# Fuel Switching from Coal to Gas:
# The Impact of Coal Stockpiling at U.S. Coal-fired Plants

Sul-Ki Lee*

Division of Economics and Business, Colorado School of Mines

July 7, 2017

**Abstract**

Do coal stockpiles of coal-fired plants influence the generation decisions of power plant operators? A theoretical model suggests that the combination of min-take coal contracts and coal storage constraints reduce the sensitivity of firms to changes in relative input prices. This finding indicates that the magnitude of fuel switching between coal and natural gas would be larger if min-take contracts were unwound, and therefore coal plants' storage constraints are less binding. An econometric analysis confirms that firms are less sensitive to price fluctuations when stockpile levels are higher. The magnitude is economically substantial: lifting the effects of coal storage restriction on the fuel price elasticity of coal-fired generation leads to an 18 percent increase in the carbon abatement under a $20 carbon tax.

**Keywords:** Coal stockpiling, fuel switching, fuel costs, electricity generation, short run inefficiency.

**JEL classification:** D8, Q4, Q5

*816 15th Street, Golden, CO, 80401, United States, sulee@mines.edu

# 1 Introduction

Tightening environmental regulations on coal generation and a boom in hydraulic fracturing natural gas recovery methods in the U.S. has lead to a large shift from coal-based to natural gas-based electricity generation (i.e. fuel switching) over the past decade. However, plant-level coal purchase decisions have hindered reductions in coal generation. For example, coal plants in the U.S. are generally obligated to purchase a certain amount of coal in each period by a long-term contract—the min-take contract. This type of contract between coal mines and coal plants is common in the U.S. for a variety of reasons involving asset specificity of coal, the importance of reliable electricity generation, and relationship specificity (Joskow, 1987; Lange, 2012). The implication of the min-take contracts in the context of fuel switching is that even if coal is a relatively more expensive input than natural gas, the coal plants are obligated to procure coal at a min-take term. If the min-take term is larger than a coal plant's optimal level of burning coal, then the plant is likely to store the excess coal, resulting in higher stockpile levels. Stockpiles may reach the storage capacity as natural gas prices remain low, and the plants that can no longer store coal are forced to burn it.

In this paper, I investigate if sizable coal stockpiles at U.S. coal-fired plants, accumulated through contractual obligations during periods of low natural gas prices, decrease the sensitivity of power generators to fuel price changes. I find that high coal stockpile levels restrict the degree of fuel switching from coal to gas. To the extent that coal is more carbon intensive than natural gas, coal stockpiling impedes carbon abatement from the electricity generation sector. In that regard, higher relative coal-to-gas fuel prices have more potential for reducing GHG emissions than currently believed. This paper reveals that assuming no impact of coal storage constraints on a coal plant's sensitivity to changes in relative input prices leads to a 18 percent larger carbon reductions under a hypothetical \$20/t$CO_2$ carbon tax.[1]

This study links coal stockpiling with fuel switching literature. Many studies have examined fuel switching to show that lower natural gas prices lead to lower coal-fired generation and more electricity from natural gas. Since natural gas contains less carbon than coal per unit of energy, this means that higher coal-to-gas relative fuel prices result in lower greenhouse gas (GHG) emissions.

[1] I use metric tons in this paper unless noted otherwise

Other research endeavors that aim to examine the impact of hypothetical carbon tax typically first derive the response of coal- and gas-fired generation with respect to the changes in relative fuel prices then apply the estimated fuel price responsiveness to the hypothetical carbon tax. From literature, we know that the impact of the relative fuel price on carbon emissions and fuel switching is nonlinear (Cullen and Mansur, 2014; Lu et al., 2012); and that higher coal prices cause a decrease in heat-rates (Linn et al., 2014). The joint impact of low natural gas prices and high wind generation level is much larger than the independent impact of each on the reduction in coal-fired generation (Fell and Kaffine, 2014), and low natural gas prices have reduced marginal emission rates from electricity generation (Holladay and LaRiviere, 2015). Finally, the larger the impact of low gas prices on emissions abatement, the smaller the impact on the electricity prices and consumer welfare (Linn et al., 2014).

In terms of stockpiling, optimal inventory management researchers have demonstrated that to purchase up to the level of $S$ when the inventory level is less than or equal to the level of $s$—the $(S, s)$ policy—is optimal for a variety of cases (e.g., Chen et al., 2013; Hall and Rust, 2007; Scarf, 1959). Jha (2014) develops a model based on the inventory optimization literature and concludes that the $(S, s)$ policy is also optimal in the context of coal stockpile management of coal plants. The decline in gas prices and the subsequent increases in coal stockpiles under the min-take contract imply that it is less likely that the coal stockpile level falls below $s$. If this holds, then more coal plants may buy coal at the min-take term. As long as the coal plant is still restricted by the long-term coal purchase contract and natural gas prices continue to be low, the coal stockpile will remain at a high level and cause short-run inefficiency in the form of restricted fuel price elasticity of coal-fired generation.

This paper is organized as follows: Section 2 conceptualizes my economic hypothesis using dynamic optimization models to show how stockpiling plays a role in fuel switching behavior of power plants. Section 3 describes the data and econometric model. Section 4 presents the results, while Section 5 conducts a counterfactual experiment, and Section 6 concludes.

## 2 Conceptual Model

If the coal demand curve of coal-fired plants was downward sloping, we would observe less coal procurement with reductions in natural gas prices. Coal plants are, however, obligated to purchase a certain amount of coal in each period by min-take contracts. Coal plants' contractual obligations imply that under low enough natural gas prices—for instance, lower than or close to coal prices in terms of dollars per kWh—optimal coal procurement levels might be at a level lower than what is restricted by the min-take contract. In this case. coal plants are forced to buy *more* coal than the optimal level (optimal under no min-take contract), and the min-take contract inhibits the potential of a reduction in coal-fired generation. This is not necessarily true, however, as long as coal plants have idle coal storage capacity. Even if a coal plant manager purchases coal at the min-take term which is greater amount than if no min-take contract exist, the manager may find it best to store coal rather than burn it when coal storage constraint is non-binding.

Once stockpiles are near capacity, however, the coal plants have to burn the excess coal which ends up with more coal-fired generation (or equivalently, less fuel switching[2]) than there would have been. To summarize, a min-take contract itself does not necessarily hinder fuel switching from coal to gas. Only if the min-take contract is combined with binding coal storage capacity is the degree of fuel switching restricted.

Consider an electricity utility ($X$) which owns a coal- and a gas-fired plant.[3] $X$ buys coal ($M_t$) from a coal mine at the contract price ($p_t^c$) via a long-term min-take contract. The min-take term is $u_t$; therefore, $M_t \geq u_t$. $X$ holds coal stockpiles ($S_{t-1}$).[4] The coal storage capacity of $X$ is $\bar{S}$. For simplicity, the coal-fired generation level is measured by the amount of coal burned. The objective of $X$ is to minimize costs subject to meeting the electricity demand or to maximize profits.

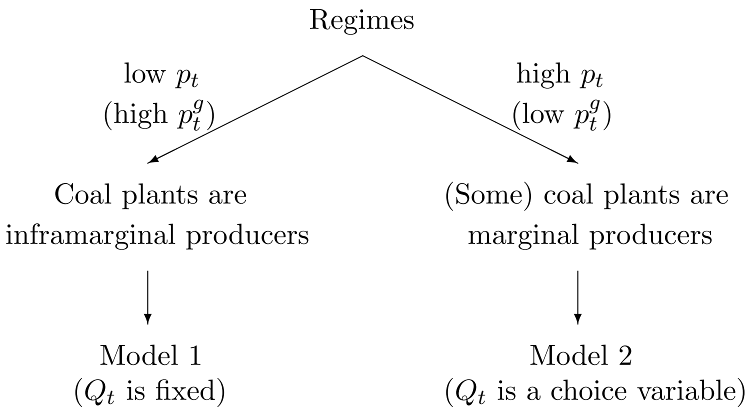
Before the decrease in the price of natural gas, coal plants served as inframarginal base-loaders,

[2]Fuel switching indicates substitution between coal and natural gas in the power plants. Also, throughout the paper, I specifically focus on electricity utilities that own both coal- and gas-fired plants. This is why more coal-fired generation under low natural gas prices is equivalent to less fuel switching from coal to gas in this context.

[3]The discussion will be focused on the operation of the coal plant; the existence of the gas plant is reflected through the *relative* fuel prices.

[4]The EIA coal stockpile data reports end-of-period stockpile levels. To keep the notation consistent with the data, I let $S_t$ indicate the end-of-period stockpile levels. Accordingly, $S_{t-1}$ indicates the beginning-of-period, or equivalently, the end-of-previous-period stocks.

Figure 1: Regime change




*Notes*:
1. $p_t^g$ is natural gas prices
2. $p_t$ is relative fuel prices defined as $p_t^c/p_t^g$

meaning that they fully utilized their generation capacities (Fell and Kaffine, 2014). Accordingly, the plants' generation levels were not one of the choice variables—rather, they chose the level of coal procurement ($M_t$) to minimize costs (Model 1 in Figure 1). Modeling $X$'s optimization in the Appendix (Section A.1) reveals that the decrease in natural gas prices (or, equivalently, the increase in relative fuel prices) reduces the optimal level of coal purchase ($\partial M_t/\partial p_t < 0$). If $M_t$ continues to decline as a result of the decline in natural gas prices, it eventually approaches $u_t$. This impact would be particularly large for less efficient coal plants since low natural gas prices enabled efficient natural gas plants to take the place of less efficient coal plants. The replaced coal plants are now marginal producers, and the level of electricity generation becomes a choice variable (Model 2 in Figure 1).

Appendix A.2 shows the new optimization problem of $X$ once the optimal level of $M_t$ reaches $u_t$, and the plant becomes a marginal producer. The choice variable of this problem is the level of coal-fired generation, $Q_t$. The result shows that when the stockpile capacity constraint is binding (i.e., $S_{t-1} = \bar{S}$) the price response of coal-fired generation is smaller than that under no such binding constraint.

From this framework, it is expected that one would observe smaller fuel price responsiveness of coal-fired generation when the coal stockpile levels are high. This hypothesis is tested in Section 3 and Section 4.[5]

Note that the logic above is particularly compelling in the short run. Coal plants can re-sign the contract with the coal mines in the long run, for instance, and they can adjust the min-take term to duly incorporate any market disturbances such as the changes in relative fuel prices. However, since the contracts are on a long-term basis, coal plants are constrained by the existing min-take term in the short run.

Coal plants can also expand its coal storage capacity in the long run. Although coal stockpiling is a good way of ensuring stable electricity supply, increasing storage capacity may not be feasible at least in the short run for two primary reasons. First, coal tends to self-heat which causes spontaneous ignition and combustion if a large amount of coal is piled (Speight, 2013). Second, coal plants store coal on-site, usually in an open area. It means that the capacity of coal storage is determined by the acreage of the yard that a coal plant owns. Purchasing more land to expand storage capacity is not practical in the short run.

# 3 Empirical Analysis

## 3.1 Data

Plant-level monthly data for utility-owned coal plants are used, comprising over 16,000 observations. Data spans from 2002 to 2012 and over 99 percent of the plants among the 171 plants in the final data set are in a regulated electricity market. Main variables from the data are electricity generation level, generation capacity, coal stockpile level, and fuel costs.

The major data sources are plant-level monthly electricity utility data Form EIA 906 and order-level data Forms EIA 923 and FERC 423 . EIA 906 provides plant-level fuel stock data from 2002 to 2007. FERC 423 collects order-level fuel cost data as well as other plant-specific information of the utility-owned plants from 2002 to 2007. EIA 923 provides fuel stock, fuel cost and other

[5] Although the min-take contracts play an important role in this theoretical model, data are not available for min-take terms. For this reason, the empirical analysis of this paper focuses on coal stockpiling. Since the min-take contracts are long-term based as well as common in the U.S. coal-based electricity generation sector (Lange, 2012), omitting min-take contracts does not invalidate the analysis.

useful information from 2008 to 2012. All order-level data are aggregated to monthly plant-level. This study uses a proprietary data set obtained from a research contract with EIA. From the three Forms, coal plants that use bituminous or sub-bituminous coal are used in the empirical analysis.[6]

EIA 923 and FERC 423 provide plant-level fuel cost data which are taken to represent fuel price data. That is, the coal procurement price for coal-fired plants and the natural gas procurement price for natural gas plants are available through these two Forms. In order to introduce the 'relative' fuel price that each plant is subject to, however, a hypothetical variable is required—the *natural gas price* that each *coal-fired plant* is facing. Given that the conceptual model is based on the optimization of an electricity utility, it is reasonable to compute average fuel costs of gas-fired plants that are located in the same state with the coal-fired plant.

Table 1 shows descriptive statistics of the variables. Panel A is for the entire period, and panels B and C provide a comparison between two periods (before and after the natural gas price shock). The variable in columns (3)—"Coal stockpile deviation from MOY avg."—is defined as the level of coal stockpile minus within-plant month-of-year (MOY) average coal stockpile levels. This variable captures the idea of *excess* coal while incorporating seasonality in coal stockpiles.

A distinct increasing pattern in relative fuel prices is observed from panels B and C in column (1). This is primarily due to the huge drop in the natural gas prices around 2008. The average stockpile level has increased in the second period as shown in column (2). The increases in the coal stockpile level deviation from plant-level MOY average in column (3) exhibit similar patterns. The negative value in Panel B in column (3) indicates that coal-fired plants stored less amount of coal than the MOY average levels in the first period. Electricity generation and generation capacity were at relatively stable levels during the entire period.

[6]Lignite is a very low-priced coal; therefore, coal-fired generation from lignite coal is generally excluded from fuel switching discussion. In EIA 923, bituminous and sub-bituminous account for approximately 99 percent in terms of heat content delivered to the U.S. coal-fired plants between 2008 and 2012.

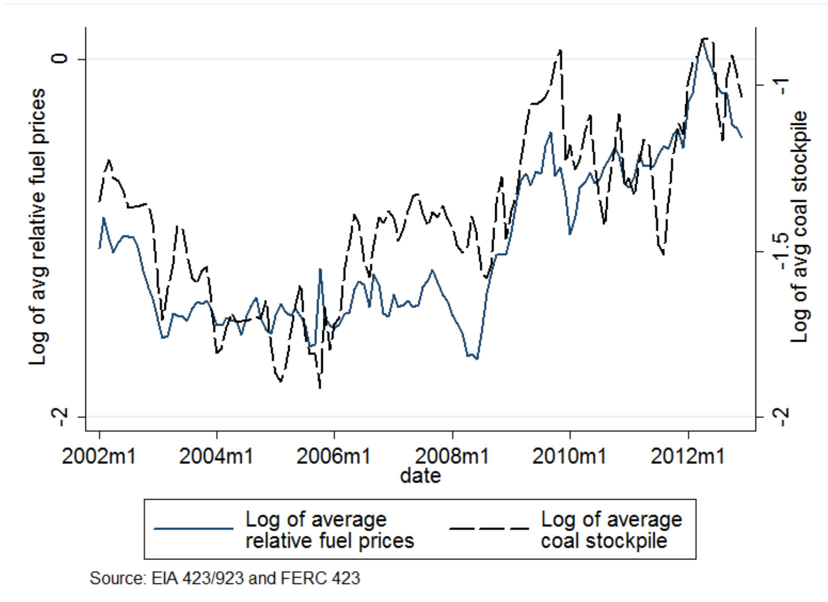
Table 1: Descriptive Statistics

| stats | (1)<br>Relative fuel cost | (2)<br>Coal Stockpile<br>(1,000 metric tons) | (3)<br>Coal stockpile deviation from MOY avg.<br>(1,000 metric tons) | (4)<br>Coal generation<br>(GWh) | (5)<br>Generation capacity<br>(MW) |
|---|---|---|---|---|---|
| *Panel A*: The whole period (2002–2012) | | | | | |
| mean | 0.42 | 416.83 | 12.28 | 426.81 | 975.84 |
| sd | 0.26 | 437.78 | 232.47 | 400.47 | 764.33 |
| *Panel B*: Period 1 (2002–2008) | | | | | |
| mean | 0.28 | 354.64 | -37.55 | 440.67 | 933.38 |
| sd | 0.11 | 363.88 | 185.11 | 410.91 | 767.08 |
| *Panel C*: Period 2 (2009–2012) | | | | | |
| mean | 0.64 | 513.41 | 89.67 | 405.27 | 1041.78 |
| sd | 0.27 | 518.04 | 273.71 | 382.73 | 755.39 |

*Notes*:
1. A distinct increasing pattern of relative fuel prices is observed from panels B and C in column (1). This is primarily due to the plunge in natural gas prices.
2. In column (2), the average level of stockpile has increased after the natural gas price shock.
3. In columns (3), coal stockpile levels deviation from month-of-year (MOY) average is defined as the level of coal stockpile minus plant-level MOY average levels.
4. Electricity generation and generation capacity were relatively stable during the whole period (columns (5) and (6)).

Figure 2 displays the time trend of the average relative fuel price and the average coal stockpiles. The solid line represents average relative fuel price (average coal prices divided by average natural gas prices) over time, and the dashed line displays average coal stockpiles held by U.S. coal-fired plants from 2002 to 2012. Both time series show an increasing trend, and average relative fuel price spiked in 2009. The oscillating average coal stockpile level implies the seasonality of the electricity demand. Coal stockpile levels are low during peak seasons—summer and winter—when the plants generate a large amount of electricity and consume copious amounts of fuel.

Figure 2: Trends of the relative fuel price and the coal stockpiles




*Notes*:
1. Both series are based on logged values.
2. The solid line represents average relative fuel price (average coal prices divided by average natural gas prices) over time.
3. The dashed line exhibits average coal stockpile held by U.S. coal-fired plants.
4. Both time series show an increasing trend. Notably, the average relative fuel price spiked in 2009.
5. The seasonality in the average coal stockpile level implies the seasonality of the electricity demand.

## 3.2 Econometric Model

I analyze if fuel price responsiveness of coal-fired generation is smaller at high coal stockpile levels. This can be done by adding interaction terms to a model where fuel price elasticity can be derived. The econometric model is presented in Equation (1).

$$\log Q_{it} = \beta_0 + \boldsymbol{\beta_1 g}(\log p_{it}, \log z_{i,t-1}) + \beta_2 \log Cap_{it} + \theta_i + \eta_m + \xi_y + \mu_{NERC,m} + \nu_{it} \qquad (1)$$

where

$$\begin{aligned}\boldsymbol{\beta_1 g}(\log p_{it}, \log z_{i,t-1}) =& \beta_{11} \log p_{it} \log z_{i,t-1} + \beta_{12} \log p_{it} (\log z_{i,t-1})^2 \\ &+ \beta_{13} (\log p_{it})^2 \log z_{i,t-1} + \beta_{14} (\log p_{it})^2 (\log z_{i,t-1})^2 \\ &+ \beta_{15} \log p_{it} + \beta_{16} (\log p_{it})^2 + \beta_{17} \log z_{i,t-1} + \beta_{18} (\log z_{i,t-1})^2.\end{aligned} \tag{2}$$

In Equation (1), $Q_{it}$ is the coal-fired generation of plant $i$ at time $t$; $p_{it}$ is the relative fuel price ($p_{it} = p^c_{it}/p^n_{st}$) defined as the ratio between coal prices ($p^c_{it}$) and the state-level gas prices ($p^n_{st}$); $z_{i,t-1}$ is the policy variable explained in detail below; $Cap_{it}$ is generation capacity; $\theta_i$ is plant fixed effects; $\eta_m$ is month-of-year (MOY) fixed effects; $\xi_y$ is year fixed effects; $\mu_{NERC,m}$ is NERC region by MOY fixed effects that captures the fact that coal plants in different regions tend to shut off the generator for maintenance at different times of the year because the demand pattern varies over regions; and $\nu_{it}$ is an error term. Following the argument of Cullen and Mansur (2014) that the impact of the relative fuel prices is nonlinear, $\log p_{it}$ is allowed to be quadratic in the $\boldsymbol{g}(\cdot)$ function presented in Equation (2). Also, since the theoretical model in Section 2 and A.2 predicts that the impact of coal stockpiling on the relative fuel price elasticity of coal-fired generation is supposed to be particularly significant when the level of coal stockpile is fairly high (i.e. near capacity), I let $\log z_{i,t-1}$ be quadratic too. Including interaction terms of $\log p_{it}$ and $\log z_{i,t-1}$ yields the $\boldsymbol{g}(\log p_{it}, \log z_{i,t-1})$ function in Equation (2).

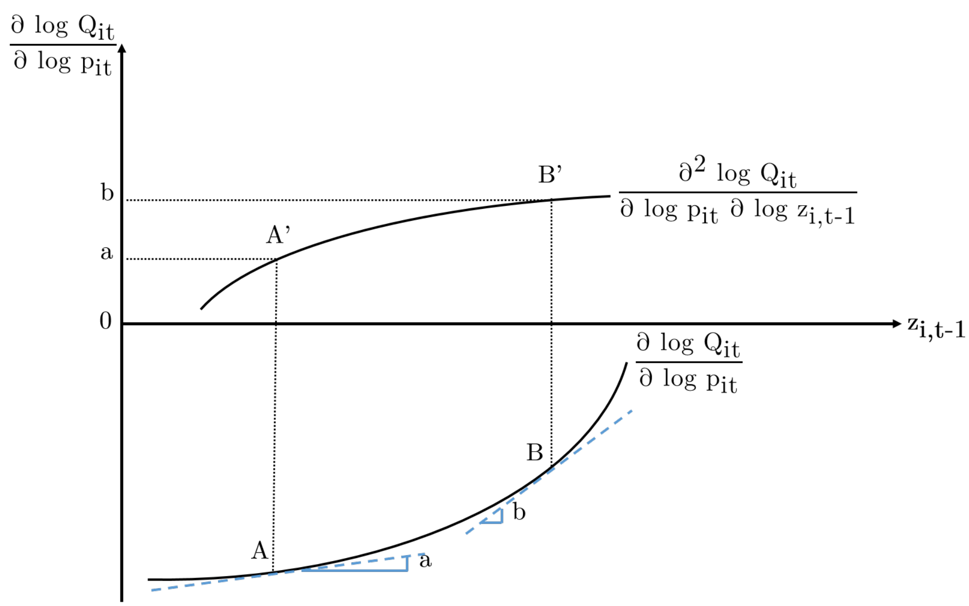
The policy variable ($z_{i,t-1}$) is a measure of coal stockpiles at the beginning of the current period. Although one might simply use the level of coal stockpiles, the deviation from within-plant MOY average stockpile level is also used for the purpose of robustness checking. Since this variable can be negative, and log is not defined on negative values, I use $\tilde{\boldsymbol{g}}(\cdot)$, rather than $\boldsymbol{g}(\cdot)$, to represent fuel price responsiveness when my policy variable is the deviation from MOY average:

$$\begin{aligned}\boldsymbol{\beta_1 \tilde{g}}(\log p_{it}, \log z_{i,t-1}) =& \boldsymbol{\beta_1^+} \left[\mathbb{I}(z_{i,t-1} > \bar{z}_{im}) \times \boldsymbol{g}(\log p_{it}, \log z_{i,t-1})\right] \\ &+ \boldsymbol{\beta_1^-} \left[\mathbb{I}(z_{i,t-1} \leq \bar{z}_{im}) \times \boldsymbol{g}(\log p_{it}, \log(-z_{i,t-1}))\right],\end{aligned} \tag{3}$$

where $\bar{z}_{im}$ is plant-level MOY average coal stockpile. $\mathbb{I}(\cdot)$ is an indicator function and takes on a value of one if the condition in the parenthesis is met and zero otherwise. In Equation (3), $\boldsymbol{\beta_1^+}$ captures the impact of above-MOY-average stockpile levels and their interaction terms on the coal-fired generation.

Estimating Equation (1) gives a number of coefficients including those for the interaction terms, inhibiting a straightforward interpretation of the coefficient estimates. A graphical representation of the results helps the hypothesis testing. The conceptual model of this paper predicts that the price elasticity ($|\partial \log Q_{it}/\partial \log p_{it}|$) and coal stockpiles have an inverse relationship. This relationship implies that $\partial \log Q_{it}/\partial \log p_{it}$ (henceforth the *first derivative*) is increasing in $z_{i,t-1}$ for a coal plant with downward sloping demand curve. To show that the first derivative has a statistically significant and positive relationship with $z_{i,t-1}$, I show that the *cross derivative* (i.e., $\partial^2 \log Q_{it}/\partial \log p_{it} \partial \log z_{i,t-1}$) takes on a positive value. As displayed in Figure 3, the hypothesis that the first derivative is increasing can be easily tested by checking if the cross derivative and its confidence interval lie above zero.

Figure 3: The first and cross derivatives



From Equation (1) and Equation (2), the cross derivative is obtained as follows:

$$\frac{\partial^2 \log Q_{it}}{\partial \log p_{it} \partial \log z_{i,t-1}} = \beta_{11} + 2\beta_{12} \log z_{i,t-1} + 2\beta_{13} \log p_{it} + 4\beta_{14} \log p_{it} \log z_{i,t-1}.$$

Similarly, if $\tilde{\boldsymbol{g}}(\cdot)$ is used instead of $\boldsymbol{g}(\cdot)$, the cross derivative is given:

$$\frac{\partial^2 \log Q_{it}}{\partial \log p_{it} \partial \log z_{i,t-1}} = \beta_{11}^{+} + 2\beta_{12}^{+} \log z_{i,t-1} + 2\beta_{13}^{+} \log p_{it} + 4\beta_{14}^{+} \log p_{it} \log z_{i,t-1}.$$

In another model specification, I bin observations by within-plant quintiles of coal stockpile levels and use dummy variables for each of the five bins to see if there are significant differences among coefficients for each bin. The binning specification is carried out by the following regression model:

$$\begin{aligned} \log Q_{it} = \beta_0 + \sum_{j=1}^{5} \beta_{1,j} BIN_{j,t-1} \log p_{it} + \sum_{j=1}^{5} \beta_{2,j} BIN_{j,t-1} (\log p_{it})^2 + \sum_{j=1}^{5} \beta_3 BIN_{j,t-1} \\ + \beta_4 \log Cap_{it} + \theta_i + \eta_m + \xi_y + \mu_{NERC,m} + \nu_{it}. \end{aligned} \tag{4}$$

In Equation (4), $BIN_{j,t-1}$ is a dummy variable. If coal stockpile levels at the end of the previous month (i.e., at $t-1$) were below the 20th percentile, $BIN_{1,t-1} = 1$ and $BIN_{j,t-1} = 0$ for all other $j$ values. Price elasticities in the bins with large coal stockpiles (e.g., $BIN_{4,t-1}$ or $BIN_{5,t-1}$) are expected to be smaller than those for bins with smaller coal stockpiles. For the fifth bin ($BIN_{5,t-1}$), for instance, price elasticity is defined as

$$|\epsilon_5| = \left| \frac{\partial \log Q_{it}}{\partial \log p_{it}} \right|_{j=5} = |\beta_{1,5} + 2\beta_{2,5} \log p_{it}| \,. \tag{5}$$

Identification relies on two assumptions. First, although Equation (1) is effectively a coal demand function of a coal plant, simultaneity is not likely present. Because fuel procurement cost is determined primarily by long-term contracts, the level of coal consumption at a power plant ($Q_{it}$) does not significantly affect fuel costs, $p_{it}$. Second, the level of coal stocks at the end of a month

($z_{it}$) is a function of the level of electricity generation for the month ($Q_{it}$), and vice versa.[7] This may appear to bring up the simultaneity issue, but by using last month's coal stock (i.e., stock of the beginning of the month, $z_{i,t-1}$), the potential difficulty is alleviated because it is clear that the beginning-of-month stock has an impact on the electricity generation of this month through the channel presented in the theoretical model section. However, this month's generation cannot have any impact on the beginning-of-month coal stock. Of course, the beginning of month stock is determined by the last month's generation. It means that Equation (1) is in a sense an AR(1) model, and weak exogeneity is guaranteed in a sound AR(1) panel model.

## 4 Results

Table 2 displays results from estimating Equation (1). Columns (1) through (3) show the results where the level of the coal stockpile is used as the policy variable (i.e., using $\boldsymbol{g(\cdot)}$ function in Equation (2)), whereas the policy variables in columns (4) through (6) are the deviation of coal stockpile levels from MOY averages ("Dev MOY avg", using $\tilde{\boldsymbol{g}}\boldsymbol{(\cdot)}$ function in Equation (3)). Standard errors are clustered at the plant-level. Note that clustering at the NERC-level or state-level barely change the results.

From the results in Table 2, point estimates of the cross derivative can be calculated. For example, using the coefficients in column (3), the cross derivative is computed as:[8]

$$\begin{aligned}\frac{\partial^2 \log Q_{it}}{\partial \log p_{it} \partial \log z_{i,t-1}} &= 0.3285 + 2 \cdot 0.0621 \cdot \log z_{i,t-1} + 2 \cdot 0.0875 \cdot \log p_{it} \\ &\quad + 4 \cdot 0.0236 \cdot \log p_{it} \log z_{i,t-1} \\ &= 0.3254 + 0.1076 \log z_{i,t-1}.\end{aligned} \tag{6}$$

Equation (6) indicates that the cross derivative is *positive* for any value of $z_{i,t-1}$ greater than $-3.0242$. Given that the median of $\log z_{i,t-1}$ in column (3) is $-1.3581$, it is expected that the cross

[7] $z_{it} = z_{i,t-1} + M_{it} - Q_{it}$, and $Q_{it} = z_{i,t-1} + M_{it} - z_{it}$.

[8] In Equation 6, average value for the year 2012 (-0.176) was used for $\log p_{it}$.

derivative is positive at high stockpile levels.

Table 2: Results of regression

| VARIABLES | (1) log(Gen) | (2) log(Gen) | (3) log(Gen) | (4) log(Gen) | (5) log(Gen) | (6) log(Gen) |
|---|---|---|---|---|---|---|
| $\log p_{it} \times \log z_{i,t-1}$ | 0.3167*** | 0.3255*** | 0.3285*** | 0.3283** | 0.3095** | 0.3159** |
| | (0.107) | (0.106) | (0.106) | (0.144) | (0.136) | (0.136) |
| $\log p_{it} \times (\log z_{i,t-1})^2$ | 0.0621** | 0.0622** | 0.0621** | 0.0327 | 0.0293 | 0.0298 |
| | (0.027) | (0.026) | (0.026) | (0.022) | (0.020) | (0.020) |
| $(\log p_{it})^2 \times \log z_{i,t-1}$ | 0.0826** | 0.0855** | 0.0875** | 0.0818 | 0.0726 | 0.0745 |
| | (0.042) | (0.042) | (0.042) | (0.054) | (0.052) | (0.052) |
| $(\log p_{it})^2 \times (\log z_{i,t-1})^2$ | 0.0216* | 0.0235** | 0.0236** | 0.0080 | 0.0066 | 0.0066 |
| | (0.011) | (0.011) | (0.011) | (0.009) | (0.008) | (0.008) |
| $\log p_{it}$ | -0.6206*** | -0.4454*** | -0.4427*** | -0.2288 | -0.1154 | -0.1057 |
| | (0.092) | (0.102) | (0.102) | (0.202) | (0.200) | (0.202) |
| $(\log p_{it})^2$ | -0.2296*** | -0.2016*** | -0.1978*** | -0.1244* | -0.1151 | -0.1097 |
| | (0.037) | (0.039) | (0.040) | (0.074) | (0.076) | (0.076) |
| $\log z_{i,t-1}$ | 0.3138*** | 0.2911*** | 0.2896*** | 0.1810** | 0.1779** | 0.1824** |
| | (0.088) | (0.082) | (0.083) | (0.089) | (0.082) | (0.082) |
| $(\log z_{i,t-1})^2$ | 0.0559*** | 0.0511*** | 0.0510*** | 0.0176 | 0.0164 | 0.0169 |
| | (0.019) | (0.018) | (0.018) | (0.013) | (0.012) | (0.012) |
| Generation capacity | 0.0031 | 0.3022** | 0.3017** | 0.0019 | 0.2919** | 0.2913** |
| | (0.002) | (0.135) | (0.136) | (0.002) | (0.143) | (0.142) |
| Observations | 16,135 | 16,135 | 16,135 | 16,136 | 16,136 | 16,136 |
| R-squared | 0.143 | 0.201 | 0.210 | 0.145 | 0.203 | 0.213 |
| Number of plantcode | 171 | 171 | 171 | 171 | 171 | 171 |
| Policy variable | | Coal stockpiles | | | Dev MOY avg | |
| Time FE | N | Y | Y | N | Y | Y |
| Nerc × month FE | N | N | Y | N | N | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

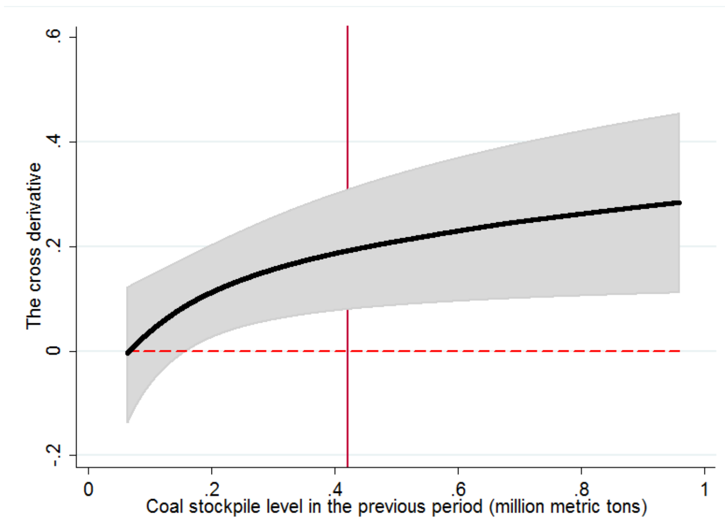
*Notes*:
1. $p_{it}$: relative fuel prices (i.e., coal prices divided by natural gas prices)
2. $z_{it}$: the level of coal stockpile in column (1) through (3) or the level of coal stockpile deviation from month-of-year average ("Dev MOY avg") in columns (4) through (6). Note that MOY average is calculated for each plant.
3. Standard errors are clustered at the plant level. Clustering at the NERC level or state level do not change the results substantially.

This is graphically presented in Figure 4.[9] In the figure, the thick solid line represents predicted cross derivative ($\partial^2 \log Q_{it}/\partial \log p_{it} \partial \log z_{i,t-1}$). It is smoothed using the locally weighted scatterplot smoothing method for better visualization. The grey area displays the 95 percent confidence interval of the predicted cross derivative. The horizontal dashed line plots $\partial^2 \log Q_{it}/\partial \log p_{it} \partial \log z_{i,t-1} = 0$, which assists one to easily investigate if the black line or the grey area lie above zero. If the black

[9] Note that Figure 4 is created based on observations that are between 10th and 90th percentile values of coal stockpile level.

line or grey area are above zero, it means that the first derivative ($\partial \log Q_{it}/\partial \log p_{it}$) is *increasing* in $z_{i,t=1}$, and the relative fuel price elasticity of coal-fired generation ($|\partial \log Q_{it}/\partial \log p_{it}|$) is *decreasing* when the coal stockpile is near capacity. Supporting this hypothesis, the point estimate as well as the 95 percent confidence interval of the cross derivative in Figure 4 are above zero (above the horizontal dashed line) around high stockpile levels.

Figure 4: Predicted cross derivative from column (3) in Table 2




*Notes*:
1. Policy variable on the horizontal axis ($z_{i,t-1}$) is the coal stockpile level.
2. The thick solid line represents predicted cross derivative ($\partial^2 \log Q_{it}/\partial \log p_{it} \partial \log z_{i,t-1}$). It is smoothed using the locally weighted scatterplot smoothing (LOWESS) method.
3. The relative fuel prices are fixed at the December 2012 average levels.
4. The grey area indicates 95% confidence interval of the thick solid line.
5. The vertical line on the figure represents the mean value of the policy variable.
6. Observations below 10th and above 90th percentile of coal stockpile levels are omitted in the figure.

Similarly, the point estimate of the cross derivative using the results in columns (6) in Table 2 is:

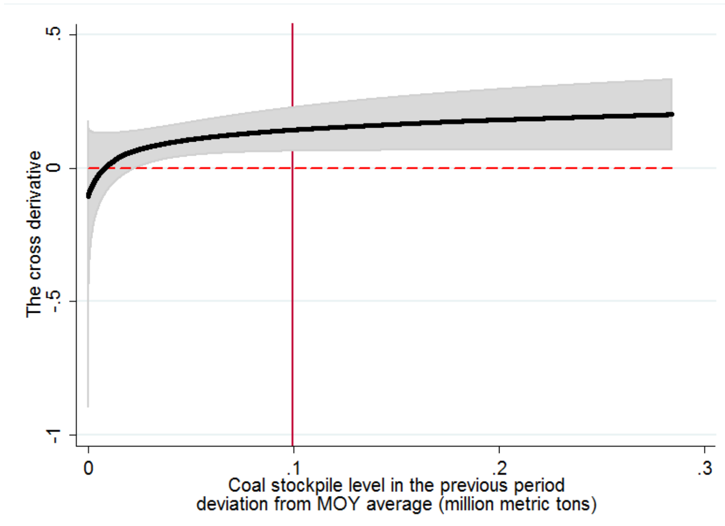
$$\frac{\partial^2 \log Q_{it}}{\partial \log p_{it} \partial \log z_{i,t-1}} = 0.2671 + 0.0538 \log z_{i,t-1} > 0 \text{ if } \log z_{i,t-1} > -4.9613$$

The median value[10] of the $\log z_{i,t-1}$ in column (6) is -2.605 which is greater than the threshold value. This is demonstrated in Figure 5 where the point estimate and its 95 percent confidence

[10]Note that the median value here is calculated based on all non-zero values of $\log z_{i,t-1}$.

interval are significantly above zero at high levels of the policy variable, meaning that coal plants are less fuel price elastic when coal stockpile levels are high.

Figure 5: Predicted cross derivative from column (6) in Table 2




*Notes*:
1. Policy variable on the horizontal axis ($z_{it}$) is the coal stockpile level deviation from plant-level MOY average.
2. The thick solid line represents predicted cross derivative ($\partial^2 \log Q_{it}/\partial \log p_{it} \partial \log z_{i,t-1}$). It is smoothed using the locally weighted scatterplot smoothing (LOWESS) method.
3. The relative fuel prices are fixed at the December 2012 average levels.
4. The grey area indicates 95% confidence interval of the thick solid line.
5. The vertical line on the figure represents the mean of the policy variable.
6. Observations below 10th and above 90th percentile of coal stockpile levels are omitted in the figure.

Table 3 shows the results for the regression model with bins in Equation (4).[11] Binning is based on the within-plant quintiles of coal stockpile levels. For instance, stockpile levels below the 20th percentile are considered as the first bin ($j = 1$). Coefficients are generally larger for higher $j$s (smaller in absolute terms), meaning that the relative fuel price response of coal-fired generation is generally smaller when the coal stockpile is at higher levels. This result applies both to the linear and the quadratic price effects. Average responsiveness of coal-fired generation with respect to relative fuel cost ($\epsilon$ in Equation (5)) for each bin derived from the results in column (3) are:

[11] Standard errors are clustered at the plant-level. Clustering at the NERC-level or state-level does not greatly change the results.

-0.5236 ($BIN_1$); -0.6981 ($BIN_2$); -0.7181 ($BIN_3$); -0.5572 ($BIN_4$); and -0.5603 ($BIN_5$). Although not monotonic, coal-fired generation levels are generally less elastic when stockpile levels are higher ($BIN_4$ and $BIN_5$) than lower ($BIN_2$ and $BIN_3$).

Table 4 shows the results of hypothesis testing. The numbers shown in the table are Wald test statistics with standard errors in parentheses. Results indicate that filing most of the coal storage capacity makes coal-fired plants less responsive to changes in fuel prices. The impact of stockpile levels above within-plant 80th percentile are statistically indistinguishable from those between 60th and 80th percentiles. However, coal-fired plants are less sensible to fuel prices at stockpile levels between 40th and 60th as well as between 20th and 40th percentiles. Note that the latter is significant only at a certain specification—column (5) in Table 4. Also, $\epsilon_1$ is not statistically different from $\epsilon_5$. Although not formally tested, this is presumably because coal-fired plants can increase output levels by a larger amount in the case of a decrease in fuel prices when they have enough coal stockpiles.

Table 3: Results of regression with binning based on the level of coal stockpile

| VARIABLES | (1) log(Gen) | (2) log(Gen) | (3) log(Gen) |
|---|---|---|---|
| $Bin_{1,t-1} \times \log p_t$ | -0.7076*** | -0.5910*** | -0.5901*** |
| | (0.105) | (0.107) | (0.109) |
| $Bin_{2,t-1} \times \log p_t$ | -0.9317*** | -0.7980*** | -0.7976*** |
| | (0.110) | (0.110) | (0.111) |
| $Bin_{3,t-1} \times \log p_t$ | -0.9663*** | -0.8243*** | -0.8236*** |
| | (0.111) | (0.112) | (0.112) |
| $Bin_{4,t-1} \times \log p_t$ | -0.7588*** | -0.6305*** | -0.6336*** |
| | (0.074) | (0.080) | (0.081) |
| $Bin_{5,t-1} \times \log p_t$ | -0.7449*** | -0.6333*** | -0.6349*** |
| | (0.075) | (0.087) | (0.087) |
| $Bin_{1,t-1} \times (\log p_t)^2$ | -0.2102*** | -0.1913*** | -0.1890*** |
| | (0.044) | (0.044) | (0.045) |
| $Bin_{2,t-1} \times (\log p_t)^2$ | -0.3060*** | -0.2833*** | -0.2826*** |
| | (0.044) | (0.044) | (0.044) |
| $Bin_{3,t-1} \times (\log p_t)^2$ | -0.3277*** | -0.3030*** | -0.2996*** |
| | (0.047) | (0.047) | (0.047) |
| $Bin_{4,t-1} \times (\log p_t)^2$ | -0.2372*** | -0.2178*** | -0.2173*** |
| | (0.033) | (0.034) | (0.035) |
| $Bin_{5,t-1} \times (\log p_t)^2$ | -0.2243*** | -0.2132*** | -0.2121*** |
| | (0.035) | (0.037) | (0.037) |
| Generation capacity | 0.0033* | 0.3021* | 0.3015* |
| | (0.002) | (0.155) | (0.155) |
| Observations | 16,136 | 16,136 | 16,136 |
| R-squared | 0.130 | 0.187 | 0.196 |
| Number of plantcode | 171 | 171 | 171 |
| Time FE | N | Y | N |
| Nerc × month FE | Y | N | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

*Notes*:
1. Binning is based on the level of coal stockpile. For instance, any stockpile level below 20th percentile value is located in the first bin ($BIN_{1,t-1}$). Also, percentile values are calculated based on within-plant stockpile levels.
2. Standard errors are clustered at the plant level. Clustering at the NERC level or state level do not change the results substantially.

Table 4: Hypothesis testing based on binning specification

| Null hypothesis | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| $H_0 : \epsilon_1 - \epsilon_5 < 0$ | -0.0288 | -0.0290 | -0.0308 | -0.0308 | -0.0308 |
| | (0.088) | (0.085) | (0.085) | (0.106) | (0.078) |
| $H_0 : \epsilon_2 - \epsilon_5 < 0$ | -0.1374 | -0.1223 | -0.1200 | -0.1200 | -0.1200* |
| | (0.097) | (0.092) | (0.093) | (0.105) | (0.062) |
| $H_0 : \epsilon_3 - \epsilon_5 < 0$ | -0.1588* | -0.1368* | -0.1357* | -0.1357 | -0.1357*** |
| | (0.083) | (0.081) | (0.081) | (0.104) | (0.034) |
| $H_0 : \epsilon_4 - \epsilon_5 < 0$ | -0.0061 | -0.0055 | -0.0044 | -0.0044 | -0.0044 |
| | (0.068) | (0.066) | (0.066) | (0.067) | (0.029) |
| Time FE | N | Y | Y | Y | Y |
| Nerc × month FE | N | N | Y | Y | Y |
| Standard errors clustred at | Plant-level | Plant-level | Plant-level | State-level | NERC-level |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

*Notes*:
1. $\epsilon_j = \partial \log Q_{it} / \partial \log p_{it}|_j = \beta_{1,j} + 2\beta_{2,j} \log p_{it}$
2. The four vertical lines are the 20th, 40th, 60th and 80th percentiles of the level of coal stockpile from left to right, respectively.

# 5 Counterfactual Experiment

From the perspective of the policy implication, it is important to recognize the role of coal stockpiling. For instance, a carbon tax would impact the relative fuel costs between coal and gas. Although both coal- and natural gas-fired generation would become more costly due to such a carbon tax, generally the impact is expected to be larger for coal to the extent that coal is more carbon intensive than natural gas (Cullen and Mansur, 2014). That is, a carbon tax will result in higher relative fuel costs for coal plants. The decrease in natural gas prices, primarily caused by an increase in hydraulic fracturing, much resembles the changes in relative fuel costs due to a carbon tax; thus, the role of coal stockpiling in fuel switching under low natural gas can be directly applied to the context of the impact of a carbon tax.

The purpose of this section is to measure the extent to which binding coal storage constraints (and, implicitly, min-take contracts) affect the potential impact of a hypothetical carbon tax. I use variation in fuel costs and the response of coal-fired generation estimated from Section 4 to estimate the responsive of coal generators to this hypothetical carbon tax. Benchmark $CO_2$ abatement is calculated based on the parameter estimates in column (3) in Table (2), and counterfactual $CO_2$ mitigation is acquired by assuming that coal stockpile levels do not have any impact on the fuel price elasticity of coal-fired generation (i.e., the coefficients of the interaction terms in the first four rows in Table (2) are zero).

Suppose that a carbon tax of 20 USD per every metric ton of $CO_2$ emitted was imposed in 2012.[12] According to the U.S. Energy Information Administration (EIA)[13] carbon intensity of coal-fired generation is 95 $kgCO_2$/MMBtu for coal-fired generation and 53 $kgCO_2$/MMBtu for gas-fired generation. Given the carbon intensity, a \$20/$tCO_2$ carbon tax is equivalent to a 190.6 cents per MMBtu increase in fuel costs for coal plants and a 106.2 cents per MMBtu increase for natural gas plants. Relative fuel prices under the \$20/$tCO_2$ carbon tax is thus

$$p_{\text{ctax}} = \frac{p^c + 190.6}{p^g + 106.2}$$

In this framework, I can estimate the reduction in coal generation from the change in input fuel prices under this hypothetical carbon policy. From Equation (1), percentage changes in coal-fired generation for a one percent change in relative fuel prices is:

$$\begin{aligned} \frac{\partial \log Q_{it}}{\partial \log p_{it}} =& \beta_{11} \log z_{i,t-1} + \beta_{12} (\log z_{i,t-1})^2 + 2\beta_{13} \log p_{it} \log z_{i,t-1} + 2\beta_{14} \log p_{it} (\log z_{i,t-1})^2 \\ &+ \beta_{15} + 2\beta_{16} \log p_{it} \end{aligned} \tag{7}$$

By multiplying $\partial \log Q_{it}/\partial \log p_{it}$ to the percentage changes in relative fuel prices under the carbon tax, I get the changes in coal-fired generation levels, $\Delta Q$.

By assuming that all decreases in coal-fired generation are met by more electricity generation from natural gas-based power plants, I compute the decrease in $CO_2$ emission from coal-fired generation ($\Delta E^c$) as well as the increase in $CO_2$ emission from gas-fired generation ($\Delta E^g$). For

[12]There has been endeavor in using fuel cost data to report that the impact of a \$20/$tCO_2$ carbon tax varies (Cullen and Mansur, 2014; Holladay and LaRiviere, 2015; Lu et al., 2012). Following this literature, I also assume a \$20 carbon tax.

[13]Source: http://www.eia.gov/tools/faqs/faq.cfm?id=73&t=11 (accessed on July 6, 2017)

example, the decrease in $CO_2$ emissions from coal-fired generation is

$$\Delta E^c = CI^c \left(\frac{ton}{MMBtu}\right) \cdot HR^c \left(\frac{Btu}{kWh}\right) \cdot 10^{-6} \left(\frac{MMBtu}{Btu}\right) \cdot \Delta Q \ (kWh)$$

where $CI^c$ is carbon intensity and $HR^c$ is the heat rate of coal-fired generation. The net decrease in $CO_2$ emissions under the \$20 carbon tax is $\Delta E = |\Delta E^c| - |\Delta E^g|$. This would be the benchmark annual $CO_2$ abatement in 2012.

To observe the effects of the carbon tax without coal stockpiling, repeat all the steps above using an econometric specification where all coefficients for stockpile-related interaction terms are assumed to be zero (i.e., $\beta_{11} = \beta_{12} = \beta_{13} = \beta_{14} = 0$ in Equation (7)). In other words, the role of coal stockpiling is intentionally neglected this time.

The net annual $CO_2$ abatement in the benchmark where the coal stockpiling is incorporated is 55 $MMTCO_2E$, which is roughly a 3.34 percent reduction compared to non-tax emissions level. However, in the counterfactual the carbon tax reduces $CO_2$ emission by 65 $MMTCO_2E$ (a 3.95 percent reduction). This result is consistent with the hypothesis that stockpiling inhibits fuel switching from coal to natural gas which is less carbon intensive. This result means that the U.S. electricity generation sector has greater potential to mitigate carbon emissions under a carbon tax than previously though if there is no binding coal stockpiling constraint.

Of course the absence of such binding constraint might change the behavior of the coal plants. For instance, coefficients such as $\beta_{15}$ and $\beta_{16}$ in Equation (7) might change. In addition, the theoretical model implies that the min-take contracts are an important factor that have caused high coal stockpile levels. Since min-take contracts have their own virtue as discussed in Section 1, it is reasonable to expect that we will observe min-take contracts in the future. However, the coal plants have a larger incentive to be more flexible about contract terms under low natural gas prices and high coal stockpile levels. To summarize, lifting the impact of coal stockpiling will result in approximately 18 percent (or, equivalently, 10 $MMTCO_2E$) larger reductions in carbon emission under a \$20/$tCO_2$ carbon tax.

# 6 Conclusion

Tightening environmental regulations as well as the recent drop in natural gas prices triggered coal to natural gas fuel switching in the U.S. power generation sector. Although the impact of the relative coal to gas fuel prices on the fuel switching has been discussed, the role of coal stockpiling has been widely ignored. As the results of this paper indicate, coal stockpiling is an important component in forecasting the impact of the changes in the relative fuel cost on the fuel mix. Had there been no binding coal storage constraint, the degree of fuel switching must have been higher. As revealed in the result of the counterfactual experiment in this paper, the absence of coal stockpiling will increase the carbon mitigation effect of a $20/tCO$_2$ carbon tax by 18 percent.

This paper has found evidence that the large coal stockpiles of the U.S. coal-fired plants along with the min-take contracts jointly have a significant impact on coal-fired generation in a way that restricts the degree of coal to gas fuel switching. This result is consistent over a series of robustness check, which buttresses the hypothesis. Although the min-take contracts are not directly incorporated into the empirical model of this paper due to limited data availability, the theoretical model predicts that the min-take contracts are an important driver of the recent increase in coal stockpile levels.

The impact of the large coal stockpiles on the coal-fired generation level is expected to be especially noticeable in the short run, because the coal plants can re-sign the contract or expand its coal storage capacity in the long run. Moreover, the shock in the natural gas prices is not likely perpetual. However, it does not negate the importance of this study—this paper provides useful insight into what will happen shortly after a shock in relative fuel costs due to a carbon tax, for instance. The establishment of a carbon tax will in essence result in an increase in relative coal prices; therefore, one would expect the same role of the coal stockpile *ceteris paribus*.

# References

Chen, Y., W. Xue, and J. Yang (2013). Technical note—optimal inventory policy in the presence of a long-term supplier and a spot market. *Operations Research 61*(1), 88–97.

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

Fell, H. and D. T. Kaffine (2014). A one-two punch: Joint effects of natural gas abundance and renewables on coal-fired power plants. Working Paper 2014-10, Colorado School of Mines.

Hall, G. and J. Rust (2007). The (S, s) policy is an optimal trading strategy in a class of commodity price speculation problems. *Economic Theory 30*(3), 515–538.

Holladay, J. S. and J. LaRiviere (2015). The impact of cheap natural gas on marginal emissions from electricity generation and implications for energy. Working Paper 2015-07, University of Tennessee.

Jha, A. (2014). Dynamic regulatory distortions: coal procurement at US power plants. http://web.stanford.edu/~akshayaj/dynamic_reg_distortion.pdf.

Joskow, P. L. (1987). Contract duration and relationship-specific investments: Empirical evidence from coal markets. *The American Economic Review*, 168–185.

Lange, I. (2012). Hedging in coal contracts under the acid rain program. *Land Economics 88*(3), 561–570.

Linn, J., E. Mastrangelo, and D. Burtraw (2014). Regulating greenhouse gases from coal power plants under the Clean Air Act. *Journal of the Association of Environmental and Resource Economists 1*(1), 97–134.

Linn, J., L. Muehlenbachs, and Y. Wang (2014). How do natural gas prices affect electricity consumers and the environment? *Resources for the Future Discussion Paper* (14-19).

Lu, X., J. Salovaara, and M. B. McElroy (2012). Implications of the recent reductions in natural gas prices for emissions of $CO_2$ from the US power sector. *Environmental science & technology 46*(5), 3014–3021.

Scarf, H. E. (1959). The optimality of (S,s) policies in the dynamic inventory problem. *Mathematical methods in the social sciences*.

Speight, J. G. (2013). *Coal-fired power generation handbook.* John Wiley & Sons.

# Appendix

## A Dynamic Optimization Model

### A.1 The impact of the low natural gas prices on the optimal level of coal purchase

The $X$'s cost minimization problem is:

$$\begin{aligned} &\max_{M_t} \int_0^T -\left[p_t M_t^2 + h \cdot \left(S_{t-1} + M_t - \bar{Q}\right)\right] e^{-rt} dt \\ s.t. \quad &\dot{S}_t = M_t - \bar{Q}, \quad S_t \geq 0, \quad S_{t-1} + M_t - \bar{Q} \geq 0, \quad S_{t-1} \leq \bar{S}, \quad M_t \geq u_t \end{aligned} \tag{A.1}$$

where $p_t$ is the relative fuel costs; $M_t$ is coal procurement; $h$ is unit holding cost; $S_{t-1}$ is beginning-of-period (or, equivalently, end-of-last-period) coal stockpile level; $\bar{Q}$ is the electricity demand that $X$ assigns to the coal plant, $\bar{Q}$ is fixed at the generation capacity because coal plants served as inframarginal electricity producers before fracking boom; $r$ is discount rate; $u_t$ is the min-take term; and $\bar{S}$ is the coal storage capacity.

Costs consist of ordering cost ($p_t M_t^2$) and holding cost ($h \cdot (S_{t-1} + M_t - \bar{Q})$).[14] In inventory management literature (Scarf, 1959; Chen et al., 2013), there is one more cost element—shortage cost, which captures the opportunity cost inherent in failure to meet electricity demand. Thus, shortage cost is incurred only when the electricity demand is above the coal stockpile plus coal purchase (i.e. stock-out). However, since coal plants supply the base load of electricity and significant adjustments to generation are costly, coal stock-outs are fairly scarce (Jha, 2014). For this

[14] Including generation cost has no impact on the solution of the problem, because the level of generation is not a choice variable but fixed at the generation capacity.

reason, this paper excludes shortage cost from the total cost, and impose a restriction of no coal stock-out ($S_{t-1}+M_t-\bar{Q} \geq 0$) while the shadow value associated with the restriction being assumed to be large enough to make the restriction hold. Other constraints in Equation (A.1) include: (1) Changes in coal stockpile equals coal procurement minus coal burned ($\dot{S}_t = M_t - \bar{Q}$); (2) coal stockpile should be non-negative ($S_t \geq 0$); (3) coal stockpile level should be less than its capacity ($S_t \leq \bar{S}$); and (4) the min-take restriction ($M_t \geq u_t$).

Although $X$ owns both coal and gas plants, this section focuses on the optimization problem from the perspective of the coal plant. By introducing the relative fuel prices ($p_t = p_t^c/p_t^n$) where $p_t^c$ is the coal prices and $p_t^n$ is the natural gas prices; however, the opportunity cost associated with producing electricity from the coal plant rather than the gas plant is incorporated.

Ordering cost ($p_t M_t^2$) is the cost incurred from coal purchase. Ordering cost increases nonlinearly as more coal is procured. This reflects the fact that if the coal plant wants to order coal at a level higher than the production capacity of the coal mine, the plant should start procuring coal from a spot market where prices are generally higher than the min-take contract prices. Note that the *relative* fuel prices are used instead of the coal prices. It reflects the fact that when natural gas prices decline, coal becomes a relatively expensive input for the electricity utility that utilizes two inputs—coal and natural gas. Throughout the discussion, it is assumed that $X$ expects high $p_t$ to continue at least in the short run.[15]

Holding cost ($h \cdot \left(S_{t-1} + M_t - \bar{Q}\right)$) is assumed to be the product of unit holding cost ($h > 0$) and the end-of-period stockpile level. At the beginning of period $t$, the plant holds $S_{t-1}$ of coal stocks. Then the plant purchases coal ($M_t$), and it burns a certain amount of coal ($\bar{Q}$) to generate electricity.[16] Holding cost is incurred only if the realized electricity demand is less than the beginning-of-period coal stock plus coal purchase (i.e., only if $S_{t-1} + M_t - \bar{Q} > 0$).

[15] It is reasonable in a sense that the recent decline in natural gas prices was triggered by the upsurge in natural gas production due to a new technology, 'fracking'. The market shock will typically not persist interminably. The Energy Information Administration's Annual Energy Outlook 2015 projects that the natural gas prices will rise to reach its historical levels over the next few years. Yet, at the same time, the natural gas prices will not be recovered instantly.

[16] Note that coal-fired generation $\bar{Q}$ equals electricity demand assigned to the coal plant in this discussion.

Hamiltonian from Equation (A.1) is:

$$H = -\left[p_t M_t^2 + h \cdot \left(S_{t-1} + M_t - \bar{Q}\right)\right] + \lambda_t \left(M_t - \bar{Q}\right) + \psi_t \left(S_{t-1} + M_t - \bar{Q}\right) + \sigma_t \left(\bar{S} - S_{t-1}\right) + \gamma_t \left(M_t - u_t\right)$$

Necessary conditions for Equation (A.1) are:

$$\frac{\partial H}{\partial M_t} = -2p_t M_t - h + \lambda_t + \psi_t + \gamma_t = 0 \tag{A.2}$$

and

$$\frac{\partial H}{\partial S_{t-1}} = -h + \psi_t - \sigma_t = -\dot{\lambda}_t + r\lambda_t. \tag{A.3}$$

From Equation (A.3),

$$\begin{aligned} \lambda_t &= Ce^{rt} - \frac{h}{r} - e^{rt} \int e^{-rt} \psi_t dt \\ &= Ce^{rt} - \frac{h}{r} - e^{rt} G_t \end{aligned} \tag{A.4}$$

where $C$ is a constant of integration and $G_t = \int e^{-rt}\psi_t dt$. Assume that $X$ disposes remaining coal at the end of the $T$th period. Let $V(S_t)$ be the salvage value as a function of $S_t$, and $\partial V(S_T)/\partial S_T = K > 0$. From the transversality condition, Equation (A.4) can be updated as:

$$\lambda_t = \left(K + \frac{h}{r}\right) e^{r(t-T)} - \frac{h}{r} - e^{rt}\left(G_t - G_T\right) \tag{A.5}$$

Substituting Equation (A.5) into Equation (A.2) yields:

$$\frac{\partial M_t}{\partial p_t} = \frac{1}{2p_t^2}\left[h + \frac{h}{r} + e^{rt}\left(G_t - G_T\right) - \psi_t - \gamma_t - \left(K + \frac{h}{r}\right) e^{r(t-T)}\right] < 0 \tag{A.6}$$

where $G_t = \int e^{-rt}\psi_t dt$.[17] In the Equation above, $K$ is the salvage value of coal stockpiles. Among the terms inside the bracket in Equation (A.6), only two (i.e., $h$ and $h/r$) are positive. Although the value of each term is not known, I can predict that $\partial M_t/\partial p_t$ is negative, especially when it

[17] $\sigma_t$ equals zero, because I assume in this section that the coal storage capacity is non-binding.

is assumed that the shadow price associated with coal stock-out constraint (i.e., $\psi_t$) is sufficiently large. Equation (A.6) implies that coal plants reduce coal procurement when the relative fuel prices increase. However, because of the min-take constraint ($M_t \geq u_t$), persistent high relative fuel prices will result in $M_t = u_t$.

## A.2 The impact of binding coal storage capacity on the optimal level of coal-fired generation

The results from section A.1 suggest that inefficient coal plants will choose $M_t$ such that $M_t = u_t$ under the continual low natural gas prices. Assume that those plants are now marginal producers which do not fully utilize their generation capacity. $X$ has to determine the level of electricity generation ($Q_t$) from the coal plant. Since the purchase quantity is fixed at $u_t$, the cost does not include ordering costs. The optimization problem of $X$ is a profit maximization in Equation (A.7).

$$\begin{gathered}\max_{Q_t} \int_0^T \left[p_t^e Q_t - C\left(p_t, Q_t\right) - h \cdot \left(S_{t-1} - u_t - Q_t\right)\right] e^{-rt} dt \\ s.t.\ \dot{S}_t = u_t - Q_t,\ S_{t-1} \leq \bar{S},\ S_{t-1} + u_t - Q_t \geq 0\end{gathered} \tag{A.7}$$

where $p_t^e$ is the electricity price and $C(\cdot)$ is generation cost. Generation cost follows the following functional form:

$$C(p_t, Q_t) = p_t HR\left(\frac{Q_t}{Q^M}\right) Q_t$$

where $HR\left(\frac{Q_t}{Q^M}\right)$ is the heat-rate of the plant which is an inverse measure of efficiency, and $Q^M$ is the generation capacity of a plant. Heat-rate is defined as the amount of energy used to generate unit electricity, and it is known that heat-rate declines (i.e., efficiency increases) as capacity factor (i.e., $Q_t/Q^M$) rises. Thus, $HR(\cdot)$ is defined:

$$HR\left(\frac{Q_t}{Q_M}\right) = a + b\frac{Q_t}{Q^M}$$

where $a, b \in \mathbb{R}$, $a > 0$ and $b < 0$. Note that the functional form of the heat-rate does not affect the result as long as the heat-rate is a monotonically decreasing function in $Q_t$.

Hamiltonian is defined as:

$$
\begin{aligned}
H =& p_t^e Q_t - a p_t Q_t - b p_t Q_t^2/Q^M - h\left(S_{t-1} - u_t - Q_t\right) \\
& + \lambda_t\left(u_t - Q_t\right) + \sigma_t\left(\bar{S} - S_{t-1}\right) + \psi\left(S_{t-1} + u_t - Q_t\right).
\end{aligned}
\tag{A.8}
$$

and necessary conditions are given in Equation (A.9) through (A.10).

$$
\frac{\partial H}{\partial Q_t} = p_t^e - a p_t - 2 b p_t Q_t/Q^M + h - \lambda_t - \psi_t = 0 \tag{A.9}
$$

$$
\frac{\partial H}{\partial S_{t-1}} = -h - \sigma_t + \psi_t = -\dot{\lambda}_t + r\lambda_t \tag{A.10}
$$

From Equation (A.10),

$$
\begin{aligned}
\lambda_t &= C_1 e^{rt} - \frac{h}{r} + e^{rt}\int e^{-rt}\sigma_t dt - e^{rt}\int e^{-rt}\psi_t dt \\
&= C_1 e^{rt} - \frac{h}{r} + e^{rt} F_t - e^{rt} G_t
\end{aligned}
\tag{A.11}
$$

where $C_1$ is a constant of integration, $F_t = \int e^{-rt}\sigma_t dt$ and $G_t = \int e^{-rt}\psi_t dt$. Applying the transversality condition as in the previous appendix section yields:

$$
\lambda_t = \left(K + \frac{h}{r}\right) e^{r(t-T)} - \frac{h}{r} + e^{rt}\left(F_t - F_T\right) - e^{rt}\left(G_t - G_T\right) \tag{A.12}
$$

where $F_t = \int e^{-rt}\sigma_t dt$ and $G_t = \int e^{-rt}\psi_t dt$. We have the following Kuhn-Tucker condition for the coal storage constraint:

$$
\sigma_t \geq 0, \quad \frac{\partial H}{\partial \sigma_t} = \bar{S} - S_{t-1} \geq 0, \quad \text{and} \quad \sigma_t\left(\bar{S} - S_{t-1}\right) = 0 \tag{A.13}
$$

Now consider the following two cases from Equation (A.13): (1) $\bar{S} - S_{t-1} > 0$ and $\sigma_t = 0$ and (2) $\bar{S} - S_{t-1} = 0$ and $\sigma_t > 0$

**Non-binding stockpile capacity constraint** In this case, $\sigma_t$ equals zero. From Equation (A.12), substituting $\sigma_t = 0$ gives us:

$$\lambda_t = \left(K + \frac{h}{r}\right) e^{r(t-T)} - \frac{h}{r} - e^{rt} \left(G_t - G_T\right) \tag{A.14}$$

Substitute Equation (A.14) into Equation (A.9) and rearrange to get the following equation:

$$\frac{\partial Q_t}{\partial p_t} = \frac{1}{2bp_t^2} \left[\psi_t + \left(K + \frac{h}{r}\right) e^{r(t-T)} - e^{rt} \left(G_t - G_T\right) - p_t^e - h - \frac{h}{r}\right] = \phi < 0 \tag{A.15}$$

In Equation (A.15), the first three terms in the bracket are positive and the last three terms are negative. Again, assuming that the shadow price associated with the coal stock-out constraint ($\psi_t$) is sufficiently large, the sign of the bracket should be positive. We also know that $b$ is less than zero; thus, the whole term ($\partial Q_t / \partial p_t$) is negative. In other words, the optimal level of coal-fired generation decreases as the relative fuel price increases. In the Equation, $\phi$ denotes the first derivative ($\partial Q_t / \partial p_t$) in the case of non-binding coal stock capacity constraint.

**Binding stockpile capacity constraint** Now consider a case where the coal stock capacity is binding. Accordingly, the shadow value ($\sigma_t$) has a positive non-zero value. Equation (A.12) is now

$$\lambda_t = \left(K + \frac{h}{r}\right) e^{r(t-T)} - \frac{h}{r} + e^{rt} \left(F_t - F_T\right) - e^{rt} \left(G_t - G_T\right) \tag{A.16}$$

Substituting Equation (A.16) into Equation (A.9) and rearrange to get:

$$\frac{\partial Q_t}{\partial p_t} = \phi + \frac{e^{rt} \left(F_t - F_T\right)}{2bp_t^2} = \omega < 0 \tag{A.17}$$

where $\phi$ is as shown in Equation (A.15). The fraction in Equation (A.17) is positive since (1) $b < 0$; (2) $p_t^2 > 0$; (3) $e^{rt} > 0$; and (4) $F_t = \int e^{-rt} \sigma_t dt$ is an increasing function, so $F_t - F_T < 0$ for any $t < T$. This indicates that $|\omega| < |\phi|$.

To summarize, the price responsiveness under the binding stock capacity constraint ($|\omega|$) is smaller than the price responsiveness under the non-binding stock capacity constraint $|\phi|$. This supports the hypothesis that the impact of the recent low natural gas prices caused fuel switching; however, high coal stockpile levels restricted the impact, thus forcing the U.S. coal plants to generate electricity at a higher level than they would have chosen under a non-binding coal stockpile constraint.