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Poverty Mapping in the Kyrgyz Republic[1]

Methodology and Key Findings

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I. Introduction

1. This report describes the process of and results from a poverty mapping exercise for the Kyrgyz Republic, using the Kyrgyz Integrated Household Survey (KIHS 2009)[2] and the Population and Housing Census (2009).

2. Poverty mapping is an exercise to estimate poverty incidence at a level where a typical household income and expenditure survey cannot produce statistically reliable poverty estimates due to high sampling errors. In the Kyrgyz Republic, official poverty rates are not produced below oblast level, as the sampling errors of the survey data become non-negligible. Various poverty mapping methodologies were devised to overcome increasing imprecision of poverty estimates as they are disaggregated.

3. The poverty mapping methodology used for this exercise is the Small Area Estimation (SAE) method developed by Elbers, et al. (2003). This methodology is one of the most commonly used poverty mapping methodologies around the world and has been widely tested and validated. The method takes advantage of the strengths of both sources: the breadth of data in the integrated survey, including expenditure data, and the size and coverage in the Census, meaning that data were collected from all households in the country as opposed to 'sampled' from a primary sampling unit.

4. The goal for the poverty maps of the Kyrgyz Republic was to obtain poverty estimates at rayon or district level, a level at which the survey is not representative. For the purposes of this poverty map, all 7 oblasts of the Kyrgyz Republic have been considered and one out of the two cities holding a similar status to oblasts, for which data was collected in the survey.3 These include Issyk-Kul, Jalalabad, Naryn, Batken, Osh, Talas, Chui and Bishkek city. Oblasts are further disaggregated into 40 administrative units called "rayons" (equivalent to districts) and 13 towns4 Bishkek is also divided into 4 rayons,

5. This poverty mapping exercise has been conducted jointly with the National Statistics Committee (NSC). The World Bank team has provided hands-on training on the poverty mapping method to the NSC members. Since then, the NSC team and the World Bank team have continued to work together and have cooperated on the technical and methodological aspects of the analysis.

Poverty mapping and Kyrgyzstan

6. Kyrgyzstan's landscape is blessed with a dramatic range of weather conditions and altitudes from snow-capped peaks, dry deserts, vast grasslands, to fertile farmlands. This rich terrain supports a rich diversity of plant and animal life. Kyrgyzstan is also rich in cultural diversity - the life style varies from a traditional nomadic style to the modern lifestyles in Bishkek. The landscape has shaped and preserved this nomadic lifestyle and culture for centuries while also allowing for economic growth in cities like Bishkek and Osh. Kyrgyzstan is a land-locked country surrounded by four countries: Kazakhstan in the north,

[2] We use the KIHS 2009, in spite of the availability of the KIHS 2010. The 2009 KIHS was conducted the same year as the census. Poverty mapping involves the assumption that the parameters of the consumption model remain constant between the survey and the census, and only the household variables change. This assumption holds true if the survey and the census are from the same year, and this is usually given the highest preference.

[3] The Government of the Kyrgyz Republic has identified Bishkek and Osh City as cities with "republican subordination" which, in effects, gives these two cities oblast status.

[4] Throughout the report the term rayon is used both for towns and rayon for brevity.

China to the east and south-east, Tajikistan to the south-west and Uzbekistan to the west. Trade with these countries shapes economic opportunities for border areas.

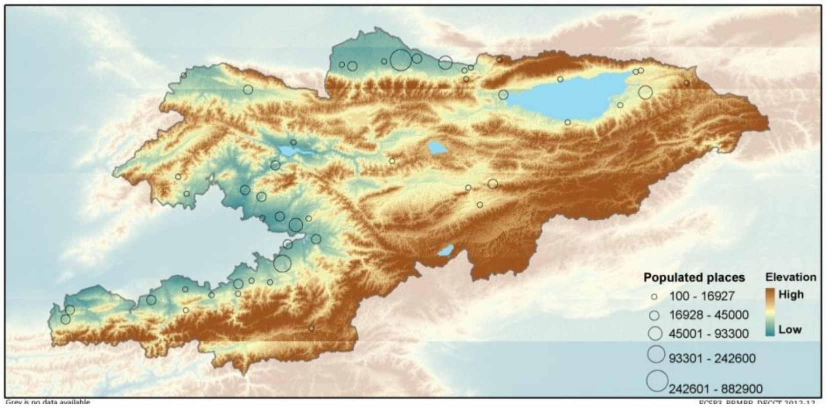
7. Poverty mapping is useful for a country with strong regional diversity. For example, Atamanov et al. (forthcoming) suggests discernible welfare disparities between the capital city of Bishkek and the rural and urban areas in the rest of the country. It shows that educational attainment and household demographics differ significantly depending on the area of residence. Such diversities can be observed even among rural areas. The rural areas of Chui (in relatively close proximity to the capital, Bishkek) appear to enjoy significantly better living standards than rural areas in the rest of the country.

8. National poverty rates alone cannot tell us the living standards faced by people in different parts of the country. Disaggregated poverty indicators will help policy makers provide resources to the areas that need it the most in an objective and transparent manner. Besides poverty maps, Kyrgyzstan has other rich geo-referenced databases which include rayon level public expenditure data created by the government of Kyrgyzstan and the World Bank.

Figure 1: Administrative Map of Kyrgyzstan

Source: nationsonline.org

Figure 2: Elevation Map of Kyrgyzstan



Source: SRTM[5]

II. Methodology and Data

II.1. Methodology

9. The selection of the specific poverty mapping methodology is critical; numerous methods are available and have been documented by Bigman and Deichmann (2000). An SAE method developed by Elbers et al. (2003) (henceforth referred to as ELL) has gained wide popularity amongst development practitioners around the world.

10. This Kyrgyz poverty map adopted the SAE method developed by ELL. It imputes consumption levels into census households based on a consumption model estimated from the household survey. In order for this to be possible, the consumption model must include explanatory variables (household and individual characteristics) that are available in both the census and the survey. By applying the estimated coefficients to the "common" variables from the census data, consumption expenditures of census households are imputed. Poverty and inequality statistics for small areas are then calculated with the imputed consumption of census households.

11. One advantage of this method is that it not only estimates poverty incidence but also estimates standard errors of poverty estimates. Since poverty estimates are computed based on imputed consumption, they cannot escape imputation errors, which are their standard errors. ELL analyzed the properties of such imputation errors in detail and derived a procedure to compute standard errors of poverty estimates. Box 1 below provides greater detail on this method.

II.2. Main Data Sources and Issues faced

12. The ELL method generally makes use of household survey and population census data. The Kyrgyzstan poverty map is no exception, using the unit record Kyrgyz Integrated Household Survey

[5] Jarvis , A., H.I. Reuter, A. Nelson, E. Guevara, 2008, Hole-filled SRTM for the globe Version 4, available from the CGIAR-CSI SRTM 90m Database (http://srtm.csi.cgiar.org)

(2009) and the Population and Housing Census (2009).[6] The household survey and the Census for the Kyrgyz Republic were from the same year, 2009, so there was some confidence that the requisite requirement for poverty mapping would be fulfilled – the common variables between the survey and the census would be comparable.

Box 1: The Small Area Estimation Method Developed by ELL (2003)

The method proposed by ELL has two stages. In the first part, a model of log per capita consumption expenditures ($\ln y_{ch}$) is estimated in the survey data:

$$\ln y_{ch} = X_{ch}{}' \beta + Z' \gamma + u_{ch}$$

where $X_{ch}{}'$ is the vector of explanatory variables for household *h* in cluster *c*, β is the vector of associated regression coefficients, Z' is the vector of location specific variables with γ being the associated vector of coefficients, and u_{ch} is the regression disturbances due to the discrepancy between the predicted household consumption and the actual value. This disturbance term is decomposed into two independent components: $u_{ch} = \eta_c + \varepsilon_{ch}$ with a cluster-specific effect, η_c and a household-specific effect, ε_{ch}. This error structure allows for both a location effect – common to all households in the same area – and heteroskedasticity in the household-specific errors. The location variables can be at any level – rayon and village, and can be drawn from any data source that includes all the locations in the country. All parameters regarding the regression coefficients (β , γ) and distributions of the disturbance terms are estimated by Feasible Generalized Least Square (FGLS). In the second part of the analysis, poverty estimates and their standard errors are computed. There are two sources of errors involved in the estimation process: errors in the estimated regression coefficients ($\hat{\beta}$, $\hat{\gamma}$) and the disturbance terms, both of which affect poverty estimates and their levels of accuracy. ELL propose a way to properly calculate poverty estimates as well as measure their standard errors while taking into account these sources of bias. A simulated value of expenditure for each census household is calculated with predicted log expenditures $X_{ch}{}' \hat{\beta} + Z' \hat{\gamma}$ and random draws from the estimated distributions of the disturbance terms, η_c and ε_{ch}. These simulations are typically repeated 100 times.[7] For any given location (such as a *rayon)*, the mean across the 100 simulations of a poverty statistic provides a point estimate of the statistic, and the standard deviation provides an estimate of the standard error.

13. The census data covered roughly 1.2 million households, while the household survey covered around 4,500 households. A wide range of household information was collected including educational attainments, labor activities and occupation, residential information, and employment and housing conditions. As is the practice in all countries, the Census did not include household consumption and

[6] Details of Kyrgyz Integrated Household Survey (2009) are available in Annex.
[7] In the case of this Kyrgyz poverty mapping, we did not find much difference in results by increasing the number of replications.

income levels, but its wide coverage of household characteristics is an advantage for imputing household consumption precisely.

II.3. Technical Challenges

14. The ELL poverty mapping methodology has been continued to be updated to improve statistical accuracy of poverty estimates in response to findings from the latest studies by experts and researchers. To this end, the World Bank research department prepares a variety of documents and manuals to inform development practitioners of the latest developments and methodological improvements in the ELL method, and they provide recommendations so that the latest findings are reflected in the ongoing poverty mapping exercise. These improvements are also reflected in the updated versions of the PovMap2 software produced by the World Bank to assist with application of the procedure.

15. The present Kyrgyzstan Poverty Mapping Exercise has faced two main technical challenges: (i) some inconsistencies in reporting between the Census and the Kyrgyz Integrated Household Survey 2009; (ii) potential over-assessment of the precision of poverty estimates; and (iii) significant differences in consumption pattern across oblasts

Addressing inconsistencies between the census and the household survey

16. As per the recommendation of ELL, a national level model was created using the consumption variable from the KIHS and several household and region level variables on the right hand side, that were also present in the census. These common variables included the household size, educational level of household head and other household members, employment status of household head and other household members, employment industry, household characteristics (such as availability of electricity, sanitation facilities, size of living area and so on).

17. However, in order to generate reliable poverty maps, these variables need to have a similar mean and distribution across the census and survey. In the case of Kyrgyzstan, this was not achieved, and an important variable, household size, was different in the survey and census. As is common in some country surveys and censuses, the definition of a household differed during the implementation of the survey and census. This could explain the difference in the mean household size across the survey and census. This difference in definition also prevented a feasible adjustment procedure to the household identifier in either the survey or the census prior to implementation of the modeling and simulation exercises. This may have occurred because surveys and censuses are not necessarily designed for an exercise such as poverty mapping and often serve other purposes. For the purpose of poverty mapping, however, the difference in the way a household was defined – household in the survey, and housing unit in the census – also caused a number of other household level variables to not be strongly comparable across the survey and census.

18. In order to ensure robustness of the estimates, the Kyrgyz poverty mapping exercise minimizes the use of household and individual level variables, and instead uses many village aggregates of census variables to predict household expenditures. By construction, the latter group of variables is comparable in that the means and distributions are similar between the census and the survey since they are created from the census. However, a challenge of using such location aggregates of census variables is that they cannot explain variation of household expenditure within the location. Therefore, if the location is larger, its ability to explain variation of household expenditures will be limited. To minimize such a problem, the

Kyrgyzstan poverty mapping created as many village aggregates of census variables as possible to more closely predict household expenditure.[8] However, when comparable, household level variables were used.

Addressing possible over-statement of the precision of estimates

19. In a recent contribution, Tarozzi and Deaton (2009) highlighted a number of concerns with the ELL methodology. Notably, they show that, under certain circumstances, the ELL method can result in an overly optimistic assessment of the statistical precision of the poverty map estimates. The present Kyrgyzstan Poverty Mapping Exercise has paid special attention to this concern and has undertaken a number of steps to address these issues.

20. The specific concerns raised by Tarozzi and Deaton (2009) can be summarized as follows. First, differences in consumption patterns can bias both poverty estimates and the standard errors. The ELL method estimates a consumption model that is assumed to apply to all households within each domain. The implicit assumption is that the relationship between household expenditures and its correlates is the same for all households within the domain, and that all remaining differences are due not to structural factors, but are attributable to errors. This is not a minor assumption and is explicitly acknowledged as such in ELL (2003)

21. Second, Tarozzi and Deaton (2009) caution that the misspecification in the error structure can lead to overstating the precision of poverty estimates. PovMap2, the software used for poverty mapping, in its current configuration can incorporate only two layers of errors (or residuals): at the levels of the household and at the level of some unit of aggregation above the household. In the case of the Kyrgyzstan poverty mapping exercise, the two layers of errors were selected to be households and the clusters (i.e., rayon). However, as noted by Tarozzi and Deaton (2008), there could be correlation in errors also at the oblast level. Tarozzi and Deaton (2009) show that if the ELL method is applied and the possible correlation of errors at these higher levels of aggregation are ignored, then standard errors on poverty estimates could be sharply understated – resulting in an overly optimistic assessment of the precision of the poverty estimates. An obvious solution to this issue is to introduce multiple layers of errors during the consumption modeling. This, however, is not a practical solution given the structure of the available PovMap2 software and, more importantly, given the sampling design of most household surveys, including the Kyrgyz Integrated Household Survey.

22. Alternative remedies to resolve this issue were explored in the Kyrgyz Poverty Mapping Exercise. These are suggestive, but are not able to entirely remove the potential concern. Apart from setting the cluster level to rayon, dummies for each oblast were also included, and even interacted with rayon and household level variables.

Different consumption models for each oblast

23. The latest recommendation from the World Bank research department is not to use multiple consumption models to predict household expenditures. Increasing the number of consumption models is

[8] In other words, location characteristics can explain well between-location effects but cannot explain within-location effects. To explain the within-location effects, further disaggregated location specific characteristics need to be constructed. Location characteristics have additional benefits to minimize the risk of biases indicated by Tarozzi and Deaton (2009), as described below.

good to reflect differences in consumption patterns across areas. However, it is sometimes problematic since the number of observations for each area becomes small and, as a result, the regression coefficients become less stable. The World Bank research department now recommends one model for each poverty map and if there is any geographic variation in consumption pattern, then they recommend the use of area dummies and their interactions with other variables.

24. The Kyrgyzstan poverty mapping exercise tries to follow the recommendations as much as possible. However, analysis shows clear evidence of heterogeneity in consumption models across oblasts. Therefore, the Kyrgyzstan poverty mapping produces a separate consumption model for each oblast. This issue will be discussed in the next section where production of poverty mapping exercise is described.

III. Production of Poverty Maps

Creation of village level aggregates of variables in the Census

25. As stated before, household and individual level variables are not always comparable between the Census and the Survey. For example, Table 1 shows average household sizes are largely different for some oblasts such as Jalalabad, Osh, Talas, and Chui. Furthermore, the direction of difference is not uniform. For Chui oblast, the census average is smaller than the survey average. On the other hand, for Jalalabad, Osh and Talas, the census average is larger than the survey average. Such differences are also observed for other household and individual level variables. This restricts the use of household and individual level variables for predicting household expenditures. However, the use of the variable household size in a few models is justified due to the fact that the census mean still lies within the survey confidence intervals. The household size variable therefore was included in the final models unless the coefficient of the variable is statistically significant.

Table 1:Average Household Size per oblast in Census and Survey

Oblast	CENSUS Oblast-level	SURVEY Oblast-level	Std. error	95% confidence interval	
Issyk-Kul oblast	4.29	4.62	0.61	3.25	6.00
Jalalabad oblast	5.48	4.98	0.52	3.83	6.13
Naryn oblast	5.05	4.94	0.52	3.77	6.11
Batken oblast	5.44	5.27	0.51	4.12	6.42
Osh oblast	5.99	5.01	0.59	3.69	6.34
Talas oblast	5.16	4.82	0.52	3.65	6.00
Chui oblast	3.84	4.42	0.59	3.10	5.74
Bishkek city	3.78	3.84	0.53	2.58	5.10

Source: The World Bank and NSC team calculations based on KIHS 2009 and Populaiton Census 2009.

26. To overcome the limited availability of household and individual level variables to predict household expenditure, many location specific variables are created. In Kyrgyzstan, due to confidentiality reasons, the National Statistical Office, in its goal to ensure the anonymity of respondents includes

location identifiers only down to the rayon level in the Census and household surveys. As a result, originally, this poverty mapping exercise created rayon level means of variables including household size, household education and employment variables, and other household characteristics. These census means were then merged into the survey, effectively creating an entire array of rayon level means that were entirely comparable between the survey and census because they were created in one dataset.

27. Although these rayon level aggregates of the census variables effectively solved the issue of comparability between the census and the survey, the rayons were too large (only 56 rayons exist in Kyrgyzstan) and rayon level variables thus leave a significant portion of variation in household expenditure unexplained by these models. As a result, consumption models with rayon level variables cannot produce reliable poverty estimates.

28. In response to this challenge, the Kyrgyz National Statistical Office used village level codes to create more disaggregated location variables. With this added level of disaggregation, many village level means of census variables were created and merged into the survey as well. Kyrgyzstan has only 56 rayons while it has almost 1800 villages in the Census. Even the Survey includes nearly 200 villages in the dataset. Inclusion of village level aggregates of the census variables significantly improves the ability of consumption models to explain the variation of household expenditures within rayons.

One Model vs. Multiple Models

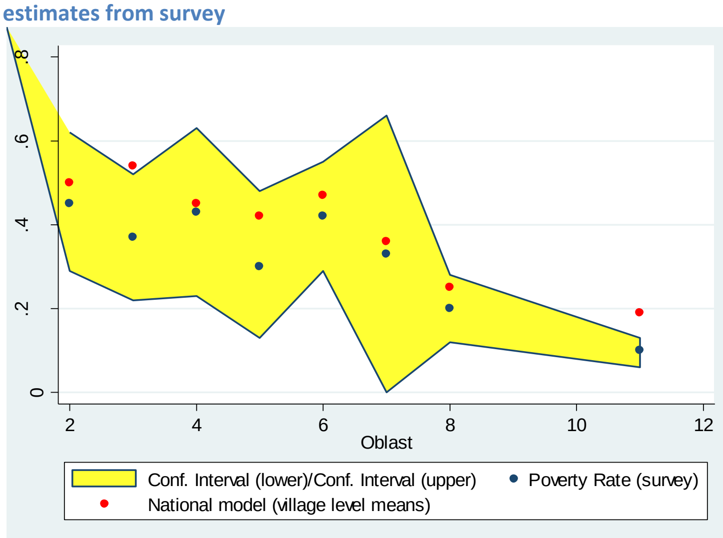
29. Following recommendations from the research group at the World Bank, only one consumption model was created to predict household expenditures. As a preliminary validation exercise for poverty mapping, poverty rates at oblast level using just one (national level) consumption model, predicted by the ELL method, were compared with those directly estimated from household expenditure in the Survey. Note that even poverty rates from the direct estimation in the Survey have sizeable standard errors at the oblast level. Therefore, if poverty rates produced by the ELL method differ significantly from the direct estimates (or lie outside their confidence intervals), this can be seen as evidence that poverty rates derived from the ELL method are likely to be far off from the true levels.

30.

31. Figure 3: Poverty Estimates from PovMap (National Model) vs poverty estimates from survey

32. shows results from using the ELL method for just one (national level) consumption model to estimate poverty rates at the oblast level. It appears that using just one model makes it avoidable that a few oblasts will have imputed poverty rates that are outside the confidence interval of the survey direct estimates.

Figure 3: Poverty Estimates from PovMap (National Model) vs poverty estimates from survey



Source: The World Bank and NSC team calculations based on KIHS 2009 and Populaiton Census 2009.

Note: Oblast codes for this graph are as follows: 2-Issyk-Kul, 3-Jalalabad, 4-Naryn, 5-Batken, 6-Osh, 7-Talas, 8-Chui, 11-Bishkek

33. In

34. Figure 3: Poverty Estimates from PovMap (National Model) vs poverty estimates from survey

35. , the red dots, representing the oblast level poverty estimates simulated by this national model are quite close to survey estimates for Issyk-Kul, Naryn, Osh, Talas and Chui. However, they are moderately different for Batken, and very different in the case of Jalalabad and Bishkek for which the national model predicts a poverty estimate outside the confidence interval of the survey estimates.

Grouping Oblasts

36. When the national model was not successful, the next move was to take a step lower to oblast level. However, increasing the number of consumption models does not necessarily improve the statistical performance of poverty mapping. As the number of models rises, the sample size in the survey data for each model declines, lowering the accuracy of each consumption model. Therefore, an attempt was made to ensure that a single model had a minimum of 600 observations, to reduce the risk of high standard errors.

37. From the table above, it was inferred that the best course of action would be to construct individual models for Issyk-kul, Jalalabad, Chui and Bishkek city, and one consolidated model for Naryn, Batken, Osh and Talas. The details of the five consumption models are included in the appendix.

Table 2: No. of observations per oblast	
Oblast	**No. of Observations**
Issyk-Kul oblast	648
Jalalabad oblast	659
Naryn oblast	524
Batken oblast	503
Osh[9] oblast	340
Talas oblast	528
Chui oblast	646
Bishkek city	727

Source: The World Bank and NSC team calculations based on KIHS 2009 and Populaiton Census 2009.

Final Groups for Models

Table 3: Model selection	
Model number	**Oblasts**
Model #1	Issyk-Kul
Model #2	Jalalabad
Model #3	Chui
Model #4	Bishkek
Model #5	Naryn, Batken, Osh, Talas

38. Each oblast was treated in a unique manner, expanding on its strengths. In some oblasts such as Bishkek city, household sizes remained comparable between the census and the survey, so this household variable was used. In Jalalabad, on the other hand, household sizes were not comparable so it was not used. Similarly, it was assessed what household variables were and were not comparable and an attempt was made to use as many as possible of those that were. When no plausible household level variable was comparable, the census-generated village level means were used. In this way, it was possible to capitalize on the earlier attempts at poverty mapping described above, by using information from old models to determine what was important in each oblast.

Explanatory power of consumption models

39. Both R-square and Adjusted R-square statistics provide information on how well a consumption model can predict the actual consumption expenditure of each census household. Specifically, R-square is a statistic that indicates how well the predicted expenditure from a consumption model fits the actual household expenditure. The higher the R-square, the better the predicted expenditure fits the actual

[9] Excluding Osh city

household expenditure. Adjusted R-square is a modification of R-square that adjusts for the number of regressors in a model. R-square always increases when a new variable is added to a model, but adjusted R-square increases only if the new variable improves the model more than would be expected by chance.

40. In the Kyrgyzstan Poverty Mapping Exercise, the adjusted R-square is generally quite high: 4 out of 5 models record an adjusted R-square of over 43 percent and one model recorded an adjusted R-square over 55 percent. For example, recent poverty mapping exercises in other countries, like Bangladesh and India, some models have the adjusted R-squares less than 40 percent.

Table 4: Adjusted R2 of the different models

Model number	Oblasts	Adj. R^2
Model #1	Issyk-Kul	56.77%
Model #2	Jalalabad	48.14%
Model #3	Chui	42.66%
Model #4	Bishkek	36.36%
Model #5	Naryn, Batken, Osh, Talas	47.48%

Source: The World Bank and NSC team calculations based on KIHS 2009 and Populaiton Census 2009.

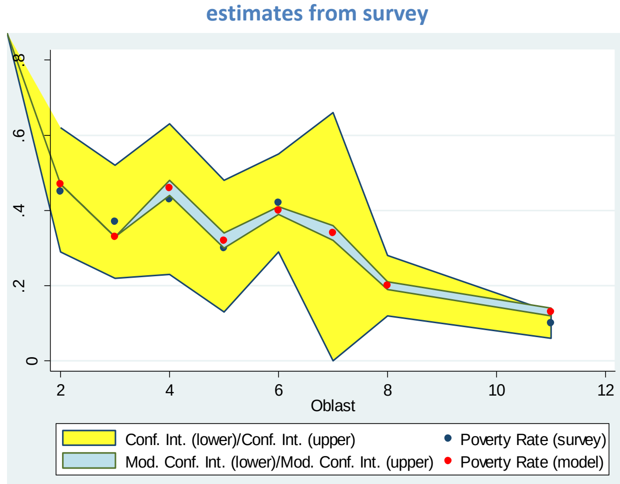
Results of Poverty Mapping

41. The results from this grouping of models were successful and the poverty estimates obtained at oblast level were not only well within survey confidence intervals but also had very low standard errors. In addition, as stated above, the models had consistently high R^2 s.

Table 5: Estimated poverty rates

Oblast	Poverty Rate	Std. Error.
Issyk-Kul oblast	47%	0.00
Jalalabad oblast	33%	0.00
Naryn oblast	46%	0.02
Batken oblast	32%	0.02
Osh oblast	40%	0.01
Talas oblast	34%	0.02
Chui oblast	20%	0.01
Bishkek city	13%	0.01

Figure 4: Poverty estimates from PovMap (5 models) vs poverty estimates from survey



Source: The World Bank and NSC team calculations based on KIHS 2009 and Populaiton Census 2009.

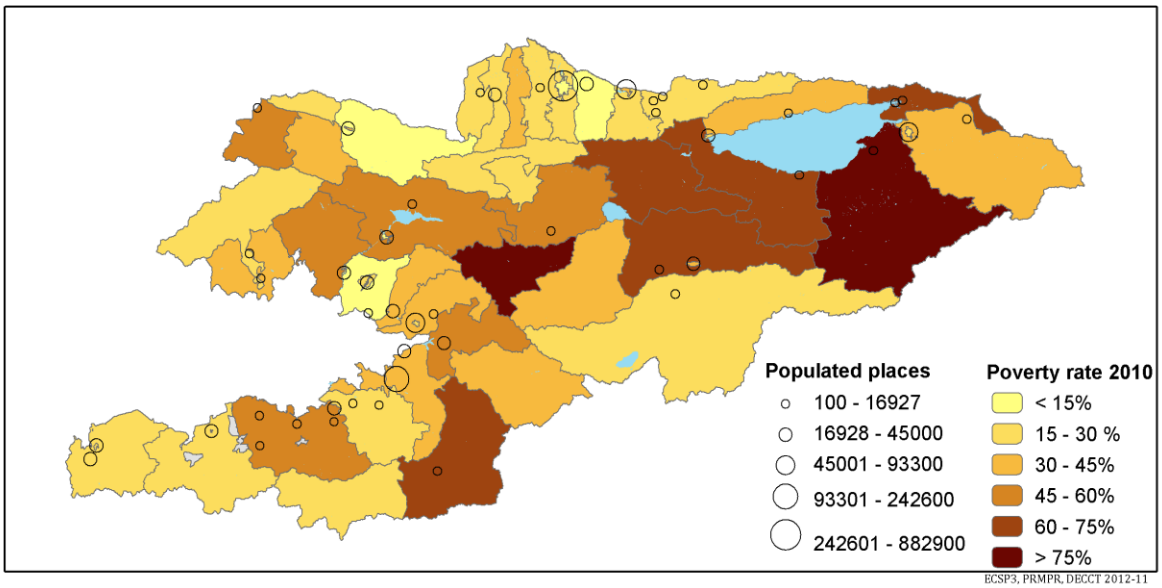
Note: Oblast codes for this graph are as follows: 2-Issyk-Kul, 3-Jalalabad, 4-Naryn, 5-Batken, 6-Osh, 7-Talas, 8-Chui, 11-Bishkek

IV. Maps

42. It is a natural perception that the incidence of poverty can vary markedly across localities within a state or even within a smaller entity such as a rayon. The KIHS data, which is representative only at the oblast level, does not allow for reliable estimates of poverty rates at the rayon level. As described in section I, the ELL poverty mapping procedure combines census and survey data to generate estimates of poverty incidence and inequality at levels of disaggregation such as the rayon. This section examines the spatial patterns of estimated poverty and how they correlate with well-known determinants of poverty like education, employment in agriculture, among others. In addition, this section provides a snapshot of poor areas through poverty maps, including distributions of the poor population.

IV.1. Poverty Map

Figure 5: Poverty Map and Administrative Map of the Kyrgyz Republic



Source: The World Bank and NSC team calculations based on KIHS 2009 and Populaiton Census 2009.

Note: For oblast boundaries, please refer to Figure 1. The above map shows the various rayons, and and the circles depict some towns and cities that are often considered rayons themselves. The smaller circles depict selected populated areas, often rural areas.

43. Using the rayon-level poverty estimates simulated by the poverty mapping exercise, visual representation of the incidence was created on maps of Kyrgyzstan[10], using shape-files. One of its most striking features is to be able to visually depict spatial disparities that may not be obvious on examining data.

44. In the poverty map above, the darker colors indicate higher incidence of poverty. The poorer areas appear to be in the central parts of Kyrgyzstan. The border areas of Kyrgyzstan have a lower incidence of poverty, probably due to their access and connectivity with surrounding countries – particularly with affluent countries such as China to the east and south-east and Kazakhstan to the north.

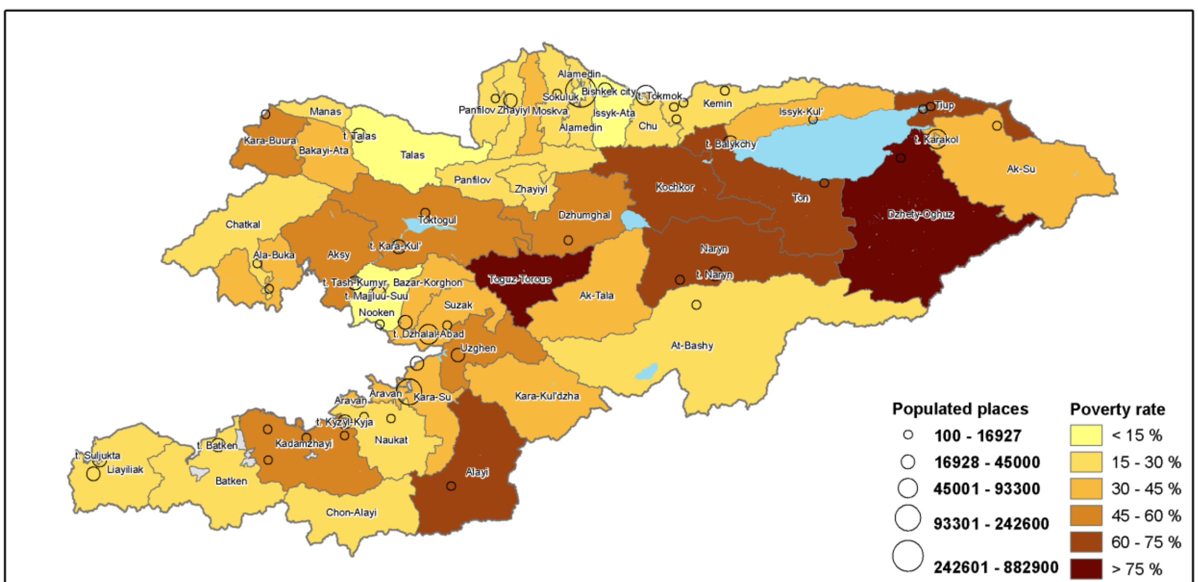
[10] By Brian Blankespoor (DECCT, The World Bank)

The circles in the map identify populated areas – most notably the capital city of Bishkek, which predictably has a high population along with a low incidence of poverty.

45. Although a poverty headcount rate is no doubt among the more important poverty statistics, it can be misleading at times for poverty alleviation purposes. For example, an area may exhibit a high poverty rate, but might be sparsely populated, resulting in few poor people residing there. In contrast, a large city might exhibit a low poverty rate, but represent a large concentration of the poor due to its high population density. For this reason, a combination of information on which places have a high degree of poverty (a map of poverty headcount rates) and where poor people live (a map of poor population) is useful for the governments and the development partners to identify most in need areas and gauge the scale of resources needed for the identified areas.

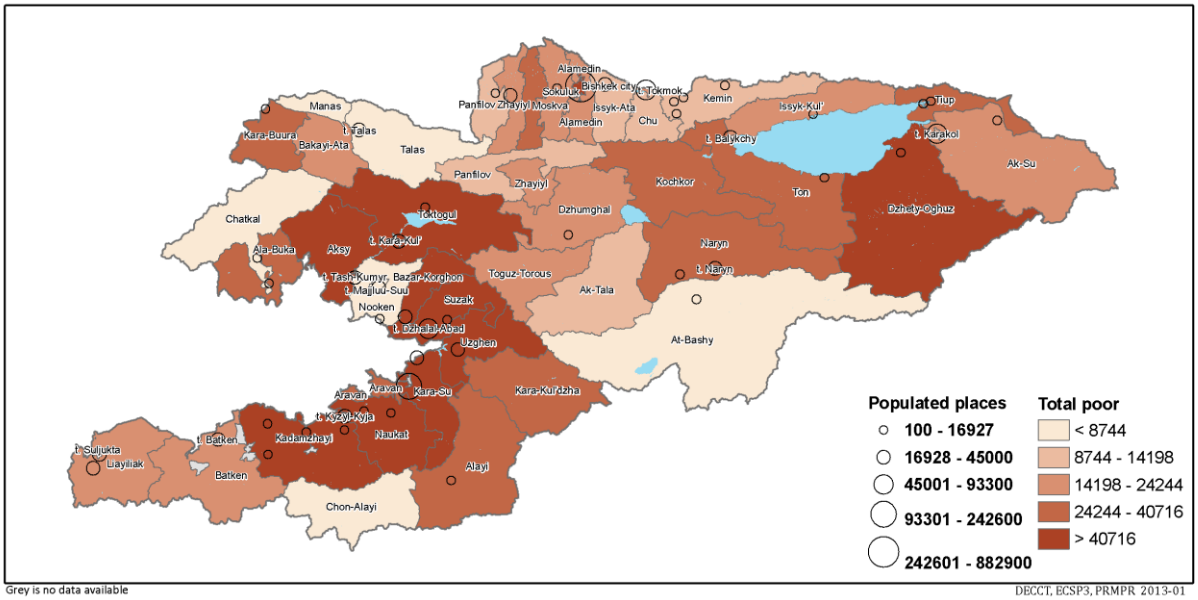
46. According to the World Development Report (WDR) of 2009, such maps not only help identify the most in need areas, but also provide useful information on urban-rural linkages. The WDR 2009 argues that, if a country has many poor people living in poor areas (usually remote and rural areas), the country, or at least the poor in the country, have not been able to fully exploit positive externalities from urban agglomeration. In contrast, if many poor people are living in rich areas (usually large cities), the country and even the poor have been able to enjoy the benefits of urban agglomeration.

Figure 6: Poverty Map and Poor Population Map of the Kyrgyz Republic



Grey is no data available

DECCT, ECSP3, PRMPR 2013-01



Grey is no data available

DECCT, ECSP3, PRMPR 2013-01

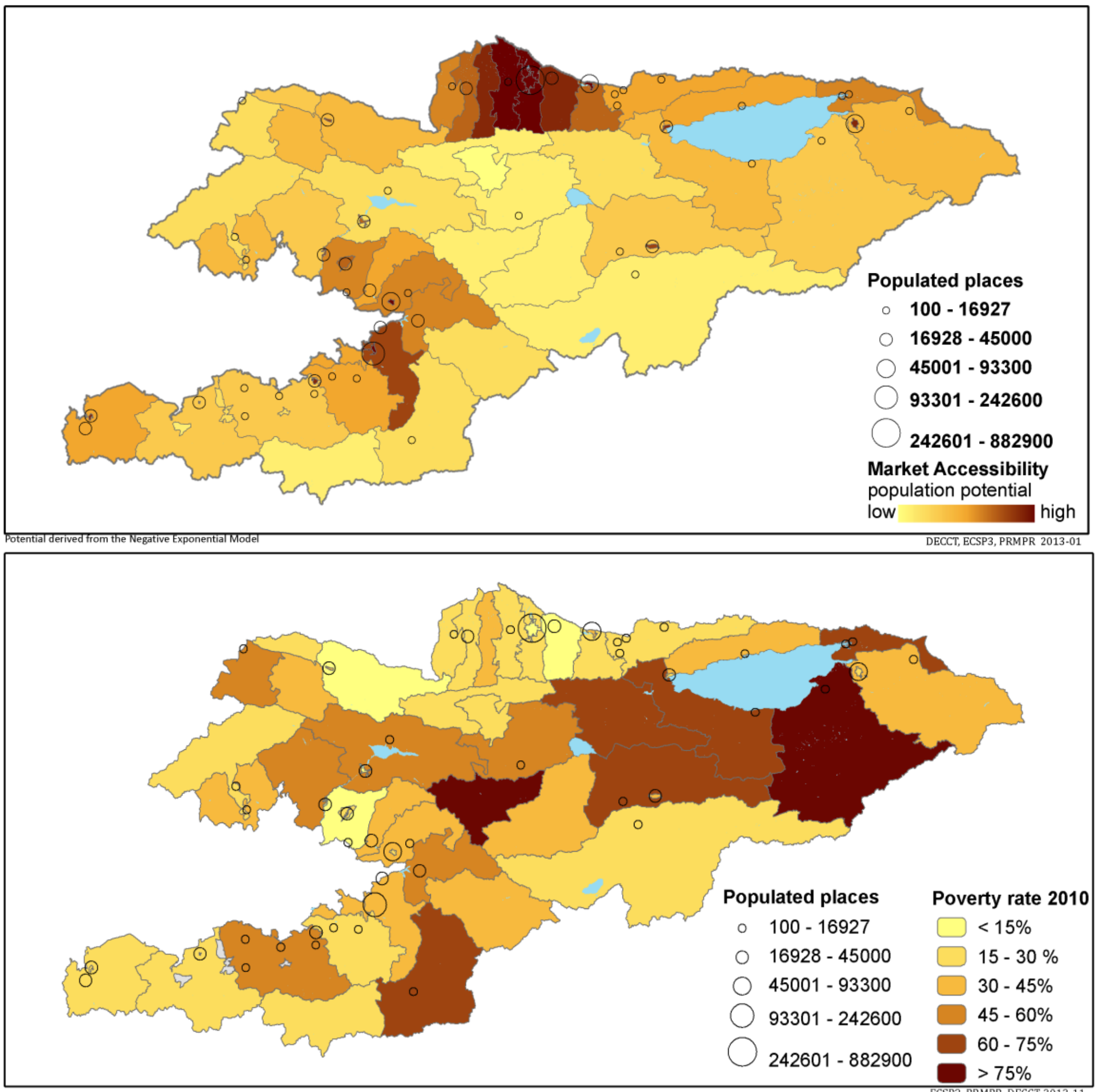
Source: The World Bank and NSC team calculations based on KIHS 2009 and Populaiton Census 2009.

47. While the map of the distribution of the poor population above appears to be largely consistent with the poverty map (first map in Figure 6), it must be noted that while a few districts (rayons) to the east have poverty rates lower that 30%, they do have a sizeable share of the poor population. The opposite may also be true, such as in the rayon Toguz-Torous, the poverty rate is greater than 75%, but the actual poor population in absolute terms is moderate. When formulating policy, particularly for alleviating poverty, it is important to note these nuances, as looking at a poverty map may suggest a very different policy initiative than when both maps are studied in conjunction.

IV.2. Comparisons with maps of other socio-economic indicators

48. This section presents maps on the distribution of indicators that may provide some insight into welfare outcomes and access to public services.

Figure 7: Market Accessibility Map and Poverty Map of the Kyrgyz Republic



Source: Market Accessibility from Blankespoor (2013) and the poverty map from the World Bank and NSC team estimations.

49. The market accessibility potential index is a measure of how far an area is from a group of select major cities. In principle, the formula is a sum of population of the select major cities weighted by travel time to reach there. Therefore, the index takes a larger score if surrounding cities are larger or travel time to these cities is shorter. Geographic Information System software is used to find the shortest route and estimate travel time based on road network data.

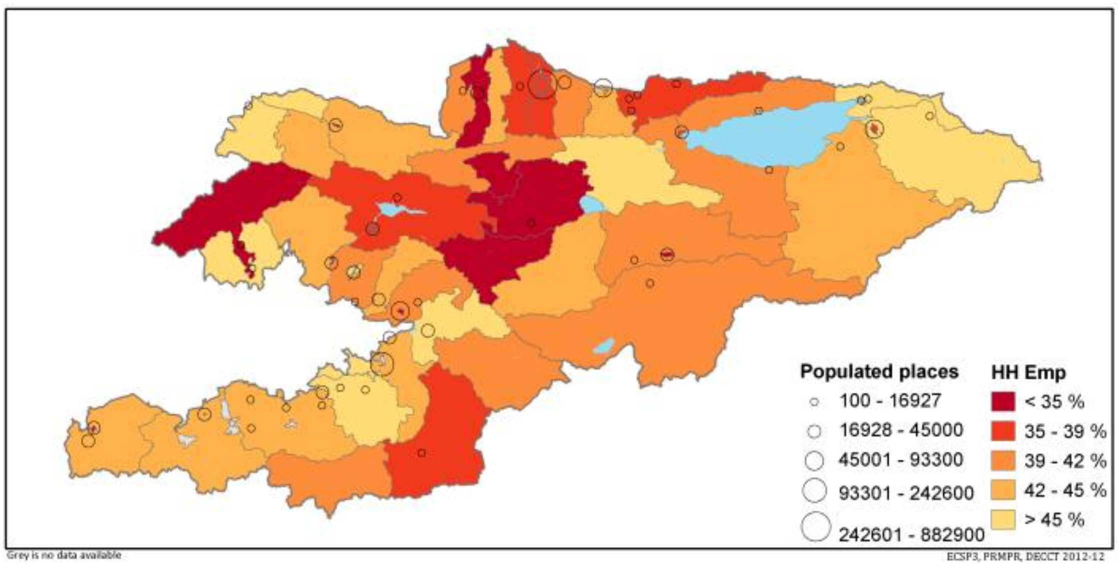
50. Predictably, areas near Bishkek and Osh city exhibit high market accessibility since both are large cities. In contrast, central areas farthest from these cities have the lowest market accessibility. Some

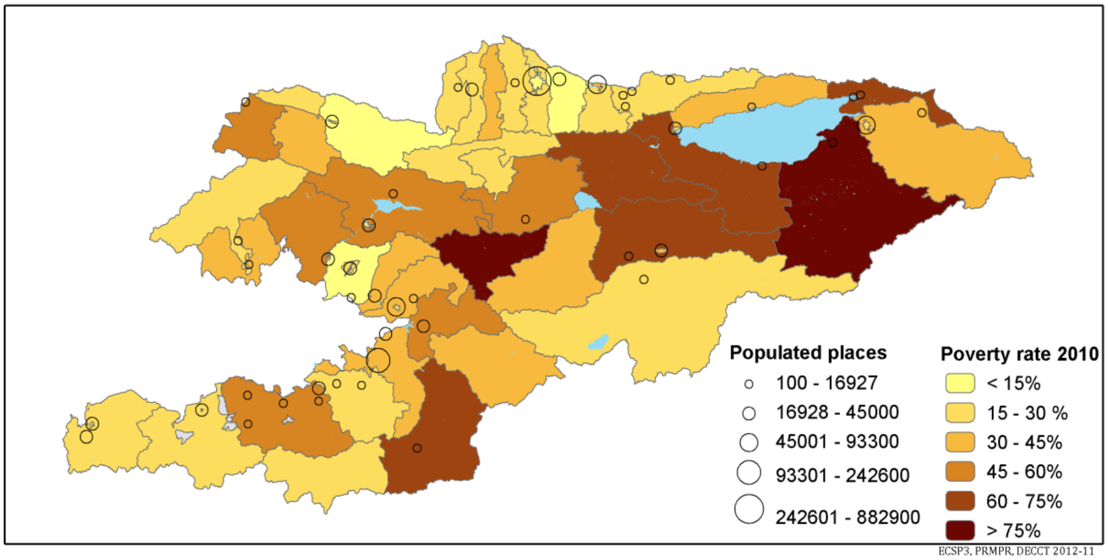
mid-size cities (according to their being population centers) in the eastern areas (also due to Lake Issyk-Kul) also have high market accessibility.

51. It is interesting to note that this is largely consistent with the poverty map, with the areas around Bishkek and Osh having very low incidence of poverty. However, in terms of poor population, the numbers are quite high even in these areas, particularly around Osh city. However, this is also owing to the fact that, in general the population of these areas is quite high.

52. In the figure below, it is striking to note that the percentage of household members who are employed is lower in a few of the less poorer regions of Kygyzstan, more notably the Bishkek area. This could be because there may not be a need for too many household members to work as the working members earn enough to support the whole household. In contrast to this scenario, is the low percentage of employed household members in some poor areas such as a few central and southern districts. This may represent a shortage of employment opportunities in the region.

Figure 8: Average percent of the household employed

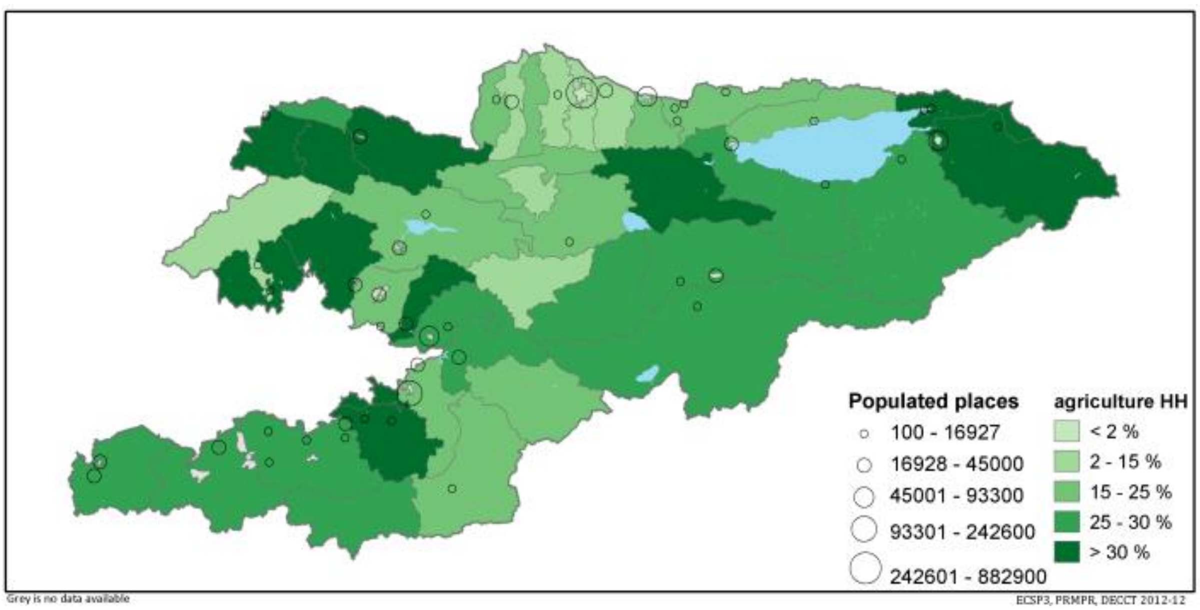


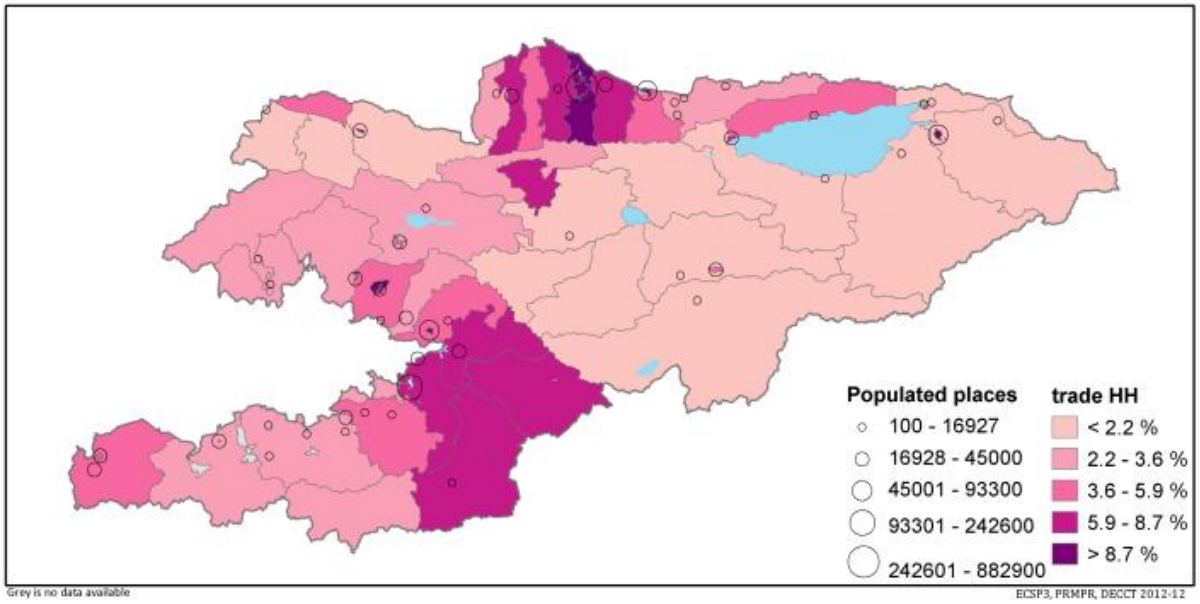


Source: The World Bank and NSC team calculations based on KIHS 2009 and Populaiton Census 2009.

53. Interestingly, the regions with higher percentages of employment in agriculture also have reasonably high levels of employment among household members (percentage of household members who are employed). This corroborates the fact that agriculture, being quite labor intensive might often involve the participation of several members of the household, explaining at least in part the high percentages of family employment in agricultural areas.

Figure 9: Sectors of employment: Agriculture and Trade



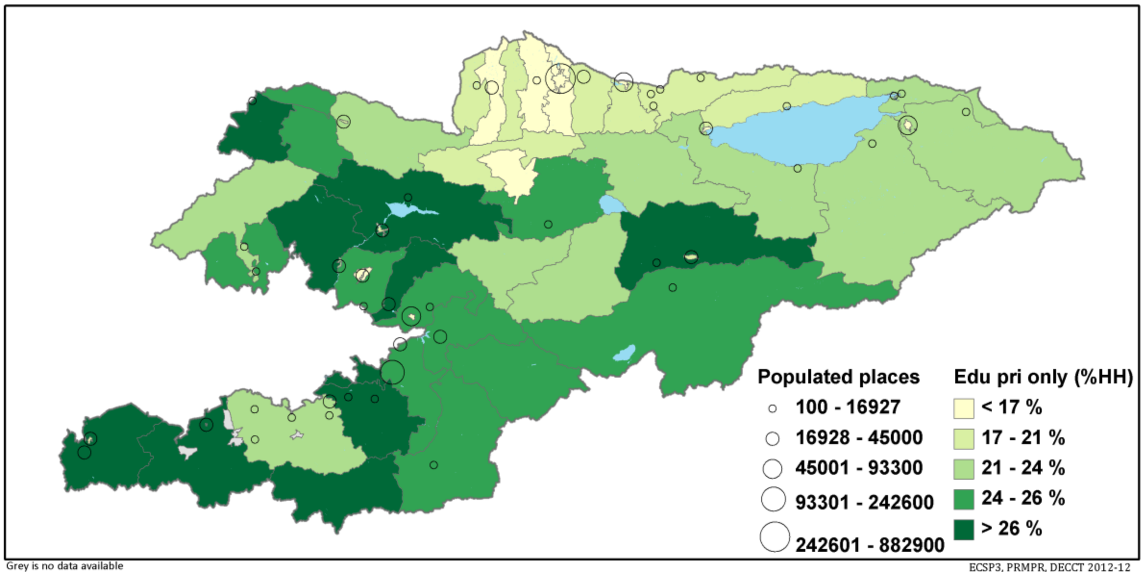


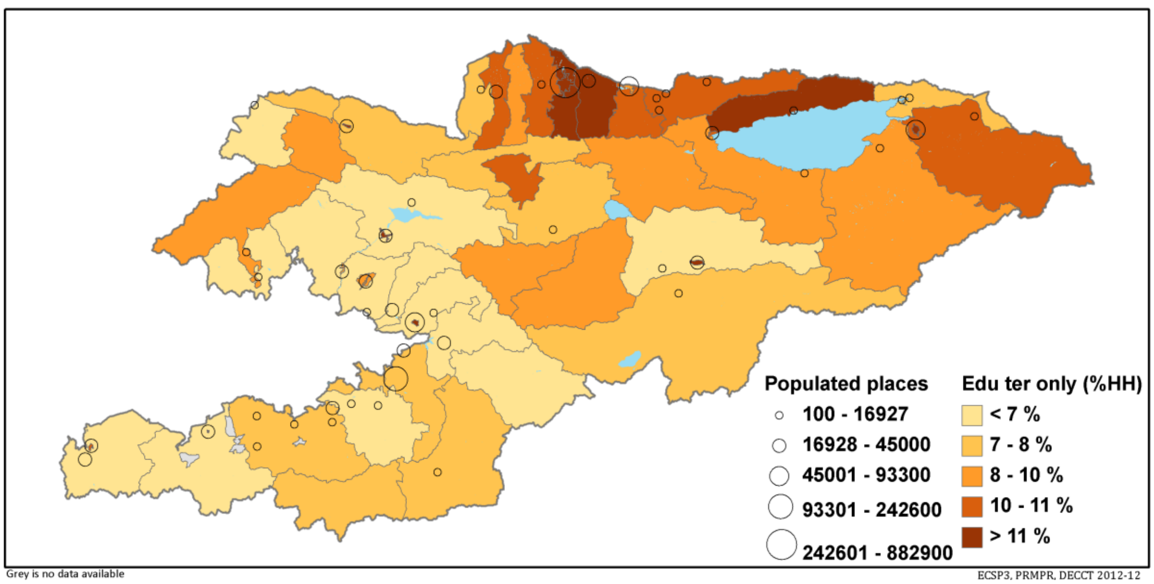
Source: The World Bank and NSC team calculations based on KIHS 2009 and Populaiton Census 2009.

54. The above figure depicts the percentage of the employed involved in trade confirms what can be seen in the market accessibility map, namely that the two big trade centers in Kyrgyzstan are around Bishkek and Osh city.

55. The figures below indicate that relatively poor regions in the center and western parts of the country are coincident to regions where there is a high percentage of population whose highest educational qualification is the completion of primary school. People with higher levels of education (tertiary) appear to be concentrated around the capital area in the north, which is consistent with it being the educational center. However, the same does not apply to Osh city where a quarter of the population has at the most completed primary education.

Figure 10: Education (primary, secondary, tertiary)





Source: The World Bank and NSC team calculations based on KIHS 2009 and Populaiton Census 2009.

V. Conclusion

56. This report summarizes the steps towards creating the latest poverty map of Kyrgyzstan and overlays the poverty map with maps of other socio-economic indicators. Despite some methodological challenges to constructing this map, we were able to produce it making the most of the data available to us. To overcome this limitation, several village level aggregates of the available variables from the Census were created. The more disaggregated the location variables, the more accurately household expenditure can be estimated. Therefore, the success of this new Kyrgyzstan poverty mapping exercise should rightly be attributed to the National Statistics Committee's effort to make the village codes

available for the analysis. Their effort made it possible to create these highly disaggregated means, in place of the rayon level means that were available earlier.

57. Interesting observations come out after comparing the poverty map with the other maps. Poverty incidence in border areas is in general low, with a few exceptions. This likely reflects the importance of trade with neighboring countries. Reasonably high correlation between market accessibility and poverty incidence further supports this hypothesis. A comparison between poverty incidence and poor population reveals that big cities like Osh or Bishkek exhibit low incidence of poverty, but a high concentration of poor population. This indicates that a low incidence of poverty does not necessarily imply that poverty alleviation policies are not needed, and close attention must be paid to these pockets of poverty. The correlation between education outcomes and poverty incidence is relatively limited.

58. A poverty map is a good monitoring instrument, but it becomes useful only if it is actively used for policy making. Overlaying the poverty map with maps of other socio-economic indicators makes it easy to identify what the key bottlenecks to poverty could be. Also, linking a poverty map and maps of other outcome indicators with distribution of public expenditures would be highly useful to see how outcomes and inputs are related. In fact, the Government of Kyrgyzstan and the World Bank have recently completed the creation of a public expenditure database, which is organized by the World Bank's software "BOOST". This software enables one to see the linkage between distribution of the public expenditure and outcomes like poverty, making such crucial information easily accessible to policy makers.

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Appendix 1.

Model for Issyk-Kul R2=0.5817 adjR2=0.5677

Model variables		OLS Consumption Model		GLS Consumption Model	
	Variables	Coeff.	Std. Err.	Coeff.	Std. Err.
intercept		4.7298	0.2604	4.6614	0.203
AGE	Age	-0.0061	0.0013	-0.0074	0.0013
HHSIZE_MEAN_2	Village level average of household size squared	-0.0145	0.0064	-0.0093	0.0039
HH_CHILD_RATIO	Ratio of no. of children to total HH members	-1.2133	0.0917	-1.2069	0.0897
HH_EDU_DUMMY1	Ratio of no. of HH members with higher prof. degree	0.3548	0.0685	0.3776	0.0734
HH_EDU_DUMMY3	Ratio of no. of HH members with secondary prof. degree	0.2964	0.0705	0.3686	0.0576
HH_EDU_DUMMY4	Ratio of no. of HH members with primary vocational degree	0.3787	0.0902	0.3841	0.0877
HH_EDU_DUMMY9_MEAN	Village level mean of ratio of HH members who are illiterate	9.2419	3.2261	8.6219	2.8604
HH_IND_COMM_MEAN	Village level mean of ratio of HH members employed in commerce	3.1398	0.9229	3.7405	0.6876
HH_WORKING_AGE_RATIO	Ratio of no. of working age members to total HH members	-0.3975	0.0669	-0.4181	0.0631
RAYON_2225_1	Rayon dummy	-0.6482	0.1234	-0.6448	0.1155
SEX_1	Sex dummy	0.1501	0.0304	0.1412	0.0278
_HH_EDU_DUMMY2_MEAN$RAYON_2205#0	Interaction term of education level with Rayon dummy	-19.0382	3.4875	-19.499	3.3543
_HH_EDU_DUMMY2_MEAN$RAYON_2210#0	Interaction term of education level with Rayon dummy	24.1624	2.8543	24.1552	2.6967
_HH_EDU_DUMMY2_MEAN$RAYON_2225#1	Interaction term of education level with Rayon dummy	21.5727	6.6281	23.2605	7.1796
_HH_EDU_DUMMY3_MEAN$RAYON_2205#0	Interaction term of education level with Rayon dummy	3.2954	1.5184	3.2989	1.3025
_HH_EDU_DUMMY3_MEAN$RAYON_2220#1	Interaction term of education level with Rayon dummy	-3.2455	1.0268	-2.3185	0.6806
_HH_EDU_DUMMY3_MEAN$RAYON_2225#0	Interaction term of education level with Rayon dummy	-7.7737	1.281	-7.7892	1.0704
_HH_EDU_DUMMY6_MEAN$RAYON_2225#0	Interaction term of education level with Rayon dummy	2.3507	0.8248	2.4664	0.5744
_HH_IND_COMM$RAYON_2210#0	Interaction term of occupation (commerce) with Rayon dummy	0.3902	0.1192	0.327	0.1095
_HH_IND_FIN$RAYON_2420#0	Interaction term of occupation (finance) with Rayon dummy	0.5023	0.1004	0.494	0.096
_HH_IND_MFG$RAYON_2210#0	Interaction term of occupation (manufacturing) with Rayon dummy	0.4187	0.1556	0.3585	0.1576

Model for Jalalabad R2=0.4948 adjR2=0.4814

Model variables		OLS Consumption Model		GLS Consumption Model	
	Variables	Coeff.	Std. Err.	Coeff.	Std. Err.
intercept		3.8074	0.061	3.8044	0.0562
HH_IND_DUM10	Ratio of HH members employed in unspecified activities	0.2387	0.1192	0.2687	0.1198
HH_IND_FIN	Ratio of HH members employed in finance	0.2181	0.0668	0.1702	0.0675
HH_IND_TRADE_MEAN	Village level mean of ratio of HH members employed in trade	1.6479	0.6232	1.6501	0.5669
HH_IND_TRANS	Ratio of HH members employed in transport	0.2721	0.0661	0.281	0.0657
HH_OLD_RATIO	Ratio of over 60 (age) members to total HH members	0.5387	0.0654	0.5778	0.0559
HH_WORKING_AGE_RATIO	Ratio of no. of working age members to total HH members	0.5475	0.0573	0.5454	0.0554
RAYON_3215_1	Rayon dummy	0.2819	0.0333	0.2661	0.0315
RAYON_3223_1	Rayon dummy	-0.3232	0.0873	-0.3202	0.0795
RAYON_3230_1	Rayon dummy	0.174	0.0614	0.1707	0.0592
RAYON_3420_1	Rayon dummy	0.2526	0.0377	0.2268	0.0313

SEX_1	Sex dummy	0.1093	0.0233	0.1145	0.0253
SEX_MEAN	Village level mean of sex dummy	-1.3787	0.2866	-1.3518	0.258
TOILET_MEAN	Toilet dummy	0.5566	0.0783	0.5539	0.0707
_HH_EDU_DUMMY1$RAYON_3225#0	Interaction term of education level with Rayon dummy	0.5226	0.0638	0.5333	0.0597
_HH_EDU_DUMMY3$RAYON_3225#0	Interaction term of education level with Rayon dummy	0.2879	0.0698	0.2559	0.0647
_HH_EDU_DUMMY5$RAYON_3211#0	Interaction term of education level with Rayon dummy	0.1139	0.0448	0.1153	0.0431
_HH_EDU_DUMMY9$RAYON_3420#0	Interaction term of education level with Rayon dummy	-0.3619	0.1435	-0.3307	0.1428

Model for Naryn, Batken, Osh and Talas R2=0.4825 adjR2=0.4748

Model variables		OLS Consumption Model		GLS Consumption Model	
	Variables	Coeff.	Std. Err.	Coeff.	Std. Err.
intercept		5.3557	0.1455	5.5569	0.1671
DWELL_OWN_3	Type of Dwelling owned	0.1202	0.0412	0.0864	0.0379
HHSIZE	HH size	-0.3039	0.0173	-0.2999	0.0155
HHSIZE2	HH size squared	0.0163	0.0018	0.0163	0.0015
HH_EDU_DUMMY4_MEAN	Village level mean of ratio of HH members who have primary vocational degree	-1.9698	0.5132	-2.1148	0.6958
HH_IND_MFG_MEAN	Village level mean of ratio of HH members employed in manufacturing	-3.0806	1.0958	-3.283	1.1281
RAYON_4245_1	Rayon dummy	-0.4322	0.0643	-0.467	0.0885
RAYON_5236_1	Rayon dummy	0.1766	0.0672	0.1916	0.0558
RAYON_6226_1	Rayon dummy	-1.5245	0.3033	-1.7451	0.3631
RAYON_7215_1	Rayon dummy	-0.1352	0.0446	-0.111	0.0587
SEX_MEAN	Village level mean of sex dummy	-1.2629	0.2903	-1.475	0.326
_HHSIZE_MEAN$RAYON_4210#1	Interaction term of HH size village mean with Rayon dummy	-0.0499	0.02	-0.0482	0.0231
_HHSIZE_MEAN$RAYON_4220#0	Interaction term of HH size village mean with Rayon dummy	-0.0349	0.0083	-0.041	0.0125
_HHSIZE_MEAN$RAYON_4235#0	Interaction term of HH size village mean with Rayon dummy	0.0499	0.0083	0.0478	0.0132
_HHSIZE_MEAN$RAYON_5258#0	Interaction term of HH size village mean with Rayon dummy	0.0193	0.0056	0.0191	0.0071
_HHSIZE_MEAN$RAYON_5410#0	Interaction term of HH size village mean with Rayon dummy	-0.0529	0.016	-0.0702	0.0247
_HHSIZE_MEAN$RAYON_5430#1	Interaction term of HH size village mean with Rayon dummy	0.0458	0.0107	0.0449	0.0245
_HHSIZE_MEAN$RAYON_6226#1	Interaction term of HH size village mean with Rayon dummy	0.2334	0.0547	0.2765	0.0669
_HHSIZE_MEAN$RAYON_6255#0	Interaction term of HH size village mean with Rayon dummy	0.0257	0.007	0.0242	0.0091
_HHSIZE_MEAN$RAYON_7232#1	Interaction term of HH size village mean with Rayon dummy	0.1424	0.0165	0.1138	0.0222
_HH_IND_EGW_MEAN$RAYON_4210#1	Interaction term of occupation (elec, gas & water) with Rayon dummy	150.291	45.9702	153.1182	56.1497
_HH_IND_EGW_MEAN$RAYON_5236#1	Interaction term of occupation (elec, gas & water) with Rayon dummy	-138.0274	30.4097	-145.8496	24.7981
_HH_IND_EGW_MEAN$RAYON_7225#1	Interaction term of occupation (elec, gas & water) with Rayon dummy	103.0942	15.9168	90.9723	16.9299
_HH_IND_EGW_MEAN$RAYON_7232#1	Interaction term of occupation (elec, gas & water) with Rayon dummy	117.3779	26.8047	94.4326	28.458
_HH_IND_TRADE_MEAN$RAYON_4245#1	Interaction term of occupation (trade) with Rayon dummy	16.564	3.2646	19.6583	5.8034
_HH_IND_TRADE_MEAN$RAYON_5420#1	Interaction term of occupation (trade) with Rayon dummy	4.517	0.8034	3.9496	1.5151
_HH_IND_TRADE_MEAN$RAYON_6207#1	Interaction term of occupation (trade) with Rayon dummy	-4.5712	0.8202	-4.4963	0.761
_HH_IND_TRADE_MEAN$RAYON_6246#0	Interaction term of occupation (trade) with Rayon dummy	3.1006	0.4536	3.2844	0.5129
_HH_IND_TRADE_MEAN$RAYON_7232#1	Interaction term of occupation (trade) with Rayon dummy	-42.0566	7.0623	-32.3349	8.6524

Model for Chui R2=0.4435 adjR2=0.4266

Model variables		OLS Consumption Model		GLS Consumption Model	
	Variables	Coeff.	Std. Err.	Coeff.	Std. Err.
intercept		5.3555	0.2084	5.362	0.2084
DWELL_OWN_1	Type of Dwelling owned	-0.7755	0.2274	-0.631	0.2549
EMP_STAT_MEAN	Village mean of employment status	-0.7767	0.2593	-0.8517	0.27
HH_CHILD_RATIO	Ratio of no. of children to total HH members	-0.8311	0.0768	-0.8291	0.071
HH_EDU_DUMMY1	Ratio of HH members with higher prof. degree	0.6574	0.0809	0.7124	0.0766
HH_EDU_DUMMY1_MEAN	Village mean of Ratio of HH members with higher prof. degree	-2.6785	0.7601	-2.7466	0.7278
HH_EDU_DUMMY3	Ratio of no. of HH members with secondary prof. degree	0.3445	0.0711	0.3343	0.0653
HH_EDU_DUMMY3_MEAN	Village mean of Ratio of HH members with secondary prof. degree	5.7011	1.2784	4.8174	1.178
HH_EDU_DUMMY4	Ratio of HH members who have primary vocational degree	0.2886	0.0946	0.2998	0.0881
HH_EDU_DUMMY4_MEAN	Village level mean of ratio of HH members who have primary vocational degree	-6.0554	1.1588	-4.8151	1.0928
HH_EDU_DUMMY5	Ratio of HH members who have completed secondary school	0.1504	0.0691	0.1423	0.0671
HH_IND_DUM10	Ratio of HH members employed in unspecified activities	0.5719	0.2442	0.624	0.0771
HH_IND_EGW	Ratio of HH members employed in elec, gas & water	-1.0636	0.4938	-1.6214	0.1852
HH_IND_UNEMP	Ratio of HH members unemployed	-0.2884	0.054	-0.2952	0.0528
HH_WORKING_AGE_RATIO	Ratio of no. of working age members to total HH members	-0.2786	0.0585	-0.2708	0.0586
RAYON_8203_1	Rayon dummy	1.2581	0.2798	1.7707	0.1948
RAYON_8222_1	Rayon dummy	0.1911	0.051	0.1998	0.0482
RAYON_8400_1	Rayon dummy	-0.1863	0.0509	-0.1404	0.0589
_HHSIZE_MEAN$RAYON_8203#1	Rayon dummy	-0.2478	0.0686	-0.363	0.0488
_HHSIZE_MEAN$RAYON_8206#1	Interaction term of HH size village mean with Rayon dummy	0.061	0.0142	0.072	0.0116

Model for Bishkek city R2=0.3698 adjR2=0.3636

Model variables		OLS Consumption Model		GLS Consumption Model	
	Variables	Coeff.	Std. Err.	Coeff.	Std. Err.
intercept		5.1026	0.0889	5.1042	0.0894
AGE	Age	-0.0049	0.001	-0.0051	0.001
HHSIZE	HH size	-0.294	0.0331	-0.2918	0.0332
HHSIZE2	HH size squared	0.0222	0.0047	0.0213	0.0048
HH_EDU_DUMMY1	Ratio of HH members with higher prof. degree	0.1885	0.0388	0.1795	0.0374
HH_EMP_STAT	Ratio of employed in HH	0.303	0.0418	0.3065	0.042
LIVING_AREA	Area of living quarters	0.0063	0.0009	0.0068	0.0009
_TOILET$RAYON_11204_11	Interaction term of toilet and rayon	-0.1234	0.0553	-0.1156	0.0548

Table. Poverty Rates and Standard Error per Rayon				
Rayon	**Rayon name**	**Population**	**Poverty rate**	**Standard error of poverty**
41704210	Ak-Talaa	29650	0.383	0.0372
41704220	At-Bashy	49029	0.1764	0.025
41704230	Jumgal	40015	0.4636	0.0327
41704235	Kochkor	57519	0.6178	0.0265
41704245	Naryn	42785	0.7016	0.0243
41704400	Naryn town	33051	0.3495	0.063
41705214	Batken	68308	0.2254	0.0287
41705236	Leilek	99865	0.2422	0.0405
41705258	Kadamjai	152713	0.4638	0.0227
41705410	Batken town	18795	0.0945	0.0356
41705420	Sulukta	18333	0.1772	0.0449
41705430	Kyzyl-Kia	43089	0.2778	0.0802
41706207	Alai	59687	0.6206	0.0472
41706211	Aravan	97757	0.3209	0.0255
41706226	Kara-Suu	327038	0.423	0.0262
41706242	Nookat	233756	0.2831	0.0232
41706246	Kara-Kulja	85844	0.4382	0.0297
41706255	Uzgen	219523	0.469	0.0315
41706259	Chon-Alai	22241	0.2585	0.0273
41707215	Kara-Buura	57248	0.5887	0.0366
41707220	Bakai-Ata	41990	0.4295	0.031
41707225	Manas	32344	0.1806	0.0303
41707232	Talas	55297	0.0814	0.028
41707400	Talas town	30830	0.3545	0.0831
41702205	Aksui	60705	0.3141	0.0051
41702210	Jeti-Oguz	76727	0.8031	0.0084
41702215	Issyk-Kul	73003	0.3053	0.0048
41702220	Ton	47437	0.6332	0.014
41702225	Tup	55903	0.6951	0.01
41702410	Karakol	59828	0.1837	0.0071
41702420	Balykchi	41858	0.2876	0.0059
41703204	Ala-Buka	86547	0.3438	0.0061
41703207	Bazar-Korgon	138485	0.3715	0.006
41703211	Aksyi	112016	0.4964	0.006
41703215	Nooken	115364	0.0758	0.0058
41703220	Suzak	231232	0.3683	0.0056
41703223	Toguz-Toro	21853	0.7845	0.0082
41703225	Toktogul	85209	0.5321	0.0066
41703230	Chatkal	20888	0.162	0.0095
41703410	Jalal-Abad	84168	0.1509	0.0061
41703420	Tash-Kumyr	33651	0.0876	0.0147

41703430	Maili-Suu	19863	0.1585	0.0075
41703440	Kara-Kul	22164	0.0561	0.0053
41708203	Alamudun	140275	0.1508	0.0086
41708206	Issyk-Ata	128786	0.1102	0.0098
41708209	Jayil	89813	0.2275	0.0142
41708213	Kemin	41942	0.242	0.0126
41708217	Moscow	80799	0.3219	0.0111
41708219	Panfilov	41029	0.2196	0.0125
41708222	Sokuluk	151280	0.1529	0.0094
41708223	Chui	43959	0.2817	0.0101
41708400	Tokmok	51935	0.3463	0.0307
41711201	Leninsky	189128	0.1126	0.0067
41711202	Oktyabrsky	214786	0.117	0.0066
41711203	Pervomaysky	146427	0.1108	0.0067
41711204	Sverdlovsky	193976	0.1776	0.0075

Appendix 2. Sampling of the Kyrgyz Integrated Household Survey 2009 (Shamsiya Ibraghimova, 2012)

The 1999 Population Census was used as a sample frame of KIHS. The smallest territorial units available in the computer database were the portfolios, which were compiled during the Census operation, of up to 400 persons in each. Based on the Census data, 13,067 portfolios have been compiled, which were sufficiently homogenous in terms of the number of Census questionnaires. The available Census data allowed using a two-stage sample design:

- On the first stage, by using Census portfolios as primary sampling units, and the number of households as a portfolio size, a certain number of portfolios was selected (*primary sampling units* - PSU) through the haphazard procedure, with probability proportional to the portfolio size.
- On the second stage, by using household listings from the selected PSUs, a certain number of households were randomly selected, with probability proportional to the household size.

Prior to the formulation of the sample for household survey across the country, measures have been taken to determine the size of the sample and to identify the optimal method for households selection, i.e., the design of the sample was developed in the initial phase of sample formulation. More detailed discussion of sample design and formulation can be found in the report of the Consultant on Sampling, Mr. Juan Muñoz (Annex A).

The first factor taken into account when designing the sample was the need to report survey data broken into rural and urban areas by country regions. These 15 groups (*seven oblasts including rural and urban areas, and Bishkek city*) became the main focal areas for integrated household budgets and labor force survey estimates. Each of these areas were represented by a separate stratum, therefore, the initial task was to distribute 5,000 households across 15 strata.

Due to the fact that the survey was planned to incorporate a section on labor force, there was also a need, when distributing households among strata, to account for fluctuations of unemployment levels in each of the strata, and unemployment homogeneity in each of the selected census portfolios.

Obviously, it was envisaged that the results of the survey will be used for comparative analysis between oblasts, as well as for obtaining acceptable estimations both at the national and at the regional levels. It was also considered in the sample design that the number of sampled households should be divisible by 11 (number of households per PSU), the number of PSUs should be a multiple of 6 (workload per 1 interviewer) and divisible by 12 to provide for a 12-percent rotation of the sample.

Upon consideration of various methods of sample composition, finally a sample distribution method was selected with standard error smoothing.

Table: Sample distribution by regions

Oblast	Number of PSUs			Number of households			Standard error		
	urban	rural	total	urban	rural	total	urban	rural	total
Bishkek	72	0	72	792	0	792	2,4%	0%	2,4%
Issykkulskaya oblast	36	24	60	396	264	660	4,0%	2,8%	2,3%
Jalalabadskaya oblast	36	24	60	396	264	660	3,8%	2,1%	1,8%
Narynskaya oblast	24	24	48	264	264	528	4,5%	2,7%	2,4%
Batkenskaya oblast	24	24	48	264	264	528	5,1%	2,4%	2,2%
Oshskaya oblast	36	24	60	396	264	660	3,7%	1,6%	1,5%
Talasskaya oblast	24	24	48	264	264	528	3,8%	2,3%	2,0%
Chuiskaya oblast	24	36	60	264	396	660	4,4%	2,7%	2,3%
Country Total	**276**	**180**	**456**	**3 036**	**1 980**	**5 016**	**1,5%**	**0,9%**	**0,8%**

Whereas such sample distribution increases standard error by 0.1% for the country overall, the estimate deviations by strata with such sample distribution will be smoothed out significantly.

The following conclusions may be drawn from the consideration of the selected portfolios profiles, which impact on the design of the sample:

- All strata are sufficiently large, and, therefore, the accuracy of the sample will be determined by the absolute size of the sample.
- Unemployment is much higher in urban areas than in rural areas. Thus, although two thirds of the country population are rural dwellers, urban areas require more surveying.
- Intra-portfolio unemployment rate correlation suggests that out from the given number of households, the maximum possible number of PSUs should be visited with a small number of households in each.
- When determining the number of PSUs, it should be taken into account that the PSU number must be a multiple of 6 to regulate workload per interviewer, and also be a multiple of 12 to ensure the 12-percent rotation of the sample.

In this manner, on the *first sampling stage* portfolios have been randomly selected in each of 16 strata, with probability proportional to the number of households in portfolios. In total, 456 portfolios have been selected for the country.

On the second stage, 11 households have been randomly selected in each portfolio, with probability proportional to the size of the households. Then the codes have been identified of the households included in the sample, and the listings prepared with indication of PSU locations and households addresses.

Considering the fact that household selection probability varies between strata, for the purpose of survey data spreading over the country as a whole, spreading coefficients need to be calculated by strata. Spreading coefficients are obtained from the following formula:

$$W_i = \frac{N_i}{n_i},$$

where W_i - is a household's weight in stratum *i*;

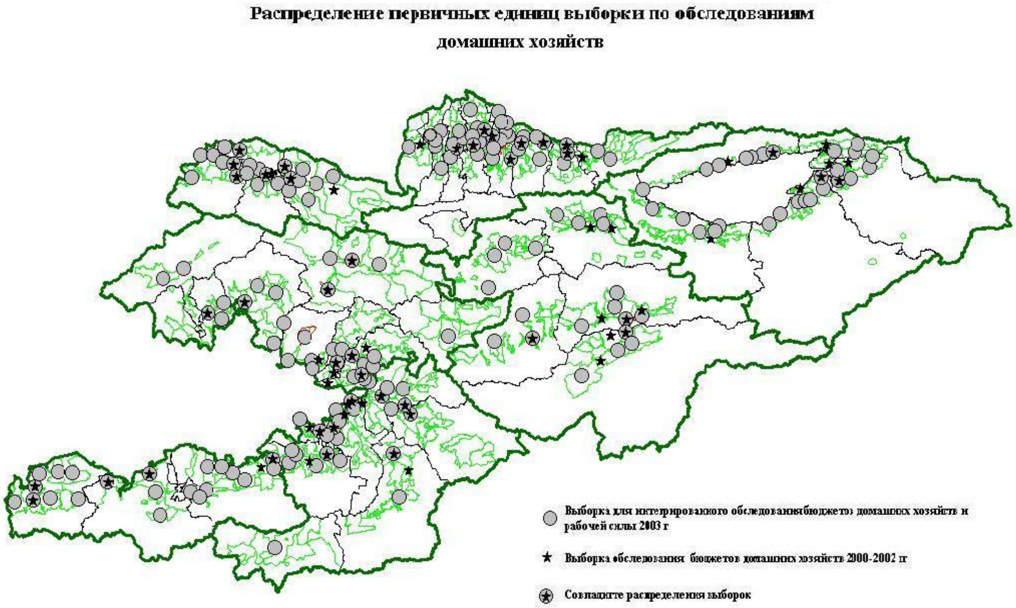
N_i - number of households in stratum *i*;

n_i - number of households in stratum *i* included in the sample.

In the course of sample selection, problems have been encountered, which are related with incompleteness of the address part of the households' entries. The work carried out on preparation of the household lists for each PSU detected that there are populated areas in the Kyrgyz Republic, where street names and house numbers are not available. Where such areas were included in the sample, additional work was carried out on refining household lists by using Village Councils' (at present Village Districts) data on availability of the household economic record books ('economic books') and accounts therein. These data were collected for each population center in rural areas in February and April 2002. For each population center, a certain number of economic books were selected, equal to the number of census portfolios selected for such population center. Then, depending on the number of personal accounts in the selected book, the sampling interval was calculated (number of accounts / 11), and then a systematic selection of personal accounts was made starting from the randomly selected beginning (within the sampling interval) and using the sampling interval so calculated. In this manner, the rule of random household selection was observed, preventing potentially subjective approach to the selection of households in the localities.

Under the new sample design, the number of primary sample units was increased almost 3.8 times (the old sample is marked with asterisks). However, attention should be drawn to the fact that the size of the sample increased only 1.7 times. Sample distribution may be clearly seen on the map, where PSUs included in the new sample are marked with grey circles. It also may be seen that on some occasions the same PSUs were included in the new sample, which have been used in the old sample. Such cases are marked with starlets inside the gray circles.

Figure: PSU distribution across regions of the country.



Source: NSC publication

Thus, the sample size was determined of 5,016 households. To prevent biased sample selection, any substitution of addresses is inadmissible on all subsequent stages of the work.

Household survey in the Kyrgyz Republic is conducted on the continuous basis, i.e., quarterly. Households included in the sample are surveyed in accordance with a certain timetable, and thereafter new households are selected as a substitution for them.

As a matter of practice, a number of HHs drops out from the survey during the year for various reasons. Due to this, the need arises to substitute the dropouts for new ones for the next year. In order to retain the distribution of the number of the surveyed HHs by months, it is recommended to conduct surveys of the new HHs during those specific months, when the previous HHs have been dropped.