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Mapping Poverty in Rural China:

How Much Does the Environment Matter?

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Abstract

In this paper, we apply a recently developed small-area estimation technique to derive geographically detailed estimates of consumption-based poverty and inequality in rural Shaanxi, China. We also investigate whether using environmental variables derived mainly from satellite remote sensing improves upon traditional approaches that only use household survey and census data. According to our results, ignoring environmental variables in statistical analyses that predict small-area poverty rates leads to targeting errors. In other words, using environmental variables both helps more accurately identify poor areas (so they should be able to receive more transfers of poor area funds) and identify non-poor areas (which would allow policy makers to reduce poverty funds in these better off areas and redirect them to poor areas). Using area-based targeting may be an efficient way to reach the poor since many counties and townships in rural Shaanxi have low levels of inequality, even though, on average, there is more within-group than between-group inequality. Using information on locations that are, in fact, receiving poverty assistance, our analysis also produces evidence that official poverty policy in Shaanxi targets particular areas which in reality are no poorer than other areas that do not get targeted.

Keywords

China
environment
poverty
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JEL Classification

O15, O53, P36, Q56

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I. Introduction

China has made remarkable progress in its war on poverty since the launching of economic reforms that began in 1978 (Lin, 1992). Economic growth of about 9 percent per annum since the late 1970s has helped to lift several hundred million people out of absolute poverty. Over the past two decades of reform, the proportion of the population living in poverty fell from 64 percent in 1981 to 10 percent in 2004, with the reduction in poverty greatest in China's coastal and central regions where economic growth has been fastest (Ravallion and Chen, 2007; Chen and Ravallion, 2008).

However, even with the success to date, substantial challenges remain as there are still more than 100 million rural absolute poor (those living under $1/day – measured as expenditures on consumption). Most of these poor reside in western (inland) China and are concentrated in remote townships and villages, often in mountainous areas with low rainfall, or lands with limited potential for even subsistence levels of production (World Bank, 2001; Ravallion and Chen, 2007). However, even in western China there are pockets of relative wealth amid poverty which are disguised with more aggregated levels of data (e.g., province-level data) that most poverty analysts rely upon (for example, Ravallion and Chen, 2007), as are the pockets of poverty in the more prosperous eastern provinces.

The concentration of the poor in particular areas suggests that geographic targeting of poverty reduction assistance might be useful. However, geographic targeting requires finely detailed spatial targeting to prevent leakage of benefits to non-poor areas and to ensure that aid is channeled to areas in which those that are truly poor live. Previous research has shown that geographic targeting is most effective when the geographic units are relatively small (Baker and Grosh, 1994). Unfortunately, such targeting is currently impossible since the coverage of household surveys (that is the size of the sample) that are used to measure poverty in China are too small to permit measuring poverty at fine enough level of spatial disaggregation. For example, China's rural household survey samples 80,000 households but yields poverty estimates that are representative only for each province ($n = 31$).

Hence, it is this context that small area estimation, a recently developed empirical approach, might be useful (Hentschel et al., 2000 and Elbers et al., 2003). In this approach analysts combine household survey data (that are limited in their coverage) with other data sources. In particular, census data can be disaggregated to a fine level such as counties or townships. In other words, with census data, there are observations on all counties (townships) in each province. The combination of data sources are needed, however, since in China the census only asks about sources of income, not levels of income. Census data also does not include any details on components of consumption. As a result, the census cannot be used directly to measure poverty.

To implement the small area estimation method, several steps are needed. Household survey data are used to estimate a model of consumption. When creating the model, however, the explanatory variables on the right hand side of the consumption function need to be restricted to those variables that are also available from a recent census. The coefficients from this estimated model are then combined with the overlapping variables from the census (which cover all households), and consumption and income levels are predicted for each household in the census. Using such data, we can then predict the odds of being poor for each census household and add these up to yield estimated poverty rates for disaggregated (small) geographic units (Hentschel et al., 2000). These welfare indicators are then plotted on a map, which is conventionally called a poverty map. Elbers, Lanjouw and Lanjouw (2003), hereafter denoted as ELL, show that the incidence of poverty calculated from a census, using the imputed consumption figures is close to that calculated from survey data but with a much greater level of statistical precision. The ability to produce reliable estimates of poverty for small geographic areas, without the added costs of fielding additional household surveys has made this technique popular in developing countries and in some cases the poverty maps are used by governments to target financial resources to particularly needy areas.

One problem with the way that small area estimation and poverty mapping techniques are often applied is that many studies neglect information on the environmental factors that influence each area's rate of poverty. If considered, it is possible that the estimates of poverty could be sharpened. The precision of poverty estimation could be helped by considering environmental factors since there are clear theoretical links between poverty and the environment (Ekbom and Bojo, 1999). Empirically it also has been shown that there are significant differences in poverty and welfare levels between people with similar characteristics living in different geographical areas (Jalan and Ravallion, 1998). Hence, if it is possible to measure differences in environmental conditions at a fine enough level (such as rainfall, soil fertility, access to markets of each town), it stands to reason that using the information contained in these environmental variables should be relevant for poverty maps. Curiously, even though environmental factors have been identified as contributors to differences in living standards in different areas, there has been little empirical work to ascertain their relationship with poverty rates (although there are exceptions, for example, Gibson et al., 2005 and Okwi et al., 2005). The major problem in performing this type of analysis has been lack of data (and/or the inability to merge environmental data with census data). Despite the data difficulties, the fact still remains that if not accounted for, poor environments and low levels of geographical capital may mask poverty where it really is (or predict poverty where it is not).

To bridge these gaps in the existing research, in this paper we not only use census and household survey data, we also combine them with a set of environmental variables (in part, derived from high resolution satellite imagery; and in part derived from other sources), to construct poverty maps for rural areas of Shaanxi province in China. Shaanxi is selected because it is an area of high poverty in China. The incidence of rural poverty in Shaanxi in 2000 was 2.9 times as high as the national average. Furthermore, Shaanxi has had one of the slowest rates of poverty reduction in rural China since 1981 (Ravallion and Chen, 2007). In the current application, Shaanxi also is a strategic choice since it has considerable environmental heterogeneity (Huang et al., 2007). In this paper, we construct and compare two poverty maps: one created with and one created without environmental variables. These maps allow us to precisely predict poverty rates all the way down to township level (while there are 31 provinces in China and approximately 2000 counties, there are more than 40,000 townships, which means this is a fairly low level of disaggregation). Based on comparisons of the two poverty maps, we then assess how much leakage and under coverage results when environmental variables are excluded from poverty mapping exercises. We also estimate between-area and within-area inequality decompositions, to establish the viability of targeting based on geographic location. This step is important because if most inequality is due to within-area sources, targeting poor areas is still likely to see a lot of leakage to non-poor households, while the untargeted areas are also likely to include many poor households, leading to problems of undercoverage. Finally, we contrast the results of our poverty maps with the official designation of 'poor counties' and examine some of the environmental correlates of county-level poverty in rural Shaanxi.

To meet our specific objectives, the rest of the paper proceeds as follows. The next two sections describe the data and provide a brief explanation of the methodology. Section 4 presents the results of the estimation. Section 5 uses the results and examines the targeting implications when the analysis accounts for (and when it does not account for) the environmental factors. In section 6, we contrast the results of our poverty maps with the official designation of 'poor counties' and examine some of the environmental correlates of county-level poverty. The final section concludes.

II. Data

The data mainly come from three sources: (i) the 2000 Population Census; (ii) the 2001 Rural Household and Income Expenditure Survey conducted by the China's National Bureau of Statistics; and (iii) satellite remote sensing. Table 1 indicates which variables come from each of these three sources, distinguishing between those available for the sample and those available for the population. The methodology, which will be discussed below, requires the model of consumption to be estimated on the sample observations and the coefficients then applied to population data on the same variables. Table 1 also presents the mean values of the explanatory variables available in both the household survey and the population census that were selected for inclusion in the model of consumption.

Table 1. Availability of data and sources

	Sample	Survey Mean	Population	Census Mean
Welfare Indicator(s)				
Per capita expenditure	HIES	1,090.68	n.a.	n.a.
Demographic Characteristics				
Number of persons aged 6 and below	HIES	0.24	Census	0.29
Number of persons between 7 & 15 years of age	HIES	0.98	Census	0.79
Number of persons between 16 & 60 years of age	HIES	2.88	Census	2.27
Number of persons aged 61 and above	HIES	0.27	Census	0.37
Education Characteristics				
# of labor force in HH completed primary school	HIES	0.75	Census	0.84
# of labor force in HH completed junior high school	HIES	1.25	Census	1.06
# of labor force in HH completed senior high school	HIES	0.29	Census	0.21
# of labor force in HH completed vocational school	HIES	0.03	Census	0.04
# of labor force in HH with college degree and above	HIES	0.01	Census	0.01
Dweling Characteristics				
Housing area (in square meter)	HIES	101.23	Census	118.01
Brick house (dummy = 1; 0 otherwise)	HIES	0.52	Census	0.55
Household uses LPG as main source of cooking (dummy = 1; 0 otherwise)	HIES	0.01	Census	0.02
Household economic activities				
Number of household members engage in non-agriculture activities	HIES	0.57	Census	0.38
Geophysical variable(s) at county level				
Total areas of land	Geo	249,641	Geo	219,993
Percentage of plain area	Geo	0.16	Geo	0.17
Percentage of loam in the soil	Geo	0.29	Geo	0.30
Percentage of organic matter	Geo	0.63	Geo	0.75
Annual rainfall	Geo	650.06	Geo	681.85
Temperature	Geo	10.08	Geo	10.18
Density of highway in m/1000 ha (log)	Geo	9.2	Geo	11.00
Slope (log)	Geo	0.99	Geo	1.07
Elevation (log)	Geo	6.83	Geo	6.81

The latest population census was conducted in November 2000. Like the census in many other countries, the Chinese version did not collect information on income and expenditure. As a result, the census cannot be used directly to measure poverty.[1] The census, however, provides information on a number of characteristics that are likely to be correlated with consumption and poverty. It includes information on demographics, education, economic activities and the attributes of the dwelling. In this paper we use a 1 percent sample of the census (henceforth, a micro-census), which was designed to be representative at the township level. The census listed 2,144 townships in Shaanxi and almost 76,000 rural households from these townships are listed in the micro-census.

The 2001 Rural Household Income and Expenditure Survey (RHIES), as its name implies, collected information on the income and expenditure of households. Apart from this, the survey also collected information on household characteristics, employment, seasonal labor migration, agricultural production, dwelling characteristics, ownership of durable goods and fixed assets and access to public infrastructure. The RHIES used a random multi stage systematic sampling of 1,400 households in Shaanxi. In the first stage, 25 counties were selected, in which between 4 – 8 townships were selected from each county. From each township, 1 village was selected and 10 households were selected from each selected village.

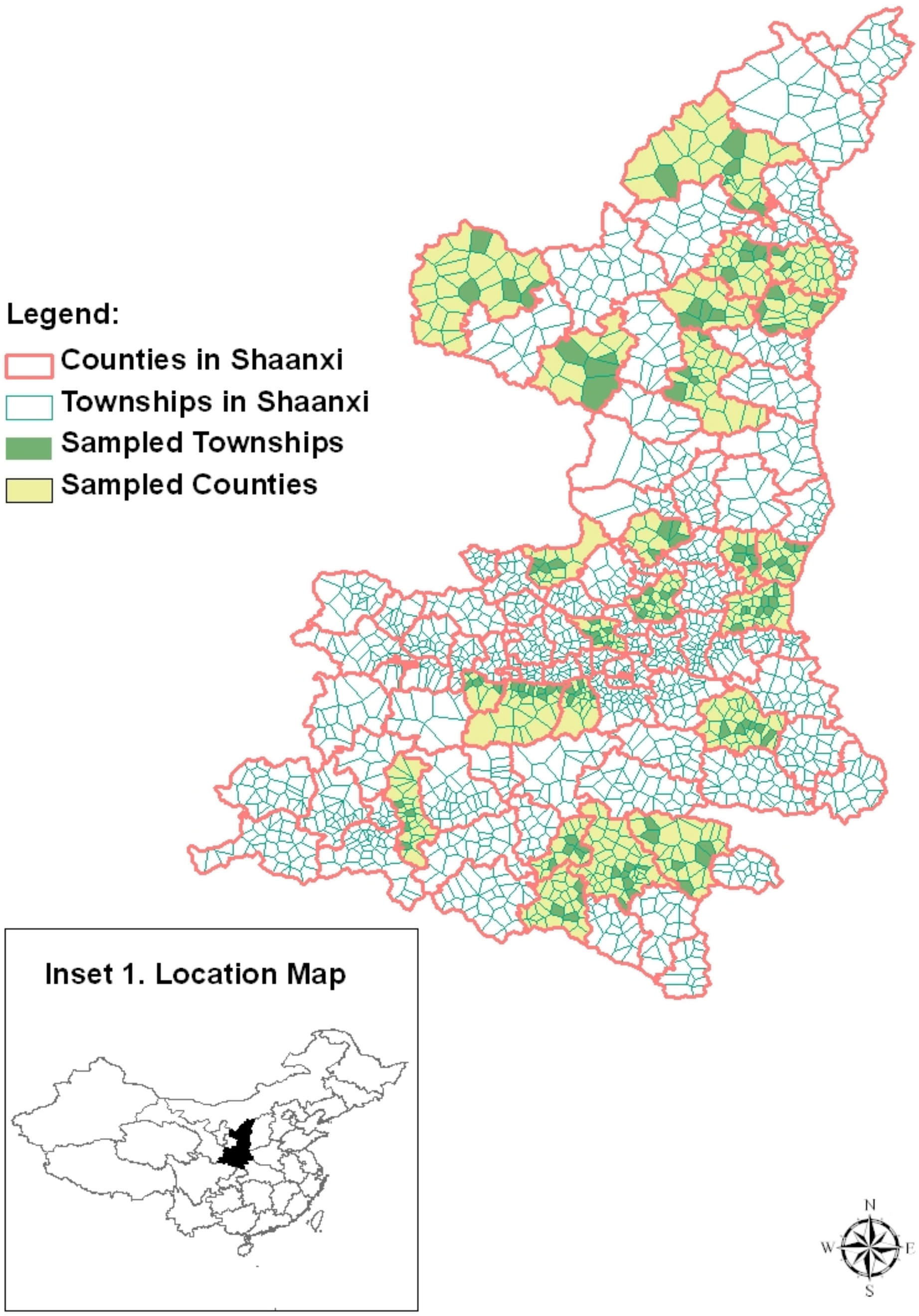
Despite the fact that the RHIES collected high quality data on the living standards of households and its members, it is sample and the size of the sample is small relative to population that it is trying to represent. Figure 1 shows that 24 (124) sampled counties (townships) were selected from among the 107 (2144) counties (townships) in the province.[2] The sample size in this survey is therefore too small to allow an estimation of the incidence of poverty at either the county or township level. As a result, poverty

[1] Many countries construct basic needs indicators to rank areas by combining census information such as access to public services and level of education and use these indicators to build poverty maps. Hentschel et al. (2000) note that such indicators are deemed to be poor proxies for household consumption as they are constructed in an ad-hoc manner. In contrast, Schady (2002) compares a number of geographic targeting indicators available to policy makers in Peru and found that all of the targeting indicators perform approximately as well as each other, suggesting that in Peru the choice of indicator is not important.

[2] In the context of China, administrative levels start from the national level, go down to province (*sheng*), prefecture (*di qu*), county (*xian*) and township (*xiang).*

estimates from this source of data must occur at a high level of aggregation, such as province or possibly prefecture level.

Figure 1. Sampled Counties and Townships in the Rural Household Income and Expenditure Survey for Shaanxi



The environmental component of this research uses a variety of spatially referenced variables that provides information on temperature, rainfall, topography and land cover for Shaanxi, which can be considered part of what Ravallion (1998) calls *geographic capital*. The environmental data are from satellite remote sensing data provided by the US Landsat TM/ETM images which have a spatial resolution of 30 by 30 meters. These data have been interpreted (with the aid of considerable ground-truthing) and aggregated into 1 kilometer by 1 kilometer spatial units by the Chinese Academy of Sciences (Liu et al., 2003a and 2003b). These data have previously been used by Deng et al. (2002, 2003 and 2008).

In addition, we also have access to a number of other spatially referenced variables. The data for measuring *rainfall* (measured in millimeters per year) and *temperature* (measured in degrees centigrade per year) are from the Chinese Academy of Sciences (CAS) data center. These were initially collected and organized by the Meteorological Observation Bureau of China from more than 600 national climatic and meteorological data centers. The *elevation* and *terrain slope* variables, which measure the nature of the terrain of each county, are generated from China's digital elevation model data set that are part of the basic CAS data base. Information on the properties of soil also is part of our set of geographic and climatic variables from the CAS data center. Originally collected by a special nationwide research and documentation project (the *Second Round of China's National Soil Survey*) organized by the State Council and run by a consortium of universities, research institutes and soils extension centers, we use the data to specify two variables: the loam and organic content of the soil (measured in percent).

III. Overview of the Methodology

Following Elbers et al. (2003), the econometric analysis in this study consists of two stages. In the first stage, a model of (log) per capita consumption expenditure y_i is estimated:

$$\ln\, y_i = \mathbf{x}_i \boldsymbol{\beta} + u_i \tag{1}$$

where $\mathbf{x}_i$ is the vector of explanatory variables for the ith household and is restricted to those variables that can also be found in the census, $\boldsymbol{\beta}$ is a vector of parameters and u_i is the error term. This error term can be decomposed into two independent components: a cluster specific effect η_c and a household specific effect ε_{ci}. This complex error structure allows for both spatial autocorrelation (that is, a 'location effect' common to all households in the same area) and heteroskedasticity (non-constant variance) in the household component of the error term.

In the second stage of the analysis, the estimated regression coefficients from equation (1) are applied to data from the 2000 Population Census using the characteristics included in the vector $\mathbf{x}_i$ to obtain predicted consumption for each household within the micro census. While it is possible to directly predict consumption by simply combining the characteristics for census household j, $\mathbf{x}_j^c$ with $\hat{\boldsymbol{\beta}}$ from equation (1), a more refined methodology is needed to account for the complex nature of the disturbance term (Elbers et al., 2003). Specifically, estimates of the distribution for both η and ε are obtained from the residuals of equation (1) and from an auxiliary equation that explains the heteroskedasticity in the household-specific part of the residual. Following Elbers et al. (2003), the auxiliary equation is estimated using a logistic model of the variance of ε_{ci} conditional on $\mathbf{z}_{ci}$:

$$\ln\left[\frac{\varepsilon_{ci}^2}{A-\varepsilon_{ci}^2}\right] = \mathbf{z}_{ci}'\hat{\alpha} + r_{ci} \qquad (2)$$

where $\mathbf{z}_{ci}$ is a set of potential variables that best explain the variations in ε_{ci}^2, and A is set equal to $1.05\times\max\{\varepsilon_{ci}^2\}$. In this stage, we also conduct a series of simulations, and for each simulation, we draw a set of beta and alpha coefficients, $\tilde{\boldsymbol{\beta}}$ and $\tilde{\boldsymbol{\alpha}}$, from the multivariate normal distributions described by the first stage point estimates and their associated variance-covariance matrices. Additionally, we draw $\tilde{\sigma}_\eta^2$, a simulated value of the variance of the location error component. Combining the alpha coefficients with census data, for each census household we estimate $\tilde{\sigma}_{\varepsilon,ci}^2$, the household-specific variance of the household error component. Then for each household we draw simulated disturbance terms, $\tilde{\eta}_c$ and $\tilde{\varepsilon}_{ci}$ from their corresponding distributions. We simulate a value of expenditure for each household, $\hat{y}_j^c$ based on both predicted log expenditure, $\mathbf{x}_j'^c\tilde{\boldsymbol{\beta}}$ and the disturbance terms:

$$\hat{y}_j^c = \exp\,(\mathbf{x}_j'^c\tilde{\boldsymbol{\beta}} + \tilde{\eta}_c + \tilde{\varepsilon}_{ci}) \tag{3}$$

Finally, the full set of simulated $\hat{y}_j^c$ values are used to calculate expected values of distributional statistics, including poverty measures for each 'local area' and for higher level aggregations of local areas. We repeat this procedure 100 times, drawing a new set of coefficients and disturbance terms for each simulation. For any given location (such as a county or township) the mean across the 100 simulations for a given statistic such as the headcount poverty rate, provides the point estimate of those statistics for that location, while the standard deviation serves as an estimate of the standard error.

As discussed earlier, most applications of ELL's (2003) method do not include any environmental variables and instead rely mainly on census and survey variables (see Table 2). However, there are a number of geographic variables that may help to explain the spatial patterns in poverty in rural Shaanxi. For example, agro-climatic variables such as rainfall or topography may influence poverty. Thus, to take into account the environment and spatial components of poverty, we add another vector of variables $\mathbf{E}_i$, so that equations (1) and (3) can be re-written as

$$\ln\, y_i = \mathbf{x}_i'\boldsymbol{\beta} + \mathbf{E}_i'\boldsymbol{\gamma} + u_i \tag{1a}$$

$$\ln\, \hat{y}_j^c = \exp(\mathbf{x}_c'^j\tilde{\boldsymbol{\beta}} + \mathbf{E}_c'^j\tilde{\boldsymbol{\gamma}} + \tilde{\eta}_c + \tilde{\varepsilon}_{ci}) \tag{3a}$$

where y_i, $\mathbf{x}_i$ and u_i are as above. Since the environmental variables from the satellite imagery are geo-referenced, they can be linked to both the sample and census households and thus fit naturally in the estimation framework.

Table 2. Selected Applications of Elbers, Lanjouw and Lanjouw's (2003) Method

Author(s)	Country Studies	Main Data Sources
Mistiaen, Özler, Razafimanantena and Razafindravonona (2002)	Madagascar	▪ 1993/1994 Household Survey ▪ 1993 Population Census
Alderman, Babita, Dembynes, Makhatha, and Özler (2003)	South Africa	▪ 1995 Household Survey and Expenditure Survey ▪ 1996 Population Census
Suryahadi, Widyanti, Perwira,Sumarto, Elbers and Pradhan (2003)	Indonesia	▪ 1999 Consumption Module and Core Socio-Economic Survey ▪ 2000 Population Census ▪ 1999 Village Census
Fujii (2004)	Cambodia	▪ 1997 Socioeconomic Survey ▪ 1998 Population Census
Benson, Chamberlin and Rhinehart (2005)	Malawi	▪ 1997/1998 Integrated Household Survey ▪ 1998 Population and Housing Census
Gibson, Datt, Allen, Hwang, Bourke, and Parajuli (2005)	Papua New Guinea	▪ 1996 Household Survey ▪ 2000 National Census ▪ PNG Resource Inventory System ▪ Mapping Agricultural System Project
Hoogeveen (2005)	Uganda	▪ 1992 Integrated Household Survey ▪ 1991 Population and Housing Census
Minot and Baulch (2005)	Vietnam	▪ 1998 Living Standards Survey ▪ 1999 Population and Housing Census
Simler and Nhate (2005)	Mozambique	▪ 1996/1997 National Household Survey on Living Conditions ▪ 1997 Population Census
Ahmad and Goh (2007)	China (Yunnan Province)	▪ 2000 Urban and Rural Household Surveys ▪ 2000 Population Census
Healy and Jitsuchon (2007)	Thailand	▪ 2000 Socio-Economic Survey ▪ 2000 Population and Housing Census
Vishwanath and Yoshida (2007)	Sri Lanka	▪ 2002 Household Income and Expenditure Survey ▪ 2001 Population and Housing Census
López-Calva, Rodríguez-Chamussy and Székely (2007)	Mexico	▪ 2000 Household Survey ▪ 2000 Population Census

IV. Results

The first stage model of consumption, which is estimated for 1,360 rural households from the sample survey is reported in Table 3.[3] We also include the township level means of the household level variables from the census. The use of census means in the survey model of consumption has been recommended by Elbers et al. (2003) as a way to proxy for location-specific correlates of consumption, which can help to make the cluster specific variance η_c smaller and improve precision of the second stage predictions.

The resulting model indicates that per capita consumption is higher for households with larger dwellings (as a proxy for housing quality and wealth), with a greater number of their members who completed senior high school and above, engaged in the non-agricultural sector and using LPG as main cooking fuel. On the other hand, consumption is lower for households with a greater proportion of kids aged 6 years and below, greater proportion of youths aged 7 – 15 years, greater proportion of adults and greater proportion of elderly in the household. An important point to note about these results is that none of these relationships should be treated as causal since the purpose of the first stage model is just to have the best prediction model of consumption.

Inclusion of environmental variables raises the value of the R^2 (goodness of fit statistic) of the consumption model from 0.21 to 0.26. Moreover, the environmental variables are jointly statistically significant with a *F-statistic* of 8.04. This means that, according to our analysis, consumption is highly related to the characteristics of the environment of where people live. The environmental variables show that consumption is lower for households in areas on steep slopes, with higher temperature and soils with higher percentage of organic matter. Soils with lower percentage of loam and lower annual rainfall are correlated with lower consumption. On the other hand, consumption is higher for households in areas with higher total areas of land and higher density of highways.

[3] The RHIES surveyed 1,400 households, however, there are 40 households that we do not have information on the location of townships they reside in, which left an estimation sample of 1,360 households.

Table 3. First-Stage Regression Model of Per Capita Expenditure

	Without Environmental Variables		With Environmental Variables	
	Coeff	se	coeff	se
Household Level Characteristics				
# HH members age < 6	-0.262***	0.045	-0.270***	0.043
# HH members age 7 - 15 years	-0.114***	0.020	-0.116***	0.020
# HH members age 16 - 60 years	-0.087***	0.026	-0.095***	0.026
# HH members age >60 years	-0.203***	0.036	-0.222***	0.034
# HH members completed primary school	-0.109***	0.032	-0.096***	0.031
# HH members completed junior high school	-0.046	0.029	-0.044	0.029
# HH members completed senior high school	0.048	0.044	0.034	0.043
# HH members completed vocational degree	0.216**	0.093	0.144	0.093
# HH members with college degree and above	0.461**	0.231	0.450**	0.219
# HH members engaged in non-agricultural activities	0.092***	0.027	0.101***	0.027
Housing area (meter square)	0.002***	0.000	0.003***	0.000
House made of brick (dummy = 1; 0 otherwise)	0.026	0.042	0.024	0.042
HH uses LPG as main cooking fuel (dummy = 1 ; 0 otherwise)	0.502***	0.122	0.442***	0.136
Census Means at Township Level				
# of kids in the household	0.400**	0.195	0.438**	0.206
# of youths in the household	-0.051	0.123	-0.173	0.123
# of adults in the household	0.139	0.128	-0.075	0.132
# of elderly in the household	0.284	0.191	0.520***	0.191
# HH members completed primary school	-0.038	0.126	-0.024	0.131
# HH members completed junior high school	0.098	0.107	0.125	0.124
# HH members completed senior high school	0.366*	0.211	0.274	0.226
# HH members completed vocational degree	0.213	0.458	-0.233	0.470
# HH members with college degree and above	-0.135	0.489	0.023	0.476
# of HH members engaged in nonagricultural activities	0.396	0.368	0.139	0.374
Married Household Head (dummy = 1; 0 otherwise)	-4.670***	1.684	-2.825	1.721
3 generations living under the same roof (dummy = 1; 0 otherwise)	-0.003***	0.001	-0.002*	0.001
Housing area (meter square)	0.176**	0.077	0.323***	0.097
House made of brick (dummy = 1; 0 otherwise)	0.031	0.087	0.137	0.089

Environmental Variables

Total area of land			0.176***	0.058
Elevation (log)			0.085	0.107
Density of highway (log)			0.033***	0.007
% loam in the soil			0.015***	0.005
Annual rainfall (log)			0.465***	0.136
Slope (log)			-0.078**	0.038
% organic matter in soil texture			-0.350***	0.091
% plain area			0.163*	0.096
Temperature			-0.077***	0.018
Constant	6.393***	0.346	2.128*	1.206
Number of observations	1,360		1,360	
R-squared	0.218		0.259	

Note: *** significant at 1%; ** significant at 5%; * significant at 1%;

According to the small area estimation approach, in the next step, the parameter estimates derived in the first stage model were then applied to the census data to impute the consumption expenditure for small areas using the methodology described in the previous section. We also calculate bootstrapped standard errors for these welfare estimates, taking into account the complex error structure (that is, accounting for both spatial effects and heteroskedasticity). To derive the estimates of headcount poverty, we employ a poverty line of 700 Yuan per capita, which is derived from a national rural poverty line. In applying this poverty line, however, we also adjusted for spatial price differences. The poverty line in China (in 2001) was based on baskets of locally consumed food that provided 2,100 calories per day with allowances for non-food items.

Table 4 presents the estimated headcount poverty rates from the model with environmental variables at the province, prefecture, county and township levels. The results show that poverty is relatively pronounced in rural Shaanxi. According to our analysis, 42 percent of the population is below the poverty line. Table 4 also provides the summary of the precision of poverty headcount estimates at various levels of geographical disaggregation. At the prefecture level, the standard errors range from 0.03 to 0.06, while at the county level they range from 0.05 to 0.13. To demonstrate the precision of our estimates for rural Shaanxi, we count the number of prefectures, counties and townships with estimated poverty rates that are statistically significant at the 5%

significance level. We found that 100 (96.26) percent of the prefecture (county) level poverty estimates are statistically significant at the 5 percent level. At the township level however, there are great variations in the precision of poverty headcount estimates with standard errors ranging from 5 percent to 50 percent and about 30 percent of the estimates are not statistically significant at the 5 percent level.

Table 4. Precision of the Poverty Estimates
at Different Level of Geographical Disaggregation

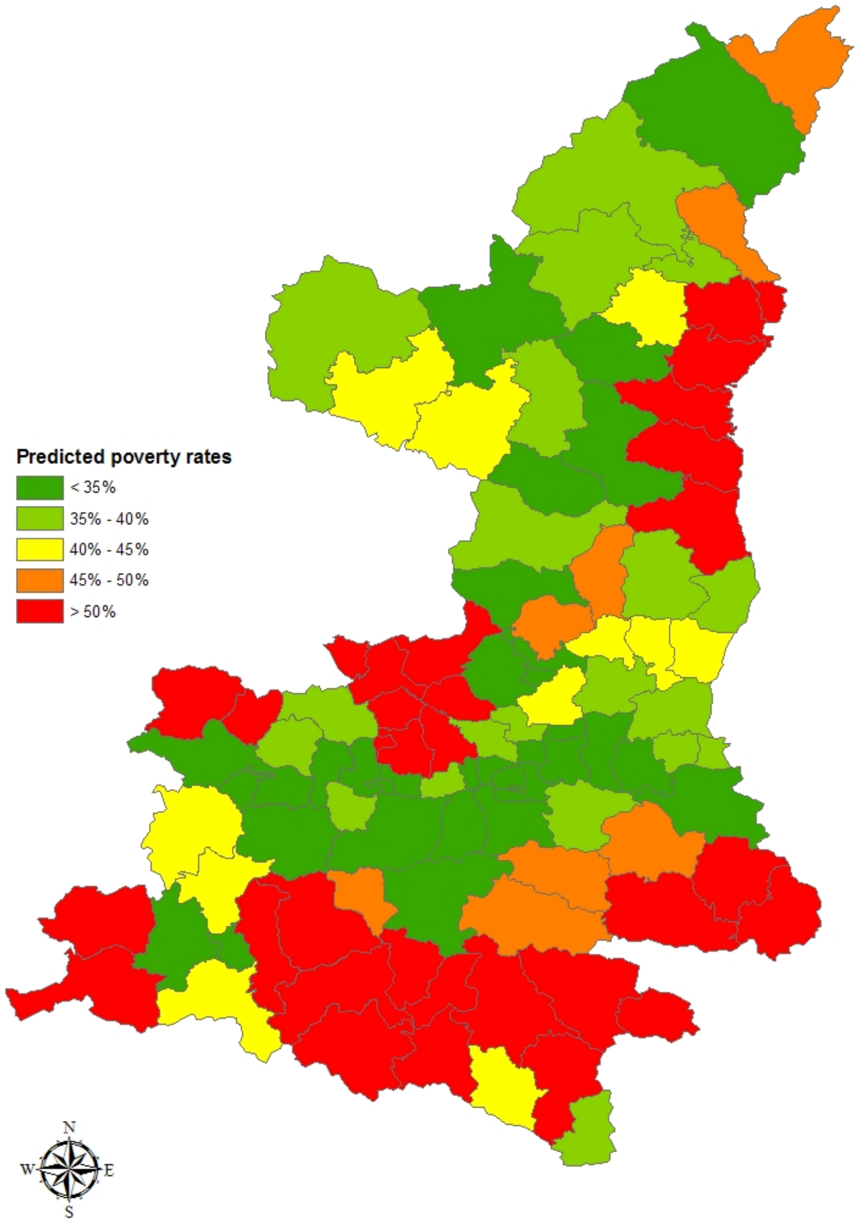
	Province	Prefecture	County	Township
Mean $\hat{P}_0$	0.420	0.419	0.418	0.442
Median $\hat{P}_0$		0.416	0.388	0.419
Min $\hat{P}_0$		0.231	0.061	0.020
Max $\hat{P}_0$		0.600	0.822	0.876
Mean Std Error ($\hat{P}_0$)	0.023	0.047	0.083	0.177
Median Std Error ($\hat{P}_0$)		0.048	0.079	0.177
Min Std Error ($\hat{P}_0$)		0.032	0.046	0.050
Max Std Error ($\hat{P}_0$)		0.060	0.134	0.501
% of $\hat{P}_0$ with t-value > 1.96	n.a.	100	96.26	71.19

Note: Estimates are from the model with environmental variables in column 4 of Table 3.

Figure 2 shows the predicted headcount poverty rates for each county in rural Shaanxi, using the model with environmental variables. The poverty map shows significant spatial variation of poverty within the province. The median of the estimated headcount poverty rates at the county level is 39 percent, ranging from 6 percent to 82 percent.[4] As can be seen from Figure 2, the highest poverty rates are found in the eastern region of the north part of the province (*Shaanbei*) and in the southern counties of Shaanxi (*Shaannan*). The lowest poverty rates are found in central Shaanxi. In contrast to the northeast of Shaanxi,

[4] In Appendix Table 1, we report estimates of poverty headcount, poverty severity and GE(0) along with their standard errors for each county in rural Shaanxi.

Figure 2. Predicted Poverty Rates with Environmental Variables



where precipitation is rare, and to the southern region, which consists of the high mountainous zone of *Qingling* and *Daba* mountains (an area with lower temperature and poor soils), the central region has a temperate semi-wet climate and the terrain is relatively flat (Huang et al., 2007). Perhaps most fundamentally, Figure 2 shows that there is a significant spatial variation of poverty within the province. This heterogeneity would be missed if high resolution poverty maps were not used. Thus, simply concentrating on provincial-level averages of poverty statistics (or other welfare indicators) would almost certainly prove to be a misleading guide for any targeted interventions.

Figure 3. Predicted Poverty Rates without Environmental Variables

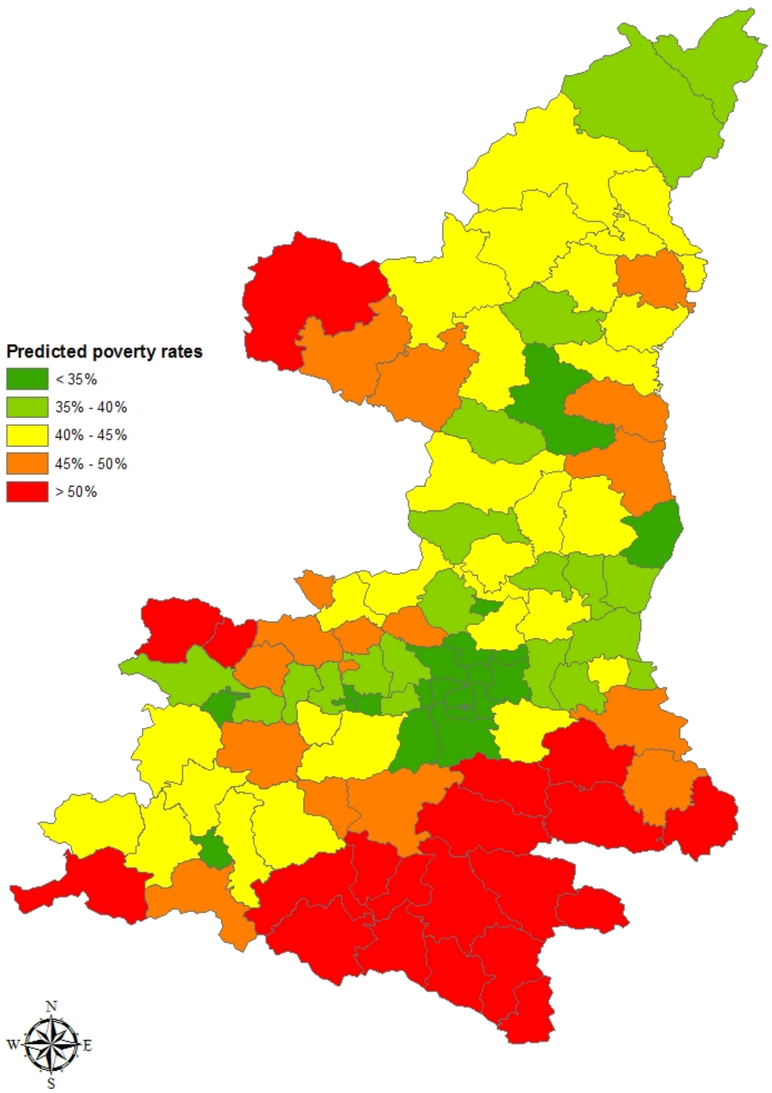


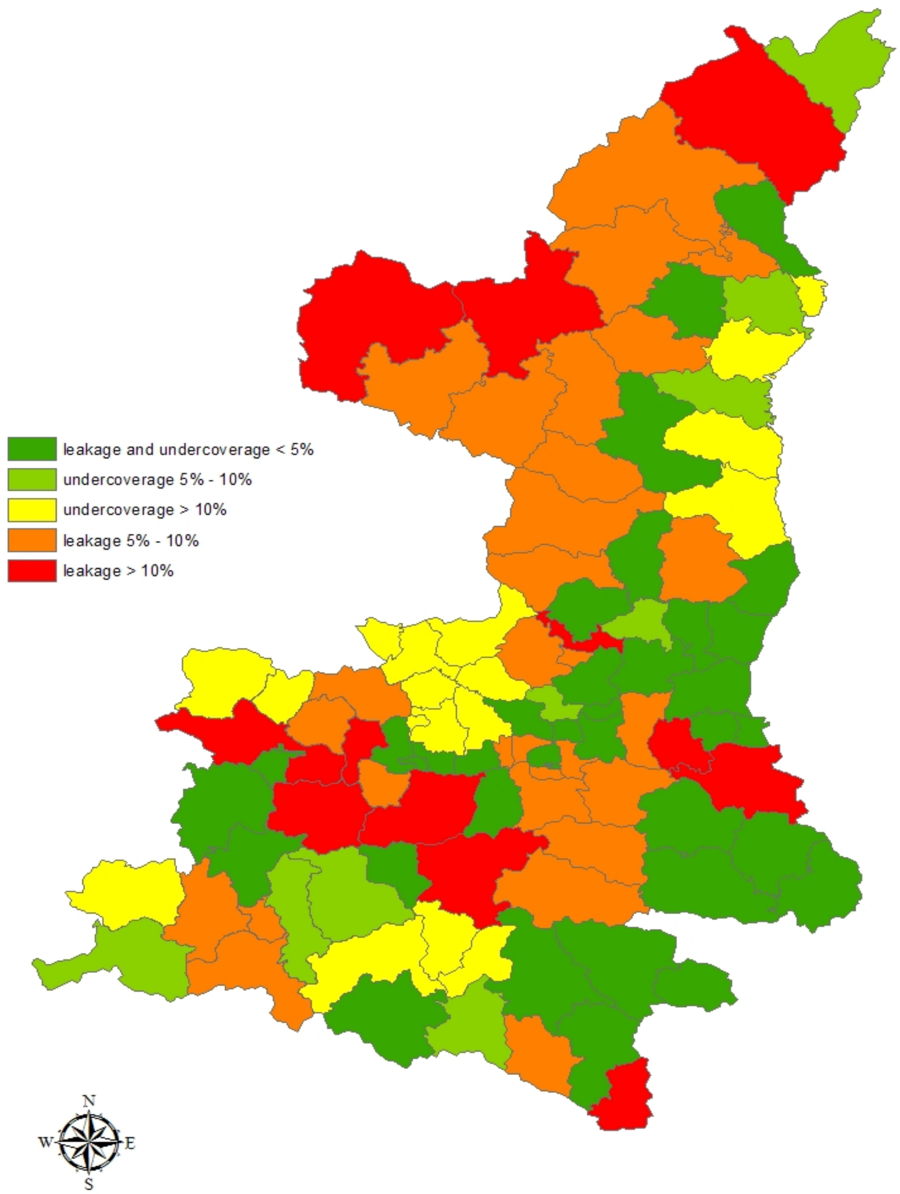
Figure 3 shows the predicted headcount poverty rates for each county in rural Shaanxi when using the model that ignores the environmental variables. The poverty map looks rather different. The lower poverty rates in several of the southern counties are missed. At the same time, poverty rates are overstated in some of the counties in the central region. The model also loses some of its contrasts between adjacent areas of high and low poverty.

V. Targeting Implications

A comparison of the two poverty maps lets us calculate how much leakage and under-coverage results when environmental variables are excluded from the model used to form the poverty predictions (Figure 4). The under-coverage rate is the number of predicted poor from the full model (i.e., the model that includes census *and* environmental variables) which are mis-classified as non-poor when the environmental variables are excluded. Conversely the leakage rate is the number of predicted non-poor from the full model which are mis-classified as poor when the environmental variables are excluded.

Figure 4 shows that there is considerable mis-targeting when the environmental variables are excluded. Specifically, a total of 29 counties, containing 24.74% of the rural population, have either leakage or undercoverage rates exceeding 10% when environmental variables are left out of the model. The counties where the undercoverage rates are highest are located predominantly on the easter and western regions of *Shaanbei* (northern Shaanxi) and *Shaannan* (southern Shaanxi).

Figure 4. Leakage and Undercoverage Rates



Further evidence that targeting is likely to be more accurate when environmental variables are used to construct the poverty map comes from Receiver Operating Characteristic (ROC) curves. A ROC curve plots the probability of a variable correctly classifying a poor person as poor on the vertical axis against one minus the probability of the same variable correctly classifying a non-poor person as non-poor on the horizontal axis. The closer a ROC curve is to the 45° line, the weaker is the diagnostic power of the variable that is being considered as a targeting indicator. The greater the area under a ROC curve and the closer it is to the left-hand side vertical and top horizontal axes, the greater is the efficacy of a diagnostic variable.

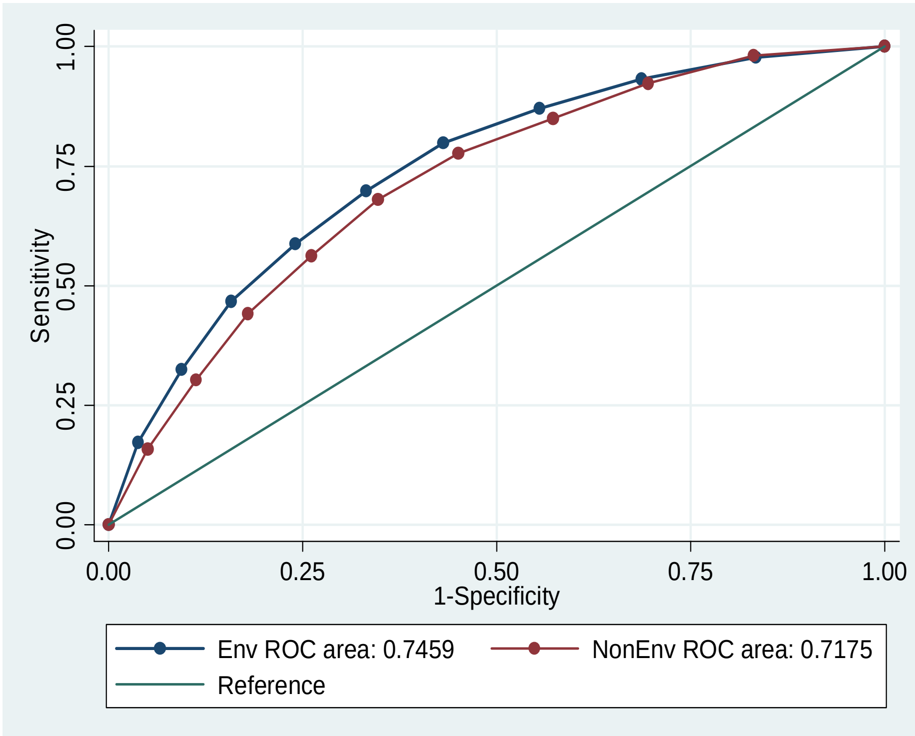
In order to construct ROC curves for poverty targeting in rural Shaanxi, we first used the household survey data to indicate the actual poverty status of each of the 1,360 sample households used in the estimation. Specifically, we created a dummy variable equal to one for those households whose per capita expenditure c_i was below the poverty line z of 700 Yuan per year. The two first-stage regression models (i.e. the one just with survey variables and the Census means, and the one that also added environmental variables) were then estimated. Noting that for poor households, $c_i < z$, so $\ln\left(c_i/z\right) < 0$, the probability of the *i*th household's (log) per capita expenditure deflated by the regional poverty line being less than zero is:

$$\operatorname{prob}\left(\ln\left(\hat{c}_i/z\right)\right) < 0 = \Phi\left(\left(-\mathbf{x}_i\hat{\mathbf{b}}\right)\Big/\hat{\sigma}\right) \tag{4}$$

where Φ is the standard cumulative normal and $\hat{\sigma}$ is the standard error of the regression. These probabilities were estimated for all of the sample households, both with and without environmental variables being included in the $\mathbf{x}_i$ vector. These predicted probabilities were then collapsed into decile groups and the decile indicators were compared with the actual poverty status of the household, using ROC curves.

Figure 5 shows the comparison of the ROC curves of consumption models with and without environmental variables. The area under the ROC curve drops from 0.75 to 0.72 when environmental variables are left out from the model. Furthermore, the ROC curve for the model without environmental variables is significantly (*p<0.001*) closer to the 45^o line. The result suggests that a poverty mapping model that includes environmental variables does significantly better at identifying the poor than does a model that is only based on census and survey information.

Figure 5. Comparion of the Targeting Performance of Consumption Models with and without Environmental Variables



Further evidence of the feasibility of targeting transfers at different levels of geographical disaggregation comes from a decomposition of inequality between and within areas. The between-area component of inequality asks how much overall inequality would remain if it were assumed that within areas all individuals had the same consumption level (equal to the average per capita consumption level of the area), and hence, the only variation in consumption that one would observe would be attributable to differences in average consumption levels between areas. The within-area component of inequality asks the analogous question about how much overall inequality would remain if differences between areas in average per capita consumption were assumed away. If most of the inequality was due to within-area sources, targeting poor areas would still be likely to see a significant amount of leakage to non-poor households. At the same time, the untargeted areas would also likely include many poor households, which would ultimately lead to a problem of undercoverage. Of course, by "definition" the contribution of the between- and within-area components of inequality will vary with the choice of targeting level. At finer levels of disaggregation, more of the total inequality will be due to between-area sources.

In this paper we decompose inequality using Shorrocks' (1980, 1984) generalized entropy class of inequality measures:

$$\begin{aligned} GE(c) &= -\sum_i f_i \log\left(\frac{y_i}{\mu}\right) && \text{for } c = 0 \\ GE(c) &= \sum_i f_i \frac{y_i}{\mu} \log\left(\frac{y_i}{\mu}\right) && \text{for } c = 1 \end{aligned} \tag{5}$$

where f_i is the population share of household *i*, y_i per capita consumption of household *i*, μ is average per capita consumption and *c* is a parameter that is to be defined by the analyst. Lower values of *c* are associated with greater sensitivity to inequality amongst the poor and higher values of *c* place more weight on inequality amongst the rich. A *c* value of 0 provides the Theil L or mean log deviation and a value of 1 yields the well known Theil index. This class of inequality measures can be decomposed into a between and within group component along the following lines:

$$\begin{aligned} GE(c) &= \left[g_j \log\left(\frac{\mu}{\mu_j}\right)\right] + \sum_j GE_j\, g_j && \text{for } c = 0 \\ GE(c) &= \left[\sum_j g_j \left(\frac{\mu_j}{\mu}\right) \log\left(\frac{\mu_j}{\mu}\right)\right] + \sum_j GE_j g_j \left(\frac{\mu_j}{\mu}\right) && \text{for } c = 1 \end{aligned} \tag{6}$$

where *j* refers to subgroups, g_j refers to the population share of group *j* and GE_j refers to inequality in group *j*. The between-group component of inequality is captured by the first term of the equation. It can be interpreted as a measure of what would be the level of inequality in the population if everyone within the group had the same (the group average) consumption level μ_j. The second term reflects what would be the overall inequality level if there were no differences in mean consumption across groups but each group had its actual within-group inequality GE_j. Ratios of the respective components with the overall inequality level provide a measure of the percentage contribution of between-group and within-group inequality to total inequality.

Table 5. Decomposition of Inequality into Between and Within Area Component

	GE(0)	GE(1)
Total	**0.402**	**0.583**
Within Prefecture	0.367	0.490
Between Prefecture	0.035	0.092
Within as % of Total	*0.914*	*0.841*
Within County	0.300	0.422
Between County	0.102	0.161
Within as % of Total	*0.747*	*0.723*
Within Township	0.246	0.287
Between Township	0.156	0.296
Within as % of Total	*0.612*	*0.492*

Note: Estimates are from the model with environmental variables in column 4 of Table 3.

In Table 5 we examine how the relative contribution of within-group inequality evolves at progressively lower levels of regional disaggregation, using predicted consumption from the model with environmental variables. According to the generalized entropy class of inequality measures, more than 90 percent of consumption inequality in rural Shaanxi is due to within- rather than between-prefecture sources. The relative unimportance of between-prefecture variation suggests that any geographical targeting should be carried out for areas much smaller than prefectures.[5] In fact, targeting at the county level rather than at the township level may be preferred – given that there is a relatively large reduction in within inequality as we move from prefecture to county (from 91.4% to

[5] On average, a prefecture in rural Shanxi has 3.6 million people.

75%) but not too much of a penalty from the larger standard errors that arises when using poverty predictions at the township level (see the discussion above).

One caution for area-based targeting may appear to come from the result that a large proportion of the inequality in rural Shaanxi is due to within-group inequality even when the groups are relatively small (such as township). Approximately, 8% of the inequality in Shaanxi is between prefectures, 25% between counties and 39% between townships. These results seem to be in line with findings from other poverty mapping studies. For example, Gibson et al. (2005) found that 78% of consumption inequality in rural Papua New Guinea is due to within district (a level of jurisdiction which is the second to the lowest level of government administration). By the same token, Elbers et al. (2003) found that in Ecuador, Madagascar and Mozambique no less than three quarters of all inequality is attributable to within-community differences, even when the community is defined as the lowest level of government administrative unit.

The reader should note that while these findings mean that, on average, most of the inequality in Shaanxi would be found within small geographical units, it does not exclude the possibility that some counties and townships have very low levels of inequality. Figures 6a and 6b illustrate our argument. In each figure, counties and townships are ranked from lowest to highest inequality and plotted against the level of inequality at the provincial level. We observe not only that many counties and townships have very small levels of inequality, but also the vast majority of the counties (86%) and townships (96%) have point estimates of inequality that are lower than the provincial level of inequality suggesting that area-based targeting in most parts of rural Shaanxi may still be feasible. Notably, this pattern of most areas being fairly equal and the within-area component being raised by a few very unequal areas is less apparent at the prefecture level where 30% of prefectures have inequality levels that exceed the provincial level inequality.

Figure 6a. Distribution across counties of county-level inequality

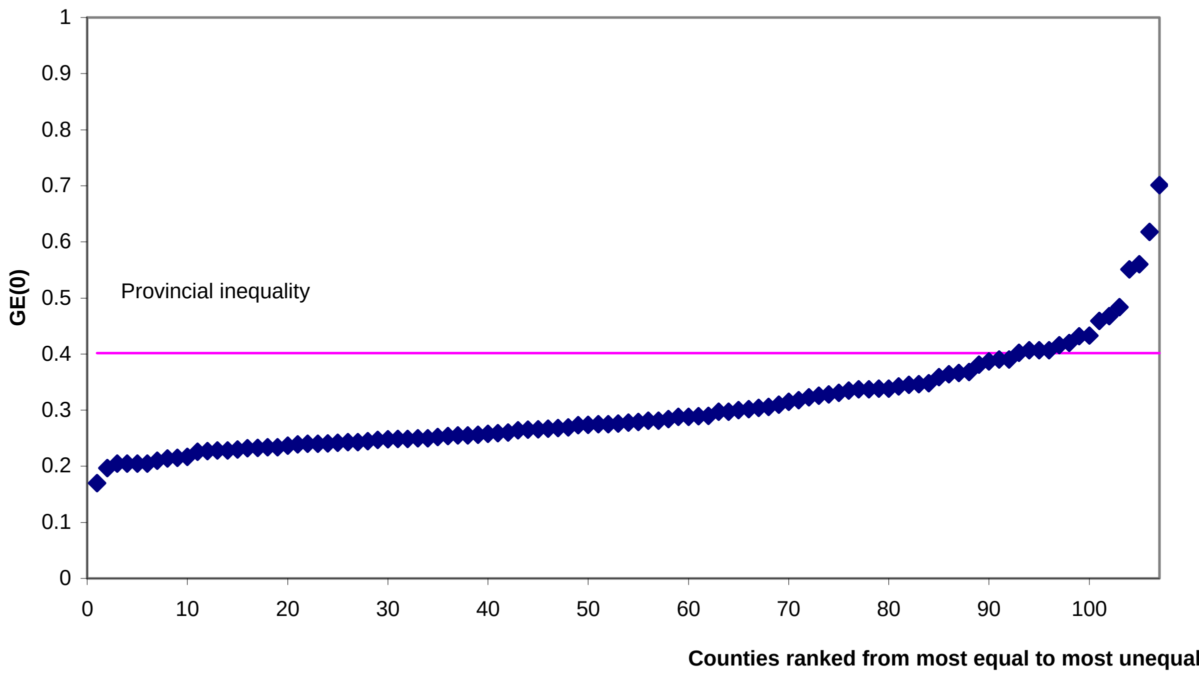
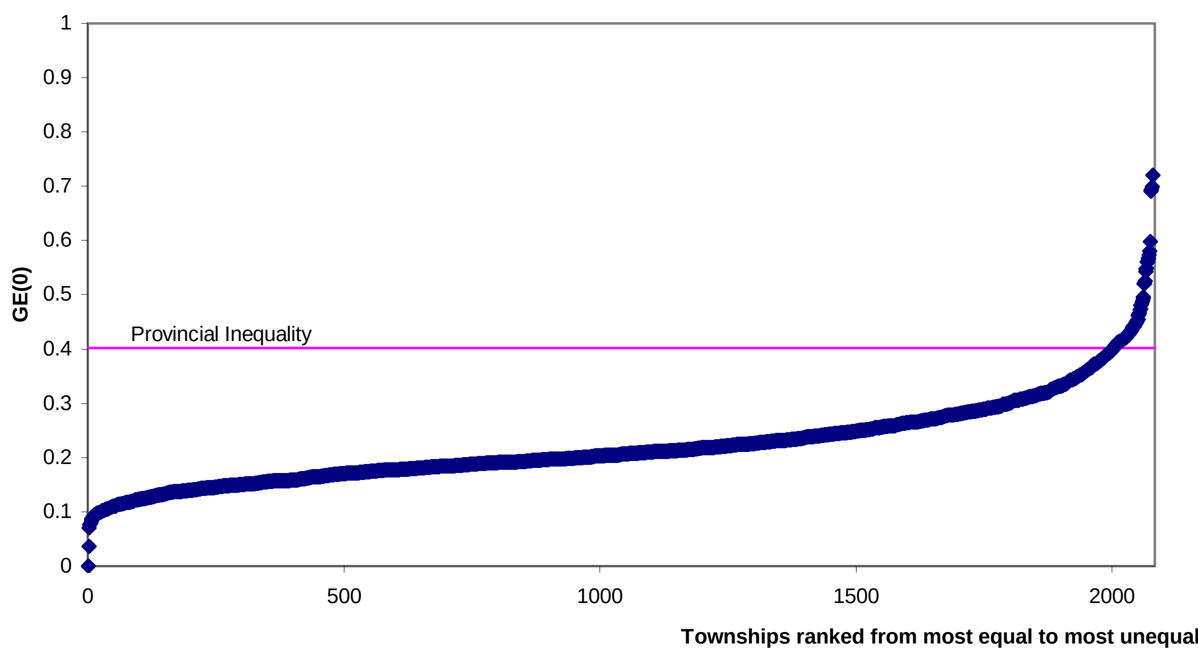


Figure 6b. Distribution across townships of township-level inequality



VI. Do the Officially Designated Poor Counties Really Target the Poor Areas?

China's poverty reduction efforts have, from the outset, been development-oriented and targeted to poor areas. The emphasis has been on area-based investments in improving basic infrastructure and facilities for agricultural production (World Bank, 2001). Furthermore, the national government poverty reduction funding is available only to those counties designated as poor and the poor residing in counties not designated as poor are excluded from this support.[6] In this section, we assess the poverty incidence in the 46 designated poor counties in Shaanxi.[7] In addition, we also compare the estimates of poverty derived from our application of the small-area estimation method with the official designation of poor counties.

On average, our predicted poverty estimates are higher in the officially designated poor counties compared to those counties that are not designated as poor (Table 6). However, these averages disguise a number of discrepancies that appear when we compare the 'officially designated poor counties' in Shaanxi with the poor counties from the small area estimation method with environmental variables. In this comparison, a county is considered to be 'poor' if its predicted poverty headcount is greater than the median of the predicted headcount at the county level of 0.39.

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[6] Counties remained the basic units for state poverty reduction investments till 2001. The latest effort undertaken by the government is through the Integrated Village Development Program (IVDP) initiated in 2001 as a continuation and further refinement of the earlier focus on 592 designated poor counties. The move to village-level targeting was a response to expressed concerns that the previous county-level targeting had failed to reach many of China's poor (Park et al., 2002). Poor villages were selected according to a weighted poverty index based on eight indicators. The eight indicators were: grain production per capita, cash income per capita, percent of low quality houses, percent of households with poor access to potable water, percent of natural villages with reliable access to electricity, percent of natural villages with all-weather road access to the county seat, percent of women with long-term health problems, percent of eligible children not attending school. The designated poor counties would still exercise overall administration of poverty reduction funds (Wang, 2004).

[7] According to the Leading Group Office of Poverty Alleviation and Development, there are 50 officially designated poor counties in Shaanxi (http://cpad.gov.cn/). However, when we go through the list of the poor counties, we found that 4 prefectures are included in the list and for each prefecture, several counties are designated as poor and these counties also appear in the list.

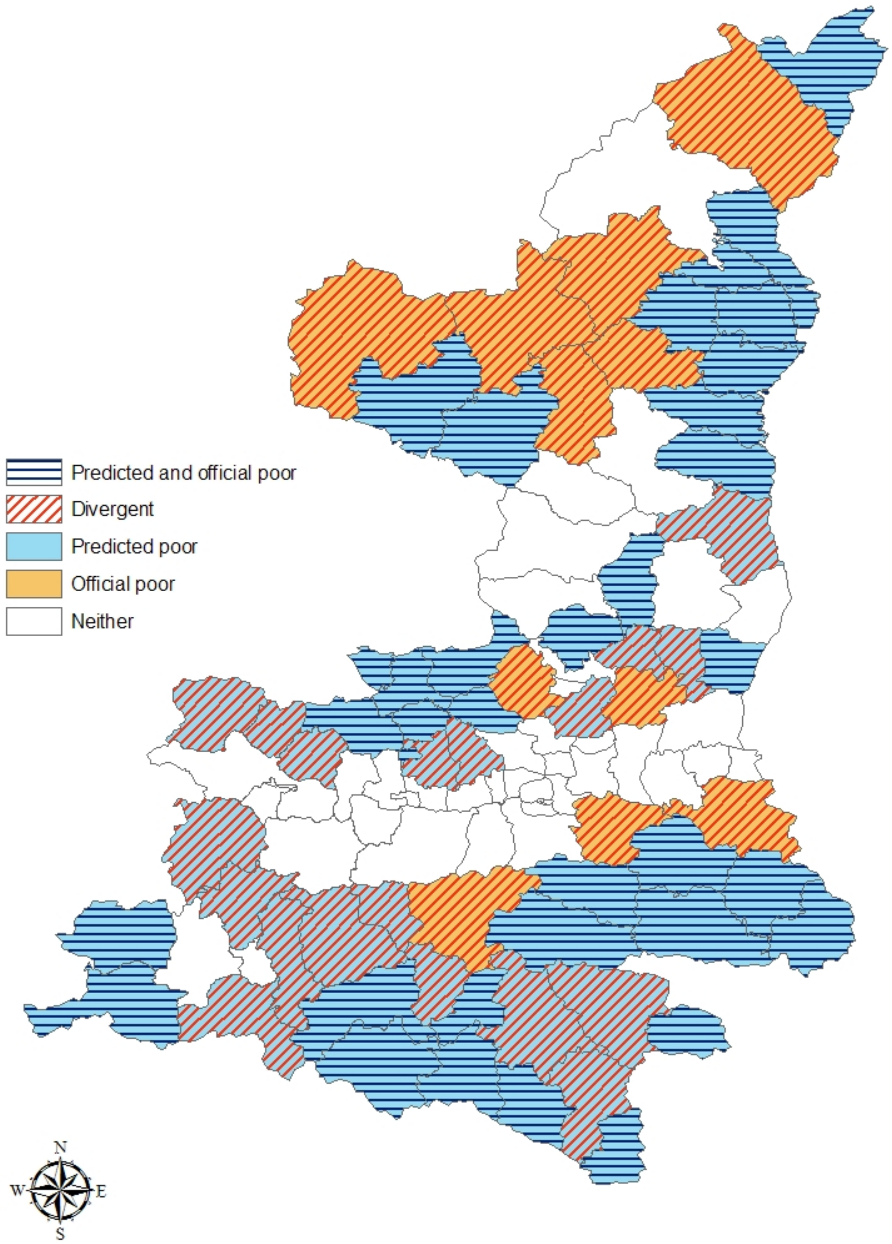
Table 6. Predicted Poverty Rates in Officially Poor and Officially Non-poor Counties

	$\hat{P}_0$	$\hat{P}_1$	$\hat{P}_2$
Non-poor Counties	0.361	0.132	0.065
Officially Designated Poor Counties	0.493	0.191	0.098

Note: Estimates are based on the model with environmental variables.

As can be seen from Figure 7, there is a reasonable correspondence between the 'designated poor counties' (*n = 46*) and 'poor counties' (*n = 54*) derived from the imputation procedure. By the same token, there also are notable divergences between the two methods. In particular, 11 out of 46 'designated poor counties' have predicted poverty rates which are below the median of the predicted headcount at the county level where the western region of *Shaanbei* has 6 designated poor counties which are not predicted as poor. Likewise, Southern Shaanxi has 10 counties that are the reverse. Similarly, out of 61 non-poor counties, we found that there are 20 counties with predicted headcount rates greater than the median of the predicted headcount. These findings suggest that under the current poverty reduction scheme in Shaanxi, there could be a substantial proportion of poor households being excluded say from the allocation of transfers while a number of non-poor households might be deemed as potential beneficiaries.

Figure 7. Comparisons of the Designated Poor Areas with the Poor Areas from the Small Area Estimation Method



The poverty maps we presented earlier show considerable spatial variation among counties in Shaanxi. In the following section we use the county level poverty estimates to investigate the extent to which geographic variables may have an effect on the incidence of poverty in a county. Table 7 shows the results of regressing county-level poverty rates (both the head count poverty and severity of poverty) on the vector of environmental variables. [8] The model explains four fifths of the variation in rural poverty rates. Only two variables (total area of land and elevation) do not seem to be related to the predicted county level poverty rates. Moreover, almost all of the coefficients have the expected sign. The results indicate that steeper slope and soils with higher organic matter contribute to rural poverty. Furthermore, counties with higher annual precipitation and higher shares of plain area are associated with lower poverty rates. The result also suggests that higher road density and soils with higher percentage of loam are negatively related to the incidence of poverty. These results indicate that counties with unfavorable agro-climatic conditions could be hindered from the process of economic development.

Table 7 also reports results from OLS regressions of inequality on a set environmental variable at the county level. The quantitative importance and statistical significance of these variables to poverty severity remains broadly unchanged with the correlates for poverty headcount. In rural Shaanxi, there is evidence that county with higher road density, annual precipitation, elevation, percentage of loam in the soil and share of plain area tend to have a higher level of inequality. On the other hand, inequality is negatively associated with the steepness of the terrain, the total area of land and temperature.

[8] Unlike the poverty headcount, poverty severity index gives heavier weight to the poverty of the very poor.

Table 7. Environmental Correlates of Poverty and Inequality

	OLS Analysis for All Counties			Probit Analysis for Designated Poor Counties	
	$y=\hat{P}_0$	$y=\hat{P}_2$	$y=\hat{GE}(0)$	coefficient	marginal effect[a]
Total area of land	-0.002	-0.016*	-0.062***	0.391	0.144
	(0.018)	(0.009)	(0.011)	(0.255)	(0.096)
Annual rainfall (log)	-0.224***	-0.120***	0.080***	-0.342	-0.126
	(0.025)	(0.014)	(0.016)	(0.505)	(0.1883)
Slope (log)	0.031*	0.017**	-0.030**	-0.075	-0.028
	(0.016)	(0.007)	(0.012)	(0.297)	(0.109)
Elevation (log)	0.030	0.020	0.043*	-0.788	-0.291
	(0.035)	(0.017)	(0.023)	(0.776)	(0.279)
Density of highway (log)	-0.016***	-0.008***	0.005***	-0.106**	-0.040**
	(0.001)	(0.001)	(0.001)	(0.049)	(0.017)
% of loam in the soil	-0.006***	-0.003***	0.002**	-0.043	-0.016
	(0.002)	(0.001)	(0.001)	(0.042)	(0.016)
% of organic matter in the soil	0.176***	0.096***	-0.037***	0.189	0.069
	(0.016)	(0.009)	(0.012)	(0.337)	(0.124)
% plain area	-0.181***	-0.080***	0.074***	-1.352***	-0.365***
	(0.023)	(0.010)	(0.024)	(0.512)	(0.075)
Temperature	0.056***	0.024***	-0.018***	0.075	0.028
	(0.006)	(0.003)	(0.004)	(0.110)	(0.041)
Constant	1.008**	0.687***	0.440*	2.212	
	(0.391)	(0.202)	(0.247)	(6.752)	
Number of observations	107	107	107	107	
R-squared[b]	0.819	0.804	0.652	0.260	

Note: Robust standard errors in parentheses. *** significant at 1%; ** significant at 5% ; * significant at 10%
[a]The marginal effect shows the effect of a one unit change in the explanatory variable on the probability of being designated as poor county.
[b] Pseudo R-squared for Probit model.

Finally, we examine whether environmental variables could lead to the determination of poor county status by estimating a Probit function for officially designated poor counties. The last two columns of Table 7 give the coefficients and the marginal effects on the probability of poor county designation at the sample means for officially poor counties. Out of 9 environmental variables used in the model, only the density of highways and the share of plain area have estimated coefficients that are statistically significant. The results show that the probability of the designation would decrease for counties with higher shares of the area accounted for by plain area as well as higher road density. The official designation neglects the facts that, in terms of poverty, it is better to live in a wetter county that has less steep terrain, has better soil and with a more moderate temperature. This finding is somewhat troubling because it indicates that the current poor area designated system in China seems to neglect the role of environmental conditions which would likely to affect the targeting precision of China's poverty program. In contrast, we found that environmental variables are strongly associated with poverty and inequality (i.e. 80 percent of the variation in rural poverty at the county level in rural Shaanxi can be explained by a various number of agro-climatic variables). For this reason, environmental variables could be an improvement for designing and evaluating poverty reduction strategies and they should be introduced into the analysis.

VII. Conclusions

In this paper, we have estimated various measures of welfare for small geographic areas in Shaanxi by combining the census and household survey data. We have also utilized the environmental variables derived from high resolution satellite imagery (and other spatially referenced variables) to construct poverty maps for rural Shaanxi province in China to assess if these variables have any important links with poverty. Methods to incorporate environmental information are particularly important since standardized household surveys rarely collect these types of data. To our knowledge, this paper is the first of its kind to utilize the environmental variables to provide estimates of poverty and inequality for lower level units of administration in China.

The results suggest that environmental variables do matter in poverty and inequality analysis. We found that soil characteristics, topography and rainfall proved to be important explanatory variables in describing poverty and inequality. In terms of targeting implications, our results appear to suggest that targeting is more accurate when environmental variables are included in the poverty map. From a policy perspective, the result suggests that the current data and method used in many poverty mapping exercises may cause social loses due to the failure to correctly identify and target poor areas. For this reason, environmental variables could be an improvement for designing poverty alleviation programs and they should be introduced into the analysis.

We found not only that many counties and townships have very small levels of inequality, but also the vast majority of the counties and townships have point estimates of inequality that are lower than the provincial level of inequality suggesting that area-based targeting in much of rural Shaanxi may still be feasible. Furthermore, any effort to spatially target townships rather than counties must not only carefully weight the marginal benefits against the marginal cost of this fine-tuned targeting, but also needs to take into account the statistical precision of welfare estimates that are being used.

With regards to the comparisons of the results of our poverty maps with the official designation of ‘poor counties’ in rural Shaanxi, we found that there seems to be evidence that policy makers in China target particular areas which in reality are no poorer than other areas do not get targeted. Therefore, poverty mapping if it can be done accurately and carefully can help channel China’s growing fiscal resources directly to the places that they are needed. In this way, poverty mapping analysis can be used to not only reveal patterns that are not otherwise visible, but also could be an effective way in addressing politically sensitive questions in an objective manner.

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Appendix Table 1. Predicted County-Level Poverty and Inequality Rates

County Name	$\hat{P}_0$	s.e.($\hat{P}_0$)	$\hat{P}_2$	s.e.($\hat{P}_2$)	$\hat{G}E(0)$	s.e. ($\hat{G}E(0)$)
Xincheng Qu	0.061	0.053	0.005	0.005	0.240	0.109
Beilin Qu	0.062	0.057	0.006	0.007	0.264	0.129
Lianhu Qu	0.061	0.046	0.006	0.006	0.348	0.161
Baqiao Qu	0.180	0.068	0.023	0.011	0.368	0.108
Weiyang Qu	0.108	0.051	0.012	0.007	0.618	0.372
Yanta Qu	0.117	0.060	0.013	0.010	0.551	0.249
Yanliang Qu	0.280	0.081	0.040	0.016	0.335	0.076
Lintong Qu	0.301	0.079	0.043	0.015	0.304	0.059
Chang'an Xian	0.248	0.071	0.033	0.012	0.338	0.078
Lantian Xian	0.363	0.055	0.059	0.014	0.276	0.027
Zhouzhi Xian	0.305	0.060	0.046	0.014	0.278	0.032
Hu Xian	0.346	0.064	0.054	0.015	0.288	0.040
Gaoling Xian	0.340	0.112	0.065	0.026	0.459	0.147
Wangyi Qu	0.217	0.088	0.033	0.019	0.364	0.108
Yintai Qu	0.317	0.097	0.060	0.024	0.420	0.088
Yao Xian	0.290	0.067	0.045	0.014	0.346	0.052
Yijun Xian	0.458	0.074	0.089	0.023	0.297	0.048
Weibin Qu	0.260	0.069	0.045	0.019	0.331	0.076
Jintai Qu	0.155	0.093	0.020	0.015	0.255	0.080
Baoji Xian	0.148	0.064	0.019	0.010	0.416	0.180
Fengxiang Xian	0.388	0.073	0.069	0.019	0.300	0.036
Qishan Xian	0.200	0.086	0.031	0.017	0.407	0.096
Fufeng Xian	0.326	0.100	0.053	0.020	0.338	0.072
Mei Xian	0.356	0.064	0.063	0.017	0.318	0.044
Long Xian	0.679	0.111	0.181	0.053	0.266	0.038
Qianyang Xian	0.715	0.092	0.197	0.050	0.279	0.060
Linyou Xian	0.398	0.087	0.077	0.028	0.323	0.070
Feng Xian	0.430	0.084	0.079	0.029	0.265	0.045
Taibai Xian	0.309	0.113	0.063	0.036	0.381	0.095
Qindu Qu	0.249	0.089	0.039	0.017	0.701	0.296
Yangling Qu	0.292	0.120	0.046	0.025	0.407	0.138
Weicheng Qu	0.221	0.074	0.038	0.015	0.560	0.162
Sanyuan Xian	0.384	0.086	0.065	0.021	0.407	0.092
Jingyang Xian	0.378	0.074	0.061	0.019	0.337	0.057
Qian Xian	0.566	0.134	0.117	0.045	0.326	0.097
Liquan Xian	0.676	0.113	0.159	0.053	0.243	0.042
Yongshou Xian	0.709	0.091	0.194	0.050	0.275	0.046
Bin Xian	0.712	0.095	0.184	0.049	0.249	0.058
Changwu Xian	0.737	0.096	0.215	0.056	0.275	0.049
Xunyi Xian	0.584	0.075	0.123	0.029	0.245	0.031

County Name	$\hat{P}_0$	s.e.($\hat{P}_0$)	$\hat{P}_2$	s.e.($\hat{P}_2$)	$\hat{GE}(0)$	s.e. ($\hat{GE}(0)$)
Chunhua Xian	0.739	0.092	0.205	0.057	0.248	0.034
Wugong Xian	0.346	0.114	0.062	0.026	0.433	0.141
Xingping Shi	0.366	0.120	0.066	0.028	0.402	0.106
Linwei Qu	0.303	0.091	0.046	0.018	0.342	0.069
Hua Xian	0.243	0.085	0.039	0.020	0.390	0.104
Tongguan Xian	0.363	0.119	0.076	0.033	0.484	0.159
Dali Xian	0.384	0.067	0.055	0.014	0.258	0.038
Heyang Xian	0.433	0.071	0.072	0.017	0.315	0.064
Chengcheng Xian	0.415	0.084	0.070	0.021	0.328	0.078
Pucheng Xian	0.378	0.072	0.055	0.015	0.274	0.050
Baishui Xian	0.449	0.097	0.085	0.030	0.345	0.058
Fuping Xian	0.430	0.060	0.070	0.016	0.288	0.064
Hancheng Shi	0.370	0.102	0.052	0.021	0.249	0.048
Huayin Shi	0.375	0.132	0.067	0.036	0.387	0.090
Baota Qu	0.294	0.067	0.040	0.012	0.240	0.037
Yanchang Xian	0.641	0.086	0.144	0.037	0.226	0.030
Yanchuan Xian	0.526	0.070	0.102	0.024	0.255	0.040
Zichang Xian	0.300	0.069	0.045	0.016	0.256	0.041
Ansai Xian	0.351	0.068	0.051	0.014	0.227	0.031
Zhidan Xian	0.425	0.077	0.076	0.024	0.269	0.048
Wuqi Xian	0.410	0.075	0.068	0.020	0.230	0.029
Ganquan Xian	0.348	0.074	0.055	0.020	0.254	0.047
Fu Xian	0.375	0.070	0.059	0.018	0.243	0.039
Luochuan Xian	0.453	0.079	0.089	0.025	0.306	0.046
Yichuan Xian	0.671	0.115	0.154	0.054	0.205	0.033
Huanglong Xian	0.370	0.076	0.066	0.023	0.297	0.081
Huangling Xian	0.340	0.074	0.053	0.017	0.302	0.060
Hantai Qu	0.266	0.076	0.043	0.016	0.468	0.133
Nanzheng Xian	0.417	0.076	0.070	0.019	0.268	0.029
Chenggu Xian	0.533	0.088	0.094	0.027	0.232	0.024
Yang Xian	0.536	0.107	0.088	0.030	0.197	0.025
Xixiang Xian	0.646	0.101	0.130	0.042	0.205	0.027
Mian Xian	0.338	0.071	0.051	0.015	0.289	0.042
Ningqiang Xian	0.583	0.083	0.111	0.030	0.228	0.031
Lueyang Xian	0.548	0.094	0.108	0.031	0.281	0.056
Zhenba Xian	0.614	0.103	0.137	0.042	0.252	0.040
Liuba Xian	0.439	0.084	0.085	0.026	0.310	0.074
Foping Xian	0.471	0.092	0.106	0.034	0.432	0.145
Yuyang Qu	0.360	0.087	0.050	0.018	0.217	0.031
Shenmu Xian	0.250	0.088	0.028	0.013	0.250	0.070
Fugu Xian	0.472	0.101	0.082	0.028	0.237	0.029
Hengshan Xian	0.362	0.071	0.056	0.017	0.239	0.029
Jingbian Xian	0.336	0.063	0.053	0.015	0.250	0.039
Dingbian Xian	0.371	0.086	0.058	0.021	0.233	0.038

County Name	$\hat{P}_0$	s.e.($\hat{P}_0$)	$\hat{P}_2$	s.e.($\hat{P}_2$)	$\hat{G}E(0)$	s.e. ($\hat{G}E(0)$)
Suide Xian	0.557	0.063	0.111	0.023	0.247	0.026
Mizhi Xian	0.396	0.070	0.082	0.023	0.366	0.057
Jia Xian	0.486	0.059	0.090	0.020	0.260	0.029
Wubao Xian	0.638	0.097	0.181	0.051	0.359	0.085
Qingjian Xian	0.572	0.078	0.117	0.030	0.290	0.090
Zizhou Xian	0.404	0.063	0.068	0.017	0.267	0.031
Hanbin Qu	0.574	0.079	0.091	0.022	0.215	0.055
Hanyin Xian	0.690	0.096	0.147	0.043	0.214	0.049
Shiquan Xian	0.822	0.069	0.211	0.054	0.170	0.025
Ningshan Xian	0.314	0.078	0.050	0.018	0.337	0.082
Ziyang Xian	0.683	0.075	0.145	0.033	0.205	0.027
Langao Xian	0.439	0.088	0.078	0.023	0.284	0.055
Pingli Xian	0.545	0.081	0.092	0.022	0.210	0.030
Zhenping Xian	0.395	0.106	0.085	0.035	0.390	0.090
Xunyang Xian	0.593	0.090	0.103	0.027	0.205	0.029
Baihe Xian	0.638	0.090	0.135	0.040	0.259	0.055
Shangzhou Shi	0.468	0.072	0.081	0.019	0.241	0.021
Luonan Xian	0.308	0.101	0.045	0.022	0.281	0.050
Danfeng Xian	0.528	0.070	0.098	0.024	0.242	0.026
Shangnan Xian	0.546	0.101	0.097	0.032	0.228	0.038
Shanyang Xian	0.574	0.075	0.102	0.024	0.234	0.070
Zhen'an Xian	0.469	0.076	0.073	0.020	0.234	0.036
Zhashui Xian	0.484	0.064	0.088	0.019	0.273	0.041

Note: Estimates are from the model with environmental variables in column 4 of Table 3.
Counties are arrayed by administrative code.