Environment and Development Economics (2018), **23**, 234–256
doi:10.1017/S1355770X17000353

RESEARCH ARTICLE

Poverty, rural population distribution and climate change

Edward B. Barbier[1]* and Jacob P. Hochard[2]

[1] Department of Economics, Colorado State University, Fort Collins, CO, USA and [2] Department of Economics and Institute for Coastal Science and Policy, East Carolina University, Greenville, NC, USA
*Corresponding author. Email: edward.barbier@colostate.edu

(Submitted 15 December 2016; revised 25 May 2017; accepted 12 July 2017; first published online 17 November 2017)

Abstract

Our spatial analysis indicates that in 2000 over one third of the rural population in developing countries was located on less favored agricultural land and areas, which are constrained by biophysical conditions or poor market access. We examine whether these spatial distributions of rural population in 2000 influence subsequent changes in the rate of poverty from 2000 to 2012 in 83 developing countries. We find no evidence of a direct impact on changes in poverty, but there is a significant indirect impact via the elasticity of poverty reduction with respect to growth. If climate change leads to more people concentrated in these areas, or an increase in unfavorable agricultural regions, then the poverty-reducing impact of overall per capita income growth could be further weakened. Reducing poverty will require targeting rural populations in less favored lands and remote areas and encouraging out-migration.

Keywords: Climate change; developing countries; less favored areas; population distribution; poverty; spatial analysis

1. Introduction

The purpose of this paper is to explore whether the distribution of rural population in remote and poor quality agricultural areas in developing countries affects overall poverty reduction, and whether this relationship has implications for the impact of climate change on poverty. There is growing evidence that less favorable agricultural areas of developing countries contain significant numbers of poor populations. The main reasons cited are that production on marginal 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.[1] Climate change impacts, such as drought, erosion, and changes in precipitation, temperature and hydrology, may impact directly the livelihoods of these households

[1]See, for example, Fan and Hazell (2001), Coxhead *et al.* (2002), Jalan and Ravallion (2002), Fan and Chan-Kang (2004), González-Vega *et al.* (2004), Holden *et al.* (2004), Zhang and Fan (2004), Barrett (2008), Barbier (2010), Coomes *et al.* (2011), Battacharya and Innes (2013), Emran and Hou (2013), Lang *et al.* (2013), Gerber *et al.* (2014), Gollin and Rogerson (2014) and Barrett and Bevis (2015).

through causing declining agricultural productivity and income, or indirectly through affecting land and natural resource use (McSweeney, 2005; Carter *et al.*, 2007; Debela *et al.*, 2012; López-Feldman, 2014; Wunder *et al.*, 2014; Angelsen and Dokken, 2015; Hallegatte *et al.*, 2015, 2017; Robinson, 2016). The wide-scale impacts of climate change are likely to result in an increase in the unfavorable regions for agricultural production in developing countries, thus possibly influencing the share of rural populations located in these areas (Dasgupta *et al.*, 2011; Lambin and Meyfroidt, 2011; de Sherbinin, 2014; GCEC, 2014; Hallegatte *et al.*, 2015, 2017).

If the spatial concentration of rural populations in remote and poor quality agricultural areas is increasing, then there may be implications for the reduction of overall poverty in developing countries. A larger share of rural population in such areas may signify more people 'trapped' in poverty and thus may influence directly the change in poverty over time in a developing country. Alternatively, the poverty-reducing impacts of growth in mean incomes may be negatively impacted by a larger share of rural population in remote and poor quality agricultural areas, if the incomes of households in these disadvantaged locations are relatively stagnant compared to other regions.

Investigating such relationships is relevant to recent empirical analyses that have sought to determine the influence of growth as opposed to income distribution on poverty reduction across developing countries.[2] 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 that initial income inequality may influence how much growth reduces poverty. 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, and that high levels of initial poverty reduce how much income growth reduces poverty over time. That is, the 'poverty-adjusted growth rate' is the key determinant of changes in poverty incidence across developing countries.

This paper follows a similar analytical approach to determine whether changes in poverty across developing countries are influenced by another factor, the spatial distribution of rural populations in remote and poor quality agricultural areas. In particular, we examine whether this influence on poverty is direct, or whether it occurs through altering the poverty-reducing impact of growth in mean income.

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 (figure 1, boxes A and B). 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 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).

To explore whether the shares of rural population on less favored agricultural land and remote areas affect poverty reduction across developing countries, we adopt the

[2]See, for example, Datt and Ravallion (1992), Kakwani (1993), Ravallion (1997, 2001, 2012), Ravallion and Chen (1997), Kakwani and Pernia (2000), Dollar and Kraay (2002), Bourguignon (2003), Adams and Page (2005), Kraay (2006), and Son and Kakwani (2008). See also Ferreira (2012) for a review of this literature.

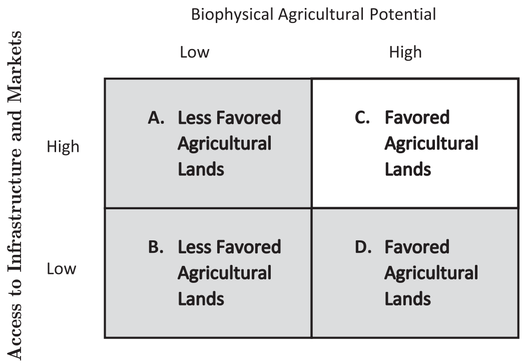

Figure 1. Classification of less-favored agricultural lands and areas. *Notes: Less-favored agricultural lands* (A and B) are susceptible to low productivity and degradation, because their agricultural potential is constrained bio-physically by terrain, poor soil quality or limited rainfall. *Less-favored agricultural areas* (A, B and D, shaded gray) include less favored agricultural lands (A and B) plus favorable agricultural lands that are remote (D); i.e., lands in rural areas with high agricultural potential but with limited access to infrastructure and markets. *Source*: Based on the definition and classification of less-favored areas in Pender and Hazell (2000).

following approach. 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. Utilizing the standard poverty-income distribution relationship, we then show that such spatial distributions of rural population could influence poverty not only directly but also indirectly via per capita income. To analyze these two possible influences, we follow an estimation strategy similar to that of 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 from 2000 to 2012, 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 and areas, both as separate explanatory variables and interacted with mean income growth. We find no evidence of a direct impact of these spatial distributions of rural populations in 2000 on subsequent poverty changes over 2000 to 2012, but there is a significant indirect impact via the elasticity of poverty reduction with respect to growth. That is, a higher share of rural populations in less favored agricultural land and areas is associated with a weaker poverty-reducing impact of growth in average income. For example, on average in our sample of developing countries, growth in per capita income is approximately 3.4 per cent annually, and the share of rural populations on less favored agricultural lands is around 40 per cent. We estimate that, as a consequence, income growth would reduce poverty by 2.8 to 3.2 per cent annually. However, a country with the same income growth but a higher share of rural population on less favored agricultural areas, such as 60 per cent, would expect to see a rate of poverty reduction of 1.8 to 2.1 per cent. In contrast, a country with only 20 per

https://doi.org/10.1017/S1355770X17000353 Published online by Cambridge University Press

cent of its rural population in these poor agricultural areas can expect a rate of poverty reduction of 3.8 to 4.3 per cent.

Thus, the 'spatial distribution-adjusted' growth rate is a significant factor explaining changes in poverty. Although we find this impact to be robust with respect to all four measures of the concentration of rural population on less favored agricultural land and areas, the most important effect is associated with the share of rural population on less favored agricultural land that is also remote (figure 1, box B). Overall, there should be concern that, as more rural people are located on remote and marginal agricultural land, the poverty-reducing impact of per capita income growth will be lower in developing countries. Finally, we discuss the implications of our analysis for the potential impacts of climate change on poverty. Already, there is growing evidence that the livelihoods of populations in marginal areas are highly vulnerable to the risks posed by climate change (Hallegatte *et al.*, 2015, 2017). Our results suggest that, if climate change leads to more people concentrated in these areas, or an increase in unfavorable regions for agriculture through changing precipitation, drought, salinity and other climate impacts, then the poverty-reducing impact of overall per capita income growth could be further weakened.

2. The spatial distribution of rural populations in developing countries

One of the first studies to determine the spatial distribution of populations 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–lives 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 per cent 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).

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 with poor market access. Around 430 million people in developing countries in 2000 lived in such distant rural areas, and nearly half (49 per cent) 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 (see 'Technical notes, data sources and mapping methods' in online appendix B). Less favored agricultural land consists of irrigated land on terrain greater than 8 per cent median slope; rainfed land with a length of growing period (LGP) of more than 120 days but either on terrain greater than 8 per cent 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 identified by using FAO Global Agro-Ecological Zones (GAEZ) Data Portal version 3 datasets (available online at 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. 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.[3] Almost 36 per cent of the 2000 rural population in these developing countries was located on less favored agricultural land, although this share ranged from 23 per cent in the Middle East and North Africa to 56 per cent in Europe and Central Asia. Over 37 per cent of the rural population in 2000 was in less favored agricultural areas, and about 8 per cent on remote less favored agricultural lands. The latter also amounted to 22 per cent of all the rural population on less favored agricultural land, with this share varying from 12 per cent in Europe and Central Asia to 30 per cent 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 might influence overall poverty, as measured by a poverty headcount indicator. In subsequent sections, we examine empirically how the spatial distribution of rural population in 2000 may have affected poverty changes across developing countries in the subsequent 2000–2012 period.

3. Spatial distribution and poverty

To illustrate the potential influence of the shares of rural population on less favored agricultural land and remote areas on poverty, we begin by defining a standard poverty relationship, which depends both on the average income of the population and the properties of the Lorenz curve that determine income distribution. If people living in these disadvantaged regions have lower incomes, then the share of the rural population with poorer access to markets and located on low quality agricultural land should affect average income of the entire population and thus also the properties of the Lorenz curve. We adjust the corresponding measure of poverty, the poverty headcount index, accordingly.

[3] Low and middle-income economies are those in which 2012 gross national income (GNI) per capita was US$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.

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 (%) 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 & Caribbean	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 US$12,615 or less (World Bank, 2014).

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, $y = F^{-1}(p) = y(p)$.[4] 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,

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

where $\mu = \int_0^\infty y dF(y) = \int_0^\infty y f(y) dy$ 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

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

https://doi.org/10.1017/S1355770X17000353 Published online by Cambridge University Press

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

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

Expression (2) indicates that the level of poverty may change due to a change in the mean income μ relative to the poverty line or due to a change in the properties of the Lorenz curve that determine relative income inequalities.[5]

Our conjecture is that the spatial distribution of population, especially the proportion of rural populations on less favored agricultural land and remote areas, may also influence the incidence of poverty, as measured by (2). Denote s as the share of the rural population in these marginal agricultural locations. Because of the poor agricultural productivity and/or returns to these lands, households living in these locations are likely to experience stagnant and low standards of living compared to identical households with access to better land, markets and infrastructure. It follows that a larger share of rural population on less favored agricultural land and remote areas s adversely impacts average income, i.e., $\mu = \mu(s), \mu' < 0$. However, if s influences average income, then from (1) it also influences the Lorenz curve $L(p)$.

This suggests that (2) can be expressed as

$$H = L_p^{-1}\left(\frac{z}{\mu}(s);\, s\right). \tag{3}$$

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 less favorable agricultural land and remote areas s also affects poverty. This *direct influence* of the spatial distribution of the rural population on poverty changes is an empirically testable hypothesis. In addition, if s influences average income μ, then it may also affect the poverty-reducing impacts of income growth, which has been the focus of extensive cross-country poverty analysis.[6] This *indirect influence* of the spatial distribution of the rural population on poverty

[5] Following Datt and Ravallion (1992), equation (2) can also be written as $H = H(z/\mu, L)$, where L is a vector of parameters that fully describes the Lorenz curve. Such a specification is useful for decomposing the influence of changes of income growth, from that of income distribution, on poverty. This is also convenient for analyzing the theoretical 'growth elasticity' of poverty with respect to mean income, under the assumption that the Lorenz curve does not change (Kakwani, 1993). This theoretical elasticity is always negative, and moreover, for a given density at the poverty line, the absolute value of the elasticity is decreasing in H. However, as we are interested in how actual growth processes and spatial distributions of rural populations influence poverty, our focus is on estimating the empirical growth elasticity of poverty with respect to mean income. This elasticity does not hold the Lorenz curve constant (i.e., it is likely to shift with the data), and thus could take any sign or magnitude, which is consistent with the general form (2).

[6] There have been two approaches to estimating the poverty-reducing impacts of income growth in the literature. Some studies have decomposed the impacts on poverty arising from income growth as opposed to income distribution, with the former measured by the theoretical growth elasticity of poverty. This is the response of the headcount rate of poverty to the growth in mean income, which is the slope of the distribution of income at the poverty line (Kakwani, 1993). However, this approach requires the assumption of a

https://doi.org/10.1017/S1355770X17000353 Published online by Cambridge University Press

changes via income growth is a second hypothesis worth exploring empirically. As (3) indicates, the key variables for such an empirical analysis of both hypotheses are the spatial distribution of rural population s, the poverty headcount index H, a given poverty line z, and mean income μ.

4. 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, which represent s, are:

- the share (per cent) of the rural population on less favored agricultural land (henceforth s_1),
- the share (per cent) of the rural population in less favored agricultural areas (s_2),
- the share (per cent) of the rural population on remote less favored agricultural land (s_3), and
- the share (per cent) of the rural population on less favored agricultural lands located 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,[7] we obtain our cross-country measures of a given poverty line z, the poverty headcount index H, and mean income μ from PovcalNet, the online 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 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.[8] 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

constant Lorenz curve, which needs to be specified or fitted to the data. See, for example, Datt and Ravallion (1992), Kakwani (1993), Kakwani and Pernia (2000), Kraay (2006) and Son and Kakwani (2008). An alternative approach is to estimate the growth elasticity of poverty with respect to mean income empirically, where the change in poverty between two periods of time is explained by the growth of income. See, for example, Ravallion (1997, 2001, 2012), Ravallion and Chen (1997), Dollar and Kraay (2002), Bourguignon (2003) and Adams and Page (2005).

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

[8] 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 was 1998, and for Kenya 1997.

Table 2. Descriptive statistics of key poverty analysis variables

Key variables	Descriptive statistics: Mean	Median	Standard deviation
Initial headcount poverty rate (% of population), H	46.41	42.85	29.56
Annualized growth (%) in the poverty rate (US$2/day), $\gamma(H)$	−7.70	−4.26	10.28
Annualized growth (%) in the mean survey income, $\gamma(\mu)$	3.36	3.32	3.52
Annualized poverty-adjusted growth (%) in the mean survey income, $\gamma(\mu)(1 - H)$	1.74	1.11	2.41
Annualized growth (%) in household private consumption per capita	3.17	3.11	3.39
Annualized poverty-adjusted growth (%) in household private consumption per capita	1.96	1.58	2.17
Gini index, initial survey year	42.40	41.85	8.76
Share (%) of rural population on less favored agricultural land (2000), s_1	38.15	38.37	20.95
Share (%) of rural population in less favored agricultural areas (2000), s_2	40.04	41.37	20.79
Share (%) of rural population located on remote less favored agricultural land (2000), s_3	8.50	7.06	8.40
Share (%) of rural population on less favored agricultural land located on remote land (2000), s_4	24.74	23.55	18.81

Notes: Based on a sample of 83 developing countries. See online appendix tables A1–A3.

the poverty line. We follow Ravallion (2012) and choose a poverty line z of US$2 per person per day at 2005 PPP. In the initial survey year, the median poverty headcount index across all 83 countries was 42.85 per cent, but ranged widely from 0.29 to 95.44 per cent. By the final survey year, the median poverty headcount was 27.86 per cent, and it varied from 0.08 to 93.49 per cent.

Mean income μ is the average monthly (2005 PPP US$) 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 US$100 across all 83 countries, and ranged from US$24 to 2,003. In the final survey year, median income was US$115, and varied from US$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. Table 2 summarizes the descriptive statistics for the key variables used in the poverty analysis for our sample of 83 developing countries.

We also employ a number of control variables in our analysis, following the approach of similar poverty analyses.[9] 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

[9] See, for example, Dollar and Kraay (2002), Adams and Page (2005), Kraay (2006) and Ravallion (2012).

https://doi.org/10.1017/S1355770X17000353 Published online by Cambridge University Press

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).

5. Estimation strategy and results

Our estimation strategy follows previous literature that estimates the growth elasticity of poverty with respect to mean income empirically, where the change in poverty between two periods of time is explained by the growth of income (Ravallion, 1997, 2001, 2012; Ravallion and Chen, 1997; Dollar and Kraay, 2002; Bourguignon, 2003; Adams and Page, 2005). As noted in the Introduction, this literature generally confirms that the estimated growth elasticity of poverty is positive, although initial income inequality can also mitigate the poverty-reducing impact of income growth. In addition, Ravallion (2012) also examines whether initial level of poverty affects directly the change in poverty over two periods of time, or whether initial poverty exerts a significant indirect impact via the elasticity of poverty reduction with respect to growth.

Consequently, 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 that of Ravallion (2012). Thus, our basic regression is

$$\gamma_i(H_{it}) = \alpha_0 + \alpha_1 \ln(v_{it-\tau}) + (\beta_0 + \beta_1 v_{it-\tau})\, \gamma_i(\mu_{it}) + w_{it}, \tag{4}$$

where i is each country observation, t is the final survey date, τ is the length of time between surveys, and ω_{it} is the error term. In equation (1), the dependent variable of the regression is

$$\gamma_i(H_{it}) \equiv \ln\left(\frac{H_{it}}{H_{it-\tau}}\right)/\tau,$$

which is the annualized change in log headcount poverty rate for US$2 a day between surveys, and thus represents growth in poverty.[10] As noted above, across our sample of 83 countries, the median survey spell is eight years, and it varies from two to eleven years (i.e., the full 2000–2012 period). A standard hypothesis in the literature is that changes in poverty over time will be influenced by growth in income (Ravallion, 2001, 2012; Dollar and Kraay, 2002; Adams and Page, 2005; Kraay, 2006). That is, as the mean per capita income across surveyed households rises, one would expect their average poverty rate to fall. Thus, a key explanatory variable in determining changes in poverty between surveys in equation (1) is the annual growth in income per person, which is represented by the annualized change in log survey mean income between surveys $\gamma_i(\mu_{it}) \equiv \ln(\mu_{it}/\mu_{it-\tau})/\tau$.

[10] As a robustness check on our regression results, we follow Ravallion (2012) and replicate our analysis with a US$1.25 per day poverty line, which we find gives similar results to the US$2 a day poverty line.

https://doi.org/10.1017/S1355770X17000353 Published online by Cambridge University Press

Equation (4) also specifies that the change in poverty over time could be influenced by the initial level of another variable of interest $v_{it-\tau}$. In Ravallion (2012), this variable of interest is the initial poverty level $H_{it-\tau}$. In our analysis, we are also interested in how each of the four spatial distribution variables in 2000, i.e., $s_{kit-\tau}$, might influence the change in poverty. As indicated in (4), any such variable of interest could have a *direct impact* on changes in poverty over time, $\alpha_1 \ln(v_{it-\tau})\gamma_i(\mu_{it})$, or it could affect the poverty-reducing impact of income growth, $(\beta_0 + \beta_1 v_{it-\tau})\gamma_i(\mu_{it})$.

It follows that two tests of restrictions on the various parameters estimated by (4) determine the direct and indirect influence of any variable of interest $v_{it-\tau}$ on the annualized change in poverty (Ravallion, 2012). 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 is $(1 - v_{it-\tau})\gamma_i(\mu_{it})$. From (4), the expected sign of the coefficient of this regressor is negative. Thus, in the case that both restrictions $\alpha_1 = 0$ and $\beta_0 + \beta_1 = 0$ hold, then the regression becomes

$$\gamma_i(H_{it}) = \alpha_0 + \beta_1(1 - v_{it-\tau})\gamma_i(\mu_{it}) + w_{it}, \quad \beta_1 < 0.$$

Our strategy for estimating (4) 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 (4), 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 (4) 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 'poverty-adjusted' growth rate is influenced by the 'spatial distribution-adjusted' growth rate, we estimate IV, SUR and 3SLS regressions of (4) taking this into account. That is, if $H_{it-\tau}$ is affected by any $s_{kit-\tau}$, which is a possibility implied by equation (3), then $(1 - H_{it-\tau})\gamma_i(\mu_{it})$ is determined by $(1 - s_{kit-\tau})\gamma_i(\mu_{it})$. 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 (4), 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.[11] 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 $(1 - H_{it-\tau})\gamma_i(\mu_{it})$ is the relevant

[11] As explained in Ravallion (2001, 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. Another possible measurement error is that the PovcalNet database combines surveys based on income and expenditure (Smeeding and Latner, 2015). These two possible measurement errors are the main rationale for employing the growth rate in private consumption per capita from the national accounts as an instrument for the growth in mean survey income from the PovcalNet database.

Table 3. Estimates of the effect of the spatial distribution of the rural population $s_{4it-\tau}$ and income growth $\gamma_i(\mu_{it})$ on the proportionate change in poverty $\gamma_i(H_{it})$

	Complete specification		Dropping initial ln s_4		Imposing homogeneity	
	OLS (1)	IV (2)	OLS (3)	IV (4)	OLS (5)	IV (6)
Constant	−0.052 (−1.243)	0.514 (0.856)	−0.023 (−1.722)†	0.328 (0.535)	−0.020 (−2.136)*	0.119 (1.114)
Share (%) of the rural population in 2000 on less favored agricultural lands on remote land, ln$s_{4it-\tau}$	0.010 (0.724)	−0.162 (−0.623)	–	–	–	–
Growth rate, annualized change in log survey mean, $\gamma_i(\mu_{it})$	−2.225 (−3.843)**	−12.541 (−1.305)	−2.487 (−5.516)**	−8.317 (−1.197)	–	–
Growth rate interacted with 2000 spatial distribution variable, $\gamma_i(\mu_{it})s_{4it-\tau}$	3.120 (1.450)	39.609 (0.655)	4.198 (2.713)**	−14.137 (−0.269)	–	–
Spatial distribution-adjusted growth rate, $\gamma_i(\mu_{it}) \cdot (1 - s_{4it-\tau})$	–	–	–	–	−2.097 (−5.018)**	−7.187 (−1.919)*
Observations	80	79	80	79	80	79
R^2	0.33	–	0.33	–	0.31	–
Log likelihood (*F*-test when imposing homogeneity)	32.02**	22.62**	84.18**	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 US$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.

regressor. When homogeneity is imposed on (4), 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 is significant, and their inclusion did not change, or improve, the poverty-adjusted growth regression results. 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 3 depicts the results of our third set of regressions.[12] Only the estimations corresponding to the share (per cent) 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

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

https://doi.org/10.1017/S1355770X17000353 Published online by Cambridge University Press

other three s_k spatial distribution measures (see supplementary statistical tables A1–A3 in online appendix A). In all regressions in table 3, 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 $(1 - s_{kit-\tau})\gamma_i(\mu_{it})$ 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 ranges 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 (4).

Repeating the regressions of table 3 but using the other three s_k spatial distribution measures instead of s_4 produces a similar outcome (see online appendix tables A1–A3).[13] When homogeneity is imposed, the coefficient on the spatial distribution-adjusted growth rate $(1 - s_{kit-\tau})\gamma_i(\mu_{it})$ is significant and negative, but only in the OLS and not the IV estimations. For the regressions using the share (per cent) of the rural population on less favored agricultural land $s_{1it-\tau}$ to adjust growth, the estimated elasticity is −1.40, for the share (per cent) of the rural population on less favored agricultural areas $s_{2it-\tau}$ the elasticity is −1.59, and for the share (per cent) of the rural population on remote less favored agricultural land $s_{3it-\tau}$ the elasticity is −1.67.

In the final set of regressions, we estimate IV, SUR and 3SLS poverty-adjusted growth regressions, allowing for the possibility that the poverty adjusted growth rate is determined by the spatial distribution adjusted growth rate 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. Thus, for these regressions, the relevant system of equations is

$$\gamma_i(H_{it}) = \alpha_0 + \beta_1(1 - H_{it-\tau})\gamma_i(\mu_{it}) + w_{it}, \tag{4a}$$

$$(1 - H_{it-\tau})\gamma_i(\mu_{it}) = \delta_0 + \delta_1(1 - s_{kit-\tau})\gamma_i(\mu_{it}) + \varepsilon_{it}, \quad k = 1, \ldots, 4. \tag{4b}$$

In all regressions of (4a) and (4b), and for all spatial distribution measures of $s_{kit-\tau}$ the results are robust, and the coefficients significant and with the expected signs (see online appendix tables A1–A3). 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 4 depicts the 3SLS estimations corresponding to the share (per cent) of the rural population in 2000 on less favored agricultural lands on remote land (s_4). The elasticity

[13] In the case of s_3, neither the null $\alpha_1 = 0$ nor the homogeneity restriction $\beta_0 + \beta_1 = 0$ can be rejected. For s_1 and s_2, the null hypothesis $\alpha_1 = 0$ cannot be rejected as well; however, the homogeneity test suggests that the restriction $\beta_0 + \beta_1 = 0$ can be rejected. Further estimations and tests of estimations of (4) without the s_1 and s_2 variables and imposing homogeneity indicate that this restriction should apply. See online appendix tables A1–A3 for further details.

Table 4. 3SLS estimates of the effect of spatial distribution-adjusted growth $(1 - s_{4it-\tau})\gamma_i(\mu_{it})$ 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**	94.17**	3.77**	17.90**

Notes: The dependent variable in the first equation is the annualized change in log poverty rate for US$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.

of the poverty-adjusted growth rate with respect to 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 using private consumption as an instrument 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 4 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.

6. Effects on poverty-reducing impacts of income growth

Table 5 summarizes the implications of our empirical results of each of the four s_k spatial distribution variables for the poverty-reducing impacts of growth in income per capita. For comparison, the table also shows the impacts on changes in poverty from growth in average income only. 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 per cent in average income growth in our sample of developing countries, from 3.36 to 6.88 per cent, would reduce poverty by an additional 4.97 per cent each year.

As table 5 indicates, this poverty-reducing effect of per capita income growth is altered significantly when we adjust income growth for each of the spatial population distribution variables, s_1, s_2, s_3 and s_4. A higher share of the rural population on less favored agricultural lands and areas diminishes the poverty-reducing impact of per capita income growth, whereas a lower share enhances the effect of income growth on lowering poverty.

For example, consider an annual per capita income rate of 3.4 per cent, which is the mean for the sample of 83 countries (see table 2). A country with a high share of rural population on less favored agricultural land s_1, such as 59 per cent (one-standard-deviation above the mean for all 83 countries), would expect to see a rate of poverty reduction of only 1.8 to 1.9 per cent per year. However, if 38 per cent of a country's population is on less favored agricultural land (the mean for all 83 countries), then poverty would be reduced by 2.7 to 2.9 per cent annually. If a country has only 17 of its rural population on less favored agricultural land (one-standard-deviation below the mean), then poverty would decline 3.6 to 3.9 per cent each year. As table 5 indicates, a similar pattern emerges for the other spatial distribution variables; as s_2, s_3 and s_4 increase, the poverty-reducing impact of income growth is diminished. A one-standard-deviation change (also 21 per cent) in the share of rural population located in less favored agricultural areas (s_2) would mean that poverty would decline by only 1.8 to 1.9 per cent 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 per cent, would lead to a rate of poverty reduction of 3.5 to 4.7 per cent annually. Finally, a one-standard-deviation change in the share

https://doi.org/10.1017/S1355770X17000353 Published online by Cambridge University Press

Table 5. Effects of the spatial distribution of rural population on the poverty-reducing impact of growth in income per capita

Key spatial distribution variable	Estimated parameters β_1		δ_1		Poverty-reducing impact of growth
Share (%) of rural population on less favored agricultural land, s_1	−2.15 (−3.85)**	−2.36 (−3.76)**	0.61 (8.97)**	0.59 (6.19)**	
Evaluated at:					
$s_1 = 17.2\%$					−3.63% to − 3.90%
$s_1 = 38.1\%$					−2.71% to − 2.91%
$s_1 = 59.1\%$					−1.79% to − 1.93%
Share (%) of rural population in less favored agricultural areas, s_2	−2.15 (−3.85)**	−2.39 (−3.99)**	0.65 (9.17)**	0.67 (6.63)**	
Evaluated at:					
$s_2 = 19.3\%$					−3.78% to − 4.32%
$s_2 = 40.0\%$					−2.81% to − 3.21%
$s_2 = 60.8\%$					−1.83% to − 2.10%
Share (%) of rural population on remote less favored agricultural land, s_3	−2.35 (−4.78)**	−2.92 (−6.113)**	0.53 (12.30)**	0.57 (10.50)**	
Evaluated at:					
$s_3 = 0.1\%$					−4.15% to − 5.61%
$s_3 = 8.5\%$					−3.80% to − 5.13%
$s_3 = 16.9\%$					−3.45% to − 4.66%
Share (%) of rural population on less favored agricultural land located on remote land, s_4	−2.37 (−4.81)**	−3.05 (−6.87)**	0.63 (12.51)**	0.69 (11.53)**	
Evaluated at:					
$s_4 = 5.9\%$					−4.74% to − 6.62%
$s_4 = 24.7\%$					−3.79% to − 5.30%
$s_4 = 43.6\%$					−2.85% to − 3.97%
Growth in average income only	Estimated parameter	% change in poverty at the mean		% change in poverty of one standard deviation change	
Annualized growth (%) in the mean survey income, $\gamma(\mu)$	−1.41	-4.74		4.97	

Notes: The estimates of the poverty-reducing impact of growth in income per capita are $\beta_1\delta_1(1 - s_{kit-\tau}/100)\gamma(\mu_{it})$ for each spatial population distribution variable s_k, where the annualized growth rate in survey income per capita $\gamma(\mu)$ is evaluated at the mean for the sample of 83 countries, which is 3.36% (see table 2). Parameter estimates for β_1 and δ_1 are from three-stage least squares (3SL3) estimations, with and without controls. t-ratios are in parentheses; **significant at the 1% level; $N = 79$ or 80. See also online appendix tables A1–A3.
The values for each spatial distribution variable correspond, respectively, to one-standard-deviation below the mean, the mean, and one-standard-deviation above the mean for the sample of 83 developing countries in 2000 (see table 2).

of rural population on less favored agricultural land located on remote land (s_4) by 19 per cent causes the poverty-reducing impact of average income growth to be only 2.9 to 4 per cent per year.[14]

In sum, our estimation results confirm that the spatial distribution of rural population 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 population 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, as the results in table 5 indicate.

7. Implications for climate change impacts on poverty

There is growing evidence that climate change and associated risks are likely to impact adversely the livelihoods of populations living in marginal and remote agricultural areas, both directly through causing declining agricultural productivity and income, or indirectly through affecting land and natural resource use (McSweeney, 2005; Carter *et al.*, 2007; Debela *et al.*, 2012; López-Feldman, 2014; Wunder *et al.*, 2014; Angelsen and Dokken, 2015; Hallegatte *et al.*, 2015; Narloch and Bangalore, 2016; Robinson, 2016). An analysis of environmental reliance, poverty and climate vulnerability among more than 7,300 households in forest-adjacent communities in 24 developing countries found that the poor tend to live in the less favorable areas, generate 29 per cent of their income from environmental resources, and are more exposed to extreme and variable climate conditions (Angelsen and Dokken, 2015). The poor rural households from Sub-Saharan Africa located in less-favored arid areas already experience declining incomes directly from extreme climate conditions and from high forest loss, and face further loss of future forest benefits from climate change (Angelsen and Dokken, 2015). In rural Uganda, poorer households attempt to diversify their income sources from use of forests and outside employment; however, large negative shocks, such as droughts and other climate-related disasters force more reliance on forest resources, which leads to more land and natural resource degradation especially among those households with below-average and poor quality land holdings (Debela *et al.*, 2012). In Vietnam, poorer rural households are much more exposed to multiple environment risks, including climate change, and such risk induce not only lower consumption levels but also lower consumption growth over time (Narloch and Bangalore, 2016). Finally, the probability of participation in resource extraction increases considerably when these households experience climate-related impacts and other shocks to their agricultural systems (López-Feldman, 2014).

[14] Note that although the range of elasticity estimates depicted in table 5 and reported here are for the 3SLS estimations with and without control variables, our preferred estimations are with controls. For example, using the elasticity estimates from columns (5) and (6) in table 2, at an initial distribution for the share (per cent) of the rural population in 2000 on remote less favored agricultural lands (s_4) of 6 per cent (about one standard deviation below the mean), one can expect a rate of poverty reduction of 4.7 per cent per year. However, if s_4 is 44 per cent (about one standard deviation above the mean), the rate of poverty reduction is only 2.8 per cent per annum. From table 2, the mean for the share (per cent) of the rural population in 2000 on less favored agricultural lands on remote land (s_4) is around 25 per cent and the standard deviation is 19 per cent. Mean annualized growth in survey income is 3.36 per cent. Using these figures and the elasticity estimates reported in columns (5) and (6) in table 4, we get $-2.37 \times 0.63 \times (1 - 0.06) \times 3.36 = 4.7$, and $-2.37 \times 0.63 \times (1 - 0.44) \times 3.36 = 2.8$.

https://doi.org/10.1017/S1355770X17000353 Published online by Cambridge University Press

Overall, cross-country evidence appears to confirm that for poor households in LFAA, 'forests and other wildlands are 'options of last resort', which people only select as their primary safety net response when shocks are particularly severe and when, due to adverse household and village conditioning factors, they do not have any easier way out' (Wunder *et al.*, 2014: S39).

Thus, the livelihoods of populations living in marginal and remote agricultural areas already highly dependent on agricultural land and resource commons, and their economic activities display low and even declining labor productivity (Barbier, 2010). Geographical isolation further raises substantially the costs of agricultural commerce and crop production in remote markets, distorts or insulates these markets from economy-wide policy changes, and thus discourages smallholder market participation and investment in improved farming systems and land management (Coxhead *et al.*, 2002; González-Vega *et al.*, 2004; Holden *et al.*, 2004; Shively and Fisher, 2004; Jansen *et al.*, 2006; Barrett, 2008; Narain *et al.*, 2008; Ansoms and McKay, 2010). Climate change impacts, such as drought, erosion, increases in salinity, and changes in precipitation, temperature and hydrology, may impact directly such households through causing declining agricultural productivity and income, or indirectly through causing more overuse and degradation of land and natural resources. Both impacts can lead to larger numbers of rural populations concentrated on less favorable agricultural lands and areas which, as our analysis indicates, will diminish the poverty-reducing impacts of growth in average incomes (see table 5).

The regional scale of climate change impacts may also influence the spatial distribution of rural populations in some developing countries. If changes in precipitation, hydrology, sea level rise, and the frequency of drought occur over significantly large areas, then the likely result is an increase in the unfavorable regions for agricultural production in developing countries (i.e., areas A and B in figure 1). Thus, the share of rural populations on less-favored agricultural lands could increase (Hallegatte *et al.*, 2015, 2017). A number of agricultural regions in the developing world have been identified as climate change 'hotspots' that are vulnerable to biophysical decline from climate-induced impacts, including North Africa, the Sahel, the Horn of Africa, parts of southern Africa, Central America, the Andes, western China, Central Asia, and India and South Asia (de Sherbinin, 2014). From 2000 to 2030, agricultural land with poor biophysical conditions and productivity is expected to increase worldwide by 1–2.9 million ha annually, with climate change a major factor (Lambin and Meyfroidt, 2011). Case studies in China, Ethiopia, Mexico, Uganda, Rwanda, Chile, and Indonesia indicate declines in overall agricultural productivity due to climate change of around 3 to 7 per cent per year, an order of magnitude larger than the estimated cost of remediation (GCEC, 2014). Around 4 to 9 per cent of coastal agricultural areas in developing countries are likely to be exposed to salt water intrusion and storm surge damages caused by the accelerated sea-level rise accompanying climate change (Dasgupta *et al.*, 2011).

Already there is evidence that the concentration of rural population in less favorable agricultural regions has increased since 2000. For example, Barbier *et al.* (2016) find that around 1.5 billion rural people in 2010 lived on less favored agricultural land, which is a 14 per cent increase in the nearly 1.32 billion located on this land in 2000 (see table 1). If this trend continues, and is accelerated by the impacts of future climate change, it could possibly increase the share of rural populations located in unfavorable agricultural areas. As our analysis suggests, the poverty-reducing impacts of per capita income growth in developing countries will be further diminished.

8. 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 time of travel 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).

Our spatial analysis of the distribution of rural populations across 124 developing countries in 2000 reveals that around 36 per cent were located on less favored agricultural land, and over 37 per cent in less favored agricultural areas. About 8 per cent of the rural population was concentrated on remote less favored agricultural lands, which also accounted for 22 per cent of all the rural population on less favored agricultural land in developing countries. Given this evidence confirming that a substantial share 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 population 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.

Nevertheless, fostering economic growth may still be one of the most effective ways over the long-term in reducing widespread poverty in such disadvantaged agricultural regions. After all, all of our estimates indicate that the poverty-reducing impact of income growth is still positive, even after adjusting for the spatial distribution of rural population in marginal and remote agricultural areas. Of particular concern is that, as our analysis bears out, large concentrations of rural populations in such disadvantaged agricultural areas clearly has a retarding impact on the poverty-reducing effect of overall growth.

Promoting economic growth over the long-term may also be the most effective means of reducing the vulnerability of developing countries to the impacts of climate change (Hallegatte *et al.*, 2015, 2017). But the changes in precipitation, hydrology, sea level rise, and the frequency of drought resulting from climate change are likely to increase in the unfavorable regions for agricultural production in developing countries. In addition, if climate change leads to a significantly larger share of rural populations on less favored agricultural land, then our analysis suggests that growth in average incomes may have less of a poverty-reducing impact in developing countries. Moreover, the income-generating benefits of economic growth may bypass rural households coping with the low productivity and high degradation of less favored agricultural lands, especially in remote locations with limited market access.

Thus, growth alone may be necessary but not sufficient to address the problem posed by large concentrations of rural populations on less favorable and remote agricultural areas, as well as the vulnerability of these populations to climate change. Instead, such rural poverty 'sinks' may need more direct measures. As the World Bank (2008: 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 is those people 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.

Agricultural research, rural roads and education appear to be the most effective investments in improving land productivity and reducing poverty in less favored agricultural regions (Fan and Hazell, 2001; Fan and Chan-Kang, 2004; Barrett, 2008; Barbier, 2010; Emran and Hou, 2013). Evidence from China, India and Uganda indicate that investing in poorer agricultural regions may yield higher returns than similar investments in irrigated and high potential rainfed areas, mainly because the former areas suffer from chronic underinvestment compared to the better agricultural lands (Fan and Hazell, 2001; Fan and Chan-Kang, 2004). In some regions, such as low-lying coastal agricultural areas, investments are needed to control the immediate threat of sea level rise, increasing flooding and salt water intrusion. For example, studies of the current capacity, infrastructure and coping strategies of rural communities in coastal Bangladesh reveal that they are inadequate to deal with the likely increase in coastal cyclone and storm surge hazards associated with climate change (Dasgupta *et al.*, 2010; Paul and Routray, 2011). Although the estimated additional investment necessary to cope with these hazards in Bangladesh is around US$2.4 billion with an annual recurrent cost of US$50 million, these costs are likely to be half of the additional financial costs of future agricultural damages and other risks associated with climate change (Dasgupta *et al.*, 2010).

Supplementary material

The supplementary material for this article can be found at https://doi.org/10.1017/S1355770X17000353

Acknowledgements. The research was supported by the Economics of Land Degradation (ELD) Initiative, through financial support by the Deutsche Gesellschaft für Internationale Zusammernabeit (GIZ), Germany, under grant #81163559. We benefited from the advice and comments of Stephane Hallegatte, Richard Thomas, Emmanuelle Quillerou, Mark Schauer, Mike Toman, Stephan Kroll, Dale Manning and Hannes Etter.

References

Adams Jr RH and Page J (2005) Do international migration and remittances reduce poverty in developing countries? *World Development* **33**(10), 1645–1669.

Angelsen A and Dokken T (2015) Environmental reliance, climate exposure, and vulnerability: a cross-sectional analysis of structural and stochastic poverty, Policy Research Working Paper 7474, World Bank, Washington, DC.

Ansoms A and McKay A (2010) A quantitative analysis of poverty and livelihood profiles: the case of rural Rwanda. *Food Policy* **35**(6), 584–598.

Barbier EB (2010) Poverty, development and environment. *Environment and Development Economics* **15**(6), 635–660.

Barbier EB, López RE and Hochard JP (2016) Debt, poverty and resource management in a rural smallholder economy. *Environmental and Resource Economics* **63**(2), 411–427.

Barrett CB (2008) Smallholder market participation: concepts and evidence from eastern and southern Africa. *Food Policy* **33**(4), 299–317.

Barrett CB and Bevis LEM (2015) The self-reinforcing feedback between low soil fertility and chronic poverty. *Nature Geoscience* **8**(12), 907–912.

Battacharya H and Innes R (2013) Income and the environment in rural India: is there a poverty trap? *American Journal of Agricultural Economics* **95**(1), 42–69.

Bourguignon F (2003) The growth elasticity of poverty reduction: explaining heterogeneity across countries and time periods. In Eicher TS and Turnovsky SJ (eds). *Inequality and Growth: Theory and Policy Implications*. Cambridge, MA: MIT Press, pp. 3–26.

Carter MR, Little PD, Mogues T and Negatu W (2007) Poverty traps and natural disasters in Ethiopia and Honduras. *World Development* **35**, 835–856.

CGIAR (TAC Secretariat) (1999) CGIAR study on marginal lands: report on the study on CGIAR research priority for marginal lands, Marginal Lands Study Paper No. 1, Food and Agricultural Organization of the United Nations, Rome.

Comprehensive Assessment of Water Management in Agriculture (CAWMA) (2008) *Water for Food, Water for Life: A Comprehensive Assessment of Water Management in Agriculture*. London: Earthscan and International Water Management Institute, Colombo, Sri Lanka.

Coomes OT, Takasaki Y and Rhemtulla JM (2011) Land-use poverty traps identified in shifting cultivation systems shape long-term tropical forest cover. *Proceedings of the National Academy of Sciences* **108**(304), 13925–13930.

Coxhead I, Shively GE and Shuai X (2002) Development policies, resource constraints, and agricultural expansion on the Philippine land frontier. *Environment and Development Economics* **7**(2), 341–364.

Dasgupta S, Huq M, Khan ZH, Ahmed MMZ, Mukherjee N, Khan MF and Pandey K (2010) Vulnerability of Bangladesh to cyclones in changing climate: potential damages and adaptation cost, Policy Research Working Paper 5280, The World Bank, Washington, DC.

Dasgupta S, Laplante B, Murray S and Wheeler D (2011) Exposure of developing countries to sea-level rise and storm surges. *Climatic Change* **106**(4), 567–579.

Datt G and Ravallion M (1992) Growth and redistribution components of changes in poverty measures: a decomposition with applications to Brazil and India in the 1980s. *Journal of Development Economics* **38**(2), 275–295.

Debela B, Shively GE, Angelsen A and Wik M (2012) Economic shocks, diversification, and forest use in Uganda. *Land Economics* **88**(1), 139–154.

de Sherbinin A (2014) Climate change hotspots mapping: what have we learned? *Climatic Change* **123**, 23–37.

Dollar D and Kraay A (2002) Growth is good for the poor. *Journal of Economic Growth* **7**(3), 195–225.

Emran MS and Hou Z (2013) Access to markets and rural poverty: evidence from household consumption in China. *Review of Economics and Statistics* **95**(2), 682–697.

Fan S and Chan-Kang C (2004) Returns to investment in less-favoured areas in developing countries: a synthesis of evidence and implications for Africa. *Food Policy* **29**(4), 431–444.

Fan S and Hazell P (2001) Returns to public investment in the less-favored areas of India and China. *American Journal of Agricultural Economics* **83**(5), 1217–1222.

Ferreira FHG (2012) Distributions in motion: economic growth, inequality, and poverty dynamics, chapter 13. In Jefferson PN (ed.). *The Oxford Handbook of the Economics of Poverty*. Oxford: Oxford University Press, pp. 427–462.

Gastwirth JL (1971) A general definition of the Lorenz curve. *Econometrica* **39**(6), 1037–1039.

Gerber N, Nkonya E and von Braun J (2014) Land degradation, poverty and marginality, chapter 12. In von Braun J and Gatzweiler FW (eds). *Marginality: Addressing the Nexus of Poverty, Exclusion and Ecology*. Berlin: Springer, pp. 181–202.

Global Commission on the Economy and Climate (GCEC) (2014) *The New Climate Economy Report*, Chapter 3–Land Use. Better Growth, Better Climate. Available at http://static.newclimateeconomy.report/wp-content/uploads/2014/08/NCE_Chapter3_LandUse.pdf

Gollin D and Rogerson R (2014) Productivity, transport costs and subsistence agriculture. *Journal of Development Economics* **107**, 38–48.

González-Vega C, Rodríguez-Meza J, Southgate D and Maldonado JH (2004) Poverty, structural transformation, and land use in El Salvador: learning from household panel data. *American Journal of Agricultural Economics* **86**(5), 1367–1374.

Hallegatte S, Bangalore M, Bonanigo L, Fay M, Kane T, Narloch U, Rozenberg J, Treguer D and Vogt-Schilb A (2015) *Shock Waves: Managing the Impacts of Climate Change on Poverty*. Washington, DC: The World Bank.

Hallegatte S, Vogt-Schilb A, Bangalore M and Rozenberg J (2017) Unbreakable: Building the Resilience of the Poor in the Face of Natural Disasters, Climate Change and Development Series, Overview booklet, World Bank, Washington, DC.

Holden S, Shiferaw B and Pender J (2004) Non-farm income, household welfare, and sustainable land management in a less-favoured area in the Ethiopian highlands. *Food Policy* **29**(4), 369–392.

Jalan J and Ravallion M (2002) Geographic poverty traps? A micro model of consumption growth in rural China. *Journal of Applied Econometrics* **17**, 329–346.

Jansen HGP, Rodriguez A, Damon A, Pender J, Chenier J and Schipper R (2006) Determinants of income-earning strategies and adoption of conservation practices in hillside communities in rural Honduras. *Agricultural Systems* **88**, 92–110.

Kakwani N (1993) Poverty and economic growth with application to Côte d'Ivoire. *Review of Income and Wealth* **39**(2), 121–139.

Kakwani N and Pernia EM (2000) What is pro-poor growth? *Asian Development Review* 16(1), 1–22.

Kraay A (2006) When is growth pro-poor? Evidence from a panel of countries. *Journal of Development Economics* **80**(1), 198–227.

Lambin EF and Meyfroidt P (2011) Global land use change, economic globalization, and the looming land scarcity. *Proceedings of the National Academy of Sciences* **108**(9), 3465–3472.

Lang C, Barrett CB and Naschold F (2013) Targeting maps: an asset-based approach to geographic targeting. *World Development* **41**, 232–244.

López-Feldman A (2014) Shocks, income and wealth: do they affect the extraction of natural resources by households? *World Development* **64**, S91–S100.

McSweeney K (2005) Natural insurance, forest access, and compound misfortune: forest resources in smallholder coping strategies before and after Hurricane Mitch in northeastern Honduras. *World Development* **33**(9), 1453–1471.

Narain U, Gupta S and van't Veld K (2008) Poverty and resource dependence in rural India. *Ecological Economics* **66**(1), 161–176.

Narloch U and Bangalore M (2016) Environmental risks and poverty: analyzing geo-spatial and household data from Vietnam, Policy Research Working Paper 7763, World Bank, Washington, DC.

Nelson A (2008) Travel time to major cities: a global map of accessibility, Global Environment Monitoring Unit–Joint Research Centre of the European Commission, Ispra Italy. Available at http://gem.jrc.ec.europa.eu/.

Paul SK and Routray JK (2011) Household response to cyclone induced surge in coastal Bangladesh: coping strategies and explanatory variables. *Natural Hazards* **57**(2), 477–499.

Pender J and Hazell P (2000) Promoting sustainable development in less-favored areas: overview, Brief 1. In Pender J and Hazell P (eds). *Promoting Sustainable Development in Less-Favored Areas, 2020 Vision Initiative, Policy Brief Series, Focus 4*. Washington, DC: International Food Policy Research Institute. Brief 1, pp. 3–4.

Ravallion M (1997) Can high-inequality developing countries escape absolute poverty? *Economics Letters* **56**(1), 51–57.

Ravallion M (2001) Growth, inequality and poverty: looking beyond averages. *World Development* **29**(11), 1803–1815.

Ravallion M (2012) Why don't we see poverty convergence? *American Economic Review* **102**(1), 504–523.

Ravallion M and Chen S (1997) What can new survey data tell us about recent changes in distribution and poverty? *World Bank Economic Review* **11**(2), 357–382.

Robinson EJZ (2016) Resource-dependent livelihoods and the natural resource base. *Annual Reviews of Resource Economics* **8**, 281–301.

Shively GE and Fisher M (2004) Smallholder labor and deforestation: a systems approach. *American Journal of Agricultural Economics* **86**(5), 1361–1366.

Smeeding T and Latner JP (2015) PovcalNet, WDI and 'all the Ginis': a critical review. *Journal of Economic Inequality* **13**(4), 603–629.

Son HH and Kakwani N (2008) Global estimates of pro-poor growth. *World Development* **36**(6), 1048–1066.

World Bank (2003) *World Development Report 2003*. Washington, DC: World Bank.

World Bank (2008) *World Development Report 2008: Agricultural Development*. Washington, DC: World Bank.

World Bank (2014) *World Development Indicators*. Washington, DC: World Bank. Available at http://databank.worldbank.org/data/home.aspx.

Wunder S, Börner J, Shively GE and Wyman M (2014) Safety nets, gap filling and forests: a global-comparative perspective. *World Development* **64**, S29–S42.

Zhang X and Fan S (2004) How productive is infrastructure? A new approach and evidence from rural India. *American Journal of Agricultural Economics* **86**(2), 494–501.

Cite this article: Barbier EB, Hochard JP (2018). Poverty, rural population distribution and climate change. *Environment and Development Economics* **23**, 234–256. https://doi.org/10.1017/S1355770X17000353