occur every six months, with the final round preliminarily scheduled for mid-2023.
- Prespecified capacity volume targets—determined by carefully crafted calculations influenced by occurrences in the market (e.g., closures independent of the auctions)—are set uniquely for each round (Round 1 targeted 4 GW, and Round 2 targeted 1.5 GW).
- Each round has a maximum allowable bid (in EUR per MW). The value decreases each round for two reasons: (1) to reflect forgone revenue, which is lower for each additional round that a plant does not go offline, and (2) to encourage earlier participation.
- Winners are compensated the amount bided per MW decommissioned.
- As shown in Equation C2, bids are rescaled based on emissions.
- For energy security purposes, no coal-fired power plant in Germany's southern region could participate in the first round. These plants were then disadvantaged in subsequent rounds via a grid adjustment factor.
- In the case of undersubscription to the auction, the German government can order forced closures equal to the target capacity less subscription capacity gap.

The process relies on a "carrot" and "stick" approach. The "carrot"—a reward incentivizing a particular behavior—is the financial compensation for successful bidders who agree to decommission sooner than planned. The "stick"— a penalty incentivizing a particular behavior—is the ability of the government to order forced closures in the case of under subscription.

Importantly, the success of the auctions in Germany relies on additional policies, particularly those designed to reduce coal emissions and profitability (e.g., carbon pricing, air quality standards, and financial support for cleaner alternatives). Challenging market conditions

[38] The *Energiewende* translates to "energy turnaround" and is a term for the ongoing energy transition in Germany to a cleaner but affordable and reliable energy supply.

create an incentive for reverse auction participation. Moreover, as discussed in the report, Germany can afford to reduce its coal capacity because it has a fleet of modern gas-power plants.[39] Finally, Scott et al. (2022) pointed out that the practicality of reverse auction policy depends on the host country's political, legal, and financial context. Specifically, Germany has political support for the coal industry, strong laws protecting businesses from exploitation (i.e., expropriation and asset devaluation), and a large national budget. We note that these are all characteristics of the U.S. as well.

German's Bid Adjustment Procedure

One of the critical features of the German reverse auction policy is that each power plant's (firm's) bid is subject to a CO_2 emissions intensity adjustment factor [116]. Plants submit their bids in EUR per MW, but they also submit their CO_2 emissions over the past three years. The combination of these two pieces of information comprises the emission rate adjusted bid as shown in Equation C2:

Equation C2. Reverse Auctions: Germany's Bid Adjustment Procedure.

$$Emission\ Rate\ Adjusted\ Bid\ \left[\frac{EUR}{Avg.CO_2}\right] = Firm\ Bid\ \left[\frac{EUR}{MW}\right] \times Adjustment\ \left[\frac{MW}{Avg.CO_2}\right]$$

Hence, the final evaluation is the per-ton cost to the regulators of removing annual amounts of CO_2 utilizing the auction. In other words, it is not the lowest willingness-to-accept that wins the auction but rather the submission that results in the lowest CO_2 abatement costs.

The following example shows how a firm offering a higher bid could win the auction over a firm offering a lower bid. Let us consider Firm A, willing to accept 100,000 EUR per MW, and Firm B, willing to accept 120,000 EUR per MW to decommission early. With a lower bid, Firm A would win in a purely completive reverse auction. However, now let us consider their CO_2 emission intensity per unit of capacity—we set Firm A's to be 1,000 tons per MW and Firm B's to be 2,000 tons per MW. Using the adjustment process outlined in Equation C2, we see the following final amounts competing in the auction:

Equation C3. Reverse Auctions: Bid Adjustment Example.

$$\boldsymbol{Firm\ A}\text{: } 100{,}000\ \frac{EUR}{MW} * \frac{MW}{1{,}000\ ton\ CO_2} = 100\frac{EUR}{ton\ CO_2}$$

$$\boldsymbol{Firm\ B}\text{: } 120{,}000\ \frac{EUR}{MW} * \frac{MW}{2{,}000\ ton\ CO_2} = 60\frac{EUR}{ton\ CO_2}$$

As can be seen in Equation C3, Firm B's higher 120,000 EUR per MW is the lower competing amount when adjusted for CO_2 emission intensity. This is because buying out Firm B's capacity abates CO_2 at 60 EUR per annual ton, 40 EUR less per annual ton than buying out Firm A's capacity.

[39] While not investigated in this study, the Russo-Ukrainian War has put strain on energy markets (particularly gas markets) in Germany and the rest of the European Union.

This adjustment makes sense given the goals of the German Coal Commission—not to compensate struggling firms but rather to accelerate national decarbonization. The procedure works to strategically do the former to best achieve the latter.

Relevant Key Takeaways from Agora Energiewende

Here, we review some of the main takeaways from the *Agora Energiewende* report [116].

The German bid adjustment design provides an advantage for modern plants with higher capacity factors—emitting more CO_2 per unit of capacity because they operate more. Contrarily, it creates a disadvantage for older, less efficient plants with lower capacity factors and, correspondingly, lower CO_2 per unit of capacity. The other criterion to consider here, though, is electricity generation. Newer power plants typically generate power at lower emission rates (i.e., emissions per MWh) than older plants. Hence, the German model may lead to more emissions per unit of output because they are removing their "best" coal-fired power plants, considering the tradeoff of emissions for power. This observation drives one of our study's critical considerations, using CO_2 (and other criteria) normalized by generation rather than capacity (see Table C9).

The coal phase-out via reverse auctions makes the German grid more resource constrained. As a result, coal plants that remain part of the system become more valuable as others go offline—with higher utilization rates and, in turn, higher revenues. This drives a new, paradoxical incentive for coal plants to stay online while their competition goes offline. That said, Scott et al. (2022) noted that operators who opportunistically take advantage of this situation risk surpassing an opportunity for compensation in an increasingly challenging political and economic environment, where, for example, the threat of forced closure is already a reality and alternative fuel sources are gaining further support and becoming more competitive.

The reverse auction policy could have incentivized unprofitable coal plants to prolong their operations. In other words, operators could have intended to go offline without the policy, but with its announcement, they kept running with the goal of winning compensation. Scott et al. (2022) noted this as a high-risk strategy that would only be relevant for coal plants that otherwise would have shut down between 2018 and 2020. We offer another related perspective that is, perhaps, of greater concern. Coal plants that *would have shut down in the future* without compensation will certainly not do so while there is the opportunity for a payout. This is markedly costly to the government and, in turn, the German people, who are paying firms millions of dollars to do what they would have done without the policy. This will ultimately depend on whether the German Coal Commission initiates more rounds of the auction or lets the remainder of the coal fleet hang operate for as long as possible (until a certain point—e.g., the currently set 2038 cutoff date for coal). We will return to this point when we discuss our empirical work for this study, looking at the U.S. Our policy design setup herein, where all plants are guaranteed to be bought out at some point before 2035, makes this a more significant concern.

Many bids offered in the first few rounds of the German reverse auctions have been much lower than the maximum allowable amount. The targeted capacity was removed in the first two rounds without paying any participating firm the maximum allowable EUR per MW. The third and fourth rounds also had bid submissions notably below the maximum allowable value.[40] Scott et al. (2022) commented that financial and investor pressure likely incentivized some of the significantly lower bids in the auctions. Another important observation was that coal plants could have submitted markedly low bids in the second round because they did not anticipate that a third

[40] Figure 7 of Scott et al. (2022) [116] shows the range of bids as compared to the maximum for these four rounds.

round would take place. We emphasize three points regarding the bided values in the German reverse auctions. (1) The maximum allowable bid set forth by the German government is far lower (for every round) than our chosen $650,000 per MW, which we set considering the net book value of coal assets [113] or natural gas generator construction costs [115]. (2) Many firms accepted far lower than the maximum allowable bid. (3) Some firm decisionmaking was linked to the uncertainty about the policy's future. We will revisit these three points when discussing the U.S. reverse auction policy analysis.

U.S. Reverse Auction Policy Analysis Design

We now turn to our policy analysis. In this study, we evaluate hypothetical series of reverse auctions in the U.S. designed to retire an equal amount of capacity each year such that the coal fleet is completely offline by 2035. This is approximately 18.1 GW annually for 15 years from 2020 to 2034.

Our goals for this reverse auction assessment are as follows. Our first goal is determining the benefits of a gradual, rather than one-time, buyout or replacement. Benefits, however, could vary depending on which plants exit when. To characterize this variability, we find the range of possible outcomes (i.e., minimum and maximum of avoided damages through 2035). Then, our second goal is to evaluate how different policy designs—specifically, different bid adjustment factors—may influence the retirement order and the resulting avoided damages.

Assuming Away Varying Firm Decisionmaking

We do not assess firm behavior in this study. Instead, we make two admittedly restrictive assumptions so that decisionmaking is the same for every firm: (1) every coal plant opts into each round of the reverse auction program and submits bids until it wins and is compensated for retiring and (2) all firms submit the maximum allowable bid.

The "winners schedule," or retirement order, is, therefore, determined by the bid adjustment factor, ceteris paribus. The order is not influenced by decisionmaking in the context of the auction because we set firm behavior to be uniform. We dub these assumptions as "restrictive" because, in the real world, firm behavior would almost certainly vary greatly. Regarding the first assumption, many coal plants may choose not to participate in the reverse auction unless somehow forced. Regarding the second assumption, many coal plants may submit lower bids to outcompete other plants.

These assumptions allow us to evaluate the welfare advantage of selecting "the best" bid adjustment factor. While the bid adjustment factor will not dictate the order when introducing varying coal plant behavior, it can still influence the order to best accomplish the policy's goal (e.g., to minimize future damages).[41]

Reverse Auction Buyout Costs

Table C8 shows the reverse auction policy costs, considering future and discounted present values (with an SDR of 3%). The future cost per MW equals our maximum allowable bid—the net book value of coal assets in the U.S. of $650 thousand per MW [113] or the cost to construct a natural gas generator in the U.S. of $1.12 million per MW [115].

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[41] The best bid adjustment factor may vary depending on decisionmaker preferences (e.g., avoided damages versus retained net generation).

Because we design the policy to remove the entire coal fleet, the future values of costs are equivalent to those in Table C6. However, the discounted present values are lower at $145 billion and $249 billion because the payments occur over time. In this reverse auction analysis, we work with discounted present values—for both costs and benefits—to stay analogous to the one-time 2020 buyout analysis. We want to ensure that future damages are considered in the same context throughout this study to avoid potential confusion. That said, because this is a gradual buyout, there are other defendable ways to treat the time value of money (e.g., discounting the benefits of avoided future damages to the year the coal plant wins an auction and retires).

Table C8. U.S. coal plant reverse auction policy costs.

Year	n	Future Value		2020 Present Value	
		Buyout	**Replace**	**Buyout**	**Replace**
2020	0	11.8	20.3	11.8	20.3
2021	1	11.8	20.3	11.4	19.7
2022	2	11.8	20.3	11.1	19.1
2023	3	11.8	20.3	10.8	18.5
2024	4	11.8	20.3	10.4	18.0
2025	5	11.8	20.3	10.1	17.5
2026	6	11.8	20.3	9.84	17.0
2027	7	11.8	20.3	9.56	16.5
2028	8	11.8	20.3	9.28	16.0
2029	9	11.8	20.3	9.01	15.5
2030	10	11.8	20.3	8.75	15.1
2031	11	11.8	20.3	8.49	14.6
2032	12	11.8	20.3	8.24	14.2
2033	13	11.8	20.3	8.00	13.8
2034	14	11.8	20.3	7.77	13.4
Total		**176**	**304**	**145**	**249**

Sources: Buyout considers net book value per MW from RMI [113]. Replacement considers natural gas generator construction costs per MW from the EIA [115].
Notes: Costs are in 2020 U.S. dollars. Cost per round considers that approximately 18.1 GW are bought out each year. 2020 present value considers a discount rate of 3%.

The costs in Table C8 are strictly those under our analysis' assumptions that all coal plants submit the maximum allowable bid and that the government would set the maximum allowable bid to be $650,000 per MW or $1,120,000 per MW for every auction round. Under real-world conditions, the costs would likely be much lower than $176 billion or $304 billion over fifteen years. The first point here is that in some or all reverse auction rounds, the U.S. government could set a lower maximum bid value than $650,000 per MW. The German government's maximums for the first four reverse auction rounds were much lower than this value—e.g., the first round's maximum bid was 165,000 EUR per MW [116].[42] Also, as previously noted, the German government reduces the maximum allowable bid each round.

While our selected maximum aligns with the net book value of assets across the coal fleet [113] or the cost to construct a natural gas generator [115], lower values may still entice firms to

[42] While not exactly one-to-one, EUR and USD have similar value. It is also important to note that the net book value of coal plants in Germany could be lower than the net book value of coal plants in the U.S.

participate. This would be intuitive for coal plants with assets worth less than the average—they theoretically should participate at any bidding amount greater than or equal to their unique net book value per unit of capacity. However, this would likely not be the only driver of plant participation at lower values. As is the case in Germany, market conditions for coal are becoming increasingly challenging in the U.S., where regulations have made it harder for them to operate. At the same time, alternative fuel sources continue to become more competitive. Risk-averse firms may prefer a guaranteed payout—even one substantially lower than their assets' net book value—rather than move forward in a market where they are likely already struggling. Overall, evidence from Germany shows that a lower maximum allowable bid (or one that decreases over time) could still (or even better) stimulate participation among coal plants [116].

The second point is that reverse auctions are inherently competitive, where firms strive to outbid their competitors. Hence, the price per MW for the U.S. government would be driven down even without lowering the maximum allowable bid. Figure 7 of the *Agora Energiewende* report shows how powerful these market forces are, as many German coal plants were willing to accept nearly nothing to decommission [116]. While certainly not a guarantee, this provides evidence that reverse auction competition makes buyouts far more affordable than the conservative cost estimates in this paper.

Comparison to Germany's Coal Exit Act

One difference between our design and Germany's Coal Exit Act is that we run the simulation annually rather than every six months. We decide to remain in parallel with our forecasted data, which is annual, as it is derived using annual historical data.

Another key feature that differentiates our simulation and the German design is that, for our analysis, every coal-fired power plant is bought out. The question is not if but when a plant wins a reverse auction round and compensation to go offline. Circling back to some of the discussion points surrounding the Coal Exit Act in Germany, we point out how coal plants that would go offline sometime in the future without policy intervention is of greater concern with our design. We guarantee that each firm will be compensated, including many that may have planned to go offline before their auction-scheduled exit in a "no auction" scenario. This creates more costs for the American public in two ways: (1) compensating coal plants that would have gone offline either way and (2) driving more damages from emissions in years that coal plants are waiting for their buyout when they would have otherwise decommissioned sooner. These are serious concerns that policy design efforts should consider.

Another point to revisit is that coal plants submitted lower bids in the Coal Exit Act's second round because they were unsure that a third round would occur [116]. This benefited the German government, which paid less to participating firms because of risk-averse decisionmaking under uncertainty. Because our design has a guaranteed 15-year schedule, the U.S. government would not benefit from this firm behavior. Moreover, if every plant knew full well that, at some point over the next 15 years, they would receive $650,000 per MW or $1,120,000 per MW so long as they held out and continued to submit the maximum possible bid, they could do so and inhibit competition among bidding.[43] As such, policymakers may find it more advantageous not to reveal the long-term plans of a coal phase-out program or rather to take a dynamic approach, where the number of rounds and their details are determined in real-time. Besides catalyzing competition and

[43] This assumes that coal plants are pulling in enough revenue such that they are not accruing great enough losses rendering this strategy ineffective, which could be the case.

driving lower bids, the government could adapt over time as policy performance information is gathered during the first rounds.

Bid Adjustment Options

Ultimately, the analysis herein focuses on possible bid adjustment schemes. Again, we do not predict firm behavior (i.e., all firms are assumed to fully participate and submit the maximum allowable bid in every round) but rather assess how the policy can be designed to drive the greatest welfare advantage to the U.S. public by influencing the reverse auction outcomes. Given uniform coal plant decisionmaking, the bid adjustment factor (e.g., CO_2 per MW) determines the "winners schedule."

Table C9 summarizes our considered bid adjustment factors in this study. The eight options consist of four *impact variables* and two *normalizers*. The impact variables are the German-selected CO_2 emissions, SO_2 emissions (i.e., the most damaging of criteria air pollution from coal, see Table B2), damages, and nearby population counts. All impact variables consider the average across three years of historical data—2017, 2018, and 2019. For the base case damage category, damages are just from criteria air pollution (given the assumption for this research that natural gas substitutes in for coal and could offset GHG-derived benefits completely [76]). Nearby population counts are totals within 350 miles. Plant-to-population distances are determined using plant coordinates to counties' population-weighted coordinates.[44] The normalizers are the German-selected capacity and net generation averaged over the past three years.

Table C9. U.S. coal plant reverse auction bid adjustment factor options.

Impact Variable	Normalizer	1/Adjustment
CO_2 Emissions	Capacity	(3-Year Average of CO_2) / MW
	Generation	(3-Year Average of CO_2) / (3-Year Average of MWh)
SO_2 Emissions	Capacity	(3-Year Average of SO_2) / MW
	Generation	(3-Year Average of SO_2) / (3-Year Average of MWh)
Damages	Capacity	(3-Year Average of Damage) / MW
	Generation	(3-Year Average of Damage) / (3-Year Average of MWh)
Population	Capacity	Population Within 350 Miles × MW
	Generation	Population Within 350 Miles × (3-Year Average of MWh)

Sources: CO_2 emissions per unit of capacity is the adjustment factor used in the Coal Exit Act [116].
Notes: Three-year averages include data from 2017, 2018, and 2019. Population within 350 miles is determined using plant coordinates to population-weighted county coordinates. Damages include those from SO_2, NO_x, and primary $PM_{2.5}$ for base case damages. Damages include those from the criteria air pollutants and CO_2 impacts incurred domestically for domestic damages. Damages include those from the criteria air pollutants and all CO_2 impacts for global damages.

While the emissions and damages impact variables are normalized by unit of capacity and generation such that they are "distributed" across the totals at coal plants (emissions or damages per MW or MWh), the population impact variable is multiplicative. In other words, we consider the total population within a radius of 350 miles times the capacity or average generation at the plant. Since the population bid adjustment scheme is ignorant of the scale of emissions and damages, the size of a coal plant and or its operations is the next best option for differentiating, for example, a coal plant that is 100 MW and another that is 1 GW when their nearby population count

[44] Populations within 350 miles whose county's population-weighted centroid is outside the radius are excluded.

is equivalent. The multiplicative approach makes it such that we look at population counts within 350 miles of capacity or generation rather than within 350 miles of coal plants themselves, whose capacity and generation could vary significantly from plant to plant.

Bid Adjustment Interpretation

One substantial advantage of the German approach is the ease of interpreting the emission rate-adjusted bid (Equation C2). The units work out such that a bid in EUR per MW translates to EUR per annual ton of CO_2 seamlessly with the bid adjustment factor of CO_2 per MW. Using SO_2 or damages per MW would also result in this straightforward interpretation. However, the multiplicative population by MW approach confounds this interpretation—the final units are EUR/(Population $\times$ MW^2).

Pivoting to the net generation normalizer, we effectively must consider the capacity factor of the coal plant (i.e., generation versus total possible generation) to make sense of the units. This, again, confounds the simplistic interpretation offered by the German design.

The resulting ranking of bids should not be affected; instead, it is the understanding of what the bid adjustment factor does to the original bid that is thrown off. For example, if a firm submits a bid in EUR per MW and the adjustment factor is the inverse of CO_2 per MWh, the final metric would be in (EUR $\times$ MWh)/(MW $\times$ CO_2). That said, because bids are paid out on a pre-adjustment basis, so long as program regulators and participants are willing to accept the bid adjustment factor-determined ranking, the final units should not matter.

Determining the Population Radius

We use 350 miles as the distance for nearby population accounting because it results in the best "winners schedule" (with the lowest future base case damages with a per unit of capacity normalizer) across evaluated options, including 10 miles and every 50 miles from 50 to 500 miles. We run our auction simulation for each milage option shown and track the damages and net generation of the coal fleet through 2035. We prefer schedules that result in lower damages and higher net generation.

A 350-mile radius maximizes benefits at $283 billion when normalizing by capacity. (When normalizing by generation, a 400-mile radius maximizes benefits at $317 billion. We prioritize maximizing benefits when normalizing by capacity because benefits exceed $315 billion for any radius of 300 miles or greater when normalizing by generation.) Retained generation is greatest when accounting for populations just within 10 miles for both normalizers; however, we prioritize minimizing damages.

Running the Reverse Auction Simulations

Because we assume that each plant participates in and submits the maximum allowable bid for every reverse auction round until they are bought out as a winner for a particular round, the only differentiator among coal plants is the variable considered for bid adjustment. Hence, the eight options effectively serve as the schedulers of the program's "winners schedule."

For each year from 2020 through 2034, approximately 18.1 GW of coal capacity are removed. The coal plants making up the total each year are the coal plants with, for example, the greatest CO_2 per MW on average from 2017 to 2019—if we employ the German design. Once a coal plant wins a round of the reverse auction, its forecasted damages and net generation through 2035 are set to zero for the following years. Therefore, the final damages and retained net generation accumulate over the considered timeline from coal plants that have yet to win a reverse auction. The benefits of avoided damages result from forecasted damages that do not occur because a coal plant was removed via reverse auction.

Reverse Auction Simulation Results

This subsection discusses the results of our U.S. reverse auction simulations. We discuss the outcomes considering base case, domestic, and global damages. When looking at base case damages, average damages over three years for bid adjustment (see Table C9) considers criteria air pollution. Future benefits (or damages) are those from criteria air pollution minus (or plus) offsets from additional natural gas damages (or forgone damages). When looking at the other damage categories, all empirical work—i.e., average damages over three years for bid adjustment and resulting benefits and damages through 2035—considers that category of damages.

Optimal Outcomes

As reference points, we determine the best and worst possible outcomes of the reverse auctions. We accomplish this by optimizing for the maximum and minimum avoided damages and retained generation. This, critically, ignores any bid adjustment process and chooses the order of coal plant removal that results in these "optimal" outcomes.

Table C10. U.S. coal plant reverse auction outcomes maximizing and minimizing benefits and net generation.

Considered Damages	Optimized Criterion		Benefits (Billion $)	Damages (Billion $)	Generation (PWh)	Percent of Benefits	Percent of Generation
Base Case	Avoided Damage Benefits	Max.	429	161	5.83	73%	43%
		Min.	100	489	8.51	17%	63%
	Retained Net Generation	Max.	155	434	9.87	26%	73%
		Min.	374	216	4.45	63%	33%
Domestic	Avoided Damage Benefits	Max.	495	198	5.22	71%	39%
		Min.	130	564	8.84	19%	65%
	Retained Net Generation	Max.	184	510	9.87	26%	73%
		Min.	440	254	4.45	63%	33%
Global	Avoided Damage Benefits	Max.	839	413	4.87	67%	36%
		Min.	293	959	9.12	23%	67%
	Retained Net Generation	Max.	337	914	9.87	27%	73%
		Min.	801	451	4.45	64%	33%

Notes: Benefits and damages are in 2020 present values and are in 2020 U.S. dollars. Coal plants are removed via the reverse auction program in an order that maximizes or minimizes the criterion of focus. Base case benefits and damages are out of a forecasted $589 billion total. Domestic benefits and damages are out of a forecasted $694 billion total. Global benefits and damages are out of a forecasted $1,252 billion total. Generation is that retained out of a forecasted 13.6 PWh total. See Table C3 (and Table C4) for forecasts.

Table C10 shows the reverse auction outcomes maximizing and minimizing benefits and retained net generation. Considering base case damages, the maximum benefits that the reverse auction policy could achieve are $429 billion, and the minimum benefits are $100 billion. The maximum retained net generation the reverse auction policy could achieve is 9.87 thousand TWh, and the minimum net generation is 4.45 thousand TWh.

These values provide us with intervals within which our reverse auction results must lie. No bid adjustment factor could result in benefits or retained generation outcomes that are higher than the maximums or lower than the minimums.

Evaluating the Winners Schedules with Damages Over Time

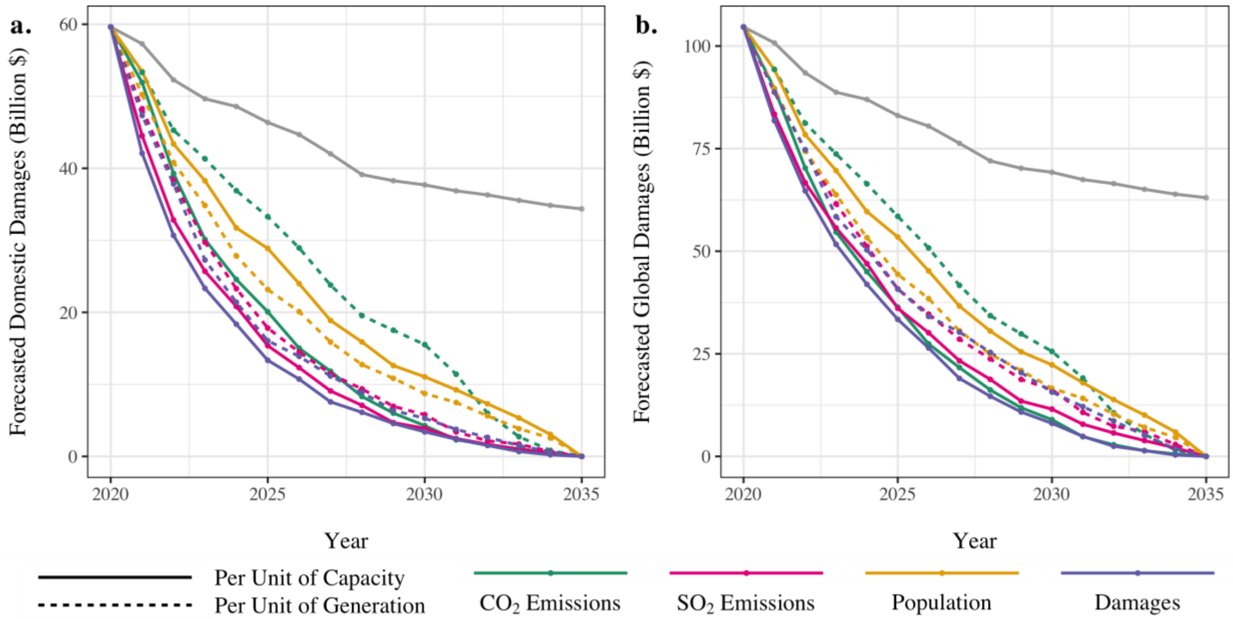
Table C11 reports the data comprising Figure 3(A) of the manuscript, showing forecasted annual damages (base case category) by bid adjustment factor compared to a no auction scenario (gray line). The annual benefits are the difference between each auction's damages and the no auction counterfactual.

Figure C5, like Figure 3(A) of the manuscript, shows forecasted annual damages by bid adjustment factor compared to a no auction scenario (gray line). Figure C5(a) shows the analysis considering domestically incurred damages, and Figure C5(b) shows the analysis considering globally incurred damages. The vertical distance between the gray line (no auction scenario) and each simulation's line shows the annual benefits of the auction.

Table C11. Forecasted annual damages of U.S. coal plant reverse auctions by bid adjustment factor.

Year	**Per Unit of Capacity**				**Per Unit of Generation**				**No Auction**
	CO_2	**SO_2**	**Population**	**Damage**	**CO_2**	**SO_2**	**Population**	**Damage**	
2020	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1
2021	44.7	37.1	45.7	34.8	45.6	40.6	42.8	39.7	49.0
2022	33.3	26.4	36.8	25.2	38.5	31.4	34.5	31.0	44.5
2023	25.4	20.1	32.5	18.4	35.2	23.8	29.5	21.5	42.3
2024	20.6	15.9	26.7	14.0	31.3	18.1	23.2	16.4	41.4
2025	16.9	11.5	24.4	9.8	28.5	13.5	19.4	11.9	39.5
2026	12.6	9.0	20.2	7.7	24.8	10.8	16.8	10.3	38.0
2027	9.88	6.43	15.73	5.25	20.36	8.31	13.26	7.93	35.6
2028	6.75	4.92	13.30	4.05	16.73	6.70	10.59	6.07	33.0
2029	4.85	3.07	10.34	3.04	15.15	4.77	9.06	4.19	32.4
2030	3.35	2.50	9.06	2.05	13.56	3.88	7.35	3.45	31.9
2031	1.82	1.48	7.70	1.40	9.89	2.09	6.31	2.33	31.2
2032	1.39	0.94	6.16	0.93	5.08	1.22	4.82	1.48	30.7
2033	0.958	0.435	4.510	0.406	2.225	0.914	3.270	0.719	30.1
2034	0.473	0.180	2.553	0.133	0.672	0.260	2.189	0.267	29.5
2035	0	0	0	0	0	0	0	0	29.1
Total	**234**	**191**	**307**	**178**	**338**	**217**	**274**	**208**	**589**

Notes: Data are damages in 2020 present values and in billions of 2020 U.S. dollars. Coal plants are removed via the reverse auction program in an order that aligns with the bid adjustment factor, removing the influence of firm behavior. Data for Figure 3(A) of the manuscript.



Notes: Damages are in 2020 present values and are in 2020 U.S. dollars. Coal plants are removed via the reverse auction program in an order that aligns with the bid adjustment factor, removing the influence of firm behavior. (a) shows reverse auction analysis results considering domestic damages. (b) shows reverse auction analysis results considering global damages. Gray line shows forecasted damages with no reverse auction policy.

Figure C5. Forecasted Annual Damages with U.S. Coal Plant Reverse Auctions by Bid Adjustment Factor.

Figure 3(A), Table C11, and Figure C5 show that any reverse auction, regardless of design, would drive substantial benefits compared to the no auction counterfactual. Given the concave-up decreasing shape of most auction designs' forecasted damage curves, we see that the most damaging plants are targeted first. In contrast, the least damaging plants are targeted last. This is most prominent for the damages bid adjustment factors (it is least prominent for the population bid adjustment factors and CO_2 per unit of generation).

Overall, we can conclude that the damages per unit of capacity bid adjustment factor results in the greatest annual benefits. For base case and domestic damages, SO_2 per unit of capacity offers a close second-best option. For global damages, both CO_2 per unit of capacity and SO_2 per unit of capacity offer strong second-best options. Notably, normalizing by generation rather than capacity results in greater yearly damages for every impact variable besides population. Therefore, if decisionmaker preferences are heavily skewed towards avoiding future damages, we suggest a per unit of capacity normalizer. However, regulators may also want to consider retaining net generation from the coal fleet as part of the decisionmaking equation.

Evaluating the Winners Schedules Across Multiple Criteria

Table C12 reports the data comprising Figure 3(B) of the manuscript, showing the multi-criteria assessment of total avoided damages versus total retained generation by bid adjustment factor. (Damages align with the totals reported at the bottom of Table C11; benefits can be computed by subtracting those damages from $589 billion—the no auction case.)

Figure C6, like Figure 3(B) of the manuscript, shows the multi-criteria assessment of total avoided damages versus total retained generation by bid adjustment factor. Figure C6(a) shows the analysis considering domestically incurred damages, and Figure C6(b) shows the analysis considering globally incurred damages. The black dashed line is the maximum avoided damages (see Table C10).

In Figure 3(B) of the manuscript and Figure C6, the further a point is to the right, the greater its avoided damages. The further a point is up, the greater its retained net generation. Therefore, the further a point is both up and to the right, the greater its welfare advantage under multiple criteria (i.e., both avoided damages and retained generation).

Table C12. Multi-criteria assessment of U.S. coal plant reverse auctions by bid adjustment factor.

Considered Damages	Bid Adjustment Factor		Benefits (Billion $)	Damages (Billion $)	Generation (PWh)	Percent of Benefits	Percent of Generation
Base Case Damages	CO_2	Per Unit of Capacity	355	234	5.60	60%	41%
	SO_2		398	191	6.43	68%	48%
	Population		283	307	6.99	48%	52%
	Damages		411	178	6.51	70%	48%
	CO_2	Per Unit of Generation	251	338	7.89	43%	58%
	SO_2		372	217	7.03	63%	52%
	Population		315	274	6.28	54%	46%
	Damages		381	208	7.42	65%	55%
Domestic Damages	CO_2	Per Unit of Capacity	417	277	5.60	60%	41%
	SO_2		452	242	6.43	65%	47%
	Population		331	363	6.99	48%	52%
	Damages		469	225	6.42	68%	47%
	CO_2	Per Unit of Generation	297	396	7.89	43%	58%
	SO_2		420	273	7.03	61%	52%
	Population		369	324	6.28	53%	46%
	Damages		430	264	7.39	62%	55%
Global Damages	CO_2	Per Unit of Capacity	756	496	5.60	60%	41%
	SO_2		742	510	6.43	59%	47%
	Population		584	668	6.99	47%	52%
	Damages		786	466	6.10	63%	45%
	CO_2	Per Unit of Generation	554	698	7.89	44%	58%
	SO_2		681	571	7.03	54%	52%
	Population		654	598	6.28	52%	46%
	Damages		680	571	7.49	54%	55%

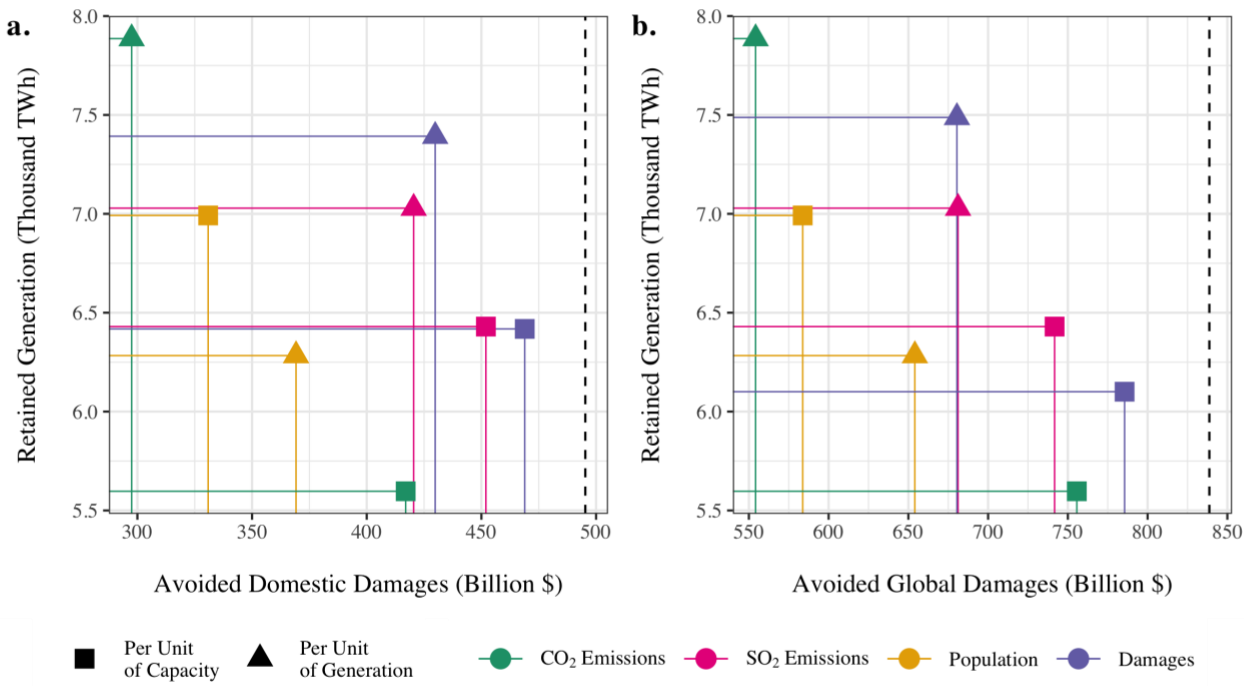
Notes: Evaluated criteria include avoided damages and retained generation. Avoided damages are in 2020 present values and are in 2020 U.S. dollars. Coal plants are removed via the reverse auction program in an order that aligns with the bid adjustment factor, removing the influence of firm behavior. Base case benefits and damages are out of a forecasted $589 billion total. Domestic benefits and damages are out of a forecasted $694 billion total. Global benefits and damages are out of a forecasted $1,252 billion total. Generation is that retained out of a forecasted 13.6 PWh total. See Table C3 (and Table C4) for forecasts.

Figure 3(B), Table C12, and Figure C6 reveal that a damages per unit of capacity bid adjustment factor results in the greatest avoided damages (i.e., the points are furthest to the right in the figures). Additionally, SO_2 per unit of capacity is far to the right in Figure 3(B) of the manuscript and Figure C6(a) herein, and both CO_2 and SO_2 per unit of capacity are far to the right in Figure C6(b).

However, Figure 3(B), Table C12, and Figure C6 also reveal the advantage of using a per unit of generation normalizer. Using this bid adjustment approach, we can trade off some avoided damage to retaining additional net generation from the coal fleet (i.e., the points move up and to the left compared to their per unit of capacity counterparts in the figures).

Significantly, any point further up and to the right relative to another point dominates it under the considered criteria. We would choose the dominant point regardless of our preferences for avoiding future damages vs. retaining net generation. This is because there is an advantage for both criteria by selecting the dominating bid adjustment factor relative to the dominated bid adjustment factor.

Focusing on the base case damage analysis, we see that three bid adjustment factors are non-dominated: air pollution damages per unit of capacity, CO_2 per unit of generation, and damages per unit of generation. Notably, the bid adjustment factors defined in terms of SO_2 are only dominated by their counterparts defined in terms of damages. In the case where decision-makers are hesitant to use damages (we will revisit this concept), SO_2 is a strong second option. Interestingly, the German-selected CO_2 per unit of capacity is dominated by four other options (SO_2 and damages with both normalizers).



Notes: Evaluated criteria include avoided damages and retained generation. Avoided damages are in 2020 present values and are in 2020 U.S. dollars. Coal plants are removed via the reverse auction program in an order that aligns with the bid adjustment factor, removing the influence of firm behavior. (a) shows reverse auction analysis results considering domestic damages. (b) shows reverse auction analysis results considering global damages. Black dashed line shows maximum possible avoided damage benefits (Table C10).

Figure C6. Multi-Criteria Assessment of U.S. Coal Plant Reverse Auctions by Bid Adjustment Factor.

Focusing on the domestic damage analysis, we see that four bid adjustment factors are non-dominated: SO_2 per unit of capacity, damages per unit of capacity, CO_2 per unit of generation, and damages per unit of generation. [45] We also see four bid adjustment factors dominate at least one other option: SO_2 per unit of capacity, damages per unit of capacity, SO_2 per unit of generation, and damages per unit of generation. Interestingly, the German-selected CO_2 per unit of capacity is dominated by four other options (SO_2 and damages with both normalizers).

Focusing on the global damage analysis, we see that the list of non-dominated options changes slightly (i.e., SO_2 per unit of generation is not dominated by damages per unit of generation, offering slightly greater avoided damages). Also, the interior of the grid changes such that there are fewer instances where one point dominates another. Importantly, the German-selected CO_2 per unit of capacity is now dominated by only one other option, damages per unit of capacity.

There is no best option among those non-dominated without knowing more about decisionmaker preferences. However, we do know that the preferred option lies among those that are non-dominated.

We could further center in on a list of preferred bid adjustment factors considering which options are *supported* non-dominated solutions. Unsupported non-dominated solutions reside in *duality gaps*—i.e., interior triangles created by two supported non-dominated points [117]. Looking at Figure 3(B) on the manuscript, we see no unsupported non-dominated solutions when considering base case damages. Looking at Figure C6(a) and Figure C6(b), we see there are unsupported non-dominated solutions when considering domestic or global damages. SO_2 per unit of capacity in Figure C6(b) provides a strong visual example. If we were to draw a line between the two damage-based bid adjustment factors, SO_2 per unit of capacity falls within the resulting interior triangle.

Pivoting to the two other unsupported non-dominated options (SO_2 per unit of capacity considering domestic damages and SO_2 per unit of generation considering global damages), we now discuss this concept in plain English and its resulting implications. For SO_2 per unit of capacity to beat out damages per unit of capacity in Figure C6(a), policymakers would have to have a much greater preference for retaining generation than avoiding damage. This is because, to go from one point to the other, they would have to give up a lot of avoided damages to get a small amount of retained generation. However, if this were the case, decisionmakers would likely be drawn to the damages per unit of generation option as it would get them much more of what they prefer (retained generation). Considering a shift from damages per unit of capacity to either (1) SO_2 per unit of capacity or (2) damages per unit of generation, additional units of retained generation are "cheaper" in terms of avoided damages that must be given up. The same logic applies for SO_2 per unit of generation to beat out damages per unit of generation in Figure C6(b).

There are exceptions to this mathematically based logic. The first would be if policymakers have strong preferences on the margin (i.e., they want to be in the realm of the two options, but, in that realm, they are willing to trade "a lot for a little"). The second would be if policymakers set specific constraints for one (or both) criterion (or criteria). For example, preferences could be very high for avoiding damage but only after a certain amount of generation is "retained."[46] The third would be if decisionmakers are hesitant to employ a supported non-dominated solution for reasons external to this multi-criteria framework. For example, they could prefer using SO_2 over damages

[45] Notably, SO_2 per unit of capacity is only just non-dominated compared to damages per unit of capacity, offering an ever so slight advantage for retained generation.

[46] Retained is in quotations because these forecasts are subject to dynamics with time. In other words, if the grid requires more power from the remaining coal fleet, plants could increase their operations in real time and fill in as much as is needed (or as much as is possible with existing capacity).

because they have an aversion to the latter. Emissions come with far less uncertainty than damages. Hence, an unsupported non-dominated solution (or even a dominated solution) using SO_2 may still be preferred in the real world.

U.S. Reverse Auction Policy Analysis Caveats

We offer some critical caveats regarding this work:

- Perhaps the most important to reiterate is the concern of *dynamics with time*. As Scott et al. (2022) [116] discussed, a coal phase-out via reverse auctions makes the grid more resource-constrained, and correspondingly, coal plants that remain part of the system will become more valuable and be utilized more. This will result in more emissions (and damages) and more net generation from the remaining coal plants than is forecasted using historical data.
- We do not consider power system impacts when determining the order of removal.
- We again mention that we "assume away" varying firm behavior. In actuality, the bid adjustment factor is just one of a variety of variables that will drive the auctions' outcomes.
- Policy costs for any reverse auction design are assumed to be \$176 billion over 15 years (or \$145 billion in 2020 present value) or \$304 billion over 15 years (or \$249 billion in 2020 present value). However, this assumes that all payouts equal the net book value of coal assets or the costs to install a new natural gas generator. Smart policy design (e.g., a decreasing maximum bid) and program competition (i.e., firms attempting to outbid their competitors), however, could significantly decrease these amounts.

We emphasize that none of these caveats invalidate the comparative analysis findings because the caveats apply to all investigated options.

Overall, this analysis provides guidance to regulators in that (1) any reverse auction design gradually removing the coal fleet results in substantial benefits and (2) choosing non-dominated bid adjustment factors, such as damages per unit of capacity or damages per unit of generation, provide a welfare advantage over dominated options (e.g., the German-selected CO_2 per unit of capacity).

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