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Introduction

The Appalachian mountain region has long been characterized by deep poverty which led to the formation of the Appalachian Regional Commission (ARC) in 1965. The ARC region covers West Virginia and parts of 12 other states, running from New York to Mississippi (Ziliak 2012). The ARC region had an average county poverty rate of over 40 percent in 1960, about double the national average (Deaton and Niman 2012; Ziliak 2012). While the poverty gap between the ARC region and the rest of the nation closed significantly by 1990, it remained nearly twice as large in Central Appalachia.

There are many reasons for higher poverty in Appalachia in general and Central Appalachia in particular. Possible causes include a low-paying industry structure, below average education, low household mobility, and remoteness from to cities (Weber et al. 2005; Partridge and Rickman 2005; Lobao 2004). A key distinction between Central Appalachia and the rest of the ARC region is its historic dependence on coal mining. There is long literature arguing that the area's dependence on coal mining has contributed to its deep poverty through weaker local governance, entrepreneurship, and educational attainment, as well as degrading the environment, poor health outcomes, and limitations on other economic opportunities (Deaton and Niman 2012; James and Aadland 2011).

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These factors are broadly associated with the natural resources curse in the international development literature. More recently, the process of mountain top mining (MTM) has expanded coal mining's environmental footprint in the region, possibly increasing health risks and further reducing the chances for long-term amenity-led growth that can alleviate poverty (Deller 2010; Woods and Gordon 2011).

This study reinvestigates the causes of county poverty rates in Appalachia with a special focus on coal mining's role. Using data over the 1990-2010 period we assess whether coal mining continues to have a positive association with poverty rates, even as the industry's relative size has declined. We also appraise whether MTM is associated with higher poverty. We do this by comparing the ARC region to the rest of the U.S. and by using more disaggregated employment data that allows us to differentiate the effects of coal mining from other mining (versus aggregating all mining together as in past research). The results suggest that any potential adverse effects of coal mining on poverty have declined over time. Below, we first develop an empirical model followed by the empirical results. The final section provides our concluding thoughts.

Model

We use a disequilibrium partial-adjustment poverty model similar to Levernier, Partridge, and Rickman (2000) and Partridge and Rickman (2005; 2008a). The model assumes a county's current equilibrium poverty rate is a function of its characteristics, such as job growth and demographics. Over time, changes in characteristics influence the county's poverty rate, though there may be a lag between actual change in the poverty rate. For instance, when a county's education levels increase, it may be years before more educated workers are employed in better paying jobs that reduce the poverty rate. Because of sluggish adjustment to a new equilibrium, the current poverty rate is assumed to be a function of the past poverty rate and its current characteristics.

Formally, the partial-adjustment model can be written as:

$$POV_{it}^{*} = \beta X_{it} \tag{1}$$

where POV_{it}^{*} is the equilibrium poverty rate of county i in year t, X_{it} is a vector of the characteristics of county i in year t, and β is a vector that captures the relationship between POV_{it}^{*} and X_{it}. Because the actual poverty rate in year t (POV_{it}) does not instantaneously adjust to βX_{it}, the difference between the equilibrium poverty rate and the previous poverty rate k years in the past is a fraction, $\alpha (0 \leq \alpha \leq 1)$, of the difference between the actual poverty rate and the previous poverty rate k years in the past.

$$POV_{it} - POV_{it-k} = \alpha(POV_{it-k}^{*} - POV_{it-k}) \tag{2}$$

Combining Equation 1 and Equation 2, the current (actual) poverty rate is a function of the past poverty rate and the county's characteristics, expressed by Equation 3 below.

$$POV_{it} = (1 - \alpha)POV_{it-k} + \alpha\beta X_{it} \tag{3}$$

Empirical implementation

We use Ordinary Least Squares (OLS) to estimate an empirical model using Equation 3. OLS has shortcomings that we try to mitigate. For example, high poverty rates may deter firms from creating employment—producing endogeneity. Alternatively, coal mining may not be a random event, but geological availability of coal and the fact that demand for coal is driven by national and world markets reduces simultaneity with local outcomes. Generally, we lag the explanatory variables to mitigate reverse causality.

The empirical models are estimated over two samples: 1) ARC counties and 2) all other US counties (RUS hereafter). Unless otherwise indicated, data sources are described in Partridge and Rickman (2005, 2008a). The ARC region is of keen interest because its historically high poverty rates have been associated with coal mining—especially in Central Appalachia, raising the possibility of a natural resources curse (Deaton and Niman 2012). Coal mining and MTM are much more intense in this region. Intense coal mining such as now seen in the Great Plains is a more recent trend. A finding that coal mining has a different effect in the RUS compared to the ARC region would suggest that something particular about Appalachian coal mining contributes to high poverty (e.g., how it affects culture or governance).[1] Yet, James and Aadland (2011) and Papyrakis and Gerlagh (2007) find evidence of a natural resources curse in which mining is negatively related to economic outcomes across the entire country.

The dependent variable is the total poverty rate. We first measure it in 1999 using data from the 2000 Census (referred to as the 2000 poverty rate) and the 2010 poverty rate from the U.S. Census Bureau Small Area Income and Poverty Estimates (SAIPE http://www.census.gov/did/www/saipe/).[2] Beginning with a base model similar to Partridge and Rickman (2005; 2008a), we add the mining and MTM variables:

$$POV_{it} = \alpha POV_{it-10} + \beta MTM + \varphi MINING + \psi MTM * MINING + \lambda NPOV_{it-10} + \gamma DIST_i + \theta CITY_i + \delta ECON_{it-10} + \phi DEM_{it-10} + \sigma_s + \varepsilon_{it} \quad (4)$$

where POV_{it-10} is the ten-year lagged poverty rate measured in 1989 (from the 1990 Census) for the 2000 poverty rate model and measured in 1999 in the 2010 model. MTM is a dummy variable for the presence of an active MTM site between 1976 and 2005 (source described below). Though using a dummy variable does not capture mining intensity, it is useful to assess an average association between MTM and poverty. Regression coefficients are represented by α, β, φ, ψ, λ, γ, θ, δ, and ϕ. State fixed effects are reflected by σ_s to capture factors such as state welfare policies, tax and regulatory policies, and cultural and historic factors. The error term is denoted by ε_{it}. We correct for potential heteroskedasticity by estimating robust standard errors.

The MTM data is from satellite imagery of 59 counties in Kentucky, Tennessee, Virginia, and West Virginia from 1976-2005, where the vast majority of MTM has occurred (though it may miss MTM sites elsewhere). This data is also employed by Hendryx (2011) and others. The MTM mines were identified by calculating the percentage of ridge-top that comprised the mine's total area (Skytruth 2009).

There are multiple ways MTM may influence poverty rates. First, greater coal mining in general may displace workers in other sectors, including industries that may not desire the local labor climate associated with mining. Second, MTM counties are faced with a host of negative externalities that may increase poverty. MTM requires the removal of timber and other vegetation and the resulting waste disposal causes elevated airborne particulate levels and contaminates surface and ground water (McAuley and Kozar 2006; US Department of Labor 2010). The ensuing lost productivity and healthcare expenses could increase poverty. Blasting can also damage nearby structures. Environmental damage may negatively impact tourism, leading to greater poverty for affected workers and reducing the possibility of long-term amenity-led growth. MTM is especially capital-intensive, requiring fewer workers than traditional coal mining (Woods and Gordon 2011). Alternatively, MTM operations (and coal mining in general) may decrease poverty by providing jobs to lower middle-class workers or workers on the precipice of poverty.[3] Thus, the impact of MTM on poverty is not clear *a priori*.

We include three (place of work) employment shares for (1) coal mining; (2) oil and gas mining, and (3) other mining activities using four digit NAICS codes using data from the EMSI consulting company.[4] We include the contemporaneous ten-year percent change in the three mining sectors' employment (1990-00 and 2000-10), which should be exogenous because they are almost exclusively traded on national and international markets. Thus, we ask whether new mining operations have different marginal effects than long-term legacy effects associated with the lagged mining shares. We also ascertain whether coal mining has different effects than other extractive industries.

Including the mining employment shares (especially coal) also controls for any effect that would be captured by the MTM variable which is attributable to employment in mining, but not exclusively to MTM. We also interact the mining employment share variables and the percent change in mining employment share variables with the MTM variable. This allows us to parse out whether the effects of the level and growth of coal mining are different in MTM counties.

The *a priori* impact of shares or percent change of extractive industries is unclear. Black, McKinnish, and Sanders (2005) find that about 100 new coal mining jobs added on net about 25 indirect jobs in Appalachian coal communities. However, in terms of attracting population and reducing poverty, it is not clear whether the economic benefits outweigh the negative environmental and health externalities linked to mining.

$NPOV$ is the average poverty rate of counties contiguous to county i measured in 1990. $DIST$ is a vector of distance variables that reflect distance to increasingly larger cities. Proximity to agglomeration economies may influence poverty in several ways. For example, spatial mismatch between low income workers and jobs are reduced by agglomeration economies (Partridge and Rickman 2008). Communities that are closer to larger cities benefit from stronger commuting linkages, knowledge spillovers, and tighter input-output links. Thus, we include kilometers to the nearest metro area as well as incremental distances in kilometers to the nearest metro area with a population of at least 250,000 residents, 500,000 residents, and 1.5 million residents (see Partridge and Rickman 2008). We also include the 1990 population of the nearest metropolitan area.

CITY is a vector that includes the lagged county population and indicators of single metro counties, small MSA counties (metro areas with under 1 million residents), and large MSA counties (metro areas with over 1 million residents). The ECON vector has measures of county job growth from the U.S. Bureau of Economic Analysis (BEA). Partridge and Rickman (2005, 2008a) identify different lagged and contemporaneous job growth effects. Each model includes total job growth for the immediate five years prior to the poverty measurement and job growth from the prior five and ten years.

Demographic factors in the DEM vector include age, race, and education. Recent immigrant shares and the single-male and single-female household shares are also included to control for challenges faced by these social groups. Demographic variables are lagged ten years prior to the dependent variable to mitigate concerns about endogenous relationships with the dependent variable. These variables are from the 1990 and 2000 U.S. Census.

Empirical Results

Table 1 contains selected descriptive statistics measured in 1990 and 2000. The ARC region consists of 413 counties and the RUS sample has 2,596 counties.[5] From the table, we see progressively increasing poverty rates, with the lowest poverty rates in the RUS, higher rates in the ARC region, and the highest in the 37 MTM counties. Poverty decreased across all three samples from 1990 to 2000, in line with the vigorous 1990s economic expansion. Generating new jobs is potentially a key factor in the location of MTM. Counties experiencing low job growth may feel pressure "do something" to help create jobs. Indeed, the ARC region has slower job growth than the RUS. And MTM counties have even slower job growth in each of the four periods.

Figures 1a and 1b show coal mining's share of total county employment for 2000 in the ARC region and the U.S. The cross-hatching in figure 1a shows where MTM is concentrated, which tends to be in areas with the highest poverty rates. Most coal mining in the ARC region occurs in Central Appalachia. Figure 1b shows that RUS mining shares are well below those in Central Appalachia.

Table 2 includes the results for several model specifications of 2000 county poverty rates for the ARC sample and the RUS. Both samples include two base specifications, with an additional model for the ARC county sample that includes MTM and the MTM interaction variables. Because there are no MTM counties outside of the ARC region, those models are not estimated for the RUS sample. For brevity, we report the most germane results. Other results are available on request.

The models perform quite well. The signs and magnitudes of most coefficients are consistent with past research (Partridge and Rickman 2005; 2008). Lagged poverty rates are positively and significantly related to current poverty rates, suggesting significant persistence in poverty, especially for ARC counties. The three mining shares are not statistically significant for the RUS 2000 model. In ARC counties, coal mining is positive and statistically significant but other mining shares are not statistically significant. These results are supportive of the stereotype that Appalachian coal mining is associated with higher poverty, but the same does not apply to other types of mining, nor does the stereotype apply to the RUS.

Model 2 adds the corresponding ten-year percent change in county shares of coal mining, oil and gas mining, and other mining. With the exception of a positive poverty link between oil and gas employment in the RUS sample, there is no statistical association between change in mining employment and poverty. These results suggest that poverty's association with coal mining is more of a legacy effect than a contemporaneous association with coal production.

Model 3 shows that though MTM is positively correlated with 2000 ARC poverty rates, the effect is not statistically significant. We also interact the MTM dummy with coal's share of total employment and the percent change in coal employment. Again these terms are statistically insignificant and suggest MTM has no added link to poverty in high-concentration coal counties or in counties with rising coal mining employment.

Though we do not report results for distance and education variables, they have a statistically significant impact similar to that found by Partridge and Rickman (2008). In short, poverty rates are positively related to distance to higher tiered MAs. The largest effect comes from the distance to the nearest MA, implying that proximity to any size MA has an important impact on poverty, most likely through commuting access (Partridge and Rickman 2008). The education variables are negative and significant, the high school graduate share having the largest marginal effect. In 2000, high school graduation seemed to be the threshold that most directly pushed workers above poverty.

The regression results for the 2010 poverty model are reported in table 3. Past poverty is again a significant contributor to current poverty, but unlike the 2000 poverty model, persistence is higher in the RUS sample. Poverty in the ARC region is less persistent in the 2000s than the 1990s, which may indicate a weakening of historical disadvantages that kept Appalachian poverty high for decades. The MTM variable is negative and significantly related to poverty for the 2010 model. This result is suggestive that MTM operations are bringing poverty-reducing jobs to areas surrounding their sites. Yet we caution that there could be other reasons. For one, poor people may be displaced by MTM and move outside of the county.

In both Models 4 and 5, the positive relationship between coal mining's initial employment share and poverty disappears in the 2010 poverty model. The coal share coefficient is negative and statistically significant in the 2010 RUS model and negative and insignificant in the 2010 ARC model. This result suggests that the negative legacy of large coal operations may be dissipating. In Model 5, percent change in coal employment now has a negative and significant relationship with poverty in the ARC model, whereas the association is negative and statistically insignificant in the RUS model. Interestingly, the oil and gas mining share is now positive and significantly associated with poverty in the ARC model and this positive effect is even greater than coal's positive effect in the 2000 model. All levels of education have a negative and significant relationship with 2010 poverty, but the poverty-reducing threshold for education has seemingly moved from a high school to an Associate's degree, suggesting a growing demand for skills.

Conclusion

Coal mining has long been associated with higher poverty in Appalachia, consistent with a natural resources curse. This study reassessed coal mining's link to poverty in Appalachia, including the more modern influence of MTM, with its broader environmental footprint. We find that coal's positive association with poverty changed to a negative association post-2000. Moreover, we find weak evidence that MTM is now associated with lower poverty, though we are careful not claim that this is a permanent effect. Hence, we tentatively conclude that there may be a reversal in coal mining's natural resource curse in Appalachia.

A limitation of this study is that while coal mining is determined by geology and national and global demand, a nonrandom pattern of the location of coal mining may exist—in particular for MTM (e.g., in business-friendly locales). Hence, future work should assess the potential nonrandom nature of mining location via the use of instrumental variables to appraise whether the effects of coal mining are truly changing.

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Table 1. Means and Standard Deviations of Selected Variables by Region: 1990 and 2000

	US		ARC		MTM	
	1990	2000	1990	2000	1990	2000
Poverty	16.34	13.78	19.06	16.38	30.04	26.34
	(7.79)	(6.38)	(7.90)	(6.39)	(7.25)	(6.31)
MTM	0.00		0.09		1.00	
	(0.00)		(0.29)		(0.00)	
Km to nearest MA	74.41		53.02		72.08	
	(62.10)		(31.85)		(26.33)	
Incremental distance MA of 250k	61.84		22.7		3.06	
	(103.27)		(31.02)		(9.62)	
Incremental distance MA of 500k	41.12		38.68		116.84	
	(69.19)		(50.85)		(60.12)	
Incremental distance MA of 1.5m	88.48		99.39		64.38	
	(121.57)		(98.25)		(72.18)	
Nearest metro population	455,918		213,224		193,341	
	(1,460,000)		(346,714)		(84,147)	
Employment growth 1990-95 (2000-05)	11.25	3.06	9.25	2.29	5.67	0.57
	(18.62)	(10.94)	(9.41)	(9.67)	(9.27)	(7.40)
Employment growth 1995-2000 (2005-2010)	9.43	1.26	7.58	-1.45	1.00	-0.38
	(9.97)	(7.76)	(10.67)	(6.84)	(7.40)	(6.49)
Percent high school graduate	34.35	34.39	34.55	37.4	30.01	34.44
	(6.02)	(6.44)	(6.73)	(6.41)	(4.29)	(4.29)
Percent some college	17.07	21.1	12.14	16.05	10.28	13.73
	(4.33)	(4.10)	(2.94)	(3.12)	(2.03)	(2.35)
Percent associates degree	5.55	5.85	4.06	4.8	2.69	3.63
	(2.10)	(1.99)	(1.63)	(1.66)	(1.03)	(1.11)
Percent college grad	13.89	16.97	10.48	12.96	7.63	9.23
N	2,596	2,596	413	413	37	37

See the text or Partridge and Rickman (2005, 2008) for more complete list of control variables and their definitions.

Table 2. Determinants of 2000 (1999) poverty rates

	(1) Base		*(2) Levels and Change*		*(3) MTM*
Dependent variable: 2000 poverty	US	ARC	US	ARC	ARC
Total poverty 1990 (1989)	0.54***	0.60***	0.54***	0.61***	0.61***
	(26.56)	(13.59)	(26.48)	(13.57)	(13.36)
MTM present in county dummy					0.82
					(1.41)
MTM*Share of coal					0.03
					(0.54)
MTM*Change in share of coal					-1.9E-03
					(-0.85)
Share of oil and gas	0.04	-0.04	0.04	-0.03	-0.03
	(1.15)	(-0.62)	(1.15)	(-0.56)	(-0.46)
Share of coal	0.01	0.09*	0.01	0.09*	0.04
	(0.34)	(1.88)	(0.36)	(1.88)	(0.76)
Share other mining	1.7E-07	-2.7E-06	1.8E-07	-2.6E-06	-2.5E-06
	(0.28)	(-1.13)	(0.30)	(-1.07)	(-1.06)
Change in share of oil and gas			1.5E-05***	7.0E-05	3.6E-05
			(6.27)	(0.19)	(0.10)
Change in share of coal			3.6E-06	2.9E-04	3.0E-04
			(0.90)	(1.06)	(1.11)
Change in share other mining			-2.2E-05	-9.9E-05	-6.6E-05
			(-0.29)	(-0.10)	(-0.06)
Constant	0.30	3.06	0.20	2.58	3.06
	(0.16)	(0.53)	(0.11)	(0.47)	(0.55)
N	2,606	417	2,596	413	413
R-sq	0.91	0.94	0.91	0.94	0.94

See the text or Partridge and Rickman (2005, 2008) for more complete list of control variables and their definitions.

*****=p<.01, **=p<.05, *=p<.10**

Table 3. Determinants of 2010 county poverty rates

	(4) Base		(5) Levels and Change		(6) MTM
Dependent variable: 2010 poverty	US	ARC	US	ARC	ARC
Total poverty 2000 (1999)	0.70***	0.54***	0.70***	0.54***	0.55***
	(30.96)	(9.80)	(30.81)	(9.62)	(10.29)
MTM present in county dummy					-2.05***
					(-2.86)
MTM*Share of coal					-0.04
					(-0.41)
MTM*Change in share of coal					-6.9E-04
					(-0.25)
Share of oil and gas	-0.05	0.14*	-0.05	0.14*	0.13*
	(-1.22)	(1.85)	(-1.20)	(1.85)	(1.67)
Share of coal	-0.14***	-0.06	-0.14***	-0.06	0.03
	(-2.82)	(-1.19)	(-2.86)	(-1.19)	(0.28)
Share other mining	2.2E-07	-2.3E-06	2.2E-07	-2.2E-06	-1.5E-06
	(0.54)	(-0.57)	(0.55)	(-0.55)	(-0.30)
Change in share of oil and gas			-3.9E-06	-1.0E-04	-1.4E-05
			(-1.40)	(-0.34)	(-0.05)
Change in share of coal			-3.3E-06	-2.4E-04*	-2.8E-04*
			(-1.10)	(-1.77)	(-1.92)
Change in share other mining			1.9E-05	-1.9E-04	-2.9E-04
			(0.31)	(-0.20)	(-0.28)
Constant	14.92***	18.21***	14.95***	20.21***	20.99***
	(6.98)	(3.24)	(6.98)	(3.75)	(3.90)
N	2,606	417	2,596	413	413
R-sq	0.90	0.88	0.90	0.88	0.89

See the text or Partridge and Rickman (2005, 2008) for more complete list of control variables and their definitions.

*****=p<.01, **=p<.05, *=p<.10**

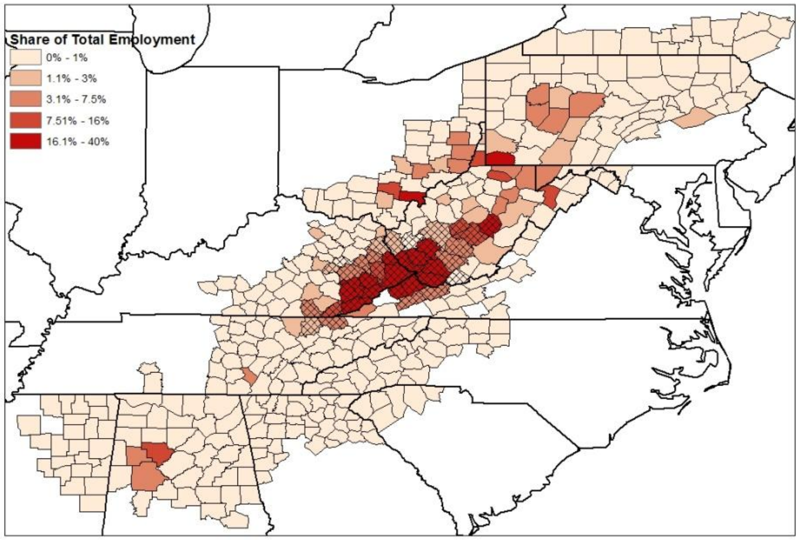

Figure 1a. Coal mining share of total county employment and MTM in 1990

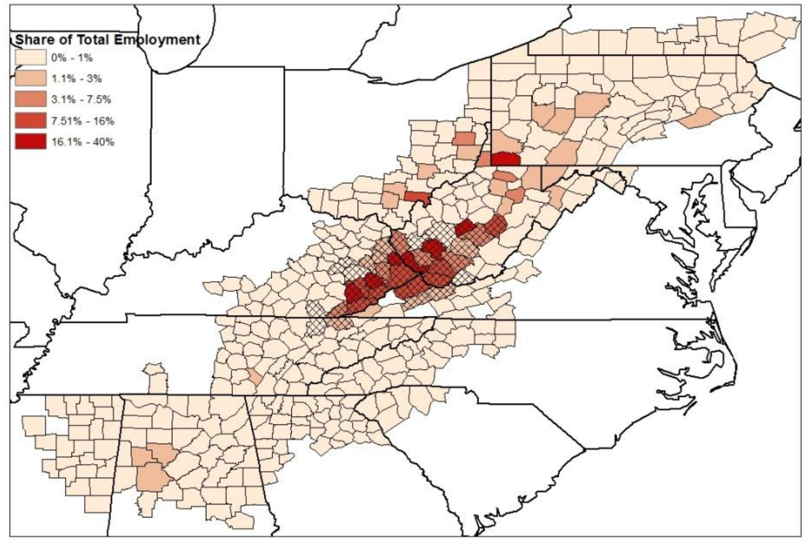

Figure 1b. Coal mining share of total county employment and MTM in 2000

[1]Coal mining aside, the ARC region faces considerably different economic and demographic conditions than the RUS, suggesting that its poverty process differs from the RUS. We tested for differences in model coefficients across samples and find statistically significant differences between the ARC region and RUS.

[2]We could not use the American Survey Data because it only contains poverty estimates for five year averages (2006-2010) for all counties.

[3]Woods and Gordon (2011) did not find that MTM increased employment in nearby communities, though they considered very local labor markets that do not account for commuting patterns and they did not use place-of-work employment data.

[4]EMSI uses many data sets to help "unsuppress" data from the U.S. Department of Labor *Quarterly Census of Employment and Wages*—e.g., see Dorfman, Partridge, and Galloway (2011).

[5]About 80 counties are omitted due to data availability (Partridge and Rickman 2005; 2008). A few states have zero mining employment in 1990 or 2000. Here, the denominator in calculating percent change averages the 1990 and 2000 values. Also to account for the small base problem and tiny fractions in the EMSI algorithm, all mining values less than 2 are treated as zero in this calculation.