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Assessing Individual Poverty Status Using Repeated Cross-sectional Surveys

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Abstract

Aim of the paper is to introduce a methodology able to estimate vulnerability to poverty and poverty dynamics in absence of longitudinal data. Considering repeated cross-sectional data, we propose a way to directly estimates the probability of being poor in the next period based on a large information set that includes individual characteristics and contextual variables. The joint inclusion of contextual variables along with individual covariates allows to separate idiosyncratic from aggregate shocks. We also allow the effects of the predictors of poverty status to vary over time, removing the traditional hypothesis of time-invariance of the predictors. Macroeconomic forecasts that can potentially influence, directly and indirectly, individual poverty status, are included in the model for better estimate and forecast the probability of each individual to be poor. Methodologically, we estimate a logistic hierarchical model with different levels of variation within a bayesian framework. We empirically illustrate our approach for Kyrgyz Republic using independent cross-sectional Kyrgyz Integrated households budget and labor force surveys (KIHS) available over the period 2013–2017.

Keywords: poverty dynamics; vulnerability to poverty; hierarchical models.
JEL classification: C31; I32; C53.

1 Introduction

The growing interest in poverty dynamics to shape the design and implementation of social development strategies requires an effort in collecting reliable data over time. When available, longitudinal or panel data are used to study poverty dynamics and mobility in and out of poverty to evaluate how the poor react differently to macro-economic shocks, or generally to changes of the contextual environment where they live. Longitudinal data also contribute to the empirical literature on vulnerability to poverty, where vulnerability is defined as the (in)ability of individuals to protect themselves to fall into poverty when an adverse event occurs (Lopez-Calva and Ortiz-Juarez, 2014). The importance of longitudinal data is widely

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accepted, however the availability of reliable panel data spanning over a sufficient time period is very rare in developing countries and cross-sectional surveys, evenly or unevenly repeated over time, are the only data available. To estimate mobility and vulnerability to poverty in absence of true longitudinal data, different approaches have been proposed in the literature. These approaches can be roughly classified into three main methodologies: the well-established mean pseudo-panel approach, the more recent construction of synthetic panels, and the use of dynamic modelling of individual data. Mean pseudo-panel approaches (Deaton, 1985; Moffit, 1993; McKenzie, 2004) use aggregation, where inference is done at cohort rather than at unit level. Clearly, the lack of individual indicators does not allow to precisely identify transitions, but only level changes. Only period and cohort effects are disentangled. Synthetic-panel approaches (Dang et al., 2014) generally use two cross-sectional data: observed incomes of individuals interviewed in the second round are compared to "artificial" incomes as if the same individuals (with the same time-invariant characteristics) had been surveyed in the first round. Artificial incomes are predicted based on parameters of an income model estimated in the first round of cross-sectional data that includes only time-invariant covariates and assumptions on the joint distribution of the error terms are crucial for estimation of mobility. The latter approach, originally proposed by Chaudhuri (2002) in the vulnerability to poverty literature, uses the parameters of an individual income/consumption dynamic model to estimate vulnerability as expected expected poverty (VEP). According to the VEP concept, the vulnerability to poverty of individual i in period t is defined as the probability of being poor at time $(t+1)$ given the individual information set $\Im_t$ at time t, or, equivalently, as the probability that her/his income or consumption at time $t+1$ is less than the corresponding poverty line z, i.e:

$$v_{it} = \text{prob}\{\text{poor}_{i,t+1} = 1|\Im_t\} = \text{prob}\{c_{i,t+1} < z|\Im_t\}. \tag{1}$$

The expected value of consumption, $\mathbb{E}(c_{i,t+1})$, and the variance are based on a set of observable individual characteristics: $\mathbb{E}(c_{i,t+1}) = c(X_i, \beta_{t+1})$, and uncertainty about future consumption stems only from idiosyncratic shocks. These idiosyncratic shocks to consumption are independent and identically distributed (i.i.d.) over time for each individual, but not i.i.d. across individuals. Estimation of (1) requires some strong simplified assumptions (Gallardo, 2018): the model assumes a probability distribution for $c_{i,t+1}$, which is usually a log-normal distribution; it rules out the possibility of contextual effects and/or aggregate shocks (Gunther and Harttgen, 2009); it assumes that the parameters of the distribution remain invariant over time, $\beta_{t+1} = \beta$, implying that the structure of the economy is relatively stable over time.

In this paper, we propose a dynamic logistic multilevel modelling that tries to overcome the previous assumptions. Particularly, the proposed methodology tries to to directly estimate the probability of being poor in the next period, avoiding the assumption on the expected distribution of income/consumption; it includes contextual variables as a second hierarchical level to separate idiosyncratic shocks from aggregate shocks to poverty; it is able to model the parameters β_t, allowing the effect of predictors to vary over time. Finally, the inclusion of macroeconomic forecasts that can potentially influence, directly and indirectly, individual poverty status extends the information set and allows estimates of vulnerability to poverty which are contextual-dependent.

The paper is articulated as follows. Section 2 illustrates our approach. Repeated cross-sectional data consist of independent observations drawn from the same context (e.g. the same region) at many different time-points, and can therefore be treated as clustered within regions and time. Our dynamic multilevel model explicitly accounts for the hierarchical nature of the data and for their different levels of variation: individuals (families), region-years, regions and time. Individual-region-year data are clustered within region-year, region-years data are clustered within regions and also within years, with the potential for predictors at all four levels. The model is able to distinguish between cross-sectional and longitudinal associations between macro-economic variables and poverty, taking into account the clustering of each observation (individual or family) within region&years. Overall, the proposed methodology relies on dynamic multilevel models that treat individual poverty status as a function of individuals' characteristics and circumstances, in interaction with time-varying and time-constant features of their economic contexts. The complexity of these dynamic hierarchical models has prevented their use so far because of their well-known problems of convergence. Casting them in the Bayesian statistical framework offers a reasonable solution and recent developments of simulation techniques such as Markov chain Monte Carlo (MCMC) facilitates fitting these models with the aim of exploring real world complexities of data. Section 3 empirically illustrates the dynamic logistic model for Kyrgyz Republic using independent cross-sectional Kyrgyz Integrated households budget and labor force surveys (KIHS) available over the period 2013–2017. Section 4 shows the most significant results. To anticipate our main findings, some significant associations between poverty status and individual/macro predictors hold both cross-sectionally and longitudinally. Particularly, at micro level education plays an important role in predicting poverty and its influence increases over time remaining important across regions. At regional level, unemployment rate matters substantially for poverty and this association holds cross-sectionally but not longitudinally. That is, there is a significant effect of enduring differences in oblast's level of unemployment, but the longitudinal variation in the level of unemployment over the period is weakly associated with variation in poverty risk. Moreover, unemployment rate affects individual poverty differently according to where people live: rural or urban areas. Per capita gross regional product is not associated with poverty neither cross-sectionally nor longitudinally. Instead is per capita GDP at country level that manifests a trickle-down effect over time. Section 6 presents some concluding remarks, potential developments of the methodology and suggestions for future research.

2 A dynamic logistic hierarchical model

2.1 Specification

The dynamic multilevel model treats individual poverty status as a function of individuals' characteristics and circumstances, in interaction with time-varying features of their economic contexts. Let $\pi_{i[jt]} = P(Y_{i[jt]=1})$ be the probability that members of household i resident in region j fall into poverty at time t, where Y is a binary variable equal to 1 if household is poor. The probability of being poor is directly estimated by the following *varying-intercepts* and *varying-slopes* multilevel logistic model:

$$\pi_{ijt} = logit^{-1}(\underbrace{\alpha_{jt} + \beta_{jt}x_{ijt}}_{\text{time-space varying}} + \underbrace{\beta z_{ijt}}_{\text{time-space invariant}} + error) \tag{2}$$

where

- $logit^{-1}$ is the inverse-logistic function, jt indexes the area j where household i resides at time t,

- x are individual-level predictors with time-space varying coefficients,

- z are individual-level predictors with time-space invariant coefficients,

- α_{jt} (intercept), β_{jt} (slope) are the varying-parameters of the model.

What makes model (2) dynamically multilevel is the inclusion of contextual variables and the modelling of α and β. Therefore, we include contextual predictors at both regional level and time level, allowing α_{jt} and β_{jt} to vary across regions and across time:

$$\alpha_{jt} \sim \mathrm{N}(\alpha_j + \alpha_t + \gamma^{\alpha} U_{jt}, \sigma^2_{\alpha}), \tag{3}$$

$$\beta_{jt} \sim \mathrm{N}(\beta_j + \beta_t + \gamma^{\beta} U_{jt}, \sigma^2_{\beta}), \tag{4}$$

where

- U_{jt} are contextual predictors at regional and time level,

- α_j and β_j can be further modelled to capture cross-sectional contextual effects,

- α_t and β_t can be further modelled to capture the dynamics of national macro-economic effects.

Once, the model has been estimated, the probability of being poor at time (t+1), vulnerability to poverty, can be estimated as:

$$v_{it} = \widehat{\pi}_{i,t+1} = f(\underbrace{x_{i,t}}_{\substack{\text{individual}\\ \text{predictors}}}, \underbrace{\widehat{\alpha_{j,t+1}}}_{\substack{\text{endogenous}\\ \text{time-forecast}}}, \underbrace{\widehat{\beta_{j,t+1}}}_{\substack{\text{endogenous}\\ \text{time-forecast}}}, \underbrace{U_{j,t+1}}_{\substack{\text{exogenous}\\ \text{forecast}}}) \tag{5}$$

2.2 Estimation

The complexity of these dynamic hierarchical models has prevented their use so far because of their well-known problems of convergence. Casting them in a Bayesian statistical framework offers a reasonable solution. While in maximum likelihood estimation a single optimal value for each of the parameters is looked for, in a Bayesian approach the posterior distribution of the parameters (target distribution) is obtained. The posterior distribution is proportional to the likelihood multiplied by a prior distribution of the parameters, and inferences are typically summarized by random draws from this product. In vast majority of cases posterior distribution is not directly available and simulation techniques (as Markov chain Monte Carlo, MCMC) are required to obtain a sample consisting of many draws from the target posterior distribution. MCMC generates samples from the posterior distribution by constructing a reversible Markov-chain that has as its equilibrium distribution the target posterior distribution. The final estimate will depend on the information that comes from the data and from the priors; the more information is contained in the data, the less influential are priors. Point estimates are the medians computed from simulations. The standard deviations are computed from the same set of draws and are proportional to the median absolute deviation (MAD) from the median. Therefore, we focus our convergence assessment on posterior summaries rather than on raw parameters of the model.

3 Modeling poverty dynamics in Kyrgyzstan

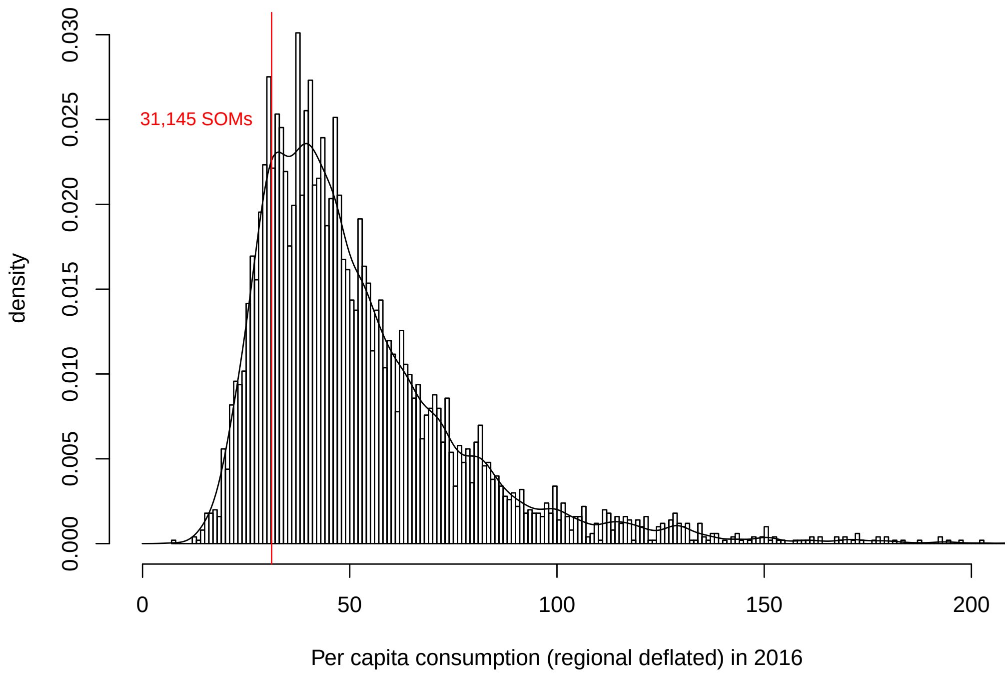
3.1 The data

The Kyrgyz Republic is committed to achieving the sustainable development goals, including the goal I – poverty alleviation. Poverty and welfare developments are primary indicators of the social and economic situation in the country and assessment of policies, which have been used by the Government. At the same time, policy decisions and preparation of government interventions require a good understanding of drivers of poverty reduction and an assessment of their future impact for poverty and welfare developments in the country. Forecasting is one of necessary tools for proper development of public policy and for ensuring financial resources for policy decisions. The availability of poverty predictions complements macro-economic short-term forecasts (e.g. GDP growth, employment, inflation) and serve to promote the importance of distributional issues when assessing current economic and social developments (Navicke et al., 2014). Recent best international practices are oriented towards econometric models able to simultaneously deal with macro and micro data in order to evaluate how macro-variables like per capita GDP and unemployment rate, available at country and regional level, could affect the individual poverty risk. Combined micro-macro modelling has been recently considered to be the appropriate approach for analysis focusing on the impact of macroeconomic policies and shocks on poverty (Bourguignon et al., 2008).

The overall objective of the task has been to develop a national poverty forecasting methodology in the Kyrgyz Republic that combines micro and macro-economic forecasts. The poverty forecasting technique has strong links with the existing macroeconomic forecasting system in the Kyrgyz Republic. developed by the Ministry of Economics.

Estimation of poverty by the National Statistics Committee (NSC) is based on objective measurements of household consumption and follows a basic needs poverty line. The basic needs or absolute poverty line is the estimated Kyrgyz som value of a minimum consumption basket which includes a component for food (the food poverty line) and a component for non-food goods and services. The food poverty line is the estimated expenditure level that is required to reach 2,100 calories per day per person, which is considered the minimum nutritional daily requirement for an average person. The share of non-food consumption is subsequently estimated for the households that are located just above the food poverty line. This share is used to estimate the allowance for non-food consumption. The two calculations (for food and non-food consumption) are used to estimate the total poverty line. The poverty line is estimated at least every five years and adjusted for inflation in subsequent years. Poor households are defined as those households whose *per capita* consumption falls below the official poverty line established by NSC. All members of a poor household are identified as poor. This means that poverty estimates do not account for potential intra-household resource allocation. Figure 1 shows the household per capita consumption dis-

Figure 1: *Distribution of per capita consumption and the poverty line in 2016*



tribution in Kyrgyzstan along with the official poverty line in 2016.

The data source to estimate the poverty rate in the country is the Kyrgyz Republic Integrated Sample Household Budget and Labor Force Survey (KIHS). The KIHS collects data on social and demographic characteristics of the population, employment and unemployment, consumption and expenditures of households, income, availability of personal property and personal living condition. The KIHS was introduced in 2003 by the National Statistics Committee (NSC) and covers around 5,000 households and around 20,000 individuals on a quarterly basis in accordance with the Kyrgyz Republic Government Regulation on household Sample Survey Statistics n.25 (17 January 2004) and n.281 (10 June 2008). The sample of KIHS is drawn using stratified two-stage random sampling. The country is divided into 16 strata, representing urban and rural dimensions of the seven oblasts (Batken, Jalal-Abad, Issyk-Kul, Naryn, Osh, Talas and Chui), the city of Bishkek and Osh city. In the first stage of sampling, rural and urban Oblast are selected and in the second stage a sample of households is drawn from each stratum. The households in the sample are associated with sampling weights. Sampling weights permit inferences from households included in the sample to the population from which they were drawn. In the KIHS both household weights and population weights are available. The sample size is sufficiently large to allow for robust estimates of poverty at the national, urban-rural, and oblast levels. The survey is longitudinal across the four quarters of the year, but cross sectional across years. A fresh sample of households is drawn every year. For our model, we used the repeated cross-sectional annual data from the KIHS over the period 2013–2017.

3.2 The core model

Building the dynamic logistic model involves the following steps:

- Selection of the main significant individual predictors that can explain poverty.
- Selection of predictors whose effect is time(-space) varying and predictors whose effect is stationary.
- Modelling of time and space-varying parameters, using macro-economic variables at oblast and national level.
- Diagnostics and validation.
- Forecast of the probability to be poor for each household in the sample: having predicted the parameters of the model, forecasts are determined by uprating the macro-variables (the socio-economic environment where the household lives).

We can group the selected household-level predictors in three separate blocks:

- Demographic predictors: age of the household head, gender, and family size.
- Socio-economic predictors: educational level, share of employed members of the household, area of residence (urban or rural).
- Access to services, ownership of durable goods, and housing conditions: availability of a satellite antenna in the household, availability of a landline, ownership of a car, an electric stove, a washing machine, number of residential rooms in the housing unit.

The first block of predictors includes those demographic characteristics that may have a strong impact on the risk of poverty, particularly the number of components of the household. The age of the household head deals with the stage in the life cycle of a household. The second block captures characteristics of the household related to the labour market. The educational level attained by the household is supposed to capture the human capital attributes of the household. The educational level is provided by two variables: the share of highly (tertiary) educated members of the household and the share of professionally educated members. The ratio of the number of family members employed to the total number of components allows one to measure the burden weighing on members in occupation. The third block of variables represents a set of control variables related to the overall standard of living of the household. The possession of durables also concerns the way consumption is measured. Consumption of durables is estimated at the cost of services the household receives from the goods in its possession during the period.

The individual level variables have been selected on the basis of an exploratory analysis that reveals the association between each predictor and the poverty status of an household. There is, of course, the possibility that omitted variables can affect poverty risk, which may lead to omitted variable bias.

All these variables concern the characteristics of the household but not the variables that define the environment where the households live. A multi-level analysis can test the effects of macro-economic aggregates on individual's odds of poverty. Specifically at oblast (regional) level we selected the unemployment rate (U_{jt}) and at national level the per capita gross national product (GDP_t) to model the varying-intercept α_{jt} (see equation 3). We seek to identify separate longitudinal and cross-sectional associations between unemployment and poverty status. To do so, following Fairbrother and Martin (2013), we calculated the average unemployment rate for each oblast over the period. This average should capture the structural association of enduring differences in oblasts' unemployment. The cyclical association between regional unemployment and poverty, instead, should be evaluated using as predictor the unemployment deviation from the regional mean. Note that the cross-sectional component of unemployment ($\bar{U}_j$) and the longitudinal component ($U_{jt} - \bar{U}_j$) are orthogonal and their effects can be estimated separately. Per capita GDP at national level enters the model as third level predictor of the α_t coefficient.

Since the main goal of our paper is to investigate the behavior of poverty status determinants over time, we first identify which are the predictors with time-varying pattern, i.e. which coefficients should be treated as random and then which of the possible covariances between errors should be estimated. The reason for this step is, that, having our model a large number of predictors, passively assuming all parameters to vary randomly could result in a excessively and unnecessarily complex model. Instead, we identify the random coefficients by fitting a model separately for each year and then examine the estimated coefficients of the predictors. Coefficients that are prime candidates for being treated as fixed are those that are small in size and almost unvarying over time.

Level of education and the household size were the predictors with large variability across oblast and time. We modelled the coefficients β_{jt} associated to these predictors.

Overall, the model presents the following structure:

$$\begin{aligned} \pi_{i[jt]} = \text{logit}^{-1} \Big(& \alpha_{jt}^{oblast-year} + \beta_{jt}^{ED,oblast-year} \cdot x_{i,EDUC} + \\ & + \beta_{jt}^{S,oblast-year} \cdot x_{i,SIZE} + \sum_{k=1}^{K} \beta_k^{fixed} \cdot x_{i,k} \Big) \end{aligned} \tag{6}$$

The main feature of the priors (or higher levels model) for the varying intercepts in Equation 6 is that every group of state level and time level parameters are normally distributed around a regional mean and a time mean respectively.

$$\begin{aligned} \alpha_j^{oblast} &\sim \text{N}\Big(\gamma_0 + \gamma_1 \cdot \bar{U}_j + \gamma_2 \cdot \bar{U}_j \text{Area};\ \sigma^2_{\alpha,oblast}\Big) \\ \alpha_t^{year} &\sim \text{N}\Big((\delta_0 + \delta_1 \cdot GDP_t^{country};\ \sigma^2_{\alpha,year}\Big) \end{aligned} \tag{7}$$

Additionally, the region-time interaction effects (oblast-year) have a structured model of their own:

$$\alpha_{jt}^{oblast-year} \sim \text{N}\Big(\alpha_j^{oblast} + \alpha_t^{year} + \alpha \cdot (U_{jt} - \bar{U}_j);\ \sigma^2_{\alpha,oblast-year}\Big) \tag{8}$$

Analogously, the varying slopes in Equation 6 are structured as follows:

$$
\begin{aligned}
\beta_{jt}^{ED,oblast-year} &\sim \mathrm{N}\left(\beta_{j}^{ED,oblast} + \beta_{t}^{ED,year};\ \sigma^2_{\beta,ED,oblast-year}\right)\\
\beta_{j}^{ED,oblast} &\sim \mathrm{N}\left(\zeta_0 + \zeta_1 \cdot \bar{U}_j;\ \sigma^2_{\beta,ED,oblast}\right)\\
\beta_{t}^{ED,year} &\sim \mathrm{N}\left(\xi_0 + \xi_1 \cdot \text{time};\ \sigma^2_{\beta,ED,year}\right)\\
\beta_{jt}^{S,oblast-year} &\sim \mathrm{N}\left(\beta_{j}^{S,oblast} + \beta_{t}^{S,year};\ \sigma^2_{\beta,S,oblast-year}\right)\\
\beta_{j}^{S,oblast} &\sim \mathrm{N}\left(\phi_0;\ \sigma^2_{\beta,S,oblast}\right)\\
\beta_{t}^{S,year} &\sim \mathrm{N}\left(\psi_0;\ \sigma^2_{\beta,S,year}\right)
\end{aligned} \tag{9}
$$

There is specific data pre-processing, however continuous predictors are mean centered and scaled by two times their standard deviation. Centering predictors in multilevel models reduces the correlation between (slope and intercept) random effects, and this makes it possible to interpret the magnitudes of one set of random effects separate from the others and to improve the numerical stability of the estimation algorithm. Standardization is obtained by dividing the centered inputs by two standard deviations, so that the resulting coefficients can be interpreted roughly in the same way as those of binary predictors (Gelman, 2008).

3.3 Convergence and post-processing

The "core" model has been estimated using Stan. Stan, a programming language designed to make statistical modeling easier and faster, especially for Bayesian estimation problems, can help estimate complex models with large numbers of parameters as the dynamic multilevel models. The library `rstanarm` in R which is based on the `lme4` syntax (Carpenter et al. 2017; Stan Development Team 2017) allowed us to use Stan into R. Once specified, the dynamic poverty model has been estimated by a fully Bayesian model using the function `stan_glmer`. Through the Hamiltonian Monte Carlo sampling we drew posterior distributions of the estimated parameters assessing the uncertainties in a Bayesian analysis described by a numerically calculated posterior distribution. Particularly, we run the MCMC algorithm on three separate chain for 5,000 iterations each. We saved only the last 2,500 every 50 iterations to form a posterior sample of size 1,000 for each of three chain. These posterior samples allowed the posterior estimation of the parameters.

4 Main empirical results

4.1 The role of individual predictors

Figure 2 reports the "population-average" coefficients, that comprises the estimated "fixed" coefficients of the individual predictors along with the "fixed" part of $\widehat{\beta}_{jt}$. From the output of the model, we can see which are the predictors that influence the probability of being poor in a positive way and those who influence poverty status negatively. Moreover, based on their size, we can also understand the most important predictors. Moreover, using the "divide by 4 rule"[1] we can get the idea of how is the influence of each predictor on poverty status. For example, having a car influence negatively the probability of being poor of at maximum around 18.5% (-0.74/4), all other things be equals.

Summing up, the main results of the model can be summarized as follows:

- Individual factors that negatively affect the probability of being poor (roughly in order of 'importance'):
  - Share of employed members in the household;
  - Share of highly educated members in the household;
  - Availability of an electric stove (stationary);
  - Availability of refrigerator;
  - Number of rooms.
- Individual factors that positively affect the probability of being poor (roughly in order of 'importance'):
  - Household size;
  - Age (over 50) of the household head;
  - Gender (female) of the household head.

4.2 Effects of regional-level and time-level variables

We now turn to the effects of macro-variables on the time-space varying intercept α_{jt}. The estimated intercept is:

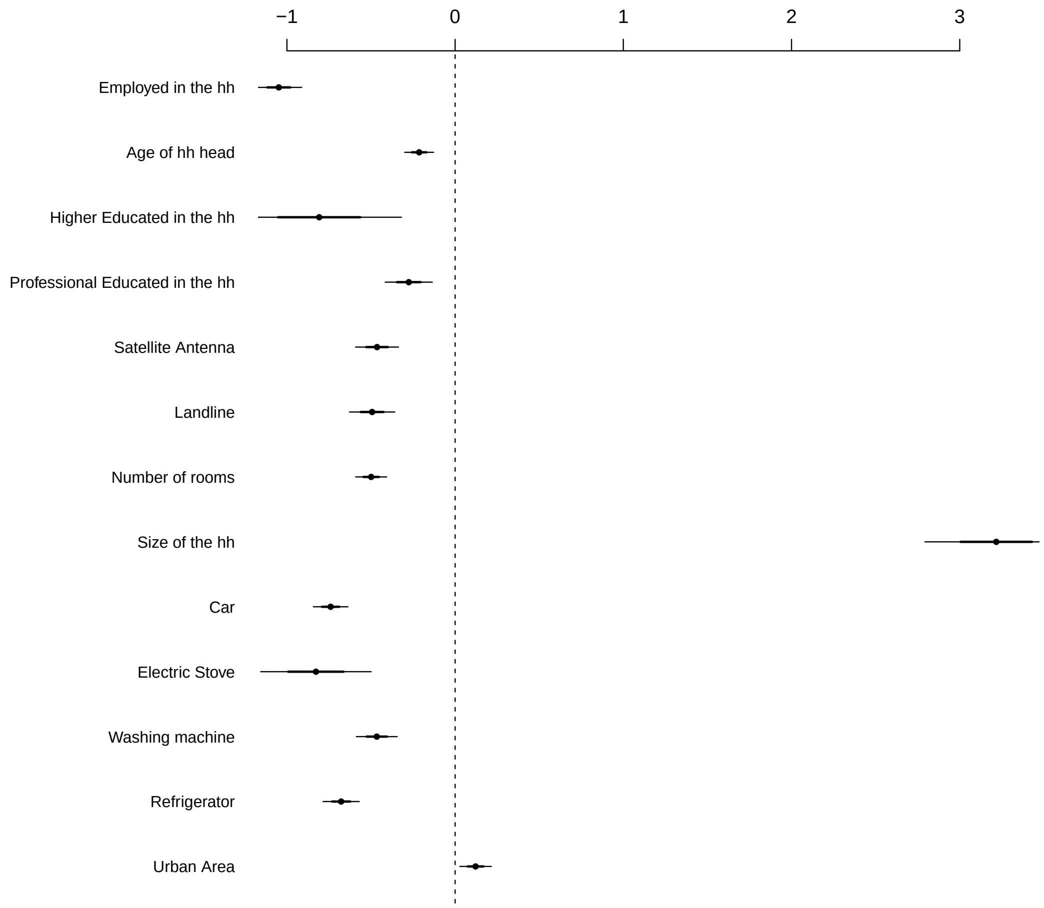
$$\alpha_{jt}^{oblast-year} = -1.71 + 0.75 * \bar{U}_j - 0.31 * \bar{U}_j * \text{Urban} + 0.08 * (U_{jt} - \bar{U}_j) - 0.058 * GDP_t + \text{errors}$$

The unemployment rate matters substantially for poverty and this association holds cross-sectionally but less longitudinally: there is a significant effect of enduring differences in oblasts' level of unemployment, but the longitudinal variation in the level of unemployment (measured as deviation from the regional mean) over the period is weakly associated with variation in poverty risk (coefficient around 0.08). There is a significant interaction between unemployment and area of residence: if the area of residence is urban the impact of the regional unemployment rate in the probability to be poor is lower. There is a significant trickle-down effect of national GDP: the growth of per capita GDP over time reduces the time-varying intercept α_t, as shown in Figure 3. The evident declining trend of the intercept translates into a lower probability of being poor over time for all the households in the sample.

Figure 4 reports, for a selected number of oblasts, the estimated time and space intercepts α_{jt}, for both rural and urban areas (straight and dotted lines). For some oblasts the time pattern is clearly decreasing although there are significant differences between urban and rural areas. In the region of Chui (bottom left panel) α_{jt} shows instead an increasing evolution. The lower right panel reports the estimated time-varying intercepts $\alpha_{\text{Bishkek},t}$ and $\alpha_{\text{Osh City},t}$ both only urban areas. The picture is completely different: a decreasing pattern for Osh city and an irregular time pattern for the capital of the country Bishkek.

[1] We applied the "divide by 4 rule" to get an upper bound of the predictive difference in the probability of being in favor of redistribution moving from the baseline category to the comparison category (Gelman and Hill, 2007, p. 82).

Figure 2: *Estimated "fixed" coefficients of individual predictors along with the "fixed" part of* $\widehat{\beta}_{jt}$.



Going back to the core model 6, we look now at the time-space varying effects of the slopes $\beta_{jt}^{oblast-year}$. The evolution of the coefficient associated to the percentage of high educated members in the household is:

$$\beta_{jt}^{ED,oblast-year} = -0.81 + 0.21 * \bar{U}_j - 0.18 * time + \text{errors}$$

The equation shows that the negative effect of having educated members in the household on the probability to be poor grows over time. Figure 5 shows for each year 2013–2018, the probability to be poor of a 5-member household with identical characteristics but the percentage of high educated people in the family. The curves for all the years decrease over time for every given percentage of high educated members in the households. The 2018 forecast follows the same tendency.

The coefficients

$$\beta_{jt}^{ED,oblast-year}$$

are also affected by the unemployment rate of the oblast: where the unemployment rate is

Figure 3: *Time-varying effect on π_i by oblast due to GDP growth*

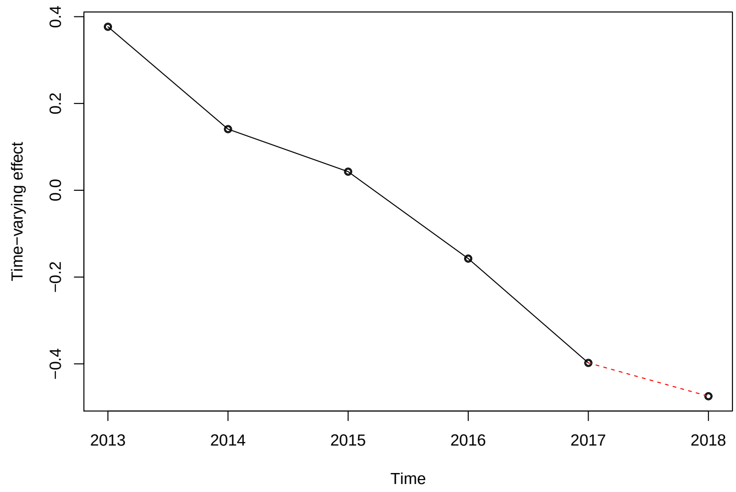
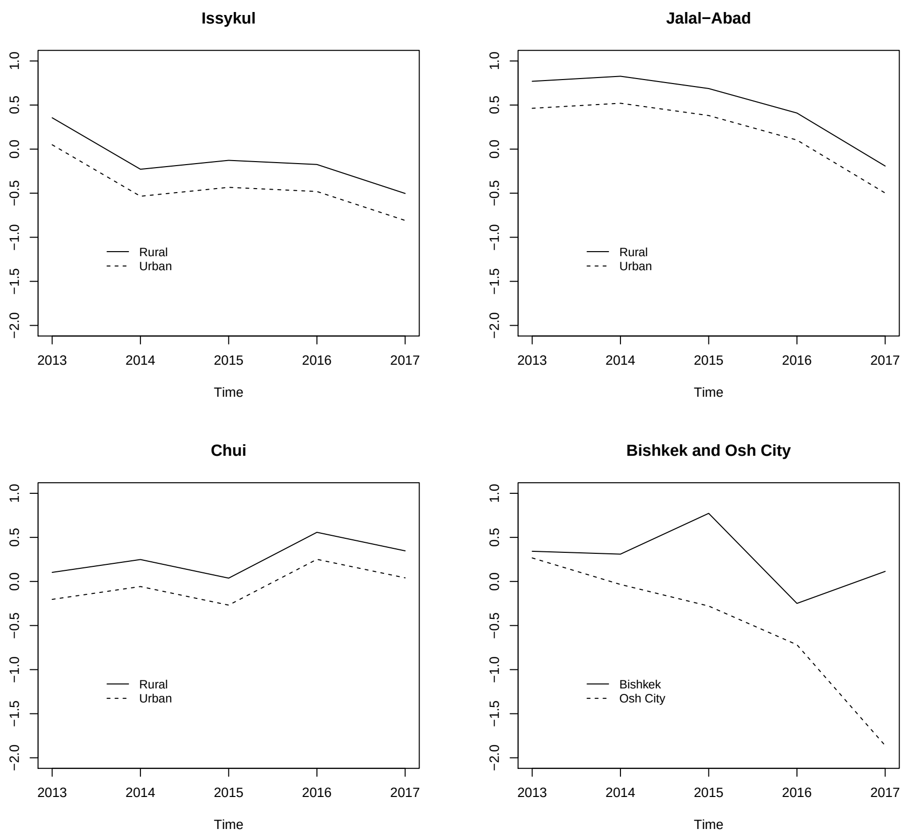
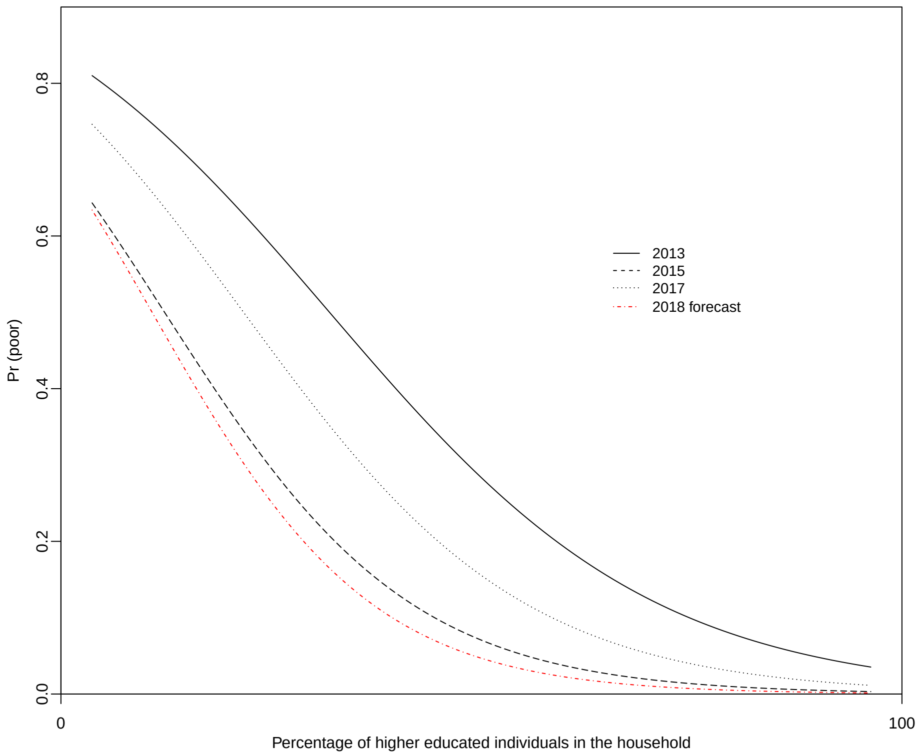


Figure 4: *Time-varying effect on π_i by oblast.*



high, the impact of having educated members in the household is less. The negative effect

Figure 5: *Probabilities to be poor of an average 5-member hh by level of education.*

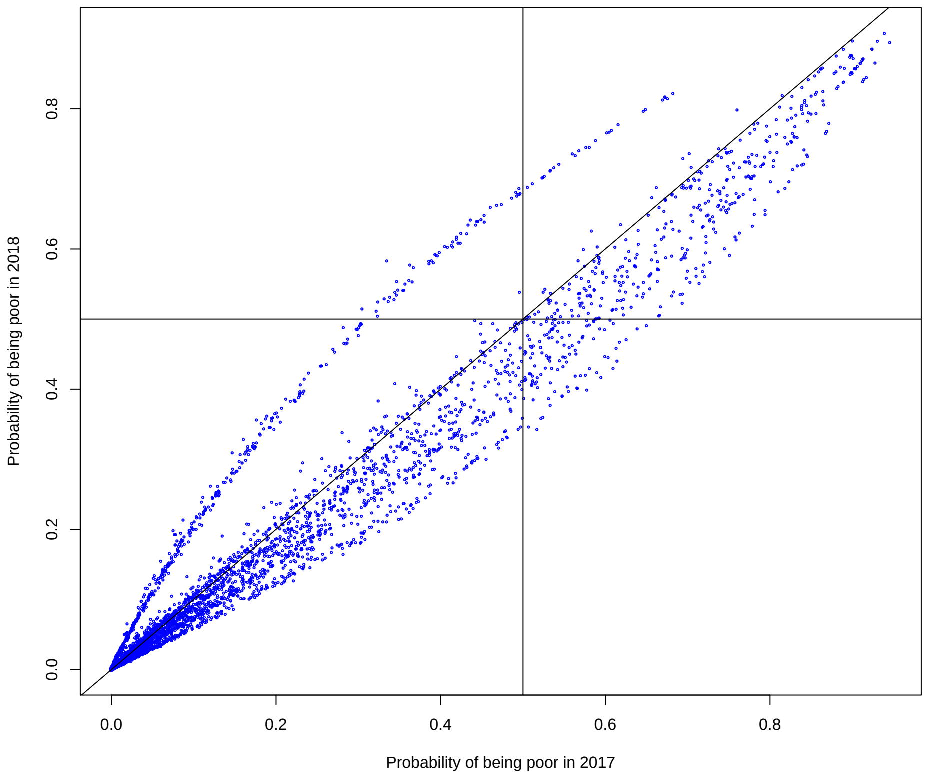


of education on π_i is weaker in oblasts with high unemployment rate.

5 Mobility analysis

The dynamic model 6 estimates for each household i of the sample the probability of being poor, i.e. the in-sample predictions. The out-of-sample predictions refer to the year 2018. As stated in Section 2, these 2018 probabilities forecast are conditioned on the assumed time invariant characteristics of the households in 2017, on the time-varying effects of some predictors (level of education and household size), on the macro-economic forecast of unemployment rate and per capita GDP in 2018. Figure 6 shows the scatterplot of the estimated probabilities in 2017 and the forecast probabilities in 2018. As evident form the graph, the majority of households has a lower probability to be poor in 2018 than in 2017 with some notable exceptions of households resident in some specific areas.

Figure 6: *Scatterplot of the estimated probabilities in 2017 and forecast probabilities in 2018*



Based on these predicted probability, we can estimate the number of people that transit in and out vulnerability status. Setting a cut-off value equal to 0.5 means that when the predicted probability of being poor is above 50% then the household is predicted to be poor. In this way we can have a "hard" classification of households according their actual and expected poverty status: poverty or not-poverty. Table 1 shows the expected mobility in and out of poverty of Kyrgyz households in 2017–2018. The expected probability to escape from poverty during this period is around 25%, while the probability of falling into poverty is 1.3%.

Table 2 shows, instead, the expected mobility in and out of poverty of Kyrgyz individuals in 2017–2018, obtained using the sample population weights available in the survey. For the

Table 1: *Expected transition matrix of the households, 2017–2018*

	2018		
2017	Not poor	Poor	
Not poor	98.7%	1.3%	100%
Poor	25.2%	74.8%	100%

individuals, the expected probability of stepping out of poverty is much lower than households: 19.3% *versus* 25.2%. This is essentially due to the fact that large size households have less probability to leave the status of poverty even when positive aggregate shocks occur.

Table 2: *Expected transition matrix of the households, 2017–2018*

	2018		
2017	Not poor	Poor	
Not poor	97.0%	3.0%	100%
Poor	19.3%	80.7%	100%

6 Concluding remarks

In this analysis we tried to answer the question on how to evaluate mobility in and out of poverty when longitudinal data are not available. We distinguished between cross-sectional and longitudinal associations between macro-economic variables and poverty, taking into account the clustering of each observation (individuals or households) within region&years. The proposed methodology relies on dynamic multilevel models that estimate directly the probability of individual poverty status as a function of individuals' characteristics and circumstances, in interaction with time-varying and time-constant features of their economic contexts. The proposed methodology overcomes some strong assumptions that underlie the existing methodologies to evaluate poverty dynamics in absence of panel data.

We combined five years of households surveys and fit a Bayesian multilevel logistic regression dynamic model to estimate poverty status as a function of the year, the region, regional-level variables and national-level variables and various individual characteristics.

We illustrated our methodology estimating a dynamic multilevel model for the Kyrgyz Republic in the years 2013–2018. The model explicitly accounts for the hierarchical nature of our data: households that reside in oblasts and over time. We found that level of education plays an important role in predicting poverty and its influence increases over time and remains important across regions. At regional level, unemployment rate matters substantially for poverty and this association holds cross-sectionally but not longitudinally. The longitudinal variation in the level of unemployment (measured as deviation from the regional mean) over the period does not show a strong association with poverty risk. Unemployment rate affects individual poverty differently according to where people live: rural or urban areas. Per capita gross regional product is not associated with poverty neither cross-sectionally nor longitudinally. Instead is per capita gdp at country level that manifests a trickle down effect over time. The expected probability of escape from poverty between 2017 and 2018 is less than 20%, which is a much larger than the probability to fall into poverty.

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