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MAPPING POVERTY IN AFGHANISTAN

Technical Report

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MAPPING POVERTY IN AFGHANISTAN: Technical Report

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Executive Summary

Poverty maps are visualizations of imputed estimates of poverty for small areas, typically below the level of survey-based statistics. This technical report accompanies the first set of poverty maps ever produced for Afghanistan, offering new insights into the spatial distribution of welfare at the district and nahia (urban sub-district) level. Direct estimates of poverty based on the Afghanistan Living Conditions Surveys allow for welfare measurement for the 34 provinces of the country. From the provincial estimates, we know that poverty tends to be higher in rural areas and is highest in the Southwest, Northeast, and West-Central regions of the country (ALCS 2016-17). However, the poverty maps yield a finer resolution of poverty down to the district and nahia[1] level and reveal the heterogeneity in poverty rates and poverty density within provinces previously masked by the provincial estimates. This report includes results for the poverty maps in Kabul and Herat provinces, and is the first in a series of poverty maps.

Methodology and Data

The poverty maps for Afghanistan were produced using the well-established small area estimation methodology of *Elbers, Lanjouw, and Lanjouw (2003)* to produce reliable yet highly disaggregated poverty estimates. This poverty mapping method combines the different strengths of household survey and census data[2]. While survey data with household consumption information may be used to measure poverty, the typical sample size of the survey usually limits the extent of disaggregation of the results. On the other hand, census data covers practically the entire population but lacks the detailed consumption information to measure poverty.

Small area estimation involves modeling a relationship between household welfare, measured by *consumption per capita* in Afghanistan, and various household, individual, and location characteristics. The chosen model is then applied to the census data to impute household welfare for all households and subsequently simulate poverty for small areas. The poverty mapping methodology relies on sophisticated modeling of the error terms to improve the poverty estimates.

The main data sources for these poverty maps are the 2016-17 Afghanistan Living Conditions Survey (ALCS), the Socio-Economic and Demographic Surveys (SDES), and geospatial data. The ALCS is a nationally representative multi-topic household survey that is used to measure and analyze poverty and inequality. Various data issues, stemming mainly from the change in the sample frame and geographic coding system between the survey and census, were addressed to the extent possible. For Kabul and Herat provinces, large disparities in urban population shares between the survey and census required post-stratification modifications to the survey weights in the ALCS. Furthermore, three districts were not

[1] Nahias are one administrative level below districts but are only available in urban areas.

[2] Recent census data is not available for Afghanistan, however, the National Statistics and Information Authority (NSIA) undertook a census-like household survey, the Socio-Demographic and Economic Survey, which included a full household listing and subsequently, interviewed every other household. This data source provides census-like information and is available for 13 provinces.

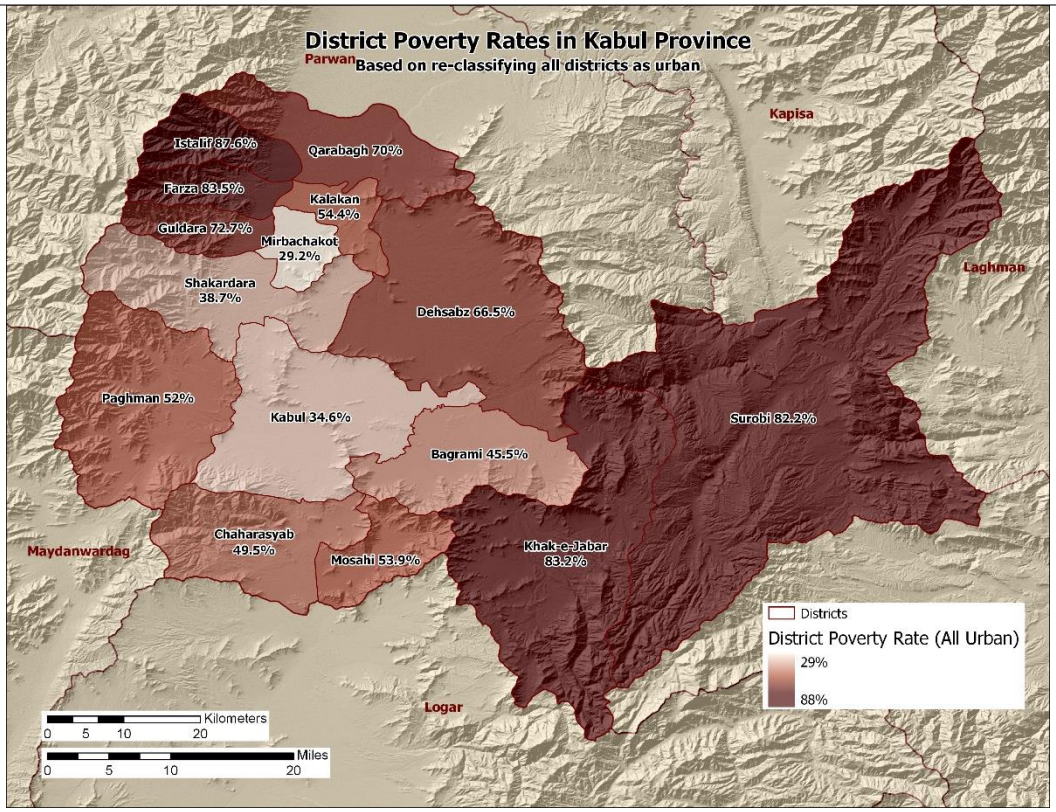
sampled in the SDES for Herat and a fourth one excluded from the model due to small sample size. Due to various data modifications that were made, the resulting provincial poverty estimates from the ALCS (maintaining comparability with SDES) differ slightly from previously published poverty measures for 2016-17; the direct provincial poverty estimates from the ALCS 2016-17 changed from 34.3 percent to 41.5 percent in Kabul province and 47.9 percent to 43.0 percent in Herat province. In addition to ALCS and SDES data, we incorporated geospatial data, data on conflict, and other innovative sources which improved the quality of the poverty maps. With that said, this first set of poverty maps is useful in understanding the geographic distribution of poverty in Kabul and Herat provinces and can help inform the allocation of scarce resources to areas that need them most.

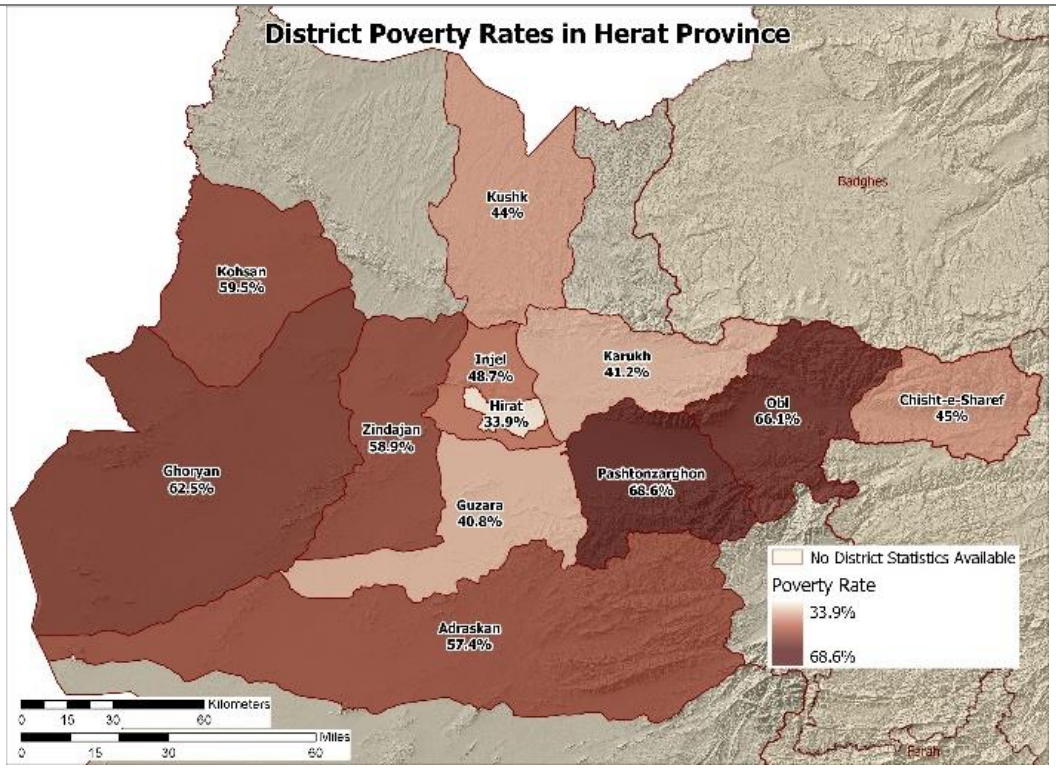
Results

With the poverty maps, considerable heterogeneity in poverty rates is revealed within provinces (Map E1). As we move from the province down to the district level estimates, pockets of poverty and prosperity come into focus. Poverty rates as high as those found in the Istalif, Farza, and Khak-e-Jabar district, where over 80 percent of the population are poor, emerge in Kabul district, while Mirbachakot, Kabul Center, and Shakardara show that less than 35 percent of residents are poor. In Herat province, poverty tends to be highest in Ghoryan, Pashtonzarghon, and Obi districts, with poverty rates of over 60 percent. Also, the largest urban agglomeration in both provinces, Kabul and Herat districts (provincial centers), show that about one third of the district is poor.

As the population is not distributed uniformly throughout the provinces, the poverty density maps visualize estimates of the absolute number of people living below the poverty line in a given area (Map E2). As such, this information provides a valuable complement to the poverty rates. With respect to poverty density, Kabul district and Herat district (both provincial centers) have high concentrations of the poor. In Kabul district, the poverty rates are not particularly high but the high population densities renders the total number of poor in the district very high, at over 1.0 million. Similarly, Herat district, despite relatively modest poverty rates, has the highest number of poor in the province of over 320,000. In other regions, high poverty rates despite relatively low population numbers drives the high number of poor; this can be seen in the Surobi district in Kabul and Zindajan district in Herat.

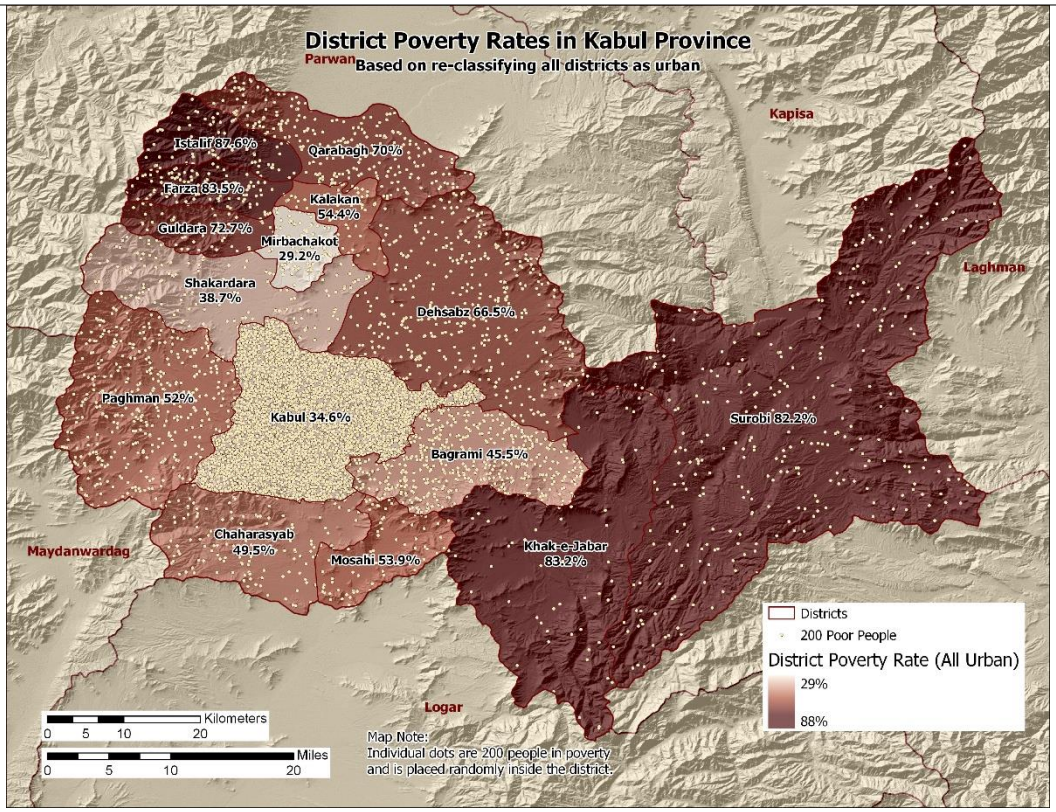
Map E1: Poverty Rates (estimated) at District Level in Kabul and Herat

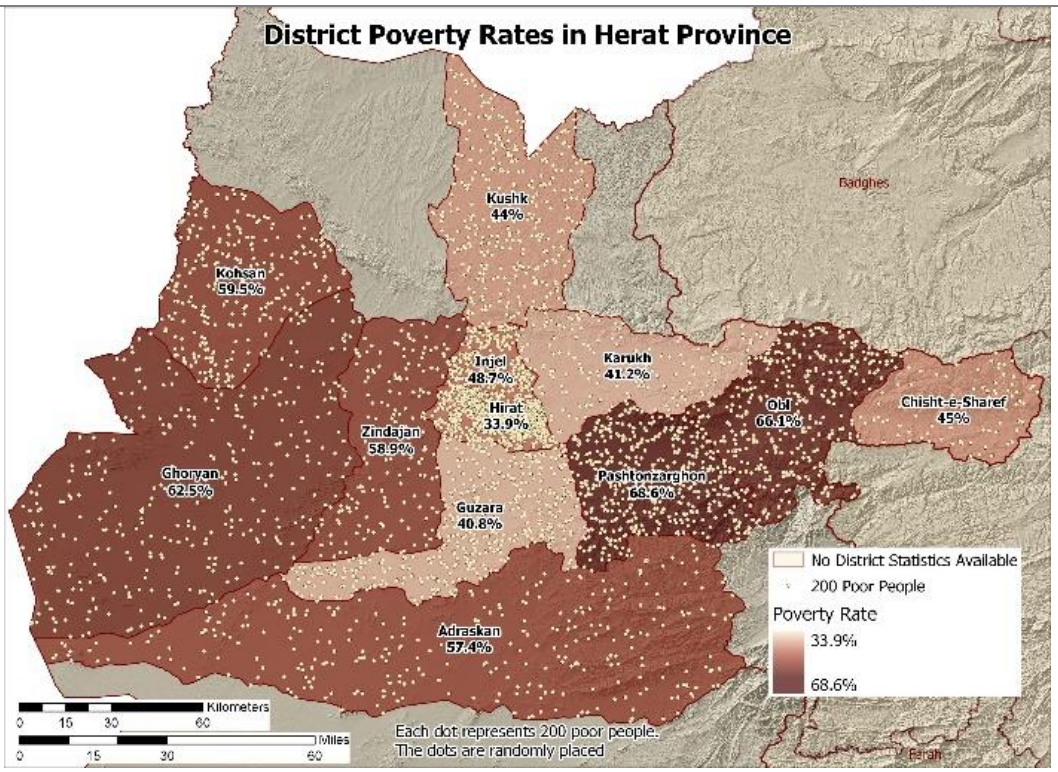




Source: Based on ALCS 2016-17 and SDES.

Map E2: Poverty Density (estimated poor population) at the District Level in Kabul and Herat





Source: Based on ALCS 2016-17 and SDES. Note: Each dot represents 200 people living below the poverty line. Dots are randomly placed within district boundaries and do not represent exact locations of the poor.

As with any survey or modeled estimates, the confidence interval of these poverty map estimates are important to consider. It should be noted that the standard errors for the direct poverty estimates from the ALCS 2016-17 survey are relatively high at 2 percent in Kabul and 3 percent in Herat province. At the provincial level, the predicted poverty estimates were close to the direct survey estimates, and they had smaller confidence intervals. The confidence intervals for the district level estimates are wider than for province level estimates, as would be expected. The median standard error for the district level estimates is 3.9 percentage points (mean of 4.1 percentage points), which translates into a fairly broad 95 percent confidence interval of 8 percentage points. As a result, some of the district level estimates within a province are not statistically different from their respective provincial estimates. Nevertheless, these geographically disaggregated welfare estimates provide for the first time, a sub-provincial picture of welfare disparities, which is critical for policy making and program design.

Recommendations

Further research is recommended to explore the spatial relationship between poverty and other socio-economic indicators. Producing maps of indicators related to poverty and overlaying them on these poverty maps could help identify spatial patterns. For instance, maps of access to basic services, market accessibility, rainfall patterns, agricultural and livestock production, educational attainment, and malnutrition, to name a few, could be helpful. District level estimates could be produced from the SDES data for some indicators and displayed on a map, however, we only have information on 13 provinces to date. This analysis could not only look at how poverty and other indicators are correlated but also shed light on underserved geographic areas. Furthermore, estimating poverty maps for the remaining 11 provinces for which we have SDES data is worthwhile.

Adopting a standard definition of urban and rural areas based on population-based parameters is highly recommended. Given that different poverty line values are applied according to the area of residence in Afghanistan, the designation of urban or rural areas can impact substantially the poverty measures for an area. Thus, the adoption and application of a standard definition across all areas of the country which is consistent across different surveys and survey years, and that is updated to reflect ground reality, would help improve poverty measurement and the monitoring of urbanization.

Updating the sampling frame of the upcoming ALCS (2019-20) based on information from the SDES is worthwhile, in light of the discrepancies observed between the household survey (ALCS 2016-17) and the half census[3] (SDES). As the sample frame and location codes for the next survey would be based on the latest SDES available for a province, the data issues could be minimized when updating the poverty maps with the next round of survey data.

[3] The SDES was implemented province-by-province in 13 provinces by undertaking a full listing of households in each of the districts. Based on the listing, every other household was selected for interviewing. Due to security-related challenges, some districts were dropped in some of the provinces.

1. Introduction

Afghanistan has been in protracted conflict for almost four decades, with direct implications on progress towards development objectives. This context of recurring episodes of violence and insecurity, economic and political instability, and the consequent displacement of populations within and outside the nation's borders has important implications on the landscape of data and evidence available for the design, implementation, monitoring and evaluation of interventions and programs, and their timeliness and relevance.

Afghans represent the world's largest and most protracted refugee population, with an estimated 3.5 million people currently living abroad as refugees for more than 4 decades. It also constitutes one of the largest populations that have been either voluntarily or involuntarily repatriated to their country of origin. An estimated 4 million refugees returned to Afghanistan between 2002 and 2005 alone, representing a 16 percent increase in population. Afghanistan is now facing a sharp increase in displacement due to the escalation of internal conflict, and a new wave of mostly involuntary returns. Currently, an estimated 1.2 million people are internally displaced and in need of humanitarian assistance, and between July and December 2016 alone, around 1 million Afghans returned from Pakistan and Iran. An estimated 1.1 million and 3 million Afghans remain in Pakistan and Iran respectively and could potentially be repatriated in 2017 if regional relations deteriorate.

Afghanistan's harsh geography coupled with increased conflict in mainly rural areas, also make for extremely challenging living conditions for Afghans, and the need for nuanced and spatially differentiated information to inform the design and implementation of programs. This geography has shaped settlement patterns and livelihoods, is correlated with natural disaster risk exposure, and implies that small distances could mask large variations in welfare. The population tends to cluster in the foothills and periphery of the Hindu Kush mountains; smaller groups are found in many of the country's interior valleys but in general, the East is more densely and the South more sparsely populated. In this localized and complex geography, the location that of households live in matters greatly as the rugged landscape leads to sharp divisions in welfare within small areas and poses severe challenges in service delivery and market integration.

Afghanistan has been successful on many fronts, particularly on human development outcomes such as education and health; its record of economic growth and poverty reduction however has been one of mixed results. From 2007 to 2012, Afghanistan witnessed unprecedented economic growth. While the benefits of growth were narrowly concentrated, the period saw major gains in health and education. Since the 2014 security transition the country has faced slow economic growth rates, a deterioration in security, and a displacement crisis, arising from both internal displacement and large numbers of returnees. As job quality remains poor and agriculture stagnant, food insecurity has risen sharply, and one in two Afghans today lives below the national poverty line. This stark deterioration in welfare poses a humanitarian crisis and is a call for concerted action.

Afghanistan has faced almost impossible odds since the 2014 drawdown of international security forces and accompanying reduction of aid. The Afghan economy has grown at an average of 2.1 percent between

2013 and 2016, and GDP per capita in 2018 is estimated to be around $100 below 2012 levels. As a consequence, the poverty rate is estimated to have increased from 34 percent in 2007/08 to 55 percent in 2016-17. Mirroring the increase in poverty, food insecurity has climbed from 30 percent in 2011-2012 to 45 percent in 2016-2017, driven by an increase in the proportion of severely and very severely food insecure population (Haque et al., 2018).

In addition, large regional disparities within Afghanistan exist with poverty rates highest in the Southwest (80 percent) and West Central (69 percent) (NSIA, 2018). In Afghanistan, official poverty rates are produced from the Afghanistan Living Conditions Survey (ALCS), the latest round of which was implemented in 2016-17. Poverty rates however can only be obtained at the national and provincial level as household sample surveys face limitations of producing statistically reliable and representative poverty indicators at lower geographically disaggregated areas due to sampling design and sample size. Therefore, survey results are unable to reveal important differences within different provinces and within larger urban districts.

Given the large disparities in poverty incidence and high levels of inequality within Afghanistan, the knowledge of living standards at more disaggregated geographical levels of districts and nahias could help inform policy design and improve decision making at a sub-province level. Therefore, poverty mapping, which aims at estimating poverty incidence at levels lower than the household survey, was applied in Kabul and Herat provinces[4]. Poverty maps utilize small area estimation techniques to obtain highly disaggregated poverty estimates from survey and census data. They are useful tools that can help accelerate poverty reduction by improving the allocation of limited resources and the targeting of development projects and programs in lagging regions.

This technical report describes the methodology and data used to produce the Kabul and Herat poverty maps, representing about 23 percent of Afghanistan's population, and presents the resulting collection of poverty maps, the first of its kind for Afghanistan. The structure of the report is as follows. Section 2 outlines the poverty mapping methodology, specifically the small area estimation approach, applied in Afghanistan. Section 3 discusses the data sources and the various technical challenges faced with the datasets. Section 4 discusses the modeling phase, including model selection, model parameters, and assumptions. Section 5 presents the poverty maps at a district and nahia level, and section 6 concludes. The Annexes contain supporting data and analysis.

2. Poverty Mapping Methodology

The poverty maps for Kabul and Herat province were produced using the well-established small area estimation methodology of *Elbers, Lanjouw, and Lanjouw, 2003* (henceforth, ELL) to produce reliable yet highly disaggregated poverty estimates. This poverty mapping method combines the different strengths of household survey and census data. While survey data with household consumption information may

[4] Kabul and Herat provinces were selected to test whether poverty mapping is possible using SDES data. Kabul is the largest province in terms of its population and Herat is one of the economic centers of the country with important trade routes to Iran.

be used to measure poverty, the typical sample size of the survey usually limits the extent of disaggregation of the results. On the other hand, census data covers the entire population but lacks the detailed consumption information to measure poverty.

Small area estimation involves modeling a relationship between household welfare, measured by *consumption per capita* in Afghanistan (for details on the poverty measurement process see the box below), and various household, individual characteristics, and location characteristics from survey as well as geospatial data sources.[5] The model is then applied to the census data to impute household welfare for all households in the census database and thereby estimate poverty for small areas. The poverty mapping methodology relies on a sophisticated modeling of the error terms to improve the poverty estimates.

Measuring Poverty in Afghanistan

The Cost of Basic Needs Approach

The measure of welfare adopted to assess population living standards is based on household expenditures. An individual is considered as poor if their level of consumption expenditures is not sufficient to satisfy basic needs, or in other words, if their consumption expenditure falls below the minimum threshold identified by the poverty line. In line with international standards, the official absolute poverty line for Afghanistan is estimated following the Cost of Basic Needs (CBN) approach and it was set using the NRVA 2007-08. The CBN absolute poverty line represents the level of per capita consumption at which the members of a household can be expected to meet their "basic needs" in terms of both food and non-food consumption.

More specifically, the food component of the poverty line captures the cost of consuming 2,100 Kcal per day following the typical food consumption patterns of the relatively poor; the non-food component of the poverty line is estimated as the median non-food expenditure of individuals with food consumption around the food poverty line. For more details, see methodology note.

Poverty lines

Poverty lines in Afghanistan are estimated at the regional-urban/rural strata level, and the national poverty line is the population weighted average of these regional-strata lines. The classification of provinces into regions for this purpose is shown in Table 1 below. These 8 regions, when split into urban-rural strata, yield 14 region-strata classifications (some regions do not have urban strata), and therefore 14 poverty lines. In 2016-17, the national average threshold for the cost of covering basic needs, the poverty line was 2,056 Afs per person per month.

The poverty mapping for Kabul and Herat provinces proceeded in three broad steps[6]: i) identifying candidate variables that may be good predictors of household welfare and are comparable across the

[5] Recently, a World Bank team has created a family of Stata commands which implement small area estimation methods, and provides users with a valid, modular, and flexible alternative to the previously applied "PovMap" software (Nguyen et al., 2017).

[6] The three steps will be summarized here, but for more technical details, please refer to ELL 2002, 2003. Also, for other examples of the application of ELL, refer to the poverty map report for Iraq (Vishwanath et el., 2015).

survey and census data; ii) specifying a consumption model from the set of candidate variables using the survey data; and iii) imputing consumption for all households in the census data by applying the parameter estimates from the welfare model and estimating poverty into small areas.

Identifying Candidate Variables in the Survey and Census Data

Before getting started with the modeling phase, the pool of suitable variables is first identified. As the model will be specified using survey data and then applied to the census data, the same set of variables will need to exist in both datasets. This requires that similar questions and response options exist in both survey and census questionnaires and that the variables are comparable across datasets.

The quality of the consumption models will depend on the number of variables common in both datasets that are good predictors of household consumption. Typical types of variables include: household demographics such as household size and dependency ratios, as well as characteristics of the household head such as age, gender, marital status, and educational attainment; ownership of assets such as TVs, stoves, furniture, and vehicles; dwelling characteristics such as the material of the walls, roof, and floor, the type of housing, toilet facilities, lighting, and water sources; and ownership of livestock and agricultural assets such as land and equipment.

Great amount of effort was spared on screening candidate model variables and candidate variables were re-defined and/or regrouped in various ways to attain comparable categories which lead to larger sample sizes. Particularly the variables of household size, source of water, toilet and lighting were re-grouped to attain comparable categories across the two datasets. In addition, variables on geospatial and location characteristics were included to further improve the model prediction and fit.

In addition to identifying the common variables and creating corresponding categories for each of the variables, the variables are examined for comparability. Only variables with similar mean values across the survey and the census are included as candidate variables in the modeling phase. Stark regional differences and the fact that the SDES was rolled-out province-by-province, necessitates the use of separate province models of household consumption.

Modeling Household Consumption with the Survey Data

Once comparable variables between the survey and census are identified, they are used to specify an econometric model of household consumption. With the survey data, the following model is specified:

$$\ln(y_{ch}) = X_{ch}\beta + u_{ch} \qquad (1)$$

where $\ln(y_{ch})$ is the log of consumption per capita of household h in cluster c, X_{ch} is the vector of selected household and location-specific characteristics, β is the vector of regression coefficients and u_{ch} is the vector of disturbances.

For the poverty map in Kabul and Herat province, we use separate province models, that is, the consumption model (1) is computed for each province separately. This allows for variation in the relationship between consumption and the selected variables across provinces.

After equation (1) is estimated using Ordinary Least Squares (OLS), the disturbance term u_{ch} is obtained and divided into two components: a cluster effect η_c common to all households in cluster c and a household-specific error component ε_{ch}:

$$u_{ch} = \eta_c + \varepsilon_{ch} \qquad (2)$$

The choice of the geographic disaggregation level (i.e. administrative sub-division) for the cluster effect is important as it can affect the standard errors of predicted results. If lower levels of disaggregation are selected, heterogeneity at the target geographic level can be captured more accurately. However, disaggregation of the cluster level at lower geographic levels comes at the cost of less reliable distributions derived from survey data (De la Fuente et al. 2015). In Afghanistan, the cluster effect was chosen at the lowest possible level of geographic disaggregation for which we can reliably predict poverty, the district level. In a few urban districts, where data is most reliable, cluster effect was chosen at a further lower geographic disaggregation level, the nahia level. A Generalized Least Squares (GLS) regression is used to estimate all the parameters for the regression coefficients and the distribution of the disturbance terms to be used in the subsequent step.

Imputing Household Consumption and Estimating Poverty with the Census Data

Once the model is specified, we impute consumption per capita in the census by drawing a vector of betas ($\hat{\beta}$), a vector of cluster effects ($\hat{\eta}_c$), and a vector of household idiosyncratic effects ($\hat{\varepsilon}_{ch}$) from their respective distributions as follows:

$$ln(\hat{y}_{ch}) = X_{ch}\hat{\beta} + \hat{\eta}_c + \hat{\varepsilon}_{ch} \qquad (3)$$

This procedure is repeated 100 times, and for each round of the simulation, the poverty rate is calculated for a given area. The average value of these 100 poverty rate estimates is the predicted point estimate for that area, and the standard error is derived from the distribution of the 100 estimates. The lowest administrative level at which poverty estimates are calculated for Afghanistan is the nahia level in urban areas and the district level in rural areas for both Kabul and Herat provinces.

The predicted estimates are derived under the assumption that the beta parameters, that is, the estimated relationship between expenditure and household and individual characteristics, are stable between the time of the survey and the census. The survey and census data for Kabul province are three years apart and during this period from 2013 to 2016, the economy underwent a downturn. As such, the underlying stability assumption for the poverty map may not be reasonable, however, the team included variables that are less likely to be time variant and tested the models substantially. In Herat province, the survey and census data were collected in the same year (SDES was collected in 2016) and the underlying stability assumption is valid.

Different distributional drawing methods, parametric and bootstrapped, were explored to identify the one that provided the best predicted poverty rates and the lowest standard errors. According to Van der Weide (2014), the performance of these two options depends on i) the size of the random area effect; ii) the number of small areas represented in the survey; and iii) the degree of non-normality of the errors.

We applied the Empirical Best estimation which applies the location errors η_c assuming a normal distribution with variance σ_η^2 and applies σ_η estimated from the bootstrapped distributions applied at the level of the primary sampling unit. The empirical best requires normality of both error terms.

tightens the error distributions by conditioning the distribution on all available data in the survey and predictions are expected to do well if there are relatively large random area effects and if many of the small areas are covered by the survey (Elbers and Van der Weide 2014, Van der Weide 2014). Trimming of predicted household expenditures was not applied.

The small area estimates for Kabul and Herat provinces are produced down to the district level and for some urban districts, down to the nahia level. These results are then presented on a map making it easier to visualize the geographic variation in poverty.

3. Data

Data Sources

The poverty maps in Kabul and Herat province rely on two data sources, the latest nationally representative household survey, the ALCS 2016-17, and the half-census, the SDES. Each of these are described below.

Household Survey Data

The 2016-17 Afghanistan Living Conditions Survey (ALCS) is a nationally representative multi-topic household survey that is used to measure and analyze poverty and inequality. The ALCS collects information related to education, health, employment, unemployment, domestic activities, income and other characteristics of individuals as well as household composition, migration, housing characteristics, expenditures, and food consumption.

The ALCS used a stratified two-stage sampling design. The first stage consisted of a random selection of primary sampling units (PSU) or enumeration areas (EA), within each strata defined by the province. The sampling frame was based on the 1979 Census but modified based on a household listing undertaken between 2003 and 2005 and further modified by the household listing undertaken in the SDES wherever available at the time of survey preparation (2015). In the second stage, 10 household were randomly selected per PSU. The total sample size was 19,838 households, 19,833 of which had data on consumption, which constitutes the sample for measuring and modeling poverty[7]. The field work for the survey was conducted from April 2016 to April 2017.

Census Data

Due to security reasons, the last (partial) official census in Afghanistan was conducted in 1979 with about two thirds of the country covered. However, between 2013 and 2017, NSIA undertook half-censuses in the form of the Socio-Demographic and Economic Surveys (SDES) to fill this critical data gap. The SDES

[7] For details on the poverty measurement methodology, please refer to Wieser, et al. (2018).

includes a full household enumeration and detailed data collection for 50 percent of households. However, due to insecurity, only 13 provinces could be covered by the SDES (and some only partially). The questionnaire used for the SDES is similar to a census form and covers few but critical questions on demographic and socio-economic attributes for every other resident. The census data was collected in different periods and years for different provinces. The SDES for Kabul province was collected in June 2013 and covered all 15 districts of Kabul province[8]. The SDES for Herat province was collected in March 2016 and covered 13 out of the 16 districts[9]. Due to security problems, the districts of Gulran, Shindand and Fersi were not covered.

Geographic Administrative Sub-Divisions

Afghanistan has 3 main administrative sub-divisions: provinces, districts, and for urban districts, nahias. At the first sub-national administrative level, Afghanistan is divided into 34 provinces. At the second sub-national administrative level, each province is further divided into districts. For example, Kabul province is divided into 15 districts and Herat province is divided into 16 districts. At the third sub-national administrative level, districts are further split into nahias but only if they are urban. Rural districts do not have a nahia sub-division.

Data Challenges

Several data challenges needed to be resolved to improve the comparability of the survey and census data. The challenges stem from systematic changes made between the implementation of the survey and the census, namely differences in the sampling frame, the geographic coding system, and the classification of urban and rural areas. The following sections describe each of the issues and the corrections that were made to harmonize definitions across the survey and census databases.

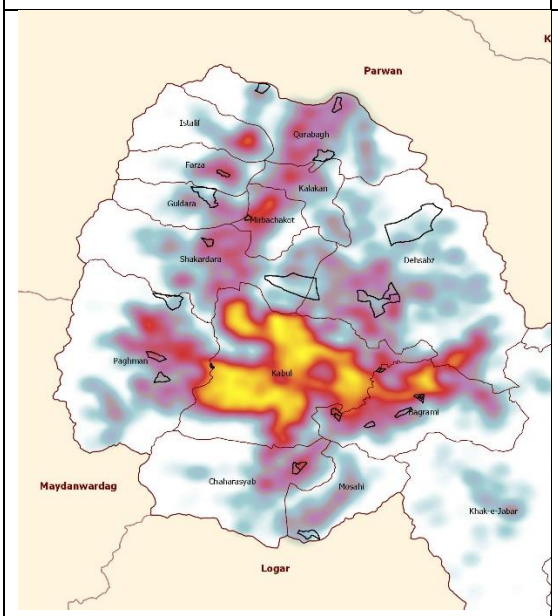
One challenge in terms of data was the use of different sampling frames between the survey and the census data for Kabul and Herat and the re-drawing of boundaries across enumeration areas but also districts. The ALCS used an updated version of the sampling frame which included changes based on SDES information. For the ALCS 2016-17, enumeration areas were redefined and did not necessarily correspond neatly with the previous definitions. Furthermore, urban and rural classifications are not well defined, in that they are not based on well-defined criteria such as population density. Therefore, the use of urban/rural is somewhat ad-hoc and defining more accurate criteria for these designations would improve the monitoring of urbanization and poverty.

[8] For more detailed information on the SDES, please refer to the SDES report for Kabul, National Statistics and Information Authority (formerly Central Statistics Organization) of Afghanistan, 2015. available at http://cso.gov.af/Content/files/English_Kabul_Web_Quality.pdf

[9] Results in this document show results for 12 districts as one of the districts only contained one enumeration area and results were not deemed representative. For more detailed information on the SDES, please refer to the SDES report for Herat, National Statistics and Information Authority (formerly Central Statistics Organization) of Afghanistan, 2017. available at http://cso.gov.af/Content/files/SDES/Highlight%20Herat%20Fr%204%20March.pdf

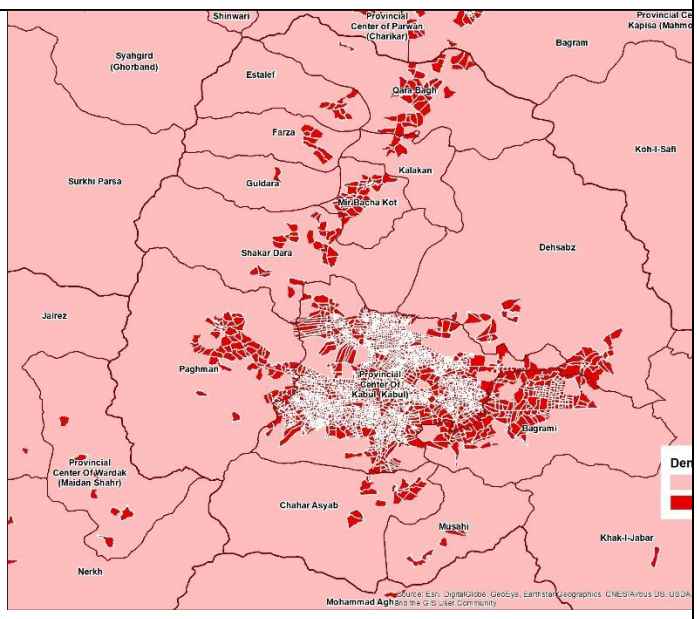
The challenges of the urban/rural definition in Kabul led to the curious outcome that only the Provincial Center of Kabul is classified as an urban area while all other 14 districts are classified as rural. The sprawling city limits of Kabul have, however, led to the fact that neighboring districts have very similar urban characteristics as does Kabul Center as can be seen by population density Map 1 and Map 2. This is important in the context of applying the respective poverty lines as we measure poverty in Afghanistan by applying different poverty lines for urban and rural areas to adjust for the difference in prices of the consumption bundle that urban and rural household face. Since the poverty line is supposed to represent the cost for a basket of basic needs, we apply different urban and rural poverty lines[10]. The question of whether the applied poverty line in these rural designated areas would be in line with a locally priced basket of basic needs is relevant. Since it is quite plausible that in these rural areas in close proximity to Kabul, the difference in the cost of living between these area and Kabul Center is less pronounced and in fact, the poverty line of Kabul Center is more relevant. Therefore, NSIA decided to apply the urban poverty line to all 15 districts of Kabul province[11].

Map 1. Kabul province heat map of population density (yellow indicates highest population density)



Source: Staff calculations, based on population data.

Map 2. Kabul province population density by enumeration area



Source: Staff calculations, based on population data.

Not all districts were sampled in the survey. In Kabul, the ALCS did not include districts Kahak-e-Jabar (district 9), Kalakan (district 10), and Surubi (district 15). In Herat, the ALCS did not include district 15 and in Kushk-e-Kuhna (district 10) only 1 enumeration area (10 households) was sampled and was thus dropped from the sample.

[10] The urban poverty line is around 3,004 Afs per person per month and the rural poverty line is 1,900 Afs per person per month.

[11] All subsequent results, except Table 1 assumes an urban classification for all districts of Kabul.

A statistically significant difference in the urban population share between survey and census was noted for Kabul and Herat provinces. Table 1 compares the urban population shares in the ALCS and SDES. The differences for both provinces are deemed too large to attribute to migration from rural to urban areas. Given the importance of having similar urban/rural population shares for the poverty results[12], post-stratification adjustments to the survey weights were made for Herat province[13] such that the urban population distribution across districts in the ALCS[14] would match that of the census.

Table 1. Comparison of urban population shares in the survey and census data

	ALCS			SDES
REGION	**Urban share (%)**	**Standard Error**	**95 % Confidence Interval**	**Urban share (%)**
KABUL	83.0	0.9	81.2 - 84.9	77.4
HERAT	27.7	1.5	24.8 - 30.6	37.2

Source: Authors' estimates based on ALCS and SDES data.

Note: Herat includes only those districts available in ALCS and SDES.

Comparability of Variables between Survey and Census

Since small area estimation involves imposing the relationship between household consumption and individual, household, and location characteristics from the survey data onto the census data, the method requires a common set of variables that are comparable across the survey and census data. As a first step, the questions in the survey and census were compared for similarities to identify common variables. As a second step, the variable means of the survey and the census were compared.

Since separate province models are specified, the comparison of variable means is conducted separately for each province and not at the national level. A variable is included as a candidate for a province model if its census and survey mean for that province are comparable. With a larger pool of comparable variables, the likelihood of finding a good predictive model of household consumption improves.

The following sets of variables were common to the census and the survey and evaluated for comparability:

- **Household characteristics:** Area of residence (nahia dummies for urban districts, district dummies for rural districts), household size categories, highest level of education in the household, average age in household, dependency ratio, number of children under 6, number of elders over 60, female proportion, adult male proportion.
- **Household head characteristics**: education level, marriage status, literacy, sex.

[12] Urban/rural classification matters for poverty measurement in Afghanistan because different poverty lines are used for rural and urban areas. A simple change in the urban/rural share can have a large impact on the poverty rates.

[13] Post-stratified weights were not applied in Kabul province as we assumed that all districts in Kabul province are urban and thus the urban share is 100 percent in SDES and ALCS.

[14] In Herat, ALCS weights were adjusted to match urban/rural shares for those districts available in the ALCS (district 10 was excluded due to small sample size and district 14 was not sampled).

- **Dwelling characteristics:** cooking fuel, source of heating, source of lighting, source of drinking water, type of toilet facility, access to sanitation, access to electricity, material of the wall, material of the floor, house ownership, overcrowding, persons per room.
- **Durable assets:** radio, tv, refrigerator, washing machine, internet, computer, bicycle, motorcycle, car.
- **Agricultural assets:** Land ownership, livestock ownership.
- **Geospatial characteristics:** Average distance of populated places to nearest water point by district, average distance in meters to nearest energy grid point by district, average number of flat areas near village by district, average elevation by district, average distance of primary roads within 5km of village by district, average distance of secondary roads within 5km of village by district, average distance of tertiary roads within 5km of village by district, average distance of footpaths within 5km of village by district.
- **Conflict:** number of incidents by district, number of civilian casualties by district.

Despite the seemingly similar nature of some questions, differences in the phrasing of questions or response categories have the potential to alter responses and undermine comparability. Large differences in answer categories were noted for some variables, particularly for educational attainment and dwelling characteristics. Great care was taken to harmonize answer categories, but some of the variables had to be removed nonetheless. Table 6 in the Annex presents the variable means for the census and the survey, as well as the standard errors and the 95 confidence intervals for survey estimates.

Household size is another important variable that is highly correlated with welfare, but the average household size showed large differences between the survey and census for Herat (Table 2). Given the importance of household size, a set of binary variables for different household size ranges were created as an alternative, which usually improved comparability enough to include in the models.

Table 2. Comparison of mean household size in the survey and census in Herat

	ALCS				SDES	Comparison
PROVINCE	**Mean household size**	**Standard Error**	**95 % Confidence Interval**		**Mean household size**	**Within 95% CI? (yes/no)**
KABUL	7.2	0.08	7.1	7.4	6.9	No
HERAT	6.5	0.09	6.4	6.7	5.7	No

Source: Authors' estimates based on ALCS and SDES data.
Note: Herat includes only those districts available in ALCS and SDES.

As a result of the necessary modifications described above, the province poverty rates were re-estimated to obtain the appropriate benchmark to assess the poverty map results (Table 5). Note that these revised poverty rates differ slightly from the official poverty estimates previously published by NSIA and analyzed in the latest World Bank poverty report. In Kabul province, the poverty rate increased from 34.3 to 41.6 percent due to the use of an urban poverty line for all enumeration areas. The switch to an urban classification for all households in Kabul province essentially means that all those households that were between the rural and urban poverty line, are classified as poor under the new definition. In Herat province, poverty rates changed to a larger extent as a result of using post-stratified weights but more

importantly, due to dropping 4 districts to ensure comparability to SDES data. Poverty rates decreased from 47.9 percent to 43.0 percent.

Table 3. Poverty rates before and after weight adjustments

	ORIGINAL ESTIMATES				ESTIMATES AFTER CORRECTIONS			
REGIONS	**Poverty Rate (%)**	**Standard Error**	**95% Confidence Interval**		**Poverty Rate (%)**	**Standard Error**	**95% Confidence Interval**	
KABUL	**33.4**	2.1	30.2	38.3	**41.5**	2.1	37.3	45.7
HERAT	**47.9**	3.2	41.7	54.2	**43.0**	3.5	36.0	50.1

Source: Authors' estimates based on ALCS 2016-17 data.

Note: Herat excludes districts 10 due to small sample size (only 1 EA sampled), districts 8, 14, and 15 due to missing data in SDES. Kabul applies urban poverty line for all households.

4. Modeling Household Welfare

The Kabul and Herat poverty maps are constructed using separate province models which allows for greater flexibility in fitting the relationship between household consumption and a set of explanatory variables. However, this requires dividing the survey data by province, so as a result fewer observations are available for each province model. As a rule of thumb, one would like to have no less than 300 observations for each model (Ahmed et al., 2014), which was satisfied for Kabul and Herat.

Model Selection

The model selection process for the consumption model (beta model) started with a stepwise weighted regression to identify an initial set of predictor variables among the large number of candidate variables. Subsequently, poverty estimates were imputed and compared with the direct survey estimates. To minimize differences between the predicted and direct poverty estimates, the model was refined by repeating the stepwise regression using a different set of candidate variables, that is, a subset of the original or with new variables. In addition, manual modifications were made to the models, drawing on results in other regional models and intuition of the relationship between consumption and predictor variables. The manual model selection process generally included variables that made sense conceptually and yielded the best results in the predicted regional poverty rate.

In a second step, an idiosyncratic model (alpha model) was defined to estimate the household effect and to account for the likely non-uniform variances of the error term in the consumption model. The idiosyncratic model is only affected by variables whose value affects the variance of the error term and – unlike the consumption model—we have no basis for deciding a priori which variables will have variances that vary systematically with the value of the variable. We therefore estimated the parameters using a stepwise regression without subsequent modifications.

In addition to significance of variables, equally important criterion is the precision of parameter estimates of variables measured by the p-values. As a general rule, only variables with p-values of 0.05 or less are included in the model. The number of variables included for Kabul was 30[15] and for Herat 20.

Table 7 in the Annex presents the results for each of the GLS models. The variables that consistently feature as predictors of consumption expenditure are household size, asset ownership (such as a computer, refrigerator, and bicycle), and dwelling characteristics such as material of the roof, lighting or toilet facilities. This is consistent with intuition about correlates of poverty. Nevertheless, we would like to caution against interpreting the regression coefficients as causal estimates. It is important to stress that unlike general regression analysis, the purpose of these regression models is not to explain the causes of consumption patterns and obtain estimates on explanatory variables. The key objective in our modeling exercise is not to obtain parameter estimates on regressors that can be readily interpreted and given economic meaning but rather to specify a model that will allow us to predict consumption to the best possible extent.

Location Effects

Consumption models cannot explain all the variation in consumption and the unexplained portion is accounted for by two sources of errors (as discussed in Section 2 on methodology), the cluster and household-specific components. Since large cluster effects can reduce the precision of poverty estimates, it is recommended to apply great effort to explain the variation in consumption by observables as much as possible[16]. To reduce the share of the variance of the cluster effect, we included three types of variables: (i) geospatial information at the district level; (ii) conflict incidence at the district level; and (ii) census aggregates at district level. These area-level means improved the precision of the predictions by capturing the differences in household standard of living due to location characteristics. In Kabul and Herat, the cluster effect was chosen at the level at the lowest possible level of geographic disaggregation for which we can reliably predict poverty, the district level. Location-specific variables were included into our pool of common variables. Including cluster-level variables has proved to be successful in the case of Kabul and Herat, reducing the ratio of variance-of-Eta over Mean Squared Error (MSE), which measures how much of the total variation measured by the MSE can be interpreted by the cluster effect, of cluster effects to 8 percent in Kabul and 8.8 percent in Herat.

Explanatory Power of Consumption Models

The adjusted R-squared measure for each of the province models indicate how well each of the models explains the variance in the observed household consumption in the survey. In the Kabul and Herat poverty models, R-squared and adjusted R-squared are generally high. In Kabul, the adjusted R-squared stands at 65.0 percent and in Herat at 63.1 percent.

[15] Counting household size dummies as only one variable.

[16] A rule of thumb is to try to reduce the share of the variance of the cluster effect to the total variance of residuals to 10 percent or less (World Bank, 2010).

Comparison of Province Poverty Predictions and Direct Survey Estimates

Since ALCS is representative at the province level, we evaluate the accuracy of the models by comparing the province level predictions with direct province estimates from the ALCS (i.e. revised estimates following data corrections). Direct and predicted poverty rates, confidence intervals of direct estimates, and standard errors of direct and predicted poverty rates are presented in Table 4. The projections are consistent with the ALCS poverty rates and estimates for all regions fall well within the 95 percent confidence interval of the ALCS mean. The prediction for Kabul is about 1.9 percentage points below the direct estimate of the ALCS. However, given that there are three years between the data collection of SDES and ALCS, it is not surprising that poverty rates cannot be replicated perfectly. In addition, the absolute value of the z-score[17], which measures the distance between the two means in the standard errors, is 0.80 and 0.01, well within the suggest threshold of |2|, indicating that both estimates represent the same poverty incidence (World Bank, 2013).

Table 4. Comparison of direct and predicted estimates

	NO. OF OBSERVATIONS		DIRECT ESTIMATE*				POVERTY MAP ESTIMATE				
Province	**ALCS**	**SDES**	**Poverty Rate**	**s.e.**	**95% Conf. Interval**		**Poverty Rate**	**s.e.**	**95% Conf. Interval**		**z-value**
KABUL	1,595	295,750	**41.5**	2.1	37.3	45.7	39.6	1.2	37.3	41.9	0.79
HERAT	897	201,654	**43.0**	3.5	36.3	50.3	43.0	1.4	40.4	45.4	0.01

Source: Authors' estimation based on ALCS and SDES data.

Note: s.e. stands for standard errors. Direct estimates (*) are based on all data modifications/corrections outlined in the section on data challenges and for Herat do not include districts 8, 10, 14, and 15 and for Kabul apply urban poverty lines for all households.

Poverty estimates cannot be seen as true values and their 95 percent confidence interval which represents the margins of errors should be taken into consideration. Checking for consistency and applying the 95 percent confidence intervals of the direct estimate from the ALCS as well as the predicted estimates from poverty mapping, we find that our predictions are in fact quite accurate in that the confidence intervals of the predicted estimates are smaller than for the direct survey estimates (Table 4, column s.e.).

5. Results

As recent economic growth has fallen below population growth, poverty has increased sharply. The 2016-17 ALCS provides the first estimates of the welfare of the Afghan people since the 2014 security transition. Since 2011, welfare has sharply deteriorated, as evidenced in the large increase in poverty rates, with over half the population living below the poverty line in 2016-17. The deterioration in welfare was experienced across the distribution, among the poorest households, as well as among the most well-off. These distributional changes imply that while the intensity of poverty has increased between 2011-12 and 2016-

[17] The z-value is calculated as $z = (FGT(0)census - FGT(0)survey)/\sqrt{(s.e.census^2 + s.e.survey^2)}$

17, inequality has declined, as the welfare loss among the top of the distribution has been relatively larger than that at the bottom of the distribution.

Even though ALCS is representative at the province level, it does not allow for estimation of poverty rates at a smaller geographic disaggregation. Poverty mapping allows us to predict poverty into smaller geographic areas, in the case of Afghanistan at the district level in rural areas and the nahia level in urban areas. This lower geographic disaggregation reveals considerable heterogeneity in poverty within provinces. Pockets of poverty and islands of prosperity otherwise hidden in the regional estimates emerge with the finer resolution at the district and nahia level. These highly disaggregated results can help inform and improve the design of policies and program that aim to reduce poverty and promote prosperity.

This section examines the poverty map results for Kabul and Herat provinces and then moves to a more detailed look at urban districts by providing nahia level poverty estimates for Kabul Center, Herat city, and Ghoryan district in Herat. The standard errors, representing the level of uncertainty associated with each of poverty map point estimates, are critical for interpreting the results. Predicted poverty rates are associated with some uncertainty (as discussed in the methodology section) which is reflected in the standard error. As the standard error for a particular poverty estimate increases, the 95 percent confidence interval around a point estimate increases. It is therefore essential to note the confidence interval associated with each of the poverty map results. Given that the standard errors increase as the results become more disaggregated, the standard errors for the district level estimates should be examined carefully and Table 9 in the Annex provides more detailed information on the imputed point estimates for each district and nahia and their standard errors for user evaluation.

The standard errors for the predicted small area estimates for Kabul and Herat are relatively low. The coefficient of variation, measured by dividing the standard error by the poverty rate of the prediction, helps to better understand the magnitude of standard errors compared to the poverty rates. Figure 1 displays the poverty rates and coefficients of variation at the district and nahia levels which helps us understand how accurate the results are. We observe that for most areas, the coefficients of variation are much below the 20 percent threshold, irrespective of whether we look at district or nahia levels. The confidence intervals of the predicated estimates are displayed in Figure 2.

Figure 1. Coefficients of variation and poverty rates at the district and nahia level

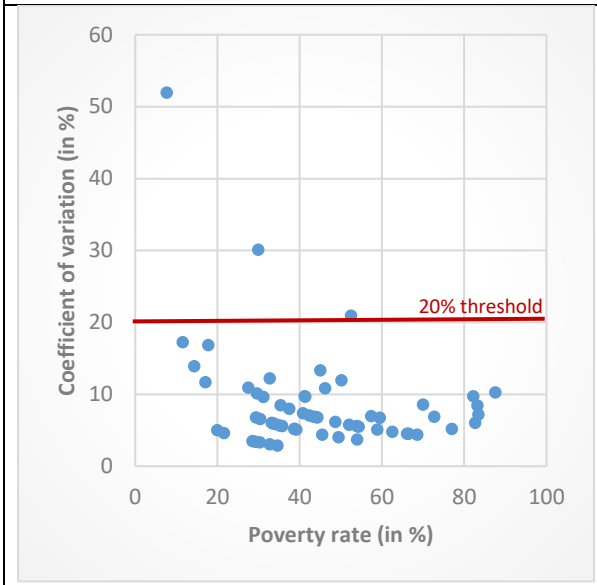
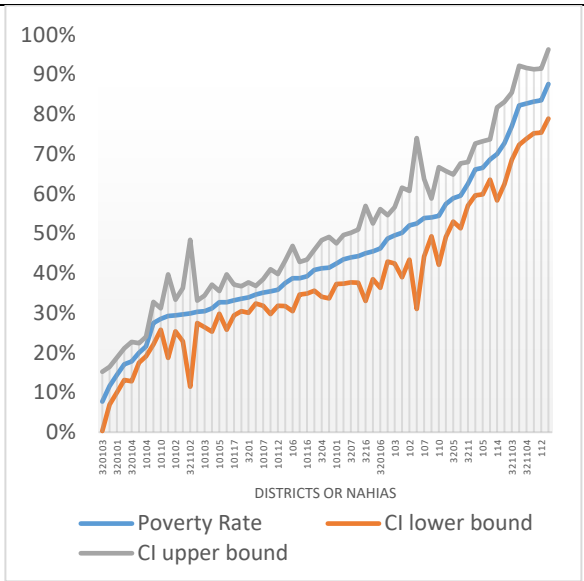


Figure 2. Coefficients of variation and poverty rates at the district and nahia level



Source: Staff calculations, based on ALCS and SDES data.

The province poverty map results for Kabul and Herat province for both the poverty rate and poverty density indicators are presented below. The poverty rate is the percentage of the population in a given area living below the poverty line, whereas the number of poor in a given area represents the poverty density. As the population distribution is not uniform throughout the country, these two indicators are complementary. It is possible for a highly populated geographic area to have a low poverty rate but a high poverty density, that is, a large number of poor people living in that area, or the converse in a sparsely populated area, a high poverty rate and low poverty density. The appropriate policy response is likely to differ for these distinct situations, so both indicators are important to evaluate.

Kabul Province Poverty Maps

Kabul province is situated in the East of the country and holds the capital Kabul Center. Kabul province has a population of 4.1 million and 8 out of 10 Kabulis live in the Provincial center Kabul Center. Kabul is situated in a valley surrounded by mountains and is located at crossroads of north-south and east-west trading routes. Kabul province is thus the economic and political powerhouse of the country.

District level estimates

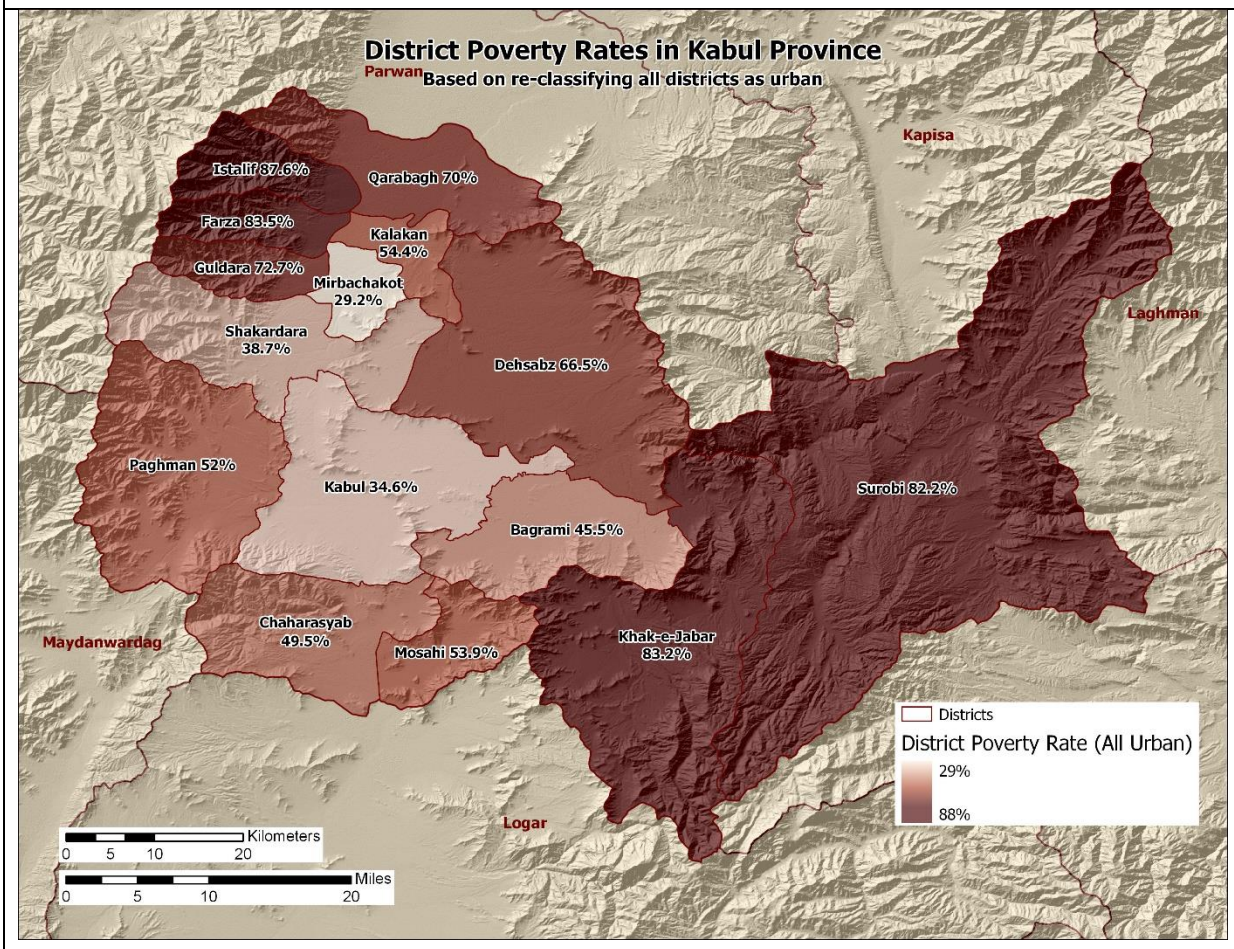
At the district level, the poverty map results show some variation in the poverty rates within Kabul. The district level poverty rates in Kabul province range from 29.2 to 87.6 percent, a spread of almost 60 percentage points. Kabul is Afghanistan's smallest province in terms of geographical area, yet, it is the most populous. The province alone accounts 13 percent of Afghanistan's population and 10 percent of Afghanistan's poor. As Map 3**Error! Reference source not found.** shows, about one third of the population living in the district of Kabul, the economic and political center, are poor. Kabul's 15 districts show a large

variation in poverty rates. In the two poorest districts, Farza and Istalif, 8 out of 10 people live in poverty (83.5 and 87.6 percent, respectively). One the other hand, the two least poor districts, Kabul Center and Mir Bacha kot, have poverty rates below of around 30 percent (34.6 and 29.2 percent, respectively).

In addition to the poverty rates, it is important to examine the poverty density, or the spatial distribution of the number of poor individuals in the country. The poverty density map (Map 4) shows one dot for every 200 poor individuals randomly placed within the administrative boundaries of the district in which the poor reside. The dots do not represent the exact location of the poor within the district. A high concentration of dots indicates a high poverty density, that is, a large number of poor individuals living in the district, whereas a low concentration indicates a low poverty density.

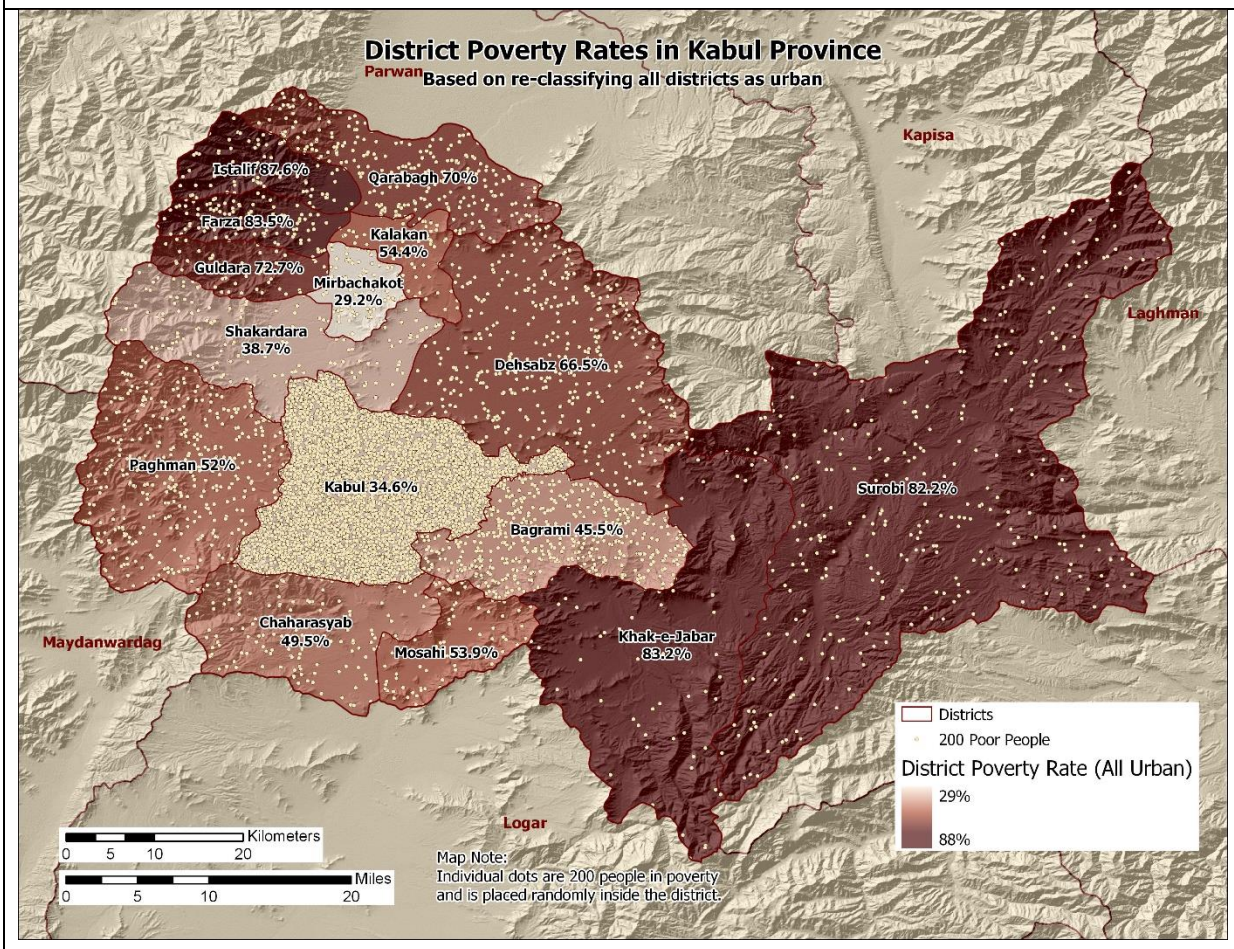
A large share of the country's poor are located in the Provincial Center, Kabul Center. Given a relatively high poverty rate of 34.6 percent and the very large population size in Kabul Center, the absolute size of the poor population is large, over 1.1 million people are poor in the Provincial Center and 9 out of 10 poor people in Kabul province live in Kabul Center. Despite the majority of the poor living in Kabul Center, DehSabz and Bagrami also have a relatively large share of the poor and over 80,000 people are poor in each of these districts. The large number of poor in Bagrami stems from a relatively large population of almost 210,000 while the poverty rate is below average at 45.5 percent. On the other hand, despite a small population of less than 80,000, Surobi has the fifth largest number of poor due to a much higher poverty rate of 82.2 percent. The four districts with the largest contribution to the pool of the poor are Kabul Center, DehSabz, Bagrami, and Paghman which account for over 80 percent of Kabul province's poor population or 1.3 million people. Despite high poverty rates, Istalif, Farza, and Khak-e-Jabar are sparsely populated due to geographic conditions and account for a very small share of Kabul rovince's poor population.

Map 3. Kabul province poverty map: poverty rates at the district level



Source: Staff calculations, based on ALCS and SDES data.

Map 4. Kabul province poverty map: Number of poor at the district level



Source: Staff calculations based on ALCS and SDES data.
Note: Each dot represents 200 people living below the poverty line. Dots are randomly placed within district boundaries and do not represent exact locations of the poor.

Nahia level estimates for Kabul provincial center

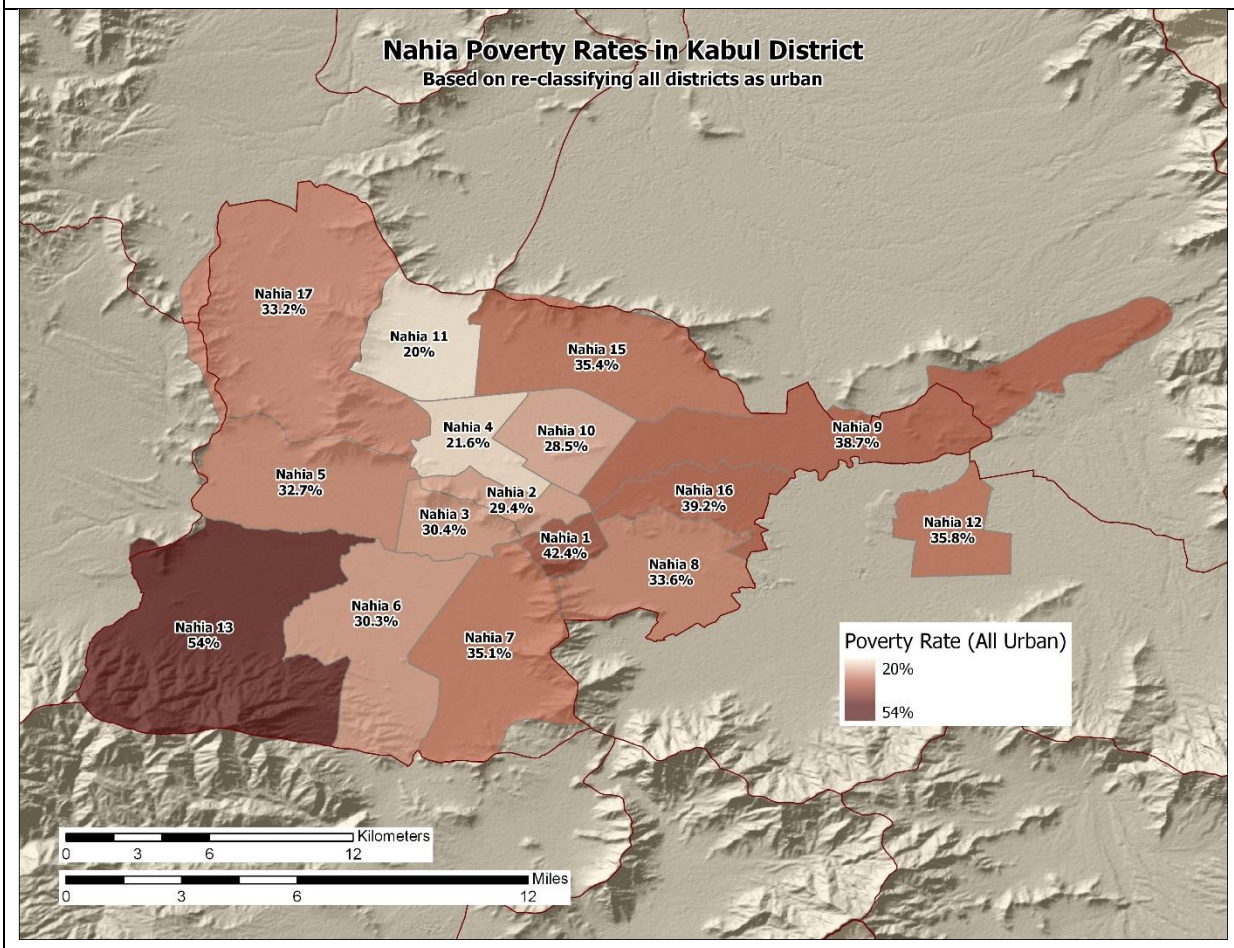
Given the large concentration of poor people in Kabul Center, we estimated poverty rates at the nahia level, the lowest level of disaggregation for these poverty maps. The spatial distribution of poverty varies considerably from the more aggregate district estimates (34.6 percent). Poverty rates tend to be higher at the edges of the city, particularly Southeast and Northeast (Map 5). Poverty rates range by 34 percentage points, from 20.0 percent in Nahia 11 to 54.0 percent in Nahia 13. The poorest nahias are Nahia 13, Nahia 1, and Nahia 16 with poverty rates of 54.0, 42.4, and 39.2 percent respectively. On the other hand, pockets of prosperity emerge in the center north of Kabul Center, nahias 4 and 11 have the lowest poverty rates of 21.6 and 20.0 percent respectively.

The largest nahias in terms of population are also those with the largest number of poor. Nahia 13 is not only the poorest, it is also the largest nahia with a population of over 400,000 people. Over 20 percent of all the poor, or over 215,000 people, in Kabul Center reside in Nahia 13 in the southwest of the city (Map

6). Nahia 7 and 8, are the second and third largest nahias in terms of population (300,000 and 270,000 people respectively) and each holds approximately 10 percent of the poor or around 100,000 people respectively.

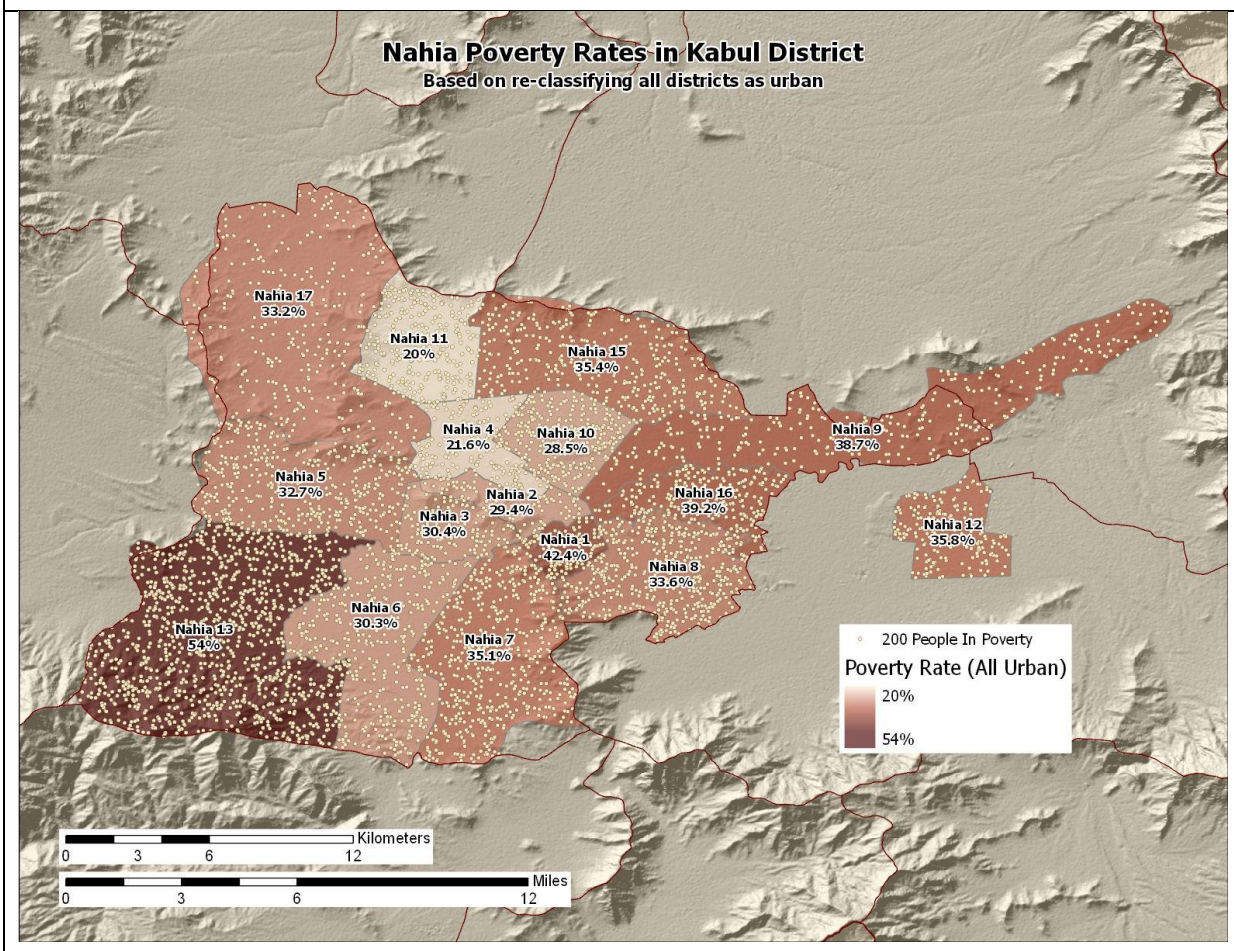
Nahia 2 of Kabul Center is by far the smallest nahia and among the least populated and thus has the lowest number of poor across the entire city. Despite its high poverty rate of 42.4 percent, nahia 1 is sparsely populated (55,000) and has among the lowest number of poor of 23,000. Map 7 presents another interesting way of poverty at the nahia level by looking at the number of poor per square kilometer. Despite the low number of poor, nahia 1 actually has a very high density of poor; a staggering 4,632 are poor per square kilometer. Nahia 10, despite moderate poverty rates, has the largest number of poor (4,756) per square kilometer. Nahia 17 in the northwest of the province has the lowest density of poor.

Map 5. Kabul provincial center poverty map: Poverty rates at the nahia level



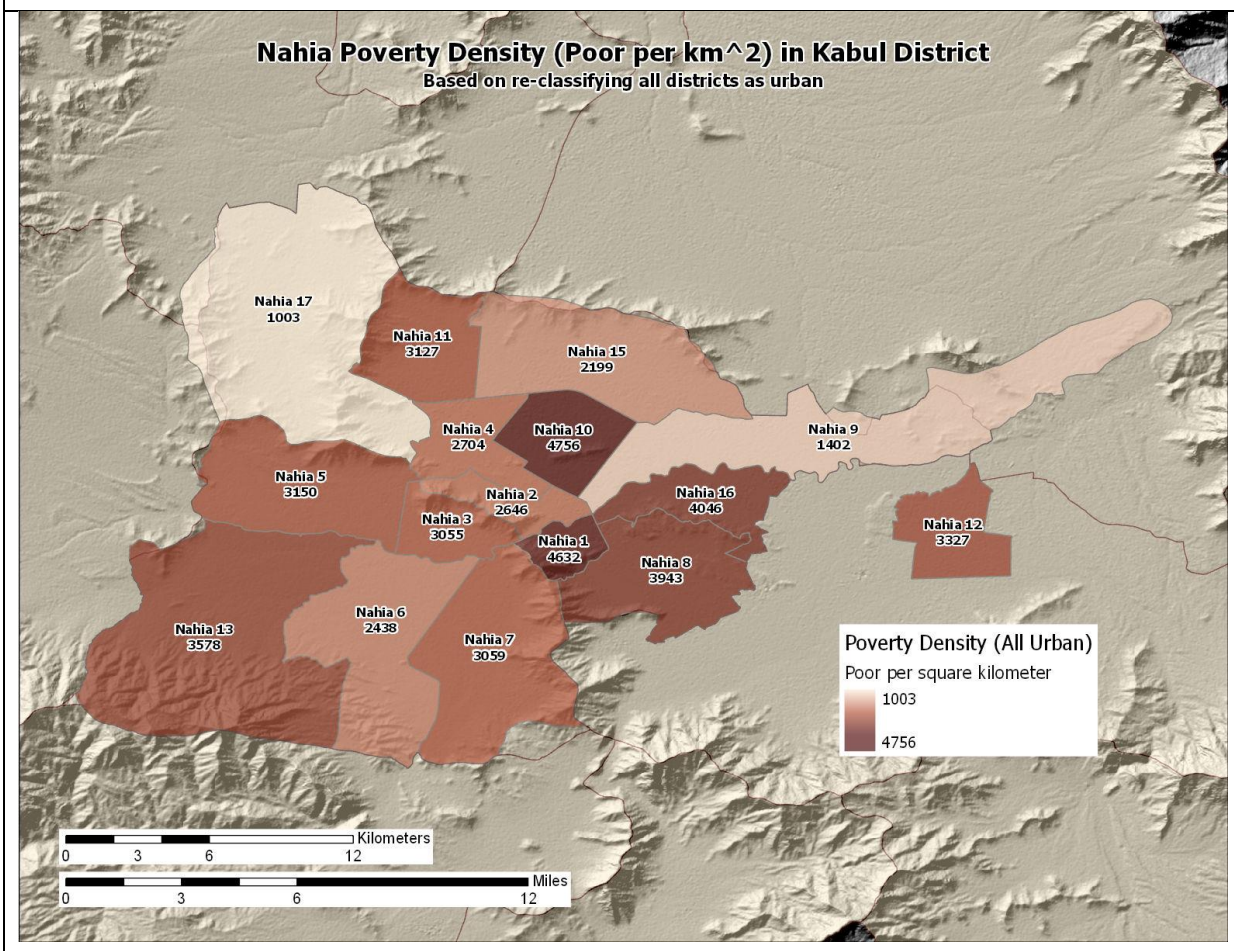
Source: Staff calculations, based on ALCS and SDES data.

Map 6. Kabul provincial center poverty map: Number of poor at the nahia level



Source: Based on ALCS and SDES data.
Note: Each dot represents 200 people living below the poverty line. Dots are randomly placed within district boundaries and do not represent exact locations of the poor.

Map 7. Kabul provincial center poverty map: Number of poor per km2 at the nahia level



Source: Staff calculations, based on ALCS and SDES data.

Herat Province Poverty Maps

Herat is located in the western part of Afghanistan and shares a border with Iran to the West and Turkmenistan to the north. It's primary city and economic center is Herat city, one of the districts of Herat province. The province is divided into 15 districts, 11 of which were included in the SDES and have district level poverty estimates. Herat is the second most populated province, after Kabul, with almost 2.8 million people (over 8 percent of the total population of Afghanistan). Due to its location, Herat is an important trading hub. Three quarters of Afghans living in Herat province reside in rural areas, with a large reliance on agriculture and horticulture, the vast majority of Afghanistan's saffron is produced in Herat.

District level estimates

Herat province has a relatively high poverty rate of 43.1 percent (yet, 12 percentage points below the national average). Poverty is very unevenly distributed across the districts of Herat province and poverty rates vary considerably within the province even at the district level (Map 8). Herat city has the lowest poverty rate of 33.9 percent and districts surrounding Herat city seem to benefit from positive spillover

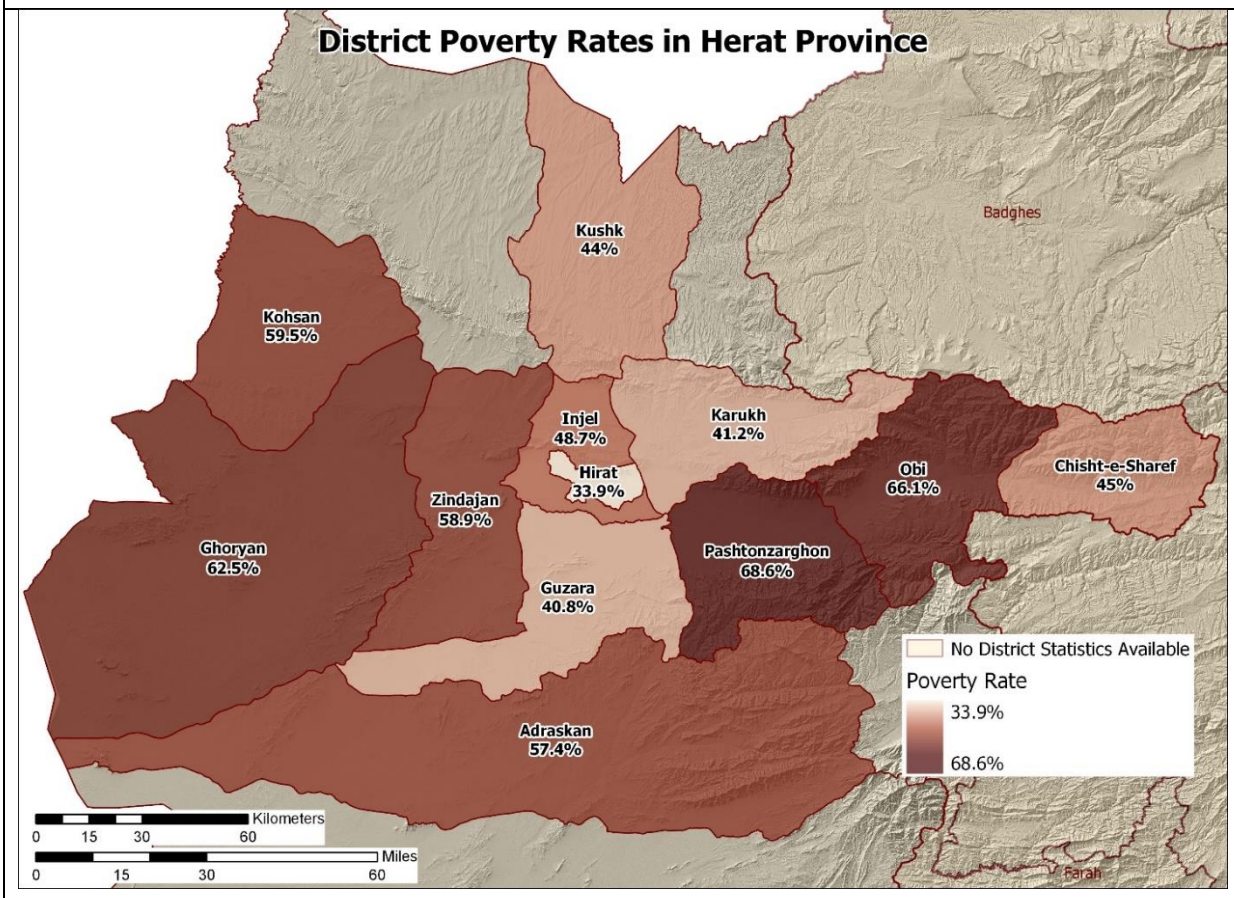
effects and relatively low poverty rates. The poorest districts of Herat province are Pashtonzarghon and Obi with 68.6 and 66.1 percent of Afghans living in poverty. There are also somewhat surprising pockets of poverty, such as high poverty rates along the border to Iran; Ghoryan district and Kohsan district have poverty rates of 62.5 and 59.5 percent respectively.

Areas with high poverty rates are typically areas that have not fully benefited from the development process. Such areas are typically rural, sparsely populated, and remote. For equity considerations, attention is often focused on areas with the highest poverty rates. However, it is also important to consider the number of people affected by poverty in a given area. Despite low poverty rates, urban and semi-urban areas often host large numbers of poor, as illustrated in Map 9. This has important policy implications if the priority is placed on reducing poverty in areas with high concentrations of poor people.

Herat is the largest district in terms of population, with almost 1 million people. Given this large share of the population, one third of the poor of the province live in Herat city. In spite of the lowest poverty rates in the province, 327,000 Afghans residing in Herat city are poor (Map 9). Due to its large population, Guzara also has a large number of poor (86,000) despite the second lowest poverty rates. The highe poverty rate in Pashtonzarghon result in the second highest number of poor people despite a relatively modest population of 136,000. Approximately 93,000 people live in poverty in Pashtonzarghon. Guzara, Pashtonzarghon and Herat city combined hold over half of the poor population in the district.

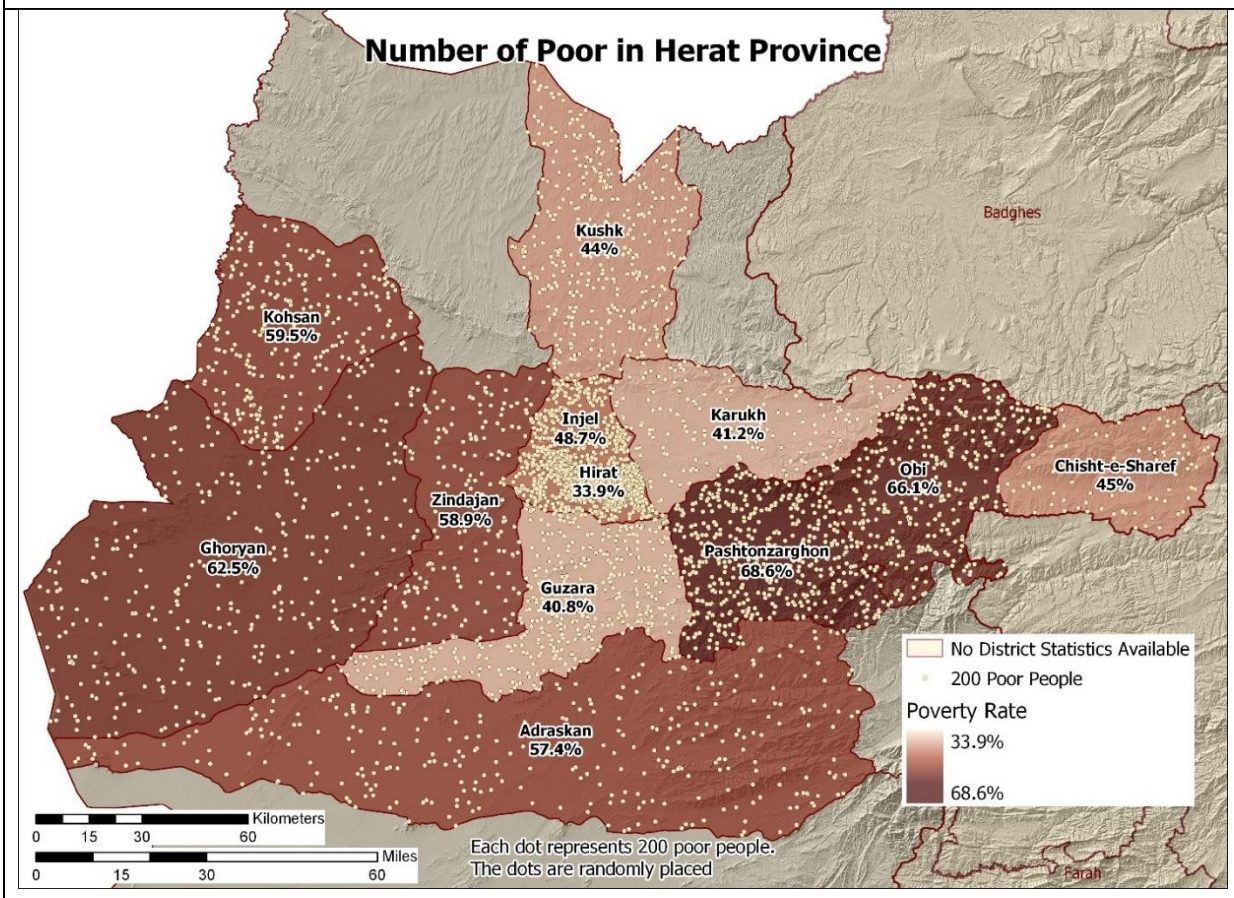
Chisht-e-Sharef has the lowest number of poor—17,000—as a result of its small population (37,000) and modest poverty rates (45 percent). Karukh and Zindajan also host relatively few poor people of around 32,000.

Map 8. Herat province poverty map: Poverty rates at the district level



Source: Staff calculations, based on ALCS and SDES data.

Map 9. Herat province poverty map: Number of poor at the district level



Source: Based on ALCS and SDES data.
Note: Each dot represents 200 people living below the poverty line. Dots are randomly placed within district boundaries and do not represent exact locations of the poor.

Nahia level estimates

Herat province has two main cities, the provincial center Herat city (provincial center) and Ghoryan city in Ghoryan province. We estimated poverty rates at the nahia level for both cities.

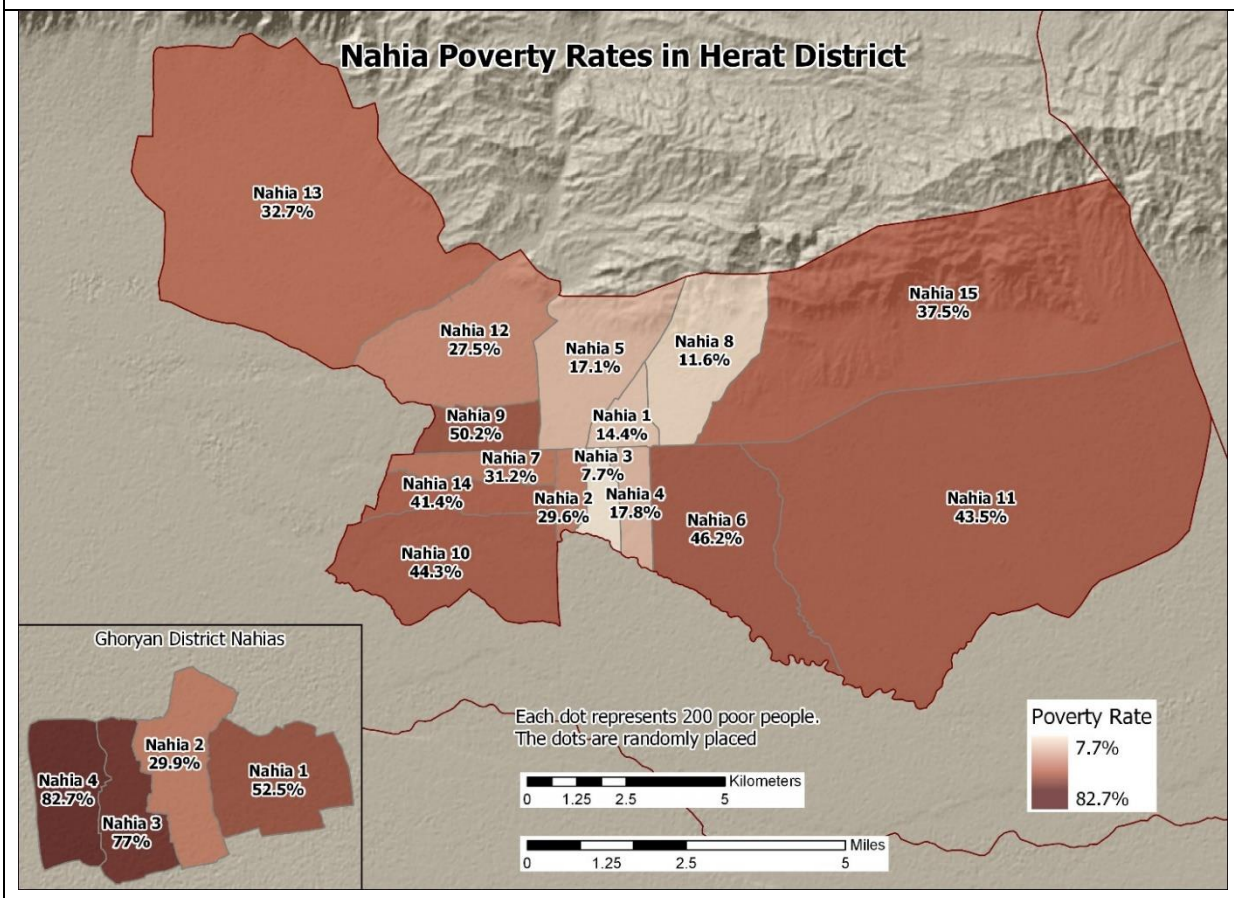
As mentioned previously, Herat city has the lowest poverty rates in the province, yet large disparities in poverty rates exist across the city, with a spread of over 40 percentage points. Nahias 1 and 3 in the center of the city and nahia 8 in the North have the lowest poverty rates of around 10 to 15 percent (Map 10). On the opposite end of the spectrum are nahias 6, 9, and 10 in which almost half of the population lives in poverty.

As a result of their very low population and low poverty rates, nahia 1, 2, and 3 host the lowest number of poor (Map 11). On the other hand, the two nahias with the largest population, Nahia 6 and 11, are also among the poorest and thus, the largest number of poor lives in these two nahias. These two nahias combined account for one third of the district's poor.

Map 12 displays the number of poor per square kilometer which may have important implications for targeting. The lowest density of poor can be found in the largest nahias (according to land area) in the west and east of Herat city. Despite their high poverty rates, nahias 11 and 13 have a very low density of poor which leads us to believe that the poor may live very spread out. Nahia 15 also has a rather low density of poor, however, given the mountainous conditions in nahia 15, the poor may live more clustered. On the other hand, nahia 7, 9, and 14 have a very high density of poor due to the rather small geographic area and high poverty rates.

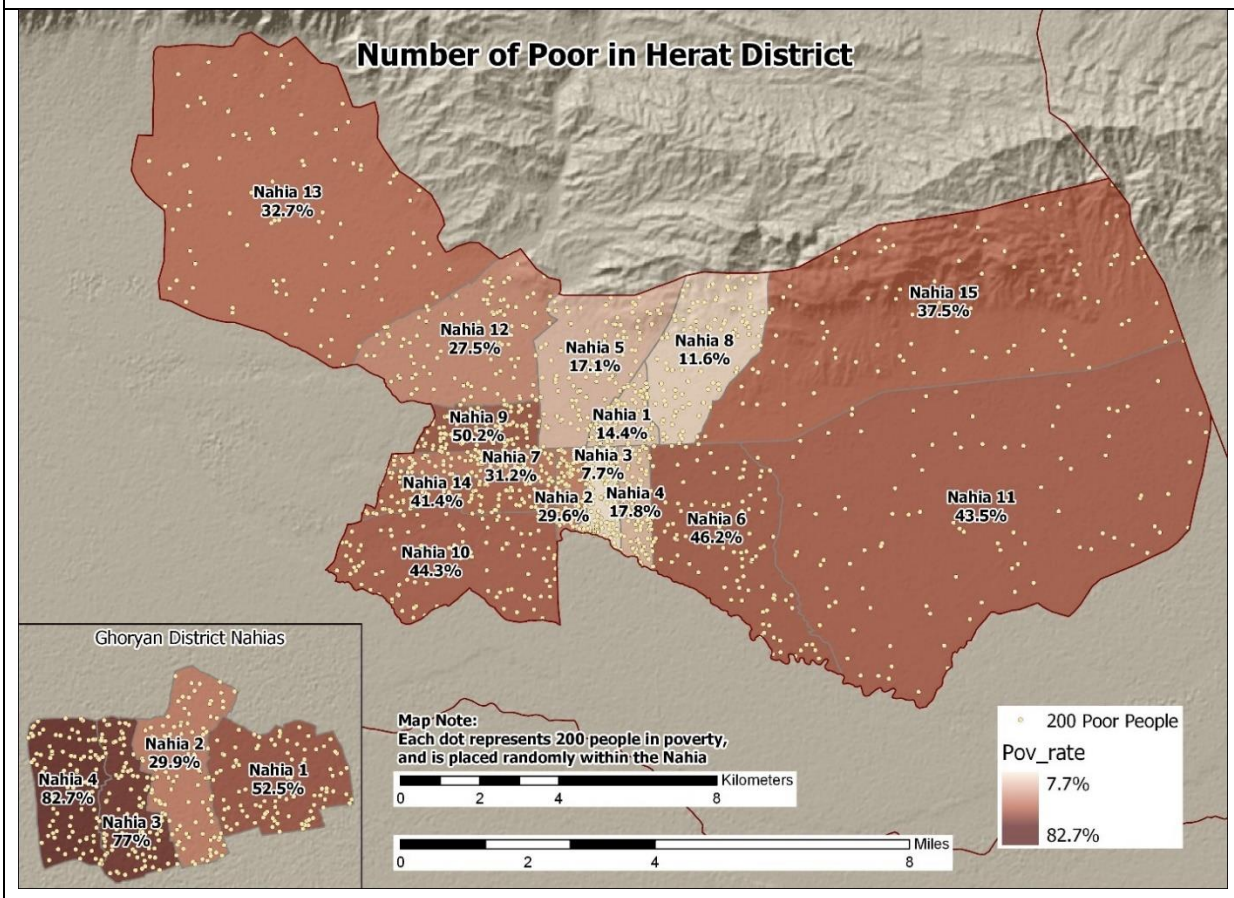
Ghoryan city is much smaller and is comprised of 4 nahias, with very large differences in poverty rates across the districts. Nahia 2 has the lowest poverty rate of 29.9 percent while nahias to the west get poorer and in nahia 4, 8 out of 10 people are poor (Map 10). Despite the highest poverty rate, around 5,000 poor people live in nahia 4 as a result of a very low population share. In comparison, nahia 2, the least poor, has an almost equal number of poor as a result of a much larger population. The largest number of poor, about 10,000 lives in nahia 3, accounting for 40 percent of all poor in Ghoryan city (Map 11). Due to its relatively low population share, the number of poor per square kilometer is relatively low between 600 and 1,800, comparable to the poverty density of the lowest nahias in Herat city (Map 12).

Map 10. Herat (provincial center) and Ghoryan urban poverty map: Poverty rates at the nahia level



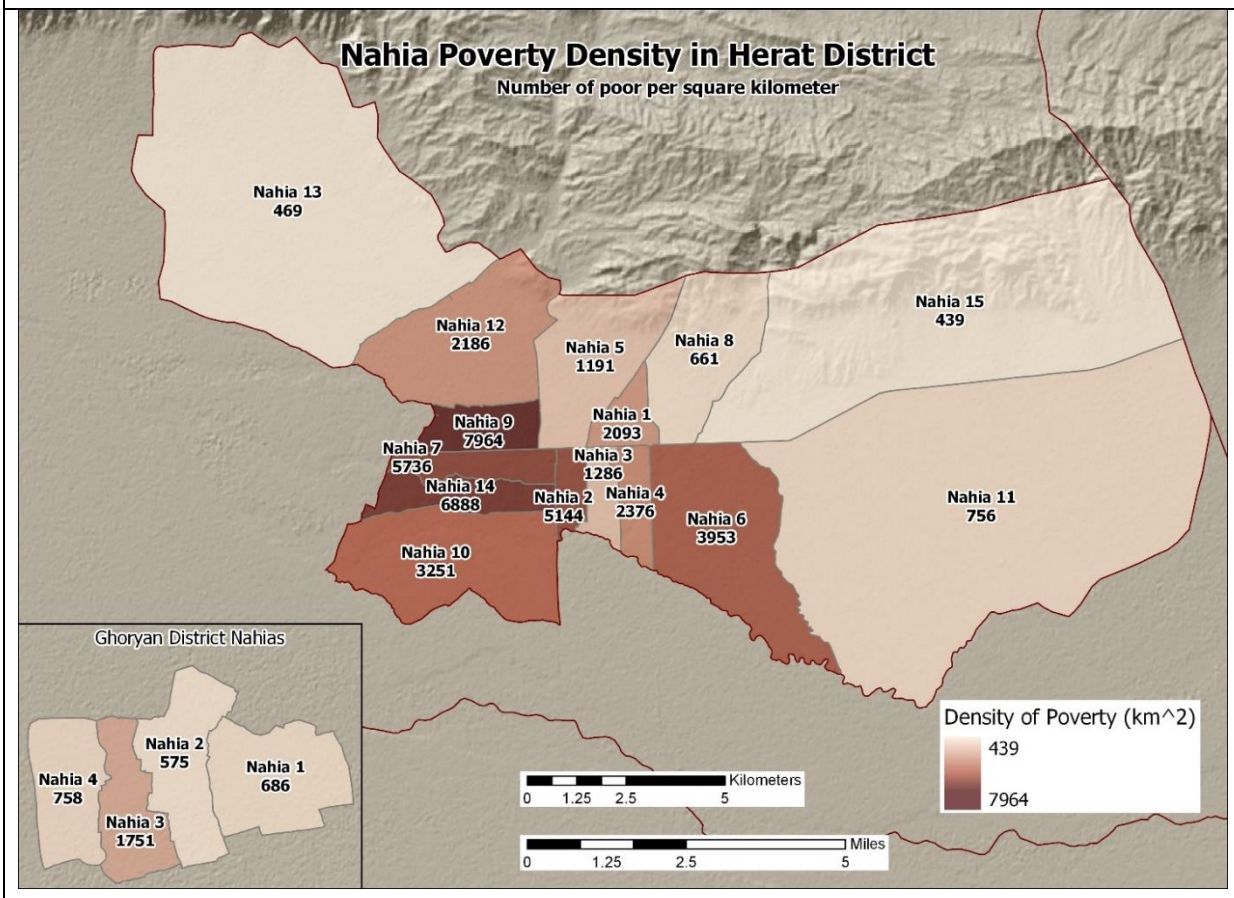
Source: Staff calculations, based on ALCS and SDES data.

Map 11. Herat (provincial center) and Ghoryan urban poverty map: Number of poor at the nahia level



Source: Staff calculations, based on ALCS and SDES data.
Note: Each dot represents 200 people living below the poverty line. Dots are randomly placed within district boundaries and do not represent exact locations of the poor.

Map 12. Herat (provincial center) and Ghoryan urban poverty map: Number of poor per km2 at the nahia level



Source: Staff calculations, based on ALCS and SDES data.

6. Conclusion

As the first set of poverty maps ever produced for Afghanistan, the poverty maps of Kabul and Herat province offer new insights into the spatial distribution of poverty in Afghanistan. Previously, poverty estimates were obtained for the 34 provinces of Afghanistan. Relying on the well-established small area estimation methods, poverty maps yield a finer resolution of poverty down to the district and nahia level and reveal the heterogeneity in poverty rates within provinces previously masked by the provincial estimates.

From the provincial estimates, we already know that poverty is very heterogeneous in Afghanistan. District and nahia poverty rates reveal differences not only across but within provinces. As we move from the province down to the district level estimates, pockets of poverty and prosperity come into focus. Poverty rates as high as those found in the Istalif, Farza, and Khak-e-Jabar district, where over 80 percent of the population are poor, emerge in Kabul district while Mirbachakot and Kabul Center show that less than 35 percent of residents are poor. In Herat province, poverty tends to be highest in Ghoryan, Pashtonzarghon, and Obi districts, with poverty rates of over 60 percent. Also, the largest urban

agglomeration in both provinces, Kabul and Herat districts, show that about one third of the district is poor.

As the population is not distributed uniformly throughout the provinces, the distribution of poor highlights the absolute number of people living below the poverty line in a given area. As such, this information provides a valuable complement to the poverty rates. With respect to poverty density, Kabul district and Herat district have high concentrations of the poor. In Kabul district, the poverty rate is the second lowest but the high population density renders the total number of poor in the district very high, at 1.1 million. Similarly, Herat district, despite relatively modest poverty rates, has the highest number of poor of over 320,000. In other regions, high poverty rates despite relatively low population numbers drives the high number of poor; this can be seen in the Surobi district in Kabul and Zindajan district in Herat.

As with any survey or modeled estimates, the confidence interval of these poverty map estimates are important to consider. It should be noted that the standard errors for the direct poverty estimates from the ALCS 2016-17 survey are fairly large even prior to doing any modeling. At the regional level, the predicted poverty estimates were close to the direct survey estimates, and they had smaller confidence intervals. The confidence intervals for the nahia level estimates are much wider, as would be expected. The mean standard error for the district level estimates is 3.9 percentage points (median of 4.1 percentage points), which translates into a fairly broad 95 percent confidence interval of 8 percentage points.

Adopting a standard definition of urban and rural areas based on population based parameters is highly recommended. Given that different poverty line values are applied according to the area of residence in Afghanistan, the designation of urban or rural areas can impact substantially the poverty measures for an area as seen in the example of Kabul. Thus, the adoption and application of a standard definition across all areas of the country would help improve poverty measurement.

Further research is recommended to explore the spatial relationship between poverty and other socio-economic indicators. Producing maps of indicators related to poverty and overlaying them on these poverty maps could help identify spatial patterns. For instance, maps of access to basic services, market accessibility, rainfall patterns, agricultural and livestock production, educational attainment, and food insecurity, to name a few, could be helpful. District level estimates could be easily produced from the SDES data for some indicators and displayed on a map. This analysis could not only look at how poverty and other indicators are correlated but also shed light on underserved geographic areas.

Expanding these poverty maps for the remaining 11 provinces in which SDES data is available would be worthwhile. In addition, incorporating data from satellite imagery or other innovative sources may further improve the quality of the poverty maps. With that said, this first set of poverty maps is useful in understanding the geographic distribution of poverty in Kabul and Herat provinces and can help inform the allocation of scarce resources to areas that need them most.

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Annex: Supplementary Tables

Table 5: Differences in Sampling between ALCS 2016-17 and SDES Data

		NUMBER OF EAS BY DISTRICT			NUMBER OF EAS BY DISTRICT		
	District	ALCS data			SDES data		
		urban	rural	total	urban	rural	total
KABUL	Kabul Center	130	--	130	1864	--	1864
KABUL	Paghman	--	6	6	2	107	109
KABUL	Chahar Asyab	--	3	3	--	34	34
KABUL	Bagrami	--	9	9	--	84	84
KABUL	DehSabz	--	4	4	--	54	54
KABUL	Shakar Dara	--	2	2	--	50	50
KABUL	Musahi	--	1	1	--	21	21
KABUL	Mir Bacha Kot	--	1	1	2	32	34
KABUL	Khak-e-Jabar	--	--	--	--	10	10
KABUL	Kalakan	--	--	--	--	20	20
KABUL	Guldara	--	1	1	--	14	14
KABUL	Farza	--	2	2	--	18	18
KABUL	Estalif	--	--	--	--	17	17
KABUL	Qara Bagh	--	3	3	2	64	66
KABUL	Surubi	--	--	--	1	50	51
HERAT	Herat City	24	--	24	705	--	705
HERAT	Enjil	--	11	11	--	250	250
HERAT	Guzara	--	6	6	--	151	151
HERAT	Karrukh	--	4	4	--	61	61
HERAT	Zendajan	--	2	2	--	65	65
HERAT	Pashton Zarghon	--	4	4	--	91	91
HERAT	Kushk	--	8	8	--	140	140
HERAT	Gulran	--	6	6	--	--	--
HERAT	Adraskan	--	4	4	--	81	81
HERAT	Kushk-E-Kuhna	--	1	1	--	47	47
HERAT	Ghoryan	3	2	5	47	55	102
HERAT	Obe	--	3	3	--	35	35
HERAT	Kohsan	--	3	3	--	59	59
HERAT	Shindand	--	7	7	--	--	--
HERAT	Fersi	--	--	--	--	--	--
HERAT	Chisht-E-Sharif	--	2	2	--	33	33

Source: Authors' estimation based on ALCS and SDES data.

Table 6: Comparison of ALCS and SDES Variable Mean Values

				ALCS		SDES
PROVINCE	*VARIABLE*	*MEAN*	*S.E.*	*95 % CONFIDENCE*		*MEAN*
KABUL	hhsize_1	0.002	0.001	0.000	0.004	0.007
KABUL	hhsize_2	0.029	0.004	0.021	0.037	0.043
KABUL	hhsize_3	0.055	0.006	0.044	0.066	0.069
KABUL	hhsize_4	0.094	0.007	0.080	0.108	0.100
KABUL	hhsize_5	0.131	0.008	0.114	0.147	0.124
KABUL	hhsize_8	0.114	0.008	0.099	0.130	0.117
KABUL	hhsize_9	0.088	0.007	0.075	0.102	0.088
KABUL	hhsize_10	0.065	0.006	0.053	0.077	0.086
KABUL	hhsize_11	0.040	0.005	0.031	0.050	0.019
KABUL	hhsize_12	0.037	0.005	0.028	0.046	0.017
KABUL	hhsize_13	0.010	0.003	0.006	0.015	0.012
KABUL	hhsize_14_	0.039	0.005	0.030	0.049	0.035
KABUL	head_female	0.014	0.003	0.008	0.019	0.015
KABUL	persons_room	3.320	0.045	3.232	3.408	2.886
KABUL	overcrowding	0.428	0.012	0.404	0.452	0.322
KABUL	wall2	0.070	0.006	0.058	0.083	0.091
KABUL	floor1	0.483	0.012	0.458	0.507	0.531
KABUL	tenure2	0.265	0.011	0.244	0.287	0.228
KABUL	cookingfuel4	0.055	0.006	0.044	0.066	0.022
KABUL	heating4	0.099	0.007	0.084	0.113	0.023
KABUL	water2	0.030	0.004	0.022	0.039	0.072
KABUL	toilet3	0.149	0.009	0.132	0.167	0.029
KABUL	toilet4	0.226	0.010	0.206	0.247	0.036
KABUL	toilet5	0.205	0.010	0.185	0.225	0.548
KABUL	access_elec	0.984	0.003	0.978	0.990	0.925
KABUL	tv_ysno	0.822	0.009	0.803	0.840	0.790
KABUL	refrigerator_ysno	0.458	0.012	0.434	0.482	0.366
KABUL	internet_ysno	0.016	0.003	0.010	0.022	0.080
KABUL	computer_ysno	0.241	0.011	0.221	0.262	0.287
KABUL	car_ysno	0.184	0.010	0.165	0.203	0.251
KABUL	agr_land	0.257	0.011	0.236	0.279	0.297
KABUL	head_edulevel5	0.275	0.011	0.253	0.297	0.315
KABUL	maxedu_level1	0.085	0.007	0.071	0.098	0.129
KABUL	maxedu_level2	0.140	0.009	0.123	0.156	0.124
KABUL	canalstream	70.7	0.407	69.9	71.5	71.1
KABUL	dist_Dist_M_Energy	6,445	96	6,257	6,632	6,646
KABUL	dist_primary_5km	20.7	0.152	20.4	21.0	20.6
KABUL	dist_secondary_5km	28.9	0.299	28.3	29.5	28.8
KABUL	dist_footpaths_5km	6.7	0.077	6.6	6.9	6.9
HERAT	adult_malep	0.123	0.003	0.116	0.130	0.143
HERAT	avg_age	22.4	0.267	21.9	22.9	22.2

			ALCS			SDES
PROVINCE	*VARIABLE*	*MEAN*	*S.E.*	*95 % CONFIDENCE*		*MEAN*
HERAT	avg_edu_yr	2.9	0.108	2.7	3.1	2.8
HERAT	canalstream	52.4	2.020	48.5	56.4	41.1
HERAT	car_ysno	0.108	0.010	0.087	0.128	0.098
HERAT	computer_ysno	0.105	0.010	0.085	0.125	0.114
HERAT	cookingfuel1	0.460	0.017	0.427	0.492	0.499
HERAT	dist_Z_in_M	1,064	8.3	1,047	1,080	1,057
HERAT	dist_footpaths_5km	0.648	0.024	0.601	0.695	0.726
HERAT	dist_nFlat	1,655	39.3	1,578	1,732	1,886
HERAT	femalep	0.497	0.005	0.487	0.507	0.499
HERAT	head_literate	0.352	0.016	0.321	0.384	0.404
HERAT	hhsize_tertile1	0.378	0.016	0.346	0.410	0.365
HERAT	inc_lag_6months	73.3	2.0	69.4	77.3	69.2
HERAT	lakeriver	12.3	0.610	11.1	13.5	10.6
HERAT	tv_ysno	0.669	0.016	0.638	0.700	0.650

Source: Authors' estimation based on ALCS and SDES data.

Note: Household-level variables are calculated using household weights. Only those variables that were included in any of the province models are displayed in this table. Means of ALCS are calculated using re-stratified weights.

Table 7: Results of GLS models for Kabul province

Variables	Coef.	s.e.	t-stat	p-value	Description of variables
access_elec	0.172	0.064	2.67	0.008	Household has/owns electricity
agr_land	0.036	0.017	2.10	0.036	Household owns/has access to agricultural land
canalstream	-0.003	0.001	-2.66	0.008	District sum of closest water source is a canal or
car_ysno	0.219	0.021	10.64	0.000	Household owns car
computer_ysno	0.125	0.020	6.23	0.000	Household owns computer
cookingfuel4	-0.069	0.038	-1.81	0.070	Household cooking fuel is animal, dung. Bushes,
dist_Dist_M_Energy	0.000	0.000	-3.23	0.001	District mean of distance in meters to nearest grid
dist_footpaths_5km	-0.135	0.041	-3.31	0.001	District mean of distance of footpaths within 5km of
dist_primary_5km	0.018	0.005	3.30	0.001	District mean of distance of primary roads within
dist_secondary_5km	0.025	0.009	2.84	0.004	District mean of distance of secondary roads within
floor1	-0.082	0.016	-5.22	0.000	Main material of the dwelling floor is dirt, mud, or
head_edulevel5	0.077	0.018	4.31	0.000	Highest household head education level attained is
head_female	-0.147	0.054	-2.73	0.006	Female headed household
heating4	-0.116	0.026	-4.40	0.000	Main source energy for heating is animal, dung,
hhsize_1	1.339	0.147	9.09	0.000	Household size is 1
hhsize_10	-0.177	0.029	-6.07	0.000	Household size is 10
hhsize_11	-0.223	0.035	-6.39	0.000	Household size is 11
hhsize_12	-0.245	0.039	-6.35	0.000	Household size is 12
hhsize_13	-0.248	0.065	-3.80	0.000	Household size is 13
hhsize_14_	-0.296	0.039	-7.63	0.000	Household size is 14 and above
hhsize_2	0.672	0.039	17.33	0.000	Household size is 2
hhsize_3	0.427	0.035	12.29	0.000	Household size is 3
hhsize_4	0.268	0.028	9.64	0.000	Household size is 4
hhsize_5	0.124	0.024	5.27	0.000	Household size is 5
hhsize_8	-0.075	0.024	-3.18	0.001	Household size is 8
hhsize_9	-0.134	0.026	-5.18	0.000	Household size is 9
internet_ysno	0.170	0.062	2.77	0.006	Household owns internet
location13	-0.159	0.031	-5.18	0.000	Household location code is 010113
location14	-0.093	0.043	-2.16	0.031	Household location code is 010115
maxedu_level1	-0.079	0.030	-2.66	0.008	Maximum level of education attained in the
maxedu_level2	-0.051	0.021	-2.43	0.015	Maximum level of education attained in the
overcrowding	-0.076	0.021	-3.55	0.000	Household with more than 3 persons per room
persons_room	-0.027	0.006	-4.26	0.000	Household density: (household size)/(number of
refrigerator_ysno	0.111	0.017	6.70	0.000	Household owns refrigerator
tenure2	-0.098	0.018	-5.60	0.000	Mode of tenure of the house is rented
toilet3	-0.139	0.021	-6.51	0.000	Toilet facility used in the household is: ventilated
toilet4	-0.170	0.021	-8.27	0.000	Toilet facility used in the household is: pit latrine
toilet5	-0.151	0.022	-6.91	0.000	Toilet facility used in the household is: vault, other,
tv_ysno	0.076	0.023	3.24	0.001	Household owns tv
wall2	0.272	0.034	7.98	0.000	Main construction material of walls is concrete or
water2	-0.144	0.041	-3.48	0.000	Main source of drinking water is public tap or
_cons	8.26176	0.1179	70.56	0.000	Intercept
Number of obs.	=	1,595			
R-squared	=	0.659			
Adjusted R-squared	=	0.650			
Root MSE	=	0.291			

Source: Authors' estimation based on ALCS and SDES data.

Table 8: Results of GLS models for Herat province

Variables	Coef.	s.e.	t-stat	p-value	Description of variables
adult_malep	0.405	0.149	2.720	0.007	Proportion of adult male (aged 25-50) in the
avg_age	0.005	0.002	2.610	0.009	Average age of household members
avg_edu_yr	0.043	0.006	7.130	0.000	Average years of schooling in the household
canalstream	-0.002	0.000	-4.010	0.000	District sum of closest water source is a canal or
car_ysno	0.440	0.045	9.870	0.000	Household owns car
computer_ysno	0.178	0.057	3.090	0.002	Household owns computer
cookingfuel1	0.168	0.045	3.700	0.000	Household cooking fuel is gas and electricity
dist_Z_in_M	0.000	0.000	4.540	0.000	District mean of elevation in meters
dist_footpaths_5km	-0.163	0.078	-2.080	0.037	District mean of distance of footpaths within 5km
dist_nFlat	0.000	0.000	3.060	0.002	District mean of number of flat areas near village
femalep	-0.264	0.088	-2.990	0.003	Proportion of female members in the household
head_literate	0.066	0.038	1.720	0.086	Literacy status of household head
hhsize_tertile1	0.237	0.032	7.300	0.000	Household size is among 1st tertile
inc_lag_6months	0.003	0.001	5.060	0.000	Number of incidents in household district during 6
lakeriver	0.004	0.001	3.400	0.001	District sum of closest water source is a lake or a
location20	0.378	0.173	2.180	0.029	Household location code is 3211
location21	0.532	0.225	2.360	0.018	Household location code is 321101
location3	0.428	0.189	2.270	0.023	Household location code is 320103
location8	0.140	0.105	1.340	0.180	Household location code is 320108
tv_ysno	0.115	0.035	3.290	0.001	Household owns tv
_cons	6.467	0.148	43.680	0.000	Intercept
Number of	=	899			
Adjusted R-squared	=	0.039			
R-squared	=	0.055			
Root MSE	=	2.428			

Source: Authors' estimation based on ALCS and SDES data.

Table 9: Poverty Headcount Ratio and Number of Poor, by District

	DISTRICT	CODE	POVERTY RATE	POVERTY RATE S.E.	CI LOWER BOUND	CI UPPER BOUND	POPULATION	NUMBER OF POOR
KABUL DISTRICTS	Kabul Center	101	0.346	0.01	0.324	0.368	3,075,162	1,064,605
	Paghman	102	0.520	0.03	0.434	0.607	149,445	77,781
	Chahar Asyab	103	0.495	0.02	0.424	0.566	56,042	27,741
	Bagrami	104	0.455	0.02	0.385	0.525	208,813	94,977
	DehSabz	105	0.665	0.03	0.598	0.732	122,173	81,240
	Shakar Dara	106	0.387	0.02	0.304	0.469	76,500	29,578
	Musahi	107	0.539	0.03	0.442	0.637	26,657	14,373
	Mir Bacha kot	108	0.292	0.01	0.187	0.397	48,982	14,299
	Khak-e-Jabar	109	0.832	0.07	0.752	0.913	12,178	10,137
	Kalakan	110	0.544	0.03	0.421	0.667	23,963	13,040
	Guldara	111	0.727	0.05	0.624	0.831	13,822	10,052
	Farza	112	0.835	0.06	0.754	0.915	24,099	20,121
	Istalif	113	0.876	0.09	0.789	0.963	16,114	14,111
	Qara Bagh	114	0.700	0.06	0.583	0.817	75,907	53,111
	Surobi	115	0.822	0.08	0.723	0.922	72,547	59,642
HERAT DISTRICTS	Hirat	3201	0.339	0.02	0.300	0.377	965,577	326,973
	Enjil	3202	0.487	0.03	0.429	0.546	266,889	130,028
	Guzara	3203	0.408	0.03	0.356	0.459	210,950	86,049
	Karukh	3204	0.412	0.04	0.341	0.483	77,830	32,072
	Zindajan	3205	0.589	0.03	0.530	0.648	57,189	33,704
	Pashtonzarghon	3206	0.686	0.03	0.635	0.737	135,912	93,234
	Kushk	3207	0.440	0.03	0.377	0.502	173,037	76,054
	Adraskan	3209	0.574	0.04	0.491	0.657	111,764	64,166
	Ghoryan	3211	0.625	0.03	0.570	0.680	111,930	69,976
	Obi	3212	0.661	0.03	0.596	0.726	109,117	72,174
	Kohsan	3213	0.595	0.04	0.513	0.676	92,580	55,061
	Chisht-e-Sharef	3216	0.450	0.06	0.330	0.569	37,276	16,758

Source: Authors' estimation based on ALCS and SDES data.

Table 10: Poverty Headcount Ratio and Number of Poor, by Nahia

	CODE	POVERTY RATE	POVERTY RATE STDERR	CI LOWER BOUND	CI UPPER BOUND	POPULATION	NUMBER OF POOR
NAHIAS KABUL CENTER	10101	0.424	0.03	0.373	0.475	55,281	23,439
	10102	0.294	0.02	0.254	0.333	60,357	17,720
	10103	0.304	0.02	0.264	0.344	89,178	27,121
	10104	0.216	0.01	0.191	0.240	136,983	29,531
	10105	0.327	0.01	0.298	0.355	263,446	86,067
	10106	0.303	0.01	0.275	0.331	256,712	77,889
	10107	0.351	0.02	0.318	0.385	293,881	103,256
	10108	0.336	0.02	0.304	0.367	273,181	91,701
	10109	0.387	0.02	0.346	0.428	139,648	54,011
	10110	0.285	0.01	0.258	0.312	211,533	60,298
	10111	0.200	0.01	0.175	0.224	263,903	52,704
	10112	0.358	0.02	0.318	0.398	115,121	41,221
	10113	0.540	0.02	0.493	0.588	401,424	216,916
	10115	0.354	0.03	0.297	0.410	200,246	70,795
	10116	0.392	0.02	0.349	0.434	126,737	49,642
	10117	0.332	0.02	0.294	0.371	187,530	62,294
NAHIAS HERAT CITY	320101	0.144	0.02	0.100	0.188	30,830	4,439
	320102	0.296	0.03	0.229	0.362	27,915	8,252
	320103	0.077	0.04	0.003	0.152	31,917	2,464
	320104	0.178	0.03	0.128	0.227	32,757	5,826
	320105	0.171	0.02	0.131	0.211	65,360	11,159
	320106	0.462	0.05	0.363	0.561	124,189	57,345
	320107	0.312	0.03	0.253	0.371	53,935	16,849
	320108	0.116	0.02	0.069	0.164	51,336	5,967
	320109	0.502	0.06	0.390	0.615	53,828	27,031
	320110	0.443	0.03	0.376	0.510	96,905	42,932
	320111	0.435	0.03	0.374	0.496	112,987	49,140
	320112	0.275	0.03	0.221	0.328	100,074	27,482
	320113	0.327	0.04	0.258	0.397	67,224	22,012
	320114	0.414	0.04	0.337	0.491	63,046	26,093
	320115	0.375	0.03	0.317	0.432	53,275	19,963
NAHIAS GHORYAN	321101	0.525	0.11	0.310	0.740	12,267	6,446
	321102	0.299	0.09	0.114	0.484	15,586	4,664
	321103	0.770	0.04	0.685	0.854	13,183	10,146
	321104	0.827	0.05	0.738	0.916	6,188	5,119

Source: Authors' estimation based on ALCS and SDES data.