Will Carbon Prices Reduce Emissions in the US Electricity Industry? Evidence from the Shale Gas Experience

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Abstract

This paper uses the unprecedent variation in US natural gas prices arising from new shale gas production to examine how the electricity industry could respond to carbon policy. Because of limited intercontinental export options in the short term, gas prices dropped as much as 75 percent in the past six years, while coal prices remained stable. As a result, the historic marginal cost advantage of coal-fired electricity generators has eroded. The substitution between the technologies is much like we might observe if firms had to pay for carbon emissions. This paper measures the emission response of the grid to the cost differential between gas and coal inputs. We argue that the low cost differentials we observe mimic the differentials we would see under carbon pricing with typical input prices. This allows us to identify emissions reductions we could expect to see from pricing carbon given the current state of technology in the electricity industry.

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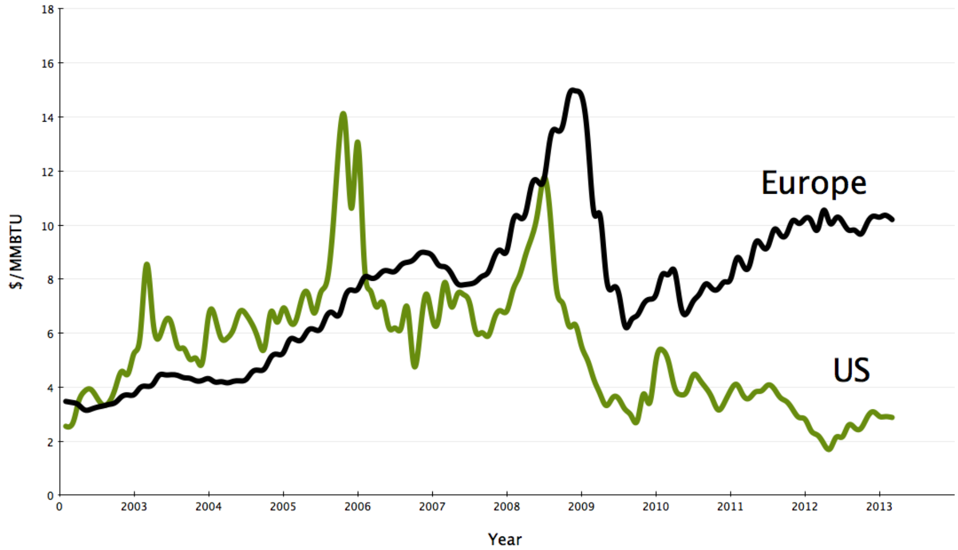
1 Introduction

In an effort to address climate change, the electricity sector has been an important focus of carbon regulation. In the US, new regulations have taken a standards-based form, rather than relying on market-based instruments. Market-based methods, such as a carbon tax or cap-and-trade systems, have come under scrutiny partly due to uncertainty over how emissions would change under such policies. In particular, we would like to know how emissions from the electricity sector respond to a range of possible prices for carbon dioxide emissions. In addition, we would like to know how other emissions from power plants, such as sulfur dioxide and nitrogen oxides, are affected by carbon prices. To answer these questions, we examine recent variation in the relative costs of competing generating technologies in the US.

Major shocks to natural gas prices have come from recent innovations in drilling technology which allow the extraction of gas from shale formations. This explosion in natural gas production combined with the inability to export sufficient quantities of natural gas outside of North America have led to gas storage facilities nearing capacity and plummeting gas prices. Prices dropped from \$12/mmBTU in 2008 to less than \$2/mmBTU in 2012. In 2012, gas in the US was less than a third of the cost of gas in Europe (see Figure 1).

Historically, coal plants have been the lowest cost fossil fuel generators on the electricity grid. As such, they operate near capacity and have provided a large share of the electricity in the US. Gas fired generators, on the other hand, have been relatively expensive due to the much higher cost of natural gas relative to coal. Consequently, gas-fired generators have

Figure 1: US and European Natural Gas Cost

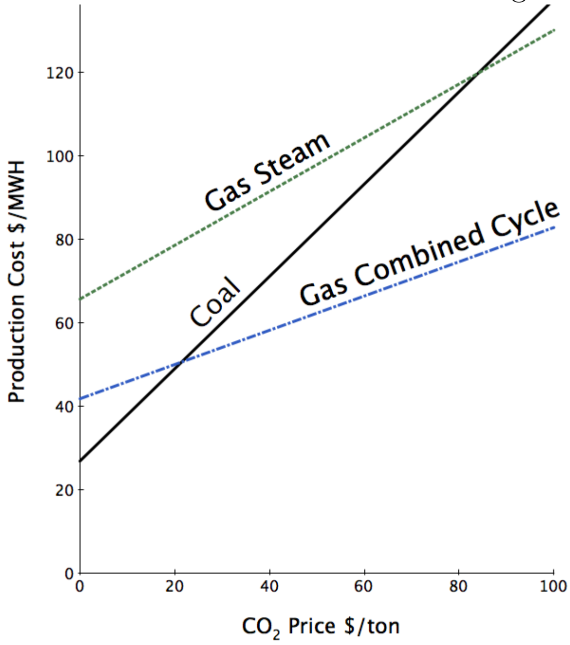


provided power for peak demand periods with lower average capacity utilization.

Lower gas prices were a boon for gas fired generators in the US. Efficient gas power plants found themselves in the position to undercut coal fired power plants. On a marginal cost basis, it was cheaper to generate a unit of electricity from gas rather than the usual low cost leader, coal.

Pricing carbon also makes gas generators more competitive with coal. Although pricing carbon dioxide emissions increases costs for both gas and coal plants, coal contains approximately twice as much carbon per unit of energy as natural gas. Thus, pricing carbon will affect the costs of coal plants more than those of an equivalent gas plant. In addition, although there is substantial efficiency variation among both gas fired and coal fired generators, the most efficient gas generators are significantly more efficient than the most efficient coal generators. These both lead to more steeply rising costs for coal plants than gas plants. Figure 2 illustrates the change in marginal costs for an average coal plant relative to gas

Figure 2: Carbon Prices and Generator Marginal Costs



fired technologies as the price of carbon increases.

As gas generators become more competitive with coal generators, they can begin to crowd out coal generators in the production process. The degree to which production switches from coal to gas generation will depend on the relative fuel prices, the relative efficiencies of the generation capacity, the excess gas capacity, and the demand for electricity. Intra-day fluctuations in electricity demand may also be important as some generators are not well suited for starting and stopping production frequently (Mansur 2008, Cullen 2013*a*). Such switching between existing generators is likely to be quite responsive to relative fuel prices as it doesn't require investment in new capital or technologies. On a longer time horizon, new generation would be expected to be built or permanently retired in response to changes in costs and the associated equilibrium electricity prices.

While lower gas prices and a price on carbon affect the relative costs of generators in similar ways, low gas prices are not expected to be permanent. The Energy Information Administration (EIA) projects that natural gas prices will return to their revert to typical levels within the next few years(EIA 2012). However, we can exploit this short term shock to gas prices to estimate the short to medium run response of the electricity industry to an equivalent price on carbon.

The rest of the paper proceeds as follows. Section 2 reviews the related literature and section 3 describes the data. In section 4, we discuss the empirical model we use to identify the impact that changes in fuel costs have had on emissions from the electricity sector. Our empirical results are reported in section 5. In section 6, we use our estimates to examine the implications for carbon pricing. Finally, we report our conclusion in section 7.

2 Literature Review

A few recent academic papers (Lu, Salovaara & McElroy 2012, Lafrancois 2012, Linn, Muehlenbachs & Wang 2013, Holladay & LaRiviere 2013, Linn, Mastrangelo & Burtraw 2013) and government reports (Logan, Heath & Macknick 2012, EPA 2013) examine how the low natural gas prices associated with fracking have reduced emissions from the power sector. Lu et al. (2012) regress the coal share of monthly generation in a given census region on (a nonlinear function of) the cost differential between natural gas and coal expressed in ¢/kWh, controlling for the capacity shares of natural gas-fired combined cycle (CCGT) power plants. For most regions, they find that coal generation shares are responsive only to cost ratios below three. The paper concludes that the drop in natural gas prices from 2008 to 2009 reduced carbon dioxide emissions from the US power sector by 4.3 percent, or half of the overall 8.8 percent reduction. Finally, they use their analysis to analyze carbon taxes and find that a \$20/ton of CO_2 tax reduces annual electricity-sector emissions by seven percent. Linn, Mastrangelo & Burtraw (2013) find that when natural gas prices are high relative to coal prices, the effect of coal prices on electricity production from coal-fired power plants is smaller than when the prices are close together.

Several studies directly examine the short run effects of a carbon tax on emissions. Newcomer, Blumsack, Apt, Lave & Morgan (2008) construct supply functions based on static, least-cost optimization. For electricity markets in the mid-Atlantic (PJM), the upper-Midwest (MISO) and Texas (ERCOT), they find that a \$20/ton tax would result in less than a 2.5% carbon reduction in PJM and MISO and less than one percent in ERCOT due to fuel-switching. Demand response drives most of the reductions in their main simulations. Similarly, Cullen (2013*a*) estimates a dynamic model of power plant production decisions and finds that a \$20/ton tax would have only a negligible effect on emissions in the Texas electricity market. A final related literature econometrically estimates the relationship between emissions either electricity consumption(Graff Zivin, Kotchen & Mansur 2013) or wind production (Callaway & Fowlie 2009, Cullen 2013*b*, Kaffine, McBee & Lieskovsky 2013, Novan 2013).

3 Data

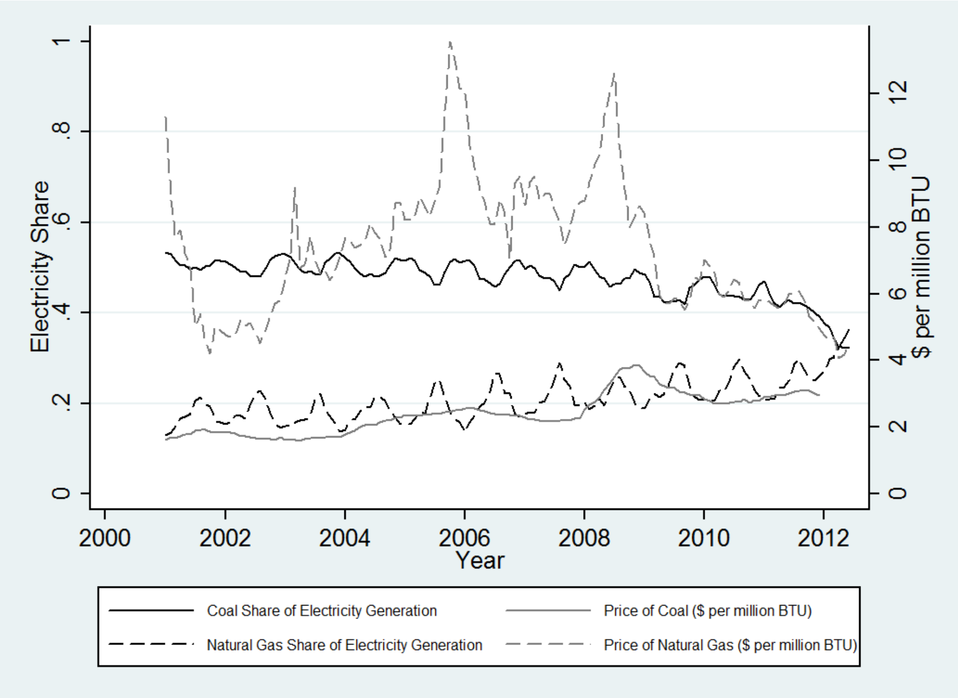
Data from the analysis is derived from four separate sources. Data from each source has been collected from the beginning of 2006 through the end of 2011[1] First, information on emissions is derived from the Environmental Protection Agency's (EPA) Continuous Emissions Monitoring System (CEMS). The EPA measures CO_2 output, as well as sulfur dioxide (SO_2) and nitrogen oxides (NO_x), from generators larger than 25 MW on an hourly basis. We aggregate this hourly generator level emissions information to construct daily carbon dioxide emissions. Generators are then aggregated by region to create a measure of daily, regional carbon dioxide emissions.

Second, we use data on electricity consumption (or load) provided by the Federal Regulatory Commissions (FERC) form 714. Form 714 provides hourly information on electricity load by region. We aggregate load to the daily level and sum across regions to arrive at daily electrical load by interconnection.

Third, we use EIA data on production of electricity from non-fossil sources and prices paid for coal deliveries by power plants. EIA provides monthly electricity production by National Electricity NERC region for nuclear and hydro power plants as well as for renewable sources such as wind, solar and geothermal. We aggregate this data to the interconnection level for a measure of non-fossil monthly electricity production. These data can also be used to examine fuel switching. Figure 3 shows the fuel prices, which are described below, as well as the monthly average electricity generation shares for coal and natural gas. While coal shares

[1]Although some of the lowest gas prices occurred in 2012, the some datasets are not yet available for that time period. We intend to update the analysis as the data becomes available.

Figure 3: Coal and Natural Gas Generation Shares and Prices by Month



have generally been declining since 2001, the rate of change has increased especially in 2012.

EIA reports coal prices by transaction (plant, month, contract type, coal type, coal source, *etc.*).[2] We use this information to create a weighted-average price for each month and interconnection. In particular, we use data from 2001 to 2012 for spot prices only (rather than long term contracts). For each interconnection, we regress coal costs on sulfur, ash, and BTU content, an indicator of surface mining, and fixed effects for each plant and month of sample. Transactions are weighted by the contract volume (in tons). We construct a coal price index using the initial coal transactions of January 2001 and adding monthly fixed effects, thereby keeping coal composition. The coal price index in shown in Figure 3.

Finally, we use data from the Intercontinental Exchange (ICE) on the spot prices for

[2]In reverse chronological order, the data sources are EIA-923, EIA-906, EIA-920, FERC 423, and EIA-423.

Table 1: Summary Statistics

Variable	Units	East	ERCOT	WECC
CO2 Emissions	1000s tons/day	5,005	527	802
		(768)	(89)	(119)
Load	GWh/day	7,456	866	1,835
		(879)	(159)	(168)
Emissions Rate	Tons/MWh	0.67	0.61	0.44
		(0.04)	(0.05)	(0.05)
Gas Price	$/mmBTU	5.49	5.10	5.04
		(2.28)	(2.13)	(1.95)
Coal Price	$/mmBTU	2.50	2.20	1.84
		(0.42)	(0.34)	(0.24)
Cost Ratio		2.31	2.45	2.86
		(1.13)	(1.23)	(1.31)
Observations		2,557	2,557	2,557

natural gas at trading hubs around the country. ICE is an independent open access electronic exchange for trading wholesale energy and metals commodities. For each gas hub, they report the average trading price for transactions on that day. For each interconnection, we weight the hub prices by the nameplate capacity of surrounding gas generators to arrive at a daily average spot price of natural gas. Although gas generators may have long term financial contracts for gas, the spot price for natural gas represents the opportunity cost to generators for using the gas to generate electricity versus selling it on the spot market. The general trends in the data are illustrated in Figure 3 using monthly averages.

Table 1 reports the mean and standard deviation for each grid. Emissions are more than six times greater in the East than in other markets, while load is only four times as large. The coal-gas cost ratio is 2.3 on average in the East and slightly larger in the other markets. All markets show substantial variation in the cost ratio.

These data allow us to trace out the emission response of the electricity system to changes in input costs while controlling for important features of the market.

4 Model

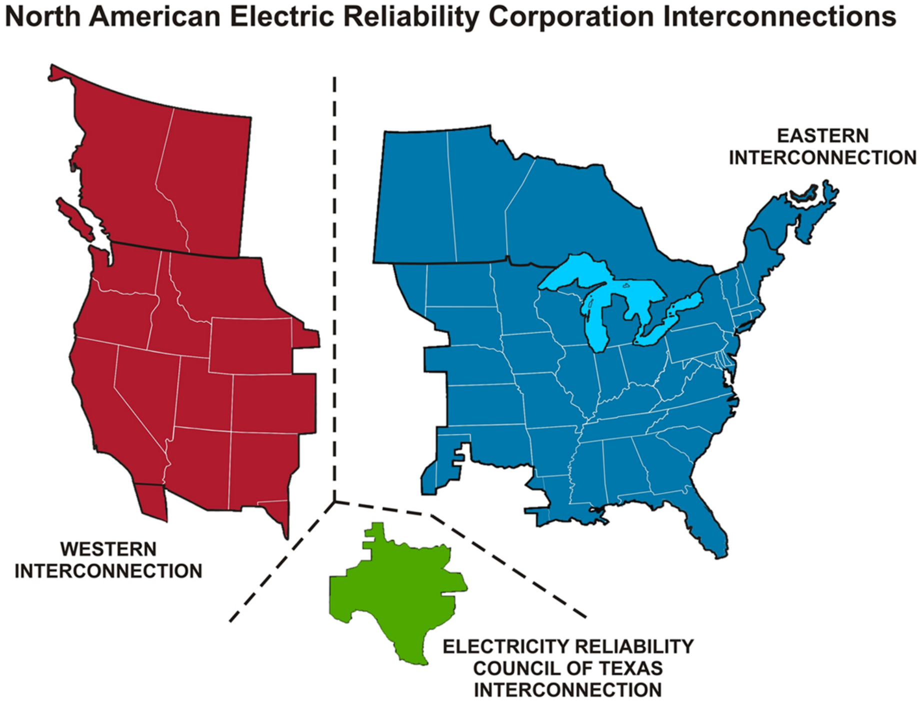
We first build a model to estimate the impact of changing fuel costs on emissions from electricity generators in the US. Due to the varied technologies on the grid and their complex interactions in electricity markets, we aim to create a simple, yet flexible model that can trace out the response of emissions to changes in relative fuel costs.

Since the composition of generators varies regionally in the US, we estimate the model separately for each of the three interconnections in the US. The coverage of these three interconnections, East, ERCOT, and West, are shown in Figure 4. Electricity produced by generators in each interconnection is synchronized, allowing electricity to flow freely throughout the interconnection. Very little energy transferred between interconnections due to the costs involved in transferring power between asynchronous grids. Thus, we are relatively confident that the emissions reduction estimated for an interconnection come from that interconnection. Analysis on a finer geographic scale is possible, but presents problems for measuring net emissions reductions in each area due to energy transfers between regions in the interconnection.

The model is a reduced form regression with daily carbon dioxide emissions in an interconnection as the dependent variable as shown below.

$$CO_{2t} = f(CR_t) + g(X_t) + \epsilon_t$$

Figure 4: Carbon Prices and Generator Marginal Costs



$$where\ CR = \frac{P_G}{P_C}$$

Here CR_t is the ratio of the cost of gas over the cost of coal where both measured in dollars per millions of BTU. The matrix X_t is a set of controls and t indexes the daily observations[3].

The ratio of fuel costs was chosen for several reasons. First, the fuel cost ratio captures how difference in fuel prices translates into marginal costs. For example, if a gas plant is 20% more efficient than a coal plant then the gas plant will have the same marginal cost when the cost ratio, $\frac{P_G}{P_C}$, equals 1.20 . Production would switch between these two generators around this point. In fact, for a given cost ratio, the ordering of generators by marginal costs will

[3]Note that gas prices change on a daily basis, while the information on coal prices changes monthly.

be identical regardless of the level of fuel costs. To illustrate, consider a high cost and low cost scenario. In the low cost scenario, let $P_G = \$4$ and $P_C = \$2$. For the high cost scenario, let $P_G = \$6$ and $P_C = \$3$. In both cases, the cost ratio is the same. Now order the all the generators on the grid from lowest marginal cost to highest marginal cost to create an industry cost curve. Since the marginal cost of generator is equal to its fuel cost multiplied by its heat rate (a measure of efficiency), the ordering of generators will be the identical in each scenario[4]. If generator A has 10% lower costs than generator B in the low cost scenario, then it will also have 10% lower costs in the high cost scenario.

Since coal costs are relatively constant over this time period, estimation by cost ratio is very similar to using other functional forms, such as differences and interactions of fuel costs. However, the cost ratio will be useful later for connecting the estimated emission reductions to a counterfactual carbon price.

A second motivation for using the cost ratio is that it serves as a parsimonious function that translates the two dimensions of fuel costs (i.e. gas and coal) into a single dimensional object that is simple to interpret.

When selecting controls included in X_t , we need to include variables that would directly affect the interconnection emissions that might also be correlated with the variation in input fuel costs. Electricity demand, sometimes called load, obviously meets this criteria. Demand for electricity on a given day, although driven by weather and day-specific demand shocks, may be correlated with the spot price for gas. This may be because electricity generators

[4]There are other components to the marginal cost of a generator (such as water for cooling towers), but these tend to be small relative to the cost of fuel.

demand more gas when electricity demand is high or simply a correlation in the demand for electricity and the demand of gas outside the electricity sector, such as home heating. For example, lower electricity demand and emissions due to a negative macro economic shock would be correlated with low prices for natural gas due to the same macro economic shock. Failing to account for electricity demand would tend to overestimate the response of emissions to the price gap. Thus we include daily electricity demand in the interconnection as a control variable. Likewise, we include data on production from non-fossil fuel electricity production. Non-fossils electricity production includes wind, solar, hydro, and nuclear power generators. While these generators are not likely to change their production in response to gas or coal prices, they may be correlated with them. For example, wind power installations have been growing at the same time as technological innovation has led to more shale gas extraction. Likewise, seasonal variation in the availability of hydroelectric generating capacity may influence the spot prices of natural gas. Finally, we include a dummy variable for each quarter in the time series to control for trends in generating capacity as well as seasonality in generator availability.

When implementing estimating equation, we use flexible functional forms for $f(.)$ and $g(.)$ to trace out the emissions response of the system. Specifically, we use a cubic spline with six knot point for cost ratio, load, and non-fossil electricity production plus quarter dummies as shown below

$$CO2_t = s(CR_t|\beta) + s(load_t|\theta) + s(unfossil_t|\alpha) + s(temp_t|\omega) + D\gamma + \epsilon$$

where the function s is a cubic spline. With the estimated coefficients, we can trace out the emissions response of the electricity generating system to changes in the relative costs of gas and coal.

5 Results

The results from the estimation for each interconnection are shown in Figures 5, 6, and 7. In the appendix, we examine the robustness of these results to various specifications.

The figures plot the change in carbon dioxide emissions against the fuel cost ratio. The percent change in emissions in relative to the highest level of predicted emissions. Dashed lines show the 95% confidence interval for the estimates. Controls, such as demand and non-fossil electricity production, are held at their average levels in the sample.

The results show statistically insignificant changes in emission for high cost ratios. That is, when gas cost is high relative to coal, changes in gas prices don't result in switching between high polluting plants and cleaner facilities. Not until the cost ratio approaches two, do emissions begin to fall. For the Eastern interconnection, emissions fall by about 11% when the cost ratio drops to one. For ERCOT and the Western interconnection, carbon emissions fall by about seven and 15 percent, respectively, when the cost ratio is one. Keep in mind that a cost ratio of one is historically a very low price for gas relative to coal. This brings much of the gas-fired fleet on par with coal-fired generators. Though the reduction in emissions is significant, it is not dramatic.

Figure 5: Eastern Interconnection CO_2 Response

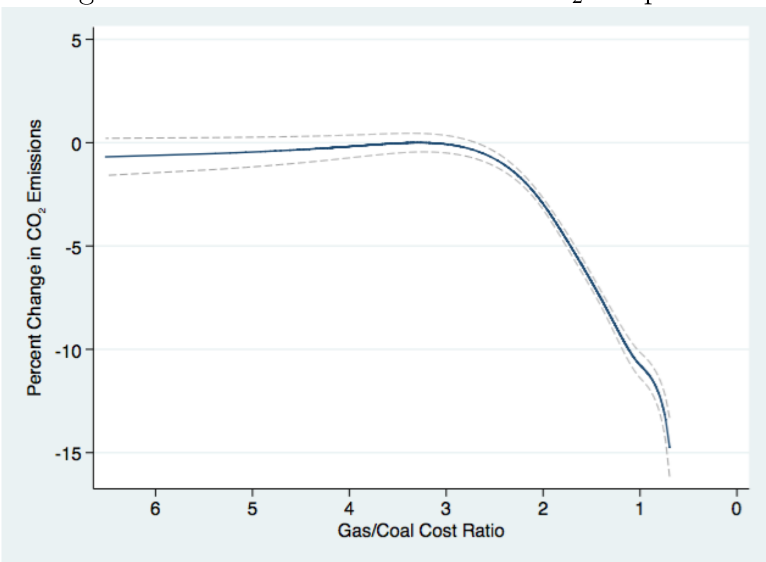


Figure 6: ERCOT Interconnection CO_2 Response

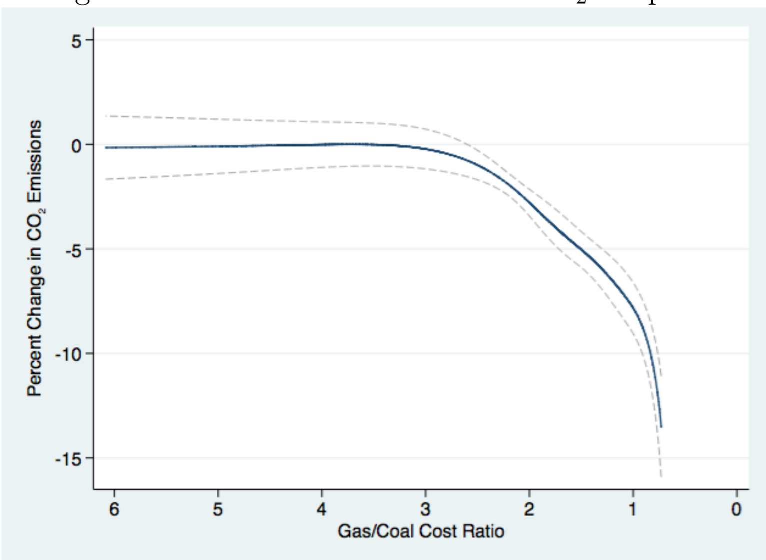
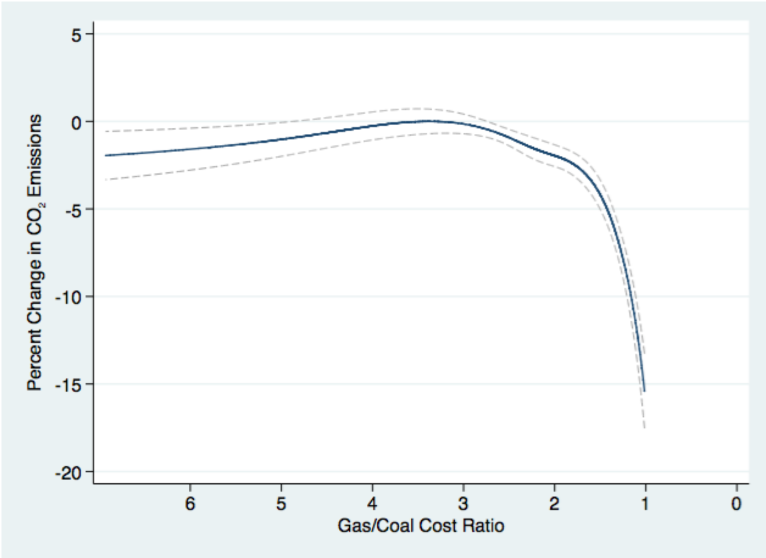


Figure 7: Western Interconnection CO_2 Response



6 Discussion of Carbon Price

In this section, we use the electricity industry's experience with low gas prices to explore how the industry may respond to a carbon tax.

As a first step, we will choose a set of baseline, long-run prices for coal and gas. For now, we will view these prices as fixed. That is, we assume that the price of fuels will not change as a result of changing demand for fuels from electricity generators. For the purposes of this paper, we use the EIA's long-run forecast for coal and gas prices. EIA's Annual Energy Outlook 2012 projects that in 2025 average delivered coal prices will be \$2.25/mmBTU and gas prices will be \$5.75/mmBTU. This implies a baseline cost ratio of 2.56 which will serve as our benchmark.

As mentioned previously, charging for carbon dioxide emissions increases the cost of burning coal more than burning gas. That is, it will decrease the gas/coal cost ratio. With

Table 2: Carbon Prices and Associated Cost Ratios

Carbon Price	Gas/Coal Price Ratio	With Carbon Price		Without Carbon Price	
		Gas Cost	Coal Cost	Gas Cost	Coal Price
$0	2.56	$5.75	$2.25	$5.75	$2.25
$10	1.93	$6.33	$3.28	$4.34	$2.25
$20	1.60	$6.91	$4.31	$3.61	$2.25
$30	1.40	$7.49	$5.34	$3.16	$2.25
$40	1.27	$8.07	$6.37	$2.85	$2.25
$50	1.17	$8.65	$7.40	$2.63	$2.25
$60	1.09	$9.23	$8.43	$2.46	$2.25
$70	1.04	$9.81	$9.46	$2.33	$2.25
$80	0.99	$10.39	$10.49	$2.23	$2.25
$90	0.95	$10.97	$11.52	$2.14	$2.25
$100	0.92	$11.55	$12.55	$2.07	$2.25

All fuel prices are in $/mmBTU

a benchmark cost ratio in place, we can back out the cost ratio under any carbon price. For example, with a benchmark cost ratio of 2.56, a $20/ton price on CO_2 would change the cost ratio 1.60[5]. Table 2 shows the mapping between carbon prices and cost ratios under the baseline prices. The middle two columns of the table show the resulting fuel costs at each carbon price under the baseline prices. The last two columns show what the gas cost would have to be without a carbon price to achieve the same cost ratio.

In the previous section, we estimated the emissions response of the grid to the cost ratio using variation like that shown in the last two columns of table 2.

For any cost ratio observed in the data, there is a matching counterfactual carbon price with the same cost ratio under the baseline fuel prices. As previously discussed, the ordering of the generators in the industry marginal cost curve will be identical, whenever the fuel cost

[5] For the calculation, we industry parameters for the carbon content of gas (116 lbs/mmBTU) and coal (206 lbs/mmBTU)

ratios are the same. The industry cost curve under a carbon tax will be proportional to the cost curve in the data with the same cost ratio.

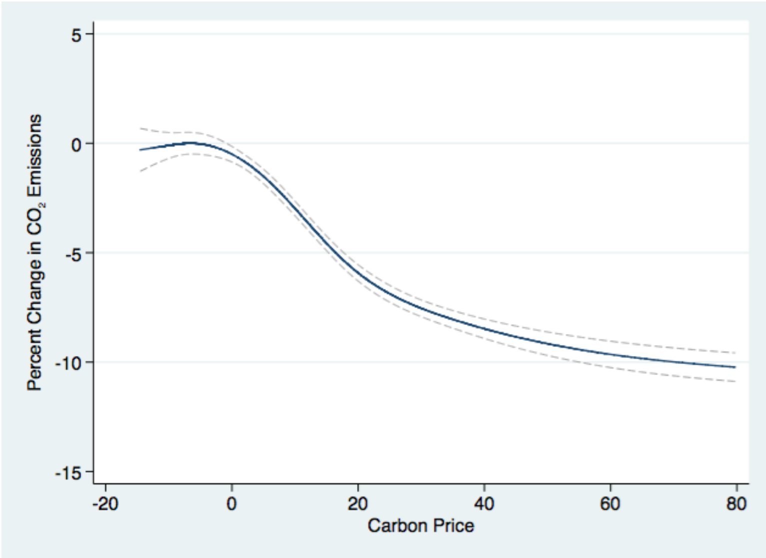
Under certain assumptions, the behavior of generators and their associated emissions will be identical for observed and counterfactual scenarios with the same cost ratios. First, although the relative costs of gas and coal may be the same in the observed and counterfactual worlds, the level of costs are not. Gas and coal costs will be much higher under a carbon price than in the data where we observe average coal costs and very low gas costs. As such, equilibrium electricity prices will be higher under a carbon tax. The degree of demand response to these higher prices will also affect the change in carbon emissions. Only with an inelastic demand curve will a straight mapping based on cost ratios be accurate. However, the results of the estimation do highlight the degree to which technology switching can contribute to emissions reductions under a carbon tax[6].

Second, it is important to point out that even if two industry cost curves are proportional, the profits of individual generators need not be identical. In particular, low cost generators may reap higher markups due to the steeper slope of the marginal cost curve in the high cost scenario. While this is not an issue when holding the generating infrastructure on the grid fixed, carbon prices do provide greater incentive for investment in clean generating technology.

Finally, a less obvious issue arises from the dynamic considerations in operating a generator. Generators make operating decisions amid fluctuating intra-day demand. This neces-

[6]The analysis also assumes that the behavior of low marginal cost renewable and nuclear generators are unaffected by higher equilibrium electricity prices. Given that these generators already have incentives to operate at full capacity whenever possible, this assumptions seems reasonable.

Figure 8: Eastern Interconnection CO_2 Response



sitates that some generators shut down and restart. Generators will start production only if they expect to cover their start-up costs while operating. Since the profits of generators will be different for the same cost ratio, firms may undertake different startup decisions if their start-up costs do not scale with the fuel prices. Although fuel costs are a central part of start-up costs, they are not the only component. Thus will not scale perfectly with fuel costs. The degree to which changes in dynamics affect would affect the outcomes is difficult to judge. However, structural dynamic estimation of electricity markets indicates that start-up costs are not a driving factor for aggregate carbon emissions changes under a carbon tax (Cullen 2013*a*).

With fixed baseline fuel costs, inelastic demand, and proportional startup costs, we can project our estimates of emissions reductions due to shocks to gas prices onto their equivalent carbon price. Figures 8, 9, and 10 show the estimated emissions reductions that would come from a carbon price under these assumptions. The figures focus on the cost ratios that

Figure 9: ERCOT Interconnection CO_2 Response

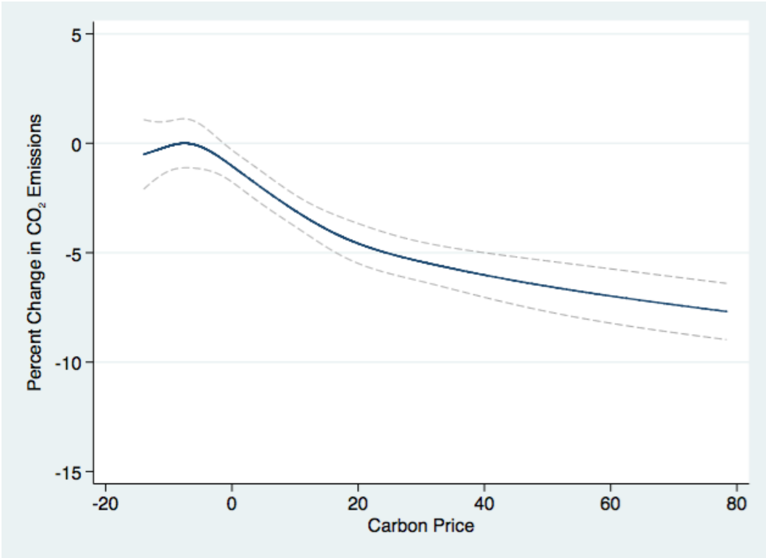
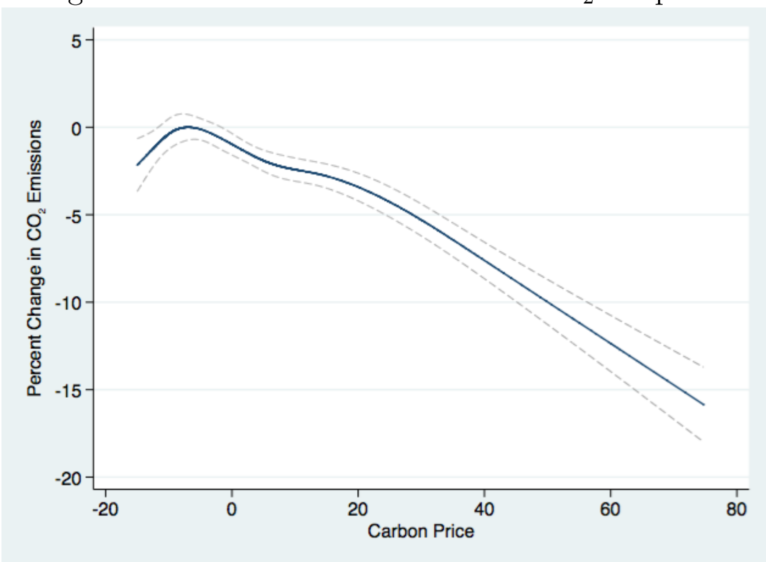


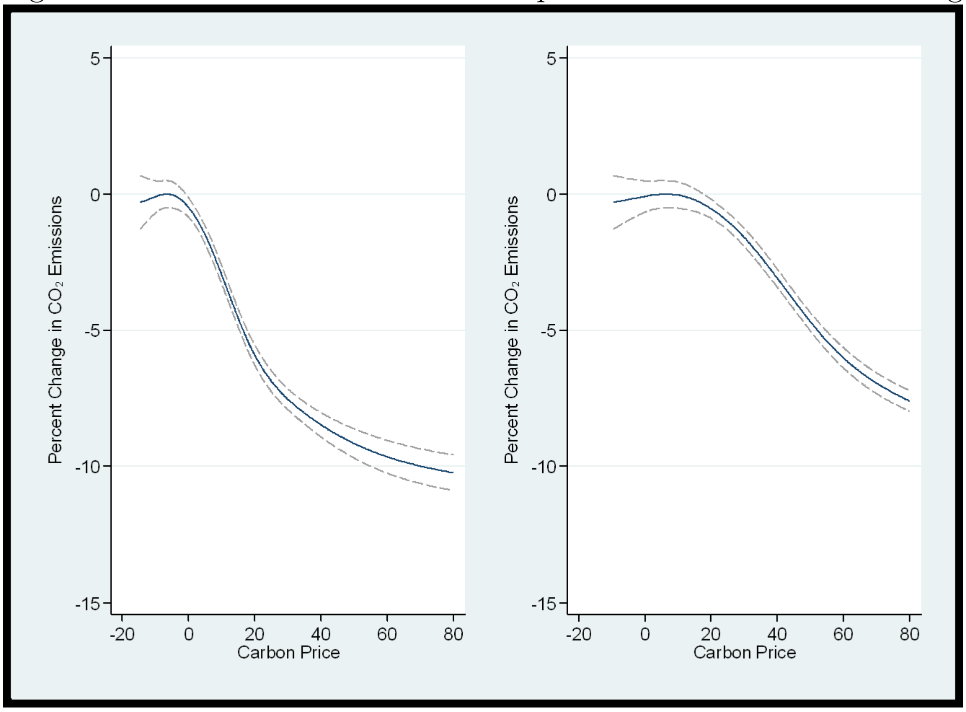
Figure 10: Western Interconnection CO_2 Response



correspond to positive carbon prices under the baseline fuel costs. They show that emissions fall more steeply at lower levels of carbon tax, but then the rate of change decreases for higher levels of carbon tax. These results indicate that much of the emissions reduction from technology switching can be captured with a relatively modest price on carbon. High price carbon on carbon do result in some further reduction in carbon dioxide emissions, but the large impact from high carbon price is likely to come from retooling the generating infrastructure.

We can also use our estimates to examine how effective carbon prices would be at reducing emissions under different initial prices. For example, we can consider a counterfactual whereby shale gas production did not happen and cost ratios remained large without a carbon price. Before shale gas, the US and Europe had similar natural gas prices. Current European prices as of 2013 are similar to US prices in the spring of 2008. Figure 11 shows the effect of carbon pricing assuming a ban on fracking (and a return to pricing from the spring of 2008). Carbon prices are much less effective at reducing carbon emissions in this case. Conversely, in order to achieve a carbon cap a trade target, a much higher carbon permit price would be required if fracking were to be banned.

Figure 11: Eastern Interconnection Response under a Ban on Fracking



7 Conclusion

This paper provides the estimates of the impact of carbon pricing on electricity sector emissions that are based on observed behavior rather than econometric or engineering simulations. We exploit significant variation in gas prices to estimate the responsiveness of carbon emissions from the electricity sector to changing relative costs in gas and coal. We have shown that the relative price changes observed in the data can inform us about the likely change in short-run carbon emissions when pricing carbon dioxide emissions.

The results indicate that much of the reduction in carbon dioxide emissions can be captured with a relatively modest carbon tax. Higher carbon prices reduce emissions at a decreasing rate.

Extensions of this research will examine the impact of the gas boom on other pollutants such as SO_2 or NO_x, incorporate elasticity measures into electricity demand and fuel supply, and characterize the heterogeneity in the regional responses to gas prices.

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Appendix

In this appendix, we test sensitivity of our main results. In order to summarize the response of the nonlinear relationship, we fit the data using a log-log specification of CO2 and cost ratio. While not an exact match (see Figure 12), the specification allows easy comparisons across models.[7]

Table 3 shows the robustness results for the East. The first column uses no controls. The elasticity of .14 states that a ten percent increase in the gas-coal cost ratio will increase emissions 1.4 percent. Further columns include controls for load, season-of-sample fixed effects, temperature, non-fossil generation, and finally other statistics of the within-day load distribution. We also show results with no time fixed effects as well as regressions with month-of-sample fixed effects. The elasticity for the main specification is .07 and does vary when excluding the other covariates. Similar findings are seen in other grids.

The sample period also matters given the constant elasticity assumption. The first column of Table 4 shows the constant elasticity for each grid using the preferred specification (the last column of Table 3. If we include only 2006 to 2009 data, the coefficient is attenuated and no longer significant in the West or Texas. In contrast, elasticities based on the data from 2010 to 2012 are two to four times greater than the estimates using the full sample. This supports our use of a flexible, nonlinear spline approach in the paper that is able to capture the large change in response once coal begins to lose its marginal cost advantage.

[7] We have also used the same spline approach as in the body of the paper for these results for completeness.

Table 3: Robustness for Constant Elasticity Regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8, Main)
ln(CR)	0.145***	0.094***	0.111***	0.089***	0.074***	0.106***	0.043***	0.072***
	(0.013)	(0.005)	(0.011)	(0.009)	(0.009)	(0.004)	(0.006)	(0.009)
Ave Load	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temperature	No	No	No	Yes	Yes	Yes	Yes	Yes
Nonfossil	No	No	No	No	Yes	Yes	Yes	Yes
Load Distribution	No	No	No	No	No	Yes	Yes	Yes
Time F.E.	No	No	Season	Season	Season	No	Month	Season
Obs	2557							

Figure 12: Robustness for Constant Elasticity Regression

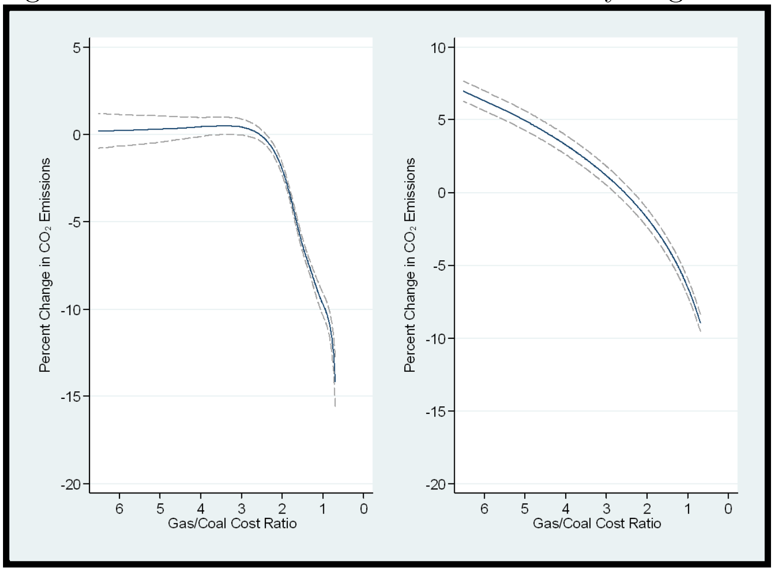

Table 4: Time Period Sensitivity for Constant Elasticity Regression

Panel A: Eastern Interconnection

	All	2006-09	2010-12
ln(CR)	0.072***	0.051***	0.135***
	(0.009)	(0.010)	(0.019)
R-Squared	0.975	0.975	0.980
Mean CR	2.31	2.93	1.49

Panel B: ERCOT Interconnection

	All	2006-09	2010-12
ln(CR)	0.061***	0.019	0.166***
	(0.014)	(0.012)	(0.034)
R-Squared	0.932	0.948	0.927
Mean CR	2.45	3.14	1.54

Panel C: WECC Interconnection

	All	2006-09	2010-12
ln(CR)	0.048***	0.010	0.188***
	(0.017)	(0.018)	(0.033)
R-Squared	0.929	0.924	0.926
Mean CR	2.86	3.58	1.91