How Does Welfare from Load Shifting Electricity Policy Vary with Market Prices? Evidence from Bulk Storage and Electricity Generation

J. Scott Holladay* Jacob LaRiviere†

June 2015

Abstract

We show that the market and environmental benefits of bulk electricity storage systematically respond in opposite ways to a change in relative fuel prices. We develop a simple model of an electricity market with clean and dirty inputs and introduce an electricity arbitrage technology. The model demonstrates that the impact of input price changes on the market and non-market returns to bulk electricity storage move in opposite directions. We then simulate installing bulk electricity storage on the electric grid. We take advantage of an exogenous change in natural gas prices thanks to natural gas fracking to simulate how the market and non-market returns to arbitrage are affected by input prices. As expected, reductions in natural gas prices have been associated with reduced market benefits to bulk electricity storage. The non-market costs of bulk electricity storage have been reduced in most, but not all, of the country.

JEL Classification: H44, L5, L9, Q4, Q5,
Keywords: Electricity storage, natural gas, air pollution, energy policy

*Department of Economics, University of Tennessee; email: jhollad3@utk.edu
†Department of Economics, University of Tennessee; email: jlarivi1@utk.edu

1 Introduction

Economists have been concerned about the optimal capacity of installed electricity generation and the optimal composition of installed electricity generation for decades. Because electricity demand must equal electricity generation each minute of each day to avoid blackouts, there is a significant amount of generation capacity which is idle for much of the year except during times of peak demand. Regulated electricity markets offering rate of return compensation for capital expenditures and average cost retail pricing exacerbate this capacity problem in many many energy markets (Borenstein et al. (2002), Wolak (2011), and Jessoe and Rapson (2014)). Due to air pollution and greenhouse gas (GHG) emissions from burning fossil fuels, the composition of electricity generation greatly affects social welfare. For example, state and national governments mandate renewable energy portfolios and provide subsidies to renewables in order to reduce fossil fuel consumption in the electricity sector (Cullen (2013), Kaffine et al. (2013), and Novan (Forthcoming)).

One second best policy which addresses both issues is subsidizing bulk electricity storage. Bulk storage allows electricity generators to generate and store electricity produced during low demand hours when the price of electricity is low and sell it to the market during high demand hours when the price of electricity is high. As a result, bulk storage has the potential to reduce the need to maintain peaking generation. In addition, bulk storage permits arbitrage between low and high priced hourly wholesale electricity markets leading directly to decreases in average wholesale electricity prices. At the same time, bulk storage has the potential to effectively change the composition of electricity generation since in increases the profitability of any electricity source which generates at night. There are two effects on pollution: first, bulk storage increases the incentive to invest in onshore wind generation thereby enabling reductions in coal, natural gas and oil fired electricity generation and reducing un-priced externalities like mercury and GHG emissions. Conversely, there is an incentive for marginal coal and natural gas fired power plants to produce more during low demand hours in order to sell the stored electricity during high demand and high priced hours. Technological advances in battery technology are predicted to reduce the cost of building bulk storage facilities (*Going with the Flow*

(2014)). Further, subsidizing bulk electricity storage is gaining support in policy circles as one feasible second best supply side policy: although not adopted, the STORAGE Act introduced to U.S. Congress on May 20, 2009 offered large subsidies to installed storage capacity (Kaplan (2009)and DOE (2013)).[1]

Carson and Novan (2013) develops a theoretical model which examines the non-market impacts of bulk storage in addition to investigating both the welfare impacts of increased bulk storage empirically. To do so they account for both market and non-market impacts of increased bulk storage. The find that bulk storage can lead to net increases in emissions due to increased fossil fuel generation but that the market based arbitrage incentives lead to large welfare increases on net.

We extend the Carson and Novan (2013) analysis by building and estimating a simple theoretical model which allows for the market and non-market benefits of bulk electricity storage to vary with changes in fossil fuel input prices. Allowing for fluctuations in input prices is important: coal, natural gas and oil are substitutes in the electricity sector and a decrease in the price of one affects the composition of electricity generation. For example, horizontal drilling and hydraulic fracturing have significantly decreased the price of natural gas. Hausman and Kellogg (2015) find that "fracking" caused a reduction of $3.50 in natural gas prices. Similarly, Holladay and LaRiviere (2015) find a structural break in the commodity price of natural gas in January 2008. Both Hausman and Kellogg (2015) and Holladay and LaRiviere (2015) find that as a result there were significant changes in both the price of wholesale electricity and the composition of electricity generation. Future fluctuations in coal and natural gas prices are probable as liquified natural gas shipping infrastructure aligns regional natural gas prices with world market prices and future GHG legislation influences relative coal and natural gas prices asymmetrically.

[1]There are two types of second best policies that regulatory bodies use to ameliorate emissions in the electricity sector. First, demand side polices 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. We focus on a single second best supply side policy in this paper: bulk storage. We note, though, that bulk storage effectively is a load shifting policy since it increases generation during low demand hours and decreases it during high demand hours.

In the theoretical model, we show that the relative market and non-market impacts of input price fluctuations on bulk electricity storage are a joint function in the level of input prices and the distribution of relative power plant productivity for each type of fossil fuel generation. Because electricity is dispatched in order of marginal cost, it is these key determinants which dictate the marginal unit during nighttime charging and the during peak demand discharge and therefore the welfare impacts of increased storage.[2] Specifically, there is a critical natural gas price for which every highly productive natural gas power plant becomes competitive with inefficient coal.

We then estimate the key parameters of the model to simulate the change in welfare from adding a small amount of bulk storage to every regions of the United States. To do so, we estimate power plant productivity distributions for coal and natural gas from EPA's Continuous Emissions Monitoring System (CEMS) data. We also obtain wholesale electricity price data from both FERC and the PJM interconnection to simulate storage charging and discharging behavior. We combine that data with findings from Holladay and LaRiviere (2015) on marginal emission rates and compare the simulated welfare impacts from adding a small amount of bulk storage in different regions of the U.S.

We find that almost everywhere the market and non-market impacts of storage move in opposite directions as natural gas prices decrease: our simulated non-market benefits increase while the simulated market benefits decrease. The reason is straightforward: with lower natural gas prices, natural gas generation now competes with coal for baseload generation at night. As a result, charging hours are relatively cleaner than when natural gas was expensive. This leads to much lower increases in emissions from bulk storage. Conversely, wholesale electricity prices, especially during peak demand hours, are much lower with low natural gas prices.[3] As a result, the market benefits to arbitrage are much lower with inexpensive natural gas.

While our model is very much stylized to address the welfare impacts of load shifting

[2]Sioshansi et al. (2009) uses an engineering approach to estimate private returns to bulk storage in a single electricity market, highlighting the importance of the fuel mix of existing generators.

[3]Due to the fall in wholesale electricity prices, the benefit of many investments in electricity generation, including nuclear has likely decreased as well (Davis (2012)).

policies for the electricity sector accounting for changing inputs, our model and approach have implications in other sectors where both private and external costs vary over time. Take the transportation sector: time of use tolls are designed to shift demand for vehicle miles travelled across time. However, we are not aware of any paper which evaluates differences in welfare from implementing time of use tolls at different gasoline prices or when alternative transport modes (e.g., additional subways, rail, etc.) are introduced thereby changing the price of driving.[4] Similar issues exist for other industries with congestion issues like bandwidth constraints and content streaming over the internet and cloud computing.

There are important environmental policy implications of our results as well. First, we provide evidence that the unanticipated decrease in natural gas prices has significantly affected the non-market benefits of bulk storage. Clearly, the social benefits of other energy sector policies have also been affected. More generally, we find evidence that evaluating the robustness of second best policy rankings due to input price fluctuations is a possibly overlooked criterion for policy makers. Second, our approach highlights the uncertainty in benefits from second best policies that support specific technologies in the energy sector as opposed to pricing externalities directly. This is important since second best policies supporting specific durable goods technologies (like wind or solar subsidies) lead to long-lived capital which doesn't quickly respond to changing market conditions, even if economic agents interacting with those public goods do. Third, our simulation evaluating the social and private benefits of bulk storage contributes to the growing literature which finds that addressing market failure by not pricing externalities directly exposes the economy to uncertain consequences (Davis (2008), Goulder et al. (2012) and Bento et al. (2013)).

The rest of the paper proceeds as follows. Section 2 describes the policy and input price market environments. Section 3 lays out a theory of the relationship between second best energy policy designed to arbitrage intra-day variation in output price, input prices and

[4]Anderson (2014) addresses a related issue by showing that the value of public transportation changes significantly within the day. While his paper looks at different public good valuations due to fluctuations in demand for the good, we are examining the market and non-market impacts of arbitrage technology in the face of varying input prices.

both market and non-market outcomes. Section 4 describes an empirical analysis of the impact of the change in natural gas prices on electricity generators and section5 conducts a set of policy simulations to illustrate how changes in input prices in the electricity generation sector have affected the market and non-market returns to intra-day electricity arbitrage. Section 6 concludes.

2 Background

Bulk electricity storage allows electricity to be generated at one time of day and sold during another. The private benefit of bulk storage is that it allows inexpensively generated electricity to be dispatched during peak demand hours when wholesale electricity prices are high. This both increases profits for off-peak electricity generators who store their generation and decreases peak wholesale electricity prices. Because electricity generation is responsible for a large share of unregulated pollutants, it is vital to carefully account for increases or decreases in emissions from adding bulk storage in any welfare calculations.[5]

There are multiple competing bulk storage technologies. Pumped hydroelectric storage, in which water is pumped up hill and electricity is generated when the water runs back downhill through a turbine, is the most widely installed. More recently technological advances in chemical batteries have reduced costs significantly pushing battery technology closer to private profitability (*Going with the Flow* (2014)). Tesla Motors, an electric car manufacturer, has introduced the first large scale consumer electricity storage using chemical battery technology in the Spring of 2015.

Bulk electricity storage would reduce the intra-day variation in electricity generation. This would in turn reduce the need to maintain relatively expensive and little-used generation capacity to meet electricity demand over peak demand hours. At least as important are the benefits to renewable electricity sources like onshore wind generation. Subsidiz-

[5]We focus here on the short-to-medium run impact of installing bulk storage. Of course, part of the incentive to encourage bulk storage is to better match wind generation which peaks overnight, with demand which peaks in the late afternoon hours. Introducing inexpensive bulk storage would likely be paired with significant expansion of wind generation leading to much improved environmental performance. For this analysis we focus on the period of time over which wind generation capacity is fixed.

ing bulk storage would also act as an indirect subsidy for on-shore wind generation which mainly produces power over night, reducing the non-market damages associated with electricity generation. Storage may also help ameliorate the supply fluctuations from solar and wind generation, further benefiting renewable generators (Fell and Linn (2013)).

Recent developments in natural gas extraction technology have led to huge reductions in natural gas prices. A suite of technological and methodological breakthroughs, collectively known as fracking have made previously inaccessible pockets of natural gas economic to extract.[6] The reduction in natural gas prices was unanticipated by the market and is forecasted by futures markets to continue for the foreseeable future. The electricity sector is the largest single consumer of natural gas and the current low natural gas price environment has led to significant changes in the relative costs of electricity from different fuels. This has led to changes in both the market price of electricity and the emissions intensity of electricity generation.[7] As a result, there is reason to believe that changes in natural gas prices have influenced the economics of bulk storage.

3 A Theory of Input Prices and Second-Best Policies

This section presents a simple partial equilibrium model that highlights how the market and non-market benefits and costs of an intra-day arbitrage technology are influenced by changes in input prices. The goal of this section is to provide intuition for the subsequent policy experiment regarding fossil fuel input prices and changes in the welfare impacts of bulk electricity storage. There are three key elements in the model: a clean and dirty input, productivity heterogeneity, and high demand and load demand periods.[8]

We model a market where two types of firms produce an identical output. The firms differ by the input used in production: one type of firm uses a clean input and one a

[6] See Joskow (2013) for a description of the fracking technologies and the impact on natural gas prices.

[7] Holladay and LaRiviere (2015) describes the changes in marginal emissions intensity across hours of the day and available generation capacity. That paper finds that emissions intensity changes are driven by changes in the marginal fuel, which is in turn driven by relative fuel prices.

[8] While there is ample evidence for each modeling assumption in the electricity sector there are similar characteristics in the transportation sector. Policies that allow hybrid or electric power vehicles to access HOV lanes or price solo drivers in HOV lanes are two examples (Bento et al. (2014)).

dirty input. We allow for heterogeneity in the productivity of firms. Using the dirty input creates an un-priced externality which negatively impacts welfare. Therefore, a regulator can improve welfare by enacting a second best policy. While sub-optimal, this situation seems more common in practice than regulators enacting first best policies. While general, the model is motivated by fossil fuel electricity production from either natural gas (the clean input) or coal (the dirty input). We build the model, perform comparative statics over the model, then analyze those comparative statics in the context of a load shifting policy like bulk storage.

Assume that there are two types of price taking firms which can produce a homogeneous output Q. One type of firm produces Q using a clean input x_c and the other type produces with a dirty input x_d. For simplicity, in each production period a firm each produces a single unit of output or doesn't produce any output. We allow there to be two periods in the model: a high demand and low demand period. Demand in each period is exogenous from the perspective of the firms and does not affect welfare in and of itself.[9] Assume that each unit of the dirty input used in producing Q is associated with a negative cost to the economy of size τ.

There is heterogeneity in the marginal productivity of both clean and dirty firms. Each clean firm $c = 1, ..., C$ has an input requirement function dictated by a single parameter $\theta_c \sim U[\underline{\theta_c}, \bar{\theta_c}]$. The parameter θ_c indexes the total input required to produce a single unit of output. As a result, the firm indexed by $\underline{\theta_c}$ is the most efficient firm. Similarly, each dirty firm $d = 1, ..., D$ has an input requirement function dictated by a single parameter $\theta_d \sim U[\underline{\theta_d}, \bar{\theta_d}]$. Therefore, the cost of production for each firm is the product of the input requirement parameter and the exogenously determined price of their input. For example, the cost of the most efficient dirty firm to produce a unit of output is $P_d * \underline{\theta_d}$.

Assume that in each independent production period firms engage in an auction for the right to supply the market with output Q. Mirroring a competitive wholesale market in the electricity sector, assume the auction's outcome is that only the Q most efficient

[9]Any welfare effects from changes in overall levels of electricity demand are second order in the context of our model. This is the primary partial equilibrium aspect of our model.

firms supply to the market and that each firm is paid a price equal to the cost of the *least* efficient (e.g., marginal) firm.[10] As a result, for a given dictated output of Q, the market clearing price is determined by the total number of clean firms and dirty firms that jointly produce to supply a quantity Q. More precisely, the marginal cost of production is dictated by:

$$MC(Q) = P_d\theta_d = P_c\theta_c \quad s.t.\; Q_d + Q_c = Q$$

where Q_d is total output from dirty firms and Q_c is total output from clean firms. Note that in the case that all type d firms are already producing, then the output cost is dictated by the most efficient type c firm and marginal costs are not equalized across firm types.

One convenient feature of this model is that total demand for output in a period, Q, along with the input price vector jointly determine the input requirement of the marginal dirty and clean firm: θ_d and θ_c. Finally, for a given price vector the total negative cost to society associated with the dirty input is $.5\tau(\theta_d + \underline{\theta_d})Q_d$. This is the area of the trapezoid representing the total number of inputs where θ_d and $\underline{\theta_d}$ represent the different levels of inputs required by the least and most efficient dirty firms respectively and Q_d is the number of firms producing. Note that this particular functional form is a result of the uniform distribution assumption. For convenience it will be convenient to assume that $\underline{\theta_d}$ below when performing comparative statics over input prices.

Consider how a decrease in price of the clean input affects the price of the output and welfare cost of the dirty input's externality for a given output level Q. Assume P_c decreases from an initial value of P_c^0 to P_c^1. If initial equilibrium is indexed by 0 and the new equilibrium is indexed by 1, then at a clean input price P_c^1 it must be that $P_d\theta_d(0) > P_c^1\theta_c(0)$. This cannot be an equilibrium (e.g., $\theta_c(0) < \theta_c(1)$ and $\theta_d(0) > \theta_d(1)$ as the marginal clean firm is less efficient and the marginal dirty firm is less efficient). As a result, production from clean firms increases and production from dirty firms decreases

[10] We wish to avoid strategic bidding behavior in this model for simplicity. It is intuitive to assume that the market price is set by a trivial markup over the second highest bid. This equilibrium mirrors that of deregulated electricity markets without market power and well-functioning regulated markets. This model is also a stylized version of the dispatch model in Borenstein et al. (2002) and Wolfram (1999).

until the marginal firm in the clean sector is less efficient than before the price change. At the same time, the marginal dirty firm would have to be more efficient than before the price decrease.

There are two important effects of the new equilibrium. First, there must be a decrease in the output price given by $P_c^0\theta_c(0) - P_c^1\theta_c(1)$. Second, there is a decrease in the cost of the externality of $.5\tau(\theta_d(1) + \theta_d(0))(Q_d(1) - Q_d(0))$.[11] The first effect is the market effect of the price decrease and the second effect is the non-market effect of the price decrease.

Now consider the implications of a second best policy in the context of this model. Assume that the second best policy alters the pattern of demand across the low demand and high periods. For example, a second best electricity policy could shift the composition of demand within a day. Load shifting policies like peak load pricing or electricity storage are two such policies in the electricity sector. Specifically, assume that the second best policy exogenously decreases demand by q during one demand period and increases it by q in another.

We now evaluate such a policy over stylized clean and dirty input requirement parameterizations and input price vectors. First, consider the stylized case where the cost of production for dirty goods is everywhere weakly lower than for clean goods: $P_d * \bar{\theta_d} = P_c\underline{\theta_c}$. Assume there are equal numbers of clean and dirty firms and that output is uniformly distributed between zero and the total number of firms: $Q \sim U[0, \bar{Q} = N_c + N_d]$. Assume that each of two output periods are random draws from the uniform distribution, with the low period demand corresponding to a random draw from the lower half of the distribution and the high period demand corresponding to a random draw from the upper half.[12]

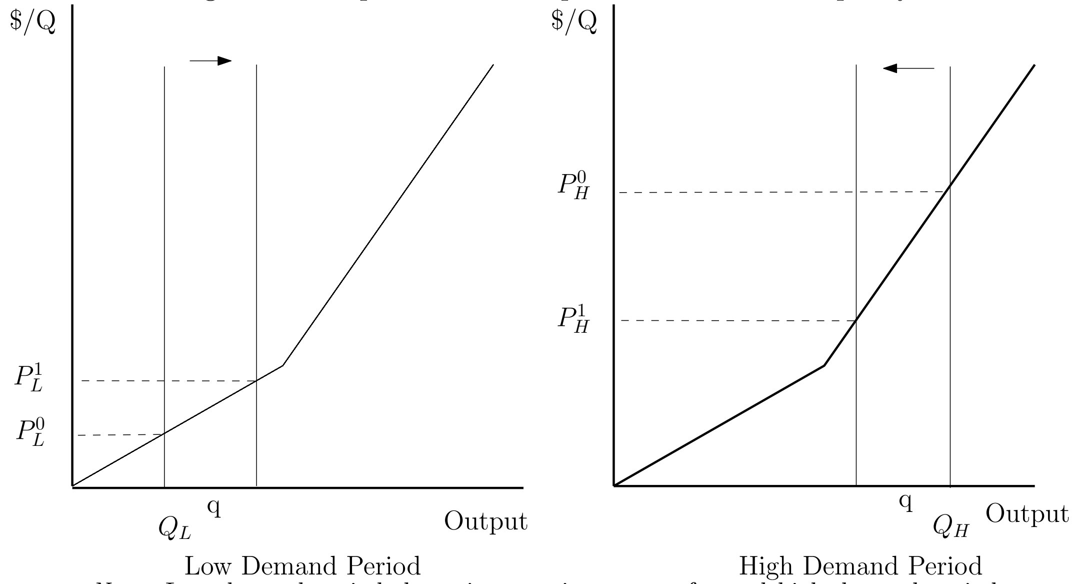
Assume that a second best policy is designed so that Q increases by q in the low demand period and decreases by q in the high demand period. This is similar to any policy which serves to shift electricity demand away from expensive peak demand periods and toward cheaper low demand periods. Given our price assumptions, on average this mimics a

[11] This is the average external cost of the dirty firms which stop producing multiplied by the decrease in the output of dirty firms.

[12] This lower and upper half random draw assumption mitigates the need to develop first and second order statistics for the uniform distribution. It isn't required for any qualitative results.

policy that increases demand for electricity when the cheaper dirty good is producing and decreases demand for electricity when the more expensive clean good is producing while keeping total demand the same over longer periods.

Figure 1: : Expensive clean input with second best policy



Note: Low demand period shows increase in output of q and high demand period shows decrease in output of q due to second best policy. Policy affects both which firms serve market and equilibrium market price across periods.

The situation described by these assumptions is shown in Figure 1. Assuming that q is small relative to the distribution of demand for electricity (e.g., $q < \frac{\overline{\theta_d}+\underline{\theta_d}}{2}$), the expected non-market effects of the above policy over T total days of demand would be to increase emissions by $\frac{1}{2}\tau T\left(\frac{q}{N_d}(\overline{\theta_d}-\underline{\theta_d})-\underline{\theta_d}\right)$. This expression is the difference non-market costs due to increases in production from dirty plants after implementing the policy, weighted by T periods. It takes this exact form due to our distributional assumptions: take $F(X)$ to be the cdf of the uniform distribution. Solving $F(\underline{\theta_d}+x)N_d = q$ for x gives the increase in the lower bound for the distribution of dirty plants after the policy is implemented. Put another way, the policy serves to decrease the lowest possible efficiency of a dirty plant since there are always at least q units of electricity being produced. The reason is that policy leads to cheaper dirty firms producing more often during low demand period and clean firms producing less during high demand periods.[13]

While there are non-market costs to this policy, there are market benefits to it as well. The market benefits stem from the more expensive clean good producing less often and the cheaper dirty good producing more often. Note that the expected market benefits of this policy is half the difference in mean costs between dirty and clean firms, weighted by the number of periods being evaluated. The resulting expression is similar to the non-market expression except it is weighted by market prices and accounts for the price differences in both the high and low demand periods:

$$\Delta_T = \frac{T}{2}\left(P_c\left(\frac{q}{N_d}(\overline{\theta_c} - \underline{\theta_c}) - \underline{\theta_c}\right) - P_d\left(\frac{q}{N_d}(\overline{\theta_d} - \underline{\theta_d}) - \underline{\theta_d}\right)\right). \tag{1}$$

Equation (1) is positive by assumption in this initial stylized case shown in Figure 1. The market benefits of this load shifting policy increase in the amount of load being shifted, q. Market benefits also increases in the price of the clean input and decreases in the price of the dirty good highlighting the fact that storage creates an arbitrage opportunity.

Now evaluate the same policy but consider the case where the price of the clean good falls so that the cost distribution of the clean input is identical to that of the dirty input. Specifically, assume that the clean input price falls to a level where $P_d * \underline{\theta_d} = P_c^1 \underline{\theta_c}$ and $P_d * \bar{\theta}_d = P_c^1 \bar{\theta}_c$. The key distinction between this stylized example and the previous one is that now there will always be both clean and dirty inputs producing at all points in time.

Figure 2 shows the same demand shifting policy under the new price vector. Under the new price assumptions the expected non-market benefits of the above policy over T periods would be zero. The reason is that clean and dirty inputs are now used equally over the entire support of possible outputs. As a result, there are no non-market gains nor non-market losses from the load shifting policy in this case. There are still non-market gains to this policy though since higher cost generation is replaced with lower cost generation via storage. The market benefits of the policy will be smaller in the second example than in the first case because the average difference in marginal costs between the low and

[13] Effectively, the policy serves to increase the lower bound of the efficiency distribution of dirty plants

high demand periods will be smaller, decreasing the benefits to arbitrage. As a result the market benefits of the policy, while still positive, decrease with a decrease in price of the clean input.

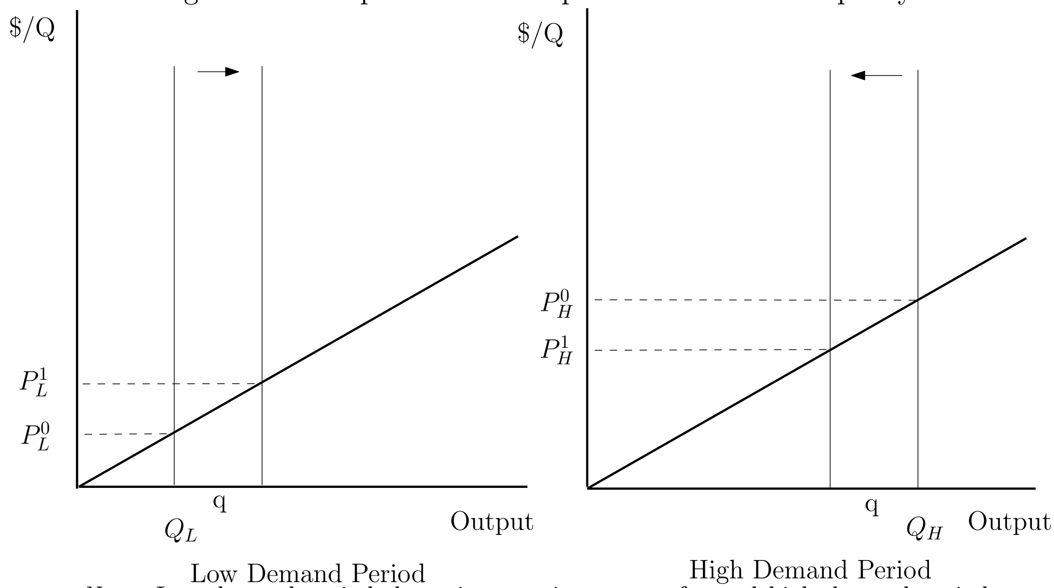
Note that observing no effect of this policy on non-market costs in Figure 2 is fully dependent on both the 1) uniform distribution assumption and the 2) cost equivalence of the most and least efficient clean and dirty plants. In the earlier example, the load shifting policy led to increases in non-market costs because lower cost dirty plants on replaced higher cost clean plants. As a result, the policy could lead to non-market cost decreases if cheap, clean generation displaces expensive, dirty generation.[14]

Similarly, clean input price decrease could feasibly lead to ambiguous the market impacts of the policy: if there are a large number of highly inefficient clean firms, then the marginal (dirty) in the high demand period would have a high cost. In that case, the gains from storage would still be high after the clean input price decrease. Our stylized case shows the opposite situation. In general, though, if the marginal costs of clean generation is higher than dirty generation and the clean input price decreases, the market impacts of storage- while still positive- decrease.

This section characterizes the change in welfare attributable to a demand shifting policy due to changes in input prices. We show that the changes depend jointly on both the market and non-market cost of the input which is on the margin when demand increases. Our example shows that a decrease in the clean input price generally leads to smaller market benefits of load shifting and but that non-market impacts are ambiguous and depend on relative prices and the distribution of efficiency levels of clean and dirty firms. We evaluate installing bulk electricity storage as an example of this type of load shifting

[14]While determining the impacts of the policy on non-market and market outcomes conditional on a set of prices and production technologies is straightforward, determining the change in market and non-market impacts from the policy *attributable to* different aspects of the decrease in the input price of the clean good requires some attention to the proper counterfactual. With respect to market impacts, for example, when the cost of the clean input decreases there is a direct benefit of lower priced output from the clean source through lower marginal cost of the marginal unit even before the policy is implemented in the high demand period. Second, there is an increase the average efficiency of dirty plants due to the lower priced clean output displacing the dirty output, thereby lowering their dirty input requirement. Parsing how these two direct effects interact with the policy is interesting but in this paper we are primarily concerned with the net effects we observe in the data over our sample period.

Figure 2: : Inexpensive clean input with second best policy



Note: Low demand period shows increase in output of q and high demand period shows decrease in output of q due to second best policy. Policy affects both which firms serve market and equilibrium market price across periods. Since clean and dirty firms are now mixed in the dispatch order over the support of Q, policy will have improved environmental impacts.

energy policy in the next section.

4 Empirical analysis

Motivated by the theoretical model above, this section describes an empirical analysis of the relationship between input price changes, electric generating unit performance and bulk storage. In this section we describe the data set and test empirical predictions of the model. The model indicates that the market and non-market impacts of bulk electricity storage are a function of the relative input prices and the productivity of generators using each fuel. Below we document how changes in the relative price of fuels and the existing distribution of generators affected the way power plants were dispatched.

4.1 Data

We collect data on electricity generation, fuel inputs and pollution emissions from the EPA's Clean Air Market database. All U.S. powerplants with a nameplate capacity above

25MW are required to install Continuous Emissions Monitoring Systems (CEMS) in each smokestack. These units frequently sample the air to measure the level of pollution emissions. These pollution emissions are used to determine how much electricity each unit is generating and how much fuel was required to generate that electricity. The results are reported to the EPA, which uses the data to ensure that power plant owners are holding pollution permits commensurate with their emissions. The data is made publicly available through EPA's Clean Air Markets Database. Data is reported hourly at the electricity generating unit level.[15] The data also includes time-invariant unit characteristics including capacity, fuel type and geographic location.

We collect data on hourly generation, fuel input and pollution emissions as well as unit characteristics for each coal or natural gas fueled electricity generating unit that reports CEMS data to EPA for the years 2005-2010 inclusive. This creates a panel of up to 52,584 observations for each of the 3,558 electricity generating units that report CEMS data during our sample period. Units that are not generating in a particular hour do not appear in the CEMS, creating an unbalanced panel. The data set is much too large to work with directly so we aggregate the data in two ways to facilitate analysis.

First, we sum across hours of the year to create a year-by-electricity generating unit sample. This creates an unbalanced panel of electricity generating units. A small number of units enter or exit during the sample and and few units that operate only a few hours a year do not generate in particular sample year.[16] The final sample contains 19,958 electricity generating-unit observations. Each observation includes the electricity generating unit's total annual generation and fuel inputs as well as its reported capacity and fuel type.

Using the summed generation and fuel inputs data we calculate the heat-rate, which is the standard measure of electricity generating unit efficiency, by dividing fuel inputs

[15]An electricity generating unit is the full set of equipment required to generate electricity. It would typically consist of one or more boilers connected to one or more generators. Most power plants have more than one generator and these generators are brought on and off line independently.

[16]We exclude oil-fired and other fuel types (burning wood or tires for example) from this portion of the analysis. We also removed a small number of units with very high or low generation or fuel inputs levels across a year. These units typically generate a very small number of hours a year or entered incorrect data.

(measured in mmBTU) by electricity generation measured in MW. This statistic maps directly to θ in the model described above. We also compared unit capacity to actual generation to calculate capacity factor, the fraction of the unit's potential capacity that utilized that year. Several model predictions relate to changes in capacity factor across fuel price levels and unit efficiency. We term this aggregation of the data the 'electricity generator' sample and use it to test the theoretical model's prediction.

We separate sample into a high natural gas price era from 2005-2007 and a low natural gas price era from 2008-2011. This approach takes advantage of the decrease in natural gas prices driven by the advent of fracking to identify the impact of input price changes on the market and non-market impacts of bulk storage. The approach is consistent with Holladay and LaRiviere (2015), which finds a structural break in natural gas prices in January of 2008. We use the exogenous variation in natural gas prices across these two sub-samples to identify the impact of prices changes in the clean input (x_c) on the market and environmental impact of bulk electricity storage.

We then create another aggregation by summing all the generation with an National Electric Reliability Council (NERC) region within an hour.[17] The NERC breaks the country up into three interconnections, the Eastern Interconnection, Texas (Texas) and the Western Interconnection (WECC), which are essentially isolated from each other electrically. The Eastern Interconnection is further divided into the six regions, from north to south NPCC, MRO, RFC, SPP, SERC and FRCC. Electricity flows across NERC regions within the Eastern Interconnection are small, but non-zero. Figure 3 maps the NERC regions. NERC regions represent the smallest unit of geography across which we can be reasonably certain that bulk storage capacity will be charged by electricity generating units in the same region.[18] The aggregation creates a balanced NERC region-by-hour of sample panel with 420,672 observations.[19] We term this aggregation the 'NERC region'

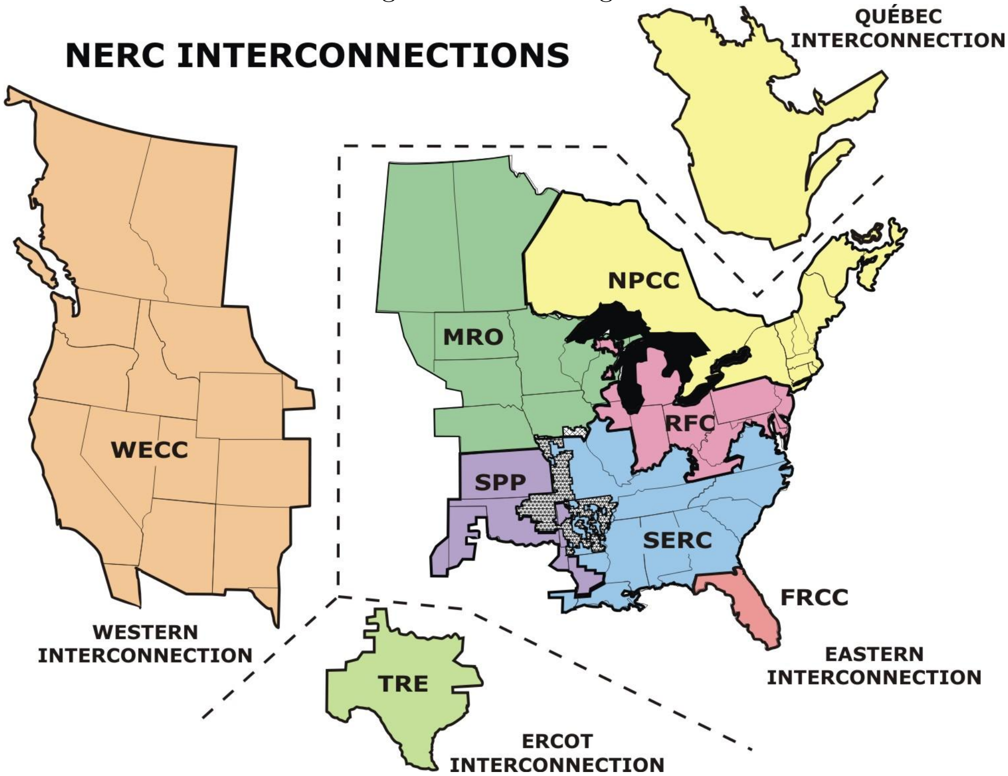
[17]In this portion of the analysis we do not exclude any fuel types, but continue to exclude units with implausibly high or low fuel input levels across a full year.

[18]Graff-Zivin et al. (2014) adopts a similar approach to evaluating the environmental impacts of electrical vehicles.

[19]That is 24 hours a day, 365 days a year for six years, plus a leap day for 52584 observations for each of the eight NERC regions.

sample and use it in our bulk storage simulations.

Figure 3: 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.

4.2 Empirical analysis

We begin our empirical analysis by estimating how the relationship between electricity generating unit dispatch and efficiency were affected by the change in natural gas prices. We employ the electricity generating unit sample for this portion of the analysis. Table 1 presents summary statistics from this sample by fuel type and natural gas price regime.

Coal fueled electricity generating units generate more electricity, use more fuel input, have a lower heat rate (meaning they are more efficient), a larger capacity and higher capacity factor compared to natural gas fueled electricity generating units. Across the two fuel price level sub-samples generation falls at coal units and increases at natural gas units when natural gas prices fall. Average heat rate improves significantly at coal plants as less productive units generate less, raising the average productivity. Average

Table 1: Electricity generating unit summary statistics

	Coal Fueled Units	
	2005-2007	2008-2010
Generation (GW)	2180.7	2044.5
	(1912.2)	(1904.1)
Heat Input	21357.5	19828.2
(billions of BTU)	(18052.7)	(17896.2)
Heat Rate	10249.8	10158.0
	(1230.0)	(1222.9)
Nameplate Cap. (MW)	339.4	345.8
	(268.6)	(269.8)
Capacity Factor	0.693	0.610
	(0.174)	(0.225)
Observations	5498	

	Natural Gas Fueled Units	
	2005-2007	2008-2010
Generation (GW)	267.2	269.9
	(440.1)	(462.8)
Heat Input	2482.0	2394.1
(billions of BTU)	(3824.6)	(3815.6)
Heat Rate	11306.0	11255.4
	(2460.7)	(2650.3)
Nameplate Cap. (MW)	190.8	185.7
	(177.8)	(175.0)
Capacity Factor	0.116	0.110
	(0.154)	(0.159)
Observations	11778	

Note: Sample statistics for coal fired electricity electricity generating units (top panel) and natural gas fired electricity generating units (bottom panel). Table reports sample means with standard deviations in parentheses. Left column reports averages for the high natural gas price era and the right column for the low gas price era. Heat input is the energy content of fuel consumed by the unit measured in billions of BTU's. Heat rate is measured as fuel input (in millions of BTU) over electricity generation in KW. Capacity factor is the fraction of the units maximum generation that is actually dispatched.

heat rate decreases slightly at natural gas units, while capacity factor remains essentially unchanged.

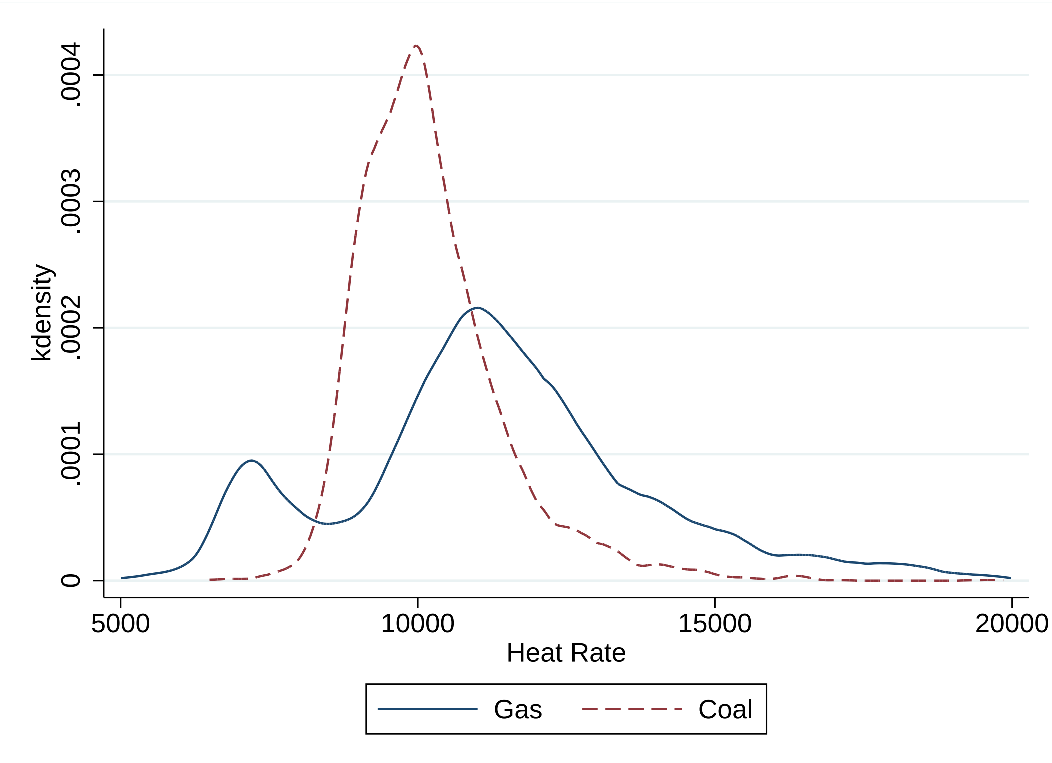
Figure 4 displays the distribution of electricity generating units by fuel type for coal $(\underline{\theta}_d, \bar{\theta}_d)$ and natural gas $(\underline{\theta}_c, \bar{\theta}_c)$ calculated from the CEMS data's hourly fuel input and electricity output. There is significant variation in the productivity within and across fuels. On average coal plants more productive than natural gas plants and there is less variation in productivity among coal plants. Natural gas plants are, on average, less productive than coal plants, but the distribution is double-peaked. The higher productivity, smaller, peak is a set of plants that employ combined cycle generation technology which uses waste heat to generate additional power. The other peak represents natural gas fueled units that employ older technologies, typically combustion turbines that do not recycle waste heat.

The model predicts that production from clean (natural gas fired) units will increase and production from dirty (coal fired) units will decrease until the marginal firm in the clean sector is less efficient than before the price change. At the same time, the marginal dirty firm would have to be more efficient than before the price decrease. We now estimate a series of regressions that take advantage of the exogenous change in natural gas prices to test for changes in capacity factor. The regressions take the form:

$$CapFactor_{jt} = \alpha + \beta HeatRate_{jt} + \eta Gas_{jt} + \gamma PriceEra_t + \phi \overline{X}_{jt} + \epsilon_{jt}, \qquad (2)$$

where j indexes electricity generating unit and t denotes year. $CapFactor$ is the portion of a unit's capacity employed over the course of the year ranging from 0 to 1. $HeatRate$ is the unit's efficiency over the course of the year measured as heat input over electricity generation output. Gas is an indicator for fuel type, equal to 0 coal and 1 for natural gas. $PriceEra$ is an indicator for the low natural gas price era that equals 0 for 2005-2007 and 1 for 2008-2010. $\overline{X}$ is a matrix of unit characteristics including capacity, an indicator for wether they can employ multiple fuels and the age of the unit in decades. We also interact the heat rate, gas and price era indicators to evaluate the changing impact of unit efficiency across fuel types and gas price levels, which the model suggests is an important

Figure 4: Distribution of power plant productivity by fuel type



Note: Density plots of the relative productivity of power plants using the dirty (coal) and clean (natural gas) input aggregated from 2005-2010. Productivity is measured here as heat rate, which is defined as fuel input/electricity output and is the typical measure of a powerplants efficiency. Coal plants are relatively tightly clustered, but natural gas plants rely on two different technologies. High productivity combined-cycle plants use waste heat to generate additional electricity. Less efficient turbine plants use only natural gas fuel and typically do not recycle their waste heat for electricity generation.

determinant of the environmental impact of bulk storage. Table 2 summarizes the results of these regressions.

Column 1 reports the elasticity of capacity factor with respect to heat rate. A one percent increase in heat rate is associated with a 0.55% decrease in capacity factor. Column 2 adds a set of electricity generating unit controls. The controls are have the expected signs, older plants have a lower capacity factor and larger plants have a higher capacity factor. Natural gas units have significantly lower capacity factors. Column 3 interacts heat rate with the fuel price era indicator. There is no significant difference in the impact of unit productivity on capacity factor across the expensive and inexpensive fuel price eras. Column 4 interacts fuel type and heat rate. Natural gas units are around four percent more sensitive to heat rate than coal units.

Finally column 5 reports a triple interaction of heat rate, fuel type and fuel price era. The coefficients allow us to evaluate the sensitivity of coal and gas plants' capacity factor to heat across fuel price levels. This specification highlights the importance of considering changing fuel prices and the distribution of unit efficiency jointly when assessing changes in the way electric generators are dispatched. Coal fueled units' capacity factor become almost one percent more sensitive to heat rate after the fall in natural gas prices. The difference between those coefficients is statistically significant at the one percent level. Natural gas units' capacity factors sensitivity to natural gas prices is essentially unchanged. This is consistent with the prediction that inefficient coal units become more exposed to natural gas competition in the low natural gas price era.

The model predicts that the impact of cheap natural will not be uniform, but will primarily affect units near the margin. Reduced natural gas prices will shift formerly marginal electricity generating units into higher levels of utilization. Coal units that were near the margin are likely to be displaced by the higher level of natural gas generation. For that reason estimates across the sample may hide the variation predicted by the simple model. To identify the impact of the reduction in natural gas prices across the electricity generating unit distribution we estimate a series of quantile regressions to analyze the impact of changing natural gas prices across the capacity factor distribution. The results

Table 2: : Capacity factor and heat rate across fuel prices

	(1) Cap. Factor	(2) Cap. Factor	(3) Cap. Factor	(4) Cap. Factor	(5) Cap. Factor
Log(Heat Rate)	-0.555***	-0.273***			
	(0.012)	(0.009)			
2005-7 Indicator × Log(Heat Rate)			-0.415***		
			(0.012)		
2008-10 Indicator × Log(Heat Rate)			-0.419***		
			(0.012)		
Coal Indicator × Log(Heat Rate)				-0.223***	
				(0.009)	
Natural Gas Indicator × Log(Heat Rate)				-0.277***	
				(0.009)	
2005-7 Ind. × Coal Ind. × Log(Heat Rate)					-0.220***
					(0.009)
2008-10 Ind. × Coal Ind. × Log(Heat Rate)					-0.229***
					(0.009)
2005-7 Ind. × Natural Gas Ind. × Log(Heat Rate)					-0.278***
					(0.009)
2008-10 Ind. × Natural Gas Ind. × Log(Heat Rate)					-0.279***
					(0.009)
Age (decades)		-0.002**	-0.069***	0.002**	-0.002**
		(0.001)	(0.001)	(0.001)	(0.001)
Multiple Fuels		0.000	-0.118***	0.001	0.001
		(0.003)	(0.004)	(0.003)	(0.003)
Nameplate Capacity (MW)		0.000***	0.000***	0.000***	0.000***
		(0.000)	(0.000)	(0.000)	(0.000)
Natural Gas Indicator		-0.497***			
		(0.005)			
Constant	5.435***	2.626***	17.899***	2.211***	2.173***
	(0.109)	(0.235)	(0.280)	(0.237)	(0.234)
R^2					
N	17272	17272	17272	17272	17272

Note: Results of regressions exploring the relationship between electric generating unit efficiency (heat rate) and dispatch intensity (capacity factor). Each column reports the results of a regression with 17,272 observations. Heat rate is calculated as fuel inputs over electricity generation so lower heat rates indicate more efficiency units. Age is measured in decades to enhance readability. Natural gas and coal indicators are binary variables that equal 1 for a particular fuel type. 2005-7 and 2008-10 indicators represent the high and low gas price eras respectively. Newey West standard errors reported in parenthesis to correct for potential serial correlation. *** significant at the 1% level, ** significant at the 5% level, * significant at the 1% level.

are presented in table 3

The estimates are simple regressions of capacity factor on heat rate and fuel price era indicators at different points of the capacity factor distribution, estimated jointly. We restrict the sample to a single fuel type and estimate $CapFactor_{jt} = \alpha(\tau)+\beta(\tau)HeatRate_{jt}+\gamma(\tau)PriceEra_t + \epsilon_{jt}$, for τ=0.1, 0.25, 0.5, 0.75 and 0.9 quantiles. The γ coefficients are the change in capacity factor during the low natural gas price era at that point in the capacity factor distribution.

Table 3: Quantile regressions for unit capacity factor and heat rate across gas price levels

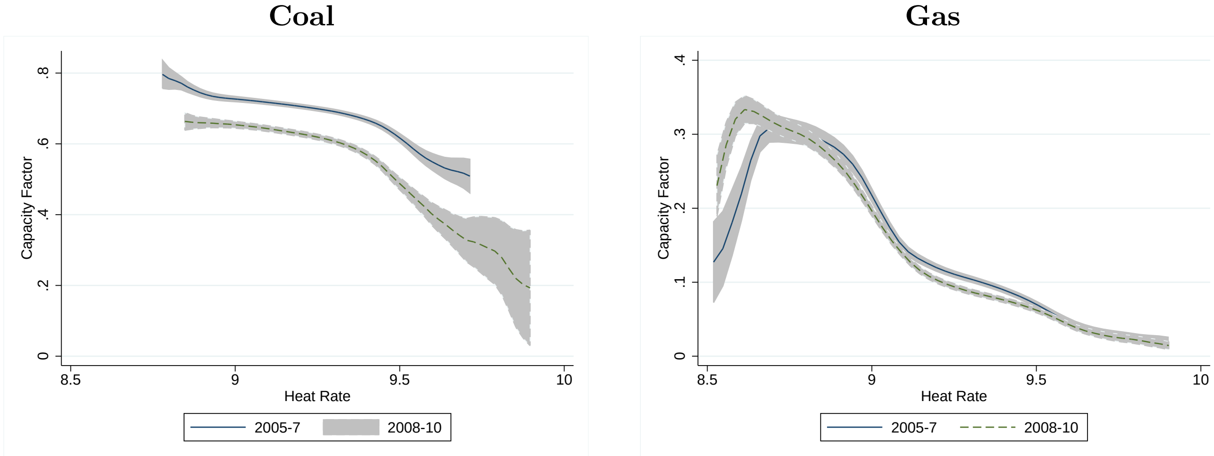
	Coal Fired Units				
	t=0.1	t=0.25	t=0.5	t=0.75	t=0.9
Log(Heat Rate)	-0.873**	-0.673**	-0.400**	-0.252**	-0.228***
	(0.067)	(0.053)	(0.033)	(0.049)	(0.059)
2008-2011 Indicator	-0.195**	-0.116**	-0.065**	-0.049**	-0.031***
	(0.011)	(0.007)	(0.006)	(0.005)	(0.007)
Constant	8.732**	6.919**	4.470**	3.192**	3.032***
	(0.609)	(0.486)	(0.300)	(0.450)	(0.545)
Pseudo-R^2	0.1618	0.0969	0.0413	0.0206	0.0132

	Natural Gas Fired Units				
	t=0.1	t=0.25	t=0.5	t=0.75	t=0.9
Log(Heat Rate)	-0.013**	-0.043**	-0.133**	-0.281**	-0.280***
	(0.001)	(0.002)	(0.007)	(0.008)	(0.016)
2008-2011 Indicator	-0.003**	-0.006**	-0.009**	-0.006**	-0.006
	(0.000)	(0.000)	(0.001)	(0.003)	(0.009)
Constant	0.133**	0.433**	1.306**	2.781**	2.910***
	(0.009)	(0.022)	(0.065)	(0.078)	(0.154)
Pseudo-R^2	0.0143	0.0299	0.0722	0.1226	0.1134

Note: Each panel reports a series of quantile regressions with electricity generating unit capacity factor as the dependent variable and log heat rate and an indicator for years 2008-2011 as the dependent variables. The top panel reports results for a sample restricted to coal fired units with X observations. The bottom panel reports results for a sample restricted to natural gas fired generators with Y observations. The 2008-2011 indicator equals 1 for years 2008-2011 and is a proxy for the low natural gas price era. Heat rate is measured as fuel input/electricity output so high heat units are less efficient. All standard errors clustered at the unit level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 1% level. The results suggest that high capacity factor natural gas units are used relatively more during the low natural gas price era.

Each column of table 3 reports results for a different quantile of the capacity factor distribution. The top panel reports results for coal fueled units and the bottom panel reports results for natural gas fired units. Coal fueled electricity generating units see their

Figure 5: Productivity and output by input type and price



Note: Productivity, measured by heat rate and output, measured by capacity factor or percentage of total possible output for coal (left panel) and natural gas (right panel). Solid line represents the sample period with relatively high natural gas prices and dotted line represents the low gas price portion of the sample. The fall in natural gas price led to increases in output in relatively less productive gas plants and decreases in output in relatively less productive coal plants.

capacity factor fall in each of the quantiles. The decrease in capacity factor is largest for the lowest capacity factor units. This implies that the least utiltized coal units see the largest reductions in generation after the fall in natural gas prices. For natural gas units there is also a small reduction in capacity factor, but reductions are extremely small, do not present a clear pattern across capacity factors and are less precisely estimated.

Figure 5 presents univariate kernel regressions of capacity factor on heat rate.[20] We run separate smoothing regressions for both coal and natural gas in each natural gas price era. The left panel presents the results for coal and the right for natural gas. In each panel the solid line represents 2005-2007 (the expensive natural gas era) and the dotted line represents 2008-2010 (the cheap natural gas era). Coal capacity factor is lower for all but the most productive (highest heat rate) plants. Natural gas capacity factor rises for a set of relatively less productive combustion turbines. The reduction in output at less productive coal plants and the increase in output at less productive gas plants are both consistent with the model: when gas prices decrease, average generation by coal decreases

[20]The regressions equations are: $CapFactor_{jt} = \alpha_{jt} + \beta HeatRate_{jt}$ on a sample restricted to a single fuel type and price level time span. They are estimated with an Epanechnikov kernel smoothing function.

(e.g., coal has a lower capacity factor).[21]

The empirical results highlight the impact of the fall in natural gas prices on electricity generating unit capacity factor by fuel type. These results suggest that changes in fuel prices will have an impact on both the market and non-market returns of bulk electricity storage through the change in the types of unit on the margin.

5 Bulk Electricity Storage Simulations

5.1 Nationwide simulation

In this section we simulate installing a small amount of bulk electricity storage across each of the eight NERC regions in the United States. For this analysis we turn to our second aggregation of the raw generation data, which we term the 'hourly' data set. We aggregate all generation in a NERC region for each hour of our sample from 2005-2010. This generates a balanced panel of 420,672 hourly generation and fuel input observations. We use this data set to implement our nationwide bulk storage simulation.

We simulate installing a small amount of high capacity electricity storage in each NERC region at the start of the study period. Following Carson and Novan (2013) and assume that this storage can charge and discharge completely in one hour and that there are no transmission constraints on the system so that storage anywhere in a NERC region can serve demand anywhere in the region.[22] In the absence of detailed price data for NERC regions across the country we also assume that the storage capacity is charged during the lowest demand hour of the day and discharged during the highest demand hour. This strategy would maximize the market returns to the storage operator. Holladay and LaRiviere (2015) report marginal emissions by hour of the day, month of year and fuel price regime. Using these estimated marginal emissions we calculate the additional

[21] Running the same kernel regressions weighting observations by capacity factor does not materially affect the results. For coal the confidence intervals overlap for the highest heat rate (least efficient) units. For natural gas the gap between fuel price levels is slightly larger for the lowest heat rate units.

[22] Several papers employing an engineering approach highlight the importance of storage location and transmission constraints in evaluating the market returns to bulk storage. See Walawalkar et al. (2007) and Sioshansi et al. (2009) for examples.

emissions that occur during the charging process and the emissions avoided during the discharge process. We then aggregate the emissions impacts for the high and low natural gas price regimes across each NERC region.

We use the aggregate generation data to identify the lowest and highest generation hours of the day, for each day of the sample. We designate those are the charging and discharging hours, respectively. We use estimated marginal emissions from Holladay and LaRiviere (2015) to determine the emissions generated during charging hours and averted during discharging hours. We calculate:

$$Storage_{h,m,r,n} = \begin{cases} ME_{h,m,r,n} & \text{if } \mathrm{Gen}_{h,m,r,n} = \mathrm{Min}_d(\mathrm{Gen}_{h,m,r,n}) \\ -ME_{h,m,r,n} & \text{if } \mathrm{Gen}_{h,m,r,n} = \mathrm{Max}_d(\mathrm{Gen}_{h,m,r,n}) \\ 0 & \text{otherwise,} \end{cases} \tag{3}$$

where $\mathrm{Storage}_{h,m,r,n}$ is the CO_2 emissions impact of adding a single MW of bulk storage to the grid in hour h, of month of year m, during gas price regime r in NERC region n. $\mathrm{ME}_{h,m,r,n}$ is the estimated marginal emissions. $\mathrm{Gen}_{h,m,r,n}$ represents the hourly generation measured in MW's and Min_d and Max_d represent the day of sample maximum and minimum load in an hour, gas price regime and NERC region.

In the simulation, storage is typically charged overnight, most commonly hours 2-4 of the day (e.g., 1am to 3am), and discharged over late afternoon hours which vary between 14-19 depending on the season. Table 4 describes the non-market (CO_2 emissions) and market (electricity price arbitrage) outcomes of installing bulk storage in PJM. Columns 1 and 2 report the emissions associated with charging ($ME_{hmr} * Charge_h$) and discharging ($ME_{hmr} * Discharge_h$) a MW of bulk storage capacity by natural gas price regime. Marginal emissions rates are higher over night when coal is on the margin and lower during the afternoon when natural gas tends to be on the margin meaning bulk storage leads to net increases in emissions. Charging becomes slightly less dirty and discharging prevents slightly more emissions in the low natural gas price era. [23]

[23] The U.S. Environmental Protection Agency uses $39 as the estimated social cost of carbon in cost-

We also approximate the electricity market returns associated with charging and discharging per MW of electricity stored. We collect annual average prices for offpeak and onpeak electricity at hubs around the country from the Federal Energy Regulatory Commissions (FERC) Electric Market Overview for each year in our simulation.[24] The overview reports average prices by peak type for twenty-six trading hubs around the country. We then assign each hub to a NERC region and average across all hubs in a region. These prices represent weighted averages across a peak type.[25]

The external (environmental) costs associated with charging are reported in columns 1 (high gas prices) and 2 (low gas prices). Charging generates additional emissions in each NERC region because it substitutes pollution intensive coal serving baseload overnight for relatively clean natural gas serving peak load during high demand hours. The external costs are highest in MRO and SPP which have extensive coal generating capacity. External costs are lowest in NPCC and WECC, regions with relatively little coal capacity.

More importantly for our application, the level of cross-region variation in external costs is essentially unchanged by the shift in relative fuel prices, but that hides significant churn. FRCC sees a significant increase in emissions associated with bulk storage during the high natural gas price era. TRE and WECC experience smaller increases in emissions from bulk storage. SERC and RFC, on the other hand, see big decreases in emissions. The changes in emissions impacts across natural gas price levels are associated with the types of generation capacity installed in each region. FRCC, TRE and WECC each have relatively little coal and significant combined cycle gas resources. SERC and RFC have very high coal capacity and much lower levels of natural gas and therefore are less exposed to the relative price change.

The market returns to arbitrage are reported in columns 3 (high gas prices) and 4

benefit analyses evaluating new regulations.

[24]The FERC Overviews are available here: http://www.ferc.gov/market-oversight/mkt-electric/overview/archives.asp. We collected price data from the Jan 2009 and Jan 2011 reports, but the same pricing data appears in various months.

[25]Storage operators will pay less to charge and get paid more to discharge than the average cost across the entire NERC region. That implies that these prices represent a lower bound on the market returns to operating bulk storage.

(low gas prices). The private returns to charging are the revenue from dispatching storage during the onpeak portion of the day minus the costs of charging offpeak. The move to inexpensive natural gas greatly reduces the private returns to storage. Natural gas generators were on the margin during the high natural gas price era leading to high electricity prices and returns to discharging storage. After the fall in natural gas prices peak electricity prices fall considerably reducing the returns to discharging. Inexpensive natural gas also greatly reduces the cross-region variation in private returns to storage.

Columns 5 and 6 report the net social returns to bulk storage including both external costs and private returns. The private returns to bulk storage are an order of magnitude larger than the external costs suggesting that bulk storage is welfare enhancing despite the associated increase in emissions. The reduction in natural gas prices is associated with big reductions in private benefits and relatively small changes in external costs reducing the welfare benefits of bulk storage.

Table 4: Private benefits and external costs of bulk electricity storage (Monthly Marginal Emissions)

	Non-market Costs		Market Benefits		Net Benefits	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
FRCC	3.99	7.08	31.89	14.07	27.89	7.00
MRO	6.69	5.76	32.76	15.16	26.07	9.40
NPCC	1.27	0.75	26.83	15.68	25.56	14.93
RFC	5.71	3.14	29.64	14.60	23.92	11.46
SERC	6.15	2.75	27.65	11.76	21.51	9.00
SPP	8.44	8.21	29.21	13.95	20.77	5.74
TRE	3.04	5.28	21.06	18.99	18.02	13.71
WECC	2.51	4.45	18.08	10.66	15.57	6.21

Note: All numbers represent average daily $/MWh. The left two columns report the per megawatt external costs of additional CO_2 emissions associated with bulk electricity storage estimated monthly. The middle two columns describe the net private benefits of bulk storage per megawatt in the high and low natural gas price regimes respectively. The right two columns report the net benefits of bulk electricity storage per megawatt. The private benefits are calculated from the average spot price of electricity during off- and on-peak hours by NERC region calculated from data reported in FERC Electric Market Reports: *National Overview* and represent a lower bound on the actual private benefits.

The results show significant variation in the private benefits and external costs across both NERC regions and natural gas price regimes. Table 5 below describes the generating capacity in each NERC region by fuel type. Regions with relatively large fractions of coal and nuclear generation, traditional base load fuels, generally enjoy the largest private benefits from bulk storage. After the fall in natural gas prices these same regions experience the biggest reduction in benefits. Regions with significant natural gas capacity, particularly efficient combined cycle units, get the smallest benefits from bulk storage.

Regions with large natural gas capacity during the high natural gas price regime would have benefited greatly from bulk storage. Storage allows intertemporal substitution of inexpensive coal and nuclear generation for high price natural gas generation. Regions with large installed coal and nuclear bases relied less heavily on expensive natural gas to serve peak load and enjoyed smaller benefits. Because coal generation is significantly more pollution intensive the impact of storage on emissions is reversed. Facilitating the substitution of relatively dirty coal generation for clean natural gas increases total emissions.

Table 5: Generating Capacity by Fuel Type and NERC Region

NERC	Coal	Oil	CC Gas	Other Gas	Nuclear	Other
FRCC	0.21	0.27	0.29	0.18	0.03	0.02
MRO	0.51	0.05	0.07	0.17	0.08	0.11
NPCC	0.11	0.24	0.26	0.12	0.13	0.15
RFC	0.51	0.05	0.13	0.15	0.12	0.04
SERC	0.43	0.04	0.14	0.17	0.12	0.09
SPP	0.40	0.05	0.20	0.26	0.02	0.07
TRE	0.20	0.01	0.34	0.35	0.06	0.04
WECC	0.19	0.01	0.22	0.19	0.05	0.33

Note: Data on generating capacity by fuel type as a percent of total capacity in NERC region. CC gas are efficient combined cycle natural gas fired units. Other gas includes various combustion turbines with lower levels of efficiency. Source: EPA Egrid for 2005 plant and unit reports.

These results are consistent with the predictions of the model. Production with the clean input (natural gas) is relatively less efficient than production from the dirty input (coal) meaning that production levels are lower for plants using the clean input. A decrease in the price of the clean input shifts production from the dirty and lowers output prices dispassionately in high demand periods. This in turn reduces the market benefits of the bulk storage technology that shifts production from high to low demand hours. At the same time the non-market costs of shifting production are reduced to the extent the clean input has displaced the dirty input in low demand periods.

5.2 Bulk Storage in PJM

We now employ the same simulation approach focusing on the PJM wholesale electricity market. PJM provides hourly price data that does not exist for regions outside of wholesale markets. Using hourly data we can directly identify which hours would be best for charging and discharging for each day in our sample rather than relying on on-peak and off peak definitions as in the previous section. To implement this simulation we collected a separate dataset consisting of hourly wholesale prices from July of 2005 through the end of 2011.[26] The data includes demand and prices for PJM, whose three regions are mapped in Figure 6. The South region consists primarily of Virginia, the Mid-Atlantic region stretches includes Maryland, Delaware, New Jersey and most of Pennsylvania, and the Western region includes West Virginia, Ohio and parts of Illinois. Figure 6 describes the area served by PJM.

The wholesale price for PJM is a load weighted average of prices at approximately 16,000 price nodes inside the PJM footprint. Figure 7 reports the average hourly real time price for PJM across fuel price regimes.[27] The changes in real time price across the high and low gas price regimes are significant. The average (unweighted) real time price for wholesale electricity falls by more than 30% the reduction is largest over the peak hours. Prices in hour 20 fall from 76.256 to 49.50, a reduction of 54%. Over the early morning hours average price reductions range from 10% to 15%. Because the largest reductions in price happen in the hours with the highest load, the load weighted average price falls by 42%, more than the unweighted average price reduction. In the appendix we report average hourly real time load and price for each month of the year.

Using the PJM data described above, we find the lowest and highest hourly wholesale

[26]Unfortunately, historical data on wholesale prices and load are only available beginning in July of 2005.

[27]We also collect hourly load data for PJM over the sample period. Load increases by approximately 1.% between regimes spread equally throughout the day. This suggests that observed changes in emissions rates are driven by re-ordering of fuel on the supply curve rather than a change in demand.

Figure 6: Average Hourly Price in PJM

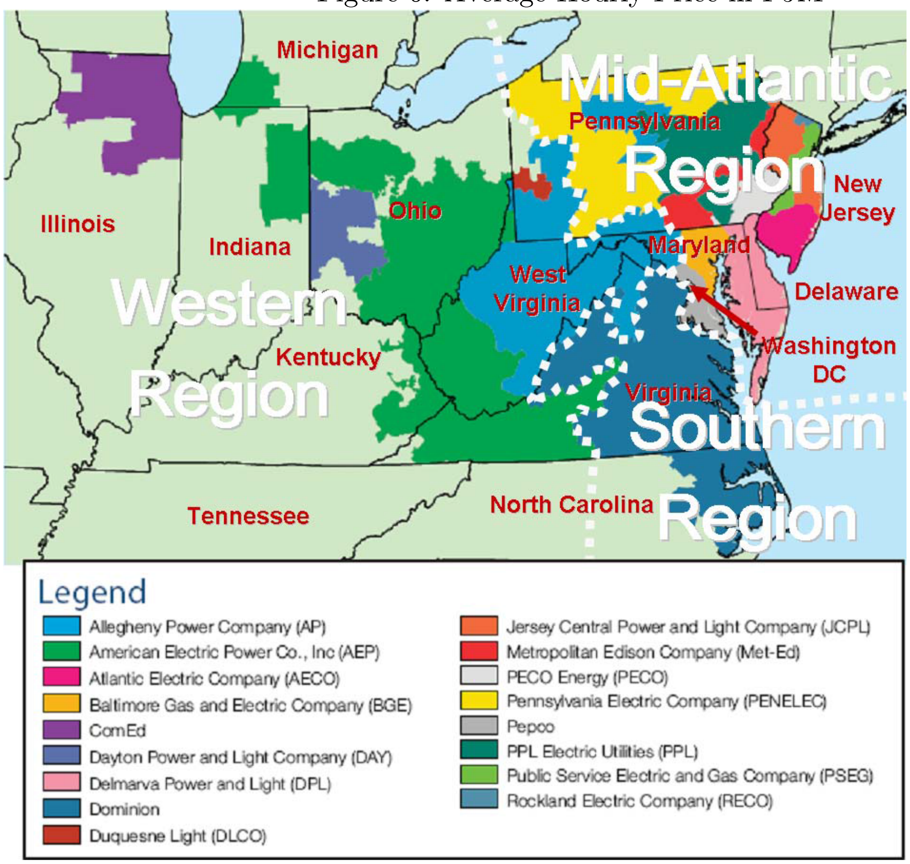
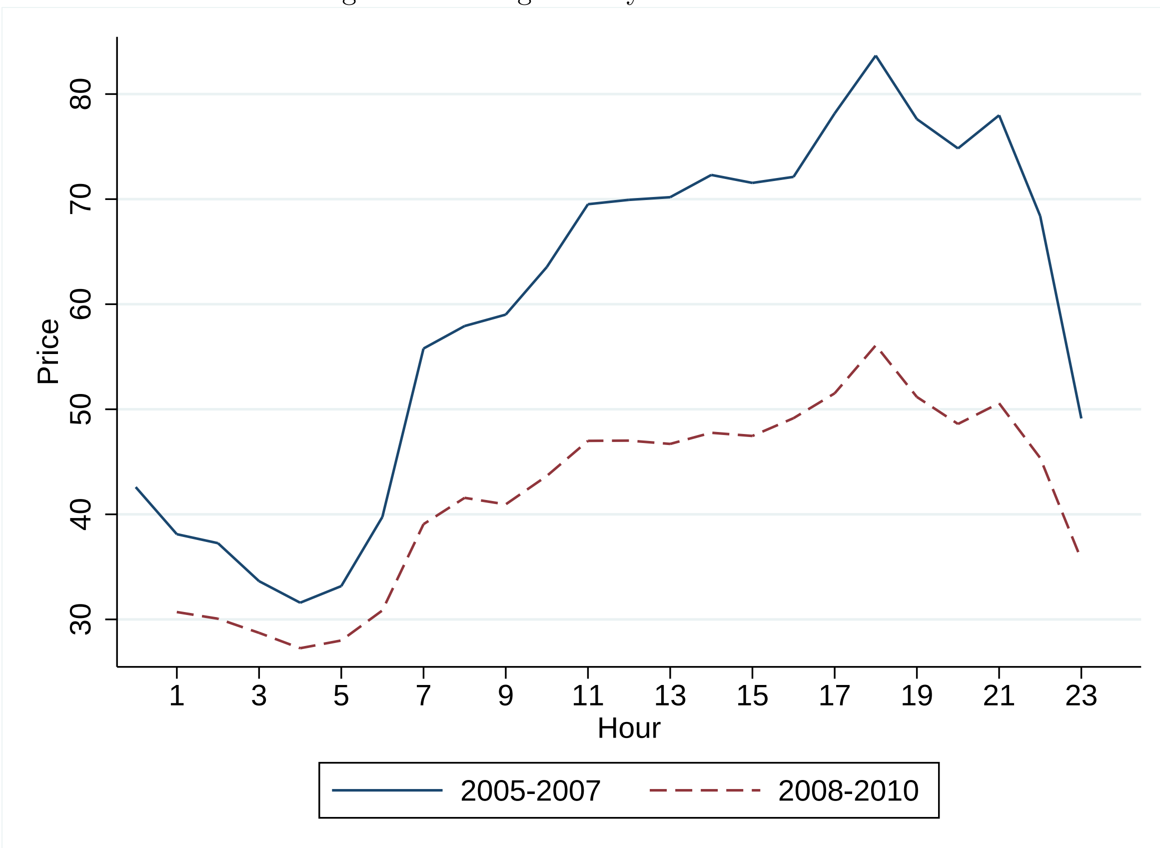


Figure 7: Average Hourly Price in PJM



Note: Average real time wholesale electricity price in PJM across fuel price eras. 2005 - 2007 represents the high natural gas price era and 2008 - Dec 2010 represents the low natural gas price era. Peak demand hour electricity prices fell by far more than off peak prices after the fall in natural gas price.

price for each hour of the day during the sample period. We denote these hours as the charging and discharging hours respectively.[28] Using the marginal emissions estimates from Holladay and LaRiviere (2015), we calculate the additional emissions that occur during the charging process and the emissions avoided during the discharge process.[29] We calculate the net CO2 emissions associated with bulk electricity storage as:

$$\Delta E_d = ME_{hmr} * Charge_h - ME_{hmr} * Discharge_h, \tag{4}$$

where the change in emissions due to the introduction of bulk storage (ΔE) is calculated for each day (d) in our sample period. We use the estimated marginal emissions reported above for each hour of the day (h), month of the year (m) and natural gas price regime (r). *Charge* and *Discharge* are indicator variables that equal 1 if the hourly PJM wholesale electricity price is the maximum or minimum of that day's 24 hourly prices.[30] The result is the daily change in emissions due to the introduction of bulk storage measured in tons of CO_2 per MW of storage capacity. We then average the emissions impacts for both the high and the low natural gas price regimes.

In the simulation, storage is typically charged in the overnight hours, most commonly hours 2-4 of the day, and discharged over late afternoon hours which vary between 14-19 depending on the season. Table 6 describes the non-market (CO_2 emissions) and market (electricity price arbitrage) outcomes of installing bulk storage in PJM. Columns 1 and 2 report the emissions associated with charging ($ME_{hmr} * Charge_h$) and discharging ($ME_{hmr} * Discharge_h$) a MW of bulk storage capacity by natural gas price regime.

[28]In less than one percent of days the lowest price hour comes after the highest price hour. In those cases we use the lowest price hour prior to the highest price hour to ensure that the storage is charged before it is discharged.

[29]The results reported here rely on emissions estimates from RFC, the NERC region that encompasses most of PJM. Changes in demand anywhere in the PJM footprint could theoretically be met with changes in generation anywhere in the Eastern Interconnection. Results using marginal and average emissions rates for the Interconnection as a whole are available by request.

[30]We assume that the storage is perfectly efficient meaning all stored electricity is returned to the grid. In reality, the efficiency of storage can vary between 70%-90% depending on the technology, although it is technological advancement along this margin which will help to make bulk storage privately profitable. In our framework considering efficiency would simply require multiplying the discharge emissions by the expected efficiency rate, which would be less than one. As a result, our emissions estimates should be considered a lower bound on the emissions impact of adding bulk electricity storage.

Marginal emissions rates are higher over night when coal is on the margin and lower during the afternoon when natural gas tends to be on the margin meaning bulk storage leads to net increases in emissions. Charging becomes slightly less dirty and discharging averts slightly more emissions in the low natural gas price era. Combined the changes in emissions intensity reduces the external costs of emissions by nearly fifty percent. We monetize the external costs associated with additional emissions using a marginal damage estimate of $39 and report the results in column 6.[31] External costs drop from $5.11 in regime 1 to $2.57 in regime 2.

We also calculate the profit associated with charging and discharging per MW of electricity stored. We replace the marginal emissions from equation 4 with hourly wholesale prices. The results are reported in columns 3 and 4. Charging becomes slightly less expensive, but the revenue from selling stored electricity during the highest demand hour of the day falls by around a third. This is not unexpected: peak electricity prices are determined by the marginal cost electricity during peak demand hours. When the natural gas price drops, so too do retail electricity prices. Taken together the net private benefits of bulk storage fall by roughly $27 after 2009. As a result, the improved environmental performance of bulk storage is an order of magnitude less than the net private benefits of bulk storage.

The results of this simulation suggest that cheap natural gas reduced the pollution intensity of bulk storage, but the market benefits of arbitraging electricity have decreased by much more. The observed changes in fuel prices resulted in both the private and external impacts of bulk electricity storage by roughly 50%. While the existing literature has emphasized the importance of evaluating storage and renewable subsidies using marginal emissions rates, these results suggest that to provide a complete picture of both the market and non-market impacts of bulk storage requires considering fuel prices (Carson and Novan (2013) and Novan (Forthcoming)).

[31] The U.S. Environmental Protection Agency uses $39 as the estimated social cost of carbon in cost-benefit analyses evaluating new regulations.

Table 6: Private and External Impacts of Bulk Electricity Storage in PJM by Gas Price Regime

Fuel Price Era	(1) Charging Emissions	(2) Discharging Emissions Averted	(3) Private Charging Costs	(4) Private Charging Revenue	(5) Net Private Benefits	(6) Net External Benefits
2005-2007	0.91	0.78	30.97	92.75	61.78	-5.11
2008-2010	0.89	0.82	27.28	61.85	34.57	-2.57

Note: This table reports the estimated market and non-market impact of introducing a MW of bulk storage to the grid in PJM. Column 1 reports the additional emissions associated with charging the bulk storage measured in tons per MW of storage. Column 2 reports the emissions averted by discharging the storage in tons per MW of storage. Column 3 reports the cost of purchasing electricity from the grid for storage and column 4 reports the revenue from discharging the storage both measured in $/MW of storage capacity . Column 5 reports the net private benefits of storage in $ per MW of storage capacity. Column 6 monetizes the emissions impact of storage by multiplying the net emissions impact times $39, the estimated marginal damages of a ton of carbon used by EPA and other U.S. government agencies.

6 Conclusion

In the future bulk electricity storage may play a large role in facilitating the introduction of renewable energy onto the grid. For the foreseeable future, new bulk storage technologies will impact existing fossil fuel generation. The advent of the cheap natural gas has serious implications for both the market and environmental impacts of bulk storage. Inexpensive natural gas has led to big reductions in peak electricity prices and much smaller reductions in off peak prices pinching the private returns to the intra-day arbitrage that bulk storage facilitates. At the same time, the shifting generation profile has made bulk storage less pollution intensive over most, but not all, of the country. More generally, these results suggest that evaluating the impact of energy policy or new energy technologies requires careful consideration of input prices.

There are several avenues for further work. We have focused on bulk electricity storage in our application, but the changes in marginal emissions across natural gas price regimes suggest that estimates of the external costs or benefits of wind power, 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. Lastly, while beyond the scope of this paper, a rigorous theoretical framework to evaluate the robustness of the welfare effects of non-pecuniary would be useful.

References

Anderson, M. L.: 2014, Subways, Strikes, and Slowdowns: The Impacts of Public Transit on Traffic Congestion, *American Economic Review* **104**(9), 2763–96.

Bento, A., Kaffine, D., Roth, K. and Zaragoza-Watkins, M.: 2014, The effects of regulation in the presence of multiple unpriced externalities: Evidence from the transportation sector, *American Economic Journal: Economic Policy* .

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.

Borenstein, S., Bushnell, J. B. and Wolak, F. A.: 2002, Measuring Market Inefficiencies in California's Restructured Wholesale Electricity Market, *American Economic Review* **92**(5), 1376–1405.

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.

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

Davis, L.: 2008, The effect of driving restrictions on air quality in mexico city, *Journal of Political Economy* **116**(1), 38–81.

Davis, L.: 2012, Prospects for nuclear power, *Journal of Economic Perspectives* **26**(1), 49–66.

DOE: 2013, Grid energy storage, *Technical report*, United States Department of Energy.

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

Going with the Flow: 2014, *The Economist Technology Quarterly* pp. 2–3.

Goulder, L. H., Jacobsen, M. R. and Van Benthem, A. A.: 2012, Unintended consequences from nested state and federal regulations: The case of the pavley greenhouse-gas-per-mile limits, *Journal of Environmental Economics and Management* **63**(2), 187–207.

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 LaRiviere, J.: 2015, Cheap natural gas, marginal emissions and the benefits of renewable energy, *Working Paper 2015-07*, University of Tennesee.

Jessoe, K. and Rapson, D.: 2014, Knowledge is (less) power: Experimental evidence from residential energy use, *American Economic Review* **104**(4), 1417–1438.

Joskow, P. L.: 2013, Natural gas: From shortages to abundance in the united states, *American Economic Review* **103**(3), 338–43.

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

Kaplan, S.: 2009, Electric power storage, *Technical Report 7-5700 R40797*, Congressional Research Service.

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

Sioshansi, R., Denholm, P., Jenkin, T. and Weiss, J.: 2009, Estimating the value of electricity storage in pjm: Arbitrage and some welfare effects, *Energy Economics* **31**(2), 269–277.

Walawalkar, R., Apt, J. and Mancini, R.: 2007, Economics of electric energy storage for energy arbitrage and regulation in new york, *Energy Policy* **35**(4), 2558–2568.

Wolak, F. A.: 2011, Do residential customers respond to hourly prices? evidence from a dynamic pricing experiment, *American Economic Review* **101**(3), 83–87.

Wolfram, C. D.: 1999, Measuring duopoly power in the british electricity spot market, *American Economic Review* **89**(4), 805–826.