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The Impact of Cheap Natural Gas on Marginal Emissions from Electricity Generation and Implications for Energy Policy

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Abstract

We use quasi-experimental variation due to the introduction of fracking to estimate the impact of a decrease in natural gas prices on marginal air pollution emissions from electricity producers. We find natural gas generation has displaced coal fired generation as the marginal fuel source significantly changing the marginal emissions profile. The impact of cheap natural gas varies across U.S. regions as a function of the existing stock of electricity generation. We demonstrate the impact of these changes on the environmental benefits of energy policy by simulating the installation wind and solar generating capacity in different regions around the U.S. We construct an hourly data set of potential renewable generation for both wind and solar power and combine that with our estimated marginal emissions. CO_2 emissions offset by wind and solar power have fallen over most, but not all of the country due to cheap natural gas.

JEL Classification: Q4, L5, Q5, H4
Keywords: energy, air pollution, climate change, natural gas

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1 Introduction

Fossil fuels account for roughly 83% of U.S. energy production despite policies aimed at increasing the share of energy produced by renewables.[1] A growing body of work evaluates emissions associated with the residential, commercial and transportation sectors (Jacobsen et al. (2012), Chong (2012), Bento et al. (2013), Kahn et al. (2014) and Allcott et al. (2014)), but electricity production both consumes the most energy and produces the most pollution of any sector in the U.S. economy.[2] Further, much of the emissions from other sectors stem from their demand for electricity. Due to its reliance on coal, natural gas and oil, the electricity sector remains the single most important source of greenhouse gasses along with many other types of pollution.

Recently, there has been a dramatic shift away from coal-fired electricity generation toward natural gas-fired generation due to the widespread adoption of hydraulic fracturing and horizontal drilling in natural gas extraction known as "fracking."[3] EIA (2012) reports that natural gas extracted in this way from shale deposits accounts for over a third of all natural gas produced in 2012 up from less than two percent in 2000. Total production of natural gas also increased by 25% over the same time frame with the increase coming entirely from shale gas extraction. This increase in production has been associated with a large decrease in market prices. Natural gas spot and futures prices peaked above $14/MMbtu in late 2005 with continued high prices through 2008 when prices began to fall rapidly as the number of fracking wells increased dramatically. By 2010 the price of natural gas had fallen below $5.00/MMbtu, where it has remained.[4] This change in price was not predicted in commodities markets: in 2008 the futures market for natural gas prices was significantly higher than realized spot market prices. McKinsey, a global

[1] As of January 2014. See Energy Information Administration data at: http://www.eia.gov/totalenergy/data/browser/xls.cfm.

[2] See http://www.eia.gov/totalenergy/data/browser/xls.cfm?tbl=T02.01&freq=m.

[3] The academic literature is beginning to evaluate the direct 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 on well-proximate housing prices.

[4] Seasonal spikes in price have occasionally led to higher gas prices, particularly in the northeast and upper midwest, but these high prices have not been sustained.

management consultancy, has suggested that the fracking boom made "a significant shift in the way we think about energy security, and the way we think about the impact of energy prices on our economy."[5]

In this paper, we identify how emissions in the electricity sector have been affected by the unanticipated price change in natural gas due to fracking.[6] To do so, we construct a large and unique data set of hourly electricity generation and pollution emissions data from the U.S. Environmental Protection Agency (E.P.A.) to estimate marginal pollution emissions from electricity production in the U.S. We use the unanticipated change in natural gas prices to identify changes in the marginal emission profile over time as a result of changes in the dispatch of electricity generation. We estimate the effect on marginal emissions due to the well-known need to account for within day variation in emissions rates to evaluate the change in emissions due to electricity sector policies (Holland and Mansur (2008), Cullen (2013), Kaffine et al. (2013), Graff-Zivin et al. (2014), Carson and Novan (2013) and Novan (Forthcoming)). We provide evidence that the natural gas price decrease was unanticipated by the markets, and therefore take our estimates for the effect of the natural gas price decrease on marginal emissions to be causal.

We use a semi-parametric econometric model with a large number of fixed effects to estimate marginal emissions for eight regions throughout the U.S.[7] We study the time period between 2005 to 2011 in our analysis for two important reasons. First, 2005-2011 saw major exogenous changes in the price of natural gas from the perspective of the electricity generators due to the emergence of fracking. Second, we are primarily interested in the intensive margin response of electricity generators for our policy experiment, which we motivate and discuss below. The 2005-2011 time period is short enough to preclude any significant increase in natural gas generation capacity due to the price change in natural

[5]McKinsey Insights and Publications interview with McKinsey partner Scott Nyquist. Available at `http://www.mckinsey.com/insights/economic_studies/the_us_growth_opportunity_in_shale_oil_and_gas`.

[6]Hausman and Kellogg (2015) focus on the market impacts of fracking. In this paper we study the impacts of fracking on marginal emissions which then affect the non-market implications of fracking.

[7]A similar identification technique has been used in other contexts to identify marginal emissions given a set of input prices by Graff-Zivin et al. (2014).

gas. We provide evidence that the decrease in natural gas prices did not spur a large increase in natural gas generation before the end of 2011.[8] As a result, we are able to isolate the causal effect of short run price fluctuations insofar as it affects the dispatch of extant generation capacity.

Our estimated marginal emissions vary dramatically across hours of the day, months of the year and regions of the U.S. Importantly, though, we focus on the change in marginal emission as a function of the relative input prices for coal and natural gas. In several regions the pattern of marginal emissions across the day switched dramatically due changes in the dispatch order of electricity generators driven by natural gas prices. We decompose the marginal emissions profile to show that observed changes are due to natural gas displacing coal-fired generation.

To demonstrate the importance of shifting marginal emissions rates on energy policy we explore the environmental benefits of renewable energy across natural gas price levels. We develop generation supply curves for wind and solar power across hours of the day, months of the year and U.S. regions. First we identify the sites in each region with the highest renewable generation potential for solar and wind generation. We then collect high frequency data on potential generation from those sites from publicly available data sources. This approach generates potential supply curves for renewable generation by source. There is significant variation in potential renewable generation across hours of the day and regions, highlighting the importance of evaluating the impacts of renewable policy using marginal emissions rates estimated by region.

We combine the estimated marginal emissions rates and potential renewable generation levels to estimate the impact of the natural gas price change on the environmental benefits of adding a small amount of renewable generation in each U.S. region. The results suggest that that inexpensive natural gas has reduced the environmental benefits of renewable generation over most, but not all of the country. Wind generation is particularly severely affected, with reduced environmental benefits ranging from 4% to 19% depending on the

[8]Including 2012 does not change the qualitative findings of our results.

region.

There is a significant literature evaluating the environmental benefits of wind generating capacity using estimates of marginal emissions rates. Kaffine et al. (2013), Cullen (2013) and Novan (Forthcoming) each estimate marginal emissions by hour and then estimate the environmental benefits of wind generation capacity in Texas. Cullen (2013) highlights the importance of dynamic effects in estimating the environmental benefits if wind generation. Novan (Forthcoming) describes the variation in environmental benefits of wind generation at different levels of demand. Each of these papers is focused primarily on the high natural gas price era or includes the high natural gas price era and the transition to the low gas era. None focuses on the impact of fuel prices on the environmental benefits of wind generation.

There is much less work on the environmental benefits of solar generating capacity. Siler-Evans et al. (2013) estimates the benefits of wind and solar renewable electricity, highlighting the regional differences in environmental and human health impacts across regions. Fell and Linn (2013) estimates the cost effectiveness of policies designed to encourage additional wind and solar generation capacity in Texas using a calibrated model of the electricity market, rather than a reduced form marginal emissions analysis. We contribute to this literature by explicitly considering how changes in natural gas price have affected marginal emissions rates and thus the environmental benefits of solar generation.

Several recent studies evaluate the impacts of the change in natural gas prices on energy policy and the environment. Holladay and Soloway (Forthcoming) estimates the impact of changes in relative fuel prices on the fuel choice and pollution emissions of New York City power plants. They find that cheap natural gas has led to rapid shifts from oil to gas fired generation associated with a nearly 2/3 reduction in SO_2 emissions. They then demonstrate this change reduces the effectiveness of real time pricing policies. Cullen and Mansur (2014) uses the fall in natural gas price to estimate how CO_2 would decrease under a carbon tax. Their results suggest that a \$10 carbon price would reduce emissions by 4%, but note that emissions reductions from a carbon tax are muted in a low natural gas price environment because coal has already largely been displace by natural gas at the lower end of the marginal cost curve.

The remainder of the paper is organized as follows: section 2 provides background on natural gas prices and electricity market geography. Section 3 describes natural gas prices and generation capacity over our study period. Section 4 introduces our data and econometric model, as well as presenting our marginal emission estimates. Section 5 introduces our renewable energy policy evaluation and provides results.

2 Background

2.1 Natural Gas Prices

Our ability to identify how marginal emissions change over time is tied to quasi-experimental variation in the price of natural gas due to the rapid expansion of horizontal drilling and hydraulic fracturing (fracking) in the U.S. in the late 2000s. 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. Horizontal drilling has been combined with hydraulic fracturing, which involves pumping hydraulic fluid underground to fracture rock formations and release oil and natural gas. Fracking and horizontal drilling, used together, allow producers to extract small pockets of natural gas that are trapped in rock formations. EIA (2012) reports that natural gas extracted in this way from shale deposits makes 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 with the increase coming entirely from shale gas extraction. Pennsylvania Department of Environmental Protection reports, for example, that the number of new Marcellus Shale wells drilled increased from roughly 200 in 2008 to over 2,000 in 2011.

Not surprisingly this increase in production has been associated with a large decrease in market prices. Natural gas prices rose significantly through the early 2000's and peaked above $14 per MMBtu in late 2005 with continued high prices through 2008 when prices began to fall rapidly. Spot market prices have been below $5 per MMBtu 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. Electric power plants are dispatched to meet demand, which is essentially perfectly inelastic, from lowest marginal cost to highest marginal cost. We show below that when gas prices were high, natural gas fired generation was used to provide peaking capacity during high demand hours while coal and nuclear fired generation served baseload.[9] 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. We provide evidence that 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. We show that natural gas price changes have significantly influenced the marginal emissions profile within a day and over space.

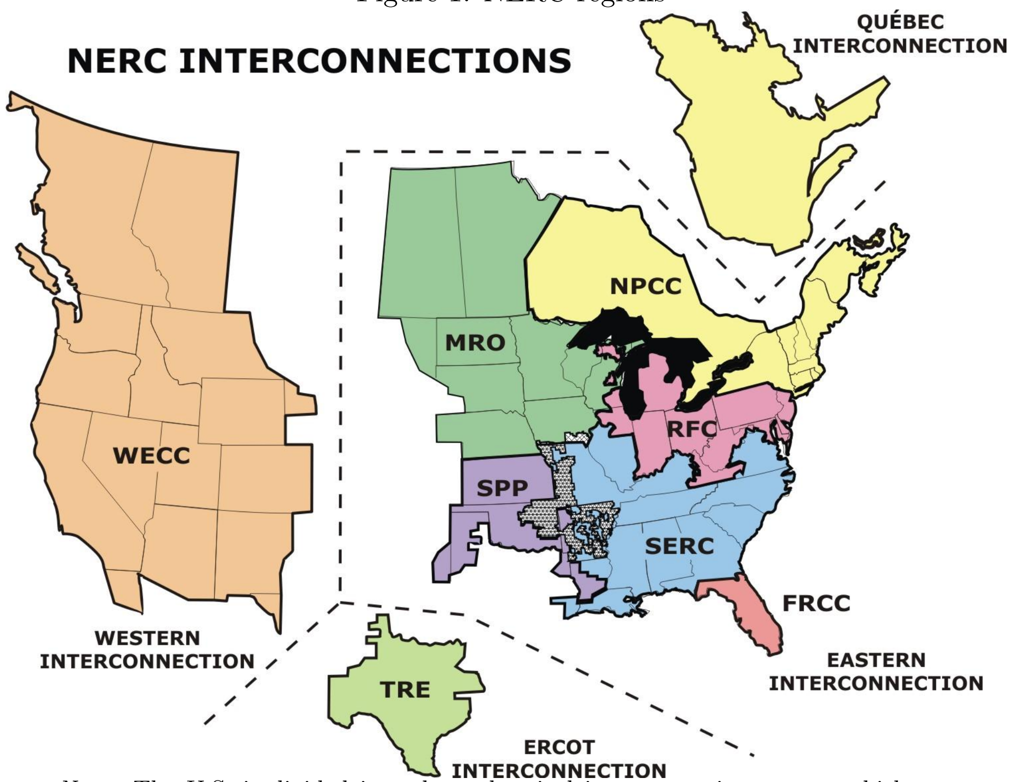
2.2 Electricity Market Geography

The National Electricity Reliability Council (NERC) breaks the country into three electrically distinct interconnections. The Eastern Interconnection, ERCOT Interconnection (essentially Texas) (TRE), and the Western Interconnection (WECC). The Eastern Interconnection is further divided into six regions across which electricity flows are small but nontrivial. The six regions, roughly from north to south, are NPCC, MRO, RFC, SERC, SPP and FRCC. Figure 1 illustrates the interconnections and regions. We follow Graff-Zivin et al. (2014) and conduct our analysis at the NERC region level. These regions represent the smallest units of geography where we can be reasonably certain that increases in renewable generation in a particular location will be offset by reductions in

[9] Oil generation also provides some peaking capacity.

fossil fuel generation in the same region. The existing mix of capacity by fuel type differs significantly across the eight NERC regions leading to significant variation in marginal emissions rates and variation in the response of marginal emissions rates to inexpensive natural gas. This variation helps us ensure that observed changes in marginal emissions rates across regimes are driven by changes in natural gas prices.

Figure 1: 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.

3 Natural Gas Prices and Electricity Generation

In this section we demonstrate that commodity markets failed to forecast the change in natural gas prices.We also show that electricity generators did not construct a significant amount of new generating capacity between the fall in natural gas prices and the end of our study period.

For ease of exposition, in this paper we divide our sample period into two regimes: a high natural gas price regime and a low natural gas price regime. This is a a natural division as we show that the drop in natural gas prices was sudden and persisted throughout the second part of our sample period.[10]

We begin our sample period in January 2005 for two reasons. It balances the sample given that we end the sample period in 2011 to focus on the short term response of electricity generators. Beginning in 2005 also avoids variation in environmental regulation. The Clear Air Interstate Rule (CAIR) Act introduced new environmental regulation for power plants in our study region.[11]

We use a Markov Switching Model to identify when the cheap natural gas era began using daily data on Henry Hub natural gas spot prices from Bloomberg, excluding weekends and holidays.[12] We estimate the following simple switching model:

$$P_{s,t} = \mu_s + \epsilon_{s,t},\ \epsilon_{s,t} \sim N(0, \sigma_s^2) \quad s = H, L \tag{1}$$

In equation (1), 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 implement 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 likelihood as the true model.[13]

The results from the Markov switching model are show in Figure 2. The top panel shows 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

[10]We present results for marginal emission estimates in which prices enter directly into the regression specification in the appendix. Those results are consistent with our preferred high versus low price regime specification.

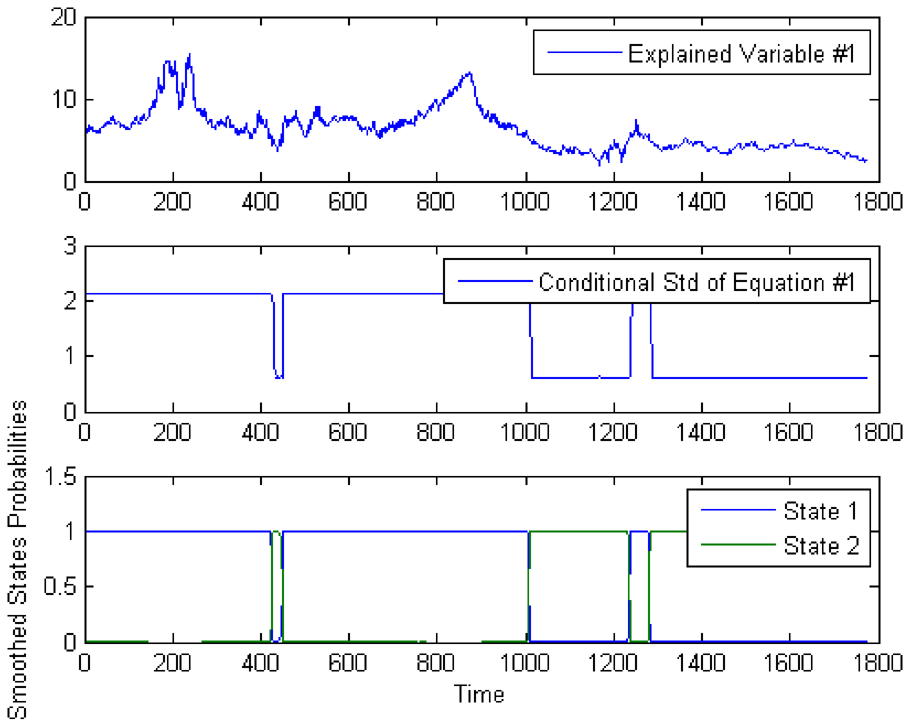
[11]The CAIR Act was litigated for nearly a decade up to and beyond the passage of the act. Discussions with industry sources suggest that generators responded before the act was implemented despite the uncertainty of its legal status.

[12]We have also estimated both a QLR and Chow test. All three models provide similar results.

[13]We employ the two dimensional solver to ensure the search algorithm does not find a local maximum. The normality assumption is motivated by the noting that the first difference of the natural gas prices looks like a white noise process.

model selects $\mu_H = 8.0$ and $\mu_L = 4.0$ as the mean natural gas prices. ρ_{11} and ρ_{22} are both precisely estimated at one. The variance across regimes are also both precisely estimated: $\sigma_H^2 = 4.463$, $\sigma_L^2 = .368$. All estimated parameters are highly significant. The relatively lower variance during the low price regime confirms the graphical depiction of lower volatility later in the data.

Figure 2: 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 and "t" indexes days (e.g., t = 1359 is January 1, 2010).

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 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.[14] 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.[15]

There is one concern with using Henry Hub spot prices. There are times of natural gas price differences across region within the U.S. often due to capacity constraints in pipelines. For example, the northeast U.S. sometimes incurs prices spikes in the winter when demand is high. However, these regional prices are highly correlated with the Henry Hub price. Further, we've estimated our main specifications removing both three and six months of data on either side of the January 8, 2009 date found in the MSM and the qualitative results do not change.[16] Those results are available from the authors upon request. Lastly, since we estimate the main econometric model at the NERC region level with a large number of time specific fixed effects, we control for these systematic differences across regions within a natural gas price region.

The more important issue for the current paper is that the drop in natural gas prices was not predicted by the market. If the drop in natural gas prices in this market was not predicted, it gives us quasi-experimental variation in input prices needed to identify the causal effect of input price variation on marginal emissions given a composition of electricity generation. We then use those estimated marginal emissions curves in order to simulate the difference in the environmental impacts of renewable generation capacity.

One convenient way to determine if the drop in natural gas prices we predicted by the market is to look at the difference between futures prices and subsequent spot prices. If these two measures diverge it is evidence that spot prices were determined by unforseen events. Figure 3 shows both spot and futures prices for natural gas (measured

[14] We 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.

[15] In an appendix we show the these results are robust to several other definitions pre- and post-fracking era.

[16] The distinction between the two regions becomes even more pronounced.

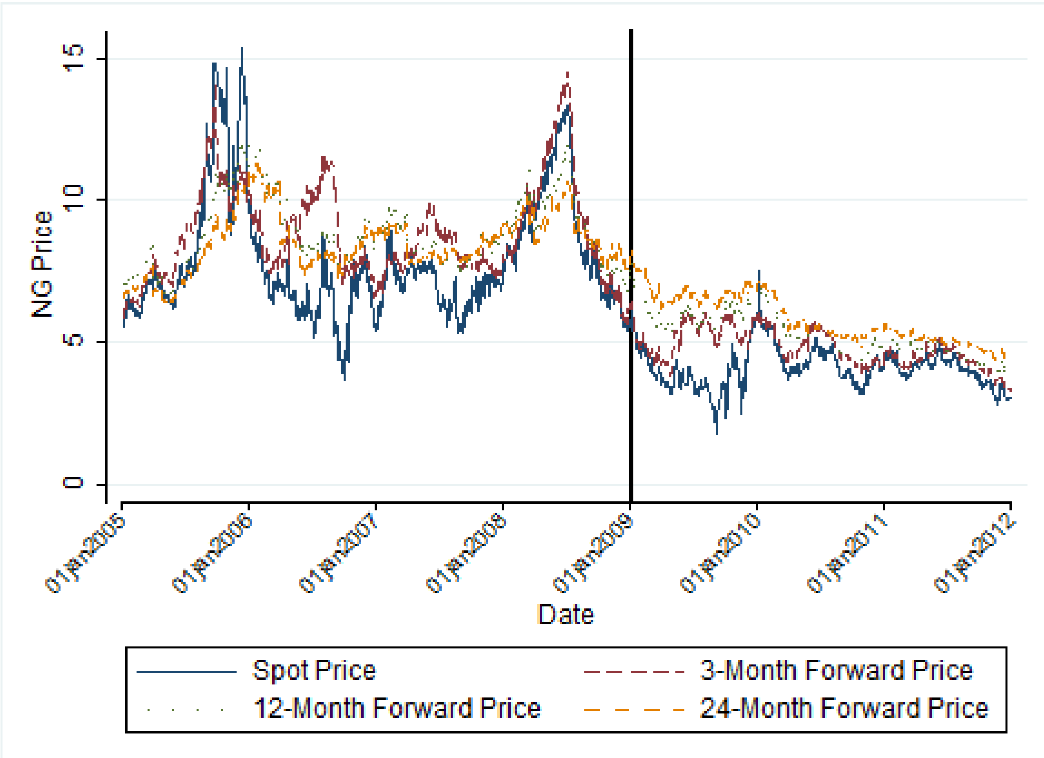
in \$/MMBtu) from January 2005 - January 2014. These data are taken from Bloomberg and show Henry Hub prices for the U.S. traded on the New York Mercantile Exchange (NYMEX). The "n" month future price is plotted on the day it was traded (rather than the date it was scheduled to be delivered). As a result, Figure 3 should be interpreted as follows: when the "n" month futures price lies directly on top of a spot price it means that the market expects the price of natural gas to be exactly the current spot price in "n" months. As a result, if the 6-month futures price was above spot price on a given date, it means that the market expects the price of natural gas to be higher than the current level in six months.

Figure 3 shows that in the second half of 2008 and through 2009, futures prices were significantly higher than spot prices for natural gas. Put another way, the markets expected that natural gas prices were going to be higher in the future rather than lower. Specifically, in late 2008, the 18 month future contract of natural gas was not significantly lower than the spot price, which ranged from \$9 to \$5.50. We take figure 3 as evidence that electricity generators could not have predicted the sustained period of low natural gas prices and built new capacity within our study period.

Figure 3 provides convincing evidence that the decrease in natural gas prices was not predicted in commodities markets. It is still possible, though, that electricity generators could quickly respond to decreases in natural gas prices once they do fall. If natural gas capacity expanded, this would be problematic for our study: it would mean that determining environmental impacts of renewable energy capacity is due to a mix of intensive and extensive margin responses. We isolate the intensive margin effect since investments in renewable capacity are often slow moving and long-lived and do not quickly respond to changing market conditions, even if economic agents interacting with the electricity market do. As a result, isolating the intensive margin response is important given our research question.[17]

[17] Another identifying assumption we need is that generation supplied by hydroelectric and renewable sources does not systematically change with natural gas prices. This is likely true given that hydroelectric dispatch responds to electricity demand, which is inelastic, and renewable generation is a function largely of weather, which is exogenous.

Figure 3: Future Versus Spot Prices for Henry Hub Natural Gas Prices



Note: Figure plots spot and futures close of trading prices for natural gas delivered at the Henry Hub terminal traded on NYMEX. Data are plotted by day the contract is written. For example, a 12 month futures contract plotted on July 1, 2008 is for natural gas to be delivered on July 1, 2009. Vertical line represents Jan. 8th 2009, the date of the regime shift described above. Figure shows during the fall in natural gas prices, futures contracts were not significantly lower than spot prices.

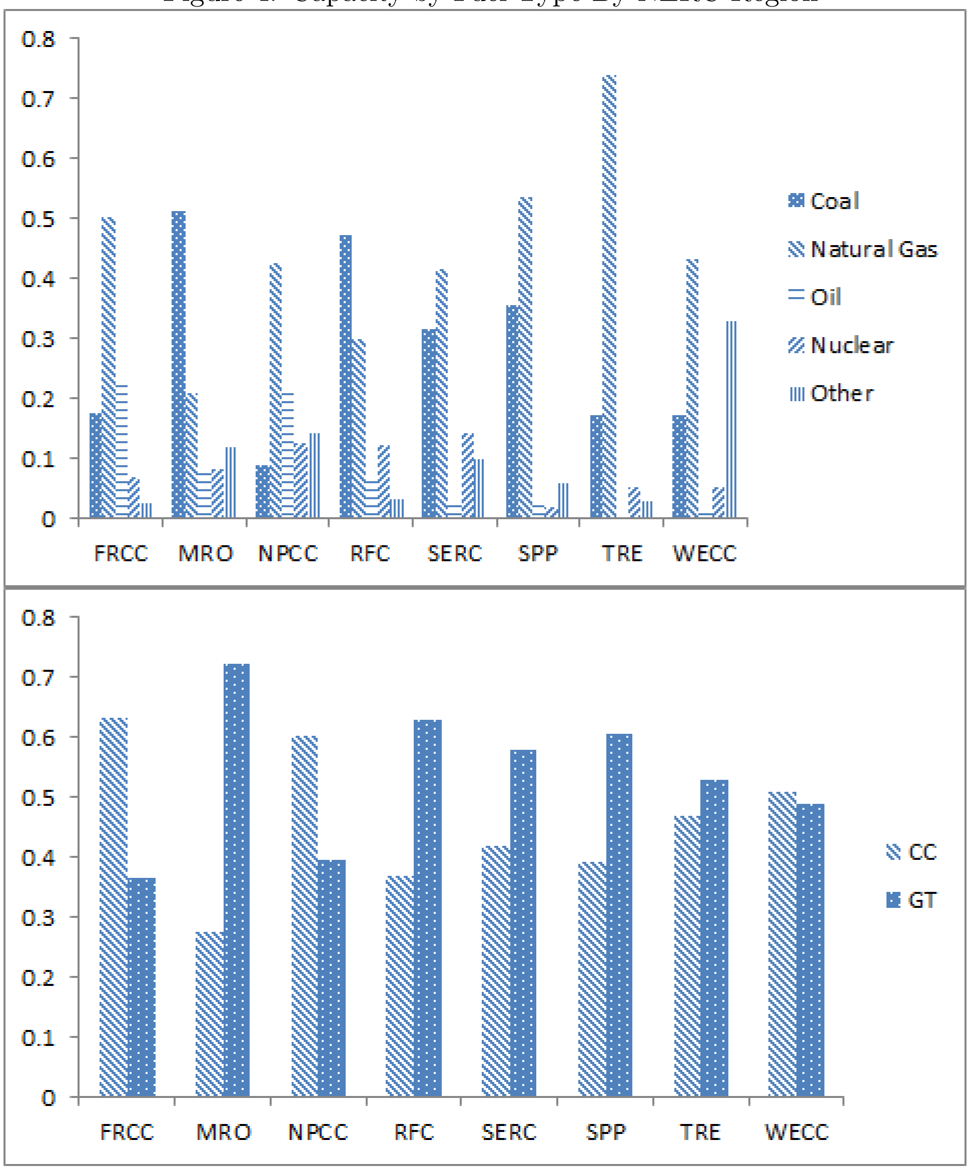
The EIA provides data that contains information on nameplate capacity by fuel type and generator type. Importantly, there is significant variation in electricity generation capacity by source. Figure 4 shows total installed capacity as of 2006 by fuel type as a percent of total capacity by National Electricity Reliability Council (NERC) region. The top panel demonstrates that different areas had significant heterogeneity in capacity for generation of different fossil fuel generation. For example, MRO (upper midwest) and RFC (Ohio Valley to New Jersey) had a large amount of coal relative to FRCC (Florida) and TRE (Texas) which had significant natural gas capacity.[18] The bottom panel shows breaks down 2006 natural gas capacity by generator type. Combined cycle (CC) capacity is significantly more efficient than gas turbine (GT) generation (EIA (2012) Table 8.2). As a result, it is reasonable to expect areas with significant CC natural gas capacity (FRCC and NPCC) to respond in different ways to the change in natural gas prices than less combined cycle capacity (e.g., MRO).

Figure 5 summarizes changes in electricity generation capacity from 2005-2011. Natural gas capacity increased by roughly 6.5% over this time period and Figure 6 shows that much of this increase was in Florida. The figure shows that increases in natural gas capacity were occurring during the study period but the rate of change in natural gas generation was roughly constant when futures markets began to predict decreases in natural gas prices in 2009.[19] If natural gas capacity where to have increased in response to decreased natural gas prices observed in 2009, then there would be a significant increase in the growth rate of installed capacity in 2010 or 2011. Instead we observe no significant deviation from the pre-trend growth rate. Coal and nuclear fueled electricity generating capacity is constant and oil fueled capacity drops by twelve percent. Total generating capacity increases by nearly four percent from 2005-2011 (compared to nine percent from 2002-2005). To put Figure 5 into context, total electricity demand was flat to decreasing over this time period.

[18] The west region WECC has significant hydroelectric power capacity as indicated by the "other" category.

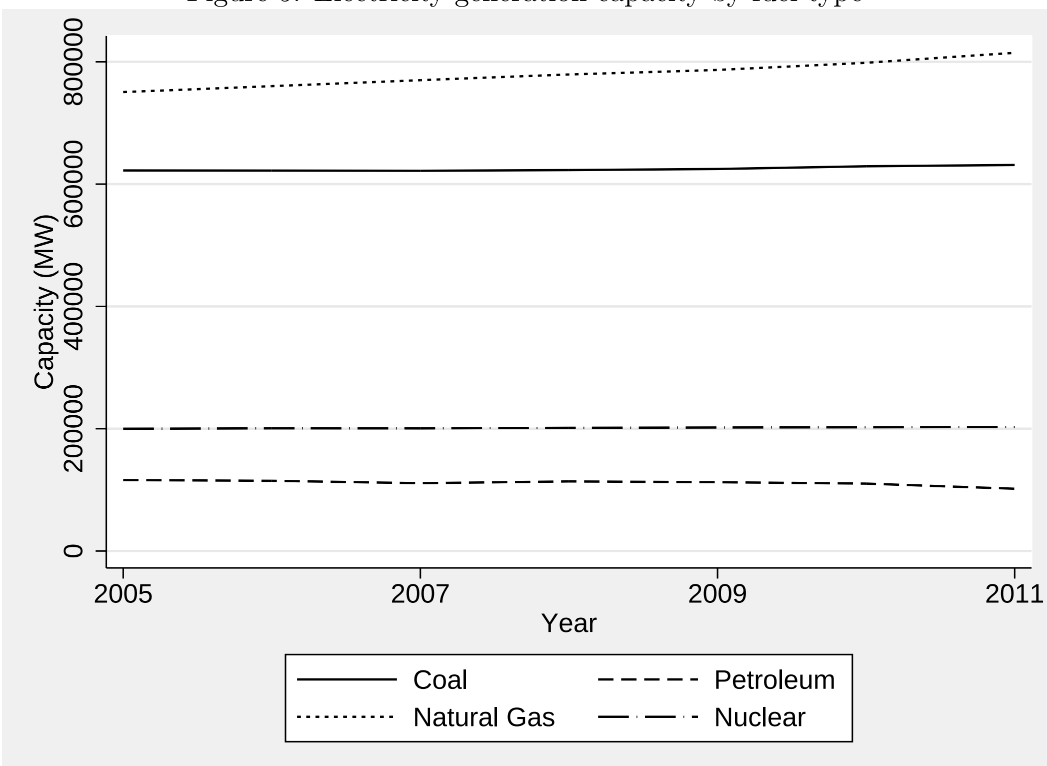
[19] While beyond the scope of this paper, the increase in natural gas capacity may be due to the implementation of air quality trading rules such as CAIR in the eastern U.S.

Figure 4: Capacity by Fuel Type By NERC Region



Note: Top panel shows 2005 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 860 and 923.

Figure 5: Electricity generation capacity by fuel type



Note: Electricity generating capacity measured in megawatts in the U.S. by fuel type from 2005-2011. Natural gas capacity increased by roughly 6.5% over this time period. Figure 4 shows that much of this increase was in Florida. Importantly, there was no change in the rate of increase in natural gas capacity over our study period. Source: Energy Information Administration Electricity Database (http://www.eia.gov/electricity/data.cfm#gencapacity).

Figure 6 shows the spatial distribution of the increase in natural gas capacity between January 2007 and December 2011 taken from the EIA 860 and 923 forms. We limit the increase in capacity from 2007-2011 since it is entirely implausible that futures market predictions could have affect increases in natural gas capacity in 2005 or 2006. Units are displayed in 1000s of MWs.[20] Figure 6 shows that much of the increase in capacity took place in Florida (FRCC) with more modest increases elsewhere. We show below that Florida had the largest share of oil-fired generation throughout the mid-2000s in the U.S. While beyond the scope of this paper, as oil prices rose in the mid-2000s the incentive to build new more efficient natural gas price may have been sufficient to motivate new investment. In sum, then, Figure 5 and Figure 6 show that there doesn't appear to be any large increase in installed natural gas fired capacity before December 2011. There is no evidence that there was any systematic increase in coal power plant retirements over the same period; even in 2012 after the industry had an extra year to respond to cheap natural gas net coal plant retirements were less than 8,000 MWs in capacity for the entire nation.[21] We take this as evidence that our empirical strategy isolates the intensive margin response of the electricity sector to decreased natural gas prices.

Lastly, Figure 7 shows the monthly generation electricity by fuel type by NERC region aggregated from EPA's hourly CEMS generation data. To construct Figure 7 we merge in NERC region identifiers from the EIA 923.[22] It is clear that in areas with significant coal generation, the share of coal generation relative to natural gas decreased toward the end of the sample once natural gas price dropped. The figure shows that natural gas generation increased over the same time period. This is consistent with natural gas generation moving further down in the dispatch order. The goal of the remainder of the paper is to show how this relative input price change affected marginal emissions and how those changes affect

[20] According to census and DOE data, per capita electricity use is .0014 MWs/hour. 1,000 MWs implies that there is enough power to supply 714,285 people with their average electricity or a bit more than .5% of the U.S. population.

[21] See http://www.eia.gov/ Annual Electricity Summary Table 4.6 "Table 4.6. Capacity Additions, Retirements and Changes by Energy Source, 2012 (Count, Megawatts)".

[22] In the few cases where matching was impossible due to mismatched or incomplete ORISPL codes, we matched plants in the CEMS data to NERC regions manually.

Figure 6: Change in natural gas capacity between 2007-2011

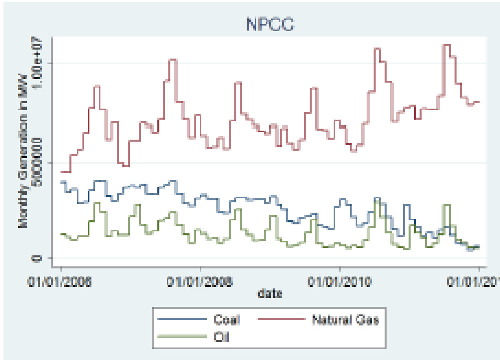
Note: Change in natural gas capacity between 2007 and 2011. Circles are located at the centroid of counties. Radius of circle corresponds to size of total change in natural gas capacity in each county. All data from EIA.

the welfare effects of second best policies.

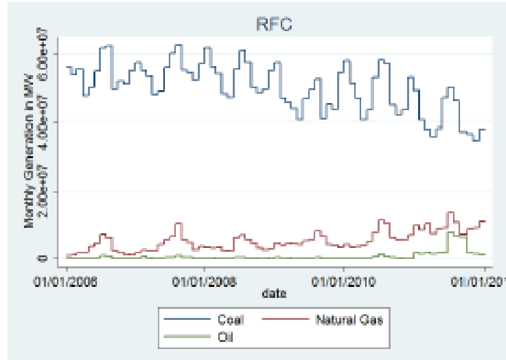
4 Estimating Marginal Emissions

In order to estimate hourly marginal emissions by U.S. region, we need hourly data on electricity generation and emissions. Fortunately, hourly data on fuel consumption, electricity production and pollution emissions for power plants are available through the EPA Clean Air Markets program. As a result, we observe hourly generation and emissions for almost all electricity generating units in the U.S. over our sample period. This allows us to estimate marginal hourly emissions and marginal fuel source. This section discusses our data and econometric specifications for estimating marginal emissions by hour and natural gas price regime.

Figure 7: Monthly Generation by Fossil Fuel



(a)



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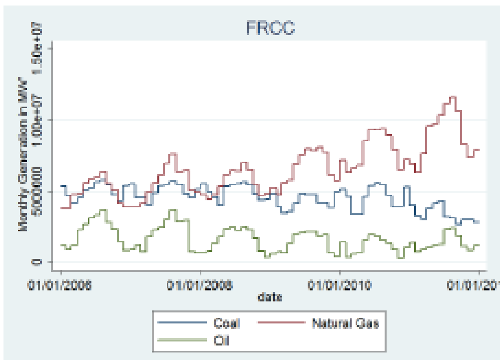

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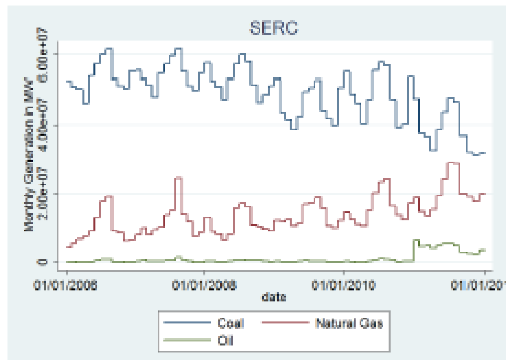

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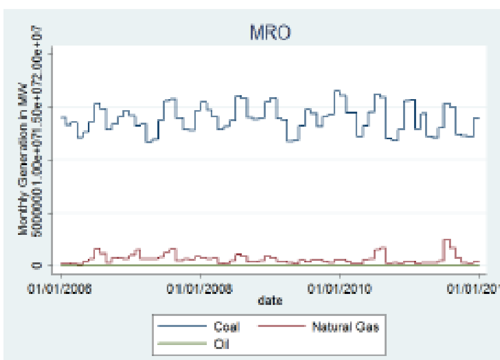

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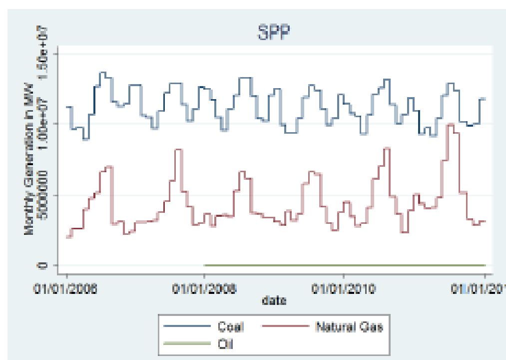
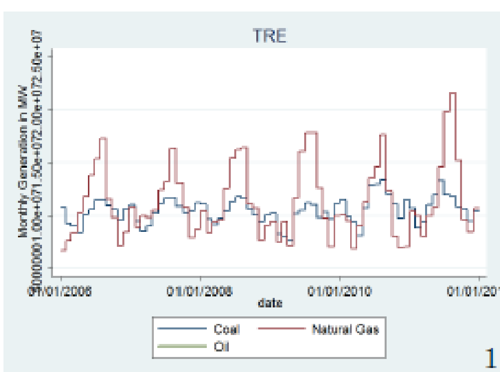
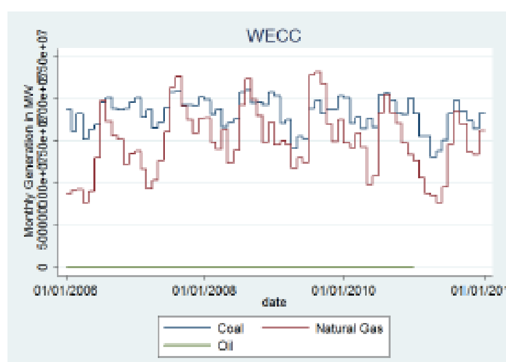


(f)



(g)



(h)

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

4.1 Data

Electricity generating units at every fossil fuel burning power plant with a capacity of greater than twenty-five MWs must install a Continuous Emissions Monitoring System (CEMS). The systems sample power plant smokestack air frequently to calculate the amount of SO_2, NO_x and CO_2 emissions.[23] The data is primarily used by EPA to confirm that plants are complying with their obligation to purchase pollution permits in the SO_2 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 of the facility. The data set does not include nuclear, hydroelectric or renewable generators, but these producers have low or zero marginal costs and no air pollution emissions so we exclude them from the analysis. From the perspective of our policy simulation, though, this is precisely the marginal emissions estimate we wish to consider.[24]

The combined U.S. data set consists of approximately 4,600 generating units (the number varies slightly over the sample period) at over 1,200 facilities. Each unit 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 unit in the data set. We follow Graff-Zivin et al. (2014) by aggregating data to conduct our analysis at the National Electricity Reliability Council (NERC) region level to ensure that we are able to identify the marginal fuel for changes in demand within regions.

4.2 Econometric Specification

We estimate a fixed effects model to identify marginal emissions across both the high and low natural gas price regimes. The specification employs a semi-parametric approach to

[23] CO_2 emissions are imputed for fossil fuel fired power plants based on fuel inputs.

[24] The dataset also excludes a portion of gross generation from combined cycle units. We are not aware of any work which addresses the magnitude of this missing generation. The data, though, do contain the appropriate level of emissions from these units.

estimate marginal emissions over hours of the day and months of the year. We call this a semi-parametric approach because we estimate marginal emissions separately for each hour of the day. We include a wide variety of fixed effects to control from ramping effects, day of week effects and year of sample. We also restrict each sample to a single NERC region in a single month of the year. We estimate:

$$E_h = \beta_{h,r}(gen_h * hour_h * regime_r) + \gamma_{h,y,r}(year * hour * dow) + \epsilon_{h,n} \tag{2}$$

In equation (2) m indexes the month of year and n indexes NERC region. E_h represents aggregate hourly CO_2 emissions measured in tons for all generators in a NERC region. The gen_h variable describes the total hourly fossil fuel generation in a NERC region, h indexes hour, m denotes month of year and $regime_r$ is a variable indexing whether the observation occurs within the high or low natural gas price regime. The γ vector is a set of year-by-hour-by-day of week fixed effects.[25] Carson and Novan (2013) highlights the variation in marginal emissions across seasons so we estimate this equation separately for each month of year, m=1,2,3 and n=FRCC, MRO, each of the eight NERC regions.[26] To address serial correlation concerns we report standard errors clustered by date.[27]

Gas fired power plants purchase much of their fuel on spot markets, but some employ longer term contracts. Most coal is purchased using long term contracts. Even though the spot market price of natural gas decreased starting in early 2009, the average relative price paid by electricity generators may have taken longer to adjust.[28] Using the high versus low price regime, as opposed to including prices directly in the estimating equation, avoids the the issue.

The coefficients of interest in equation (2), $\beta_{h,r,m}$, represent the average hourly marginal

[25]Each NERC region by month regression has 12*24*7=2016 fixed effects.

[26]Alternatively we could have estimated the model on a sample pooled across NERC regions and months which would have increased the efficiency of the estimation. However the estimates from the restricted sample are fairly precisely estimated and pooling the full sample leads to some computational burdens.

[27]We also explored using a dynamic estimating equation including by including lagged generation as in Cullen (2013), but find this makes little difference in the point estimates on the marginal emissions rates. For simplicity we report the static results here.

[28]The timing of spot input price change pass through is an important question in its own right but that we leave to future work.

emissions in an hour for a natural gas price regime for a particular month. Comparing coefficients in an hour across regimes reveals the changes in marginal emissions between the high and low natural gas price regimes. Using the complete set of fixed effects in equation (2) is important: our coefficient estimates are identified from variation in emissions for the same hour of the day for the same month-year in the same day of the week within a natural gas price regime.[29] For example, variation in emissions on Mondays in March at 8am in 2007 contributes to our identification of the coefficient on $\beta_{8,1,3}$.

We then estimate the fuel source at the margin for each NERC region across the high and low natural gas price regimes following a procedure described in Carson and Novan (2013). We estimate the following specification for each fuel type in each NERC region:

$$Gen_{h,f} = \beta_{h,r,n,f}(gen_{h,f} * hour_h * regime_r) + \gamma_{n,f}(month * year * hour * dow) + \epsilon_{h,f} \quad (3)$$

where f denotes fuel type (oil, natural gas or oil). $\text{Gen}_{h,n,f}$ represents the generation from a particular fuel type during a given hour in a NERC region whereas $\text{gen}_{h,n}$ represents the total generation during a given hour in that NERC region. The coefficients of interest, $\beta_{h,r,n,f}$, therefore represents each fuel's share of marginal generation during hour h. Changes the composition of marginal fuel across natural gas price regimes can be directly attributed to changes in operating costs of the various fuel types since changes in input prices directly affect the marginal costs of generation and therefore the dispatch order of electricity generation by fuel type.[30]

[29]Our specification also allows differences in load for the same hour will identify our coefficient $\beta_{h,r,m}$. As a result, the level of load in a particular hour is not crucial in our identification. This alleviates concerns about possible bias emerging from changing levels of generation within an hour over time (e.g., due to the recession) influences coefficient estimates in any significant way. To further show this recession effect is not a concern, in the appendix we estimate the same specification without July 2008-June 2009 and find almost identical results.

[30]The marginal costs of operating a fossil fuel plants could also be affected by environmental regulation. In an appendix we should that the costs of complying with the Clean Air Act Amendments emissions trading programs dropped during the low natural gas price regime. That suggests that the relative change in input prices across regimes actually overstates the relative costs changes and our estimates should be considered a lower bound on the impact of the natural gas price change alone.

4.3 Results

In our results section, we report regression coefficients in figures. Each model includes seven years of hourly data and thousands of fixed effects. All of our coefficient estimates are highly significant by traditional measures. Regression output is available from the authors upon request.

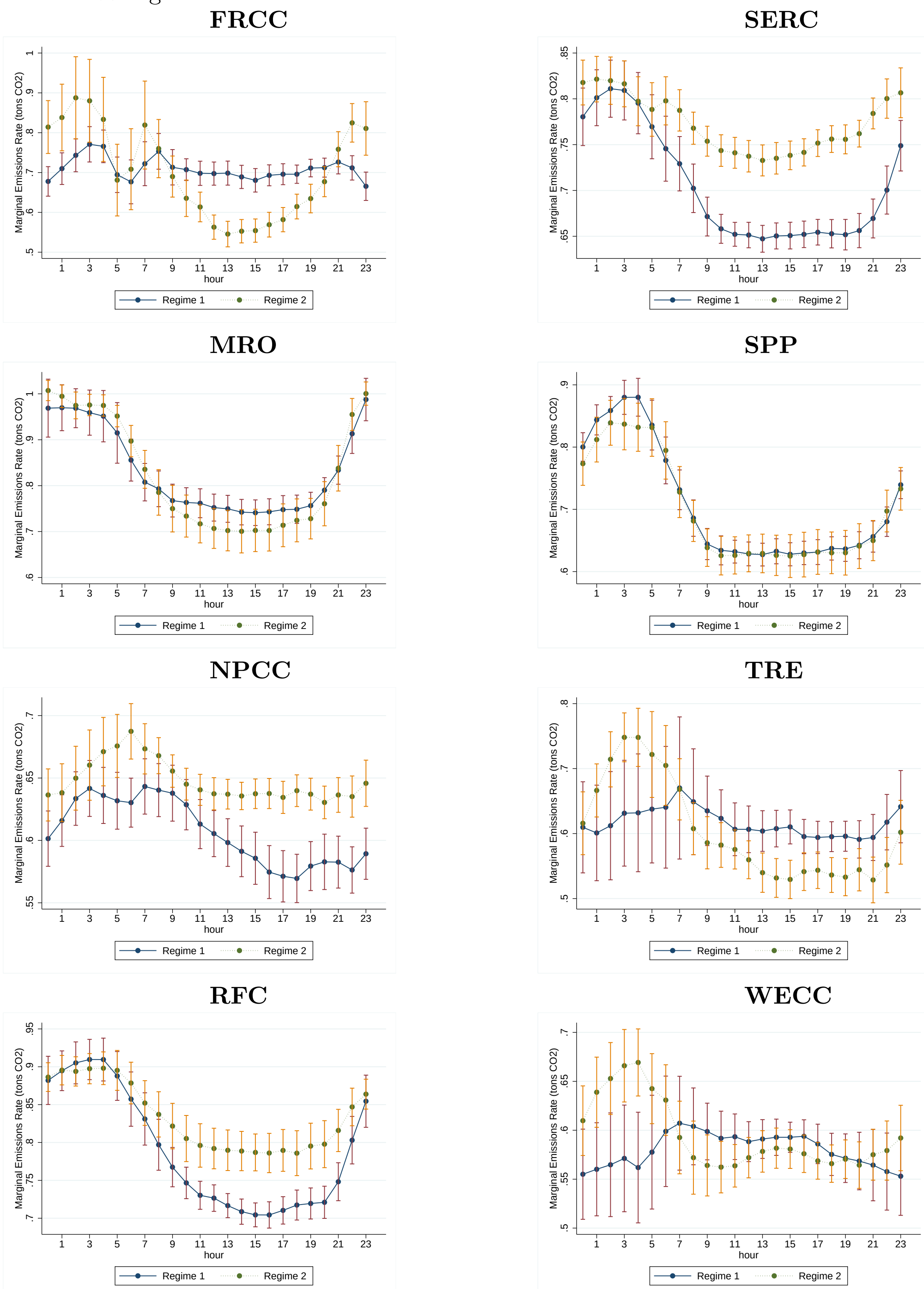
Figure 8 reports the estimated marginal emissions rate by hour for both the high and low natural gas price periods. Each panel represents a single NERC region in August. In each panel, there are two lines that represent the marginal emissions rates in each hour for a given natural gas price regime. On each line there are twenty-four point estimates of the marginal emissions rates with error bars representing the 95% confidence interval range. Each of the 48 regression coefficients reported in a panel of figure 8 are estimated from a single regression of CO_2 emissions on generation levels interacted with hour of the day and natural gas price regime indicators as described in equation 2.

Figure 8 reveals significant variation in marginal emissions rates across three dimensions: hour of day, NERC region and across natural gas price regimes. Additionally across NERC regions the change in marginal emissions rates across natural gas price regimes differs significantly. There are two (rough) patterns that emerge. In RFC, SERC and SPP low natural gas prices have flattened the marginal emissions curve across the day. During the regime 1 (the high natural gas price era) marginal emissions are typically at their highest over night.

In FRCC, TRE and WECC the pattern is essentially reversed. During regime 1 the marginal emissions curve is relatively flat across the day. During regime 2 marginal emissions increase significantly during overnight hours and fall over peak demand hours. NPCC is somewhat of an outlier with marginal emissions rates shifting up fairly consistently throughout the day during regime 2. MRO has very little natural gas fired capacity and sees very little change in marginal emissions rates.

Figure 9 displays the results across months for RFC to highlight an additional source of variation in marginal emissions rates: across load levels proxied by month of year. Again the impact of changing natural gas prices on marginal emissions rates varies significantly.

Figure 8: Marginal emissions across natural gas price regimes for August by hour of day and NERC region



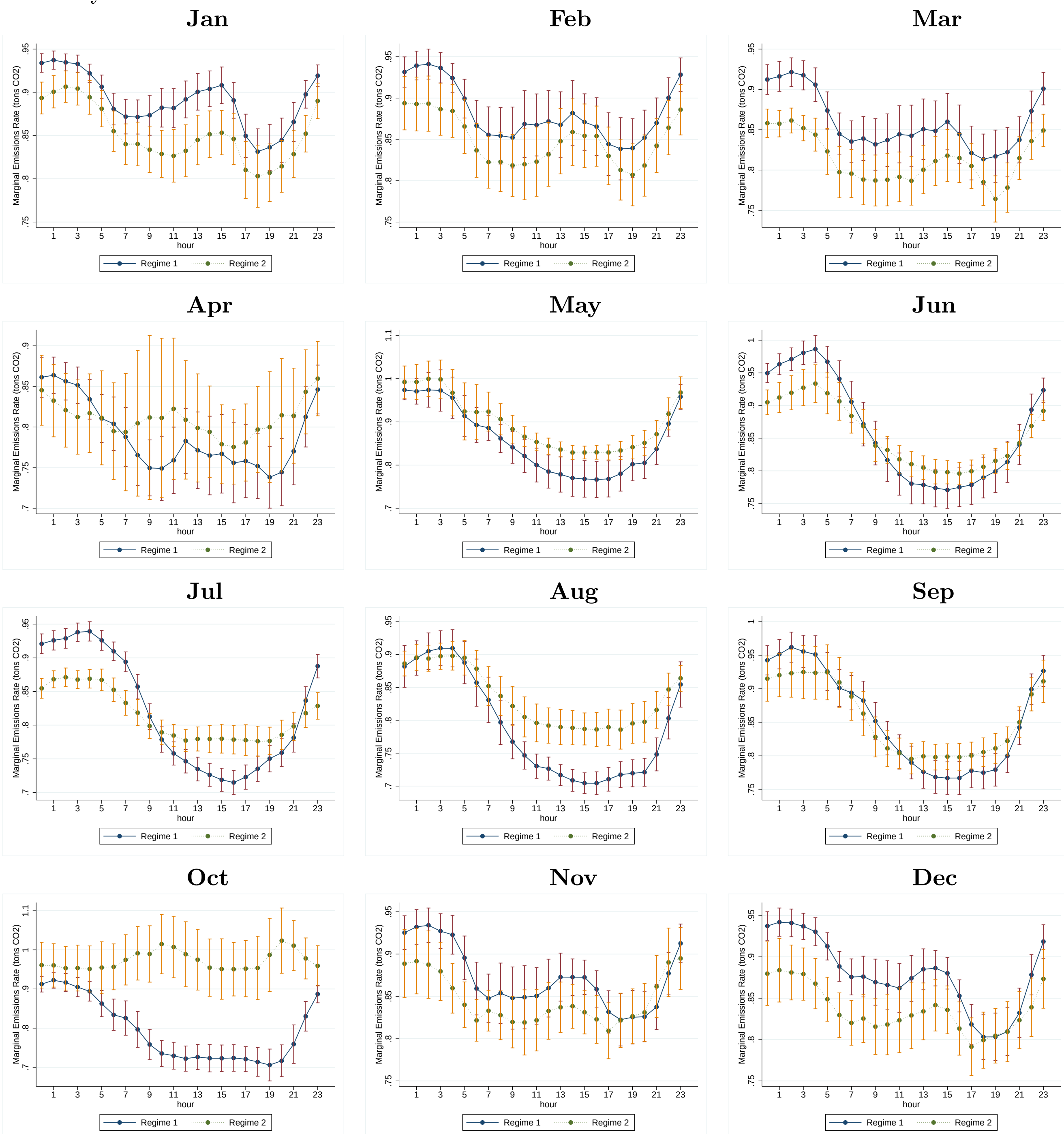
Note: Marginal emissions rates for CO_2 across natural gas fuel price regimes for each NERC region. Each panel displays estimates from a single regression with 61,296 hourly observations and robust standard errors. Regime 1 represents Jan 2005 - Jan 2009 and Regime 2 represents Jan 2009 - Dec 2011. Note that each panel is graphed on its own vertical axis to highlight the difference across fuel price regimes.

Each panel represents a single month of the year and the 48 regression coefficients are estimated from a single regression of CO_2 emissions on generation interacted with hour of the day and natural gas price regimes on a sample restricted to a single month. Changes in natural gas prices across regimes have clearly led to changes in marginal emissions rates, but the impact varies by hour-of-day and month-of-year. In winter months (November-March) marginal emissions rates have undergone a level shift downward. During the summer marginal emissions rates are slightly lower during the evening hours and higher during the highest demand hours of the day. Cheap natural gas has made the hourly marginal emissions profile smoother. In May and October the marginal emissions rates have undergone a level shift up and marginal generation is dirtier in the cheap natural gas era. The results are consistent with Novan (Forthcoming) and Carson and Novan (2013) that highlight variation in marginal emissions rates across generation levels and seasons for TRE.

The variation in marginal emissions rates across natural gas price regimes is clearly statistically significant for many of the month-hour pairs. Some hours see increased emissions rates and other decreases. These changes vary systematically across demand levels with are proxied by months. From the individual estimates of marginal emissions rates it is not obvious that the observed changes are economically or environmentally significant. Considered as whole, though these results suggest that changes in natural gas price have had a significant impact on the marginal emissions profile and that the impact is heterogenous in several dimensions.

Next we estimate equation 3 for each NERC region and find the fraction of time each fuel is on the margin by hour for each input price regime. The results for August are reported in Figure 10. We restrict the sum of the coefficient point estimates to be one in the estimation procedure, although relaxing that assumption does not significantly change the qualitative results. All point estimates are highly significant and they are very often significantly different across hours within a price regime. Each panel represent a single NERC region. Within each panel there are two graphs, each with twenty-four stacked bars that sum to 1. The left graph is displays the fraction of time each fuel is on the

Figure 9: Monthly marginal emissions in RFC across gas price regimes, hour of day and month of year



Note: Monthly marginal emissions rates for CO_2 across natural gas fuel price regimes for the RFC NERC region. Each panel displays estimates from a single regression with 61,296 hourly observations and robust standard errors clustered by day of sample. Lines connect marginal emissions rates for the expensive (regime 1) and cheap (regime 2) natural gas price eras in our data.

margin in the high natural gas price regime and the right graph presents that fraction for low natural gas regimes. As in estmiating marginal emissions rates, all coefficients are generated using one regression per NERC region with a sample restricted to the month of August.

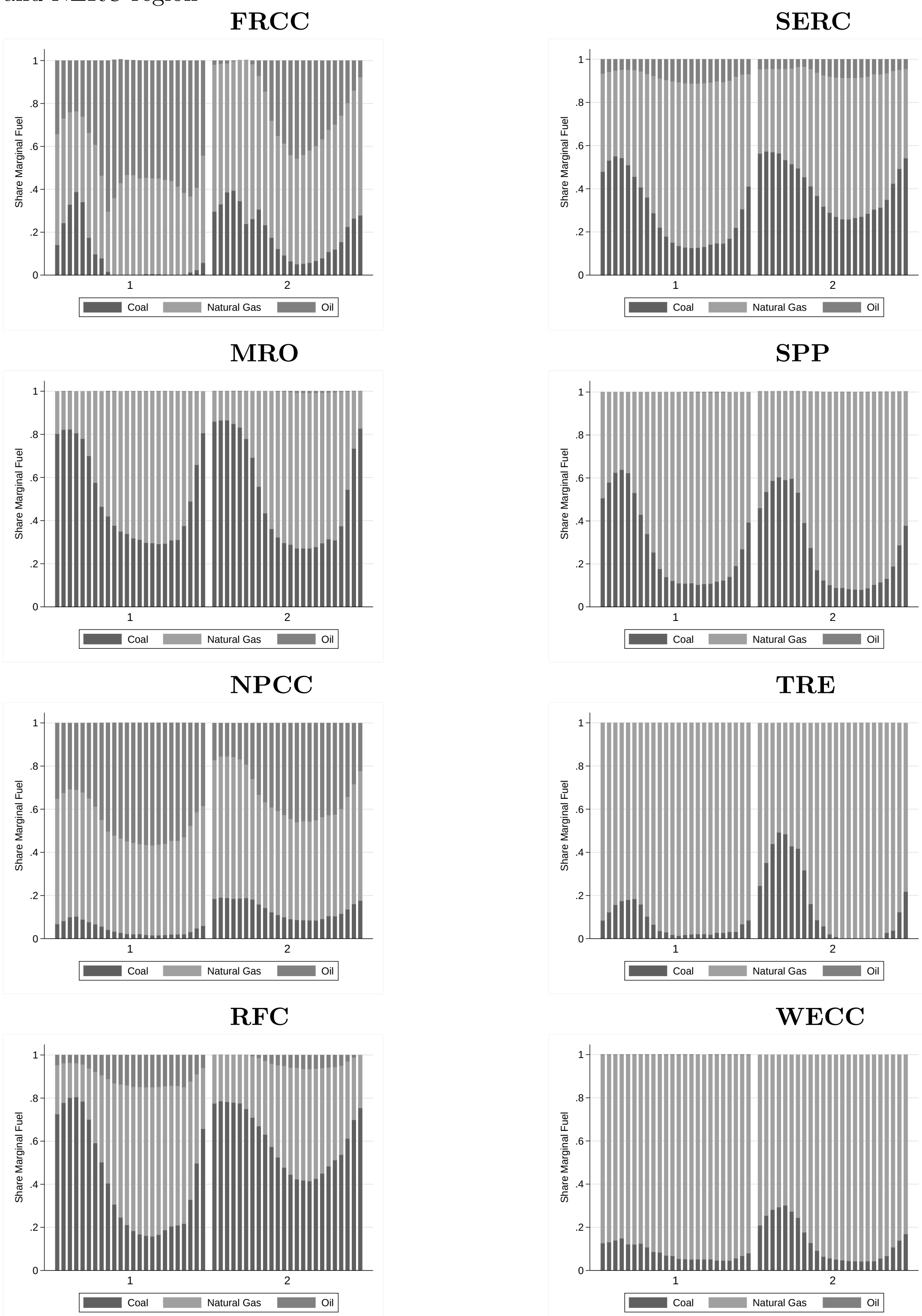
Changes in the percentage of a particular fuel on the margin and that fuel's emissions intensity are consistent with the estimated changes in marginal emissions rates. In the northeast (NPCC) and Florida (FRCC), both of which have significant oil fired capacity, oil generation is less likely to be on the margin during the low natural gas price regime. As natural gas fired generation becomes less peak following in each region the variation in the fuels on the margin within a region, by hour, drops and the marginal emissions profile across the day flattens. In other results, not reported here, we find no significant change in marginal emissions rates of a particular fuel type. As a result, we conclude that the changes in marginal emissions appear to be driven by changes in marginal fuel type. We argue marginal fuel type is in turn driven largely by the change in natural gas prices across the two regimes.

4.4 Discussion

The pattern of marginal emissions across the day and the change in marginal emissions between fuel price regimes appears to largely be driven by the mix of fuel capacities. Specifically the regions with flatter intra-day marginal emissions curves during the second natural gas price regime have more natural gas capacity and more combined cycle natural gas capacity in particular. These efficient natural gas units displace even moderately productive coal plants at low natural gas prices and become infra-marginal. The effects of this displacement vary significantly with the amount of coal and oil generation capacity available.

During regime 1 in RFC, SERC and SPP for overnight hours demand is low and high cost natural gas generators are not employed. Marginal changes in demand are served through coal leading to relatively high emissions rates. During peak demand hours marginal emissions rates fall as higher cost, relatively clean, natural gas is brought online to

Figure 10: Marginal fuel type across natural gas price regimes for August by hour of day and NERC region



Note: Marginal fuel by hour and natural gas price regime. Regime 1 represents the high natural gas price era, Jan 2005 - Jan 2009 and regime 2 represents the low natural gas price era, Jan 2009 - Dec 2011. We restrict the sum of the coefficient point estimates for fuels within a regime to be 1 in the estimation procedure. All point estimates are highly significant. Standard errors are clustered at the day level of sample level.

meet high levels of demand. During regime 2 cheap natural gas has displaced other fuels, primarily coal to serve baseload. This reduces the marginal emissions rates during the overnight hours. Because much of the natural gas capacity is dispatched to sere baseload, less is available to meet increases in demand over peak hours. This requires relatively more coal and oil generation to be ramped increasing marginal emissions rates. The new dispatch pattern flattens the marginal emissions curve throughout the day.

In FRCC, TRE and WECC the pattern is essentially reversed. During regime 1 the marginal emissions curve is relatively flat across the day. During regime 2 marginal emissions increase significantly during overnight hours and fall over peak demand hours. In all three regions coal is proportionally more on the margin during the overnight hours displacing oil (the case of FRCC) or natural gas (for TRE and WECC). This is consistent with coal being forced to the margin by natural gas generation, which now serves baseload.

The pattern of marginal emissions across the day and the change in marginal emissions between fuel price regimes appears to largely be driven by the mix of fuel capacities. Specifically the regions with flatter intra-day marginal emissions curves during the second natural gas price regime have more natural gas capacity and more combined cycle natural gas capacity in particular. These efficient natural gas units displace even moderately productive coal plants at low natural gas prices and become infra-marginal. The effects of this displacement vary significantly with the amount of coal and oil generation capacity available.

There has been significant attention paid to regional variation in marginal emissions rates (Graff-Zivin et al. (2014)) and across generation levels (Novan (Forthcoming)), but these results demonstrate that fuel prices can also have a large impact on marginal emissions rates. Variation in marginal emissions rates across NERC regions still seems to be of first order importance. The difference in marginal emissions rates between MRO and WECC is quite large relative to other sources of variation. The variation in marginal emissions rates across fuel price regimes is comparable in scale to variation across months of the year. Figure 9 highlights the variation in marginal emissions rates across months relative to the variation across fuel price regimes. Most importantly, it shows that variation in marginal emissions due to natural gas price changes varies across months of the year, suggesting both fuel prices and generation levels are important inputs to careful evaluation of marginal emissions rates.

5 Emissions Averted through Renewable Generation

In this section we demonstrate the importance of the observed changes in marginal emissions by simulating installing a small amount of wind and solar generation capacity in each NERC region. We evaluate the environmental benefits of these renewable technologies by hour and month across the two fuel price regimes identified above. The results of the simulation suggest that the environmental benefits of installing renewables have decreased almost everywhere in the cheap natural gas era. The magnitude of the change in emissions averted varies across regions and technologies.

Estimating the environmental impact of renewable generation across natural gas price regimes requires estimates of renewable generation that vary by month of year, hour of day and NERC region. Actual generation is endogenous to fuel prices and installed renewable capacity has changed significantly in some parts of the country, so we cannot use renewable generation. Instead we use rely on forecasted potential generation. The National Renewable Energy Laboratory (NREL) has compiled wind and solar potential data from detailed weather and geographic data. We use these forecasts to create representative generation curves for wind and solar power.[31]

NREL's Wind Integration National Dataset (WIND) Toolkit (Draxl et al. (2013)) was created to evaluate the impact of large scale wind deployment on the electricity grid. It contains forecast wind generation projections for around 126,000 sites throughout the 48 contiguous U.S. states. The Toolkit combines weather data including wind speed, temperature, air density and humidity with actual and simulated wind farms spread widely

[31]Cullen (2013) and Novan (Forthcoming) use wind speed, rather than potential wind generation to deal with this endogeneity. Potential generation combines a richer set of weather data with the technical capabilities of wind generators and the topology of the region to potentially produce a more accurate proxy for wind generation.

across the country. Each 2-km by 2-km cell onshore and offshore within 8-km were evaluate for wind potential and geographic suitability (including slope and areas where windfarms are not permitted. The Toolkit then uses weather models to predict weather every five minutes at a height of 100 meters from 2007-20013. The WIND toolkit combines the weather data with each of four classes of potential windfarm technologies to find the most effective technology for each cell.

We collect metadata on each of the 126,000 wind farms in the Toolkit which includes the capacity factor,[32] latitude and longitude of the installation. We map each one to a NERC region using Geographic Information Systems (GIS) software. We then identify the top percentile of windfarms measured by capacity factor in each NERC region and use a web-scraping program to collect the five minute frequency wind generation data for each of those sites. Figure 11 (left panel) illustrates the location of the top percentile wind sites within each NERC region. There is significant within region variation in the location of the best wind sites. In WECC many of the sites are clustered in Wyoming and Colorado's Front Range, but several are offshore in California.

We aggregate that generation data across all the sites in a NERC region and then across hour of the day and month of year to match the resolution of our marginal emissions estimates reported in Section 4.3. We then normalize by the number of sites in the region to get the average generation per MW of installed capacity. This process produces a representative wind generation curve for the most productive sites in a NERC region.[33] This provides a sense of how a marginal change in wind generation capacity would affect emissions.[34]

We use a similar approach to produce representative solar generation curves by NERC region, hour of day and month of year. NREL produces PVWatts, a database of potential solar generation and cost of photovoltaic (PV) systems across the world. PVWatts uses

[32]Capacity factor is the fraction of the maximum generating capacity a unit achieves.

[33]King et al. (2014) describes the validation of the simulated power output data.

[34]Larger changes in wind generation capacity could affect the stock of fossil fuel generating power plants and thus the marginal emissions of generation. Our estimates represent a "medium run" response before generating capacity can respond to fuel price changes or small changes in renewable capacity.

estimates of solar potential for 10-km by 10-km grid cells across the world. PVWatts uses the National Solar Radiation Database 1961-1990 (TMY2) data site to create hourly averages for a representative year of solar radiation. We collect metadata for each cell in the contiguous 48 U.S. states which includes both the latitude and longitude of the cell and the global horizontal irradiance (GHI) for that cell. GHI measures the total amount of solar radiation received by a surface horizontal to the ground and is the best proxy for potential generation from rooftop solar panels.[35] We geocode each cell in GIS and find the top percentile of cells measured by annual GHI. Figure 11 (right panel) describes the sites with the best rooftop-solar generation potential in each NERC region. Not surprisingly, the most productive solar sites are much more clustered geographically than the most productive wind sites.

We then use web-scraping software to collect the hourly generation for a PV installation in that cell for the representative year.[36] As with the wind generation data, we averaged potential solar generation for each site in a NERC region and then averaged over month of year and hour of day to match the resolution of our marginal emissions estimates. We again normalize potential generation to get generation per MW of installed solar capacity.

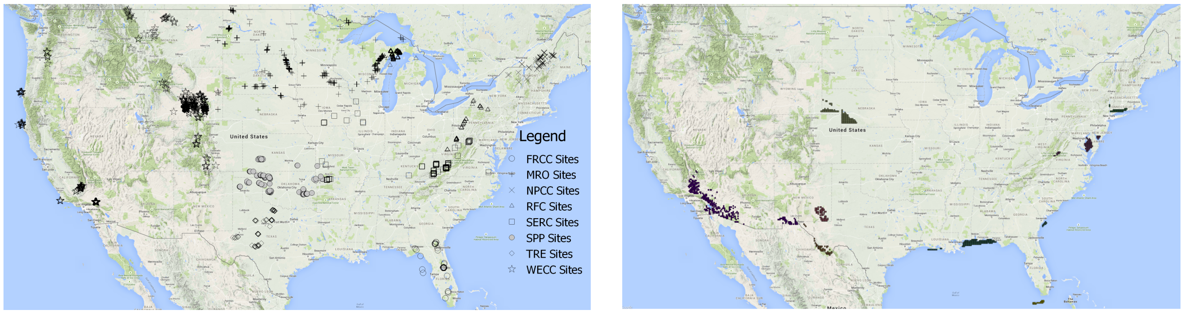
In our counterfactual simulations the emissions impact of renewable energy in a NERC region is a function of 1) estimated marginal emissions 2) renewable potential. Regions with higher potential will produce more electricity from the same renewable capacity creating greater reductions in fossil fuel generation. Potential solar and wind generation vary across NERC regions, month of the year and hour of the day. Table 1 provides summary statistics for capacity factor for wind generation and GHI for solar generation for the top percentile of sites in each NERC region. NPCC has the best wind potential of any NERC region by a considerable margin. WECC has the best solar potential followed

[35]PVWatts also reports Direct Normal Irradiance (DNI), the amount of solar radiation received by a surface that follows the sun, which is a more appropriate measure of concentrating solar thermal installations. In this study we have chosen to focus on the rooftop PV panels, the two measures of solar potential are highly correlated in our sample.

[36]PVWatts allows the user to select several characteristics of the solar generation technology. We chose a premium module that is fixed and roof mounted with an angle of 40° and an azimuth of 180° which were system defaults. We assumed zero system losses and used the closest weather station for weather data in cells without their own station.

Figure 11: Top percentile wind and solar sites by NERC region

Wind **Solar**



Note: Monthly marginal emissions rates for CO_2 across natural gas fuel price regimes for the RFC NERC region. Each panel displays estimates from a single regression with 61,296 hourly observations and robust standard errors clustered by day of sample. Lines connect marginal emissions rates for the expensive (regime 1) and cheap (regime 2) natural gas price eras in our data.

closely by TRE. Installing wind generation in NPCC will offset almost 80% more fossil fuel generation as in FRCC. Installing solar generation in WECC will offset 50% more fossil fuel generation than in NPCC.

Because our focus is on the impacts of changing natural gas prices on the environmental benefits of renewables, we choose to simulate installing an equal amount of renewable capacity in each NERC region. Identifying the best sites in each NERC region suggests that even the worst sties in the top percentile of NPCC wind sites are far more promising than the best sites in FRCC, for example. The question of how renewable potential affects the amount of capacity a NERC region can support is interesting, but beyond the scope of our analysis.

Renewable generation also varies significantly across hour of the day and month of the year. Particularly for wind generation. Figure 12 describes that variation for RFC.[37] Each panel describes the generation per MW of installed generation capacity for a particular month across hours of the day. Throughout the year the hourly pattern of generation for each technology is roughly constant, but the level shifts with the seasons. In the winter a MW of wind capacity generates between 0.6 and 0.8 MWHr's of electricity throughout the day. Over the summer that falls to between 0.4 and 0.5 MWHr's. Solar generation also

[37] We focus on RFC here to save space. Similar figures for each NERC region are available upon request.

Table 1: Wind and Solar Potential

	Capacity Factor (Wind)			
Region	Min	Median	Max	Count
FRCC	0.32	0.34	0.38	31
MRO	0.51	0.51	0.56	260
NPCC	0.59	0.61	0.65	52
RFC	0.54	0.55	0.6	135
SERC	0.48	0.5	0.57	103
SPP	0.52	0.53	0.59	151
TRE	0.53	0.54	0.56	62
WECC	0.53	0.54	0.62	393

Ground Horizontal Irradiance (Solar)				
Region	Min	Median	Max	Count
FRCC	5.54	5.54	5.56	20
MRO	4.59	4.62	4.72	128
NPCC	3.91	3.93	4.01	34
RFC	4.19	4.23	4.31	71
SERC	4.92	4.99	5.04	156
SPP	5.6	5.62	5.65	74
TRE	5.83	5.85	5.92	59
WECC	5.89	5.91	6	336

varies through the year, but on a smaller scale. During the winter peak solar generation is around 0.55 MWHr's per MW of installed capacity, but during the summer peak generation exceeds 0.65 MWHr's per MW of installed capacity.

Variation in generation and marginal emissions rates within the day make estimating the environmental benefits of renewable energy difficult with aggregate data. Using average daily (or monthly) solar generation will understate the environmental benefits of solar in regions where peak generation is particularly dirty. Similarly because wind generation dips significantly during the summer using annual average wind generation will understate the impacts of wind generation in regions with particularly dirty summer generation.

The marginal emissions estimates and representative solar and wind generation curves allow us to estimate the environmental benefits of installing renewable generation across fuel price regimes. We take the estimated marginal emissions estimated in section 4.3 for each NERC region, hour of day and month of year and match them with the appropriate potential generation level. This allows us to estimate the marginal CO_2 emissions reduction associated with a small increase in wind or solar capacity.

The results of the counterfactual simulations are summarized in table 2. Each column reports the annual reduction in CO_2 emissions associated with a 1MW change in wind capacity at the highest potential generation sites for a particular region. The first row reports the estimate for natural gas price regime 1 and the second row reports results for regime 2. Row 3 is the difference between the two estimates across fuel price regimes. These differences are attributable solely to changes in marginal emissions across regimes, which we argue is driven largely by changes in natural gas prices.

In all but one NERC region the CO_2 emissions reductions associated with increase wind capacity are lower during the cheap natural gas regime. This suggests the benefits of wind generation have fallen with natural gas prices. The CO_2 emissions reductions associated with increased wind capacity are largest in MRO due to both high wind potential and high marginal emissions rates, particularly across off peak hours when wind generation is most productive. CO_2 emissions reductions associated with capacity in FRCC have the least environmental benefit driven by FRCC's low wind potential.

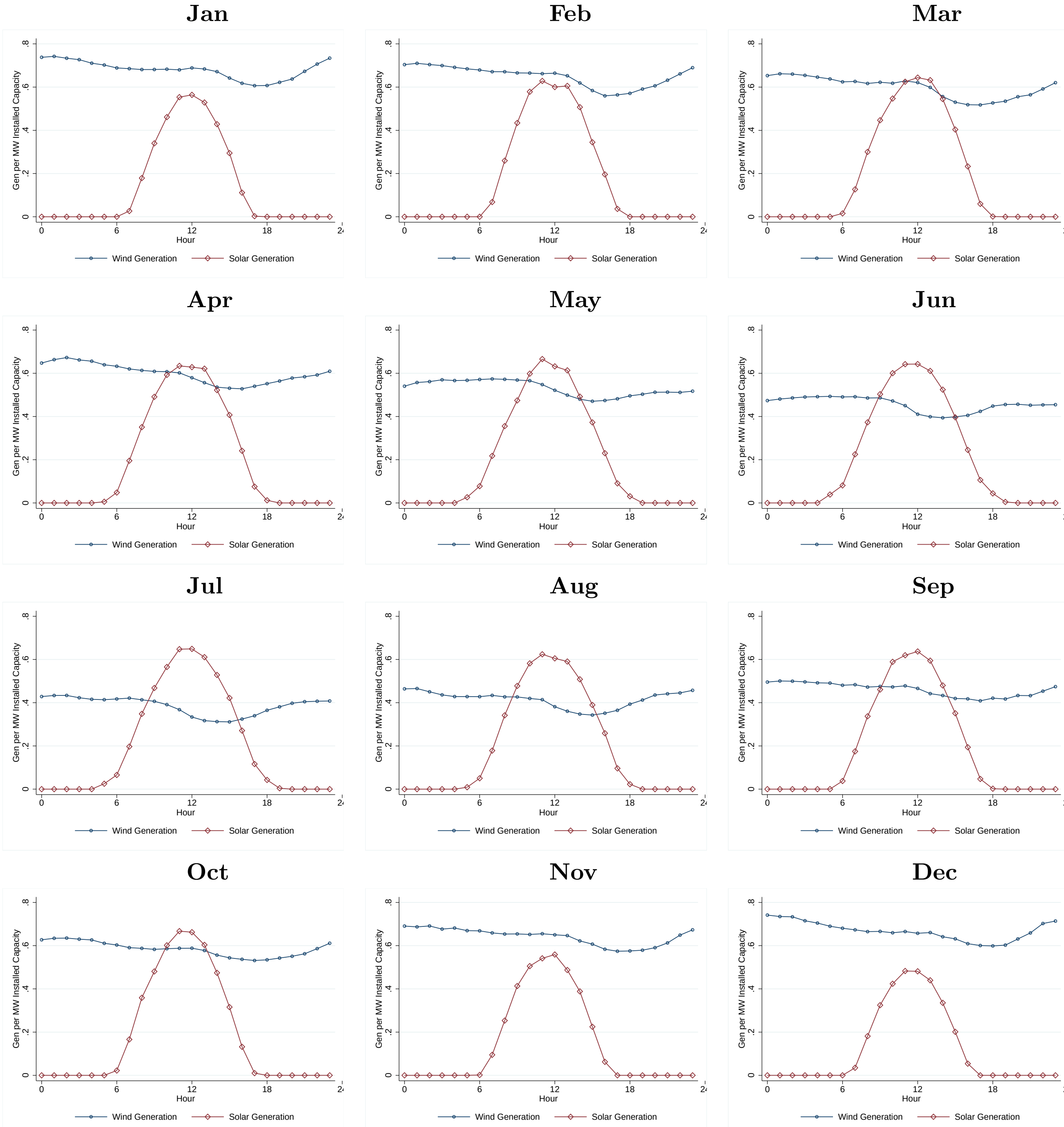


Figure 12: Monthly renewable generation in RFC by hour of day and month of year
Note: Monthly renewable generation per MW of installed capacity for the RFC NERC region. Each panel displays potential generation for solar and wind generation capacity in a particular month.

The difference in estimated environmental impacts of wind generation vary by region from a 153 ton (7.6%) reduction in FRCC to a 16 ton (0.3%) increase in RFC. Generally, the larger the level of CO_2 emissions reduction from wind generation, the smaller the change in CO_2 emissions across gas price regimes. The aggregate impact of the change in fuel prices is significant. For each MW of wind generating capacity installed, CO_2 emissions reductions fall by an average of just under 70 tons per year.[38]

Table 2: Emissions averted by wind generation

Emissions	Fuel Price	FRCC	MRO	NPCC	RFC	SERC	SPP	TRE	WECC
Marginal	Regime 1	2178.6	4290.5	3614.5	4146.5	2188.8	3573.5	2986.7	2914.7
	Regime 2	2025.4	4252.5	3572.9	4162.5	2155.8	3497.3	2864.8	2805.5
	Δ	-153.2	-38.1	-41.6	16.0	-33.0	-76.2	-121.9	-109.3

Note: Annual CO_2 emissions averted in tons per MW of installed wind generation capacity across NERC regions and fuel price regimes. Emissions averted based on estimated marginal emissions by month of year, fuel price regime and hour of the day.

We then implement the same procedure to evaluate the environmental impacts of solar capacity across NERC regions and fuel price regimes. We take hourly potential generation from solar capacity and match it with the appropriate month and NERC region's marginal emissions. The product of the potential generation and marginal emissions rate is the potential CO_2 emissions offset by a marginal increase in solar generating capacity. The results of the counterfactual simulation of installing a small amount of solar capacity in each NERC region are reported in table 3.

Table 3: Emissions averted by solar generation

Emissions	Fuel Price	FRCC	MRO	NPCC	RFC	SERC	SPP	TRE	WECC
Marginal	Regime 1	1255.9	1604.9	989.7	1284.0	1140.7	1379.9	1214.0	1237.8
	Regime 2	1122.9	1581.5	989.3	1323.9	1177.6	1344.1	1128.8	1160.1
	Δ	-133.0	-23.4	-0.4	39.9	36.9	-35.8	-85.2	-77.7

Note: Annual CO_2 emissions averted in tons per MW of installed solar generation capacity across NERC regions and fuel price regimes. Emissions averted based on estimated marginal emissions by month of year, fuel price regime and hour of the day.

The environmental benefits of wind generation tend to exceed the benefits of wind for

[38] E.I.A reports around 65,000 MW's of capacity as of the end of 2014, though of course this capacity is not spread equally across NERC regions.

two reasons. First, wind capacity is significantly more productive in the best sites of each NERC region. Second, solar generation is restricted to daylight hours and peaks when marginal emissions are at or near their daily lows as relatively high cost natural gas fired generation is brought online to serve peak demand. Emissions reductions associated with additional solar capacity are largest in MRO and lowest in NPCC. MRO's relatively poor solar potential is offset by its high marginal emissions rates even over peak hours. NPCC has both relatively low solar potential and relatively clean generation. During the cheap natural gas era the CO_2 emissions benefits of solar generation fall everywhere, except RFC and SERC. Adding solar capacity in each region would reduce emissions by 278 tons per MW of capacity per year less during the cheap natural gas era. Changes CO_2 benefits vary from nearly 12% in FRCC to increases of 3% in SERC and SPP.

The relative differences in environmental performance of wind and solar capacity are driven by when they generate. Recall that marginal emissions rates responded in opposite ways during offpeak and onpeak hours across two sets of NERC regions and across months of the year. In RFC marginal emissions rates increased during onpeak summer hours for the cheap natural gas regime. This increase in marginal emissions rates improves the environmental performance of renewables, but has a larger impact on solar which produces a larger fraction of total generation during summer afternoons. In other regions, that saw reductions in marginal emissions rates during peak demand hours, the environmental benefits of solar decreased. In some cases significantly.

While there has been significant focus on the need to evaluate the environmental impacts of energy policy using marginal emissions rates, there has been much less focus on the importance of fuel prices. Comparing the change in estimated environmental benefits across fuel price regimes to the differences between estimates using marginal and average emissions rates provides some context. Changes in fuel prices lead to estimates of environmental benefits that differ by as much as twelve percent across fuel price regimes. This exceeds the difference between estimates using marginal and average emissions in some cases. Typically the difference in estimating across fuel price regimes is smaller than the difference in using marginal versus average emissions, but the two differences are of the same order of magnitude. Failure to take into account variation in fuel prices can introduce error in estimating the environmental impact of energy policy can introduce errors of a similar scale to using average rather than marginal emissions.

6 Conclusion

The reduction in natural gas prices driven by new extraction technologies has significant implications for the environmental impacts of U.S. energy policy. We estimate a Markov Switching Model on a natural gas price time series and separate the sample into a high and low natural gas price regime. We collect data on electricity generation and pollution emissions by fuel type across the U.S. for 2005-2011 and estimate marginal emissions rates by month of year and hour of day across eight NERC regions. We demonstrate significant changes in the marginal CO_2 emissions from electricity generation across natural gas price regimes. The change appears to be driven primarily by the dispatch of efficient natural gas capacity earlier in the emissions profile. Since the change in natural gas prices was unexpected, we take these estimates to be causal.

We then evaluate how the change in marginal emissions and natural gas prices affects the environmental benefits of renewable energy capacity. We develop high frequency estimates of potential renewable generation by NERC region. We simulate installing a small amount of solar and wind capacity in each NERC region and evaluate the associated reductions in CO_2 emissions. Cheap natural gas has, for the most part, been associated with reduced environmental benefits from renewable generation. We use this application to demonstrate the importance of fuel prices when evaluating the environmental benefits on energy or environmental policy.

There are several avenues for further work. We have focused on renewable energy capacity in our application, but the changes in marginal emissions across natural gas price regimes suggest that estimates of the external costs or benefits of bulk electricity storage, plug-in hybrids and real time pricing among many other, will have to be re-estimated controlling for input prices. Also, by dividing the study period into high and low natural gas periods we have sidestepped the question of how quickly electricity generators respond to spot natural gas prices, an interesting question in its own right. We focus on the medium run impact of input price changes on marginal emissions. In the long run more natural gas generation should come online changing the way power plants of all fuel types are dispatched. To this end, there is an open question as to the level of inframarginal emissions which are offset by natural gas displacing coal as baseload generation.

References

Allcott, H., Mullainathan, S. and Taubinsky, D.: 2014, Energy policy with externalities and internalities, *Journal of Public Economics* **112**, 72 – 88.

Bento, A. M., Hughes, J. E. and Kaffine, D.: 2013, Carpooling and driver responses to fuel price changes: Evidence from traffic flows in Los Angeles, *Journal of Urban Economics* **77**(0), 41 – 56.

Carson, R. T. and Novan, K.: 2013, The private and social economics of bulk electricity storage, *Journal of Environmental Economics and Management* **66**(3), 404 – 423.

Chong, H.: 2012, Building vintage and electricity use: Old homes use less electricity in hot weather, *European Economic Review* **56**(5), 906–930.

Cullen, J.: 2013, Measuring the environmental benefits of wind-generated electricity, *American Economic Journal: Economic Policy* **5**(4), 107–33.

Cullen, J. A. and Mansur, E. T.: 2014, Inferring carbon abatement costs in electricity markets: A revealed preference approach using the shale revolution, *Working Paper 20795*, National Bureau of Economic Research.

Draxl, C., Hodge, B., Orwig, K., Jones, W., Searight, K., Getman, D., Harrold, S., McCaa, J., Cline, J. and Clark, C.: 2013, Advancements in wind integration study data modeling: The wind integration national dataset (wind) toolkit.

EIA: 2012, Annual energy outlook 2013 early release, *DOE Report 0383ER(2013)*, Energy Information Agency.

Fell, H. and Linn, J.: 2013, Renewable electricity policies, heterogeneity, and cost effectiveness, *Journal of Environmental Economics and Management* **66**(3), 688 – 707.

Graff-Zivin, J. S., Kotchen, M. J. and Mansur, E. T.: 2014, Spatial and temporal heterogeneity of marginal emissions: Implications for electric cars and other electricity-shifting policies, *Journal of Economic Behavior & Organization* **107, Part A**(0), 248 – 268.

Hausman, C. and Kellogg, R.: 2015, Welfare and distributional implications of shale gas, *Working Paper 21115*, National Bureau of Economic Research.

Holladay, J. S. and Soloway, S.: Forthcoming, The environmental impacts of fuel switching power plants, *The Energy Journal* .

Holland, S. P. and Mansur, E. T.: 2008, Is real-time pricing green? the environmental impacts of electricity demand variance, *The Review of Economics and Statistics* **90**(3), 550–561.

Jacobsen, G. D., Kotchen, M. J. and Vandenbergh, M. P.: 2012, The behavioral response to voluntary provision of an environmental public good: Evidence from residential electricity demand, *European Economic Review* **56**(5), 946–960.

Kaffine, D., McBee, B. and Lieskovsky, J.: 2013, Emissions savings from wind power generation in texas, *The Energy Journal* **34**(1), 155–175.

Kahn, M. E., Kok, N. and Quigley, J. M.: 2014, Carbon emissions from the commercial building sector: The role of climate, quality, and incentives, *Journal of Public Economics* **113**, 1–12.

King, J., Clifton, A., Hodge, B.-M. and RePPAE, L.: 2014, *Validation of Power Output for the WIND Toolkit*, National Renewable Energy Laboratory.

Muehlenbachs, L., Spiller, E. and Timmins, C.: 2012, Shale gas development and property values: Differences across drinking water sources, *NBER Working Papers 18390*, National Bureau of Economic Research, Inc.

Novan, K.: Forthcoming, Valuing the wind: Renewable energy policies and air pollution avoided, *Americian Economic Journal: Economic Policy* .

Olmstead, S. M., Muehlenbachs, L. A., Shih, J.-S., Chu, Z. and Krupnick, A. J.: 2013, Shale gas development impacts on surface water quality in Pennsylvania, *Proceedings of the National Academy of Sciences* **110**(13), 4962–4967.

Osborn, S. G., Vengosh, A., Warner, N. R. and Jackson, R. B.: 2011, Methane contamination of drinking water accompanying gas-well drilling and hydraulic fracturing, *Proceedings of the National Academy of Sciences* **108**(20), 8172–8176.

Siler-Evans, K., Azevedo, I. L., Morgan, M. G. and Apt, J.: 2013, Regional variations in the health, environmental, and climate benefits of wind and solar generation, *Proceedings of the National Academy of Sciences* **110**(29), 11768–11773.