Dynamic multi-level analysis of households' living standards and poverty: Evidence from Vietnam

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ABSTRACT

The paper investigates the role of multi-level structures in poverty analysis based on household level data. We demonstrate how multi-level models can be applied to standard poverty analysis and highlight its usefulness in terms of assessing the extent community characteristics matter in determining poverty status and dynamics. We provide two applications. The first is an example of a growth model that control for characteristics measured at the initial time period, and considers directly to what extent the same characteristics contribute to explain changes in economic wellbeing over time. In the second application we model the determinants of escaping poverty. Both applications use longitudinal data from Vietnam recorded at two points in time during the nineties, a period where Vietnam experienced strong economic growth. We demonstrate that failing to control for multi-level data structures could give incorrect inference about the effect of covariates of interest. We also demonstrate how the multi-level models can be used for regional and community level policy analysis that otherwise is difficult to implement in more standard regression analysis.

NON-TECHNICAL SUMMARY

The paper provides an illustration of how multilevel models can be used to correctly handle hierarchical data structures applied to household wellbeing and poverty dynamics. From the models we also demonstrate how to provide recommendations for policy interventions. We present two examples: A growth model with a continuous dependent variable – the log equivalent household expenditure, and a probit model for studying the determinants of poverty exit.

In both cases we find that the multilevel structure is highly relevant as attested by the intra-class correlation coefficients. Hence, failing to control for the multilevel structure will influence model predictions in significant ways, leading to possibly incorrect inference about the effect of the covariates. Whereas an alternative approach would be to simply use robust standard errors, this would omit essential information about the multilevel structure relevant for policy analysis. Multilevel models instead give us insight that is otherwise unfeasible in the more standard methods.

The growth model separates the initial economic status from the growth effect of the covariates. The estimates related to the initial condition demonstrate that Kinh ethnic origin, education, and living in a community with health facilities, are all associated with higher wealth. In contrast, households with a high percentage of unemployed members and those working in agricultural activities were disadvantaged. Also household size and the number of children are negatively associated with consumption expenditure. These effects are of course, sensitive to the equivalence scale; we adopt here the well used WHO scale which is in line with many previous studies.

The growth dimension of the model attests that, on average, household consumption growth rate between the two waves was 17%, a reflection of the economic boom experienced in Vietnam during the nineties. However, the growth trend varied substantially by households and community characteristics. We find that those who were better off initially were not necessarily the same benefiting during the economic boom. For example, households with many children benefited from the economic growth whereas farm households benefited less.

Since the Vietnam economy is dominated by rural activities, in particular agriculture, and rural areas are the poorest, we focus our attention on farm households. The model includes therefore random slopes that allow the effect of agriculture to differ by community. Standard deviations of these random effects attest that the place where farmers reside matters. Even though the average growth differential for farmer in respect to non farmer is negative there were certain communities in which farm households grew more. This is especially the case if the community is well connected to other neighbourhoods through road links. The poverty exit model highlighted that the key factors behind escaping poverty are in part similar to those associated with higher consumption in the growth model.

An important benefit of the multilevel approach is that predictions can be used to assess community and regional differences. These predictions produce groups of communities that benefit from economic growth more than others, and communities that in fact suffered during the period. Given these classifications it is straight forward to investigate differences in characteristics, which is an important tool for policy makers to target policies. Critical characteristics of a successful community include key infrastructural or socio-economic variables such as the availability of electricity and daily markets, and school enrolment. These are clearly important policy variables for promoting further poverty reduction. On the basis of community level predictions, we also derive a ranking of regions. This identifies which communities that performs badly in regions that performed well and vice versa. Such analysis provides a critical tool for better targeting policy interventions.

1. Introduction

With the emergence of large scale household surveys for Less Developed Countries (LDC), notably the World Bank Living Standard Measurement Surveys (LSMS), poverty analysis has become widespread. These surveys contain detailed information on consumption expenditure behaviour, and are ideal for poverty mapping and analysis of the determinants underlying variation in poverty across and within countries. Several of these surveys are longitudinal where households are followed over several time periods. The longitudinal dimension is extremely useful since it allows for dynamic analysis of households' living standards. Why is it for instance the case that some households are more likely to escape poverty, whereas others are less likely to do so? Such question cannot be examined in cross-sectional surveys. Examples of longitudinal LSMS surveys include Vietnam, Albania, Nicaragua, Peru and recently Bosnia-Herzegovina.

A factor that is often ignored in dynamic analysis of living standards or poverty is that households are often sampled from the same communities or villages. In so far there is correlation within communities in terms of their poverty experiences, parametric regression analysis may become unreliable unless the community effects are controlled for explicitly. In this paper we explore this issue by using data from the Vietnam LSMS surveyed in 1993, and followed up as a panel in 1998. As is well documented, Vietnam experienced a dramatic drop in overall poverty during this period. However, it is also documented that the poverty reduction was not uniform, with substantial variation across households, communities and also regions. The LSMS shows that poverty reduction was much stronger in urban areas than rural ones. However, the data also shows much stronger heterogeneity in poverty reduction in rural areas. There is in other words a significant degree of clustering across rural areas. As a result we focus our analysis on rural areas of Vietnam. Focusing on rural household has also a practical motivation: only the rural sample of the LSMS contain community level variables. We present results of the estimation of two set of models, each focusing on change in living standards or poverty. The first is a growth model for household's expenditures, while the second is a model of poverty dynamics where we focus on the determinants behind households escaping poverty.

The paper is organised as follow. Section 2 provides a review of the literature concerning poverty in Vietnam and also describes the pervasive transformation of the Vietnam economy and its institutions during the nineties. Section 3 presents the Vietnamese Living Standard Measurement Survey. Section 4 explains the statistical models. Section 5 show results, whereas in section 6 we assess the policy implications of the estimates through an *empirical bayes* analysis, a technique often applied in multi-level models. Section 7 concludes.

2 Background: political and socio-economic change in Vietnam during the nineties.

At the beginning of the 1980s, Vietnam was one of the worlds' poorest countries. Since then the country embarked on a remarkable recovery, a fact that is reflected by strong economic growth and a dramatic reduction in poverty (Glewwe *et al.,* 2002). The country also experienced a dramatic improvement in others indicators of social and economic wellbeing. For example, school enrolment rates increased during the period both for boys and girls. In particular, upper secondary enrolment rates increased from 6 to 27 percent for girls, and from 8 percent to 30 percent for boys (World Bank, 2000). Access to public health centres, clean water and other infrastructure have all increased, as well as the ownership of consumer durables. Overall these improvements have had a positive effect on households' own assessment of their living conditions. As The World Bank Vietnam Development Report states: " […] *Households report a greater sense of control over their livelihoods, reduced stress, fewer domestic and community disputes* […] ".

Much of this improvement has been attributed to the "Doi Moi" policy (translated in English as "renovation"). This was initiated in the late 1980s and roughly coincided with the collapse of the Soviet Union, on which Vietnam had been heavily dependent. The Doi Moi had many similarities with the reforms taking place in China a decade earlier. The main elements of the Doi Moi were to replace collective farms by allocating land to individual households; new legalisation encouraging private economic activity; removal of price controls; and legalisation and encouragement of Foreign Development Investment (FDI). During the nineties, immediately following the Doi Moi, Vietnam experienced dramatically strong economic growth. The average annual GDP growth was at a staggering 7 percent. In the period covered by the Vietnam LSMS panel (i.e. from 1993 to 1998), the growth rate was even higher at 8.9 percent. This was followed by significant changes in the labour market; during the 1990s the employment grew by 2.5%. Output was increased through improved productivity and prices rose as a result of expansion in export of rice. By mid 1990 Vietnam passed to be a net importer to be one of world's largest exporters of rice on the international markets. The increase in agriculture diversification was another remarkable factor of the economic change.

Given such a strong economic performance, it is not unexpected that the overall poverty rate fell. The official poverty rate, which is derived from the per capita household consumption expenditure, declined from 58% in 1993 to 37% in 1998. Though the exact number is contested, as this depends on how poverty is measured through the equivalence scale, (Justino and Litchfield, 2004; White and Masset, 2003; World Bank, 2000), there is little doubt that poverty indeed declined during this period.

The introduction of the Vietnam LSMS has sparked several poverty studies (examples include Justino and Litchfield, 2004; White and Masset, 2001 and 2003; Huong *et al*, 2003; Glewwe *et al*, 2002; Haughton *et al*, 2001). These studies suggest that female headed households, lack of education, large households (large number of children), rural households (or living in the Northern Uplands), households dependent upon agriculture, are associated with higher poverty. However the effect of demographic variables, such as the household size or the number of children[3], is less clear given its sensitivity to any imposed equivalence scale. In general the association between poverty and number of children is weakened when imposing equivalence scales that are different from per capita expenditure (White and Masset, 2003; Balisacan *et al*, 2003).

Of course, household characteristics are not the only driver behind poverty – also characteristics of the community where the household resides might matter. A benefit of the Vietnam LSMS survey is that it includes detailed community information. Justino and Litchfield (2004), using this information, find that the quality of community infrastructure is not always associated with a lower probability of being

[3] Justino and Lithcfield argue that the high cost of education might be a factor explaining higher poverty rates among household with many children (Justino and Litchfield, 2004; page 22).

poor. For example, they find that access to electricity is negatively associated with poverty, while the presence of secondary school has an opposite sign. A problem in such analysis is of course that the various community characteristics are often highly correlated, often resulting in non-intuitive parameter estimates when included together. Moreover, community variables might be endogenous with respect to poverty. This is particularly the case if government policies are implemented in response to adverse community circumstances.

Economic growth by itself is not a sufficient condition for poverty reduction (Huong *et al*, 2003; Ghura *et al*, 2002; Glewwe *et al*, 2002; Bruno *et al*, 1999) and the way in which individuals may gain from the growth depends on their individual skills, education and health, ethnicity, their religion, geographical location, and type of employment and occupations. Whereas the economic boom in Vietnam affected all geographical, ethnic, and socio-economic groups, it did so in very different ways, and the poverty reduction was certainly not uniform across the population (Justino and Litchfield, 2004; Balisacan *et al*, 2003; Glewwe *et al*, 2002). In particular, it is noted that inequality increased during the nineties (Haughton, 2001), a fact that is robust to how inequality is measured. Gains from economic growth was stronger in urban areas, for South East and Red River Delta[2], for Kinh[3] which is the main ethnic group in Vietnam, for households headed by a white collar worker and for those with higher education.

3 Data: The Vietnam LSMS

The panel was first surveyed in 1992/93 with a full follow up in 1997/98. It follows the LSMS format and includes rich information on education, employment, fertility and marital histories, together with rich information on household income and consumption expenditure. The overall quality of the panel is impressive with a very low attrition rate (Falaris, 2003). The Vietnam LSMS also provides detailed community information from a separate community questionnaire. It is available for

[2] The Red River Delta and the Mekong River Delta were the regions that benefited most from rice market liberalisation (Justino and Litchfield, 2004).

[3] In Vietnam there is a significant population of ethnic minorities that tend to be considerably poorer than the Kinh majority. An analysis of the sources of the ethnic inequalities in Vietnam can be found in Van de Walle and Gunewardana, 2001.

120 rural communities and includes information on health, schooling and main economic activities. The communities range in size from 8,000 inhabitants to 30,000.

In the analysis we use as a measure of household's living standard the household's consumption expenditure, which requires detailed information on consumption behaviour. It is a widely accepted measure in the literature on LDC and used by the World Bank (Coudouel *et al*, 2002; Deaton and Zaidi, 2002). We use here the expenditure variables constructed by the World Bank procedure which is readily available with the Vietnam LSMS survey. Poverty status is defined as a binary variable and a household is deemed poor if their consumption expenditure falls below a certain threshold. We specify the poverty line using the "Cost of Basic Needs" (CBN) approach following Ravallion and Bidani (1994). In brief this involves estimating the cost of a certain expenditure level which corresponds to a minimum calorie requirement. The construction of the poverty level consists of two steps. First, a food poverty threshold is defined as the expenditure needed to purchase a basket of goods that will give the required minimum calorie intake (this is also referred to as the extreme poverty threshold). Following FAO recommendations, for LDC, this threshold is set to 2100 calories. Secondly, the general poverty line combines the food poverty threshold with an average non-food consumption expenditure.

It is clear that the distribution of consumption expenditure within the household is unlikely to be uniform across household members, and it is probable that children consume less than adults. The standard solution is to impose an assumption on intra-household resource allocation, and adjustments can be done by applying an equivalence scale that is consistent with the assumption made – producing a measure of expenditure per equivalent adult. Here we apply the WHO (World Health Organisation) equivalence scale taking a weight of 1 for adults and 0.65 for children as used by other authors (Justino and Litchfield, 2001; White and Masset, 2002). This means that the mean poverty rate for the two waves will be different from the official ones, given that the latter is based on per capita expenditure, which in effect implies an equivalence scale that assigning weights to all household members.

The Vietnam LSMS includes a range of variables that are important determinants for the household's standard of living. Our choice of variables is based mainly on dimensions which are important for the household's income generating process, such as employment and human capital. Many of these variables are defined in terms of household ratios. That is, we are interested in the number of household members that are engaged in gainful employment as a ratio of the total number of household members. The effect of children is distinguished by their age distribution, and again expressed as a ratio of the total number of household members. We then include the average number of months that household members were working away from their village, the ratio of household members with post-compulsory education, the ratio of school attendance, the household literacy rate, the ratio of unskilled workers, and the ratio of members looking for work. We also include characteristics of the dwelling. These include whether the household has electricity and whether the household head is a home owner. Both of these measures are expected to be associated with higher household wealth. The survey also includes rich information on the characteristics of the community where the household resides. Here we include indicators for whether there is a lower secondary school, hospital facilities, whether there is a large enterprise located nearby, whether farming is organised through agricultural cooperatives, and the amount of large tractors, the latter being a measure of farming technology in the community. It should be noted that the Vietnam LSMS contains many more community level variables. However, many of these variables are highly correlated. For instance, the quality of health care in the community can be proxied by availability of doctors or pharmacies, in the same way as we here use the hospital indicator. When such variables are included separately they tend to have significant effect in most of the regression analysis, but many become insignificant when combined together, which is driven by the strong correlation. We have therefore made an effort to include one variable from different dimensions – *hospital* referring to health conditions of the community, *agricultural cooperatives* to the way the agricultural sector is organised, the number of *large tractors* being a measure of advancement in agriculture, and *low secondary schools* as a measure of the educational infrastructure.

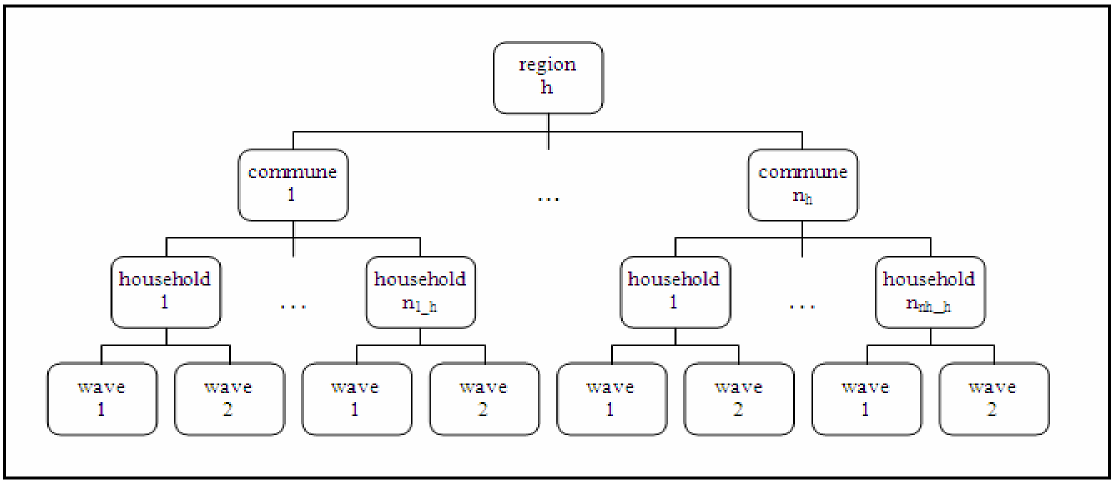
4 Methods: Multilevel models for living standards and poverty dynamics.

In this section we present two multilevel models to study poverty in rural Vietnam. The first model exploits the longitudinal information in form of a growth model of consumption expenditure, whereas the second model presents an application of poverty dynamics, in particular a model of poverty exit. The multilevel structure is highly relevant in both models and is driven by the fact that the economic growth, and consequently changes in the economic structure of the country, varied substantially across communities and regions (Glewwe *et al*, 2002). The multilevel structure of the Vietnam LSMS is illustrated in Figure 1. The time dimension, i.e. the two waves of the LSMS, represents the lowest level, i.e. level 1. The household is at the second level, community the third level, and the region, the most aggregate level, is the fourth[4].

The arguments for using multilevel models to analyse hierarchical data are well known (Skrondal and Rabe-Hesketh, 2004; Snijders and Bosker, 1999; Goldstein, 1995; Hox, 1995; Di Prete and Forristal, 1994). When units are clustered classical regression analysis are not appropriate since the underlying hypothesis of independence of the observations is violated. In our case, households in the same communities tend to be more similar to each other than households in different communities. As a result of this dependency, standard errors are estimated with a downward bias and, hence, inferences about the effects of the covariates might be spurious (Hox, 1995). A standard solution is to use robust methods for estimating the standard errors. But, when the multilevel structure is not only a mere nuisance factor but instead a key dimension of the analysis, multilevel models are more appropriate. As we will see in the following sections, the multilevel approach exploits the richness of hierarchical data structures in a way that offer highly interesting policy analysis that is not possible in more standard regression analysis.

[4] In our models we have not included regional because they are too few (there are seven regions all together). This hampers accurate estimation of the standard deviation of the random effect (Maas and Hox, 2004). However, standard errors are corrected for any intra-regional correlation.

Figure 1 – *The representation of the multilevel structure of the Vietnam LSMS*



4.1 A growth multi-level model of household expenditure

The typical growth model consists of regression analysis where controls are made for variables measured in the initial time period, a time trend, and the interaction between control variables *and* the time trend. The benefit of this approach is that it enables a decomposition of the growth pattern by background characteristics. Moreover, the effect of the initial status can be compared with the growth effect. For example, large households being associated with *lower* expenditure in the initial wave, might be associated with higher growth over time, as is reflected by the interaction with the time trend. Similar comparisons can be made for all background characteristics. However, these models are not normally extended to take into account multilevel structures.

A multi-stage formulation of the growth model

Based on the multilevel structure in Figure 1 we can easily derive a *multi-stage* formulation of our growth model (Bryk and Raudenbush, 1987). First, the dependent variable is here defined as the logarithm of the equivalent household consumption at the waves surveyed in 1993 and 1998 respectively[5]. Community is denoted by *k*, *j* denotes the household, whereas *i* refer to time (i.e. the two waves).

$$Log(equivalent\ consumption)_{ijk} = \beta_{0jk} + \beta_{1jk} TIME_{ijk} + e_{ijk} \tag{1}$$

Equation (1) represents a simple linear model for log-consumption growth between the two waves. The intercept β_{0jk} represents the "initial status", namely the log-consumption for the household *jk* in the first wave, and the β_{1jk} represents the variation in the log-consumption between the two waves[6]. As the subscripts indicate these parameters are household and community specific.

$$\begin{cases} \beta_{0jk} = \beta_{0\_0k} + \beta_{0\_1k} FARM_{jk} + \sum_{s=2}^{16} \beta_{0\_s} x_{sjk} + u_{0jk} \\ \beta_{1jk} = \beta_{1\_0k} + \beta_{1\_1k} FARM_{jk} + \sum_{s=2}^{16} \beta_{1\_s} x_{sjk} + u_{1jk} \end{cases} \tag{2}$$

The first equation in (2) gives the parameterisation of the intercept (i.e. initial wave), whereas the second equation gives the parameters of the slope (growth between waves), both being further parameterised in (3). The initial status β_{0jk} is regressed on a range of background variables, all being time invariant since they are measured at the initial wave. u_{0jk} is the random component of the intercept and is assumed normal with zero mean and variance to be estimated[7]. The same assumption is made for the others random components. β_{1jk}, being the slope of *TIME* in the second equation of (3), represents the growth in log-consumption between the two waves. This is also regressed on a set of background variables, introducing interactions with the time trend.

[5] Household expenditures are deflated by geographical location and time using the price indexes provided in the survey.

[6] It is easy to see that the exponentiated slope of *TIME* represent the ratio between the consumption expenditure in the second wave over the consumption expenditure in the first wave. We can calculate the consumption growth rate between the two waves as follows:

e^{β} - 1 = [consumption (wave 2) – consumption (wave 1)] / consumption (wave 1)

[7] u_{0jk} can be interpreted as the deviation of the intercept for a specific household, due to unobservable household specific factors. Similar interpretations apply for the other random components.

$$\begin{cases} \beta_{0\_0k} = \beta_{0\_0\_0} + \sum_{m=17}^{22} \beta_{0\_m} C_{mk} + v_{0k} \\ \beta_{0\_1k} = \beta_{0\_1\_0} + v_{1k} \\ \beta_{1\_0k} = \beta_{1\_0\_0} + \sum_{m=17}^{22} \beta_{1\_m} C_{mk} + v_{2k} \\ \beta_{1\_1kh} = \beta_{1\_1\_0} + \beta_{1\_1\_1} ROAD_k + v_{3k} \end{cases} \tag{3}$$

From (3) we see that β_{0_0k} is a function of community level variables C_{mk} measured at the initial wave, explaining the initial log-consumption. Similarly β_{1_0k} is a function of community level variables, but now interacted with the time trend, and hence explaining the log-consumption growth. Given the importance of agriculture in rural Vietnam we put special focus on farm households and their development by allowing the effect of the *FARM* indicator[8] to differ by community, both on the initial log-consumption and on the log-consumption growth. This is reflected by the parameterisations of the second and the fourth equations in (3). Note however, that in the fourth equation, *FARM* is not only interacted by *TIME* (i.e. the time trend), but also with *ROAD*, which is a community level variable reflecting the transport infrastructure of the community. This means that we are allowing the "growth effect" for farmers (namely the interaction *FARM*TIME*) to be different depending on whether the community is well connected with surrounding areas. The set-up enables us to test whether farm households in communities with good access to infrastructure show stronger growth in log-consumption. Good access to roads implies easier exchange of goods, information and technology and may as a result facilitate growth, especially in a period of general economic growth like the nineties. v_{0k}, v_{1k}, v_{2k} and v_{3k} are all normal random error terms at the community level with zero mean and variances to be estimated.

The model in the reduced form

A reduced form version of the multi-level model is obtained by substituting equations (2) and (3) into equation (1):

[8] The FARM variable is a simple dichotomous variable taking the value one if the household's main activity is related to agriculture, zero otherwise.

$$
\begin{aligned}
&Log(equivalent\ conumption)_{ijk} = \\
&\beta_{0\_0\_0} + \beta_{1\_0\_0} TIME_{ijk} + \beta_{0\_1\_0} FARM_{jk} + \sum_{s=2}^{16} \beta_{0\_s} X_{sjk} + \sum_{m=17}^{22} \beta_{0\_m} C_{mk} \\
&+ \beta_{1\_1\_0} FARM_{jk} * TIME_{ijk} + \sum_{s=2}^{16} \beta_{1\_s} X_{sjk} * TIME_{ijk} + \sum_{m=17}^{22} \beta_{1\_m} C_{mk} * TIME_{ijk} \\
&+ \beta_{1\_1\_1} ROAD_k * FARM_{jk} * TIME_{ijk} \\
&+ e_{ijk} + u_{0jk} + (u_{1jk} + v_{2k}) TIME_{ijk} + v_{0k} + v_{1k} FARM_{jk} + v_{3k} FARM_{jk} * TIME_{ijk}
\end{aligned} \tag{4}
$$

The first three rows of the reduced form model can be thought of as the "fixed part", whereas the last one represents the "random part". e_{ijk} is the idiosyncratic error, u_{0jk} refers to the household random intercept and v_{0k} to the random intercept at the community level. u_{1jk} and v_{2k} are the random components of the slope of the time trend, respectively, at household and at community level[9], v_{1k} is the random component of the slope of the *FARM* variable at community level, whereas v_{3k} is the random component of the slope of the interaction of *FARM* and *TIME*, again at the community level. Consistent with the literature (see for example Skrondal and Rabe-Hesketh, 2004), we allow the random effects at the same level to be correlated, while random effects at different levels are assumed uncorrelated. The results from the model estimation are presented in section 5.

4.2 A multi-level model for poverty dynamics

In this application we focus on why some households are able to escape poverty. We limit therefore our sample to include households that were classified as poor in the first wave. Thus, the analysis focuses on household and community determinants of poverty exit. We specify a two level random intercept probit model, where the first level is now the household (*j*) and the second is the community (*k*). We define the following binary variable:

[9] The global slope of *TIME* is $\beta_{1\_0\_0}$+ u_{1jk} +v_{2k}. The fixed component is given by $\beta_{1\_0\_0}$ (that represents the average slope over households and communities) and two random components given by u_{1jk} and v_{2k} (that represents, respectively, the deviation from $\beta_{1\_0\_0}$ for the household *jk* and for the community *k*). Similar reasoning applies for the other random slopes.

$$Y_{jk} = \begin{cases} 1 = \text{"poverty exit"} & \text{if} \quad Y^*_{jk} > 0 \\ 0 = \text{"remain poor"} & \text{otherwise} \end{cases}$$

where Y^* is an unobservable continuous variable that in our case could be interpreted as the "ability" to escape out of poverty. We model the latent variable Y^* using a two level random intercept model

$$\begin{aligned} Y^*{}_{jk} &= \beta_0 + \sum_{s=1}^{16} \beta_s \Delta x_{sjk} + \sum_{m=17}^{20} \beta_m \Delta C_{mk} \\ &+ u_{jk} + v_k \end{aligned} \tag{5}$$

Equation (5) is the reduced form specification of our model where the covariates are constructed by taking the first difference of the original variables which were measured at the first and second waves (both at household and community level).

As was the case in the growth model, equation (5) consists of a fixed part (the first row) and a random component (the second row). u_{jk} is the random error at the household level, whereas v_k is the community level random effect. We assume, as in the classical probit model, u_{jk} to be distributed as a standard normal, while v_k is assumed normal with zero mean and variance to be estimated.

4.3 Intra-class correlation coefficients

A useful way to demonstrate the importance of clustering, here at household and community levels, is to decompose the total variability into between and within clusters and to calculate intra-class correlation coefficients (*ICC*). In a simple two-level random intercept model *ICC* gives the correlation between units belonging to the same second level cluster and reflects therefore the "closeness" of observations in the same cluster relative to the "closeness" of observations in different clusters. The *ICC* for a two level model is defined as:

$$\rho = \frac{\Psi}{\Psi + \theta} \tag{6}$$

where ψ and θ are, respectively, the second and first level variances and ρ corresponds to the proportion of the *between* cluster variance out of the total variance. The higher is ρ the more important is the clustering. For a general l-level model, the overall error term can be decomposed into l additive components, given the assumption of independence between random effects belonging to different levels. Section 5 reports the results together with the *ICC* calculations.

5 Results

In this section we report the parameter estimates of the growth and the poverty exit models respectively. The discussion is in both cases preceded by the analysis of the *ICC* calculations that makes evident the importance of clustering

Growth model

The decomposition of the total variability and *ICC* values for the growth model are reported in Table 1. The calculations refer to two types of models: 1) a two level model (including time and household levels) and 2) a three level model that also includes the community level. The latter is represented by equation (4). Both models are preceded by the null version, meaning that covariates are omitted. It is clear that the cluster effects are considerable. It is important to note, however, from the first column, that a large part (more than 50%) of the total variability is explained by the *time* level. This is chiefly driven by the dramatic economic growth that took place between the two waves.

The second column shows that the introducing covariates reduce both variances at wave and household level[10]. In the third column we decompose the variation at household level (shown in the first column) into the two components reflecting 1) the household and 2) the community level.

[10] We refer to the covariates included into the final model (see equation 4). They are covariates defined at time, household and community level. In general, the introduction of a covariate at a given level reduces the variability at that level, has an unpredictable effect on the variability at higher levels and has no effects on variability at lower levels .levels.

Table 1 – *Variance decomposition and intra-class correlation coefficients for different specifications of the growth model*

Level	2-levels null model	2-levels model	3-levels null model	3-levels model
		Variance decomposition		
waves	0.1428	0.0798	0.1428	0.0798
household	0.1067	0.0812	0.0457	0.0471
community			0.0609	0.0394
		Intra-class correlations		
household	0.4277 *** (0.0142)	0.5043*** (0.0133)		
community			0.2442*** (0.0266)	0.2372*** (0 .0271)
household, community			0.4277 *** (0.0233)	0.5211*** (0.0201)

Notes: Standard errors for *ICC* are calculated using delta method. This is a valid approximation since we have a sufficient number of clusters both at household and at community level. ***: Significant at 1% level.

The fourth column shows again that introducing covariates reduce the variances at wave and community level, while the variance at household level is almost unchanged. The calculations tell us that the community level variation is about 23% of the total, while when we cumulate this with the household level we obtain the 52% of the total variation. All in all this demonstrates the importance of the clustering, justifying the use of a three level model.

The results of the growth model are presented in Table 2. The model is run with and without standard error adjustment, but the difference is very small as expected. To ease interpretation and help assessing the magnitude of the parameter estimates we present the exponentiated estimate minus one which can be interpreted as the effect of a unitary increase in a covariate on the relative variation of consumption expenditure.

The time trend (i.e. *TIME*) reflects the average increase in consumption between the two waves (17%). As expected its parameter estimate is positive and highly significant. But the remaining estimates show that those who were relatively better off initially were not necessarily benefiting from the economic boom of the nineties (and vice versa of course) to the same extent. The estimate of the random part shows a significant and negative correlation between the random intercept and the random slope at household level. This suggests that households with high consumption levels in 1993 experienced lower growth, on average, compared to those starting at lower levels, and explains to a large extent why many of the coefficients change sign when measured in the growth dimension (as opposed to the initial time period). Whereas there were no significant differences between male and female headed households in 1993, the latter fared worse during the nineties. In contrast the *Kinh* ethnic origin (the main ethnic population in Vietnam), had higher expenditure initially and excelled further during the nineties. Large households with many children were associated with lower expenditure in 1993, but all of these households benefited clearly from the economic growth.

Farm households clearly lost out during the nineties. Not only were they associated with a lower expenditure in the initial wave (their consumption was about 14% lower than non farmers), their relative economic situation also worsened during the nineties (their growth was 7% lower than that of non farmers). In contrast, unskilled workers and those looking for work, both worse off in 1993, benefited in the period leading up to 1998. These estimates are manifestations of the structural change taking place in Vietnam during this period. In particular, these effects reflect a shift from agriculture towards industrialisation, including the service industry, improving the conditions for low skilled workers, but worsening the situation for farmers. Whereas immigrant households were associated with higher levels of expenditure in 1993, our estimates show that during the nineties they lost out. The pattern is difficult to explain. It is natural to think that migrants choose location according to job prospects, services and infrastructures. They might also be privileged or have higher human capital, which explains why they were better off. But it is somewhat difficult to see why they were less effective in exploiting the opportunities arising during the period of economic growth. Education also shows some mixed effects. Whereas educational variables are all positively associated with higher consumption in 1993, the growth effects are more ambiguous. Finally, there are some characteristics that are important for the initial wave, but show no effect in the growth dimension. This includes home ownership, and living in a dwelling with electricity, the latter being a proxy of the household wealth.

As previously mentioned the Vietnam LSMS contains a wealth of community variables. The multilevel model enables us to estimate their effects appropriately.

However, there is high correlation between these variables. For instance, the survey includes several measures of the health facilities in the community, but including several of them in a regression often leads to collinearity. As a result we include variables capturing different dimensions of critical community characteristics. These include education, proxied by whether there is a secondary school in the community, health, here proxied by hospital, industrialisation measured by presence of a "big" enterprise, the way agriculture is organised, measured by whether it is organised as a cooperative or not, and, the number of large tractors – a proxy of agricultural development. As is clear, educational infrastructure and presence of a large enterprise has very little effect on household expenditure, whereas health facilities are associated with a higher initial level of expenditure, but in the growth dimension there is no significant effect. This is in contrast to variables reflecting the agricultural sector. Our estimates show that communities dominated by cooperatives were less well off in 1993. The parameter is strong and highly significant, indicating that the difference in household expenditure in these communities compared to those without cooperatives was substantial. In contrast, households residing in communities with more modern agriculture had clearly higher expenditure levels. Looking at the time interaction, we see that the coefficients switch sign, implying that less modern agriculture communities gained relatively more than those already enjoying more modern forms of agriculture. So, though cooperative farming arrangements used less modern technology, they have seemed well adept to exploit the opportunities following the economic growth. As such, these households are clearly recovering and catching up, but interestingly this recovery takes place at the community level.

The final interaction between farm households and *ROAD*, which is here a proxy for the infrastructure of the community in which the farmer lives, shows an interesting positive effect, suggesting that though farm households did not gain an overall benefit, those residing in communities with easy access to roads and other transport facilities, certainly did. This is an indication that the economic growth had differential impact on farmers depending upon their community characteristics, in this case obviously related to the available transport links to surrounding area.

Further differential effects for farmers are evident when we consider the random effects. Recall that we have allowed for a random slope parameter for farmers in both dimensions (i.e. the initial period and in growth). Both are significant, suggesting that the farm initial status and growth differ significantly across communities. Hence, for a correct interpretation of the parameters estimates for farm households we have also to consider the standard deviation of this random effect. This analysis is elaborated in Table 3.

We have also allowed for a correlation between the random terms. The correlation between the random intercept at community level and the random slope for *FARM* is very small and insignificant (-0.0043). The correlation between the random slope of the interaction term between *FARM* and *TIME*, *and*, the random intercept is also negative, but here more substantial although again not significant. However, the meaning of this *negative* sign is that in poorer communities farmer growth was higher.

The correlation between the random slope of farm variable and the one related to the interaction of *FARM* and *TIME* is highly negative and significant, meaning that those farm households which were relatively worse off initially in 1993, benefited more during the nineties, relatively speaking, compared to those farm households that were better off in the initial wave. In some sense this is an indication that ineffective farms found it easier to expand and improve than farms that are already well off, possibly having gained significant growth prior to 1993.

Table 2 - Random coefficient growth model.

	INITIAL TIME PERIOD (1993)		INTERACTED WITH TIME TREND	
	PARAMETER ESTIMATE (β)	EFFECT ON THE RELATIVE VARIATION (e^{β}-1)	PARAMETER ESTIMATE (β)	EFFECT ON THE RELATIVE VARIATION (e^{β}-1)
HOUSEHOLD LEVEL				
Gender of Household head	0.0203	2.05	-0.0363**	-3.56
	(0.0170)		(0.0178)	
Age of Household head	0.0082	0.82	0.0050	0.50
	(0.0059)		(0.0062)	
Ethnic origin is Kinh	0.0927***	9.71	0.0491*	5.03
	(0.0286)		(0.0280)	
Household size	-0.0477***	-4.66	0.0238***	2.41
	(0.0036)		(0.0037)	
Percentage of children 0 - 4	-0.0016**	-0.16	0.0026***	0.26
	(0.0007)		(0.0007)	
Percentage of children 5 - 9	-0.0004	-0.04	0.0030***	0.30
	(0.0006)		(0.0006)	
Percentage of workers	-0.0015***	-0.15	0.0006	0.06
	(0.0004)		(0.0004)	
Months away for work per capita	0.0019	0.19	-0.0014	-0.14
	(0.0051)		(0.0053)	
Percentage of born elsewhere (immigrated)	0.0017***	0.17	-0.0009***	-0.09
	(0.0003)		(0.0004)	
Farm household	-0.1387***	-12.95	-0.0736*	-7.10
	(0.0228)		(0.0438)	
Percentage with post compulsory education	0.0029***	0.29	0.0009***	0.09
	(0.0003)		(0.0003)	
Percentage unskilled	-0.0023***	-0.23	0.0010**	0.10
	(0.0004)		(0.0005)	
Percentage ever attended school	0.0031***	0.31	-0.0011*	-0.11
	(0.0006)		(0.0006)	
Household literacy rate	0.0011*	0.11	-0.0002	-0.02
	(0.0006)		(0.0006)	
Percentage looking for work	-0.0095***	-0.95	0.0101***	1.02
	(0.0027)		(0.0028)	
Owner of dwelling	0.1138***	12.05	-0.0349	-3.43
	(0.0403)		(0.0420)	
Dwelling has electricity	0.2156***	24.06	-0.0235	-2.32
	(0.0204)		(0.0200)	
COMMUNITY LEVEL				
Lower secondary school	0.0048	0.48	0.0186	1.88
	(0.0632)		(0.0337)	
Hospital	0.1696*	18.48	-0.0693	-6.70
	(0.0934)		(0.0605)	
Big enterprise	0.0036	0.36	-0.0300	-2.96
	(0.0427)		(0.0254)	
Agricultural cooperative	-0.3175***	-27.20	0.0685***	7.09
	(0.0448)		(0.0265)	
Number of large tractors	0.0129***	1.30	-0.0057***	-0.57

	(0.0033)		(0.0017)	
ROAD * FARM			0.1242***	13.22
			(0.0421)	
TIME	0.1570*	17.00		
	(0.0812)			
Constant	6.8708***			
	RANDOM PART			
TIME LEVEL				
Residual error (sd)	0.1495			
HOUSEHOLD LEVEL				
Random intercept (sd)	0.3232***			
Random slope of TIME (sd)	0.3101**			
Correlation between random slope of TIME and the random intercept	-0.5336**			
COMMUNITY LEVEL				
Random intercept (sd)	0.1948***			
Random slope of FARM (sd)	0.0979***			
Random slope of TIME * FARM (sd)	0.1535***			
Correlation between random slope of FARM and random intercept	-0.0043			
Correlation between random slope of TIME* FARM and random intercept	-0.1602			
Correlation between random slope of FARM and random slope of FARM * TIME	-0.6223**			

Notes: ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level. Significance of random effects are based on likelihood ratio tests. sd = standard deviation.

As we have seen, the estimated random effects are significant and should not be ignored in the modelling. However, it is difficult to assess the magnitude or the importance of these effects. As a result we calculate predicted levels of consumption expenditure for a range of hypothetical values of the random intercepts. In Table 3 we compare these predictions with the case where the random intercept is set to zero. For random slopes, we compare two households with a unitary difference in the value of the covariates. We can see that the effects are generally substantial, confirming their importance for the modelling and also in terms of policy implications. For example, the predicted consumption expenditure for a household with a value of 0.3232 of the random intercept (equal to the estimated standard deviation of the random intercept) is 38% higher than those who have a random intercept equal to 0 (and hence a global intercept equal to the average).

Table 3 – Sensitivity analysis of the impact of random effects

Interpretation of random intercepts		
	Hypothetical values of the random intercept	Effect of random intercept in terms of percentage relative difference in household consumption compared to a value of zero.
Random intercept at household level (u_0)	$-2*sd(u_o)= -0.6464$	-47.61
	$-1*sd(u_o)= -0.3232$	-27.62
	$+1*sd(u_o)= +0.3232$	38.15
	$+2*sd(u_o)= +0.6464$	90.87
Random intercept at community level (v_0)	$-2*sd(v_o)= -0.3896$	-32.27
	$-1*sd(v_o)= -0.1948$	-17.70
	$+1*sd(v_o)= +0.1948$	21.51
	$+2*sd(v_o)= +0.3896$	47.64
Interpretation of random slopes		
	Some hypothetical values of the slope	Effect of an unitary difference in the covariate in terms of percentual relative difference in household consumption for different values of the slope
Slope of TIME ($\beta_{1\_0} + u_1$)	$\beta_{1\_0} - 2*sd(u_1) = -0.4632$	–37.07
	$\beta_{1\_0} - 1*sd(u_1) = -0.1531$	–14.20
	$\beta_{1\_0} = +0.1570$	17.00
	$\beta_{1\_0} + 1*sd(u_1) = +0.4671$	59.54
	$\beta_{1\_0} + 2*sd(u_1) = +0.7772$	117.54
Slope of FARM ($\beta_{0\_1\_0} + v_1$)	$\beta_{0\_1\_0} - 2*sd(v_1) = -0.3345$	–28.43
	$\beta_{0\_1\_0} - 2*sd(v_1) = -0.2366$	–21.07
	$\beta_{0\_1\_0} = -0.1387$	–12.95
	$\beta_{0\_1\_0} + 1*sd(v_1) = -0.0408$	–4.00
	$\beta_{0\_1\_0} + 2*sd(v_1) = +0.0571$	5.88
Slope of FARM*TIME ($\beta_{1\_1\_0} + v_2$)	$\beta_{1\_1\_0} - 2*sd(v_2) = -0.3806$	–31.65
	$\beta_{1\_1\_0} - 1*sd(v_2) = -0.2271$	–20.32
	$\beta_{1\_1\_0} = -0.0736$	–7.10
	$\beta_{1\_1\_0} + 1*sd(v_2) = +0.0799$	8.32
	$\beta_{1\_1\_0} + 2*sd(v_2) = +0.2334$	26.29

Similarly, the predicted consumption expenditure for a household living in communities with a random intercept equal to 0.1948 is 22% higher than consumption for the reference household.

As far as random slopes are concerned, we observe that consumption growth between the two waves varied considerably by households – the average growth being 17%. If we set the random slope of TIME to -0.4632, which is equivalent to minus two times its standard deviations, we obtain a predicted growth of -37%. In contrast, setting its value to *plus* two times its standard deviations we obtain a growth of 118%.

Also farmers' relative conditions vary considerably by community. On average, farmers' expenditure was 13% lower than that of non farmers. However, it is clear from Table 3 that many experienced even lower expenditure. For instance, by imposing a negative value of the random effect (equivalent to minus one of the standard deviation) produce an expenditure level that is 20% lower than non-farmers. Obviously, the gap between farmers and non-farmers is smaller for lower values of the random effect. Only for very large positive values of the random effect, do we find farmers to be less poor than non-farmers. The policy implications are important, in the sense that policy makers might want to consider the heterogeneity of farming communities, bearing in mind that some fare considerably worse than others.

Poverty exit model

We start presenting, as above, variance decomposition and *ICC* calculations. In a multilevel probit model we assume that the error at the first level is distributed as a standardised normal random variable. The *ICC* is calculated as before but this is now seen as the correlation between the latent responses instead of the correlation of the outcomes. In the Table 4 we show *ICC* calculations for the two level model represented by equation (5). Calculations are also made for the null version. Introducing covariates reduce the community level variation. As a result, correlation among households living in the same community (measured by the *ICC*) is lower but still not negligible and significant. Hence, as for the growth model we can see that the clustering effects, here only at community level, are considerable.

Table 4 – Variance decomposition and intra-class correlations for the poverty exit model

Level	2-levels null model	2-levels model
	Variance decomposition	
Household	1.0000	1.0000
Community	0.4581	0.3723
	Intra-class correlations	
Community	0.3142 *** (0.0403)	0.2713*** (0.0415)

Notes: Standard errors for *ICC* are calculated using delta method. This is a valid approximation since we have a sufficient number of clusters at community level. ***: Significant at 1% level.

The results from the poverty exit model are presented in Table 5. Note that we present here the specifications with and without the multilevel model. Since the probit is non-linear, inclusion of the community level may also affect the parameter estimates and not only the estimated standard errors as is in the linear case (i.e. the growth model)[11].

The nonlinearity of the probit model implies that calculated marginal effects depend on the covariate values. To ease interpretation we compute predicted probabilities for selected exemplificative households. These are presented in table 6. We define a reference household where all covariates and the random effect are set to zero. We then consider the effect on the predicted probabilities by changing the covariate values. For binary variables we consider changes from 1 to 0 (= −1) and from 0 to 1 (= +1). For continuous and discrete variables we considered respectively, the mean and the median of the positive changes and the mean and the median of the negative changes.

The results confirm many of the patterns found in the growth models, but there are also interesting differences. Households with an increase in the percentage of members with post compulsory education and members immigrating from elsewhere have higher exit probabilities. In contrast, households increasing in size, increasing percentage of children, and percentage of unskilled workers, generally find it harder to escape poverty. From Table 6 we can see that the estimated probability of escaping poverty for a household grown in size by one unit is four percentage points lower than households having no change. In a similar way, households that experienced an increase in the proportion of children aged between 0 and 4 years of 21% had an estimated probability of escaping poverty of 12 percentage points lower than the reference household As is clear, the model gives a different picture than the growth model. There we showed that large households and households with many children benefited during the nineties.

[11] We also run these models with standard error adjustment controlling for additional cluster effects of communities and regions for the non multilevel probit model and regions for the 2-levels probit. Results are similar to those of the models presented in the table.

Table 5 - Poverty exit

(Comparison between a single level probit and 2-level random intercept probit)

	single level	2-levels
Change in		
Household head sex	0.1046	0.0247
	(0.1285)	(0.1414)
Household head age	-0.0008	-0.0058*
	(0.0030)	(0.0033)
Household size	-0.0942***	-0.1031***
	(0.0197)	(0.0224)
Percentage of kids 0-4	-0.0165***	-0.0151***
	(0.0032)	(0.0036)
Percentage of kids 0-4	-0.0100***	-0.0108***
	(0.0028)	(0.0031)
Months away per capita	0.0551**	0.0300
	(0.0275)	(0.0296)
Percentage immigrated	0.0063***	0.0071***
	(0.0019)	(0.0021)
Farmer household	-0.0451	0.0748
	(0.0826)	(0.0925)
Percentage workers	-0.0029*	-0.0015
	(0.0017)	(0.0019)
Percentage post compulsory education	0.0057***	0.0046***
	(0.0016)	(0.0018)
Percentage unskilled workers	-0.0029***	-0.0034**
	(0.0011)	(0.0014)
Percentage ever attended school	-0.0006	-0.0012
	(0.0021)	(0.0024)
Percentage littered	0.0002	0.0008
	(0.0019)	(0.0022)
Percentage looking for work	-0.0137*	-0.0116
	(0.0074)	(0.0084)
Own dwelling	0.1487	0.1210
	(0.1757)	(0.1982)
Electricity	0.1671**	0.0339
	(0.0687)	(0.0885)
Market	0.0372	0.0471
	(0.0627)	(0.1322)
Agricultural cooperative	0.0457	0.0207
	(0.0759)	(0.1704)
Number large tractors	0.0058***	0.0068**
	(0.0016)	(0.0031)
Rice price index	1.6621***	1.0325
	(0.3868)	(0.7745)
Constant	-0.2214	0.2875
	(0.1550)	(0.2232)
RANDOM PART		
Community level random intercept		
(standard deviation)		0.6101***
		(0.2713)

Notes: ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Table 6 - Sensitivity analysis of fixed effects for the 2-level random intercept probit

Variable	Hypothetical changes[2]	Predicted probability of escaping out of poverty	Difference in respect to the reference household (percentage points)
Reference household[1]	---	61.31	0.00
Household head sex	-1	60.36	-0.95
	1	62.26	0.94
Household head age	5.2	60.15	-1.16
	-27.2	67.19	5.88
Household size	-1	65.20	3.88
	1	57.32	-4.00
Percentage of kids 0-4	-20.84	72.65	11.33
	20.61	49.05	-12.26
Percentage of kids 5-9	-22.52	70.22	8.91
	24.78	50.79	-10.52
Months away per capita	-2.15	58.82	-2.49
	2.01	63.60	2.29
Percentage immigrated	-34.99	51.56	-9.76
	23.3	67.47	6.16
Farmer household	-1	58.42	-2.89
	1	64.14	2.83
Percentage workers	-22.96	62.63	1.31
	25.28	59.85	-1.46
Percentage post compulsory education	-23.21	57.17	-4.14
	27.14	66.00	4.68
Percentage unskilled workers	-42.58	66.72	5.41
	51.55	54.47	-6.85
Percentage ever attended school	-22.89	62.36	1.05
	26.47	60.09	-1.22
Percentage littered	-25.51	60.53	-0.78
	25.75	62.10	0.79
Percentage looking for work	-25.65	72.07	10.76
	26.26	49.32	-12.00
Own dwelling	-1	56.61	-4.70
	1	65.85	4.54
Electricity	-1	60.01	-1.30
	1	62.60	1.29
Market	-1	59.50	-1.81
	1	63.10	1.79
Agricultural cooperative	-1	60.52	-0.79
	1	62.10	0.79
Number large tractors	-2	60.79	-0.52
	6	62.87	1.55
Rice price index	---	---	---
	0.18	68.20	6.89

Notes: 1) Reference household have all covariates set to zero. 2) For dummy variables we consider the change from 1 to 0 (= -1) and the change from 0 to 1 (= 1). For continuous variables we take the mean of negative changes and the mean of positive changes. For discrete variables we take the median of negative changes and the median of positive changes because these have a concrete interpretation.

However, this result should not be confused with the estimates of the poverty exit model. Here we condition on the change in the covariates, which confirms that having more children, is still negatively associated with escaping poverty. Consequently the two models show two different dimensions of dynamics. The first shows that relatively speaking large families improved their living conditions over the period, whereas the poverty exit model shows that there is still a positive relationship between *having more* children and poverty[12]. As for the community variables, we found an increase in large tractors, generally reflecting increased modernity and technical progress in the agricultural sector, is associated with a significant reduction in poverty. Again holding these estimates up against those of the growth model, demonstrate how the poverty exit model provides different and additional information.

Many of the included variables are found to have little effect on exiting poverty. We note however, that some of these variables only loose their significance once the multi-level structure is controlled for. The most noticeable examples are access to electricity and the rice price index, both losing their significance in the multilevel model. The rice price index is simply a measure of the change in the rice price specific to each community. The positive effect in the simple probit suggests that households residing in communities where the rice price increased, with the possible consequence of increased revenues among farmers that sell rice (which is a large proportion of the sample), are able to escape poverty much easier than households in other communities. In fact, it has been argued that the increase in rice price has been one of the main contributors to reduce rural poverty in Vietnam during the nineties (Huong *et al*, 2003; Niimi *et al*, 2003; Haughton *et al*, 2001). However, it is well known that economic improvements are followed by higher inflation, including rice price inflation. Controlling for such geographical variations, as we do with the multilevel model, shows that the rice price itself played less of a role in explaining poverty reduction. Unobserved factors operating at community level, such as land quality (and hence rice quality), the accessibility to international markets and so on, could also be associated with the rice price inflation. Of course, the multi-level model will capture such unobserved factors, revealing the spurious nature of the

[12] Note that while the growth model uses the whole sample, the probit model use only the sub-sample of households that was poor in 1993.

relationship found in the non multilevel model[13]. A similar argument applies for the variable capturing access to electricity, as this variable also marks differences in geographic specific growth patterns. It is clear that households gaining access to electricity live in areas with reduced poverty. Again, the multilevel model suggests that access to electricity by itself – is *not* a causal factor behind poverty reduction.

The two-level model includes only a community random intercept. It is highly significant and important, as reflected by the *ICC* calculations. In Table 7 we asses the importance of this random effect. As in the growth model, different values of the random intercept produce very different predicted probabilities. Considering a reference household where all covariates and the random effect are set to zero, we see that subtracting two times the standard deviation from the random intercept give a probability of escaping poverty of 17.5%, which is 43.7 percentage points lower than the reference household. In contrast, adding two times its standard deviations gives a probability of escaping poverty of 93.4%, which is 32.1 percentage points higher than the reference household. These figures suggest of course, that the community where the household resides matter considerably for poverty exit. The importance of the community random effects are analysed further in the next section.

Table 7 - Sensitivity analysis of the random effect two-level probit model

	Hypothethical value of the random intercept	Probability of escaping out of poverty	Difference in respect to the reference household (percentage points)
Random intercept at community level (v0)	–2*sd(vo)= -1.2202	17.55	-43.76
	–1*sd(vo)= -0.6101	37.35	-23.96
	+1*sd(vo)= +0.6101	81.53	20.22
	+2*sd(vo)= +1.2202	93.42	32.10

[13] Rice inflation is not the only key variable in this context. Glewwe *et al* (2002) argue that increased productivity in rice production was important, while Van de Walle (1996) argue that improvements in water irrigation were important for reducing poverty among farmers.

6 Policy analysis: Empirical Bayes predictions

In this section we develop a tool for better understanding the implications of the estimated multilevel poverty exit model. As we have seen, the estimated random effect is highly relevant, meaning that there is substantial variation in how communities are able to cope in terms of economic progress and poverty reduction.

From the estimated model we are able to make predictions about the random effect, and therefore compare communities[14]. There are two main statistical approaches to assign values a posteriori to the random effects. The first uses a *Maximum Likelihood* (ML) procedure where parameter estimates for the fixed part is assumed known. The obtained estimates for the random effects are treated as parameters to be estimated through maximising the likelihood function. The second approach is based on *Empirical Bayes* (EB) predictions. In contrast to the ML approach, EB uses information about the prior distribution of the random effects, in addition to the observed responses. EB predictions are consequently the mean of the posterior distribution of the random effect. In this case the random effects are treated as proper random variables hence the term *prediction* is used in contraposition to ML *estimates*. Since the posterior distribution is a compromise between the prior distribution and the likelihood the EB lies between the ML estimates and the mean of the prior. For linear models, EB predictions could be obtained from the ML estimates using the formula:

$$\hat{EB} = \hat{ML} * \widehat{S} \tag{7}$$

where $\widehat{S}$ is termed the shrinkage factor whose value is bounded by 0 and 1. $\widehat{S}$ can be thought of as a measure of the reliability of the ML estimator and depends on the variance components and on the cluster size.

[14] This kind of analysis is commonly found in the education literature, where the focus is on school performance (Aitkin *et al*, 1986; Goldstein and Thomas, 1996). Controlling for characteristics of schools, students, and class attributes, schools can be classified according to their effectiveness. In essence this is based on predictions about the unobserved heterogeneity at school level (random intercept). This allows the identification of the contribution of each school to the individual results of the pupils: a positive value indicates a school performance greater than the mean, vice versa a negative value.

In the following analysis we apply the EB approach to the multilevel model of poverty exit[15]. With this analysis we investigate the extent communities differed in promoting poverty exit among its households. The random intercept at community level represent the combined effect of all omitted covariates at community level that cause some households to be more inclined to escape poverty than others according to the place they live only. Consequently we use predictions of the random intercept to produce a ranking of communities. As explained below, a ranking of regions is possible taking the means of the predictions at community level by region.

Communities are ordered from the lowest (worst) prediction of the community level random intercept to the highest (best). It is important to note that these predictions control for household observed characteristics, which means that the following analysis allow us to answer one of the key research question that arise in multilevel research (Subramanian *et al*, 2003): are there significant contextual differences among communities, after taking into account the compositional characteristics of communities[16]?. Therefore a ranking based on these predictions is more informative than the ones based on the row poverty exit rates or other similar measures.

Figure 2 show these predictions with a 95% confidence interval for pair wise comparisons based on *comparative standard errors*[17]. An overlap in terms of the confidence intervals indicates that communities are not significantly different, whereas non-overlap reflects that they are. For simplicity we make a classification of communities into three groups: 1) bad, 2) medium and 3) good.

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[15] Similar analysis could be made for the growth model (or any other cross sectional model). Obviously the interpretations will change depending on the application and the model. In the growth model, the analysis would inform us whether certain communities were different in encouraging consumption growth for the households over the time period of the nineties. Analysis based on a cross sectional model, say for the 1993 wave, would investigate if communities were different in encouraging high living standard for households in 1993. Analysis of this kind could be based also on a random slope model instead of a simpler random intercept as in our case. But in this case the analysis becomes complex since intercept rankings change for the values of the variables given random coefficients.

[16] In multilevel socio-economic research it's important to distinguish between two sources of variation in the outcome at cluster level: contextual (relating to differences in specific areas' characteristics) and compositional (relating to characteristics of the households or individuals living in different places).

[17] We represent intervals centred on the EB predictions and with lengths equals to 2*1.39 times the comparative standard errors. These are the square root of the variances of the prediction errors (Skrondal and Rabe-Hesketh, 2004). They are referred to as the comparative standard errors because they can be used for inferences regarding differences between predictions of the random effects. They have to be distinguished from the sampling standard deviation that is the square root of sampling variance of the EB predictions distribution. These are referred as *diagnostic standard error*s since they can be used to find aberrant predictions.

Figure 2 – Empirical Bayes predictions at community level

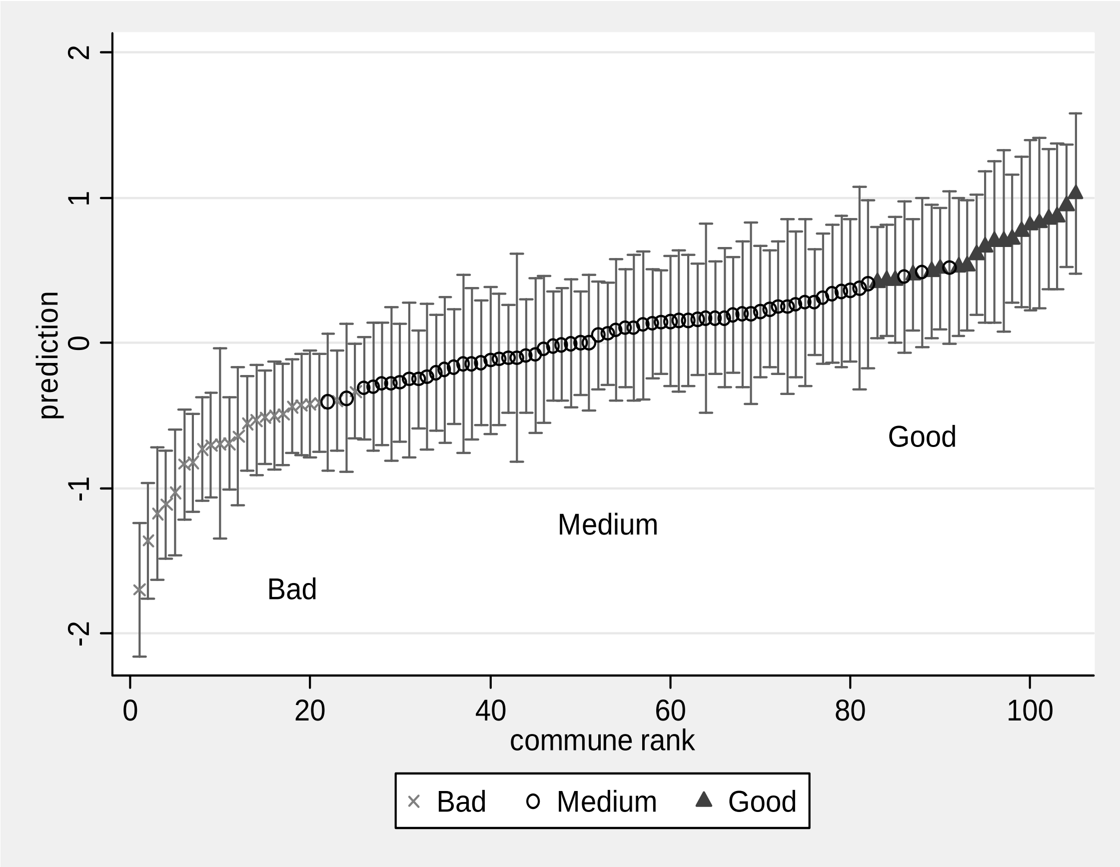


Figure shows 95% confidence intervals for pair wise comparisons (interval lengths are equals to 2 * 1.39 times the comparative standard errors and centred on the predictions)

The classification of the groups is of course somewhat arbitrary. We chose to include into the "bad" and "good" group communities that had significantly different predictions from each other (with no interval overlap)[18]. The "Medium" group collects the remaining communities.

Based on this ranking we can now tabulate, and compare differences in a range of characteristics of "good" and "bad" communities. Table 8 gives the results for a range of variables, some of which are measured at the first wave, other at the

[18] As we can see from the figure, none of the interval for "bad" communities overlaps with intervals of the "good" group and vice versa. Hence, we concentrate on the comparisons of these two groups whose communities are significantly different. We have to note that intervals completely below or up 0 are not necessarily related to predictions significantly different from 0 because intervals are based on comparative standard errors instead of diagnostic standard errors.

second, and some measuring the differences between the two waves. We presented into the table only variables whose means are significantly different in the two groups.

Table 8 – Comparing characteristics of “bad” and “good” communities

Characteristic	Mean “bad”	Mean “good”	Difference
Principal ethnic group (Kinh = 1; W1)	0.65	1.00	-0.35***
Principal religious group (Buddhists = 1; W1)	0.48	0.84	-0.36***
Presence of road (Road is present =1; W1)	0.91	1.00	-0.09*
Road is impassable (W1)	0.39	0.15	0.24**
Electricity (W1)	0.35	0.55	-0.20*
Radio station (W1)	0.30	0.60	-0.30**
Daily market (W1)	0.26	0.60	-0.34**
Distance upper secondary school (W1)	9.54	5.80	3.74**
Number of large tractors (W1)	0.83	2.65	-1.82**
Use of fertiliser (W1)	0.91	1.00	-0.09*
Percentage of households with a radio (W1)	38.43	53.10	-14.67*
Percentage of households with a television (W1)	7.70	16.20	-8.50**
School enrolment rate (age 11-14; W1)	3.65	6.80	-3.15*
Manufacturing is present (W2)	0.43	0.70	-0.27**
N. of households with subsidised credit (W2)	187.68	280.94	-93.26*
N. of households with fiscal advantages (W2)	53.36	176.18	-122.82**
Credit availability for non agric. investments (W2)	0.35	0.67	-0.32**
Change in the Time to catch up a doctor (ΔW)	283.08	-63.33	364.41**
Poverty rates (W1)	87.78	68.30	19.48***
Poverty rates (W2)	74.91	25.70	52.02***

Note: for quantitative variable we tested the difference between the means in the two groups. For binary variables we tested the difference between the percentages of 1s in the two groups. In both cases, we made one tail tests to verify if “good” communities have, on average, significantly better characteristics than “bad”.W1 = variable measured at first wave. W2 = wave measured at second wave. ΔW = variation between the two waves. Significance at *** 1%; ** 5%; * 10%.

Apart from ethnic and religious differences (here measured at the community level), there are important structural gaps between “good” and “bad” communities. The “good” communities are better in almost all dimensions, including infra structure, education, communication, access to trading markets, and the technological level in agriculture, the latter being particularly strong. They are also more likely to have some manufacturing present in the community. The “good” communities consequently perform better in community characteristics that reflect economic outcomes. From the ones we included, we see that “good” communities have higher educational enrolment and have better access to mass-communication, and better access to credit. It is of interest to observe that households in the same communities are more likely to receive fiscal advantages like a reduction or exemption in taxation. Finally, we have computed the poverty rates in the two time periods. As expected, those classified as “good” have lower poverty in both periods, but the difference is particularly noticeable in the second wave, where the poverty rate for “good” communities is considerably lower than for the “bad” ones. Hence, likewise to the literature aforementioned in section 2, we find that poverty rates reduced in both kinds of communities but inequality seems to have risen. It is also clear that “bad” communities have structural deficits in many dimensions, and as such the analysis indicates several avenues for poverty reduction in those communities classified as “bad”.

Even though our statistical model does not include explicitly the regional level, we can still analyse regional differences based on the community level EB predictions. As suggested by Testa and Grilli (2006), we take the regional means of EB community predictions to compare regions. EB predictions at community level become therefore a combination of community and regional effects. If we take the means by regions, community effects tend to balance out each other and hence we obtain a regional measure of “effectiveness”[19] of poverty reduction. An important aspect of any policy implementation is to decide at which level the policy should be introduced. A national level policy might be inefficient if only specific communities are in need of the policy in question. Likewise, policies targeted at specific communities, might be better implemented at the national or regional level. The following EB analysis provides a tool to identify how such policies should be implemented.

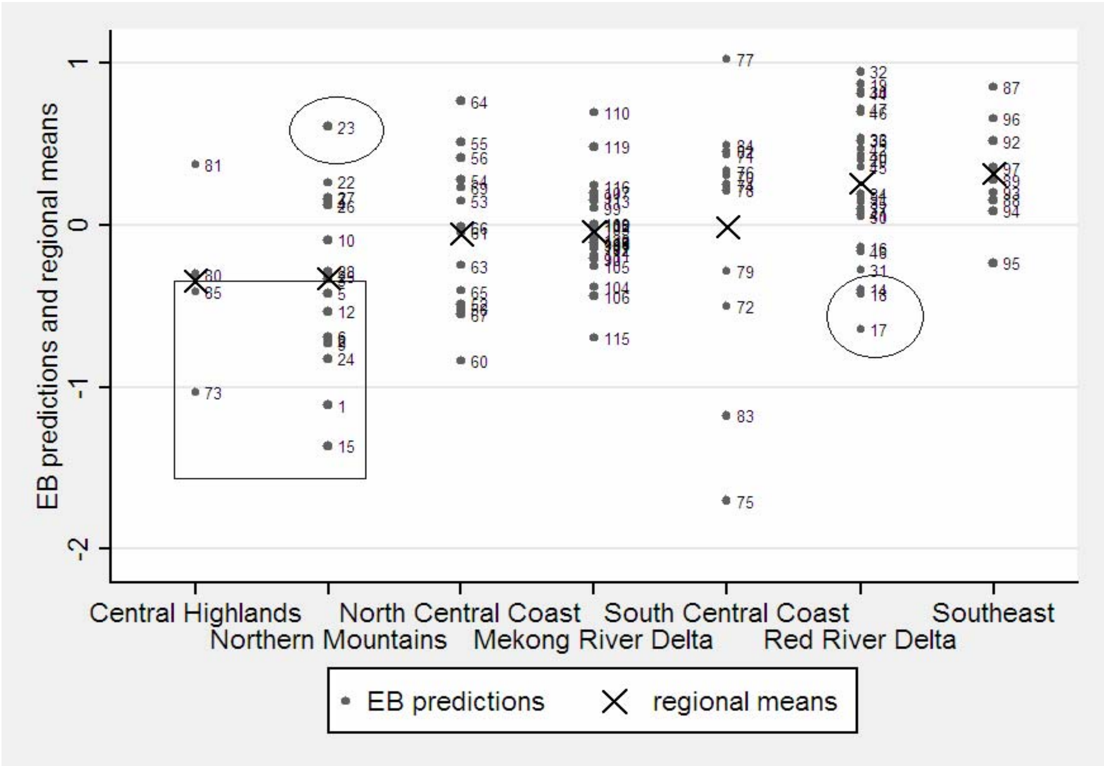
Figure 3 plots the EB predictions by region, where regions are ranked on the basis of the mean of the EB predictions. For simplicity, we consider the first two regions as “bad” and the last two one as “good”. The others, which have values very close to 0, make up the “medium” group.

We can now identify two kind of “anomalous” communities: “good” communities belonging to “bad” region and vice versa: “bad” communities belonging to “good” regions. These communities are circled in Figure 3. For example,

[19] EB predictions plotted in figure 2 are, indeed, a mix of community and regional effects and indicate the advantage or disadvantage to live in an area due both to the regional and community specific effect. To obtain a pure community effect we could subtract from these predictions the respective regional mean.

community number 17 is classified as “bad” despite belonging to a “good” region. The worst possible situation is, obviously, if a “bad” community belongs to a “bad” region since there negative effects relating to the two geographical dimensions cumulate (Subramanian *et al*, 2003). In Figure 3, these communities are included into the rectangle.

Figure 3 – Empirical Bayes predictions and regional means by region.



Note: Communities doubly disadvantaged (“bad” communities in “bad” regions) are highlighted by the rectangle. “Anomalous” communities (“good” communities in “bad” regions and vice versa) are circled

7 Conclusions

In this paper we provide an illustration of how multilevel models can be used to correctly handle hierarchical data structures applied to household wellbeing and poverty dynamics. From the models we have also demonstrated how to provide suggestions for policy interventions. We provide two examples: A growth model with a continuous dependent variable, the log equivalent household expenditure, and a probit model for studying the determinants of poverty exit.

In both cases we found that the multilevel structure is highly relevant as attested by the intra-class correlation coefficients. Hence, failing to control for the multilevel structure will influence model predictions in significant ways, leading to possibly incorrect inference about the effect of the covariates. Whereas an alternative approach would be to simply use robust standard errors, this would omit essential information about the multilevel structure relevant for policy analysis. Multilevel models instead give us insight that is otherwise unfeasible in the more standard methods.

The growth model separates the initial effect from the growth effect of the covariates. The estimates related to the initial condition demonstrate that Kinh ethnic origin, education, and living in a community with health facilities, are all associated with higher wealth. In contrast, households with a high percentage of unemployed members and those working in agricultural activities were disadvantaged. Also household size and the number of children are negatively associated with consumption expenditure. These effects are of course, sensitive to the equivalence scale; we adopted here the well used WHO scale which is in line with many previous studies.

The growth dimension of the model attests that, on average, household consumption growth rate between the two waves was 17%, a reflection of the economic boom experienced in Vietnam during the nineties. However, the growth trend varied substantially by households and community characteristics. We find that those who were better off initially were not necessarily the same benefiting during the economic boom. For example, households with many children benefited from the economic growth whereas farm households benefited less.

Since the Vietnam economy is dominated by rural activities, in particular agriculture, and rural areas are the poorest, we focus our attention on farm households. The model includes therefore random slopes that allow the effect of agriculture to differ by community. Standard deviations of these random effects attest that the place where farmers reside matters. Even though the average growth differential for farmer in respect to non farmer was negative there were certain communities in which farm households grew more. This is especially the case if the community is well connected to other neighbourhoods through road links. The poverty exit model highlighted that the key factors behind escaping poverty are in part similar to those associated with higher consumption in the growth model.

An important benefit of the multilevel approach is that predictions can be used to assess community and regional differences. These predictions produce groups of communities that benefited from economic growth more than others, and communities that in fact suffered during the period. Given these classifications it is straight forward to investigate differences in characteristics, which is an important tool for policy makers to target policies. Critical characteristics of a successful community include key infrastructural or socio-economic variables such as the availability of electricity and daily markets, school enrolment rates. These are clearly important policy variables for further promoting poverty reduction. On the basis of community level predictions, we also derived a ranking of regions. This identifies which communities that performed badly in regions that performed well and vice versa. Such analysis provides a critical tool for better targeting policy interventions.

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