A Hedonic Price Model of Coal Purchases in the U.S. Energy Sector
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Question and hypothesis

What is the current price of sulfur content in U.S. coal and does it differ by destination which would suggest price discrimination? Studies, primarily in the 1990's and 2000's, find a negative price on the sulfur component of coal which is fitting of an inferior characteristic. This study first updates the sulfur discount using new and comparatively novel data due to improved energy sector reporting requirements. As plants install advanced abatement technologies such as flue gas desulfurization (FGD), they can consume dirtier coal to capture that discount. Recent studies have claimed mines recognize the advantage and may price discriminate, charging a premium based on whether the purchasing plant has FGD installed. Accordingly, I test two null hypotheses: the price effect of sulfur in coal is zero and so is FGD, an indicator of whether a plant has the abatement technology installed. The alternative hypotheses are that the price of sulfur in coal is negative, suggesting an inferior characteristic, and that FGD installation is positive, ceteris paribus, suggesting price discrimination.

Methods

I use a hedonic price model as first discussed in Rosen (1974), and estimate it with a linear, additive model of covariates. My data is of coal purchases at U.S. power plants from the Energy Information Administration (EIA) from 2008 through 2014. This data is collected through mandatory reporting requirements at U.S. power plants on forms *Annual electric generator report* (EIA-860) and *Power plant operations* (EIA-923) and is publicly available. Through another programming language, I download the EIA data (available in several separate files) and merge it for use in R. I use purchase-order level data for power plants that includes the price of the coal, measures of several physical properties (heat in BTU's, sulfur, ash, and mercury content), plant characteristics (FGD installation and others), as well as source mine identification number. As travel costs are potentially substantial for bulk commodities, I then use mine geocoordinate data from the Mine Safety and Health Administration (MSHA) to estimate distance from each purchase order listed mine to power plants as a proxy for travel costs.

As this results in a rather large panel dataset, over 92,000 observations, composed of several repeat measures at each plant, I use a pooled OLS model to account for unobservable characteristics at the plant level. This is equivalent to a fixed effects model in the dimension of location but not time. The data does not fit a fixed effect model across time. The time unit in the data is monthly but several observations may occur each month as I use purchase data and any month may include several orders. Obviously, this could be condensed into monthly data, but by sacrificing a great deal of valuable price data. Instead, I include time factor variables and preserve the rich quality and depth of the data. The preferred specification of the hedonic price model I estimate is:

$$Fuelcost = \beta_1 Avesulfur + \beta_1 FGD + \beta_2 AveBTU + \beta_3 Aveash + \beta_4 Quantity + \beta_5 distances + \sum_{i=1}^{6} YEAR_{2008+i}$$

I estimate the model in both level-level for use in deriving the price contribution of sulfur, and as log-log transformation for interpretation. The log-log transformation presents coefficients that approximate percent changes in the independent variable from a percent change in the dependent- interpretable as elasticities. In testing specification, the primary data of interest, the coefficient on sulfur content indicating its contribution to price, is robust to specification as is the sign on FGD. Alternate methods included different estimation techniques and specifications including quadratic transformations which were tested and had little impact on the primary coefficients of interest, sulfur content (*Avesulfur*), and FGD equipment in operation (*FGD*).

Results

Using the pooled OLS model to control for plant unobservables and adding time factors, I estimate both level-level (table 1) and log-log (table 2) specifications of the hedonic price model. The mean fuel cost in the period of observation is 254.6 cents per million BTU (MMBtu). The coefficient on sulfur content, *Avesulfur*, where sulfur content is measured in percent by weight in table 1 of -22.6 then implies a 22.6 cents per MMBtu discount for a 1-percent by weight increase in sulfur content. At the mean sulfur content of 1.3-percent, this implies a 29.4 cent per MMBtu discount over a sulfur free alternative- a 12-percent discount. Turning to the coefficient on the dummy variable *FGD* which would imply price discrimination against plants with abatement technology installed if positive, I instead find a small negative shift. The coefficient value of -8.15 suggests 8.15 cents per MMBtu cheaper fuel prices at FGD enabled plants after controlling for a variety of covariates. While statistically significant, it is a small effect and does not support the price discrimination Busse & Keohane (2007) suggest in their study using less detailed data and which covered a smaller geographic space.

Table 1. Hedonic price model estimate of U.S. coal

Fuelcost	Estimate	Std. Error	t-value	Pr(>|t|)	
Avesulfur	-22.6190	0.2963	-76.3289	0.0000	***
FGD	-8.1469	1.1154	-7.3042	0.0000	***
AveBTU	15.9700	0.1505	106.0889	0.0000	***
Aveash	1.7403	0.0809	21.5136	0.0000	***
Quantity	-0.0001	0.0000	-20.1426	0.0000	***
distances	0.0018	0.0015	1.2540	0.2098	
Year:					
2010	3.8544	0.5223	7.3797	0.0000	***
2011	22.6080	0.5287	42.7646	0.0000	***
2012	32.8830	0.5626	58.4533	0.0000	***
2013	28.7060	0.5808	49.4233	0.0000	***
2014	21.1590	0.5900	35.8624	0.0000	***
Significance codes: 0 ‘***’, 0.001 ‘**’, 0.01 ‘*’, 0.05 ‘.’, 0.1 ‘ ’ 1					

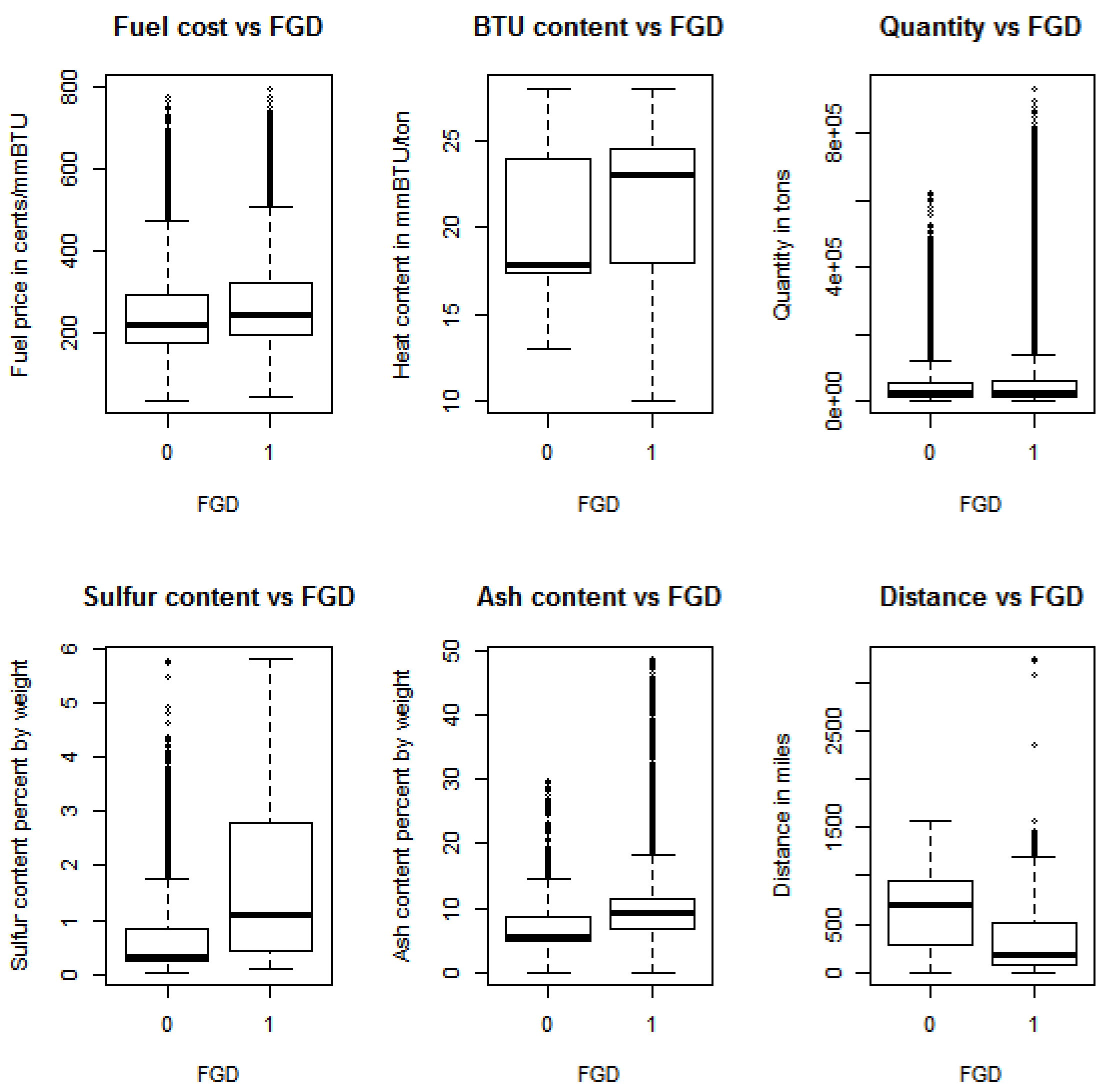
Table 2 presents the same model estimated in log-log form for ease of interpretation as well as to make the data more statistically well-behaved. The coefficient on sulfur content (*lnAvesulfur*) of -0.1036 suggests a 1-percent change in sulfur content results in a 10.3-percent change in price. This is small in magnitude to the effect of the normal characteristic BTU content, but sulfur content has the second largest effect on fuel price. This is expected due to its extensive regulation and potential impact of abatement on profitability.

Table 2. Natural log transformation of U.S. coal hedonic price model

lnFuelcost	Estimate	Std. Error	t-value	Pr(>|t|)	
lnAvesulfur	-0.1036	0.0016	-64.4523	0.0000	***
FGD	-0.0246	0.0040	-6.1392	0.0000	***
lnAveBTU	1.3318	0.0107	124.8354	0.0000	***
lnAveash	0.0848	0.0029	28.8473	0.0000	***
lnQuantity	-0.0098	0.0005	-18.7160	0.0000	***
lndistances	0.0086	0.0012	7.0368	0.0000	***
Year:					
2010	0.0237	0.0019	12.6210	0.0000	***
2011	0.1105	0.0019	58.1867	0.0000	***
2012	0.1579	0.0020	78.1413	0.0000	***
2013	0.1472	0.0021	70.5941	0.0000	***
2014	0.1249	0.0021	59.0101	0.0000	***
Significance codes: 0 ‘***’, 0.001 ‘**’, 0.01 ‘*’, 0.05 ‘.’, 0.1 ‘ ’ 1					

As the dataset I use is large relative to the complexity needed to answer the question at hand- over 92,000 observations at a fine temporal and geospatial scale, my results come up statistically significant with a high degree of confidence for most coefficients. While my null hypotheses are rejected outright, the sign and magnitude of coefficients is more telling. The effect of sulfur content on fuel costs is a rather large discount as expected. The small effect and negative sign on FGD is unexpected, however, and may indicate a more complex relationship. Figure 1 presents boxplots of the regression factors used in my analysis against the FGD indicator where 0 indicates no FGD equipment in operation at the plant and 1 indicates FGD in operation. The first box plot, *Fuel cost vs FGD* plots the dependent variable of my analysis by FGD type and shows the relatively close means and that both have quite a few outliers as expected in the large data. The presence of any quantity discount, indicative of market power on the part of power plants is also similar between the two categories (*Quantity vs FGD*). From that point, the results diverge- FGD installed plants buy higher quality coal in BTU content (*BTU content vs FGD*), but lower quality in sulfur and ash (*Sulfur content vs FGD*) and (*Ash content vs FGD*) as expected. They also purchase coal from comparatively closer sources on average, something of a surprise. Rather than installing FGD and then sourcing dirty coal from mines that may be further away, the decision to install FGD appears endogenous to location and based on the quality of local coal in terms of BTU content, sulfur, and ash. While the microeconomic model I develop in my thesis helps explain this, it is beyond the context of this paper to explore further.

Figure 1. Relationship between FGD installation (dichotomous choice variable) and regression covariates



In Conclusion, sulfur content of coal is a significant contributor to price, resulting in a roughly 12-percent discount on average relative to a zero-sulfur alternative. However, plants with FGD installed to enable consumption of dirtier coal do not face higher prices as one may expect based on conventional microeconomic theory. Further analysis suggests instead that the decision to install abatement technology is endogenous to local coal supply characteristics resulting in a more complicated relationship.

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