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PROLONGING COAL'S SUNSET:  
THE CAUSES AND CONSEQUENCES OF LOCAL PROTECTIONISM FOR  
A DECLINING POLLUTING INDUSTRY

Jonathan Eyer  
Matthew E. Kahn

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**ABSTRACT**

In recent years, the share of U.S electricity generated by coal has fallen from nearly 50% to 33%. The costs of this transition are spatially concentrated, and mining states have already lost income due to the reduced demand for coal. Coal states have enacted policies to encourage local power plants to purchase from within state mines. We document that power plants in states and counties with substantial mining activity are more likely to be coal fired and to purchase more within political boundary coal. These results are robust to including flexible controls for the distance from power plants to mines. While coal states benefits from local protectionism, these efforts impose social costs because coal mining and coal burning creates significant environmental consequences. We quantify these effects and find that a one-percentage point increase in the proportion of coal plants in a NERC region with an in-state coal mine results in approximately 2.3 million additional annual tons of CO<sub>2</sub> emissions.

Jonathan Eyer

University of Southern California

3710 McClintock Avenue, RTH 314

Los Angeles, California 90089-2902

jeyer@usc.edu

Matthew E. Kahn

Department of Economics

University of Southern California

KAP

Los Angeles, CA 90089

and NBER

kahnme@usc.edu

## **Introduction**

To mitigate the global challenge of climate change, nations must burn less coal. In recent years, the share of U.S electricity generated by coal has fallen from nearly 50% to 33%. The U.S reduction in coal use for generating power is especially notable because it has occurred without the U.S imposing carbon pricing or a carbon tax (Cragg et. al. 2013). The substitution away from coal is mainly due to the rise of the adoption of fracking technology and some states sharply ratcheting up their renewable portfolio standards (Venkatesh et al 2012 and Burtraw et al, 2012). While competition from natural gas is unlikely to abate, changes in policies such as opening additional federal lands to coal mining or rolling back carbon dioxide emissions standards on new coal plants threaten to reverse or slow this trend.

While environmentalists cheer for coal's sunset, there are interest groups with strong incentives to protect this declining industry. Reduced power plant demand for coal imposes spatially concentrated costs borne by traditional coal mining communities in states such as West Virginia, Kentucky, and Wyoming, and the low skill workers who engage in mining and providing services in mining areas. There were 261 coal mines in the United States that shipped coal to the electricity sector in 2014. These mines are located in rural areas where the population is white and has less education. Workers in these regions have fewer alternative job prospects. Their local economies experience slower economic growth and lower productivity than the rest of the nation (Islam, Minier, and Ziliak 2015 and Bollinger, Ziliak, and Troske 2011).

In this paper, we document that power plants are more likely to use coal to generate power and are more likely to purchase locally mined coal if the power plant and the coal mine are located in the same state, county, or congressional district. This finding is robust to flexibly controlling for the distance between mines and power plants. Using a county border pairs research design, we further test the robustness of this finding.

A distinctive feature of the coal industry is that its consumption and production entails large Pigouvian externalities (Davis 2011, Mueller and Mendelsohn 2012). In such a case, local protectionism causes two inefficiency losses. First, there is the usual deadweight loss from not exhausting the gains to trade between demanders and low cost suppliers. Second, there is

deadweight loss caused by prolonging the use of a dirty technology that causes social harm. By supporting local coal mines, the transition to natural gas and renewable electricity sources is slowed and this results in additional emissions of greenhouse gases and criteria air pollutants.

Since climate change is a global externality, local and state elected leaders have weak incentives to internalize this externality. Instead, they have strong incentives to protect local coal mines as this improves the local economy through providing high-paying jobs as well as indirectly through the local spending multiplier. We study the environmental implications of this local protectionism for local air quality and overall CO<sub>2</sub> emissions. By quantifying the social costs associated with protection of a declining industry, this piece of our empirics is the mirror opposite of other research that attempts to measure the social benefits of protecting infant industries (see Goodstein 1995). This literature argues that society ostensibly props up infant industries because they convey a social good (Melitz 2005).

In the last section of the paper, we explore possible mechanisms for our core finding of “excess” within state coal trade between power plants and mines. We argue that local politicians have strong incentives to engage in protecting local coal interests. Coal states provide large financial incentives to encourage local coal purchases. West Virginia provides incentives that reduce the production cost for local coal mines and encourages local buyers to buy from these sellers. Maryland and Virginia offer a \$3 per ton tax credit for utilities buying in-state coal (Bowen and Deskins 2015). Oklahoma offers credits of \$5 per ton to both coal mines and power plants, effectively contributing \$10 to every ton of Oklahoman coal that is burned for electricity generation in the state. Both Oklahoma and Illinois have enacted laws aimed at forcing power plants to purchase their coal from in-state mines rather than cheaper coal from Wyoming. We also present alternative mechanisms that lead to increased local demand for coal.

### **The Spatial Economics of Coal Trading**

We present a simple framework for studying bilateral trade between power plants and coal mines. Consider the case where coal is produced by a set of spatially-differentiated mines using a homogeneous production function, and converted into electricity using a homogeneous production function by power plants that seek to minimize their cost of production subject to

generating a given level of electricity.<sup>1</sup> Further, suppose there are no long-term contracts such that coal is sold on a spot market.

Given these assumptions, we expect that a “gravity model” of bilateral trade will have significant explanatory power (Lee and Swagel 1997). If coal markets are competitive, power plants will purchase coal from the closest mine, at a price that is at most equal to the production price of coal plus the transportation cost from the second closest mine. If a power plant purchases from a mine that is not its closest prospective trading partner, it is indicative of deviation from perfect competition.<sup>2</sup>

The cost of coal transportation is a substantial portion of total coal generation costs. Shipping coal by rail – the predominant transportation method – generally costs on the order of 2-8 cents per ton per mile, so each additional 100 miles of transportation increases the delivered price of coal by \$2-\$8 per ton. Given that coal prices are generally below \$50 per ton, power plants have a substantial incentive to purchase coal from close mines. These costs are a significant portion of total operating costs for a coal-fired power plant. Based on EIA reports of average operating expenses and average heat input for coal-fired power plants, the transportation costs of moving coal 100 miles would account for about 0.2 cents per kWh, around 5% of total operating expenses.<sup>3</sup> In 2012, the median power plant purchased 960,000 tons of coal while the median coal mine delivered nearly 1.2 million tons of coal.

Figure One maps the 372 coal fired power plants in the United States and the 161 coal mines in the U.S that either purchased coal in 2014 or shipped coal to the electricity sector in 2014. Several clear geographic patterns emerge. Coal mining is concentrated in Appalachia (Kentucky, West Virginia, Ohio and Pennsylvania), in southern Illinois and Indiana, and in Wyoming. While the majority of mines are in the Appalachia region, the largest mines are in

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<sup>1</sup> In reality, even publicly-owned utilities that own their own power plants should purchase from other power plants if the electricity can be provided at lower cost.

<sup>2</sup> Neither coal production nor electricity generation technologies are homogenous, of course, and other considerations such as uncertainty about mine production, could lead power plants to seek out more distant trading partners.

<sup>3</sup> EIA quotes 3.904 cents per kwh for fossil steam plants in 2014 and 0.00052 tons of coal per kwh. We assume a transportation cost of \$4 per 100 miles, the midpoint of our range.

Wyoming, which has relatively low-quality but easily accessible coal deposits with low sulfur content. Coal power plants exist throughout the country, but are most prevalent in the Midwest, Mid Atlantic, and South. For each power plant, we calculate the Euclidean distance to the coal mines with which it trades. Table 1 reports the empirical distribution of these distances where we weight the observations by the quantity of coal the power plant consumed in 2014. We find that 30% of total power plant coal is purchased from mines that are less than 80 miles away.

### **The Empirical Strategy**

We examine the effects of political boundaries on the trading patterns of pairs of power plants and coal mines. We examine the likelihood of trading, prices and contract characteristics, and the placement and potential closure of coal fired power plants. In each case, our key hypotheses focus on the coefficient estimates for our border variables. Our identification strategy relies on the assumption that our flexible controls for distance capture any affect associated with transportation costs between power plants and mines.

Our sunset hypothesis posits that all else equal, there will be more coal trade when the buyer and seller are in the same jurisdiction, and that the contractual lock-in will be stronger. This econometric strategy combines the standard trade gravity model with Holmes' (1999) borders approach. In a later section, we will report tests of heterogeneous treatment effects along a number of dimensions.

The distinctive feature of our econometric framework is the vector of dummy variables indicating if the origin mine and potential destination power plant share a common political jurisdiction. Power plants and mines that are within the same jurisdiction are, of course, relatively close to each other and have lower transportation costs than power plants that are far away. By explicitly controlling for the distance between power plants and mines, our political jurisdiction variable compares the likelihood of buying coal from an in-state mine relative to a similarly distance out-of-state mine.

#### *Coal Purchases and Quantities*

We estimate a series of regressions to test the hypothesis that coal trading varies across political boundaries in ways beyond what would be predicted by a gravity model. In each case, our linear index of interest is given in equation (1)

$$Y_{ijt} = A + g(\text{distance}_{ij}) + B_1 * \text{Border}_{ijt} + B_2 * \text{Power Plant Characteristics}_{it} + B_3 * \text{Mine Characteristics}_{jt} + \gamma_t + U_{ijt} \quad (1)$$

and we vary the definition of the dependent variable Y to reflect different dimensions along which coal mines and power plants interact. The subscript i denotes the power plant, j denotes the mine, and t denotes the year. In equation (1), the key explanatory variables of interest are the vector of border dummies. We include three dummies indicating whether the mine and the plant are located in the same state, same Congressional District and same county. A key point to note is that we flexibly model the role of distance on trade. This g() polynomial, splines, and distance bins that we report below allow us to flexibly control for proxies for transportation costs.<sup>4</sup>

In our first set of results, the dependent variable is a dummy variable, *Trade<sub>ijt</sub>*, that equals one if power plant i trades with mine j in year t. We estimate the probability of *Trade<sub>ijt</sub>* in a logistic regression, assuming that *Trade<sub>ijt</sub>* = 1 if *Y<sub>ijt</sub>* > 0.

Similarly, we estimate OLS versions of equation (1) in which the dependent variable *Y<sub>ijt</sub>* is defined as *Quantity<sub>ijt</sub>*, the amount of coal in tons that is traded between each power plant and mine combination. We estimate this model using both the full sample of possible power plant mine combinations as well as a restricted model in which we focus on quantity behavior among only those combinations in which a trade takes place.<sup>5</sup>

### *A Border Pairs Test*

One potential concern is that our cross-political boundary results might merely be the effect of non-linear distance effects that are not captured by our distance controls. In order to

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<sup>4</sup> In the Web Appendix, we estimate the relationship between distance and the EIA-reported transportation costs between states. Distance and year fixed effects result in an adjusted R-Squared of between 0.35 and 0.64 depending on the distance specification.

<sup>5</sup> In the Web Appendix, we also estimate a Heckit version of equation (1) to study the joint determinants of whether a trade occurs and the quantity given that a trade takes place.

address this concern, we estimate the effect of the political boundary on coal trading in a border pairs framework in the spirit of Black (1999) and Holmes (1998). Following Dube, Lester, and Reich (2010), we rely on controls for contiguous counties that are in different states to better control for unobserved characteristics of power plant locations that could bias our estimates of the cross state effect. Our approach relies on the typical continuity assumption that characteristics on either side of a boundary are the same. Under this assumption, the effect of the border can be treated as randomly assigned. In our case, we assume that power plants in counties on either side of a state border are otherwise comparable and then estimate the causal effect of crossing the border on the probability that a mine buys coal from a power plant.

Following Dube, Lester, and Reich (2010), we limit our sample to only counties along state borders that are adjacent to a county in another state that also has a coal-fired power plant. There are 69 counties that both have a coal-fired power plant and are adjacent to a county in a different state that also has a coal fired power plant and a total of 89 unique county boundary pairs (some counties appear in more than one pair). There are 105 power plants in these 69 counties. Figure 2 shows the set of power plants in this sample.

We create a set of adjacent county fixed effects for each pair of cross-state adjacent counties. Each pair of adjacent-county power plants receives a unique fixed effect. For example, there are two power plants in Clark County, Nevada and one power plant in neighboring San Bernardino County, California. Each of the three power plants receives a value of one for the Clark County-San Bernardino County dummy variable and all other power plants in the country receive a zero for this fixed effect. If a county borders two neighboring-state counties with a power plant, plants in that county would receive a one for the fixed effects corresponding to each county pairs. When we consider the likelihood that some mine in, for example, Nevada sells coal to each of these plants, the county pair specific fixed effect captures the characteristics of the region and the difference in the probability of transaction between the Nevada plants and the California plant is driven by the state border.

In order to implement this strategy, we modify equation (1) to reflect the addition of these bordering county fixed effects as



$$Y_{ijpt} = \Delta_p + \gamma_t + g(\text{distance}_{ij}) + B_1 * \text{Border}_{ijt} + B_2 * \text{Power Plant Characteristics}_{it} + B_3 * \text{Mine Characteristics}_{jt} + \gamma_t + U_{ijpt} \quad (2)$$

Note that this new regression differs from equation (1) because we now restrict the set of observations we include in the regression and we also include a set of  $\Delta_p$  county border fixed effects. Initially, we do not restrict the set of coal mining counties with which a power plant can trade, so for each of our 105 power plants we observe 400 potential trading partners in each year. We again estimate a logistic regression of the probability that a mine and a power plant trade in a given year as determined by  $\text{Trade}_{ijpt} = 1$  if  $Y_{ijpt} > 0$ .

Next, we further restrict the sample so that each power plant can only buy coal from mines in its own state or in its adjacent county's state. Figure 3 shows the set of cross-state power plant pairs in Ohio, Kentucky, West Virginia, and Indiana, as well as the mines in each of these states. Each of the power plants along the Ohio-West Virginia border have a choice set of coal mine trading partners of Ohio or West Virginia mines. Similarly, each of the power plants along the Indiana-Kentucky border have a choice set of coal mine trading partners of Indiana and Kentucky mines. As in the unrestricted border pairs framework, each pair of adjacent counties receives a fixed effect to control for unobserved regional variation. By limiting our sample to only those mines that could be in-state trading partners for at least one of the power plants in a pair, we ensure that each mine has at least one in-state potential trading partner and at least one out-of-state potential trading partner to serve as a counterfactual.

### *Price and Contract Characteristics*

In our next set of empirical results, we examine several of the characteristics of trades. In this analysis, we restrict our study to only trades, rather than all possible power plant-mine interactions because trade characteristics like price and contracting status cannot be observed for trades that did not occur. We also focus on a monthly time-scale (the sharpest time-step reported in our data) rather than an annual time-scale to avoid issues associated with aggregating prices and contract characteristics over months in a year. In this regression, we first estimate a version of equation (1) but the dependent variable in this case is the price of coal in dollars per MMBTU from a power plant to a mine.

We then estimate two models regarding the contractual characteristics of powerplant-mine interactions. Joskow (1985) notes the importance of relationship-specific capital in the coal market, with larger quantity contracts tending to be longer duration contracts. As a corollary, we look for the presence of relationship-specific political capital in coal trades, expecting that plant-mine pairs in which political capital is prevalent or more important will be more likely to lock into long-term contracts than plant-mine pairings in which political capital does not exist. Similarly, coal mines that have guaranteed a level of demand by entering into long lasting contracts will be more likely to hire or retain workers than plants that have not guaranteed trading partners. We estimate two modified versions of equation (1). In the first case, we estimate a logistic regression for whether or not a trade was governed by a contract. In the second case, we estimate a Poisson model in which the dependent variable is the number of months a contract extends following an observed contracted coal purchase.

#### *Power Plant Placement and Closures*

Our gravity model estimates depend on the fact that a power plant is open at a point in time and located at a given location. These two decisions are choices and may thus be affected by access to coal mines. If coal plants are placed in coal mining jurisdictions more frequently than market forces would imply, our estimates of coal mines' effect on local coal demand will be an underestimate of the full power exerted by mining interests.

To study the locational choice of power plants and their choice over whether to close, we estimate a multinomial logit of whether a county has a coal-fired power plant, a non-coal fired power plant, or no power plants as a function of whether or not the county has an in-state or in-county coal mine. We assume that for a county,  $i$ , the index associated with each of these three power plant placement decisions is given as specified in equation (3).

$$Index_i = B_1 * In\ Jurisdiction\ Mine_i + B_2 Distance\ to\ Closest\ Mine_i + B_3 * Population_i + U_i. \quad (3)$$

We control for the Euclidean distance between the county centroid and the closest coal mine. As a result, our political boundary effects are estimated holding constant the cost associated with moving coal from the closest mine to the power plant. Because power plants are

often located near population centers, we include the county's population in the power plant siting decision.

Competition from natural gas has led to substantial reductions in coal-fired electricity capacity over the past decade. We examine the universe of coal-fired generators and estimate the likelihood that a generator is retired by 2014 as a function of whether or not the generator has an in-state coal mine.<sup>6</sup> We estimate a logit regression for whether or not a generator is retired in our sample as  $Retired_i = 1$  if  $Y_i > 0$  where

$$Y_i = B_1 * Power\ Plant_i + B_2 * In\ Jurisdiction\ Mine_i + B_3 * Distance\ to\ Closest\ Mine_i + U_i \quad (4)$$

If the coefficient on our In Jurisdiction Mine coefficient is less than zero, power plants with an in-state coal mine are less likely to retire than plants without an in-state coal mine, even after controlling for the distance to the geographically closest potential trading partner.

### **Power Plant and Mine Data**

In this study, our main unit of analysis will be a coal mine's trading with each power plant in each year. The EIA collects data on fuel deliveries to the plants in the power sector. Since 2008, fuel deliveries have been collected on the EIA-923 form, which covers monthly fuel deliveries by both utilities and non-utility deliveries. Between 2002 and 2008, utility fuel deliveries were reported through the FERC-423, while non-utility deliveries were collected via survey with the EIA-423 for plants in excessive of 50 MW. Prior to 2002, only the FERC-423 existed, and collected only utility fuel purchases.

Since the earlier data do not report the mine-specific MSHA ID, we treat a mine's location as the mine's county of origin, which is reported much more consistently and aggregate coal deliveries to the plant-coal county-year (aggregating across months in the year). We then construct a data set containing 5,289,000 rows. Our unit of analysis is a coal mine/power plant/year. In our data set, there are 410 coal mine counties, 516 power plants and 25 years (1990-2014) in our sample. For each mining county, we calculate the latitude and longitude of

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<sup>6</sup> The EIA reports retirements at the generator-level rather than the plant-level.

the county centroid and compute the distance between the county centroid and each power plant. Finally, we calculate the total annual quantity of coal that is shipped for each county and the total annual quantity of coal that is received for each power plant and drop plant-coal county-year observations in which the plant received no coal or the coal county shipped no coal. This leaves 1.9 million observations from the initial matrix of 5.2 million plant-mine-year combinations. We supplement the EIA/FERC data with additional power plant-specific characteristics such as the utility type of the power plant operator (e.g. municipally-owned, investor-owned, independent power producer, etc).

In the recent EIA sample (2008-2014), characteristics of the delivered coal are also reported for each transaction. These characteristics include the price of the delivered cost of coal, as well as the ash, sulfur, and heat content for the fuels. The more recent data also report characteristics of the trade such as whether or not the trade occurred pursuant to a contract and the duration of any contracts. This sample also contains the mine-specific MSHA ID of each coal mine rather than only the county of origin. We exploit the increased precision of coal mine locations in this data and compute the distance between each mine (rather than the county centroid of the mine) and each power plant based on the reported latitudes and longitudes of each mine and plant. We then overlay state, county, and congressional boundary shape files onto our geospatial data on power plant and coal county/mine location and create indicator variables for whether a power plant – coal county/mine combination are in the same state, county, or congressional district.

### **Results on Coal Trading**

Table 2 reports estimates of equation (1) and shows that coal purchases are generally local. Columns 3 and 4 show the percentage of coal deliveries to power plants in each state that were from in-state and out-of-state coal mines, respectively. Columns 5 and 6 show the percentage of coal deliveries from mines in each state that were to in-state and out-of-state power plants, respectively. Columns 4 and 5 are blank if a state does not have any coal mines that shipped to the power sector throughout the duration of our sample.

The average state receives 24% of its total coal consumption from in-state mines, although this is biased downward because many states do not produce coal at all and must purchase all of their coal from out-of-state mines. The average across only the states that produce

coal is 48%. The states that receive the lowest-percentage of total coal purchases from in-state mines were Kansas (20), Maryland (24), Missouri (29), Oklahoma (40) and Tennessee (47). In each of these states, coal is the dominant source of electricity generation but coal mining is a relatively small industry.

### *Coal Purchases and Quantities Results*

The prevalence for intra-state trades is not driven merely by distance. Across each distance specification, we consistently find a positive and statistically significant effect of being within state lines on the probability that a power plant will purchase coal from a mine. Table 3 presents these results. A power plant is 0.3 percentage points more likely to purchase coal from an in-state mine than from an out-of-state mine that is the same distance away. This effect is quite large in context. Across our entire sample, the probability that a plant-mine combination engages in a trade in a given year is about 2 percent. We find even stronger effects at the county boundary. Intra-county trades are approximately 2 percentage points more likely to occur than inter-county trades. The effect of the congressional district is comparable in magnitude to the effect of the state boundary. These effects are consistent regardless of the approach to controlling for transportation distance using either polynomials or a restricted cubic spline. Using the 10-mile bins – the finest granularity of distance control – the state effect is reduced slightly. Mines and power plants that share a state are 0.2 percentage points more likely to trade than those that are in different states. The effect of the county boundary is reduced by an order of magnitude, and the statistical significance is weaker for both the county and congressional boundary estimates. Also, note the relationship between the political boundaries. A mine that is in the same county and congressional district as a power plant is obviously in the same state as well, so the net effect is the sum of the three coefficients.

The probability that a power plant and a mine trade is increasing in both power plant purchases and in mine shipments. This indicates that plants that buy a lot of coal tend to purchase from more mines than plants that buy a relatively small amount of coal. Similarly, mines that produce a lot of coal sell to more power plants than small mines.

We find similar results when we examine the joint distribution of a trade occurring and the amount of coal that is purchased. These results are reported in Table 4. A power plant will

buy approximately 8,000 more tons of coal from an in-state mine than it would buy from an out-of-state mine of comparable distance. The effect of the congressional border is approximately 100,000 tons, around eight times the magnitude of the cross-state effect. The effect of the county border is substantial; a mine will buy 1.4 million more tons of coal from an in-county power plant than it would buy from an out-of-county power plant. In each case except the cross-state effect in the splined distance control and the state and congressional boundary effect in the ten-mile bins, the estimates are strikingly similar across distance controls.

We also estimate the effect of political boundaries on the intensive margin of coal trading. Table 5 presents the regression results for this specification. Only the intra-county effect persists on the intensive margin, except in the case where we include the ten-mile bins where we find suggestive evidence that plants buy more from cross-state mines than in-state mines. Surprisingly, the magnitude of the effect is only slightly smaller than the case in which we consider the quantity in all observations.

### *Border Pairs Results*

Our border pair models presented in Tables 6 and 7 report further evidence of political boundary effects in coal purchasing. In estimating equation (2), we include all mines as potential trading partners, each of the 105 power plants in the 69 counties that both have a coal-fired power plant and border a county with a coal-fired power plant can trade with any of the 400 mines.

We find that plants are approximately 4 percentage points more likely to purchase coal from in-state mines than from mines in a different state. Again, this effect is robust to a range of controls for the distance between the power plant and the coal mine. The same state boundary also corresponds in some cases to a shared congressional district and county which we omit from the estimation. Using the border pairs subsample, we find larger overall effects than our baseline specification. The combined effect of the three boundaries in our baseline results is around 2-3 percentage points.

Next, we further restrict our sample by limiting each pair of adjacent-county power plants to only being able to purchase coal from mines in either state of the adjacent counties. For example, the power plants in Mobile County, Alabama and Jackson County, Mississippi would

have as potential trading partners the coal mines in Alabama and Mississippi but we drop the power plant-mine observations in which the mines are in other states. In this specification, the border variable captures the relative difference in the probability of a trade between each mine in Alabama and the plants in Mobile, County Alabama and Jackson County, Mississippi. Our neighboring county-pair fixed effect captures unobserved characteristics of the Mobile/Jackson area and the remaining difference in probability is assigned to the border effect. The results are slightly larger in the specification that limits a power plant's potential trading partners to only the in-state mines on either end of the border. In this specification, the effect of a sharing a state is in the neighborhood of 5 percentage points.

#### *Price and Contract Characteristics Results*

When we focus on the characteristics of the trades (i.e. transacted price, contracted vs spot, and contract duration), we substantially reduce our sample size because we do not observe trade characteristics for trades that do not occur. After focusing only on trades that occur, the correlation between our cross-boundary variables increases because many of the, for example, different-county but same-state observations that induced orthogonality between the political boundary controls did not result in trades. As such, we highlight the results of F-tests for the joint significance of our political-boundary variables in each of these cases.

Evidence of jurisdictional effects on price after controlling for distance are mixed, at best. The point estimates in Table 8 indicate that there is a price discount associated with in-county coal purchases of about 12-15 cents per million BTUs. This suggests that coal mines are able to extract higher prices from power plants that are outside their county than from those who are within the county. Again, these regressions include controls for the distance between the power plant and the coal mine, so it is unlikely that this is simply reflecting transportation costs. However, only in the case of the spline distance control is there any evidence that the cross-boundary controls are jointly different from zero. This suggests that the mines are not able to extract different prices from plants that are across jurisdictional lines than from plants within their jurisdiction. Similarly, when we control for distance using the ten-mile bins, we do not find statistical significance for any of our key explanatory variables, and the F-test suggests joint insignificance. The weak evidence of plants extracting lower prices from in-state mines provides

further suggestive evidence that the relationship between plants and mines is driven by a political mechanism rather than a cost minimizing mechanism.

In Table 9 we estimate the effect of our boundary effects on the probability that a trade is associated with a long-term contract rather than a spot trade. Similarly, in Table 10 we estimate the effect of our boundary effects on the length of the contract for those trades that are associated with contracts. Each of our political boundary controls is negative but statistically insignificant when we examine whether power plants and mines enter into contracts or interact on the spot market. We also find that both the county and state boundaries affect contract duration. Specifically, we find that contracts are longer between power plants and mines that are within the same but shorter between power plants and mines that are within the same state. The magnitude of the two coefficients are relatively similar but of opposite signs, indicating that mines and power plants that are in the same state but not in the same county, tend to be shorter than contracts between cross-state firms as well as shorter than contracts between intra-county firms.

These results are broadly consistent with state specific/relationship-specific capital being present. Joskow (1984) who attributed the longer duration of relatively high quality contracts to relationship-specific capital. Moreover, the effect of the boundary control on contracting duration and prevalence indicates the potential for a different type of relationship specific capital. While Joskow (1984) focused on the physical characteristics of the plants and the coal that they burned, our result is consistent with relationship-specific political capital inducing power plants and mines to operate together.

### *Power Plant Placement and Closures Results*

In Table 11, we report estimates of equation (3). We find a jurisdictional effect in power plant placement decisions. After controlling for the distance to the closest coal mine, the probability of having a coal fired power plant in a county is about 0.5 percentage points higher if there is a coal mine in the county than if there is not a coal mine in the county. Note that this indicates that even after controlling for the distance to the closest coal mine, a county is more likely to have a coal burning power plant if there is an in-county coal mine. Surprisingly, the



effect of having an in-state but out-of-county coal mine actually serves to decrease the probability that there is a coal power plant in the county. This effect is quite small relative to the in-county effect.

In Table 12, we find a jurisdictional effect in coal power plant closures. A power plant (or rather a generator) that is in a state with a coal mine is approximately 7 percentage points less likely to have closed by 2014 than a coal power plant without a potential in-state trading partner. In each case, these results suggest that coal mines' political influence on the electricity sector exceeds our primary estimates which take coal plant stock as exogenous.

### **The Social Cost of Within Coal Mining States Transactions**

Coal burning features a high carbon intensity of roughly 2300 pounds per MWH of power. In addition to producing this global externality, coal use by power plants creates many local negative environmental and health externalities. These externalities are shown to reduce nearby home values (Davis 2011). In an area suffering from high unemployment, these may be secondary concerns.

We estimate the environmental implications of local coal protectionism in two complementary fashions. First, we estimate the local impacts of coal consumption using data on ambient air pollution levels in counties that have power plants that purchase coal for the electricity sector and in surrounding counties. Second, we estimate aggregate emissions from the electricity sector due to coal protection. The former approach allows for a more specific consideration of who is affected by pollution, while the latter approach provides an aggregate effect of coal mining protection that takes into account general equilibrium impacts in the electricity sector.

In order to examine the effect of coal protectionism on ambient pollution, we obtain daily pollution monitor data on SO<sub>2</sub> and PM<sub>10</sub> from the EPA's AQM database. We then aggregate these data to the county-year level by averaging across daily monitor observations for each monitor in a county and merge them with the total amount of delivered coal to a county for electricity generation, as derived from the fuel deliveries data. Finally, in order to examine total emissions, we obtain CO<sub>2</sub>, SO<sub>2</sub>, and NO<sub>x</sub> emissions from the EPA's Air Markets Program Data

(AMPD). AMPD reports emissions for each power plant that is covered under any air markets program. Most power plants are covered by at least one air markets program in the latter half of our sample. We then aggregate CO<sub>2</sub>, SO<sub>2</sub>, and NO<sub>x</sub> emissions across power plants in each NERC region up to the monthly level.

In order to examine the effect of coal protection on ambient air quality, we estimate

$$Y_{jst} = B_1 * In\ Jurisdiction\ Mine_{st} + B_2 * CoalPercentage_{st} + County\ Characteristics_j + \gamma_t + U_{jst} \quad (5)$$

Where  $Y_{jst}$  is the average measurement of ambient pollution levels for sulfur dioxide and particulate matter in county  $j$  in state  $s$  at year  $t$ , *In Jurisdiction Mine* is a logical vector indicating whether or not state  $s$  has at least one coal mine in its state, and *CoalPercentage* is the percentage of electricity generated in state  $s$  that came from coal.

Similarly, in order to examine the effect of coal protection on total greenhouse gas emissions, we estimate

$$Y_{nt} = B_1 * In\ Jurisdiction\ Mine\ Percentage_{nt} + B_2 * NERC\ Characteristics_n + T_t + U_{nt} \quad (6)$$

where  $Y_{nt}$  is the CO<sub>2</sub>, NO<sub>x</sub>, and SO<sub>2</sub> emissions from AMPD regulated power plants in nerc  $n$  in year  $t$ , *In Jurisdiction Mine Percentage* is the proportion of coal-fired power plants in a NERC region that have an in-state coal mine and *NERC Characteristics* is a matrix of NERC characteristics.

If coal power plants with nearby coal mines are more likely to continue to operate – or operate at higher levels of generation – than coal power plants without nearby coal mines, we would expect a positive coefficient on the *In Jurisdiction Mine Percentage* variable.

Tables 13 and 14 present these regression results. As we would expect purchases of coal by electricity generators at the state level results in increased SO<sub>2</sub> concentrations in counties within the state. Based on our OLS regression results presented in Table 4, we would expect that the effect of having an in-state coal plant would increase SO<sub>2</sub> concentrations by approximately 40 percent relative to monitors in states that do not have coal plants. We do not find statistically

significant effects of coal plants on PM10 levels, although most of the states that have the highest annual concentrations of PM10 in our sample are also prone to fires, which can cause spikes in PM pollution, and such effects could be driving the variation in PM10 readings in our sample.

We also find that the percentage of power plants in a NERC region that have an in-state coal mine trading option leads to increases in CO<sub>2</sub>, SO<sub>2</sub>, and NO<sub>x</sub> emissions. In the case of CO<sub>2</sub>, for every percentage point increase in the proportion of power plants in a NERC region that are close to an in-state mine, an extra 2.3 million tons of CO<sub>2</sub> is emitted. Assuming a social cost of carbon of \$40 per short ton, these results suggest that each percentage point increase in the number of coal-fired power plants in a NERC region with a potential in-state trading partner results in \$92 million per year in added social costs. Based on the average prevalence of in-state mines in our data set (53%), this would indicate that around 8% of CO<sub>2</sub> emissions from the electricity sector are attributable to this effect.

## **Mechanisms**

Our main explanation for *within political boundary trading* focuses on political intervention. Elected officials such as a mining state's governors, Congressmen and local officials have an incentive to help their constituents. Miners and the members of their communities are typically low skill people with long time roots to the area. Local elected officials in coal states are aware that their constituents face significant dislocation costs and seek to protect them from long-lasting negative income shocks by stabilizing demand for their constituents' output. The conversion of a power plant in Kentucky from coal to natural gas, for example, resulted in substantial opposition from state officials representing the area on the grounds that the reduction in coal demand would harm the local economy.

Elected officials in coal areas have strong incentives to take actions that increase the demand for coal. Mining is a high paying job for low skill workers. Indeed, the average wage for all U.S. coal miners was \$82,000 in 2013 according to the National Mining Association. The average wage across all industries, by contrast, was under \$50,000. Coal mining counties tend to

have a slightly weaker economy than non-coal mining economies. In 2014, the average unemployment rate in counties with coal mines was 6.8 while the average unemployment rate in counties without coal mines was 6.5.<sup>7</sup> Because coal mining activity is concentrated in relatively rural communities and require relatively little education, these statistics actually underestimate the coal mining wage premium. Further, mining jobs create a local multiplier effect in their community, resulting in additional job opportunities and economic activity.

By boosting coal demand and raising local wages and home prices, elected officials can achieve stability for local families. Stable families and their communities go hand in hand in areas that do not have alternative industries to turn to. Families enjoying job security are less likely to experience divorce, substance abuse and economic hardship. Labor economists have emphasized the possibility of scarring due to duration dependence associated with experiencing unemployment (Borjas and Heckman 1980, Black and Sanders 2002, Black, McKinnish and Sanders 2003, 2005a, 2005b). If coal miners lose their jobs and become unemployed, the duration dependence hypothesis posits that they will become increasingly less likely to find a new job and are unlikely to find a new job that pays as well.

The children who grow up in such families are likely to be especially affected. Based on Heckman's dynamic complementarity model, the early years of life are crucial for raising the chances of a child achieving her full potential (Heckman 2007). If the household's income declines and if the family divorces, such a child is less likely to succeed. This sad dynamic shows how reduced coal demand translates into widening income inequality and increased poverty in these rural areas.

Elected officials in coal areas will understand this dynamic and this creates an incentive (due to both altruism for constituents as well as the desire to be re-elected) for local politicians to use their clout to encourage in state coal power plants to "buy locally". In this sense, local

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<sup>7</sup> This comparison excludes Wyoming which has a substantial natural gas and petroleum industry and an unemployment rate that is far below the national average.

elected officials internalize the social benefits from boosting coal demand but have only weak incentives to internalize the social costs of coal burning.<sup>8</sup>

There are alternative mechanisms that could contribute to within jurisdiction coal trade. Past investments by local power plants to optimize the power generation process as a function of local coal purchases may create a “lock in” effect through the asset specificity of past investments (Joskow 1985). One possible explanation for why the two parties would be willing to “lock in” to a long term relationship is because they anticipate that there will be less future political risk between two contracting parties since they are both represented by the same political leaders.

To provide some evidence on the relevance of different potential mechanisms for understanding “within border” coal trade, we study how the propensity to purchase in state coal grows with state leverage over power plants and in times of recession. One might expect that elected officials would be more likely to use their clout to encourage the demand or in state coal mining when the economy is weak.

Government-owned utilities would be more susceptible to job protectionary pressure than independent power producers who would be more concerned with profit maximization and less concerned with local stakeholders. We would therefore expect a smaller border effect when a greater proportion of power plants were controlled by independent power producers. Cicala (2014) documents that when utilities were forced to divest their power plants to new owners during electricity deregulation that fuel procurement costs declined for coal plants. If political protectionism is responsible for some of Cicala’s (2014) effect, we would expect our border protection estimate to be smaller after deregulation than before it.

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<sup>8</sup> The claim that local officials internalize the local benefits of coal trading is related to earlier research on cross-store spillovers in demand at a shopping mall. Gould, Pashigian, and Pendergrast (2005) document that by offering a rent discount, the mall owner can attract an anchor tenant who attracts plenty of customers. Anticipating that there will be walking traffic, other mall tenants are willing to pay more for commercial leases to have access to these potential customers.

In order to investigate this dynamic over time we estimate our primary specification as a cross section for each year between 1990 and 2014, dropping the time specific fixed effects. Estimating the model separately for each year, rather than estimating a single model with interactions between the time fixed-effects and the political boundary variables lets our distance control adjust over time so that changes in the political protectionism over time are not confounded with changes in shipping infrastructure or cost. Figure 4 shows the 95 percent confidence interval on the same state coefficient over time (the same Congressional District and same county patterns yield similar findings). From 1990-1995, the coefficients increased indicating relatively greater protectionary behavior. Between 1995 and approximately 2000, there was relatively less protectionary behavior. Protectionary behavior was relatively consistent between 2000 and 2006 after which it generally decreased through 2014.

The majority of our sample falls after electricity deregulation was already in effect or being implemented so we do not have pre-deregulation coefficients with which to compare against the early 1990s results. Still, it is surprising that protectionist behavior is growing during the expansion of deregulation during the early 1990s. This provides some suggestive evidence our political jurisdiction effect is not driving the reductions in procurement costs noted by Cicala (2014).

We also note that changes in political climate throughout our sample period. The magnitude of the boundary effect is generally decreasing (less local purchasing) during the 1990s, the late 2000s and the 2010s, while it is increasing (more local purchasing) during the early and mid-2000s. Note that the 1992-2000 and 2008-2014 periods with declining local protectionary power aligns with a Democratic Presidential Administration, while the increasing protectionary power of the 2000s aligns with the Republican Bush Administration. We do not, however, attempt to assign any causality between the political climate and the effect.

## **Conclusion**

The phase out of coal would be a Hicksian Pareto improvement for the United States. Based on a Social Cost of Carbon of \$30 a ton, the current national externality from coal associated with in-state mine purchasing (abstracting from criteria air pollution costs) was \$4

billion in 2014.<sup>9</sup> While it may be socially efficient to phase out coal, the costs of such a transition are spatially concentrated.

States that specialize in mining have incentives to promote the growth (or at least slow the decline) of one of their key industries. Given the durability of housing capital and the built up social networks established in mining areas, its residents face both migration costs and asset losses if the demand for coal mining declines. Such individuals face a fundamental job retraining challenge that middle-aged workers who have worked in mines will have trouble transitioning to other jobs. In this sense, there are local “Social Benefits of Carbon” and these benefits have been ignored in studying issues related to the political economy of phasing out coal. Local officials in coal areas are well aware that many of their constituents depend on the continuing viability of the coal industry. Local officials internalize the benefits of coal’s prolonged sunset but they ignore the social environmental costs associated with such implicit subsidies. Our examination of the sunset of the coal industry revisits recent research that has examined how rural communities have gained from the fracking boom (Feyrer, Mansur, and Sacerdote (2015) and Alcott and Kenniston (2014)).

We have introduced a detection approach to measure “excess” within border transactions. Our empirical research design exploits the fact that coal mines and power plants vary with respect to their geographic location. Some lie within the same political jurisdiction while others do not. This variation allows us to use a flexible distance polynomial between pairs of power plants and coal mines to recover key border effects. We document an increased likelihood of trade and larger trade quantities when partners are within the same state, county, and congressional district.

The costs of the CO<sub>2</sub> emissions associated with this local “excess demand” are substantial, nearly \$100 million a year in excess social carbon costs. Still, sustained low natural gas prices may limit the duration of coal’s sunset as market forces drive additional natural gas capacity to supplant coal plants. Given the proximity of environmental tipping points associated with particular levels of CO<sub>2</sub> concentrations as well as uncertainty about energy policy under the Trump Administration, coal protectionism may still cause major environmental costs.

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<sup>9</sup> 2600000 tons of coal \* 53 percent of plants close to an in-state mine \* 30 dollars per ton = \$4.1 billion

Future research could consider how to design a coal buyout that compensates coal miners and their communities for their expected losses. Harstad (2012) has proposed a mechanism of “buying coal” from marginal unregulated coal producers and then keeping these purchased deposits in the ground after restricting production among regulated coal producers. His proposal could be modified to address the problem of coal’s sunset by purchasing domestic coal reserves and by paying coal miners to mine the purchased coal. This would compensate mine owners and workers for their losses associated with natural gas production and environmental regulations.



## References

- Allcott H, Keniston D. Dutch disease or agglomeration? The local economic effects of natural resource booms in modern America. National Bureau of Economic Research; 2014 Sep 18.
- Autor DH, Dorn D, Hanson GH. The China shock: Learning from labor market adjustment to large changes in trade. *Annual Review of Economics*. 2016 Sep;8(1).
- Baer P, Harte, J, Haya, B, Herzog AV, Holdren, J, Hultman, NE, Kammen, DM, Norgaard, RB, Raymond, L. Equity and Greenhouse Gas Responsibility, *Science*. 2000; 289(5488):pp2287.
- Black, Daniel K, Sanders S. The impact of economic conditions on participation in disability programs: Evidence from the coal boom and bust. *American Economic Review*. 2002 Mar 1:27-50.
- Black DA, McKinnish TG, Sanders SG. Does the availability of high-wage jobs for low-skilled men affect welfare expenditures? Evidence from shocks to the steel and coal industries. *Journal of Public Economics*. 2003 Sep 30;87(9):1921-42.
- Black DA, McKinnish TG, Sanders SG. Tight labor markets and the demand for education: Evidence from the coal boom and bust. *Industrial & Labor Relations Review*. 2005 Oct 1;59(1):3-16.
- Black D, McKinnish T, Sanders S. The economic impact of the coal boom and bust\*. *The Economic Journal*. 2005 Apr 1;115(503):449-76.
- Black SE. Do better schools matter? Parental valuation of elementary education. *Quarterly journal of economics*. 1999 May 1:577-99.
- Bollinger C, JP Ziliak, and KR Troske. "Skill upgrading and wages in Appalachia". *Journal of Labor Economics*. 2011 Oct, 29(4):819-857.
- Bowen, Eric, John Deskins 2015. "Government Incentives to Promote Demand for West Virginia Coal" West Virginia University. <http://www.be.wvu.edu/bber/pdfs/BBER-2015-01.pdf>
- Burtraw, D., Palmer K., Paul, A., and Woerman, M. "Secular Trends, Environmental Regulations, and Electricity Markets". *The Electricity Journal*. 2012. 25(6).
- Cicala S. When does regulation distort costs? lessons from fuel procurement in us electricity generation. *The American Economic Review*. 2014 Jan 1;105(1):411-44.

Cragg MI, Zhou Y, Gurney K, Kahn ME. Carbon geography: the political economy of congressional support for legislation intended to mitigate greenhouse gas production. *Economic Inquiry*. 2013 Apr 1;51(2):1640-50.

Davis LW. The effect of power plants on local housing values and rents. *Review of Economics and Statistics*. 2011 Nov 1;93(4):1391-402.

DeLeire T, Eliason P, Timmins C. Measuring the employment impacts of shale gas development. McCourt School of Public Policy, Georgetown University. 2014 Aug.

Dube A, Lester TW, Reich M. Minimum Wage Effects Across State Borders: Estimates Using Contiguous Counties. *The Review of Economics and Statistics*, 2010 Nov 1; 92(4):945-964.

Feyrer J, Mansur ET, Sacerdote B. Geographic Dispersion of Economic Shocks: Evidence from the Fracking Revolution. *American Economic Review*, forthcoming.

Gibbons S, Heblich S, Lho E, Timmins C. Fear of Fracking: The Impact of the Shale Gas Exploration on House Prices in Britain. Department of Economics, University of Bristol, UK; 2016 Mar 3.

Glaeser EL, Gyourko J. Durable housing and urban decline. *Journal of Political Economy*. 2005;113(2):345-75.

Goodstein, E. The Economic Roots of Environmental Decline: Property Rights or Path Dependence? *Journal of Economic Issues*. 1995; 29(4): 1029-1043.

Gould ED, Pashigian BP, Prendergast CJ. Contracts, externalities, and incentives in shopping malls. *Review of Economics and Statistics*. 2005 Aug;87(3):411-22.

Haerer D, Pratson L. Employment trends in the US Electricity Sector, 2008–2012. *Energy Policy*. 2015 Jul 31; 82:85-98.

Harstad B. Buy coal! A case for supply-side environmental policy. *Journal of Political Economy*. 2012 Feb;120(1):77-115.

Heckman JJ. The economics, technology, and neuroscience of human capability formation. *Proceedings of the national Academy of Sciences*. 2007 Aug 14;104(33):13250-5.

Heckman JJ, Borjas GJ. Does unemployment cause future unemployment? Definitions, questions and answers from a continuous time model of heterogeneity and state dependence. *Economica*. 1980 Aug 1;47(187):247-83.

Holmes TJ. The effect of state policies on the location of manufacturing: Evidence from state borders. *Journal of political Economy*. 1998 Aug;106(4):667-705.

Islam, TM., J. Minier, and JP Ziliak. "On Persistent Poverty in a Rich Country". *Southern Economic Journal*. 2015 Jan 1, 81(3):653-78

Joskow PL. Contract duration and relationship-specific investments: Empirical evidence from coal markets. *The American Economic Review*. 1987 Mar 1:168-85.

Joskow PL. Vertical integration and long-term contracts: The case of coal-burning electric generating plants. *Journal of Law, Economics, & Organization*. 1985 Apr 1;1(1):33-80.

Joskow PL. Price adjustments in long-term contracts: The case of coal. *JL & Econ*. 1988; 31:47.

Joskow PL. The performance of long-term contracts: further evidence from coal markets. *The Rand Journal of Economics*. 1990 Jul 1:251-74.

Joskow PL, Schmalensee R. The Performance of Coal-Burning Electric Generating Units in the United States. *Journal of Applied Econometrics*. 1987 Apr;2(2):85-109.

Kentucky Coal Facts,

[http://energy.ky.gov/Coal%20Facts%20Library/Kentucky%20Coal%20Facts%20-%202014th%20Edition%20\(2014\).pdf](http://energy.ky.gov/Coal%20Facts%20Library/Kentucky%20Coal%20Facts%20-%202014th%20Edition%20(2014).pdf)

Knudsen EI, Heckman JJ, Cameron JL, Shonkoff JP. Economic, neurobiological, and behavioral perspectives on building America's future workforce. *Proceedings of the National Academy of Sciences*. 2006 Jul 5;103(27):10155-62.

Lee JW, Swagel P. Trade barriers and trade flows across countries and industries. *Review of Economics and Statistics*. 1997 Aug;79(3):372-82.

McKinsey 2015

<http://www.mckinsey.com/~media/McKinsey/Industries/Metals%20and%20Mining/Our%20Insights/Downsizing%20the%20US%20coal%20industry/Downsizing%20the%20US%20coal%20industry.ashx>

Melitz MJ. When and how should infant industries be protected? *Journal of International Economics*. 2005 May 31;66(1):177-96.

Muller NZ, Mendelsohn R, Nordhaus W. Environmental accounting for pollution in the United States economy. *The American Economic Review*. 2011 Aug 1:1649-75.

Muehlenbachs, Lucija, et al. *The Impact of the Fracking Boom on Rents in Pennsylvania*. Working Paper. Retrieved from: [http://public.econ.duke.edu/~timmins/fracking\\_rents.pdf](http://public.econ.duke.edu/~timmins/fracking_rents.pdf)

Munasib, A., & Rickman, DS (2015). Regional Economic Impacts of the Shale Gas and Tight Oil Boom: A synthetic control analysis. *Regional Science and Urban Economics*, 50, 1–17, 2015.

Pashigian BP, Gould ED. Internalizing Externalities: The Pricing of Space in Shopping Malls 1. *The Journal of Law and Economics*. 1998 Apr;41(1):115-42.

Tegen S. Comparing statewide economic impacts of new generation from wind, coal, and natural gas in Arizona, Colorado, and Michigan. National Renewable Energy Laboratory; 2006 May 1.

Tomblin, Earl 2016. State of the State Address  
<http://www.governor.wv.gov/media/pressreleases/2016/Documents/WEBSITE%20COPY.pdf>

Venkatesh, A., Jaramillo, P., Griffin, W.M., and Matthews, H.S. “Implications of changing natural gas prices in the United States electricity sector for SO<sub>2</sub>, NO<sub>x</sub>, and life cycle GHG emissions”. *Environmental Research Letters*. 2012, 7(3).

**Table 1**

The Quantity Weighted Distribution of the Distance between Coal Mines and Power Plants in 2014

0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
2.5	14.5	26.4	79.0	177.9	333.2	632.4	785.1	904.4	1058.0	1793.4

This table reports the empirical deciles of the distance distribution between pairs of coal mines and power plants that trade with each other. The units are miles. 50% of all coal traded travels less than 333.2 miles from the mine to the power plant.

**Table 2:**  
**Coal Consumption and Deliveries by Source and Destination**

State FIPS	State Name	In State Consumption Share	Out of State Consumption Share	In State Delivery Share	Out of State Delivery Share
1	Alabama	0.4	0.6	0.96	0.04
4	Arizona	0.4	0.6	0.72	0.28
5	Arkansas	0	1	0	1
6	California	0	1	-	-
8	Colorado	0.58	0.42	0.49	0.51
9	Connecticut	0	1	-	-
10	Delaware	0	1	-	-
11	District of Columbia	0	1	-	-
12	Florida	0	1	-	-
13	Georgia	0	1	-	-
17	Illinois	0.22	0.78	0.31	0.69
18	Indiana	0.49	0.51	0.81	0.19
19	Iowa	0	1	1	0
20	Kansas	0.01	0.99	0.53	0.47
21	Kentucky	0.52	0.48	0.3	0.7
22	Louisiana	0.24	0.76	1	0
23	Maine	0	1	-	-
24	Maryland	0.11	0.89	0.26	0.74
25	Massachusetts	0	1	-	-
26	Michigan	0	1	-	-
27	Minnesota	0	1	-	-
28	Mississippi	0.23	0.77	1	0
29	Missouri	0.01	0.99	0.65	0.35
30	Montana	0.95	0.05	0.34	0.66
31	Nebraska	0	1	-	-
32	Nevada	0	1	-	-
33	New Hampshire	0	1	-	-
34	New Jersey	0	1	-	-
35	New Mexico	1	0	0.63	0.37
36	New York	0	1	-	-
37	North	0	1	-	-

	Carolina				
38	North Dakota	0.98	0.02	0.98	0.02
39	Ohio	0.65	0.35	0.38	0.62
40	Oklahoma	0.02	0.98	0.95	0.05
41	Oregon	0	1	-	-
42	Pennsylvania	0.68	0.32	0.57	0.43
44	Rhode Island	0	1	-	-
45	South Carolina	0	1	-	-
46	South Dakota	0	1	-	-
47	Tennessee	0.03	0.97	0.33	0.67
48	Texas	0.48	0.52	1	0
49	Utah	0.87	0.13	0.76	0.24
51	Virginia	0.5	0.5	0.32	0.68
53	Washington	0.55	0.45	-	-
54	West Virginia	0.55	0.45	0.34	0.66
55	Wisconsin	0	1	-	-
56	Wyoming	1	0	0.08	0.92

**Table 3**

The Effect of Political Boundaries on the Probability of Trade

	(1)	(2)	(3)	(4)
Same State	0.0027*** (0.0009)	0.0033*** (0.0012)	0.0039*** (0.0013)	0.0020*** (0.0004)
Same County	0.0170*** (0.0061)	0.0191*** (0.0069)	0.0265*** (0.0094)	0.0045* (0.0026)
Same Congress	0.0020** (0.0007)	0.0020** (0.0009)	0.0035*** (0.0126)	0.0005 (0.0003)
Total Mine Production	0.0001*** (0.0000)	0.0001*** (0.0000)	0.0001*** (0.0000)	0.00004 *** (0.0000)
Total Plant Purchases	0.0002** (0.0001)	0.0003** (0.0001)	0.0003** (0.0001)	0.0001 *** (0.0000)
Distance Control	4 Degree Polynomial	3 Degree Polynomial	Spline	10 mile bins
Year FE	X	X	X	X
Plant Location Control	X	X	X	X
Average Frequency of Any Trade	0.020	0.020	0.020	0.020

Note: Coefficients correspond to a logistic regression estimating the probability that a power-plant purchased coal from a given mine. See Equation 1. Total Mine Production and Total Plant Purchases are expressed in millions of tons. Plant Location Control is a 4-degree polynomial in a power plants latitude and a 4-degree polynomial in a power plant's longitude. Standard errors are clustered at the plant-level and at the mine-level. \*\*\*:  $p < 0.01$ , \*\*:  $p < 0.05$ , \*:  $p < 0.10$



**Table 4**

The Effect of Political Boundaries on the Quantity of Coal Traded

	(1)	(2)	(3)	(4) <sup>1</sup>
Same State	0.0123*** (0.0045)	0.0135*** (0.0045)	0.0066 (0.0035)	0.0128* (0.0069)
Same County	1.3956*** (0.2420)	1.3961*** (0.2421)	1.3907*** (0.2422)	1.5075*** (0.3759)
Same Congress	0.0996*** (0.0219)	0.1007*** (0.0218)	0.0930*** (0.0217)	0.0315* (0.0177)
Total Mine Production	0.0024*** (0.0000)	0.0025*** (0.0000)	0.0025*** (0.0000)	0.0027*** (0.0000)
Total Plant Purchases	0.0047** (0.0002)	0.0047** (0.0020)	0.0047** (0.0020)	0.0052** (0.0025)
Distance Control	4 Degree Polynomial	3 Degree Polynomial	Spline	10 mile bins
Year FE	X	X	X	X
Plant Location Control	X	X	X	X
Average Quantity (Millions of Tons)	0.010	0.010	0.010	0.011

Note: Coefficients correspond to an OLS regression estimating the quantity of coal that a power plant purchased coal from a given mine in millions of tons. See Equation 1. Total Mine Production and Total Plant Purchases are expressed in millions of tons. Plant Location Control is a 4-degree polynomial in a power plants latitude and a 4-degree polynomial in a power plant's longitude. Standard errors are clustered at the plant-level and at the mine-level. \*\*\*:  $p < 0.01$ , \*\*:  $p < 0.05$ , \*:  $p < 0.10$

1: Specification 4 is estimated using a random sample of 100000 observations.

**Table 5**

The Effect of Political Boundaries on the Coal Quantity Traded Given a Trade Occurred

	(1)	(2)	(3)	(4) <sup>1</sup>
Same State	0.0357 (0.0460)	0.0503 (0.0463)	0.0040 (0.0404)	0.0258 (0.0483)
Same County	1.0784*** (0.2126)	1.092*** (0.2124)	1.0535*** (0.2158)	1.2169*** (0.4506)
Same Congress	0.1152 (0.0724)	0.1305 (0.0725)	0.0963 (0.0721)	0.0602 (0.1132)
Total Mine Production	0.0048*** (0.0006)	0.0048*** (0.0005)	0.0046*** (0.0006)	0.0043*** (0.0007)
Total Plant Purchases	0.2363*** (0.0661)	0.2370*** (0.0662)	0.2334*** (0.0651)	0.2167*** (0.029)
Distance Control	4 Degree Polynomial	3 Degree Polynomial	Spline	10 mile bins
Year FE	X	X	X	X
Plant Location Control	X	X	X	X
Average Quantity (Millions of Tons)	0.526	0.526	0.526	0.526

Note: Coefficients correspond to an OLS regression estimating the quantity of coal that a power plant purchased coal from a given mine in millions of tons. The sample is restricted to only the observations that resulted in trades. See Equation 1. Total Mine Production and Total Plant Purchases are expressed in millions of tons. Plant Location Control is a 4-degree polynomial in a power plants latitude and a 4-degree polynomial in a power plant's longitude. Standard errors are clustered at the plant-level and at the mine-level. \*\*\*:  $p < 0.01$ , \*\*:  $p < 0.05$ , \*:  $p < 0.10$

1: Specification 4 is estimated using a random sample of 100000 observations.

**Table 6**

The Effect of Political Boundary on the Probability of Trade Using a Border Pairs Design

	(1)	(2)	(3)	(4)
Same State	0.0385*** (0.0112)	0.0500*** (0.0155)	0.0366*** (0.011)	0.0353*** (0.0181)
Total Mine Production	0.0034*** (0.0006)	0.0034*** (0.0006)	0.0035*** (0.0006)	0.0035*** (0.0006)
Total Plant Purchases	0.0013*** (0.0001)	0.0013*** (0.0001)	0.0013*** (0.0001)	0.0013*** (0.0001)
Distance Control	4 Degree Polynomial	3 Degree Polynomial	Spline	10 mile bins
Year FE	X	X	X	X
Plant Location Control	X	X	X	X
Bordering County Pair FE	X	X	X	X
Average Frequency of Any Trade	0.021	0.021	0.021	0.021

Note: Coefficients correspond to a logistic regression estimating the probability that a power-plant purchased coal from a given mine. See Equation 2. Total Mine Production and Total Plant Purchases are expressed in millions of tons. Plant Location Control is a 4-degree polynomial in a power plants latitude and a 4-degree polynomial in a power plant's longitude. Bordering County Pair FE is a set of fixed effects corresponding to the county of the power plant. Standard errors are clustered at the plant-level and at the mine-level. \*\*\*:  $p < 0.01$ , \*\*:  $p < 0.05$ , \*:  $p < 0.10$

**Table 7**

The Effect of Political Boundaries on the Probability of Trade Using a Border Pairs Design and the In-State Mine Sample

	(1)	(2)	(3)	(4)
Same State	0.0351* (0.0210)	0.0358* (0.0091)	0.0463** (0.0188)	0.0323 (0.0211)
Total Mine Production	0.0138*** (0.0034)	0.0137*** (0.0021)	0.0135*** (0.0033)	0.0139*** (0.0034)
Total Plant Purchases	0.0015 (0.0015)	0.0007 (0.0006)	0.0016 (0.0017)	0.0018 (0.0016)
Distance Control	4 Degree Polynomial	3 Degree Polynomial	Spline	10 mile bins
Year FE	X	X	X	X
Plant Location Control	X	X	X	X
Bordering County Pair FE	X	X	X	X
Average Frequency of Any Trade	0.089	0.089	0.089	0.089

Note: Coefficients correspond to a logistic regression estimating the probability that a power-plant purchased coal from a given mine. See Equation 2. Total Mine Production and Total Plant Purchases are expressed in millions of tons. Plant Location Control is a 4-degree polynomial in a power plants latitude and a 4-degree polynomial in a power plant's longitude. Bordering County Pair FE is a set of fixed effects corresponding to the county of the power plant. Standard errors are clustered at the plant-level and at the mine-level. \*\*\*:  $p < 0.01$ , \*\*:  $p < 0.05$ , \*:  $p < 0.10$

**Table 8**

The Effect of Political Boundaries on the Transacted Price

	(1)	(2)	(3)	(4)
Same State	2.3187 (7.6746)	2.2735 (7.6611)	3.1584 (7.6784)	-0.2732 (6.6747)
Same County	-12.9112* (7.4321)	-13.7154* (7.1786)	-15.4026** (7.3800)	-3.9116 (6.764)
Same Congress	-0.27447 (6.8827)	-0.96891 (6.7208)	-2.6153 (7.0211)	1.4332 (5.8513)
Quantity (Millions of Tons)	-73.518*** (16.4936)	-73.6208*** (16.4107)	-73.9827*** (16.0911)	-73.7290*** (15.8487)
Distance Control	4 Degree Polynomial	3 Degree Polynomial	Spline	10 mile bins
Year FE	X	X	X	X
Mine FE	X	X	X	X
Average Price (Cents per MM BTU)	226.1	226.1	226.1	226.1
F-Test for Joint- Significance	1.4879 (p=0.21)	1.8976 (p=0.13)	2.2662* (p=0.078)	1.4762 (p=0.219)

Note: Coefficients correspond to an OLS regression estimating the price of coal that a power plant purchased from a mine that a power-plant purchased coal from a given mine in cents per BTU. See Equation 1. Quantity is the amount of coal that was shipped from the mine to the power plant in millions of tons. Standard errors are clustered at the plant-level and at the mine-level. \*\*\*:  $p < 0.01$ , \*\*:  $p < 0.05$ , \*:  $p < 0.10$

**Table 9**

## The Effect of Political Boundaries on Contracting Decision

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Same Congress	0.0239 (0.027)	0.024 (0.0261)	0.0266 (0.027)	0.1992 (0.1961)				
Same County	0.0351 (0.0274)	0.0352 (0.0279)	0.037 (0.027)	0.6374 (0.4193)				
Same State	0.0199 (0.0191)	0.0199 (0.0193)	0.0187 (0.0193)	0.2906 (0.3201)	0.0289* (0.0175)	0.0346* (0.0181)	.02907* (0.0172)	0.3188* (0.1740)
Quantity (Millions of Tons)	1.4057*** (0.1615)	1.4058*** (0.1612)	1.4035*** (0.1628)	1.4488*** (1.984)	1.4188*** (0.1629)	1.4239*** (0.1619)	1.4211*** (0.1635)	14.473*** (1.9823)
Distance Control	4 Degree Polynomial	3 Degree Polynomial	Spline	10 mile bin	4 Degree Polynomial	3 Degree Polynomial	Spline	10 mile bin
Year FE	X	X	X	X	X	X	X	X
Plant Location Control	X	X	X	X	X	X	X	X
Contracting Frequency	0.845	0.845	0.845	0.845	0.845	0.845	0.845	0.845
Jointly Different from Zero?	5.84 (p=0.119)	5.58 (p=0.134)	6.21 (p =0.102)	6.749 (p=0.080)				

Note: Coefficients correspond to a logistic regression estimating whether a coal purchase was the result of a contract. See Equation 1. Quantity is the amount of coal that was shipped from the mine to the power plant in millions of tons. Plant Location Control is a 4-degree polynomial in a power plants latitude and a 4-degree polynomial in a power plant's longitude. Standard errors are clustered at the plant-level. \*\*\*:  $p < 0.01$ , \*\*:  $p < 0.05$ , \*:  $p < 0.10$ .

**Table 10**  
**The Effect of Political Boundaries on Contract Duration**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Same Congress	-3.8777 (3.9216)	-3.6729 (4.0485)	-3.2607 (4.0862)	-4.0058 (3.8313)				
Same County	10.942* (6.5345)	11.646* (6.5705)	13.31* (6.9363)	17.788** (8.3207)				
Same State	-10.548*** (2.7912)	-10.573*** (2.776)	-10.907*** (2.7579)	-10.344*** (2.6485)	-10.961*** (3.115)	-10.901*** (3.709)	-10.934*** (3.083)	-10.848*** (2.8808)
Quantity	34.68*** (11.102)	34.833*** (11.072)	34.643*** (11.04)	28.928*** (10.399)	36.913*** (10.67)	37.092*** (10.592)	37.244*** (10.582)	30.768*** (10.616)
Distance Control	4 Degree Polynomial	3 Degree Polynomial	Spline	10 mile bin	4 Degree Polynomial	3 Degree Polynomial	Spline	10 mile bin
Year FE	X	X	X	X	X	X	X	X
Plant Location Control	X	X	X	X	X	X	X	X
Average Contract Length	30.0	30.0	30.0	30.0	30.0	30.0	30.0	30.0
Jointly Different from Zero?	19.3*** (p=0.0002)	18.4*** (p=0.0003)	21.2*** (p<0.0001)	20.747*** (p=0.0001)				

Note: Coefficients correspond to an OLS regression estimating the duration of coal contracts in months for those trades that are identified as being associated with contracts. See Equation 1. Plant Location Control is a 4-degree polynomial in a power plants latitude and a 4-degree polynomial in a power plant's longitude. Standard errors are clustered at the plant-level. \*\*\*:  $p < 0.01$ , \*\*:  $p < 0.05$ , \*:  $p < 0.10$

Table 11

## The Effect of Intra-Jurisdictional Mines on Power Plant Siting

	No Plant	Coal Plant	Non-Coal Plants Only
Mine in State	0.0097*** (0.0015)	-0.0011** (0.0005)	-0.0008*** (0.0002)
Mine in County	-0.0030 (0.0045)	0.0054*** (0.0016)	-0.0023 (0.0048)
Population	$-1.28 \times 10^{-6}$ *** ( $1.12 \times 10^{-7}$ )	$1.62 \times 10^{-7}$ *** ( $2.08 \times 10^{-8}$ )	$1.12 \times 10^{-6}$ *** ( $9.78 \times 10^{-8}$ )
Distance to Closest Coal Mine	0.0065*** (0.002)	-0.0129*** (0.00029)	0.0063*** (0.00019)

Note: Coefficients correspond to a multinomial logit regression of whether a county has no power plant, a coal power plant, or only non-coal power plants. See Equation 3. \*\*\*:  $p < 0.01$ , \*\*:  $p < 0.05$ , \*:  $p < 0.10$



**Table 12**

The Effect of a Intra-Jurisdictional Mine on the Probability of a Power Plant Closure

	(1)
Mine in State	-0.0696** (0.0296)
Nameplate Capacity (MW)	-0.0004*** (0.0000)
Opening Year	-0.0006*** (0.0000)
Distance to Closest Coal Mine	-0.0001 (0.0001)

Note: Coefficients correspond to a logistic regression of whether or not a coal power plant closes throughout the duration of our sample. See Equation 4. \*\*\*:  $p < 0.01$ , \*\*:  $p < 0.05$ , \*:  $p < 0.10$ . Standard errors are White-Robust.

Table 13

The Effect of Coal Consumption on Local Ambient Air Pollutant Concentrations

	SO2	PM10
Any Coal Plants In State?	0.3896*** (0.1088)	-0.04071 (0.02799)
Percentage of Generation from Coal	0.8233*** (0.1544)	-0.04923 (0.0369)
Log County Population	0.0269 (0.0195)	0.0740*** (0.0036)
Year FE	X	X
Highest Concentration States	IN, MO, PA, TN, WV	AZ, CA, NE, NM, NM
Lowest Concentration States	ME, MN, NM, SD, WA	CT, ND, NH, NY, RI

Note: Coefficients correspond to an OLS regression of log average annual pollutant concentration in counties with pollution monitors. See Equation 5. Standard errors are clustered at the state level. \*\*\*:  $p < 0.01$ , \*\*:  $p < 0.05$ , \*:  $p < 0.10$ .

Table 14

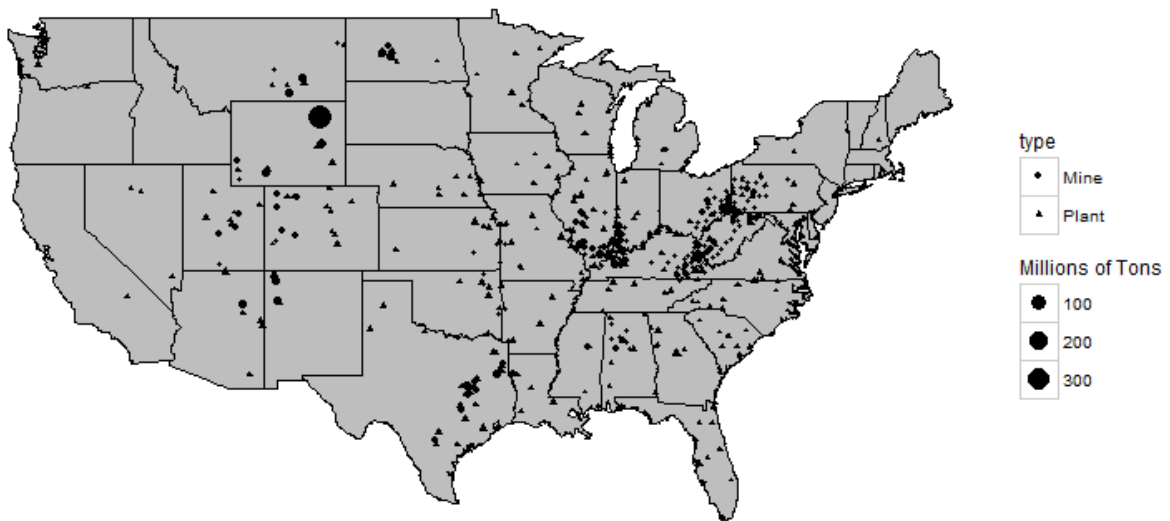
## The Effect of In-State Mines on NERC-level emissions

	CO2	SO2	NOX
Percentage of Plants with In-State Mine	2.264*** (0.0318)	0.0014** (0.0004)	0.0029*** (0.0001)
Coal Percentage of Capacity	26.607 (129.584)	-0.8810 (1.715)	-0.0784 (0.405)
Year FE	X	X	X
NERC FE	X	X	X

Note: Coefficients correspond to an OLS regression of NERC level pollution emissions from AMPD regulated sources in millions of tons. See Equation 6. Standard errors are clustered at the NERC level. \*\*\*:  $p < 0.01$ , \*\*:  $p < 0.05$ , \*:  $p < 0.10$

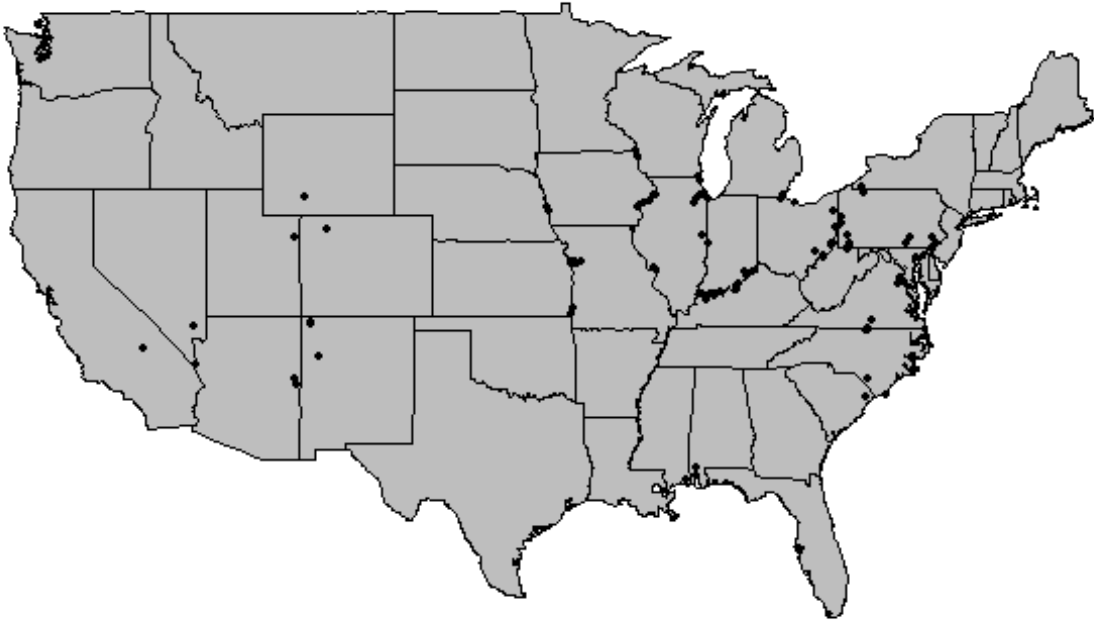
**Figure 1**

**Power Plant Purchases and Mine Sales in 2014**



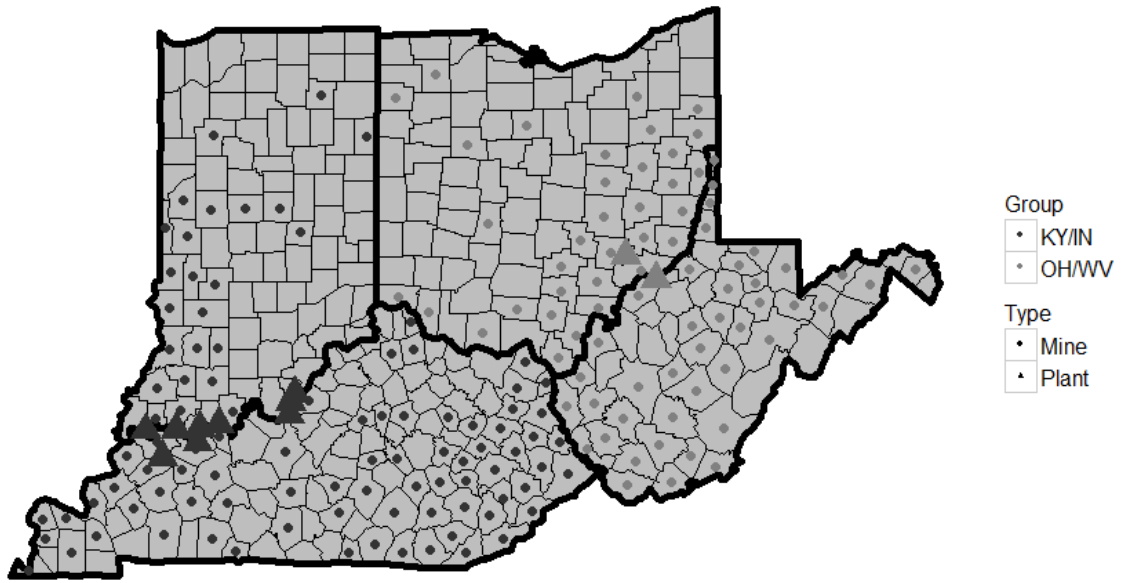
**Figure 2**

**Power Plants Included in the Border Pairs Framework**



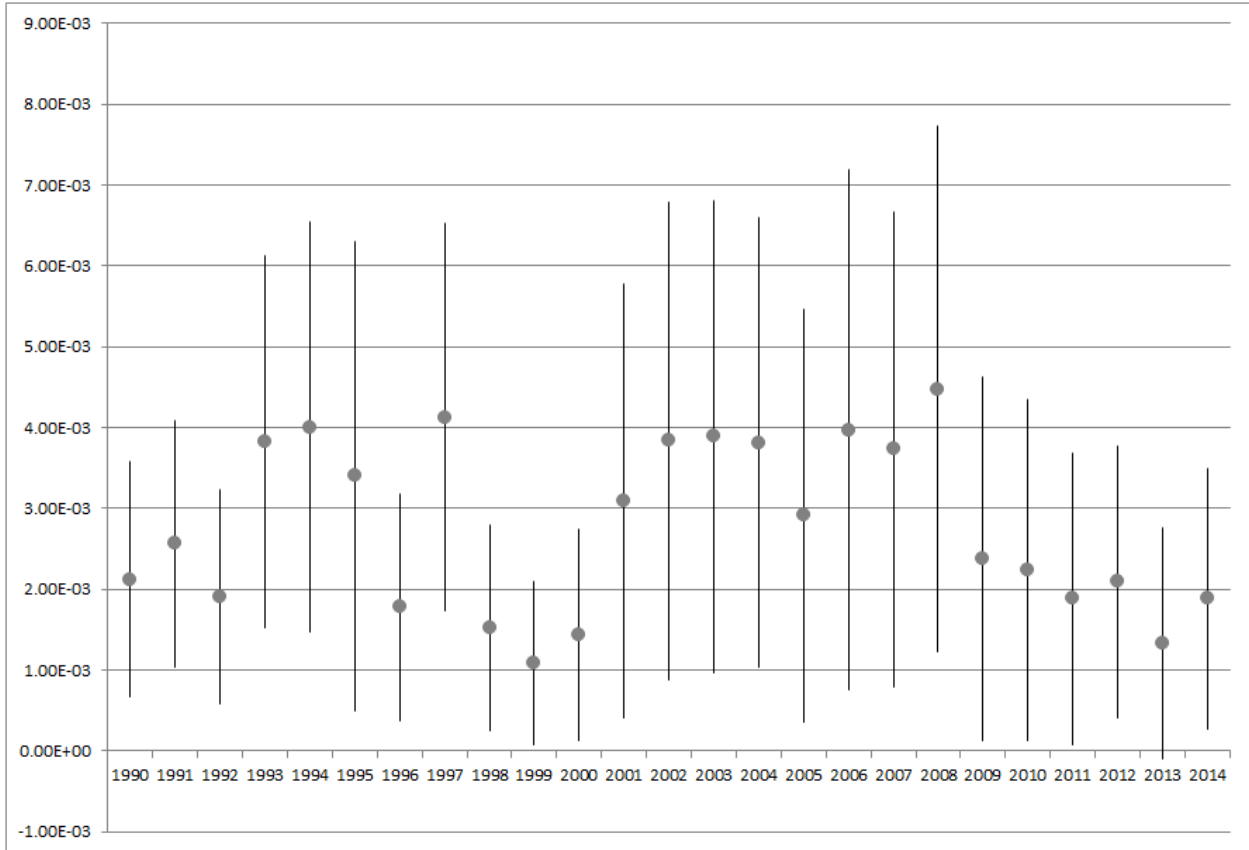
**Figure 3**

**Power Plants and Mines in the Border Pairs Design in Indiana, Ohio, West Virginia, and Kentucky**



**Figure 4**

**The Same State Coefficient Over Time**



**Web Appendix Table A1**

The Effect of Distance on Transportation Cost

	(1)	(2)	(3)	(4)
Distance Control	4 Degree Polynomial	3 Degree Polynomial	Spline	10 mile bins
Year FE	X	X	X	X
Adjusted R-Squared	0.357	0.0350	0.346	0.638
Observations	417	417	417	417
Years	2008-2014	2008-2014	2008-2014	2008-2014

Note: Coefficients correspond to an OLS regression of rail transportation costs for coal shipments. The unit of observation is the year-origin state-destination state. Distances are calculated using the latitude and longitude of the midpoint of each state.



### Appendix Table A2

The Effect of Political Boundaries on Trade Based on a Generalized Tobit Specification

<b>Quantity</b>	(1)	(2)	(3)	(4)
Same State	0.0121 (0.0452)	0.0281 (0.0442)	0.0416 (0.0434)	-0.0188 (0.0521)
Total Mine Production	0.178*** (0.0232)	0.181*** (0.0238)	0.183*** (0.0243)	0.173*** (0.0220)
Total Plant Purchases	0.00333** (0.00163)	0.00368** (0.00160)	0.00396*** (0.00153)	0.00281 (0.00175)
<b>Selection</b>				
Same State	0.284*** (0.0242)	0.287*** (0.0241)	0.294*** (0.0239)	0.284*** (0.0242)
Total Mine Production	0.0272*** (0.00398)	0.0278*** (0.00398)	0.0279*** (0.00398)	0.0277*** (0.00398)
Total Plant Purchases	0.0106*** (0.00154)	0.0105*** (0.00155)	0.0106*** (0.00155)	0.0108*** (0.00154)
Distance Control	4 Degree Polynomial	3 Degree Polynomial	Spline	10 mile bins
Year FE	X	X	X	X
Average Frequency of Any Trade	0.058	0.058	0.058	0.058
Average Quantity of Coal Traded	0.421	0.421	0.421	0.421

Note: Coefficients correspond to a Heckit regression of trade occurrence and quantities. The upper panel corresponds to the quantity of coal traded in millions of tons. The lower panel corresponds to whether or not a trade occurred. See Equation 1. Standard errors are clustered at the plant-mine level. \*\*\*:  $p < 0.01$ , \*\*:  $p < 0.05$ , \*:  $p < 0.10$ .