Institute of Social Studies

Working Paper

No. 468

Spatial inequalities explained:

Evidence from Burkina Faso

Johannes Gräb and Michael Grimm

February 2009

ISSN 0921-0210

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Spatial inequalities explained — Evidence from Burkina Faso*

Johannes Gräb†
University of Göttingen, Germany

and

Michael Grimm‡
Institute of Social Studies, The Hague, The Netherlands

Abstract—Empirical evidence suggests that regional disparities in incomes are often very high, that these disparities do not necessarily disappear as economies grow and that these disparities are itself an important driver of growth. We use a novel approach based on multilevel modeling to decompose the sources of spatial disparities in incomes among households in Burkina Faso. We show that spatial disparities are not only driven by the spatial concentration of households with particular endowments but to a large extent also by disparities in community endowments. Climatic differences across regions do also matter, but to a much smaller extent.

Key words: Spatial inequality, poverty, multilevel modeling, decomposition, Sub-Saharan Africa.

***JEL* codes:** C21, I32, O12, R12.

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*We thank the Institut National de la Statistique et de la Démographie (INSD) in Burkina Faso for providing the household survey data. We are also grateful to Hartmut Janus and Bakary Kindé for their great hospitality and assistance during the data collection process in Burkina Faso. The paper benefited from discussions with Channing Arndt, Luc Christiansen, Pedro Goulart, Bert Helmsing, Jan van Heemst, Stephan Klasen, Jann Lay, Andrew McKay, Patrick Nolen, Robert Sparrow, Stefan Sperlich and Finn Tarp. Valuable comments were received at seminar presentations at ISS and the University of Göttingen and at the Nordic Conference on Development Economics (Stockholm, 2008), the ESRC Conference on 'Economic Growth in Developing Countries' (Brighton, 2008), the WIDER conference on 'Frontiers of Poverty Analysis' (Helsinki, 2008), the 55th North American Meetings of the Regional Science Association International (New York, 2008) as well as at the 2nd World Conference of the Spatial Econometric Association (New York, 2008). Financial support for this research by the German Research Foundation is greatly acknowledged. All remaining errors are of course ours.

† University of Göttingen, Department of Economics and Center for Statistics, Platz der Göttinger Sieben 3, 37073 Göttingen, Germany. Email: jgraeb@uni-goettingen.de.

‡ Institute of Social Studies, Kortenaerkade 12, P.O.Box 29776, 2502LT The Hague, The Netherlands. Email: grimm@iss.nl.

1 Introduction

Empirical evidence suggests that regional disparities in growth and poverty are often very high, that these regional disparities do not necessarily disappear as economies grow and develop and that these disparities are itself often an important driver of the overall performance of an economy.[1] Often such regional inequalities are closely linked to key policy choices (e.g. trade policy) and patterns of public spending. But in most cases lagging regions also suffer under infrastructure bottlenecks, adverse agroclimatic conditions, import competition and limited scope for non-agricultural activities.

Burkina Faso is one among many Sub-saharan African countries where the regional pattern of living standards is particularly puzzling. Some of the observed inequality can be related to cotton production given that cotton is the main export commodity of the Burkinabe economy. However, despite the cotton boom which Burkina Faso knew in the middle and end of the 1990s, some cotton producing provinces did grow slower than other non-cotton provinces. In particular the traditionally poor and arid North of the country knew a quite good development during that time. Hence, from these observations it is difficult to guess to what extent agro-climatic factors, trade exposure and population structure matter for disparities in the level and change in living standards. Explaining where such disparities come from could help to design development strategies and interventions to reduce them in a cost-effective way.

Standard poverty assessments usually address such issues simply by undertaking a rather descriptive analysis of growth patterns across regions and by performing decompositions of inequality indices by regional units. However, such decompositions make it very difficult to disentangle what is due to heterogeneity in household characteristics and what is due to heterogeneity in area-specific characteristics or endowments. In other words poor areas could simply be poor because households with poor endowments are geographically concentrated.

To deal with this problem, Ravallion and Wodon (1999) relied on two consecutive cross-sections of household survey data for Bangladesh to run separate regressions for each year and for each of the urban and rural sectors. They included a wide range of household characteristics and attributed the remaining part of the observed variance to geographic effects. They then undertake a number of robustness checks to exclude that there is a bias due to omitted household characteristics which are spatially correlated. The authors conclude that there are sizeable spatial differences in the returns to given household characteristics, i.e. the same household might be poor in one but not in the other region.

Another approach was chosen by Jalan and Ravallion (2002) and later by De Vreyer et al. (2009). They used several waves of panel-data to implement a quasi-differencing method to identify the impact of locally determined geographic and socioeconomic variables on household's consumption growth

[1] The 'Operationalizing Pro-Poor Growth Project', for instance, which was coordinated by the World Bank and British, French and German donors, shows various cases in point (see Besley and Cord (2007); Grimm et al. (2007)).

while removing unobserved household and community fixed effects. These authors find, for rural China and Peru respectively, robust evidence of geographic poverty traps and highlight in particular the socio-economic features of villages and the provision of public goods, such as rural roads, as important area-specific determinants.

Benson et al. (2005) have used alternatively spatially regression and geographically weighted regression techniques to allow regression error terms to be spatially correlated and to assess the degree to which determinants of poverty and the prevalence of poverty vary across space. For rural Malawi the authors find not much evidence for local poverty traps, characterized for instance by low agricultural productivity, and emphasize that the determinants of poverty vary spatially in their effects across the country. However, they find some evidence that regions with more opportunities for non-agricultural earnings and more markets, public infrastructure and services show less poverty.

While all these studies suggest that poverty reduction efforts have to be targeted at the sub-national level, they do not provide a decomposition of the variance in living standards observed within and between spatial units. In this paper we suggest a novel methodology to address this issue. We build a multilevel random coefficient model able to decompose the variance in living standards across four spatial levels; households, communities, provinces and (agro-climatic) regions.[2] Moreover, our model allows to decompose the variance measured on each level in a component accounting for the variance in level-specific characteristics and components accounting for a sorting of lower-level characteristics across these levels. For instance, the variance in households' living standards between communities might be driven by the variance in community-specific endowments and by a sorting of households with favorable and unfavorable characteristics across communities.

To implement our approach for Burkina Faso, we build a very detailed and exhaustive data set combining household living standard measurement survey data, population census data, agricultural survey data and a number of statistics collected at the provincial level.

The remainder of our paper is organized as follows. In Section 2 we describe spatial inequality and its development over time in Burkina Faso. In Section 3 we present our data and the empirical strategy. In Section 4 we discuss our results. In Section 5 we conclude.

2 Regional growth and inequality in Burkina Faso

Burkina Faso is one of the poorest countries in the world. GDP per capita is estimated at only PPP US$ 1,213 and according to the Human Development Index, the country was ranked 176th out of 177 countries (UNDP, 2007). It is a landlocked country in the middle of West-Africa with a population of roughly 13.4 million. It has a very low human capital base and only very few natural resources. The country depends highly on cotton exports, which account for

[2] Similar techniques have been applied by Bolstad and Manda (2001) and Ecob (1996) to study spatial inequality in child mortality and health.

almost 60 percent of total export earnings, as well as on international aid. More than 80 percent of the Burkinabe population lives in rural areas working predominantly in the agricultural sector, which suffers from very limited rainfall and recurrent severe droughts. The country experienced sustained growth with moderate poverty reduction during the last 15 years however accompanied by important variations over time and space (Grimm and Günther (2007)).

If income levels and growth rates as well as poverty shares are compared across Burkina's 13 regions (see Table1),[3] one can state that the Western regions, where the bulk of cotton is produced—Hauts Bassins, Mouhoun and Cascades—are richer than the remaining regions (abstracting from the two urban centers Ouagadougou and Bobo-Diolassou). However, in terms of growth in the subsequent period, the non-cotton and initially very poor Eastern regions—Sahel, Est and Centre-Nord—performed better than all cotton regions, despite the very favorable development of cotton exports and the widespread belief that cotton exports were the driver of Burkina Faso's growth. In terms of poverty, Hauts-Bassins has still, given its relatively high income level (by Burkinabe standards) moderate poverty without however any significant poverty reduction since 1994. Mouhon, another of the important cotton regions, had ever and has still very high poverty levels. The cotton region Cascade achieved to halve poverty between 1994 and 2003 (Grimm and Günther (2007)).

[3]The household survey data is presented in detail in Section 3.

Table 1: Descriptive Regional Growth and Poverty Statistics

	1994			1998				2003					
	Pop.-share	PC Exp*	P0**	Pop.-share	PC Exp*	Growth 94-98	P0**	Pop.-share	PC Exp*	Growth 98-03	Growth 94-03	P0**	Change in P0 94-03 (%points)
Burkina Faso	100	100	55.51	100	82	-17.5	61.81	100	108	31.5	8.5	47.20	-8.3
Eastern regions	32.9	69.3	68.44	23.9	70.9	63.0	72.18	22.6	89.2	65.3	39.5	46.90	-21.5
Sahel	5.5	74.2	62.88	6.4	67.5	-9.0	59.32	5.8	124.6	84.5	67.9	36.89	-26.0
Est	8.8	81.1	64.53	8.6	63.4	-21.9	66.74	8.5	100.6	58.7	24.0	42.05	-22.5
Centre-nord	8.8	69.7	65.04	8.9	51.2	-26.6	78.35	8.3	104.8	104.7	50.3	36.01	-29.0
Nord	9.8	55.6	78.09	9.6	54.8	-1.4	79.89	8.6	66.2	20.8	19.1	68.97	-9.1
Western regions	20.5	89.7	51.77	21.5	89.0	-18.2	59.13	22.8	82.6	22.1	-0.1	51.71	-0.1
Cascades	2.2	85.4	58.34	3.0	94.6	10.7	48.16	3.6	124.3	31.4	45.5	38.35	-20.0
Hauts Bassins***	8.1	95.1	40.18	8.0	75.7	-20.5	54.80	6.9	105.2	39.0	10.5	41.43	1.3
Mouhoun	10.2	86.2	59.52	10.6	65.7	-23.8	65.46	12.2	70.4	7.1	-18.4	61.55	2.0
Central regions	35.1	86.4	60.45	44.5	81.8	-18.8	65.15	42.5	79.2	27.4	-0.6	55.49	-5.0
Sud-ouest	4.9	108.7	54.12	4.2	62.0	-43.0	64.20	4.9	75.9	22.3	-30.2	57.94	3.8
Centre-ouest	10.2	90.2	61.89	10.7	76.1	-15.6	61.83	8.6	108.8	42.9	20.6	42.13	-19.8
Plateau	5.0	78.6	63.28	5.6	56.9	-27.7	67.67	6.1	78.3	37.6	-0.5	60.53	-2.7
Centre-est	8.0	81.3	57.42	8.0	71.2	-12.5	70.30	8.3	88.3	24.0	8.5	56.35	-1.1
Centre****	2.0	67.4	63.55	2.0	73.8	9.5	52.35	1.8	68.8	-6.8	2.0	66.48	2.9
Centre-sud	5.0	80.2	64.56	4.4	55.4	-31.0	67.33	4.3	65.1	17.6	-18.8	65.89	1.3
Urban Centers	11.6	246.7	10.38	10.1	282.4	-5.6	21.69	12.2	218.4	1.7	-4.0	16.38	6.0
Ouagadougou	8.2	258.8	8.44	7.3	255.6	-1.2	20.51	8.3	270.2	5.7	4.4	13.64	5.2
Bobo	3.4	217.8	15.03	2.8	173.9	-20.2	24.74	3.8	164.2	-5.6	-24.6	22.37	7.3

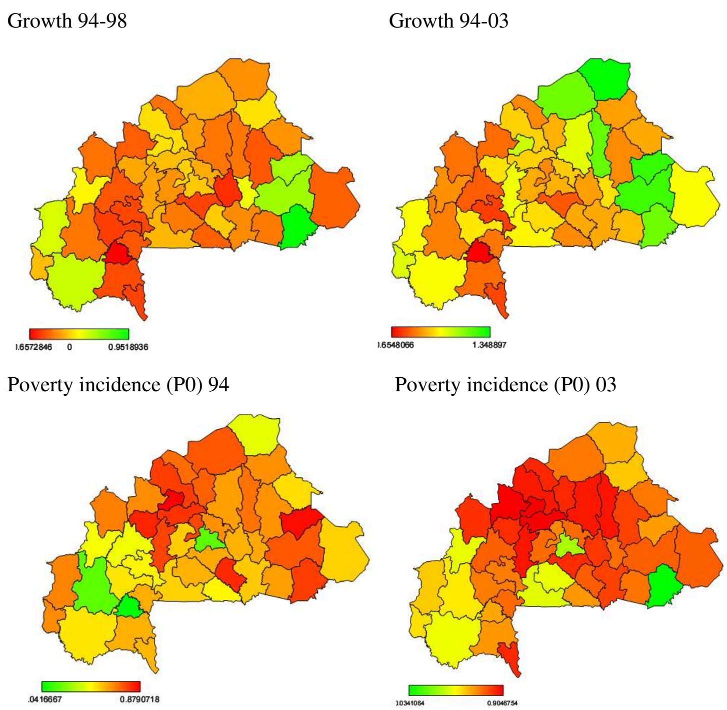
Source: EP1, EP2, EP3, estimations by the authors

** Average per capita expenditure in Burkina Faso 1994 = 100 ; ** Poverty headcount ratio, i.e. the share of the population below the poverty line*

**** Without Bobo ; **** Without Ouagadougou*

To see if the observed pattern of economic growth and poverty reduction follows a similar pattern on the provincial level, i.e. to see whether provinces in a given region develop similarly, we further disaggregate the data according to Burkina Faso's 45 provinces. The results are presented using maps (Figure 1). These maps indicate two important aspects. First, neither does economic growth occur on some widespread regional level nor does there seem to be a high regional concentration of poverty. The intensity of growth and poverty rather varies across provinces over the whole country. Second, the set of provinces with the highest poverty incidence changes over time. Similar to what Benson et al. (2005) have found for rural Malawi, there do not seem to be spatial poverty traps in Burkina Faso.

Figure 1: Growth and Poverty Incidence on Provincial Level

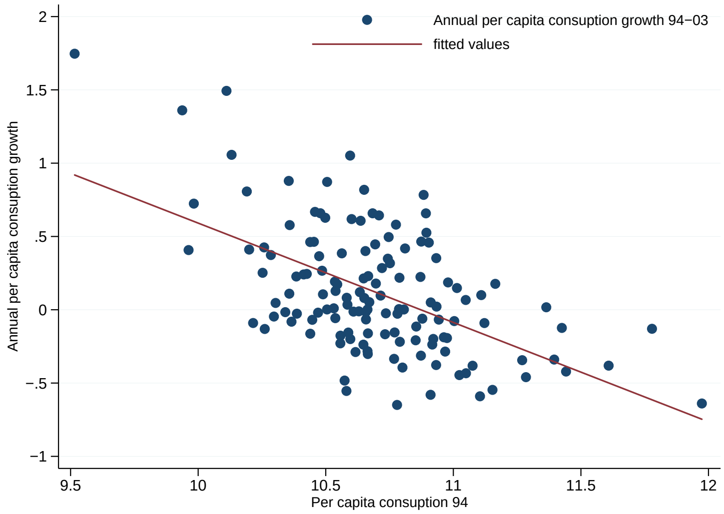


If we disaggregate our data further by the 135 districts (*Départements*) which are covered by the household surveys[4] and plot household expenditures per capita in 1994 against growth of household expenditures per capita over the period 1994 to 2003, the data suggest β-convergence in living standards across these local units. However such kind of convergence might be exaggerated if expenditures per capita are measured with error (see e.g., Sala-i-Martin (1996)). Although we provide below some evidence why such convergence could have occurred, we do not find robust empirical evidence for these channels and we cannot rule out that measurement error plays an important role. First, because we do not find evidence for σ convergence, which would be immune to the mea-

[4]In total Burkina Faso has 301 districts (*Départements*).

surement error problem (see e.g., Sala-i-Martin (1996)). Second, we find a much smaller β-convergence coefficient if we regress the growth rate of expenditures from 1998 to 2003 on expenditure levels in 1994, which again could be sign of measurement error. However one should note that 1998 is a very particular year, since the 1997/98 harvest was affected by a severe drought, even by Burkinabe standards.

Figure 2: Convergence in Burkina Faso, initial per capita income (in ln) and growth on the department level (in%) (135 observations), 1994-2003



Hence, the question arises how income disparities between households and across spatial units can be explained. What is the contribution of the variance in household characteristics and level-specific endowments such as public services, infrastructure and climate? To what extent does the spatial clustering of households play a role? Are the effects of relevant factors similar across spatial units or do they vary significantly across the country? Answers to this kind of questions have not yet been given for Burkina Faso, but seem crucial to appropriately target poverty alleviation strategies. The only study we have found that did research in that direction for the case of Burkina Faso is Bigman et al. (2000). Similar to our study, the authors use a very detailed data set combining information from the household, village, district and provincial level and construct a poverty map on the level of villages. From that map the authors conclude that differences in the incidence of poverty among regions are primarily due to differences in agro-climatic conditions, whereas differences in the incidence of poverty among villages within the same region do often reflect past policy biases that led to differences in the quality of roads or public services.

3 Data and Empirical Strategy

3.1 Data

Burkina Faso is organized in 13 agro-climatic regions, 45 provinces and 301 districts (départements). It has 26 cities and towns (population > 5,000) and roughly 9,000 villages. According to the last census in 2006 the urbanization rate was about 16 percent and the average population density 48.4 persons per km^2. The two major cities are Ouagadougou, the capital, with a population of roughly 1.1 million and Bobo-Dioulasso with a population of about 0.4 million. The third city, Koudougou only has a population of 83.4 thousand.[5] The variables we use have been collected from a large number of sources and on different levels of that organizational structure. However, it was very difficult to find and get access to data on agro-climatic characteristics, infrastructure and public services and if it existed to match these data to other sources. This seems to be a problem in many of the least developed countries and may explain why only very few attempts have been made so far to analyze the effects of area-specific characteristics on households' living standards.

First, household data is drawn from three nation-wide representative household surveys, the Enquête Prioritaires (EP), conducted in 1994 (EP I), 1998 (EP II) and 2003 (EP III) covering around 8,500 different households in each year. These surveys were conducted by the Institut National de la Statistique et de la Démographie (INSD) with technical and financial support of the World Bank. These surveys contain relatively detailed information on household's socio-demographic characteristics, education, employment, agricultural and non-agricultural activities as well as consumption, income and some assets.[6]

Given the usual low quality of income data in poor rural settings, we use household expenditure per capita as an indicator of households' living standards. Expenditures were deflated over time and space using appropriate price deflators. A critical issue in our study are of course the deflators used to correct for price differences across space. For this purpose we use deflators provided by the INSD in each survey year for Burkina Faso's 13 regions (based on price data collected on 37 different regional markets).

Second, we can draw data on the community (or cluster) level from several sources. Although, except in 1998, the above mentioned household surveys were not linked to any village survey, the questionnaires contain some questions regarding the time needed to reach the next primary and secondary school, the next health center, road, market and drinking water point. In 1998 a specific community survey was added to the household survey which collected further community data for 325 of the 425 communities covered by the survey. Further community variables were constructed simply by aggregating household characteristics at the community level. However, a community panel cannot be constructed because each survey year does not cover exactly the same communities.

Third, data on the size of agricultural production units, fertilizer use and

[5] Statistics taken from INSD, see http://www.insd.bf.

[6] A detailed description of these data sets can be found in Grimm and Günther (2007).

the use of modern production technologies in agriculture are drawn from a yearly agricultural survey called Enquête Agricole. This survey is conducted by the Ministry of Agriculture in collaboration with INSD. Since the data set uses a different survey design than the EPs, we merged the information to the other data sources on the provincial level, the smallest common regional unit. The average size of agricultural production units, fertilizer use and information about modern production technologies are therefore provincial averages.

Fourth, data on agro-climatic conditions such as monthly rainfall for the period 1993-2006 on the provincial level, and monthly minimum and maximum temperatures on the regional level were obtained from the Directorate of Meteorology (Direction de la Météorologie).

Fifth, data on the provision of public services, infrastructure and population densities, also at the provincial level, were obtained from the Ministry of Infrastructure (Direction Génerale de l'Amenagement du Territoire). Note that we do not have any data on project aid, hence the effect of aid will be in the unobservables.

Hence, as stated above, the data set we use is organized in four levels: the household, the community (or cluster), the province and the region. Table 2 shows all used variables along with their means and standard deviations and their source.

Table 2: Determinants of spatial inequality

Variable		**Descriptive Statistics**						**Source***	**Level**
Name	Label	1994		1998		2003			
		Mean	Std dev	Mean	Std dev	Mean	Std dev		
HHsize	HH size	7.53	5.50	7.50	5.18	6.36	4.07	EP	Household
Children Adult	Children (0-6) per adult	0.54	0.51	0.50	0.49	0.49	0.48	EP	Household
Youth Adult	Youth (7-14) per adult	0.51	0.54	0.51	0.55	0.47	0.54	EP	Household
Elderly Adult	Elderly (55+) per adult	0.13	0.30	0.13	0.30	0.12	0.30	EP	Household
Age	Age of HH head	45.79	15.21	46.08	15.01	44.23	15.17	EP	Household
Sex	Sex of HH head	1.09	0.29	1.09	0.28	1.09	0.29	EP	Household
Literate Head	Literate HH head	0.25	0.43	0.24	0.42	0.26	0.44	EP	Household
Literate Adult	% of literate adults in hh	0.36	0.49	0.33	0.46	0.37	0.47	EP	Household
Cotton	HH primarily engaged in cotton farming	0.06	0.23	0.12	0.33	0.13	0.34	EP	Household
Livestock	HH engaged in some livestock herding	0.56	0.50	0.63	0.48	0.65	0.48	EP	Household
Muslim	HH head is Muslim	0.58	0.49	0.54	0.50			EP	Household
Christian	HH head is Christian	0.24	0.43	0.25	0.43			EP	Household
Mossi	HH head is Mossi	0.49	0.50	0.50	0.50			EP	Household
ZD Religion	Variation of religious groups**	0.74	0.52	0.78	0.50			EP	Community
ZD Ethnicity	Variation of ethnicity**	2.05	1.88	2.29	2.79			EP	Community
ZD Cotton	% of HHs primarily engaged in cotton	0.06	0.14	0.12	0.25	0.13	0.25	EP	Community
ZD Livestock	% of HHs engaged in some livestock	0.56	0.31	0.63	0.34	0.65	0.32	EP	Community
ZD Literate	% of literate adults in community	0.36	0.32	0.33	0.29	0.37	0.30	EP	Community
ZD Literate Head	% of literate HH heads in community	0.25	0.23	0.24	0.23	0.26	0.23	EP	Community
ZD Hhsize	Avg HH size in community	7.53	2.19	7.51	2.39	6.36	1.56	EP	Community
ZD Children Adult	Avg number of children per adult	0.54	0.17	0.50	0.17	0.49	0.17	EP	Community
ZD Youth Adult	Avg number of youth per adult	0.51	0.16	0.51	0.17	0.47	0.16	EP	Community
ZD Elderly Adult	Avg number of elderly per adult	0.13	0.09	0.13	0.10	0.12	0.08	EP	Community
Electricity	1 HH in community has electricity	0.24	0.43	0.28	0.45	0.32	0.47	EP	Community
ZD Urban	Urban community	0.32	0.47	0.31	0.46	0.31	0.46	EP	Community
Primary Access	Next primary school within 30 min	0.92	0.27	0.89	0.31	0.94	0.23	EP	Community
Secondary Access	Next secondary school within 30 min	0.53	0.50	0.46	0.50	0.49	0.50	EP	Community
Healthcenter Access	Next health center within 30 min	0.83	0.37	0.77	0.42	0.74	0.44	EP	Community
Market Access	Next market within 30 min	0.95	0.22	0.92	0.28	0.90	0.31	EP	Community

Variable		Descriptive Statistics						Source*	Level
Name	Label	1994		1998		2003			
		Mean	Std dev	Mean	Std dev	Mean	Std dev		
Road	Access to road			0.65	0.48			EC	Community
Next Road	Distance to next road in km			9.30	13.52			EC	Community
Next Tarred Road	Distance to next tarred road in km			79.50	87.67			EC	Community
Freshwater	Access to fresh water point			0.95	0.22			EC	Community
Market	Access to market			0.55	0.50			EC	Community
Next Market	Distance to next market in km			3.72	6.02			EC	Community
School	Access to school			0.67	0.47			EC	Community
Formation	Access to formation center			0.06	0.24			EC	Community
Hospital	Access to hospital			0.33	0.47			EC	Community
Pharmacy	Access to pharmacy			0.31	0.46			EC	Community
Next Hospital	Distance to next hospital in km			6.84	7.36			EC	Community
Next Pharmacy	Distance to next pharmacy in km			8.07	9.18			EC	Community
Malaria	Malaria most frequent disease			0.72	0.45			EC	Community
Rain Mean	Avg rainfall in region	82.67	17.87	70.88	17.65	82.65	24.12	DM	Province
Rain Var	Variation of rainfall	12623	4678	7712	3376	10233	3627	DM	Province
Pop Density	Population density	24.39	58.35	18.88	50.44	21.00	59.44	MI	Province
Landsize	Avg size of cultivated land per HH in ha			4.03	1.68	5.41	2.08	EA	Province
Fertilizer	Use of fertilizer			0.33	0.25	0.15	0.14	EA	Province
Modernequipment	Use of modern agricult. equipment			0.70	0.20	0.69	0.28	EA	Province
Tempmax	Avg max temperature	34.46	0.76	35.21	0.99	35.76	1.02	DM	Region
Tarred Size	Density of tarred roads (km/km2)	0.01	0.01	0.01	0.01	0.01	0.01	MI	Region

* EP=Enquete Prioritaire; EC= Enquete Communitaire; EA=Enquete Agricole; DM=Direction De La Meteorologie Burkina Faso; MI=Ministere Des Infrastructures

**Measured as the variance of the shares in a community

3.2 Empirical strategy

To analyze the determinants of income levels and to decompose the variance in income levels across spatial units, we use a multilevel (also hierarchical or mixed) regression model.[7] Multilevel models are widely used in social science, sociology and health research to specify the effect of social context on individual level outcomes.[8] Due to the often observed lack of hierarchical data and probably due to the very time consuming estimation procedure, multilevel models are less popular in economics than in these other disciplines.[9]

3.2.1 A multilevel model

A multilevel model can be best described by beginning with a two level random coefficient model with only one explanatory variable. The idea of the model is, that the regression coefficient on the first level (e.g. households), i, is treated as a random variable at the second level (e.g. communities), j.

The model equation reads:

$$Y_{ij} = \beta_{0j} + \beta_{1j} X_{ij} + \varepsilon_{ij}. \tag{1}$$

The regression coefficients β_{0j} and β_{1j} can be expressed as:

$$\beta_{0j} = \gamma_{00} + U_{0j} \tag{2}$$

$$\beta_{1j} = \gamma_{10} + U_{1j} \tag{3}$$

Equation 2 shows that for each unit j on the second level, a specific intercept, U_{0j}, is introduced into the model. These intercepts are however not directly estimated as a fixed coefficient within the model. Multilevel models estimate the variance of these U_{0j}. They are therefore often referred to as *random intercepts*. Equation 3 shows that a specific β-coefficient, U_{1j}, is introduced allowing the effects associated with the covariates to vary across units on the second level. Since only the variance of these coefficients is estimated, it is referred to as a *random coefficient*. Models that do only include random intercepts are called random intercept models, while models that include random intercepts *and* random coefficients are called random coefficient models.

Finally, the combined model can be expressed as consisting of a fixed part (first term) and a random part (second term):[10]

$$Y_{ij} = (\gamma_{00} + \gamma_{10} X_{ij}) + (U_{0j} + U_{1j} X_{ij} + \varepsilon_{ij}) \tag{4}$$

[7] For a comprehensive overview of the statistical theory underlying multilevel modeling and of various illustrative applications, see e.g. Goldstein (2003) and Hox (1995)

[8] For a good overview of applications in that area, see DiPrete and Forristal (1994).

[9] Economists rely on these models in particular for out of sample predictions to perform small area estimations, for instance to construct a poverty map (see Elbers et al. (2003) and Jiang and Lahiri (2006)). A paper which deals with causal multilevel models is, for example, Aassve and Arpino (2007).

[10] Fixed effects are hereafter denoted as coefficients which are directly estimated by the model. For random effects only the variance and its standard error is estimated.

It is straightforward to extend the model to more than two levels. The model can also be used to check for significant variation of the random intercepts and slope coefficients across units on each level. Moreover, it is possible to analyze the covariance of the random intercepts and slopes.

3.2.2 Strengths of a multilevel model

Multilevel models offer several advantages over other models. They allow to combine nested data from different sources, to decompose variation across levels and to model the variation of effects across spatial units. In what follows we discuss each of these advantages.

Efficient Estimation

Since we built our data set using several different and independent data sets, variables are observed on multiple nested levels (see figure 2). Clustering stemming from this nested structure requires to account for intra-group correlations. Under the assumption that individuals and households on the same level are more alike than individuals and households from different levels, within group residuals are likely to be correlated. The classical linear regression model however assumes residuals to be independent among individuals by modeling the unexplained variability solely as the variance of the residual. Applying standard OLS regression to nested data leads to an underestimation of standard errors and, hence, statistical inference can be wrong. In a multi-level data set the unexplained variance should be decomposed into the variance on all nested levels. This is exactly done by the multilevel model allowing to obtain efficient estimates (see Goldstein (2003)).

Variance partitioning

In a multilevel random intercept model, the decomposition of the error term allows to assess how much of the total variance is attributable to variation on the different nested levels. Moreover it can be assessed how much of the variance measured on each level is due to the variance in level-specific characteristics and how much is due to sorting of lower-level characteristics across these levels. For instance, the variance in households' living standards between communities might be driven by the variance in community-specific endowments and by a sorting of households with favorable and unfavorable characteristics across communities. More precisely, sticking to this two-level example, we can answer the following questions:

1. How much of the total variance in incomes between households is attributable to differences between communities?
2. How much of the variance between communities can be explained by differences in observed household characteristics between theses communities?
3. How much of the variance between communities can be explained by differences of observed community characteristics?

The contribution of the variance at each level to the total variance can be measured with the so-called 'variance partition coefficient', also called the 'intra-class correlation coefficient' ('icc', hereafter), ρ.[11] Since a multilevel model implicitly assumes errors to be independently distributed across levels, the total variance of the dependent variable can be decomposed as the *sum* of the variance on each level. If we use again the two-level model as an example, the decomposition of the variance by level reads:

$$\mathrm{var}(Y_{ij}|X_{ij}) = \mathrm{var}(U_{0j}) + \mathrm{var}(\varepsilon_{ij}) = \sigma^2_{u_0} + \sigma^2_{\varepsilon}. \qquad (5)$$

Accordingly, the icc of the second level can be expressed by:

$$\rho = \frac{\sigma^2_{u_0}}{\sigma^2_{u_0} + \sigma^2_{\varepsilon}}. \qquad (6)$$

The intra-class correlation coefficient measures the correlation of the residual of the response variable of households stemming from the same community. A high ρ in equation 6 would point to a large impact of the second level, for instance the community, on first level outcomes, i.e. on the level of households.

Finally, the decomposition allows to draw conclusions on the explanatory power of the used covariates with respect to the variation on the different levels (see Borgoni et al. (2002)). For instance, we can answer the question whether the observed spatial pattern in income levels can rather be explained by differences in regional variables, like geographic traits, by differences in community characteristics like access to certain public goods or rather by differences in household characteristics, like household size and education. This is a major conceptual advantage of a multilevel model. If we ran a household income regression with explanatory variables on higher levels, but without a multilevel structure, significant coefficients of these variables are likely to pick up variation which is at least partly due to omitted household level variables. In contrast, if we introduce a random intercept on each level, we can test the explanatory power of level-specific variables on each level separately. Whenever an introduced variable reduces the variance of the level-specific error term, we can conclude that this variable explains part of the variance in incomes on that level (see Ecob (1996)).

Area-specific returns

A multilevel model designed as a multilevel random coefficient model ('RC' hereafter), allows to take into account a possible variation in the factor coefficients across spatial units. Finding significant variation in the effects of individual characteristics across spatial units suggests that area modifies the association between individual characteristics and income (see Merlo et al. (2005b)). In our case, for instance, it will be interesting to see whether effects associated with education, cotton cultivation or household composition are constant across spatial units.

[11] It is called 'intra-class correlation coefficient' since it measures the degree to which observations in the same unit of a given level, e.g. households within a given community, are dependent.

Covariance structure of random effects

Finally, the RC model allows us to investigate the covariance structure of the random intercepts and random slope coefficients. For instance, it might be that communities with lower average income levels (a lower intercept) have higher returns associated with education or cotton cultivation. A significant negative correlation, for example, could explain the convergence described in Section 2.

To conclude, based on these methodological considerations, we belief that a multilevel model is particularly suitable to identify the sources of spatial inequalities. Our methodology is capable of decomposing spatial inequality into the contribution of household and area-specific characteristics, of identifying the key spatial determinants of inequality and of tracking variations in returns across space, thereby preserving simultaneously most of the advantages of the methods used by Ravallion and Wodon (1999), Jalan and Ravallion (2002) and Benson et al. (2005). Complementing the geographical analogue of the Oaxaca-Blinder decomposition proposed by Ravallion and Wodon (1999), our decomposition methodology allows to attribute weights to the contribution of the various levels to total inequality. Moreover, in addition to the identification of higher level variable effects on household income, which is done in Jalan and Ravallion (2002) using a GMM-type approach, our model differentiates in principle between significant higher level effects explaining higher level inequality and significant higher level effects just picking up omitted household characteristics.

Obviously, our methodology also has some drawbacks. In the absence of panel data, we cannot exclude that we run with some of our explanatory variables into endogeneity problems. However, the methodology we propose is just as applicable to panel data as is is to cross sectional data. It should also be noted that our method does only control for unobserved heterogeneity on each level as long as the independence assumption between unobserved characteristics and the regressors holds. In the context of hierarchical data, multilevel models assume area effects to be independent of the covariates and any unobserved individual effects. In the absence of panel data, as in our case, one could of course estimate an OLS model and introduce dummy variables for each higher level unit to satisfy the independence assumption. However, doing this would impose severe restrictions on the model. Due to the few observations that we observe per first level unit (maximum 20 households per community), introducing dummy variables would lead to a significant over-parametrization (Lombardía and Sperlich, 2007). Simultaneously, effects of all higher level variables, which are key for our analysis, could not be identified. Thus, we will construct our multilevel model in a way that we can benefit from all the advantages of a multilevel model while using our large data set to control as much as possible for unobserved heterogeneity.

3.2.3 Modeling Strategy

We use an iterative procedure to estimate the sources of spatial inequality. We start with a multilevel random intercept model (**M0**), that will not include any covariates. We will then iteratively introduce household level variables (**M1**), community variables (**M2**) and provincial and regional variables (**M3**) into the model. At each stage, our main concern is about two questions:

1. What are the key characteristics determining per capita income disparities?
2. To what extent are the characteristics responsible for the spatial variation observed on each level?

Finally, we will augment our multilevel model in section 4.5 by allowing coefficients of household characteristics to vary across communities and by modeling the covariances of the random effects on that level (**M4**). Investigating the variance of the random coefficients and the correlation between random intercepts and slopes, the model can help answer the following questions:

3. Does area modify the association between household characteristics and respective outcomes?
4. What might be the explanation for such a modification?

We estimate our model for three points in time: 1994, 1998 and 2003. This will also allow to get some insights into the dynamics of spatial inequality and its determinants. Our full four level random coefficient model reads:

$$\begin{aligned} Y_{ijkl} = (\gamma_{0000} + \sum_{p=1}^{P} \gamma_{p000} X_{pijkl} + \sum_{q=1}^{Q} \gamma_{0q00} C_{qjkl} + \sum_{r=1}^{R} \gamma_{00r0} P_{rkl} + \sum_{m=1}^{M} \gamma_{000m} R_{ml}) \\ + (U_{0jkl} + V_{00kl} + W_{000l} + \sum_{p=1}^{P} U_{pjkl} X_{pijkl} + \varepsilon_{ijkl}) \end{aligned} \quad (7)$$

where i stands for households, j for communities, k for provinces and l for regions. X, C, P and R are vectors of household, community, provincial and regional characteristics, respectively. The models will be estimated using Stata and its implemented mixed model command 'xtmixed'.[12]

[12]The estimation procedure is based on an iterative generalised least squares approach (discussed in Goldstein (2003)). This procedure starts with the estimation of the fixed effects coefficients using ordinary least squares. The resulting residuals are stored. Afterwards, an iterative procedure begins, starting with a generalised least squares regression in a first step. Then, in a second step the residuals of this regression are used to compute the variance of the random coefficients. These steps are then iterated.

4 Results: Sources of spatial inequality

4.1 Model M0: The null model

For each year for which we estimate our model, we begin by a four level null model where we introduce nothing but a random intercept on the community, the provincial and the regional level. Using a likelihood ratio test we check whether the three level model, nested in the four level model, performs better than the four level model (see Goldstein (2003)). Since this is not the case for any of the three years under consideration, we will use a four level model in the following.

Our base model, M0, reads:

$$Y_{ijkl} = \gamma_{0000} + U_{0jkl} + V_{00kl} + W_{000l} + \varepsilon_{ijkl}, \tag{8}$$

where Y_{ijkl} stands for household expenditure per capita. The results of model M0 for each year are shown in tables 3 - 5.

Table 3: Models - 1994 - Fixed effects

	M0		M1		M2		M4	
Household level								
HHsize			-0.040	***	-0.040	***	-0.042	***
Children Adult			-0.054	***	-0.053	***	-0.042	***
Youth Adult			-0.060	***	-0.055	***	-0.238	***
Elderly Adult								
Age			-0.006	***	-0.006	***	-0.004	***
Sex								
Literate Head			0.038	***	0.036	***	0.260	***
Literate Adult			0.440	***	0.367	***	0.337	***
Cotton								
Livestock								
Muslim								
Christian			0.056	***	0.048	**	0.018	
Mossi								
Community level								
ZD Religion								
ZD Ethnicity					0.039	***	0.030	***
ZD Cotton								
ZD Livestock								
ZD Literate Adult					0.549	***	0.390	***
ZD Literate Head								
ZD Hhsize								
ZD Children Adult								
ZD Youth Adult					-0.092	**	-0.029	
ZD Elderly Adult								
Electricity					0.169	***	0.176	***
ZD Urban					0.164	***	0.144	***
Primary Access								
Secondary Access								
Healthcenter Access								
Market Access								
Provincial level								
Landsize								
Rain								
Pop. Density								
Tarred Road								
Size								
Regional Level								
Ltempmax								
Constant	11.080	***	11.590	***	11.350	***	11.330	***
AIC	19423		17065		16780		16187	
LR test	0.000		-		-		0.000	
Obs	8595		8595		8595		8595	

Table 4: Models - 1998 - Fixed effects

	M0	**M1**		**M2**		**M3**		**M4**		**M***	
Household level											
HHsize		-0.040	***	-0.038	***	-0.039	***	-0.044	***	-0.038	***
Children Adult		-0.234	***	-0.229	***	-0.230	***	-0.238	***	-0.175	***
Youth Adult		-0.180	***	-0.169	***	-0.169	***	-0.163	***	-0.148	***
Elderly Adult		0.084	***	0.091	***	0.090	***	0.093	***	0.112	***
Age		-0.006	***	-0.006	***	-0.006	***	-0.006	***	-0.006	***
Sex											
Literate Head		0.328	***	0.277	***	0.278	***	0.270	***	0.244	***
Literate Adult		0.270	***	0.253	***	0.252	***	0.214	***	0.151	***
Cotton		0.055	*	0.084	***	0.102	***	0.107	***	0.098	***
Livestock											
Muslim		0.040	**	0.036	**	0.036	**	0.052	***	0.060	***
Christian											
Mossi											
Community Level											
ZD Religion											
ZD Ethnicity				0.010	**	0.011	**	0.010	**	0.010	*
ZD Cotton											
ZD Livestock											
ZD Literate Adult											
ZD Literate Head				0.672	***	0.753	***	0.482	***	0.345	***
ZD Hhsize											
ZD Children Adult											
ZD Youth Adult											
ZD Elderly Adult											
Electricity				0.184	***	0.211	***	0.170	***	0.120	**
ZD Urban				0.129	**	0.196	***	0.213	***	0.345	***
Primary Access											
Secondary Access											
Healthcenter Access				0.054	*	0.059	*	0.051	*		
Market Access											

	M0		M1		M2		M3		M4		M*	
Malaria											-.068	***
Hospital											.058	**
Road											.047	**
Provincial level												
Landsize												
Rain							0.203	*	0.227	*	0.229	*
Pop. Density												
Tarred Road												
Size												
Regional Level												
Ltempmax							1.600		1.470		1.390	
Constant	10.860	***	11.480	***	11.390	***	4.620		5.000		5.28	
AIC	19284		16474		16197		16200		15988		11714	
LR test	0.000		-		-		-		0.000		-	
Obs	8477		8477		8477		8477		8477		6277	

To obtain the contribution of the variance at each level to the total variance, we calculate the icc for each level. Recall that the icc (e.g. for level 2) is written as:

$$\rho = \frac{\sigma^2_{u0}}{\sigma^2_{u0} + \sigma^2_{v00} + \sigma^2_{w000} + \sigma^2_{\varepsilon}} \tag{9}$$

The icc for all years and levels are shown in Table 6. For instance, the intra-class correlation coefficient, ρ, for the community level in the year 1998, is equal to approximately 26.5%.[13] In words, in 1998 26.5 percent of the total variance is situated at the community level. In this case, the icc measures the correlation of the residual of the response variable of households stemming from the same community. The high icc of the community level, which is almost as high in 1994 (19.2 percent) and 2003 (20.5 percent), depicts two things. First, it underlines the importance of using a multilevel approach to get efficient estimates. Second, it suggests strong community effects which are relatively stable over time. The latter finding is particularly interesting in our case, since it means that the more households' incomes within a community are alike, the more likely is it that incomes are directly related to the contextual environment of the communities (see Merlo et al. (2005a)).

Clearly, most of the variance exists at the household level. It should be emphasized, however, that household expenditure data in developing countries is usually measured with error, given that it is generally very difficult to get precise information on expenditures if simple recall questions are used. Our model attributes the total variance which is due to measurement error in the expenditure data to the household level component. If we were able to account for these errors, the contribution of the household level variance to the total variance would probably be lower, and, in consequence, the contribution of the higher levels higher. The contribution of the variance on the provincial and regional level is relatively low. We conclude—at this stage—that differences in household incomes are mainly driven by household and community (or cluster) characteristics and to a smaller extent by regional characteristics. The contribution of the provincial level is very low. In fact, in Burkina Faso regions rather than provinces follow agro-climatic zones, this can explain why regions make a higher contribution than provinces.

As explained above the finding of a significant contribution of higher level characteristics on income does not necessarily have to be the result of differences in higher level characteristics itself. For instance, differences between communities might result from a systematic distribution of household characteristics across communities, i.e. similar households are spatially concentrated. To see whether this is the case, we have to test the proportional change in the icc after accounting for household characteristics, i.e. to control for systematic differences in household characteristics across higher levels. However, it should be noted, that household characteristics might lie in the causal pathway between area characteristics and household income, e.g. better and more schools may lead to better education outcomes. Including household characteristics will probably lead to an understatement of the importance of area characteristics.

[13] $\rho = \frac{.221}{.221+.025+.078+.510} \approx 26.5$ percent.

Table 5: Models - 2003 - Fixed effects

	M0		M1		M2		M4	
Household level								
HHsize			-0.054	***	-0.054	***	-0.060	***
Children Adult			-0.227	***	-0.219	***	-0.206	***
Youth Adult			-0.190	***	-0.178	***	-0.183	***
Elderly Adult								
Age			-0.004	**	-0.004	**	-0.004	**
Sex			-0.060		-0.064		-0.074	
Literate Head			0.272	***	0.232	***	0.252	***
Literate Adult			0.268	***	0.2538	***	0.212	***
Cotton			0.079	***	0.117	***	0.105	***
Livestock			0.034	***	0.083	***	0.096	***
Muslim								
Christian								
Mossi								
Community level								
ZD Religion								
ZD Ethnicity								
ZD Cotton								
ZD Livestock					-0.347	***	-0.370	***
ZD Literate Adult					-0.260	*	-0.290	**
ZD Literate Head					0.827	***	0.706	***
ZD Hhsize								
ZD Children Adult								
ZD Youth Adult								
ZD Elderly Adult								
Electricity					0.138	***	0.146	***
ZD Urban								
Primary Access								
Secondary Access								
Healthcenter Access								
Market Access					0.088	**	0.075	*
Provincial level								
Landsize								
Rain								
Pop. Density								
Tarred Road								
Size								
Regional Level								
Ltempmax								
Constant	11.150	***	11.780	***	12.080	***	11.870	***
AIC	19143		16305		16132		15976	
LR test	0.000		-		-		0.000	
Obs	8488		8488		8488		8488	

Table 6: Intraclass correlation coefficients (ICC)

	1994			1998				2003		
	M0	**M1**	**M2**	**M0**	**M1**	**M2**	**M3**	**M0**	**M1**	**M2**
Region	9.6%	7.8%	3.5%	9.3%	5.0%	1.2%	1.4%	11.1%	6.2%	3.9%
Province	4.1%	2.1%	1.0%	3.0%	3.1%	2.1%	2.0%	3.3%	6.3%	7.8%
Community	21.9%	15.9%	7.4%	26.5%	18.9%	9.0%	9.3%	20.5%	15.1%	9.0%
Households	64.4%	74.2%	88.1%	61.2%	72.9%	87.7%	87.3%	65.2%	72.5%	79.3%

Hence, it is important to carefully discuss the household level variables and the potential influence of area characteristics on these variables.

4.2 Model M1: The role of household characteristics

In the second step, we add explanatory variables on the household level to the random intercept model. We call this model 'M1'. The results are presented—for each year separately—in Tables 3 - 5. Since we use maximum likelihood techniques for estimation, we rely on the Akaike Information criterion (AIC) to select the best model. We estimated other versions of M1 with a much larger set of potentially important explanatory variables, but present here only those models with the lowest AIC.

Key household level characteristics

All household variables have the expected sign and are in line with standard regression results. In particular, household composition has a considerable effect on income levels. In terms of per capita incomes, smaller households seem to be significantly better off in all years under consideration. The dependency ratios, measured via the children (0-6 years) per adult ratio, the youth (7-14 years) per adult ratio and the elderly (55 years and older) per adult ratio do all have a significant effect. While young household members lower per capita income in all years, the old-age dependency ratio is insignificant in 1994 and 2003 (thus dropped from the regression for those years) and negative in the drought year 1998 when food prices were extremely high.

Age of the household head has a significant negative effect on household income in all years. The household head being a male adult does not seem to play a major role concerning income since its effect is only significantly positive in 2003. The education of the household head is, as expected, very important in all years. Households with a literate head and households with a higher percentage of literate adults have on average a higher household income. Ethnicity has no influence on household income. Religion does. Belonging to one of the two large religious groups in Burkina Faso—Islam and Christianity–has a positive, but only hardly significant effect on income.

The effect of cotton farming differs across periods. Cotton farmers were better off in 1998 and 2003. In 1994 cotton did not yet have a significant effect. This is plausible, since the 'cotton boom' set in after the devaluation of the CFA Franc in January 1994, enhanced by a very favorable evolution of cotton prices and accompanied by a substantial expansion of land used for cultivation. Farmers who were also engaged in livestock herding which is often done to diversify risk, and hence, to lower the vulnerability to external shocks, were significantly better off in 2003. However, a deeper analysis of this issue would require to take into account the possible endogeneity, since richer farmers are more likely to be engaged in livestock herding than poorer farmers. For the latter, the income constraint does not allow to buy any livestock. Obviously, it is now interesting to see whether for all these household characteristics the effects differ across communities.

Contribution of household characteristics to spatial variation

For all years the community and regional variance components decline after the incorporation of household level covariates. For the provincial component the direction of the change is unstable for the different years which is not surprising given the small size and low significance of the provincial random intercept. The proportional changes of the icc of the community and regional variance components are surprisingly stable across survey years (see Table 7). Controlling for household level characteristics reduces the icc of the community by around 50 percent.

Table 7: Proportional change of ICC

	1994		1998			2003	
	M1	**M2**	**M1**	**M2**	**M3**	**M1**	**M2**
Region	-42.5%	-62.1%	-65.4%	-79.6%	15.5%	-62.4%	-42.3%
Province	-64.0%	-60.4%	-33.7%	-45.0%	-3.2%	29.0%	13.2%
Community	-49.1%	-61.1%	-54.6%	-60.5%	3.4%	-50.3%	-45.8%
Households	-19.1%	-0.2%	-23.9%	-0.2%	0.0%	-25.1%	-0.2%

Abstracting from unobserved household characteristics we would conclude that 50 percent of the community level variation in income levels is due to a systematic distribution of household characteristics across communities while the rest is due to community characteristics. Clearly, this is an unrealistic assumption and would lead to an overestimation of the importance of area-specific effects. Instead we have to consider that household characteristics are itself influenced by higher level factors. Levels as well as returns to education, cotton farming and livestock herding might be influenced by community characteristics, which could be responsible for an underestimation of area importance. Testing the explanatory power of community characteristics itself is therefore essential to draw conclusions on the contribution of community differences on household income disparities.

On the regional level the inclusion of household level variables was also nonambiguous. In 1998 and 2003 observed household characteristics can explain about 60 percent of the total unexplained regional variance (40 percent in 1994). Given that we controlled for household characteristics to the extent possible, we conclude for regions as well that large scale variables have a non-negligible impact on household level income.

4.3 Model M2: The role of community characteristics

To test for the meaningfulness of our results which indicate a high importance of community characteristics, we will check the proportional change of the icc after the incorporation of community characteristics (Model M2). The remaining significant variation of the community level random intercept could be either due to unobserved household characteristics leaving the community icc more or less unchanged or due to community characteristics (observed or not) lowering the community icc towards zero. Again, we use the AIC as a model selection criterion and present only the best fits of the M2 model (see Tables 3 - 5). All community variables which were tested for significance are listed in Table 2.

Key community level characteristics

If the community matters, the question is of course which are the relevant factors. Tables 3 - 5 reveal a distinct pattern across the three years. Urban communities with a high ethnic fragmentation[14], a high share of literate household heads and adults, and access to electricity are better off, on average. Besides the direct effect of having a literate adult in the household, there seems to exist a contextual or spill-over effect of better educated on less educated individuals within communities. However, access to primary and secondary schools—as measured by the time needed to reach them—does not turn out to be significant. Education is the only household characteristic which appears to have some spill-over effects. Except for youth per adult in 1994, all community averages of household level characteristics turn out to be insignificant. This is also true for communities with a higher share of cotton farmers, even though cotton farmers themselves are better off in 1998 and 2003, and cotton is always found to be a factor with some contextual effect in a community.

Since we do not have a direct measure of electricity in a community, we coded a community to have access to electricity if at least one household in that community had access. Electricity might be a good proxy for infrastructure, such as access to roads, in a community, since power transmission lines are usually found along (gravel) roads. Since at the community level we only have information on electricity but not on other infrastructure such as roads, we interpret the positive effect of electricity carefully as a general positive effect of community infrastructure on household income. Though, access to schools, access to health-centers and access to markets turns out to be insignificant. The effect of these kind of public services might be, at least to some extent, captured by the significant positive effect of urban communities since all these services are usually provided in urban areas.

As mentioned in Section 3, in 1998, the household survey was accompanied by a community survey for 325 out of the 425 clusters. This much larger community level dataset in 1998 can however only be examined at the cost of loosing a fourth of all households in the sample. Hence, we report regression results using data for the community survey separately in model M* in table 4. Of all community survey variables listed in table 2 only access to a road and to a hospital and a high malaria incidence in a cluster affect significantly household income. Signs are as expected. These results confirm the findings derived from model M2. Beyond the positive effect of urbanicity, access to markets and schools do not seem to play a major role in determining household income. Access to roads however—as already suggested by the positive effect of electricity in model M2, which we thought to be highly correlated with road access—seems crucial in raising the potential for income generation.

[14]Ethnic fragmentation is measured as the variance of the shares of each ethnicity in a community.

Contribution of community characteristics to spatial variation

After accounting for community factors, the community icc reduces significantly in all years (see Table 7). Around 60 percent of the remaining unexplained community level variation in M1 could be explained by observed community factors in 1994 and 1998. In 2003 it was still more than 40 percent. Although we only have a modest database on community level variables, this small set of variables is capable of explaining a significant part of the observed between community differences. Hence, in addition to simply specifying some significant relationship between contextual variables and household income as done above, we conclude that these variables are actually responsible for a large part of the community level disparity.[15] Community endowments have a significant effect household income.

The variance partitioning does even allow to quantify its contribution to total income variation. The very limited set of neighborhood characteristics contributes to approximately 7%[16] of household income variation. Since we are neglecting any measurement error as well as any effects from the community on household characteristics this result can be seen as a lower bound of the contribution of community characteristics to total income variation.

However, the question remains whether provincial and regional income disparities, that were persistent after controlling for household characteristics, are actually driven by differences in provincial and regional endowments or whether they are mainly driven by differences in community characteristics between these areas. Table 7 shows that around 60 percent of the remaining regional level variation in 1994, 80 percent in 1998 and 40 percent in 2003, can be explained by differences in observed community endowments. After the consideration of household and community level determinants, less than 5 percent in 1994 and 1998 and less than 12 percent in 2003 of the remaining total unexplained variation is situated at the provincial and regional level together. Here again, it should be noted that lower level factors are likely to be driven by macro factors, and, hence, we risk to understate the influence of variables on higher aggregation levels. Moreover, likelihood ratio tests show that both levels still have a significant impact.

4.4 Model M3: The role of provincial and regional characteristics

In model M3 we incorporate provincial and regional level variables. However, except for the 1998 rainfall variable (the drought year), all provincial and regional variables turned out to be insignificant. Population density, the density of tarred and gravel roads, the average maximum temperature or the variation of rainfall did not show a significant effect, once household and community level characteristics were included. The remaining unexplained variation could not be lowered in any of the three years under consideration. Table 8 summa-

[15] The remaining unexplained community variation cannot not be dissolved with our data at hand.

[16] For instance for the year 1998: ICC(M0)*(1-proportional change of ICC(M1))*proportional change of ICC(M2)$=.265 * (1 - .546) * .605 = 7.3$ percent

rizes the contribution of observed and unobserved characteristics to the total variance and the variance on each spatial level.

Table 8: Contribution of observed and unobserved characteristics on the variation on each level

	1994	1998	2003
Household level	**64.4%**	**61.2%**	**65.2%**
Household variables	19.1%	23.9%	25.1%
Unobserved	80.9%	76.1%	74.9%
Community level	**21.9%**	**26.5%**	**20.5%**
Household variables	49.1%	54.6%	50.3%
Community variables	31.1%	27.5%	22.7%
Unobserved	19.8%	17.9%	27.0%
Provincial level	**4.1%**	**3.0%**	**3.3%**
Household variables	64.0%	33.7%	$< 10^{-3}$
Community variables	21.7%	29.8%	$< 10^{-3}$
Provincial/Regional variables	$< 10^{-3}$	1.2%	$< 10^{-3}$
Unobserved	14.3%	35.3%	$> 99\%$
Regional level	**9.6%**	**9.3%**	**11.1%**
Household variables	42.5%	65.4%	62.4%
Community variables	35.7%	27.5%	15.9%
Provincial/Regional variables	$< 10^{-3}$	$< 10^{-3}$	$< 10^{-3}$
Unobserved	21.8%	7.1%	21.7%

The result of insignificant macro-level variables might seem surprising, but it is in fact quite consistent with other findings in the literature. Jalan and Ravallion (2002) and Benson et al. (2005) do also not find a significant effect of population density on household income. Benson et al. (2005) even confirm our result of a missing effect of access to roads which is according to Jacoby (2000) the result of a low infrastructure elasticity of poverty.

Burkinabe households seem to have adapted their income generation process to the inherent climatical disadvantages in a way that the amount and the variation of rainfall in 'normal times' does not have a significant impact on their income. However, the occurrence of substantial climatic shocks, such as a drought or an abnormal distribution of rainfall over the year, do play an important role, as revealed by the significant positive rainfall coefficient in the drought year 1998. Consistent with this result, Benson et al. (2005) find the effect of the amount of rainfall on income in Malawi only to be significant when it is exceptionally high. Similarly, Dercon (2004) only finds significant effects for Ethiopia when looking at severe droughts.

Our results are also in line with those by Bigman et al. (2000) who conclude that regional inequality in Burkina Faso is driven by agro-climatic conditions, and disparities between villages are driven by differences in infrastructure. However, compared to Bigman et al. (2000), we stress the importance of community characteristics even more. Our analysis suggests that a large part of regional disparity is actually driven by differences in community characteristics between these regions. Hence, we think the actual impact of agro-climatic conditions is lower than suggested by Bigman et al. (2000).

4.5 Model M4: Variations in household level effects across communities

In a next step, we allow household level variables to differ in their impact across communities. Thus, in addition to random intercepts, we now also add random coefficients (see equation 7) at the community level. Covariances of random effects are modeled unstructured, i.e. all variances-covariances are distinctly estimated. We use an iterative procedure to test for significant variance-covariances of all significant household level variables included in model M2. We use likelihood-ratio tests by estimating the likelihood deviance for the model without the specific random effect and for the model with the specific random effect. We keep those random effects in model M4 whenever the test-statistic—the difference between the deviances of the two models—is significant, i.e. if we get a χ^2 below 5% (Goldstein, 2003). In addition, variances and covariances are regarded as insignificant when their standard error is larger than their estimate (Tseloni, 2006). All estimates and their standard errors for model M4 are shown in Tables 9 - 11.

Table 9: Models - 1994 - Random effects

	M0		**M1**		**M2**		**M4**	
	Est.	Std.Err.	Est.	Std.Err.	Est.	Std.Err.	Est.	Std.Err.
Variances								
var(region)	0.075	0.047	0.043	0.023	0.016	0.008	0.015	0.008
var(province)	0.032	0.018	0.012	0.007	0.005	0.003	0.006	0.003
var(community)	0.171	0.014	0.087	0.008	0.034	0.004	0.091	0.012
var (household)	0.502	0.008	0.406	0.006	0.406	0.006	0.360	0.006
var(hhsize)							0.000	0.000
var(youth adult)							0.018	0.006
var(literate head)							0.055	0.013
Covariances								
cov(hhsize, youth adult)							0.000	0.001
cov(hhsize, lit. head)							-0.002	0.001
cov(youth ad, lit. head)							-0.007	0.007
cov(hhsize, cons)							-0.005	0.001
cov(youth ad, cons)							-0.018	0.007
cov(literate head, cons)							0.009	0.009

Table 10: Models - 1998 - Random effects

	M0		M1		M2		M3		M4	
	Est.	Std.Err.	Est.	Std.Err.	Est.	Std.Err.	Est.	Std.Err.	Est.	Std.Err.
Variances										
var(region)	0.078	0.048	0.027	0.020	0.005	0.004	0.006	0.005	0.005	0.004
var(province)	0.025	0.016	0.017	0.010	0.009	0.005	0.009	0.005	0.009	0.009
var(community)	0.221	0.018	0.100	0.009	0.040	0.004	0.041	0.004	0.104	0.104
var (household)	0.510	0.008	0.388	0.006	0.387	0.006	0.387	0.006	0.357	0.357
var(hhsize)									0.001	0.000
var(Children adult)									0.027	0.008
var(literate head)									0.085	0.016
Covariances										
cov(hhsize,Children adult)									0.002	0.001
cov(hhsize, lit. head)									-0.003	0.001
cov(Children ad, lit. head)									-0.026	0.008
cov(hhsize, cons)									-0.006	0.001
cov(Children ad, cons)									-0.031	0.009
cov(lit. head, cons)									0.038	0.011

Table 11: Models - 2003 - Random effects

	M0		M1		M2		M4	
	Est.	Std.Err.	Est.	Std.Err.	Est.	Std.Err.	Est.	Std.Err.
Variances								
var(region)	0.085	0.045	0.032	0.021	0.019	0.013	0.019	0.0137
var(province)	0.025	0.013	0.032	0.012	0.037	0.011	0.041	0.0122
var(community)	0.157	0.013	0.078	0.007	0.042	0.005	0.066	0.0114
var (household)	0.502	0.008	0.376	0.006	0.375	0.006	0.350	0.0059
var(hhsize)							0.001	0.000
var(youth adult)							0.005	0.004
var(literate head)							0.074	0.014
Covariances								
cov(hhsize, youth adult)							0.002	0.0007
cov(hhsize, lit. head)							-0.003	0.0011
cov(youth ad, lit. head)							-0.012	0.0069
cov(hhsize, cons)							-0.004	0.0011
cov(youth ad, cons)							-0.013	0.0061
cov(literate head, cons)							0.016	0.0094

Spatially varying household effects

The results of our analysis are, once again, relatively homogeneous across time. We find indeed, that returns associated with education, household size and effects related to dependency ratios (children per adult and youth per adult) vary significantly across communities in all three years. On the other hand, returns associated with age and gender of the household head, with cotton farming and livestock herding do not vary significantly across communities in either year.

The variation of returns across communities is not only statistically but also economically meaningful. The fixed effect estimate of the variable 'literate head' of .26 in 1994 states that households with a literate head have on average a per capita income which is higher by 26 percent compared to households with an illiterate head. The variance of the random effect of the household head variable states however that this return differs significantly between communities. For instance for 1994, the effect varies from minus 21 percent $(((.26-2*\sqrt{.055})*100))$ to plus 73 percent $(((.26+2*\sqrt{.055})*100))$ between the 2.5th and 97.5th quantile of Burkinabe communities. Similar variations are stated for 1998 and 2003. The effects associated with changes in the household composition vary also substantially across communities.

Determinants of spatially varying effects

We conclude that the community has an influence on effects associated with household characteristics, in particular with education. From a policy point of view, it is important to know what drives these community effects. In the case of returns to education, it might be channeled through unobserved factors like labor market characteristics or the access to modern (agricultural) production technologies. These factors will rather be found in better developed communities. However, higher returns to education could also be the result—decreasing marginal returns to education assumed—of higher marginal effects in some poor and remote communities. While the former case would rather lead to income divergence across communities, the latter could lead to income convergence.

To get further insights we can calculate the best linear unbiased predictors (BLUP) of the random effects and check if variations in returns across communities follow a distinct pattern across the 13 agro-climatic regions in Burkina Faso.[17] We cannot, however, find any evidence for a North-South or East-West pattern in returns to education across the 13 regions in any year. The same is true for the household size and dependency ratios. We conclude that returns to these factors are driven by small scale community characteristics but not by any regional factor.

We can also examine the covariance of random effects and random intercepts. For the returns to education the covariance between its random effect and the random community intercept turns out to be insignificant in 1994 and positively significant in 1998 and 2003. On average returns to education are higher in richer communities, ceteris paribus. Again, this may point to the impact of unobserved community factors on educational returns. As stated above, labor markets are usually better developed in richer communities in a sense that they are offering more opportunities for a better educated and trained work force. Moreover, modern agricultural inputs which may require skilled labor are rather found in richer communities. Hence, there is little evidence for higher returns to education in poorer communities. This is probably due to a only weakly competitive labor market and the general low demand for skilled labor in rural areas of poor countries such as Burkina Faso. Therefore, we conclude that disparities in returns to education cannot explain convergence across districts.

Regarding the effect of household size, the covariance with the community intercept is significantly negative in all years. The same is true for the effects associated with dependency ratios; children and youth per adult. This is an interesting result, stating that an additional household member, at working age or not, lowers per capita income more in richer than in poorer communities. In the Burkinabe context, it might just show that it is easier for an agricultural than for an urban household to feed and sustain an additional household member.[18]

5 Concluding remarks

The objective of this paper was to analyze the sources of spatial disparities in income among households in Burkina Faso. We find that about 60 percent of the total variance in incomes stems from variance between households, 20 percent from the variance between communities, less than 5 percent from the

[17] Since the regression coefficients associated with the household characteristics—which are random variables at the community level—are directly determined by the observed community level factors (see equation 3) further regression analysis it not feasible.

[18] Our finding of a negative covariance between intercepts and household size and dependency ratios do also hold when Ouagadougou is dropped from the regression.

variance between provinces and about 10 percent from the variance between (agro-climatic) regions. Within each level community characteristics play a very important role. In particular our findings suggest that communities and provinces are not only poor because the households which live there are poor but also because the endowments of these communities are very weak (and vice versa for rich communities). Differences in observed community characteristics account also for a large part of the regional variation. Hence, community characteristics matter.

We also find that the effects associated with household's education and their size and composition are community-specific. For instance, we find higher returns to education in the rather richer communities. In contrast, returns to cotton farming and livestock herding are more or less constant across these spatial units.

One may tend to conclude from our analysis that poverty alleviation policies should intervene at the community level, since at that level we identify the most important source of variance, and hence interventions at the regional or national level would risk to waste resources. However, political and institutional constraints might make it difficult to intervene at that level. This has to be studied case by case.

Finally, it should be noted that our analysis is constrained by the limited availability and the modest quality of data the different spatial levels. In Burkina Faso, as well as in many other developing countries, community surveys are missing. Geo-referenced data is also often not available. However, as we show, small-scale area data is key to understand and tackle spatial disparities in income.

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