

The Effect of Abundant Natural Gas on Air Pollution from Electricity Production

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Abstract

We estimate the impact of large changes in the relative prices of natural gas and coal from 2005-2011, due primarily to “fracking,” on regional electricity marginal costs and air pollution emissions from electricity producers. We find strong evidence that natural gas is displacing coal as baseload. We estimate marginal emissions over the generation profile for each region in the U.S. using a novel identification strategy and find fuel prices significantly influence marginal emission rates. We then evaluate two supply-side policies to highlight the influence of fuel prices on non-market benefits of supply side policies as a function of fuel prices.

JEL Classification: Q4, Q5, D8

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1 Introduction

Governments often use both pecuniary and non-pecuniary policy instruments to address market failures. While pecuniary policies are desirable from an efficiency standpoint because they change relative prices explicitly, non-pecuniary policies are often used due to their political appeal. To this end, a growing body of work in economics attempts to estimate the marginal impact of different policies on existing externalities, such as pollution emissions or traffic (Holland and Mansur (2008), Zivin et al. (2012), Cullen (2012), Kaffine et al. (2013), and Novan (2012), Anderson (2013), Bento et al. (2013)). Due to both its economic importance and reliance on pollution generating fossil fuels, electricity generation receives considerable attention from economists. Electricity expenditures account for roughly 3% of GDP. Electricity generation is also the largest point source for most pollutants in the United States and is the largest single source of CO₂ emissions worldwide (U.S. EPA 2012).

There are two types of policies that regulatory bodies use to ameliorate emissions in the electricity sector. First, demand side policies seek to reduce electricity usage. One popular demand side policy in the U.S. is efficiency standards for durable goods. Second, supply side policies seek to alter the composition of electricity generation. For example, wind farm subsidies have led to increases in wind generation in the U.S. For both demand side and supply side policies, it is not always clear how to best estimate margin emissions and the best technique often varies as a function of the policy being evaluated. Furthermore, it is unclear how stable estimated marginal emissions are over time. This is especially true in the electricity sector as fossil fuel input prices can change significantly over time.

Recently, the importance of fuel price has become very clear in evaluating an electricity sector policy, especially on the supply side. The wide implementation of hydraulic fracturing and horizontal drilling for natural gas extraction since 2008 quickly and drastically decreased the price of natural gas in the United States.¹ Coal prices have risen slightly over the same time span. Taken together, it is likely that the dispatch order for electricity generation has changed and with it, the

¹The academic literature is beginning to evaluate the environmental impacts of “fracking”: Olmstead et al. (2013) and Osborn et al. (2011) estimate the water quality impacts of fracking and Muehlenbachs et al. (2012) estimates the hedonic impacts.

marginal emissions associated with any supply side policy. Government around the world must account for this change when evaluating energy policies.

The goal of this paper is to contribute to the economics literature in several ways. First, we construct a large and unique dataset to estimate marginal pollution emissions for three important pollutants (carbon dioxide, sulfur dioxide and nitrogen oxide) across the electricity generation profile for the different regions of the United States. We collect and evaluate supply side data since we are interested in supply side policies. Second, we estimate marginal cost curves and marginal emissions over the entire generation profile for each NERC region using a novel identification strategy, first differencing both hourly emissions and hourly generation, and compare that strategy to alternative strategies found in the literature. Third, we use an exogenous change in relative fuel prices, caused mainly by the introduction of hydraulic fracturing, to identify changes in this marginal emission profile over time. Lastly, we use these marginal emissions curves to simulate the forgone emissions from two supply side policies: the introduction of bulk electricity storage and an expansion of hydroelectric capacity. As a result, we are able to show precisely how estimated forgone emissions from an important energy policy vary over space, fuel input prices and identification strategies.

We find several interesting results. First, marginal cost curves show the dramatic effects of cheap natural gas now mixing with coal even in the lower deciles of fossil fuel generation. Second, estimated marginal emissions vary dramatically over 1) the load profile within each NERC region, 2) across NERC regions, 3) as a function of input prices and 4) as a function of identification strategy. In several regions for particular levels of generation, the estimated marginal emission rate has increased as the price of natural gas has fallen. We present evidence that this is due to highly efficient natural gas plants being dispatched earlier in the load profile. Third, we find that by using estimates from long differences, introducing bulk storage would lead to the largest emissions increase in Florida in an era of cheap natural gas. Conversely, when using estimates from first differences, we find that bulk storage increases emissions in the Southwest far more than any other part of the country.

One key contribution of this paper is in highlighting the importance of using high frequency versus low frequency variation to identify policy relevant parameters. Comparing high frequency

and low frequency sources of identification is novel in this marginal emissions literature, but the labor literature has considered the issue carefully. Nuemark and Wascher (1992) and Baker et al. (1999) highlight the importance of comparing high and low frequency variation in assessing the impact of minimum wage laws on employment outcomes. Their results suggest that low frequency variation and high frequency variation identify different effects and can lead to differences in estimated marginal effects of minimum wage rules. In the context of demand side policies, Zivin et al. (2012) rely on long differences by using month-by-year and day-of-week fixed effects as the source of identification for evaluating the impact of electric cars on electricity generation emissions since electric cars charge at night. Conversely, policies affecting the entire dispatch order or pieces of the dispatch order, such as a zero marginal cost fuel source like nuclear, hydroelectric or bulk storage, are best identified using short differences since the timing of when a particular level of load is generated varies greatly throughout the year. In this regard, Cullen (2012) and Novan (2012) use high frequency variation to identify the marginal forgone emissions from wind generation.

There are several implications of this paper. First, it highlights the vital importance of how the frequency of variation used to identify policy parameters significantly effects estimated parameters. The proper frequency for one policy may not be the proper frequency for another. Second, the carbon damages of bulk storage of electric power seem to be large in the medium term in an era of cheap natural gas. This finding is a short run result, though, as new gas plants could be built or relative fuel prices could change yet again. Lastly, natural gas generation is occurring much earlier in the dispatch order than it used to due to input price changes. This highlights the importance of re-evaluating the marginal foregone emissions of both demand side and supply side energy policies.

The remainder of this paper is organized as follows: section 2 gives background on both the electricity industry and the evolution of fossil fuel prices in the U.S. Section 3 introduces the data used in analysis. Section 4 introduces our empirical approaches and presents results. Section 5 presents our policy experiment and robustness checks. Section 6 offers concluding remarks.

2 Background

A suite of technological advances in extracting natural resources have had huge impacts on fossil fuel prices. Horizontal drilling, in which a drill tip can bore thousands of feet underground and then turn at a near 90 degree angle and be driven horizontally for several thousand more feet allows a single drilling rig to drill as many as eight wells. This technique, has been combined with hydraulic fracturing, which involves pumping hydraulic fluid underground to fracture rock formations and release oil and natural gas. These two techniques, used together, allow producers to extract small pockets of natural gas that are trapped in rock formations. *Annual Energy Outlook 2013 Early Release* (2012) reports that natural gas extracted in this way from shale deposits makes, which is up just over a third of all natural gas produced in 2012 up from less than two percent in 2000. Total production increased by 25% over the same time frame and more than one hundred percent of the increase has come the growth in shale gas extraction.

Not surprisingly this increase in production has been associated with a large decrease in market prices. Gas prices rose significantly through the early 2000's and peaked above \$14 in late 2005 with continued high prices through 2008 when prices began to fall rapidly. Spot market prices have been below \$5 since 2009 and are forecasted to remain depressed for the foreseeable future as improved extraction technology allows more shale plays to be developed.

The electricity generation sector is the largest consumer of natural gas in the U.S. and the effects of the price shock in the industry have been pronounced. When gas prices where high, natural gas fired generation was used to provide peaking capacity and coal and nuclear fired generation served baseload. This led to high marginal costs during times of high demand and for existing natural gas generators to be fired for a small fraction of the year. As natural gas prices drop, the distinction between natural gas plants serving peak-load and coal plants serving base-load has blurred. Efficient natural gas plants now have lower marginal costs than some inefficient coal plants meaning that some of these coals plants are operating at less than peak capacity while natural gas plants are operating for a much larger fraction of the day.

Figure 1 summarizes the potential impact of these changes over time. The top panel describes generating capacity by fuel type from 1990-2012; the level of production is shown in the middle

panel and the dispatch rate is displayed in the bottom panel. There has been relatively little response at the extensive margin. Natural gas generating capacity has grown slowly during the natural gas price collapse while coal capacity has slightly decreased. There has been a noticeable response at the intensive margin with existing natural gas capacity being used more intensely as the price of fuel has fallen. The bottom panel displays dispatch rates, the fraction of the time that the existing capacity is turned on and dispatching electricity to the grid.²

Electricity generators are the largest single source of carbon emissions, accounting for roughly a third of total emissions and among the largest emitters of SO₂. They are also a significant point source for NO_x emissions. The profile of emissions varies significantly across space and time. The largest determinants of pollution levels are the mix of fuels burned to generate electricity. Coal and diesel oil are pollution intensive fuel sources, while natural gas is somewhat cleaner.³ The collapse of natural gas prices has changed the relative cost of generating electricity using these fuels. In this paper we estimate the impact of this price drop relative to coal prices on fuel mix and pollution emissions.

3 Data and Empirical Specification

The data set was constructed by combining two publicly available data sources. Power plant data on fuel consumption, electricity production and pollution emissions are available through the EPA Clean Air Markets program. Electricity generating units at every fossil fuel burning power plant with a capacity of greater than twenty-five MW must install a Constant Emissions Monitoring System (CEMS). The systems sample the air frequently to calculate the amount of SO₂, NO_x and CO₂ emissions escaping from the stack. The data is primarily used by EPA to confirm that plants are complying with their obligation to purchase pollution permits in the SO₂ and NO_x markets to cover all their emissions. The CEMS data also includes the primary and secondary fuel type of the plant along with a variety of other plant attributes useful in identifying the location and ownership

²Dispatch rate is calculated by dividing the level of production measured in megawatt-hours and dividing by capacity measured in megawatts. The resulting quotient is the number of hours over the course of the year that capacity was on. That product is divided by 8,670 to create a dispatch rate that ranges from 0 to 1.

³Renewable sources of electricity generate no emissions, but are typically not dispatchable to serve load. Hydro-electricity is an exception that we analyze in section 6

of the facility. The data set does not include nuclear or renewable generators, but these producers have low or zero marginal costs and no air pollution emissions so we exclude them from the analysis for the time being.⁴

The CEMS data provides a quantity of fuel input measured in millions of British thermal units (MMBtu). This data is merged with price indices for power plant fuel from the Energy Information Agency’s Form 906 reported in the EIA’s Electric Power Annual. These data are collected from a mandatory survey of electric power producers that provides the cost of fuel per MMBtu for coal, petroleum and natural gas. That data is only available through 2010 so we must use monthly data for 2011 from EIA’s Electric Power Monthly report, which breaks down petroleum fuel costs into liquids and coke. We use comparable data from the 2010 Electric Power Monthly report to estimate the fraction of liquid to coke consumption consistent with the single petroleum price observed from the annual data. We then assume that same ratio was in place in 2011 and interpolate a price for all petroleum fuel in 2011. The results of the analysis are not sensitive to other estimation strategies.

The combined U.S. data set consists of approximately 17,484 stacks (the number varies slightly over the sample period) at 5,492 electric power plants. Each stack is observed hourly over the sample period 2005-2011. To avoid duplicate date and time observations we average the repeated hours at the end of daylight savings time in the fall when the clock “falls back.” This produces approximately 61,300 observations for each stack in the data set. We follow Zivin et al. (2012) by aggregating data to conduct our analysis at the National Electricity Reliability Council (NERC) region level. NERC is charged with ensuring the reliable provision of power and separates the U.S. into three interconnections across which very little electricity flows. Figure 2 illustrates the interconnections which are essentially isolated from each other electrically. The Eastern Interconnection is further divided into six sub-regions across which electricity flows are small but nontrivial.

3.1 Building Regional Supply Curves

We employ the Continuous Emissions Monitoring System (CEMS) data from the EPA to create marginal cost curves for fossil fueled generation by NERC regions. Several studies, typically in the

⁴In the robustness checks section we will evaluate the potential impact of renewable generation on the relationship between generation and pollution

engineering literature, have used this data source to estimate supply curves for the electricity sector for various geographic regions.⁵ The procedure employed in this literature has suffered from two major shortcomings. First the supply curves are typically estimated at the stack or facility level, ignoring any intraplant heterogeneity in efficiency. Figure 3 displays the observed productivity of a single stack across its production quantity for two coal and two natural gas fired generators. There is significant variation in efficiency within fuel types and stacks suggesting that there could be value in estimating these supply curves allowing for intraplant heterogeneity.

The second shortcoming of the engineering approach is to ignore the possibility of imports and exports affecting the supply curve. Estimating the marginal cost of fossil fuel emissions over a state or other administrative boundary fails to account for the interconnected nature of the grid. If changes in market conditions shift relative to costs across states, for example, imports may flow from the low-cost production region to the higher cost production region, altering the effective supply curve for that region.

We address each of these factors in estimating a set of marginal cost curves during the high natural gas price regime (2005-2008) and the low natural gas price regime (2009-2011) which allows us to evaluate the market impacts of cheap natural gas.⁶ We specifically allow for intraplant heterogeneity in production efficiency by calculating stack level decile production bins based on the observed stack production across the high and low gas price regimes. We then calculate an average efficiency within each stack's decile production bin. That calculation allows us to estimate how efficiently a power plant turns fuel inputs (measured in mmBTU) into electricity output measured in megawatts. As expected the results indicate that there can be significant intraplant variation in that measure of efficiency and that the estimated marginal cost curves are substantially different.

We address the import/export issue by building our marginal cost curves at the interconnection level. Because there are very few connections across the interconnection boundaries we can safely ignore imports and exports at this level. We also estimate NERC region supply curves in the

⁵See Newcomer and Apt (2009) and Sahraei-Ardakani et al. (2011) for examples.

⁶Later we estimate a Markov Switching Model (MSM) to allow the data to determine when the break between the high natural gas price and low natural gas price regime occurs. The MSM selects January 8th, 2009 as the break date. As a result, using years for constructing marginal cost curves gives an accurate depiction of the change in electricity supply curves as a function of the decline in natural gas prices.

Eastern Interconnection, where imports and exports may play a larger role. Using the estimated supply curves we can predict changes in imports and exports across the regions at an aggregate level.

As stated above, we begin by segmenting the data for each stack into production deciles and calculate average heat rates across the deciles. We multiply that average heat rate by the fuel price for the fuel source of that stack to estimate a marginal cost for that quantity of production. We then simulate a merit dispatch system where the lowest marginal cost decile in the entire system is the first dispatched, and each decile of unit production is dispatched in turn one at a time until every decile of unit production in the region has been dispatched. This procedure orders the quantity-price pair for each decile, which we graph as marginal cost curves.

Figure 7 displays the marginal cost curves by natural gas price regime for each interconnection. Fuel types are illustrated with different marker shapes to describe how the fuel mix varies at different load levels. The top left panel is the marginal cost curve for the eastern interconnection during the high natural gas price regime. Coal fired generation is relatively homogenous in cost and makes up the vast majority of the load generation profile. After coal fired generation is exhausted, natural gas fired generation comes online. This fuel transition generates a sharp nonlinearity in the supply curve. There is more heterogeneity in natural gas efficiency levels causing the supply curve to slope sharply upwards. Diesel oil fired generation also comes online at these higher marginal costs creating some overlap in the marginal cost curve.

The top right panel describes the marginal cost curve for the eastern interconnection during the low natural gas price regime. The baseload fraction of the supply curve is still served by coal, but increases in coal prices have shifted the curve up slightly. While we cannot be certain as to the origin of the coal price increases, we show below that it cannot be due to an increase in the domestic demand for coal. The reduction in natural gas prices has reduced the size of the nonlinearity in the marginal cost curve. The fuel transition region of the supply curve now shows significant overlap between coal and natural gas fired generation. The most efficient natural gas facilities are coming online at lower load levels while the least efficient coal plants are being ramped down at lower load levels than in the high gas price regime.

The next two rows show that this pattern repeats itself across the other interconnections. During times of high natural gas prices there was a significant break in the marginal cost curve at the fuel transition. This nonlinearity has been smoothed by the reduction in gas prices and in each case there has been significant displacement of coal capacity by natural gas.

The impact of changing fossil fuel prices is also apparent in actual dispatch of generation by fuel type. Figure 5 displays total generation by fuel type by NERC region from 2005-2011. In most regions, coal generation has unambiguously fallen since 2005 while natural gas generation has risen. The spatial heterogeneity is a function of heterogeneity in installed capacity across these regions. The top panel in Figure 6 shows 2006 generation capacity by fuel type taken from EIA form 860. The bottom panel shows natural gas capacity by “prime mover” or boiler type. Combined cycle (CC) natural gas stacks tend to be newer and significantly more efficient than gas turbine (GT) stacks. As a result, the ability for a region to take advantage of low natural gas price is a function of installed capacity of natural gas generation, in addition to the level CC versus GT stacks. These differences likely have significant environmental impacts across regions. Table 1 summarizes the installed generating capacity by fuel type in each region.

4 Estimating Marginal Emissions

This section introduces the different estimation strategies for marginal emissions used in this paper. We start with a model of the data generating process and discuss the implications of using long differences (e.g., various fixed effects) versus short differences (e.g., first differencing) in the context of estimating marginal emissions for supply side electricity policies. We then present estimation results for each specification for three different pollutants: CO_2 , NO_x and SO_2 over different input prices using the two different techniques.

Dispatch of electricity generating power plants in the U.S. occurs as a function of marginal cost of generation. Put another way, cheaper electricity comes online before more expensive electricity. Other considerations, such as the extent to which increases in generation within a day must occur to meet within day changes in generation, often called ramping, may also affect dispatch. However, on any particular day, the minimum level of electricity generation, or baseload, varies significantly.

Furthermore, demand for electricity for different months or years is affected by changing weather or changing economic activity. Finally, weekend and holiday electricity demand profiles versus weekday demand profiles are often different. As a result, when estimating emissions as a function of generation it is important to permit flexibility in ramping over the generation profile across days, month and years.

Taking these determinants of electricity demand and therefore generation together, consider the following model of hourly emissions as a function of a particular level of hourly electricity generation:

$$e(Q_t) = \delta_{dow} + \delta_{my} + g(Q_t)\beta + f(\{P_t^{ng}, P_t^{coal}\}) + \epsilon_t. \quad (1)$$

Emissions in this model is e_t which is a function of generation at a particular time t : Q_t . The parameter of interest in this specification would be $\hat{\beta}$ which is the estimate of marginal emissions. Emissions will also vary as a function of the hour of day (δ_h), the day of week δ_{dow} , and month-years (δ_{my}) in addition to a stochastic term ϵ_t . This specification has been used in marginal emission studies examining demand side policies (Holland and Mansur (2008) and Zivin et al. (2012)).⁷ To that end, these studies use fixed effects estimators to isolate the marginal emissions associated with their policy.⁸ Finally, we allow for some function of the history of natural gas and coal prices to affect emissions, $f(\{P_t^{ng}, P_t^{coal}\})$, as these prices affect the dispatch order of power plants. As in Baker et al. (1999), we refer to these fixed effects estimators as long differences insofar as they use low frequency variation to identify the parameter of interest. In equation (1), for example, marginal emission estimates would be identified from variation in generation within a particular day within a particular month-year for a given load level.

An alternative identification strategy to estimate marginal emissions across the generation profile uses high frequency variation. Specifically, consider a first differenced model of marginal emissions which takes the following form:

⁷It is also possible that average temperature within a day or other weather variables could be important, but we abstract from those concerns for the time being.

⁸This takes the form of using alternative independent variables to Q_t . For example, Zivin et al. (2012) uses month by year fixed effects and day of week fixed effects within a region to estimate marginal emissions as a function of load for various hours within a day.

$$\Delta e(\Delta Q_t) = \Delta Q_t \beta + g(\{P_t^{ng}, P_t^{coal}\}) + \Delta \epsilon_t. \quad (2)$$

In equation (2), all fixed effects are removed from the estimating equation through differencing and the effect of fossil fuel prices may take a different form, but the changes in generation identifying coefficient of interest, β , are different. Specifically, changes in generation across consecutive hours now identify marginal emissions over the generation profile. As a result, we term this identification strategy as using short differences or high frequency variation.

Now consider the relative benefits of each identification strategy in estimating marginal emissions over the load profile. Marginal emissions will vary over the load profile as a function of the efficiency and fuel mix of generating units on the margin. As a result, it is vital to allow estimated marginal emissions to be flexible over the load profile. Using fixed effects jointly with a flexibly estimated marginal emissions rate imposes structure that either month of year or day of week fixed effects affects margin emission symmetrically over the generation profile. As a result, first differencing offers the advantage of a more flexible relationship between marginal emissions over the generation profile over time. This is especially important for our purposes here as we estimate changes in marginal emissions during a time period when the key determinant of the dispatch order, fossil fuel prices, is changing over time.

Lastly, it is important to mention two main reasons why these identification strategies could yield different estimates. First is that the fixed effects in (1) are not fixed. If these effects change over time then the fixed effect approach is misspecified. This could be a concern as fossil fuel price change significantly over time in our dataset. For this reason much of this literature is careful to use month by year fixed effects. Second, errors terms could be serially correlated. Even if steps are taken to correct for serial correlation the effect will likely be larger in a specification with long differences as these effects could potentially accumulate over time (Nuemark and Wascher (1992)).

4.1 Cheap Natural Gas

In addition to using low frequency and high frequency to estimate marginal emissions we estimate separate marginal emission coefficients for the time before hydraulic fracturing reduced the price

of natural gas and afterward. This is a crude measure of fossil fuel price differences over this time period. In a robustness check, we allow for relative levels of coal and natural gas prices to directly influence marginal emissions. Estimating marginal emissions pre and post cheap natural gas offers vivid insight on the role of fossil fuels on the emissions profile in the United States.

We perform a Markov Switching Model to identify when the cheap natural gas era began. We collected daily data on Henry Hub natural gas spot prices from a Bloomberg terminal excluding weekends and when the market is closed. To analyze this data, we estimate the following simple switching model:

$$P_{s,t} = \mu_s + \epsilon_{s,t}, \quad \epsilon_{s,t} \sim N(0, \sigma_s^2) \quad s = H, L \quad (3)$$

In equation (3), s indexes the state and t indexes time. We estimate a two by two matrix of transition probabilities (ρ_{ss} for $s = H, L$) as well. In order to ensure a global maximum, we perform a two dimensional solver in which we assign values for μ_H and μ_L manually then estimate the other six parameters (σ_s^2, ρ_{ss} for $s = H, L$). We then choose the model with the highest log likelihood as the true model.⁹

The results from the Markov switching model are show in Figure 4. Top panel shows the price data for Henry Hub spot prices. The second panel shows the standard deviation in the system conditional on the estimated state. The third panel shows the probability of being in each regime. Note that $t=1$ is January 1, 2005 and $t=1000$ is January 6, 2009. The model selects $\mu_H = 8.0$ and $\mu_L = 4.0$ as the mean natural gas prices although the log likelihoods are close for nearby parameter values of both parameters in both the positive and negative direction. ρ_{11} and ρ_{22} are both precisely estimated at one. The variance across regimes are also both precisely estimated: $\sigma_H^2 = 4.463$, $\sigma_L^2 = .368$. The relatively lower variance in the low price regime confirms the optical test of lower volatility later in the data.

Starting on January 8, 2009, the model is very confident in a sustained period of low gas prices interrupted by a fifty day span around $t= 1200$ (e.g., late 2009). Given the low estimated variance

⁹We employ this method to ensure the search algorithm doesn't find a local maximum, which is a problem that occurs when this method is not employed.

in regime two relative to regime one, the model selects prices in this interval to reflect the high price regime. We attribute this increase to seasonal demand for natural gas for heating. While more robustness checks are needed, we take the switching model as evidence of a low natural gas price regime beginning in early 2009.¹⁰

We begin the analysis in 2005 to avoid variation in environmental regulation. The Clear Air Interstate Rule (CAIR) Act introduced new environmental regulation for power plants in our study region.¹¹ The second regime begins on January 8, 2009 and runs through the end of the study period in 2011. The differences in electricity generator behavior across these two natural gas price regimes will be the source of quasi-experimental variation that allows us to identify changes in marginal emissions in electricity market and the behavior of producers therein.

One important caveat is that this analysis has is no way controlled for demand. The identifying assumption to attribute the fall in natural gas prices is the increase in supply. While this is true in identifying the precise date of the beginning of cheap natural gas, we are able to make causal inference of the effect a change in the short run supply elasticity on the RTO manager's decisions by controlling for demand below.

4.2 Estimating Equations

We estimate three main econometric models to the identify marginal emissions over all eight NERC regions in the US and how those marginal emissions rates have changes over time as natural gas prices have fallen. Each specification uses a semi-parametric approach to estimate marginal emissions over the generation profile for each NERC region. First consider a specification using high frequency variation by employing first differences:

¹⁰We also performed a rolling Chow test on first differenced spot and futures natural gas prices. We run the first difference of the same sequence of Henry Hub natural gas spot prices on seasonal dummies and a time trend. We then create a dummy variable equal to one if the time period is after the date indicated. There is evidence of a break in prices between March and May 2009. We have estimated all of our models below using alternative break dates in that range and all results are qualitatively identical.

¹¹The CAIR Act was litigated for nearly a decade up to and beyond the passage of the act. Discussions with industry sources suggest that generators responded before the act was implemented despite the uncertainty of its legal status. In future work we plan to control for pollution permit prices in the region which should alleviate any concerns from attributing changing electricity generator behavior to natural gas prices rather than environmental regulation.

$$\Delta E_t = \beta_{r,d} \sum_{r=L,H} \sum_{d=1}^{20} Bin_{dr} \Delta Load_{rt} + \epsilon_t \quad (4)$$

E_t represents hourly emissions of CO₂ for all stacks in the region, $Load_t$ describes the total hourly generation in the region, d indexes twenty load quintiles and r is a variable indexing if the observation occurs within a particular natural gas price regime. The BIN_h variable divides hours into generation level by vigintiles (20 equally sized bins), where the quintiles are defined over the total hourly generation in a NERC region over the entire study period. The lowest level of total generation we observe for a given NERC region during our study period receives a $BIN_h=1$ and the highest observed level of generation is placed in $BIN_h=20$. By comparing marginal emissions within a generation bin we are able to hold the level of production constant and isolate changes in marginal emissions associated with the changing composition of fuel sources at different levels of production. To address serial correlation concerns and be consistent with the existing literature we estimate a Newey-West error structure with 24 lags.

This equation in differences captures the high frequency variation in emissions rates across NERC regions and load levels. The coefficients of interest are the average change in pollution emissions for a one megawatt change in generation within the region. We produce an estimate of that coefficient for each of twenty generation vigintiles. For each NERC region each natural gas price regime is graphed as a separate line. Comparing the lines allows us to understand the change in marginal emissions intensity within a decile of the load distribution across regimes for that region. We report each NERC region separately to reduce the impact of imports and exports on the results.

Our second specification using fixed effects to estimate marginal emissions over the generation profile:

$$E_t = \beta_{r,d} \sum_{r=L,H} \sum_{d=1}^{20} Bin_{dr} Load_{rt} + \alpha_{my} + \epsilon_t. \quad (5)$$

In the low frequency specification, α is a set of month-by-year fixed effects. We again employ a Newey-West error structure with 24 lags. The identification of the load coefficient in this regression

comes from different levels of emissions within a generation vigintiles within a month and year. We then compare these coefficients across the natural gas price regimes.

Our third and final specification again uses high frequency variation but in this specification we explicitly account for the relative prices of natural gas and coal over the sample period.

$$\Delta E_t = \beta_{r,d} \sum_{r=L,H} \sum_{d=1}^{20} Bin_{dr} \Delta Load_{rt} (P_{coal,t} - P_{ng,t}) + \gamma_{r,d} \sum_{r=L,H} \sum_{d=1}^{20} Bin_{dr} \Delta Load_{rt} + \epsilon_t \quad (6)$$

In this specification we use one month forward contracts for Henry Hub natural gas prices and Powder River Basin coal prices. This specification acknowledges the changing coal price which occurs over our sample period and uses it to identify the marginal impact of a one dollar change in the relative prices of these fossil fuels. The interpretation of the estimated coefficient β is the marginal emissions within a load bin associated with a 1\$ change in the relative fuel price. Positive β 's imply that in an increase in coal prices or decrease in natural gas prices are associated with increasing emissions. The coefficients are likely to vary across both NERC regions and the supply curve as different fuels become the marginal producer.

5 Results

We report the results of estimating equation 4 separately for each NERC region in figure 8.¹² Each panel includes the estimated marginal emissions rate in a NERC region across each load vigintile. The solid line connects point estimates from natural gas price regime 1 and the dotted line connects estimates from regime 2. Vertical bars represent the 95% confidence interval around the point estimate.

The results display the variation in marginal emissions across three dimensions. Comparing panels, there is significant variation in marginal emissions levels across space. MRO (roughly, the midwestern states) has the highest level of marginal emissions and NPCC (New England) the lowest. The fraction of generation capacity fueled by coal is highly correlated with marginal emissions

¹²For MRO, we trim all observations below the 0.1th and above the 99.9th percentile. The CEMS data shows anomalies with what appears to be double counting of certain hours during 2005 and 2006.

intensity in the lower generation deciles across regions. There is significantly more variation in marginal emissions rates at low levels of generation than at high. The average natural gas emissions rate is just over 0.5 tons of carbon per MW hour of generation. As the fraction of generation from natural gas increases the emissions rates tend to converge to that level.

The lines on the graphs illustrate changing marginal emissions rates across levels of generation. The majority of marginal emissions rates across NERC regions and fuel price regimes are (weakly) decreasing in generation level. MRO has the largest decrease in marginal emissions rates, while NPCC is almost flat and imprecisely estimated. MRO, RFC (mid-Atlantic states) and SERC (southeastern states) decrease quickly at high levels of generation while TRE (Texas) and WECC (the Western half of the U.S.) decrease at a decreasing rate. Because marginal emissions rates are largely determined by the marginal fuel type we can use the marginal emissions rates and generation capacity data to determine what fuels are on the margin at various load levels across the country. Large decreases in the marginal emissions rate typically indicate a shift from fossil fuel generation to natural gas. The quantity and efficiency of natural gas generation in a region determine where in the generation profile these decreases in emissions intensity will occur.

Finally, comparing the two lines in each graph illustrates the impact of relative fuel prices on marginal emissions rate across regions and generation levels. For example, the top left panel displays the results for FRCC (most of the state of Florida). At low levels of generation marginal emissions are higher in regime 1 than regime 2, but starting in the 11th vigintile marginal emissions in regime 2 drops sharply, while regime 1 marginal emissions increased slightly. The results suggest that the environmental benefits of reduced generation at higher levels of demand are lower during regime 2 when the relative price of natural gas generation is significantly lower. This is consistent with the hypothesis that FRCC's relatively inefficient gas turbines are being dispatched more frequently and at much lower levels of demand than during regime 1.

Statistically significant changes in marginal emissions rates occur in each region at various levels of generation. The magnitude of the difference in marginal emissions rates is a function of the fraction of natural gas fired generation in the region. TRE and WECC, which have substantial combined cycle natural gas generating capacity, have the largest magnitude difference between fuel

price regimes. RFC and SERC, which small levels of natural gas generation have smaller differences in marginal emissions rates. In NPCC, which has by far the lowest level of coal-fired generation, the estimated marginal emissions rates are less precise.

The graphs in Figure 8 describe the variation in marginal emissions rates across geography, generation levels and fuel price regimes. The variation in emissions rates across regions is the largest source of variation of the dimensions we explore. The same environmental policy implemented in different regions is likely to have significantly different environmental impacts due only to the differences in emissions rates, which in turn are due to differences in installed generation capacity.

Figure 9 displays the coefficient estimates and their standard error using long differences (e.g., low frequency variation) as shown in equation 5. As before, marginal emission rates are shown for each vigintile and regime. Estimates from this specification show that marginal emission rates fall significantly in regime 2 relative to regime 1 in all regions except in the upper midwest (MRO) where there is very little natural gas capacity and the northeast (NPCC) where natural gas had already been dispatched in regime 1. While there are several important differences, the low frequency estimates are consistent with the high frequency estimates in that emissions are broadly decreasing over the generation profile and emission rates change the most in locations where there is more natural gas capacity. The same three sources of heterogeneity (e.g., spatial, generation level and input price regime) in marginal emissions rates described using first differences are evident using low frequency variation. As before, there is significant differences in emission rates across NERC regions, the generation profile and input price regime. In each case where the estimated coefficients are statistically significantly different across regimes, the regime 2 coefficient is lower.

While there are broad similarities in the regression results, there are several key differences between the estimates from using high frequency variation versus low frequency variation. First, the low frequency coefficients are much more precisely estimated. Second, the low frequency estimates are smooth, monotonically decreasing and everywhere lower in regime two relative to regime one in all regions (except MRO) while the high frequency estimates are not. Third, the levels of the estimated coefficients are significantly different across the two identification strategies. Specifically, the estimated emission rates using month-by-year fixed effects seem unreasonably low: in MRO

which relies heavily on coal is estimated to be cleaner than NPCC which uses natural gas intensely.

These differences can be explained by carefully consider the source of identification across the two specifications. Using differences across consecutive hours to estimate emission rates means that observations in the middle of ramping periods will receive excessive weight in the estimation procedure. This is important given our focus on input prices: if natural gas facilities are serving baseload and coal plants are operating at less than capacity as the supply curve analysis suggests is possible, then coal facilities may need to respond to large changes in load. This could lead to large pollution impacts of serving the large increases in demand across the morning hours that electricity grid operators refer to as the morning ramp. If less flexible coal generation is forced to respond to the ramp it could swamp the environmental benefits that cheap natural gas is providing.

As a result we estimate the same specification separately for ramping and non-ramping periods. We define deciles for the difference in generation within each vigintile. We define the top and bottom decile of changes in generation as ramping periods and deciles 2-9 as non-ramping periods. Specifically we estimate:

$$\Delta E_t = \beta_{r,d,ramp} \sum_{r=L,H} \sum_{d=1}^{20} Bin_{dr} \Delta Load_{rt} * Ramp_t + \epsilon_t \quad (7)$$

where $Ramp_t$ is a binary variable equal to 1 if change in generation is in the top or bottom decile of changes in generation level within a vigintile.

Figures 10 and 11 summarize the results of these regressions for each NERC region. The left panel of each graph displays the coefficients for ramping hours across regimes in a NERC region and the right panel displays coefficients in non-ramping hours. For the most part the difference between ramping and non-ramping hours are not large or statistically significant, but the graphs do highlight how the change in fuel prices can have differential impacts across these different types of hours. In FRCC the ramping hours with high levels of generation are cleaner in regime 2, but ramping hours at low levels of generation are dirtier. Non-ramping hours are cleaner across the generation distribution. TRE also displays significant differences in ramping behavior at intermediate generation levels. In general, then, eliminating ramping hours increases the precision of coefficient estimates on the high frequency specification. This highlights the increased variation

in emission levels that occur during ramping events.

The second major difference in estimates from the identification strategies is that low frequency estimates are smooth, monotonically decreasing and everywhere lower in regime two relative to regime one in all regions (except MRO) while the high frequency estimates are not. The right column of Figures 10 and 11 show that using high frequency variation shows there is significant heterogeneity in how emissions rates change over the generation profile. Specifically, we find that emission rates fall over some portions of the generation profile and increases for others. This is consistent with natural gas generation replacing coal over some portions of the generation profile and coal replacing natural gas for others. For example, in SERC it appears that significantly more natural gas is used as baseload generation (lower emission rates for vigintiles 1-12) and no longer being used to serve only high demand periods where emission rates are now higher.

The third major difference is the level of coefficient estimates. In the long differences specification, we employ month-by-year fixed effects to estimate average emissions rates in a generation vigintile. These fixed effects remove all variation specific to that particular month relative to other months. Because price changes are the key element in our analysis, this is precisely the variation we would like to embed in our coefficient estimates. Put another way, if emissions levels across the entire generation profile change in a given month, those estimated levels in the low frequency specification will not reflect those changes.

The results indicate that the source of variation can have significant impact on the estimated marginal emissions rate. Given that the goal of this paper is to understand the impact of changing fuel prices on emissions, we prefer the first differences identification strategy. The first differences strategy maintains the intertemporal emission rate differences over time and highlights where in the generation profile different generation sources move to over time. These are both critical pieces of information to evaluate supply side energy policies and how their non-market benefits (e.g., foregone emissions) change with input prices.

Finally, we turn to the coefficients estimated from equation 6, analyzing the impact of changes in the price spread between coal and natural gas on marginal emissions intensity. Table 2 reports the estimated coefficients. The coefficients can be interpreted as the impact of a one dollar change

in in the spread between coal and natural gas prices (defined as coal price minus natural gas price) on marginal emissions rate for a given NERC region and generation level. Once again, there is significant variation in marginal emissions rates across both regions and generation levels. A dollar increase in the price spread between coal and natural gas increases marginal emissions by 2.16 tons on average, but this average hides a great deal of variation within and across regions. During fuel price regime 1 the median spread was \$0.99 and during regime 2 the median increased to \$5.32. Marginal emissions increased by 9.4 tons between the two regimes.

The columns of table 2 describe the variation in marginal emissions as fuel prices change across the generation profile. In MRO an increase in the fuel price spread decreases marginal emissions at low levels of generation as coal becomes relatively less attractive, but increases marginal emissions at high generation levels as the displaced coal is brought online. FRCC displays almost exactly the opposite pattern.

6 Policy Analysis

To illustrate the economic significance of the variation in marginal emissions rates we provide two descriptive policy analyses. We begin by estimating the emissions impact of installation of a significant amount of electricity storage capacity in each NERC region. Electricity storage refers to a broad class of technologies that covert electricity to potential energy when prices are low and convert that potential back to electricity when prices rise. These technologies could be employed to reduce the large variation in electricity prices associated changing demand throughout the day and provide dynamically efficient generation. They also are attractive in situations where renewable electricity generation is curtailed due to low demand.

Carson and Novan (2013) analyzes both the pecuniary and nonpecuniary impacts of electricity storage in Texas. In this descriptive analysis we focus on the environmental impacts of installing 500 megawatts of storage capacity in each NERC region across both fuel price regimes. We simulate the impact of electricity storage by estimating the marginal emissions impact of increasing generation in the lowest load vigintile by 500 MW to charge the storage and reducing generating by 500MW in the highest vigintile. Estimating marginal damages rather than relying on averages is, of course,

crucial as average emissions rates would suggest zero net environmental impact of storage. Our marginal emissions estimates illustrate the error in that approach.

Table 3 summarizes the CO₂ emissions impact of installing 500MW of electricity storage capacity. The results illustrate the importance of evaluating energy policy taking into account the sources of marginal emissions variation described above. Relying on estimates from high frequency variation in the data, our preferred specification, during fuel price regime 1 energy storage systems would reduce overall emissions in only FRCC and NPCC. In the era of cheap natural gas, energy storage increases emissions in all regions. Still, differences in the size of the increase in emissions are significant. 500MW of electricity storage in NPCC would increase emissions by 36 tons, while the same amount of storage in SPP would increase emissions by 258 tons.¹³ Cheap natural gas has increased the nonpecuniary costs of electricity storage in some regions, but in SPP the emissions associated with storage have dropped by nearly half. Changes in fuel prices have fundamentally changed the environmental impact of energy storage in different ways in different parts of the country.

As another simple policy experiment, we consider the air emissions impact of installing hydroelectricity capacity.¹⁴ Hydroelectric power has been studied in similar contexts; it has low marginal cost and is easily ramped up and down, but it is limited by the amount of water stored behind the dam, so it tends to be dispatched at times when demand is highest (Kotchen et al. (2006)). We simulate the impact of hydroelectricity generation by assuming that these facilities are dispatched in only the highest vigintile.¹⁵ This simulation relies on estimating the marginal emissions across the generation profile. Using average emissions will lead to incorrect estimates of the environmental impact of this policy.

Table 4 summarizes the emissions impact of installing 1,000 MW of hydroelectricity capacity in each NERC region, across fuel price regimes and identification strategies. As with the electricity

¹³All emissions estimates in this section represent the per-hour change in emissions. To calculate annual effects we would simply multiply the hourly estimates by $\frac{365*24}{20}$ to account for the number of hours in a year spent in a single generation bin.

¹⁴This simple policy experiment ignores the different levels of hydro potential across regions and a variety of other environmental impacts from installing a hydroelectric facility.

¹⁵This ignores that many hydroelectric facilities are also tasked with maintaining water levels and preventing flooding which may cause them to generate electricity at times that do not maximize revenue.

storage policy above, there is significant variation in the environmental impacts of this energy policy across regions, fuel prices and identification strategies. Cheap natural gas had reduced the CO₂ emissions benefits of hydroelectricity in four of the eight NERC regions. During regime 1 hydro had the largest CO₂ benefit in FRCC and RFC, but with the advent of cheap natural gas RFC becomes the region with by far the largest benefits. SPP is the least attractive location for new hydro generation base on CO₂ emissions averted.

The policy experiments above include variation across the three dimensions identified in section 5, but considering the source of identification and fuel prices is important for a wide class of generation side policies. Any electricity sector policy that impacts the entire supply curve, for example: changes in the level of nuclear generation, wind generation, carbon prices, requires analyzing average emissions rates across the full generation profile taking fuel prices into account.

7 Robustness Checks

In this section we present a series of robustness checks to expand on the results presented this far. We begin by analyzing the marginal CO₂ emissions from generation in in ramping versus non-ramping hours. When then estimate the impacts of the observed fuel price change on other pollutants emitted by electricity generation. Finally, we discuss the impact of environmental regulation on the generation profile and estimated marginal emissions.

7.1 Other Pollutants

We focus on CO₂ because it is a largely unregulated pollutant for electricity generators.¹⁶ Other pollutants are regulated under the Clean Air Act and its amendments and, presumably, are less of a policy priority. Changes in emissions levels of SO₂ and NO_x represent transfers among polluters and traders in those pollution markets. Still it may be worthwhile to describe how changes in natural gas prices have affected pollution levels from those pollutants.

¹⁶The Regional Greenhouse Gas Initiative (RGGI) is a voluntary cap and trade program for electric power plants. States have been given to opportunity to opt into the enterprise and electricity generators in those states come under the regulation. Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New York, Rhode Island, and Vermont have opted in to date. All other CO₂ emissions from electricity generators are unregulated.

We re-estimate equation 4 to identify the marginal emissions rate over generation deciles for both SO_2 and NO_x emissions. Figure 12 displays the results for SO_2 emissions over NERC regions. The results are broadly similar to those for CO_2 emissions. Most regions experience a statistically significant reduction in marginal emissions over the generation production profile. The FRCC, SERC and RFC regions see the largest reductions in emissions intensity while WECC see almost no difference over the entire production profile. Figure 13 displays the results for NO_x emissions as the dependent variable.

7.2 Environmental Regulations

Changes in environmental regulation intensity could also shift the electricity fuel type mix by making natural gas fired generation relatively more attractive. If increases in environmental regulation stringency coincided with changes in natural gas prices we could mistakenly attribute the observed changes in marginal emissions rates to natural gas prices. There are three major cap-and-trade programs that electricity generators are subject to. Under the Clean Air Act and its amendments power plants must purchase emissions permits to cover their emissions of SO_2 and NO_x . During our study period the EPA introduced a new cap-and-trade program known as the Clean Air Interstate Rule. The regulation was officially promulgated in 2005, but permits did not begin trading till 2007. Several court challenges have threatened the validity of the program, but permits have continued to trade. Figure 14 describes the price of pollution permits under each program over the life of the markets.

Pollution permit prices have been strongly correlated with natural gas prices over the study period. As coal fired generation has been replaced by natural gas as baseload the price of permits have fallen. SO_2 permits that consistently traded over \$500 during peak natural gas prices are now trading for less than \$5. This suggests that the costs of complying with environmental regulation has actually fallen during the low natural gas price regime. The reduction in permit prices has actually made coal fired generation relatively more attractive in regime 2 implying that the change in marginal emissions rates described above actually understates the changes that would be expected had the environmental policy regime remained neutral.

8 Conclusion

Technological advances have led to a rapid decrease in the price of natural gas. This price change, along with smaller increases in coal and oil prices, have led to significant changes in the dispatch of electricity generators. In this paper we estimate the impact of this change in fuel prices on marginal emissions across the country. Along the way, we have shown that the source of identification used to estimate the marginal emissions rate matters crucially.

We employ a data set consisting of hourly observations on generation quantity, fuel input and pollution emissions for every power plan in the U.S. between 2005-2011. We then employ a Markov Switching model to separate the time period into a high and low natural gas price regime, and then estimate regional electricity marginal cost curves for both price regimes. The supply curves suggest that natural gas fired generation is replacing coal to fuel baseload serving powerplants.

We then estimate the marginal emissions levels across generation levels and regions for both gas price regimes. The existing literature has relied on two sources of variation to estimate marginal emissions. Taking advantage of the large dataset we can use both low and high frequency variation to identify marginal emissions levels. The results allow us to compare the sources of identification and place the existing literature in context. We find that cheap natural gas has reduced marginal emissions at most, but not all, generation levels and that the impacts are heterogenous geographically. The results suggest that accurately estimating the impact of energy policies such as the benefits of wind energy, electric vehicles or real time pricing requires careful attention to location, load level and input fuel prices.

We use the marginal emissions estimates to evaluate two different supply side energy policies. We argue that the environmental impacts of these policies are best evaluated using high frequency variation in electricity generation and pollution emissions. The results suggest that cheap natural gas has had a significant impact on the environmental impact of electricity storage and hydroelectricity generation. The relative attractiveness of these policies has changed across regions with the large shift in fuel prices. We find that the northeast is the most attractive region to site electricity storage, while Florida is the most attractive place to site new hydro generation from a CO₂ perspective.

It is important to note that the marginal emissions rates we have calculated in this paper are medium term estimates. In the long run the generation mix will likely respond to the change in fuel prices and this change will further effect the marginal emissions rate. Because the regional differences in marginal emissions rates were a first order determinant of the environmental impact of energy policy, these changes in the generation mix will need to be carefully modeled to estimate the long run environmental impact of energy policy.

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Figures and Tables

Table 1: Capacity and fuel mix by NERC region

	Nameplate capacity	Coal	Oil	Gas	Nuclear	Renewable
FRCC	59	0.27	0.18	0.40	0.14	0.02
MRO	53	0.73	0.01	0.05	0.14	0.07
NPCC	79	0.14	0.14	0.30	0.27	0.15
RFC	246	0.64	0.02	0.06	0.27	0.01
SERC	288	0.56	0.02	0.13	0.24	0.05
SPP	61	0.63	0.01	0.28	0.04	0.04
TRE	89	0.38	0.00	0.48	0.12	0.02
WECC	186	0.32	0.01	0.28	0.11	0.29
Total	1,063	0.49	0.03	0.20	0.19	0.09

Note: Total generating capacity in GW (1,000's of MW). Excludes 'other fossil fuel' and 'unknown' categories which range between 0% and 1.9% of total regional generation. Source: Authors' calculation from EPA's 2005 EGrid data.

Table 2: Marginal emissions due to change in fuel price spread across generation levels and NERC regions

	FRCC	MRO	NPCC	RFC	SERC	SPP	TRE	WECC	Average
1	5.1	-15.6*	18.2*	2.4	4	25.9*	-4.7	-25*	1.3
2	4.7	-11.8*	9.1*	2.2	0.1	19.2*	-4.3	-21.7*	-0.3
3	4.7	-9.4*	2.6	-0.9	3.5	14.8*	0.8	-18.1*	-0.3
4	22.6*	-12.3*	-6.9	-4.2*	1.2	5	3.5	-4.1	0.6
5	9*	-6.3*	1.7	-2.3	0.9	9*	5.6	-0.8	2.1
6	7.8*	-3.8	-2.2	-5.3*	-7.4*	4.8	4.8*	-0.1	-0.2
7	3.4	-4	-9.1*	-6.7*	-1.7	4.6	8.3*	-0.9	-0.8
8	2.4	6.3*	-6.3	-4.9*	1.3	3.5	7*	-2.4	0.9
9	0.3	5.2*	-3	-5.7*	-1	-0.5	5*	0.4	0.1
10	5.6*	10.1*	-1.8	-4.7*	0.1	1.6	6.6*	3.9*	2.7
11	0.4	5.2	3.9	0.4	-0.6	6.1*	1.8	0.7	2.2
12	-2.9*	71.8*	2.6	-4.3	-5.4	-4	3.8*	-1.6	7.5
13	-6.2*	11.2*	-3.1	-7.1*	-1.8	-11.2	1.6	1.2	-1.9
14	-5.4*	117.5*	1.9	-5.4	7.7	-27	2.5	3.2*	11.9
15	-9.6*	74.2*	4.4	3.5	1.3	-5	3.2*	0.5	9.1
16	-14.1*	11.5*	-7.7*	-0.3	2.2	-6.1	2.3	1.6	-1.3
17	-14.8*	5.1	-3.3	-0.7	2.4	8.8*	0.3	0.7	-0.2
18	-13.6*	55.9*	-2.7	-2.8*	11.1*	4.4	-2.2	1.6	6.5
19	-15.9*	1.2*	-3.6	1.7	5	-4.6	-4.1*	-0.6	-2.6
20	-31.9*	109.4*	0.5	7.9*	13*	-50.3*	-0.9	1	6.1
Average	-2.4	21.1	-0.2	-1.9	1.8	-0.1	2.0	-3.0	2.2

Note: The tables report the marginal emissions associated with a change in the coal/natural gas fuel price. for each NERC region across generation levels. Coefficients have been scaled by 1,000 to improve readability, so the proper interpretation is the change in emissions associated with a 1,000MW increase in generation due a \$1 increase in fuel price spread. Each column displays estimates from a single regression with 61,296 hourly observations and Newey West standard errors with 24 lags.

Table 3: Emissions impact of electricity storage across region, fuel price and identification strategy

	Regime 1		Regime 2	
	High Frequency	Low Frequency	High Frequency	Low Frequency
FRCC	-25.1	94.9	103.3	118.1
MRO	197.8	-5.3	194.9	-145.7
NPCC	-12.9	94.5	36.1	108.7
RFC	112.3	59.0	103.1	66.7
SERC	143.4	80.6	147.1	74.1
SPP	196.8	136.4	258.3	113.5
TRE	72.6	96.6	90.6	97.6
WECC	108.3	129.1	57.1	109.1

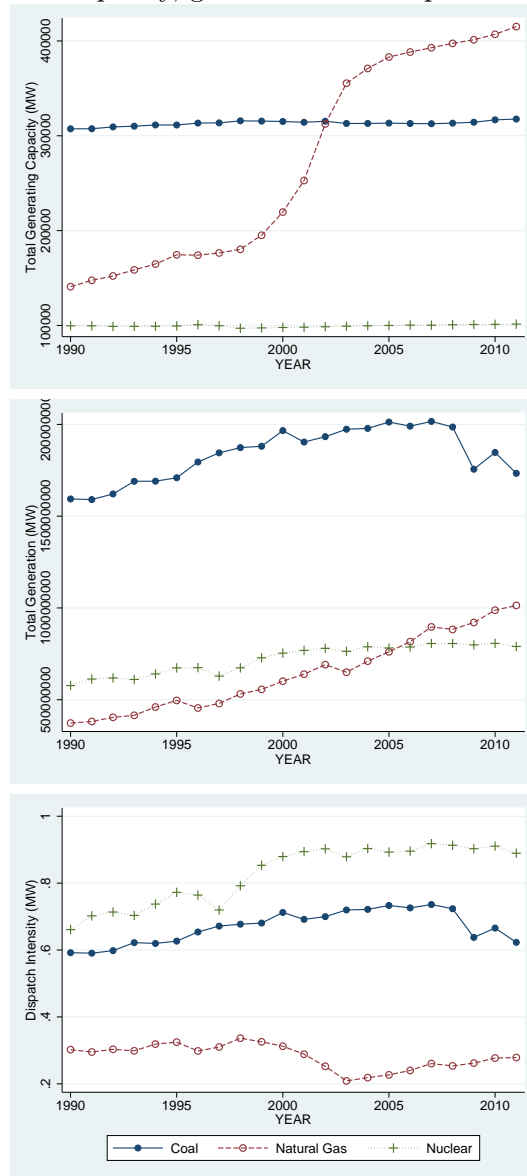
*Note:*CO2 emissions associated with a 500MW electricity storage installation in each NERC region by identification strategy and fuel price regime. Estimated by subtracting marginal emissions rates in the top generation vigintile from marginal emissions in the bottom vigintile.

Table 4: Marginal emissions rate in top vigintile by NERC region and identification strategy

	Regime 1		Regime 2	
	High Frequency	Low Frequency	High Frequency	Low Frequency
FRCC	667	750	531	677
MRO	649	254	646	587
NPCC	573	663	575	683
RFC	667	911	708	897
SERC	605	862	669	853
SPP	568	869	406	848
TRE	542	722	536	682
WECC	551	745	556	713

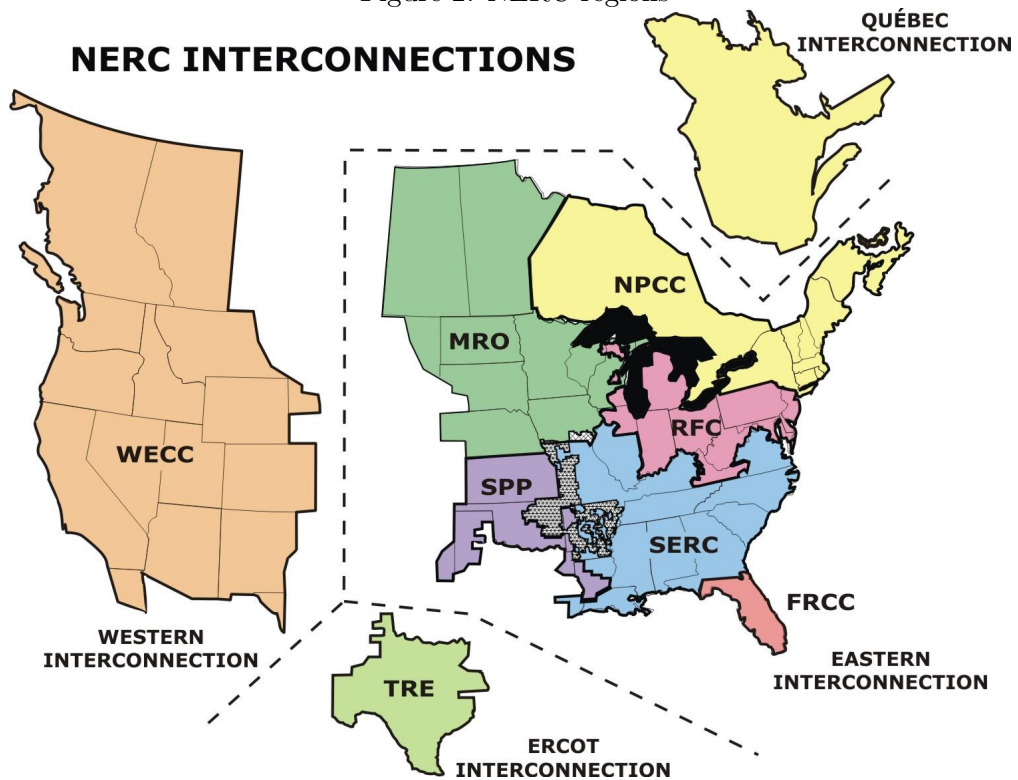
Note:CO2 emissions reductions associated with the introduction of 1000 MW of hydro generation in each NERC region, fuel price regime by identification strategy.

Figure 1: Capacity, generation and dispatch intensity



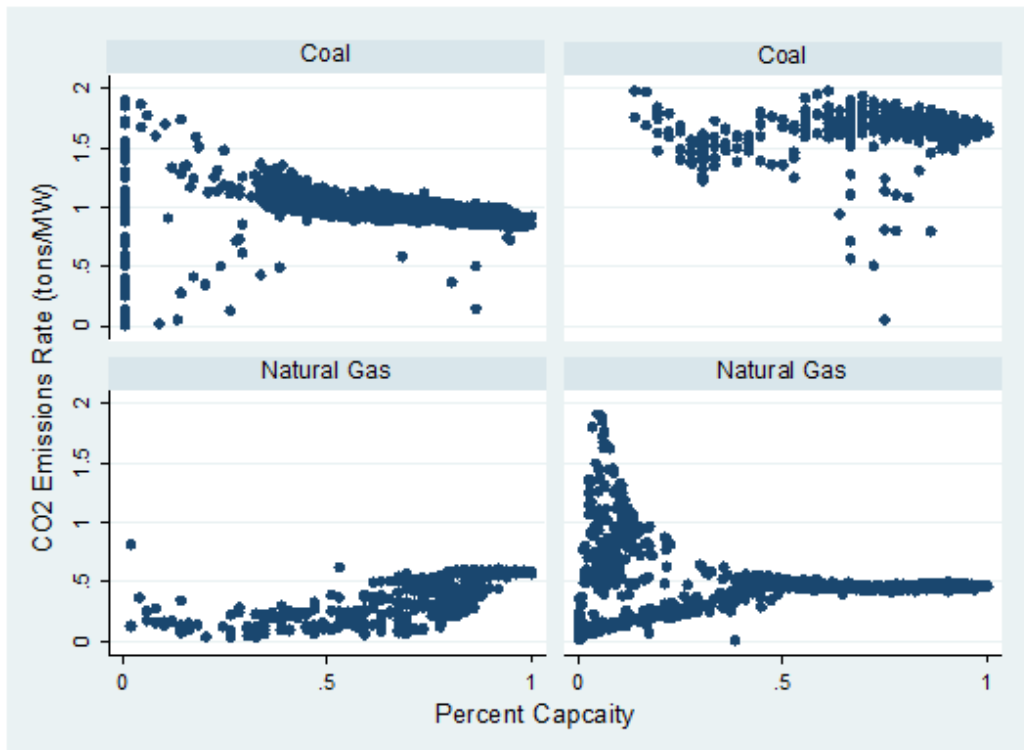
Note: The top panel display total generating capacity measured in megawatts in the U.S. by fuel type from 1990-2012. The middle panel describes the total generation in the U.S. measured in megawatt hours by fuel type from 1990-2012. The bottom panel describes dispatch intensity, a measure of how intensely existing capacity is utilized, by fuel type from 1990-2012. Data in the top two panels is taken from EIA's Electric Power Data and the bottom panel is calculated from the data presented in the top two.

Figure 2: NERC regions



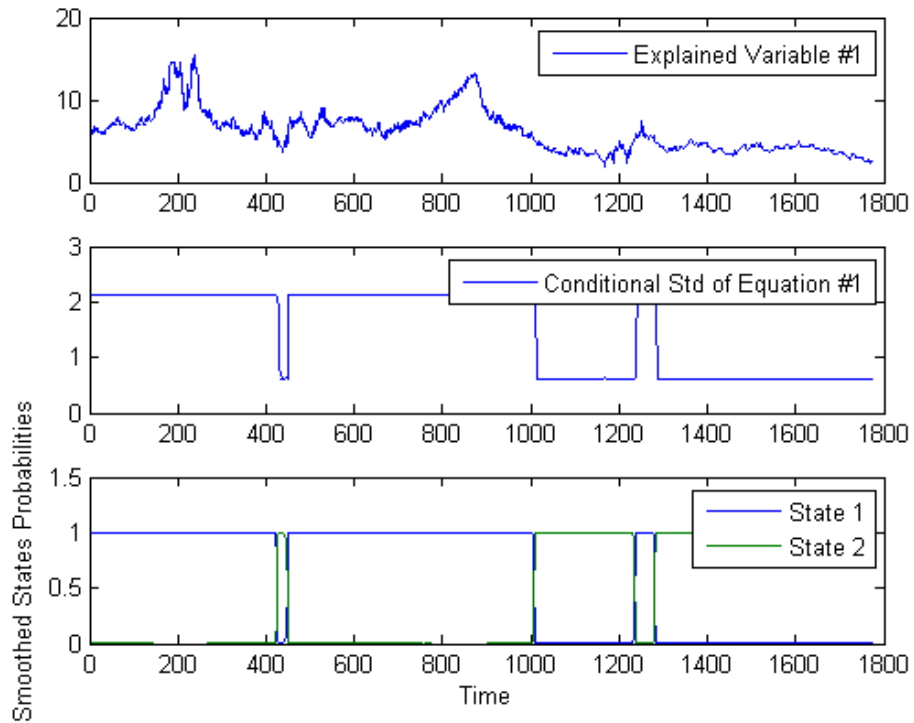
Note: The U.S. is divided into three electrical interconnections across which very little energy flows. The Eastern Interconnection is divided into six smaller regions as well.

Figure 3: Pollution intensity by fuel type and production level



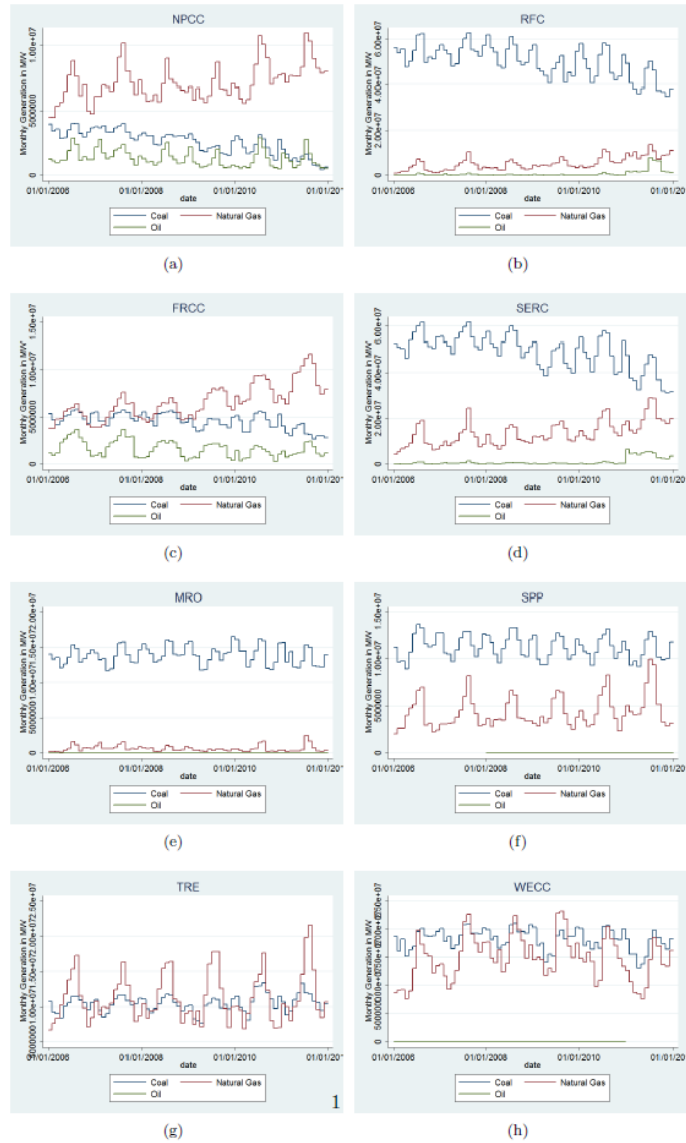
Note: The top two panels display the CO₂ emissions intensity for two different coal fired units across their observed production quantity. The bottom two panels display the same information for two different natural gas fired units. Taken together the graphs illustrate the emissions intensity heterogeneity across fuel types, units of the same fuel type and within a unit across production levels.

Figure 4: Markov switching model for natural gas price regime



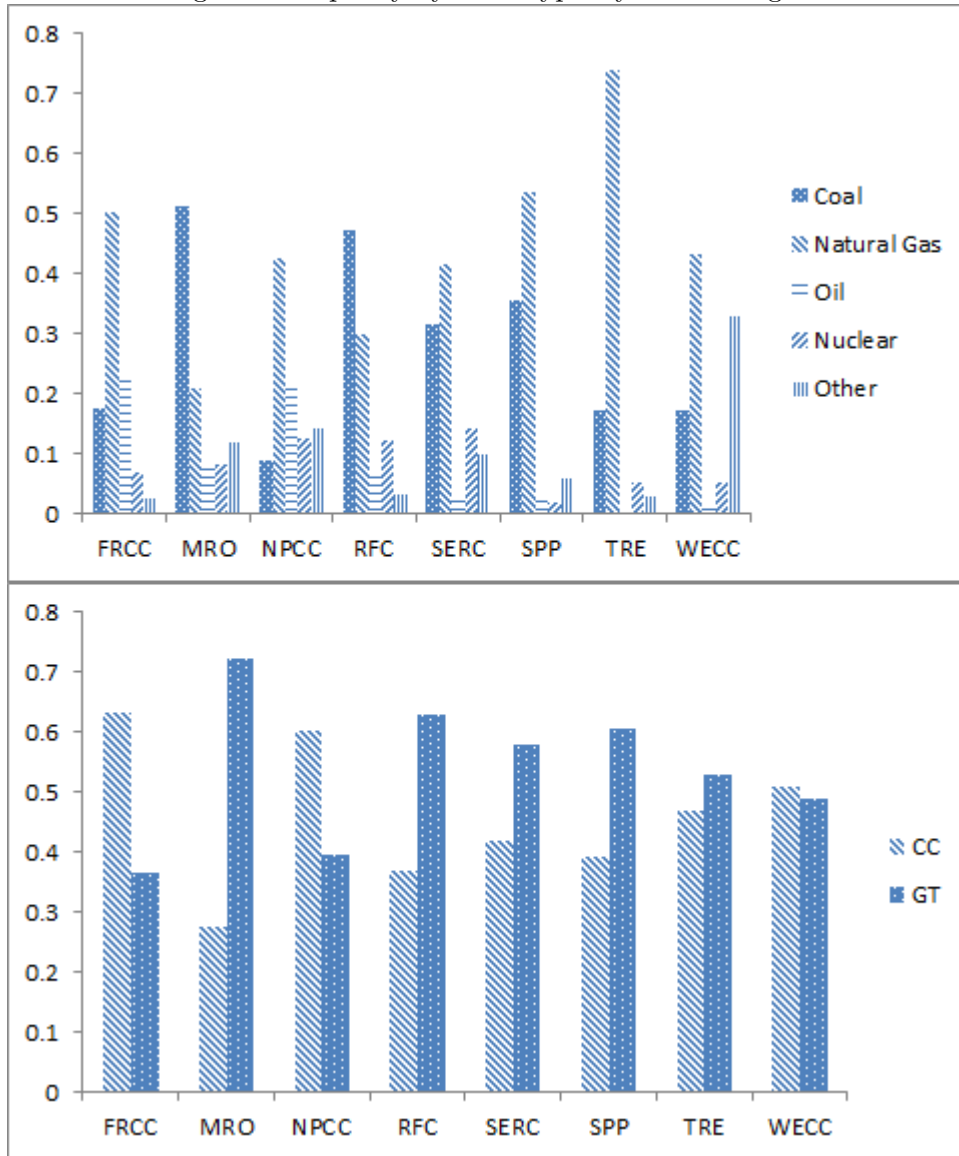
Note: Markov Switching Model estimation of regime switch. The high state is indexed by one and the low state by two. Top panel shows the price data for Henry Hub spot prices. The second panel shows the standard deviation in the system conditional on the estimated state. The third panel shows the probability of being in each regime. Note that $t=1000$ is January 6, 2009.

Figure 5: Monthly Generation by Fossil Fuel



Note: Aggregated monthly generation by fossil fuel type from 2005-2011. Data are aggregated from hourly generation CEMS data from the EPA.

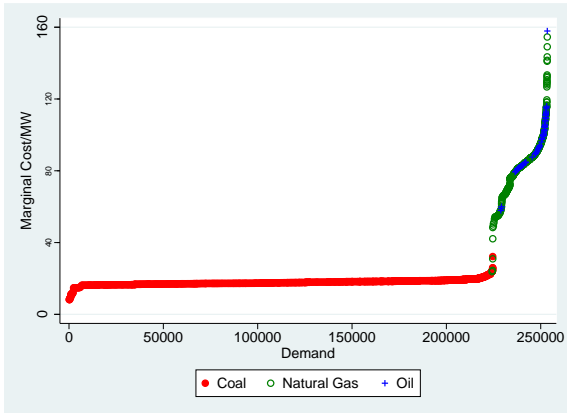
Figure 6: Capacity by Fuel Type By NERC Region



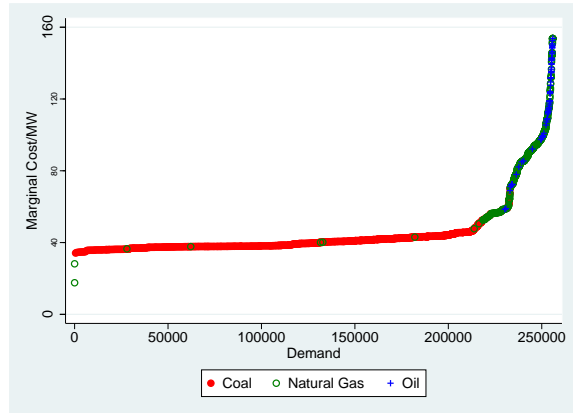
Note: Top panel shows 2006 Capacity by NERC region by fuel type. Bottom panel shows Natural gas capacity by NERC region broken down by prime mover. All data from EIA.

Figure 7: Marginal cost curves by natural gas price regime

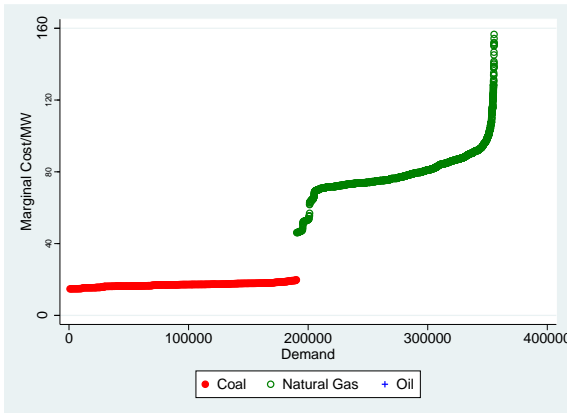
Eastern Interconnection Regime 1



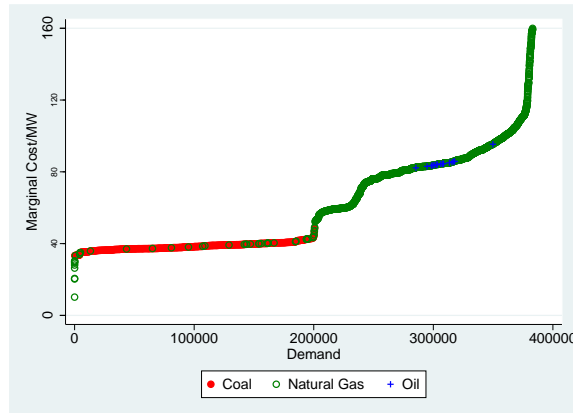
Eastern Interconnection Regime 2



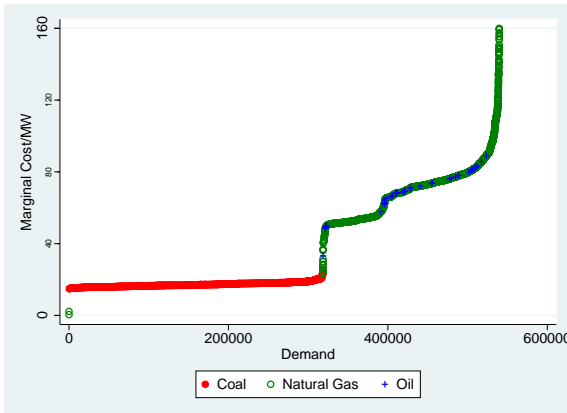
Texas Interconnection Regime 1



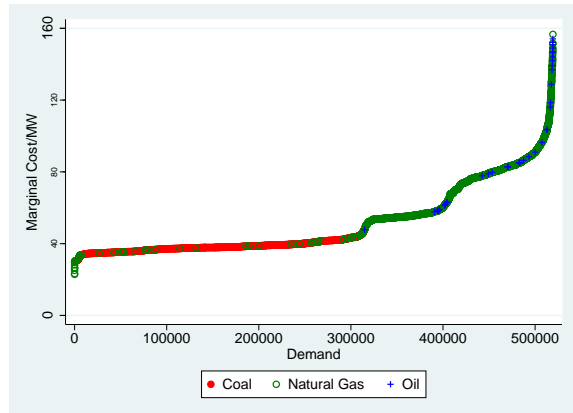
Texas Interconnection Regime 2



Western Interconnection Regime 1

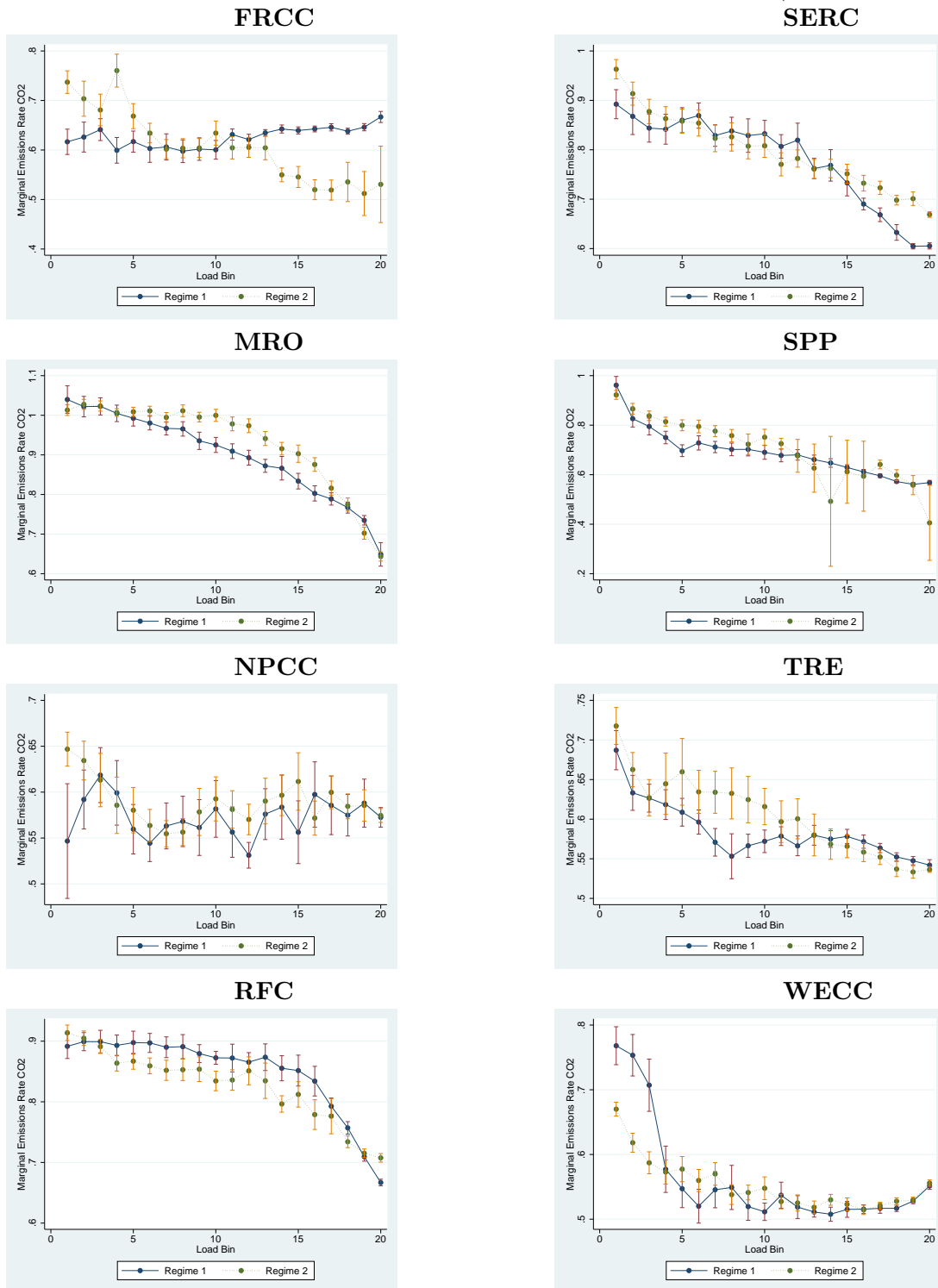


Western Interconnection Regime 2



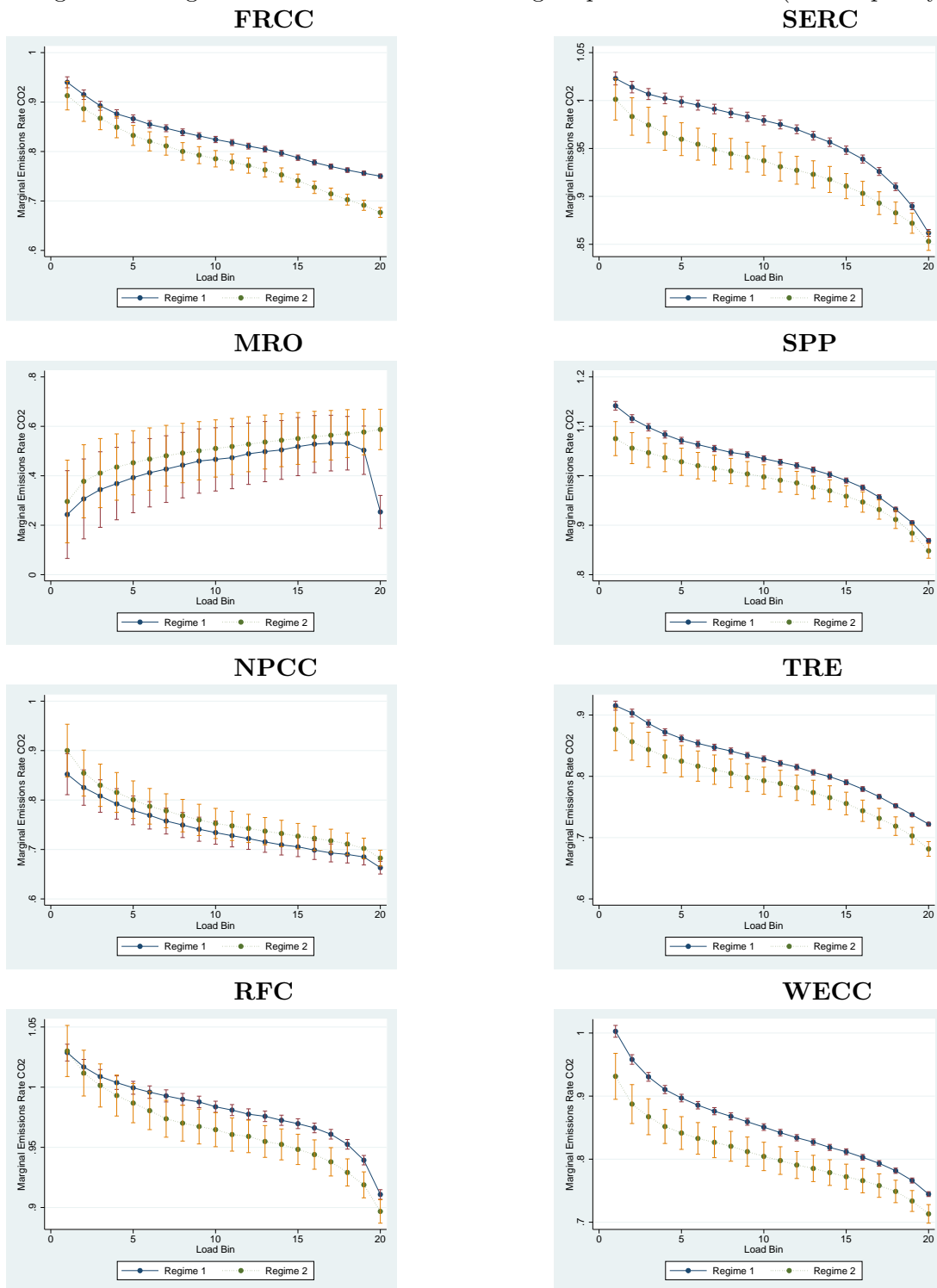
Note: Marginal cost curves by fuel type and interconnection. Regime 1 encompasses high natural gas prices and regime 2 coincides with the natural gas price fall. Generation data are from CEMS and input price data are from EIA.

Figure 8: Marginal emissions across NERC region production levels (high frequency variation)



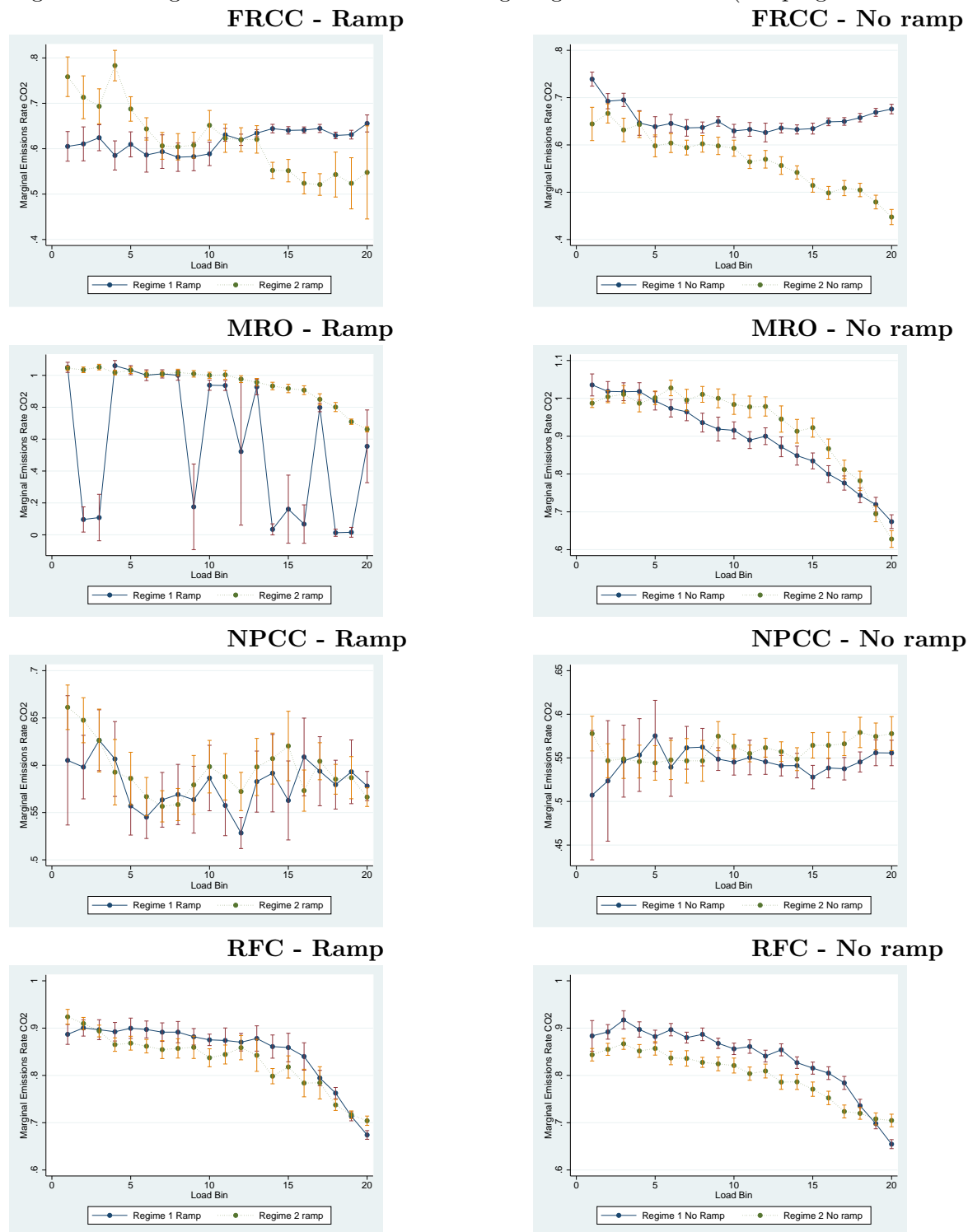
Note: Marginal emissions rates estimating using high frequency variation (first differences) across to natural gas fuel price regimes for each NERC region. Each panel displays estimates from a single regression with 61,296 hourly observations and robust standard errors.

Figure 9: Marginal emissions across NERC region production levels (low frequency variation)



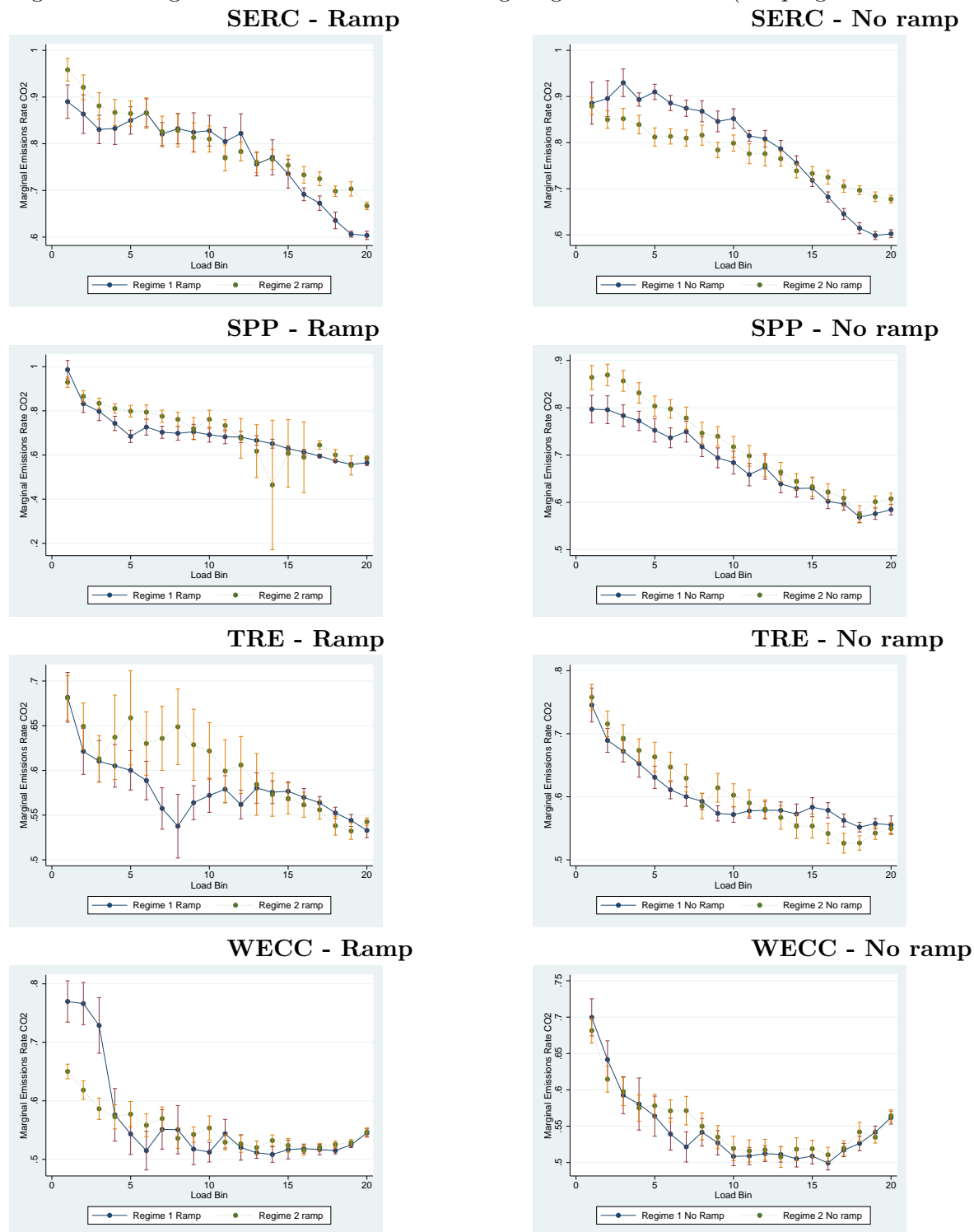
Note: Emissions intensity compared to overall emissions intensity across NERC regions. Each panel displays estimates from a single regression with 61,296 hourly observations and Newey West standard errors with 24 lags.

Figure 10: Marginal emissions across NERC region generation levels (ramping versus stable cont.)



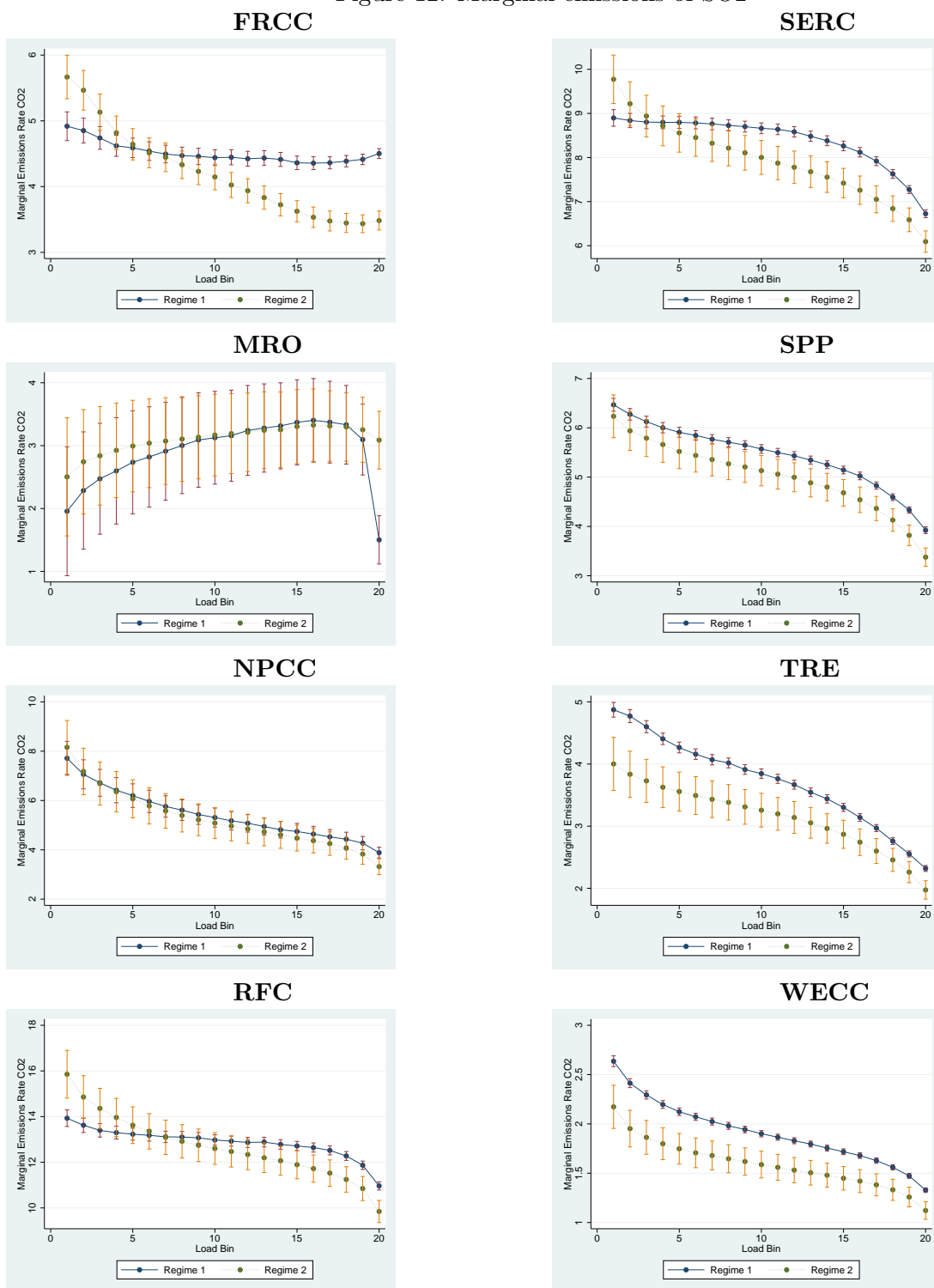
Note: Ramp rate emissions intensity compared to overall emissions intensity across NERC regions. We define the top and bottom decile of changes in generation as ramping periods and deciles 2-9 as non-ramping periods. Data from CEMS.

Figure 11: Marginal emissions across NERC region generation levels (ramping versus stable cont.)



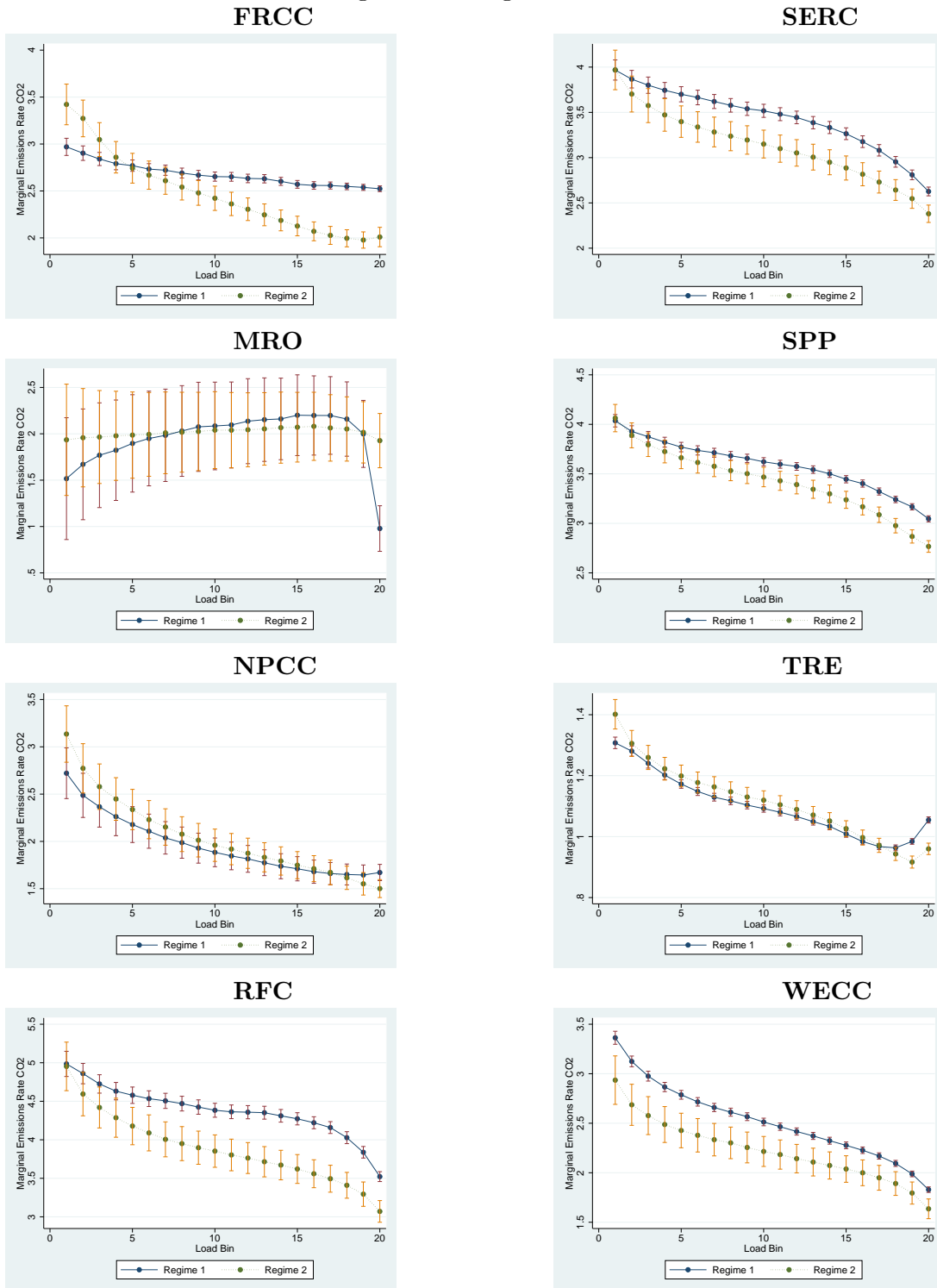
Note: Ramp rate emissions intensity compared to overall emissions intensity across NERC regions. We define the top and bottom decile of changes in generation as ramping periods and deciles 2-9 as non-ramping periods. Data from CEMS.

Figure 12: Marginal emissions of SO2



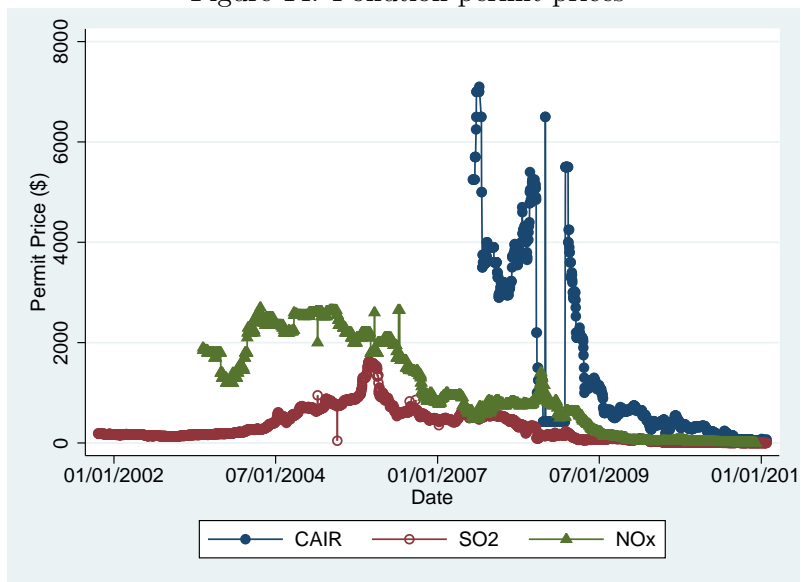
Note: Marginal emissions of SO2 across generation quantity deciles during high and low gas price regimes. Low frequency specification used. Data from CEMS.

Figure 13: Marginal emissions of NOx



Note: Marginal emissions of NOx across generation quantity deciles during high and low gas price regimes. Low frequency specification used. Data from CEMS.

Figure 14: Pollution permit prices



Note: Pollution permit prices over the study period for three tradeable permit programs. CAIR is the Clean Air Interstate Act which began trading in 2007. SO₂ and NO_x prices are part of the Clean Air Act Amendments cost containment schemes. Permit prices have fallen in tandem with natural gas prices.