Government of Mongolia

НҮБ-ЫН ХӨГЖЛИЙН ХӨТӨЛБӨРИЙН
“ЯДУУРЛЫН СУДАЛГАА, ХӨДӨЛМӨР ЭРХЛЭЛТИЙГ
ДЭМЖИХ БОДЛОГЫГ ХӨГЖҮҮЛЭХ” ТӨСӨЛ

UNDP Mongolia

MONGOLIA CENSUS-BASED POVERTY MAP:

Region, Aimag and Soum Level Results

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National Statistical Office (NSO)
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**UNDP PROJECT "POVERTY RESEARCH AND
EMPLOYMENT FACILITATION FOR POLICY DEVELOPMENT" II**

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[1] This project was funded by the United Nation Development Programme (UNDP). The work was undertaken by Harold Coulombe and Thomas Otter (consultants) with full support from the National Statistic Office (NSO) staff, in particular Mr. BYAMBATSEREN Pandi (Chairman), Mr. DAGVADORJ CH, (General Manager), Mrs. OYUNCHIMEG Dandar (Head of Population and Social Statistics Department), Mrs TSERENKHAND Bideriya (Head of Data Processing and Technology Department), Mrs. AMARTUVSHIN Tserennadmid (Senior Officer, Population and Social Statistics Department) and Mr. DAVAAJARGAL Davaatseren (Officer, Population and Social Statistics Department). GIS issues were kindly solved by Mr. MYAGMARSUREN L from NSO Information Technology Department. We would also thanks Mrs Doljinsuren Jambal and Mrs Tsetsgee Puntsag from UNDP to make that project possible. The authors can be reached at hcoulombe@videotron.ca.

ABSTRACT

This paper documents the construction and presents the main results of a poverty map of Mongolia based on the LSMS 2002/03 survey and the Census 2000. The methodology takes advantages of detailed information found in the survey and the exhaustive coverage of the census. It permits the calculation of poverty indicators at low levels of desegregation; aimag and soum in the case of Mongolia. The heterogeneity of the country in terms of poverty across aimag and soum should make the poverty map a useful statistical tool in any poverty alleviating programmes or projects. Our aimag-level results are also broken down by gender of household head.

INTRODUCTION

1. This paper documents the construction and shows some results of a poverty map based on data from the 2002/03 Living Standards Measurement Survey (LSMS) and the Housing & Population Census 2000. Based on a methodology developped by Elbers et al. (2002, 2003), we calculate poverty indicators at low levels of aggregation, using the detailed information found in the survey and the exhaustive coverage of the Census. Results at region, aimag and soum levels are presented.

2. In the past decade poverty profiles[2] have been developed into useful tools to characterize, assess and monitor poverty. Based on information collected in household surveys, including detailed information on expenditures and incomes, those profiles present the characteristics of the population according to their level of - monetary and non-monetary - standard of living, help assessing the poverty reducing effect of some policies and compare poverty level between regions, groups or over time. While these household survey-based studies have greatly improved our knowledge of welfare level of households in general and of the poorer ones in particular, the approach has a number of limitations. In particular, policy makers and planners need finely disaggregated information in order to implement their anti-poverty schemes. Typically they need information for small geographic units such as city neighbourhoods, towns or even villages. Telling a Mongolian policy maker that the neediest people are in the rural areas would not be too impressive as that information is well known and not useful since it would be too vague; telling them in which aimags or even soums the poorest households are concentrated would be more useful and convincing! Using aimag-level information often hides the existence of poverty pockets in otherwise relatively well-off aimag which would lead to poorly targeted schemes if soum-level information is not used. Having better information at local level would necessarily minimize leaks and therefore permit more cost-effective and efficient anti-poverty schemes. Poverty indicators are needed at a local level as spatial inequalities can be important within a given region.

3. The methodology used have been developed by Elbers, Lanjouw and Lanjouw (2002, 2003) and should be seen as more sophisticated than other methods[3] as it uses information on household expenditure, is fully consistent with poverty profile figures, and permits the computation of standard errors of those poverty indicators. Since those types of poverty maps are fully compatible with poverty profile results, they should be seen as a natural extension to poverty profiles, a way to operationalise poverty profile results. This report documents the construction of the Mongolia poverty map but the map would reach its full potential once a series of applications under consideration would be undertaken.

4. The remaining of this paper is structured as follow: we first present the methodology in layman words, follow by a description of the data used. The paper ends by a discussion of the results – including gender-specific ones – and on furthers work to undertake. A more technical presentation of the methodology can be found in Annex 1; along with some more detailed results (Annexes 2 to 4).

[2] See NSO (2004) for the latest published poverty profile in Mongolia.
[3] See Henninger (1998) for a review of the different mapping techniques.

METHODOLOGY[4]

5. The basic idea behind the methodology is rather straightforward. First a regression model of per capita expenditure is estimated using LSMS survey data, limiting the set of explanatory variables to those which are common to both that survey and the latest Census. Next, the coefficients from that model are applied to the Census data set to predict the expenditure level of every household in the Census. And finally, these predicted household expenditures are used to construct a series of welfare indicators (e.g. poverty level, depth, severity, inequality) for different geographical subgroups.

6. Although it is conceptually simple, its proper implementation requires complex computations. Those complexities are mainly coming from the need to take into account spatial autocorrelation (expenditure from households within the same local area are correlated) and heteroskedasticity in the development of the predictive model. Taking into account those econometric issues insure unbiased predictions. A further issue making computation non-trivial is our willingness to compute standard errors for each welfare statistics. Those standard errors are important since they would tell us how low we can disaggregate the poverty indicators. As we disaggregate our results at lower and lower levels, the number of households on which the econometric models are based decrease as well and therefore yield less and less precise estimates. At a certain point, the estimated poverty indicators would become too imprecise to be used with confidence. The computation of those standard errors would help us to decide where to stop the disaggregation process. The methodology used is further discussed in Annex 1.

DATA

7. The construction of such poverty maps is very demanding in terms of data. The uttermost requirement is a household survey having an expenditure module and a population and housing census. If not already done, a monetary-based poverty profile would have to be constructed from the survey. The household-level welfare index and the poverty line from such poverty profile would be used in the construction of the poverty maps. Apart from household-level information, community level characteristics is also useful in the construction of poverty map as differences in geography, history, ethnicity, access to markets, public services and infrastructure, and other aspects of public policy can all lead to important differences in standard of living, defined in monetary terms or not. In the case of Mongolia, some of that information was available.

Census:

8. The latest Population and Housing Census was conducted in January 2000. The questionnaire is relatively detailed but does not contain any information on neither household incomes nor household expenditures. At the individual level, it covers demography, education and economic activities. At the household level, dwelling characteristics are covered. The Census database turns out more than 2.2 million individuals grouped into around 541,000 households. The Census field

[4] The methodology has been applied to a myriad of developing countries, including in Asia. For example, Coulombe and Wodon (2007) described the West and Central Africa Poverty Map Initiative in which 15 countries participated.

work grouped households into around 11,000 enumeration areas (EAs) of 50 households each on average.

LSMS Survey:

9. The Living Standard Measurement Survey is a national survey having collected expenditure data at household level. Having been administrated in 2002/03, it is also the most appropriate survey time wise. It also collected information similar to the one found in the Census questionnaire.

10. The welfare index to be used in our regression models (per capita expenditure) is the same as the one used in the Government-sponsored poverty profile based on the LSMS database (NSO, 2004). Using the same household-level welfare index and the associated poverty lines would ensure full consistency between that poverty profile and the new poverty map. It will also permit to test whether the predicted poverty indicators match those found in the poverty profile at strata level, the lowest statistically robust level achievable in LSMS.

Administrative Layers

11. The administrative structure of Mongolia is rather straightforward. The top tier is composed of 21 aimags and the Capital City regouped into five regions while 331 soums ands the nine Capital's districts make the lower level administrative level. Table 1 presents some descriptive statistics on the size of those different administrative levels. The different aimag vary a lot in terms of population, from Govisumber with only 12,449 people to the capital of the country having close to 773,000 individuals in 2000. Those 22 aimags/capital can be further divided into 340 soums/districts. The population of the different soums/districts vary tremendously between small rural soum like Choir (873 people) to the largest Ulaanbaatar district, namely Songinokhairkhan.

Table 1: Descriptive Statistics on the Mongolian Administrative Structure

Administrative	# of	Number of Households			Number of Individuals		
Unit	Units	Median	Minimum	Maximum	Median	Minimum	Maximum
Region	5	104,914	47,464	159,991	445,613	205,395	772,969
Aimag (see note)	22	18,708	2,953	159,991	85,328	12,449	772,969
Soum (see note)	340	770	207	31,962	3,270	873	159,346

Note: *For our analysis, we consider Ulaanbaatar's nine districts as soums, and the Capital City as an Aimag. From an administrative point of view, Ulaanbaatar is at the same level as Aimags, and both soums and the capital's districts are sub-aimag administrative level.*
Source: *Authors' calculation based on the Census 2000*

RESULTS

12. In order to maximise accuracy of the poverty estimates we have estimated the model at the lowest geographical level for which the LSMS survey is deemed representative; the four strata used in the sampling design: Ulaan Baatar, Aimag Center, Soum Center and Countryside. A household level expenditure model has been developed for each of these strata using explanatory variables which are common to both the LSMS and the Census.

Stage 1: Aligning the data

13. The first task was to make sure the variables deemed common to both the census and the survey were really measuring the same characteristics. In the first instance, we compared the questions and modalities in both questionnaires to isolate potential variables. We then compared the means of those (dichotomized) variables and tested whether they were equal using a 95% confidence interval. Restricting ourselves to those variables should ensure the predicted welfare figures would be consistent with survey-based poverty profile[5]. As noted above that comparison exercise was done at strata level. The two-stage sample design of the survey was taken into account in the computation of the standard errors. The results are presented in Annex 2.

Stage 2: Survey-based regressions

14. Annex 3 presents the strata-specific regression (Ordinary Least Squares) results based on LSMS. The ultimate choice of the independent variables was based on a backward stepwise selection model. A check of the results confirmed that almost all the coefficients are of expected sign. As said earlier, those models are not for discussions. They are exclusively prediction models, not determinants of poverty models that can be analyzed in terms of causal relationships. In the models used for the poverty map we were only concerned by the predictive power of the regressors without regards, for example, to endogenous variables. At that stage, we attempt to control location effect by incorporating cluster average of some of the variables. We also ran a series of regressions using the base model residuals as dependant variables. Those results – not shown here – would be used in the last stage in order to correct for heteroskedasticity[6].

15. The R^2s of the different regressions vary from 0.35 to 0.55. Although they might appear to be on the low side, they are typical of survey-based cross-section regressions and can be favourably compared with results from other non-Mongolian poverty maps. While those coefficients look "credible", it is important to note those models were purely predictive in the statistical sense and should not be viewed as determinant of welfare or poverty. For all the different strata the relatively low R^2s are mainly due to four important factors. First, in many areas households are rather homogeneous in terms of observable characteristics even if there consumptions vary relatively more. That necessarily

[5] We also deleted or redefined dichotomic variables being less that 0.03 or larger than 0.97 to avoid serious multicollinearity problems in our econometric models.
[6] As described in the methodology section and Annexe 1, two statistical problems are likely to violate Ordinary Least Squares assumptions. Spatial autocorrelation (expenditure from households within a same cluster are surely correlated, i.e. there are location effects) are minimized by incorporating in the regressions Enumeration Areas's means of some key variables. The heteroskedasticity (error terms are not constant across observations) is corrected by modelizing the error terms. Correcting for those two problems yields unbiased estimates. See Elbers et al. (2002, 2003) and Mistiaen et al. (2002) for more details.

yields lower R^2. Second, a large number of potential correlates are simply not observables using surveys with closed-questionnaires. Third, many good predictors had been discarded at first stage since their distributions (mean and standard error) did not appears to be identical. And finally, many indicators do not take into account the quality of the correlates. Not taking into account the wide variation in quality of the different observable correlates makes many of those potential correlates useless in term of predictive power.

Stage 3: Welfare indicators[7]

16. Based on the results from the previous stage, we applied the estimated parameters[8] to the Census data to compute a series of poverty indicators: the headcount ratio (P_0), the poverty gap index (P_1) and the poverty severity index (P_2). Table 2 presents estimated poverty figures for each stratum and compares them with actual figures from the latest survey-based poverty profiles. For each stratum and poverty indicators, the equality of LSMS-based and Census-based indicators cannot be rejected (at 95%)[9]. The census-based headcount ratio is minute for all strata except for the Aimag Center strata for which the difference is 2.7 percentage points. Although census-based poverty figures can only be compared with the ones provided by the LSMS survey at stratum level, equality of those poverty figures provided an excellent reliability test of the methodology used here.

[7] *The computation of the welfare indicator has been greatly eased thanks to PovMap, a software especially written to implement the methodology used here. We used the February 2005 version developed by Qinghua Zhao (2005).*
[8] *Apart from regression models explaining household welfare level, we also estimated a model for the heteroskedasticity in the household component of the error. We also estimated the parametric distributions of both error terms for the simulations. See the methodological annexe for further details.*
[9] *It is worth noting that the standard errors of the mean of the Census-based figures are systematically lower that the ones calculated from LSMS.*

Table 2: Poverty Rates based on LSMS (actual) and Census 2000 (predicted), by stratum

	Poverty Headcount (P_0)		Poverty Gap Index (P_1)		Poverty Severity Index (P_2)	
	LSMS (Actual)	Census (Predicted)	LSMS (Actual)	Census (Predicted)	LSMS (Actual)	Census (Predicted)
Ulaan Baatar	0.273	0.278	0.081	0.074	0.033	0.029
	(0.026)	(0.016)	(0.010)	(0.006)	(0.005)	(0.003)
Aimag Center	0.339	0.366	0.105	0.113	0.047	0.050
	(0.022)	(0.017)	(0.010)	(0.008)	(0.007)	(0.005)
Soum Center	0.445	0.439	0.144	0.145	0.064	0.066
	(0.030)	(0.023)	(0.015)	(0.012)	(0.009)	(0.007)
Countryside	0.427	0.421	0.126	0.128	0.051	0.054
	(0.033)	(0.024)	(0.013)	(0.011)	(0.007)[9]	(0.006)

Sources: *Authors' calculation based on LSMS 2002/03 and Census 2000*
Note: *Robust standard errors are in parentheses.*

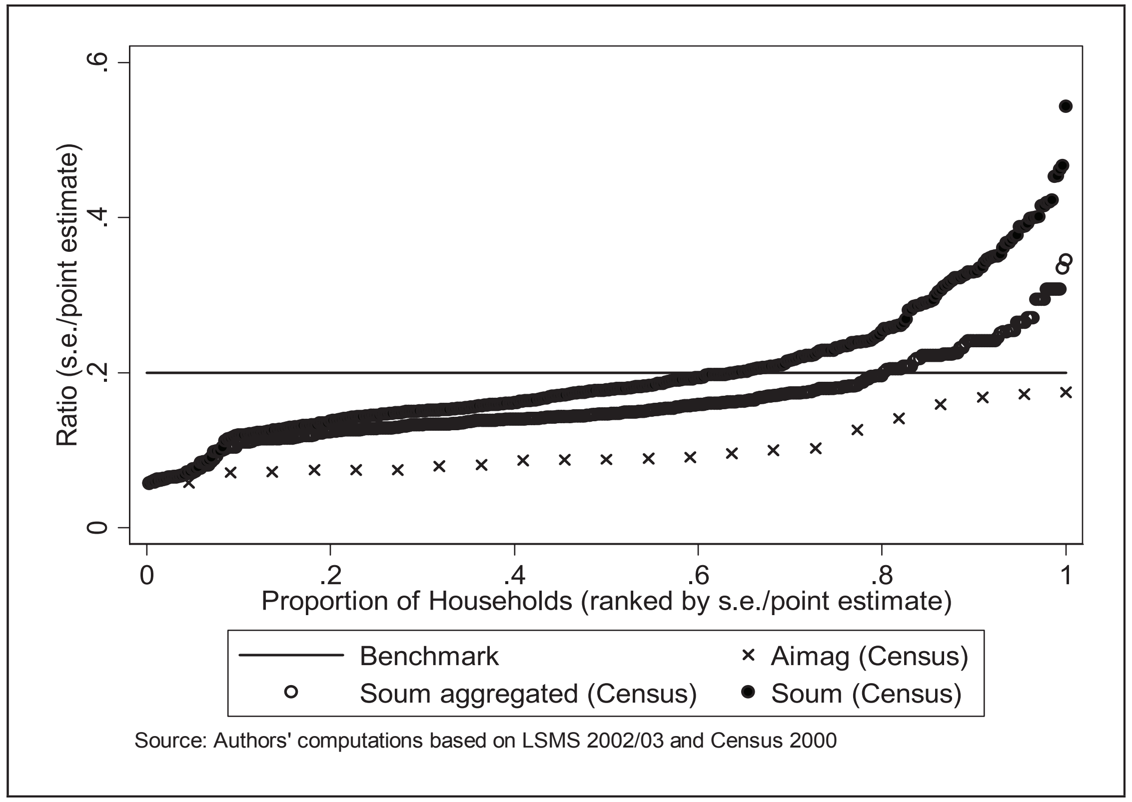
17. After having established the reliability of the different predictive models, we estimated poverty figures for the three disaggregated levels described in Table 1: region, aimag and soum. Before presenting the actual results we need to determine whether those results are precise enough to be useful. As discussed in the methodological section, the precision of the poverty estimates decline as the number of households in the different administrative units is getting smaller. While we expect the aimag-level poverty estimates to be precise enough it is legitimate to be more interrogative about soum-level estimates.

How low **can** we go?

18. In order to make an "objective" judgement on the precision of those estimates we computed coefficients of variation for both lower levels under study (aimag and soum) and then compared them with an arbitrary but commonly-used benchmark. Figure 1 presents the headcount incidence coefficients of variation of the aimag- and soum-level estimates and compared them to a 0.2 benchmark. The lower curve (represented by **x**s) in Figure 1 clearly shows that our aimag-level headcount poverty estimates does relatively well while the precision of soum-level estimates fair badly as shown by the upper curve on Figure 1. Close of two-third of the soums have coefficients of variation above our 0.2 benchmark. Since the main cause of those low level of precision (i.e. high coefficients of variation) is the small population of those soums the natural solution had been to aggregate some soums together. The original 340 soums had been aggregated into 243 geographical entities on which all the soum-level estimates have been based. We aggregated together soums having common borders and lower population levels. The main implications would be to have some of the lowly populated soums having the same poverty estimates. However it permits to have more precise estimates at soum level. As shown in Figure 1, the coefficients of variation of those "aggregated soums" are much lower although some of them still have some high coefficients of variation. Are those aggregated soums having higher coefficients of variations create problems? Figure 2 plots coefficients of variation against poverty headcount for each aggregated soums. It

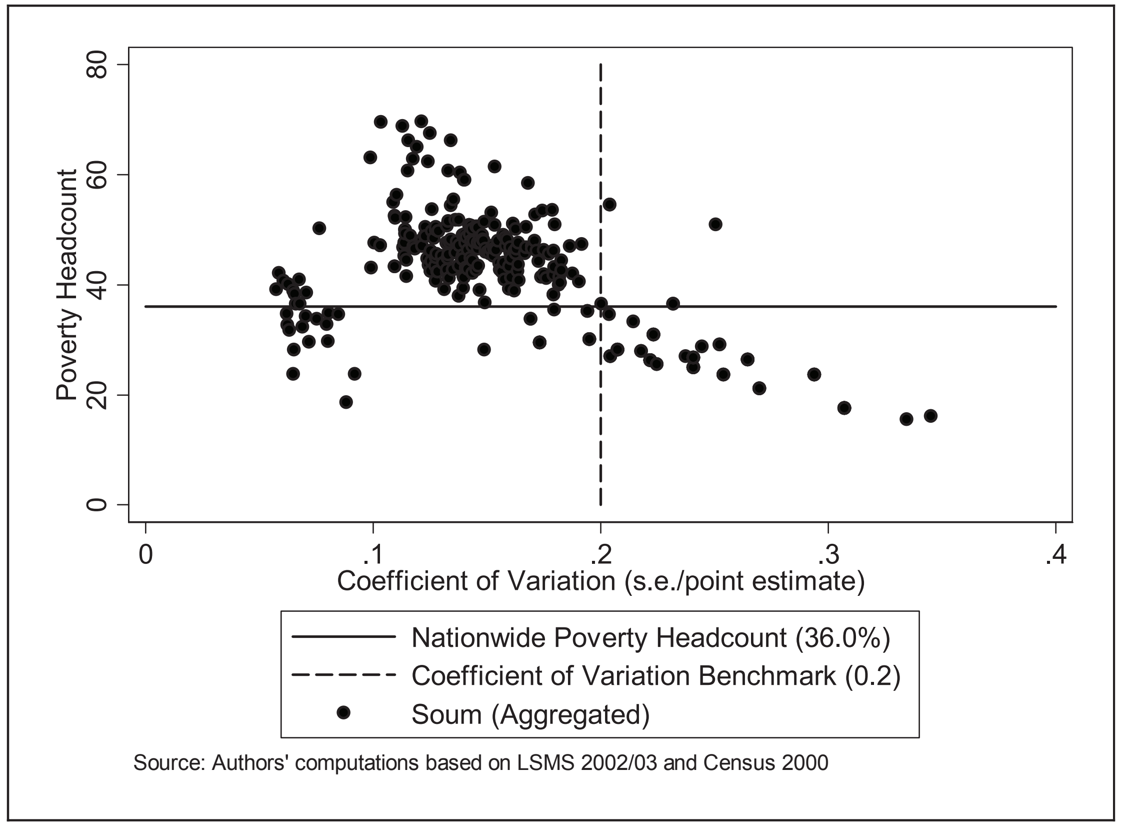
shows that amongst the soums with higher coefficients of variation a single soum has also a poverty headcount level above the national level (36.0%). Since one of the main applications of the poverty map would be to target the poorest aimags and soums we believe that level of precision of the relevant "aggregated soums" is acceptable and suitable for targeting purposes. It is clear that our poverty estimates at disaggregated levels would be good guides to policy-makers.

Figure 1: Poverty Headcount Accuracy, by disaggregation administrative level



19. Table 3 presents poverty figures for each of the 5 regions and 22 aimags/Capital City along with an urban/rural breakdown. The figures at soum-level are also presented in Annexe 4. The standard errors are also presented and are – for most cases – relatively small which make the predicted poverty figures quite reliable. Those disaggregated estimates are the first ever monetary-based poverty figures available in Mongolia. Since those administrative entities are based on geography a natural way to present the figures is with maps.

Figure 2: Poverty Headcount Versus Coefficients of Variation, soum level



20. Maps 1 to 3 reproduce Table 3 figures and Annex 4 poverty headcount figures at Region, Aimag and Soum levels respectively. Furthermore Maps 4 to 8 present the same figures as the soum-level Map 3 but magnify the maps by presenting them region by region. Using maps instead of tables permit to establish geographical pattern difficult to see from tables. Comparing all first three maps, it is salient how dissagregating poverty figures permits to recognize a finer poverty pattern. Map 1 shows that the Western Region is the poorest regions in Mongolia while the remaining of the country is rather less poor and homogeneous in term of monetary poverty. That level of aggregation is usually the lowest level possible when one used survey data. However Map 2 shows that those regions are far from being homogeneous. For example, the poverty in the Western region seems to be concentrated in the Khovd aimag while the other aimags in the Western region have poverty level more typically found in the Central region. Similarly the Dornod aimag pushes up poverty in the Eastern region while the other aimags found in that region has poverty level lower than the national average. Examining Maps 3 to 8 show that within a given aimag soums tend to be relatively homogeneous. In some cases (Omnogobi, Dornod and Bayankhongor aimags) all the different soums are in the same poverty intervals as their respective aimag. Furthermore, in most cases only a few soums stand out as poorer or as richer than the remaining of their aimag.

How low **should** we go?

21. We just demonstrated that we can use the aimag and soum poverty figures with some confidence; however it might be the case that those disaggregated figures does not yield much

more information. Within a rather homogenous aimag, it might be possible that the different soums are not statistically different from each others in terms of monetary poverty. To test whether any additional information about poverty levels is gain when we disaggregated from aimags to soums, we compared soum poverty levels with their respective aimag and with the nationwide poverty level. It is possible to show that out of 340 soums, 59 are poorer than the national average and 21 soums are richer. When compared to the poverty level of their respective aimag, 76 soums are poorer and 60 richer. The figures are very similar if we take poverty depth or poverty severity as our poverty indicators. This shows clearly the value added of using soums instead of aimags as the appropriate level to, for example, target poverty. Those results are only indicative of the benefit of poverty maps disaggregated at aimag and soums levels. Further research would be needed to properly construct proper targeting indicators.

Table 3: Poverty Indices, by Region and Aimag

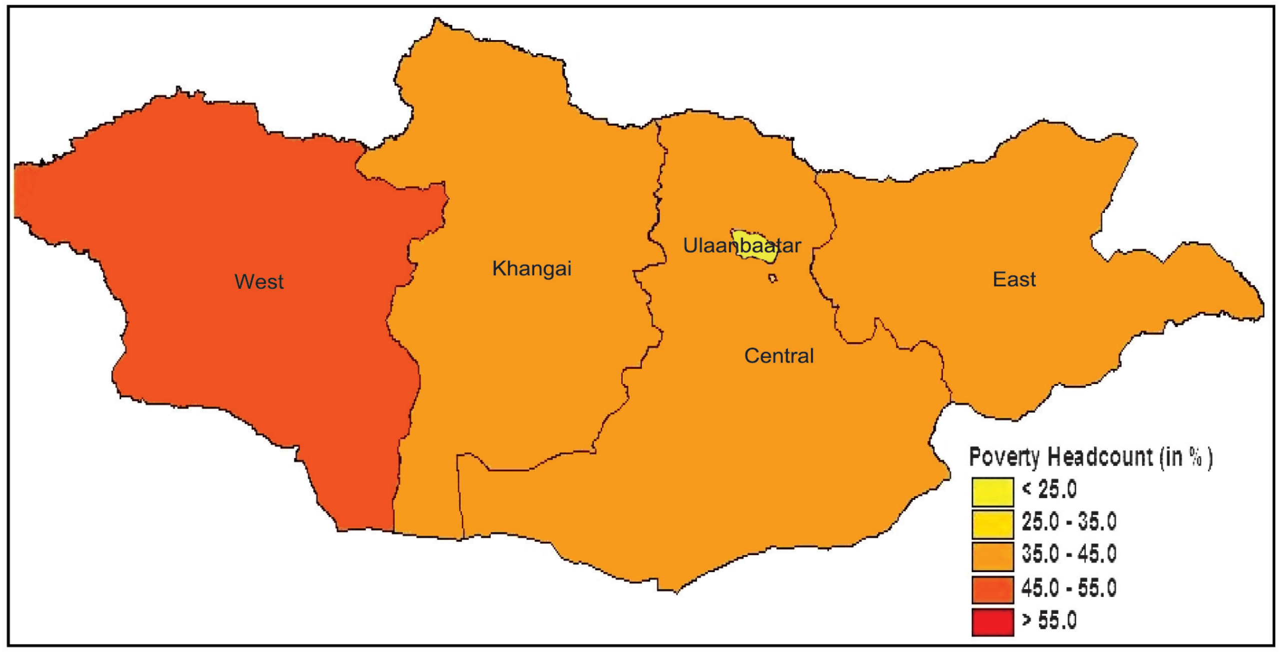
		Urban			Rural			Total		
Census Code	Administrative Structure: Regions & Aimags	Population	Poverty Headcount (P0)	Poverty Gap Index (P1)	Population	Poverty Headcount (P0)	Poverty Gap Index (P1)	Population	Poverty Headcount (P0)	Poverty Gap Index (P1)
10000	**WEST**	**112,629**	**0.362**	**0.109**	**310,797**	**0.500**	**0.163**	**423,426**	**0.463**	**0.149**
			(0.019)	***(0.009)***		***(0.030)***	***(0.015)***		***(0.027)***	***(0.014)***
10200	Bayan-Olgii	26,146	0.365	0.109	65,456	0.462	0.142	91,602	0.434	0.132
			(0.024)	*(0.011)*		*(0.049)*	*(0.022)*		*(0.042)*	*(0.019)*
10500	Govi-Altai	15,905	0.161	0.040	48,236	0.472	0.146	64,141	0.395	0.120
			(0.056)	*(0.017)*		*(0.034)*	*(0.016)*		*(0.039)*	*(0.016)*
10900	Zavkhan	18,548	0.389	0.118	72,234	0.448	0.137	90,782	0.436	0.133
			(0.025)	*(0.011)*		*(0.034)*	*(0.015)*		*(0.032)*	*(0.015)*
11500	Uvs	26,421	0.421	0.131	63,735	0.486	0.156	90,156	0.467	0.149
			(0.025)	*(0.012)*		*(0.047)*	*(0.023)*		*(0.041)*	*(0.020)*
11600	Khovd	25,609	0.401	0.124	61,136	0.638	0.239	86,745	0.568	0.205
			(0.025)	*(0.011)*		*(0.055)*	*(0.037)*		*(0.046)*	*(0.029)*
20000	**HIGHLANDS**	**174,706**	**0.373**	**0.117**	**378,209**	**0.407**	**0.125**	**552,915**	**0.396**	**0.122**
			(0.023)	***(0.011)***		***(0.028)***	***(0.013)***		***(0.026)***	***(0.012)***
20100	Arkhangai	18,870	0.342	0.101	79,204	0.441	0.133	98,074	0.422	0.126
			(0.024)	*(0.010)*		*(0.033)*	*(0.014)*		*(0.031)*	*(0.014)*
20300	Bayankhongor	22,532	0.409	0.128	63,082	0.492	0.155	85,614	0.470	0.148
			(0.028)	*(0.013)*		*(0.035)*	*(0.017)*		(0.033)	*(0.016)*
20400	Bulgan	12,953	0.329	0.096	49,944	0.238	0.067	62,897	0.257	0.073
			(0.026)	*(0.010)*		*(0.047)*	*(0.015)*		*(0.043)*	*(0.014)*
21000	Ovorkhangai	19,621	0.155	0.037	92,327	0.316	0.089	111,948	0.288	0.080
			(0.052)	*(0.015)*		*(0.049)*	*(0.017)*		*(0.050)*	*(0.017)*
21700	Khovsgol	29,780	0.392	0.121	90,347	0.502	0.166	120,127	0.475	0.155
			(0.023)	*(0.010)*		*(0.048)*	*(0.025)*		*(0.042)*	*(0.021)*
22100	Orkhon	70,950	0.430	0.141	3,305	0.408	0.128	74,255	0.429	0.140

			(0.043)	(0.020)		(0.067)	(0.029)		(0.044)	(0.021)
30000	**CENTRAL**	**160,479**	**0.327**	**0.097**	**285,134**	**0.421**	**0.134**	**445,613**	**0.387**	**0.121**
			(0.019)	**(0.008)**		**(0.026)**	**(0.012)**		**(0.024)**	**(0.011)**
30600	Dornogovi	18,175	0.323	0.096	32,905	0.393	0.122	51,080	0.368	0.113
			(0.022)	(0.009)		(0.039)	(0.017)		(0.033)	(0.014)
30800	Dundgovi	14,574	0.385	0.118	37,241	0.438	0.133	51,815	0.423	0.129
			(0.027)	(0.012)		(0.040)	(0.018)		(0.037)	(0.016)
31100	Omnogovi	14,097	0.365	0.113	31,684	0.265	0.073	45,781	0.296	0.085
			(0.025)	(0.011)		(0.057)	(0.018)		(0.047)	(0.016)
31300	Selenge	22,740	0.346	0.105	78,003	0.480	0.162	100,743	0.450	0.149
			(0.029)	(0.013)		(0.034)	(0.017)		(0.033)	(0.016)
31400	Tov	14,711	0.338	0.102	83,992	0.426	0.131	98,703	0.413	0.127
			(0.025)	(0.011)		(0.030)	(0.014)		(0.029)	(0.013)
31900	Darkhan-Uul	67,119	0.296	0.085	17,923	0.414	0.136	85,042	0.321	0.096
			(0.021)	(0.008)		(0.041)	(0.018)		(0.025)	(0.010)
32200	Govisumber	9,063	0.348	0.105	3,386	0.545	0.216	12,449	0.402	0.136
			(0.028)	(0.012)		(0.111)	(0.075)		(0.051)	(0.029)
40000	**EAST**	**74,421**	**0.440**	**0.146**	**130,974**	**0.336**	**0.100**	**205,395**	**0.374**	**0.117**
			(0.031)	**(0.016)**		**(0.039)**	**(0.015)**		**(0.036)**	**(0.015)**
40700	Dornod	40,548	0.476	0.165	35,996	0.486	0.159	76,544	0.481	0.162
			(0.048)	(0.024)		(0.037)	(0.018)		(0.043)	(0.021)
41200	Sukhbaatar	15,576	0.383	0.117	41,063	0.272	0.074	56,639	0.303	0.086
			(0.025)	(0.011)		(0.063)	(0.021)		(0.053)	(0.018)
41800	Khentii	18,297	0.407	0.128	53,915	0.285	0.081	72,212	0.316	0.093
			(0.025)	(0.012)		(0.051)	(0.018)		(0.044)	(0.016)
50000	**ULAANBAATAR**	**772,969**	**0.278**	**0.074**	**:**	**:**	**:**	**772,969**	**0.278**	**0.074**
			(0.016)	**(0.006)**					**(0.016)**	**(0.006)**
52000	Ulaanbaatar	772,969	0.278	0.074	:	:	:	772,969	0.278	0.074
			(0.016)	(0.006)					(0.016)	(0.006)

Source: Authors' calculations based on the LSMS 2002/03 and Census 2000
Note 1: Robust standard errors are in parentheses.
Note 2: The Regions are shown in bold while their associated Aimags are listed below

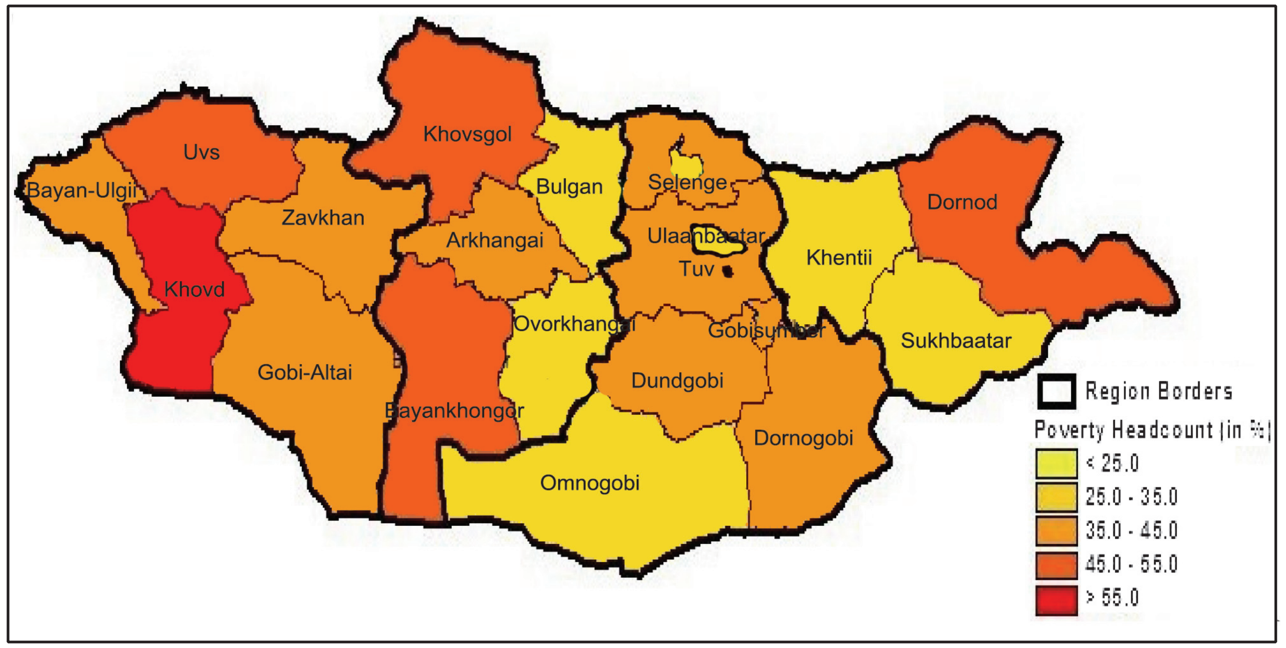
MONGOLIA CENSUS-BASED POVERTY MAP
Region, Aimag and Soum Level Results

Map 1: Region-Level Poverty Headcount Map



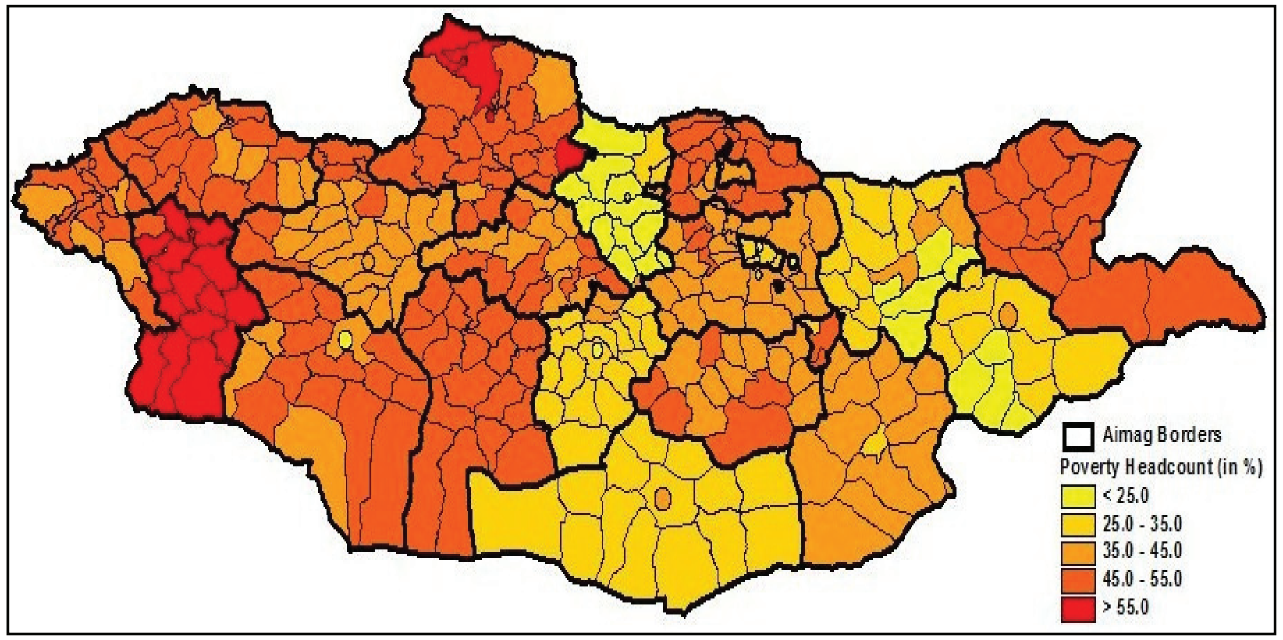
Source: Authors' calculations based on the LSMS 2002/2003 and Census 2000

Map 2: Aimag-Level Poverty Headcount Map



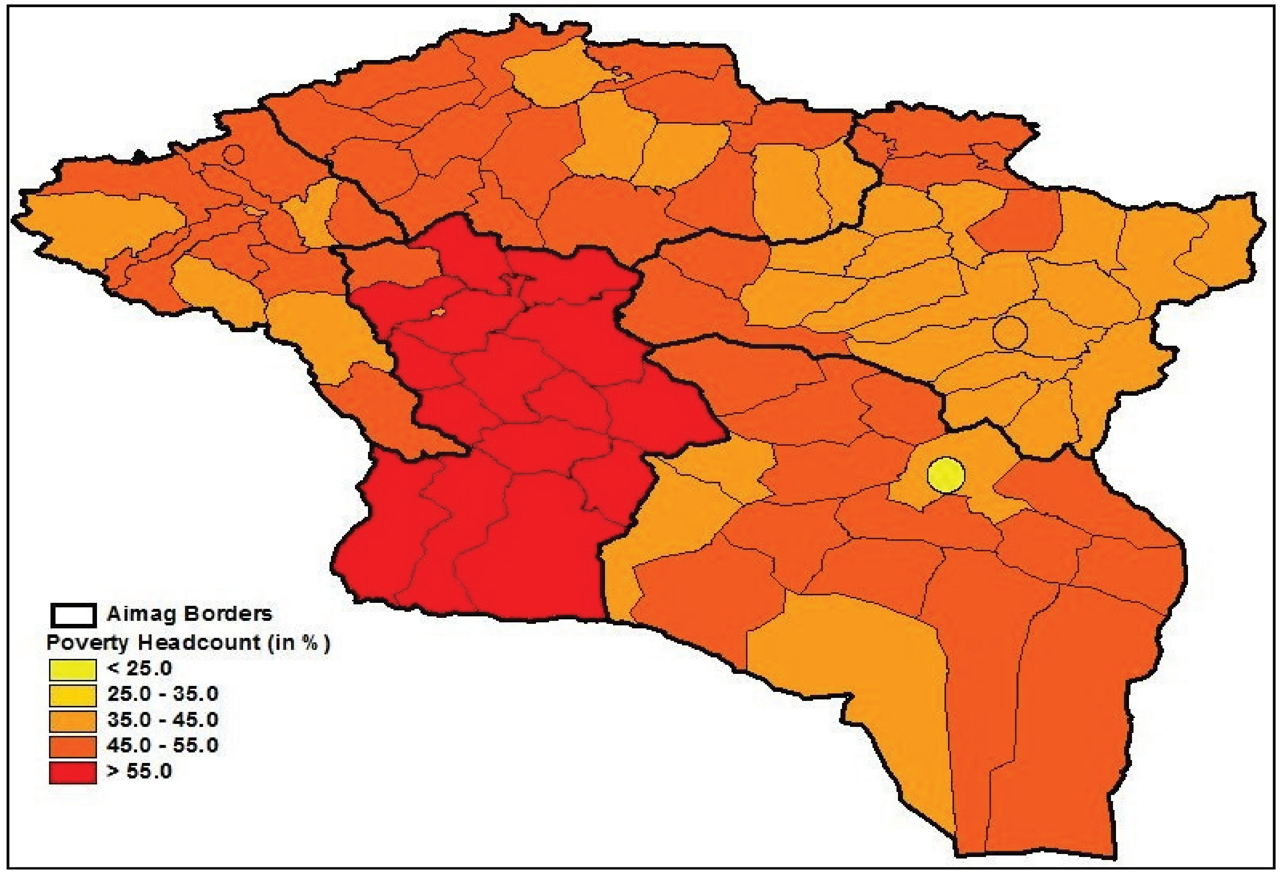
Source: Authors' calculations based on the LSMS 2002/2003 and Census 2000

Map 3: Soum-Level Poverty Headcount Map



Source: Authors' calculations based on the LSMS 2002/2003 and Census 2000

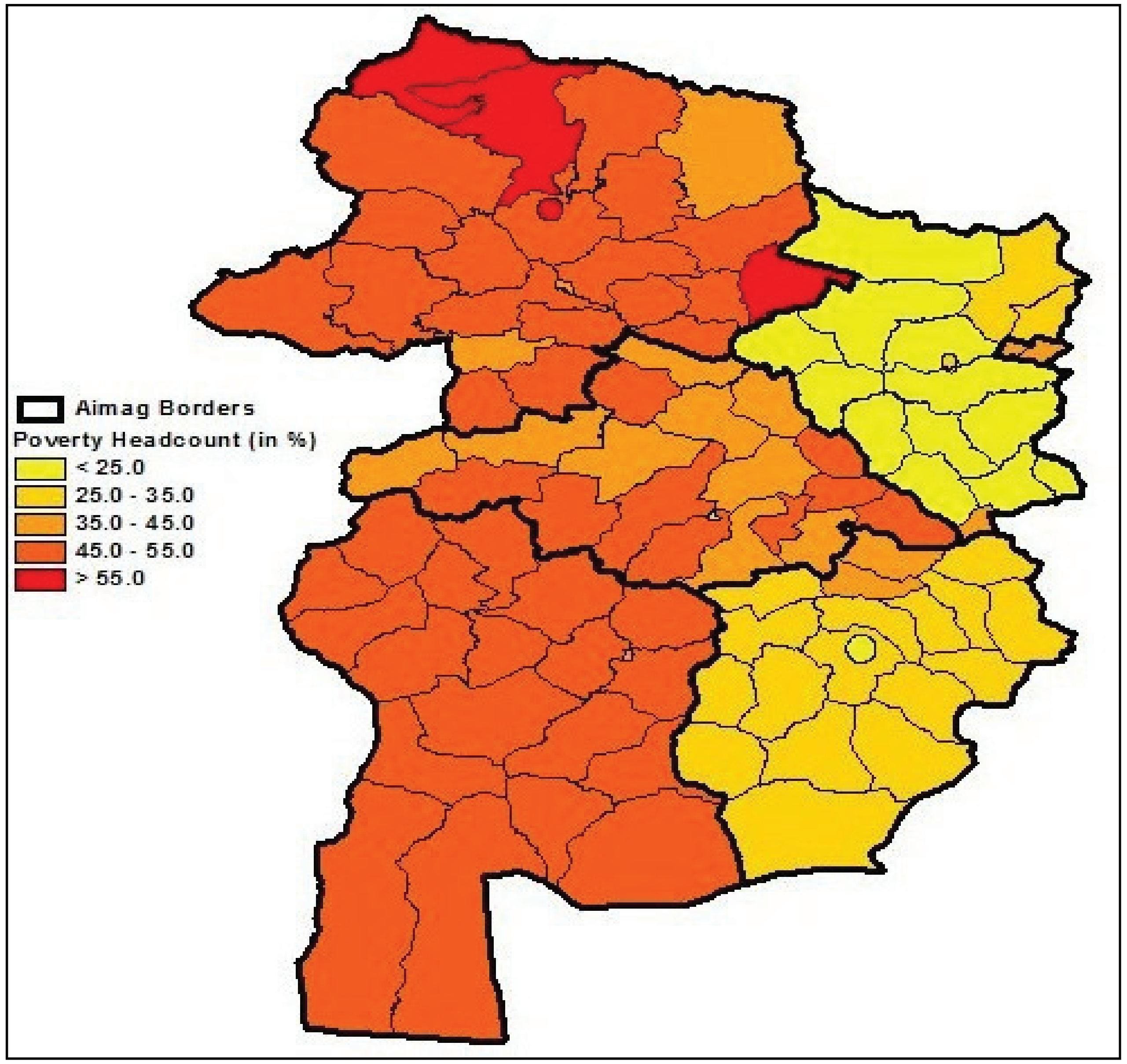
Map 4: Soum Poverty Map, West Region



Source: Authors' calculations based on the LSMS 2002/2003 and Census 2000

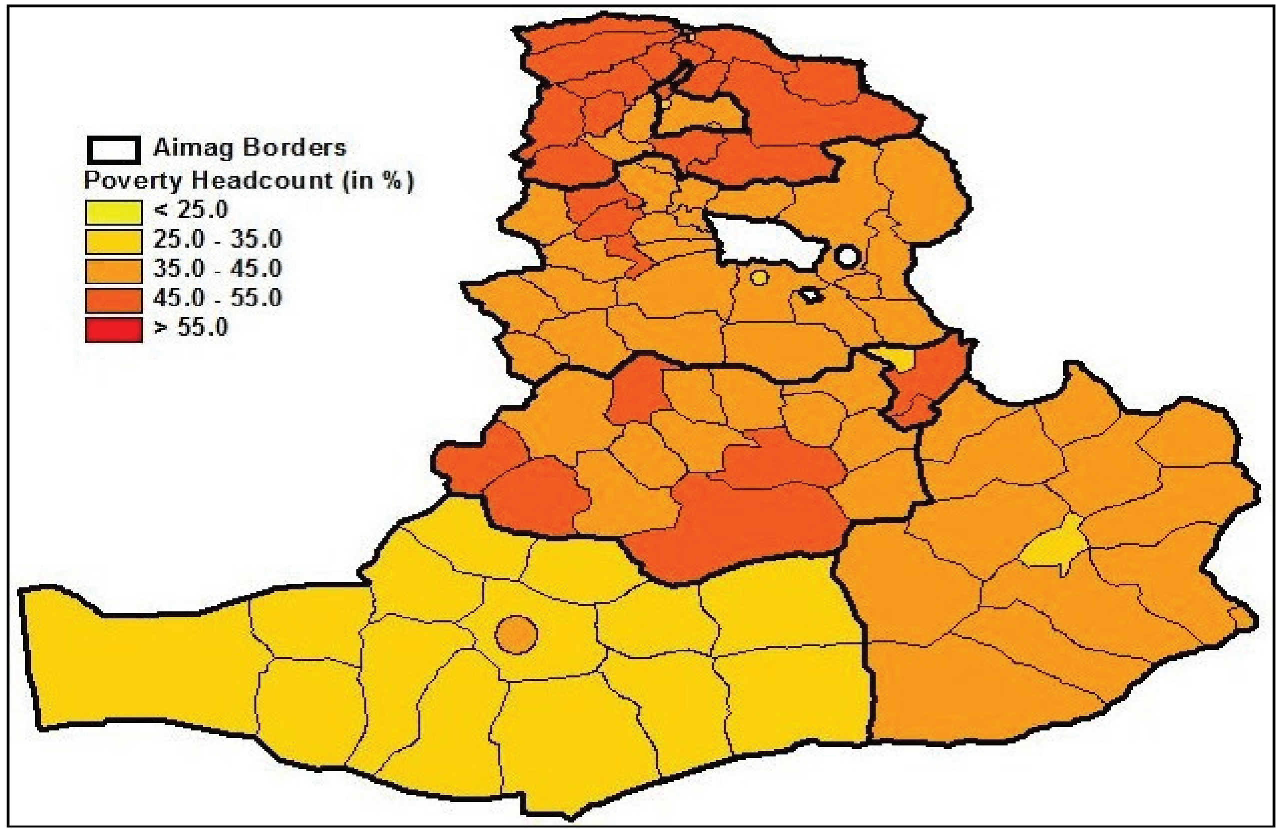
MONGOLIA CENSUS-BASED POVERTY MAP
Region, Aimag and Soum Level Results

Map 5: Soum Poverty Map, Khangai Region



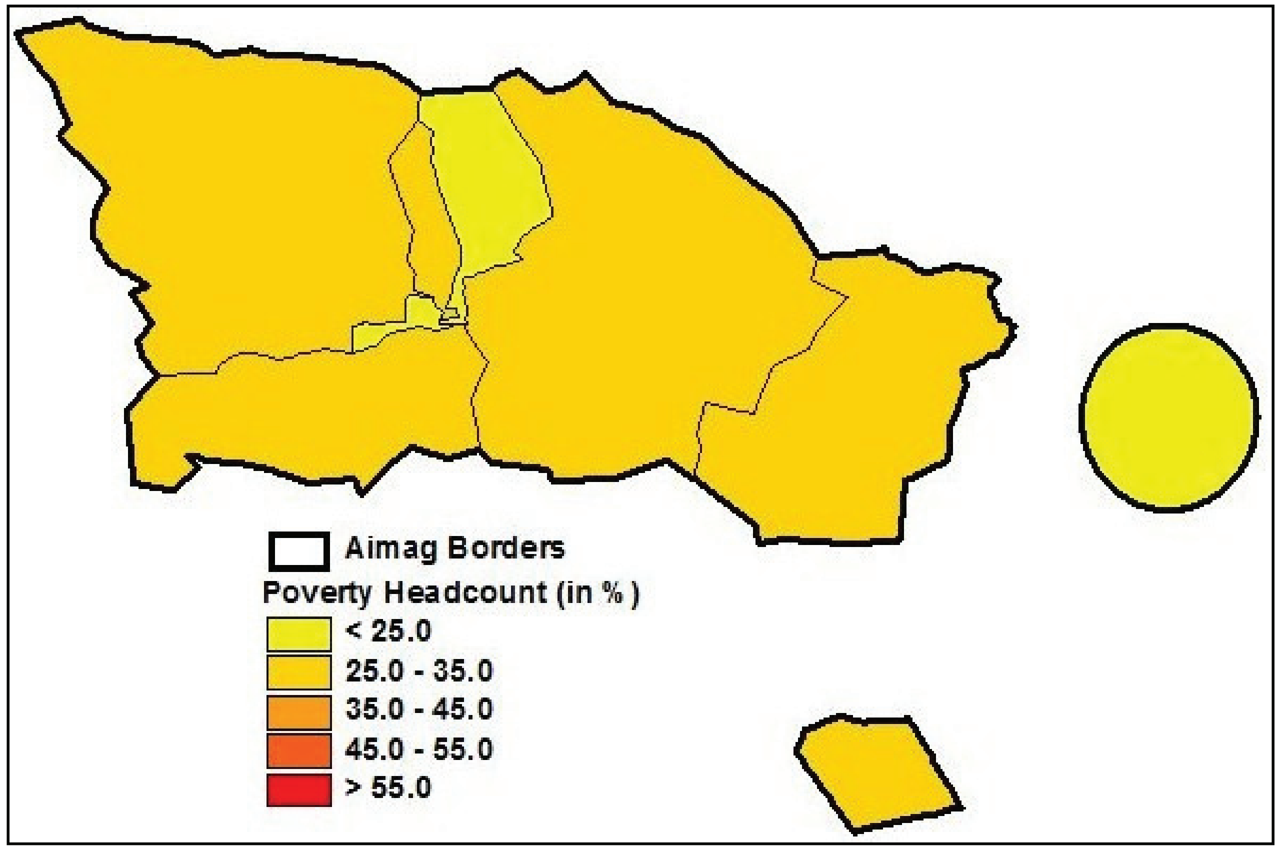
Source: Authors' calculations based on the LSMS 2002/2003 and Census 2000

Map 6: Soum Poverty Map, Central Region



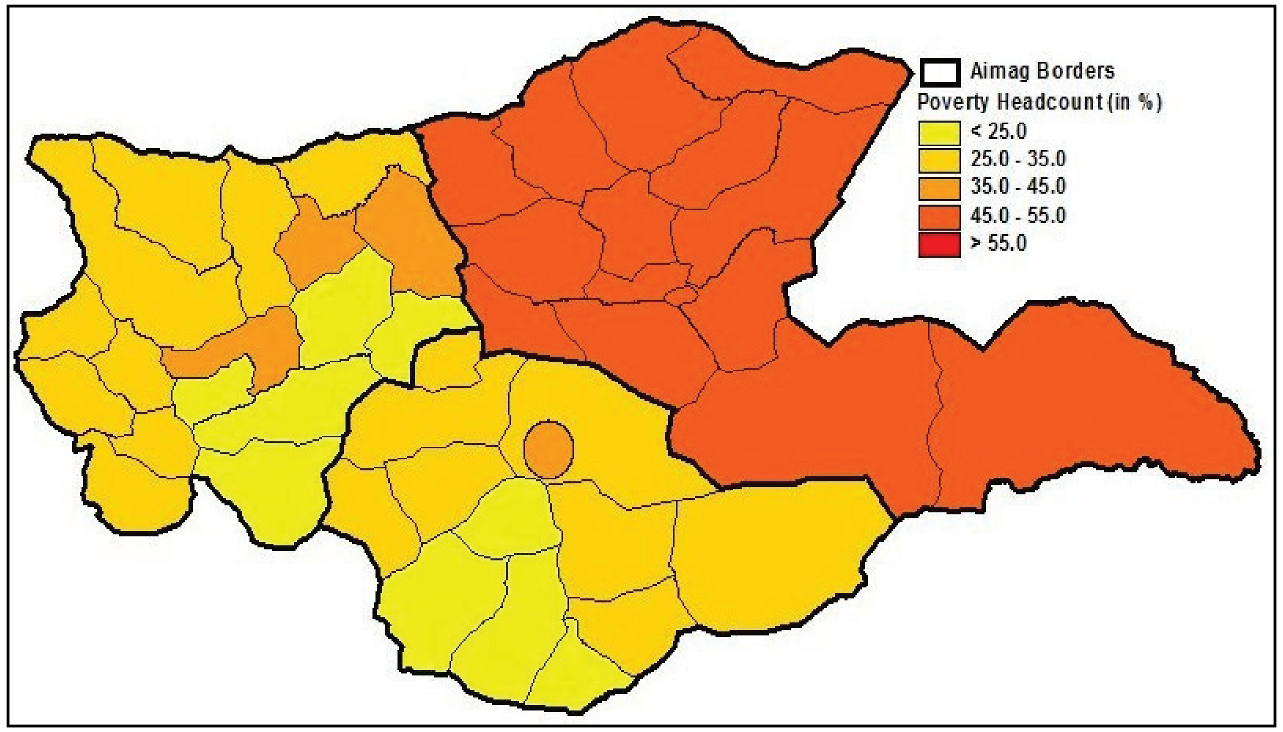
Source: Authors' calculations based on the LSMS 2002/2003 and Census 2000

Map 7: District Poverty Map, Ulaanbaatar Region



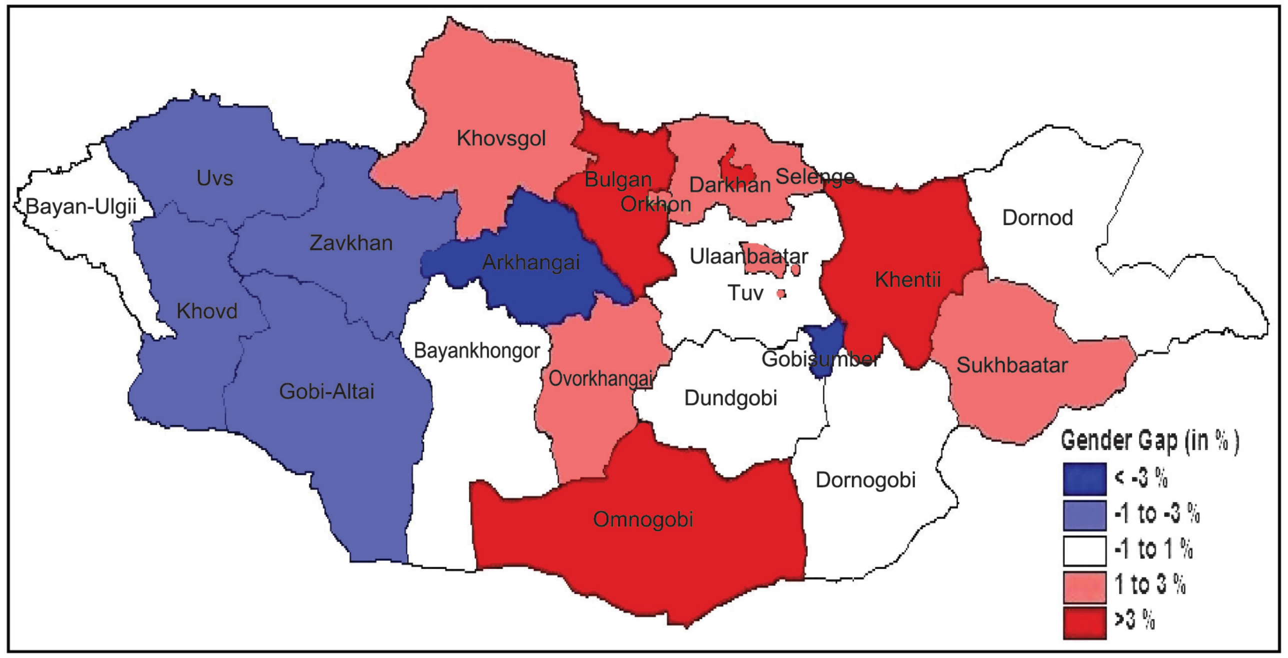
Source: Authors' calculations based on the LSMS 2002/2003 and Census 2000

Map 8: Soum Poverty Map, East Region



Source: Authors' calculations based on the LSMS 2002/2003 and Census 2000

Map 9: Gender Gap in Poverty Headcount, by Aimag



Source: Authors' calculations based on the LSMS 2002/2003 and Census 2000

GENDER

22. Although the methodology used to construct poverty maps is mainly geared toward geographical-based outcomes, it is possible to compute poverty indicators for any groups having large enough population size. In Mongolia, around 16 percent of households are headed by a female. On average, those female-headed households are not poorer since both male- and female-headed housedolds have a 37 percent poverty rate. However, Map 9 shows the existence of a mild gender gap in some aimags; but also that the gap is "reverse" in some other aimags. It should be noted that none of those gender gap are significantly different from zero (using a 95% confidence interval).

CONCLUDING REMARKS

23. This paper has documented the construction of a series of region-, aimag- and soum-level poverty maps for Mongolia. The methodology developed by Elbers et al. (2003) has permitted to obtain the first ever reliable poverty estimates at those local levels in Mongolia. Those finely disaggregated poverty figures are fully compatible with the latest Mongolia Poverty Profile.

24. One of the main advantages of the methodology used here is the possibility of computing standard errors of the different poverty estimates and therefore to have an idea of the reliability of those estimates. We concluded that the figures presented here are precise enough to be useful to planners, policy-makers and researchers.

25. However interesting those results, they would acquire their full potential if they are use. How? Amongst others, those results can be used to design budget allocation rules to be applied by the different administrative levels toward their subdivisions: the central government toward the regions, and the regions toward their aimags and soums. That map could become an important tool in support of the decentralization process currently undertaken in Mongolia. Poverty being a multi-dimensional phenomenon such monetary-based target indicators should be supplemented by alternative measures of poverty based on education, health or infrastructure. The construction of a series of MDG[10] maps is currently undertaken. In particular merging the poverty map with education and health maps would yields powerful targeting tools. Others uses of the poverty map would include the evaluation of locally targeted anti-poverty schemes (Social funds, Town/village development schemes), impact analysis etc. And finally, researchers could use it in a multitude of ways such as the study of relationship between poverty distribution and different socio-economic outcomes.

[10] *Millennium Development Goals (MDGs).*

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ANNEX 1: Methodology

The basic idea behind the methodology developed by Elbers, Lanjouw and Lanjouw (2002, 2003) is unchallenging. At first a regression model of log of per capita expenditure is estimated using survey data, employing a set of explanatory variables which are common to both a survey and a census. Next, parameters from the regression are used to predict expenditure for every household in the census. And third, a series of welfare indicators are constructed for different geographical subgroups.

The term "welfare indicator" embrace a whole set of indicators based on household expenditures. This note put emphasis on poverty headcount (P_0) but the usual poverty and inequality indicators can be computed (Atkinson inequality measures, generalised Entropy class inequalities index, FGT poverty measures and Gini).

Although the idea is rather simple its proper implementation require complex computation if one want to take into account spatial autocorrelation and heteroskedasticity in the regression model. Furthermore, proper calculation of the different welfare indicators and its standard errors increase tremendously its complexities.

The discussion below is divided into three parts, one for each stage necessary in the construction of a poverty map. This discussion borrows from the original theoretical papers of Elbers, Lanjouw and Lanjouw as well as from Mistiaen et al. (2002).

First stage

In the first instance, we need to determine a set of explanatory variables from both databases that are meeting some criteria of comparability. In order to be able to reproduce a poverty map consistent with the associated poverty profile, it is important to restrict ourselves to variables that are fully comparable between the census and the survey used. We start by checking the wording of the different questions as well as the proposed answer options. From the set of selected questions we then build a series of variables which would be tested for comparability. Although we might want to test the comparability of the whole distributions of each variable, in practice we restrain ourselves to test only the equality of their means. In order to maximise the predictability power of the second-stage models all analysis would be performed at the strata level, including the comparability of the different variables from which the definitive models would be determined.

The list of all potential variables and their equality of means test results are presented in Annex 2.

Second stage

We first model per capita household expenditure using the survey database. In order to maximise accuracy we estimate the model at the lowest geographical level for which the survey is representative. In the case of the LSMS that level is the sampling strata: Ulaanbaatar, Aimag centers, Soums centers and countryside.

Let specify a household level expenditure (y_{ch}) model for household h in location c, $\mathbf{x}_{ch}$ is a set of explanatory variables, and u_{ch} is the residual:

$$\ln y_{ch} = \mathrm{E}[\ln y_{ch} \mid \mathbf{x_{ch}}] + u_{ch} \qquad (1)$$

The locations represent clusters as defined in the first stage of typical household sampling design. It usually also represents census enumeration areas, although it does not have to be. The explanatory variables need to be present in both the survey and the census, and need to be defined similarly. It also needs to have the same moments in order to properly measure the different welfare indicators. The set of potential variables had been defined in the first stage.

If we linearise the previous equation, we model the household's logarithmic per capita expenditure as

$$\ln y_{ch} = \mathbf{x}'_{\mathbf{ch}}\boldsymbol{\beta} + u_{ch} \qquad (2)$$

The vector of disturbances $\boldsymbol{u}$ is distributed F (0,Σ). The model (2) is estimated by Generalised Least Square (GLS). To estimate this model we need first to estimate the error variance-covariance matrix in order to take into account possible spatial autocorrelation (expenditure from households within a same cluster are surely correlated) and heteroskedasticity. To do so we first specify the error terms as

$$u_{ch} = \eta_c + \varepsilon_{ch} \qquad (3)$$

where η_c is the location effect and ε_{ch} is the individual component of the error term.

In practice we first estimate equation (2) by simple OLS and use the residuals as estimate of the overall disturbances, given by $\hat{\mu}_{ch}$. We then decomposed those residuals between uncorrelated household and location components:

$$\hat{u}_{ch} = \hat{\eta}_c + e_{ch} \qquad (4)$$

The location term ($\hat{\eta}_c$) is estimated as cluster means of the overall residuals and therefore the household component (e_{ch}) is simply deducted. The heteroskedasticity in the latest error component is modelled by the regressing its squared (e^2_{ch}) on a long list of all independent variables of model (2), their squared and interactions as well as the imputed welfare. A logistic model is used[11].

Both error computations are used to produce two matrices which are them sum to $\hat{\Sigma}$, the estimated variance-covariance matrix of the original model (2). That latest matrix permits to estimate the final set of coefficients of the main model (2).

[11] See Mistiaen et al. (2002) for further details on how the theoretical model is estimated in practice.

Third stage

To complete the map we associate the estimated parameters from the second stage with the corresponding characteristics of each household found in the census to predict the log of per capita expenditure and the simulated disturbances.

Since the very complex disturbance structure has made the computation of the variance of the imputed welfare index intractable, bootstrapping techniques have been used to get a measure of the dispersion of that imputed welfare index. From the previous stage, a series of coefficients and disturbance terms have been drawn from their corresponding distributions. We then, for each household found in the census, simulate a value of welfare index ($\hat{y}_{ch}^{r}$) based on the predicted values and the disturbance terms:

$$\hat{y}_{ch}^{r} = \exp(\mathbf{x}_{ch}^{'}\tilde{\beta}^{r} + \tilde{\eta}_{c}^{r} + \tilde{\varepsilon}_{ch}^{r}) \qquad (5)$$

That process is repeated 100 times, each time redrawing the full set of coefficients and disturbances terms. The means of the simulated welfare index become our point estimate and the standard deviation of our welfare index is the standard errors of these simulated estimates.

ANNEX 2A: Definition of the different predictors

hhsize	Household size
kid06	Number of children aged between 0 and 6
boy714	Number of boys aged between 7 and 14
girl714	Number of girls aged between 7 and 14
male	Number of adult males between 15 and 64
female	Number of adult females between 15 and 64
elderly	Number of elderly aged 65 or more
hd_male	=1 if household head is a male; 0 if not
hd_literate	=1 if household head is literate; 0 if not
hd_noneduc	=1 if household head has no formal education; 0 if not
hd_primary	=1 if household head went to primary school (at most); 0 if not
hd_secondary	=1 if household head went to secondary school (at most); 0 if not
hd_tertiary	=1 if household head went to post secondary school; 0 if not
hd_single	=1 if household head is single; 0 if not
hd_couple	=1 if household head is in couple; 0 if not
hd_primesec	=1 if household head works in the primary sector; 0 if not
hd_secesec	=1 if household head works in the secondary sector; 0 if not
hd_teresec	=1 if household head works in the tertiairy sector; 0 if not
hd_occupied	=1 if household head works; 0 if not
hd_empl	=1 if household head works as an employee; 0 if not
hd_selfempl	=1 if household head is self-employed; 0 if not
hd_age	Age of household head (in years)
no_spouse	=1 if there is no spouse in the household; 0 if not
sp_literate	=1 if spouse is literate; 0 if not
sp_noneduc	=1 if spouse has no formal education; 0 if not
sp_primary	=1 if spouse went to primary school (at most); 0 if not
sp_secondary	=1 if spouse went to secondary school (at most); 0 if not
sp_tertiary	=1 if spouse went to post secondary school; 0 if not
sp_primesec	=1 if spouse works in the primary sector; 0 if not
sp_secesec	=1 if spouse works in the secondary sector; 0 if not
sp_teresec	=1 if spouse works in the tertiairy sector; 0 if not
sp_occupied	=1 if spouse works; 0 if not
sp_empl	=1 if spouse works as an employee; 0 if not
sp_selfempl	=1 if spouse is self-employed; 0 if not
sp_age	Age of spouse (in years)
pocc	Proportion of household members being occupied
psch	Proportion of household members currently going to school
type_house	=1 if household lives in a house; 0 if not
type_apart	=1 if household lives in an apartment; 0 if not
type_ger	=1 if household lives in an ger; 0 if not
type_other	=1 if household lives in another type of building; 0 if not
prop_private	=1 if household owns its dwelling; 0 if not
sqm	Dwelling floor area in squared meters for all types of dwelling
sqm2	Sqm squared
sqm_ger	Dwelling floor area in squared meters for ger only; 0 if not
sqm2_ger	Sqm_ger squared

ANNEX 2A: Definition of the different predictors (continued...)

water_pipe	=1 if household uses pipe as their main source water; 0 if not
water_well	=1 if household uses well as their main sources of water; 0 if not
water_hand	=1 if household uses handwell as their main source of water; 0 if not
water_other	=1 if household uses river, spring etc. as their main source of water; 0 if not
wc_in	=1 if household uses inside toilet; 0 if not
wc_out	=1 if household uses outside toilet; 0 if not
waste_tube	=1 if household uses tube for waste disposal (non ger); 0 if not
waster_noplace	=1 if household has no specific place for waste disposal (non ger); 0 if not
waste_other	=1 if household use other types of waste disposal (non ger); 0 if not
waste_ger1	=1 if household has a specific place for waste disposal (ger); 0 if not
waste_ger0	=1 if household has no specific place for waste disposal (ger); 0 if not
kitchen_in	=1 if household has an inside kitchen (non ger); 0 if not
kitchen_out	=1 if household has an outside kitchen (non ger); 0 if not
kitchen_ger	=1 if household has a kitchen specific to ger; 0 if not
heat_central	=1 if household has a central heating system (non ger); 0 if not
heat_noncentral	=1 if household has a non central heating system (non ger); 0 if not
heat_ger	=1 if household has a stove as heating system (ger); 0 if not
bath_in	=1 if household owns a bath (non ger); 0 if not
bath_no	=1 if household does not own a bath (non ger); 0 if not
bath_ger	=1 if household does not own a bath (ger); 0 if not
light	=1 if household has electricity; 0 if not
phone	=1 if household has a phone; 0 if not
pc_camel	Number of per capita camel (at soum level)
pc_cattle	Number of per capita cattle (at soum level)
pc_goat	Number of per capita goat (at soum level)
pc_horse	Number of per capita horse (at soum level)
pc_sheep	Number of per capita sheep (at soum level)
D1	=1 if household resides in Arkhangai aimag; 0 if not
D2	=1 if household resides in Bayan-olgii aimag; 0 if not
D3	=1 if household resides in Bayankhongor aimag; 0 if not
D4	=1 if household resides in Bulgan aimag; 0 if not
D5	=1 if household resides in Govi-altai aimag; 0 if not
D6	=1 if household resides in Dornogovi aimag; 0 if not
D7	=1 if household resides in Dornod aimag; 0 if not
D8	=1 if household resides in Dundgovi aimag; 0 if not
D9	=1 if household resides in Zavkhan aimag; 0 if not
D10	=1 if household resides in Ovorkhangai aimag; 0 if not
D11	=1 if household resides in Omnogovi aimag; 0 if not
D12	=1 if household resides in Sukhbaatar aimag; 0 if not
D13	=1 if household resides in Selenge aimag; 0 if not
D14	=1 if household resides in Tov aimag; 0 if not
D15	=1 if household resides in Uvs aimag; 0 if not
D16	=1 if household resides in Khovd aimag; 0 if not
D17	=1 if household resides in Khovsgol aimag; 0 if not
D18	=1 if household resides in Khentii aimag; 0 if not
D19	=1 if household resides in Darkhan-uul aimag; 0 if not
D20	=1 if household resides in Ulaanbaatar aimag; 0 if not
D21	=1 if household resides in Orkhon aimag; 0 if not
D22	=1 if household resides in Govisumber aimag; 0 if not

MONGOLIA CENSUS-BASED POVERTY MAP
Region, Aimag and Soum Level Results

ANNEX 2B: Aligning the Data, Test on Equality of Means

	Ulanbataar				Aimag Centers			
	Census	Survey		Test on equality	Census	Survey		Test on equality
	Mean	Mean	s.d.	of means (95%)	Mean	Mean	s.d.	of means (95%)
lnhhsize	1.457	1.375	0.020	Rejected	1.375	1.377	0.018	Not Rejected
hhsize	4.831	4.394	0.080	Rejected	4.411	4.346	0.071	Not Rejected
kid06	0.549	0.426	0.025	Rejected	0.591	0.433	0.024	Rejected
boy714	0.450	0.386	0.022	Rejected	0.521	0.458	0.025	Rejected
girl714	0.452	0.389	0.027	Rejected	0.526	0.504	0.024	Not Rejected
male	1.542	1.458	0.037	Rejected	1.271	1.362	0.038	Rejected
female	1.669	1.601	0.037	Not Rejected	1.358	1.547	0.037	Rejected
elderly	0.169	0.234	0.019	Rejected	0.145	0.147	0.016	Not Rejected
psch	0.220	0.275	0.009	Rejected	0.233	0.299	0.009	Rejected
pocc	0.305	0.331	0.010	Rejected	0.270	0.330	0.011	Rejected
hd_age	42.13	47.28	0.59	Rejected	41.22	45.04	0.46	Rejected
hd_age2	1966.5	2425.0	57.3	Rejected	1881.2	2205.3	46.4	Rejected
hd_occupied	0.539	0.574	0.019	Not Rejected	0.511	0.630	0.021	Rejected
hd_male	0.813	0.776	0.016	Rejected	0.821	0.831	0.014	Not Rejected
hd_literate	0.995	0.980	0.005	Rejected	0.986	0.992	0.003	Not Rejected
hd_noneduc	0.017	0.019	0.005	Not Rejected	0.039	0.028	0.007	Not Rejected
hd_primary	0.275	0.254	0.019	Not Rejected	0.394	0.286	0.020	Rejected
hd_secondary	0.459	0.483	0.023	Not Rejected	0.435	0.533	0.020	Rejected
hd_tertiary	0.249	0.230	0.025	Not Rejected	0.132	0.150	0.016	Not Rejected
hd_single	0.253	0.285	0.016	Not Rejected	0.240	0.224	0.015	Not Rejected
hd_couple	0.747	0.715	0.016	Not Rejected	0.760	0.776	0.015	Not Rejected
hd_primesec	0.031	0.023	0.006	Not Rejected	0.110	0.048	0.013	Rejected
hd_secsec	0.121	0.101	0.013	Not Rejected	0.102	0.089	0.012	Not Rejected
hd_tersec	0.387	0.425	0.018	Rejected	0.299	0.435	0.023	Rejected
hd_empl	0.407	0.408	0.019	Not Rejected	0.352	0.405	0.019	Rejected
hd_selfempl	0.132	0.148	0.015	Not Rejected	0.159	0.178	0.016	Not Rejected
sp_age	26.7	28.9	0.7	Rejected	26.6	31.4	0.7	Rejected
sp_age2	1122.4	1321.6	42.3	Rejected	1075.1	1383.9	40.7	Rejected
sp_occupied	0.343	0.385	0.020	Rejected	0.336	0.471	0.020	Rejected
sp_literate	0.691	0.679	0.017	Not Rejected	0.712	0.763	0.016	Rejected
sp_noneduc	0.005	0.004	0.002	Not Rejected	0.012	0.012	0.003	Not Rejected
sp_primary	0.147	0.113	0.013	Rejected	0.207	0.183	0.015	Not Rejected
sp_secondary	0.382	0.422	0.020	Not Rejected	0.406	0.471	0.018	Rejected
sp_tertiary	0.157	0.128	0.016	Not Rejected	0.087	0.096	0.013	Not Rejected
sp_primesec	0.010	0.004	0.002	Rejected	0.054	0.025	0.007	Rejected
sp_secsec	0.072	0.059	0.010	Not Rejected	0.047	0.035	0.006	Rejected
sp_tersec	0.261	0.304	0.018	Rejected	0.235	0.368	0.020	Rejected
sp_empl	0.269	0.275	0.019	Not Rejected	0.234	0.300	0.017	Rejected
sp_selfempl	0.074	0.098	0.012	Rejected	0.102	0.133	0.013	Rejected
no_spouse	0.309	0.321	0.017	Not Rejected	0.288	0.237	0.016	Rejected
type_house	0.301	0.396	0.036	Rejected	0.294	0.374	0.039	Rejected
type_apart	0.446	0.451	0.044	Not Rejected	0.301	0.327	0.045	Not Rejected
type_other	0.031	0.000	0.000	Rejected	0.026	0.000	0.000	Rejected
type_ger	0.220	0.153	0.019	Rejected	0.377	0.298	0.037	Rejected
Sqm	30.2	39.3	0.7	Rejected	31.2	38.6	1.0	Rejected
sqm2	1200.7	1771.0	62.3	Rejected	1298.1	1748.1	113.6	Rejected
sqm_ger	6.2	4.3	0.5	Rejected	11.5	9.8	1.3	Not Rejected

ANNEX 2B: Aligning the Data, Test on Equality of Means (continued...)

sqm2_ger	183.6	123.8	15.5	Rejected	396.9	370.5	66.8	Not Rejected
heat_central	0.469	0.447	0.045	Not Rejected	0.302	0.305	0.043	Not Rejected
heat_noncent.	0.311	0.400	0.036	Rejected	0.321	0.396	0.038	Not Rejected
heat_ger	0.220	0.153	0.019	Rejected	0.377	0.298	0.037	Rejected
water_pipe	0.475	0.467	0.046	Not Rejected	0.320	0.357	0.046	Not Rejected
water_well	0.444	0.423	0.044	Not Rejected	0.417	0.389	0.039	Not Rejected
water_hand	0.005	0.001	0.001	Rejected	0.084	0.035	0.011	Rejected
water_other	0.076	0.109	0.026	Not Rejected	0.179	0.219	0.030	Not Rejected
waste_tube	0.230	0.237	0.038	Not Rejected	0.019	0.043	0.015	Not Rejected
waste_noplace	0.051	0.042	0.014	Not Rejected	0.062	0.071	0.015	Not Rejected
waste_other	0.499	0.567	0.036	Not Rejected	0.542	0.588	0.036	Not Rejected
waste_ger1	0.160	0.126	0.017	Rejected	0.289	0.272	0.034	Not Rejected
waste_ger0	0.060	0.028	0.011	Rejected	0.088	0.026	0.010	Rejected
wc_in	0.484	0.483	0.045	Not Rejected	0.331	0.358	0.045	Not Rejected
wc_out	0.516	0.517	0.045	Not Rejected	0.669	0.642	0.045	Not Rejected
kitchen_in	0.668	0.627	0.035	Not Rejected	0.512	0.510	0.041	Not Rejected
kitchen_out	0.112	0.219	0.026	Rejected	0.112	0.192	0.024	Rejected
kitchen_ger	0.220	0.000	0.000	Rejected	0.377	0.000	0.000	Rejected
bath_in	0.458	0.463	0.045	Not Rejected	0.292	0.335	0.045	Not Rejected
bath_no	0.322	0.401	0.036	Rejected	0.331	0.375	0.038	Not Rejected
bath_ger	0.220	0.153	0.019	Rejected	0.377	0.298	0.037	Rejected
prop_private	0.875	0.931	0.020	Rejected	0.866	0.934	0.020	Rejected
light	0.977	0.991	0.003	Rejected	0.915	0.796	0.035	Rejected
phone	0.347	0.440	0.036	Rejected	0.234	0.410	0.024	Rejected
d1	0.000	0.000	0.000	Not Rejected	0.037	0.033	0.019	Not Rejected
d2	0.000	0.000	0.000	Not Rejected	0.045	0.042	0.021	Not Rejected
d3	0.000	0.000	0.000	Not Rejected	0.043	0.046	0.020	Not Rejected
d4	0.000	0.000	0.000	Not Rejected	0.027	0.022	0.015	Not Rejected
d5	0.000	0.000	0.000	Not Rejected	0.030	0.033	0.019	Not Rejected
d6	0.000	0.000	0.000	Not Rejected	0.036	0.032	0.017	Not Rejected
d7	0.000	0.000	0.000	Not Rejected	0.078	0.087	0.030	Not Rejected
d8	0.000	0.000	0.000	Not Rejected	0.028	0.022	0.015	Not Rejected
d9	0.000	0.000	0.000	Not Rejected	0.035	0.032	0.017	Not Rejected
d10	0.000	0.000	0.000	Not Rejected	0.038	0.043	0.021	Not Rejected
d11	0.000	0.000	0.000	Not Rejected	0.028	0.022	0.015	Not Rejected
d12	0.000	0.000	0.000	Not Rejected	0.030	0.033	0.019	Not Rejected
d13	0.000	0.000	0.000	Not Rejected	0.044	0.042	0.019	Not Rejected
d14	0.000	0.000	0.000	Not Rejected	0.029	0.033	0.019	Not Rejected
d15	0.000	0.000	0.000	Not Rejected	0.048	0.054	0.023	Not Rejected
d16	0.000	0.000	0.000	Not Rejected	0.044	0.043	0.018	Not Rejected
d17	0.000	0.000	0.000	Not Rejected	0.056	0.055	0.024	Not Rejected
d18	0.000	0.000	0.000	Not Rejected	0.036	0.033	0.019	Not Rejected
d19	0.000	0.000	0.000	Not Rejected	0.129	0.131	0.034	Not Rejected
d20	1.000	1.000	0.000	Not Rejected	0.000	0.000	0.000	Not Rejected
d21	0.000	0.000	0.000	Not Rejected	0.140	0.142	0.036	Not Rejected
d22	0.000	0.000	0.000	Not Rejected	0.018	0.022	0.015	Not Rejected
pc_camel	0.000	0.000	0.000	Not Rejected	0.012	0.011	0.002	Not Rejected
pc_cattle	0.061	0.057	0.006	Not Rejected	0.273	0.273	0.020	Not Rejected
pc_goat	0.094	0.088	0.013	Not Rejected	1.005	0.968	0.086	Not Rejected
pc_horse	0.024	0.021	0.004	Not Rejected	0.204	0.199	0.023	Not Rejected
pc_sheep	0.130	0.119	0.021	Not Rejected	1.179	1.151	0.101	Not Rejected

ANNEX 2B: Aligning the Data, Test on Equality of Means (continued...)

	Soum center				Countryside			
	Census	Survey		Test on equality	Census	Survey		Test on equality
	Mean	Mean	s.d.	of means (95%)	Mean	Mean	s.d.	of means (95%)
lnhhsize	1.362	1.386	0.020	Not Rejected	1.289	1.300	0.028	Not Rejected
hhsize	4.385	4.415	0.074	Not Rejected	4.125	4.141	0.094	Not Rejected
kid06	0.673	0.493	0.035	Rejected	0.791	0.742	0.042	Not Rejected
boy714	0.582	0.468	0.027	Rejected	0.384	0.443	0.027	Rejected
girl714	0.585	0.505	0.032	Rejected	0.358	0.414	0.028	Not Rejected
male	1.185	1.434	0.045	Rejected	1.252	1.254	0.038	Not Rejected
female	1.214	1.555	0.035	Rejected	1.175	1.243	0.038	Not Rejected
elderly	0.146	0.107	0.013	Rejected	0.164	0.184	0.018	Not Rejected
psch	0.240	0.295	0.010	Rejected	0.389	0.150	0.008	Rejected
pocc	0.262	0.368	0.013	Rejected	0.515	0.563	0.014	Rejected
hd_age	41.4	43.9	0.5	Rejected	40.9	41.6	0.7	Not Rejected
hd_age2	1919.3	2088.9	50.0	Rejected	1928.7	1968.4	62.6	Not Rejected
hd_occupied	0.525	0.686	0.022	Rejected	0.799	0.861	0.017	Rejected
hd_male	0.831	0.851	0.015	Not Rejected	0.876	0.871	0.016	Not Rejected
hd_literate	0.980	0.986	0.004	Not Rejected	0.963	0.953	0.009	Not Rejected
hd_noneduc	0.059	0.035	0.007	Rejected	0.102	0.128	0.013	Not Rejected
hd_primary	0.488	0.396	0.022	Rejected	0.722	0.655	0.019	Rejected
hd_secondary	0.381	0.491	0.023	Rejected	0.166	0.197	0.017	Not Rejected
hd_tertiary	0.072	0.075	0.011	Not Rejected	0.010	0.012	0.005	Not Rejected
hd_single	0.245	0.210	0.018	Not Rejected	0.249	0.237	0.022	Not Rejected
hd_couple	0.755	0.790	0.018	Not Rejected	0.751	0.763	0.022	Not Rejected
hd_primesec	0.202	0.081	0.013	Rejected	0.765	0.055	0.019	Rejected
hd_secsec	0.057	0.047	0.008	Not Rejected	0.003	0.009	0.004	Not Rejected
hd_tersec	0.267	0.335	0.022	Rejected	0.031	0.056	0.011	Rejected
hd_empl	0.310	0.351	0.023	Not Rejected	0.049	0.057	0.012	Not Rejected
hd_selfempl	0.214	0.116	0.013	Rejected	0.750	0.064	0.019	Rejected
sp_age	26.4	30.5	0.8	Rejected	26.2	27.9	0.9	Not Rejected
sp_age2	1050.2	1273.4	43.7	Rejected	1064.1	1152.0	51.2	Not Rejected
sp_occupied	0.348	0.555	0.020	Rejected	0.585	0.653	0.026	Rejected
sp_literate	0.721	0.776	0.017	Rejected	0.728	0.751	0.022	Not Rejected
sp_noneduc	0.018	0.007	0.003	Rejected	0.039	0.050	0.009	Not Rejected
sp_primary	0.258	0.213	0.018	Rejected	0.489	0.433	0.021	Rejected
sp_secondary	0.395	0.504	0.023	Rejected	0.196	0.262	0.020	Rejected
sp_tertiary	0.049	0.048	0.008	Not Rejected	0.004	0.004	0.002	Not Rejected
sp_primesec	0.096	0.026	0.007	Rejected	0.564	0.034	0.012	Rejected
sp_secsec	0.026	0.035	0.010	Not Rejected	0.001	0.003	0.002	Not Rejected
sp_tersec	0.226	0.318	0.023	Rejected	0.020	0.036	0.008	Rejected
sp_empl	0.220	0.285	0.021	Rejected	0.024	0.034	0.008	Not Rejected
sp_selfempl	0.128	0.096	0.013	Rejected	0.561	0.038	0.012	Rejected
no_spouse	0.279	0.224	0.017	Rejected	0.272	0.249	0.022	Not Rejected
type_house	0.358	0.386	0.040	Not Rejected	0.089	0.095	0.027	Not Rejected
type_apart	0.100	0.120	0.035	Not Rejected	0.006	0.001	0.001	Rejected
type_other	0.026	0.002	0.002	Rejected	0.005	0.000	0.000	Rejected
type_ger	0.515	0.493	0.042	Not Rejected	0.899	0.904	0.027	Not Rejected
sqm	31.2	35.7	0.9	Rejected	30.4	29.5	0.9	Not Rejected
sqm2	1266.1	1524.4	90.2	Rejected	1065.4	961.1	65.1	Not Rejected
sqm_ger	15.8	15.1	1.4	Not Rejected	27.5	26.0	1.1	Not Rejected
sqm2_ger	538.9	514.6	66.9	Not Rejected	940.0	818.3	65.9	Not Rejected

ANNEX 2B: Aligning the Data, Test on Equality of Means (continued...)

heat_central	0.054	0.070	0.028	Not Rejected	0.001	0.000	0.000	Not Rejected
heat_noncent.	0.432	0.437	0.040	Not Rejected	0.100	0.095	0.027	Not Rejected
heat_ger	0.515	0.493	0.042	Not Rejected	0.899	0.904	0.027	Not Rejected
water_pipe	0.069	0.097	0.033	Not Rejected	0.002	0.004	0.002	Not Rejected
water_well	0.351	0.514	0.041	Rejected	0.080	0.218	0.027	Rejected
water_hand	0.184	0.123	0.023	Rejected	0.232	0.250	0.029	Not Rejected
water_other	0.396	0.266	0.031	Rejected	0.685	0.527	0.040	Rejected
waste_tube	0.001	0.007	0.006	Not Rejected	0.000	0.000	0.000	Rejected
waste_noplace	0.061	0.127	0.025	Rejected	0.033	0.058	0.021	Not Rejected
waste_other	0.423	0.373	0.032	Not Rejected	0.068	0.038	0.011	Rejected
waste_ger1	0.443	0.361	0.036	Rejected	0.596	0.286	0.024	Rejected
waste_ger0	0.072	0.131	0.019	Rejected	0.303	0.618	0.030	Rejected
wc_in	0.064	0.099	0.034	Not Rejected	0.001	0.010	0.003	Rejected
wc_out	0.936	0.900	0.034	Not Rejected	0.999	0.990	0.003	Rejected
kitchen_in	0.365	0.279	0.034	Rejected	0.032	0.038	0.012	Not Rejected
kitchen_out	0.121	0.228	0.028	Rejected	0.069	0.057	0.019	Not Rejected
kitchen_ger	0.515	0.001	0.001	Rejected	0.899	0.000	0.000	Rejected
bath_in	0.056	0.074	0.028	Not Rejected	0.002	0.004	0.003	Not Rejected
bath_no	0.429	0.440	0.042	Not Rejected	0.099	0.096	0.027	Not Rejected
bath_ger	0.515	0.493	0.042	Not Rejected	0.899	0.904	0.027	Not Rejected
prop_private	0.893	0.943	0.015	Rejected	0.985	0.986	0.006	Not Rejected
light	0.815	0.622	0.043	Rejected	0.094	0.113	0.022	Not Rejected
phone	0.074	0.168	0.022	Rejected	0.004	0.027	0.006	Rejected
d1	0.050	0.039	0.014	Not Rejected	0.094	0.095	0.032	Not Rejected
d2	0.038	0.016	0.008	Rejected	0.063	0.050	0.024	Not Rejected
d3	0.038	0.034	0.012	Not Rejected	0.073	0.096	0.040	Not Rejected
d4	0.052	0.034	0.016	Not Rejected	0.043	0.044	0.022	Not Rejected
d5	0.037	0.050	0.023	Not Rejected	0.047	0.035	0.019	Not Rejected
d6	0.042	0.027	0.014	Not Rejected	0.022	0.042	0.021	Not Rejected
d7	0.040	0.034	0.017	Not Rejected	0.024	0.038	0.024	Not Rejected
d8	0.027	0.027	0.014	Not Rejected	0.039	0.042	0.021	Not Rejected
d9	0.059	0.059	0.024	Not Rejected	0.071	0.038	0.019	Not Rejected
d10	0.064	0.083	0.030	Not Rejected	0.100	0.126	0.037	Not Rejected
d11	0.022	0.012	0.007	Not Rejected	0.038	0.053	0.026	Not Rejected
d12	0.032	0.030	0.023	Not Rejected	0.037	0.041	0.021	Not Rejected
d13	0.138	0.167	0.042	Not Rejected	0.022	0.000	0.000	Rejected
d14	0.095	0.099	0.036	Not Rejected	0.066	0.055	0.022	Not Rejected
d15	0.048	0.026	0.019	Not Rejected	0.061	0.041	0.023	Not Rejected
d16	0.044	0.065	0.023	Not Rejected	0.053	0.078	0.037	Not Rejected
d17	0.069	0.064	0.025	Not Rejected	0.094	0.077	0.035	Not Rejected
d18	0.065	0.054	0.023	Not Rejected	0.041	0.041	0.021	Not Rejected
d19	0.028	0.079	0.038	Not Rejected	0.008	0.007	0.004	Not Rejected
d20	0.000	0.000	0.000	Not Rejected	0.000	0.000	0.000	Not Rejected
d21	0.006	0.000	0.000	Rejected	0.002	0.000	0.000	Rejected
d22	0.005	0.000	0.000	Rejected	0.002	0.000	0.000	Rejected
pc_camel	0.195	0.141	0.025	Rejected	0.290	0.305	0.058	Not Rejected
pc_cattle	1.703	1.445	0.122	Rejected	1.940	1.799	0.152	Not Rejected
pc_goat	7.059	6.832	0.614	Not Rejected	9.390	10.909	0.694	Rejected
pc_horse	1.727	1.514	0.142	Not Rejected	2.017	2.215	0.127	Not Rejected
pc_sheep	8.875	7.595	0.618	Rejected	10.865	11.273	0.502	Not Rejected

ANNEX 3: Survey-Based Regression models

Strata 1: Ulaan Baatar

======================= OLS Result ========================

Number of observation	900
R-square	0.548672
Adj. R-square	0.541533

Var	Coef.	Std.Err.	t	Prob>ltl
Intercept	10.7544755	0.0822209	130.8	<.0001
LNHHSIZE	-0.7228205	0.0385762	-18.737	<.0001
FEMALE	0.0739601	0.017629	4.195	<.0001
HD_COUPLE	0.1412452	0.0342318	4.126	<.0001
HD_SECONDARY	0.1045362	0.0345605	3.025	0.0026
HD_TERTIARY	0.1019642	0.0462966	2.202	0.0279
HD_SELFEMPL	0.0873552	0.041443	2.108	0.0353
SP_TERTIARY	0.1661477	0.049679	3.344	0.0009
TYPE_APART	-0.129166	0.0524122	-2.464	0.0139
KITCHEN_IN	0.2376894	0.0401674	5.917	<.0001
BATH_IN	0.3572596	0.0592011	6.035	<.0001
MWATER_PIPE	-0.2610317	0.0758072	-3.443	0.0006
MHD_SECSEC	-0.5801557	0.2027296	-2.862	0.0043
MPHONE	0.3889401	0.102858	3.781	0.0002
MPOCC	1.0832016	0.2347806	4.614	<.0001

Strata 2: Aimag Centers

======================= OLS Result ========================

Number of observation	832
R-square	0.402116
Adj. R-square	0.392614

Var	Coef.	Std.Err.	t	Prob>ltl
Intercept	11.150459	0.0624307	178.605	<.0001
LNHHSIZE	-0.6854656	0.0400043	-17.135	<.0001
HD_NONEDUC	-0.2721329	0.1039825	-2.617	0.009
HD_TERTIARY	0.2538077	0.0528382	4.803	<.0001
HD_COUPLE	0.193304	0.0456093	4.238	<.0001
HD_SELFEMPL	0.1068693	0.0437938	2.44	0.0149
SP_PRIMARY	-0.2046923	0.0460533	-4.445	<.0001
SP_TERTIARY	0.1458033	0.0650776	2.24	0.0253
WASTE_NOPLACE	-0.2265559	0.0647765	-3.498	0.0005
KITCHEN_IN	0.2058542	0.0359761	5.722	<.0001
D5	0.4039239	0.0948102	4.26	<.0001
D7	-0.1922775	0.0596822	-3.222	0.0013
D10	0.3799135	0.082687	4.595	<.0001
D21	-0.216682	0.0490518	-4.417	<.0001

Strata 3: Soum Centers

======================== OLS Result ==========================

Number of observation	881
R-square	0.349448
Adj. R-square	0.338166

Var	Coef.	Std.Err.	t	Prob>ltl
Intercept	10.6423217	0.08134	130.838	<.0001
LNHHSIZE	-0.6681926	0.039669	-16.844	<.0001
HD_TERTIARY	0.2462252	0.0645601	3.814	0.0001
HD_COUPLE	0.2239208	0.0477714	4.687	<.0001
SP_TERTIARY	0.2393702	0.0799199	2.995	0.0028
TYPE_APART	-0.2168486	0.084169	-2.576	0.0101
HEAT_CENTRAL	0.7584392	0.1257711	6.03	<.0001
HEAT_NONCENTRA	0.5746234	0.0988173	5.815	<.0001
BATH_NO	-0.4257321	0.0930059	-4.577	<.0001
D17	-0.2265886	0.0698406	-3.244	0.0012
PC_HORSE	0.0833704	0.0138399	6.024	<.0001
MWATER_PIPE	-0.6093846	0.2221793	-2.743	0.0062
MWC_IN	0.3985698	0.2414164	1.651	0.0991
MHD_PRIMESEC	0.3883673	0.1127084	3.446	0.0006
MHD_TERSEC	0.4593803	0.1393908	3.296	0.001
MPHONE	.3799708	0.1837432	2.068	0.0389

Strata 4: Countryside

======================== OLS Result ==========================

Number of observation	681
R-square	0.517706
Adj. R-square	0.506827

Var	Coef.	Std.Err.	t	Prob>ltl
Intercept	11.9171628	0.5268165	22.621	<.0001
LNHHSIZE	-0.7935577	0.0394921	-20.094	<.0001
FEMALE	0.0804277	0.023412	3.435	0.0006
SP_AGE	0.0057955	0.0009655	6.003	<.0001
SP_NONEDUC	-0.2177647	0.0768717	-2.833	0.0048
TYPE_HOUSE	-0.7321858	0.527898	-1.387	0.1659
SQM_GER	0.0272382	0.0074248	3.669	0.0003
SQM2_GER	-0.0002809	0.0000975	-2.882	0.0041
WATER_HAND	0.1000438	0.0390071	2.565	0.0105
HEAT_GER	-1.4127738	0.5424259	-2.605	0.0094
D4	0.5057022	0.0791851	6.386	<.0001
D10	0.3167776	0.0506464	6.255	<.0001
D11	0.3895039	0.0744912	5.229	<.0001
D12	0.4536723	0.0848734	5.345	<.0001
D16	-0.3249821	0.0653646	-4.972	<.0001
D18	0.4197939	0.0834939	5.028	<.0001

ANNEX 4: Poverty Indices, by Region, Aimag and Soum

Census Code	Administrative Structure	Population	Poverty Headcount (P0)	Poverty Gap Index (P1)	Poverty Severity Index (P2)	Number of Poor Individuals
10000	**West**	**423,426**	**0.463**	**0.149**	**0.066**	**196,046**
			(0.027)	***(0.014)***	***(0.008)***	
10200	**Bayan-olgii**	**91,602**	**0.434**	**0.132**	**0.056**	**39,755**
			(0.042)	***(0.019)***	***(0.010)***	
10201	Altai	3,770	0.433	0.128	0.053	1,632
			(0.069)	*(0.031)*	*(0.016)*	
10202	Altantsogts	2,987	0.432	0.131	0.055	1,290
			(0.077)	*(0.034)*	*(0.018)*	
10203	Bayannuur	5,045	0.466	0.143	0.061	2,351
			(0.068)	*(0.030)*	*(0.016)*	
10204	Bugat	3,470	0.468	0.145	0.062	1,624
			(0.078)	*(0.038)*	*(0.021)*	
10205	Bulgan	5,716	0.471	0.145	0.062	2,692
			(0.072)	*(0.033)*	*(0.018)*	
10206	Buyant	2,860	0.480	0.149	0.064	1,373
			(0.082)	*(0.037)*	*(0.021)*	
10207	Deluun	7,824	0.435	0.128	0.053	3,403
			(0.064)	*(0.029)*	*(0.015)*	
10208	Nogoonnuur	6,946	0.478	0.149	0.065	3,320
			(0.064)	*(0.030)*	*(0.017)*	
10209	Sagsai	4,459	0.458	0.139	0.059	2,042
			(0.073)	*(0.032)*	*(0.017)*	
10210	Tolbo	4,408	0.470	0.143	0.060	2,072
			(0.074)	*(0.034)*	*(0.018)*	
10211	Ulaankhus	7,845	0.492	0.155	0.067	3,860
			(0.069)	*(0.033)*	*(0.018)*	
10212	Tsengel	7,826	0.444	0.135	0.057	3,475
			(0.064)	*(0.028)*	*(0.015)*	
10213	Olgii	26,146	0.365	0.109	0.046	9,543
			(0.024)	*(0.011)*	*(0.006)*	
10214	Tsagaannuur	2,300	0.482	0.163	0.075	1,109
			(0.065)	*(0.032)*	*(0.019)*	
10500	**Govi-altai**	**64,141**	**0.395**	**0.120**	**0.051**	**25,336**
			(0.039)	***(0.016)***	***(0.008)***	
10501	Altai	2,512	0.427	0.131	0.056	1,073
			(0.067)	*(0.029)*	*(0.016)*	
10502	Bayan-Uul	3,605	0.471	0.144	0.061	1,698
			(0.049)	*(0.022)*	*(0.011)*	
10503	Biger	2,711	0.459	0.138	0.058	1,244
			(0.069)	*(0.030)*	*(0.016)*	
10504	Bugat	2,826	0.515	0.165	0.073	1,455
			(0.077)	*(0.037)*	*(0.021)*	

10505	Darvi	2,120	0.446	0.134	0.056	946
			(0.062)	*(0.026)*	*(0.014)*	
10506	Delger	4,067	0.457	0.144	0.063	1,859
			(0.076)	*(0.036)*	*(0.020)*	
10507	Jargalan	2,737	0.471	0.144	0.061	1,289
			(0.049)	*(0.022)*	*(0.011)*	
10508	Taishir	1,841	0.425	0.123	0.051	782
			(0.078)	*(0.032)*	*(0.016)*	
10509	Tonkhil	2,941	0.446	0.134	0.056	1,312
			(0.062)	*(0.026)*	*(0.014)*	
10510	Togrog	2,181	0.477	0.149	0.064	1,040
			(0.078)	*(0.035)*	*(0.019)*	
10511	Khaliun	3,241	0.482	0.147	0.062	1,562
			(0.077)	*(0.034)*	*(0.018)*	
10512	Khokhmorit	2,726	0.471	0.144	0.061	1,284
			(0.049)	*(0.022)*	*(0.011)*	
10513	Tsogt	4,417	0.500	0.162	0.072	2,209
			(0.064)	*(0.030)*	*(0.017)*	
10514	Tseel	2,707	0.476	0.149	0.064	1,289
			(0.063)	*(0.029)*	*(0.016)*	
10515	Chandmana	2,731	0.490	0.152	0.066	1,338
			(0.077)	*(0.037)*	*(0.021)*	
10516	Sharga	2,377	0.465	0.140	0.059	1,105
			(0.079)	*(0.034)*	*(0.018)*	
10517	Erdene	2,496	0.508	0.160	0.070	1,268
			(0.078)	*(0.037)*	*(0.021)*	
10518	Yosonbulag	15,905	0.161	0.040	0.015	2,561
			(0.056)	*(0.017)*	*(0.007)*	
10900	**Zavkhan**	**90,782**	**0.436**	**0.133**	**0.057**	**39,581**
			(0.032)	***(0.015)***	***(0.008)***	
10901	Aldarkhaan	4,332	0.440	0.131	0.055	1,906
			(0.069)	*(0.032)*	*(0.017)*	
10902	Bayantes	2,699	0.509	0.168	0.076	1,374
			(0.072)	*(0.037)*	*(0.021)*	
10903	Bayankhairkhan	2,627	0.509	0.168	0.076	1,337
			(0.072)	*(0.037)*	*(0.021)*	
10904	Dorvoljin	9,820	0.453	0.143	0.062	4,448
			(0.051)	*(0.023)*	*(0.013)*	
10905	Zavkhanmandal	2,675	0.440	0.130	0.054	1,177
			(0.068)	*(0.031)*	*(0.017)*	
10906	Ider	1,508	0.428	0.129	0.054	645
			(0.057)	*(0.025)*	*(0.013)*	
10907	Ikh-Uul	3,545	0.422	0.125	0.052	1,496
			(0.056)	*(0.024)*	*(0.013)*	
10908	Nomrog	6,710	0.468	0.145	0.062	3,140
			(0.053)	*(0.026)*	*(0.014)*	
10909	Otgon	2,659	0.420	0.125	0.052	1,117
			(0.079)	*(0.032)*	*(0.016)*	

MONGOLIA CENSUS-BASED POVERTY MAP
Region, Aimag and Soum Level Results

10910	Santmargats	3,539	0.439	0.131	0.055	1,554
			(0.057)	*(0.024)*	*(0.013)*	
10911	Songino	2,295	0.421	0.126	0.053	966
			(0.061)	*(0.026)*	*(0.013)*	
10912	Tosontsengel	2,228	0.422	0.125	0.052	940
			(0.056)	*(0.024)*	*(0.013)*	
10913	Tudevtei	2,484	0.421	0.126	0.053	1,046
			(0.061)	*(0.026)*	*(0.013)*	
10914	Tes	3,219	0.504	0.167	0.075	1,622
			(0.074)	*(0.036)*	*(0.020)*	
10915	Telmen	3,464	0.428	0.129	0.054	1,483
			(0.057)	*(0.025)*	*(0.013)*	
10916	Urgamal	2,078	0.453	0.143	0.062	941
			(0.051)	*(0.023)*	*(0.013)*	
10917	Uliastai	18,548	0.389	0.118	0.050	7,215
			(0.025)	*(0.011)*	*(0.006)*	
10918	Tsagaankhairkhan	2,000	0.425	0.126	0.052	850
			(0.053)	*(0.023)*	*(0.012)*	
10919	Tsagaanchuluut	2,096	0.425	0.126	0.052	891
			(0.053)	*(0.023)*	*(0.012)*	
10920	Tsetsen-Uul	2,680	0.439	0.131	0.055	1,177
			(0.057)	*(0.024)*	*(0.013)*	
10921	Shiluustei	2,625	0.425	0.126	0.052	1,116
			(0.053)	*(0.023)*	*(0.012)*	
10922	Erdenekhairkhan	2,625	0.445	0.132	0.055	1,168
			(0.051)	*(0.022)*	*(0.012)*	
10923	Yaruu	3,267	0.445	0.132	0.055	1,454
			(0.051)	*(0.022)*	*(0.012)*	
10924	Asgat	1,059	0.504	0.167	0.075	534
			(0.074)	*(0.036)*	*(0.020)*	
11500	**Uvs**	**90,156**	**0.467**	**0.149**	**0.066**	**42,103**
			(0.041)	***(0.020)***	***(0.011)***	
11501	Baruunturuun	4,818	0.507	0.169	0.077	2,443
			(0.073)	*(0.036)*	*(0.021)*	
11502	Bokhmoron	2,449	0.483	0.153	0.067	1,183
			(0.071)	*(0.034)*	*(0.019)*	
11503	Davst	1,872	0.474	0.150	0.066	887
			(0.091)	*(0.041)*	*(0.023)*	
11504	Zavkhan	2,712	0.479	0.152	0.067	1,299
			(0.069)	*(0.034)*	*(0.019)*	
11505	Zuungovi	2,735	0.507	0.169	0.077	1,387
			(0.073)	*(0.036)*	*(0.021)*	
11506	Zuunkhangai	3,329	0.450	0.138	0.059	1,498
			(0.058)	*(0.026)*	*(0.014)*	
11507	Malchin	3,336	0.443	0.135	0.057	1,478
			(0.077)	*(0.035)*	*(0.019)*	
11508	Naranbulag	4,430	0.479	0.152	0.067	2,122
			(0.065)	*(0.031)*	*(0.017)*	

11509	Olgii	3,014	0.479	0.152	0.067	1,444
			(0.069)	*(0.034)*	*(0.019)*	
11510	Omnogovi	4,835	0.516	0.170	0.076	2,495
			(0.069)	*(0.033)*	*(0.018)*	
11511	Ondorkhangai	4,088	0.450	0.138	0.059	1,840
			(0.058)	*(0.026)*	*(0.014)*	
11512	Sagil	2,574	0.487	0.157	0.070	1,254
			(0.069)	*(0.034)*	*(0.020)*	
11513	Tarialan	5,392	0.550	0.189	0.087	2,966
			(0.060)	*(0.031)*	*(0.018)*	
11514	Turgen	2,107	0.487	0.157	0.070	1,026
			(0.069)	*(0.034)*	*(0.020)*	
11515	Tes	6,902	0.510	0.167	0.074	3,520
			(0.128)	*(0.063)*	*(0.035)*	
11516	Khovd	2,966	0.476	0.149	0.065	1,412
			(0.070)	*(0.031)*	*(0.017)*	
11517	Khyargas	3,164	0.418	0.126	0.053	1,323
			(0.073)	*(0.033)*	*(0.018)*	
11518	Tsagaankhairkhan	3,012	0.462	0.147	0.064	1,392
			(0.079)	*(0.035)*	*(0.019)*	
11519	Uvsnuur	26,421	0.421	0.131	0.057	11,123
			(0.025)	*(0.012)*	*(0.007)*	
11600	**Khovd**	**86,745**	**0.568**	**0.205**	**0.098**	**49,271**
			(0.046)	***(0.029)***	***(0.018)***	
11601	Altai	3,073	0.628	0.233	0.113	1,930
			(0.074)	*(0.044)*	*(0.028)*	
11602	Bulgan	9,082	0.631	0.235	0.114	5,731
			(0.062)	*(0.040)*	*(0.026)*	
11603	Buyant	3,827	0.624	0.231	0.111	2,388
			(0.078)	*(0.046)*	*(0.028)*	
11604	Darvi	2,880	0.607	0.218	0.103	1,748
			(0.081)	*(0.048)*	*(0.029)*	
11605	Duut	2,019	0.615	0.223	0.106	1,242
			(0.094)	*(0.055)*	*(0.033)*	
11606	Zereg	3,474	0.662	0.255	0.127	2,300
			(0.076)	*(0.052)*	*(0.034)*	
11607	Mankhan	5,099	0.695	0.271	0.135	3,544
			(0.072)	*(0.050)*	*(0.033)*	
11608	Dorgon	2,957	0.675	0.263	0.132	1,996
			(0.084)	*(0.055)*	*(0.036)*	
11609	Myangad	3,974	0.688	0.263	0.130	2,734
			(0.078)	*(0.053)*	*(0.034)*	
11610	Most	4,146	0.662	0.250	0.122	2,745
			(0.089)	*(0.056)*	*(0.035)*	
11611	Monkhkhairkhan	2,633	0.697	0.275	0.138	1,835
			(0.085)	*(0.056)*	*(0.037)*	
11612	Uench	4,564	0.607	0.225	0.109	2,770
			(0.070)	*(0.044)*	*(0.028)*	

11613	Khovd	4,463	0.650	0.245	0.120	2,901
			(0.078)	*(0.051)*	*(0.032)*	
11614	Tsetseg	2,545	0.591	0.215	0.102	1,504
			(0.083)	*(0.049)*	*(0.031)*	
11615	Chandmana	3,367	0.604	0.216	0.102	2,034
			(0.084)	*(0.048)*	*(0.029)*	
11616	Erdeneburen	3,033	0.534	0.176	0.079	1,620
			(0.093)	*(0.047)*	*(0.026)*	
11617	Jargalant	25,609	0.401	0.124	0.054	10,269
			(0.025)	*(0.011)*	*(0.006)*	
20000	Highlands	552,915	0.396	0.122	0.053	218,954
			(0.026)	*(0.012)*	*(0.007)*	
20100	**Arkhangai**	**98,074**	**0.422**	**0.126**	**0.053**	**41,387**
			(0.031)	***(0.014)***	***(0.007)***	
20101	Ikh-Tamir	6,369	0.465	0.142	0.061	2,962
			(0.055)	*(0.025)*	*(0.014)*	
20102	Chuluut	3,973	0.482	0.152	0.066	1,915
			(0.059)	*(0.027)*	*(0.015)*	
20103	Khangai	3,732	0.455	0.138	0.058	1,698
			(0.061)	*(0.026)*	*(0.014)*	
20104	Tariat	5,918	0.436	0.128	0.053	2,580
			(0.054)	*(0.023)*	*(0.012)*	
20105	Ondor-Ulaan	6,233	0.427	0.126	0.052	2,661
			(0.058)	*(0.024)*	*(0.013)*	
20106	Erdenemandal	6,209	0.415	0.122	0.050	2,577
			(0.048)	*(0.020)*	*(0.011)*	
20107	Jargalant	4,796	0.462	0.142	0.060	2,216
			(0.058)	*(0.026)*	*(0.014)*	
20108	Tsetserleg	4,302	0.449	0.134	0.056	1,932
			(0.060)	*(0.024)*	*(0.013)*	
20109	Khairhan	3,908	0.394	0.115	0.047	1,540
			(0.055)	*(0.024)*	*(0.013)*	
20110	Battsengel	4,002	0.367	0.105	0.042	1,469
			(0.055)	*(0.021)*	*(0.010)*	
20111	Olziit	3,201	0.457	0.141	0.060	1,463
			(0.074)	*(0.033)*	*(0.018)*	
20112	Ogiinuur	3,274	0.456	0.137	0.058	1,493
			(0.058)	*(0.025)*	*(0.013)*	
20113	Khashaat	4,192	0.453	0.136	0.057	1,899
			(0.069)	*(0.030)*	*(0.016)*	
20114	Khotont	5,502	0.434	0.128	0.053	2,388
			(0.055)	*(0.022)*	*(0.011)*	
20115	Tsenher	5,215	0.492	0.153	0.065	2,566
			(0.056)	*(0.026)*	*(0.014)*	
20116	Tovshruuleh	3,726	0.453	0.139	0.059	1,688
			(0.059)	*(0.026)*	*(0.014)*	
20117	Bulgan	2,342	0.411	0.121	0.050	963
			(0.072)	*(0.030)*	*(0.015)*	

20118	Erdenebulgan	18,870	0.342	0.101	0.043	6,454
			(0.024)	*(0.010)*	*(0.005)*	
20119	Tsakhir	2,310	0.399	0.117	0.049	922
			(0.073)	*(0.030)*	*(0.015)*	
20300	**Bayankhongor**	**85,614**	**0.470**	**0.148**	**0.064**	**40,239**
			(0.033)	*(0.016)*	*(0.009)*	
20301	Galuut	5,171	0.488	0.153	0.066	2,523
			(0.060)	*(0.027)*	*(0.015)*	
20302	Bayan-Ovoo	2,387	0.464	0.143	0.061	1,108
			(0.070)	*(0.031)*	*(0.017)*	
20303	Erdenetsogt	4,617	0.525	0.172	0.077	2,424
			(0.057)	*(0.029)*	*(0.017)*	
20304	Olziit	3,686	0.466	0.145	0.062	1,718
			(0.070)	*(0.032)*	*(0.018)*	
20305	Jinst	2,378	0.506	0.160	0.069	1,203
			(0.074)	*(0.035)*	*(0.019)*	
20306	Bogd	3,185	0.489	0.152	0.065	1,557
			(0.060)	*(0.028)*	*(0.015)*	
20307	Bayanlig	3,703	0.518	0.168	0.075	1,918
			(0.071)	*(0.035)*	*(0.020)*	
20308	Bayangovi	2,893	0.482	0.151	0.065	1,394
			(0.072)	*(0.035)*	*(0.020)*	
20309	Shinejinst	2,458	0.498	0.158	0.068	1,224
			(0.064)	*(0.031)*	*(0.017)*	
20310	Bayan-Ondor	2,675	0.498	0.158	0.068	1,332
			(0.064)	*(0.031)*	*(0.017)*	
20311	Bayantsagaan	3,750	0.491	0.152	0.064	1,841
			(0.068)	*(0.030)*	*(0.016)*	
20312	Baatsagaan	4,364	0.523	0.166	0.072	2,282
			(0.060)	*(0.028)*	*(0.015)*	
20313	Bombogor	2,739	0.531	0.178	0.081	1,454
			(0.081)	*(0.042)*	*(0.024)*	
20314	Buutsagaan	4,233	0.505	0.160	0.069	2,138
			(0.062)	*(0.029)*	*(0.016)*	
20315	Khureemaral	2,549	0.471	0.147	0.063	1,201
			(0.080)	*(0.036)*	*(0.020)*	
20316	Bayanbulag	2,639	0.456	0.138	0.058	1,203
			(0.081)	*(0.036)*	*(0.019)*	
20317	Gurvanbulag	2,941	0.465	0.141	0.059	1,368
			(0.076)	*(0.034)*	*(0.019)*	
20318	Zag	2,566	0.462	0.142	0.061	1,185
			(0.083)	*(0.036)*	*(0.020)*	
20319	Jargalant	4,148	0.476	0.148	0.063	1,974
			(0.067)	*(0.031)*	*(0.017)*	
20320	Bayankhongor	22,532	0.409	0.128	0.056	9,216
			(0.028)	*(0.013)*	*(0.007)*	
20400	**Bulgan**	**62,897**	**0.257**	**0.073**	**0.030**	**16,165**
			(0.043)	*(0.014)*	*(0.006)*	

20401	Bayan-Agt	2,896	0.176	0.043	0.016	510
			(0.054)	*(0.015)*	*(0.006)*	
20402	Bugat	2,266	0.212	0.056	0.022	480
			(0.057)	*(0.018)*	*(0.008)*	
20403	Buregkhangai	2,289	0.176	0.043	0.016	403
			(0.054)	*(0.015)*	*(0.006)*	
20404	Gurvanbulag	3,637	0.237	0.065	0.026	862
			(0.060)	*(0.020)*	*(0.009)*	
20405	Dashinchilen	2,889	0.237	0.065	0.026	685
			(0.060)	*(0.020)*	*(0.009)*	
20406	Mogod	2,854	0.176	0.043	0.016	502
			(0.054)	*(0.015)*	*(0.006)*	
20407	Orkhon	3,691	0.176	0.043	0.016	650
			(0.054)	*(0.015)*	*(0.006)*	
20408	Saikhan	3,893	0.176	0.043	0.016	685
			(0.054)	*(0.015)*	*(0.006)*	
20409	Selenge	3,899	0.338	0.105	0.046	1,318
			(0.057)	*(0.022)*	*(0.011)*	
20410	Teshig	3,191	0.212	0.056	0.022	676
			(0.057)	*(0.018)*	*(0.008)*	
20411	Khangal	4,842	0.338	0.105	0.046	1,637
			(0.057)	*(0.022)*	*(0.011)*	
20412	Khishig-Ondor	3,541	0.176	0.043	0.016	623
			(0.054)	*(0.015)*	*(0.006)*	
20413	Khutag-Ondor	4,721	0.212	0.056	0.022	1,001
			(0.057)	*(0.018)*	*(0.008)*	
20414	Bulgan	12,953	0.329	0.096	0.040	4,262
			(0.026)	*(0.010)*	*(0.005)*	
20415	Bayannuur	1,899	0.237	0.065	0.026	450
			(0.060)	*(0.020)*	*(0.009)*	
20416	Rashaant	3,436	0.413	0.139	0.064	1,419
			(0.066)	*(0.028)*	*(0.016)*	
21000	**Ovorkhangai**	**111,948**	**0.288**	**0.080**	**0.033**	**32,241**
			(0.050)	***(0.017)***	***(0.008)***	
21001	Bayan-Ondor	4,698	0.255	0.065	0.024	1,198
			(0.057)	*(0.019)*	*(0.008)*	
21002	Burd	4,004	0.255	0.065	0.024	1,021
			(0.057)	*(0.019)*	*(0.008)*	
21003	Bat-Olzii	5,691	0.346	0.101	0.042	1,969
			(0.071)	*(0.027)*	*(0.014)*	
21004	Baruunbayan-Ulaan	2,809	0.291	0.078	0.031	817
			(0.073)	*(0.027)*	*(0.013)*	
21005	Bayangol	4,598	0.270	0.071	0.028	1,241
			(0.055)	*(0.019)*	*(0.009)*	
21006	Guchin-Us	2,404	0.291	0.078	0.031	700
			(0.073)	*(0.027)*	*(0.013)*	
21007	Yesonzuil	3,703	0.279	0.074	0.029	1,033
			(0.061)	*(0.021)*	*(0.010)*	

21008	Olziit	3,147	0.279	0.074	0.029	878
			(0.061)	*(0.021)*	*(0.010)*	
21009	Zuunbayan-Ulaan	5,791	0.288	0.076	0.029	1,668
			(0.071)	*(0.024)*	*(0.011)*	
21010	Bogd	5,782	0.333	0.091	0.036	1,925
			(0.071)	*(0.027)*	*(0.013)*	
21011	Nariinteel	4,131	0.301	0.083	0.033	1,243
			(0.059)	*(0.021)*	*(0.009)*	
21012	Sant	4,346	0.270	0.071	0.028	1,173
			(0.055)	*(0.019)*	*(0.009)*	
21013	Taragt	4,912	0.270	0.069	0.026	1,326
			(0.064)	*(0.021)*	*(0.010)*	
21014	Togrog	2,949	0.270	0.071	0.028	796
			(0.055)	*(0.019)*	*(0.009)*	
21015	Uyanga	7,733	0.301	0.083	0.033	2,328
			(0.059)	*(0.021)*	*(0.009)*	
21016	Khairkhandulaan	4,297	0.301	0.083	0.033	1,293
			(0.059)	*(0.021)*	*(0.009)*	
21017	Khujirt	7,684	0.355	0.107	0.046	2,728
			(0.064)	*(0.025)*	*(0.013)*	
21018	Kharkhorin	13,648	0.428	0.138	0.062	5,841
			(0.061)	*(0.026)*	*(0.014)*	
21019	Arvairkheer	19,621	0.155	0.037	0.014	3,041
			(0.052)	*(0.015)*	*(0.006)*	
21700	**Khovsgol**	**120,127**	**0.475**	**0.155**	**0.070**	**57,060**
			(0.042)	***(0.021)***	***(0.012)***	
21701	Alag-Erdene	3,008	0.486	0.153	0.067	1,462
			(0.077)	*(0.038)*	*(0.022)*	
21702	Arbulag	4,296	0.489	0.155	0.068	2,101
			(0.057)	*(0.028)*	*(0.016)*	
21703	Bayanzurh	3,977	0.518	0.171	0.078	2,060
			(0.071)	*(0.037)*	*(0.022)*	
21704	Burentogtokh	4,554	0.465	0.148	0.065	2,118
			(0.071)	*(0.036)*	*(0.020)*	
21705	Galt	5,391	0.485	0.155	0.069	2,615
			(0.062)	*(0.030)*	*(0.017)*	
21706	Jargalant	5,112	0.505	0.172	0.080	2,582
			(0.064)	*(0.033)*	*(0.020)*	
21707	Ikh-Uul	4,032	0.476	0.153	0.068	1,919
			(0.070)	*(0.033)*	*(0.019)*	
21708	Rashaant	3,337	0.463	0.144	0.063	1,545
			(0.071)	*(0.034)*	*(0.019)*	
21709	Renchinlkhumbe	4,327	0.563	0.192	0.088	2,436
			(0.062)	*(0.032)*	*(0.019)*	
21710	Tarialan	6,258	0.555	0.198	0.095	3,473
			(0.075)	*(0.042)*	*(0.026)*	
21711	Tosontsengel	4,264	0.492	0.158	0.070	2,098
			(0.070)	*(0.035)*	*(0.020)*	

21712	Tomorbulag	4,199	0.453	0.136	0.057	1,902
			(0.063)	*(0.028)*	*(0.015)*	
21713	Tunel	3,595	0.507	0.169	0.077	1,823
			(0.067)	*(0.035)*	*(0.021)*	
21714	Ulaan-Uul	3,746	0.544	0.184	0.084	2,038
			(0.073)	*(0.038)*	*(0.022)*	
21715	Khankh	2,175	0.536	0.184	0.085	1,166
			(0.096)	*(0.050)*	*(0.029)*	
21716	Tsagaan-Uul	5,772	0.497	0.162	0.072	2,869
			(0.063)	*(0.031)*	*(0.018)*	
21717	Tsagaan-Uur	2,445	0.444	0.140	0.061	1,086
			(0.081)	*(0.038)*	*(0.021)*	
21718	Tsetserleg	5,827	0.504	0.172	0.080	2,937
			(0.084)	*(0.044)*	*(0.026)*	
21719	Chandmana-Ondor	2,986	0.501	0.168	0.077	1,496
			(0.081)	*(0.041)*	*(0.024)*	
21720	Shine-Ider	4,276	0.428	0.130	0.055	1,830
			(0.062)	*(0.028)*	*(0.015)*	
21721	Khatgal	2,637	0.591	0.217	0.106	1,558
			(0.083)	*(0.046)*	*(0.028)*	
21722	Moron	29,780	0.392	0.121	0.053	11,674
			(0.023)	*(0.010)*	*(0.006)*	
21723	Erdenebulgan	2,790	0.527	0.177	0.081	1,470
			(0.090)	*(0.046)*	*(0.026)*	
21724	Tsagaannuur	1,343	0.585	0.210	0.100	786
			(0.098)	*(0.055)*	*(0.034)*	
22100	**Orkhon**	**74,255**	**0.429**	**0.140**	**0.064**	**31,855**
			(0.044)	***(0.021)***	***(0.012)***	
22101	Bayan-Ondor	70,950	0.430	0.141	0.064	30,509
			(0.043)	*(0.020)*	*(0.012)*	
22102	Jargalant	3,305	0.408	0.128	0.056	1,348
			(0.067)	*(0.029)*	*(0.015)*	
30000	**Central**	**445,609**	**0.387**	**0.121**	**0.053**	**172,451**
			(0.024)	***(0.011)***	***(0.006)***	
30600	**Dornogovi**	**51,076**	**0.368**	**0.113**	**0.049**	**18,796**
			(0.033)	***(0.014)***	***(0.008)***	
30601	Airag	3,557	0.390	0.122	0.053	1,387
			(0.057)	*(0.026)*	*(0.014)*	
30602	Altanshiree	1,586	0.392	0.119	0.050	622
			(0.063)	*(0.026)*	*(0.014)*	
30603	Dalanjargalan	2,400	0.390	0.122	0.053	936
			(0.057)	*(0.026)*	*(0.014)*	
30604	Delgerekh	1,910	0.392	0.119	0.050	749
			(0.063)	*(0.026)*	*(0.014)*	
30605	Ikhkhet	2,789	0.366	0.112	0.048	1,021
			(0.073)	*(0.031)*	*(0.017)*	
30606	Mandakh	1,879	0.424	0.130	0.055	797
			(0.066)	*(0.028)*	*(0.015)*	

30607	Orgon	2,092	0.392	0.119	0.050	820
			(0.063)	*(0.026)*	*(0.014)*	
30608	Saikhandulaan	1,342	0.424	0.130	0.055	569
			(0.066)	*(0.028)*	*(0.015)*	
30609	Ulaanbadrakh	1,766	0.448	0.137	0.058	791
			(0.062)	*(0.028)*	*(0.015)*	
30610	Khatanbulag	3,149	0.448	0.137	0.058	1,411
			(0.062)	*(0.028)*	*(0.015)*	
30611	Khovsgol	1,749	0.448	0.137	0.058	784
			(0.062)	*(0.028)*	*(0.015)*	
30612	Erdene	2,632	0.353	0.113	0.050	929
			(0.069)	*(0.028)*	*(0.015)*	
30613	Sainshand	18,175	0.323	0.096	0.041	5,871
			(0.022)	*(0.009)*	*(0.005)*	
30614	Zamiin-Uud	6,054	0.353	0.113	0.050	2,137
			(0.069)	*(0.028)*	*(0.015)*	
30800	**Dundgovi**	**51,815**	**0.423**	**0.129**	**0.055**	**21,918**
			(0.037)	***(0.016)***	***(0.009)***	
30801	Delgertsogt	2,497	0.417	0.126	0.053	1,041
			(0.058)	*(0.024)*	*(0.013)*	
30802	Deren	2,526	0.417	0.126	0.053	1,053
			(0.058)	*(0.024)*	*(0.013)*	
30803	Govi-Ugtaal	1,900	0.381	0.111	0.046	724
			(0.068)	*(0.028)*	*(0.014)*	
30804	Tsagaandelger	1,684	0.381	0.111	0.046	642
			(0.068)	*(0.028)*	*(0.014)*	
30805	Bayanjargalan	1,413	0.418	0.126	0.053	591
			(0.075)	*(0.031)*	*(0.016)*	
30806	Ondorshil	1,542	0.418	0.126	0.053	645
			(0.075)	*(0.031)*	*(0.016)*	
30807	Gurvansaikhan	2,507	0.463	0.142	0.061	1,161
			(0.081)	*(0.035)*	*(0.018)*	
30808	Olziit	2,992	0.479	0.148	0.063	1,433
			(0.074)	*(0.034)*	*(0.018)*	
30809	Khuld	2,443	0.404	0.118	0.049	987
			(0.074)	*(0.030)*	*(0.015)*	
30810	Luus	1,950	0.404	0.118	0.049	788
			(0.074)	*(0.030)*	*(0.015)*	
30811	Delgerkhangai	2,687	0.490	0.155	0.067	1,317
			(0.073)	*(0.034)*	*(0.019)*	
30812	Saihan-Ovoo	2,813	0.501	0.158	0.069	1,409
			(0.072)	*(0.035)*	*(0.020)*	
30813	Erdenedalai	6,987	0.423	0.126	0.053	2,956
			(0.054)	*(0.023)*	*(0.012)*	
30814	Saintsagaan	14,574	0.385	0.118	0.051	5,611
			(0.027)	*(0.012)*	*(0.007)*	
30815	Adaatsag	3,300	0.470	0.146	0.063	1,551
			(0.088)	*(0.040)*	*(0.021)*	

31100	**Omnogovi**	**45,781**	**0.296**	**0.085**	**0.036**	**13,551**
			(0.047)	***(0.016)***	***(0.008)***	
31101	Bayandalai	2,350	0.268	0.075	0.030	630
			(0.064)	*(0.021)*	*(0.010)*	
31102	Bayan-Ovoo	1,591	0.262	0.072	0.029	417
			(0.058)	*(0.019)*	*(0.009)*	
31103	Bulgan	2,390	0.262	0.072	0.029	626
			(0.058)	*(0.019)*	*(0.009)*	
31104	Gurvantes	3,300	0.268	0.075	0.030	884
			(0.064)	*(0.021)*	*(0.010)*	
31105	Mandal-Ovoo	2,317	0.262	0.072	0.029	607
			(0.058)	*(0.019)*	*(0.009)*	
31106	Manlai	2,261	0.262	0.072	0.029	592
			(0.058)	*(0.019)*	*(0.009)*	
31107	Nomgon	2,971	0.268	0.075	0.030	796
			(0.064)	*(0.021)*	*(0.010)*	
31108	Noyon	1,516	0.268	0.075	0.030	406
			(0.064)	*(0.021)*	*(0.010)*	
31109	Sevrei	2,279	0.268	0.075	0.030	611
			(0.064)	*(0.021)*	*(0.010)*	
31110	Khanbogd	2,285	0.262	0.072	0.029	599
			(0.058)	*(0.019)*	*(0.009)*	
31111	Khankhongor	2,437	0.262	0.072	0.029	638
			(0.058)	*(0.019)*	*(0.009)*	
31112	Khurmen	1,956	0.268	0.075	0.030	524
			(0.064)	*(0.021)*	*(0.010)*	
31113	Tsogt-Ovoo	1,885	0.262	0.072	0.029	494
			(0.058)	*(0.019)*	*(0.009)*	
31114	Tsogttsetsii	2,146	0.262	0.072	0.029	562
			(0.058)	*(0.019)*	*(0.009)*	
31115	Dalanzadgad	14,097	0.365	0.113	0.049	5,145
			(0.025)	*(0.011)*	*(0.006)*	
31300	**Selenge**	**100,743**	**0.450**	**0.149**	**0.068**	**45,334**
			(0.033)	***(0.016)***	***(0.009)***	
31301	Altanbulag	3,595	0.472	0.157	0.072	1,697
			(0.065)	*(0.031)*	*(0.018)*	
31302	Yoroo	6,187	0.470	0.158	0.073	2,908
			(0.068)	*(0.034)*	*(0.019)*	
31303	Zuunburen	2,568	0.510	0.174	0.080	1,310
			(0.082)	*(0.041)*	*(0.024)*	
31304	Mandal	22,991	0.502	0.177	0.084	11,541
			(0.038)	*(0.021)*	*(0.013)*	
31305	Orkhon	2,897	0.414	0.127	0.054	1,199
			(0.075)	*(0.032)*	*(0.017)*	
31306	Sant	2,128	0.509	0.173	0.080	1,083
			(0.092)	*(0.048)*	*(0.028)*	
31307	Tsagaannuur	4,238	0.480	0.157	0.070	2,034
			(0.069)	*(0.033)*	*(0.018)*	

31308	Bayangol	5,595	0.471	0.154	0.069	2,635
			(0.057)	*(0.028)*	*(0.016)*	
31309	Saikhan	9,169	0.437	0.142	0.064	4,007
			(0.072)	*(0.030)*	*(0.016)*	
31310	Orkhontuul	3,852	0.459	0.154	0.071	1,768
			(0.069)	*(0.036)*	*(0.022)*	
31311	Baruunburen	3,000	0.480	0.154	0.068	1,440
			(0.071)	*(0.033)*	*(0.018)*	
31312	Shaamar	4,859	0.500	0.169	0.078	2,430
			(0.057)	*(0.028)*	*(0.016)*	
31313	Khuder	1,860	0.472	0.157	0.072	878
			(0.065)	*(0.031)*	*(0.018)*	
31314	Sukhbaatar	22,740	0.346	0.105	0.046	7,868
			(0.029)	*(0.013)*	*(0.007)*	
31315	Javkhlant	1,839	0.500	0.169	0.078	920
			(0.057)	*(0.028)*	*(0.016)*	
31316	Tushig	1,795	0.480	0.157	0.070	862
			(0.069)	*(0.033)*	*(0.018)*	
31317	Khushaat	1,430	0.510	0.174	0.080	729
			(0.082)	*(0.041)*	*(0.024)*	
31400	**Tov**	**98,703**	**0.413**	**0.127**	**0.054**	**40,764**
			(0.029)	***(0.013)***	***(0.007)***	
31401	Altanbulag	3,721	0.407	0.122	0.051	1,514
			(0.052)	*(0.022)*	*(0.012)*	
31402	Batsumber	6,577	0.413	0.125	0.053	2,716
			(0.058)	*(0.026)*	*(0.014)*	
31403	Bayan	2,498	0.412	0.127	0.054	1,029
			(0.055)	*(0.024)*	*(0.013)*	
31404	Bayan-Onjuul	2,553	0.425	0.124	0.051	1,085
			(0.069)	*(0.028)*	*(0.014)*	
31405	Bayandelger	2,098	0.435	0.133	0.057	913
			(0.060)	*(0.026)*	*(0.014)*	
31406	Bayanjargalan	1,841	0.412	0.127	0.054	758
			(0.055)	*(0.024)*	*(0.013)*	
31407	Bayantsagaan	2,749	0.414	0.120	0.049	1,138
			(0.072)	*(0.032)*	*(0.017)*	
31408	Bayantsogt	2,491	0.405	0.121	0.051	1,009
			(0.077)	*(0.033)*	*(0.017)*	
31409	Bornuur	4,303	0.443	0.142	0.063	1,906
			(0.056)	*(0.025)*	*(0.014)*	
31410	Buren	3,489	0.409	0.122	0.051	1,427
			(0.065)	*(0.027)*	*(0.014)*	
31411	Delgerkhaan	2,474	0.447	0.137	0.058	1,106
			(0.072)	*(0.032)*	*(0.018)*	
31412	Jargalant	5,597	0.433	0.139	0.062	2,424
			(0.047)	*(0.022)*	*(0.012)*	
31413	Zaamar	6,200	0.431	0.135	0.058	2,672
			(0.061)	*(0.027)*	*(0.015)*	

MONGOLIA CENSUS-BASED POVERTY MAP
Region, Aimag and Soum Level Results

31414	Lun	3,335	0.379	0.110	0.045	1,264
			(0.052)	*(0.021)*	*(0.011)*	
31415	Mongonmorit	2,447	0.435	0.133	0.057	1,064
			(0.060)	*(0.026)*	*(0.014)*	
31416	Ondorshireet	2,273	0.379	0.110	0.045	861
			(0.052)	*(0.021)*	*(0.011)*	
31417	Sergelen	2,054	0.389	0.115	0.048	799
			(0.063)	*(0.027)*	*(0.014)*	
31418	Ugtaaltsaidam	3,588	0.456	0.140	0.060	1,636
			(0.069)	*(0.031)*	*(0.017)*	
31419	Erdene	3,222	0.448	0.141	0.061	1,443
			(0.056)	*(0.026)*	*(0.015)*	
31420	Erdenesant	5,542	0.449	0.137	0.059	2,488
			(0.064)	*(0.029)*	*(0.016)*	
31421	Bayanchandmana	3,282	0.443	0.142	0.063	1,454
			(0.056)	*(0.025)*	*(0.014)*	
31422	Zuunmod	14,711	0.338	0.102	0.044	4,972
			(0.025)	*(0.011)*	*(0.006)*	
31423	Sumber	2,026	0.433	0.139	0.062	877
			(0.047)	*(0.022)*	*(0.012)*	
31424	Tseel	3,752	0.461	0.150	0.067	1,730
			(0.075)	*(0.034)*	*(0.019)*	
31425	Arkhust	2,089	0.412	0.127	0.054	861
			(0.055)	*(0.024)*	*(0.013)*	
31426	Argalant	2,017	0.407	0.122	0.051	821
			(0.052)	*(0.022)*	*(0.012)*	
31427	Bayanhangai	1,774	0.456	0.140	0.060	809
			(0.069)	*(0.031)*	*(0.017)*	
31900	**Darkhan-uul**	**85,042**	**0.321**	**0.096**	**0.041**	**27,298**
			(0.025)	*(0.010)*	*(0.006)*	
31901	Darkhan	67,119	0.296	0.085	0.035	19,867
			(0.021)	*(0.008)*	*(0.004)*	
31902	Khongor	5,644	0.424	0.140	0.063	2,393
			(0.054)	*(0.026)*	*(0.015)*	
31903	Orkhon	3,377	0.458	0.148	0.066	1,547
			(0.062)	*(0.029)*	*(0.016)*	
31904	Sharingol	8,902	0.392	0.130	0.060	3,490
			(0.051)	*(0.022)*	*(0.012)*	
32200	**Govisumber**	**12,449**	**0.402**	**0.136**	**0.064**	**5,004**
			(0.051)	*(0.029)*	*(0.019)*	
32201	Bayantal	9,063	0.348	0.105	0.046	3,154
			(0.028)	*(0.012)*	*(0.006)*	
32202	Choir	873	0.545	0.216	0.114	476
			(0.111)	*(0.075)*	*(0.053)*	
32203	Shiveegovi	2,513	0.545	0.216	0.114	1,370
			(0.111)	*(0.075)*	*(0.053)*	
40000	East	205,395	0.374	0.117	0.052	76,818
			(0.036)	*(0.015)*	*(0.008)*	

40700	**Dornod**	**76,544**	**0.481**	**0.162**	**0.075**	**36,818**
			(0.043)	*(0.021)*	*(0.012)*	
40701	Bayandun	2,894	0.481	0.153	0.067	1,392
			(0.071)	*(0.034)*	*(0.019)*	
40702	Bayantumen	1,942	0.477	0.156	0.069	926
			(0.054)	*(0.026)*	*(0.015)*	
40703	Bulgan	2,002	0.477	0.156	0.069	955
			(0.054)	*(0.026)*	*(0.015)*	
40704	Gurvanzagal	1,343	0.470	0.153	0.068	631
			(0.055)	*(0.026)*	*(0.014)*	
40705	Dashbalbar	4,078	0.463	0.147	0.064	1,888
			(0.066)	*(0.029)*	*(0.016)*	
40706	Matad	2,342	0.468	0.154	0.069	1,096
			(0.075)	*(0.034)*	*(0.019)*	
40707	Khalkhgol	3,730	0.537	0.183	0.083	2,003
			(0.068)	*(0.034)*	*(0.020)*	
40708	Kholonbuir	1,770	0.477	0.156	0.069	844
			(0.054)	*(0.026)*	*(0.015)*	
40709	Sergelen	2,491	0.476	0.153	0.068	1,186
			(0.063)	*(0.029)*	*(0.016)*	
40710	Tsagaan-Ovoo	3,712	0.476	0.153	0.068	1,767
			(0.063)	*(0.029)*	*(0.016)*	
40711	Bayan-Uul	4,828	0.522	0.179	0.082	2,520
			(0.057)	*(0.029)*	*(0.017)*	
40712	Choibalsan	3,272	0.470	0.153	0.068	1,538
			(0.055)	*(0.026)*	*(0.014)*	
40713	Chuluunhoroot	1,592	0.470	0.153	0.068	748
			(0.055)	*(0.026)*	*(0.014)*	
40714	Kherlen	40,548	0.476	0.165	0.078	19,301
			(0.048)	*(0.024)*	*(0.014)*	
41200	**Sukhbaatar**	**56,639**	**0.303**	**0.086**	**0.036**	**17,162**
			(0.053)	*(0.018)*	*(0.009)*	
41201	Asgat	1,920	0.264	0.071	0.028	507
			(0.070)	*(0.023)*	*(0.011)*	
41202	Bayandelger	4,724	0.236	0.061	0.023	1,115
			(0.069)	*(0.022)*	*(0.010)*	
41203	Dariganga	2,734	0.264	0.071	0.028	722
			(0.070)	*(0.023)*	*(0.011)*	
41204	Monkhkhaan	4,739	0.309	0.089	0.037	1,464
			(0.069)	*(0.026)*	*(0.012)*	
41205	Naran	1,828	0.236	0.061	0.023	431
			(0.069)	*(0.022)*	*(0.010)*	
41206	Ongon	3,785	0.236	0.061	0.023	893
			(0.069)	*(0.022)*	*(0.010)*	
41207	Sukhbaatar	3,211	0.264	0.071	0.028	848
			(0.070)	*(0.023)*	*(0.011)*	
41208	Tuvshinshiree	3,400	0.309	0.089	0.037	1,051
			(0.069)	*(0.026)*	*(0.012)*	

41209	Tumentsogt	2,880	0.309	0.089	0.037	890
			(0.069)	*(0.026)*	*(0.012)*	
41210	Uulbayan	3,946	0.309	0.089	0.037	1,219
			(0.069)	*(0.026)*	*(0.012)*	
41211	Khalzan	1,900	0.236	0.061	0.023	448
			(0.069)	*(0.022)*	*(0.010)*	
41212	Erdenetsagaan	5,996	0.264	0.071	0.028	1,583
			(0.070)	*(0.023)*	*(0.011)*	
41213	Baruun-Urt	15,576	0.383	0.117	0.051	5,966
			(0.025)	*(0.011)*	*(0.006)*	
41800	**Khentii**	**72,212**	**0.316**	**0.093**	**0.039**	**22,819**
			(0.044)	***(0.016)***	***(0.008)***	
41801	Galshar	2,741	0.250	0.066	0.026	685
			(0.060)	*(0.020)*	*(0.009)*	
41802	Bayankhutag	2,113	0.250	0.066	0.026	528
			(0.060)	*(0.020)*	*(0.009)*	
41803	Bayanmonkh	1,704	0.295	0.087	0.037	503
			(0.051)	*(0.019)*	*(0.009)*	
41804	Darkhan	9,169	0.295	0.087	0.037	2,705
			(0.051)	*(0.019)*	*(0.009)*	
41805	Delgerkhaan	3,042	0.295	0.087	0.037	897
			(0.051)	*(0.019)*	*(0.009)*	
41806	Jargaltkhaan	2,112	0.295	0.087	0.037	623
			(0.051)	*(0.019)*	*(0.009)*	
41807	Dadal	2,212	0.282	0.080	0.033	624
			(0.059)	*(0.021)*	*(0.010)*	
41808	Omnodelger	5,769	0.282	0.080	0.033	1,627
			(0.059)	*(0.021)*	*(0.010)*	
41809	Batshireet	2,316	0.282	0.080	0.033	653
			(0.059)	*(0.021)*	*(0.010)*	
41810	Binder	3,893	0.282	0.080	0.033	1,098
			(0.059)	*(0.021)*	*(0.010)*	
41811	Bayan-Adraga	2,421	0.365	0.109	0.046	884
			(0.085)	*(0.034)*	*(0.017)*	
41812	Tsenkhermandal	2,623	0.295	0.087	0.037	774
			(0.051)	*(0.019)*	*(0.009)*	
41813	Norovlin	2,879	0.365	0.109	0.046	1,051
			(0.085)	*(0.034)*	*(0.017)*	
41814	Batnorov	6,683	0.250	0.066	0.026	1,671
			(0.060)	*(0.020)*	*(0.009)*	
41815	Bayan-Ovoo	1,696	0.250	0.066	0.026	424
			(0.060)	*(0.020)*	*(0.009)*	
41816	Moron	2,542	0.250	0.066	0.026	636
			(0.060)	*(0.020)*	*(0.009)*	
41817	Kherlen	18,297	0.407	0.128	0.057	7,447
			(0.025)	*(0.012)*	*(0.007)*	

50000	**UlaanBaatar**	**772,969**	**0.278**	**0.074**	**0.029**	**214,885**
			(0.016)	***(0.006)***	***(0.003)***	
52000	**Ulaanbaatar**	**772,969**	**0.278**	**0.074**	**0.029**	**214,885**
			(0.016)	***(0.006)***	***(0.003)***	
52001	Khan-Uul	70,441	0.347	0.098	0.039	24,443
			(0.022)	*(0.009)*	*(0.004)*	
52002	Baganuur	21,167	0.238	0.064	0.025	5,038
			(0.022)	*(0.008)*	*(0.004)*	
52003	Bayanzurkh	150,090	0.282	0.075	0.029	42,325
			(0.018)	*(0.007)*	*(0.003)*	
52004	Nalaikh	23,662	0.297	0.077	0.029	7,028
			(0.024)	*(0.009)*	*(0.004)*	
52005	Bayangol	143,659	0.186	0.045	0.016	26,721
			(0.016)	*(0.005)*	*(0.002)*	
52006	Sukhbaatar	92,901	0.238	0.063	0.024	22,110
			(0.015)	*(0.006)*	*(0.003)*	
52007	Chingeltei	108,132	0.327	0.090	0.035	35,359
			(0.020)	*(0.008)*	*(0.004)*	
52008	Bagakhangai	3,571	0.282	0.074	0.028	1,007
			(0.042)	*(0.015)*	*(0.007)*	
52009	Songinokhairkhan	159,346	0.317	0.087	0.034	50,513
			(0.020)	*(0.008)*	*(0.004)*	

Source: *Authors' calculations based on the LSMS 2002/03 and Census 2000*
Note 1: *Robust standard errors are in parentheses.*
Note 2: *The Regions are shown in bold and are highlighted in yellow. The associated Aimags are listed in bold and the Soums are shown below their respective Aimags.*