The Impact of Surface Coal Mining on Residential Property Values: A Hedonic Price Analysis

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Abstract

The use of certain surface mining techniques is currently a heavily-debated environmental issue and one where consideration of non-market values is likely to lead to the creation of better public policy. This study uses the hedonic pricing method to investigate the impact that surface coal mines have on residential property values. The results of our statistical analysis show that as the number of surface mines and their average production increases, the median value of housing units in a county significantly decreases. In particular, for the three model specifications we explored, we estimate that the addition of a surface mine to the average county decreases aggregate property values by between .34% and 1.7%.

I. Introduction

Coal is a leading source of energy in the United States, but a number of negative externalities result from its extraction process. Supporters of coal claim that the benefits of coal come in the form of job creation, economic prosperity, and energy security (World Coal Institute, 2009). On the other hand, there exist harmful externalities associated with coal mining, so the social costs of this practice are generally more difficult to measure. Lower water and air quality levels increase healthcare costs, and loss of aesthetic value can lead to a decline in recreation-based tourism and lower property values. Fully monetizing the costs and benefits associated with a coal mine is necessary for properly determining the best public policy options.

Coal serves as an appealing source of energy for a number of reasons. In 2008, electricity from coal accounted for 49.5 percent of all electric power generated in the United States (U.S. Department of Energy, 2010). Coal mining also supports a large number of jobs, although this number is declining, largely due to higher levels of productivity per worker associated with increases in mining technology and new mining techniques. In 2008, the number of employees in U.S. coal mines amounted to 86,859 (U.S. Department of Energy, 2010). According to the World Coal Association, coal is more abundant than other non-renewable sources of energy such as oil and natural gas. At current levels of production, coal will be available for the next 119 years (2011). In addition, coal prices have historically been lower and more predictable than the prices of its nonrenewable counterparts.

Although both underground and surface coal mining harm the environment, the externalities associated with surface mining are generally greater. Although surface mining is only feasible when the coal seams are near the surface, the technique accounts for 67 percent of coal production in the United States (U.S. Department of Energy, 2010). There are various

methods for surface mining including area, contour, auger, and mountaintop removal mining. Area mining is generally done over broad and shallow areas on flat land. Contour mining occurs in more mountainous areas and involves removing a wedge from the side of the mountain at the level of the seam. Auger mining occurs on the level surfaces created by contour mines and aims to collect the coal that contour mining could not reach. Mountaintop removal coal mining involves removing large amounts of "overburden," or rocks located above the coal seam, and then dumping this overburden into an adjacent valley (Methods of Mining, 2006). For most surface mining methods, explosives are first used to break up the overburden. Large "dragline" shovels are then used to remove these materials from the site, exposing the coal seam which is then systematically drilled. A large number of trucks are then needed to transport the mined coal to the plant where it will be used (World Coal Institute, 2009).

This entire process is known to have a number of negative environmental consequences. The ecological damage to areas surrounding surface mines is extensive. Because surface mines can range in size from several square kilometers to dozens of square kilometers, they require the clearing of large areas of forest. This directly threatens biodiversity and disrupts ecological processes such as nutrient cycling, which in turn affects downstream food webs. The removal of topsoil and upper layers of rock alters the natural flow of water and does not allow for proper ground absorption and filtration. This, added to the chemicals released during the breaking up of the coal seams, concentrates downstream and "bioaccumulates" in organisms. One example of the impact of this bioaccumulation is higher than normal levels of selenium, a chemical released during mining, in certain species. High selenium levels cause deformities in fish larvae and result in reproductive failure in fish and their predators (Palmer et al. 2010).

Surface mining has also been shown to have detrimental effects on human health. Ground water samples used for residential supply have been found to contain high levels of chemicals associated with coal mining such as sulfate, iron, manganese, and aluminum. In West Virginia, increases in sulfate levels in major watersheds have been linked to increasing coal mining in the area (Palmer and Bernhardt 2011). Additionally, high levels of hazardous, airborne dust have been documented near surface mining operations. As the rate of county-level coal production increases, so do the rates of chronic pulmonary disorders, hypertension, lung cancer, and chronic heart, lung, and kidney diseases (Palmer et al. 2010).

Finally, surface mines decrease the amenity value of the landscape. The process reduces once beautiful mountains to barren, grey landscapes. In addition, the effects of mining on land are irreversible: it is clear that the deep ecological transformations caused by mining cannot be undone using current reclamation and mitigation techniques (Palmer and Bernhardt 2011).

Measuring the social cost mining has on the environment is difficult due to the absence of relevant markets. One approach that can be used to estimate the effects of environmental quality is the hedonic pricing method. Applied to the housing market, the method uses variation in housing prices to identify the value of property characteristics such as the structural attributes of the house and neighborhood quality. Through statistical modeling, at least in a conceptual sense, one can hold all features of a property constant and tease out the independent effects of a particular characteristic, such as environmental quality.

II. Methods

Literature Review

This methodology has been applied extensively in the fields of environmental economics, labor economics, and public economics in order to estimate non-market values such as those associated with occupational risk, pollution, and education. It is important to estimate non-market values such as those related to the environment, as otherwise, when assessing public projects and policies, environmental values are often not fully integrated into the discussion or not placed on equal footing with the more directly measured financial costs related to environmental protection.

Most of the previous hedonic studies attempt to isolate a single environmental amenity such as air, water, or noise pollution. The nature of this study requires finding the combined social cost of multiple environmental amenities associated with surface coal mining. The greatest of these may be aesthetic value, but loss of value from poor water and air quality are also considered. In addition, because coal mines are large and intensive operations, noise pollution from the use of explosives and heightened truck traffic going to and from the mine are also undesirable characteristics that may impact housing values. For these reasons, studies focused on locally undesirable land uses are most relevant.

Williamson, et al. (2008) used a hedonic modeling approach to estimate the willingness to pay for the cleanup of waterways damaged by mine runoff. They found that the implicit cost of living near an affected stream was $4,783 per household, and that, if all the waterways in the Cheat River Watershed in West Virginia were restored, properties located within a quarter mile

of the restoration would benefit by $1.7 million. Boxall, et al. (2005) examined the implicit costs of rural residential property values near oil and gas facilities. They found that property values within 4 kilometers of the facilities were estimated to be reduced between 4 and 8 percent. Herriges, et al. (2003) examined the effect of livestock feeding operations on residential property values. Their results suggest a drop in 10 percent if a residence is located near or upwind of a new livestock operation. McCluskey and Rausser (2001) utilized a hedonic price framework to estimate the effect of nearby hazardous waste sites and the perceived risk associated with them on property values. They found that these characteristics also lower property values. Finally, Ihlanfeldt and Taylor (2004) also carried out a study examining the impact of hazardous waste sites on property values. They found that the loss in value of all properties, not just residential properties, in Fulton County, Georgia, could be as large as $1 billion.

All of these studies were able to focus on a small number of counties and use geographic software to estimate the exact distance of a property to a certain undesirable entity. Their results consistently show that as a property gets closer to this undesirable factor, the market value of the property lowers significantly. These previous studies lend credibility the hedonic pricing methodology, and they show how it is applied to the study of undesirable land uses that are similar in nature to surface coal mines.

Study Area

This study uses county-level data from each county in the following states: Alabama, Kentucky, Maryland, Ohio, Pennsylvania, Tennessee, Virginia, West Virginia, Illinois, Indiana, New Mexico, Texas, and Wyoming (Fig. 1). These thirteen states were chosen because they met

a certain threshold for high surface coal mining activity. This threshold was defined as having a minimum of five active surface coal mines in a state based on 2005 data. For each state that was chosen, every county within that state was included in the analysis, not just those with mining activity. This provides more variation in variables of interest related to mining and thus helps to identify the effect of mining operations on housing prices. In total, there are 1154 observations (i.e. counties) with available data. The average area of the counties is 769.05 square miles, and there are on average 30,446 housing units per county. The mean value for an owner-occupied housing unit in the study area is $76,658.06 (in 1999 dollars).

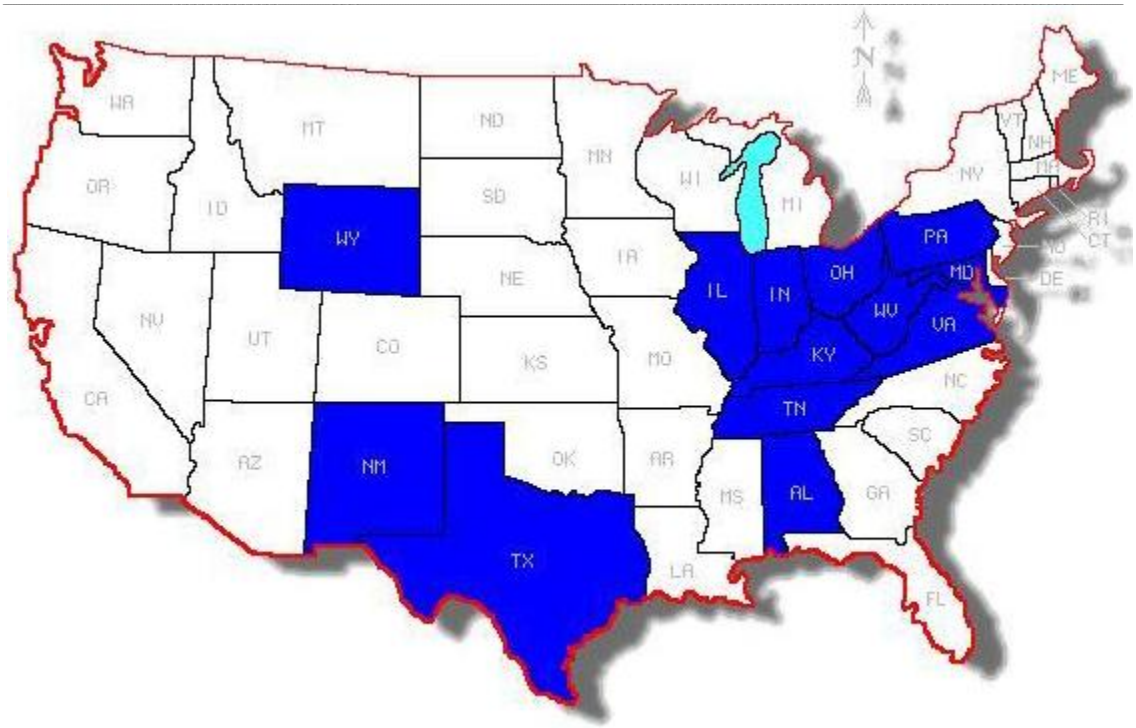


Figure 1: Study Area
Source: "Map-Maker" Utility < http://monarch.tamu.edu/~maps2/us.htm>

Data Acquisition

Table 1 offers a summary of the variables included in the models. This study uses cross-section data for counties in the year 2000. The data come from a variety of sources. Structural housing characteristics come from the US Census 2000. These characteristics include median number of bedrooms, percentage of houses that lack complete kitchen facilities, the median age of the home, and the prevalence of certain heating fuel sources. Out of the possible fuel sources, including LP gas, utility gas, electricity, kerosene, coal, wood, solar, and other, only LP gas, utility gas, and electricity were included in the models because these sources are found in the vast majority of housing units. A variable for housing units without any fuel source was also included. "Utility gas" includes gas pumped through pipes from a central system, "LP gas" includes liquid propane gas stored in bottles or tanks, and "electricity" is generally supplied through above or underground power lines. Due to the limitations of county level census data, other seemingly important structural variables were not included in the models. The effects of these variables may be captured in the magnitudes of the estimated coefficients of structural variables that are included in the models. For example, although a variable for average square feet is not available, one for median number of bedrooms is included. As the number of bedrooms in house increases, one generally expects the square footage to increase. While the estimated magnitude of the impact of the bedroom variable may be inflated because it also implies other characteristics, this should not bias the estimated coefficients on non-structural variables, such as the number of coal mines in a county, because they are not related.

Variables describing coal mining activity come from the "Coal Industry Annual 2000" report compiled by the Energy Information Administration. This reports the number of active underground and surface coal mines by county for a particular year. It also reports county-level information on the production of these mines in thousand short tons of coal. Since counties vary

in size, a variable for number of mines per 1000 square miles was created. Because data on the size of each individual mine was not available, looking at the number of mines and their average production provides an alternative way to measure the impact of surface coal mines in a particular county.

Additional information including median housing value, median income, median age, housing density, and transportation and commuting information was obtained from the US Census 2000. A variable that ranks a county's proximity to an urban center was taken from the Urban Influence Codes compiled by the United States Department of Agriculture's Economic Research Service. This variable helps describe how much access a county has to a metropolitan area, which is an indicator of access to other amenities. Other variables that describe socioeconomic characteristics of the counties were taken from the 2004 Typology Codes published by the United States Department of Agriculture's Economic Research Service. They are variables that indicate low education levels, recreation activity, low employment levels, persistent child poverty, and whether or not a county is a retirement destination. These variables describe county characteristics that may or may not be appealing to homebuyers, so they are expected to have some impact on the median housing price for a given county. Additional environmental characteristic variables were included because they are also expected to affect the appeal of living in a certain county. Their addition allows for a more complete assessment of how much people are willing to pay for environmental quality, a fundamental aspect of this study.

Climatic information such as average temperature in July and mean sunlight and humidity was obtained from the Area Resource File compiled by the Department of Health and Human Services' Health Resources and Services Administration. Finally, regional topology was

controlled for using a scale that comes from the 1970 U.S. Geological survey. This measure was included because different topologies might be associated with different levels of aesthetic beauty, e.g., people may prefer a view of a mountainous landscape over flat plains. Overall, a considerable amount of data has been obtained in an attempt to adequately model the key determinants of housing prices.

III. Theoretical Framework

The construction of a linear regression model makes it possible to disentangle the various effects that structural, neighborhood, and environmental characteristics have on property values. Hedonic pricing analysis works conceptually by comparing the prices of houses that are otherwise statistically identical except for the existence of a particular environmental amenity or nuisance. For example, if a researcher can compare the market value of two physically identical houses, one located near a busy airport and the other located in a quieter area, the difference in prices suggests the approximate price homeowners are willing to pay to avoid the noise pollution caused by the landing and departure of airplanes.

Rosen (1974) established a theoretical framework for analyzing hedonic prices. He defines hedonic prices as "the implicit prices of attributes" that are revealed through "observed prices of differentiated products and the specific amounts of characteristics associated with them." Each property can be viewed as a product that has a price *p* that is determined by a set of attributes $\mathbf{z}= (z_1, z_2, ..., z_n)$, of *n* different characteristics with known values. The function $p(\mathbf{z})= p(z_1, z_2, ..., z_n)$ defines the implicit effect that any variable z_l has on the price of the commodity. By analyzing how *p* changes with respect to a change in z_l, keeping all other variables constant, the impact of z_l can be isolated. So, extending this framework to this study in particular, *p* is the

median value of an owner-occupied housing unit in a given county and **z** is the set of all the relevant characteristics that determine *p*. This framework can also be applied to commodities other than houses. For example, consider automobiles of the same make and model, one with a sun roof and the other without. The market price for these two vehicles will be different, and that difference in prices reveals the value that the consumer places on having the sunroof.

Freeman (1979) provides a framework under which the price of a housing unit is a function of certain structural, neighborhood, and environmental characteristics. Following this framework, the objective of our analysis can be stated as estimating the unknown parameters in the following linear equation:

$$\text{Median Property Value} = \beta_0 + \sum_{j=1}^{J} S_{ij} * \gamma_j + \sum_{k=1}^{K} N_{ik} * \alpha_k + \sum_{m=1}^{M} E_{im} * \delta_m + \beta_1 SMA_i + \beta_2 PSM_i + \varepsilon$$

where β_0, β_1, β_2, and the γ_j, α_k, δ_m are parameters to be estimated; S_{ij} is the set of *j* structural characteristics for county *i*; N_{ik} is the set of *k* neighborhood characteristics for county *i*; E_{im} is the set of *m* environmental characteristics for county *i*; SMA_i is the number of active surface mines per 1000 square miles in county *i*; PSM_i is the average production of each mine in county *I*; and ε is a random error term.

In their meta-analysis, Smith and Huang (1995) found that the estimated impact of environmental quality in a hedonic analysis can vary widely due to differences in the assumed functional form of the hedonic equation. For this reason, three different functional forms were explored to test the sensitivity of our results. In addition to testing the linear model, a semi-log

model using the natural log of the dependent variable was tested, as well as a quadratic model using the square of the SMA variable. The semi-log form is typical for hedonic price analyses.

IV. Results

The hedonic equation was estimated using Ordinary Least Squares (OLS), a method commonly used in economics and other fields for estimating unknown parameters in linear regressions, and the results are presented in Table 2. For all three specifications, the hypothesis that the model errors are homoskedastic was rejected on the basis of the White Test ($p<0.01$ in all cases). As such, this study reports heteroskedasticity-robust standard errors, and for the purpose of hypothesis-testing employ t and F tests that are robust to heteroskedasticity. The R^2 value reported for the semi-log model suggests that 86.4 percent of the variation in ln(medianvalue) is explained by the variation in characteristics. This suggests that the model has good overall fit. The linear and quadratic models also exhibit good overall fit, with 81.2 percent of the variation in medianvalue explained by the variation in characteristics.

Many of the variables in the models are statistically significant at the 10% level and better. However, the variables *house, perpov, perchldpov, commutetime, meanhumidity*, and *lackkitchen* are only statistically significant in the semi-log model. On the other hand, the variables *PSM* and *lpgas* were significant in the linear and quadratic models, while not significant in the semi-log model. Thus, when evaluating the total cost of a surface mine to a county, this production variable was only included for those two models.

The signs of the coefficient for most of the statistically significant variables were as predicted, but there were some exceptions. For example, the signs for the coefficients on

meantempjuly and *meanhumidity* were wrongly predicted. This is most likely due to a misunderstanding of people's preferences; in this case preferences related to climate.

The signs of the other estimated coefficients are consistent with expectations. When evaluating the effect with the semi-log model, the coefficient multiplied by 100% is approximately equal to the expected change in housing price associated with a one-unit increase in the housing characteristic. For example, the semi-log regression suggests that a one unit increase in the number of bedrooms increases the median housing value by 42.81 percent, *ceteris paribus*. The coefficients in the linear model are interpreted as the expected change in housing value associated with a one-unit increase in the housing characteristic. From the linear model, one additional bedroom is expected to increase median housing value by $49,098, *ceteris paribus*. It is likely that the variable *bedroom* may be accounting for other structural characteristics not available in the data set such as average square feet, and this would explain why the magnitude of the estimated effect is larger than one might expect.

Table 3 presents estimates of the total cost stemming from the presence of an additional surface mine to the average county. In the semi-log model, *SMA* is significant at better than a 99 percent confidence level. The coefficient for *PSM* is negative but not significant, so it cannot be used to explain loss in housing value. *SMA*'s coefficient suggests that a one unit increase in *SMA* causes median housing value to decrease by .262 percent, *ceteris paribus*. To put this effect into proper perspective, for a county of 1000 square miles with a median price of $76,658, the addition of one surface mine decreases housing value by $261.10. Evaluating this at the average sized county of only 769.05 square miles increases the effect by the same magnitude as the decrease in county size, which is about 23 percent. Therefore, the overall loss to the average sized county with 30,446 housing units would amount to $7,949,359.26. This is approximately

.34 percent of the estimated aggregate value of all the housing units in the county. This amount changes when counties with higher or lower median housing values are examined, because the coefficient given by the semi-log model indicates an expected percent change in housing value.

The estimated impact given by the linear model is similar. In this model, both SMA and PSM were statistically significant, so both were used to derive the total cost to an average county. The coefficient on PSM reveals the estimated change in housing value as the average production of a surface mine increases by 1 thousand short tons. Multiplying this effect by 968.3, the mean production of all the mines in the data set, yields an estimation of the effect of adding a single surface mine to a county. The SMA and PSM effects were added together to show the total impact of an additional surface mine. The result is that, at any level of housing value, the linear model estimates the total loss to an average county to be $35,630,985.55, or 1.5 percent.

From the results of the quadratic model, the effect of *SMA* and SMA^2 on median value can be determined by taking the derivative of the model with respect to *SMA*. When this effect is added to the effect of PSM, the addition of one surface coal mine to an average county is expected to result in a total loss of $40,146,061.87, or about 1.7 percent.

For each of these models, this study examined the marginal effect of a surface mine in the average county. It may be more relevant to look at how the estimated parameters affect the average county *with* surface mines. As shown in table 3, the average costs to a county increase significantly when the average of counties containing at least one surface mine is assessed. Note that the first column estimates the cost of the addition of 1 surface mine while the second column measures the cost of 4.84 surface mines because this is the average number of surface mines in

the set of counties with at least one mine. The numbers in the second column are much larger and give a better idea of the aggregate impact on a county that allows surface coal mining.

Finally, a new log-linear model was created in order to assess how this impact varied across states. Indicator variables for each state were interacted with the *SMA* and *PSM* variables. The results can be found in table 4. Tests showed that only two of the states, Maryland and New Mexico, had statistically significant indications of heterogeneity.

V. Conclusion

The results clearly show a negative relationship between proximity to surface mines and property values. Statistically significant parameters across all three models give information on the marginal affects of surface mining, and extrapolating these affects to the county level reveals considerable monetary losses.

Nevertheless, this study has certain limitations, and they may affect the estimated parameters. The use of county level data does not give exact information on how much prices change as the distance from a mine decreases; it only shows the aggregate impact. Obviously, the impact of a surface mine would be expected to be much higher if a property is located within one mile of a mine than if the property is located much further away. In some counties, the housing units in one county may be located closer to mines on average than the housing units in another county, and this is not accounted for in this study. In addition, other regressions were calculated that included a variable for the number of underground coal mines in a county. Surprisingly, underground mines were not found to have a statistically significant impact on housing values. This finding suggests that the aesthetic characteristics of surface mines are

responsible for a large portion of the negative impacts on housing value. Taking these findings into consideration, the estimated effects of mining operations on housing values presented in this study represent lower bounds on the actual social costs. Investigating how the magnitude of the impact changes with different levels of income would be an interesting addition to this study.

The results of this study have significant implications for regional economics associated with coal mining. Although this study provides only a cross section of information, the loss in property values affects a county government year after year in the form of lower tax revenue. Additional costs to a county come in the form of increased health care costs and lower worker productivity associated with worsened health outcomes, lower potential future benefits from recreation and tourism due to a permanent loss of natural beauty, and depreciation of public infrastructure from heightened truck traffic to and from the mine. In conclusion, the decision to grant a permit for an additional surface mine should take into account all of the costs and benefits involved, recalling that the costs estimated in this study are certainly a lower bound of the total social costs associated with surface coal mining.

VI. Appendices

Table 1: Variable Definition and Descriptive Statistics

Variables (predicted sign)	Description	Mean	Standard Deviation
lnmedianvalue	Natural log of the median owner-occupied housing value	11.1716	.3858589
medianvalue	Median owner-occupied housing value in 1999 dollars	76,658.06	31996.14
Structural Housing characteristics (Percentage terms multiplied by 100)			

yrmoved (+)	Median years owner has lived in unit (2000 – the median year moved into the unit	10.60	2.69
withtelephone (+)	Percentage of housing units with active phone lines	97.31	2.46
medianyr (+)	Median age of structure (2000 – the median year the structure was built)	30.41	9.06
Utilitygas (?)	Percentage of housing units that use utility gas as their main heating fuel source	38.99	23.76
lpgas (?)	Percentage of housing units that use lp gas as their main heating fuel source	15.49	11.92
electricity (?)	Percentage of housing units that use electricity as their main heating source	33.47	17.32
nofuelused (-)	Percentage of housing units without a main heating source	0.212	0.250
bedrooms (+)	Median number of bedrooms	2.65	.163
lackplumbing (-)	Percentage of housing units without attached plumbing facilities	02.41	02.74
lackkitchen (-)	Percentage of housing units with kitchen facilities	02.43	2.50
multiunitaverage (-)	Average number of units in multi-unit structures	9.61	4.24
Neighborhood Characteristics			
averagefamilysize (+)	Average family size	3.02	.160
medianage (-)	Median Age	37.21	3.45
urbinf2003 (-)	Urban Influence Code (1-12, 12 being most rural)	4.73	3.22
loweduc (-)	Low-education county indicator. 0=no 1=yes	.264	.441
house (-)	Housing stress county indicator. 0=no 1=yes	.092	.289
Lowemp (-)	Low-employment county indicator. 0=no 1=yes	.176	.381
perpov (-)	Persistent poverty county indicator. 0=no 1=yes	.127	.333
poploss (-)	Population loss county indicator. 0=no 1=yes	.176	.381

retire (+)	Retirement destination county indicator. 0=no 1=yes	.117	.322
perchldpov (-)	Persistent child poverty county indicator (0=no 1=yes). This code identifies counties in which the poverty rate for related children under 18 years old was 20% or more in 1970, 1980, 1990, and 2000.	.245	.430
hurban (+)	Percentage of housing units that are in an urban area	41.81	30.74
hoccupied (+)	Percentage of housing units that are occupied	87.10	08.18
mediantaxes (-)	Median annual property taxes	751.47	503.77
hdensity (-)	Housing units per square mile	96.51	299.92
hsecond (+)	Number of housing units used seasonally or recreationally per square mile	1.368	3.41
pubtrans (+)	Percentage of workers who use public transportation to commute to work	73.43	1.72
commutetime (-)	Average commute time to work	35.37	2.35
Environmental Amenities/Disamenities			
SMA (-)	Number of active surface coal mines per 1000 square miles in 2000	1.12	5.27
$(SMA)^2$		28.96	274.61
PSM (-)	Average production of surface coal mines (thousand short tons)	123.34	981.65
areawater (+)	Percentage of area covered in water	3.22	9.19
rec (+)	Nonmetro recreation county indicator. 0=no 1=yes	.051	.220
meansunlightjan (+)	Mean hours of sunlight in January	146.46	32.71
meantempjuly (+)	Mean temperature in July	77.14	4.37
meanhumidity (-)	Mean percent humidity	57.36	11.83
topography (+)	Topography Index (1-21, 1 denoting flat plains and 21 denoting high mountains)	9.374	6.521

Table 2:
EstimatedModels

Functional Form	Semi-log	Linear	Quadratic
Variable			
medianage	0.0043 (0.0037)	444.0283 (414.7073)	442.3667 (414.7175)
averagefamsize	-0.0459 (0.0777)	-10357.26 (7977.115)	-10362.2 (7975.201)
urbinf2003	-0.0140*** (0.0022)	-792.9691*** (165.021)	-803.9273*** (165.5227)
house	0.0425* (0.0243)	4129.135 (3040.406)	4139.028 (3042.519)
loweduc	-0.0944*** (0.0134)	-4413.927*** (1059.716)	-4425.635*** (1058.602)
lowemp	-0.1024*** (0.0165)	-7354.024*** (1429.006)	-7282.371*** (1429.83)
perpov	-0.0375* (0.0197)	774.2805 (1425.461)	712.8252 (1426.04)
poploss	-0.0881*** (0.0143)	-3611.463*** (1150.058)	-3548.95*** (1153.338)
retire	0.0779*** (0.019)	4113.66* (2209.802)	4120.807* (2210.321)
perchldpov	-0.0348** (0.0152)	-1706.735 (1150.48)	-1650.114 (1153.431)
bedrooms	0.4281*** (0.0668)	49098.09*** (7665.924)	48994.06*** (7670.649)
mediantaxes	0.0002*** (0.000)	21.76041*** (2.223831)	21.77649*** (2.225826)
hdensity	0.0001 (0.000)	0.6004672 (6.060686)	0.5144152 (6.068895)
multiunitaverage	-0.0003 (0.0014)	-183.8308 (125.3423)	-181.4202 (125.2022)

hsecond	0.0068** (0.0033)	1279.904*** (476.116)	1283.473*** (477.0053)
pubtrans	1.4470** (0.594)	249636.1*** (82313.31)	248803.9*** (82422.56)
commutetime	-0.0075** (0.0032)	-480.9568 (297.5946)	-470.7546 (298.0907)
rec	0.1492*** (0.0347)	11115.37*** (3767.916)	11097.99*** (3769.386)
meansunlightjun	0.0006** (0.0003)	85.74775*** (31.91855)	83.88674*** (31.99138)
meantempjuly	-0.0234*** (0.003)	-1926.48*** (569.5452)	-1923.309*** (569.5783)
meanhumidity	0.0021** (0.0009)	66.01063 (121.2604)	66.01124 (121.2415)
topographyscale	0.0007 (0.001)	-22.71876 (106.0935)	-11.8279 (107.0773)
SMA	-0.00262*** (0.0008)	-151.3041** (71.73426)	-310.1191** (156.319)
SMA^2			3.180568 (2.220739)
PSM	-0.00000183 (0.00000367)	-0.7734457*** (0.2940602)	-0.7346433** (0.2986165)
withtelephone	0.0036 (0.0056)	253.2251 (360.5779)	244.0537 (359.7755)
hurban	0.0010*** (0.0003)	115.7853*** (30.47541)	115.5976*** (30.47198)
hoccupied	0.0042*** (0.0014)	415.4373*** (146.2556)	414.8725*** (146.2862)
utilitygas	-0.0017*** (0.0005)	-46.22617 (48.23904)	-46.76733 (48.2288)
lpgas	0.0005 (0.0007)	152.4441** (62.42661)	148.6893** (62.40292)

electricity	-0.0016*	38.88532	36.21042
	(0.0008)	(130.0477)	(129.9611)
nofuelused	0.0146	1166.423	1183.708
	(0.0314)	(2982.391)	(2976.569)
lackplumbing	0.0123	-843.3022	-897.7498
	(0.0083)	(1121.125)	(1125.883)
lackkitchen	-0.0288***	1119.594	1170.905
	(0.0098)	(1179.344)	(1183.074)
areawater	0.0012**	98.40562*	98.49913*
	(0.0006)	(55.30375)	(55.35375)
medianyr	-0.0084***	-770.052***	-769.5062***
	(0.0012)	(101.0962)	(101.0693)
yrmoved	-0.0112***	-826.6547***	-807.7528***
	(0.0037)	(287.5181)	(288.9943)
constant	11.5853***	61760.27	62660.93
	(0.6868)	(75487.15)	(75478.26)
Observations	1154	1154	1154
R^2	0.864	0.812	0.812
F-statistic (p value)	180.55 (0.000)	112.97 (0.000)	110.34 (0.000)

*Note: ***, ** and * indicate the estimated coefficient is statistically significant at the 1%, 5% and 10% level, respectively. Robust standard errors are in parentheses.*

Table 3. Estimated Total Costs for Average Counties

	Mean County [95% Confidence Interval]	Mean County with Surface Mine [95% Confidence Interval]
Area (square miles)	769.05	893.50
Number of Housing Units	30,446	27,752
Median Housing Unit Value	$76,658	$64,380
Semi-Log	-$7,949,363.31 (-.34%)	-$27,187,743.14 (-1.5%)
	[-$3,090,239.31, -$12,779,057.37]	[-$43,705,853.60, -$10,568,975.72]

Linear	-$35,630,985.55 (-1.5%)	-$145,102,579.90 (-8.1%)
	[-$63,314,339.60, -$7,947,621.18]	[-$257,839,458.57, -$32,365,659.50]
Quadratic	-$40,146,061.87 (-1.7%)	-$155,661,333.15 (-8.7%)
	[-$52,724,337.86, -$27,620,290.85]	[-$310,583,468.56, -$2,532,468.62]

All prices in 1999 Dollars

Table 4. Variations by State (Log-linear model)

Interaction	Coefficient	Robust Std Err.	p-value
SMA*Alabama	-0.0090005	0.0022352	0.002
SMA*Illinois	0.0020589	0.0181367	0.911
SMA*Indiana	-0.0055216	0.0023496	0.037
SMA*Kentucky	-0.0018533	0.0006934	0.02
SMA*Maryland	-0.8588935	0.1392049	0.000
SMA*NewMexico	-1.52383	0.6453059	0.036
SMA*Ohio	-0.0047291	0.0023792	0.07
SMA*Pennsylvania	-0.0004721	0.0006613	0.489
SMA*Tennessee	-0.0114443	0.0034847	0.007
SMA*Texas	0.0191925	0.004981	0.002
SMA*Virginia	0.0034625	0.0018551	0.087
SMA*WestVirginia	-0.0074979	0.0016452	0.001
SMA*Wyoming	-0.1075964	0.0395013	0.018
PSM*Alabama	0.0007307	0.0001723	0.001
PSM*Illinois	-2.21E-06	0.000083	0.979
PSM*Indiana	-0.0000203	8.60E-06	0.036
PSM*Kentucky	-0.0001156	0.000012	0.000
PSM*Marlyand	0.1617564	0.0261008	0.000
PSM*NewMexico	0.0001841	0.0000865	0.055
PSM*Ohio	0.0001014	0.0000445	0.042
PSM*Pennsylvania	0.0001789	0.0001583	0.28
PSM*Tennessee	0.0005212	0.0001631	0.008
PSM*Texas	-4.49E-07	2.11E-06	0.835
PSM*Virginia	-0.00177	0.0007548	0.037
PSM*WestVirginia	0.0000146	9.12E-06	0.135
PSM*Wyoming	4.29E-06	5.14E-06	0.421

Standard Errors Clustered by State

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