WPS6355

Policy Research Working Paper 6355

# Vietnam's Evolving Poverty Map

## Patterns and Implications for Policy

*Peter Lanjouw*
*Marleen Marra*
*Cuong Nguyen*

The World Bank
Development Research Group
Poverty and Inequality Team
February 2013

Policy Research Working Paper 6355


## Abstract

This paper uses small area estimation techniques to update Vietnam's province and district-level poverty map to 2009. It finds that poverty rates continue to be highest in the northern and central mountainous regions, where ethnic minorities make up a large fraction of the population. Poverty has fallen in most provinces and districts over this decade, but the pace of poverty reduction has been least pronounced in those localities with high initial poverty or inequality levels. As a result, poverty rates have become more spatially concentrated over time, which is consistent with widely observed growth processes linked to agglomeration. The authors hypothesize that this makes geographic targeting of the poor more relevant as a means to re-balance growing welfare disparities between geographic areas. Simulations indicate that in both 1999 and 2009, geographic targeting for poverty alleviation improves upon a uniform lump-sum transfer and this becomes more evident the more spatially disaggregated the target populations. The analysis further indicates that the gains from geographic targeting have become more pronounced over time in Vietnam. Although poverty reduction in Vietnam has been impressive, further progress may thus warrant increased attention to geographic targeting.


This paper is a product of the Poverty and Inequality Team, Development Research Group. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The authors may be contacted at planjouw@worldbank.org, mmarra1@worldbank.org, and c_nguyenviet@yahoo.com.

# Vietnam's Evolving Poverty Map:
# Patterns and Implications for Policy

Peter Lanjouw, Marleen Marra and Cuong Nguyen[1]

JEL classification: I31, I32, O15

Keywords: Poverty, inequality, small area estimation, population census, household survey, targeting efficiency, Vietnam.

[1] Development Economics Research Group (DECRG) World Bank, DECRG,World Bank, and National Economics University, Hanoi. This study is an outgrowth of analysis undertaken as part of the Vietnam Poverty Assessment managed by Valerie Kozel under the POV Sector Board. We are grateful for her advice and guidance. The study is funded by the World Bank. We would like to thank Tran Ngoc Truong and Lo Thi Duc (GSO) for assistance in data analysis.

Email: planjouw@worldbank.org; mmarra1@worldbank.org; c_nguyenviet@yahoo.com

## 1. Introduction

Vietnam represents one of the great international success stories in achieving poverty reduction during recent decades. Concerns have been raised, however, that the pace of poverty reduction has slowed in recent years. In response, the Government of Vietnam has launched a variety of policies and initiatives to restore momentum in poverty reduction, and it is perceived that in order to buttress the impact of these policy measures, programs must become better targeted at the poor. One route towards better targeting is to exploit geographic variation in welfare outcomes. International evidence suggests that transfers will have a larger impact on poverty when they are targeted to finely delineated communities and localities (Baker and Grosh, 1994; Bigman and Fofack, 2000; Elbers *et al.* 2007).

Geographic targeting of the poor may be most effective in those settings where economic growth originates in areas with high factor productivity, which then results in the emergence of lagging regions. The 2009 World Development Report published by the World Bank, entitled "Spatial Disparities and Development Policy", demonstrates that economic activity and growth is spatially concentrated in many developing countries due to agglomeration benefits deriving from networks, technological change and human capital externalities. The report argues that countries should embrace this development rather than insist on geographically balanced growth. However, the report further argues that policy makers should explore opportunities to ensure that the benefits from such spatially concentrated growth are distributed broadly across the population. One means to that end is to promote the movement of people; barriers to trade and factor mobility should be removed. Another is to implement spatially targeted re-distribution policies that permit countries to support these growth processes while pursuing an equitable distribution of wellbeing.

A major obstacle to detailed spatial targeting is scarcity of reliable information on welfare levels at the local level. Estimation of poverty in small geographical units such as districts and communes poses considerable data demands. Income or expenditure data are commonly used as indicators of economic wellbeing and such information are routinely collected in household sample surveys. While representative at a national level, their sample sizes are typically too small to yield reliable estimates of poverty at the level of districts or communes. Censuses do not suffer from small sample problems as they cover the entire population. But while censuses also collect valuable information on individual and household characteristics that provide insights into living standards, they rarely include the income or expenditure information needed to measure poverty directly.

Small area estimation techniques have been developed to estimate poverty at the small area level. One popular approach, introduced by Elbers, Lanjouw and Lanjouw (2002, 2003) – henceforth ELL - combines household survey data and census data at the unit record level. The approach exploits the census's coverage of the entire population and the household survey's detailed information on income and expenditure. First, an expenditure (or income) model is estimated using the household survey data. The dependent variable is expenditure (or income), and the explanatory variables are a set of household and community characteristics that are comparable and that are available in both the household survey and the census. Subsequently, the parameter estimates from the expenditure model are applied to the census data in order to predict expenditure of all households in the population. From there it is a straightforward procedure to estimate poverty measures in small areas such as communes and districts.

The small area estimation method has been applied in a large number of countries to produce maps of not only poverty measures but also other welfare indicators (see Bedi *et al.*, 2007 for a review of applications). In Vietnam, a number of poverty maps have been developed using the ELL small area estimation method. Minot (2000) combines the 1993 Vietnam Living Standard Survey (VLSS) and the 1994 Agricultural Census to estimate poverty at the local level in rural areas of Vietnam. Minot *et al.* (2003) construct a poverty map using a 1998 VLSS and a 33% sample of the 1999 Population and Housing Census. Nguyen (2009) applies the 2002 VHLSS to the 33% sample of 1999 Population and Housing Census to produce a poverty map for 2002. Nguyen et al. (2009) further update the rural poverty map for 2006 using the 2006 VHLSS and the 2006 Rural Agriculture and Fishery Census.

The General Statistics Office of Vietnam recently published the 2009 Population and Housing Census and the 2010 Vietnam Household Living Standard Survey. These datasets permit a new updating of the Vietnam poverty and inequality maps. This paper presents new estimates of expenditure poverty at the province and district level of Vietnam. The estimates are based on the 15-percent sample of the 2009 Population and Housing Census in combination with the 2010 Vietnam Household Living Standard Survey. In addition, we estimate poverty at the provincial and district level for different groups including rural and urban, Kinh/Hoa and ethnic minority people. We also report small area estimates of inequality and examine in which provinces and districts the richest 15% of Vietnam are to be found. Finally, we compare the 1999 and 2009 poverty maps and analyze how evidence on local level changes can inform social policy making in Vietnam.

We simulate the impact of spatial targeting of a hypothetical budget, directed in turn to localities defined in terms of increasing spatial disaggregation to assess the gains from geographic targeting. The departure point of this analysis is a paper by Ravallion (1993) showing how spatial disaggregation to the regional level in Indonesia improves targeting, albeit to only a modest extent. In contrast, Elbers, Fujii, Lanjouw, Özler, and Yin (2007) apply an approach identical to the one employed here and find that in the case of Ecuador, Madagascar and Cambodia, when the geographic disaggregation is to a considerably finer level the gains from spatial targeting become very pronounced.

Vietnam has previously employed geographic targeting based on a fairly arbitrary list of poor communes, and is currently using a bottom-up approach to define who is poor and eligible for social assistance. Doubts about the effectiveness and transparency of both methods have been raised (Litvack, 1999; Baulch and Minot, 2002; van de Walle, 2002, Nguyen et al., 2010). Although poverty reduction in Vietnam has been impressive over the last decade, geographic targeting based on more clearly objective criteria may be needed to maintain further progress. Our simulations for 1999 and 2009, involving two snap-shots of the spatial distribution of poverty and a variety of alternative administrative levels of targeting, allow us to track the effectiveness of geographic targeting at different levels of spatial disaggregation as well as under alternative settings of the spatial distribution of poverty. At the same time, and as is noted further below, our simulations are highly stylized and predicated on simplifying assumptions, and as such can at best provide suggestive guidance to the design of policy.

The paper is structured as follows. The second and third sections introduce the estimation method and data sources used in this paper, respectively. The fourth section presents the empirical findings on the geographical distribution of poverty. The fifth section presents inequality and wealthy maps. Next, the change in poverty during the period 1999-2009 at the disaggregated levels is discussed in the sixth section. The simulation of the impact of spatial targeting of transfers on poverty reduction is presented in the seventh section. Finally, the eighth section concludes.

## 2. Methodology

To estimate the poverty rate in small areas such as districts, we employ the small area estimation method developed by Elbers, Lanjouw and Lanjouw (2002, 2003). The method involves three broad steps. In the first step, we select a set of variables that are common to both the household survey and the population census. The common variables include household characteristics, as well as characteristics of small areas such as villages and/or communes via area mean variables computed from the census. Area mean variables include, for example, the average household size at the commune level as calculated from the census, or the total population of the commune. These variables are then “inserted” into the household survey so that they can be included as candidate variables in the modeling stage. All variables common to the survey and census are subject to careful comparison; they need to be similar in terms of their means and distribution and in terms of the framing of the question.

In the second step, we regress observed expenditure in the household survey on the selected common variables. More specifically, we estimate the following model:

$$ln(y_{ch}) = X_{ch}\beta + \eta_c + \varepsilon_{ch}, \qquad (1)$$

where $\ln(y_{ch})$ is log of per capita expenditure of household *h* in cluster *c*, $X_{ch}$ the vector of the common variables, $\beta$ the vector of regression coefficients, $\eta_c$ the cluster-specific random effect and $\varepsilon_{ch}$ the household-specific random effect. The subscript *ch* refers to household *h* living in cluster *c*. We estimate different models for the six regions separately, to allow for variation in the relationship between expenditure and the selected variables in these areas. Table 1 in the Appendix lists the selected variables that are included in the regression models, i.e. selected on the basis of being common to both the survey and census and contributing significant explanatory power.

In the third step, we predict expenditure of a household in the census as follows:

$$\hat{\ln}(y_{ch}) = x_{ch}^{T}\hat{\beta} + \hat{\eta}_c + \hat{\varepsilon}_{ch}, \qquad (2)$$

where $\hat{\beta}$, $\hat{\eta}_c$ and $\hat{\varepsilon}_{ch}$ denote the estimates for $\beta$, $\eta_c$ and $\varepsilon_{ch}$. The predicted expenditure is used to calculate the poverty rate of small areas. It should be noted that the point estimates as well as the standard errors of the poverty rate and per capita expenditure are calculated by Monte-Carlo simulations. In each simulation, a set of values $\hat{\beta}$, $\hat{\eta}_c$ and $\hat{\varepsilon}_{ch}$ are drawn from their estimated distributions, and an estimate of expenditure and the poverty rates are obtained. After *k* simulations, we can obtain average expenditure and its standard deviation over the *k* different simulated values. Since we are restricted to a 15% sample of the 2009 Population Census (as opposed to the full census), we add an additional sample error component to the standard deviation. For this, we in effect treated the census as a survey, taking account its complex design and sample weights.

The predicted expenditure for all households in the population census are subsequently aggregated to generate district- and province level welfare measures. In 2009, we apply the GSO-World Bank official poverty line of 7,836,000 VND/person/year, and in 1999 the line is 1,789,871 VND/person/year (Minot et al, 2003). As poverty measure we use the popular headcount rate. We also estimate the Gini coefficient as our primary indicator of income inequality at the local level.

## 3. Data sources

As described in the methodology section, the 2009 poverty maps are based on two data sets. The first is the 15-percent sample of the Vietnam Population and Housing Census (VPHC). The 2009 VPHC was conducted by the General Statistics Office of Vietnam in April 2009, with (technical) support from the United Nations Population Fund (UNFP), and includes two modules. The first module is used to collect basic demographic and housing data for the whole population. Data include age, gender, race and education of individuals. The second module, which underpins our small area poverty estimates, contains more elaborate data. Individual data include demographics, education, employment, disability and migration. Household data include durable assets and housing conditions. The 15-percent sample is representative at the district level, and is selected on the basis of a cluster sampling technique, covering 3,692,042 households with 14,177,590 individuals (Central Population and Housing Census Steering Committee, 2009).

The second dataset is the 2010 Vietnam Household Living Standard Survey (VHLSS). The 2010 VHLSS is also conducted by GSO with technical support from the World Bank. It includes very detailed data on individuals, households and communes. Individual data consist of information on demographics, education, employment, health and migration. Household-level data include information on durables ownership, assets, production, income and expenditure, and participation in government programs. There are 9,402 households with 37,012 individuals covered in this data set. This 2010 VHLSS is representative for rural/urban areas and 6 geographic regions. Only 3 households are sampled from each commune. Thus, 9,402 households are sampled from 3,113 communes which belong to 686 districts. The 2010 VHLSS differs from earlier rounds (2002-2008) in terms of content as well as sampling design. The principal changes include shortening of the questionnaire, reframing of the consumption modules, and drawing of the sample from the 2009 instead of the 1999 Population Census.

To compare the 2009 results with those of 1999, we used the 1999 SAE poverty rates from Minot et al. (2003).[2] These are based on the 1998 VLSS and a 33% sample of the 1999 VPHC. The survey is implemented by GSO with funding from the Swedish International Development Agency and UNDP and with technical assistance of the World Bank. It includes 6,000 households. The 33% sample of the 1999 census includes 5,553,811 households.

## 4. The 2009 poverty map

### *4.1 Consumption models*

The first step in the poverty mapping method is to select common explanatory variables in the census and household survey. After carefully screening the questionnaires and examining the data (comparing summary statistics), we have 20 household variables (Table A.1 in Appendix). We also constructed commune level data from the census and merged these variables with the household survey. For example, we constructed the percentage of Kinh people per commune, the average household size of communes, the proportion of households per commune having motorbike, etc. Note that these variables are comparable across the census and survey by construction. The total number of explanatory variables for estimation of the expenditure model is 39.

We estimate six separate regressions of log of per capita expenditure for six regions. To allow for the difference in coefficients between urban and rural areas, we interact the urban variable with all the remaining explanatory variables.

A forward stepwise technique is used so that only variables which are significant at least at the 5% level are kept. We select explanatory variables that are robust in explaining expenditure. This means that these variables have unchanged signs and are significant when the models are changing. The regression results of the large models are presented in the tables in Appendix I. The R-squared is very high. The Mekong River Delta has the lowest R-squared

[2] In Section 6 we note that caution must be exercised in comparing poverty between 1999 and 2009 as the underlying household survey data are not strictly comparable.

of 0.5. The Central Highlands have the highest R-squared of 0.74. Other regions have an R-squared above 0.6.[3]

### 4.2 *Spatial patterns of poverty*

Table 1 presents the regional estimates of the poverty rate and per capita expenditure which are computed directly using per capita expenditure data of the 2010 VHLSS and those estimated from the poverty mapping method. The 2012 VHLSS is representative at the regional level, and the regional poverty rate directly estimated from expenditure data can be thus regarded as the benchmark against which to compare the poverty map estimates. Table 1 reveals that estimates of the poverty rate are quite similar across the two approaches.

Table 1: Per capita expenditure and poverty indexes

| | Estimates from the 2010 VHLSS | | | | Predictions from SAE | | | |
|---|---|---|---|---|---|---|---|---|
| | Per capita expenditure (thousand VND) | P0 | P1 | P2 | Per capita expenditure (thousand VND) | P0 | P1 | P2 |
| Northern Mountain | 10927.1 | 44.87 | 0.1558 | 0.0701 | 10826.4 | 43.85 | 0.1483 | 0.0679 |
| | (250.2) | (1.54) | (0.0069) | (0.0042) | (340.9) | (1.76) | (0.0082) | (0.0046) |
| Red River Delta | 21546.0 | 11.95 | 0.0265 | 0.0088 | 20515.2 | 10.65 | 0.0203 | 0.0060 |
| | (605.6) | (0.85) | (0.0025) | (0.0010) | (592.2) | (1.02) | (0.0025) | (0.0009) |
| Central Coast | 14222.6 | 23.73 | 0.0635 | 0.0251 | 14002.1 | 22.48 | 0.0520 | 0.0180 |
| | (267.3) | (1.33) | (0.0051) | (0.0028) | (268.7) | (1.05) | (0.0031) | (0.0013) |
| Central Highlands | 13069.0 | 32.74 | 0.1149 | 0.0542 | 12931.0 | 33.29 | 0.1146 | 0.0536 |
| | (490.9) | (2.75) | (0.0128) | (0.0077) | (351.8) | (1.25) | (0.0056) | (0.0032) |
| South East | 24297.4 | 7.02 | 0.0172 | 0.0064 | 23350.9 | 7.07 | 0.0139 | 0.0043 |
| | (935.9) | (0.96) | (0.0036) | (0.0018) | (844.9) | (0.84) | (0.0020) | (0.0007) |
| Mekong River Delta | 14858.2 | 18.71 | 0.0425 | 0.0143 | 14497.9 | 17.45 | 0.0359 | 0.0112 |
| | (265.8) | (1.10) | (0.0033) | (0.0015) | (280.7) | (1.08) | (0.0029) | (0.0011) |

Standard errors are in parentheses.
Source: Estimation from the 2009 VPHC and the 2010 VHLSS.

[3] We conduct two exercises to shed light on the question how well the models do in predicting per capita expenditure. Firstly, within the 2010 VHLSS, we randomly split the six regions into two samples, and estimating the regional models in the first sample, we predicted expenditure in the second sample and compared the results to the actual per capita expenditure. We find that the observed poverty rates are in all regions' subsamples similar to the predicted ones. Secondly, we also examine the sensitivity of the expenditure poverty rate of districts and provinces to different expenditure models. We estimate two expenditure models: one with a large number of explanatory variables and another with a smaller number of explanatory variables. Both models give very similar estimates of poverty indexes at the district and province level. For interpretation in this paper, we will use the estimates from the large model, which give lower standard errors of welfare estimates.

Table A.8 in the Appendix presents by province, the predicted per capita expenditure, poverty rate, number of poor, and share in the total number of poor in the country. Lai Chau, Ha Giang and Dien Bien are three poorest provinces with the poverty rate of more than 70%. As expected, Hanoi and Ho Chi Minh city are the richest cities, followed by Da Nang, Hai Phong, Quang Ninh, Binh Duong, Ba Ria-Vung Tau.

Figure 1 shows the spatial distribution of poverty by provinces and districts in 2009. Poverty rates are highest in the mountainous Northern areas and lowest in the Mekong and Red River Deltas. Disaggregating down to the district level reveals a greater degree of heterogeneity in terms of both pockets of extreme poverty and pockets with particularly low levels of poverty. As we shall see below, such heterogeneity across sub-national localities translates into gains from spatial targeting of anti-poverty resources.

Figure 2 graphs the density of the poor across the country. Because of their large populations, the Mekong and Red River Delta regions still account for a significant number of the poor in the country. However, as we shall see below, the picture in 2009 is much less accentuated than at the time of the preceding census, and as such indicates a clear attenuation of the pattern described in earlier studies of poverty in Vietnam (see Minot et al, 2003) where the distribution of the number of poor people was inversely correlated with the spatial distribution communities' poverty rates. Then, poverty rates were highest in relative sparsely populated localities and these thus accounted for only a modest fraction of the poor. Today, poverty rates remain spatially concentrated but the distribution of poor people is more evenly spread across the country. Consequently Vietnam's poorest communities account for a larger share of the poor population.

Despite the ongoing urbanization process, poverty in Vietnam is currently still largely a rural phenomenon: 95 percent of the poor live in rural areas. The poverty rate in urban areas is generally low, and there is a large difference in poverty rates between urban and rural areas even within a province and a district; see Figure 3. Figure 4 shows clearly that poverty is markedly higher amongst ethnic minorities than Kinh and Hoa households. Even within the same mountain or delta region, there remains a large gap in poverty between ethnic minority households and Kinh (Hoa) households.

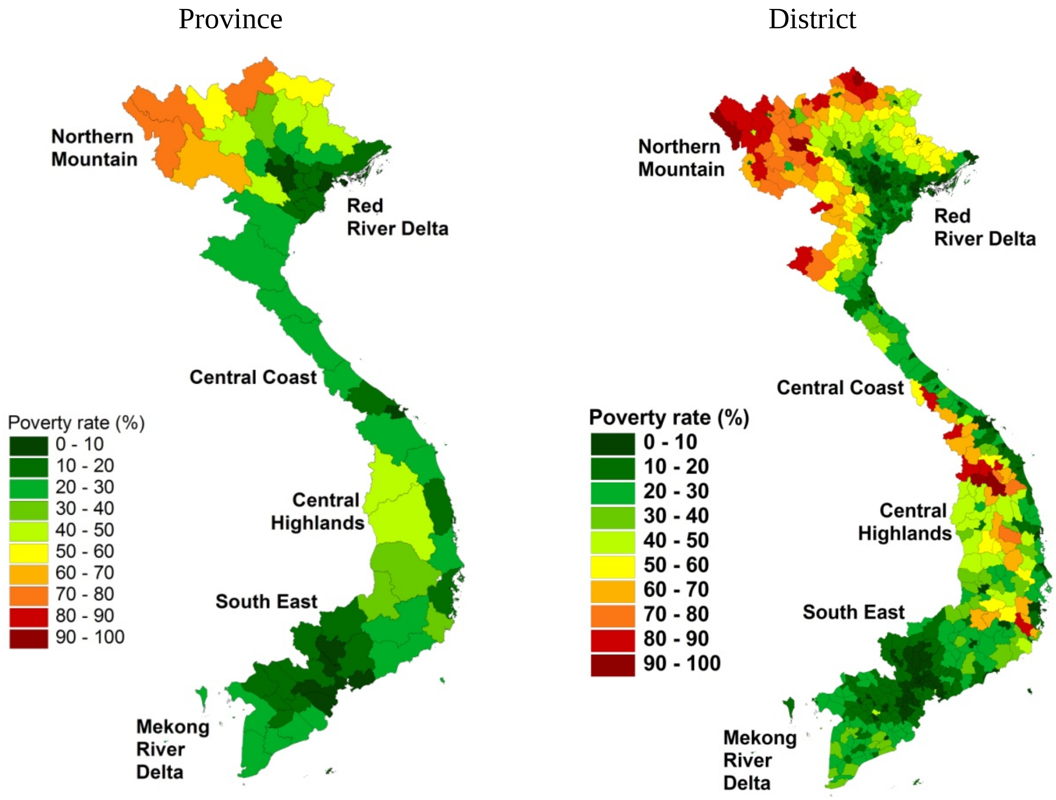


Figure 1. The poverty rate of provinces and districts in 2009

Source: The 2009 poverty rates are estimated from the 2009 VPHC and the 2010 VHLSS.

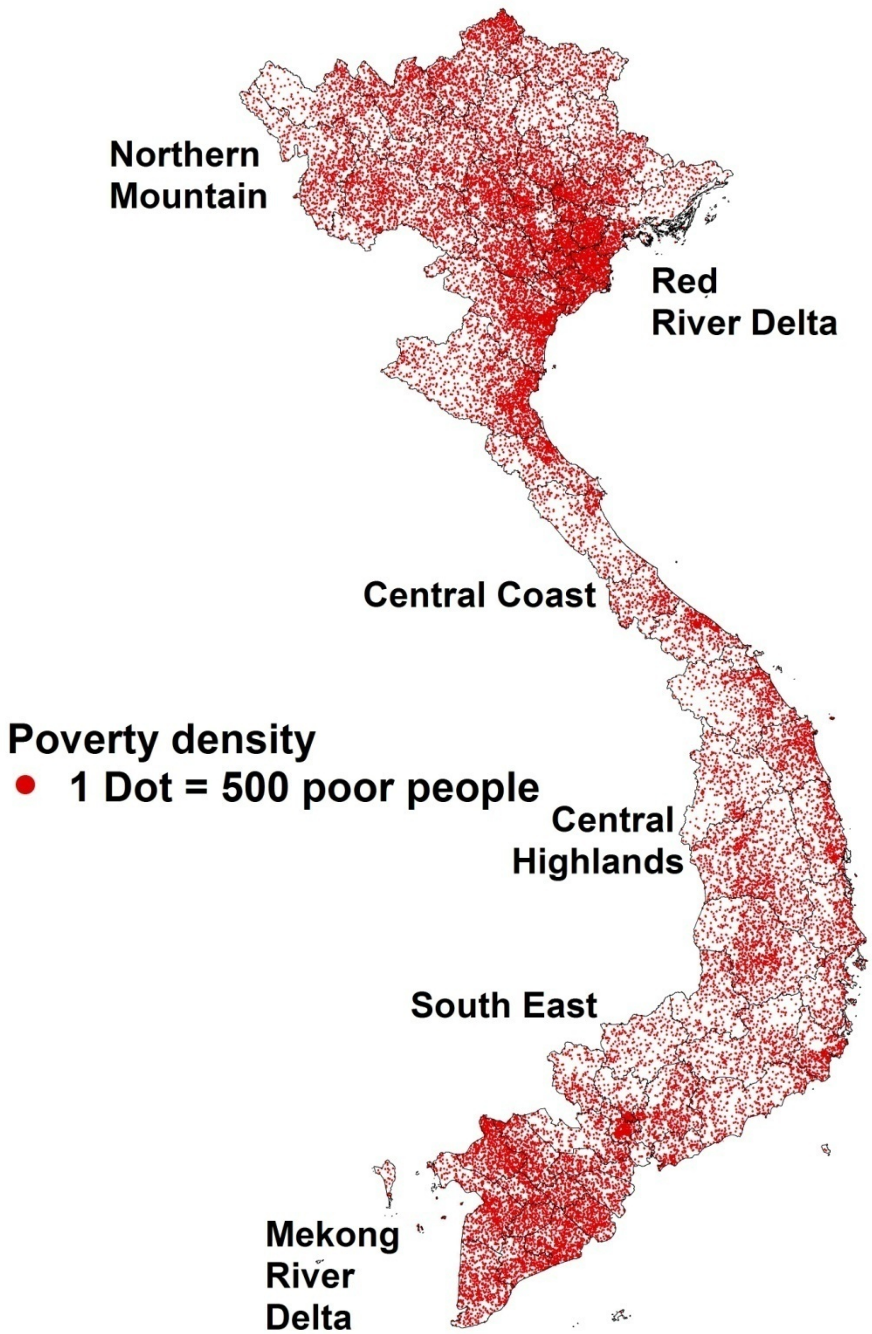


Figure 2. The poverty density in 2009 (number of poor people)

Source: The 2009 poverty rates are estimated from the 2009 VPHC and the 2010 VHLSS.

Urban provinces and districts    Rural provinces and districts

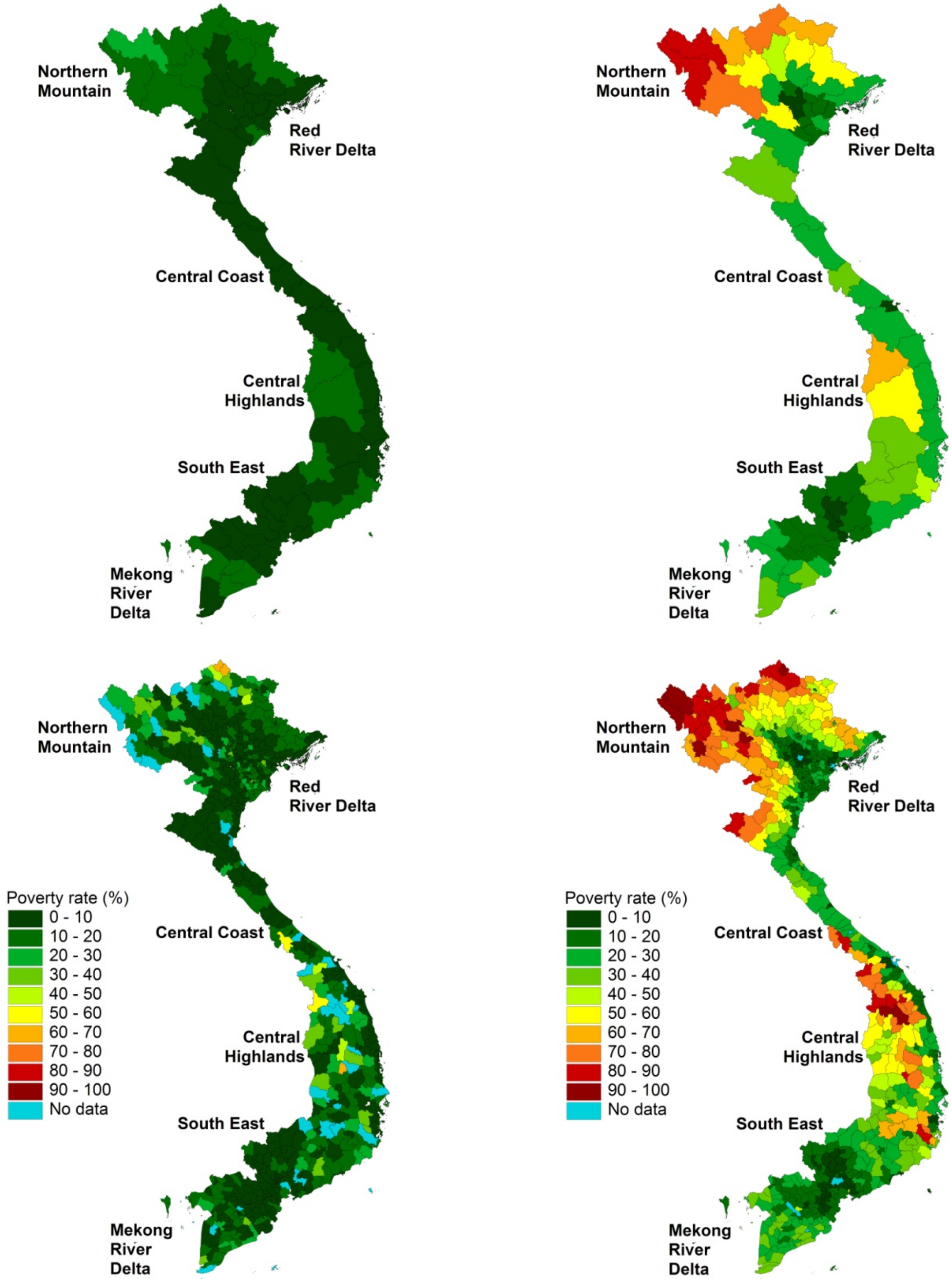


Figure 3. The poverty rate of urban and rural people (%)
Source: Estimation from the 2009 VPHC and the 2010 VHLSS.

Kinh/Hoa people; provinces and districts

Ethnic minority people; provinces and districts

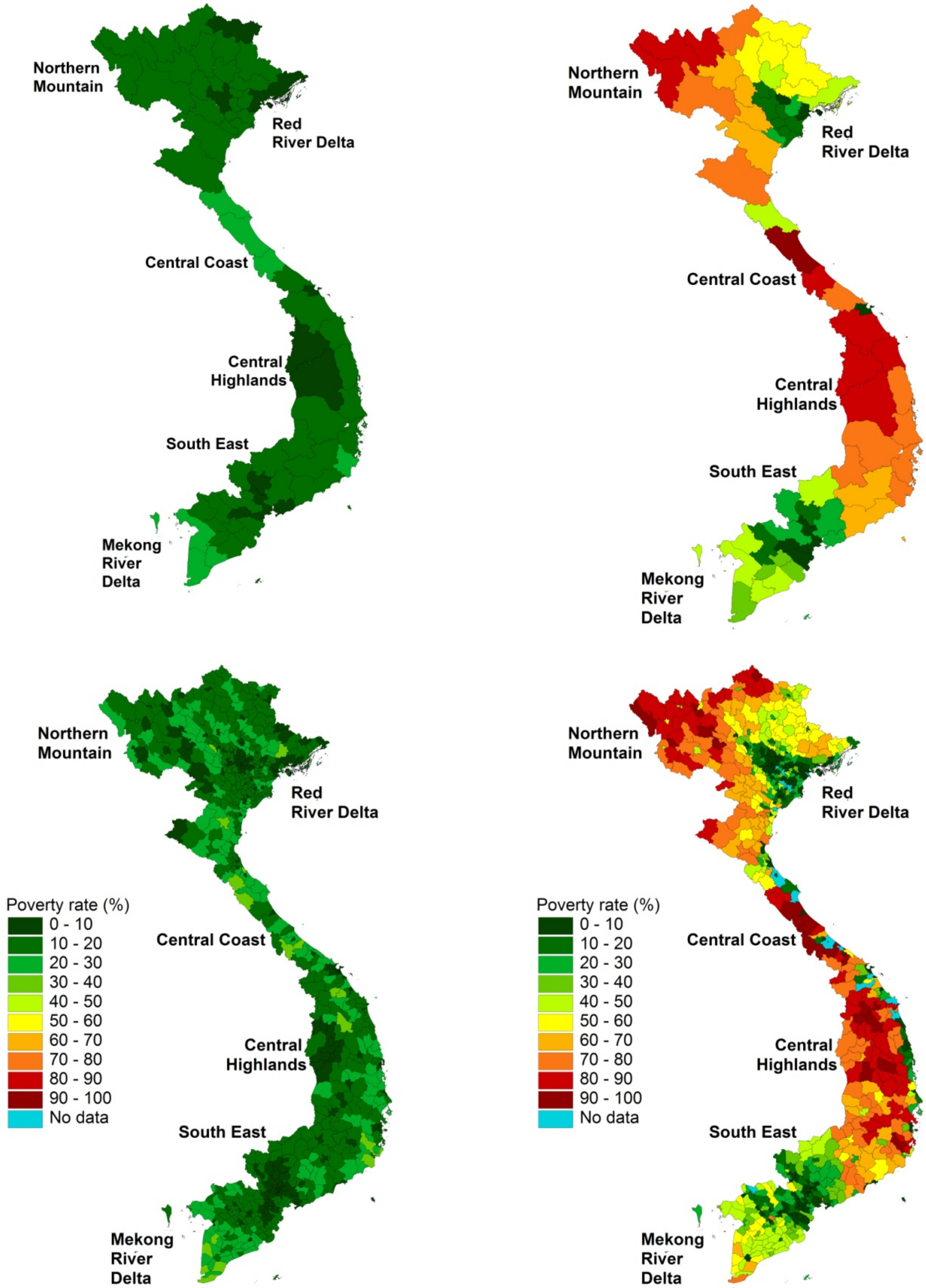


Figure 4. The poverty rate of Kinh/Hoa and ethnic minority people (%)
Source: Estimation from the 2009 VPHC and the 2010 VHLSS.

### *4.3 Poverty correlates*

This section considers a few province- and district-level correlates of local headcount rates, in an attempt to look beyond its spatial distribution to more generalizable patterns. The results refer to figures 1-5 in the appendix.

The data displays a clear positive relationship between poverty rate and Gini index. A more equal distribution is associated with a lower poverty rate (Figure A.1 appendix). However, what is also clear from this Figure is that at any particular poverty rate there is heterogeneity across provinces and districts in terms of inequality outcomes.

Although Vietnam remains a rural country, the urbanization process has been accelerating in recent years. About 30 percent of people now reside in urban areas (General Statistics Office, 2011). Overall, urban areas tend to have lower poverty, and as a result it is a general tendency that poverty is lower as the urban population share increases (Ravallion et al., 2007). In Vietnam, poverty is negatively correlated with the urban population share at the provincial and district level (Figure A.2 Appendix).

Also, poverty is substantially higher in areas with large concentrations of ethnic minorities (Figure A.3 Appendix). This finding relates to the earlier one that the poor are now concentrated in Northern mountain and central highlands where there are large population shares of such ethnic minorities. It also follows that poverty rates are higher in areas with low population and low population density (Figures A.4 and A.5 Appendix).

## 5. The 2009 inequality and wealth maps

We now turn, briefly, to the spatial distribution of inequality across provinces and districts. Table A.9 in the Appendix presents the Gini index and the ratio of the $90^{th}$ to $10^{th}$ expenditure percentile (a measure of “absolute” inequality) for all provinces. In addition, we also estimate the percentage of people belonging to the richest 20% of the population.

Figures 5 and 6 show that both relative and absolute inequality tends to be higher in provinces and districts with higher poverty rates. Areas with high poverty rates in Northern mountains have higher expenditure inequality than other, richer, areas. This finding is noteworthy in light of the common (often implicit) view that in poor communities everyone is similarly poor. But the finding also resonates with other empirical studies of inequality at the local level (see Elbers et al, 2004). While there are certainly poor localities where everyone is similarly poor, the evidence shows that there should certainly be no presumption that inequality will be lower in poorer communities.

Figure 7 presents a map of "the rich". As can be expected, the location of the top quintile of the per capita expenditure distribution is spatially concentrated in the delta regions, especially in Hanoi and Ho Chi Minh cities as well as in the immediate surrounding areas.

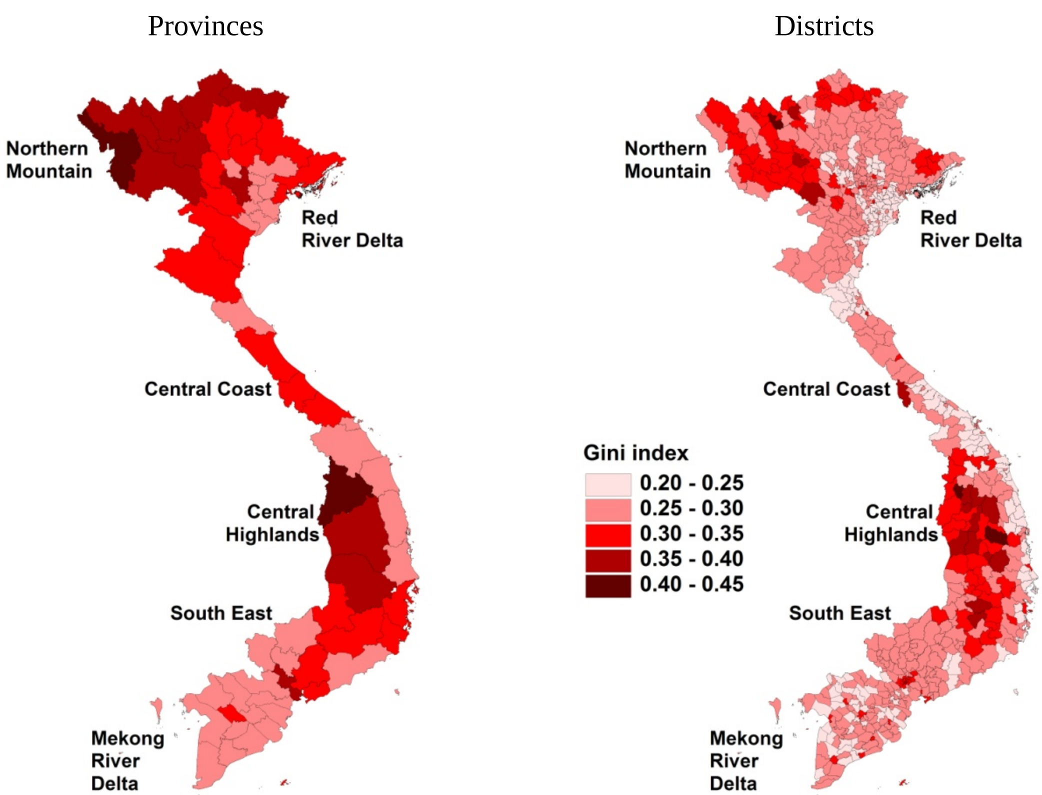


Figure 5: Inequality: Gini index

Source: Estimation from the 2009 VPHC and the 2010 VHLSS.

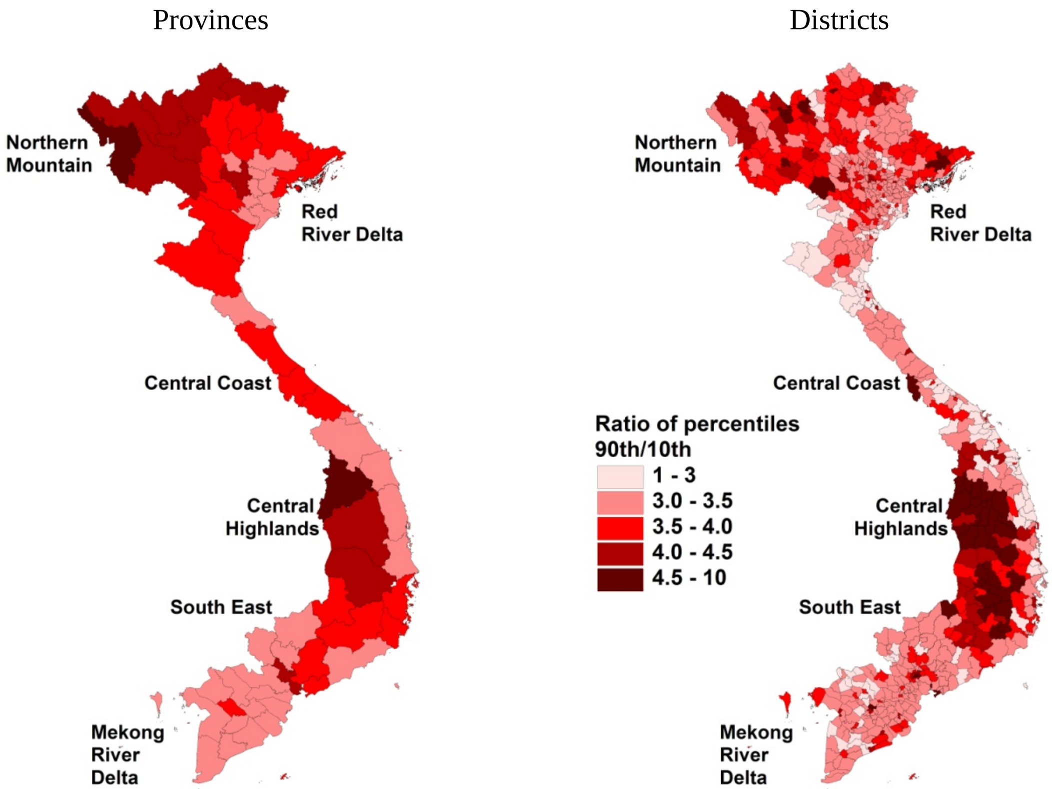


Figure 6: Inequality: Ratio of the 90th to the 10th expenditure percentile.
Source: Estimation from the 2009 VPHC and the 2010 VHLSS.

Provinces Districts

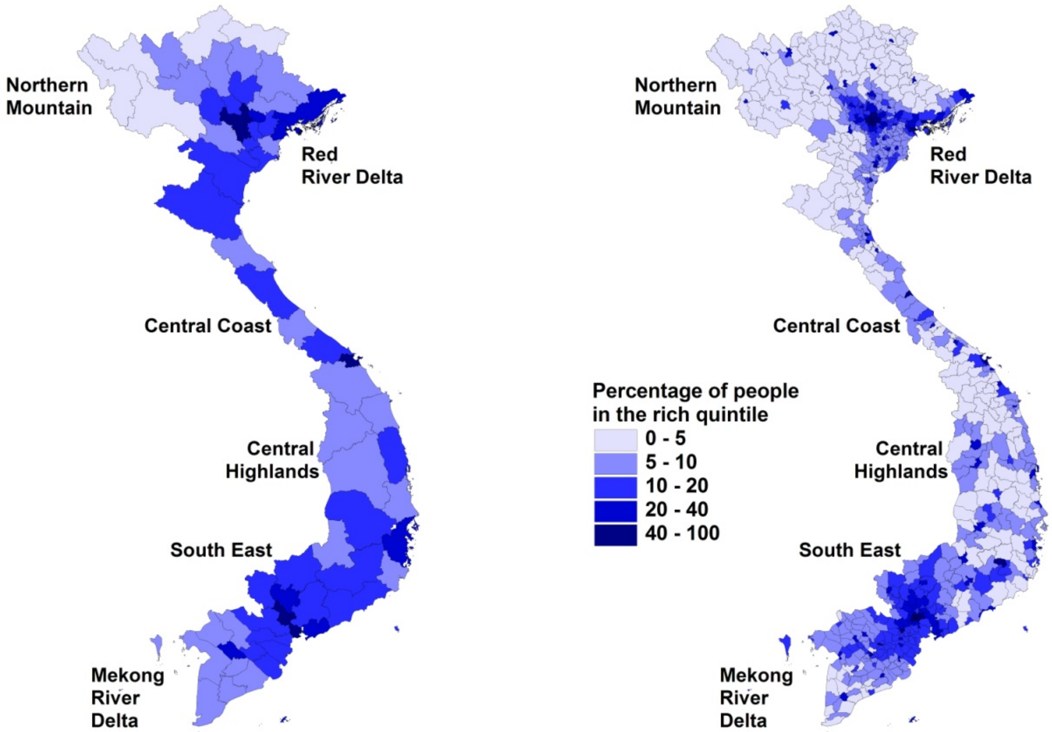


Figure 7: The percentage of people in the richest expenditure quintile (%)
Source: Estimation from the 2009 VPHC and the 2010 VHLSS.

## 6. The evolution of local-level poverty between 1999 and 2009

Between 1999 and 2009 poverty in Vietnam declined markedly. A precise statement regarding the rate of poverty decline over this time period is problematic due to changes in the sampling frame and consumption module for the 2010 VHLSS. However, the broad statement that poverty has fallen sharply during the decade of the 2000s is robust: comparing the 1998 VHLSS with the 2008 VHLSS data (which does not suffer from non-comparability), and utilizing a single fixed poverty line in real expenditure terms (first defined in 1993) implies a reduction in the incidence of poverty from about 47% in 1998 to 15% in 2008. Rather than scrutinizing precise poverty levels here, we focus on changes in the geographic profile of poverty, as revealed by the 1999 and 2009 poverty maps.

Figures 8-10 indicate that poverty has fallen most rapidly in the delta provinces. Northern mountainous and central highland provinces as well as districts have experienced slower poverty reduction than other delta provinces and districts. An examination of the changing spatial distribution of the poor population is particularly interesting. Figure 10 graphs the density of the poor across the country in 1999 and 2009. In 1999, the poor were highly concentrated in Delta regions such as Red River Delta and Mekong River Delta, since these areas have high population density. By 2009, the poor have become more evenly spread. The number of poor has decreased remarkably in delta regions, but much less markedly in the Northern mountains and Central highlands.

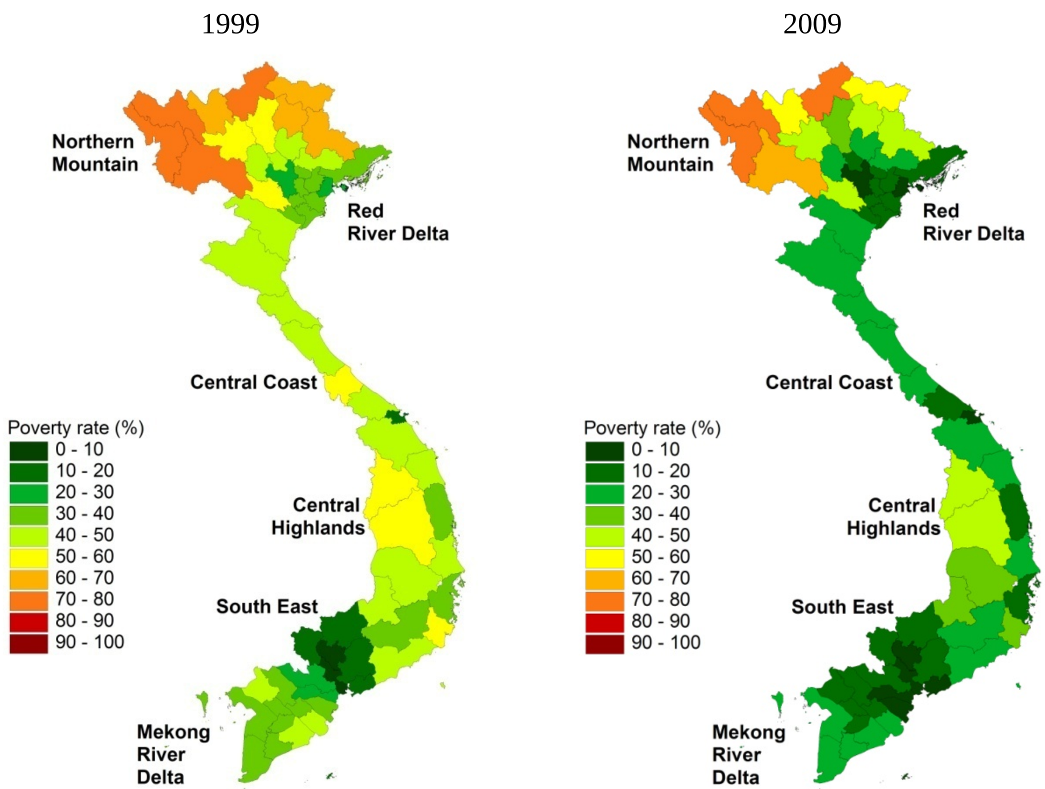


Figure 8. The poverty rate of provinces in 1999 and 2009 (%)
Source: The 2009 poverty rates are estimated from the 2009 VPHC and the 2010 VHLSS. The 1999 poverty rates are obtained from Minot et al. (2002).

When matching the districts of 1999 and 2009 and comparing their poverty rates, three observations can be made. First, we observe a positive correlation between the 1999 and the 2009 poverty rate, which makes sense in that areas are poor for a reason, and although they can outgrow poverty, it can be a lengthy process. Second, an inverse U-shaped relationship between initial poverty and poverty reduction can be discerned. Both areas that initially had low headcount rates, and those with high headcount rates, were relatively slow in reducing poverty over the reference period, while areas with average headcount rates were able to improve living standards most rapidly. This has the direct effect that poverty rates become more concentrated over time, as very poor districts seem to be 'trapped' in poverty. Third, we observe a negative relation between the rate of poverty decline and the initial level of the Gini index. Provinces and districts with low expenditure inequality in 1999 were generally able to achieve more rapid reduction in poverty between 1999 and 2009. All these observations are supported by figures A6-A8 in the Appendix.

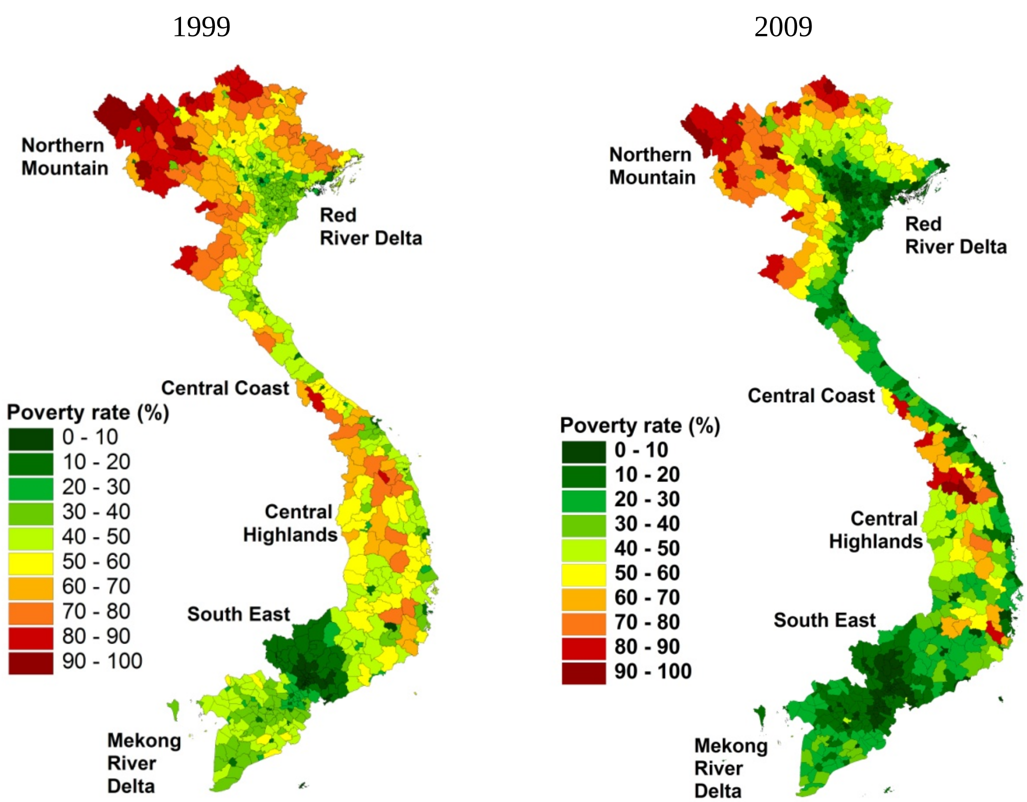


Figure 9. The poverty rate of districts (%)

Source: The 2009 poverty rates are estimated from the 2009 VPHC and the 2010 VHLSS. The 1999 poverty rates are obtained from Minot et al. (2002).

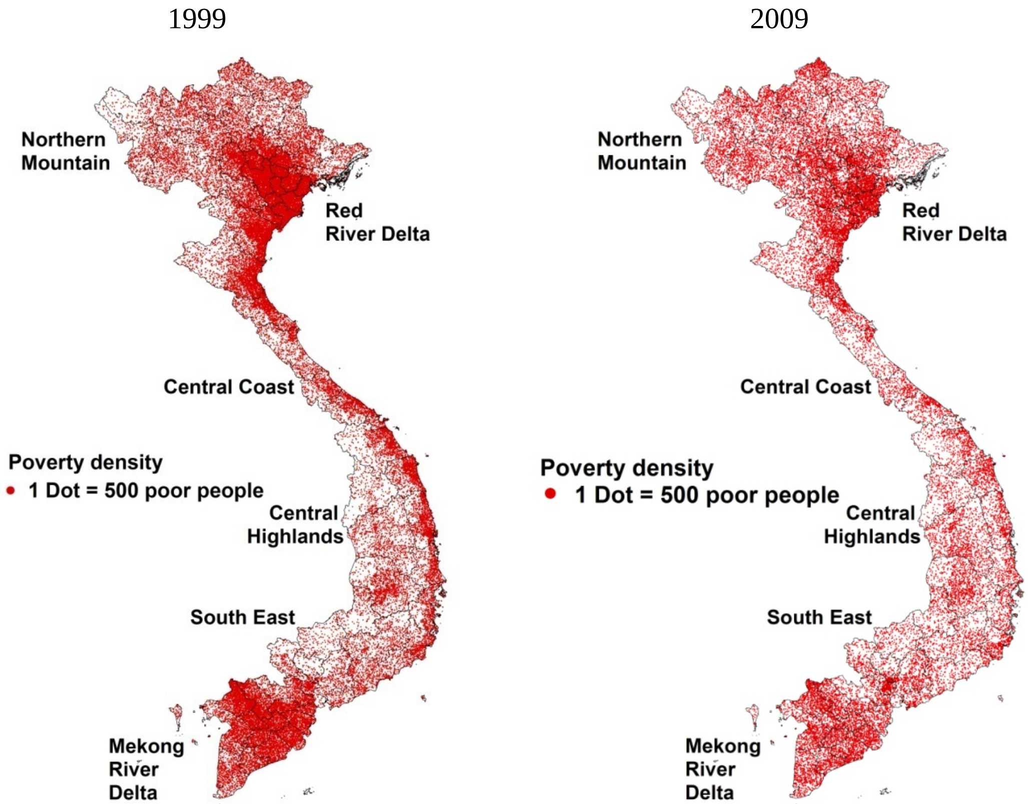


Figure 10. The poverty density (number of the poor people)
Source: The 2009 poverty rates are estimated from the 2009 VPHC and the 2010 VHLSS. The 1999 poverty rates are obtained from Minot et al. (2002).

## 7. The spatial distribution of poverty and gains from spatial targeting

The preceding sections have documented some noteworthy patterns in the spatial distribution of poverty and its evolution in Vietnam between 1999 and 2009. What do these patterns imply for the design of policy? This section asks how much the high degree of spatial disaggregation offered by the Vietnam poverty maps can help to improve targeting schemes aimed at reducing poverty in the country. As social assistance policies are generally bound by scarcity of funds, they should ideally target beneficiaries whose needs are most urgent in order to have the highest impact. However, as Coady and Morley (2003) show from evaluating social assistance programs in Mexico, Brazil, Bangladesh, Nicaragua, Honduras, and Chile, it is generally difficult to avoid errors of *leakage* (reaching the non-poor) and of *under-coverage* (not reaching the poor). Improving targeting aims to reduce these errors, resulting in a more effective poverty reduction policy.

The current process for targeting the poor in Vietnam employs a "bottom up" approach. At the aggregate level, overall progress in tracking poverty over time is undertaken by the Ministry of Labor, War Invalids, and Social Affairs (MOLISA) on the basis of an income poverty line[4] applied it to the periodic rounds of VHLSS survey data. Identification of households eligible to receive targeted assistance is undertaken at the village level. Village committees use their own widely varying criteria to compose a list of poor households. Criteria may include food security, housing, assets, etc. This list is submitted for review to a commune-level committee of Hunger Eradication and Poverty Reduction. The committee checks that households on the list are below MOLISA's income poverty line by conducting simple surveys of randomly selected households from the list. The refined list is then sent to the People's Committee and the People's Council, which are empowered to make further adjustments to it as well (Nguyen et al., 2010). Households that make it to the final 'poor list' are then in principle eligible for certain social assistance programs such as free health insurance or subsidies.

Previously, Vietnam would redistribute funds by means of geographic targeting. However, it is generally felt that there was a large margin of error in this approach; the "list of poor communes" that MOLISA used to target the poor was constructed somewhat arbitrarily and failed to capture the majority of poor people. One study estimates that although leakage was limited with this practice – about 8% of non-poor were misclassified as being poor – under-coverage was substantial with 80% of the poor not being reached (Baulch and Minot, 2002).

Concerns have also been voiced about the way that funding is distributed once the poor are identified. Although funds are allocated in a redistributive way to the provinces, intra-provincial distribution is to a large extent left to the discretion of provincial authorities and it

[4] Which is different – usually lower - from the expenditure poverty line set by the General Statistics Office and The World Bank that is used by the international research community to study poverty.

is suggested that this is the first of many bottlenecks to a fair and transparent system (Litvack, 1999; van de Walle, 2002). Often, communities are urged to collect funds through fees and levees themselves, which is obviously hardest for the most deprived communities. It is not surprising that statistics show a large gap between eligible households and actual beneficiaries (van de Walle, 2002).

As we have shown in previous sections, poverty has become much more spatially concentrated over time in Vietnam. We have noted in the introductory section that this is likely a common consequence of spatial concentration of economic growth due to agglomeration externalities. Absent an effective means to redistribute incomes to lagging regions this process is likely to result in a growing spatial concentration of poverty. Geographic targeting of resources to combat poverty offer one possible means to attenuate such a process.

To assess effectiveness of geographic targeting in Vietnam, we consider the geographic distribution of a hypothetical budget to the population of Vietnam. We assume that we have no information about the poverty status of this population other than the geographic location of residence and the level of poverty in each location. As a benchmark case we make the extreme assumption of no knowledge whatsoever about the spatial distribution of poverty – in which case our given budget is distributed uniformly to the entire population.[5] We set up a series of comparisons to this benchmark, where we assume knowledge about poverty levels in progressively smaller sub-populations. For a given level of disaggregation, we ask how knowledge about poverty outcomes across localities can be incorporated into the design of a transfer scheme so as to improve the overall targeting performance relative to the benchmark case. In light of the observations made above concerning the evolving spatial distribution of poverty (in Vietnam and beyond), we ask whether and how our conclusions differ between 1999 and 2009.

[5] Actually, comparing this no-knowledge benchmark against the successfulness of the geographic targeting approach that Vietnam exercised a decade ago as assessed by Baulch and Minot (2002), it is not that extreme. They found that only 20% of the poor were reached. If the total population gets distributed an equal part of the budget, 100% the poor would be reached by definition. The only thing is that the amount received is probably so little in that scenario that it is questionable how many people would get lifted out of poverty.

The transfer scheme makes use of our knowledge of the spatial distribution of poverty in such a way that poverty is minimized at the national level. We consider the gains from spatial targeting at alternative levels of disaggregation. As poverty measure we use the squared poverty gap, which is particularly sensitive to the severity of poverty by calculating the distance between a poor person's income level and the poverty line and giving more weight to larger distances.[6] We specify a poverty line that accords with a poverty rate of around 20% nationally, in each respective year,  and we postulate a modest hypothetical budget that would be insufficient, in and of itself, to eliminate all poverty, even if it were perfectly targeted at the household level. Our results show that in both 1999 and 2009 there are potentially large gains in targeting performance from disaggregating to the local level. These benefits are even more clearly seen when we examine the squared poverty gap as our poverty measure of choice. The impact on the headcount rate is, unsurprisingly, more muted, given that we are not able to "optimize" our transfer scheme with respect to this poverty measure.

The benefits from spatial targeting become increasingly evident as one makes use of more and more disaggregated data on poverty. We show that a given impact on poverty can be achieved at considerably less expense with detailed spatial targeting than with a uniform transfer. Importantly, we find that the benefits from spatial targeting, at any level of disaggregation, are more evident in 2009 rather than 1999. This follows from our earlier finding that poverty in 2009 is more spatially concentrated than was the case in 1999, and supports our assertion that in developing countries that experience uneven spatial progress geographic targeting can be a successful policy to reduce growing wealth disparities.

### *7.1. Transfer scheme*

[6] We focus on the squared poverty gap because of its appealing properties from both a conceptual and technical point of view.  The basic approach explored here would also work for other poverty measures, particularly FGT measures with values of parameter $\alpha$ greater than 1.  However, with the headcount measure (the FGT measure with $\alpha$=0) welfare 'optimization' is not well defined and the approach taken here is thus less obviously applicable (see for example Ray, 1998, pg 254-255).

We postulate that the government has a budget, *S*, available for distribution and wishes to transfer this budget in such a way as to reduce poverty. We specify a baseline case in which the government is assumed to have no knowledge of who the poor are or where they are located. It is therefore unable to distribute its budget in any manner other than a lump-sum transfer to the entire population of size *N*. We thus calculate the impact of transferring *S/N* to the entire population.

Kanbur (1987) shows that to minimize poverty summarized by the Foster-Greer-Thorbecke (FGT) class of poverty measures with parameter value $\alpha>1$, the group with the higher FGT($\alpha$-*1*) should be targeted on the margin.[7] Hence, to minimize the squared poverty gap (equal to a poverty measure from the FGT class with $\alpha$=2), target populations should be ranked by the poverty gap (FGT with $\alpha$=1) and lump-sum transfers made until the poverty gap of the poorest locality becomes equal to that in the next poorest one, and so on, until the budget is exhausted.

### *7.2. Budget and Poverty Lines*

We assume that the budget available for distribution has been exogenously set. As is intuitively clear, the potential benefits from targeting will vary with the overall size of budget. In the limit, as the budget goes to infinity, there is no need for targeting, as even a uniform transfer will eliminate poverty. As a benchmark, we identify the per capita consumption value of the 25th percentile of the consumption distribution.[8] We scale this consumption value by the total population. Our benchmark budget is set to equal 5% of this total value.

[7] Following Foster, Greer and Thorbecke (1984) the FGT class of poverty measures take the following form:

$$FGT(\alpha) = (\frac{1}{\sum w_i})\sum w_i (1-(x_i / z))^{\alpha}$$

where $x_i$ is per capita expenditure for those individuals with weight $w_i$ who are below the poverty line and zero for those above, z is the poverty line and $\sum w_i$ is total population size. $\alpha$ takes a value of 0 for the Headcount Index, 1 for the Poverty Gap and 2 for the Squared Poverty Gap. For further discussion, see Ravallion (1994).

[8] The consumption distribution is constructed on the basis of the average, across *r* replications, of household-level predicted per-capita consumption in the population census.

Gains from targeting also vary with the choice of poverty line. The higher the poverty line, the less need for targeting, as leakage to the non-poor diminishes to zero. In this study, we select as benchmark the a poverty line that yields a poverty rate of exactly 20% in both 1999 and 2009, respectively.

### *7.3. Simulating the impact of uniform transfers*

Our policy simulation in the benchmark case of uniform transfers is calculated in a very straightforward manner. Budget *S* is divided by total population *N*. The resulting transfer *a* is added to each predicted expenditure in our database, to yield $y_{ch}^{(r)} + a$. For each replication *r* we estimate post-transfer national poverty. The average across the *r* replications of the estimated post-transfer poverty rates yields our expected poverty rate associated with the benchmark, untargeted lump-sum transfer scheme. This new estimated poverty rate can be compared to the original national-level poverty estimate from the poverty map to gauge the impact of the transfer.

### *7.4. Simulating the impact of "optimal" geographic targeting*

Simulating the impact of the "optimal" targeting scheme is a bit more complicated. Following Kanbur (1987) we want to equalize the following expression across the poorest locations of a country:

$$G_c(a_c) = \int_0^z (z - y - a_c)^+ \, dF_c(y), \qquad (3)$$

which is *z* times the poverty gap in location *c* , after every person in the location has received a transfer $a_c$. $F_c(y)$ is the average of the R simulated expenditure distributions of *c*. The function $(x)^+$ gives the 'positive part' of its argument, i.e. $(x)^+=x$, if *x* is positive, otherwise 0. Transfers $a_c$ (which must be nonnegative) add up to a given budget *S*:

$$\sum_c N_c a_c = S, \qquad (4)$$

where $N_c$ is the population size of location *c*. After transfers there is a group of locations all sharing the same (maximum) poverty gap rate in the country. These are the only locations receiving transfers. We describe in the Appendix how this problem is solved given that we are working with a database of incomes for every household in the population census.

### *7.5. Results of spatial targeting simulation*

Table 2 presents the basic results from our simulations. There are a number of conclusions to be drawn. First, the availability of disaggregated data on poverty can help to improve on a uniform lump-sum transfer across the entire population. Targeting transfers to poor localities, in accordance with the optimization scheme outlined above, yields lower values of the national FGT2 than when the budget is transferred as a uniform lump-sum transfer to the entire population. Second, the more disaggregated the poverty map, the greater the improvement over the uniform lump-sum transfer. The simulations here suggest that with estimates of poverty at the province, district and commune levels, further improvements in terms of impact on the FGT2 with a given budget are attainable, and are non-negligible. Third, while the general patterns we observe are similar across our two poverty maps for 1999 and 2009 respectively, they are not identical. Notably, we see in Table 2 that while commune-level targeting in 1999 would reduce the FGT2 from a level of 0.0110, following a uniform transfer, to 0.0058 with commune level targeting (a 43 percentage point reduction), the improvement from commune level targeting in 2009 would be 66 percentage points – the FGT2 declining from 0.0166 to 0.0057 (Table 3). With district level targeting rather than commune-level targeting, the gains are slightly less marked but nonetheless a striking 58 percentage point reduction compared to uniform transfers.

Table 3 repeats the simulations presented in Table 2 but focuses now on the headcount, or FGT0, measure of poverty. As mentioned above the optimization procedure outlined in Kanbur (1987) applies to the squared poverty gap or FGT2 measure. There is no analogous optimization algorithm for the FGT0 measure. We report in Table 3, however, the resulting FGT0 estimates from having applied the procedure to allocate our budget in such a way as to minimize the resulting FGT2 measure. Table 3 reveals that the gains in terms of the FGT0 of geographic targeting are far less marked than was observed when the FGT2 measure was our reference measure.

Table 2: Impact on FGT2 of Targeting at Different Levels of Geographic Disaggregation
Optimal Targeting Scheme

| | 1999 | 2009 | 1999 | 2009 |
|---|---|---|---|---|
| Original FGT2 | 0.0159 | 0.0234 | 1.00 | 1.00 |
| FGT2 after: | | | | |
| Uniform transfer | 0.0110 | 0.0166 | 0.69 (1.00) | 0.71 (1.00) |
| Province Level Targeting | 0.0080 | 0.0096 | 0.50 (0.72) | 0.41 (0.58) |
| District-level targeting | 0.0066 | 0.0070 | 0.42 (0.61) | 0.30 (0.42) |
| Commune-level targeting | 0.0058 | 0.0057 | 0.36 (0.57) | 0.24 (0.34) |

Note: Budget=5% of (Total Population * 25$^{th}$ Percentile Per Capita Expenditure).

Poverty Line= Per capita expenditure defining bottom quintile of population (pre-transfer).

The two last columns are the poverty gap indexes normalized to one. The figures in parentheses are the ratio of normalized FGT2 in the case of targeting transfer to the normalized FGT2 in the case of uniform transfer.

The number of provinces, districts and communes in 1999 is 61, 614, and 10474, respectively.

The number of provinces, districts and communes in 2009 is 63, 685, and 10896, respectively.

Table 3: Impact on FGT0 of Targeting at Different Levels of Geographic Disaggregation
Optimal Targeting Scheme

| | 1999 | 2009 | 1999 | 2009 |
|---|---|---|---|---|
| Original FGT2 | 0.2000 | 0.2000 | 1.00 | 1.00 |
| FGT2 after: | | | | |
| Uniform transfer | 0.1673 | 0.1724 | 0.84 (1.00) | 0.86 (1.00) |
| Province Level Targeting | 0.1522 | 0.1555 | 0.76 (0.90) | 0.78 (0.91) |
| District-level targeting | 0.1443 | 0.1465 | 0.72 (0.86) | 0.73 (0.85) |
| Commune-level targeting | 0.1390 | 0.1372 | 0.70 (0.83) | 0.69 (0.80) |

Note: Budget=5% of (Total Population * 25$^{th}$ Percentile Per Capita Expenditure).

Poverty Line= Per capita expenditure defining bottom quintile of population (pre-transfer).

The two last columns are the poverty gap indexes normalized to one. The figures in parentheses are the ratio of normalized P0 in the case of targeting transfer to the normalized P0 in the case of uniform transfer.

The number of provinces, districts and communes in 1999 is 61, 614, and 10474, respectively.

The number of provinces, districts and communes in 2009 is 63, 685, and 10896, respectively.

We only have access to a 15% sample of the Population Census, which is not representative on a commune-level. Therefore, it must be noted that the commune-level estimates of poverty may not be representative of the actual welfare levels, making our district-level results more on the point. However, as the government does have the full Census in its possession, a potential geographic targeting policy could successfully target aggregation levels as low as commune or even village, reaping the benefits of more disaggregated spatial targeting. After distributing funds on the village level though, the localities must implement their own intra-village distribution; making this a hybrid approach of geographic targeting and possibly the same village-level lists of poor that are extant now. The reason is that with this methodology, estimates on a household level are probably too noisy to yield useful results.

A related note of concern must be raised on the issue of *elite capture*. The presented gains from targeting are obtained assuming that whichever spatial unit is targeted, resources distributed within the unit are distributed uniformly. In reality, the power of the local elites is known to affect the way decentralized benefits reach the poor. For instance, Galasso and Ravallion (2005) show that the results of the Food for Education program in Bangladesh is better in communities with more land equality and they argue that this reflects greater elite capture when the poor are less powerful. Araujo et al., (2008) find that localities with more inequality (as measured by the expenditure share of the top 1%, 3%, 5%, 10% and 20% of the population) reduces the probability that latrine projects that are especially pro-poor are implemented in Ecuador, holding the level of poverty in the community constant. These findings may be especially worrying as we show in this paper that poverty is correlated with inequality in Vietnam. Also numerous studies show that that even at the lowest administrative levels the scope for political elite capture should not be assumed away[9].

On the one hand, one may say that elite capture will challenge our findings as presented in Tables 2-3, but on the other hand it enforces the need to establish an objective framework for poverty targeting. Plus, as this phenomenon occurs at all levels, distributing social assistance from the commune- or village level down to poor households would still be an improvement from the current provincial level.

## 8. Conclusions

This paper combines the 2009 Vietnam Population Census and the 2010 Vietnam Household Living Standard Survey to estimate poverty and inequality indexes for all the

[9] See for example the World Bank Policy Research Report, “Localizing Development: Does Participation Work?” (World Bank, 2012).

provinces and districts of Vietnam. Then, using the disaggregated data on poverty indexes, we simulate the effect of cash transfers on poverty under different targeting scenarios.

It is found that there is a large variation in poverty between districts and provinces. Mountainous and highland districts have high poverty incidence and severity in 2009. Rural and ethnic minority people account for a large proportion of the poor. There is a strong relationship between inequality and poverty: areas with low inequality are also more likely to have low poverty rates. The spatial distribution of the poor population has changed significantly during the period 1999-2009. In 1999, the poor were highly concentrated in delta regions such as Red River Delta and Mekong River Delta, partly because of the high population density in these areas. Since 1999, the number of the poor people has decreased remarkably in delta regions, but much less markedly in the Northern mountains and central highlands. While the distribution of poor people seems more evenly distributed across the country in 2009, areas with high poverty rates are more concentrated in Mountainous areas than they were a decade ago. Most provinces and districts experienced poverty reduction during 1999-2009, but the extent of poverty decline has been greatest in areas with average poverty levels in 1999. Provinces and districts with high initial poverty achieved smaller reductions in poverty.

We show that poverty rates have become more concentrated in Vietnam between 1999 and 2009. This phenomenon is likely not unique to Vietnam and may be widespread in developing countries. Economic activity and growth are becoming more spatially concentrated, due to agglomeration benefits related to network, technology and human capital externalities. This suggests that spatially targeted re-distribution policy executed alongside the development of high-potential areas may offer one means for a country to maintain growth while also maintaining an equitable distribution of wealth. As poverty becomes more spatially concentrated, the effectiveness of geographic targeting is likely to improve.

We take advantage of the high resolution available in our poverty maps to show that the more finely defined the beneficiary populations, the greater the gains from geographic targeting of anti-poverty resources over a uniform lump-sum transfer. For instance, in 2009 district level targeting is found to result in a 58 percentage point reduction in poverty severity compared to uniform transfers. This is also a significant improvement over the same level of targeting in 1999, which would 'only' improve the lump-sump transfer by 39 percentage points.

It should be emphasized, however, that our stylized analysis of targeting cannot be used to directly evaluate existing poverty alleviation efforts in Vietnam. One possible exercise that could inform policy makers' deliberations is to compare the hypothetical "optimal" provincial and district-level budgetary distribution deriving from an exercise as has been presented above with the actual provincial and district-level distribution that is currently in place. There is no presumption that these two should line up exactly. However, it could be of interest to follow up with further investigation if such an exercise were to reveal glaring inconsistencies.

There are, furthermore, important caveats that attach to the geographic targeting findings reported here. First, we assume that the government is willing to accept that households with equal pre-transfer per-capita consumption levels might enjoy different post-transfer consumption levels. Second, we assume in this paper that the budget available for distribution is exogenously determined. We abstract entirely from the question of how the transfers are to be financed. Political economy considerations could influence options for resource mobilization (see for example, Gelbach and Pritchett, 2002). Third, we do not address the very real possibility that the costs of administering a given transfer scheme may increase with the degree of disaggregation. Fourth, we do not allow for behavioral responses in the population.

Fifth, we do not address the possibility that inequalities in power and influence that prevail in a community influence how transfers are allocated. Such factors could result in an overestimation of the impact of spatial targeting on poverty reduction, especially as we show that inequality and poverty are correlated in Vietnam. Such elite capture on the other hand enforces the need to establish an objective framework for targeting the poor and for distribution of social funds. As elite capture is known to occur at all administrative levels, distributing social assistance directly to the commune- or village level down to poor households would still be an improvement from the current provincial level distribution.

For all these reasons, the findings of the geographic targeting exercise should be viewed as illustrative only. At all times, the gains from targeting should be juxtaposed against the potential costs and political-economy considerations, as well as scrutinized against other possible policy objectives. In practice, a hybrid approach combining geographic targeting between villages and means-tested targeting within villages may be the best way forward. Policymakers in Vietnam will need to assess such programs on a case-by-case basis to determine just how far to rely on fine-geographic targeting as the central element in their poverty alleviation strategy.

## References


Araujo, M., Ferreira, F., Lanjouw, P., Özler, B., 2006, "Local inequality and project choice: Theory and evidence from Ecuador", Journal of Public Economics, 92(5-6), pp: 1022-1046

Baker, J. and Grosh, M., 1994, "Poverty reduction through geographic targeting: how well does it work?" *World Development*, 22 (7), pp. 983-995

Baulch, B., and Minot, N., 2002, "The Spatial Distribution of Poverty in Vietnam and the Potential for Geographic Targeting", WPS 2829, The World Bank.

Bedi, T., Coudouel A., and Simer S., 2007, "*More than a Pretty Picture: Using Poverty Maps to Design Better Policies and Interventions*." Washington, DC: World Bank; 2007.

Bigman, D. and Fofack, H., 2000, "*Geographic Targeting for Poverty Alleviation: Methodology and Applications*." Washington DC: World Bank Regional and Sectoral Studies.

Central Census and Housing Census Steering Committee, 2009, "The 2009 Vietnam Population and Housing Census of 00.00 hours 1th April 2009: Implementation and Preliminary Result", Hanoi: August 2009.

Coady, D. and Morley, S., 2003, "From Social Assistance to Social Development: Targeted Education Subsidies in Developing Countries." Center for Global Development and International Food Policy Research Institute.

Elbers, C., Lanjouw, J. and Lanjouw, P., 2002, "Micro-Level estimation of welfare" Policy Research Working Paper No. WPS 2911. The World Bank.

Elbers, C., Lanjouw, J. and Lanjouw, P., 2003, "Micro-level estimation of poverty and inequality", *Econometrica*, 71(1), pp. 355-364.

Elbers, C., Fujii, T., Lanjouw, P., Ozler, B., Yin, W., 2007, "Poverty Alleviation through geographic targeting: how much does disaggregation help?" *Journal of Development Economics* 83, pp.198-213.

Foster, J., Greer, J., and Thorbecke, E., 1984, "A Class of Decomposable Poverty Measures", Econometrics, Vol. 52(3), pp. 761-766

Galasso, E., and Ravallion, M., 2005, "Decentralized Targeting of an Antipoverty Program", Journal of Public Economics, 89, pp. 705-727.

Gelbach, J. and Pritchett, L. , 2002, "Is More for the Poor Less for the Poor? The Politics of Means-Tested Targeting." *Topics in Economic Analysis and Policy*, Vol 2(1).

General Statistics Office, GSO, 2011, "Migration and Urbanization in Vietnam: Patterns, Trends and Differentials", Monograph, General Statistics Office of Vietnam , Hanoi, Vietnam.

Kanbur, R., 1987, "Measurement and Alleviation of Poverty", *IMF Staff Papers*, 34:60-85.

Liefner, I., 2009, “Spatial Disparities of Knowledge Absorption, Technological Change, and Prosperity: Theoretical Considerations and Empirical Evidence from China, in: World Development Report, 2009, “Spatial Disparities and Development Policy” The World Bank.

Litvack, J., 1999, "The Dilemmas of Change: Revitalizing Social Services in a Period of Transition," pp. 47-69, chapter 3 in Litvack and Rondinelli (eds)1999.

Minot, N., Baulch, B., and Epprecht, M., 2003, “*Poverty and Inequality in Vietnam: Spatial Patterns and Geographic Determinants*.” Final report of project “Poverty Mapping and Market Access in Vietnam” conducted by IFPRI and IDS.

Nguyen Viet Cuong & Tran Ngoc Truong & Roy Van Der Weide, 2010. "Poverty and Inequality Maps in Rural Vietnam: An Application of Small Area Estimation," *Asian Economic Journal*, East Asian Economic Association, vol. 24(4), pages 355-390, December.

Ravallion, M., 1993, “Poverty Alleviation Through Regional Targeting: A Case Study of Indonesia”, in *The Economics of Rural Organization: Theory, Practice and Policy,* editors Braverman, A., Hoff, K. and Stiglitz, J. World Bank and Oxford University Press.

Ravallion, M., 1994, "Poverty Comparisons". Chur, Switzerland: Harwood Academic Press.

Ravallion, M. and Chao, K., 1988, “Targeted Policies for Poverty Alleviation Under Imperfect Information: Algorithms and Applications”, *Journal of Policy Modeling* 11: 213-24.

Ravallion, M., S. Chen and P. Sangraula, 2007, “New evidence on the urbanization of global poverty”, World Bank Policy Research Working Paper 4199.

Ray, D., 1998, "*Development Economics"*, Princeton: Princeton University Press

Van de Walle, D., 2002, “"The static and dynamic incidence of Vietnam's public safety net”, WPS 2791. The World Bank.

World Bank World Development Report, 2009, “Spatial Disparities and Development Policy”, The World Bank.

World Bank Policy Research Report, 2012, “Localizing Development: Does Participation Work?”, The World Bank.

## Appendix I: SAE tables and graphs

Table A.1: Selected common variables that significantly explain expenditure in the regional models

| Variable | Type | Census | | VHLSS | |
|---|---|---|---|---|---|
| | | Mean | Std. Dev. | Mean | Std. Dev. |
| Urban (yes=1; no=0) | Binary | 0.31 | 0.46 | 0.30 | 0.46 |
| Household size | Discrete | 3.78 | 1.67 | 3.87 | 1.55 |
| Ethnic minorities (yes=1; Kinh & Hoa=0) | Binary | 0.12 | 0.33 | 0.13 | 0.33 |
| Proportion of children below 15 years old in household | Continuous | 0.22 | 0.21 | 0.21 | 0.21 |
| Proportion of elderly above 60 years old in household | Continuous | 0.11 | 0.26 | 0.13 | 0.26 |
| Proportion of female members in household | Continuous | 0.52 | 0.23 | 0.52 | 0.21 |
| Proportion of members without education degree | Continuous | 0.33 | 0.31 | 0.32 | 0.31 |
| Proportion of members with primary school degree | Continuous | 0.25 | 0.27 | 0.23 | 0.26 |
| Proportion of members with lower-secondary school degree | Continuous | 0.22 | 0.27 | 0.21 | 0.26 |
| Proportion of members with upper-secondary school degree | Continuous | 0.21 | 0.30 | 0.24 | 0.30 |
| Log of living area per capita (log of m2) | Continuous | 2.86 | 0.69 | 2.81 | 0.65 |
| Having motorbike (yes=1; no=0) | Binary | 0.72 | 0.45 | 0.76 | 0.43 |
| Having television (yes=1; no=0) | Binary | 0.87 | 0.34 | 0.89 | 0.31 |
| Solid wall (yes=1; no=0) | Binary | 0.77 | 0.42 | 0.79 | 0.41 |
| Semi-solid wall (yes=1; no=0) | Binary | 0.12 | 0.32 | 0.12 | 0.33 |
| Temporary wall (yes=1; no=0) | Binary | 0.11 | 0.31 | 0.09 | 0.29 |
| Solid roof (yes=1; no=0) | Binary | 0.17 | 0.38 | 0.20 | 0.40 |
| Semi-solid roof (yes=1; no=0) | Binary | 0.33 | 0.47 | 0.32 | 0.47 |
| Temporary roof (yes=1; no=0) | Binary | 0.50 | 0.50 | 0.48 | 0.50 |
| Having tap water (yes=1; no=0) | Binary | 0.25 | 0.43 | 0.26 | 0.44 |
| Number of observations | | 3,692,042 | | 9,361 | |

Source: Estimation from the 2009 VPHC and the 2010 VHLSS.

Table A.2: GLS regressions of log of per capita expenditure: Northern Mountains

| Explanatory variables | Coefficient | Std. Err. | \|Prob\|>t |
|---|---|---|---|
| Intercept | 8.5918 | 0.1496 | 0.0000 |
| Commune proportion of households having computer | 0.3807 | 0.1898 | 0.0450 |
| Commune proportion of households having motorbike | 0.3579 | 0.0936 | 0.0001 |
| Having television (yes=1; no=0) | 0.2173 | 0.0286 | 0.0000 |
| Ethnic minorities (yes=1; no=0) | -0.2192 | 0.0271 | 0.0000 |
| Household size | -0.0608 | 0.0075 | 0.0000 |
| Average household size of commune | -0.0679 | 0.0232 | 0.0034 |
| Log of per capita living area | 0.2739 | 0.0204 | 0.0000 |
| Proportion of hh members with upper-secondary school and above | 0.5013 | 0.0401 | 0.0000 |
| Proportion of elderly in household | -0.1550 | 0.0423 | 0.0003 |
| Proportion of hh households without primary school | -0.2000 | 0.0396 | 0.0000 |
| Having house with solid roof (yes=1; no=0) | 0.0948 | 0.0289 | 0.0011 |
| Commune proportion of households having toilet (not flush) | -0.1045 | 0.0477 | 0.0287 |
| Having house with solid wall (yes=1; no=0) | 0.0788 | 0.0276 | 0.0044 |
| Number of observations | 1659 | | |
| R2-adjusted | 0.681 | | |
| Rho | 0.185 | | |

Source: Estimation from the 2009 VPC and the 2010 VHLSS

Table A.3: GLS regressions of log of per capita expenditure: Red River Delta

| Explanatory variables | Coefficient | Std. Err. | \|Prob\|>t |
|---|---|---|---|
| Intercept | 8.4466 | 0.1854 | 0.0000 |
| Commune proportion of households having computer | 1.3569 | 0.1358 | 0.0000 |
| Commune proportion of households having fridge | 0.3495 | 0.0932 | 0.0002 |
| Having television (yes=1; no=0) | 0.0957 | 0.0393 | 0.0151 |
| Log of the number of firms in commune | 0.0242 | 0.0123 | 0.0489 |
| Log of per capita living area | 0.3754 | 0.0158 | 0.0000 |
| Commune average of log of per capita living area | -0.2190 | 0.0491 | 0.0000 |
| Proportion of elderly in household | -0.1803 | 0.0401 | 0.0000 |
| Commune proportion of elderly | -1.3343 | 0.3697 | 0.0003 |
| Proportion of hh households without primary school | -0.4193 | 0.0423 | 0.0000 |
| Commune proportion of people working in private sector | 0.8795 | 0.3962 | 0.0265 |
| Proportion of hh members with lower-secondary school | -0.1744 | 0.0372 | 0.0000 |
| Commune proportion of households having semi-solid roof house | 0.1721 | 0.0730 | 0.0185 |
| Commune proportion of households having flush toilet | 0.2590 | 0.0612 | 0.0000 |
| Household having house with solid wall | 0.4842 | 0.1115 | 0.0000 |
| Urban * log of household size | -0.2063 | 0.0247 | 0.0000 |
| Number of observations | 1992 | | |
| R2-adjusted | 0.642 | | |
| Rho | 0.121 | | |

Source: Estimation from the 2009 VPC and the 2010 VHLSS

Table A.4: GLS regressions of log of per capita expenditure: Central Coast

| Explanatory variables | Coefficient | Std. Err. | \|Prob\|>t |
|---|---|---|---|
| Intercept | 8.1055 | 0.0630 | 0.0000 |
| Commune proportion of households having fridge | 0.8839 | 0.1103 | 0.0000 |
| Having television (yes=1; no=0) | 0.1278 | 0.0281 | 0.0000 |
| Ethnic minorities (yes=1; no=0) | -0.1967 | 0.0359 | 0.0000 |
| Log of per capita living area | 0.3264 | 0.0178 | 0.0000 |
| Number of children in household | -0.0419 | 0.0101 | 0.0000 |
| Proportion of hh members with upper-secondary school and above | 0.4643 | 0.0381 | 0.0000 |
| Proportion of elderly in household | -0.1142 | 0.0373 | 0.0022 |
| Proportion of hh households without primary school | -0.1541 | 0.0374 | 0.0000 |
| Commune proportion of people working in private sector | 1.6262 | 0.5154 | 0.0016 |
| Having house with solid roof (yes=1; no=0) | 0.1865 | 0.0340 | 0.0000 |
| Households with solid wall house | 0.0929 | 0.0317 | 0.0034 |
| Urban * Commune proportion of households having fridge | -0.5982 | 0.1379 | 0.0000 |
| Urban * Commune proportion of people not working | 0.8664 | 0.1940 | 0.0000 |
| Number of observations | 2058 | | |
| R2-adjusted | 0.623 | | |
| Rho | 0.204 | | |

Source: Estimation from the 2009 VPC and the 2010 VHLSS

Table A.5: GLS regressions of log of per capita expenditure: Central Highlands

| Explanatory variables | Coefficient | Std. Err. | \|Prob\|>t |
|---|---|---|---|
| Intercept | 9.0661 | 0.3468 | 0.0000 |
| Commune proportion of households having fridge | 0.5340 | 0.1818 | 0.0034 |
| Having motorbike (yes=1; no=0) | 0.3287 | 0.0413 | 0.0000 |
| Commune proportion of households having motorbike | 0.5420 | 0.1655 | 0.0011 |
| Ethnic minorities (yes=1; no=0) | -0.3864 | 0.0403 | 0.0000 |
| Average household size of commune | -0.0906 | 0.0410 | 0.0276 |
| Log of per capita living area | 0.3863 | 0.0273 | 0.0000 |
| Commune average of log of per capita living area | -0.3485 | 0.1070 | 0.0012 |
| Number of children in household | -0.0675 | 0.0138 | 0.0000 |
| Proportion of hh households without primary school | -0.3597 | 0.0579 | 0.0000 |
| Having tap water (yes=1; no=0) | 0.2221 | 0.0630 | 0.0005 |
| Urban * Commune proportion of households with solid roof | 2.1727 | 0.7504 | 0.0039 |
| Urban * House with semi-solid wall | -0.3171 | 0.1316 | 0.0162 |
| Number of observations | 651 | | |
| R2-adjusted | 0.737 | | |
| Rho | 0.097 | | |

Source: Estimation from the 2009 VPC and the 2010 VHLSS

Table A.6: GLS regressions of log of per capita expenditure: South East

| Explanatory variables | Coefficient | Std. Err. | \|Prob\|>t |
|---|---|---|---|
| Intercept | 8.2988 | 0.0980 | 0.0000 |
| Commune proportion of households having fridge | 0.2220 | 0.1021 | 0.0298 |
| Having motorbike (yes=1; no=0) | 0.3132 | 0.0429 | 0.0000 |
| Household size | -0.0625 | 0.0092 | 0.0000 |
| Log of the number of firms in commune | 0.0414 | 0.0130 | 0.0015 |
| Log of per capita living area | 0.3747 | 0.0203 | 0.0000 |
| Proportion of hh household members with upper-secondary and above | 0.3884 | 0.0486 | 0.0000 |
| Proportion of hh household members without primary school | -0.2159 | 0.0518 | 0.0000 |
| Commune proportion of people working in private sector | 1.4060 | 0.2721 | 0.0000 |
| Having house with solid roof (yes=1; no=0) | 0.1758 | 0.0546 | 0.0013 |
| Commune proportion of households having house with solid roof (yes=1; no=0) | 0.4413 | 0.1391 | 0.0016 |
| Number of observations | 1110 | | |
| R2-adjusted | 0.625 | | |
| Rho | 0.105 | | |

Source: Estimation from the 2009 VPC and the 2010 VHLSS

Table A.7: GLS regressions of log of per capita expenditure: Mekong River Delta

| Explanatory variables | Coefficient | Std. Err. | \|Prob\|>t |
|---|---|---|---|
| Intercept | 8.4582 | 0.0995 | 0.0000 |
| Commune proportion of households having computer | 1.1220 | 0.1964 | 0.0000 |
| Commune proportion of households having motorbike | 0.2074 | 0.0915 | 0.0235 |
| Having television (yes=1; no=0) | 0.1442 | 0.0290 | 0.0000 |
| Commune proportion of hh head with primary school | -0.3499 | 0.1700 | 0.0397 |
| Ethnic minorities (yes=1; no=0) | -0.1847 | 0.0434 | 0.0000 |
| Log of per capita living area | 0.3634 | 0.0183 | 0.0000 |
| Number of children in household | -0.0595 | 0.0117 | 0.0000 |
| Proportion of hh households without primary school | -0.3614 | 0.0328 | 0.0000 |
| Having house with solid roof (yes=1; no=0) | 0.3596 | 0.0656 | 0.0000 |
| Having tap water (yes=1; no=0) | 0.0736 | 0.0267 | 0.0058 |
| Number of observations | 1891 | | |
| R2-adjusted | 0.497 | | |
| Rho | 0.098 | | |

Source: Estimation from the 2009 VPC and the 2010 VHLSS

Table A.8: Predicted per capita expenditure and poverty rate of provinces

| Province | Number of people | Share in total pop. (%) | Per capita expenditure (thousand VND) | | The poverty rate (%) | | Number of poor people | Share in total poverty rate |
|---|---|---|---|---|---|---|---|---|
| | | | Mean | Std. Err. | Mean | Std. Err. | | |
| *Northern Mountain* | | | | | | | | |
| Ha Giang | 724352 | 0.84 | 7422.7 | 448.1 | 71.46 | 2.99 | 517586 | 3.07 |
| Cao Bang | 510884 | 0.60 | 9325.7 | 515.1 | 53.11 | 3.26 | 271348 | 1.61 |
| Bac Kan | 294660 | 0.34 | 10136.1 | 792.0 | 45.97 | 5.32 | 135448 | 0.80 |
| Tuyen Quang | 725467 | 0.85 | 11238.3 | 917.9 | 39.95 | 5.41 | 289798 | 1.72 |
| Lao Cai | 613074 | 0.71 | 9711.5 | 817.8 | 56.77 | 3.90 | 348018 | 2.06 |
| Dien Bien | 491046 | 0.57 | 7625.9 | 611.7 | 71.06 | 3.65 | 348953 | 2.07 |
| Lai Chau | 370134 | 0.43 | 6809.2 | 465.3 | 76.41 | 2.99 | 282805 | 1.68 |
| Son La | 1080641 | 1.26 | 8326.0 | 590.3 | 63.60 | 4.02 | 687305 | 4.08 |
| Yen Bai | 740904 | 0.86 | 10621.9 | 794.5 | 45.33 | 4.72 | 335860 | 1.99 |
| Hoa Binh | 786963 | 0.92 | 10439.0 | 675.5 | 47.31 | 4.23 | 372330 | 2.21 |
| Thai Nguyen | 1124785 | 1.31 | 14170.5 | 1117.1 | 21.99 | 3.42 | 247386 | 1.47 |
| Lang Son | 731886 | 0.85 | 10292.1 | 715.1 | 45.69 | 4.29 | 334364 | 1.98 |
| Bac Giang | 1555720 | 1.81 | 12823.4 | 889.4 | 23.83 | 4.33 | 370722 | 2.20 |
| Phu Tho | 1313926 | 1.53 | 13535.9 | 806.9 | 23.62 | 3.20 | 310380 | 1.84 |
| *Red River Delta* | | | | | | | | |
| Ha Noi | 6448837 | 7.52 | 29344.6 | 1375.7 | 4.94 | 0.89 | 318488 | 1.89 |
| Quang Ninh | 1144381 | 1.33 | 18538.0 | 1243.9 | 12.12 | 1.81 | 138656 | 0.82 |
| Vinh Phuc | 1000838 | 1.17 | 15743.1 | 869.0 | 11.99 | 2.83 | 119989 | 0.71 |
| Bac Ninh | 1024151 | 1.19 | 17590.4 | 1145.4 | 10.19 | 2.37 | 104327 | 0.62 |
| Hai Duong | 1703492 | 1.99 | 15261.3 | 827.5 | 14.84 | 2.73 | 252716 | 1.50 |
| Hai Phong | 1837302 | 2.14 | 20316.9 | 1140.2 | 7.93 | 1.62 | 145625 | 0.86 |
| Hung Yên | 1128702 | 1.32 | 16063.4 | 812.6 | 12.78 | 2.36 | 144273 | 0.86 |
| Thai Bình | 1780953 | 2.08 | 13578.2 | 873.7 | 18.95 | 3.86 | 337435 | 2.00 |
| Ha Nam | 785057 | 0.92 | 14269.8 | 1011.8 | 16.56 | 4.07 | 130009 | 0.77 |
| Nam Dinh | 1825770 | 2.13 | 14866.4 | 814.6 | 14.04 | 2.70 | 256321 | 1.52 |
| Ninh Bình | 898458 | 1.05 | 14955.3 | 878.3 | 15.28 | 3.33 | 137314 | 0.81 |
| *Central Coast* | | | | | | | | |
| Thanh Hoa | 3400238 | 3.96 | 13118.2 | 474.9 | 26.48 | 2.09 | 900393 | 5.34 |
| Nghe An | 2913054 | 3.40 | 13356.4 | 576.6 | 26.74 | 2.57 | 778900 | 4.62 |
| Ha Tinh | 1227554 | 1.43 | 13222.9 | 578.5 | 21.55 | 2.97 | 264499 | 1.57 |
| Quang Binh | 846924 | 0.99 | 13847.2 | 798.8 | 23.20 | 4.14 | 196475 | 1.17 |
| Quang Tri | 597984 | 0.70 | 12567.1 | 621.0 | 29.55 | 3.15 | 176710 | 1.05 |
| Thua Thiên Hue | 1087578 | 1.27 | 14453.7 | 955.1 | 19.43 | 3.03 | 211283 | 1.25 |
| Da Nang | 887068 | 1.03 | 23087.9 | 1311.7 | 2.39 | 1.05 | 21218 | 0.13 |
| Quang Nam | 1419502 | 1.65 | 12703.2 | 528.7 | 23.47 | 2.73 | 333146 | 1.98 |
| Quang Ngãi | 1217159 | 1.42 | 12955.1 | 573.2 | 23.65 | 2.80 | 287827 | 1.71 |
| Binh Dinh | 1485943 | 1.73 | 14498.9 | 834.9 | 16.68 | 3.16 | 247882 | 1.47 |
| Phú Yên | 861993 | 1.00 | 13377.2 | 793.1 | 22.08 | 3.47 | 190348 | 1.13 |
| Khanh Hoa | 1156902 | 1.35 | 16778.1 | 1244.5 | 15.51 | 2.87 | 179462 | 1.06 |
| Ninh Thuan | 564128 | 0.66 | 11626.1 | 799.1 | 34.52 | 4.36 | 194759 | 1.16 |
| Binh Thuan | 1169450 | 1.36 | 13428.5 | 693.8 | 21.44 | 3.04 | 250692 | 1.49 |
| *Central Highlands* | | | | | | | | |
| Kon Tum | 430036 | 0.50 | 11112.5 | 796.7 | 47.58 | 3.37 | 204624 | 1.21 |
| Gia Lai | 1272791 | 1.48 | 11222.1 | 439.8 | 43.34 | 2.07 | 551632 | 3.27 |
| Dak Lak | 1728380 | 2.01 | 13445.5 | 639.8 | 30.32 | 2.03 | 524104 | 3.11 |
| Dak Nong | 489441 | 0.57 | 11719.4 | 500.0 | 32.50 | 2.83 | 159063 | 0.94 |
| Lâm Dong | 1186786 | 1.38 | 15173.1 | 687.8 | 21.96 | 1.97 | 260629 | 1.55 |

| Province | Number of people | Share in total pop. (%) | Per capita expenditure (thousand VND) | | The poverty rate (%) | | Number of poor people | Share in total poverty rate |
|---|---|---|---|---|---|---|---|---|
| | | | Mean | Std. Err. | Mean | Std. Err. | | |
| South East | | | | | | | | |
| Binh Phuoc | 874961 | 1.02 | 14370.4 | 849.9 | 17.20 | 3.58 | 150477 | 0.89 |
| Tay Ninh | 1066402 | 1.24 | 15459.4 | 737.6 | 11.78 | 2.51 | 125615 | 0.75 |
| Binh Duong | 1482635 | 1.73 | 18378.5 | 1168.5 | 7.82 | 2.10 | 115901 | 0.69 |
| Dong Nai | 2483210 | 2.89 | 17293.1 | 1129.8 | 11.73 | 2.21 | 291223 | 1.73 |
| Ba Ria - Vung Tau | 994836 | 1.16 | 18704.2 | 1336.3 | 9.97 | 2.22 | 99206 | 0.59 |
| Ho Chí Minh | 7123340 | 8.30 | 29431.0 | 1342.5 | 2.94 | 0.51 | 209427 | 1.24 |
| *Mekong River Delta* | | | | | | | | |
| Long An | 1436913 | 1.67 | 16334.8 | 703.5 | 10.97 | 1.64 | 157596 | 0.93 |
| Tien Giang | 1670215 | 1.95 | 16578.6 | 875.9 | 9.53 | 2.14 | 159215 | 0.94 |
| Ben Tre | 1254588 | 1.46 | 16022.7 | 745.8 | 10.00 | 2.00 | 125506 | 0.74 |
| Tra Vinh | 1000932 | 1.17 | 13507.1 | 688.8 | 22.28 | 3.09 | 222988 | 1.32 |
| Vinh Long | 1028365 | 1.20 | 16038.5 | 887.7 | 11.76 | 2.26 | 120947 | 0.72 |
| Dong Thap | 1665420 | 1.94 | 13820.8 | 605.6 | 15.58 | 2.42 | 259532 | 1.54 |
| An Giang | 2144772 | 2.50 | 13739.4 | 595.5 | 18.22 | 2.50 | 390808 | 2.32 |
| Kiên Giang | 1683149 | 1.96 | 13057.1 | 580.7 | 24.02 | 2.62 | 404319 | 2.40 |
| Can Tho | 1187088 | 1.38 | 17911.6 | 1029.2 | 11.70 | 1.97 | 138868 | 0.82 |
| Hau Giang | 756625 | 0.88 | 13369.3 | 690.7 | 19.68 | 3.41 | 148915 | 0.88 |
| Soc Trang | 1289441 | 1.50 | 12561.6 | 604.5 | 27.28 | 3.10 | 351709 | 2.09 |
| Bac Liêu | 856249 | 1.00 | 12533.0 | 670.7 | 23.30 | 3.74 | 199528 | 1.18 |
| Ca Mau | 1205107 | 1.40 | 12456.9 | 682.5 | 26.36 | 3.48 | 317609 | 1.88 |

Source: Estimation from the 2009 VPHC and the 2010 VHLSS.

Table A.9: Inequality measures and the proportion of the richest quintile households of provinces

| Provinces | Gini index | | Ratio of 90th to 10th expenditure percentile | | The percentage of people belong the 20% richest | |
|---|---|---|---|---|---|---|
| | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. |
| **Northern Mountain** | | | | | | |
| Ha Giang | 0.374 | 0.018 | 4.93 | 0.35 | 3.55 | 0.89 |
| Cao Bang | 0.351 | 0.016 | 5.10 | 0.40 | 4.73 | 1.14 |
| Bac Kan | 0.321 | 0.018 | 4.21 | 0.32 | 5.31 | 1.62 |
| Tuyen Quang | 0.329 | 0.021 | 4.38 | 0.37 | 7.54 | 2.13 |
| Lao Cai | 0.397 | 0.019 | 6.12 | 0.53 | 7.38 | 1.99 |
| Dien Bien | 0.404 | 0.023 | 5.82 | 0.56 | 4.51 | 1.29 |
| Lai Chau | 0.376 | 0.017 | 4.82 | 0.29 | 2.99 | 0.80 |
| Son La | 0.360 | 0.013 | 4.82 | 0.27 | 4.20 | 1.02 |
| Yen Bai | 0.354 | 0.019 | 5.20 | 0.46 | 7.24 | 1.91 |
| Hoa Binh | 0.345 | 0.018 | 4.70 | 0.35 | 6.83 | 1.57 |
| Thai Nguyen | 0.308 | 0.021 | 4.11 | 0.42 | 13.33 | 3.44 |
| Lang Son | 0.325 | 0.018 | 4.31 | 0.32 | 5.77 | 1.69 |
| Bac Giang | 0.281 | 0.012 | 3.60 | 0.22 | 8.55 | 2.29 |
| Phu Tho | 0.305 | 0.013 | 4.01 | 0.26 | 11.30 | 2.21 |
| **Red River Delta** | | | | | | |
| Ha Noi | 0.382 | 0.013 | 6.02 | 0.40 | 49.03 | 2.16 |
| Quang Ninh | 0.324 | 0.015 | 4.50 | 0.34 | 25.76 | 3.65 |
| Vinh Phuc | 0.275 | 0.012 | 3.47 | 0.19 | 15.81 | 2.73 |
| Bac Ninh | 0.297 | 0.014 | 3.85 | 0.26 | 22.08 | 3.55 |
| Hai Duong | 0.289 | 0.013 | 3.63 | 0.18 | 14.49 | 2.33 |
| Hai Phong | 0.322 | 0.014 | 4.32 | 0.28 | 30.29 | 3.26 |
| Hung Yên | 0.290 | 0.012 | 3.68 | 0.21 | 16.96 | 2.49 |
| Thai Bình | 0.271 | 0.014 | 3.36 | 0.19 | 9.40 | 2.33 |
| Ha Nam | 0.273 | 0.015 | 3.41 | 0.23 | 11.33 | 2.95 |
| Nam Dinh | 0.271 | 0.014 | 3.40 | 0.19 | 12.97 | 2.50 |
| Ninh Bình | 0.283 | 0.016 | 3.57 | 0.24 | 13.63 | 2.55 |
| **Central Coast** | | | | | | |
| Thanh Hoa | 0.316 | 0.011 | 3.95 | 0.15 | 10.11 | 1.15 |
| Nghe An | 0.328 | 0.016 | 4.15 | 0.21 | 10.88 | 1.33 |
| Ha Tinh | 0.287 | 0.009 | 3.45 | 0.14 | 9.40 | 1.39 |
| Quang Binh | 0.322 | 0.017 | 3.99 | 0.26 | 11.75 | 1.81 |
| Quang Tri | 0.323 | 0.012 | 4.42 | 0.25 | 9.45 | 1.51 |
| Thua Thiên Hue | 0.305 | 0.016 | 3.90 | 0.29 | 13.22 | 2.80 |
| Da Nang | 0.283 | 0.011 | 3.63 | 0.21 | 40.11 | 4.16 |
| Quang Nam | 0.281 | 0.009 | 3.55 | 0.17 | 8.04 | 1.42 |
| Quang Ngãi | 0.290 | 0.012 | 3.76 | 0.20 | 8.72 | 1.58 |
| Binh Dinh | 0.293 | 0.015 | 3.57 | 0.23 | 12.42 | 2.28 |
| Phú Yên | 0.297 | 0.015 | 3.60 | 0.22 | 9.69 | 2.02 |
| Khanh Hoa | 0.325 | 0.017 | 4.44 | 0.35 | 20.18 | 3.50 |
| Ninh Thuan | 0.313 | 0.015 | 4.19 | 0.30 | 7.28 | 1.92 |
| Binh Thuan | 0.287 | 0.012 | 3.64 | 0.19 | 10.02 | 1.91 |
| **Central Highlands** | | | | | | |

| Provinces | Gini index | | Ratio of $90^{th}$ to $10^{th}$ expenditure percentile | | The percentage of people belong the 20% richest | |
|---|---|---|---|---|---|---|
| | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. |
| Kon Tum | 0.414 | 0.011 | 7.60 | 0.47 | 9.97 | 2.04 |
| Gia Lai | 0.374 | 0.008 | 6.18 | 0.24 | 8.87 | 1.16 |
| Dak Lak | 0.356 | 0.011 | 5.34 | 0.25 | 12.50 | 1.70 |
| Dak Nong | 0.307 | 0.007 | 4.44 | 0.15 | 7.03 | 1.19 |
| Lâm Dong | 0.337 | 0.010 | 4.98 | 0.23 | 16.80 | 2.00 |
| South East | | | | | | |
| Binh Phuoc | 0.294 | 0.009 | 3.53 | 0.16 | 11.53 | 1.91 |
| Tay Ninh | 0.287 | 0.008 | 3.35 | 0.14 | 13.49 | 1.79 |
| Binh Duong | 0.300 | 0.008 | 3.62 | 0.15 | 22.47 | 3.65 |
| Dong Nai | 0.319 | 0.014 | 3.93 | 0.27 | 19.47 | 3.27 |
| Ba Ria - Vung Tau | 0.331 | 0.015 | 4.14 | 0.28 | 23.46 | 3.70 |
| Ho Chí Minh | 0.357 | 0.009 | 4.73 | 0.18 | 51.17 | 2.87 |
| **Mekong River Delta** | | | | | | |
| Long An | 0.285 | 0.009 | 3.57 | 0.13 | 17.55 | 2.15 |
| Tien Giang | 0.277 | 0.010 | 3.46 | 0.14 | 18.18 | 2.72 |
| Ben Tre | 0.269 | 0.009 | 3.36 | 0.13 | 16.29 | 2.33 |
| Tra Vinh | 0.294 | 0.009 | 3.76 | 0.15 | 10.49 | 1.80 |
| Vinh Long | 0.284 | 0.011 | 3.58 | 0.17 | 16.81 | 2.66 |
| Dong Thap | 0.261 | 0.007 | 3.18 | 0.10 | 9.59 | 1.60 |
| An Giang | 0.278 | 0.009 | 3.39 | 0.13 | 9.98 | 1.49 |
| Kiên Giang | 0.293 | 0.010 | 3.72 | 0.14 | 9.43 | 1.48 |
| Can Tho | 0.328 | 0.017 | 4.29 | 0.33 | 22.59 | 2.76 |
| Hau Giang | 0.271 | 0.008 | 3.39 | 0.12 | 9.22 | 1.70 |
| Soc Trang | 0.298 | 0.011 | 3.79 | 0.16 | 8.44 | 1.46 |
| Bac Liêu | 0.271 | 0.010 | 3.32 | 0.13 | 7.25 | 1.56 |
| Ca Mau | 0.288 | 0.012 | 3.58 | 0.17 | 7.76 | 1.63 |

Source: Estimation from the 2009 VPHC and the 2010 VHLSS.

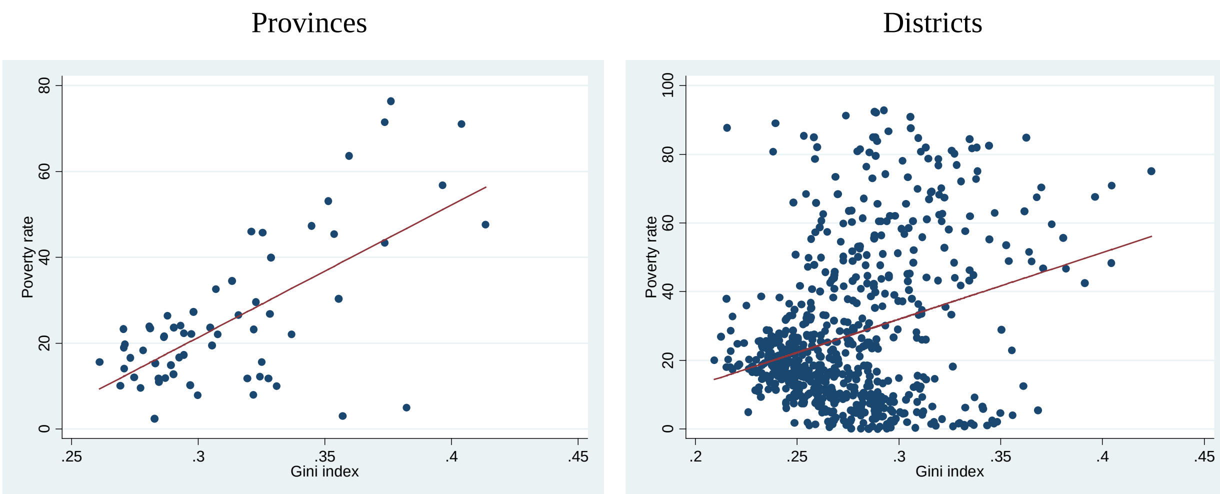


Figure A.1. Poverty rate (%) and Gini index

Source: Estimation from the 2009 VPHC and the 2010 VHLSS

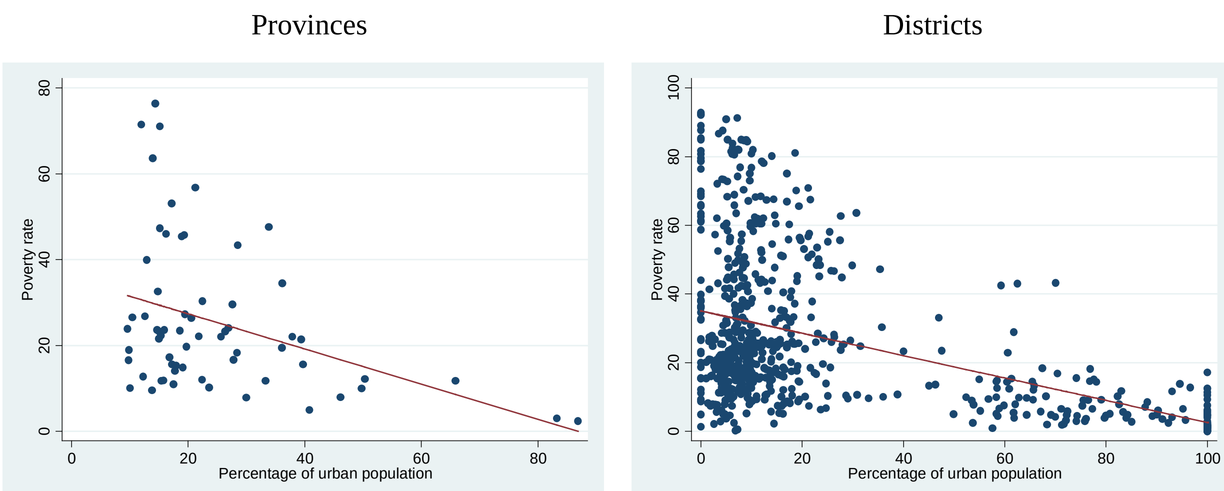


Figure A.2. Poverty rate (%) and the proportion of urban population (%)

Source: Estimation from the 2009 VPHC and the 2010 VHLSS.

Provinces Districts

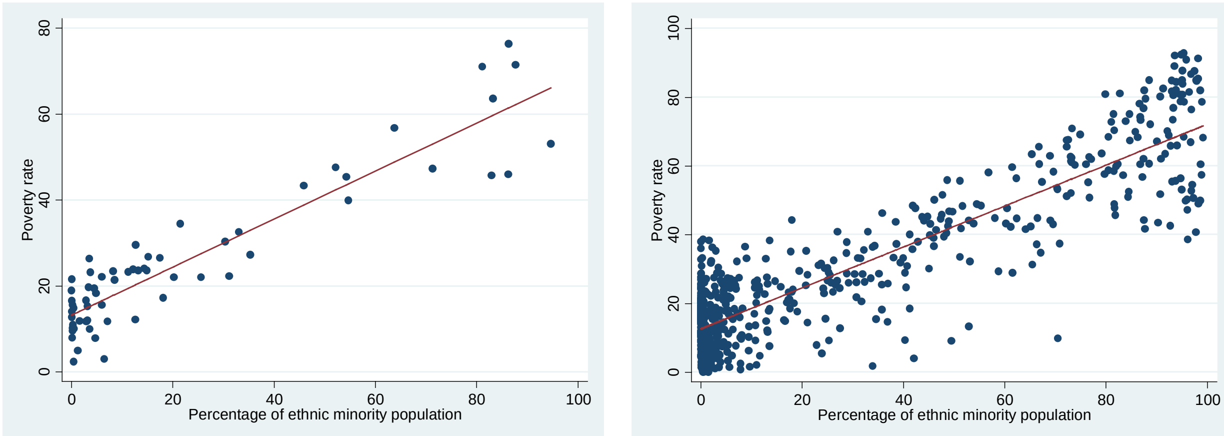


Figure A.3. Poverty rate (%) and the proportion of ethnic minorities (%)

Source: Estimation from the 2009 VPHC and the 2010 VHLSS.

Provinces Districts

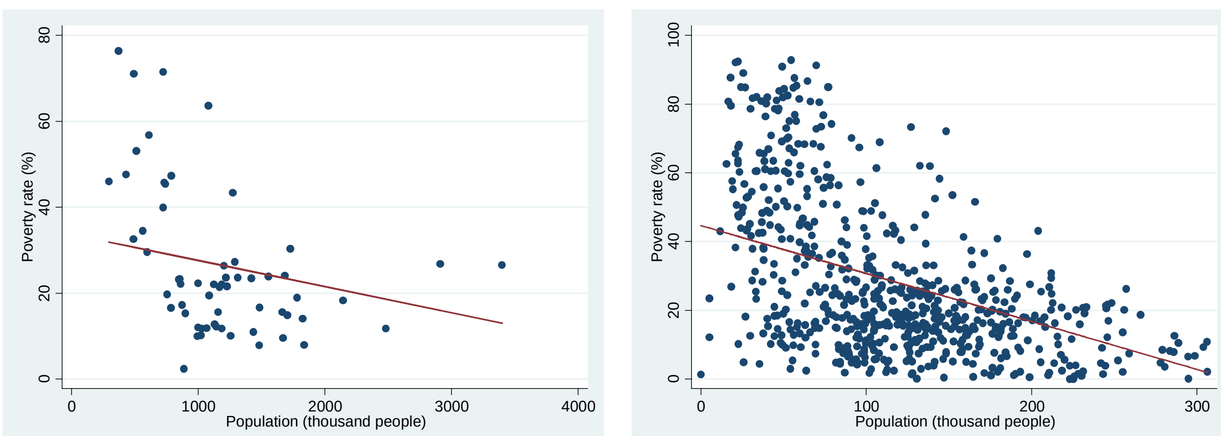


Figure A.4. Poverty rate (%) and population (thousand people)

Source: Estimation from the 2009 VPHC and the 2010 VHLSS.

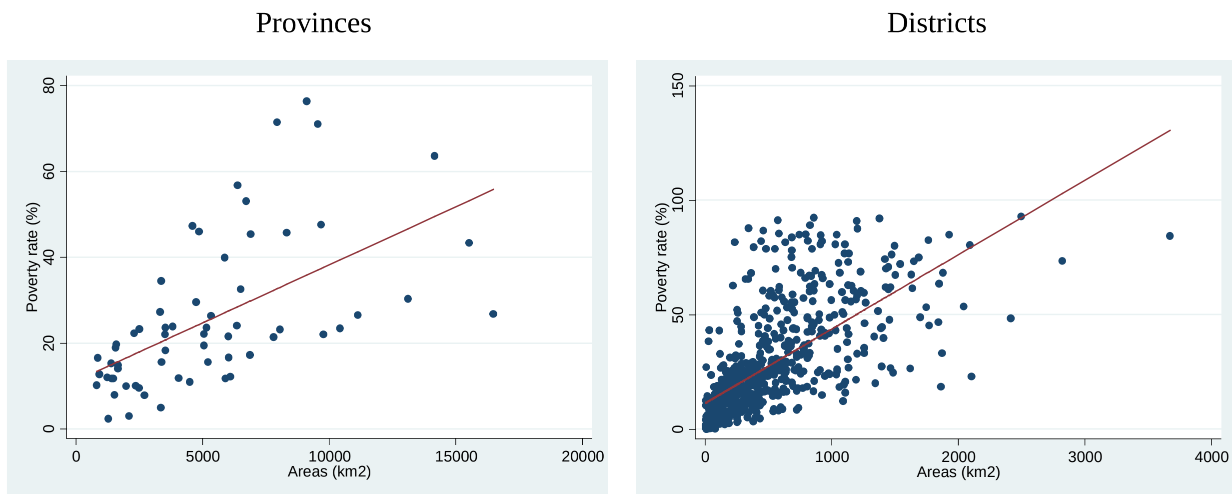


Figure A.5. Poverty rate (%) and size of areas (km2)

Source: Estimation from the 2009 VPHC and the 2010 VHLSS.

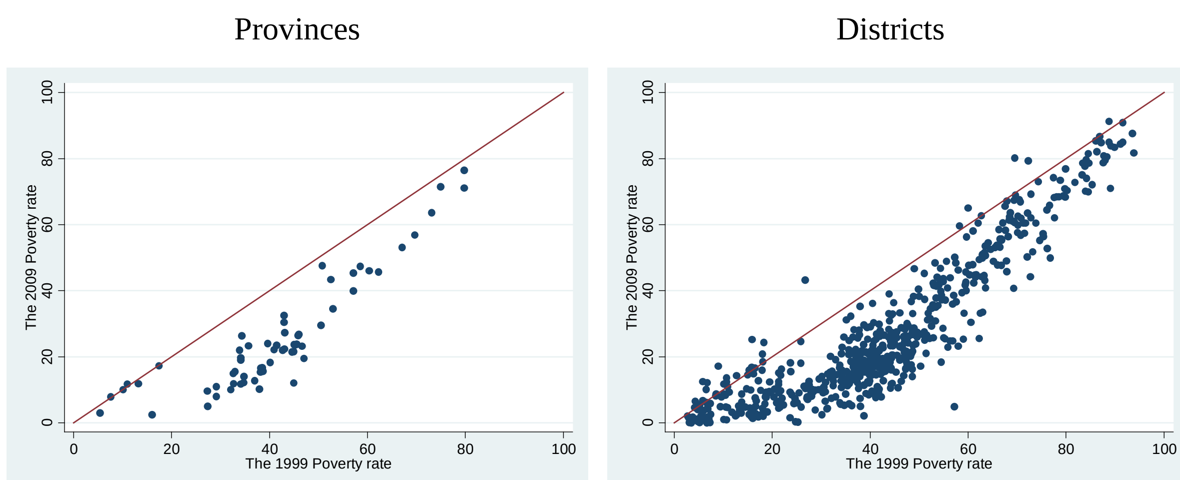


Figure A.6: Poverty rates in 1999 and 2009

Source: The 2009 poverty rates are estimated from the 2009 VPHC and the 2010 VHLSS. The 1999 poverty rates are obtained from Minot et al. (2002).

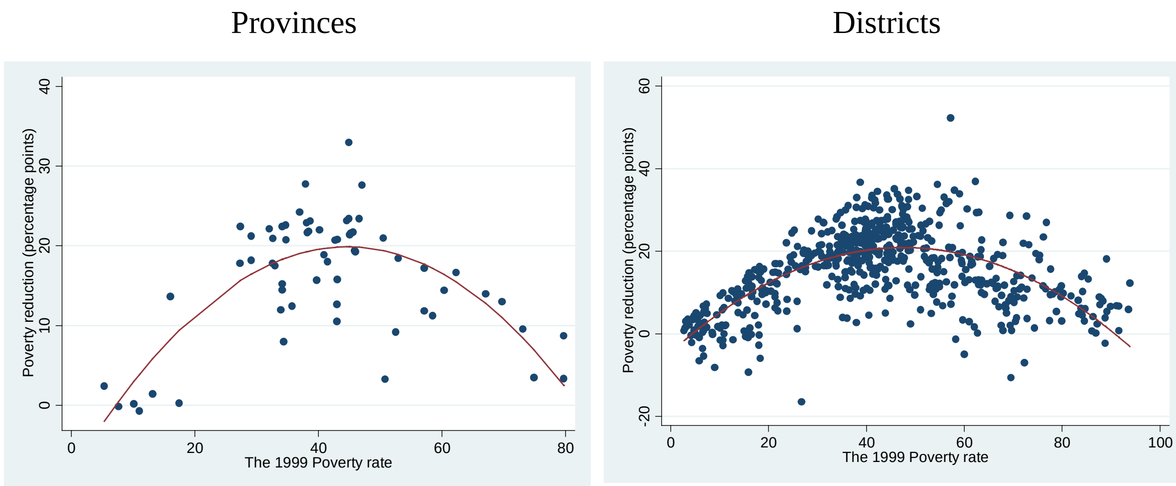


Figure A.7: Poverty reduction during 1999-2009 and the poverty rate in 1999

Source: The 2009 poverty rates are estimated from the 2009 VPHC and the 2010 VHLSS. The 1999 poverty rates are obtained from Minot et al. (2002).

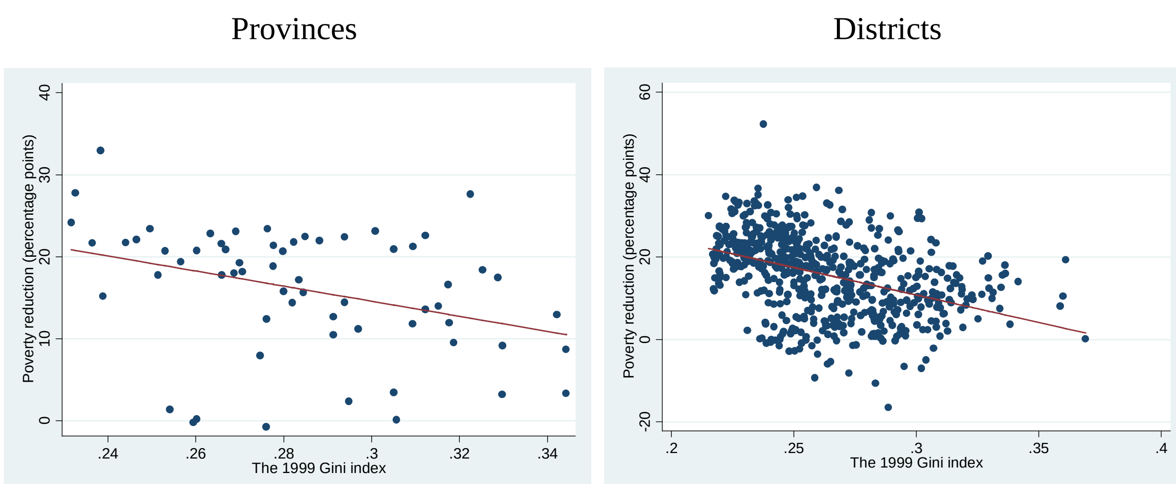


Figure A.8: Poverty reduction during 1999-2009 and the Gini index in 1999

Source: The 2009 poverty rates are estimated from the 2009 VPHC and the 2010 VHLSS. The 1999 poverty rates are obtained from Minot et al. (2002).

## Appendix II: Simulating the Impact of "Optimal" Geographic Targeting

As described in Elbers et al (2007) and in the text, given our interest to minimize the FGT2, optimal geographic targeting implies that after transfers there is a group of locations all sharing the same (maximum) poverty gap in the country. We determine the level of transfers going to each location by first solving a different problem. Following the notation introduced in Section III consider the minimum budget *S(G)* needed to bring down all locations' poverty gaps to at most the level *G/z*. This amounts to transferring an amount $a_c(G)$ to locations with before-transfer poverty gaps above *G/z*, such that $G_c(a_c(G)) = G$. Once we know how to compute *S(G)*, we simply adjust *G* until *S(G)* equals the originally given budget for transfers *S*. To implement this scheme we must solve the following equation for $a_c$:

$$G = \int_0^z (z - y - a_c)^+ dF_c(y)\,. \qquad \text{(A.1)}$$

In what follows we drop the location index *c* for ease of notation. Using integration by parts it can be shown that

$$G(a) = \int_0^z (z - y - a)^+ dF(y) = \int_0^{z-a} F(y)dy. \qquad \text{(A.2)}$$

In other words we need to compute the surface under the expenditure distribution between expenditure levels *y=0* and *y=z-t*, for values of *t* up to *z*. Instead of computing *G*(*t*) exactly, we use a simple approximation. For this to work we split the interval [*0,z*] in *n* equal segments and assume that the 'poverty mapping' software has generated expected headcounts for poverty lines *z k/n*, where *k=0, …,n*. In other words we have a table of *F*(*z k/n*). Using the table we approximate *F*(*y*) by linear interpolation for *y* between table values. With the approximated expenditure distribution it is easy to solve for transfers as a function of *G* (see below). In practice we find that *n*=20 gives sufficiently precise results.[10]

The computational set-up is as follows (note that the numbering we adopt means going from *z* in the direction of 0 rather than the other way around). Define $b_0=0$, and for *k=1,...,n*, $b_k$ as the surface under the (approximated) expenditure distribution between *z-kz/n* and *z*-(*k-1*)*z/n*, divided by *z*:

$$b_k = \frac{1}{2n}\big(F(z - kz/n) + F(z - (k-1)z/n)\big). \qquad \text{(A.3)}$$

Let $g_0$ be the original poverty gap, or in terms of the discussion above, $g_0=G(0)/z$. For*k=1,...n*, put

$$g_k = g_{k-1} - b_k\,. \qquad \text{(A.4)}$$

[10] Other interpolation schemes are possible. For instance, if the *poverty gap* is given at table values *zk/n* an even simpler computation presents itself. Often the poverty mapping software will give percentiles of the expenditure distribution. These can also be used for interpolation, but the formulas are more cumbersome, since the percentiles are not equally spaced.

The $g_k$ are the poverty gaps of the approximated expenditure distribution for successively lower poverty lines $z\text{-}kz/n$. Let $a_k$ be the per capita transfer needed to bring down the poverty line to $z\text{-}kz/n$:

$$a_k = kz/n. \tag{A.5}$$

We can now solve for per capita transfers as a function of the intended poverty gap $g<g_0$:

1. Find $k$ such that $g_{k+1} \leq g < g_k$.

2. The per capita transfers resulting in poverty gap $g$ are

$$a(g) = a_k + \frac{g_k - g}{g_k - g_{k+1}} \cdot \frac{z}{n}. \tag{A.6}$$

This scheme can be implemented using standard spreadsheet software.