5-2011

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

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May 2011

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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 decreases the median property value between $7,526,981.84 and $14,779,928.35.

I. Introduction

Coal is a leading source of energy in the United States, but its extraction process creates a number of negative externalities. Supporters of coal claim the benefits of coal come in the form of job creation, economic prosperity, and energy security. On the other hand, since the external effects of mining are not directly borne by the coal industry, the social costs associated with coal mining are generally more difficult to measure. Lower water and air quality levels are felt primarily through increased health costs, and loss of aesthetic value can be identified through indicators such as 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 (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 (2011), coal is more abundant than other non-renewable sources of energy such as oil and natural gas, and at current levels of production coal will be available for the next 119 years. In addition, coal prices have historically been lower and more predictable than the prices of its nonrenewable counterparts.

This paper focuses on the practice of surface coal mining, as opposed to underground coal mining. Surface mining is only feasible when the coal seams are closer to the surface, but the technique still 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, and then dumping this overburden into an adjacent valley (Methods of Mining, 2006). Generally with most surface mining methods, explosives are first used to break up the overburden. Huge "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). Surface mines can range in size from several square kilometers to dozens of square kilometers.

This entire process is known to have a number of negative environmental consequences. The ecological damage to areas surrounding surface mines is extensive. The clearing of large areas of forest directly threatens biodiversity, and the disruption of ecological processes such as nutrient cycling is even more harmful for downstream food webs. The removal of topsoil and upper layers of rock disrupts 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 can be seen in high levels of selenium that causes deformities in fish larvae and reproductive failure in fish and the birds that eat those fish. (Palmer et al. 2010).

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 production in the area (Palmer and Bernhardt 2011). Also, high levels of hazardous, airborne dust have been documented near surface mining operations. As 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). In addition, surface mines decrease the amenity value of the landscape. Finally, the effects of mining on land are irreversible: it is prohibitively costly to reclaim the land to make it suitable for other uses after surface mining operations have ceased.

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. Literature Review

The 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 to be negative externalities associated with the existence of a coal mine. 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. For these reasons, studies focused on locally undesirable land uses are most relevant.

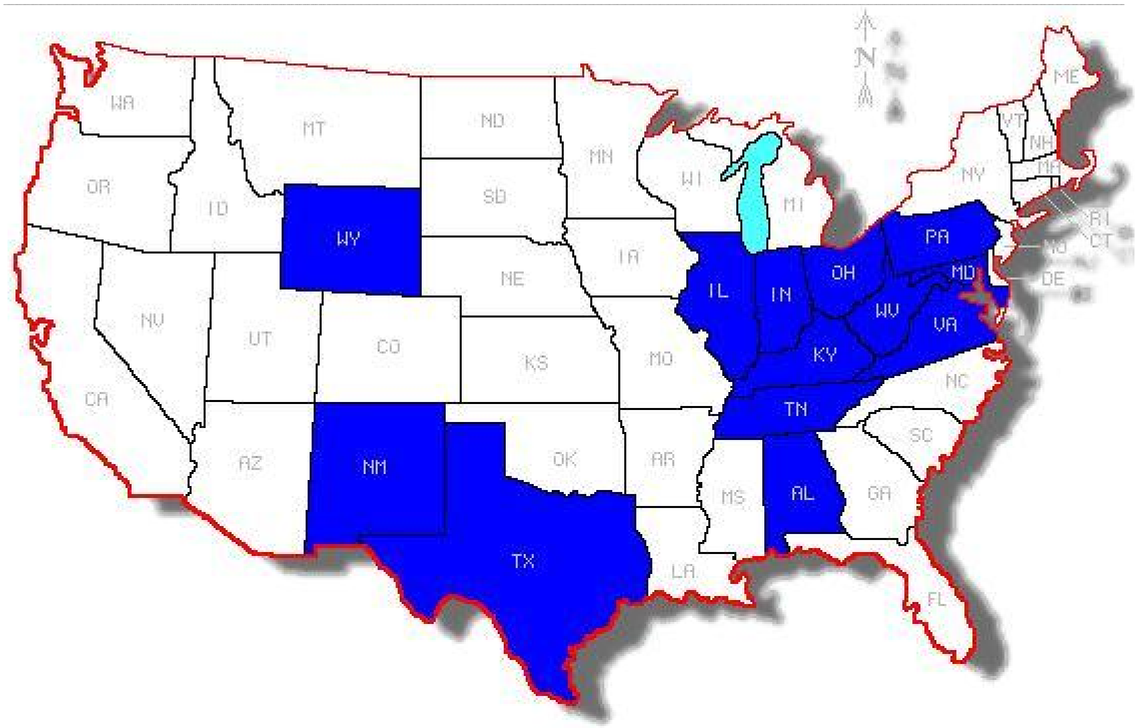
Williamson, et al. (2008) used a hedonic modeling approach to estimate the willingness to pay for the cleanup of waterways damaged by mine runoff. They found that the implicit cost of living near an affected stream was $4,783 per household, and that, if all the waterways in the Cheat River Watershed 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. This supports our hypothesis that an increase in surface coal mines will have a negative impact on residential property values.

III. 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 (see Figure 1). We chose these thirteen states because they met a certain threshold for surface coal mining activity. In this case, that means that in 2000, each of these states had a minimum of five active surface coal mines. Because mining is the variable of interest in this analysis, including many additional observations that would not yield any information regarding surface mining did not seem appropriate. However, for each state that was chosen every county within that state was used, 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>

IV. Data

Table 1 offers a summary of the variables included in the model. 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, we only included lp gas, utility gas, and electricity in the model, because these sources are found in the vast majority of housing units. We also included a variable for housing units without any fuel source. "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. Although it is unclear how each of these fuel sources might impact housing value, we felt it was important to include these structural characteristics in the model. Variables describing coal mining activity came 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. Additionally, it has county-level information on the production of these mines in thousand short tons of coal. Since counties vary in size, we created a variable for number of mines per 1000 square miles. Because data on the size of each individual mine was not available, looking at the number of mines and their average production provides and alternative way to measure the presence 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 came from the US Census 2000. The housing variable was transformed using natural log to account for the large variations in value. A variable that ranks how rural or urban a county was taken from the Urban Influence Codes complied 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. 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. They are dummy variables that measure low education levels, recreation activity, low employment levels, persistent child poverty, and whether or not a county is a retirement destination. The retirement and recreation variables may also help to describe the environmental amenities of a county. Additional environmental characteristic variables were included because they are expected to affect the appeal of living in a certain county. Their addition tells a more complete story about 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 comes from the Area Resource File compiled by the Department of Health and Human Services' Health Resources and Services Administration. Finally, we control for topology using a scale that comes from the 1970 U.S. Geological survey. We included this measure 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, we have obtained a considerable amount of data in attempt to adequately model the key determinants of housing prices.

V. Theoretical Framework

The construction of a linear regression model allows us 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 statistically 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 $\mathbf{z}$ is the set of all the relevant characteristics that determine p.

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, we can state the objective of our analysis 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, we explore three different functional forms to test the sensitivity of our results. In addition to testing the linear model, we test a semi-log model using the natural log of the dependent variable, and we test a quadratic model using the square of the SMA variable. We note that the semi-log form is typical for hedonic price analyses.

VI. Results

We estimate the hedonic equation using Ordinary Least Squares (OLS) and present the results in Table 2. For all three specifications, based on the White Test we strongly reject the hypothesis that the model errors are homoskedastic ($p<0.01$ in all cases). As such, we report 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 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 model 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 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 we cannot use it 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 $200.84. 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 30446 housing units would amount to $7,526,981.84. This amount changes when we look at counties with higher or lower median housing values, because the coefficient given by the semi-log model tells us 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 they were both used to derive the total cost to an average county. The result is that, at any level of housing value, the estimated total loss to an average county amounts to $8,596,330.45.

From the results of the quadratic model, the effect of *SMA* and SMA^2 can be determined by taking the derivative of those terms with respect to median value. When this effect is added to the effect of PSM, we see that the addition of one surface coal mine to an average county is expected to result in a total loss of $14,779,928.35.

For each of these models, we have looked at 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 we deal with the average of counties containing at least one surface mine.

VII. Conclusion

This study has certain limitations, and they may affect the estimated parameters. The use of county level data does not give more exact information on how much prices change as they get you get closer to a mine; 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, we ran other regressions 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 things into consideration, the estimated effects of mining operations on housing values presented in this study represent lower bounds on the actual social costs. More so, investigating how the magnitude of the impact changes with different levels of income would be an interesting addition to this study.

Nevertheless, the results from this study are still valuable. Although we just look at 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 and keep in mind that the costs estimated in this study are certainly a lower bound of the total social costs associated with surface coal mining.

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: Estimated Models

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

hsecond	0.0068**	1279.904***	1283.473***
	(0.0033)	(476.116)	(477.0053)
pubtrans	1.4470**	249636.1***	248803.9***
	(0.594)	(82313.31)	(82422.56)
commutetime	-0.0075**	-480.9568	-470.7546
	(0.0032)	(297.5946)	(298.0907)
rec	0.1492***	11115.37***	11097.99***
	(0.0347)	(3767.916)	(3769.386)
meansunlightjun	0.0006**	85.74775***	83.88674***
	(0.0003)	(31.91855)	(31.99138)
meantempjuly	-0.0234***	-1926.48***	-1923.309***
	(0.003)	(569.5452)	(569.5783)
meanhumidity	0.0021**	66.01063	66.01124
	(0.0009)	(121.2604)	(121.2415)
topographyscale	0.0007	-22.71876	-11.8279
	(0.001)	(106.0935)	(107.0773)
SMA	-0.00262***	-151.3041**	-310.1191**
	(0.0008)	(71.73426)	(156.319)
SMA^2			3.180568
			(2.220739)
PSM	-0.00000183	-0.7734457***	-0.7346433**
	(0.00000367)	(0.2940602)	(0.2986165)
withtelephone	0.0036	253.2251	244.0537
	(0.0056)	(360.5779)	(359.7755)
hurban	0.0010***	115.7853***	115.5976***
	(0.0003)	(30.47541)	(30.47198)
hoccupied	0.0042***	415.4373***	414.8725***
	(0.0014)	(146.2556)	(146.2862)
utilitygas	-0.0017***	-46.22617	-46.76733
	(0.0005)	(48.23904)	(48.2288)
lpgas	0.0005	152.4441**	148.6893**
	(0.0007)	(62.42661)	(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
Average Surface Mine Production	123.34	968.30
Semi-Log	-$7,526,981.84	-$25,006,744.22
	(-$12,100,292.83, -$2,926,100.06)	(-$40,273,556.63, -$9,738,975.60)
Linear	-$8,596,330.45	-$43,256,897.59
	(-$16,016,459.98, -$1,133,361.09)	(-$79,666,173.12, -$6,847,353.33)
Quadratic	-$14,779,928.35	-$30,422,658.52
	(-$29,309,723.14, -$250,183.07)	(-$58,557,371.75, -$2,287,919.11)

All prices in 1999 Dollars

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