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Poverty and the Spatial Distribution of Rural Population

Edward B. Barbier
Jacob P. Hochard

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Abstract

According to global spatial data sets in 2000 more than one-third of the rural population in developing countries was located on less favored agricultural land and areas. Less favored agricultural lands are susceptible to low productivity and degradation, because their agricultural potential is constrained biophysically by terrain, poor soil quality, or limited rainfall. Less favored agricultural areas include less favored agricultural lands plus favorable agricultural land that is remote, that is, land in rural areas with high agricultural potential but with limited access. The paper presents tests of whether these spatial distributions of rural population influence poverty directly or indirectly via income growth in 83 developing countries from 2000 to 2012. The analysis finds no evidence of a direct impact on poverty, but there is a significant indirect impact via the elasticity of poverty reduction with respect to growth. Reducing poverty requires targeting rural populations in less favored lands and remote areas, in addition to encouraging out-migration in some areas.

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Edward B. Barbier*

Jacob P. Hochard*

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*Department of Economics and Finance, University of Wyoming, Laramie, WY 82071; Corresponding author: ebarbier@uwyo.edu. We are grateful for the comments provided by Stephan Kroll, Dale Manning and Mike Toman. The research was supported in part by the World Bank Knowledge for Change Program. The contents of the paper reflects the authors' own views, which should not be attributed to the World Bank or its member countries.

Poverty and the Spatial Distribution of Rural Population

Edward B. Barbier*

Jacob P. Hochard*

Beginning with Datt and Ravallion (1992), a series of empirical analyses have sought to decompose the influence of growth as opposed to income distribution on poverty reduction across developing countries.[1] As noted by Ravallion (2012), the consensus in this literature is that higher growth rates tend to yield more rapid rates of absolute poverty reduction, although there is also evidence of a strong interaction between initial inequality and growth in mean incomes in explaining poverty changes. However, Ravallion (2012) also finds that the initial level of poverty is a relevant predictor of the influence of income distribution on the elasticity of poverty reduction with respect to growth, and this "poverty-adjusted growth rate" is the key determinant of changes in poverty incidence.

This paper explores whether poverty across developing countries is influenced by another factor, the spatial distribution of rural populations. Two types of spatial distributions are considered, the concentration of rural populations on *less favored agricultural lands*, and their concentration in *less favored agricultural areas*. As shown in Figure 1, these two land classifications are related (Pender and Hazell 2000). Less favored agricultural lands are susceptible to low productivity and degradation, because their agricultural potential is constrained biophysically by terrain, poor soil quality or limited rainfall (box A and B in Figure 1). Less favored agricultural areas include less favored agricultural lands plus favorable agricultural land that is remote; i.e., land in rural areas with high agricultural potential but with limited access to infrastructure and markets (box D). Thus, in Figure 1, less favored agricultural areas are the shaded grey

[1] See, for example, Adams and Page (2005); Bourguignon (2003); Dollar and Kraay (2002); Kraay (2006); Ravallion (1997), (2001) and (2012); Ravallion and Chen (1997).

boxes A, B, and D. Of these areas, the most critical may be less favored agricultural lands that are also remote due to poor market access (box B).

A number of studies of the spatial location of populations in marginal areas indicate that it is the rural poor of developing economies whose livelihoods are most dependent on less favored lands and areas (Barbier 2010 and 2012; CAWMA 2008; CGIAR 1999; Fan and Chan-Kang 2004; Pender 2008; Pender and Hazell 2000; World Bank 2003 and 2008). However, as the World Bank (2008, p. 49) concludes, “the extreme poor in more marginal areas are especially vulnerable” and “one concern is the existence of geographical poverty traps”. Such traps may occur because production on less favored agricultural lands is subject to low yields and soil degradation, while lack of access to markets and infrastructure may constrain the ability of poor households to improve their farming systems and livelihoods or obtain off-farm employment. Such characteristics tend to reinforce rural poverty, given that the rural poor have few productive assets and migrate only temporarily and for short distances for outside work (Banerjeee and Duflo 2007 and 2012). If the spatial concentration of rural populations on less favored agricultural lands and areas perpetuates geographical poverty traps, such “spatial inequality” may have significant implications for the reduction of overall poverty in developing countries (Barbier 2012; Bird et al. 2002 and 2010; Jalan and Ravallion 2002; Kanbur and Venables 2005).

In sum, the key hypothesis examined in this paper is that the spatial distribution of rural population on less favored agricultural land and remote areas influences the incidence of poverty across developing countries. First, we briefly summarize recent evidence of the geographical location of rural population in marginal lands and areas across developing countries and regions, including a new spatial analysis conducted for this paper for rural populations across all developing countries in 2000. A model of spatial distribution and poverty is then developed to explain the potential influence of this distribution on the rate of change in poverty. To analyze this influence, we follow an estimation strategy similar to Ravallion (2012). Using the World Bank’s PovcalNet national household survey database, we identify 83 developing countries with at least two suitable surveys over the 2000 to 2012 period for which we have also estimated the spatial distribution of rural population in 2000. For these countries, we first replicate the analysis by Ravallion (2012) to determine the relative influence of initial poverty and mean survey income growth on changes in poverty, and confirm his main finding that it is the poverty-adjusted growth rate that is the key determinant of poverty reduction. We then repeat this analysis but with various measures of the share of rural populations on less favored agricultural land, both as separate explanatory variables and interacted with mean income growth. We find that the "spatial distribution-adjusted" growth rate is the main factor explaining changes in poverty, and the most important effect is associated with the share of rural population on less favored agricultural land that is also remote (box B in Figure 1). Finally, taking into account that the initial level of poverty may be endogenous with respect to our various spatial distribution measures, we specify the poverty-adjusted growth rate to be instrumented or determined by the spatial distribution-adjusted growth rate, and obtain similar results as our previous analysis. These findings suggest that, as more rural people are located on remote and marginal agricultural land, the poverty-reducing impact of income growth tends to be lower across a wide range of developing countries.

The Spatial Distribution of Rural Populations in Developing Countries

One of the first studies to determine the distribution of the rural poor on less favored lands globally was CGIAR (1999), which concluded that nearly two-thirds of the rural population of developing countries—almost 1.8 billion people—live on less-favored lands, including marginal agricultural lands, forest and woodland areas, and arid zones. By applying national rural poverty percentages, CGIAR (1999) determined that 633 million poor people lived on less favored lands in developing countries, or around two-thirds of the total rural poor (see also CAWMA 2008).

A subsequent analysis by the World Bank (2003) sought to identify the percentage of total population in a selection of low and middle-income economies located on “fragile lands” in 2000. This classification comprised four categories of land: terrain greater than 8% median slope, soil unsuitable for rainfed agriculture, arid and dry semi-arid land without access to irrigation, and forests (deciduous, evergreen and mixed). The study estimated that nearly 1.3 billion people in 2000 – almost a fifth of the world’s population – lived in such areas in developing regions, and concluded that since 1950, the estimated population in developing economies on “fragile lands” may have doubled (World Bank 2003).

A subsequent analysis by the World Bank (2008) employed the definition proposed by Pender and Hazell (2000) for less favored areas to determine the spatial distribution of rural populations in 2000. However, the analysis was able to determine only the distribution of rural population on lands limited by rainfall (arid and semi-arid lands) and in remote areas. The latter are defined as locations with poor market access, requiring five or more hours to reach a market town of 5,000 or more. Around 430 million people in developing countries in 2000 lived in such distant rural areas, and nearly half (49%) of these populations were located in arid and semi-arid regions characterized by frequent moisture stress that limits agricultural production (World Bank 2008).

Using a variety of global spatially referenced data sets, we analyzed the spatial distribution of rural population across developing countries in 2000, following the classification of less favored agricultural land and areas of Figure 1. Less favored agricultural land consists of irrigated land on terrain greater than 8% median slope; rainfed land with a length of growing period (LGP) of more than 120 days but either on terrain greater than 8% median slope or with poor soil quality; semi-arid land (land with LGP 60-119 days); and arid land (land with LGP $<$ 60-119 days). These various land areas were determined by employing in Arc GIS 10.1 the data sets from the FAO Global Agro-Ecological Zones (GAEZ) Data Portal version 3 (Available online: http://gaez.fao.org/) combined with national boundaries from the Gridded Population of the World, Version 3 (GPWv3) of the Center for International Earth Science Information Network (CIESIN) and Centro Internacional de Agricultura Tropical

(CIAT). Agricultural land extent was obtained from the Pilot Analysis of Global Ecosystems (PAGE) (http://www.ifpri.org/dataset/pilot-analysis-global-ecosystems-page), and rural populations determined from the rural-urban extent data set that was published as part of CIESIN Global Rural Urban Mapping Project (GRUMPv1). Market accessibility was used to identify remote areas using Nelson (2008) as released by the Global Environment Monitoring Unit of the Joint Research Centre of the European Commission. Following Nelson (2008), we identify market access as less than five hours of travel to a market city with a population of 50,000 or more.

The results of this analysis for the main regions comprising 124 of the 139 low and middle-income economies as classified by the World Bank (2014) are depicted in Table 1.[2] Almost 36% of the 2000 rural population in these developing countries was located on less favored agricultural land, although this share ranged from 23% in the Middle East and North Africa to 56% in Europe and Central Asia. Over 37% of the rural population in 2000 was in less favored agricultural areas, and about 8% on remote less favored agricultural lands. The latter also amounted to 22% of all the rural population on less favored agricultural land, with this share varying from 12% in Europe and Central Asia to 30% in Sub-Saharan Africa.

Given the evidence that a sizable proportion of the rural population was located on less favored lands and in remote areas in 2000, we explore next how this spatial population distribution may have influenced overall poverty, as measured by a poverty headcount indicator. In subsequent sections, we use this framework as the basis of examining empirically how the spatial distribution of rural population in 2000 may have affected poverty across developing countries in the subsequent 2000-2012 period.

[2] Low and middle-income economies are those in which 2012 Gross National Income (GNI) per capita was $12,615 or less. The 15 developing economies excluded from Table 1 due to lack of spatial resolution or data on agricultural land area in 2000 are American Samoa, Cape Verde, Fiji, French Polynesia, Kiribati, Maldives, Marshall Islands, Mauritius, Montenegro, Samoa, Serbia, Seychelles, South Sudan, Tonga and Tuvalu.

A Model of Spatial Distribution and Poverty

Following Gastwirth (1971), the inverse of the continuously differentiable cumulative distribution function $F(y)$ defines the quantile function for p; i.e., the income level y below which we find a proportion p of the population. That is, $y = F^{-1}(p) = y(p)$.[3] This leads directly to derivation of the Lorenz curve, the graphical representation of the fraction of total income that the holders of the lowest pth fraction of incomes possess

$$L(p) = \frac{1}{\mu}\int_0^p F^{-1}(t)\,dt, \quad L_p = \frac{\partial L}{\partial p} = \frac{y(p)}{\mu} > 0, \ L_{pp} > 0, \ 0 \le p \le 1 \tag{1}$$

where $\mu = \int_0^\infty y\,dF(y) = \int_0^\infty yf(y)dy$ is the mean income of the population. Thus the derivative of the Lorenz curve with respect to p gives the ratio of the income of that share of the population to the average income of the entire population n. As $y'(p) > 0$, the Lorenz curve is an increasing and convex function of p.

Defining H as the poverty headcount index, i.e. the share of the population with income no higher than a defined poverty line z, it follows that $H = F(z)$ and thus $z = F^{-1}(H)$. Inverting the derivative of the Lorenz curve in (1), and evaluating it at $p = H$, yields

$$H = p = L_p^{-1}\left(z/\mu\right). \tag{2}$$

Our conjecture is that the spatial distribution of population, especially the location of rural populations on less favored agricultural land or in remote areas, may

[3] If p is defined as that proportion of the population with income less than y, it follows that $p = \int_0^y f(t)\,dt = F(y)$.

also exert an independent influence on the incidence of poverty. We now show how (2) can be modified to reflect this influence.[4]

Suppose that agricultural land in an economy can be denoted by some spatial characteristic x. For example, x could represent the biophysical conditions of a given location where agriculture takes place, such as the quality of soils, type of terrain and rainfall availability. Thus agricultural land could be ranked from "less favorable" to "more favorable" based on these biophysical conditions. Alternatively, x could represent the location of agricultural land with respect to the closest markets, and so it could be ranked from "more remote" to "less remote". This is essentially the classification of less favored agricultural lands and areas as represented in Figure 1.

As we are interested in the spatial distribution of rural populations on agricultural land, suppose that x can be associated with the agricultural land of a member of that population in a specific location. If x is a continuous random variable with cumulative distribution function $G\left(x\right)$, then the latter function represents the proportion of the rural population in all locations that have agricultural land with a given spatial characteristic less than or equal to x. For example, if x represents agricultural land designated by biophysical conditions, x could be all such land that has certain soil, terrain and rainfall characteristics. Similarly, x could be all land located a certain distance from a market town of a given size.

Defining q as the proportion of the rural population with agricultural land that has a spatial characteristic that is ranked less than x, and the density function is $g\left(x\right) = G'\left(x\right)$, then it follows that $q = \int_0^x g\left(t\right) dt = G\left(x\right)$. The inverse of the distribution function $G\left(x\right)$ defines the level of the spatial characteristic x that determines the

[4] The approach we take here is similar to methods that others have used to decompose the effects of income distribution (i.e. the Gini index) and mean income growth on changes in poverty; e.g., see Bourguignon (2003), Ferreira (2012) and Kraay (2006).

proportion q of the rural population that has agricultural land ranked below that level of x. That is, $x = G^{-1}\left(q\right)$.

Now let w be a specific level of x that can distinguish two distinct types of agricultural land by a given spatial characteristic. For example, for biophysical conditions, w may be a given level of soil quality, terrain and rainfall that distinguishes all less favored from favored agricultural land, or w could distinguish all remote from less remote agricultural land. Denoting s as the share of the rural population on agricultural land with a spatial characteristic no better than w, it follows that $s = G\left(w\right)$ and $w = G^{-1}(s) = w\left(s\right)$. Thus $w\left(s\right)$ is the spatial trait distinguishing agricultural land for a proportion s of the rural population.

We now postulate that the Lorenz curve for a given distribution of income in the economy will be affected by the proportion s of the rural population that is located on agricultural land that is ranked below w, i.e. $L\left(p, w\left(s\right)\right)$. That is, if a greater share of the rural population is located on agricultural land with characteristics less than w, then because of the poor agricultural productivity and/or returns to this land, the cumulative distribution of income in the entire economy that accrues to the bottom p share of population will be impacted. It follows that (2) now becomes

$$H = L_p^{-1}\left(z/\mu, w\left(s\right)\right) \ . \qquad (3)$$

As before, the incidence of poverty is inversely related to the mean income of the population, but now the share of the rural population on agricultural land with traits lower than w also affects poverty.

Taking the total derivative of (3) $dH = -L_{pp}^{-1}\frac{z}{\mu^2}d\mu + L_{pw}^{-1}w'ds$, and dividing by (3), yields

$$\frac{dH}{H} = -\frac{L_{pp}^{-1}}{L_p^{-1}}\frac{z}{\mu}\frac{d\mu}{\mu} + \frac{L_{pw}^{-1}}{L_p^{-1}}w'ds \, . \qquad (4)$$

For a given poverty line z, the rate of change in poverty can be decomposed into the effect of mean income growth ($d\mu/\mu$) and the effect of the share of the rural population located on agricultural land (ds) as defined by a specific spatial characteristic w (e.g., biophysical conditions, access to infrastructure and markets). As the Lorenz curve is increasing and convex, the partial elasticity of poverty with respect to growth $-\frac{L_{pp}^{-1}}{L_p^{-1}}\frac{z}{\mu}$ is always positive, which indicates that growth reduces poverty. This accords with the empirical results of cross-country poverty analysis.[5] However, as $L_{pw}^{-1}w'$ cannot be signed, a change in the spatial distribution of the rural population may increase or decrease poverty.

Suppose, for argument's sake, that $L_{pw}^{-1}w' > 0$. It follows from (4) that a rise in the share of the rural population on agricultural land with spatial traits determined by w will lead to a proportionate increase in the incidence of poverty in the entire economy. This *direct influence* of the spatial distribution of the rural population on poverty changes is one hypothesis that can be tested empirically. In addition, as (3) indicates, s influences L_p^{-1} and thus potentially the growth elasticity of poverty reduction as represented by the first term on the left-hand side of (4). Specifically, if $L_{pw}^{-1}w' > 0$, then a possible effect of s is to mitigate the poverty-reducing effect of growth $d\mu/\mu$. This *indirect influence* of the spatial distribution of the rural population on poverty changes is a second hypothesis worth exploring empirically.

Data and Descriptive Statistics

As indicated in Table 1, we have estimated four spatial distribution variables for the rural population in 2000 for 124 low and middle-income economies. These variables,

[5] See, for example, Adams and Page (2005); Bourguignon (2003); Datt and Ravallion (2002); Dollar and Kraay (2002); Kraay (2006); Ravallion (1997), (2001) and (2012); and Ravallion and Chen (1997).

which are our proxies for $s = G\left(w\right)$, are the share (%) of the rural population on less favored agricultural land (henceforth s_1), the share (%) of the rural population on less favored agricultural areas (s_2), the share (%) of the rural population on remote less favored agricultural land (s_3), and the share (%) of the rural population on less favored agricultural lands on remote land (s_4). We use these variables to test the two hypotheses concerning the direct and indirect influences that the spatial distribution of the rural population has on poverty changes for developing countries from 2000 to 2012.

Following the recent poverty analysis literature[6], we obtain our cross-country measures of a given poverty line z, the poverty headcount index H, and mean income μ from PovcalNet, the on-line tool for poverty measurement developed by the Development Research Group of the World Bank (Available online at http://iresearch.worldbank.org/PovcalNet/). PovcalNet produces internationally comparable country level poverty and income distribution estimates based on more than 850 standardized household surveys across 127 developing countries. From this database, we identify 83 low and middle-income economies with at least two suitable household surveys from 2000 to 2012. The longest available spell between surveys is used for each country, and both surveys use the same welfare indicator, either consumption or income per person. The median interval between surveys is eight years, and it varies from two to eleven years.[7] All monetary measures are in constant 2005 prices and are at Purchasing Power Parity (PPP).

The poverty headcount index H is the percentage of the population living in households with consumption per capita (or income when consumption is not available) below the poverty line. We follow Ravallion (2012) and choose a poverty line z of \$2.00 per person per day at 2005 PPP, which is the median poverty line among developing

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[6] See, for example, Adams and Page (2005), Bourguignon (2003), Kraay (2006) and Ravallion (2001 and 2012).

[7] As far as possible, the initial survey year chosen was 2000, or for the soonest subsequent year. However, for Burundi, Gambia, Ghana, Iran, Maldives and Yemen the initial survey year was1998, and for Kenya 1997.

countries. In the initial survey year, the median poverty headcount index across all 83 countries was 42.85%, but ranged widely from 0.29% to 95.44%. By the final survey year, the median poverty headcount was 27.86%, and it varied from 0.08% to 93.49%.

Mean income μ is the average monthly (2005 PPP $) per capita income or consumption expenditure from the household surveys for each country in the relevant year. In the initial survey year, the median per capita monthly income was $100 across all 83 countries, and ranged from $24 to $2,003. In the final survey year, median income was $115, and varied from $28 to $2,012. Finally, inequality is measured by the usual Gini index, which was also obtained from the PovcalNet cross-country household surveys for the relevant years.

We also employ a number of control variables in our analysis, following the approach of similar poverty analyses.[8] The controls are inflation, government consumption as a share of GDP, arable land per capita, agricultural value added as a share of GDP and per worker, investment as a share of GDP, trade openness, primary school enrollment, and life expectancy. These variables were obtained from the World Development Indicators (World Bank 2014), and as far as possible, for 2000 and our sample of 83 countries. Other controls include a dummy for landlocked country as defined by UNDP (http://unctad.org/en/pages/aldc/Landlocked%20Developing%20Countries/List-of-land-locked-developing-countries.aspx), for small island developing states as defined by UNESCO (http://www.unesco.org/new/en/natural-sciences/priority-areas/sids/about-unesco-and-sids/sids-list/), and distance from equator for each country. We also employ rule of law and democracy (voice and accountability) indices, from the Worldwide Governance Indicators (http://data.worldbank.org/data-catalog/worldwide-governance-indicators), which were averaged over 1996-2000 for each country. Finally, we use regional dummies for the six main developing country regions (see Table 1).

[8] See, for example, Adams and Page (2005); Dollar and Kraay (2000); Kray (2006) and Ravallion (2012).

Estimation Strategy and Results

To analyze the possible direct and indirect influences of our spatial distribution variables s_k in 2000 on poverty changes from 2000 to 2012 in our 83 sample countries, we follow a similar estimation strategy to Ravallion (2012). Thus, our basic regression is

$$\gamma_i\left(H_{it}\right) = \alpha_0 + \alpha_1 \ln\left(v_{it-\tau}\right) + \left(\beta_0 + \beta_1 v_{it-\tau}\right)\gamma_i\left(\mu_{it}\right) + \omega_{it}, \tag{5}$$

where i is each country observation, t is the final survey date, τ is the length of spell between surveys, and ω_{it} is the error term. The annualized growth rate in the poverty headcount between surveys is $\gamma_i\left(H_{it}\right) \equiv \ln\left(H_{it}/H_{it-\tau}\right)/\tau$, and $\gamma_i\left(\mu_{it}\right)$ is similarly defined as the annualized growth rate in mean income. The initial level of the variable of interest is $v_{it-\tau}$, which in Ravallion (2012) is the initial poverty level $H_{it-\tau}$, whereas in much of our analysis, it is one of the four spatial distribution variables in 2000, i.e. $s_{kit-\tau}$.

Two tests of restrictions on the various parameters estimated by (5) determine the direct and indirect influence of $v_{it-\tau}$ on the annualized change in poverty. For example, rejection of the null hypothesis $\alpha_1 = 0$ for $H_{it-\tau}$ or $s_{kit-\tau}$ indicates that initial poverty or spatial distribution levels have a direct influence on changes in poverty over time, and subsequently, the magnitude of α_1 determines whether this influence is positive or negative. Failure to reject the null hypothesis of homogeneity, i.e. $\beta_0 + \beta_1 = 0$, confirms that initial poverty or spatial distribution levels have an indirect influence through "adjusting" the growth elasticity of poverty reduction. That is, the restriction implies $\beta_0 = -\beta_1$ and the correct regressor in (5) is $\left(1 - v_{it-\tau}\right)\gamma_i\left(\mu_{it}\right)$. From (4), the expected sign of the coefficient of this regressor is negative. Thus, in the case that the restrictions $\alpha_1 = 0$ and $\beta_0 + \beta_1 = 0$ both hold, then regression (5) becomes $\gamma_i\left(H_{it}\right) = \alpha_0 + \beta_1\left(1 - v_{it-\tau}\right)\gamma_i\left(\mu_{it}\right) + \omega_{it},\ \beta_1 < 0$.

Our strategy for estimating (5) involves four sets of regressions. First, we replicate the analysis by Ravallion (2012), using the initial poverty level $H_{it-\tau}$ for $v_{it-\tau}$ in (5), for our sample of 83 countries over 2000 to 2012. Second, we repeat the analysis but include separately (in log form) each of our four spatial distribution variables $s_{kit-\tau}$ as independent regressors. Third, we re-estimate (5) for our sample of countries, but this time using each of our four spatial distribution variables $s_{kit-\tau}$ for $v_{it-\tau}$. Finally, allowing for the possibility that the initial level of poverty $H_{it-\tau}$ is endogenous with respect to our four $s_{kit-\tau}$ measures, we estimate IV, SUR and 3SLS regressions of (5) taking this into account; i.e., the "poverty-adjusted" growth rate is determined by the "spatial distribution-adjusted" growth rate. That is, if $H_{it-\tau}$ is endogenous with respect to any $s_{kit-\tau}$, then $\left(1-H_{it-\tau}\right)\gamma_i\left(\mu_{it}\right)$ is determined by $\left(1-s_{kit-\tau}\right)\gamma_i\left(\mu_{it}\right)$. For all four steps, we estimate the regressions both with and without additional control variables.

Our replication of the estimations in Ravallion (2012, Table 4) for our sample of 83 countries produces similar results. We conduct both OLS and IV regressions of (5), with the latter estimations using the growth rate in private consumption per capita from the national accounts from World Bank (2014) as the instrument for the growth in mean survey income.[9] For all OLS and IV specifications, the null $\alpha_1 = 0$ cannot be rejected, and thus the initial level of poverty $H_{it-\tau}$ has no direct influence on poverty changes over time. However, the homogeneity restriction $\beta_0 + \beta_1 = 0$ also cannot be rejected, confirming that the poverty-adjusted growth rate $\left(1-H_{it-\tau}\right)\gamma_i\left(\mu_{it}\right)$ is the relevant regressor. When homogeneity is imposed on (5), we obtain a significant and negative poverty-adjusted growth elasticity, which is -2.83 for OLS and -4.85 for IV. The corresponding estimates in Ravallion (2012, Table 4) are -2.47 and -3.09, respectively.

In our second set of estimations, we find that including each additional $\ln s_{kit-\tau}$ variable in the previous poverty analysis regressions has no effect on the results. None of the coefficients on these spatial distribution measures are significant, and their inclusion did not change, or improve, the poverty-adjusted growth regression results.

[9] As explained in Ravallion (2001) and (2012), using this instrument takes into account the possibility of a spurious negative correlation resulting from common measurement errors, given that the poverty measure and the mean per capita monthly income are based on the same household surveys.

For example, for the OLS regressions, the estimated poverty-adjusted growth elasticity remained significant and ranged from -2.89 to -3.00, and for IV, from -4.85 to -4.96.

Table 2 depicts the results of our third set of regressions.[10] Only the estimations corresponding to the share (%) of the rural population in 2000 on less favored agricultural lands on remote land (s_4) are shown; however, similar results are obtained for the other three s_k spatial distribution measures. In all regressions in Table 2, the null $\alpha_1 = 0$ cannot be rejected, and thus the 2000 spatial distribution measure $s_{4it-\tau}$ has no direct influence on poverty changes over time. The homogeneity restriction $\beta_0 + \beta_1 = 0$ also cannot be rejected, confirming that the spatial distribution-adjusted growth rate $\left(1 - s_{4it-\tau}\right)\gamma_i\left(\mu_{it}\right)$ is the relevant regressor. In the model imposing homogeneity, the elasticity of growth adjusted for $s_{4it-\tau}$ is significant in both OLS and IV. However, there is considerable difference in the estimated elasticity, which range from -2.10 in the OLS regression (column 5) to -7.19 in the IV estimation (column 6). These results do not change when additional control variables are added to the regressions that impose homogeneity on (5).

Repeating the regressions of Table 2 but using the other three s_k spatial distribution measures instead of s_4 produces a similar outcome. Neither the null $\alpha_1 = 0$ nor the homogeneity restriction $\beta_0 + \beta_1 = 0$ can be rejected. When homogeneity is imposed, the coefficient on the spatial distribution-adjusted growth rate $\left(1 - s_{kit-\tau}\right)\gamma_i\left(\mu_{it}\right)$ is significant and negative, but only in the OLS and not the IV estimations. For the regressions using the share (%) of the rural population on less favored agricultural land $s_{1it-\tau}$ to adjust growth, the estimated elasticity is -1.42, for the share (%) of the rural population on less favored agricultural areas $s_{2it-\tau}$ the elasticity is -1.59, and for the share (%) of the rural population on remote less favored agricultural land $s_{3it-\tau}$ the elasticity is -1.67.

[10] For three of the countries, Fiji, Maldives and Serbia, insufficient spatial resolution or lack of data prevented constructing spatial distribution variables s_k. Private consumption per capita data were not available for Jamaica.

In the final set of regressions, we estimate IV, SUR and 3SLS poverty-adjusted growth regressions, allowing for the possibility that the initial level of poverty $H_{it-\tau}$ is endogenous with respect to each of our four $s_{kit-\tau}$ measures. We use both the growth in mean survey income as our measure of $\gamma_i(\mu_{it})$ and also instrument for this variable with the growth rate in private consumption per capita. As explained in Ravallion (2001) and (2012), using this instrument takes into account the possibility of a spurious negative correlation resulting from common measurement errors, given that the poverty measure and the mean per capita monthly income are based on the same household surveys. In all regressions, and for all spatial distribution measures of $s_{kit-\tau}$ the results are robust, and the coefficients significant and with the expected signs. That is, the estimated poverty-adjusted elasticity for $(1-H_{it-\tau})\gamma_i(\mu_{it})$ is significant and negative, and in the first stage of the SUR and 3SLS regressions, this variable is positively and significantly influenced by $(1-s_{kit-\tau})\gamma_i(\mu_{it})$. These results are also robust when additional control variables are included in the regressions, although almost all the controls are individually and jointly insignificant in all IV, SUR and 3SLS regressions, with the exception of agricultural value added per worker, investment as a share of GDP and the Europe and Central Asia dummy.

Table 3 depicts the 3SLS estimations corresponding to the share (%) of the rural population in 2000 on less favored agricultural lands on remote land (s_4). The elasticity of the poverty-adjusted growth rate in mean survey income is negative and significant (see columns (1) and (5)). Moreover, its value (-2.37 to -3.05) corresponds closely to the estimates for this elasticity in our first set of regressions, when we replicate Ravallion (2012, Table 4) for our sample of countries. Similarly, the elasticity of poverty-adjusted growth when private consumption is significant, negative and close to the estimates from our first set of regressions (-5.07 to -5.80). In addition, we find a positive and significant influence of spatial distribution-adjusted growth $(1-s_{4it-\tau})\gamma_i(\mu_{it})$ on poverty-adjusted growth $(1-H_{it-\tau})\gamma_i(\mu_{it})$. This elasticity is 0.63 to 0.69 for growth in mean survey income, and 0.22 to 0.46 when the latter variable is instrumented by growth in per capita consumption.

Table 3 also indicates that, when they are significant, the control variables have the expected signs. For example, investment share of GDP reduces overall poverty, and agricultural productivity increases poverty-adjusted growth. Poverty is generally lower, whereas poverty-adjusted growth generally higher, in Europe and Central Asia compared to other developing regions. However, as also found by Ravallion (2012), the initial Gini index appears not to be significant.

Table 4 summarizes the results of the poverty analysis for the four s_k spatial distribution variables for the rural population on less favored agricultural land and in less favored agricultural areas. For comparison, the table also shows the impacts on changes in poverty from an increase in income growth only, an increase in poverty adjusted growth and an increase in initial poverty levels. For example, in the absence of any change in the spatial distribution of rural populations or in initial poverty levels, a one-standard-deviation increase of 3.52% in average income growth in our sample of developing countries, from 3.36% to 6.88%, would reduce poverty by 4.97% each year.

For our sample of countries, a one-standard-deviation change in the share of rural population on less favored agricultural lands (s_1) is equivalent to increasing this spatial distribution by 21% (e.g., at the mean, this share of rural population would rise from 38% to 59%). This has the effect of increasing poverty annually by 0.92% to 0.99%. A one-standard-deviation change (also 21%) in the share of rural population located in less favored agricultural areas (s_2) causes a rise in poverty from 0.97% to 1.11% per year. A one-standard-deviation change in the share of rural population located on remote less favored agricultural land (s_3), which is 8.4%, would increase poverty by 0.35% to 0.47% annually. Finally, a one-standard-deviation change in the share of rural population on less favored agricultural land located on remote land (s_4) by 19% causes an annual increase in poverty of 0.95% to 1.32%.

Overall, our estimation results confirm that spatial distribution of rural populations in developing countries on less favored and remote agricultural land impacts overall poverty. However, the hypothesis that this spatial distribution has a direct influence on poverty is rejected. Instead, the location of rural populations on less favored agricultural land and more remote areas impacts poverty by lowering the poverty-reducing impact of income growth. This attenuating effect of a higher initial spatial distribution can be sizeable. For example, using the elasticity estimates from columns (5) and (6) in Table 3, at an initial distribution for the share (%) of the rural population in 2000 on remote less favored agricultural lands (s_4) of 6 percent (about one standard deviation below the mean), one can expect a rate of poverty reduction of 4.7% per year. However, if s_4 is 44 percent (about one standard deviation above the mean), the rate of poverty reduction is only 2.8% per annum.[11]

Conclusion

A number of studies have shown that a sizable proportion of the rural population in developing countries is concentrated on less favored agricultural lands, which are subject to low productivity and degradation due to steep slopes, poor soil quality or limited rainfall (Figure 1, boxes A and B). A large segment of the rural population is also located on less favored agricultural areas, which include less favored agricultural lands plus favorable land that is remote, due to long distances to market and limited access to infrastructure (Figure 1, boxes A, B and D). Perhaps most critical may be the rural populations located on less favored agricultural lands that are also remote due to poor access to infrastructure and markets (Figure 1, box B).

[11] From Table 4, the mean for the share (%) of the rural population in 2000 on less favored agricultural lands on remote land (s_4) is around 25% and the standard deviation is 19%. Mean annualized growth in survey income is 3.36%. Using these figures and the elasticity estimates reported in columns (5) and (6) in Table 3, we get $-2.37\times0.63\times(1-0.06)\times3.36 = 4.7$, and $-2.37\times0.63\times(1-0.44)\times3.36 = 2.8$.

Our spatial analysis of the distribution of rural populations across 124 developing countries in 2000 reveals that around 36% were located on less favored agricultural land, and over 37% in less favored agricultural areas. About 8% of the rural population was concentrated on remote less agricultural lands, which also accounted for 22% of all the rural population on less favored agricultural land in developing countries. Given this evidence confirming that a sizable proportion of the rural population is located on less favored lands and in remote areas, we developed two hypotheses as to how this spatial distribution of rural populations might impact poverty in developing countries. First, the concentration of rural populations on less favored agricultural land and areas may have a direct influence on changes in poverty, and second, it may have an indirect influence through attenuating the poverty-reducing impact of income growth.

To test these two hypotheses empirically, we followed standard cross-country poverty analysis techniques, and in particular Ravallion (2012), to examine how the spatial distribution of rural populations in 2000 influences poverty changes from 2000 to 2012 in 83 developing countries for which the relevant data are available. For these countries and time period, we found no evidence that that there is a direct influence of the location of rural populations on marginal or remote agricultural lands on changes in poverty. However, this spatial distribution of the rural population does have a significant indirect impact on the poverty-reducing growth elasticity. Thus, our conclusion is that, across a wide range of developing countries, as more rural people are located on remote and less-favored agricultural land, the result is a substantial attenuation of the poverty-reducing impact of the growth in mean incomes.

These results lend credence to recent concerns about the prevalence of geographical poverty traps in the rural areas of developing countries (Barbier 2012; Bird et al. 2002 and 2010; Jalan and Ravallion 2002; Kanbur and Venables 2005). As the World Bank (2008, p. 49) has pointed out, "in such a case, reducing rural poverty requires either a large-scale regional approach or assisting the exit of populations." It may be that both strategies will be required to alleviate the problem of the concentration of rural populations on less favored agricultural lands and remote areas, which as this paper has shown appears to be a major obstacle to the poverty-reducing effect of overall income growth in developing countries. In particular, our results suggest that the most critical and vulnerable rural population group are those located on less favored agricultural lands that are also remote from markets. It is this group that should be the main target of any strategy aimed at encouraging outmigration while investing in improving the livelihoods of those who remain in such areas. What is urgently needed to help the design of such a strategy is more randomized control trials aimed at the critical target group of the rural population to determine the key factors that create the geographical poverty trap, and how best to alleviate them (Banerjee and Duflo 2012).

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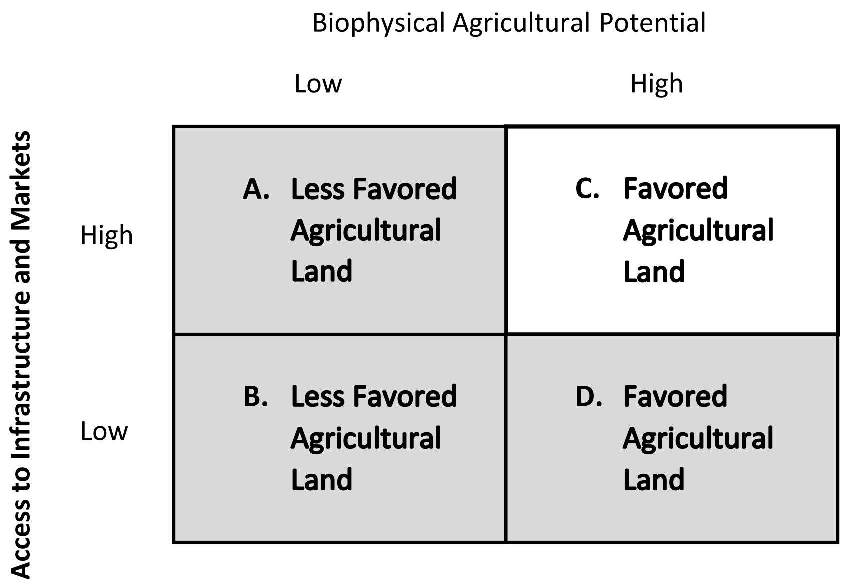
Figure 1. Classification of Less Favored Agricultural Lands and Areas



Less favored agricultural land (A and B) has low agricultural potential as it is constrained biophysically by terrain, poor soil quality or limited rainfall. *Less favored agricultural areas* (**shaded gray**) also include favored agricultural land that is remote due to poor access to infrastructure and markets (D).

Source: Based on the definition and classification of less favored areas in Pender and Hazell (2000).

Table 1. Spatial distribution of rural population by major developing region, 2000

	2000 Rural population (millions)	Share (%) of rural population on less favored agricultural land (LFAL)	Share (%) of rural population in less favored agricultural areas (LFAA)	Share (%) of rural population on remote LFAL	Share (%) of rural population on LFAL on remote LFAL
Developing country	**3,706.8**	**35.5%**	**37.3%**	**7.8%**	**21.9%**
East Asia & Pacific	1,398.4	46.1%	48.1%	11.8%	25.5%
Europe & C. Asia	173.8	55.5%	55.9%	6.9%	12.4%
Latin America & Carib.	294.1	32.3%	33.0%	4.3%	13.5%
Middle East & N. Africa	195.6	23.0%	23.1%	3.5%	15.1%
South Asia	1,090.4	24.7%	26.7%	3.9%	15.8%
Sub-Saharan Africa	554.6	29.6%	32.4%	8.9%	30.0%
Developed country	**404.7**	**42.4%**	**42.9%**	**2.5%**	**6.0%**
World	**4,111.5**	**36.1%**	**37.9%**	**7.3%**	**20.1%**

Notes: Less favored agricultural land (LFAL) consists of irrigated land on terrain greater than 8% median slope; rainfed land with a length of growing period (LGP) of more than 120 days but either on terrain greater than 8% median slope or with poor soil quality; semi-arid land (land with LGP 60-119 days); and arid land (land with LGP $<$ 60 days). These various land areas were determined by employing in Arc GIS 10.1 the datasets from the FAO Global Agro-Ecological Zones (GAEZ) Data Portal version 3 (http://gaez.fao.org/) combined with national boundaries from the Gridded Population of the World, Version 3 (GPWv3) of the Center for International Earth Science Information Network (CIESIN) and Centro Internacional de Agricultura Tropical (CIAT). Agricultural land extent was obtained from the Pilot Analysis of Global Ecosystems (PAGE) (http://www.ifpri.org/dataset/pilot-analysis-global-ecosystems-page), and rural populations determined from the rural-urban extent dataset that was published as part of CIESIN Global Rural Urban Mapping Project (GRUMPv1). Market accessibility was used to identify remote areas using Nelson (2008) as released by the Global Environment Monitoring Unit of the Joint Research Centre of the European Commission. Market access is identified as less than five hours of travel to a market city with a population of 50,000 or more.

Developing countries are all low and middle-income economies with 2012 per capita income of $12,615 or less (World Bank 2014).

Table 2. Estimates of the effect of the spatial distribution of the rural population $s_{4it-\tau}$ and income growth $\gamma_i\left(\mu_{it}\right)$ on the proportionate change in poverty $\gamma_i\left(H_{it}\right)$

	Complete specification		Dropping initial $\ln s_4$		Imposing homogeneity	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-0.052	0.515	-0.023	0.328	-0.020	0.119
	(-1.243)	(0.853)	(-1.722)†	(0.535)	(-2.135)*	(1.114)
Share (%) of the rural population in 2000 on less favored agricultural lands on remote land, $\ln s_{4it-\tau}$	0.010	-0.162	--	--	--	--
	(0.724)	(-0.621)				
Growth rate, annualized change in log survey mean, $\gamma_i(\mu_{it})$	-2.225	-12.558	-2.487	-8.317	--	--
	(-3.843)**	(-1.300)	(-5.516)**	(-1.197)		
Growth rate interacted with 2000 spatial distribution variable, $\gamma_i(\mu_{it})\cdot s_{4it-\tau}$	3.119	39.681	4.198	-14.125	--	--
	(1.450)	(0.653)	(2.713)**	(-0.269)		
Spatial distribution-adjusted growth rate, $\gamma_i(\mu_{it})\cdot(1-s_{4it-\tau})$	--	--	--	--	-2.097	-7.187
					(-5.018)**	(-1.919)*
Observations	80	79	80	79	80	79
R^2	0.33	--	0.33	--	0.31	--
Log likelihood (F-test when imposing homogeneity)	68.45**	68.10**	68.45**	68.10**	34.75**	--
Homogeneity test	0.29	0.28	1.95	0.15	--	--

Notes: The dependent variable is the annualized change in log poverty rate for $2 a day $\gamma_i(H_{it})$;t-ratios based on robust standard errors in parentheses; the IV estimations employ the growth rate in private consumption per capita from the national accounts from World Bank (2014) as the instrument for the growth in mean survey income; **significant at the 1% level; *significant at the 5% level; †significant at the 10% level.

Table 3. 3SLS estimates of the effect of spatial distribution-adjusted growth $\left(1 - s_{4it-\tau}\right)\gamma_i\left(\mu_{it}\right)$ on the elasticity of growth-adjusted poverty reduction

	Mean survey income		Private consumption		Mean survey income		Private consumption	
Dependent variable:	$\gamma_i(H_{it})$ (1)	$\gamma_i(\mu_{it})\cdot(1-H_{it-\tau})$ (2)	$\gamma_i(H_{it})$ (3)	$\gamma_i(\mu_{it})\cdot(1-H_{it-\tau})$ (4)	$\gamma_i(H_{it})$ (5)	$\gamma_i(\mu_{it})\cdot(1-H_{it-\tau})$ (6)	$\gamma_i(H_{it})$ (7)	$\gamma_i(\mu_{it})\cdot(1-H_{it-\tau})$ (8)
Constant	-0.021 (-1.838)†	-0.000 (-0.120)	0.018 (1.021)	0.007 (2.043)*	0.321 (1.726)†	-0.059 (-6.641)**	0.139 (0.768)	-0.035 (-2.431)*
Poverty-adjusted growth rate, $\gamma_i(\mu_{it})\cdot(1-H_{it-\tau})$	-3.046 (-6.866)**	--	-5.072 (-6.080)**	--	-2.370 (-4.812)**	--	-5.803 (-2.634)**	--
Spatial distribution-adjusted growth rate, $\gamma_i(\mu_{it})\cdot(1-s_{4it-\tau})$	--	0.688 (11.531)**	--	0.457 (4.920)**	--	0.634 (12.512)**	--	0.220 (2.305)*
Log agricultural value added per worker (constant 2005 US$), initial survey year	--	--	--	--	(0.002) (0.192)	0.009 (6.699)**	0.028) (1.422)	0.006 (2.967)**
Log investment share (%) of GDP, initial survey year	--	--	--	--	-0.035 (-1.664)†	--	-0.019 (-0.999)	--
Log of Gini index, initial survey year	--	--	--	--	-0.066 (-1.421)	--	-0.065 (-1.382)	--
Dummy for Europe and Central Asia	--	--	--	--	-0.097 (-3.522)**	0.003 (0.748)	-0.022 (-0.387)	0.017 (2.766)**
Number of observations	80	80	79	79	80	80	79	79
R-squared	0.48	0.62	0.30	0.23	0.57	0.79	0.21	0.42
Likelihood ratio test	53.87**	80.35**	30.52**	23.14**	74.33**	128.20**	24.40**	46.77**
F-test	71.12**	129.64**	33.44**	23.59**	19.87**	94.16**	3.77**	17.90**

Notes: The dependent variable in the first equation is the annualized change in log poverty rate for $2 a day $\gamma_i(H_{it})$, and the dependent variable in the second equation is the poverty-adjusted growth rate, $\gamma_i(\mu_{it})\cdot(1-H_{it-\tau})$;mean survey income refers to regressions that employ the growth in mean survey income $\gamma_i(\mu_{it})$; Private consumption refers to regressions that employ the growth rate in private consumption per capita from the national accounts from World Bank (2014) as the instrument for growth in mean survey income;t-ratios based on robust standard errors in parentheses; **significant at the 1% level; *significant at the 5% level; †significant at the 10% level.

Table 4. Effects of spatial distribution variables on annualized change in poverty (%)

Key variables, $v_{it\text{-}\tau}$	Descriptive Statistics: Mean	Median	Standard Deviation	% change in poverty of one standard deviation change
Annualized growth (%) in the poverty rate ($2/day), $\gamma(H_{it})$	-7.70	-4.26	10.28	--
Annualized growth (%) in the mean survey income, $\gamma(\mu_{it})$	3.36	3.32	3.52	-4.97
Annualized poverty-adjusted growth (%) in the mean survey income, $\gamma(\mu_{it})(1- H_{it\text{-}\tau})$	1.74	1.11	2.41	-6.82
Initial headcount poverty rate (% of population), $H_{it\text{-}\tau}$	46.41	42.85	29.56	2.81
% of rural population on less favored agricultural land (2000), $s_{1it\text{-}\tau}$	38.15	38.37	20.95	0.92 to 0.99
% of rural population in less favored agricultural areas (2000), $s_{2it\text{-}\tau}$	40.04	41.37	20.79	0.97 to 1.11
% of rural population located on remote less favored agricultural land (2000), $s_{3it\text{-}\tau}$	8.50	7.06	8.40	0.35 to 0.47
% of rural population on less favored agricultural land located on remote land (2000), $s_{4it\text{-}\tau}$	24.74	23.55	18.81	0.95 to 1.32

The last column reports the annual rate of change (%) in the poverty rate via a one standard-deviation change in each of the relevant $v_{it\text{-}\tau}$ variables listed in the far-left column. The penultimate column shows the one-standard-deviation change for each variable from the sample of 83 countries. For the spatial distribution variables, the lower estimate is for the 3SLS mean survey income elasticity estimations without additional control variables whereas the higher estimate includes controls.