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The Impact of a Revenue Neutral Carbon Tax on Substitution of Natural Gas for Coal in the Electricity Sector

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Abstract

Due to low natural gas prices and the environmental advantages of natural gas combined cycle (NGCC) compared to coal, NGCC is replacing coal generators as the inframarginal providers of electricity. However, on average, NGCCs are running only 54 percent of the time. Utilizing excess NGCC capacity further, in place of coal generation, is a short-term solution for reducing greenhouse gases. In this research, we evaluate the impact of a carbon tax on substitution of natural gas for coal in the electricity sector. A carbon tax would influence the economics that system operators consider when determining how much to run a power plant. Through the use of fixed effects regression and counterfactual calculations, we analyze data from 2003-2017 to evaluate the impact of a carbon tax on NGCC utilization and carbon emissions reductions through 2026. We estimate that a $220/ton carbon tax would be necessary to reach a 75 percent NGCC utilization target, but the largest marginal increase in NGCC utilization comes from a carbon tax of $1-$50/ton. A $50 carbon tax would initially reduce electricity sector carbon emissions between 9-12 percent based on assumptions about future NGCC capacity expansion. The carbon tax we propose would be simpler to implement than an economy-wide tax and would still lead to significant carbon reductions in the short-run.

Keywords: carbon tax, natural gas, electricity

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[1] Kelly A. Stevens: University of Central Florida, School of Public Administration, Kelly.Stevens@ucf.edu
[2] Deborah A. Carroll: University of Central Florida, School of Public Administration, Deborah.Carroll@ucf.edu

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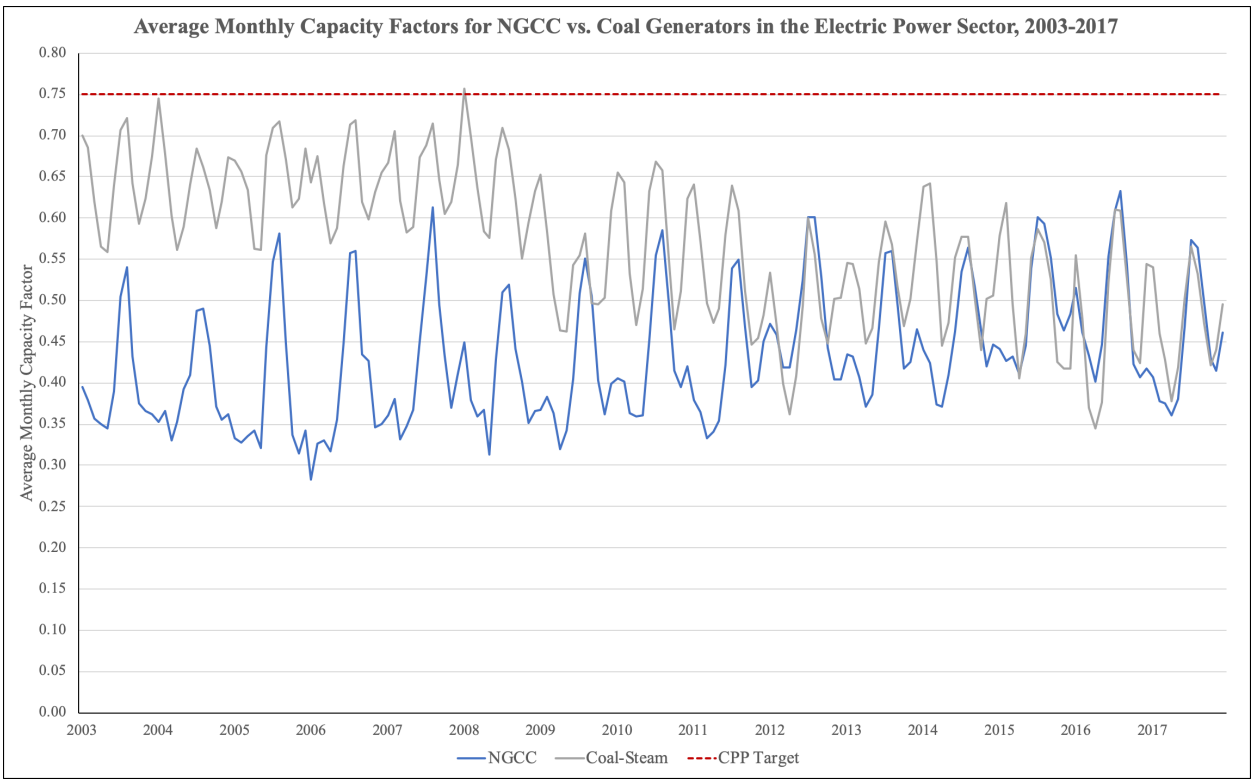
1. Introduction

The Energy Information Administration estimates 76 percent of greenhouse gas emissions in the U.S. result from burning fossil fuels, with approximately 34 percent of these emissions from electricity generation.[3] To reduce emissions, recent climate regulations include increased utilization of natural gas-fired combined cycle generators (NGCC) as a means for offsetting coal generation. Lower pollutant content and high thermal conversion efficiency of NGCC translate into 60 percent less CO_2 emissions than traditional coal generators. Due to low natural gas prices and the environmental advantages of NGCC compared to coal, studies have shown that NGCC is replacing coal generators as the inframarginal providers of electricity (Lu et al., 2012; Fell & Kaffine, 2018). As a result, there have been substantial increases in NGCC utilization in the last 15 years for some plants. However, on average, these plants are running only 54 percent of the time, leaving potential for further NGCC generation from existing sources (Figure 1). Several studies estimate that utilizing excess NGCC capacity in place of coal generation would reduce electricity sector carbon emissions by 23-42 percent (LaFrancois, 2012; Gelman et al., 2014). Because of this, the U.S. Environmental Protection Agency's (EPA) 2015 Clean Power Plan (CPP) recommended increasing average NGCC capacity factors $\left(\frac{Actual\ Electricity\ Output}{Potential\ Output}\right)$ to 75 percent on a net summer capacity basis.

In this research, we suggest that instead of utilization targets or emissions caps, a properly designed and implemented carbon tax would be a more efficient means for increasing NGCC utilization. A carbon tax would influence the economics that system operators consider when determining how much to run a power plant. Units with higher variable costs – fossil fuel-

[3] U.S. Energy Information Administration, available at: https://www.eia.gov/energyexplained/index.php?page=environment_where_ghg_come_from.

Figure 1



fired natural gas and coal plants – offer flexibility in when they run to serve load. For example, a carbon tax implemented midstream that is based upon actual CO_2 emissions would place an economic advantage on running NGCC in place of coal plants, boosting NGCC utilization. For this study, we evaluate the revenue and distributional impacts of various forms of a carbon tax on NGCC utilization and carbon emissions. Our goals are 1) to identify the carbon tax price with the greatest marginal impact on utilization, as well as the price point required to achieve the CPP's 75 percent average utilization target, and 2) to suggest the most appropriate form of carbon tax in terms of the base to which it would apply, its implementation approach, and offsetting tax relief for revenue neutrality, as the tax is intended to replace climate regulations aimed at reducing CO_2 emissions from the electricity sector.

The first part of this study uses a fixed-effects regression model of NGCC capacity factors from 2003-2017 to estimate the relationship between natural gas and coal resource prices

on NGCC utilization. With these estimates, we use a counterfactual model with different carbon tax prices to evaluate the impact of a carbon tax on NGCC utilization. Even though the CPP has been repealed,[4] the EPA has deemed the average 75 percent utilization to be achievable and effective at lowering carbon emissions. Using our models, we estimate the carbon tax price with the greatest marginal impact on utilization, as well as that which is required to raise average NGCC utilization to the CPP target of 75 percent.

Once we are able to determine the rate at which a carbon tax would produce an equivalent level of emissions reduction under proposed targets and current regulations, in the second part of this study, we estimate the revenue-generating and carbon-reducing potential of our proposed carbon tax in the short-run from 2018-2026.[5] Through further analysis of the anticipated distributional effects of the most appropriate carbon tax (including its effects on relative prices, incomes, and government spending) we will also evaluate the best approach for alleviating the burden of other taxes imposed upon affected parties to offset the revenue generated by the carbon tax with an underlying goal of enhancing free market investment while remaining revenue neutral.

Increasing output from existing NGCC plants is a low-cost solution that focuses on short-term operation decisions. Yet, a carbon tax would also have the long-term impact of encouraging investment in low to zero emitting technologies such as advanced NGCC and renewables. Additionally, a carbon tax avoids potential issues identified by Stevens (2018) with NGCC utilization targets that may unnecessarily increase compliance costs. Finally, a revenue neutral carbon tax has the potential to reduce other tax rates as the carbon tax revenue is offset in a way

[4] U.S. Environmental Protection Agency, available at: https://www.epa.gov/stationary-sources-air-pollution/electric-utility-generating-units-repealing-clean-power-plan.
[5] The most recent year of available data is 2017, so it is necessary to begin our estimates in 2018 even though the year occurs in the past.

that is vertically equitable or largely progressive for consumers at most levels of the income distribution.

2. Literature

2.1 Carbon Taxes

Carbon taxes have been utilized globally as a means to substantially reduce carbon emissions. The literature on carbon taxes suggests that emission reductions are achieved by carbon tax policies despite a number of different implementation scenarios. McKibbin et al. (2015) looked at four different policy scenarios and found long term reductions at 18 to 21 billion metric tons below the base level. A more recent study showed that a $50 per ton carbon tax, increasing at 5 percent per year, would produce an estimated ten-year emissions decline of 22 to 28 percent (Barron et al., 2018). Nystrom and Lucklow (2014) found a carbon tax beginning at $10/ton, and increasing $10 per year, that would be assessed at extraction, and with a revenue offset occurring as monthly rebates to all households, would reduce CO_2 emissions by 33 percent, save 13,000 premature deaths from improved air quality, and create 2.1 million new jobs by 2025.

One of the main reasons for the public and political opposition to carbon taxes is the claim that a carbon tax will negatively impact the economy. The trade-offs between fighting global warming and economic development are considered in any climate policy. This would largely depend on how the revenues from the tax are used. However, in the literature, there are many differing opinions on how the revenue should be used. For example, Jorgenson et al. (2015) analyzed seven options for revenue use: (1) reducing capital tax rates; (2) proportionally reducing capital and labor tax rates; (3) reducing labor tax rates; (4) increasing federal, state, and local government purchases; (5) reducing the deficit; (6) reducing the debt; and (7) a lump sum redistribution to households. Ultimately, the study determined that recycling carbon tax revenue

through reductions in capital income tax rates would provide the largest margin of economic benefits over the costs of emissions control.

In our paper, we focus on a carbon tax implemented at the federal level in the U.S. There is strong agreement in the literature that this would be feasible and have minimal negative effects on the U.S. economy. Metcalf (2008) states that there are strong economic, administrative and efficiency arguments that can be made for a carbon tax in the U.S. McKibbin et al. (2015) found that a carbon tax or a labor tax increase would both have small negative effects on GDP, consumption, and investment, but that a carbon tax would offer a way to help reduce the deficit and improve the quality of the environment with minimal disturbance to overall economic activity. Another paper by Gale, Brown and Saltiel (2013) concludes that a carbon tax in the U.S. would improve environmental outcomes, increase economic efficiency, and allow the elimination of selected other tax subsidies and spending programs.

Carbon taxes have been used for more than twenty-five years in countries and sub-national governments with different price points per ton of CO_2. These taxes have been implemented in Canada, Ireland, Japan, Mexico, Portugal, Switzerland, and Denmark, among others. Metcalf (2019) found that the tax price ranges vary from a rate of less than $1 per ton of CO_2 in Poland to up to $139 per ton in Sweden. As of early 2019, 27 national or sub-national carbon taxes were in effect worldwide.

Most of the literature agrees that a carbon tax is more economically efficient than a cap-and-trade policy. Harrison (2012) suggests, however, that cap-and-trade systems have political advantages over carbon taxes. The author notes that cap-and-trade offers lower visibility of costs to consumers and the opportunity to allocate valuable permits freely to industry. Milne (2008) also notes that the focus in the U.S. has been on cap-and-trade regimes, largely for political

reasons. The author states that while taxes seem more politically volatile, both systems need to be held to the same level of scrutiny when it comes to calculating economic impact, equity, administrative feasibility, and environmental effect.

Many of the existing or proposed carbon taxes in the world are economy-wide, extending beyond the electricity industry to other sources of pollution including transportation, industrial, and commercial sectors. However, for this study, we focus on the impact of a federal carbon tax on the electricity industry only, which is one of the largest sources of carbon emissions in the U.S. This narrower approach might help to reduce political opposition to the tax because the tax would apply to only one sector of the economy, the electric utility industry, which has recently supported carbon taxes (Walton, 2019) despite opposition by energy companies (Anderson et al., 2019).

2.2 NGCC and Coal Substitution

The main source of carbon emissions in the electricity sector is from burning fossil fuels, including coal and natural gas, to generate electricity. However, natural gas has about half the carbon emissions as coal, rendering NGCC power plants that run on natural gas environmentally advantageous to coal-fired plants. Therefore, we hypothesize in this study that a carbon tax, which would be more burdensome for coal-fired power plants, would lead to an increase in natural gas generation in place of coal.

During the early 2000s, NGCC capacity increased substantially in the U.S. in response to low natural gas price forecasts, growing energy demand, and electricity market restructuring (Joskow, 2006). Since this "natural gas capacity boom," utilization began increasing in 2005 as capacity growth slowed. NGCCs were initially used as peaking units running only when

electricity demand was at its highest. However, there has been a slow, steady shift to higher utilization (see Figure 1).

Recent studies on natural gas generation focus on particular regions of the U.S. (Kaffine, McBee & Lieskovsky, 2013; Novan, 2015), or Independent System Operators (ISO)/Regional Transmission Organizations (RTOs) (Fell and Kaffine, 2018). Other studies evaluate aggregate emissions reductions in regional areas based on generation switching (Cullen & Mansur, 2017). Others analyze the impact of decreased natural gas prices on electricity prices (Linn et al., 2014). These studies generally conclude that areas with ample natural gas capacity replace coal as natural gas prices decrease. As a result, CO_2 emissions decline since natural gas is about half as carbon intensive as coal. Some studies also find increases in renewable generation may have competed with natural gas generation at first but are now displacing coal as natural gas prices have fallen during the shale gas revolution (Fell & Kaffine, 2018).

Our study focuses specifically on capacity factors for NGCC plants as the dependent variable, rather than on natural gas generation as a whole, which can also include less efficient, single-cycle gas turbines. Our approach focuses on *utilization* rather than generation, which includes changes in capacity and therefore investments in NGCC capital. However, we also include estimates for the joint impact of modest NGCC capacity expansion (provided through EIA forecasts) with increased NGCC utilization on carbon emissions. Our analysis includes controls for the impacts of regulatory policies, plant, and area characteristics on NGCC utilization, and assumes increases in NGCC generation replace coal, as established by previous studies (Linn et al., 2014; Fell and Kaffine, 2018).

3. Model Specification and Data

To determine the impact of a carbon tax on NGCC utilization, we use a regression model to first estimate the impact of resource prices on NGCC capacity factors. Then, we use these estimates in a counterfactual calculation to predict how various carbon tax prices would affect NGCC generation and CO_2 emissions. Last, we take this information from the counterfactual to estimate carbon emissions and tax revenues from the electricity sector and then evaluate how this revenue could be offset for revenue neutrality.

3.1 NGCC Capacity Factor Regression Model

We begin with an econometric specification and estimation to evaluate the impact of resource prices on NGCC utilization using a fixed-effects regression model (see Eq. 1). Using *i* to denote the unit of observation (plant-fuel-technology group), and *t* to denote time (year-month), we estimate monthly capacity factors (*cf*) for NGCC units for each year 2003-2017. For independent variables, the function $s(\cdot)$ denotes a cubic spline used on the price ratio, using *s* to denote each state. The regression also includes a vector of policy variables ($\boldsymbol{\beta}_{\boldsymbol{Control}}^{\boldsymbol{Policy}}$), and their capacity-weighted age interactions ($\boldsymbol{\beta}_{\boldsymbol{age}}^{\boldsymbol{Policy}}$). We also include capacity-weighted age (Age_i), a vector of state weather variables ($\mathbf{W}_{\boldsymbol{s,t}}$), and area load ($\mathbf{A}_{\mathbf{a,t}}$). The fixed-effects model includes individual fixed-effects (α_i) to control for time invariant characteristics of each plant. The month and year fixed effects (θ_m, θ_y) control for seasonality and annual variation that may be due to advances in technology or learning by doing. The standard errors are clustered at the area level to address potential heteroscedasticity and errors that may be correlated within an area.

$$cf_{i,t} = \beta_0 + s(\tau_1 price\ ratio_{s,t}) + \beta_{Control}^{Policy} Policy_{i,t} + \beta_{age}^{Policy}(Age_i \cdot Policy_{i,t}) + \mathrm{X_{i,t}}\varphi_{\mathrm{X}}$$
$$+ \mathrm{W_{s,t}}\gamma_{\mathrm{Y}} + \mathrm{A_{a,t}}\mu_{\mathrm{Z}} + \theta_m + \theta_y + \alpha_i + \varepsilon_{i,t}$$

(Eq. 1)

3.2 Data

3.2.1 Electric Power Sector

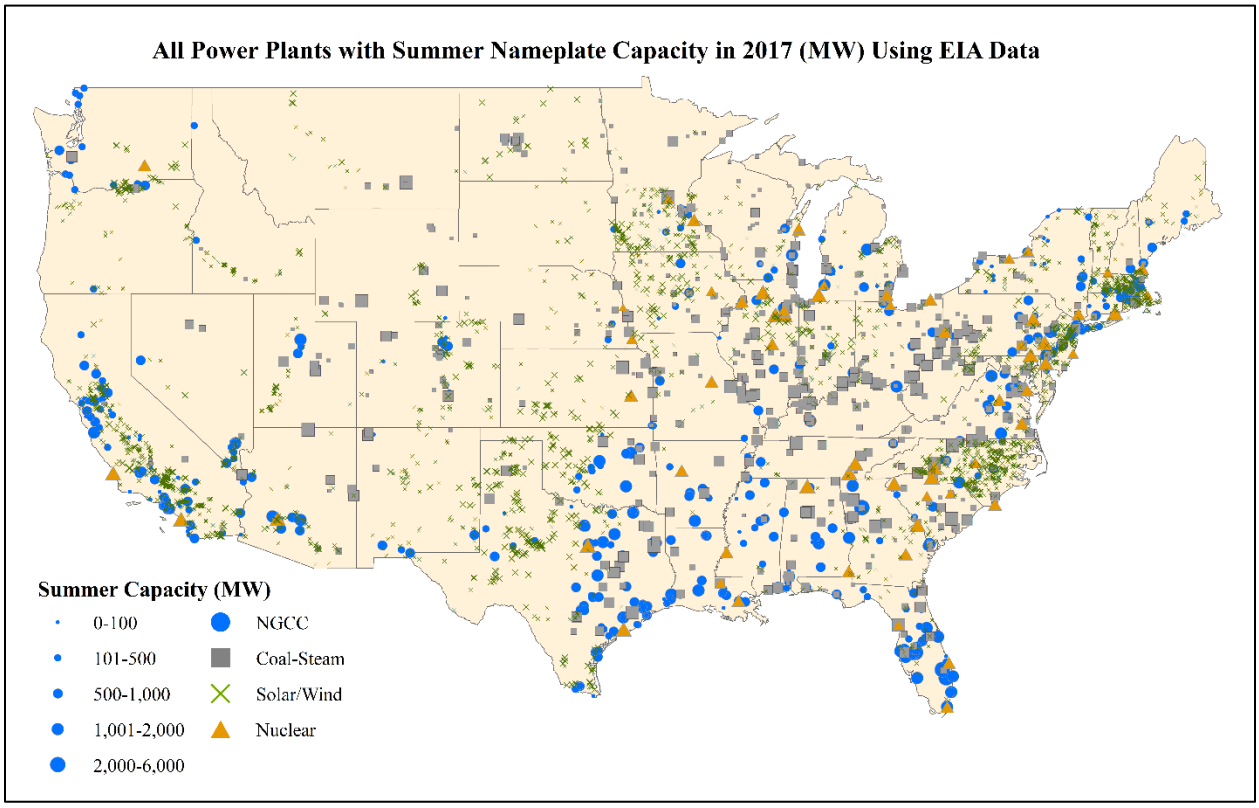
To estimate Eq. 1, we build a dataset based on the full set of power plants in the U.S. We use the publicly available EIA-860 data for plant characteristics, such as nameplate capacity, and EIA-923, 920, and 906 data for generation. We use sector information in the EIA-860 form to identify plants that are in the electric power sector only, which excludes industrial and commercial plants, which are outside the electricity sector since they produce electricity primarily for their own use (Stevens, 2018; Doyle & Fell, 2018). We remove observations that are missing capacity or generation data, or have unrealistic capacity factors, which is less than one percent of total observations.

With the EIA data, we create units of observation based on plant-fuel-technology group. The fuel type is provided through EIA energy source codes, and technology through prime mover codes.[6] This combines multiple emissions units of the same fuel and technology type from the same plant into a single observational unit to match the EIA formatting. The extraction process and combining of datasets yields significantly comparable capacity and generation totals to the published EIA summary tables.[7] Figure 2 displays the geographical distribution of all the units in the time series.

[6] All NGCC are fuel type "NG" (natural gas), and any of the following prime mover codes: CC (combined cycle total unit), CA (combined cycle steam part), CT (combined cycle combustion turbine part), or CS (combined cycle single shaft). See the EIA form 860 instructions for more information on the energy source and prime mover coding, available at: https://www.eia.gov/survey/form/eia_860/instructions.pdf.

[7] For example using EIA's electricity data browser (available at https://www.eia.gov/electricity/data/browser/), our full dataset is within one percent of EIA's total generation from the electric power sector. Our dataset of combined

Figure 2



We calculate monthly capacity factors for NGCCs using EIA's method[8] specified in Equation 2. Like EIA, we use net summer capacity for each observational unit (*i*) in each time period (*t*), which is slightly lower than total capacity because it represents the maximum output the generator can supply to system load by subtracting the typical capacity used to power station service or auxiliaries.[9]

$$capacity\ factor_{t,i} = \frac{generation_{t,i}}{capacity_i * available\ time_t} \qquad \text{(Eq. 2)}$$

cycle plants is within four percent of natural gas combined cycle generation based on EIA's Electric Power Monthly, Table 1.7.C for utility scale facility net generation by technology (available at https://www.eia.gov/electricity/monthly/current_month/epm.pdf), and within two percent of NGCC capacity based on the Electric Power Annual Table 4.7.C of net summer capacity (available at https://www.eia.gov/electricity/annual/html/epa_04_07_c.html).

[8] Details of EIA's Electric Power Annual available at https://www.eia.gov/electricity/annual/.

[9] EIA's Net Summer Capacity definition is available at https://www.eia.gov/tools/glossary/index.php?id=net%20summer%20capacity.

Our summer capacity factors are typically 4-7 percent lower than EIA's published estimates, which we believe occurs for several reasons (see Appendix A). First, EIA's capacity factors include specific information on each generator to calculate the available time they may run to account for differing online and retirement dates, which may include daily or hourly changes. However, the publicly available EIA data pertaining to online and retirement dates represent monthly aggregates. Therefore, we calculate available time as the number of hours per month ($available\ time_t$), and assume that all hours in a month are available. Second, our analysis is based on the electric power sector, whose primary purpose is to produce electricity for public sale. The EIA totals include NGCCs in the commercial and industrial sectors, which includes energy-intensive manufacturing needs that may not fluctuate as much as electricity demands from the public. When we compare our capacity factors to those provided by the Environmental Protection Agency's (EPA) Emissions & Generation Resource Integrated Database (eGRID),[10] which represent only the electric power sector, our capacity factors for NGCC are nearly identical.

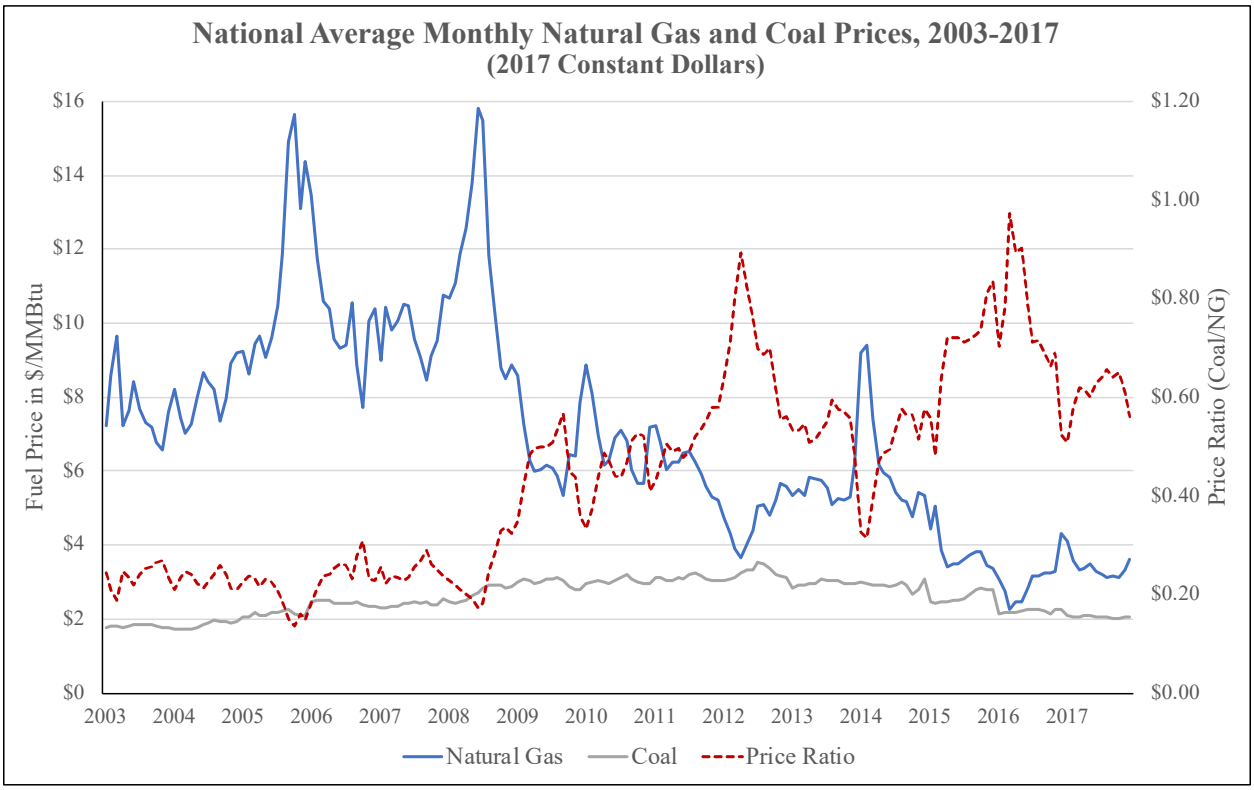
Despite the differences in our capacity factors compared to EIA's totals, our values follow the same trend as the EIA summaries. We are able to capture monthly and annual variations in average NGCC capacity factors, as seen in Appendix A. Since our values are a bit lower than EIA, we believe this will lead to more conservative estimates of total NGCC utilization and generation for the regression estimates and counterfactual calculations.

[10] EPA's eGRID is available at: https://www.epa.gov/energy/emissions-generation-resource-integrated-database-egrid.

3.2.2 Resource Price Ratio

Much of the previous literature on changes in natural gas generation focuses on the role of resource prices, namely natural gas. As seen in Figure 3, natural gas prices have fluctuated over the last twenty years with a significant decrease since the increased use of hydraulic fracturing in unconventional, shale resources in the United States to extract domestic sources of natural gas.[11]

Figure 3



In our fixed effects regression estimation, we use a restricted cubic spline with five knots for the natural gas to coal price ratio to account for changes in responsiveness when the price of natural gas is low. This is a similar approach to Cullen and Mansur (2017) and Stevens (2018).

[11] Source: Data are from EIA's Monthly Energy Review, Table 9.9.

The locations of the knots are based on percentiles recommended by Harrell (2001), which are available in Table 1. The resource prices represent our key source of information about how NGCC utilization might respond to a carbon tax. As detailed in the methodology section, we use carbon intensity values to add the carbon tax in appropriate proportions to the prices of natural gas and coal to generate a new price ratio variable with the carbon tax applied.

Table 1

Price Ratio Knot Percentiles and Locations					
Knot	**1**	**2**	**3**	**4**	**5**
Percentile	5	27.5	50	72.5	95
Price Ratio (Coal/NG)	0.157	0.278	0.403	0.601	1.026

3.2.3 Policies

Previous literature has found that NGCC and natural gas generation increases coincided with a number of important environmental policy changes (Stevens, 2018). While none of these policies explicitly targeted increasing NGCC generation as a primary goal, they are rooted in curbing conventional or greenhouse gas emissions. Since NGCC has lower emissions compared to coal-generation, it is possible for any of these policies to increase NGCC generation. Therefore, we include a series of dummy variables to control for the impact of these policies. We also anticipate that age may influence the degree of response to environmental policies since younger NGCC plants are more efficient (Stevens, 2018; Curtis, 2003). Therefore, environmental policies aiming at reducing air emissions may decrease the use of older NGCC units that are not as clean or efficient.

We add policy variables using data from the EPA's Air Markets Program Division (AMPD), which include controls for regional and national market-based environmental policies, including: Clean Air Interstate Rule (CAIR), Cross-State Air Pollution Rule (CSAPR), NOx

Table 2

Percent of NGCC Units Affected by Policies Included as Controls in this Study																
Percent of Units		**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
Acid Rain Program	ARP	68%	72%	75%	75%	76%	79%	81%	80%	80%	82%	81%	81%	83%	83%	84%
Nox Budget Program	NBP	10%	9%	8%	7%	8%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Clean Air Interstate Rule	CAIR	0%	0%	0%	0%	0%	8%	54%	53%	53%	53%	53%	54%	0%	0%	0%
Cross State Air Pollution Rule	CSAPR	0%	0%	0%	0%	0%	0%	1%	1%	1%	1%	1%	1%	58%	57%	30%
NAAQS Nonattainment	NAA	43%	48%	50%	50%	47%	47%	48%	48%	47%	48%	48%	45%	45%	36%	35%
Regional Greenhouse Gas Initiative	RGGI	0%	0%	0%	0%	0%	0%	17%	18%	17%	14%	14%	14%	14%	14%	14%
California Cap-and-Trade	CA	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	14%	13%	13%	13%	13%

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Budget Trading Program (NBP), Acid Rain Program (ARP), and the Regional Greenhouse Gas Initiative Program (RGGI).[12] We also add information on non-attainment based on the National Ambient Air Quality Standards (NAAQS) using EPA's Greenbook.[13] In addition, we added California's Greenhouse Gas Cap-and-Trade program, which had the first auction of allowances in 2012. Table 2 shows the percent of NGCC units affected by the policies each year. In our regression estimation, we include interactions of each policy with capacity-weighted age (*Age*Policy*) to determine whether the policies affect older plants differently.

3.2.4 Other Control Variables

We include several sets of other variables as controls for our econometric model. Since we are using a fixed-effects model, which accounts for time-invariant unobserved factors that may be omitted from our model specification, we do not include any control variables that do not change over time. For plant characteristics, we control for capacity-weighted age of the plant using the plant's mean capacity of each generator. This means we divide the plant's NGCC capacity by the number of NGCC generating units at each plant for a mean capacity, and we use this value to calculate the capacity-weighted age using the average age of each NGCC generator at the plant.

The availability and supply of natural gas may also influence changes in natural gas generation. Natural gas generation has two annual peaks: winter and summer. The summertime peak is the larger of the two seasonal peaks because of the greater electrical demand from cooling. In addition, natural gas is used for residential and commercial heating, thereby reducing

[12] The Air Markets Program Division (AMPD) is available at: https://ampd.epa.gov/ampd/. In email communication with the Environmental Protection Agency, who maintains this database, they stated that in most cases if the plant or unit is not in the dataset, it is not affected by any of the AMPD programs. However, EPA also noted that there are a few situations where the plant has been reporting to EPA incorrectly under a different plant code, which may be incorrectly marked as in or out of the AMPD program because of the plant code error.
[13] EPA's Greenbook is available at: https://www.epa.gov/green-book.

the availability of natural gas for power generation in the wintertime. For these reasons, we include heating degree days (HDD) and cooling degree days (CDD) from the National Ocean and Atmospheric Administration's Climate Prediction Center.[14]

We also include several variables to control for the characteristics and load of the transmission grid in which NGCC plants are situated, which may also affect NGCC generation. We define these "areas" based on a shared transmission or distribution system owner, which are provided by the EIA-860 data. Based on the full set of generators in the electricity sector (i.e. all groups, including coal and renewable generators, for example), we have 960 areas with approximately 1.3 GW of generating capacity. Of these, 154 areas contain at least one NGCC generator. To control for total electricity demand, we divide monthly demand by the maximum demand of the transmission area in the time series.

Finally, we include variables to control for other sources of generation in the area, including coal power plants, nuclear power plants, and intermittent renewable generators. As seen in the previous literature, coal and natural gas are substitutes, and natural gas and intermittent renewables may be complements (Fell & Kaffine. 2018; Cullen & Mansur, 2017; Linn et al. 2014). Therefore, we anticipate that the availability of other generation sources might affect NGCC utilization in response to changes in prices. Using the transmission areas defined above, we control for the percentage of nameplate capacity in each area provided by coal power plants, and nuclear power plants, separately. We include a percentage of generation provided by intermittent renewable generation in each area as well. We use intermittent renewable

[14] These datasets do not include variables for Alaska and Hawaii; therefore, we drop all power plants from these states. Plants in these states also face different natural resource constraints and are likely to behave differently than power plants in the contiguous U.S. There are no NGCC generators in Hawaii, and the four in Alaska represent less than 0.3 percent of all NGCC capacity in the dataset.

generation, as opposed to capacity, since generation more accurately represents the availability and quality of the intermittent resources. However, we use capacity for coal and nuclear plants instead of generation since coal generation would predominantly account for a large portion of the variation in NGCC generation without determining the effects of what contributed to the decision to switch from coal to NGCC. Table 3 provides summary statistics for all variables included in our econometric model.

Table 3

Summary Statistics

Category	Variable	Mean	Standard Deviation	Minimum	Maximum
Dependent Variable	Capacity Factor	0.42	0.30	0.00	1.00
Price Ratio	Price Ratio (MMBtu)	0.48	0.28	0.06	2.24
Policies	CAIR	0.23	0.42	0.00	1.00
	RGGI	0.10	0.29	0.00	1.00
	NBP	0.03	0.16	0.00	1.00
	CSPAR	0.11	0.31	0.00	1.00
	NAA	0.46	0.50	0.00	1.00
	ARP	0.08	0.04	0.00	1.00
	CA Cat	0.05	0.21	0.00	1.00
Capacity-Weighted Age * Policy	Capacity-Weighted Age	19.59	8.74	0.00	74.93
	Capacity-Weighted Age*CAIR	4.26	8.68	0.00	48.73
	Capacity-Weighted Age*RGGI	1.94	6.32	0.00	41.85
	Capacity-Weighted Age*NBP	0.64	4.03	0.00	45.00
	Capacity-Weighted Age*CSPAR	1.82	5.89	0.00	48.47
	Capacity-Weighted Age*NAA	9.11	11.50	0.00	74.93
	Capacity-Weighted Age*CA Cat	0.85	4.23	0.00	40.00
	Capacity-Weighted Age*ARP	14.06	9.91	0.00	74.93
Weather	HDD (Scale)	0.30	0.36	0.00	1.89
	CDD (Scale)	0.14	0.18	0.00	0.76
Area Load	Demand Ratio	0.65	0.19	-0.04	1.00
	Coal Capacity	0.17	0.19	0.00	0.83
	Nuclear Capacity	0.08	0.11	0.00	0.72
	Renewable Generation	0.04	0.09	0.00	1.00

N = 76,104

4. Methodology

After running our fixed effects regression estimation, we use the empirical results to conduct a counterfactual analysis to estimate the effect of carbon taxes on 1) NGCC capacity factors, which in turn leads to changes in 2) NGCC generation ($Generation = CF * (8760 * capacity)$), and 3) CO_2 emissions. With this information, we estimate tax revenue collected from different carbon taxes and consider ways to keep the carbon tax revenue neutral.

4.1 Counterfactual Analysis

To conduct the counterfactual analysis, we make several assumptions. First, we assume that all increases in NGCC generation resulting from increases in NGCC capacity factors will directly offset coal generation at a rate of 100 percent. Previous literature has established that much of the new NGCC generation is offsetting coal (Fell & Kaffine. 2018; Cullen & Mansur, 2017; Linn et al. 2014). However, there are many factors that can affect changes in NGCC and coal generation. For example, this assumption does not account for any decreases in coal generation due to increases in renewable generation, or for increases in retirements due to environmental policies such as the Cross-State Air Pollution Rule (CSPAR).

Second, we initially assume there will be no changes in NGCC capacity for the counterfactual. Therefore, we use NGCC capacity from 2017 (the latest year of available data) for the counterfactual analysis to calculate the impact of various carbon tax prices on NGCC utilization, generation, emissions, and tax revenue. This assumption means there will be no new NGCC capacity brought online, nor any retirements in NGCC generation, in the short run. Figure 4 shows historical values and future estimates for the reference or base case provided by the Annual Energy Outlook (AEO) from the Energy Information Administration. The AEO estimates a 46 percent increase in NGCC capacity for the electric power sector, and a less than 1

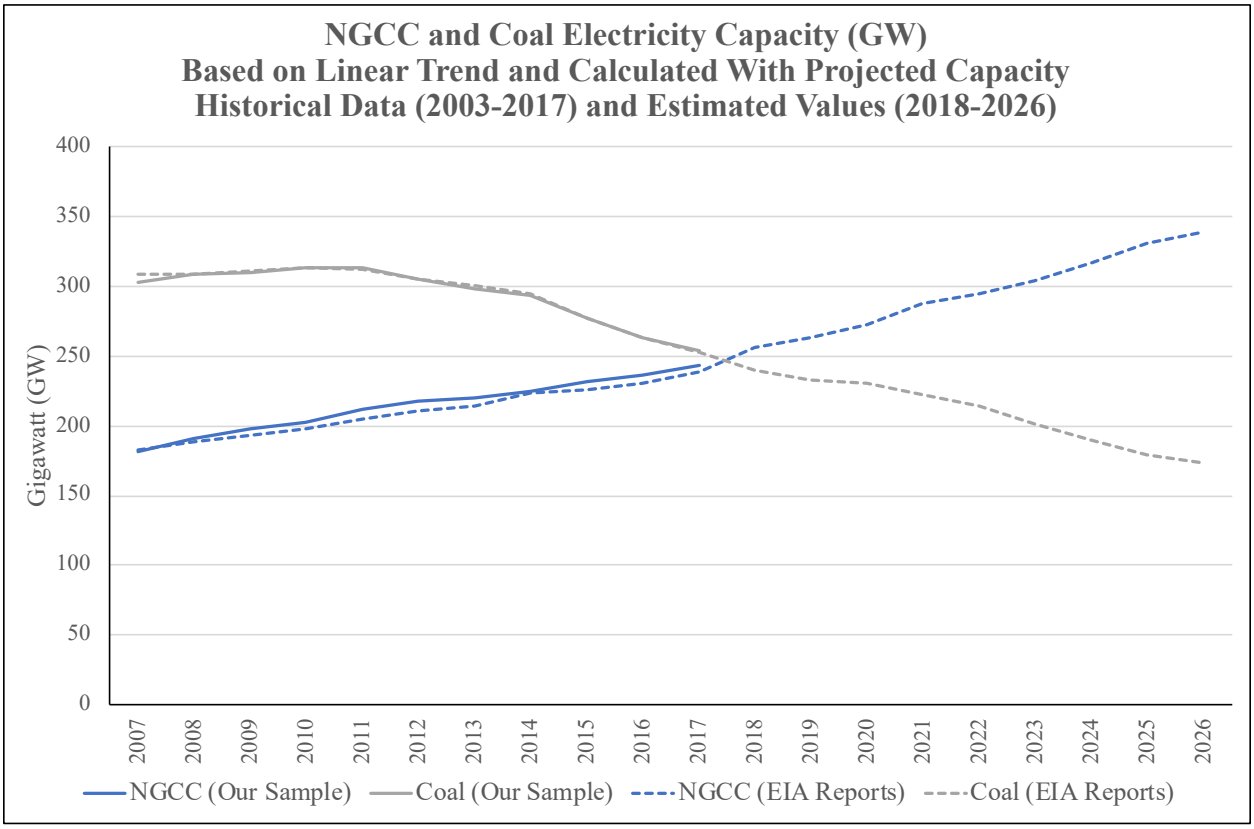
percent reduction in NGCC CHP capacity by 2026. They also estimate a 31 percent reduction in coal capacity by 2026, and a 12 percent reduction in CHP coal capacity (see Figure 4).

In our data sample spanning the years 2003 to 2017, NGCC capacity grew 80 percent, or 5.3 percent per year. The EIA forecasts approximately the same rate of NGCC capacity expansion through at least 2026. While our model does not explicitly include a control for total NGCC capacity (which would likely be endogenous), there is a steady increase in capacity over the timeseries. Therefore, our model estimation implicitly includes capacity expansion. During this time, NGCC capacity factors increased despite an increase in capacity. Therefore, capacity expansion is not the only determinant of NGCC utilization, otherwise utilization would remain stagnant with increased capacity growth. Additionally, Peters and Hertel (2018) find that low natural gas prices drive increased gas utilization in the short-run, which eventually leads to increased natural gas capacity in the long-run due to increased returns to capacity. Since our study focuses on short-term changes, we think it is reasonable to focus solely on utilization. However, we also provide an estimate for NGCC and coal generation, emissions, and tax revenue given increased NGCC capacity factors coupled with the EIA's forecasted NGCC capacity values provided in Figure 4. [15]

For conducting the counterfactual analysis, we use EIA data on the carbon intensity values of coal and NGCC (see Table 4) to calculate the CO_2 emissions per MWh of coal and NGCC generation. We use equations 3 and 4 and the values in Table 4 for our calculations. We

[15] Data obtained from the Annual Energy Outlook (2010-2019) on electricity capacity changes for the electric power sector reference case for NGCC and coal generators. The Annual Energy Outlook data are available from the EIA at: https://www.eia.gov/outlooks/aeo/data/browser/#/?id=9-AEO2019&region=0-0&cases=ref2019&start=2017&end=2026&f=A&linechart=ref2019-d111618a.4-9-AEO2019~ref2019-d111618a.6-9-AEO2019~ref2019-d111618a.18-9-AEO2019~ref2019-d111618a.16-9-AEO2019&ctype=linechart&sourcekey=0.

Figure 4



use heat rate assumptions from the EIA for the year 2017. In reality, these values can vary based on the individual generator or change over time as technology ages. Therefore, these rates are averages calculated by the EIA to represent a typical NGCC or coal-steam generator in 2017.

$$Emissions\ Factor_{resource} = (Carbon\ Intensity_{resource} * \ Heat\ Rate_{resource}) \text{ (Eq. 3)}$$

$$Emissions_{resource} = (Emissions\ Factor_{resource} * Generation_{resource}) \text{ (Eq. 4)}$$

Table 4

Carbon Intensity and Heat Rate Values Based on EIA Data

Variable	Measurement Units	NGCC	Coal	Data Sources
Carbon Intensity	KG CO_2/MMBtu	53.07	95.35	https://www.eia.gov/environment/emissions/co2_vol_mass.php
	Tons CO_2/MMBtu	0.0531	0.0954	1000 kg = 1 ton
	LBS CO_2/MMBtu	117.00	210.20	https://www.eia.gov/environment/emissions/co2_vol_mass.php
	Tons CO_2/Btu	0.000000053	0.000000095	1 MMBtu = 1,000,000 Btu
Heat Rate	**Heat Rate Assumption (Btu/kWh)***	7,649	10,043	https://www.eia.gov/electricity/annual/html/epa_08_02.html
Emissions Factor	Tons CO_2/kWh	0.00040593	0.00095760	
	Tons CO_2/MWh	0.40593243	0.95760005	1 kWh = 0.001 MWh

*Based on 2017 actual values

5. Results

5.1 NGCC Regression Estimates

Table 5 provides the fixed effects regression results with year fixed-effects and standard errors clustered at the area level. Due to our use of the cubic spline, which captures the nonlinear effect of the price ratio on NGCC utilization, we use Figures 5A and 5B along with Table 6 to interpret the regression results reported in Table 5. Figures 5A and 5B illustrate the average impact of the coal to natural gas price ratio spline on NGCC capacity factors. The dotted lines indicate the 95% confidence intervals, and the solid line is the average effect. Figure 5A, ceteris paribus, shows the NGCC capacity factor for different price ratio values holding all other variables at their mean. Figure 5B, marginal effects, is the average change in the capacity factor per unit change in the price ratio.

Figure 5A

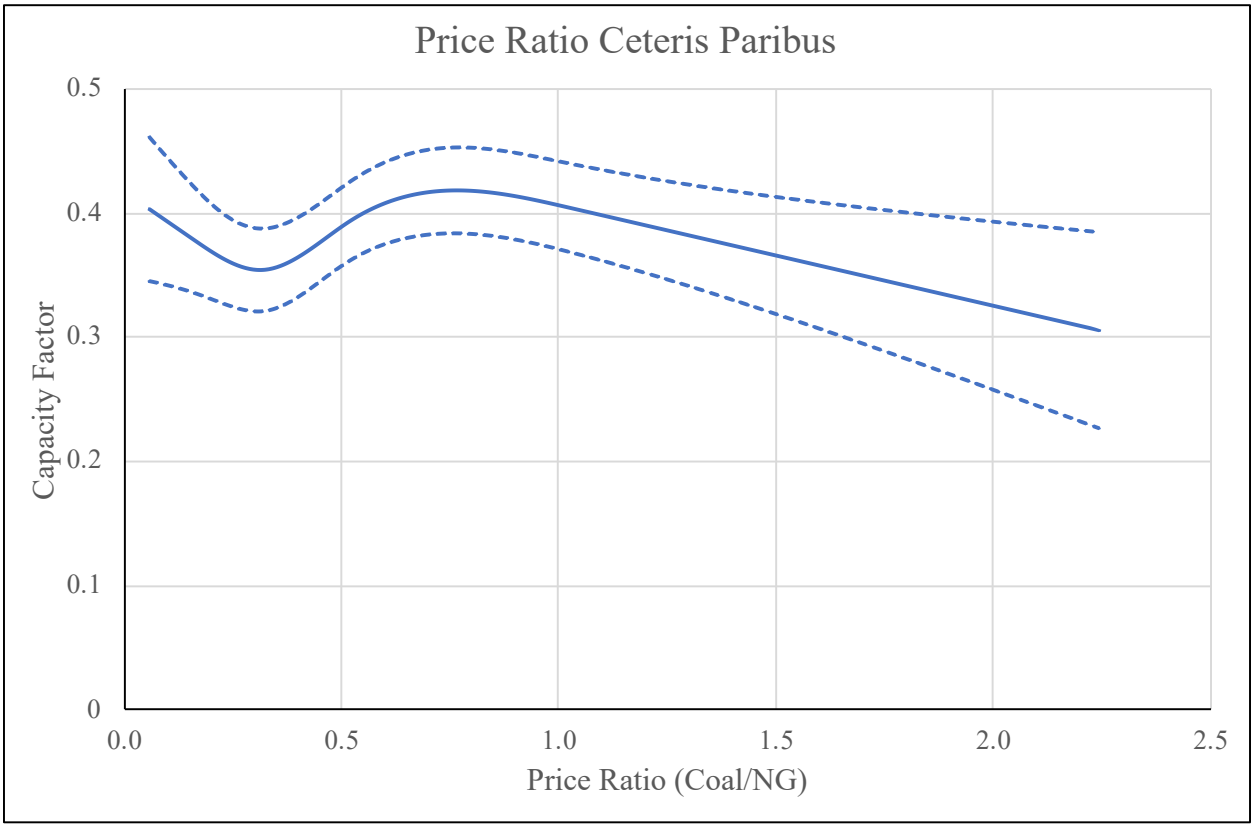


Table 5

Fixed Effects Regression Results			
Category	**Variable**	**Fixed-Effects**	
		Coefficient	**SE**
Price Ratio	Price Ratio 1	-0.398**	-0.1423
	Price Ratio 2	5.916**	-1.9606
	Price Ratio 3	-12.34*	-4.7989
	Price Ratio 4	6.381+	-3.6838
Policies	CAIR	0.165***	-0.0308
	RGGI	-0.0774	-0.0580
	NBP	0.104	-0.1083
	CSPAR	0.277***	-0.0415
	NAA	-0.0675+	-0.0366
	ARP	-0.153	-0.0943
	CA Cat	0.0657	-0.0487
Capacity-Weighted Age * Policy	Capacity-Weighted Age * CAIR	-0.00519***	-0.0012
	Capacity-Weighted Age * RGGI	0.0026	-0.0025
	Capacity-Weighted Age * NBP	-0.0019	-0.0045
	Capacity-Weighted Age * CSPAR	-0.00942***	-0.0018
	Capacity-Weighted Age * NAA	0.00371*	-0.0017
	Capacity-Weighted Age * ARP	0.000807	-0.0032
	Capacity-Weighted Age * CA Cat	-0.00506+	-0.0028
Weather	HDD	-0.0815***	-0.0153
	CDD	0.253***	-0.0411
Area Load	Demand Ratio	0.437***	-0.0429
	Coal Capacity	-0.339**	-0.1100
	Nuclear Capacity	0.101	-0.2915
	Renewable Generation	-0.392***	-0.0760
Generator	Capacity-Weighted Age	-0.000487	-0.0030
	Constant	0.402***	-0.0929
	R^2	0.228	
	N	76,104	
	Year FE	X	
	Month FE	X	
	Cluster Robust (Area) SE	X	
Standard Errors in Parentheses			
+ p<0.1,* p<0.05, ** p<0.01, ***p<0.001			

Figure 5B

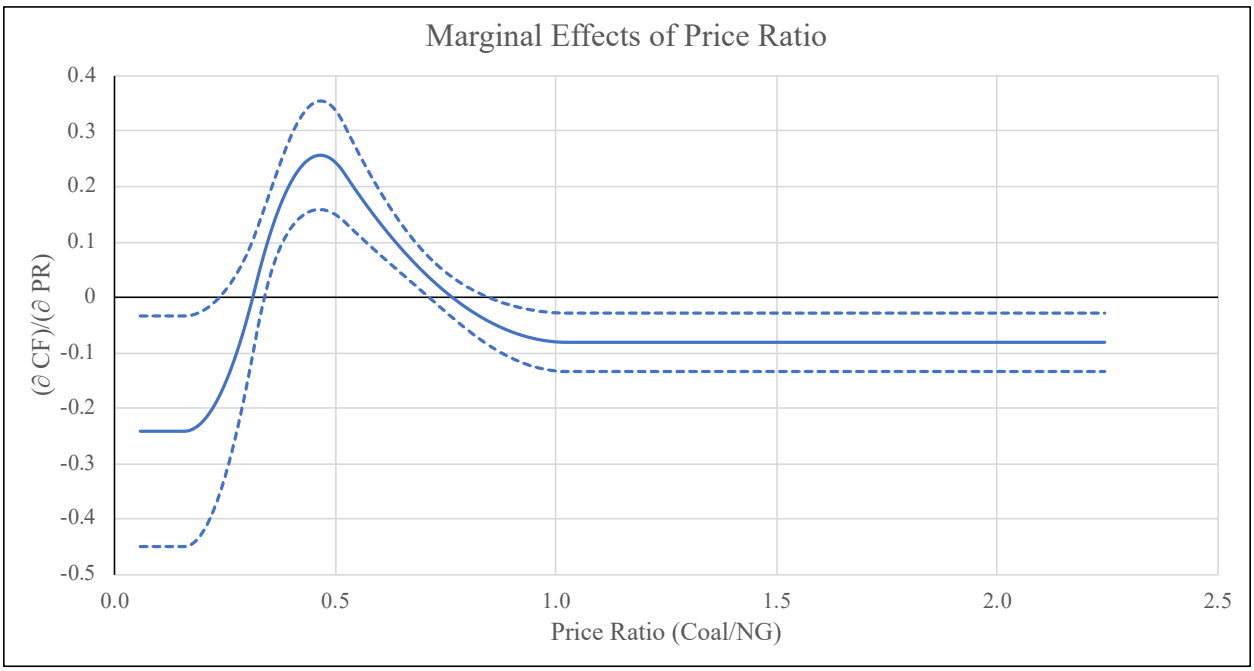


Table 6 provides the price of natural gas (in $/MMBtu) given an average coal price of $2.52 MMBtu for various price ratio values.

Table 6

Regression-Based Price Estimates for Natural Gas		
Price Ratio	**Coal**	**Natural Gas**
0.10	2.52	25.20
0.20	2.52	12.60
0.40	2.52	6.30
0.60	2.52	4.20
0.80	2.52	3.15
1.00	2.52	2.52
1.20	2.52	2.10
1.40	2.52	1.80
1.60	2.52	1.58
1.80	2.52	1.40
2.00	2.52	1.26

Again, Figures 5A and 5B provide visual interpretations of the coefficients from the price ratio variables with 95% confidence intervals. Figure 5A shows, when holding all else constant, the NGCC capacity factors are highest around a price ratio of 0.75. Using the values in Table 6, this represents a natural gas price of approximately $3.36/MMBtu, which is a relatively low natural gas price. In addition, the graph displays the marginal effects of the restricted cubic spline on the price ratio, showing a strongly significant per unit increase in NGCC utilization when the price ratio is between 0.4 and 0.6. As shown in Table 6, this is roughly a natural gas price between $4.20 and $6.30. These results are similar to the findings in Cullen and Mansur (2017) and Stevens (2018) indicating that CO_2 emissions are more responsive to natural gas prices around and below $5.00/MMBtu (see Figure 5B).

We conduct several sensitivity tests to check the robustness of our results, specifically to consider the impacts of different cubic spline specifications, time fixed-effects, and time-invariant characteristics on our empirical results. First, we check sensitivity to the number of knots in the restricted cubic spline for the price ratio variable (see Appendix B). We include several options for comparison, including a linear price ratio variable (0 knots) and 3, 4, 5, and 6 knots. We find an increase in statistical significance using any version of the restricted cubic spline compared to the linear price ratio variable. And, beyond 3 knots (4, 5 and 6 knots), we have consistent estimates across the models with little change in the R-squared values. Figure B1 illustrates the correlation between capacity factor estimates and the price ratio, ceteris paribus, using the different numbers of knots. While the correlation between the two variables is much different when estimating capacity factors using three knots, the estimates using more than three knots are all very similar. As such, we chose to use 5 knots in our estimation.

We also tested for the impact of different time fixed effects on the empirical results (Appendix C). Since our main variable of interest is the price ratio, which includes variables that vary on a monthly (natural gas) and annual (coal) basis, we anticipate that time fixed-effects may interfere with the significance of these variables.[16] So, we run regressions using year fixed-effects (base), no time fixed-effects, and year*month fixed-effects. As expected, the R-squared value increases with the year*month fixed-effects from both the year fixed-effects and the no time fixed-effects models. However, we see a slight decrease in the price ratio spline variables with the time fixed-effects specification as we see the lowest significance in the year*month fixed-effects model. As such, we use the year fixed-effects model to account for any unidentified variation across years that may affect economic conditions, unidentified national policies, and/or global conditions.

The next sensitivity test compares regression results with different NGCC generators grouped by age (Appendix D). We anticipate that younger NGCC plants have greater abilities to increase their utilization in response to changes in resource prices and therefore taxes compared to older plants. As hypothesized earlier, not only has NGCC technology improved over time, but also younger generators have less degradation from use and cycling and are therefore in better operating condition. We treat age as a static variable based on the age of the plant in 2017. As anticipated, we see generators less than 20 years old have higher estimated NGCC capacity factors (Figure D1), followed by plants aged 20-40, the base (all plants), and negative capacity factors for plants 40 years and older. We chose to use the sample with all plants versus subsets of age groups in our final estimation but point out that the sensitivity test confirms that younger plants on average have higher capacity factors. This means that as older plants retire, it will take

[16] Price data for coal are not available on a monthly basis.

a lower carbon tax to reach the utilization target of 75 percent compared to our full sample. This again suggests our estimates are likely more conservative than might be the case with actual implementation.

Finally, we analyze comparisons between CHP and non-CHP plants in our sample. Because we are using a fixed-effects regression model, all time invariant characteristics drop out of the analysis, which includes whether a plant is a combined heat and power plant (CHP) or not (non-CHP) (see Appendix E). Therefore, we run a sample of CHPs against non-CHPs in this sensitivity test, because we anticipate that CHPs have a higher capacity factor since they face different incentives to run and do not dispatch to the grid. Again, our results are largely consistent across samples, but we see in Figure E1 that CHP plants are estimated to have a higher capacity factor on average compared to non-CHP plants. However, most of the observations in our dataset represent non-CHP plants, so the inclusion of these small generators has little overall impact on our average capacity factor estimates. We include the results from an Ordinary Least Squares (OLS) regression analysis in Appendix F for comparison.

5.2 NGCC Counterfactual: 2017 Averages

We use the estimates from our fixed-effects regression to estimate the impact of a carbon tax on NGCC utilization, which we then use to estimate changes in NGCC and coal generation and emissions assuming all increases in NGCC generation directly replace coal generation. Finally, we estimate the CO_2 emissions saved from the tax given these assumptions, and corresponding revenues from the proposed carbon tax.

Figure 6A shows the average estimated NGCC capacity factor based on the 2017 fleet of NGCC plants when different carbon tax rates are applied in our counterfactual model. For example, the average estimated capacity factor for NGCC plants in 2017 with a $75/ton carbon

tax is 0.67, a 0.17 capacity factor increase over the average utilization of 0.49 in 2017. Figure 6A and 6B also show there is a higher marginal increase in capacity factor per dollar carbon tax at a low tax rate between $1-$50/ton. According to Figure 6A, as capacity factor increases beyond 0.66, the marginal increase per dollar of carbon tax begins to level off. However, to reach the 75 percent utilization target from the Clean Power Plan, there would need to be a $220/ton carbon tax, which is considerably more expensive than most values currently implemented (outside of the U.S.) as well as those being considered by extant research.

Figure 6A

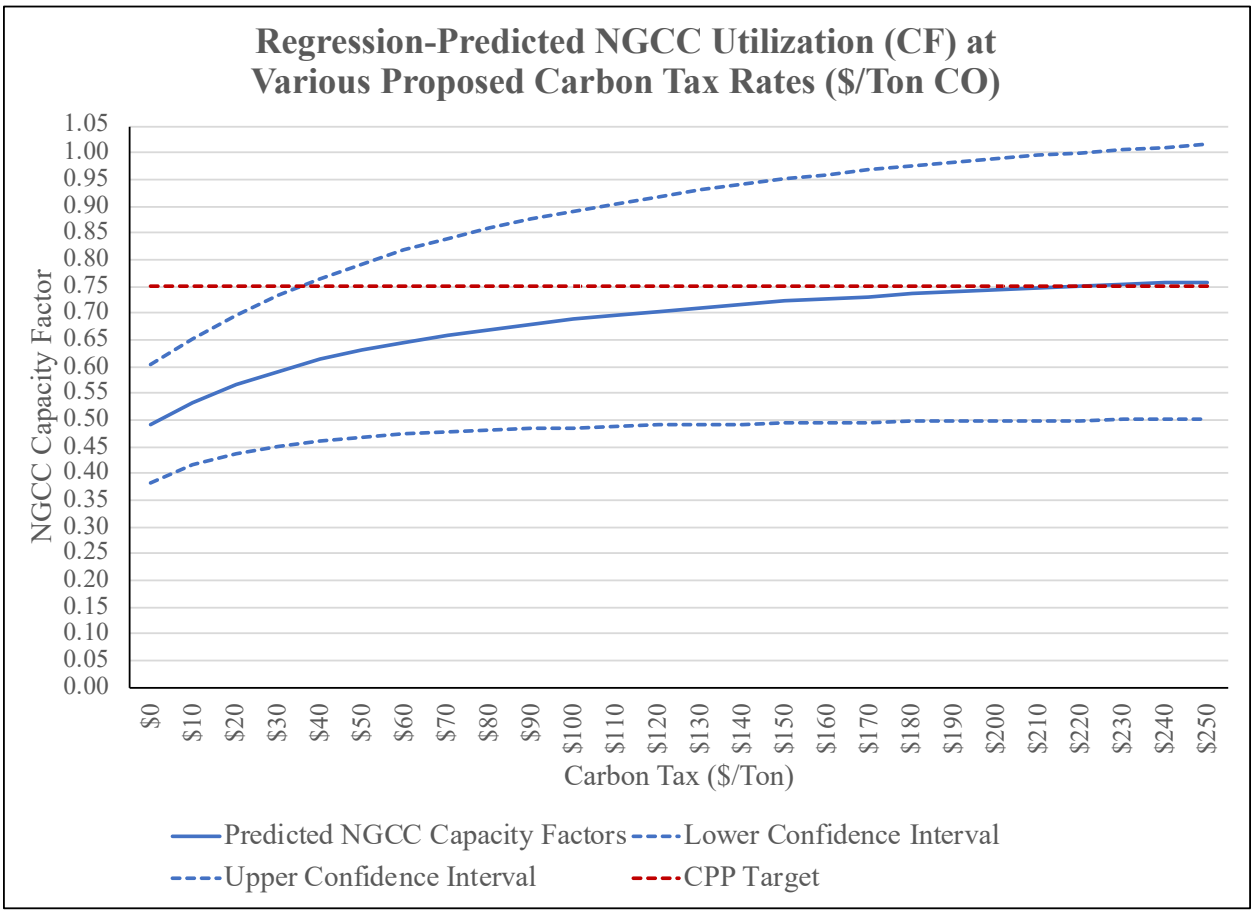


Figure 6B

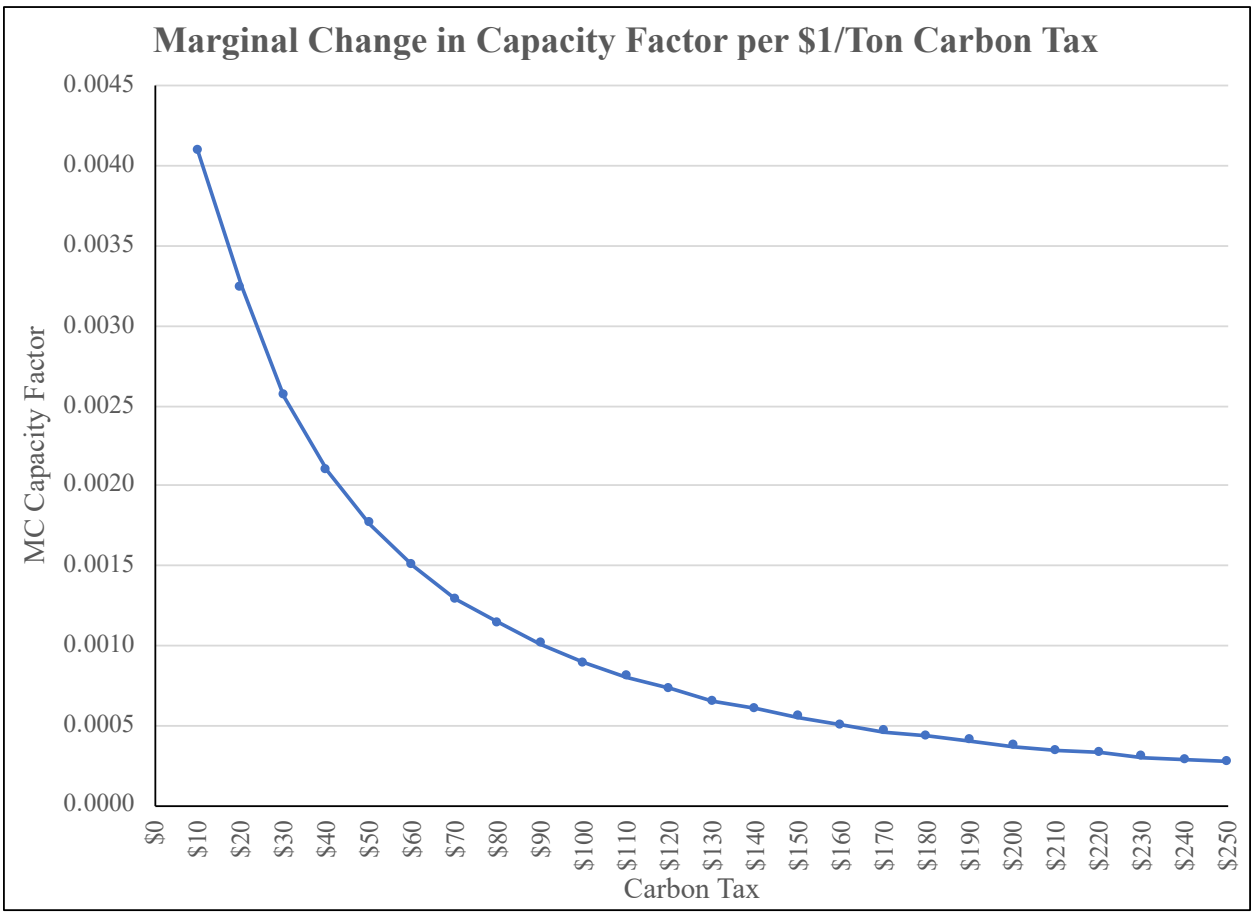
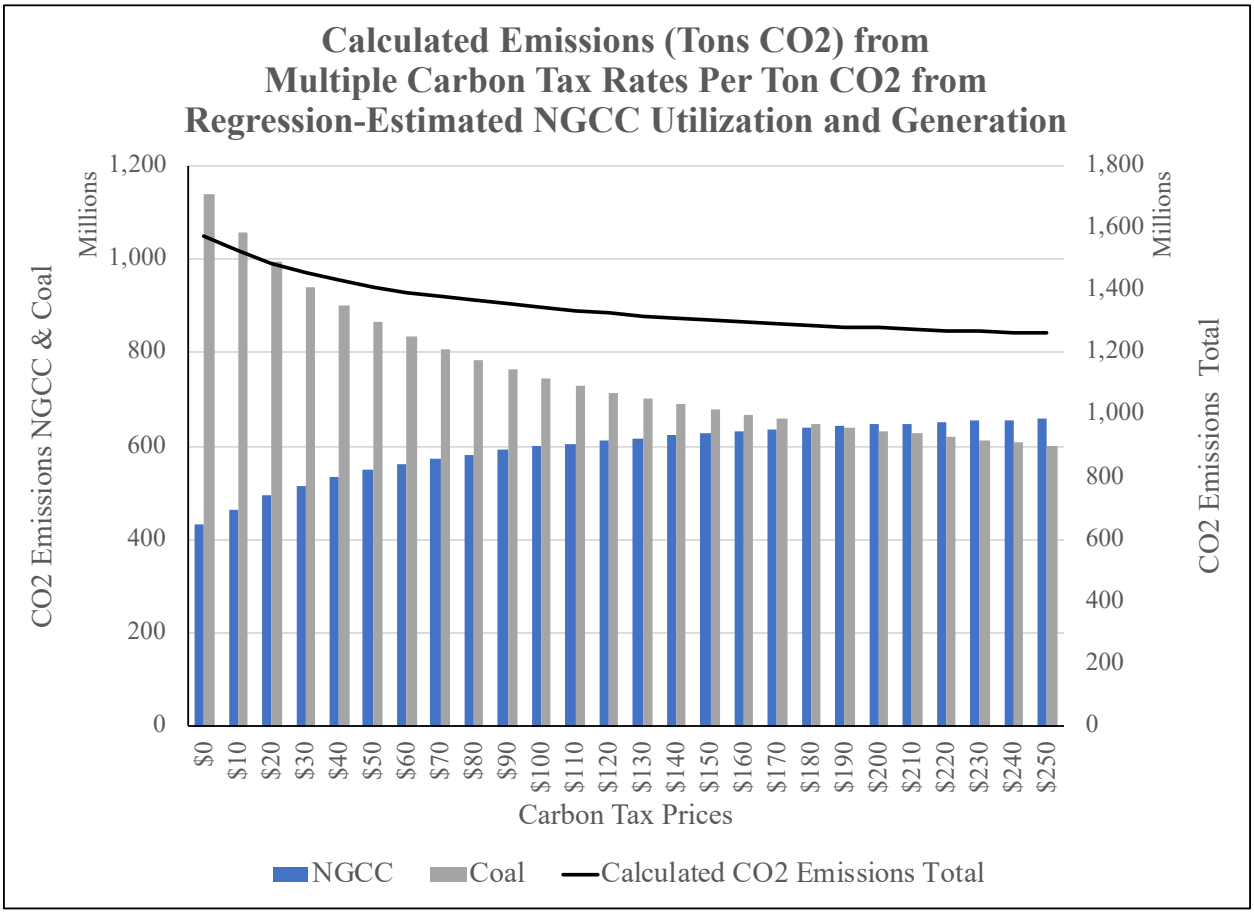


Figure 7 shows the estimates on CO_2 emissions from different carbon tax prices based on the 2017 fleet of NGCC and coal plants. As can be seen from Figure 7, at a high enough carbon tax price point, CO_2 emissions from natural gas eventually surpass coal. This occurs around $190/ton carbon tax based on our counterfactual estimates. However, since natural gas is less carbon intensive than coal, overall carbon emissions continue to decrease as the carbon tax increases. A $50 carbon tax would decrease emissions by nearly 159 million metric tons, or by 9 percent of total electric sector carbon emissions a year,[17] while a $220 carbon tax would decrease emissions by almost 300 million metric tons a year, or approximately 17 percent of electric

[17] According to EIA estimates, CO_2 emissions from the electric power sector were 1,763 million metric tons, available at: https://www.eia.gov/tools/faqs/faq.php?id=77&t=11.

sector carbon emissions. These estimates represent the emissions savings through increased NGCC utilization in place of coal generation for one year alone. These estimates do not include any additional emissions reductions from increased NGCC capacity that may be built in the short term and are therefore rather conservative. In section 5.3, we calculate the coupled impact of NGCC capacity and utilization increases.

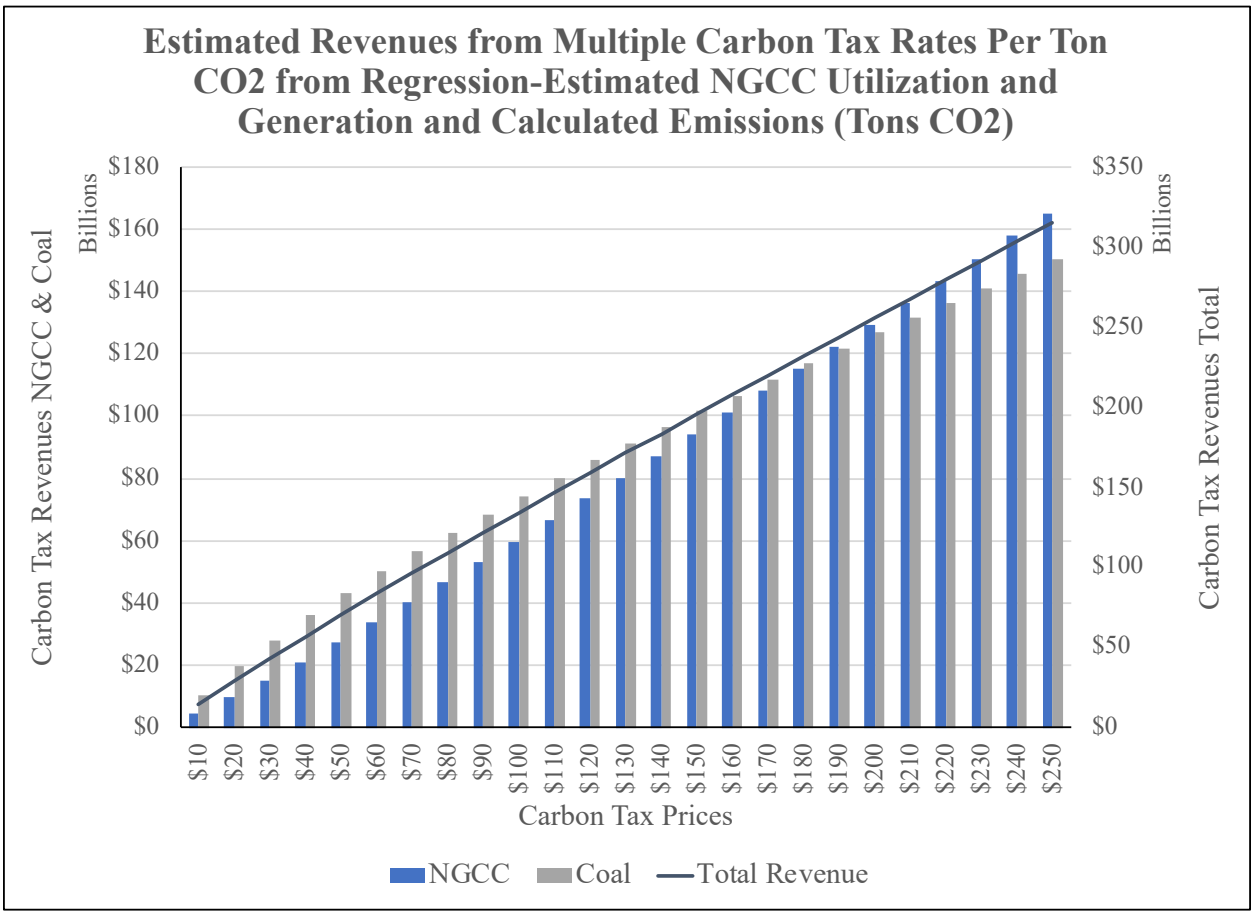
Figure 7



We then calculate tax revenue based on these emissions estimates from the counterfactual and with different carbon tax prices applied. Figure 8 shows how carbon tax revenues from both coal and NGCC generation increase with higher carbon tax prices. At $50/ton, carbon tax revenues are more than $70 billion dollars for one year alone. At $220/ton, revenues are

estimated at nearly $280 billion dollars, with about half of that revenue collected from NGCC generation.

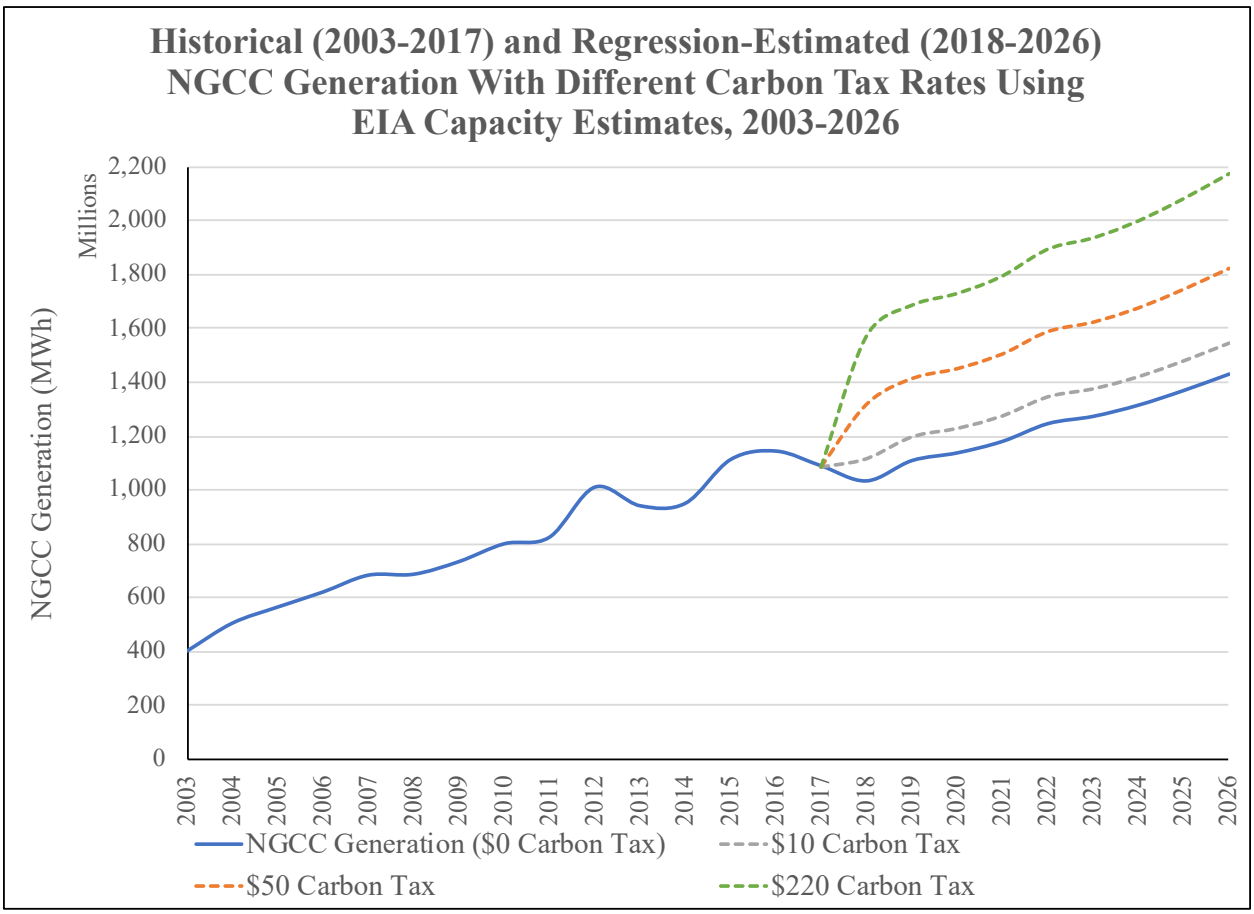
Figure 8



5.3 NGCC Counterfactual: Short-Run Changes 2018-2026

Since total generation is a factor of both utilization and capacity, in Figures 9-12, we estimate the impact of a $10, $50, and $220 carbon tax on NGCC generation calculated with EIA's future capacity estimates presented in Figure 4 and with our regression-estimated capacity factors for 2018-2026. Figure 9 shows that without a carbon tax, NGCC generation would increase 34 percent by 2026 based on EIA's estimates of NGCC capacity expansion alone. Therefore, if there is no carbon tax applied, and NGCC capacity grows more or less as it has over

Figure 9



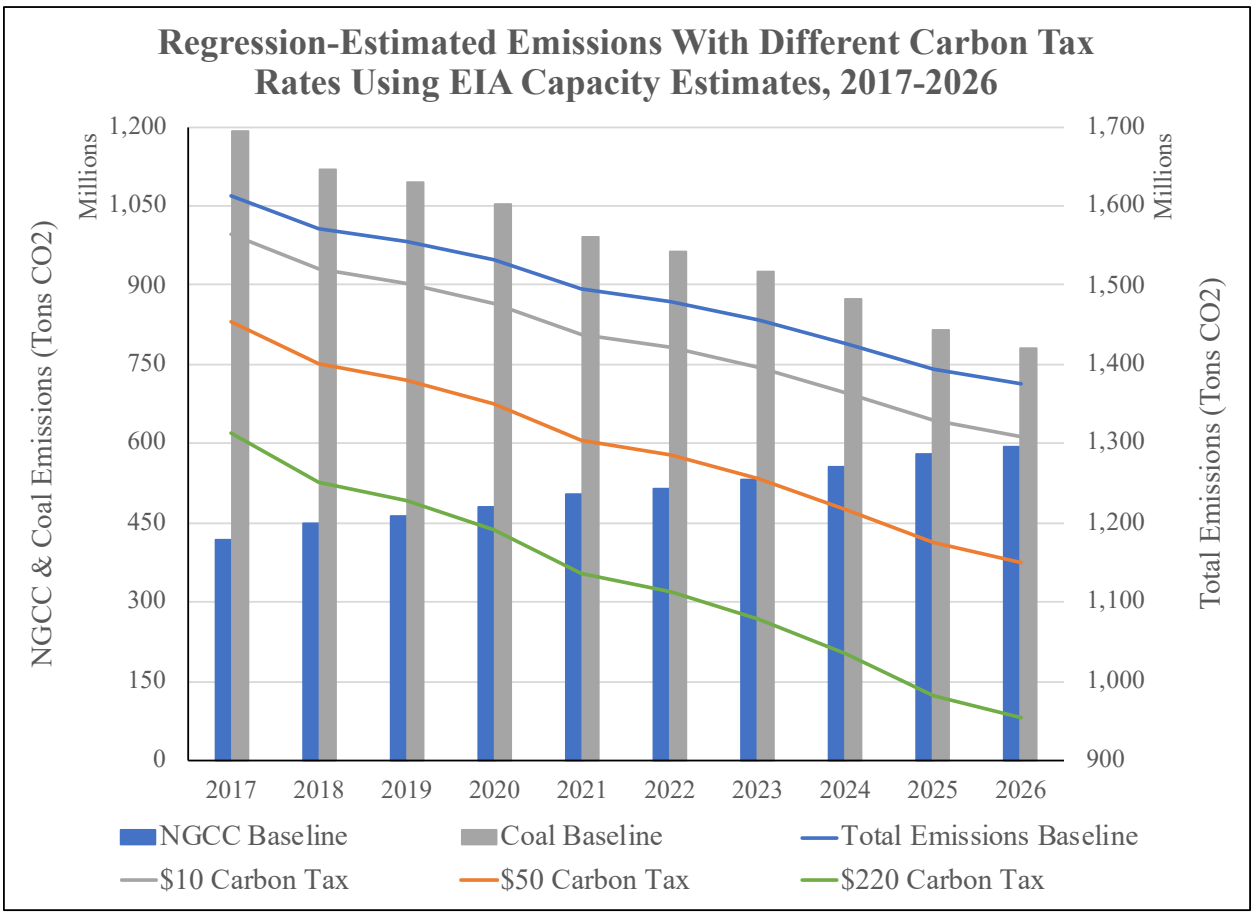
the last decade as anticipated by the EIA, and if NGCC capacity factors remain at an average rate of 0.49, then NGCC generation would increase by about one third. However, a $10 carbon tax coupled with NGCC capacity expansion would increase NGCC generation by the year 2026 by 45 percent, a $50 carbon tax by 71 percent, and a $220 carbon tax by 104 percent. Without any assumptions about capacity expansion (Figure 6A), a $10 carbon tax would increase NGCC generation by 8 percent, a $50 carbon tax by 27 percent, and a $220 carbon tax by 51 percent. Therefore, our capacity factor estimates without capacity expansion (again, excluded because of the endogeneity problem) are certainly conservative and could increase substantially depending on how much NGCC capacity actually increases. In such a case, the targeted utilization of 75

percent would likely be reachable with a lower marginal carbon tax rate than the $220 price point determined by our estimates excluding capacity expansion.

Using the regression-estimated NGCC generation values illustrated in Figure 9, we are able to calculate future coal generation based upon our assumption that any increases in NGCC generation directly offset or reduce coal generation. From our estimates of both NGCC and coal generation, we then apply the appropriate emissions factors reported in Table 4 to determine future expected CO_2 emissions from both NGCC and coal generation. Figure 10 illustrates the baseline values of future expected NGCC and coal emissions (tons CO_2), as well as total CO_2 emissions, without a carbon tax and compares the total emissions values to those expected with a $10, $50, and $220 carbon tax. As can be seen in Figure 10, as NGCC utilization is expected to increase into the future and reduce coal generation, total CO_2 emissions are projected to decline over time regardless of whether a carbon tax is adopted and implemented. However, Figure 10 also shows that a carbon tax will help to further reduce CO_2 emissions as the slopes of the total emissions trendlines in Figure 10 all increase as the carbon tax price increases.

Assuming complete substitution of natural gas for coal generation due to the carbon tax, which means total fossil-fuel generation is constant in the short-run, the increase in NGCC capacity leads to an average of 1.5 percent CO_2 emissions reduction per year through 2026. The $10 carbon tax would initially reduce emissions by 92 million metric tons a year, or 5 percent, then decline to a rate closer to 2 percent per year by 2026. The $50 carbon tax would initially reduce carbon emissions by 211 million metric tons per year (12 percent total electricity sector emissions) and decrease to 51 million metric tons on average by 2026 (3 percent). Last, the $220 carbon tax would initially reduce carbon emissions by 360 million metric tons per year (20 percent) and decrease to 73 million metric tons (4 percent) by 2026.

Figure 10

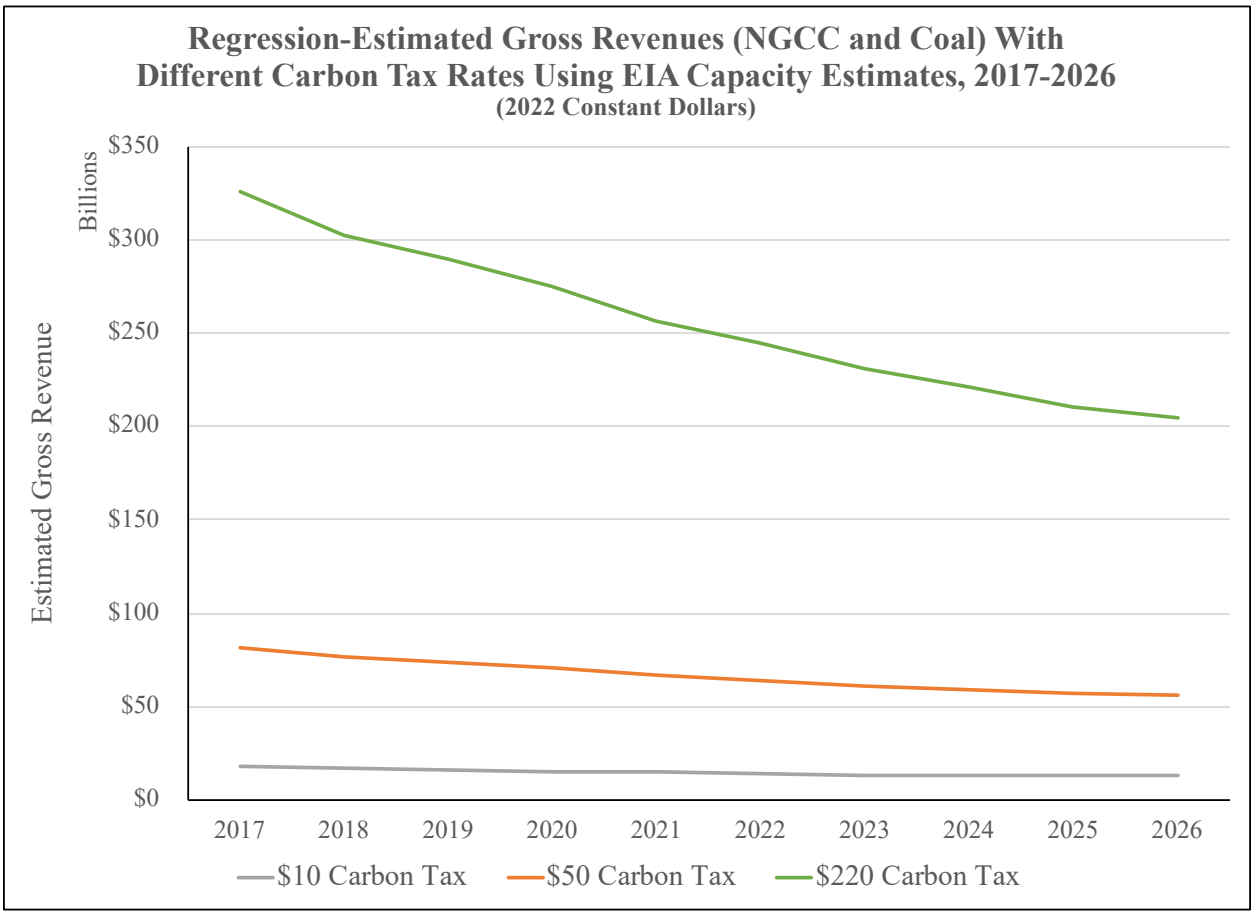


Using the emissions values reported in Figure 10, we are able to calculate the gross revenue amounts generated by a $10, $50 and $220 carbon tax. Figure 11 illustrates these revenue trends over time in 2022 constant dollars. Coinciding with the substitution of natural gas for coal we assume will result from the imposition of a carbon tax, which will lead to reductions in CO_2 emissions overall, we see declining trends in carbon tax revenues going forward. And, the slopes of the trendlines in Figure 11 also suggest that the rate of decline increases with a higher carbon tax rate. For example, gross revenues generated from a $10 carbon tax are only expected to decline by an average of $553.57 million per year through 2026, while a $220 carbon tax would result in an average annual reduction of $15.28 billion in total revenue. These declining

revenue trends are expected, as they at least partially reflect the distortionary effects of an excise-based carbon tax discussed below.

Despite the declining revenue trends over time, a carbon tax of any amount is expected to produce a substantial amount of federal tax revenue. A $220 carbon tax priced to achieve the targeted 75 percent utilization of NGCC generators for electricity production is estimated to produce $1.28 trillion in gross revenue between 2020 and 2026. Also shown in Figure 11, even the much lower marginal tax rates of $50 and $10 are expected to produce more than $435.6 billion and $97.1 billion, respectively, of carbon tax gross revenue during this same time period.

Figure 11



6. Tax Implications

In this research, we suggest that instead of utilization targets or emissions caps, a properly designed and implemented carbon tax would be a more efficient means of increasing NGCC utilization for energy production. The carbon tax is a consumption-based tax, which makes it economically more efficient because it has less distortionary effects than other forms of taxation like those imposed upon income (Pomerleau and Asen, 2019). Carbon taxes also have the added benefit of reducing the negative externalities of carbon emissions like any Pigouvian type of tax (Pomerleau and Asen, 2019). However, the extent to which a carbon tax would alter individuals' and firms' behaviors largely depends upon the way in which the carbon tax is designed and implemented, particularly with respect to the ways in which carbon tax revenues are used and/or offset to achieve neutrality, because consumption-based taxes tend to be more regressive than income-based taxes. Below we discuss some of the important implications of our proposed carbon tax designed to increase utilization of NGCC generators to offset coal generation for energy production and reduce electricity sector CO_2 emissions.

6.1 Tax Base and Point of Taxation

Our proposed carbon tax identifies a tax base of all CO_2 emissions resulting from electricity generation, the majority of which is produced by coal and NGCC generators. NGCC generators have lower pollutant content and high thermal conversion efficiency compared to coal, resulting in approximately 60 percent lower CO_2 emissions. Our exclusive focus on the electricity sector, as opposed to all industry wide energy related carbon emissions, has some advantages and disadvantages. On the one hand, our tax base is narrower than other carbon tax studies, which generally analyze a carbon tax as it would apply to all CO_2 emissions from all sources. While a narrower tax base obviously generates less revenue and has the potential to be more distortionary, we believe our analysis focusing on one particular subsector produces more

accurate revenue estimates and more realistic implementation potential within our existing tax system as electricity producers are more easily identifiable and CO_2 emissions more measurable than a carbon tax intended to apply to all production and/or consumption resulting in CO_2 emissions. Yet, we believe the economic impact and distributional considerations pertaining to our study are largely the same as those encompassing broader carbon tax implementation.

A carbon tax may be implemented at the point of production on raw fuels (upstream approach), the point of consumption (downstream approach), or at different points in between (midstream approach) before reaching final consumers (Pomerleau and Asen, 2019; Horowitz et al., 2017). An upstream approach that imposes a carbon tax on fossil fuels as they enter the economy would levy a carbon tax on natural gas as it leaves the processor and enters the pipeline system and on coal as it leaves the mine (Horowitz, 2017). This approach has the potential to capture the majority of all CO_2 emissions in the U.S. from a relatively few number of taxpayers (Metcalf and Weisbach, 2012; Pomerleau and Asen, 2019).[18] Such an approach would provide for a rather broad tax base, thereby making the tax less distortionary in application, as well as more feasible from an administrative standpoint. A downstream approach would make the carbon tax more visible to consumers and might be more easily implemented under existing tax law; however, such an approach would be administratively difficult to capture all consumption and ensure tax compliance. A carbon tax implemented midstream that is based upon actual CO_2 emissions would place an economic advantage on running NGCC in place of coal, boosting NGCC utilization. The challenge of such an approach, however, is that new tax rules may need

[18] Since our study focuses exclusively on a carbon tax applied only to CO_2 emissions resulting from electricity production for U.S. consumption, cross-border considerations pertaining to imports and exports of carbon-producing goods are not relevant and therefore excluded from our discussion.

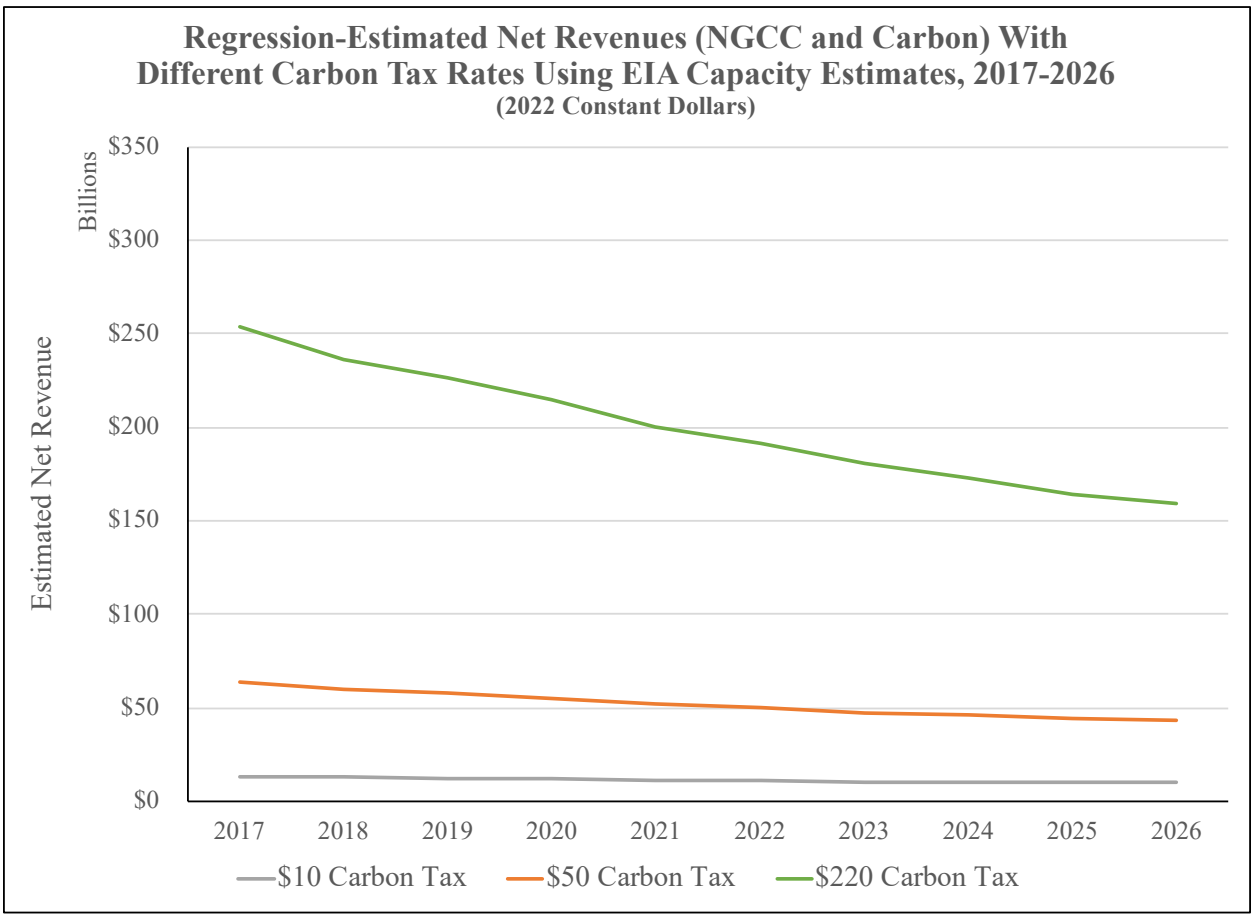
to be developed since the Internal Revenue Code might not adequately guide a carbon tax in this form.

6.2 Tax Revenue and Economic Impact

A carbon tax would influence the economics that system operators consider when determining how much to run a power plant. Units with higher variable costs – fossil fuel-fired natural gas and coal plants – offer flexibility in when they run to serve load. A carbon tax would also have the long-term impact of encouraging investment in low to zero emitting technologies such as advanced NGCC and renewables. Additionally, a carbon tax avoids potential issues Stevens (2018) identified with NGCC utilization targets that may unnecessarily increase costs of compliance. Finally, a revenue neutral carbon tax has the potential to reduce other tax rates as the carbon tax revenue is offset in a way that is vertically equitable or largely progressive for consumers at most levels of the income distribution.

We assume that the incidence of our proposed carbon tax depends primarily on consumer demand and the supply price elasticity of electricity. Because of the higher carbon intensity of coal compared to natural gas, a carbon tax applied equally to CO_2 emissions from both methods of electricity generation would effectively change the relative price of natural gas to coal. We assume, however, a constant general price level for consumers outside of this relative price change. Our approach further assumes the incidence of the tax is passed backward to producers in the form of lower prices received, thereby reducing factor incomes. Assuming mobility of labor and capital, the lower returns received by these factors of production due to the added tax burden will ultimately reduce taxes paid by factor incomes, particularly corporate and individual income and payroll taxes, which are the most likely options for revenue offset. This implication of lower income and payroll tax revenue that will most likely result from imposing a carbon tax

Figure 12



is generally referred to as an "excise tax offset" (Pomerleau and Asen, 2019). The exact amount of offset attributed to reductions in income and payroll taxes largely depends upon a number of tax design and implementation features; however, the Joint Committee on Taxation (JCT) has estimated this excise tax offset under current tax law to amount to 22 percent until the year 2026 when the Tax Cuts and Jobs Act expires (Pomerleau and Asen, 2019). Since our study provides revenue projections to the year 2026, we use the JCT's benchmark of 22 percent to estimate the net revenue that would be produced by our proposed carbon tax. It should be noted that our regression-based revenue estimates control for demand and the surrounding area's electricity production capacity but does not account for technological advancements that are nearly impossible to quantify. However, we believe the short-term focus of our analysis reduces the

potential influence of technology changes since most advancement that would markedly reduce our dependence on fossil fuels will occur over the long-term rather than during our time frame of analysis. Figure 12 provides adjusted estimates to reflect the net revenue that a $10, $50, and $220 carbon tax would likely produce in the short-term. According to our estimates, between 2020 and 2026, a $50 per metric ton carbon tax priced to achieve a large marginal impact would produce more than $339.78 billion in net revenue, and a $220 per metric ton carbon tax priced to achieve 75 percent NGCC utilization would generate more than $1.28 trillion in revenue on a net basis.

6.3 Tax Burden Distribution

Another goal of our proposed carbon tax is to maintain revenue neutrality. As such, we do not expect the revenues produced from carbon tax imposition to alter government spending or bring about any changes in environmental regulation. However, the ways in which revenues produced from a carbon tax are used has important distributional consequences. Assuming the incidence of a carbon tax imposed upon CO_2 emissions resulting from energy generation is passed on to consumers, imposition of a carbon tax reduces after-tax wages and therefore the incentive to work. And, as an excise tax, imposition of a carbon tax would make the federal tax system more regressive as it tends to place a higher tax burden on individuals with lower wages than upon those with higher wages. By raising the price of electricity, and by raising the price of electricity produced by coal generators compared to NGCC production, a carbon tax reduces the real incomes of taxpayers and therefore reduces the returns to wages in the short-term. To maintain revenue neutrality and reduce the regressivity of the carbon tax, we propose a revenue offset in the form of a reduction in the payroll tax paid by employees. This approach has been found to increase the long-term size of the economy by reducing the marginal effective tax rate

on labor income, thereby increasing the incentive to work at the same time as making the federal tax system more progressive (Pomerleau and Asen, 2019). These outcomes are superior to the expected outcomes of 1) providing a lump sum rebate, which would likely make a carbon tax less regressive, but would not alter taxpayers incentives to work and therefore would still reduce hours worked and therefore total output as measured by Gross Domestic Product (GDP), and 2) providing a corporate income tax rate reduction, which might boost overall productivity and therefore GDP, but will most likely not improve progressivity of the federal tax structure (Pomerleau and Asen, 2019).

Table 7 provides estimates for how a $10, $50, and $220 carbon tax with a full payroll tax swap might be distributed among income deciles consisting of family units and based upon the current distribution of tax burden for both payroll and excise taxes. The first three columns in Table 7 provide the number of families and the total amount of cash income for each income decile as reported by the U.S. Department of the Treasury's Office of Tax Analysis (OTA).[19] Columns four and five under the "No Carbon Tax" heading provide the distribution of payroll taxes and excises/customs duties under current 2019 tax law as reported by OTA.

The remaining columns in Table 7 consist of our calculations showing how the distribution of payroll and excises/customs tax burdens might change with the imposition of a $10, $50, or $220 excise-based carbon tax and 1) the estimated tax revenues are completely offset by reductions in payroll tax burdens, and 2) both the increase in excises/customs and the decrease in payroll taxes follow the same patterns of distribution as current tax law. So, for

[19] U.S. Department of Treasury, Office of Tax Analysis, Distribution Table: 2019 001, "Distribution of Families, Cash Income, and Federal Taxes under 2019 Current Law." Data retrieved 12/30/19 from: https://home.treasury.gov/policy-issues/tax-policy/office-of-tax-analysis.

example, the total amounts of excises and customs duties under each carbon tax scenario ($10, $50, and $220) in Table 7 each increase by the amounts of carbon tax (net) revenues we estimated that a carbon tax at each price point would generate in 2019. We use the 2019 estimated carbon tax net revenue values for our distributional analysis to ensure comparability with existing tax law and the baseline values reported by OTA. We then calculate the distribution of the additional carbon tax burden on the same basis as the distribution of excises and customs duties under current 2019 tax law and add the distributed tax revenue values to the current excises and customs duties for each income decile.

To calculate the payroll tax distribution changes, we first subtract the increased amount of excises and customs duties from total payroll taxes to reduce the payroll tax burden overall, and then we calculate the distribution of the payroll tax savings on the same basis as the distribution of payroll taxes under current 2019 tax law and subtract the distributed tax savings to the current payroll taxes for each income decile. Using this approach, Table 7 illustrates the ways in which total payroll and excise/customs taxes might decrease and increase, respectively, with the imposition of a $10, $50, and $220 carbon tax, as well as how taxpaying families within each income decile might be affected.

7. Discussion & Conclusion

In this study, we conducted an empirical analysis of NGCC utilization from 2003-2017 to estimate the impact of a carbon tax. In doing so, we determined average capacity factors, generation, CO_2 emissions, and carbon tax revenues given different carbon tax prices from $0 to $250/ton. We assumed all increases in NGCC generation would directly offset coal generation at 100 percent, which would significantly decrease CO_2 emissions in the short-run. Overall, we

Table 7

Distribution of Families, Cash Income, Payroll Taxes, and Excise and Customs Duties Under 2019 Existing Law and Different Carbon Tax Rates

Family Cash Income Decile	Number of Families	Family Cash Income	No Carbon Tax		$10 Carbon Tax		$50 Carbon Tax		$220 Carbon Tax	
			Payroll Taxes	Excises and Customs Duties	Payroll Taxes	Excises and Customs Duties	Payroll Taxes	Excises and Customs Duties	Payroll Taxes	Excises and Customs Duties
0 to 10	17.3	$89.52	$6.13	$2.15	$6.01	$2.51	$6.13	$3.21	$4.88	$5.85
10 to 20	17.8	$296.97	$21.32	$2.95	$20.90	$3.44	$21.32	$4.41	$16.96	$8.02
20 to 30	17.8	$446.23	$35.37	$3.66	$34.67	$4.26	$35.37	$5.46	$28.14	$9.94
30 to 40	17.8	$595.12	$49.08	$4.72	$48.11	$5.51	$49.08	$7.06	$39.05	$12.85
40 to 50	17.8	$798.66	$66.98	$6.37	$65.67	$7.42	$66.98	$9.51	$53.29	$17.31
50 to 60	17.8	$1,066.86	$88.10	$8.44	$86.37	$9.83	$88.10	$12.61	$70.10	$22.94
60 to 70	17.8	$1,403.47	$116.28	$11.13	$113.99	$12.97	$116.28	$16.63	$92.51	$30.26
70 to 80	17.8	$1,860.83	$160.30	$15.22	$157.14	$17.73	$160.30	$22.74	$127.53	$41.38
80 to 90	17.8	$2,568.70	$226.89	$21.54	$222.44	$25.10	$226.89	$32.18	$180.52	$58.56
90 to 100	17.8	$7,337.33	$383.05	$61.09	$375.52	$71.19	$383.05	$91.28	$304.76	$166.11
Total	177.1	$16,463.69	$1,153.49	$137.26	$1,130.82	$159.95	$1,153.49	$205.09	$917.74	$373.22

Note: The number of families is reported in millions, while all dollar values are reported in billions.

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found that a high carbon tax price of $220/ton would be necessary to reach the 75 percent NGCC utilization target from the 2015 Clean Power Plan.

From our regression estimates and counterfactual analysis, we observed a few key patterns. First, it takes a high carbon tax price of $220/ton to reach the 75 percent utilization target determined by the Clean Power Plan in 2015. It is possible this value is higher than expected for several reasons. First, our average NGCC capacity factors are slightly lower than EIA estimates. The EIA estimates include more precise information on operational data of NGCC generators and also include commercial and industrial plants, which we exclude because their power generation is not available for public sale and consumption. Since our values are consistently lower than EIA, it is more difficult to reach the 75 percent target than previously estimated by the EPA. Further clarification on what the 75 percent target includes, and how it was estimated, should be considered in future work.

We also observe that the highest marginal increase in utilization happens with a carbon tax priced at $1-$50/ton. Therefore, in order to see a rapid increase in NGCC generation, especially in the short-term, even a small carbon tax would have a significant impact on NGCC utilization and generation that replaces coal. Assuming no changes in natural gas capacity, a $50 carbon tax would reduce carbon emissions by at least 159 million metric tons a year through increased utilization alone, but with added NGCC capacity estimates from the EIA, carbon emissions would initially decrease by 211 million metric tons a year. A lower carbon tax price around $50/ton would be more politically feasible and can still generate $339 billion dollars in net carbon tax revenue.

Our estimates are fairly conservative for several reasons. First, we considered scenarios with and without any NGCC capacity growth. Some politicians and policy proposals aim to

eliminate natural gas generation as soon as possible since it is a fossil-fuel with carbon emissions. If NGCC plants last on average for about 50 years (Joskow, 2006), new plants built in 2020 would continue to operate until 2070 which slows the transition to 100 percent renewable generation. However, it is outside the scope of this research to determine if that goal is technologically or politically feasible. Yet, there are modest emissions reductions as a result of a $50 carbon tax through increased NGCC utilization with no new investments in NGCC capacity. Additionally, we do not focus on the role of renewables in this study, which could alter these estimates. It is highly likely that any carbon tax would also incentivize the production of zero and low carbon sources of electricity, such as renewables and nuclear generation, which would further reduce emissions. Future work on this topic could focus more explicitly on the complementary relationship between NGCC and intermittent renewable generators. Our regression results showed increased renewable generation displaces NGCC utilization, indicating they are competitive rather than complementary. However, previous literature suggests that high levels of fast-reacting fossil fuels, such as NGCC, will increase intermittent renewable penetration (Verdolini et al., 2018). With policies and subsidies to increase renewable penetration, NGCC utilization would also increase if they are complementary with renewables.

Finally, our estimates are conservative because they focus on the short-term impact of a carbon tax on NGCC utilization, and do not consider the impact of a rising carbon tax price, or implications beyond 2026. A carbon tax on the electricity sector would quickly act to incentivize increased NGCC utilization based on the statistically significant relationship we (and others) have found between natural gas and coal utilization in response to changes in resource prices. As natural gas becomes relatively cheaper than coal, either through policies or economic conditions, natural gas utilization increases. Therefore, a carbon tax would be an effective method for

quickly increasing NGCC utilization. Future work should consider the coupled impact of carbon taxes on changes in NGCC capacity and utilization over a longer-term, which would likely be affected by potential advancements in technology.

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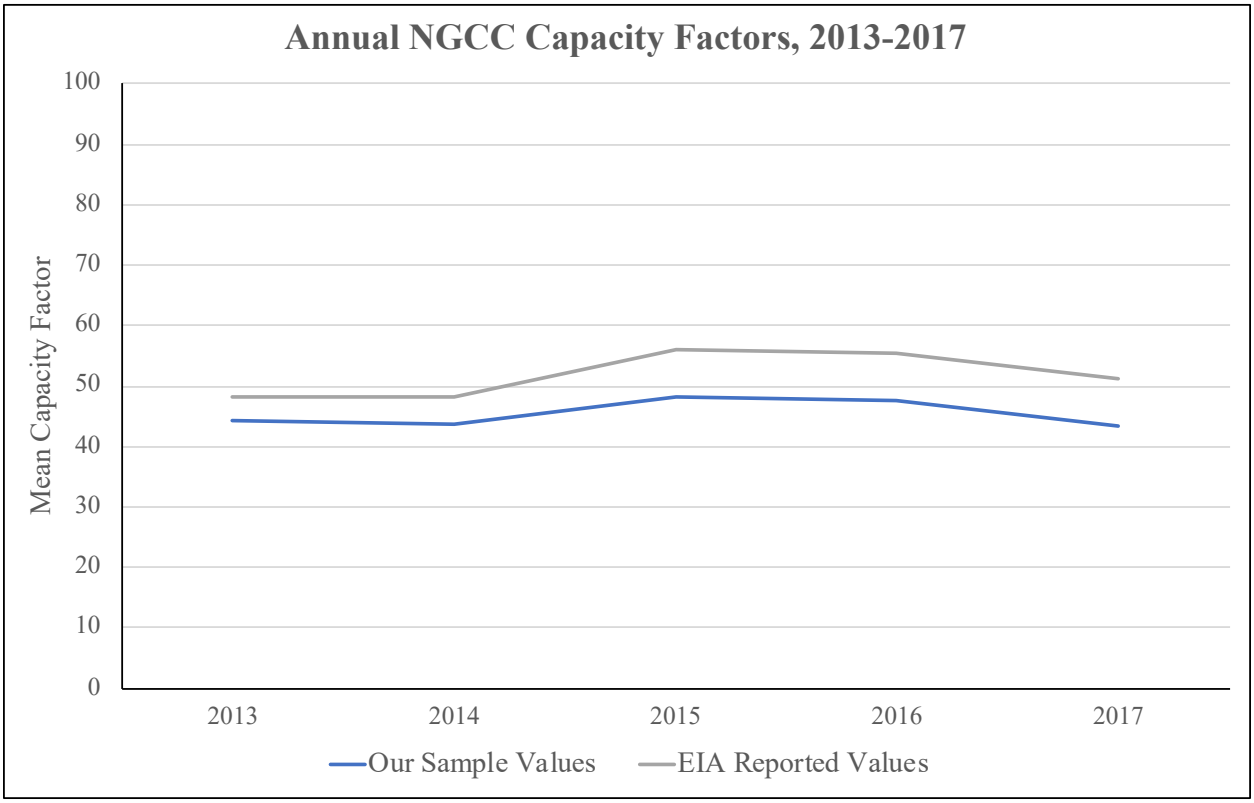
Appendix A: Capacity Factor Comparison

Figures A1 and A2 provide comparisons between mean capacity factors on an annual basis (top) and monthly basis (bottom) for the year 2017 for our sample versus EIA values provided by the EIA's Electric Power Monthly Table 6.7.A.[20]

Figure A1



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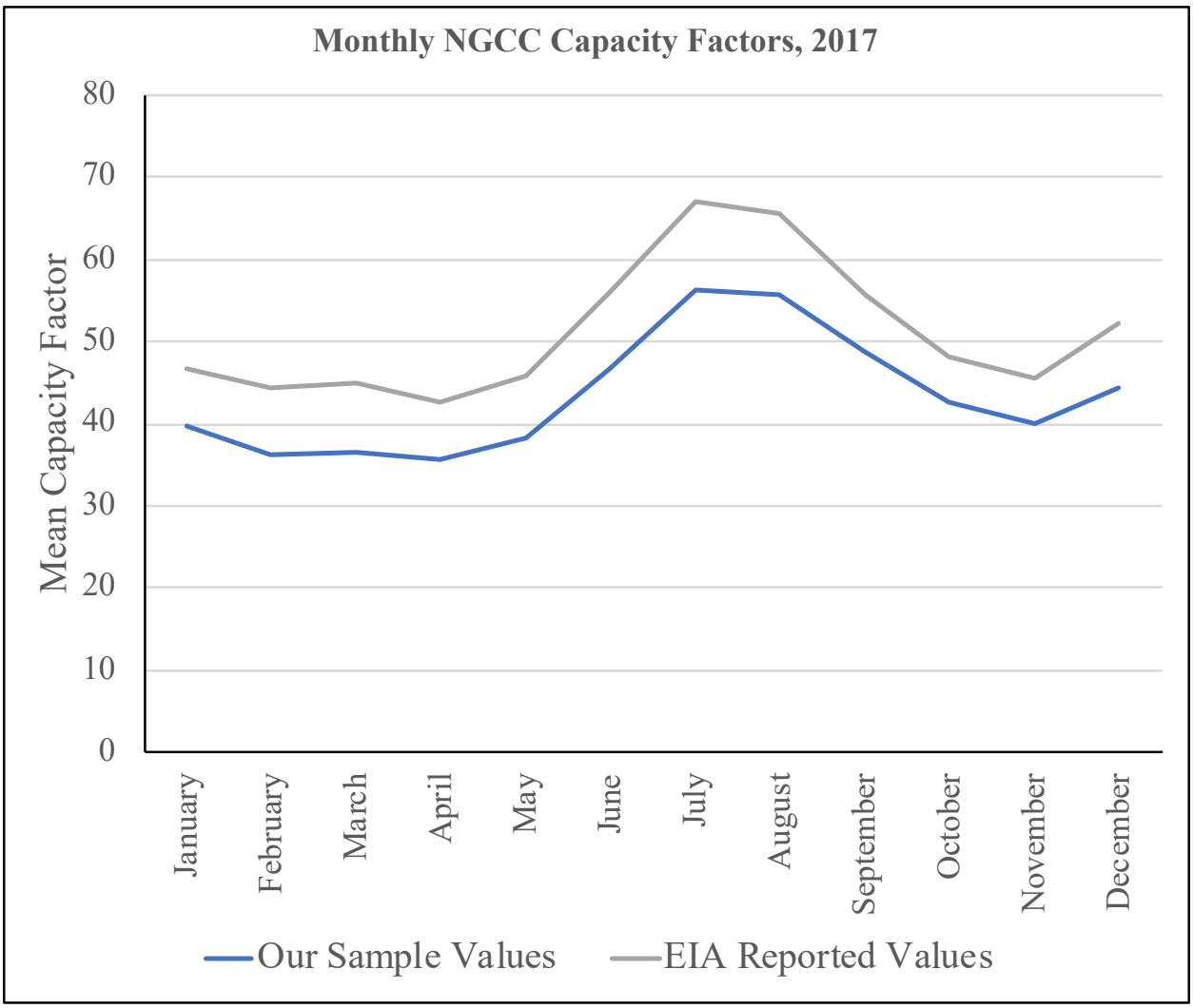
[20] EIA's Electric Power Monthly is available at: https://www.eia.gov/electricity/monthly/current_month/epm.pdf. NGCC capacity factors were only made available in the Electric Power Monthly starting in 2013.

Figure A2



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Appendix B: Number of Knots Sensitivity Testing

Table B1

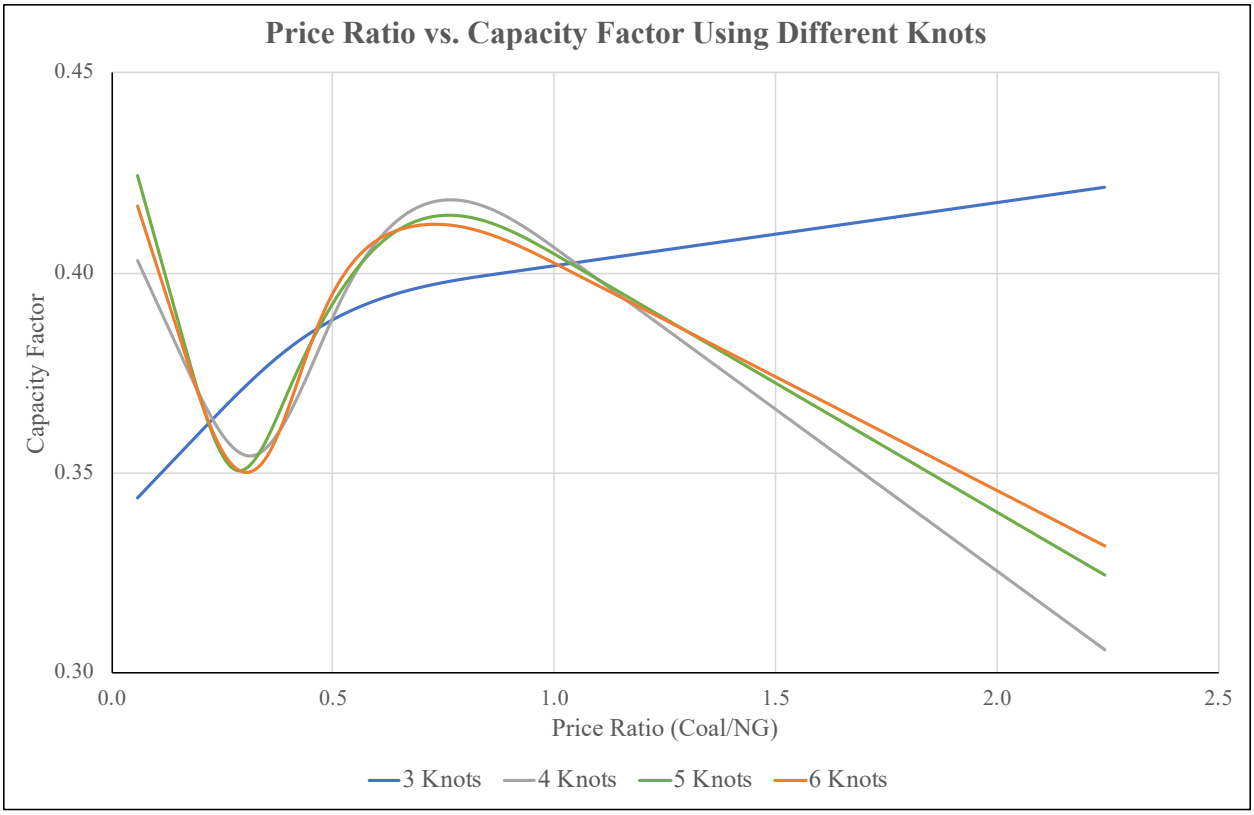
Fixed Effects Regression Results Using Different Knots

Category	Variable	Model 1: 0 Knots		Model 2: 3 Knots		Model 3: 4 Knots		Model 4: 5 Knots		Model 5: 6 Knots	
		Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Price Ratio	Price Ratio MMBtu (0 Knots)	0.0319+	-0.019								
	Price Ratio 1 (3 Knots)			0.116*	-0.0532						
	Price Ratio 2 (3 Knots)			-0.106	-0.0685						
	Price Ratio 1 (4 Knots)					-0.241*	-0.1054				
	Price Ratio 2 (4 Knots)					2.511***	-0.6532				
	Price Ratio 3 (4 Knots)					-5.265***	-1.2942				
	Price Ratio 1 (5 Knots)							-0.398**	-0.1423		
	Price Ratio 2 (5 Knots)							5.916**	-1.9606		
	Price Ratio 3 (5 Knots)							-12.34*	-4.7989		
	Price Ratio 4 (5 Knots)							6.381+	-3.6838		
	Price Ratio 1 (6 Knots)									-0.345*	-0.1485
	Price Ratio 2 (6 Knots)									4.468	-3.2841
	Price Ratio 3 (6 Knots)									-3.764	-8.2877
	Price Ratio 4 (6 Knots)									-7.58	-7.8693
	Price Ratio 5 (6 Knots)									7.942*	-3.9025
Policies	CAIR	0.173***	-0.0325	0.172***	-0.0323	0.166***	-0.0311	0.165***	-0.0308	0.164***	-0.031
	RGGI	-0.053	-0.0569	-0.0442	-0.0567	-0.0782	-0.0578	-0.0774	-0.058	-0.0785	-0.058
	NBP	0.106	-0.1102	0.109	-0.1087	0.101	-0.1099	0.104	-0.1083	0.104	-0.1085
	CSPAR	0.282***	-0.0425	0.280***	-0.0425	0.277***	-0.0414	0.277***	-0.0415	0.277***	-0.0415
	NAA	-0.0687+	-0.0371	-0.0698+	-0.0372	-0.0673+	-0.0368	-0.0675+	-0.0366	-0.0674+	-0.0366
	ARP	-0.148	-0.0968	-0.148	-0.0973	-0.154	-0.094	-0.153	-0.0943	-0.154	-0.0941
	CA Cat	0.0772	-0.0487	0.0754	-0.0485	0.0637	-0.0488	0.0657	-0.0487	0.0651	-0.0487
Capacity-Weighted Age * Policy	Capacity-Weighted Age * CAIR	-0.00526***	-0.0013	-0.00519***	-0.0012	-0.00528***	-0.0013	-0.00519***	-0.0012	-0.00518***	-0.0012
	Capacity-Weighted Age * RGGI	0.00243	-0.0025	0.00219	-0.0025	0.00272	-0.0025	0.00264	-0.0025	0.00261	-0.0025
	Capacity-Weighted Age * NBP	-0.00214	-0.0046	-0.00239	-0.0045	-0.00172	-0.0046	-0.00187	-0.0045	-0.00187	-0.0045
	Capacity-Weighted Age * CSPAR	-0.00966***	-0.0018	-0.00953***	-0.0018	-0.00945***	-0.0018	-0.00942***	-0.0018	-0.00942***	-0.0018
	Capacity-Weighted Age * NAA	0.00379*	-0.0018	0.00381*	-0.0018	0.00367*	-0.0017	0.00371*	-0.0017	0.00371*	-0.0017
	Capacity-Weighted Age * ARP	0.000513	-0.0033	0.000534	-0.0033	0.000826	-0.0032	0.000807	-0.0032	0.000839	-0.0032
	Capacity-Weighted Age * CA Cat	-0.00497+	-0.0028	-0.00500+	-0.0028	-0.00506+	-0.0028	-0.00506+	-0.0028	-0.00505+	-0.0028
Weather	HDD	-0.0810***	-0.015	-0.0816***	-0.0149	-0.0819***	-0.0153	-0.0815***	-0.0153	-0.0813***	-0.0154
	CDD	0.259***	-0.0407	0.257***	-0.0405	0.252***	-0.041	0.253***	-0.0411	0.252***	-0.0409
Area Load	Demand Ratio	0.435***	-0.043	0.435***	-0.0431	0.438***	-0.043	0.437***	-0.0429	0.437***	-0.0429
	Coal Capacity	-0.368**	-0.12	-0.366**	-0.1206	-0.340**	-0.1108	-0.339**	-0.11	-0.338**	-0.11
	Nuclear Capacity	0.0694	-0.3009	0.0683	-0.298	0.107	-0.2965	0.101	-0.2915	0.1	-0.2918
	Renewable Generation	-0.424***	-0.0795	-0.429***	-0.0797	-0.393***	-0.0758	-0.392***	-0.076	-0.392***	-0.0761
Generator	Capacity-Weighted Age	-0.000224	-0.0031	-0.000299	-0.0031	-0.000483	-0.003	-0.000487	-0.003	-0.000525	-0.003
Year	2003	0	(.)	0	(.)	0	(.)	0	(.)	0	(.)
	2004	-0.0252*	-0.012	-0.0236*	-0.0118	-0.0257*	-0.0115	-0.0261*	-0.0114	-0.0257*	-0.0114
	2005	-0.0314**	-0.0115	-0.0276*	-0.0112	-0.0386***	-0.0105	-0.0418***	-0.0105	-0.0408***	-0.0106
	2006	-0.0351*	-0.0141	-0.0329*	-0.014	-0.0379**	-0.0135	-0.0393**	-0.0133	-0.0387**	-0.0134
	2007	-0.00388	-0.0133	-0.00332	-0.0132	-0.00572	-0.0126	-0.00682	-0.0124	-0.00643	-0.0125
	2008	-0.0145	-0.0147	-0.0147	-0.0147	-0.0166	-0.0143	-0.0179	-0.014	-0.0173	-0.0142
	2009	-0.0439*	-0.0172	-0.0518**	-0.0186	-0.0429*	-0.0197	-0.0415*	-0.0202	-0.0411*	-0.0202
	2010	-0.0317+	-0.0175	-0.0404*	-0.0191	-0.033	-0.0202	-0.0313	-0.0209	-0.0309	-0.0209
	2011	-0.0463*	-0.0192	-0.0561**	-0.0199	-0.0503*	-0.0209	-0.0483*	-0.022	-0.0474*	-0.0219
	2012	0.00615	-0.0221	-0.0046	-0.0225	0.00558	-0.0237	0.00503	-0.024	0.00555	-0.0241
	2013	-0.0068	-0.0196	-0.0175	-0.021	-0.00994	-0.0225	-0.00954	-0.0229	-0.00829	-0.0232
	2014	-0.00904	-0.0197	-0.0193	-0.021	-0.0135	-0.0221	-0.0122	-0.0228	-0.0114	-0.0228
	2015	0.00225	-0.0215	-0.01	-0.0236	-0.0076	-0.0249	-0.008	-0.0249	-0.00801	-0.0249
	2016	-0.0118	-0.0211	-0.0234	-0.0236	-0.0194	-0.025	-0.0193	-0.0252	-0.0195	-0.0251
	2017	-0.00239	-0.0213	-0.0133	-0.0236	-0.00968	-0.0244	-0.00912	-0.0247	-0.00981	-0.0246
	Constant	0.318**	-0.0971	0.298**	-0.0969	0.372***	-0.0939	0.402***	-0.0929	0.393***	-0.0936
	R^2	0.224		0.224		0.228		0.228		0.228	
	N	76,104		76,104		76,104		76,104		76,104	

Standard Errors in Parentheses

+ p<0.1, * p<0.05, ** p<0.01, *** p<0.001

Figure B1



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Appendix C: Time Fixed Effects Sensitivity Testing

Table C1 provides sensitivity test results with year fixed effects (base, regular model), no time fixed effects (column 2), and year-month fixed effects (column 3). While the r-squared value goes up slightly with more time fixed effects, other variables remain consistently significant. As expected, the price ratio spline variables have higher significance with no time fixed effects, as the time fixed effects capture some of the price ratio variability.

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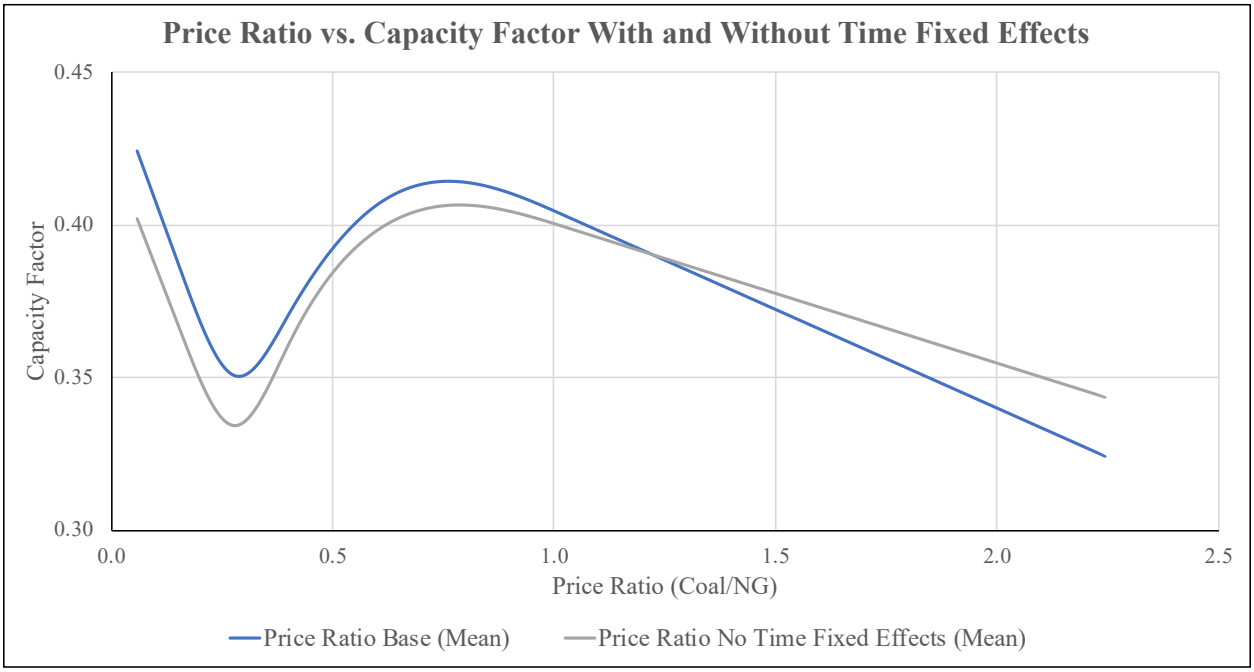
Table C1

Fixed Effects Regression Results Using Different Time Fixed Effects							
Category	**Variable**	**Model 1: Year Fixed Effects**		**Model 2: No Time Fixed Effects**		**Model 3: Year and Month Fixed Effects**	
		Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Price Ratio	Price Ratio 1	-0.398**	-0.1423	-0.376***	-0.097	-0.566**	-0.172
	Price Ratio 2	5.916**	-1.9606	6.365***	-1.7158	7.116***	-2.1009
	Price Ratio 3	-12.34*	-4.7989	-13.78**	-4.3259	-14.74**	-5.0294
	Price Ratio 4	6.381+	-3.6838	7.795*	-3.4386	7.667*	-3.769
Policies	CAIR	0.165***	-0.0308	0.158***	-0.0298	0.163***	-0.0309
	RGGI	-0.0774	-0.058	-0.0756	-0.057	-0.0884	-0.0582
	NBP	0.104	-0.1083	0.105	-0.1087	0.104	-0.1086
	CSPAR	0.277***	-0.0415	0.276***	-0.0413	0.278***	-0.0413
	NAA	-0.0675+	-0.0366	-0.0729*	-0.0358	-0.0682+	-0.0365
	ARP	-0.153	-0.0943	-0.158	-0.0963	-0.152	-0.0941
	CA Cat	0.0657	-0.0487	0.0793	-0.048	0.063	-0.0489
Capacity-Weighted Age * Policy	Capacity-Weighted Age * CAIR	-0.00519***	-0.0012	-0.00516***	-0.0012	-0.00522***	-0.0012
	Capacity-Weighted Age * RGGI	0.00264	-0.0025	0.00233	-0.0025	0.00282	-0.0025
	Capacity-Weighted Age * NBP	-0.00187	-0.0045	-0.00205	-0.0046	-0.00173	-0.0046
	Capacity-Weighted Age * CSPAR	-0.00942***	-0.0018	-0.00939***	-0.0017	-0.00947***	-0.0018
	Capacity-Weighted Age * NAA	0.00371*	-0.0017	0.00380*	-0.0017	0.00374*	-0.0017
	Capacity-Weighted Age * ARP	0.000807	-0.0032	0.000923	-0.0032	0.000765	-0.0032
	Capacity-Weighted Age * CA Cat	-0.00506+	-0.0028	-0.00529+	-0.0028	-0.00497+	-0.0028
Weather	HDD	-0.0815***	-0.0153	-0.0832***	-0.0152	-0.0901***	-0.0171
	CDD	0.253***	-0.0411	0.249***	-0.0399	0.275***	-0.0437
Area Load	Demand Ratio	0.437***	-0.0429	0.438***	-0.043	0.428***	-0.0432
	Coal Capacity	-0.339**	-0.11	-0.340**	-0.1065	-0.334**	-0.1083
	Nuclear Capacity	0.101	-0.2915	0.118	-0.2918	0.0996	-0.2918
	Renewable Generation	-0.392***	-0.076	-0.378***	-0.0725	-0.384***	-0.0761
Generator	Capacity-Weighted Age	-0.000487	-0.003	-0.000643	-0.003	-0.000421	-0.003
Year	2003	0	(.)				
	2004	-0.0261*	-0.0114				
	2005	-0.0418***	-0.0105				
	2006	-0.0393**	-0.0133				
	2007	-0.00682	-0.0124				
	2008	-0.0179	-0.014				
	2009	-0.0415*	-0.0202				
	2010	-0.0313	-0.0209				
	2011	-0.0483*	-0.022				
	2012	0.00503	-0.024				
	2013	-0.00954	-0.0229				
	2014	-0.0122	-0.0228				
	2015	-0.008	-0.0249				
	2016	-0.0193	-0.0252				
	2017	-0.00912	-0.0247				
	Constant	0.402***	-0.0929	0.377***	-0.0942	0.477***	-0.0964
	R^2	0.228		0.224		0.235	
	N	76,104		76,104		76,104	

Standard Errors in Parentheses
+ p<0.1, * p<0.05, ** p<0.01, *** p<0.001

Figure C1



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Appendix D: Group by Age Sensitivity Testing

Table D1 provides regression results after splitting the NGCC sample by age groups. Column one is the full sample, column 2 represents NGCC generators with a capacity weighted age less than or equal to 20 years old, column 3 includes NGCC generators greater than 20 but less than or equal to 40 years old, and column 4 reflects those greater than 40 years old.

Table D1

Fixed Effects Regression Results Grouping NGCC Generators by Capacity-Weighted Age

Category	Variable	Model 1: Full Sample		Model 2: Zero to 20 Years		Model 3: 20 to 40 Years		Model 4: 40 Years and Older	
		Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Price Ratio	Price Ratio 1	-0.398**	-0.1423	-0.582**	-0.1778	-0.0858	-0.1756	-0.271	-0.2636
	Price Ratio 2	5.916**	-1.9606	7.610**	-2.4697	1.053	-2.1932	0.669	-3.4441
	Price Ratio 3	-12.34*	-4.7989	-15.51*	-6.0508	-1.011	-5.2742	-0.241	-8.3786
	Price Ratio 4	6.381+	-3.6838	7.678+	-4.6114	-1.187	-4.0202	-1.232	-6.5131
Policies	CAIR	0.165***	-0.0308	0.132+	-0.0668	-0.00586	-0.0687	-0.406	-0.382
	RGGI	-0.0774	-0.058	0.0307	-0.1474	-0.0405	-0.2276	0	(.)
	NBP	0.104	-0.1083	0.185	-0.2706	0.161	-0.1901	0	(.)
	CSPAR	0.277***	-0.0415	0.239***	-0.0703	0.049	-0.1149	-0.434	-0.7239
	NAA	-0.0675+	-0.0366	-0.0758	-0.0925	-0.281+	-0.1645	-1.842***	-0.3656
	ARP	-0.153	-0.0943	-0.399**	-0.1404	-0.215	-0.297	2.818	-3.8346
	CA Cat	0.0657	-0.0487	0.239*	-0.1019	-0.0174	-0.1403	0	(.)
Capacity-Weighted Age * Policy	Capacity-Weighted Age * CAIR	-0.00519***	-0.0012	-0.00359	-0.0044	0.000466	-0.0024	0.00956	-0.0081
	Capacity-Weighted Age * RGGI	0.00264	-0.0025	-0.00584	-0.0096	0.00299	-0.0088	-0.00104	-0.0008
	Capacity-Weighted Age * NBP	-0.00187	-0.0045	-0.00766	-0.0145	-0.00536	-0.0071	-0.00111	-0.0017
	Capacity-Weighted Age * CSPAR	-0.00942***	-0.0018	-0.00963*	-0.0046	-0.000332	-0.0042	0.00891	-0.0151
	Capacity-Weighted Age * NAA	0.00371*	-0.0017	0.00527	-0.0061	0.0106+	-0.0059	0.0383***	-0.0071
	Capacity-Weighted Age * ARP	0.000807	-0.0032	0.0293**	-0.0106	0.0023	-0.0107	-0.0627	-0.0866
	Capacity-Weighted Age * CA Cat	-0.00506+	-0.0028	-0.0193*	-0.0084	-0.000916	-0.0057	0	(.)
Weather	HDD	-0.0815***	-0.0153	-0.105***	-0.0201	-0.0530*	-0.0234	-0.0386	-0.042
	CDD	0.253***	-0.0411	0.258***	-0.0509	0.208***	-0.0523	0.166	-0.1062
Area Load	Demand Ratio	0.437***	-0.0429	0.551***	-0.0584	0.327***	-0.0505	0.200***	-0.0429
	Coal Capacity	-0.339**	-0.11	-0.470***	-0.1377	0.0117	-0.1336	-0.316**	-0.0887
	Nuclear Capacity	0.101	-0.2915	0.0809	-0.5304	0.0713	-0.2269	0.530+	-0.3007
	Renewable Generation	-0.392***	-0.076	-0.684***	-0.09	-0.264***	-0.0641	0.029	-0.0262
Generator	Capacity-Weighted Age	-0.000487	-0.003	-0.0111	-0.0116	-0.00642	-0.0127	-0.00269	-0.0018
Year	2003	0	(.)	0	(.)	0	(.)	0	(.)
	2004	-0.0261*	-0.0114	0.0105	-0.0114	-0.0586**	-0.0197	-0.0403*	-0.0186
	2005	-0.0418***	-0.0105	-0.0011	-0.0151	-0.0744***	-0.0147	-0.0560*	-0.0221
	2006	-0.0393**	-0.0133	0.0185	-0.0164	-0.0908***	-0.018	-0.0711*	-0.0277
	2007	-0.00682	-0.0124	0.0607***	-0.0153	-0.0695***	-0.0159	-0.0548+	-0.0286
	2008	-0.0179	-0.014	0.0492**	-0.016	-0.0807***	-0.0197	-0.105**	-0.0343
	2009	-0.0415*	-0.0202	0.0374	-0.0237	-0.111***	-0.0249	-0.0793+	-0.0408
	2010	-0.0313	-0.0209	0.0345	-0.0253	-0.0811**	-0.025	-0.0479	-0.0407
	2011	-0.0483*	-0.022	0.0252	-0.0274	-0.106***	-0.0272	-0.0568+	-0.0303
	2012	0.00503	-0.024	0.101***	-0.0281	-0.0840**	-0.0307	-0.0655+	-0.0361
	2013	-0.00954	-0.0229	0.0823**	-0.0267	-0.0887**	-0.0292	-0.0865+	-0.0422
	2014	-0.0122	-0.0228	0.0789**	-0.026	-0.0861**	-0.0301	-0.0919*	-0.0428
	2015	-0.008	-0.0249	0.0999***	-0.0278	-0.100**	-0.0329	-0.0594	-0.0362
	2016	-0.0193	-0.0252	0.0875**	-0.03	-0.113***	-0.0307	-0.0830+	-0.0458
	2017	-0.00912	-0.0247	0.105***	-0.0289	-0.131***	-0.0279	-0.0822+	-0.0454
	Constant	0.402***	-0.0929	0.400*	-0.1684	0.537	-0.3636	0.411***	-0.0963
	R^2	0.228		0.288		0.185		0.273	
	N	76,104		46,349		27,473		2,282	

Standard Errors in Parentheses

+ p<0.1, * p<0.05, ** p<0.01, *** p<0.001

Figure D1 illustrates the price ratio, ceteris paribus, for the regression results based upon these different age groups; the base includes all observations. The plants with an average capacity-weighed age over 40 years are not included because the price ratio spline variables are all strongly insignificant and have a low sample size (less than 3 percent of the data).

Figure D1

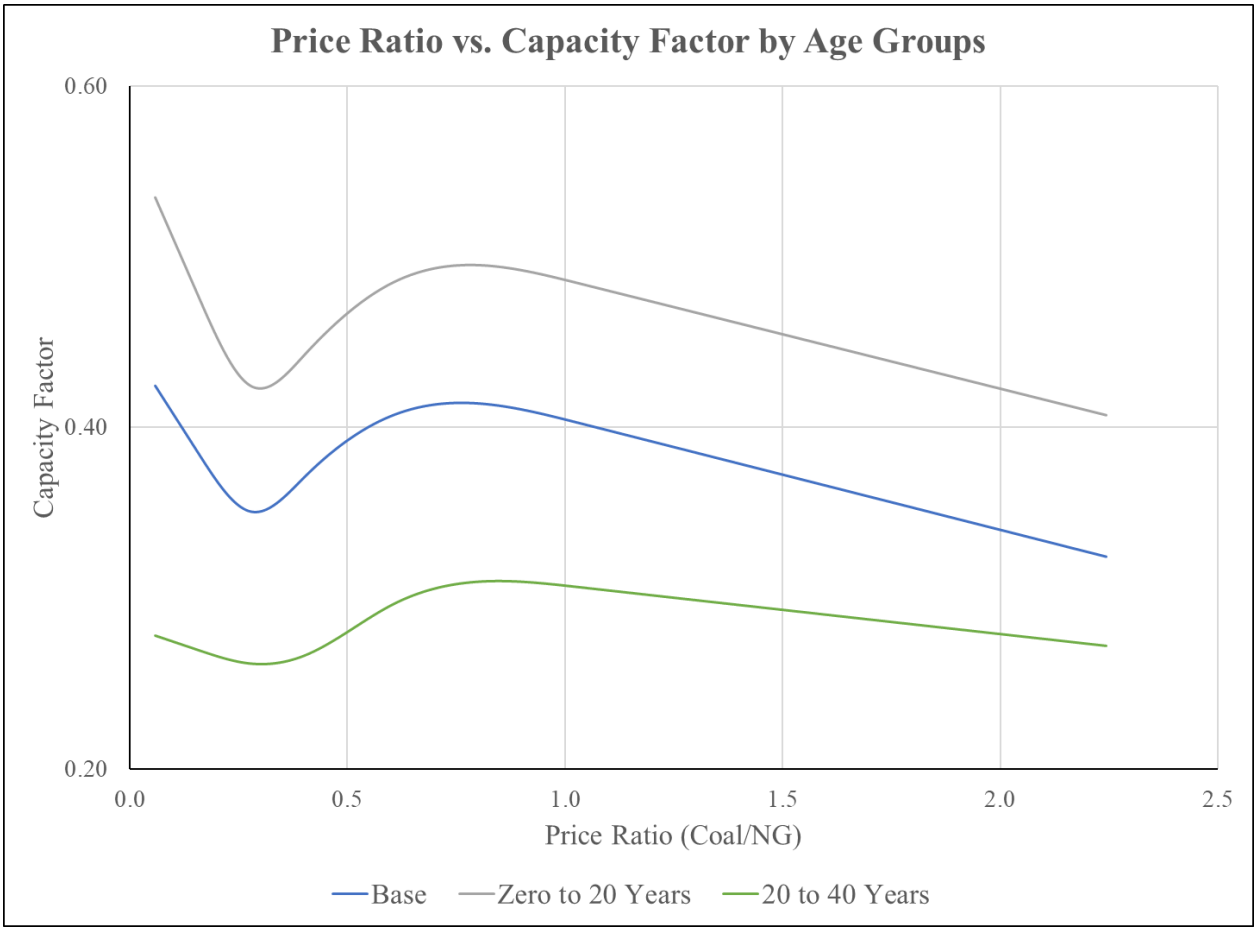

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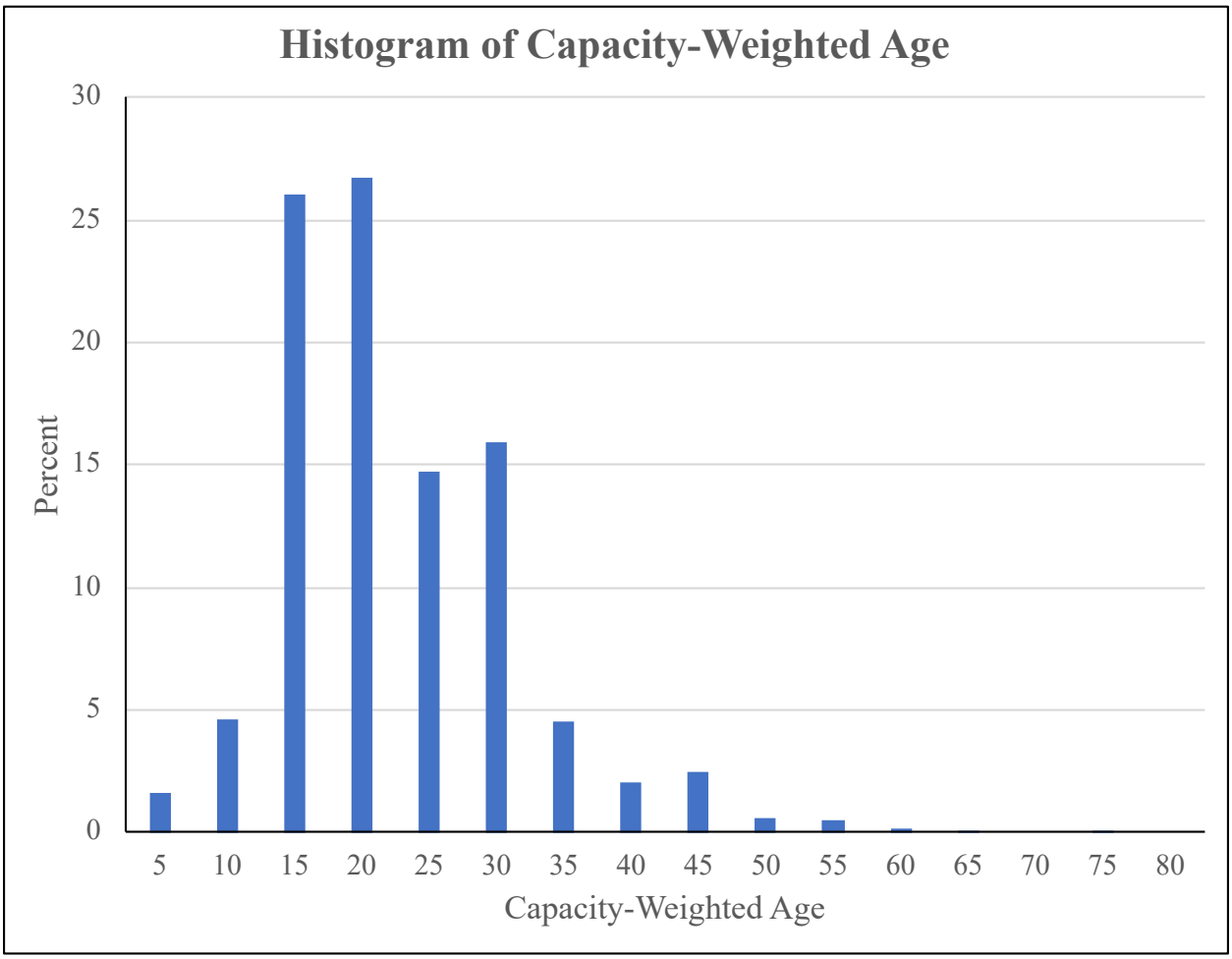
Figure D2 illustrates a histogram by capacity-weighted age of NGCC plants in our data sample with 5-year bin sizes.

Figure D2



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Appendix E: CHP Sensitivity Testing

We cannot control for combined heat and power plants (CHPs) explicitly, since the variable does not vary over time and we are using a fixed-effects regression model; therefore, we conduct additional sensitivity testing on these subsamples. They do not typically dispatch to the grid, and only make up 35 percent of our dataset in terms of number of observations and 20 percent of total NGCC generation. Table E1 provides the regression results for sensitivity testing by comparing the full dataset (column 1) to non-CHPs (column 2) and CHPs (column 3).

Table E1 shows there is a higher r-squared value on the non-CHP sample compared to the full dataset and CHP samples. In addition, the price variables are not significant in the CHP sample. We expect this, since CHPs face slightly different conditions when deciding to operate. From Figure E1, we see that CHPs have a slightly higher average capacity factor, as expected, since they are typically smaller and serve load to individual entities. Despite the fact that they have higher estimated capacity factors, the full sample estimates closely resemble the non-CHP sample.

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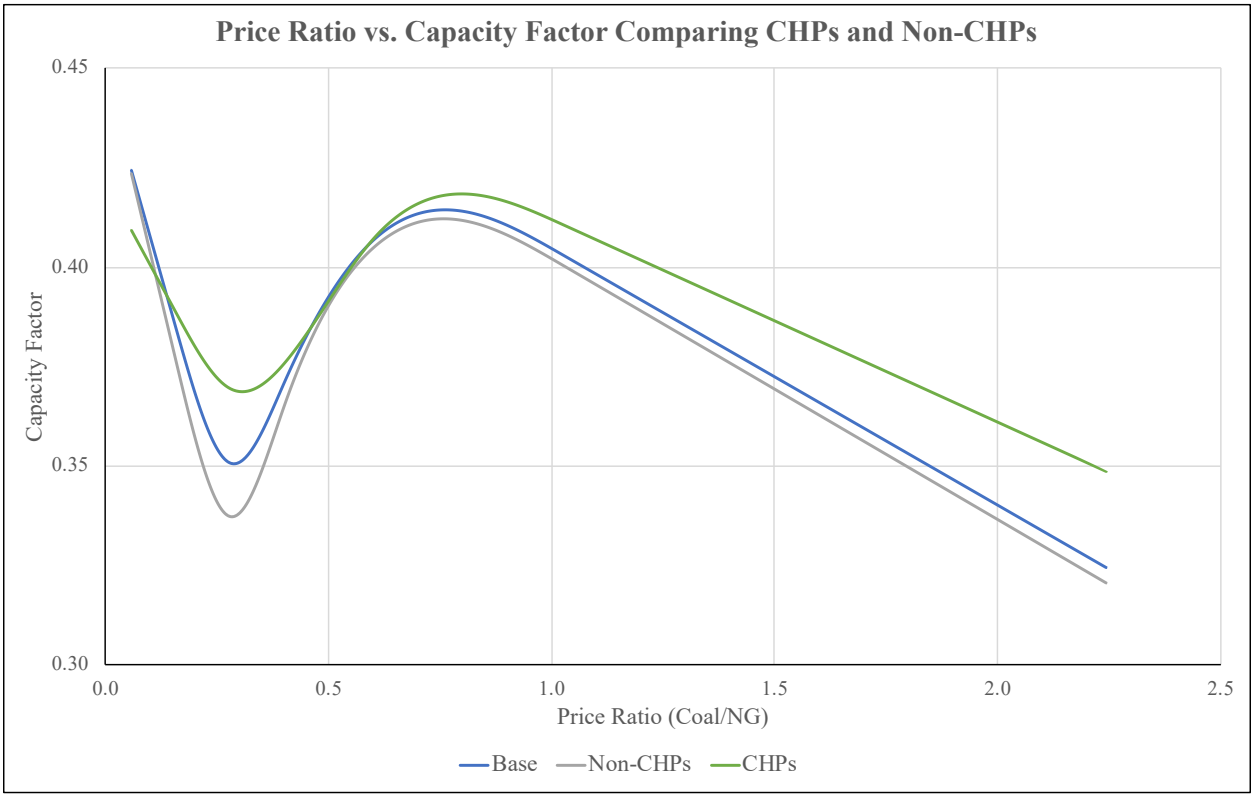
Table E1

Fixed Effects Regression Results Using Different Subsamples of Combined Heat and Power Plants (CHPs)							
Category	**Variable**	**Model 1: Full Sample**		**Model 2: Non-CHPs**		**Model 3: CHPs**	
		Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Price Ratio	Price Ratio 1	-0.398**	-0.1423	-0.472*	-0.1887	-0.207	-0.1544
	Price Ratio 2	5.916**	-1.9606	7.456**	-2.6191	2.485	-2.0569
	Price Ratio 3	-12.34*	-4.7989	-16.05*	-6.4428	-4.098	-5.1262
	Price Ratio 4	6.381+	-3.6838	8.991+	-4.9844	0.589	-4.0976
Policies	CAIR	-0.00519***	-0.0012	-0.00475***	-0.0013	-0.00268	-0.0028
	RGGI	0.00264	-0.0025	-0.00052	-0.003	0.0104+	-0.0062
	NBP	-0.00187	-0.0045	0.00112	-0.0052	0.00758	-0.0084
	CSPAR	-0.00942***	-0.0018	-0.00812***	-0.0019	-0.00606*	-0.003
	NAA	0.00371*	-0.0017	0.00331+	-0.0018	0.00343	-0.0039
	ARP	-0.00506+	-0.0028	-0.00386	-0.0037	-0.00577+	-0.0033
	CA Cat	0.000807	-0.0032	0.000906	-0.0031	-0.00587	-0.005
Capacity-Weighted Age * Policy	Capacity-Weighted Age * CAIR	0.165***	-0.0308	0.159***	-0.0339	0.0991	-0.0619
	Capacity-Weighted Age * RGGI	-0.0774	-0.058	-0.0288	-0.0678	-0.262+	-0.1526
	Capacity-Weighted Age * NBP	0.104	-0.1083	-0.0116	-0.1494	-0.112	-0.1988
	Capacity-Weighted Age * CSPAR	0.277***	-0.0415	0.260***	-0.0434	0.188**	-0.0662
	Capacity-Weighted Age * NAA	-0.0675+	-0.0366	-0.0621	-0.0417	-0.0611	-0.0779
	Capacity-Weighted Age * ARP	0.0657	-0.0487	0.0427	-0.0599	0.112+	-0.0579
	Capacity-Weighted Age * CA Cat	-0.153	-0.0943	-0.0289	-0.1066	-0.0397	-0.1329
Weather	HDD	-0.0815***	-0.0153	-0.0842***	-0.0192	-0.0749**	-0.0247
	CDD	0.253***	-0.0411	0.286***	-0.0461	0.137*	-0.0649
Area Load	Demand Ratio	0.437***	-0.0429	0.489***	-0.0507	0.294***	-0.0583
	Coal Capacity	-0.339**	-0.11	-0.462**	-0.157	-0.00367	-0.1205
	Nuclear Capacity	0.101	-0.2915	-0.104	-0.327	0.526	-0.366
	Renewable Generation	-0.392***	-0.076	-0.445***	-0.1209	-0.276***	-0.0673
Generator	Capacity-Weighted Age	-0.000487	-0.003	0.00183	-0.0031	-0.00407	-0.0037
Year	2003	0	(.)	0	(.)	0	(.)
	2004	-0.0261*	-0.0114	-0.00395	-0.0104	-0.0469*	-0.0215
	2005	-0.0418***	-0.0105	-0.016	-0.0132	-0.0633***	-0.0145
	2006	-0.0393**	-0.0133	-0.00371	-0.0139	-0.0762***	-0.0186
	2007	-0.00682	-0.0124	0.0269*	-0.0136	-0.0438**	-0.0165
	2008	-0.0179	-0.014	0.015	-0.0148	-0.0576**	-0.0199
	2009	-0.0415*	-0.0202	-0.00991	-0.0237	-0.0778**	-0.0255
	2010	-0.0313	-0.0209	-0.00616	-0.0255	-0.0501+	-0.027
	2011	-0.0483*	-0.022	-0.0249	-0.0275	-0.0644*	-0.0282
	2012	0.00503	-0.024	0.0418	-0.031	-0.0382	-0.0285
	2013	-0.00954	-0.0229	0.0253	-0.0304	-0.0469+	-0.0262
	2014	-0.0122	-0.0228	0.0227	-0.0298	-0.0514+	-0.0287
	2015	-0.008	-0.0249	0.0251	-0.0319	-0.0516	-0.0327
	2016	-0.0193	-0.0252	0.00651	-0.032	-0.0533+	-0.0304
	2017	-0.00912	-0.0247	0.0256	-0.0303	-0.0612*	-0.0282
	Constant	0.402***	-0.0929	0.225*	-0.1099	0.528***	-0.1172
	R^2	0.228		0.277		0.162	
	N	76,104		49,658		26,203	
Standard Errors in Parentheses							
+ p<0.1, * p<0.05, ** p<0.01, *** p<0.001							

Figure E1



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Appendix F: OLS Results Sensitivity Testing

Table F1

Ordinary Least Squares Regression Results			
Category	**Variable**	**Coefficient**	**SE**
Price Ratio	Price Ratio 1	-0.460*	-0.1893
	Price Ratio 2	5.901**	-2.2412
	Price Ratio 3	-10.76+	-5.4528
	Price Ratio 4	3.368	-4.2354
Policies	CAIR	0.117***	-0.0311
	RGGI	0.199**	-0.0599
	NBP	0.131	-0.1174
	CSPAR	0.140***	-0.0384
	NAA	0.0416	-0.0298
	ARP	-0.113*	-0.0537
	CA Cat	-0.147**	-0.0438
Capacity-Weighted Age * Policy	Capacity-Weighted Age * CAIR	-0.00439**	-0.0015
	Capacity-Weighted Age * RGGI	-0.0118***	-0.0035
	Capacity-Weighted Age * NBP	-0.00346	-0.0046
	Capacity-Weighted Age * CSPAR	-0.00488**	-0.0018
	Capacity-Weighted Age * NAA	0.000773	-0.0016
	Capacity-Weighted Age * ARP	-0.000311	-0.0023
	Capacity-Weighted Age * CA Cat	0.00272	-0.002
Weather	HDD	-0.0990***	-0.0221
	CDD	0.232***	-0.0463
Area Load	Demand Ratio	0.451***	-0.0429
	Coal Capacity	-0.334***	-0.0441
	Nuclear Capacity	-0.399***	-0.0907
	Renewable Generation	-0.277***	-0.0638
Generator	Capacity-Weighted Age	-0.00638***	-0.0018
Year	2003	0	(.)
	2004	-0.0231+	-0.0133
	2005	-0.0472***	-0.0129
	2006	-0.0399**	-0.0135
	2007	-0.0093	-0.0121
	2008	-0.0264+	-0.0137
	2009	-0.0352	-0.0251
	2010	-0.0322	-0.0268
	2011	-0.0501+	-0.0274
	2012	-0.00169	-0.0287
	2013	-0.0116	-0.0281
	2014	-0.0153	-0.0285
	2015	-0.00366	-0.0329
	2016	-0.0156	-0.0343
	2017	-0.0278	-0.0295
	Constant	0.546***	-0.0696
	R^2	0.253	
	N	76,104	
Standard Errors in Parentheses			
+ p<0.1, * p<0.05, ** p<0.01, *** p<0.001			