Spatial patterns of growth and poverty changes in Peru (1993 – 2005)

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1. Introduction

The period that spanned between the last two population censuses (1993 and 2005) in Peru can be characterized as a period of economic growth. In this period the Peruvian economy grew at an annual average rate of 5%. Nevertheless, this positive trend was not homogeneous within the country. Urban areas experienced a higher pace of growth than rural areas and, within the latter, there is evidence of increasing gaps in favor of the Coastal Region as compared to the Highlands and Amazon regions (Vakis et al. 2008).

Given the important methodological changes in the calculation of poverty statistics (to the extent to seriously affect their comparability across years (Herrera, 2002)), it is difficult to assess how this uneven growth affected household wellbeing throughout the country. Further, poverty estimates are available at high levels of aggregation only and cannot be used to study spatial patterns at local levels. The purpose of this paper is to document the uneven growth and poverty dynamics occurred in Peru in the period 1993-2005 and evaluate up to what point spatial characteristics affect wellbeing levels and changes of Peruvian households.

In order to estimate poverty dynamics at local levels (lower aggregation levels than those normally obtained in nationally representative households surveys), two poverty mapping estimations are performed. The first poverty mapping exercise combines the 1993 population census, with the 1994 LSMS Survey and a number of district and province[1] level characteristics coming from the 1994 Agriculture Census and the district-level municipality censuses. The second poverty mapping exercise combines the 2005 population census, with the 2006 Household Survey (ENAHO) and the previously mentioned databases for district and province level characteristics as well as a provincial representative survey (ENCO). The following section constitutes the core of the paper and it starts with the discussion of the main findings of poverty dynamics estimates. The first two subsections explore the potential role of key public and private assets on experiencing positive poverty trajectories. The last three subsections in turn, discuss identification problems associated with the spatial dimension of poverty dynamics estimation.

[1] The lower level of public administrative hierarchy is the district. Districts are grouped in provinces, which in turn are grouped in departments (also named regions).

2. Small area Estimates of Poverty in Peru

To estimate Poverty rates at low level of spatial aggregation we have combined several data sources to construct per-capita expenditure estimates for each household in both the Peruvian 1993 and 2005 Population Censuses. The methodology used, follows closely Elbers, et al (2003). Table 1 presents a comparison of the estimated poverty rates and their standard errors for each of the two census years and the household surveys. This comparison is done at the level of aggregation at which each of the two household surveys can generate statistically representative results. It is important to note that the comparison needs to be done with caution. First, in both cases the interpolation is done for the previous year than the ones where the household surveys were collected (1993 instead of 1994 and 2005 instead of 2006). Second, since the sampling frame is not incorporated fully in the interpolation exercise the standard errors may be somewhat underestimated. Further the fact that we do not account for the spatial correlation in the disturbances may be underestimating further the estimated standard errors[2].

Table 1
Comparison of Regional Poverty Rates and Census Interpolations

	ENNIV 1994		Census 1993 Interpolation		ENAHO 2006		Census 2005 Interpolation	
	FGT(0)	est. dev.	FGT(0)	est. dev.	FGT(0)	est. dev.	FGT(0)	est. dev.
Urban Costa	43.9%	4.00%	48.2%	0.08%	30.2%	1.47%	34.1%	0.74%
Rural Costa	60.9%	5.61%	51.9%	0.10%	47.4%	2.80%	49.2%	0.87%
Urban Sierra	46.0%	4.10%	46.0%	0.09%	40.2%	1.71%	49.8%	1.77%
Rural Sierra	67.7%	2.64%	62.5%	0.05%	76.7%	1.12%	72.2%	0.70%
Urban Selva	39.6%	4.06%	45.3%	0.13%	50.6%	2.89%	52.8%	1.49%
Rural Selva	70.6%	3.40%	77.8%	0.17%	62.9%	1.72%	62.9%	0.69%
Metropolitan Lima	32.2%	2.39%	36.2%	0.05%	24.2%	1.37%	28.7%	0.88%
	FGT(0)	est. dev.	FGT(0)	est. dev.	FGT(0)	est. dev.	FGT(0)	est. dev.
Costa	47.8%	3.35%	49.6%	0.06%	34.1%	1.30%	37.1%	0.74%
Sierra	59.8%	2.28%	58.5%	0.04%	63.7%	1.00%	63.1%	0.82%
Selva	56.7%	2.63%	66.8%	0.09%	57.3%	1.54%	57.9%	0.85%
Metropolitan Lima	32.2%	2.39%	36.2%	0.05%	24.2%	1.37%	28.7%	0.88%
Peru	48.9%	1.27%	51.3%	0.07%	44.8%	0.69%	46.0%	0.96%

Source: Own estimates base don Census interpolation and ENNIV 1994 and ENAHO 2005 surveys

In general our results do match with the estimated poverty rates in both years. In all cases the estimated census interpolation falls within the 99% confidence interval of the household survey estimates. Still, if we test the differences using the standard deviation

2 Lanjouw et al (2007) uses pseudo samples obtained from Mexican data to contend that confidence intervals obtained from this small area methodology do correspond to what should be expected.

estimated in both household and census and we contend that these are independent samples the test will indicate that we cannot reject that estimates are equal in the 1993 for all regions and in most of the regions for 2005. Is interesting to note that the for 2005 the most important deviations occur in Lima, in urban Costa and in urban Sierra, which are precisely the areas where poverty has been reduced the most between 2004 and 2006. In those three cases poverty rates in the census interpolation are slightly larger than the ENAHO 2006 estimates, which we believe is reasonable. In the case of the rural Sierra we may have a slight poverty underestimation in 2005. The estimates shown here reflect the fact the Peru poverty rate has been dropping from an estimate of 51% in 1993 to a 46% in 2005. Although this is a small change it hides important regional differences. In the case of the urban coast the reduction is quite large, while in the rural Sierra we are estimating an increase of poverty during the same period.

Figure 1

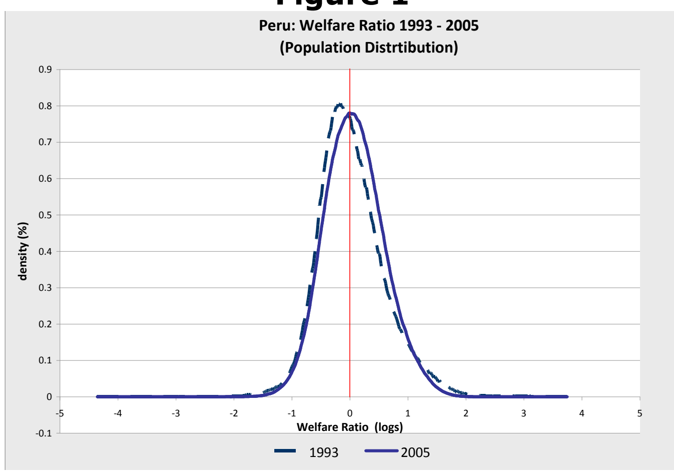
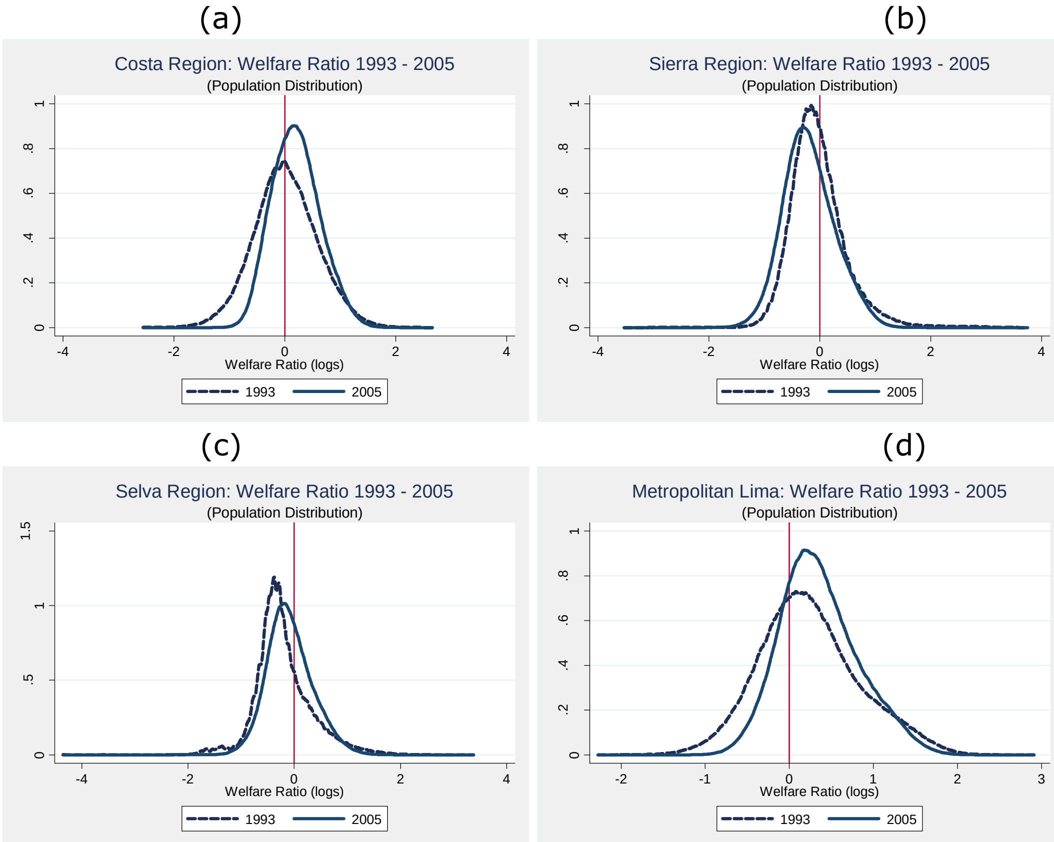


Figure 1 shows the density distribution of the log-welfare ratio (that is the logarithm of per capita expenditure divided by the poverty line) for 1993 and 2005 for the whole country. A log-welfare ratio greater than zero indicate that the household is non-poor. Here we can see that the distribution has shifted mostly to the right, indicating a reduction in poverty. Still parts of the distribution for 1993 are located to the right of the 2005 distribution indicating that there may be some segments that may be worse off. Figure 2, shows the distribution for the main regions of Peru. Here it is evident that distinct patterns of changes in wellbeing across Peruvian geography.

Figure 2
Log-Welfare Ratio Distribution by Geographic Region



As we have mention, the use of household data plus census data, allow us to obtain poverty estimates at greater disaggregation levels than the ones survey estimates can allow. In order to aid on the interpretation of the spatial patterns of poverty changes in Peru, Figure 3 maps an estimation of growth at the district level occurred between 1993 and 2005, using our estimated welfare measure of per-capita expenditure. We have colored the map in growth ranges and considering ±1% per year as very little or no growth, even if most of these districts may have been considered as having statistically significant changes if we have done a formal test[3].

Figure 3 shows that although growth has been widespread across Peru during the 1993-2005 period, areas with low or null growth tend to be spatially concentrated along the

[3] We have preferred not do so on several grounds. First we recognize that although expenditure groups are the same in both surveys the detail of the questionnaire is much larger in the ENAHO 2005 which may generate some upward bias. Second, formal statistical testing between both interpolation need further elaboration (given that the estimation do share a number of right had side variables).

highlands of Peru. To make this even more evident, Figure 4 shows the altitude of all districts in Peru. Contrasting Figure 3 and Figure 4 shows clearly that those districts that are located in high altitude areas are more likely to have shown low or null growth.

Figure 3
Per Capita Expenditure Growth 1993-2005
(Annual growth rates)

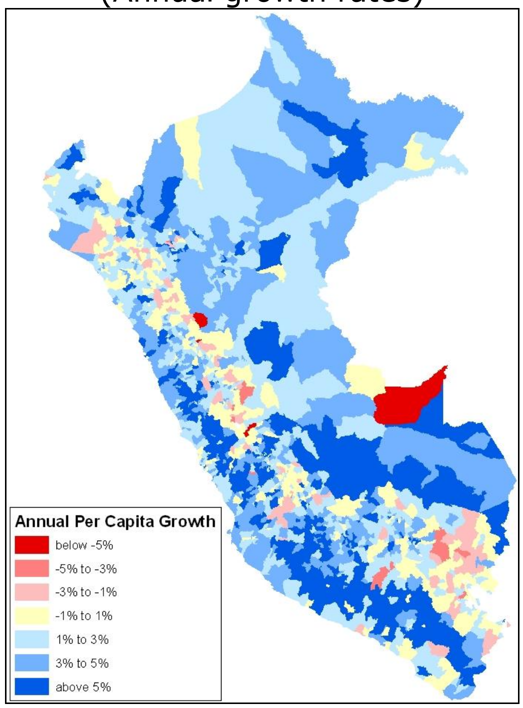
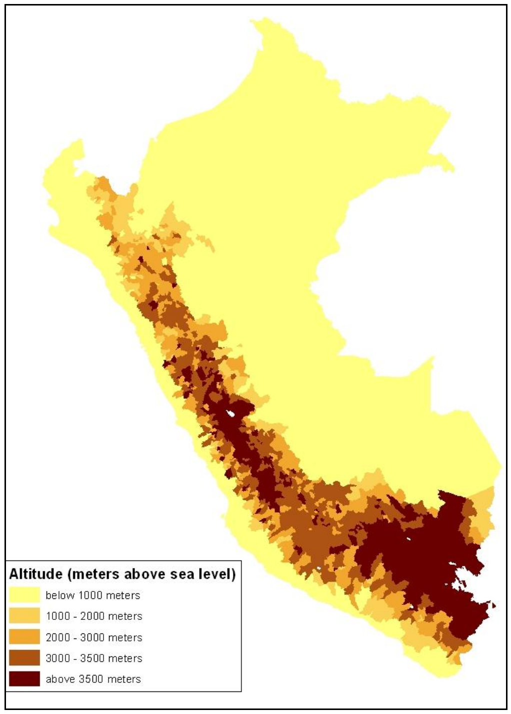


Figure 4
District Altitude



Given this patter of growth it is interesting to see how poverty has change between these two census years. Figure 5 shows the poverty rates of all districts in Peru for 1993 and 2005 while Figure 6 shows the changes in these poverty rates at the district level.

Figure 5
Poverty - District level estimates

(a) in 1993 (b) in 2005

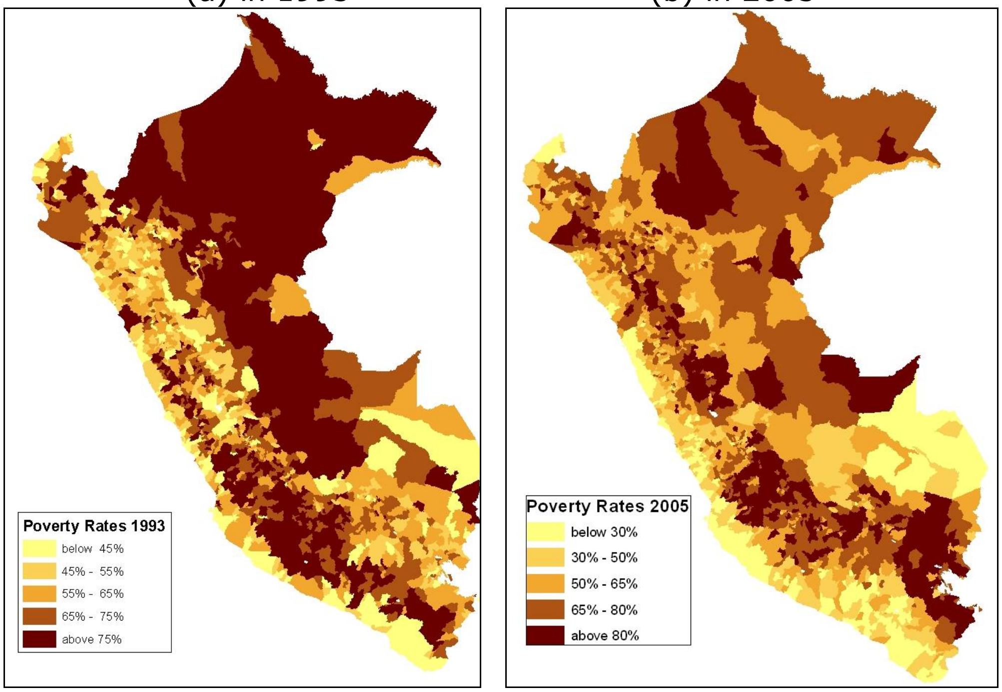
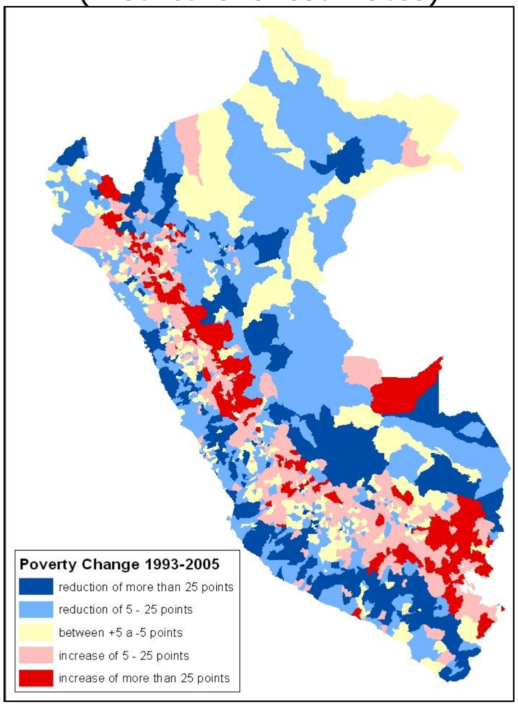


Figure 6
Poverty Change between 1993 and 2005
(District level estimates)

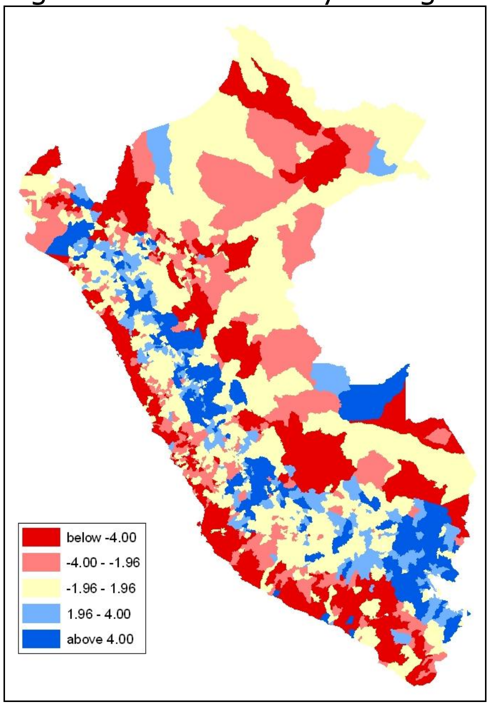


Again it is very evident the spatial pattern of both the poverty rates in both years and the changes in the poverty rates between 1993 and 2005. In 1993 and 2005 lower poverty rates can be observed along the Peruvian coastal areas, with higher rates in both Sierra and Selva. Further it is interesting to note the distinct poverty pattern between northern and southern Sierra in 1993. When one looks at poverty changes, higher reductions in poverty are spatially concentrated along the coast, a few valleys in the Sierra (parts of the Mantaro Valley in the central Sierra and La Convención in the southern Sierra) and in the upper Amazon (Bagua, Jaen and Utcubamba, which are coffee producing zones). The areas where poverty has increased are heavily concentrated in the northern Sierra (around Huánuco Region) and in the southern Sierra, especially in Puno.

One way of assessing how important are the poverty changes depicted in Figure 6 is show if these differences are statistically significant[4]. Figure 7 shows precisely this as an indicator of the statistical significance of poverty changes. Here it is again evident that poverty reductions along the Peruvian coastal areas are highly significant

4 We have calculate the statistical significance of poverty changes as follows: $z = \frac{FGT(0)_{2005} - FGT(0)_{1993}}{st.dev[FGT(0)_{1993}]}$

Figure 7
Statistical Significance of Poverty changes 1993-2005



2.1 Mean Characteristics of districts showing significant poverty changes

We have divided the 1880 districts in which Peru is divided in three groups. The first one, comprising 796 districts represents those districts where poverty has been reduced (using a 95% confidence interval as the criterion). The second group includes 680 districts in which poverty significantly increased between 1993 and 2005. Finally, we have 352 districts where poverty did not changed in a statistical significant way between the two census years. Table 2 shows that differences in the mean characteristics of those districts with significant poverty increases and significant poverty reductions, including, a significance test for mean differences in characteristics. The main characteristics of the districts have been grouped along four areas: a) human capital and demographics; b) economic activities; c) access to infrastructure; and, d) location and geographic related characteristics.

When we look at the percentage of rural population in 1993 in table 2 we find that both groups of districts, those showing poverty increase are significantly more likely to be rural. Further, when we look at household and demographics aspects it is evident that districts whose poverty rate has increased are almost three times more likely of being of indigenous origin than those coming from district whose poverty rate got reduced. Similarly districts with poverty increase are those that have a significantly higher proportion of female headed households[5].

Educational differences are also apparent when we compared districts hose poverty rates have gone down and districts with increasing poverty rates. The first group has a lower percentage of head of households that have primary education or less and higher percentage of head of households with higher education than the latter.

It is interesting to note that the type of economic activity in which households are involved is different for those that districts that have reduced poverty than those whose poverty rates have increased. This is especially clear in the rural districts where those districts diversifying away from agriculture have been able to perform better.

Access to infrastructure is, of course key factors that differentiate those districts performing better in the 1993-2005 period as oppose to those that have increased their poverty rates. For the national aggregate and for the urban and rural segments of sample is clear that those district having higher coverage of electricity, piped water and sewerage at the baseline (1993) where more likely to show a reduction in their poverty rates. However, it is interesting to note that this pattern reverses when one looks at changes in service access (a proxy o investment in infrastructure services) areas. Districts that have higher changes in access to piped water and electricity show poverty increases. This pattern may be capturing migration process as better endowed areas tend to increase their poverty rates if they received poor household migrating as a way of improving their wellbeing

Location and geographic characteristics are also very different between those districts whose poverty got reduced between 1003 and 2005 and those that confronted a poverty increase. Besides those location variables already mentioned (being in a district from Costa or Selva makes you more likely to observe a poverty reduction and being in a district from the Sierra region) ii is interesting to note that district that have lands with lower slope tend to perform better. This is so even if bioclimatic potential may be worse-off or if precipitation is lower. Within rural areas, however, we can observe that better climate conditions do affect chances of been in a district that had a reduction in poverty.

[5] We have also done the same exercise splitting the sample between those districts that are urban (50% or more of the population live in urban areas) or rural (50% or more of the population live in rural areas). The results are available upon request.

Table 2
Mean Characteristics of Districts with Significant Changes in Poverty Rates

	Districts with poverty increase n=680	Districts with poverty reduction n=796	
Human capital and demographic aspects			
Average age of household head	44.5	44.5	
Percentage of woman headed household	24.4%	21.7%	***
head of household has spanish mother tongue	57.6%	85.3%	***
Percentage of head of household with uncompleted primary education attained or less	12.2%	8.6%	***
Percentage of head of household with completed superior education attained	1.9%	3.3%	***
Drop out rates - Primary School (children between 5 and 12 years old)	26.1%	21.0%	***
Change in average age of household head (1993-2005)	2.7267	3.1705	***
Change in percentage of woman headed household (1993-2005)	-3.7%	-0.9%	***
change in percentage of head of household with uncompleted primary education attained or less (1993-2005)	27.7%	14.2%	***
change in percentage of head of household with completed superior education attained (1993-2005)	11.6%	20.1%	***
Changes in drop out rates - Primary School (children between 5 and 12 years old) (1993-2005)	-24.9%	-20.2%	***
Economic Activities			
Percentage of head of household working for Extractives industries (1993)	54.4%	40.2%	***
Percentage of head of household working for Manufacturing sector (1993)	8.1%	10.1%	***
Percentage of head of household working for Service Sector (1993)	29.0%	42.2%	***
Infrastructure			
Index of fragmentation of agricultural plots (the more the worst) (1994)	0.911	0.827	***
Land Asset index (at median prices) (1994)	20,816	33,153	**
Animal Stock index (at median prices) (1994)	6,022	4,292	
Percentage of households with piped water source within the house (1993)	26%	50%	***
Percentage of households with sewerage service within the house (1993)	20%	42%	***
Percentage of households with electricity within the house (1993)	37%	61%	***
Percentage of telephone line subscribers (1993)	3%	11%	***
Change in access to water pipe service between (1993-2005)	21%	15%	***
Change in access to sewerage between (1993-2005)	9%	12%	***
Change in access to electricity between (1993-2005)	18%	13%	***
Location and geographic characteristics			
Distance to the nearest town with 100,000 inhabitants or more (hours)	8.01	4.96	***
Altitude	2708	525	***
Percentage of population living in Costa Region	5%	48%	***
Percentage of population living in Sierra Region	87%	11%	***
Percentage of population living in Selva Region	9%	21%	**
Percentage of population living in Lima Metropolitana	0%	20%	***
Average slope	44.78	31.13	***
Bioclimate potential score (the higher the better)	67.06	36.93	***
Land potential score (the higher the better)	56.59	47.72	***
Average temperature	17.76	18.26	
Average precipitation	71.75	41.37	***
Temperature - coefficient of variation	12.4%	10.1%	***
Precipitation - coefficient of variation	107.5%	205.4%	***
Percentage of rural population in the district	71.7%	45.0%	***
change in percentage of rural population	-14.1%	-14.4%	

Note: weighted by population

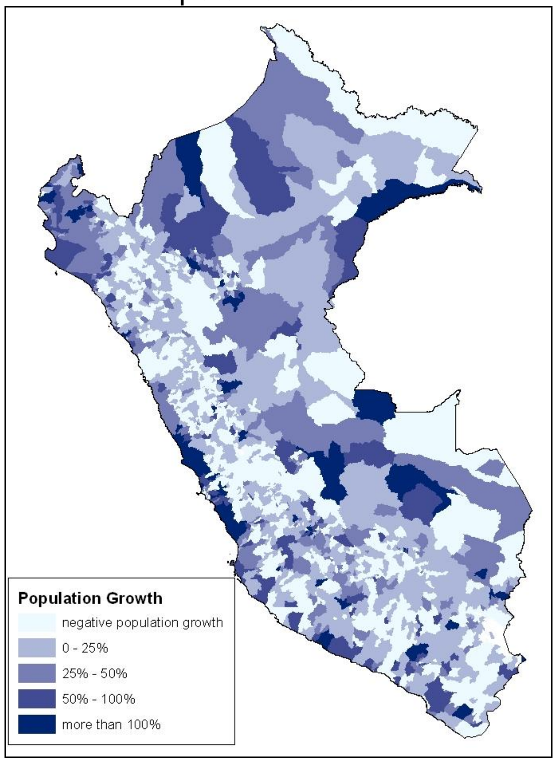
Note: there are 352 districts with no significant change in poverty status

What has changed in Peru to explain such a change in poverty? A full explanation is beyond the scope of this paper but it is clear that migration in a context of growth disparities should be at the core of any explanation[6]. As has been shown in World Bank (2005), rural poverty has been most responsive to economic growth (1993-1997 and 2001-onwards) only in the Costa and least responsive in the Sierra. Further, in periods of stagnation (1997-2001) poverty in Rural and Selva regions has increased the most, especially among those that are better linked to the product markets, the rest been able to buffer through increase in self-consumption.

During this period, migration statistics are not readily available since migration related questions were not asked in the 2005 census. However population growth spatial patterns are very clear as can be seen in Figure 8. Here we map population growth of all districts in Peru between 1993 and 2005. As can be seen in most of the Sierra region population growth has been negative. Our results show that in those areas were population has grew the least or has diminished are areas where population has increased. This pattern is consistent with the fact that younger, better educated and relatively more wealthy household are more capable to migrate, leaving behind older and less endowed households.

[6] We have looked in detail to the methodology used to construct poverty lines in 1994 and 2005 to assure reasonably comparability. We noted the 1994 poverty lines for the Sierra included a slightly larger caloric intake than the one considered in 2006. Thus if any methodological bias exists go against blaming methodological differences as a way of explaining these poverty increases. On the contrary, poverty rates on the Sierra region may be slightly underestimated, which in turn will mean that poverty has increased marginally more than what we are estimating here. The study, however, does not incorporates this adjustment.

Figure 8
Population Growth



2.2 Poverty profiles

How robust are these regularities? Table 3 and table 4 estimate that poverty profiles for both 1993 and 2005. To account for the fact that our poverty estimates are themselves the result of an estimation procedure we present both OLS estimates and estimates weighted by the inverse of the standard error of the interpolation (Douidiche et al, 2008).

Table 3

Poverty Profile 1993 (Global regression with Rural/Urban Interactions)

	Unweighted		Weighted by variability coef.	
	Urban	Rural	Urban	Rural
Private Assets				
Average age of household head	0.0100***	0.00534***	0.0109***	0.00477***
	(0.0034)	(0.0010)	(0.0035)	(0.0010)
Average of household size	0.0869***	0.00629	0.0642***	0.00785
	(0.020)	(0.0056)	(0.019)	(0.0056)
Percentage of woman headed household	0.250	0.124**	0.181	0.176***
	(0.21)	(0.057)	(0.20)	(0.054)
head of household has spanish mother tongue	-0.121**	-0.0436***	-0.112**	-0.0297***
	(0.049)	(0.010)	(0.057)	(0.010)
Drop out rates - Primary School (children between 5 and 12 years old)	0.414*	0.0971**	0.0972	0.111***
	(0.23)	(0.039)	(0.26)	(0.039)
Percentage of head of household has uncompleted primary education attained or less	0.294**	-0.0900**	0.317**	-0.0994***
	(0.14)	(0.036)	(0.14)	(0.034)
Percentage of head of household with completed superior education attained	0.0767	-0.443***	0.0422	-0.296**
	(0.24)	(0.14)	(0.20)	(0.13)
Economic Activities				
Percentage of head of household working for Extractives industries	-0.126	-0.0182	-0.224*	0.00207
	(0.14)	(0.032)	(0.13)	(0.031)
Percentage of head of household working for Manufacturing sector	-0.411**	-0.0645	-0.452***	-0.0142
	(0.18)	(0.085)	(0.16)	(0.084)
Percentage of head of household working for Service Sector	0.0217	-0.0334	-0.0799	-0.0348
	(0.14)	(0.041)	(0.13)	(0.038)
Assets				
Fragmentation index of agricultural plots	0.0294	-0.110***	0.0545*	-0.0894***
	(0.031)	(0.013)	(0.028)	(0.013)
Total number of producer agrarian units	0.0000263	-0.00174***	0.000643	-0.00101
	(0.0013)	(0.00062)	(0.0012)	(0.00080)
Animal Stock index (at median prices)	0.000647**	0.00193***	0.000542	0.00172***
	(0.00032)	(0.00020)	(0.00048)	(0.00031)
Infrastructure				
Percentage of households with piped water source within the house	0.0176	0.263***	0.102	0.258***
	(0.064)	(0.022)	(0.074)	(0.021)
Percentage of households with electricity within the house	-0.0959*	-0.162***	-0.142**	-0.168***
	(0.052)	(0.017)	(0.056)	(0.017)
Percentage of households with sewerage service within the house	-0.239***	-0.330***	-0.231***	-0.316***
	(0.067)	(0.040)	(0.077)	(0.038)
Percentage of household with residencial telephone service	-0.364***	-0.849***	-0.358***	-1.251***
	(0.14)	(0.26)	(0.12)	(0.23)
Climate, Geography and Location				
Bioclimate potential score (the higher the better)	0.00118**	-0.000369**	0.00170***	-0.000305*
	(0.00054)	(0.00016)	(0.00064)	(0.00017)
Land potential score (the higher the better)	-0.000369	-0.000243	-0.000569	0.0000592
	(0.00072)	(0.00027)	(0.00095)	(0.00028)
Precipitation - coefficient of variation	0.0165*	0.0221***	0.0250*	0.0325***
	(0.0087)	(0.0081)	(0.013)	(0.0084)
Temperature - coefficient of variation	0.564**	0.354***	0.562*	0.269**
	(0.26)	(0.10)	(0.33)	(0.11)
Average precipitation	-0.831	-2.183***	-0.327	-2.189***
	(0.95)	(0.31)	(1.25)	(0.34)
Average temperature	-0.0115	-0.0140**	-0.0136	-0.00634
	(0.0093)	(0.0070)	(0.012)	(0.0067)
Squared precipitation	0.902	6.396***	-1.078	5.838***
	(3.49)	(1.00)	(5.50)	(1.06)
Squared temperature	0.000372	0.000641***	0.000415	0.000359*
	(0.00038)	(0.00020)	(0.00050)	(0.00020)

(Continue, Poverty Profile 1993...)

	Unweighted		Weighted by variability coef.	
	Urban	Rural	Urban	Rural
Igneous Rock	-0.0000220	0.000807***	0.000558	0.000190
	(0.00074)	(0.00026)	(0.00098)	(0.00028)
Metamorfic Rock	0.0716	-0.0595***	0.109*	-0.0744***
	(0.055)	(0.014)	(0.064)	(0.014)
Slop	-0.104*	-0.0793***	-0.0924	-0.0526***
	(0.058)	(0.017)	(0.076)	(0.019)
Distance to the nearest town with 100,000 inhabitants or more (hours)	0.00168***	0.00199***	0.00134***	0.00165***
	(0.00047)	(0.00021)	(0.00043)	(0.00022)
Altitude	-0.0299	0.0121**	-0.0405**	0.0176***
	(0.019)	(0.0057)	(0.019)	(0.0058)
District of Costa Region	0.0314	-0.125***	0.0325	-0.179***
	(0.051)	(0.019)	(0.051)	(0.019)
District of Selva Region	0.132**	0.243***	0.157**	0.223***
	(0.060)	(0.017)	(0.074)	(0.019)
District of Lima Metropolitana	0.0626	-0.209***	0.0490	-0.201***
	(0.060)	(0.050)	(0.063)	(0.035)
	-0.153**	-0.0155	-0.149**	-0.0662*
	(0.061)	(0.030)	(0.068)	(0.037)
Population	-0.153**	-0.0155	-0.149**	-0.0662*
	(0.061)	(0.030)	(0.068)	(0.037)
Rural	0.0307		0.112	
	(0.23)		(0.22)	
Urban		0.335***		0.301***
		(0.096)		(0.092)
Observations	1828		1828	
Chow TEST F(34,1763)	7.09		10.42	
p-value	0.00		0.00	
R-squared	0.61		0.73	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Here we can see that poverty rate in a district is larger the higher the percentage of female headed households and the higher the percentage of head of household speaking a native language. Such correlations will not be apparent if we did not give proper weight to those districts that have more reliable estimates. Similarly, the marginal effect of education is statistically significant in both poverty profiles.

It is interesting to note that the larger the presence of both agricultural waged activities and non-agriculture non-waged activities reduces poverty rates in the 2005 poverty profile. This finding is consistent with the wealth of evidence associated that shows that income diversification can reduce poverty.

Regarding the access to public services both profiles show again that these variables (access to electricity, access to piped water and access to sewerage) correlated positively with lower poverty rates in both urban and rural settings. Access to markets, proxied here by the distance to the nearest district with at least 100,000 inhabitants, are shown to be highly correlated with poverty as longer travel times increase poverty rates. It should be highlighted here, once again, that this are mere profiles and as such they may be capturing, in the best case scenario of no endogeneity, reduced form effects. We will pursue this further in section 3.

Finally, regarding other location and geographic correlates, they continue to be highly significant even if one controls by access to key private and public assets. For example, altitude keeps correlating with higher poverty rates. Similarly, soil characteristics, and precipitation are variables that continue to be highly correlated with wellbeing outcomes.

Table 4
Poverty Profile 2005
(Global regression with Rural/Urban Interactions)

	Unweighted		Weighted by variability coef.	
	Urban	Rural	Urban	Rural
Human capital and demographic aspects				
Average Age of household head	-0.000278	-0.00447	-0.0000978	-0.00147
	(0.0034)	(0.0034)	(0.0011)	(0.0011)
Average of household size	0.0886***	0.0318	0.0626***	0.0600***
	(0.023)	(0.022)	(0.0068)	(0.0070)
Percentage of woman headed household	0.162	0.215	0.362***	0.393***
	(0.23)	(0.22)	(0.065)	(0.063)
head of household has spanish mother tongue	-0.0511	0.0440	-0.0753***	-0.0682***
	(0.063)	(0.079)	(0.013)	(0.014)
Drop out rates - Primary School (children between 5 and 12 years old)	1.253	1.297	0.574***	0.633***
	(1.80)	(2.38)	(0.20)	(0.18)
Percentage of head of household has uncompleted primary education attained or less	0.0620	0.0349	0.161***	0.220***
	(0.14)	(0.16)	(0.030)	(0.030)
Percentage of head of household with completed superior education attained	-0.507***	-0.385***	-0.174*	-0.299***
	(0.097)	(0.076)	(0.092)	(0.091)
Chronic Malnutrition Rate, children between 6 and 12 years old	0.311**	0.437***	0.255***	0.201***
	(0.13)	(0.16)	(0.030)	(0.030)
Economic Activity				
Rate of agricultural salaried jobs	0.00831	0.0806	-0.326***	-0.391***
	(0.18)	(0.23)	(0.075)	(0.077)
Rate of non agricultural salaried jobs	-0.0140	-0.0743	0.0209	-0.0342
	(0.14)	(0.17)	(0.056)	(0.056)
Rate of non agricultural non salaried jobs	-0.310**	-0.143	-0.184***	-0.166***
	(0.14)	(0.16)	(0.058)	(0.059)
Household Assets				
Fragmentation index of agricultural plots	-0.0277	0.0131	0.00434	0.0159
	(0.031)	(0.026)	(0.013)	(0.013)
Animal Stock index (at median prices)	-0.00134	-0.00198	0.0000183	0.000327
	(0.0013)	(0.0013)	(0.00061)	(0.00079)
Land Asset index (at median prices)	-0.0000322	-0.000261	0.000528**	0.000498
	(0.00035)	(0.00049)	(0.00021)	(0.00032)
Infrastructure				
Percentage of households with piped water source within the house	-0.0264	0.0612	-0.0942***	-0.100***
	(0.060)	(0.071)	(0.014)	(0.014)
Percentage of households with electricity within the house	-0.219**	-0.442***	-0.0360**	-0.0340**
	(0.087)	(0.096)	(0.015)	(0.015)
Percentage of households with sewerage service within the house	-0.120**	-0.175***	-0.0967***	-0.0162
	(0.056)	(0.067)	(0.025)	(0.023)
# of health centers	-0.000505	0.000897	-0.000684	0.000159
	(0.00079)	(0.00067)	(0.00081)	(0.0011)
# of telecom public centers	-0.0000115	0.0000187	-0.000643***	-0.000505*
	(0.000075)	(0.000052)	(0.00018)	(0.00028)
# of students per classroom	-0.000932	-0.000269	0.00103*	0.00105*
	(0.0010)	(0.00085)	(0.00058)	(0.00058)
Location, geographic and climatic characteristics				
Bioclimate potential score (the higher the better)	-0.000658	-0.000964	0.0000533	0.000235
	(0.00057)	(0.00069)	(0.00015)	(0.00017)
Land potential score (the higher the better)	0.00248***	0.00210**	0.000242	-0.000107
	(0.00072)	(0.00095)	(0.00027)	(0.00028)
Precipitation - coefficient of variation	0.00470	0.0135	-0.0143*	-0.00473
	(0.0085)	(0.013)	(0.0082)	(0.0084)
Temperature - coefficient of variation	0.0395	-0.441	-0.0244	-0.0324
	(0.29)	(0.36)	(0.10)	(0.11)
Average precipitation	0.629	1.757	0.307	0.416
	(1.07)	(1.47)	(0.33)	(0.35)
Average temperature	-0.00592	0.00571	-0.00324	-0.00756
	(0.011)	(0.013)	(0.0073)	(0.0069)
Squared precipitation	-2.478	-5.384	-1.636	-2.337**
	(3.83)	(6.06)	(1.03)	(1.08)
Squared temperature	0.000285	-0.000198	0.000319	0.000440**
	(0.00044)	(0.00058)	(0.00021)	(0.00021)

(Continue, Poverty Profile 2005...)

	Unweighted		Weighted by variability coef.	
	Urban	Rural	Urban	Rural
Soil depth	0.000279	0.000799	0.00245***	0.00223***
	(0.00076)	(0.0010)	(0.00027)	(0.00028)
Igneous Rock	-0.147**	-0.132*	-0.0141	-0.0147
	(0.061)	(0.070)	(0.014)	(0.014)
Metamorfic Rock	0.00288	-0.0266	-0.103***	-0.104***
	(0.058)	(0.074)	(0.017)	(0.019)
Average Slop	-0.000207	-0.000154	0.000512**	0.000433*
	(0.00045)	(0.00040)	(0.00022)	(0.00022)
Distance to the nearest town with 100,000 inhabitants or more (hours)	-0.0000488	-0.000103	0.00000174	0.0000298
	(0.00018)	(0.00022)	(0.000034)	(0.000036)
Aditional distance to the nearest town with 75,000 inhabitants or more (hours)	0.00146	0.000736	0.00147***	0.00184***
	(0.0011)	(0.0014)	(0.00033)	(0.00032)
Altitude	0.0426**	0.0457**	0.0422***	0.0480***
	(0.019)	(0.021)	(0.0057)	(0.0058)
District of Costa Region	-0.0404	-0.0140	0.0317*	0.0283
	(0.053)	(0.055)	(0.018)	(0.019)
District of Selva Region	-0.0774	-0.126*	-0.0587***	-0.0455**
	(0.060)	(0.074)	(0.018)	(0.019)
District of Lima Metropolitana	0.0330	0.0567	-0.0945*	-0.113***
	(0.064)	(0.068)	(0.048)	(0.033)
Population	-0.222***	-0.253***	-0.172***	-0.172***
	(0.050)	(0.057)	(0.018)	(0.019)
Urban	0.447**		0.783***	
	(0.20)		(0.20)	
Rural		0.204**		0.277***
		(0.099)		(0.095)
Observations	1828.00		1828.00	
Chow TEST F(38,1750)	2.46		2.25	
p-value	0.00		0.00	
R-squared	0.80		0.75	

Standard errors in parentheses
*** p<.1, ** p<.5, * p<.1

2.3 Spatial Correlation

A key question that we need to address is whether or not the profiles that we have estimated in the previous section are robust. If we find the residuals of this type of estimation are spatially correlated we will have evidence that there may be some specification problems in these profiles. Table 9 presents the Moran statistics for the 2005 poverty profile estimated in the previous section and also of the Log per Capita consumption model, estimated with the same set of variables.

One way of measuring how spatially correlated are our well-being indicators or the residual of the poverty profiles shown in the previous section is through the Moran Spatial autocorrelation index. This indicator compares the value of a variable at any one location with the value at all other locations:

$$I = \frac{N\sum_i \sum_j W_{i,j}(y_i - \overline{Y})(y_j - \overline{Y})}{(\sum_i \sum_j W_{i,j})\sum_i (y_i - \overline{Y})^2}$$

(1)

where W represents some indicator of contiguity between observation i and j. For example, in the simplest case if district j is adjacent to district i, W_{ij} receives a weight of 1, and 0 otherwise. A Moran statistics closer to 1 indicates a bigger difference from the Peruvian average.

As can be seen in table 5, per-capita expenditure and poverty show a very strong and highly significant spatial pattern. Moran statistics for these variables are high not only for the 1983 and 2005 periods, but they are also highly significant when we measure the spatial autocorrelation of the changes estimated for the 1993-2005 period.

Table 5
Spatial Correlation
(Moran Statistics for Selected Variable)

	1993	2005	Change 1993-2005
Per-capita Expenditure	0.6095	0.7338	0.4667
Poverty	0.5327	0.7094	0.5719
Gini	0.3663	0.2167	0.4222
Head of HH Education (more than secondary)	0.6585	0.6484	0.5144
Access to electricity	0.5964	0.5658	0.3409
Access to drinkable water	0.4995	0.4631	0.3385
Altitude		0.8675	

Note: All statistics are significant at 1%

If we look at the spatial correlation of the residuals (table 6) we can note that although the Moran statistics for the residuals is much lower than the predicted (or actual) poverty and log-per capita consumption, the spatial correlation continues to be highly significant. In other words, although controlling for key observables captures an important part of the spatial correlation that exists in these variables, the model continues to have a specification problem.

This miss specification may arise because of at least two factors. One possibility is the existence of omitted variables that vary across Peruvian geography. Although we have done our best to include location and geographic variables related to altitude soil, climate, there may be still some factors missing. An alternative explanation could be that the parameters are not constant through space. If this is the case, the residuals may be capturing such specification error.

Table 6
Moran Statistics for Selected Estimations – 2005

	Residual		Predicted		Prediction Error	
Poverty 2005						
- OLS controlling for initial conditions	0.3087	***	0.7974	***		
- OLS controlling for initial conditions & change in covariates	0.3052	***	0.7677	***		
- Spatial Lag Model	0.0627	**	0.8488	***	0.3225	***
- Spatial Error Model	-0.0309	*	0.7704	***	0.4046	***
Log Per Capita Expenditure 2005	0.3328	***	0.7839	***		
- OLS controlling for initial conditions						
- OLS controlling for initial conditions & change in covariates	0.3155	***	0.7750	***		
- Spatial Lag Model	0.1917	***	0.8000	***	0.3141	***
- Spatial Error Model	-0.0398	*	0.7755	***	0.4247	***

***p<1%, **<5%,* p<10%

One may try to correct this problem by modeling explicitly the spatial correlation. The literature typically considers two types of models; the spatial lag model and the spatial error model. The first considers that the left hand side variable (in our case poverty or per-capita expenditure) may be affected by the level of such variable of neighboring districts. If this is the case we may need to add in the profile the spatially-lagged endogenous variable. Alternatively, we may consider that there are omitted explanatory variables that are spatially correlated and if these are variables are not correlated with the other explanatory variables we may just need to adjust the estimation using a more efficient estimation technique than OLS.

Table 7 shows also the correlation of the models under these two assumptions. Although the spatial correlation of the error structure is substantially reduced the Moran statistics continues to find evidence of spatial correlation. This may happen either because we are still omitting spatially correlated variables or, alternative, because other assumption (like parameter homogeneity) may not be appropriate. It is interesting to note, as table 10 shows that spatial correlation of the residuals persist even if we model poverty change and growth instead of poverty and consumption per-capita levels.

Table 7
Spatial Autocorrelation of Residuals when modeling Poverty Change and Growth 1993-2005

	Growth		Poverty Change	
OLS	0.3020	***	0.3354	***
Spatial Lag Model	0.1278	***	0.1149	***
Spatial Error Model	-0.0320	*	-0.0329	*

***p<1%, **<5%,* p<10%

In the next section we model explicitly parameter heterogeneity as a way of capturing the spatial variation of the data. As is well known, testing parameter variation typically entails the usage of one of two procedures. The first one is the testing for structural breaks of the type covered by the Chow test. Alternatively one may try to detect unsystematic or random variations in the parameters following the Breusch and Pagan testing procedure. (Dutta and Leon, 1991).

Neglected heterogeneity can lead to inconsistent or inefficient estimators (Chesher, 1984). So far, we already know that the chow test based on splitting the sample between urban and rural areas show that parameters are significantly different across areas. A similar conclusion can be obtained if one splits the sample between Costa, Sierra and Selva regions. This is an indicator that per-capita expenditure, growth, and poverty dynamics may be correlated differently across space with household characteristics, private assets and access to public infrastructure.

2.4 Is Geography Destiny?: looking at spatial heterogeneity in Peruvian welfare dynamics.

One way to look at whether or not geographic variables are relevant after controlling for observable non-geographic characteristics is to pursue a spatial decomposition analysis as the one performed for Peru, using provincial data from 1972 and 1993, by Escobal and Torero (2000). In this exercise it was apparent that although geography was correlated with expenditure growth that correlation disappeared once we control for observable non-geographic characteristics[7]. At the same time the paper recognized that the residuals from the equations used to perform the spatial decomposition analysis had significant spatial correlation, even after trying to correct it, introducing a first order correlation adjustment (Escobal and Torero, 2000: table 9 - p. 22).

To compare these results with the ones we have obtained here we have reconstructed the decomposition exercise, looking at the differences in per-capita welfare ratio between

[7] In this case the poverty mapping exercise for 1972 was done using the parameters of a expenditure equation coming from the Peruvian LSMS 1985-86. Because of this, the paper recognizes that the results should be taken with some caution.

the Sierra and Costa regions and between Selva and Costa regions[8]. The decomposition was done for both the 1993 and 2005 profiles and for the log-welfare-ratio differences (a proxy of real expenditure growth).

Table 8 presents the decomposition exercise for 1993 of estimated district level log welfare ratio differences between Sierra and Costa regions and between Selva and Costa regions. As can be seen here, geography remains an important factor correlated with log welfare ratio differences even after sequentially controlling for infrastructure, economic environment, private assets and, finally, human capital and household characteristics. These results are consistent with Escobal and Torero (2000). Further, the fact that spatial correlation of the residuals remains significant in all specification is also consistent with Escobal and Torero (2000) evidence.

8 The welfare ratio is constructed as that is the logarithm of per capita expenditure divided by the poverty line.

Table 8
Regional Decomposition of Log Welfare Ratio
(based on national level estimates - 2005)

	Models									
	1		2		3		4		5	
***Sierra- Costa:* Log Welfare Ratio**	-0.425		-0.425		-0.425		-0.425		-0.425	
Geography	-0.449	***	-0.342	***	-0.281	***	-0.283	***	-0.180	***
Infrastructure			-0.103	***	-0.107	***	-0.112	***	-0.046	
Economic Environment					-0.058		-0.067		0.010	***
Private Assets							0.021	***	0.014	**
Human Capital and household Characteristics									-0.226	***
Residual	-0.449		-0.444		-0.446		-0.442		-0.428	
***Selva - Costa:* Log Welfare Ratio**	-0.298		-0.298		-0.298		-0.298		-0.298	
Geography	-0.375	***	-0.194	***	-0.131	***	0.127	***	-0.097	***
Infrastructure			-0.174	***	-0.174	***	-0.172	***	0.073	
Economic Environment					-0.061	**	-0.065	*	0.014	***
Private Assets							0.003	***	0.002	***
Human Capital and household Characteristics									-0.168	***
Residual	-0.375		-0.368		-0.366		-0.361		-0.323	
Number of observations	1828		1828		1828		1828		1828	
Adjusted R-square	0.480		0.590		0.610		0.620		0.730	
Spatial Correlation for Residuals	0.846	***	0.789	***	0.797	***	0.798	***	0.762	***

***p<1%, **<5%,* p<10%

Table 9 presents the decomposition exercise for 2005 showing a similar pattern. Finally, in table 10 the same decomposition exercise is performed for the log welfare ratio differences, a proxy of real consumption growth between 1993 and 2005. Here, as shown by Escobal and Torero (2000) when looking at consumption growth between 1972 and 1993 at the provincial level, the significance of geography vanishes after controlling for infrastructure. Using this as evidence, Escobal and Torero stated that "…what seem to be sizable geographic differences in living standards in Peru can be almost fully explained when one takes into account the spatial concentration of households with readily observable non-geographic characteristics, in particular public and private assets." (op. cit. p. 3)

Although the same results are found here, it is worth noting that in all specification for 1993 and 2005 decomposition, as well as for the 1993-2005 decomposition, residuals show high spatial autocorrelation. This may be the effect of omitted variables or some other specification problem like parameter heterogeneity. Regarding omitted variables, there can be two types: a) geographic omitted variables; and b) non-geographic omitted variables that are geographically correlated but are not highly correlated with the already present geographic variables. As for the first group of omitted variables, since we have considered a fairly broad array of geographic variables related to climate (precipitation, temperature and their variabilities) soil characteristics (types and quality), altitude, and bioclimatic potential, we contend that it is unlikely that that there is important omitted variables in this front. As for non-geographic omitted variables that are geographically correlated, since we do not observe them, we can only correct our model by estimating a spatially auto correlated error model. We have done so and we observe that the spatial correlation of the residuals remain systematically significant after correcting for first order correlation in all models.

Table 9

Regional Decomposition of Log Welfare Ratio
(based on national level estimates - 2005)

	Models									
	1		2		3		4		5	
***Sierra- Costa:* Log Welfare Ratio**	-0.425		-0.425		-0.425		-0.425		-0.425	
Geography	-0.449	***	-0.342	***	-0.281	***	-0.283	***	-0.180	***
Infrastructure			-0.103	***	-0.107	***	-0.112	***	-0.046	
Economic Environment					-0.058		-0.067		0.010	***
Private Assets							0.021	***	0.014	**
Human Capital and household Characteristics									-0.226	***
Residual	-0.449		-0.444		-0.446		-0.442		-0.428	
***Selva - Costa:* Log Welfare Ratio**	-0.298		-0.298		-0.298		-0.298		-0.298	
Geography	-0.375	***	-0.194	***	-0.131	***	0.127	***	-0.097	***
Infrastructure			-0.174	***	-0.174	***	-0.172	***	0.073	
Economic Environment					-0.061	**	-0.065	*	0.014	***
Private Assets							0.003	***	0.002	***
Human Capital and household Characteristics									-0.168	***
Residual	-0.375		-0.368		-0.366		-0.361		-0.323	
Number of observations	1828		1828		1828		1828		1828	
Adjusted R-square	0.480		0.590		0.610		0.620		0.730	
Spatial Correlation for Residuals	0.846	***	0.789	***	0.797	***	0.798	***	0.762	***

***p<1%, **<5%,* p<10%

Table 10
Regional Decomposition of Log Welfare Ratio Differences
(based on national level estimates 1993-2005)

	Models									
	1		2		3		4		5	
***Sierra – Costa:* Log Welfare Ratio Difference**	**-0.073**		**-0.073**		**- 0.073**		**- 0.073**		**- 0.073**	
Geography	-0.143	**	-0.240		-0.245		-0.169		-0.138	
Infrastructure			0.102	***	0.061	***	0.054	***	0.060	***
Economic Environment					0.046		0.036		0.029	
Private Assets							-0.061	***	-0.047	***
Human Capital and household Characteristics									-0.031	***
Residual	-0.143		-0.138		-0.138		-0.140		-0.128	
***Selva-Costa:* Log Welfare Ratio Difference**	**0.033**		**0.033**		**0.033**		**0.033**		**0.033**	
Geography	-0.170	*	-0.207		-0.209		-0.175		-0.079	***
Infrastructure			0.042	***	0.000	***	-0.007	***	0.017	***
Economic Environment					0.043		0.033		0.028	
Private Assets							-0.008	***	0.011	***
Human Capital and household characteristics									-0.103	***
Residual	-0.170		-0.164		-0.166		-0.156		-0.125	
Number of observations	1793		1793		1793		1793		1793	
Adjusted R-square	0.120		0.220		0.220		0.250		0.350	
Spatial Correlation for Residuals	0.725	***	0.563	***	0.561	***	0.561	***	0.670	***

***p<1%, **<5%,* p<10%

The alternative to omitted variables as a potential explanation for this persistent spatial correlation of consumption growth, after controlling for geographic observables, infrastructure, economic environment, private assets and, finally, human capital and household characteristics, is to consider spatial parameter heterogeneity. We will pursue this in the following subsection.

2.5 Spatial heterogeneity: looking beyond the Global Model

An alternative to explore the importance of spatial factors in the dynamics of expenditure and poverty in Peru is to recognize that effect of private assets or the effect of the access to public infrastructure are not constant throughout space. Spatial heterogeneity may arise may arise because environmental factors may operate differently at the local scale. It may also be the reflection of nonlinearities arising from complex. Minier, (2007) for example, shows that parameter heterogeneity may be the reflection of local institutions.

There are different ways of modeling spatial parameter heterogeneity. We can explore other dimensions of heterogeneity in the parameter space by exploring parameter variation across the welfare dimension through quantile regressions. Another way of exploring parameter heterogeneity is through spatially weighted regression, where local geographic-related parameters are estimated. Each of these ways of dealing with parameter heterogeneity are based on different assumptions. For example, a quantile regression will assume that the relationship between the explanatory variables and the consumption measure is the same in the different geographic spaces that share the observed attributes. Spatially weighted regression may be more flexible estimation but this is obtained, as we will see next, at the cost of parametrizing the way local parameters behave. In this section, we will look at how these alternatives ways of recognizing parameter heterogeneity affect our conclusions.

Next we explore how this decomposition exercise may change if we allow parameters to change across the income distribution. To do this, we estimate our district level model using quantile regressions for both urban and rural districts (where as before, rural districts are those that have the majority of the population located in rural towns). The procedure followed here follows closely Nguyen et al (2007)[9]. We estimate the rates of return at each quantile and then we are able to construct a counterfactual distribution for the log welfare ratio assuming that rural households can hold the return of assets they posses and received the average endowment that their urban counterparts in the same quintile posses.

The first graph in panel (a) in figure 9 depicts the urban gap for the log welfare ratio for 1993. The next graph in the same panel shows the urban and rural log welfare ratio wage for all quantiles, as well as the counterfactual distribution that mimics what the rural log welfare ratio will be if rural household had access to the asset endowment of their urban counterpart. Finally the third graph in panel (a) graph the decomposition of the log welfare ratio across quintiles between the effect of differences in returns and

9 A detailed analysis using quantile regressions to decompose the urban rural wellbeing gap can be found in Escobal and Ponce (2008).

differences in asset endowments. As can be seen here the counterfactual curve rises above the urban curve for all quintiles except for the bottom 10%, indicating that rates of return to assets are larger in urban than in rural areas for most of the expenditure distribution range. Further, the decomposition exercise shows that contribution of the asset endowment in explaining the urban rural log-welfare gap increases steadily through all quintiles, while the contribution of having larger returns in the rural area decreases steadily as well.

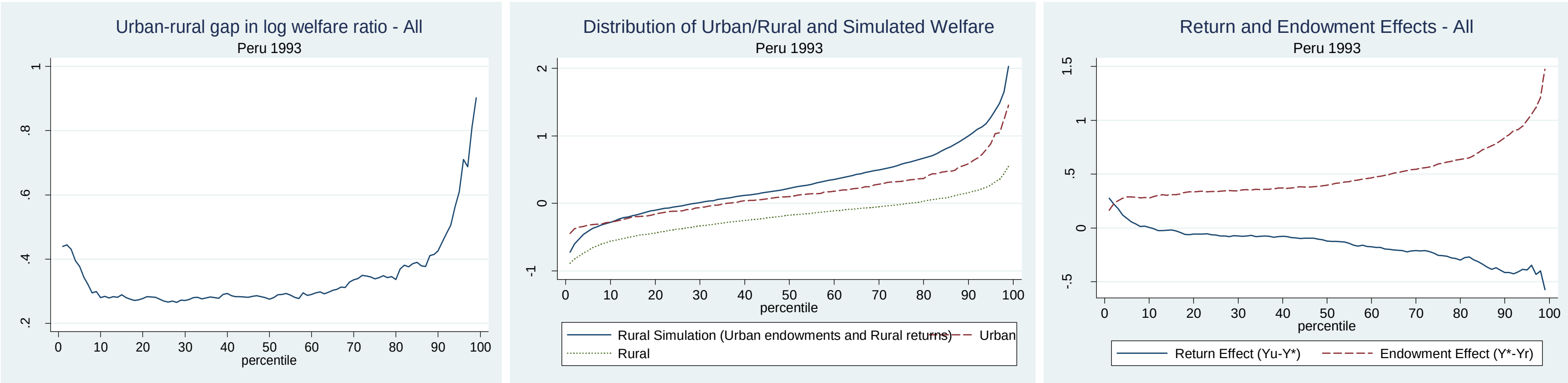
Panel (b) in figure 9 shows the three same graphs for 2005. They show a similar pattern to the one observed in 1993 with one interesting difference: the counterfactual curve does not rise above the urban curve, indicating that the marginal returns to assets in rural areas in 2005 are no longer above the marginal return to assets in urban areas throughout all quintiles.

Figure 10 compares the actual urban/rural log welfare ratio gap with the one obtained from the counterfactual distribution (with rural households having the same endowment base than the average of the corresponding urban quintile for both the district level estimates based on both interpolations (1993 and 2005). We can confirm here that the gap will be much lower if asset distribution was biased against rural dwellers and that this is so across all of the quintile distribution. In addition the increase in rate of returns to endowments in urban areas and the reduction in the rate of returns to endowments in rural areas (specially in the sierra) have made that the urban/rural log welfare ratio gap depends now more than before on the unequal distribution of assets between regions.

Figure 9

Urban Rural Gap Decomposition by Quantiles (district level)

(a) 1993 Decomposition



(b) 2005 Decomposition

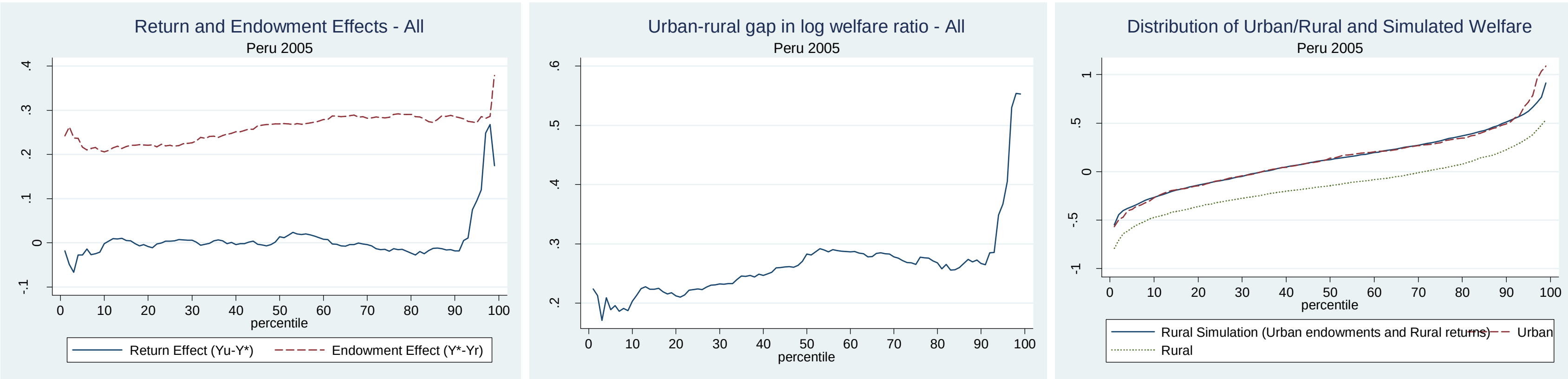
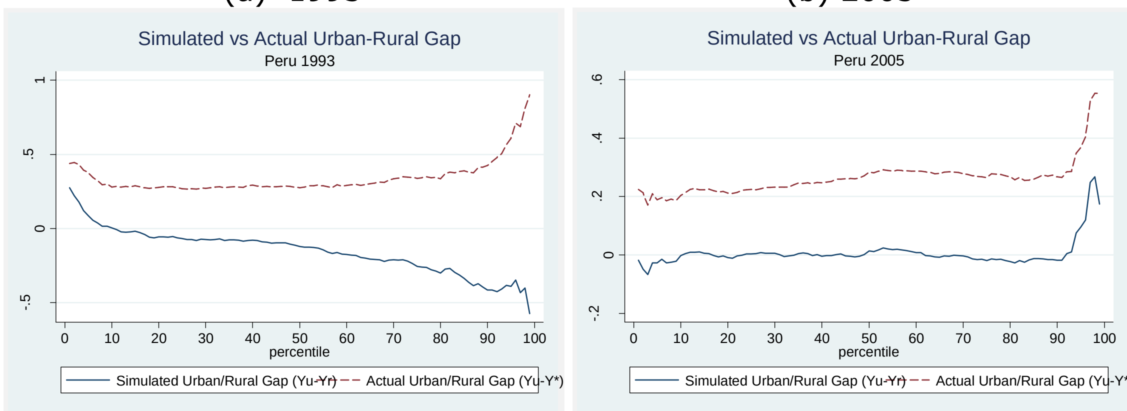


Figure 10
Urban Rural Log-Welfare Gap
(actual versus counterfactual)
(a) 1993 (b) 2005



The estimation from which decomposition exercise is done assumes, as we have mentioned that the rate of return to assets are different across quintiles; or stated slightly differently, the parameters of the estimated model are heterogeneous across the wellbeing distribution. Since we have shown in the previous subsection that there the decomposition exercise that assumed parameter heterogeneity was not able to control for non-observable geographic heterogeneity, it is sensible to ask up to what point this heterogeneity has been controlled through the quantile estimation. To check for non-observable geographic heterogeneity table 11 presents the Moran Statistics for urban and rural districts as well as for the pooled sample using the residuals coming from the quintile equations.

Table 11
Spatial Autocorrelation of Residuals when modeling log welfare ratios through quantile regressions (Moran Statistics)

	1993		2005	
Full sample	0.2021	***	0.4162	***
Urban	0.1118	***	0.2209	***
Rural	0.2418	***	0.5796	***

Souce: owns estimated based on error estimates in urban and rural quantile equations ***p<1%, **<5%,* p<10%

It is interesting to note that although the spatial correlation patterns of the residuals has decresed substantially as compared to the spatial correlation of residuals observed in the global model depicted in tables 11 and 12 (which assumed parameter heterogeneity) the spatial correlation is still highly significant. That is even if quantile regressions may be capturing some of the rate of return heterogeneity that is present in the sample, we still must recognize that welfare differences have persistence spatial characteristics, that cannot be fully accounted by observables characteristics including the most common geographic variables, infrastructure, economic environment, private assets and, finally, human capital and household characteristics. This fact remains true even if we recognize that rate of returns to assets are different between urban and rural sector and between the poor and less poor. To explore further this issue we will look next at yet another way of parameterize the spatial heterogeneity of the rate of return in urban and rural Peru.

Capturing Local Spatial heterogeneity by estimating spatially weighted regressions

To capture this spatial heterogeneity we have re-estimated our global profile allowing for parameter heterogeneity using a geographic weighted regression technique. Thus, instead of estimating:

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i \cdot x_i + \varepsilon \qquad (2)$$

we estimate the following model:

$$y(l_1,l_2) = \beta_0(l_1,l_2) + \sum_{i=1}^{k} \beta_i(l_1,l_2) \cdot x_i + \varepsilon(l_1,l_2) \qquad (3)$$

where l_1 y l_2 represent the location – longitude and latitude – of each observation.

Following Brunsdon et al.(2008) the parameters can be estimates using geographically weighted least squares (gwr) using the following weighting structure:

$$\beta(l_1,l_2) = \; X'W(l_1,l_2)X \;^{-1} \; X'W(l_1,l_2)Y \qquad (4)$$

The weights are chosen in such a way that the observations that are near to the point were the local parameter is estimated have more influence in the estimation than observations that are far apart. If we use a Gaussian weighting function, the weight for the i-th observation will look as follows:

$$w_i(l_1,l_2) = \exp \; -d/h \;^{2} \qquad (5)$$

where **d** is the distance between the i-th observation and local point (l_1,l_2) in which the parameter is estimated. **h** reflects the bandwidth, that is the area where observation do influence the local estimation. Thus the parameter estimated is basically a local interpolation in which closest observation (within the bandwidth) have greater influence in the way changes in private and public assets affect per-capita expenditure or poverty.

Table 12 shows the values and significance levels for the non-stationarity tests for both the 2005 poverty and per-capita expenditure profiles. These tests are based on Monte Carlo simulations to evaluate whether the spatial variations in the parameter estimates are simple due to random variation or are effective spatial patterns. The tests show clearly that for most of the right-hand side variables the spatial variation is highly statistically significant. For example, both the effects of initial levels of access to electricity and access increase between 1993 and 2005 have significant variation over time. Wit respect to household characteristics, the role of education, the effect of female headed households or the effect of ethnicity also varies spatially when we correlate these variables either with poverty or log per-capita expenditures. Finally, as was expected the impact of all location and geographic related variables changes across space.

Table 12

Significance Tests for Non-Stationarity

Variable	Poverty Rate 2005 Si	Poverty Rate 2005 P-Value	Per-Capita Consumption 2005 (log) Si	Per-Capita Consumption 2005 (log) P-Value
Constant	0.205	0.20	0.890	0.00
Average Age of the Head of Houlsehold (1993)	0.003	0.40	0.009	0.10
Female headed Households in 1993 (%)	0.203	0.00	0.565	0.10
Change in Female headed Households between 1993-2005 (%)	0.176	0.20	0.384	0.60
Head of Household with some secondary education or more in 1993 (%)	0.125	0.00	0.297	0.10
Change in head of Household with some secondary education between 1993-2005	0.128	0.50	0.303	0.50
Dependence ratio in household	0.090	0.10	0.226	0.20
Change in dependence ratio in household between 1993-2005 (%)	0.085	0.30	0.173	0.90
Unfitted Dwellings	0.054	0.50	0.188	0.20
Change in Unfitted Dwellings between 1993-2005 (%)	0.083	0.10	0.181	0.20
Percentage of Households that belong to any association	0.007	1.00	0.026	1.00
Head of Household has spanish as its native toungue	0.111	0.00	0.373	0.00
Percentage of Household in Province that received remmitances	1.819	0.10	5.132	0.00
Index of fragmentation of agricultural plots (1994 Agriculture Census)	0.047	0.00	0.109	0.40
Land per Farmer (1994 Agriculture Census)	0.054	0.00	0.317	0.00
Percentage of irrigated land (1994 Agriculture Census)	0.145	0.00	0.473	0.00
Livestock (1994 Agriculture Census)	0.453	0.00	1.311	0.00
Agriculture Machinery (1994 Agriculture Census)	1.923	0.00	9.434	0.00
Rate of agricultural salaried jobs	0.552	0.00	3.268	0.00
Rate of non agricultural salaried jobs	0.257	0.00	0.497	0.00
Rate of non agricultural non salaried jobs	0.210	0.00	0.489	0.00
Percentage of households with access to drinable water in 1993	0.059	0.50	0.167	0.40
Percentage of households with electricity within the house in 1993	0.071	0.00	0.158	0.10
Percentage of households with sewerage service within the house in 1993	0.097	0.20	0.295	0.00
Change in access to drinkable water between 1993-2005	0.048	0.00	0.097	0.30
Change in access to electricity between 1993-2005	0.051	0.00	0.122	0.00
Change in access to sewerage between 1993-2005	0.082	0.20	0.273	0.10
Distance to the nearest town with 100,000 inhabitants or more	0.002	0.00	0.003	0.30
Average precipitation	0.001	0.00	0.002	0.00
Average temperature	0.012	0.00	0.025	0.00
Soil Depth	0.002	0.00	0.005	0.00
Precipitation - coefficient of variation	0.090	0.00	0.365	0.00
Temperature - coefficient of variation	0.844	0.00	1.754	0.00
Altitude of District Capital	0.024	0.00	0.179	0.00
Average slope	0.001	0.10	0.002	0.00
Igneous Rock	0.196	0.00	0.480	0.00
Metamorfic Rock	0.214	0.00	0.295	0.00
Bioclimate potential score (the higher the better)	0.114	0.00	0.476	0.00
Land potential score (the higher the better)	0.161	0.00	0.407	0.00
Forest potential score (the higher the better)	0.226	0.00	0.564	0.00
Rural Population in the District (%)	0.066	0.00	0.208	0.00
Change in Rural Population in the District between 1993-2005 (%)	0.061	0.00	0.154	0.20
Bandwitch	1.689	0.00	1.049	0.00

One of the few estimates for which we cannot reject parameter stationary is that of percentage of households that belong to an association. Further the estimate of this parameter was not significantly different from zero in any of our profiles. This is consistent with the fact that these social networks may be proxies of both "bonding capital" and "bridging capital" which makes it difficult to assess its impact on poverty (Escobal and Ponce, 2007). "Bonding" capital is the kind involved in survival strategies, while "bridging" capital is the kind that increases social and economic mobility.

Another way of testing parameter heterogeneity is to look at the significance test for the bandwidth. The test is highly significant for both models (bandwidths of 1.6892 and 1.0487 for the poverty and log expenditure models, respectively, being both values significant at the 99% level).

It is interesting to note that if we estimate the residuals from the geographic weighted regressions for both models we can estimate the spatial correlation using Moran I statistics. Table 13 reports such result. First is important to highlight that both Moran statistics are lower that the ones generated from the previous model specifications (OLS, Spatial Lag Model, and Spatial Error Model) for both the 2005 poverty profile and the log per-capita expenditure model. Further for the log per-capita expenditure model we find no evidence of spatial autocorrelation at any significance level, a substantial improvement over previous models. In the case of the 2005 poverty profile model the Moran statistics is marginally significant at the 10%. Given this results, we can contend that a specification that considers parameter heterogeneity tends to fit better that data.

Table 13
Spatial Autocorrelation of Residuals when modeling Poverty and Per-capita Expenditure using Geographic Weighted Regression

	Moran I	
GWR Poverty 2005	0.0218	*
GWR Log per-capita Expenditure 2005	0.0149	

***p<1%, **<5%,* p<10%

Table 14 and table 15 show how these parameters change for both the 2005 poverty profile and the log per-capita expenditure profile. It is interesting to note that several parameters that have shown to be significantly non-stationary may even change signs, across geographic locations.

For example, although all the parameter estimates of access to infrastructure (electricity, piped water and sewerage) are on average, as expected, negative in the 2005 poverty profile equation and positive in the log-per capita equation, they have different signs across districts. Similarly the estimated parameter associated with the time needed to access a town of at least 100,000 inhabitants (a proxy for access to markets) is on average positive in the 2005 poverty profile equation and negative in the log-per capita equation, it also changes sign across space. This pattern may, at first, look puzzling, but if perfectly understandable in the context of a profile equation, that has no intention of providing any causal links between the right hand-side variables and the outcome variables, that is poverty and log per-capita expenditure.

Table 14

Spatial Variation of Esimated Betas: Poverty 2005

Variable	Mean	S.D.	Min	Quantiles 0.25	Mdn	0.75	Max
Average Age of the Head of Houlsehold (1993)	-0.007	0.003	-0.036	-0.009	-0.007	-0.006	-0.002
Female headed Households in 1993 (%)	0.254	0.203	-2.456	0.191	0.252	0.364	0.538
Change in Female headed Households between 1993-2005 (%)	-0.177	0.176	-0.871	-0.267	-0.143	-0.035	0.084
Head of Household with some secondary education or more in 1993 (%)	-0.335	0.125	-0.943	-0.410	-0.324	-0.250	0.106
Change in head of Household with some secondary education between 1993-2005	-0.351	0.128	-0.805	-0.416	-0.328	-0.273	0.335
Dependence ratio in household	0.493	0.090	0.020	0.447	0.504	0.551	1.477
Change in dependence ratio in household between 1993-2005 (%)	0.354	0.085	0.115	0.299	0.358	0.397	1.215
Unfitted Dwellings	0.006	0.054	-0.306	-0.026	0.014	0.049	0.118
Change in Unfitted Dwellings between 1993-2005 (%)	-0.043	0.083	-0.522	-0.100	-0.041	0.003	0.221
Percentage of Households that belong to any association	0.003	0.007	-0.043	0.001	0.004	0.005	0.025
Head of Household has spanish as its native toungue	-0.128	0.111	-1.823	-0.179	-0.115	-0.075	0.371
Percentage of Household in Province that received remmitances	-2.550	1.819	-7.574	-3.980	-2.310	-1.080	7.936
Index of fragmentation of agricultural plots (1994 Agriculture Census)	0.027	0.047	-0.422	0.001	0.024	0.065	0.136
Land per Farmer (1994 Agriculture Census)	-0.006	0.054	-0.516	-0.012	0.001	0.017	0.523
Percentage of irrigated land (1994 Agriculture Census)	-0.028	0.145	-3.307	-0.045	-0.021	-0.007	0.445
Livestock (1994 Agriculture Census)	0.025	0.453	-1.626	-0.006	-0.003	-0.001	10.980
Agriculture Machinery (1994 Agriculture Census)	-0.278	1.923	-24.270	-0.225	-0.022	0.218	11.330
Rate of agricultural salaried jobs	-0.059	0.552	-0.856	-0.248	-0.064	0.041	12.580
Rate of non agricultural salaried jobs	0.141	0.257	-3.499	0.027	0.125	0.247	0.792
Rate of non agricultural non salaried jobs	-0.058	0.210	-0.773	-0.124	-0.048	0.023	2.782
Percentage of households with access to drinable water in 1993	-0.035	0.059	-0.333	-0.057	-0.034	-0.013	0.143
Percentage of households with electricity within the house in 1993	-0.077	0.071	-0.414	-0.111	-0.069	-0.040	0.090
Percentage of households with sewerage service within the house in 1993	-0.175	0.097	-0.554	-0.232	-0.187	-0.131	0.624
Change in access to drinkable water between 1993-2005	-0.078	0.048	-0.226	-0.113	-0.088	-0.058	0.170
Change in access to electricity between 1993-2005	-0.022	0.051	-0.166	-0.057	-0.019	0.016	0.217
Change in access to sewerage between 1993-2005	-0.036	0.082	-1.437	-0.073	-0.057	0.003	0.312
Distance to the nearest town with 100,000 inhabitants or more	-0.001	0.002	-0.008	-0.002	-0.001	0.000	0.004
Average precipitation	-0.001	0.001	-0.002	-0.001	-0.001	0.000	0.002
Average temperature	0.006	0.011	-0.015	0.002	0.005	0.008	0.228
Soil Depth	0.002	0.002	-0.020	0.001	0.002	0.003	0.006
Precipitation - coefficient of variation	-0.029	0.090	-2.142	-0.031	-0.016	-0.007	0.171
Temperature - coefficient of variation	0.188	0.844	-0.779	-0.251	0.048	0.337	12.790
Altitude of District Capital	0.038	0.024	-0.360	0.035	0.042	0.049	0.168
Average slope	0.000	0.001	-0.002	0.000	0.000	0.001	0.010
Igneous Rock	0.038	0.196	-0.298	-0.070	-0.041	0.155	2.689
Metamorfic Rock	-0.029	0.214	-0.221	-0.086	-0.070	-0.008	4.838
Bioclimate potential score (the higher the better)	0.016	0.114	-0.357	-0.034	-0.003	0.039	2.560
Land potential score (the higher the better)	-0.032	0.161	-2.621	-0.125	0.006	0.061	0.434
Forest potential score (the higher the better)	0.128	0.226	-0.926	-0.019	0.038	0.264	0.645
Rural Population in the District (%)	-0.230	0.066	-1.132	-0.254	-0.232	-0.195	-0.112
Change in Rural Population in the District between 1993-2005 (%)	-0.206	0.060	-0.576	-0.229	-0.201	-0.169	-0.053
Constant	0.725	0.205	-2.621	0.606	0.733	0.856	2.382

Table 15

Spatial Variation of Esimated Betas: Per Capita Consumption 2005 (in Logs)

				Quantiles			
Variable	Mean	S.D.	Min	0.25	Mdn	0.75	Max
Average Age of the Head of Houlsehold (1993)	0.012	0.009	-0.008	0.007	0.011	0.015	0.158
Female headed Households in 1993 (%)	-0.198	0.565	-1.858	-0.452	-0.239	-0.011	9.373
Change in Female headed Households between 1993-2005 (%)	0.228	0.384	-1.110	-0.005	0.096	0.353	4.911
Head of Household with some secondary education or more in 1993 (%)	0.599	0.297	-0.456	0.418	0.551	0.678	5.127
Change in head of Household with some secondary education between 1993-2005	0.512	0.303	-1.589	0.351	0.493	0.667	2.401
Dependence ratio in household	-0.577	0.226	-3.520	-0.724	-0.579	-0.475	0.454
Change in dependence ratio in household between 1993-2005 (%)	-0.456	0.173	-1.823	-0.579	-0.433	-0.338	0.322
Unfitted Dwellings	-0.055	0.188	-0.583	-0.131	-0.085	-0.009	4.491
Change in Unfitted Dwellings between 1993-2005 (%)	0.023	0.181	-0.678	-0.069	0.009	0.079	2.388
Percentage of Households that belong to any association	-0.009	0.026	-0.141	-0.019	-0.011	-0.001	0.635
Head of Household has spanish as its native toungue	0.223	0.373	-0.767	0.039	0.188	0.378	7.063
Percentage of Household in Province that received remmitances	2.567	5.132	-28.880	0.097	2.414	5.720	21.280
Index of fragmentation of agricultural plots (1994 Agriculture Census)	-0.043	0.109	-0.380	-0.098	-0.039	0.019	1.616
Land per Farmer (1994 Agriculture Census)	-0.026	0.317	-1.187	-0.070	-0.016	0.021	8.767
Percentage of irrigated land (1994 Agriculture Census)	0.094	0.473	-0.803	0.006	0.030	0.102	11.880
Livestock (1994 Agriculture Census)	-0.027	1.311	-30.850	-0.006	0.011	0.029	9.972
Agriculture Machinery (1994 Agriculture Census)	-0.185	9.434	-30.500	-0.706	0.149	0.673	37.070
Rate of agricultural salaried jobs	-0.458	3.268	-90.180	-0.533	-0.239	0.041	8.460
Rate of non agricultural salaried jobs	-0.322	0.497	-5.441	-0.554	-0.232	-0.048	4.012
Rate of non agricultural non salaried jobs	0.132	0.489	-4.536	-0.174	0.133	0.429	2.335
Percentage of households with access to drinable water in 1993	-0.014	0.167	-1.567	-0.061	-0.020	0.064	0.609
Percentage of households with electricity within the house in 1993	0.109	0.158	-1.416	-0.006	0.108	0.200	1.042
Percentage of households with sewerage service within the house in 1993	0.352	0.295	-1.524	0.207	0.313	0.425	2.017
Change in access to drinkable water between 1993-2005	0.089	0.097	-0.255	0.066	0.105	0.146	1.251
Change in access to electricity between 1993-2005	0.031	0.122	-0.715	-0.045	0.020	0.114	1.338
Change in access to sewerage between 1993-2005	0.070	0.273	-6.414	-0.031	0.080	0.159	3.721
Distance to the nearest town with 100,000 inhabitants or more	0.001	0.003	-0.017	0.000	0.001	0.003	0.010
Average precipitation	0.001	0.002	-0.006	0.000	0.001	0.002	0.015
Average temperature	-0.009	0.025	-0.433	-0.019	-0.011	0.001	0.108
Soil Depth	-0.002	0.005	-0.023	-0.003	-0.001	0.000	0.057
Precipitation - coefficient of variation	0.061	0.365	-0.744	-0.004	0.021	0.063	9.276
Temperature - coefficient of variation	-0.361	1.754	-28.010	-1.199	-0.136	0.665	8.135
Altitude of District Capital	-0.054	0.179	-4.758	-0.071	-0.054	-0.032	2.395
Average slope	0.000	0.002	-0.022	-0.001	0.000	0.001	0.014
Igneous Rock	-0.057	0.480	-3.058	-0.281	-0.006	0.095	7.539
Metamorfic Rock	0.058	0.295	-2.146	-0.065	0.031	0.151	5.186
Bioclimate potential score (the higher the better)	-0.032	0.476	-12.930	-0.029	0.018	0.046	1.576
Land potential score (the higher the better)	0.048	0.407	-1.259	-0.075	0.004	0.172	7.412
Forest potential score (the higher the better)	-0.204	0.564	-6.075	-0.292	-0.010	0.100	2.105
Rural Population in the District (%)	0.045	0.208	-0.689	-0.068	0.051	0.138	3.169
Change in Rural Population in the District between 1993-2005 (%)	0.013	0.154	-0.437	-0.111	0.005	0.123	1.071
Constant	5.125	0.890	-9.025	4.731	4.978	5.511	13.120

One may hypothesize that for certain regions of the country an improved access to a certain infrastructure service may attract poor people seeking better living conditions. In those cases, poverty rates may correlate positively with access to infrastructure (and per-capita expenditure will correlate negatively). Alternatively, one may hypothesize that for certain regions greater access to infrastructure services may increase income generating opportunities and will correlate negatively with poverty.

The maps depicted in Figure 11 show how the parameter estimates of access to electricity in 1993 and increase in access in electricity between 1993 and 2005 vary across Peru. This parameter estimates may be thought as the marginal effect on log per-capita expenditures of increasing electricity access. It is interesting to note that there are several areas, typically associated with the outskirts of large urban centers like Lima, Arequipa or Iquitos, where increases in access to infrastructure services like electricity attracts poor people. Other areas, especially in the northern and southern Sierra, access to electricity are positively correlated to income and to poverty reduction. Here, the positive effect of access to infrastructure services enhancing income opportunities tends to be greater than the negative pull effect associated to immigration.

Figure 11

Marginal Impact of Electricity over Per-Capita Expenditure Growth

(red=negative, blue=positive)

(a) Access to Electricity (b) Additional Access to Electricity

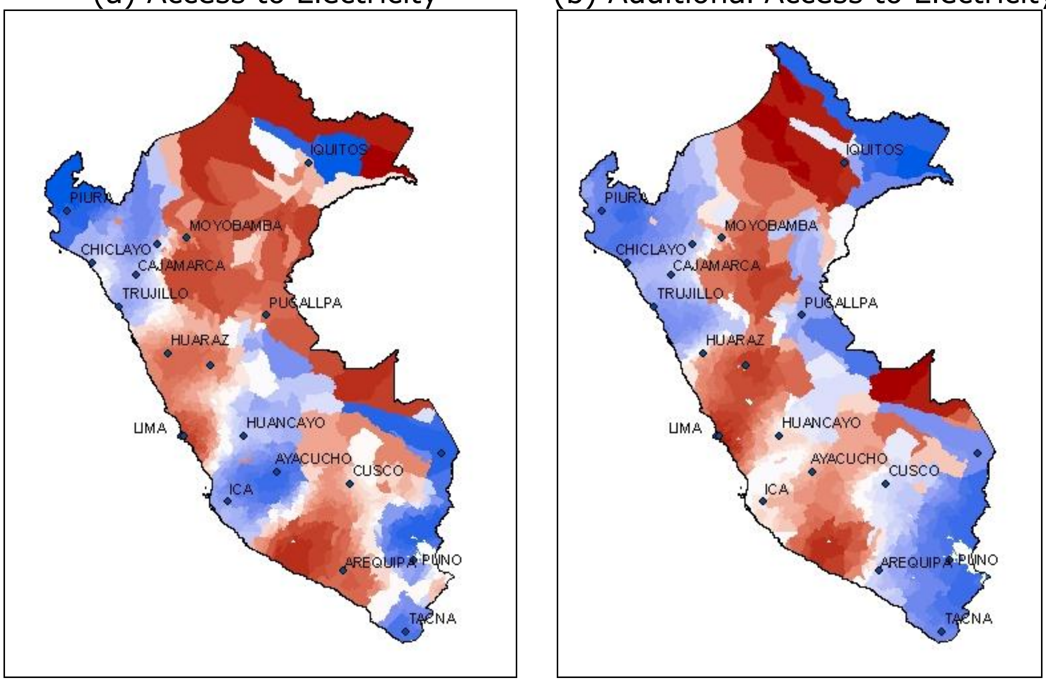


Figure 12 maps the marginal impact of reducing the time needed to access a town of 100,000 inhabitants or more (a proxy for markets). We have draw together with the parameter estimates the national and regional road networks. Here, is evident that in some areas where the road network is less dense there seems to be a positive impact of access to markets on per-capita expenditure. This is the case, especially of the southern Sierra. In the case of the Selva, the relation is not apparent, basically because rivers are the main transportation network. Of course road network is just one of the showing remoteness, as altitude and other fixed geographic variables may act as barriers.

Figure 12

Marginal Impact of reduction in time to markets over Per-Capita Expenditure Growth
(red=negative, blue=positive impact on the reduction of time)

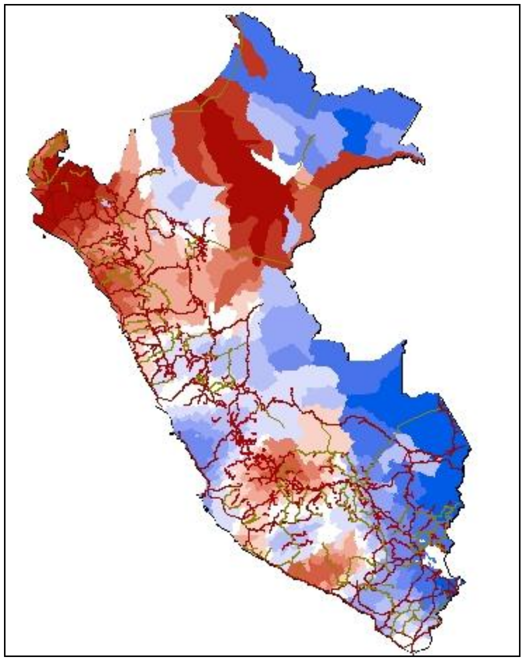
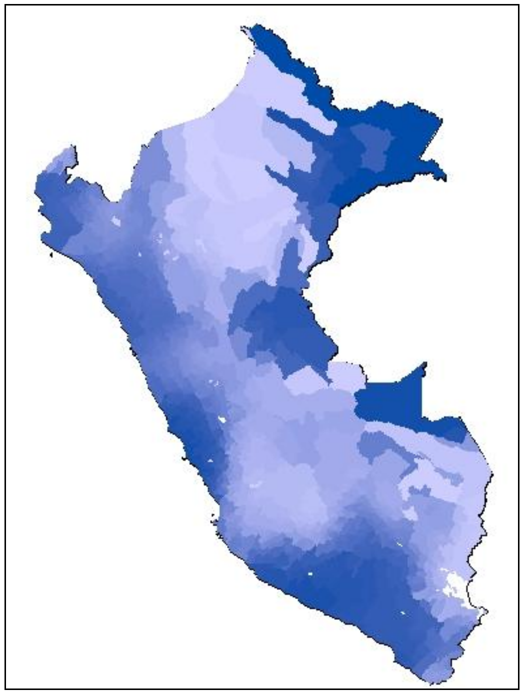


Figure 13
Marginal Impact of Education over Per-Capita Expenditure Growth
(the darker the better)



Finally, Figure 13 shows the marginal impact of education over log per-capita expenditure growth. The parameter estimates, are in this case, all positive, reflecting that independent of the channel through which education acts it has a strong a and positive impact over expenditure growth. However, in this case the impact is much stronger along the Costa and Selva region. There are a number of reasons why one may hypothesize why the marginal contribution of education is less strong in the southern Sierra. One possibility could be the lower quality of education, which is more evident in the rural areas and in particular in the Sierra region. Additionally long term exclusion through discrimination may be operating generating lower labor returns to their labor (Escobal and Ponce 2007).

3. Final Remarks

This paper aims at evaluating up to what point spatial characteristics affect wellbeing levels and changes of Peruvian household. Using poverty mapping exercises based on two contiguous censuses (1993 and 2005) we characterize the spatial distribution of poverty and poverty changes in an economy that grew on average 5% during this 12 year period. We find, indeed, that poverty and poverty changes are spatially correlated and we have also found that spatial characteristics - both first-nature and second-nature geography" are correlated with this poverty indicators. Two effects that are particularly important are altitude and distance, a variable that proxies remoteness. This indicators show clearly that access to markets may be affected by remoteness, increasing the likelihood of outward migration of the most educated and better endowed people and leaving behind the older, less educated and worst endowed people.

We found that there are a number of location specific variables (like access to infrastructure and market characteristics) as well as household specific variables that are strongly correlated with wellbeing. It seems that pure geographic factors are associated with relative consumption per-capita, as well as access to infrastructure services, and this correlation is reasonably robust even when we control for household, and location specific characteristics. However, the sign and the significance of this correlation do seem to vary across space. This may be due to the fact that relative wellbeing does seem to have a persistent spatial correlation even after controlling for available geographic variables, infrastructure and household and context-specific characteristics.

Two possible explanations could be offered to explain why there is such a persistent pattern of spatial correlation relative wellbeing even after controlling for geography and the above mentioned factors. One possibility is of course omitted variables and the second parameter heterogeneity. Omitted variables can be geographic or non-geographic related. Since we have controlled for a large range of first-nature geographic variables (like altitude, temperature, precipitation, climate variability, and soil texture and quality) we suspect that the bias is not geographic omitted variables. Another possibility is that other infrastructure services may have been omitted and these services themselves cannot be fully explained by the geographic variables already included in our profiles. Is that is the case, since we have not been able to observe them we need just to correct for spatial correlation. Although we have done this, first order spatial correlation corrected estimates continue to show significant spatially correlated errors.

This persistent pattern of spatial correlation in the residuals forced us to focus our attention in the possibility of parameter heterogeneity across space. Space can be geographic space but may also consider other dimensions like the welfare distribution space. We have explored these two dimensions of spatial heterogeneity. The first one was modeled using quantile regressions while the second one has been explored using geographically weighted regressions. Quantile estimation is based on the assumption of parameter variation across the wellbeing space. The results of both, however, highlight the fact that welfare differences have persistence spatial characteristics, that cannot be fully accounted by observables characteristics including the most common geographic variables, infrastructure, economic environment, private assets and, finally, human capital and household characteristics. Institutions are obviously a missing element that, although considered as an unobservable in this document, should be taken into account.

Recognizing the importance of the spatial dimension in such estimation procedures stands out as a key factor to better understand poverty dynamics. This involves not only identifying spatial related covariates but also exploring further spatial correlation issues and potential parameter heterogeneity.

4. References

Brunsdon, C.; S. Fotheringham y M. Charlton (1998): "Geographically Weighted Regression-Modelling Spatial Non-Stationarity". The Statistician, 47(3) 431-443.

Chesher, A. (1984): "Testing for Neglected Heterogeneity". Econometrica 52(4), 865-872.

Douidiche, M.; A. Ezzrari; and C. Ferré; and P. Lanjouw (2008): "Poverty Dynamics in Morocco's Rural Communes: Tracking Change via Small Area Estimates". Mimeo. World Bank. May 15, 2008

Dutta, J. and H. L. Leon (1991) "Testing for Heterogeneous Parameters in Least-Squares Approximations". The Review of Economic Studies, 58(2), 299-320

Elbers, C., J. Lanjouw, and P. Lanjouw (2004) Imputed welfare estimates in regression analysis. Working Paper Series No. 3294. Washington, D.C.: World Bank.

Elbers, C., P. Lanjow and J. Lanjow (2000) Welfare in Villages and Towns: Micro-Level Estimation on Poverty and Inequality. World Bank

Escobal, J. and C. Ponce (2008) "Spatial disparities in living conditions in Peru: The role of geographic differences in returns vs. differences in mobile household assets endowment, a cross section analysis". Mimeo. World Bank-LAC. Lima June 2008.

Escobal, J. and C. Ponce (2007) "Economic Opportunities for Indigenous Peoples in Rural and Urban Peru." In: Conference Edition: Economic Opportunities for Indigenous Peoples in Latin America . Washington DC.: World Bank.

Escobal, J.; M. Torero; and C. Ponce (2001) "Focalización Geográfica del Gasto Social: Mapas de Pobreza" RED CIES de POBREZA GRADE-APOYO Informe Final

Escobal, J. and M. Torero (2000): Does Geography Explain Differences in Economic Growth in Peru? Inter-American Development Bank; Latin American Research Network. Research Network Working paper #R-404. Washington D.C.

Herrera, J. (2002): "La Pobreza en el Perú en 2001: Una visión departamental ". INEI-IRD. Lima – Perú, Mayo 2002.

Lanjouw, P., J. Lanjouw, C. Elbers and G. Demombynes (2007): "How good a map? Putting small area estimation to the test". Policy Research No 4155. Working Paper Series. The World Bank

Minier, J. (2007). "Institutions and parameter heterogeneity." Journal of Macroeconomics, 29(3), 595-611.

Minot, N.; B. Baulch and M. Epprecht (2006): "Poverty and Inequality in Vietnam: Spatial Patterns and Geographic Determinants" (Research report 148. International Food Policy Research Institute. Washington D.C.

Nguyen , B.; J. Albrecht; S. Vroman; and M. Westbroo (2007): "A quantile regression decomposition of urban–rural inequality in Vietnam". In: Journal of Development Economics 83 (2007) 466–490.

Ravallion, M. and Woodon (1999) Poor areas or only poor people? Journal of Regional Science, Vol 39, No. 4, 1999, pp. 689-711

Vakis, R., J. Herrera and J. Escobal (2008) "Una mirada a la evolución reciente de la pobreza en el Perú: avances y desafíos". Lima, Banco Mundial. 121 pp.

Zhao, Q and P. Lanjow (2005) Using Povmap2. Users guide. World Bank