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Does Mining Influence Rural Economic Growth?

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Abstract. The influence of non-oil and gas mining (NAICS 212) activity on U.S. rural (nonmetropolitan) economic growth is modeled using a simple Barro-type growth framework. Because the type of mining examined tends to be clustered in regions of Appalachia and the Mountain West, we allow for spatial heterogeneity in the underlying growth process. We find that the global least square results suggest that higher dependency on non-oil and gas mining is associated with higher rates of income growth over the 2000 to 2011 time period. This relationship, however, varies significantly across the U.S. The positive relationship holds for much of the eastern part of the U.S., but a negative relationship is seen in parts of the Mountain West, and no relationship is observed for the Pacific West and much of the area associated with the Mississippi River Basin. Because of this spatial heterogeneity, care must be taken in making generalizations about non-oil and gas mining and rural economic growth.

1. Introduction

The rapid expansion of oil and gas extraction in the western Appalachian Mountains (the Marcellus fields in the Appalachian Basin) and parts of North Dakota and Montana (the Bakken fields in the Williston Basin), through the process of hydraulic fracturing, or "fracking", has renewed widespread interest in mining as a rural economic growth strategy. This "gold rush" mentality has spilled over to other parts of the rural U.S., such as parts of Wisconsin, Minnesota, and Iowa, where frack sands (sand crystals such as quartz/silica or sandstone), which are required proppants used to "prop" open underground cracks from which gas or oil is extracted, are in wide supply. Given the depth of the "Great Recession" and slow recovery, these economic opportunities are being promoted by both mine developers and many local residents as a source of well-paying jobs regardless of any potential negative consequences.

The transition from extractive based industries (e.g., agriculture, mining, and forestry) to non-extractive based activities (e.g., recreation, tourism, and amenity-driven migration[1]) has raised tension in many of these rural communities (Barieri and Valdivia, 2010; English, Marcouiller, and Cordell, 2000; Marcouiller, Clendenning, and Kedzior, 2002; Ward, 2011). Power and Barrett (2001) eloquently argue that this transition from extractive to non-extractive industries has changed not only the economic base of many rural communities, but also their self-identity. An additional layer is the strong sense of private property rights among land and mineral rights owners. In many rural areas, particularly more remote areas, land use regulations, if present, are limited. As such, the draw to return to more traditional extractive-based industries is strong in many communities.

[1] Amenity-driven migration is associated with the movement of people away from disamenities (e.g., pollution and poor weather, among others) to amenity rich areas. The importance of amenities, or quality of life, in driving migration patterns can be traced to the pioneering work of Graves (1980, 1983) and has been reaffirmed in numerous studies (e.g., Cebula and Alexander, 2006; Jenson and Deller, 2007).

It is not clear, however, whether the promotion of mining is a viable economic growth strategy for the rural U.S. Under the designation of the "resource curse" (Humphreys, Sachs, and Stiglitz, 2007) or "Dutch Disease" there is a growing literature which suggests that sustainable economic growth from resource extraction activities should be considered the exception rather than a general rule (Ross, 1999; Sachs and Warner, 1999; Watts, 2005; Rosser, 2006; Bridge, 2008). Humphreys, Sachs, and Stiglitz (2007) observe that in the international development literature mineral resource extraction as a mode of regional development has become a "pariah". Yet, in the U.S. the promises of high-valued mineral leases to land owners and an abundance of well-paying mining jobs have spurred many rural communities into promoting mining "at all costs".

This study adds to a small, but growing, U.S.-focused literature which seeks to better understand the impact of mining on rural economies. While there is a robust literature within sociology examining the socioeconomic ramifications of mining within the context of social disruption theory (see Freudenburg and Wilson (2002) for an excellent review of this literature), there has been a much narrower set of studies within the regional economics literature. Most of the economics literature on mining has favored a developing-economies perspective (the foundation of the "Dutch disease" and "resource curse" literature), with very few studies focusing on mining within the context of a developed economy, such as the U.S. By exploring a simple Barro-type neoclassic growth model using U.S. rural (nonmetropolitan) county data for the period 2000 to 2011, some additional insights into the impact of non-oil and gas extractive mining on U.S. rural economies is gained. Beyond these simple introductory comments the study is composed of five sections. A brief literature review is provided in the next section followed by a statement of the empirical model. The estimation methods, specifically Geographically Weighted Regression (GWR), are then outlined. The empirical results are then discussed, and the study is closed with a review of key findings and a summary of policy implications.

2. Literature Review

As noted by Freudenburg and Wilson (2002), one of the difficulties in assessing the literature on the impact of mining on local communities, particularly within a U.S. setting, is the scale of the "grey" literature. The vast majority of the literature takes the form of consultants' reports, state and/or federal agency reports, both university-based and advocacy groups' information reports, and working papers which have been presented at profession meetings. Few have stood the test of peer review and publication in academic journals. This creates a difficulty in drawing inferences from the literature. While much of this grey literature is well-done and objective, differentiating these from casual analysis and advocacy-based works becomes somewhat subjective. Despite these difficulties there are certain patterns and inferences that can be outlined.

For our purposes the literature exploring the impact of mining on regional and local economies can be placed into one of three categories: (1) international development (the "resource curse" literature); (2) sociology; and (3) regional economics. The last classification is perhaps the least developed literature and the category to which the current study attempts to make a contribution. The resource curse literature (e.g., Ross, 1999; Sachs and Warner, 1999; Watts, 2005; Rosser, 2006; Papyrakis and Gerlagh, 2007; Bridge, 2008), while insightful, is not particularly relevant within a U.S. setting because of the role of institutional rules. As argued by Mehlum, Moene, and Torvik (2006), in most developing countries institutions, such as private property rights, environmental regulations, and labor protection laws, are not in place or are haphazardly enforced, thus setting the stage for mining to become a "pariah". In the U.S., even in the most remote rural areas, these institutions tend to be well established and enforced. Therefore, it is not clear if the conclusions of the development literature based on resource curse analysis is transferable to the U.S.

The sociology literature tends to take a case-study approach such as Lockie et al.'s (2009) analysis of the Coppabella coal mine in Queensland, Australia, Smith, Krannich and Hunter's (2001) examination of four western U.S. communities, or Brown, Dorius, and Krannich's (2005) analysis of Delta, Utah. This literature has drawn several general conclusions ranging from short-term negative outcomes (often in the context of social disruption theory or the broader social disorganization theory) like increased crime (Lockie et al., 2009) as workers flood into the community in search of jobs, to the inherent instability within the mining industry itself which creates instability and uncertainty within local communities (e.g., Freundenburg, 1992; Freudenberg and Gramling, 1994), to communities facing stronger economic hardships after the mine closes than before the mine began operations (e.g., Cushing, 1999; Black, McKinnish and Sanders, 2005; Marchand, 2012). The story of rural mining communities could be told as: the "boom" of the mine opening creates problems for the community, the instability of mining itself creates uncertainty within the community, and the closing of the mine creates a "bust" which leaves the community worse off than before the mine.

The instability of the mining operation itself, often referred to as the "flickering effect", and its impact on the local community are widely overlooked by communities that are considering mining as an economic growth strategy. Some authors (e.g., Freudenburg, 1991; Krannich and Luloff, 1991) argue that this flickering effect can result in short-term unemployment and poverty as laid-off workers remain in the community in anticipation of the mine resuming operations. This instability creates economic uncertainty within the community and may limit the potential positive economic impacts. Businesses that one would expect to start and/or expand through the multiplier effect are reluctant to do so. This flickering effect helps explain the finding of Weinstein and Partridge (2011), who note that many economic impact studies overestimate the potential impact.

The beginning of the contemporary regional economics literature that looks at mining within a U.S. context is generally attributed to Bender et al. (1985).[2] Bender and colleagues provided a comprehensive analysis on the impact of mining on community socioeconomic well-being. This study compared "mining dependent" counties (those where 20 percent or more of total labor and proprietor income came from mining) with other nonmetropolitan counties across several socioeconomic factors. The researchers found that mining-dependent counties had higher population growth rates, higher incomes, and fewer people receiving social security than the nonmetropolitan average.

Hady and Ross (1990), both of whom were coauthors on the original Bender et al. study, conducted an update looking at 1986, which is after the U.S. mining boom years of the 1970s. On average, whether focusing on the counties that were mining dependent in 1979, 1986, or both, Hady and Ross found declining personal incomes and increasing unemployment from 1979 to 1986. Nord and Luloff (1993) extended the work of Bender et al. by decomposing mining into three types (coal, petroleum, and "other") and examined three regions of the U.S. (the South, Great Lakes, and West). Using the 1980 Census, Nord and Luloff generally confirmed the results of Bender et al., but after 1980 the economic implications of mining deteriorated across all three types of mining and all three regions. For example, by 1990 all mining-dependent counties experienced faster growth rates in poverty than other nonmetropolitan counties. Weber, Castle, and Shriver (1988) also build on Bender et al. by decomposing mining into its commodity-specific activities. They found that U.S. counties with energy-related mining experienced growth in employment and earnings during the mining boom years 1973-1985; however, counties with metal mining experienced decline in these measures during those same years. These authors also found excessively high rates of unemployment associated with extractive industries relative to other sectors. While the case study-based literature has identified predictable patterns, the regional economics-based literature has yielded less predictable patterns.

Stedman, Parkins, and Beckley (2004) and Wilson (2004) caution against making blanket generalizations and point to several inconsistencies in the literature. As noted by Weber (2012), the impact of mining on rural communities depends on the type of mining being considered, the time-period examined, and uniqueness of the local communities. One could argue that the broader resource curse literature, such as the U.S.-focused analysis by Papyrakis and Gerlagh (2007) which is rooted on strong theoretical grounds and employs solid statistical methods, is limited due to aggregation bias. By aggregating all forms of resource extractive industries (agriculture, mining, and forestry) into a single category subtle but important industrial differences are lost.

One could also argue that failure to account for the heterogeneity in the ability of communities to benefit from the positive aspects of mining while minimizing the negative impacts also results in a form of aggregation bias. For example, large mines in remote rural communities will have a different impact than a smaller mine in a more densely settled community. Unfortunately, many of the studies that build on Bender and his colleagues' original piece tend to use simple subsample equivalency testing or correlation analysis. Here "mining-dependent counties" are compared to all other rural counties and

[2] One could reasonably argue that many of the U.S.-focused mining studies within the sociology literature follow the Bender et al. (1985) empirical approach of analyzing secondary data, but the theoretical foundation of these studies is in line with social disruption or social disorganization theories as opposed to economic growth theory. One could also reasonably argue that to fully understand the impact of mining on the rural economy one should take an interdisciplinary perspective.

inferences are drawn comparing subsample means. Such an approach does not allow the researcher to control for other community characteristics that will influence the relationship between mining and various metrics of community socioeconomic well-being. The notion that the heterogeneity across communities influences how mining impacts the community is lost.

More contemporary work, such as Weber's (2012) analysis of the natural gas boom on employment and income in Colorado, Texas, and Wyoming, has embraced more rigorous statistical methods that control for some degree of this heterogeneity. This movement toward stronger empirical methodologies is particularly true within the broader resource curse literature (e.g., Sachs and Warner, 2001; Papyrakis and Gerlagh, 2007). Here a metric capturing the size of the resource-dependent industry is introduced into a growth empiric model yielding a global parameter estimate. Such global parameter estimates, generally derived with a regression class estimator, presume that the relationship between the resource-dependent industry and the metric of socioeconomic growth or well-being is the same across the sample and, as such, geographic space.

While there is a growing "resource curse" or "Dutch Disease" literature and a growing U.S.-focused literature, there are still too many unknowns about the relationship between mining and community socioeconomic well-being and economic growth to make reasonable policy recommendations. Results vary by time-period examined, industrial definitions, and region of analysis. This study focuses narrowly on the role of regional variation by relaxing the assumption that a global parameter sufficiently reflects the underlying relationship. We accomplish this by employing Geographic Weighted Regression (GWR) as detailed by Fotheringham, Brunsdon, and Chartlon (2002) and allow the underlying data generating process (i.e., economic relationships) to vary across geography.

3. Empirical Model

One of the weaknesses of the U.S.-focused literature seeking to better understand the relationship between mining activity and economic performance or socioeconomic well-being is the lack of a theoretical structure in which to frame the problem. Most studies that examine the rural U.S. are purely inductive ones where researchers seek to better understand the patterns in the data, and once patterns are identified inferences are drawn.[3] The resource curse literature, however, tends to build on a neoclassical growth structure (e.g., Sachs and Warner, 2001; Papyrakis and Gerlagh, 2007). In the neoclassical theory originally developed by Ramsey (1928), Solow (1956), Cass (1965), and Koopmans (1965), growth rates in the economy are a function of labor and capital and a given level of technology.[4] Natural resources are a form of capital at the disposal of the economy. By extracting or mining the resource, one is utilizing a form of capital which in turn promotes growth.

Empirically this framework is implemented using a Barro-type (1991, 1997) growth equation which can be expressed as:

$$\Delta g_{i,t\leftarrow t-1} = \beta g_{i,t-1} + \alpha M_{i,t-1} + \sum_{j=1}^{m} \gamma_{j,i} X_{i,t-1} + \varepsilon_{i,t} \qquad (1)$$

Here $\Delta g_{i,t\leftarrow t-1}$ is the change in income, generally per capita income, from time t-1 to t for the i^{th} region or community, $g_{i,t-1}$ is the level of per capita income lagged one period, $M_{i,t-1}$ is the measure of mining activity lagged one period, $X_{i,t-1}$ is a vector of m control variables also lagged one period, $\varepsilon_{i,t}$ is a well-behaved error term, and the parameters (β,α,γ) are to be estimated. For our purposes we are interested in how the state of the local (nonmetropolitan county) economy in year 2000 (t-1) influences growth in per capita income over the period 2000 to 2011 ($t \leftarrow t$-1). Of particular interest is the value of α, or how dependency on mining for economic activity influences subsequent growth.

As outlined by Durlauf, Kourtellos, and Tan (2005) Barro-type growth equations have been used to study three stylized facts: (1) convergence in incomes across regions over time (β-convergence); (2) properties of the cross-section income distribution (σ-convergence); and (3) the identification of growth determinants.[5] While this approach has been the focal point of a lengthy and heated debate (e.g., Levine and Renelt, 1992), the literature has consistently identified patterns of convergence: as predicted by the neoclassical growth framework, over time

[3] One could argue that the sociology-based literature is based on social disruption theory, but this is not an economic growth theory.

[4] For a more formal derivation see Barro and Sala-i-Martin (1992), Mankiw, Romer, and Weil (1992), Nijkamp and Poot (1998), and Keely and Quah (2000).

[5] In the strictest sense, our specification of the Barro-type empirical growth model outline in eq(1) is a test of β-convergence.

regional incomes will converge to a system-wide average (see Abreu, de Groot, and Florax (2005), Durlauf and Quad (1999), and Durlauf, Johnson, and Temple (2005) for detailed discussions of this literature).

While the core of the divergence debate (Durlauf, Kourtellos, and Tan's first and second stylized facts) and its resulting policy implications are of general interest, it is ancillary for many studies that use a Barro-type empirical growth framework. Many studies are interested in exploring the implications of certain local characteristics or policies on overall growth patterns (Durlauf, Kourtellos, and Tan's third stylized facts). In the resource curse literature, Papyrakis and Gerlagh (2007), for example, use total economic activity in extractive industries (agriculture, mining, and forestry) as a regressor in a simple Barro-type model. Using U.S. state data they find that higher dependency on extractive industries is associated with slower rates of economic growth over the 1986 to 2000 time period. Mehlum, Moene, and Torvik (2006) and Brunnscheweiler (2008) also use a Barro-type empirical growth model to test their hypotheses concerning the role of institutions in helping understand the nature of the resource curse. Atkinson and Hamilton (2003) adapt a Barro-type empirical growth model to explore how an individual national government's ability to manage large inflows of revenue from the resource-based industry influences the magnitude and direction of the resource curse.

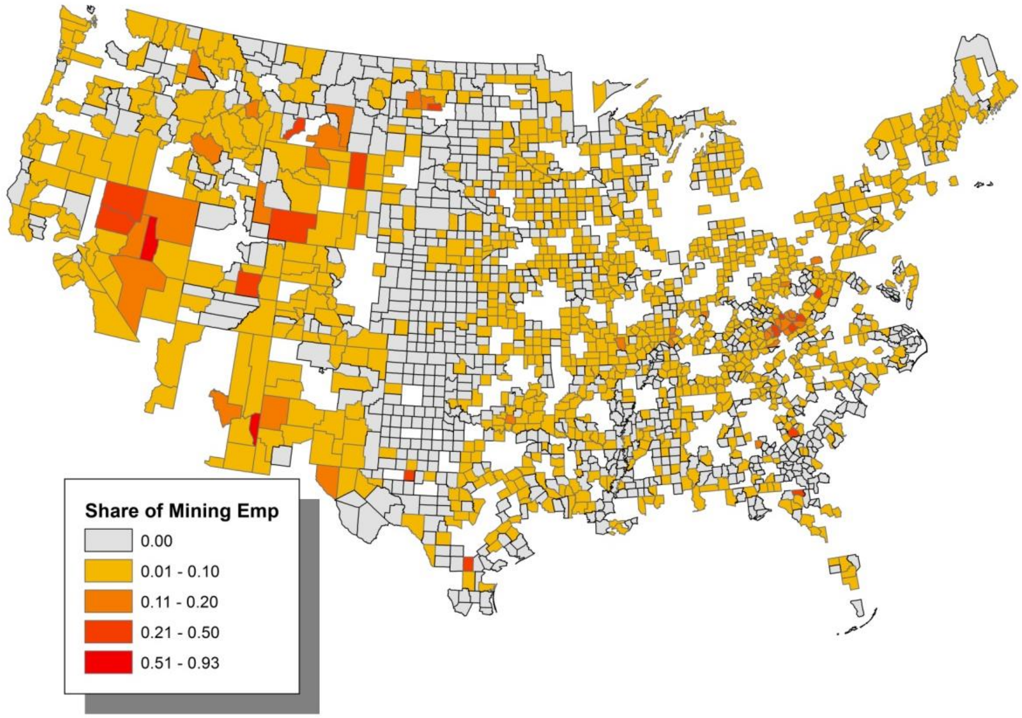
For this study we focus on non-oil and gas extractive mining (NAICS 212) employment in 2000 to explore growth in per capita income for nonmetropolitan U.S. counties from 2000 to 2011. As outlined by Sala-i-Martin (1997), Brock and Durlauf (2001) and Brock, Durlauf, and West (2003), one of the most contentious issues in modeling economic growth is the selection of the set of control variables contained in $X_{i,t-1}$. Levine and Renelt's (1992) critique, where they argue that small changes in the set of control variables can challenge the robustness of the results and hence any policy inferences, has been particularly influential in the growth literature. To address this problem we rely on the insight found in Deller and Lledo (2007). In modeling the role of amenities in the growth of U.S. nonmetropolitan counties between 1990 and 2000, Deller and Lledo employ a Bayesian Model Averaging method suggested by Brock and Durlauf (2001) to identify a set of control variables. Based on those results, ten control variables, ranging from a single age profile measure (percent of the population over age 75 years) to ethnic diversity to residential stability to deep lags, are included in this study. All together, our eclectic model contains twelve independent variables:

- per capita income ($g_{i,t-1}$)
- mining share of total employment ($M_{i,t-1}$)
- % of the population age 75+
- ethnic diversity index
- % of persons over age 25 w/bachelor's degree
- % of the population foreign born
- % of population speaking non-English at home
- % of population in same house 1985-1990
- poverty rate
- population:employment ratio
- % change in population 1990-2000
- % change in employment 1990-2000

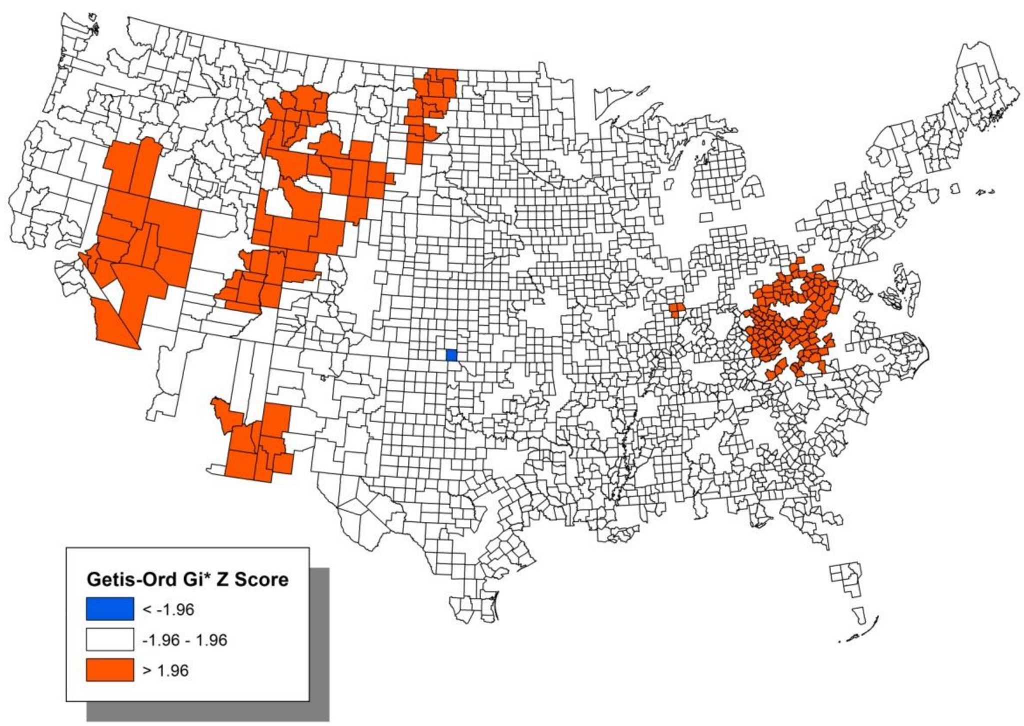
All right-hand-side variables are for 2000 unless otherwise noted.

The key variable of interest is the level of dependency on non-oil and gas mining activity for employment $M_{i,t-1}$, proxied by the percent of total county employment in mining (NAICS 212). A simple mapping of mining's share of employment reveals that nearly half (55.4 percent) of all nonmetropolitan counties in the U.S. have some level of non-oil and gas mining activity (Map 1). Of the 1,110 nonmetropolitan counties that do have some level of non-oil and gas mining, 69.7 percent have less than one percent of total employment in mining. Only a total of 99 counties have more than five percent of employment in non-oil and gas mining activity. It is important to note that many counties have simple gravel pits, which are included in our definition of mining, and these operate on a part-time basis and are often very small in scale.

There does appear to be a clustering of employment concentrations associated with these mines in parts of the Appalachia, which would be primarily coal mining, as well as parts of the Mountain West, which would be both coal and mineral mining. To test if these spatial patterns are random or significant we estimate and map the Getis-Ord G_i^* (Map 2). Here we find that the casual observations drawn from Map 1 are confirmed: there are clustering "hot spots" around the coal producing region of Appalachia as well as a small area of southern Illinois, much of the Rocky Mountain range, eastern Montana and western North Dakota, and mineral mining in much of Nevada and parts of Arizona and New Mexico.



Map 1. Non-oil and Gas Mining Employment Distribution.
Note: Analysis includes only non-metropolitan counties; metropolitan county boundaries are suppressed.



Map 2. Non-oil and Gas Mining Employment Clustering.
Note: Analysis includes only non-metropolitan counties; metropolitan county boundaries are suppressed.

This spatial clustering of both "hot" and "cold" spots raises several issues. First, from the Getis-Ord G_i^* it is clear that there exist levels of spatial dependency within the data, which is confirmed with a simple Moran's Index of 0.0901 (z-score is 19.37, p-value is less than 0.0001). This casts suspicion on the handful of U.S.-focused studies that look at the relationship between mining and rural economic growth; none that we are aware of control for spatial dependency in the data. Second, despite the presence of non-oil and gas mining operations in nearly half the U.S. rural counties, it is concentrated in specific geographic regions. This makes sense given the geology of coal and mineral deposits. This suggests that the relationship between mining and rural economic growth may not be homogenous across geography. For example, the underlying relationship may be different in the Mountain West than in the Upper Midwest or New England. Third, the degree of industry maturity could also alter the underlying relationship. In many of the "hot spots" or spatial clusters identified in Map 2 the mining industry is well established and could almost be considered an economic cluster. Here support and interconnected industries and specialized pools of labor could be better established, again altering the underlying relationships between mining and economic growth.

Unfortunately, traditional regression analysis, even spatial correction estimators such as a spatial lag or spatial error estimators, will not allow for spatial heterogeneity that may exist in the underlying relationship. By using the methods of Geographically Weighted Regression (GWR), as outlined in detail by Fotheringham, Brunsdon, and Chartlon (2002), one can extend previous models by allowing the underlying data generating process to vary over geographical space rather than assuming that the underlying process is constant over all locations. In essence, the GWR provides a systematic method for providing a unique parameter estimate for every observation in the sample. Using GWR allows us to test not only whether in a global sense there is spatial heterogeneity in that underlying relationship between mining and rural economic growth, but also for geographic-specific insights.

The GWR model can be written as:

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i) x_{ik} + \varepsilon_i, \qquad (2)$$

where (u_i,v_i) indicates that location of the i^{th} point and $\beta_k(u_i,v_i)$ is a realization of the function $\beta_k(u,v)$ at point i. The individual value of $\beta_k(u_i,v_i)$ is the value of the parameter for each observation. The GWR equation (2) recognizes that spatial variations in the parameters might exist and provides the model with a way that they can be recognized.

An issue can be raised that in equation (2) there are more unknowns than observed variables. Fotheringham et al. (2002) acknowledges this and notes that they do not consider the coefficients to be random; rather they view them as a function of locations in space. In this model, the data closer to location i are weighted more heavily in the estimation than those further from i. The model is very similar to weighted least squares in its operation. The weighting scheme can be written as follows:

$$\hat{\beta}(u_i, v_i) = (\mathbf{X}'\mathrm{W}(u_i, v_i)\mathbf{X})^{-1}\mathbf{X}'\mathrm{W}(u_i, v_i)y, \qquad (3)$$

where the estimates are weighted according to the n by n matrix $\mathrm{W}(u_i,v_i)$ whose off diagonal elements are zero and diagonal elements are the weighting of each of the n observations for regression point i.

This can be more clearly explained by considering the OLS equation:

$$\mathbf{Y} = \beta\mathbf{X} + \varepsilon \qquad (4)$$

where the β vector of parameters is estimated by

$$\hat{\beta} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y}. \qquad (5)$$

The GWR extension of this is,

$$\mathbf{Y} = (\beta \otimes \mathbf{X})1 + \varepsilon \qquad (6)$$

where each element of β is multiplied by the corresponding element of $\mathbf{X}$. The matrix β now has n sets of parameters and the following form:

$$\beta = \begin{pmatrix} \beta_0(u_1, v_1) & \dots & \beta_k(u_1, v_1) \\ \vdots & \ddots & \vdots \\ \beta_0(u_n, v_n) & \cdots & \beta_k(u_n, v_n) \end{pmatrix}. \qquad (7)$$

Each parameter above is then estimated using

$$\hat{\beta}(i) = (\mathbf{X}'\mathrm{W}(i)\mathbf{X})^{-1}\mathbf{X}'\mathrm{W}(i)\mathbf{Y}, \qquad (8)$$

where i represents a row in the matrix in (7) and

$W(i)$ is an n by n spatial weighting matrix of the form

$$W(i) = \begin{pmatrix} w_{i1} & 0 & \cdots & 0 \\ 0 & w_{i2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & w_{in} \end{pmatrix}, \tag{9}$$

where w_{in} is the weight given to data point n for location i. The function for the weighting scheme is Gaussian, with the ith observation being defined as:

$$w_{ij} = \exp\left[-\frac{1}{2}\left(\frac{d_{ij}}{b}\right)^2\right], \tag{10}$$

where d is the distance between observation i and location j, and b is the bandwidth, estimated by minimizing the Akaike Information Criterion (AIC). The spatial weighting schemes in GWR can be made to adapt themselves to the size variations in the density of the data, with larger bandwidths in sparser areas and smaller bandwidths in more highly concentrated areas. The essential idea is that for each regression point i there is an area of influence around i described by the weighting function so that observations near to i have more weight in the estimation of the parameters than those further away. This will be used to highlight the degree of misspecification in the global model.

To test for stationarity of individual parameters across space (i.e., the presence of spatial homogeneity for each variable) we use Monte Carlo significance tests first suggested by Hope (1968). In this process the observed value of the test statistic is compared with n-1 simulated values. After the observed variance of the local parameter estimate is calculated and stored, n-1 sets of variances are obtained for each variable based on different randomizations of the observed data. The p-value is then computed for the local parameters associated with each variable as described above. These p-values indicate whether the spatial variation is significant or if it most likely occurred by chance. If, based on these Monte Carlo simulations, the observed spatial variation is not significant, then one can reasonably conclude that the underlying data generating process is homogenous and the global parameter is appropriate across geographic space. If the spatial variation is significant, then the underlying data generating process is heterogeneous and the global parameter provided by least squares masks that heterogeneity. In the latter case, any policy inferences concerning the relationship between mining and economic growth could be mistaken.

4. Empirical Results

Before turning to the GWR results, consider the global parameter estimates that are derived using ordinary least squares (Table 1). Overall, the simple Barro-type growth model explains 69.4 percent of the variation in per capita growth between 2000 and 2011, which is generally consistent with other rural focused studies. Control variables that have a positive influence on per capita income growth include percent of the population over age 75, percent of the population over age 25 with a Bachelor's degree, percent of the population speaking a language other than English at home, residential stability between 1995 and 2000, and the poverty rate. Control variables with a negative influence on per capita income growth include the population–employment ratio and the two deep lagged change variables, the percent changes in population and employment from 1990 to 2000. Neither ethnic diversity nor percent of the population foreign born are statistically significant. These results are as expected and generally there are no surprises.

The coefficient on per capita income at the beginning of the study period is negative and statistically significant, which is consistent with the β-convergence hypothesis that flows from the neoclassical foundations of the Barro-type growth model. The convergence rate here is about 6.4 percent, which is slightly higher than the average found in Abreu, de Groot, and Florax's (2005) meta-analysis of Barro-type empirical models but well within the range of what they found "reasonable". The variable of interest - the percent of total county employment in mining - has a positive and statistically significant coefficient, suggesting that higher levels of mining dependency are associated with higher per capita income growth rates. But the magnitude of the relationship is modest: if the typical county with 1.1 percent of total employment in non-oil and gas doubles its share of employment to 2.2 percent, the growth rate in per capita income will increase by 0.8 percent.

But one cannot place too much weight on these results, as the spatial dependency in the data is not considered. A simple ANOVA analysis of the GWR and OLS residuals yields an F statistic of 14.12 which provides sufficient evidence that there is spatial variation in the underlying data generating process. One of the difficulties of reporting the results of GWR modeling is the volume of results that could be provided and discussed. Two common approaches are to report the quartile values of the parameter estimates as well as a mapping of the results for the variables of interest. The minimum, maximum, and median values of the GWR parameter estimates, along with the lower and upper quartile values, are provided in Table 1.

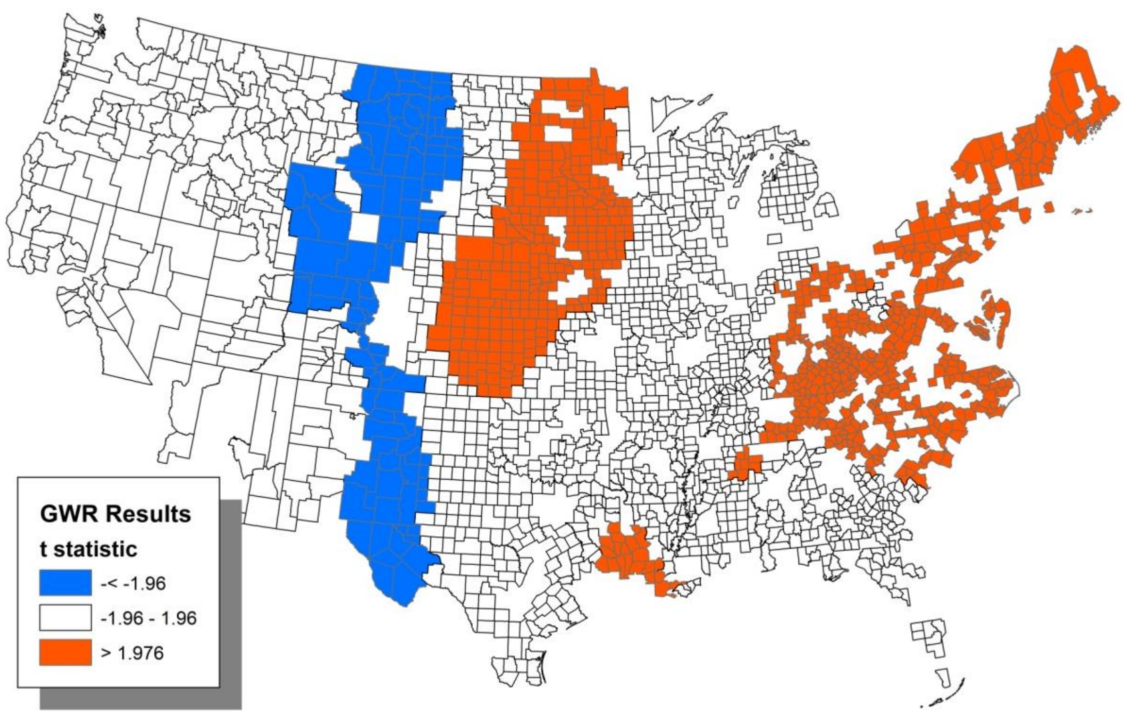
Table 1. Growth in Non-Metropolitan Counties Per Capita Income 2000-2011.

	Min	Lower Quartile	Median	Upper Quartile	Max	Monte Carlo Simulation (p-value)	Least Squares Global Estimate	OLS Marginal Significance (p-value)
Intercept	-1.865	0.000	0.104	0.447	1.332	(0.0001)	-0.00002	(0.9979)
Per Capita Income	-0.315	-0.187	-0.103	0.000	0.136	(0.9500)	-0.16887	(0.0001)
% of the Population Age 75+	-3.921	-0.430	0.000	0.820	4.862	(0.8400)	2.53739	(0.0001)
Ethnic Diversity Index	-0.606	-0.048	0.000	0.054	1.113	(0.0001)	-0.03420	(0.2941)
% of Persons>Age 25 With a Bachelor's Degree	-0.443	0.000	0.334	0.800	2.846	(0.9900)	1.43789	(0.0001)
% of the Population Foreign Born	-6.383	-0.466	0.000	0.314	2.483	(0.0001)	-0.00956	(0.9587)
% of Population Speaking Non-English at Home	-2.256	-0.114	0.000	0.298	2.036	(0.0001)	0.45201	(0.0001)
% of Population in Same House 1985-1990	-0.874	0.000	0.344	1.048	3.080	(0.0100)	0.99207	(0.0001)
Poverty Rate	-2.237	-0.249	0.000	0.220	3.959	(0.0001)	0.37600	(0.0021)
Population:Employment Ratio	-0.265	-0.006	0.000	0.026	0.159	(0.1600)	-0.05998	(0.0001)
% Change in Population 1990-2000	-1.576	-0.299	-0.016	0.000	0.410	(0.0400)	-0.28403	(0.0001)
% Change in Employment 1990-2000	-0.780	-0.094	0.000	0.015	0.211	(0.4400)	-0.08716	(0.0232)
Mining Share of Total Employment	-0.874	0.000	0.000	0.682	6.428	(0.0400)	0.41843	(0.0001)
OLS Adjusted R^2	0.6943							
GWR Adjusted R^2	0.8209							
ANOVA GWR vs OLS F Statistic	14.12							

Based on the Monte Carlo simulations to test for stationarity, seven of the twelve variables (exclusive of the intercept term) exhibit significant spatial heterogeneity. The control variables that exhibit spatial heterogeneity include the ethnic diversity index, percent of the population foreign born, percent of the population that are non-English speakers at home, residential stability, the poverty rate, and the deep lag change in population. Consider the upper and lower quartile values (the minimum and maximum values could be considered outliers and as such set aside) for each of these spatially heterogeneous control variables: many of these variable parameters at the upper and lower quartiles switch direction. For example, the lower quartile value for the percent of the population that speak non-English at home is negative while the upper quartile is positive. This suggests that the global parameter estimate provided by ordinary least squares, which is positive, is misleading for parts of the rural U.S. This speaks directly to the heterogeneity of the rural U.S.

Based on the Monte Carlo simulations, the underlying relationship between per capita income at the beginning of the period and income growth, the β-convergence result, is homogenous across the rural U.S. In other words, the convergence result holds for the whole of the study area. The more interesting result for this study is the spatial heterogeneity conclusion about the dependency on mining for employment. Again, removing the minimum and maximum values from consideration, the lower quartile and median values are for all practical purposes zero, with the upper quartile positive. At face value it appears that the positive influence mining has on employment growth is limited to only some rural areas; relying solely on the global parameter estimates to inform policy will result in erroneous inferences.

To better understand this spatial heterogeneity between mining and rural income growth we map the t-values associated with each individual parameter tied to the mining metric (Map 3). For clarity, we have three possible outcomes: a negative t-statistic with absolute value equal to or greater than 1.96, a positive t-statistic with value equal to or greater than 1.96, and t-statistics that fall between -1.96 and 1.96. We find that 5 percent of the nonmetropolitan counties included in the analysis have a statistically significant and *negative* coefficient, suggesting that higher dependency on non-oil and gas mining has a dampening effect on income growth. These counties tend to be clustered in a band from west Texas and eastern New Mexico north through Colorado, Wyoming, and eastern Montana. Given that this region of the U.S. is part of a spatial cluster (Map 2) where mining is generally more highly concentrated (Map 1), the further promotion of mining in this area may not be a viable economic growth strategy.



Map 3. GWR Results: Mining Employment on Income Growth.
Note: Analysis includes only non-metropolitan counties; metropolitan county boundaries are suppressed.

Given the strength of the least squares results it is somewhat surprising to find that mining's positive influence on per capita income growth is statistically significant for only 37 percent of nonmetropolitan counties. These counties are clustered from the Carolinas north through Ohio and northeast through New England, regions that are generally associated with coal mining. There is also a band of counties clustered in the Great Plains where the positive relationship between mining and income growth holds. Given the relative lack of mining activity in this region (Map 1) this result is somewhat surprising. The GWR results indicate that for 58 percent of counties non-oil and gas mining has no influence on income growth. Given that mining accounts for less than one percent of total employment for so many rural counties, this latter result is not unexpected.

The overall conclusion here is that the underlying relationship between rural income growth and mining, which is defined in this study as non-oil and gas mining (NAICS 212), varies significantly across the U.S. For most of the rural U.S. mining dependency for employment does not play any meaningful role in understanding growth in per capita income over the 2000 to 2011 time period. But there are parts of the U.S., particularly north of the Carolinas and in parts of the Great Plains, where higher dependency on mining is associated with higher rates of income growth. For parts of the Mountain West, however, higher dependency on mining has a negative impact on income growth. The global parameter estimates from an estimator such as least squares mask these important differences and may lead to incorrect policy inferences.

5. Conclusions

The analysis presented in this study is directed at improving our understanding of the role of non-oil and gas mining in U.S. rural economic growth. Using a Barro-type model of growth in per capita income from 2000 to 2011 we find mixed evidence. Using a Geographically Weight Regression (GWR) estimator we find that the heterogeneity of the rural U.S. makes broad statements about mining and income growth fraught with error. For over half of U.S. nonmetropolitan counties non-oil and gas mining has no role in explaining growth over the decade beginning in 2000. This is not surprising because mining accounts for such a small level of economic activity for most rural counties. Therefore it is difficult to infer that the promotion of mining will necessarily enhance growth rates; the heterogeneity of the rural U.S. dictates that care must be taken when drawing general conclusions.

More important, the evidence suggests that when there is a statistically significant relationship between mining and income growth the direction of that relationship varies across the U.S. In the eastern part of the U.S., particularly the Carolinas north through Ohio and New England, there is a positive relationship between dependency on mining for employment and income growth. But there is a narrow band along the Rocky Mountains from eastern New Mexico north to the Canadian border where higher dependency on mining is associated with slower rates of income growth. This result suggests that the "resource curse" within a rural U.S. setting may or may not apply depending on where one is within the U.S.

The overall conclusion that must be drawn from this analysis is that the heterogeneity of the rural U.S. makes broad generalizations difficult if not simply wrong. While analysts can attempt to control for certain local characteristics within the modeling work, the level of heterogeneity cannot be adequately captured with traditional estimators. Other studies that have explored spatial heterogeneity in rural areas have found similar patterns: rural crime patterns (Deller and Deller, 2012), rural poverty and tourism (Deller 2010), and the role of microenterprises in rural economic growth (Deller 2010). While we find that the overall convergence rate (β-convergence) is stable across the rural U.S., the role of the control variables and resulting policy insights varies significantly across space.

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