Poverty Mapping in El Salvador

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Poverty Mapping in El Salvador

Poverty and Equity Global Practice

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Executive Summary

Poverty mapping[1] **-- the spatial representation and analysis of human wellbeing and poverty indicators -- is becoming an increasingly important instrument for investigating and discussing socioeconomic issues, informing targeting efforts, and guiding the geographic allocation of resources**. One approach to addressing poverty is the geographic approach. In the geographic approach, poor people are identified and targeted through poverty maps. Indeed, the geographical approach is one of the methods used worldwide for targeting anti-poverty programs to reduce the gaps in social protection coverage of poor and vulnerable groups, and it has been widely implemented in several countries around the world.

In 2020, the Salvador's General Directorate of Statistics and Censuses (DIGESTYC) and the World Bank started working on the Project 'Poverty mapping in El Salvador'. The Project is part of the Government and International Bank for Reconstruction and Development (IBRD) Programme, which is performed by experts of the National Statistical Institute (NSI) and the World Bank (WB). The main objective is to calculate the shares of households living in moderate and extreme poverty at disaggregated territorial levels (municipalities). Poverty mapping enhances our understanding of the geographic distribution of people living in poverty

This report presents poverty maps at the municipality level based on the Fay-Herriot model for small-area estimations. Direct estimates of poverty indicators at the municipality level rely on information generated from household surveys. Often, though, household surveys are not representative at disaggregated levels, such as municipalities. Consequently, small sample sizes limit their precision and estimates cannot be obtained for out-of-sample domains. Due to this, we resort to small-area estimation techniques, which rely on several data sources to improve the precision of survey-based direct estimates. For the case of El Salvador, we use data from the last available Population Census conducted in 2007 and the 2019 household survey (Encuesta de Hogares de Propositos Multiples, EHPM). We also draw from population projections at the municipality level, as El Salvador is subject to high emigration rates. Many methodologies for poverty mapping require that reference years of the data sources used as a basis for small area estimations are as close to each other as possible. Due to the fact that the last available census is from 2007, we decided to use small area

[1] Poverty maps rely on small area estimates of poverty. Small area estimates are based on statistical methods to improve the precision of survey estimates in geographical areas in which survey estimates lack sufficient precision. For a more detailed description of small area estimates, see Rao and Molina (2015).

estimation techniques based on the Fay-Herriot model, which is the most appropriate model in this case.

Our results show that poverty varies at the municipality level in El Salvador. To measure poverty, we follow the national methodology defined by DIGESTYC. Additionally, we measure poverty at the household level. We generate poverty maps at the municipality for monetary poverty and multidimensional poverty. This report presents the results for the moderate and extreme poverty rate, poverty severity and poverty gaps, as well as multidimensional poverty. All poverty indicators analyzed in this report point towards the concentration of poverty in specific country areas. While there is a certain variation in the ranking of poverty across the different indicators investigated, the poorest municipalities are concentrated in the Northeast and West of El Salvador.

The poverty maps are an important contribution to the country's agenda to eliminate poverty. The generated poverty maps can be used for geographic targeting programs. They can also be combined with complementing targeting mechanisms or additional data sources to design targeted policies. The methodology applied considers that the latest Census is from 2007 and might not be a good mirror of the current status quo in the country. The maps are, therefore, an important contribution to El Salvador's agenda to eliminate poverty in the country.

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1. Motivation and Scope

For effective policymaking, it is often necessary to obtain information about poverty at disaggregated geographic levels, such as the municipality level. This information can be elevated from census data or administrative data. One challenge is that census data is often only collected roughly every ten years, and administrative data is often nonexistent in developing countries or protected by privacy regulations. Household data, which is gathered more frequently and is more accessible in developing countries, is usually not statistically representative at these disaggregated levels. This has led to a surge in small area poverty estimations. These estimations consider information from alternative data sources, such as census data or satellite data, or analyze the precision of information within an existing dataset, to generate small area estimations of income and income-related indicators.

This document generates updated small-area poverty estimates for El Salvador and describes the underlying methodology and validity of the resulting estimators. Given the limitations of household survey to generate insights on poverty at disaggregated geographical levels, such as municipalities, as well as the absence of an updated census, this document applies a small area poverty estimation technique to municipalities in El Salvador. Specifically, we apply a well-established empirical methodology to generate poverty headcount ratios at the municipality level. We show that these estimates outperform poverty headcount ratios observed directly from survey data due to methodological improvements.

Updated poverty maps are critical to improving the targeting of anti-poverty programs that use a geographical approach to reduce the gaps in social protection coverage of poor and vulnerable groups. Given the broad geographic disparities in poverty in some countries, some governments have shifted their approaches to fight poverty and social exclusion using this approach, which can also be combined with other targeting methods. Poverty maps can inform geographical targeting, which focuses on the most impoverished areas of the country. Additionally, poverty maps can be useful for the analysis of existing programs or resource allocation mechanisms. They can help to assess their effectiveness, too.

The geographical approach has been applied in several Latin American countries. This approach has been used to extend social protection to the poor, indigenous populations, and ethnic minorities. One example is the "*Red de Oportunidades Scheme*" in Panama. The program is a cash transfer scheme designed to reduce extreme poverty, with a specific component for rural and indigenous areas. The scheme was initially rolled out in regions with a larger share of indigenous populations and was subsequently extended to indigenous populations living in urban areas and poor non-indigenous populations. The share of indigenous beneficiaries increased from 36 percent in 2007 to 58 percent in 2012 (Robles, 2009). Efficiency can augment through the geographic approach and leakage to the non-poor can be minimized by targeting smaller areas, such as municipalities. Box 2 presents an overview of countries applying poverty maps.

Using geographic targeting in El Salvador over other methods of poverty alleviation has several advantages. First, it offers a decisive criterion for identifying target groups (i.e., targeting all households living in municipalities with higher-than-average extreme poverty rates or extreme poverty rates above a determined threshold). Second, it is possible to combine the criteria of geographic location (i.e., municipalities with high extreme poverty rates) with other socioeconomic characteristics of households and individuals (municipalities located in states with a significant lack of access to health and education). Additionally, geographic targeting involves local authorities in program monitoring, and can assist in the allocation of social welfare benefits and regional-development resources (Bigman and Fofack, 2000). Finally, it is administratively simple; it creates no labor disincentives, is unlikely to generate stigma effects, and is easy to combine with other targeting methods.

To reduce the cost of poverty reduction programs further, geographical targeting should be combined with other targeting methods within areas, such as targeting based on individual or household characteristics associated with poverty. Targeting strategies might combine alternative methods and strategies (see Box 1). The literature suggests that this approach further increases targeting efficiency[2]. Proxy-means tests are one of the few methods available to target chronically poor households effectively, along with demographics, geographical and community-based targeting, and self-selection. Improvements are possible in the design of tools for proxy-means testing. The potential exists to enhance the performance of targeting by combining proxy-means tests with other targeting methods. For example, the "*Orphans and Vulnerable Children Program*" in Kenya and the "*Prospera Program*" in Mexico combine geographical targeting and proxy-means testing. Brazil's "*Bolsa Família*" relies on geographical targeting and means testing. To give another example, geographical targeting, combined with community-based targeting and proxy-means testing, is used in Tanzania. In a well-designed process, multiple methods can bring together complementary strengths to minimize errors of exclusion and inclusion.

2 Grosh, M., Del Ninno, C., Tesliuc, E., & Ouerghi, A. (2008). For protection and promotion: The design and implementation of effective safety nets. World Bank Publications.

Poverty maps need to be updated to reflect the changing welfare of households over time. This is particularly important in the case of El Salvador, where several social programs use geographic targeting as one of their criteria, and updated poverty maps can significantly improve targeting. One program using this approach is the "*Rural Solidarity Communities*" (RSC). The RSC is a cash transfer program based on public education and health services usage in households in the poorest 100 of the country's 262 municipalities, according to the 2004 Social Investment Fund for Local Development (FISDL) Poverty Map. Households are eligible if they meet several criteria, including geographic criteria, captured when the program starts in their community. In rural areas, all households in a municipality, that met the eligibility requirements at the time when the Population Census was conducted by the implementing agency (FISDL), were registered in the program. All eligible households entered the program in municipalities with "severe" extreme poverty in urban areas. However, a proxy-mean test is applied to selected beneficiaries in urban municipalities with "high" extreme poverty. The non-contributory "*Universal Basic Pension*" (Adulto Mayor) is a program for older adults in municipalities with "severe" and "high" extreme poverty, and also relies on the FISDL poverty maps. Another example is the "*Temporary Income Support Program*" (PATI). PATI was designed to protect the income of vulnerable households that face adverse situations of various kinds. The program is implemented in informal urban settlements (AUP) classified with extreme or high poverty levels according to the 2004 FISDL Poverty Maps. These examples show the importance of disposing of updated poverty maps in El Salvador.

Box 1: Combining Geographic Targeting with alternative targeting methods.

There are 6 different possibilities to target beneficiaries of policy programs: Means testing, proxy means testing, categorical testing, geographic targeting, self-targeting and community-based targeting (GIZ, 2019). Several social protection programs have used combined targeting methods to target potential beneficiaries. One example is the Oportunidades Program in Mexico, which combines geographic targeting and proxy means testing. So does Kenya's Orphans and Vulnerable Children program. The Bolsa Familia program in Brazil uses geographic targeting and means testing. In Tanzania, the geographic targeting strategy is combined with community-based targeting and proxy means testing. The Bangladesh Rural Advancement Committee (BRAC) uses a combined targeting approach: First, the targeting process identifies geographic locations with a high concentration of ultra-poor households. Next, it applies a participatory wealth ranking of households. Lastly, program staff uses a questionnaire to determine the final selection of beneficiaries.

Going beyond targeting, the geographical approach can also help to inform sectoral interventions and inform subnational budget allocation. Poverty can be used as a criterion to identify target areas. A cutoff score can be used as a criterion to identify locations ("municipalities") eligible for a particular program; funding formulas can also be designed to vary benefit levels across the entire range of poverty scores. This method can also help target sectoral investments and transfers from the government budget, donor support, and other funds to those municipalities with the highest estimated level of poverty incidence and social exclusion.

In El Salvador, subnational resource allocation from central to local governments ("FODES transfers") uses poverty at a municipal level as one of the criteria. Salvadoran municipalities receive their leading financial resource from central state grants. The largest transfer is allocated through the Fund for economic and social development of the municipalities of El Salvador (Fondo para el Desarrollo Económico y Social de las Municipalidades - FODES), which allocates 6% of the national budget to municipal governments, among which 80% are allocated for investment and 20% for operating expenses. The existing formula for FODES resource allocation established in the law is based on four criteria: population, poverty, equity, and land area with the following percentages: 50%, 25%, 20%, and land area 5%, respectively. Municipalities receive an increasing amount with the poverty rankings, as established by the 2004 Poverty maps, by decile.

The report at hand is organized as follows. Section 2 documents the methodology used to produce recent small area estimates in El Salvador and the associated methodological challenges. The small area-estimates of poverty are presented, and the ranking of municipalities based on the new poverty maps and the old poverty maps are compared. It also presents a multidimensional poverty indicator for El Salvador. Section 3 concludes.

2. Estimating small-area poverty indicators for El Salvador

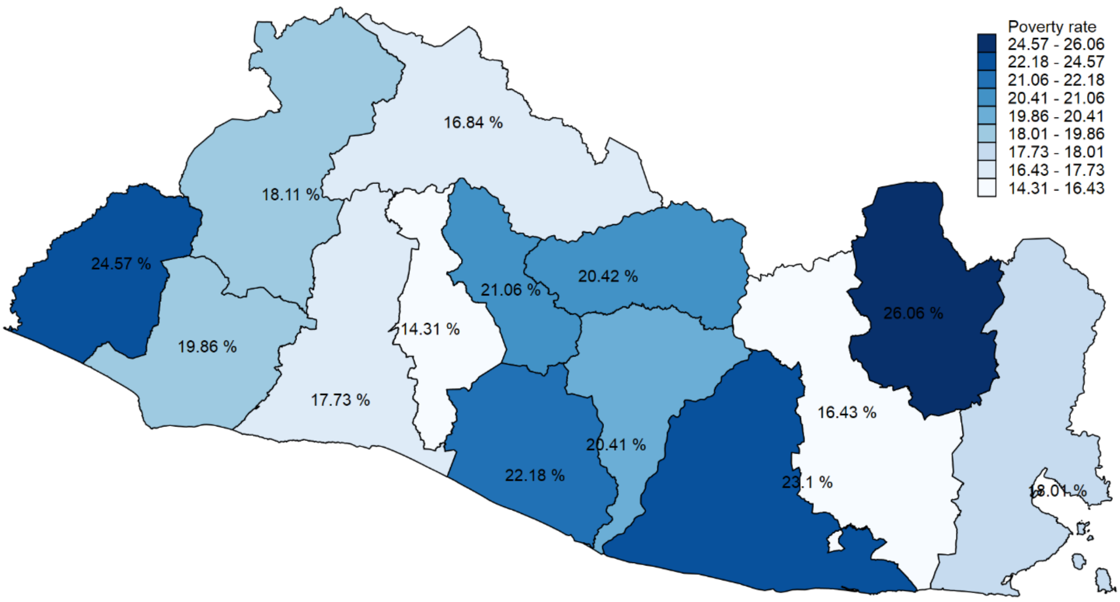
The poverty maps presented in this report are produced as a result of a collaboration between the World Bank and El Salvador's General Directorate of Statistics and Censuses (DIGESTYC).[3] Despite the usefulness of poverty maps for designing poverty targeting strategies, to the best of our knowledge, there are not any up-to-date poverty maps available for El Salvador. The following section describes the methodology used to produce such a poverty map at the

[3] Poverty maps rely on small area estimates of poverty. Small area estimates are based on statistical methods to improve the precision of survey estimates in geographical areas in which survey estimates lack sufficient precision. For a more detailed description of small area estimates, see Rao and Molina (2015).

municipality level for El Salvador from the 2019 official household survey (EHPM) and the Population Census from 2007. We also use information on population projections, provided by DIGESTYC. The resulting small area estimates, on which the maps are based, can be combined with alternative data sources to generate informed and data-based policymaking.

Available data sources in El Salvador are not representative at the disaggregated level. In developing countries, auxiliary information is often not available at the unit level, and area-level models are therefore the better choice. This is the case in El Salvador, where the latest Population Census is from 2007. Yearly household surveys, on the other hand, are not only representative at the departmental level Figure 1 shows the results for average moderate poverty rates at the household level per department. The map reveals that there is significant variation in poverty at the departmental level, with Morazán having the highest moderate poverty rate (28.06 percent). The country's data landscape leaves the country without updated poverty estimates at the municipality level.

FIGURE 1: MODERATE POVERTY RATES AT THE DEPARTMENT LEVEL



Notes: The graph plots poverty rates at the household level per department. Source: EHPM (2019).

We apply a widely used methodology for Small Area Estimation (SAE), the Fay-Herriot Model. There are several different methodologies available to produce SAE. For an overview of the different methodologies, see Guadarrama et al. (2016).[4] One can distinguish between unit-level models (such as work by Elbers et al. (2003), for example), and area-level models (such as the Fay-Herriot Model) (Eurostat, 2019). The difference is that unit-level models are estimated at the level

[4] Guadarrama, María, Isabel Molina, and J. N. K. Rao. "A comparison of small area estimation methods for poverty mapping." Statistics in Transition new series 1.17 (2016): 41-66.

of a single unit (such as a household) in a first step. In a second step, unit-level models apply model parameters estimated from household surveys to population census and generate a welfare vector for every single household in the census. From the simulated welfare vector, indicators of interest are obtained at the desired geographical level, while area-level models are directly estimated at the geographic level of interest. Given the current data sources available in El Salvador, an area-level model is therefore more appropriate. The Fay Herriot model is one of the most used area-level models. Instead of solely relying on past information from data sources with higher representation, such as the Population Census from 2007, the Fay-Herriot model also considers the varying level of precision of different domains present in national household surveys, such as the EHPM 2019.

We estimate poverty maps in El Salvador for national poverty indicators, relying on national poverty lines at the household level. We produce maps for the following poverty indicators: The national poverty rate, defined as the share of households whose disposable income is below the national poverty threshold, as well as the national extreme poverty rate, defined as the share of households whose disposable income is below the national extreme poverty threshold. We additionally estimate maps for poverty severity and poverty gaps. Lastly, we produce small area poverty estimates of multidimensional poverty at the household level, following the national definition of multidimensional poverty. The maps are produced at the municipality level for the year 2019.

Box 2: Poverty maps around the world.

A variety of countries have produced poverty maps. In the LAC region those are Colombia, Guatemala, Honduras, Jamaica, Nicaragua, Peru and St. Lucia. Colombia has put the poverty maps at use to increase the targeting efficiency of social protection programs, as well as of private investments in social projects. The maps have also encouraged synergies between private and public agencies to reduce multidimensional poverty. In Nicaragua, poverty maps have informed fund allocations across municipalities along several sectors. Nicaragua's Emergency Social Investment Fund (Fondo de Inversion Social de Emergencia, FISE) uses a poverty map to target the poor. Outside the LAC region, a variety of countries have published poverty maps, reaching from Bulgaria over Egypt to Nepal. The poverty maps form part of the Third National Development Plan in Uganda. In Zimbabwe, they are used to allocate resources geographically. In Burundi, they have informed the targeting of beneficiaries of a social safety net program.

Methodology

One method of small area estimations is based on the Fay Herriot model, initially developed by Fay and Herriot (1979)[5]. This model has recently gained increased attention in academia and by statistical offices, as well as research institutions and international organizations, due to the model's high precision. The Fay-Herriot model's underlying idea is that those small areas with low precision "borrow strength" from small areas with high precision.[6] The Fay-Herriot model is a combination of a sampling and linking model, which we describe in detail in this section.

The linking model refers to the part of the model, which approximates the relationship between auxiliary information and the outcome variable of interest $\boldsymbol{u_d}$. Only considering this part of the model results in the following equation, which creates a linear relationship between the outcome variable of interest and a number i of auxiliary variables at the domain level X_{di}:

$$u_d = X_{di}\beta_i + \pi_d\,, \;\; d = 1, \ldots, D.$$

, where β_i are the fixed effects of auxiliary variables i, and π_d are random effects. π_d are assumed to be independent and identically distributed (iid) with mean zero and variance σ_π^2. The underlying assumption is that the variance parameter σ_π^2 is known. In practice, it can be estimated via likelihood-based methods, such as the Restricted Maximum Likelihood (REML), or the Maximum Likelihood (ML). The downside is that these methods depend heavily on the distributional assumptions behind the sampling errors e_d and the random effects π_d. Importantly, the equation above cannot be estimated, as u_d is not observed. In our empirical application, u_d would be the true poverty rate at the municipality level, for example. For this reason, the Fay-Herriot model approximates these indicators by a sampling model.

The sampling model refers to the part of the model, which relies on direct estimates at the area-level of interest from non-representative surveys. A sampling model occurs when only relying on direct estimates observed in the underlying data. A sampling model can be described by the following equation:

$$\overline{u}_d = u_d + e_d\,, \;\; d = 1, \ldots, D.$$

In this case, there is no auxiliary information included, as the estimates $\overline{u}_d$ are only based on information from the survey. e_d is the sampling error, as u_d is estimated inprecisely due to low sample size and non-representativeness at the geographic level of interest. This means that sampling errors arise, as the direct estimator from

5 Fay, R.E. and Herriot, R.A. (1979). Estimates of income for small places: an application of James-Stein procedures to census data. Journal of the American Statistical Association,74, 269-277.

6 Molina and Morales (2009). Small area estimation of poverty indicators. Boletín de Estadística e Investigación Operativa. Vol. 25, No. 3, Octubre 2009, pp. 218-22.

the survey is not equal to the true underlying variable of interest u_d. The underlying assumption is that sampling errors are normally distributed with mean zero and variance σ_{ed}^2. σ_{ed}^2 can be directly estimated from the survey data at the geographic level of interest. The sampling variance likely differs at the domain level. Some domains might be subject to a more significant spread in the data than others.

Combining the sampling with the linking model results in a linear mixed model. The resulting model is a linear mixed model of the following form:

$$\overline{u}_d = X_{di}\beta_i + \pi_d + e_d \,, \; d = 1, \dots, D.$$

, where $\overline{u}_d$ is the estimator[7] of the true mean of the variable of interest (e.g., the poverty rate) at the level of interest (e.g., the municipality), X_{di} is a set of auxiliary variables linearly related to the outcome of interest at the area level of interest (e.g., the share of working population at the municipality level), π_d are independent error terms with zero means and unknown constant variance, and e_d are the sampling errors, which are independent with zero mean and heteroskedastic known variance. D is the number of domains (the respective areas of interest). In practice, the estimated variance of the direct estimators for $\overline{u}_d$ is used frequently as the known error variance. [8]

The Fay-Herriot model generates the best linear unbiased predictor (BLUP). When σ_π^2 is known, the Fay-Herriot model generates the BLUP of the true mean at the domain level of interest by applying a shrinkage factor γ_d, which gives higher weight to domains measured with higher precision.[9] The Mean Squared Error (MSE) of the BLUP is then always at least as efficient as the one of the direct estimator. This means that the Fay-Herriot model minimizes the MSE. The BLUPs gain in efficiency especially for areas with larger sampling variance. The BLUP is given by:

$$\overline{u}_d^{blup} = \gamma_d \overline{u}_d + (1 - \gamma_d) x_d \tilde{\beta}, \quad d = 1, \dots, D.$$

, with the shrinkage factor being:

$$\gamma_d = \frac{\sigma_\pi^2}{\sigma_\pi^2 + \sigma_{ed}^2}$$

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7 A direct estimator is an estimator based solely on the observed sample data in the corresponding domain (e.g., the mean income at the municipality level generated from sample data from this municipality).

8 You, Y., and B. Chapman. 2006. Small area estimation using area-level models and estimated sampling variances. Survey Methodology32: 97–103.

9 The shrinkage factor is the proportion of variance due to ud (accounting for between area variations).

The shrinkage factor depends on the error variance and the unexplained variation, accounting for precision and model strength. A detailed look at the composition of the shrinkage factor makes clear that it decreases with the error variance σ_{ed}^2. Consequently, the higher the error variance, the lower the share of BLUPs, which results from the direct estimates. This rationale is based on direct estimates with a higher variance being more imprecisely measured. Therefore, they receive less weights (importance) in the linear mixed model. At the same time, the estimates generated from the linking model part receive higher weights in these cases. Similarly, with growing unexplained variation σ_{π}^2, the shrinkage factor increases. Therefore, the weaker the linear mixed model (the higher its unexplained variation), the higher the weights given to the direct estimates observed in the underlying survey data. To summarize, he shrinkage factor accounts for model strength and precision.

Using empirical estimators for σ_{π}^2 and σ_{ed}^2 generates the Empirical BLUPs (EBLUPs). The EBLUPs are more precise than the direct estimators always if the chosen model fits the underlying data well. This is an important caveat of the Fay-Herriot model. Evaluating the model fit is therefore a crucial step in the analysis. While the BLUP estimator requires normality, the EBLUP does not. This is highly beneficial in the context of development countries, as poverty is often highly concentrated, and normality might not be fulfilled. An important caveat is that the the Fay-Herriot model requires linearity in its linking model component.

We estimate several model specifications of the Fay-Herriot model at the municipality level. Given that the Fay-Herriot model estimation takes place at the area-level of interest, it requires one line of data per area (see the next Section for a detailed overview of the underlying data used in this report). This approach requires aggregating data to the area-level of interest and running the empirical estimation at this level. Importantly, we run several different model specifications and choose the model with the lowest coefficient of variation (CV), which in our case is the Fay-Herriot model with *ampl* specification (for details, see Annex 1). The different model specifications we apply are:

- Variance estimation using restricted maximum likelihood (REML)
- Variance estimation using adjusted maximum-profile likelihood (AMPL)
- Variance estimation using adjusted residual maximum-likelihood (ARYL)
- Log-transformed estimation of direct estimators and corresponding variances, with and without out of sample predictions
- Arcsin transformation, which confines the EBLUPs to a [0;1] interval.

Data

Given the current data landscape in El Salvador, the Fay-Herriot estimation is the appropriate small-area estimation method for this setting. There is currently no representative, up-to-date information on poverty indicators available in El Salvador. The government conducted its last official population census in 2007. Since then, the country has been marked by significant structural changes as an outflow of nearly one-fourth of its population. By mid-2020, the IOM registers 1.6 million emigrants from El Salvador, compared to a total population of 6.5 million.[10] Small-area estimation methods relying solely on information from the Census might therefore not be accurate as they do not present a true mirror of the country's current status quo anymore. The Fay-Herriot Model corrects for this shortcoming through the empirical approach described above, as it also considers more recent information through the sampling model. In our case, we combine information from the household survey (our direct estimates) with information from the Population Census (our auxiliary area-level information) by incorporating the area-level information from the census into the linkage model, and the direct estimates from the survey into the sampling model.

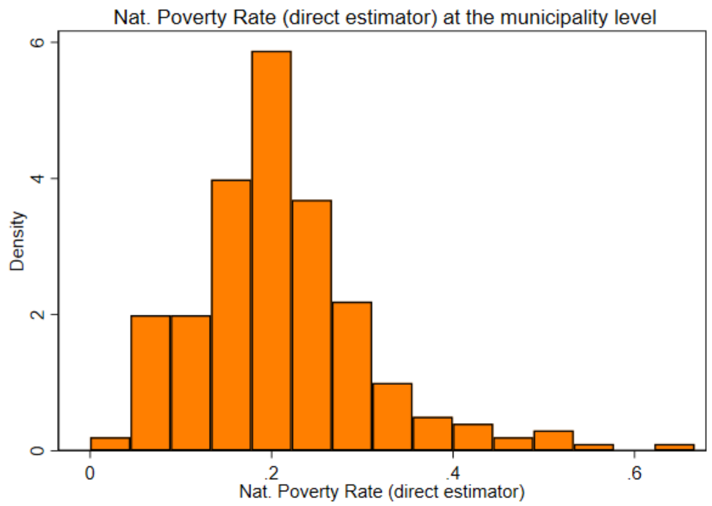
We rely on several data sources, one being the official household survey from 2019. The 2019 official household survey used for the estimation of the poverty maps is representative at the urban and rural level, for the metropolitan area of San Salvador, the department level, and 50 self-representative municipalities. While El Salvador has conducted a continuous household survey every year since 1975 (EHPM), the survey is not representative at the municipality level. The household survey of 2019 consists of a total sample of 19,968 housing units, 21,326 households, and 74,435 individuals. The EHPM (2019) was conducted monthly, from January to December of 2019. There are 14 departments and 262 municipalities in El Salvador. Two hundred twenty-six municipalities are included in the EHPM (2019). In most survey rounds, including the 2019 round[11], 50 of the 226 sampled municipalities are self-representative. The survey includes a primary sampling unit and stratification. We account for this design in our estimation of the poverty maps. Figure 2 shows the distribution of poverty rates at the municipality level from the 2019 EHPM. The only variable from the national household survey is our poverty estimate. Including independent variables from the household survey would bias our SAEs and lead to a higher random error.[12]

FIGURE 2: HISTOGRAM OF POVERTY RATES AT THE MUNICIPALITY LEVEL (2019)

[10] Source: Migration Data Portal (2018). Link: https://migrationdataportal.org/data?i=inflow_work&t=2018&cm49=340

[11] This is not the case for the 2020 household survey.

[12] Szymkowiak, Marcin, Andrzej Młodak, and Łukasz Wawrowski. "Mapping poverty at the level of subregions in Poland using indirect estimation." STATISTICS 609 (2017).



Notes: The graph plots a histogram of the national poverty headcount ratio at the municipality level relying on data from the national household survey from 2019. The x-axis reports the municipal national poverty rate and the y-axis the density. Source: EHPM (2019).

We draw auxiliary information from the 2007 Population Census as well as population estimates provided by DIGESTYC. All explanatory variables included in the model are from the 2007 Census with the exception of the population estimates at the municipality level, provided by DIGESTYC. We include the following independent variables:

- *Household-level variables*: If the household owns a car, house, radio, washing machine, has access to water, electricity, and sanitation, as well as the number of household members.
- *Condition of housing*: The condition of the housing households live in.
- *Labor market and education variables*: Labor market activity, the share of self-employed, the share of entrepreneurs, the share of public-sector workers, the share of the population with at least primary education, the share of children attending school, and the literacy rate.
- *Population characteristics:* Population estimates from 2020 and the number of children in a municipality.

We aggregate all datasets at the municipality level. Given that the Fay-Herriot model is a model performed at the area-level of interest, in our case municipalities, we aggregate all datasets at the municipality level. First, we aggregate the underlying household data at the municipality level. To do this, we consider the sampling design of the survey. Next, we aggregate our variables of interest from the census data at the municipality level. Lastly, we combine all data sources at the municipality level and run our model estimation at this same level of analysis.

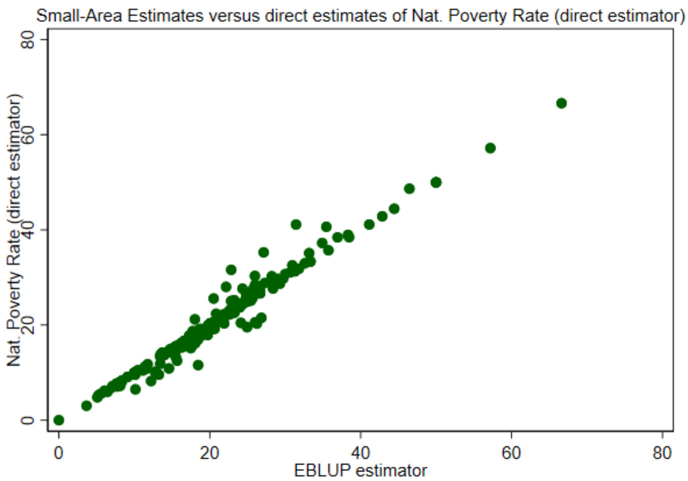
Small-area Monetary Poverty Estimates and Comparisons with previous Poverty Maps

This subsection estimates the Fay-Herriot model to construct small area estimates of monetary income poverty at the household level using the national poverty lines for El Salvador.[13]

We employ 5 different model specifications of the Fay-Herriot model and choose the best-performing model specification. We compare the performance of our 5 model specifications to each other based on two different criteria: the CVs and the MSEs. These comparisons indicate that the model specification with variance estimation using adjusted maximum-profile likelihood (AMPL) is the best performing model (for details, see Annex 1). We next report the results and poverty maps relying on this model specification.

We apply the Fay-Herriot model specifications to estimate the extreme poverty rate, the poverty rate, as well as poverty severity, and poverty gap. Figure 2 plots the direct estimator of the poverty rate at the municipality level versus the EBLUP estimators of the extreme poverty rate. Table 1 gives an overview of the direct and Fay-Herriot estimator for the municipal level's national poverty rates. We then estimate a map of the poverty rate (figure 3), extreme poverty rate (figure 4), poverty severity (figure 5), and poverty gap (figure 6). Table 2 shows the results for the small-area estimation of the extreme poverty rate at the municipality level, table 3 for poverty severity, and table 4 for the poverty gap.

FIGURE 3: SMALL AREA ESTIMATES VERSUS DIRECT ESTIMATES OF POVERTY RATES AT THE MUNICIPALITY LEVEL (FH MODEL WITH AMPL ESTIMATION)



Notes: The graph shows a scatter plot of poverty estimates (EBLUPs) generated from a Fay-Herriot model (on the x-axis) and direct estimates relying only on household survey data (on the y-axis).

[13] For the poverty maps using headcount ratios see the Annex 8.

The EBLUPs are generated from a model specification with variance estimation using adjusted maximum-profile likelihood (AMPL). Source: EHPM (2019) and Census (2007).

TABLE 1: FH MODEL WITH AMPL ESTIMATION – POVERTY RATES (2019)

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	226	20.87	9.87	0	66.62
CV (Direct estimator)	225	1768.8	1722.97	0	9018.58
EBLUP estimator	262	21.09	8.87	0	66.62
CV (FH Model)	261	1878.94	1597.07	0	11243.48
MSE EBLUP	262	.22	.29	0	1.12

Notes: The table shows summary statistics for moderate poverty rates at the municipality level in El Salvador. The first row reports the direct estimator (in %), which relies on direct observations from survey data. The indicator is only reported for 226 municipalities included in the survey. The second row presents the coefficient of variation (CV) multiplied by 100 of the direct estimator. Row 3 reports the empirical best linear unbiased predictor (EBLUP) (in %) at the municipality level generated from a Fay-Herriot model. In this case, we perform out-of-sample predictions and estimate poverty estimates for all 262 municipalities in El Salvador. We employ a variance estimation using adjusted maximum-profile likelihood (AMPL). Row 4 presents the respective CV of the EBLUPs as well as its mean squared error (MSE) multiplied by 100. Source: EHPM (2019) and Census (2007).

TABLE 2: FH MODEL WITH AMPL ESTIMATION - EXTREME POVERTY RATE (2019)

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	226	6.54	6.6	0	38.46
CV (Direct estimator)	187	3720.77	2743.43	0	10385.96
EBLUP estimator	262	6.45	5.92	-1.67	38.46
CV (FH Model)	223	3749.25	10325.05	-119066.39	62830.85
MSE EBLUP	262	.08	.11	0	.4

Notes: The table shows summary statistics for extreme poverty rates at the municipality level in El Salvador. The first row reports the direct estimator (in %), which relies on direct observations from survey data. The indicator is only reported for 226 municipalities included in the survey. The second row presents the coefficient of variation (CV) multiplied by 100 of the direct estimator. Row 3 reports the empirical best linear unbiased predictor (EBLUP) (in %) at the municipality level generated from a Fay-Herriot model. In this case, we perform out-of-sample predictions and estimate poverty estimates for all 262 municipalities in El Salvador. We employ a variance estimation using adjusted maximum-profile likelihood (AMPL). Row 4 presents the respective CV of the EBLUPs as well as its mean squared error (MSE) multiplied by 100. Source: EHPM (2019) and Census (2007).

TABLE 3: FH MODEL WITH AMPL SPECIFICATION - POVERTY SEVERITY (2019)

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	226	2.14	2.01	0	11.2
CV (Direct estimator)	217	3280.47	2597.42	0	10906.5
EBLUP estimator	262	2.06	1.77	-.15	11.2
CV (FH Model)	253	3124.12	15445.86	-134209.7	150595.84
MSE EBLUP	262	.01	.01	0	.04

Notes: The table shows summary statistics for poverty severity at the municipality level in El Salvador. The first row reports the direct estimator (in %), which relies on direct observations from survey data. The indicator is only reported for 226 municipalities included in the survey. The second row presents the coefficient of variation (CV) multiplied by 100 of the direct estimator. Row 3 reports the empirical best linear unbiased predictor (EBLUP) (in %) at the municipality level generated from a Fay-Herriot model. In this case, we perform out-of-sample predictions and estimate poverty *estimates for all 262 municipalities in El Salvador. We employ a variance estimation using adjusted maximum-profile likelihood (AMPL). Row 4 presents the respective CV of the EBLUPs as well as its mean squared error (MSE) multiplied by 100. Source: EHPM (2019) and Census (2007).*

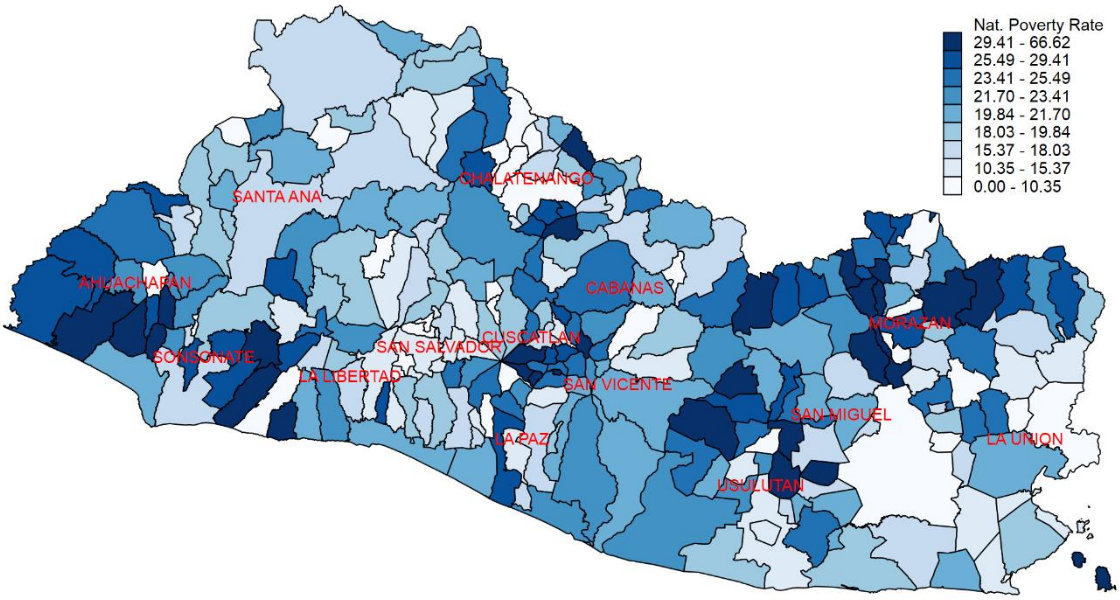
TABLE 4: FH MODEL WITH AMPL SPECIFICATION - POVERTY GAPS (2019)

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	226	5.07	4.06	0	22.95
CV (Direct estimator)	217	2771.69	2379.64	0	10906.5
EBLUP estimator	262	5	3.62	0	22.95
CV (FH Model)	253	3769.34	7463.48	0	80769.03
MSE EBLUP	262	.03	.04	0	.17

Notes: The table shows summary statistics for poverty gaps at the municipality level in El Salvador. The first row reports the direct estimator (in %), which relies on direct observations from survey data. The indicator is only reported for 226 municipalities included in the survey. The second row presents the coefficient of variation (CV) multiplied by 100 of the direct estimator. Row 3 reports the empirical best linear unbiased predictor (EBLUP) (in %) at the municipality level generated from a Fay-Herriot model. In this case, we perform out-of-sample predictions and estimate poverty estimates for all 262 municipalities in El Salvador. We employ a variance estimation using adjusted maximum-profile likelihood (AMPL). Row 4 presents the respective CV of the EBLUPs as well as its mean squared error (MSE) multiplied by 100. Source: EHPM (2019) and Census (2007).

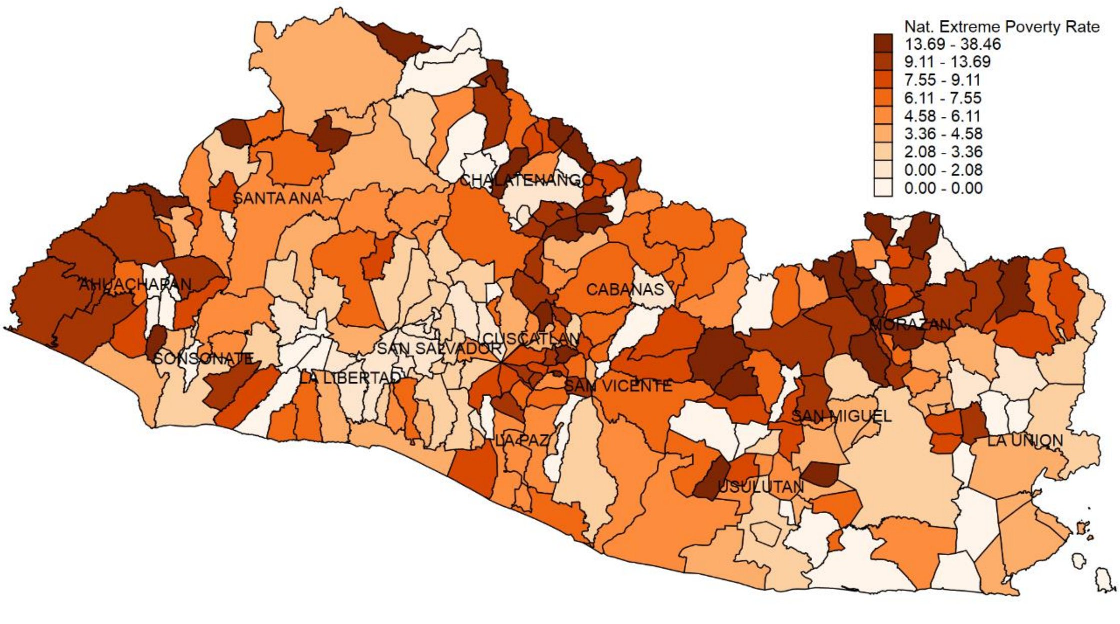
Figure 3 shows that there is considerable variation at the municipality level with respect to poverty rates. While none of the municipalities has a poverty rate larger than 66.6 percent, there are some agglomerations with significant poverty rates in the Northeast and Southwest of the country. Special attention should be paid to these municipalities as they are characterized by a high concentration of the poor. Comparing Figure 1 and 4 to each other reveals that there is significant variation at the municipality level within departments. Not all of the poorest municipalities are located in the poorest department, and vice versa.

FIGURE 4: SMALL AREA ESTIMATES OF THE NATIONAL POVERTY RATE AT THE MUNICIPALITY LEVEL (2019)



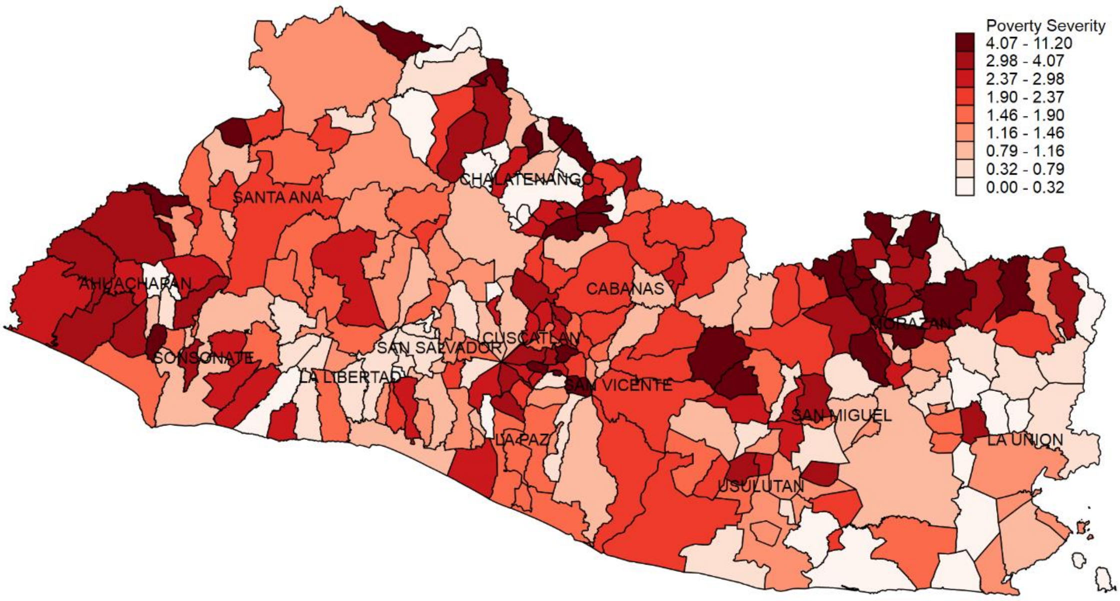
Source: World Bank estimates based on EHPM (2019) and Population Census (2007). The poverty rate is measured at the household level and reported in percent.

FIGURE 4: SMALL AREA ESTIMATES OF THE NATIONAL EXTREME POVERTY RATE AT THE MUNICIPALITY LEVEL (2019)



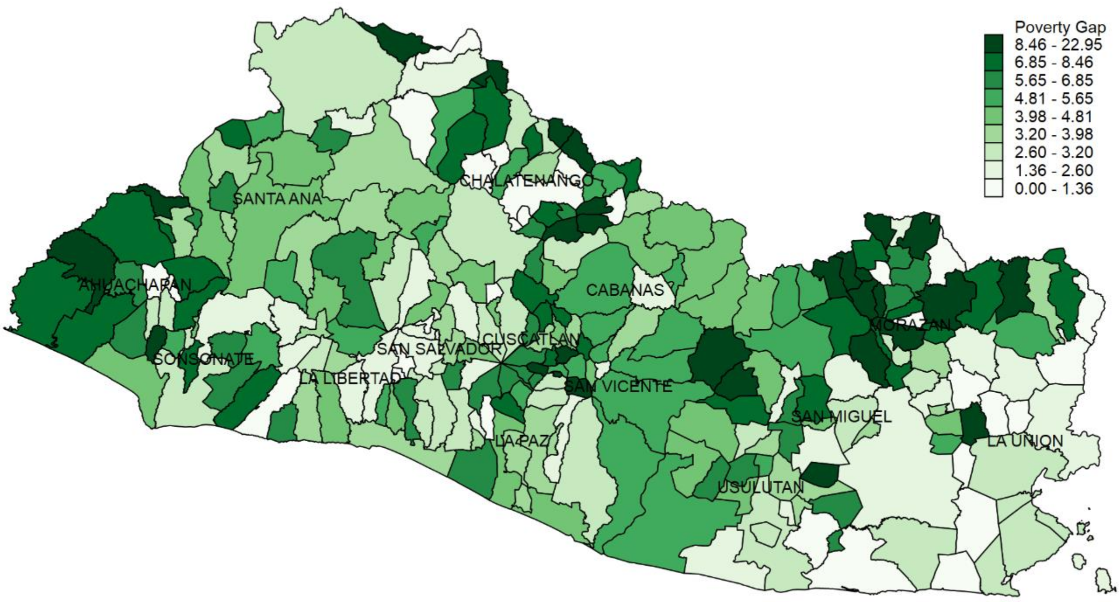
Source: World Bank estimates based on EHPM (2019) and Population Census (2007). The extreme poverty rate is measured at the household level and reported in percent.

FIGURE 5: SMALL AREA ESTIMATES OF NATIONAL POVERTY SEVERITY AT THE MUNICIPALITY LEVEL (2019)



Source: World Bank estimates based on EHPM (2019) and Population Census (2007). Poverty severity is measured at the household level and reported in percent.

FIGURE 6: SMALL AREA ESTIMATES OF THE NATIONAL POVERTY GAP AT THE MUNICIPALITY LEVEL (2019)



Source: World Bank estimates based on EHPM (2019) and Population Census (2007). The poverty gap is measured at the household level and reported in percent.

All poverty indicators point towards a concentration of poverty in individual municipalities. The municipalities with the highest poverty concentration are in the Northeast and West of El Salvador. The municipalities with the highest poverty rate are: Potonico (66.6 %), Estanzuelas (57.2 %), Santo Domingo de Guzmán (50

%), and Meanguera del Golfo (50 %). The municipalities with the lowest poverty rate are Comalapa (0 %), San Rafael (3.7 %), Chalatenango (5.1 %) as well as Apaneca (5.3 %). Most of the poorer municipalities are in the following departments: Morazán and Ahuachapán. These are also the departments that concentrate many of the municipalities with the highest extreme poverty rate (see Figure 4).

Multidimensional Poverty Maps

Multidimensional Poverty Frameworks can help to gain a deeper understanding of the drivers of poverty and the non-monetary aspects of welfare. The Monitoring Global Poverty report by the World Bank in 2017 stresses that multidimensional poverty indexes (MPIs) should accompany the monitoring of global poverty.[14] Multidimensional poverty frameworks can help to understand the underlying drivers of poverty better. They can be powerful tools to assess if certain countries, sub-regions, or demographic groups are more affected by some dimensions of poverty than others. They can serve as targeting mechanisms for sectoral interventions in the health, educational, or infrastructure sector. Recently, policymakers have made use of multidimensional poverty indexes to understand multidimensional poverty better. [15] In Colombia, for example, a multidimensional poverty map at the municipality level was used to improve the design and implementation of poverty reduction programs and policies. Similarly, Mexico has used the MPI to inform the creation of two large social protection strategies: the *National Crusade Against Hunger* as well as the *Universal Pension System*. In Buthan, the MPI is one of 5 criteria applied for the distribution of national resources to local government.

Our multidimensional poverty index follows the methodology developed by the statistical office of El Salvador; it consists of 5 dimensions and 20 indicators. The Multidimensional Poverty Index in El Salvador consists of several indicators and dimensions. It was developed in 2015 together with various national and international advisors and is the result of work conducted since 2009. [16] The different dimensions and indicators of the index are presented in Table 5. It is important to note that the individual indicators are measured at the household level and not the individual level. This means that, in many cases, all household members in a particular household are deprived in a certain dimension as soon as there is one member affected by a particular deprivation (e.g., the entire household is affected by early care deprivation as soon as one child does not

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[14] World Bank (2017). Monitoring Global Poverty: Report of the Commission on Global Poverty. Washington, DC: World Bank.

[15] OPHI and BMZ (2015). Measuring Multidimensional Poverty:Insights from Around the World. Link: https://www.ophi.org.uk/wp-content/uploads/Informing-Policy-brochure-web-file.pdf

[16] STPP y MINEC-DIGESTYC (2015). Medición multidimensional de la pobreza. El Salvador. San Salvador: Secretaría Técnica y de Planificación de la Presidencia y Ministerio de Economía, a través de la Dirección General de Estadística y Censos.

attend a nursery). In the case of El Salvador, there are five dimensions to multidimensional poverty and a total of 20 individual indicators. The national multidimensional poverty index measures the following dimensions of poverty: educational poverty, housing conditions, poverty-related to access to labor and social protection, health poverty, and the quality of the habitat.

TABLE 5: MULTIDIMENSIONAL POVERTY INDEX

INDICATOR	DEPRIVED IF LIVING IN A HOUSEHOLD WHERE…
Dimension 1: Education	
Inadequate early care	At least one child (1-3) does not attend a nursery
Non-attendance	At least one child (4-17) does not attend school
Educational legging	At least one child (10-17) is lagging behind in his/her educational performance
Low adult education	At least one adult (+18) with low education
Dimension 2: Housing conditions	
Inadequate material – roof	The roof of one's housing is made of inadequate material
Inadequate material – floor and walls	The floor and wall of one's housing is made of inadequate material
Overcrowding	The ratio of rooms to members is smaller than one 0.34
Insecure tenure	The land tenure is insecure
Dimension 3: Labor and Social Protection	
Child labor	The household is subject to child labor[17]
Unemployment	At least one household member (+16) is unemployed, or is employed but without work for at least 1 month per year
Under-employment and job insecurity	At least one household member (+16) works more than 40 hours a week and earns less than the minimum wage, or is not a permanent salaried worker, or involuntarily works less than 40 hours a week or involuntarily conducts seasonal work/did not find work during a period of longer than 1 months a year
Lack of access to social security and unemployment benefits	At least one household member (+16) has no health insurance or is no contributing member (only affiliated)
Dimension 4: Health	

[17] The definition of child labor follows its legal form, but also considers caretaking. A household is affected by child labor if at least one child engages in labor due to the official age restriction, or engages in a dangerous form of child labor. Additionally, as soon as a child (5-13) dedicates more than 28 hours per week to unpaid care work, the household is subject to child labor.

Food insecurity	Sum of food insecurity cases (by dimension and household member)[18]
Lack of access to health services	A household member did not consult with a health professional or the public sector health infrastructure due to access constraints[19]
Lack of access to water	A household has no access to portable water
Lack of access to sanitation	A household has no access to sanitation or only to a deprived from of sanitation[20]
Dimension 5: Quality of the habitat	
Lack of public spaces	Lack of soccer field, park, playgrounds, and communal houses, or without activities/too far away[21]
Crime	At least one household member has fallen victim to some form of crime[22]
Insecurity	At least one household member experiences restrictions in their activities due to perceived insecurities in the neighborhood[23]
Environmental risks and damages	The dwelling has been affected by streams of water, causing damages; landslides or is exposed to prohibited drainage systems[24]

[18] The national household survey includes eight questions on food insecurity of adults and six questions on food insecurity of minors. The degree of food insecurity depends on whether the household includes a minor or not. A household with at least one minor is food-insecure as soon as at least one of the 14 different dimensions of food insecurity affects an adult or a minor. The degree of food insecurity depends on the number of food insecurity dimensions: In the case of households with minors, the food insecurity index is 2 if the household is affected by 1-5 dimensions, 3 if the household is affected by 6-10 and 4 if it is affected by 11-15 dimensions. In the case of households without minors, the food insecurity index is 2 if the household is affected by 1-3 dimensions, 3 if it is affected by 4-6 and 4 if it is affected by 7 to 8 dimensions. The final indicator is one for a food insecurity index higher than 2, and zero otherwise.

[19] A household is deprived if a household member consulted with healer, friend/family member or nobody and did not consult with the public health system due to access constraints (too expensive or too far away, lack of medicines or personnel, too sick or due to work reasons); a household member consulted with NGOs, pharmacies, a healer's house or at home) and did not consult with the public health system due to access constraints; a household member consulted with the private health sector due to access constraints in the public health sector; a household would theoretically consult with one of the above in the case a household member gets sick in the future.

[20] A deprived form of sanitation is everything but a toilet.

[21] The household is only deprived if it is affected by all of the dimensions.

[22] As soon as one household member reports some form of victimization, the household is deprived in this dimension.

[23] As soon as one household member reports some form of restriction due to perceived insecurities, the household is deprived in this dimension.

[24] As soon as one household member reports some form of the above the household is deprived in this dimensions.

The multidimensional poverty indicator depends on the sum of all individual indicators and a predefined threshold. To define multidimensional poverty, one first creates individual indicators. Then, one aggregates all 20 indicators. A household is affected by multidimensional poverty if the sum of the indicators is larger than 7, which is the predefined multidimensional poverty threshold. In the case of El Salvador, 28.1 percent of households were multidimensionally poor in 2019. The table below presents the different indicators.

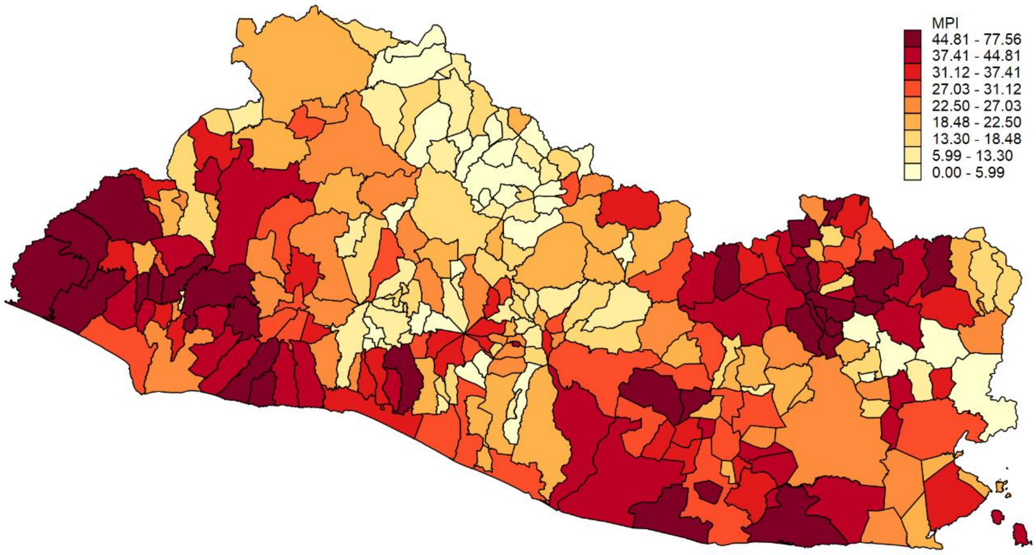
TABLE 6: MPI EL SALVADOR – SHARE OF DEPRIVED HOUSEHOLDS BY INDICATOR

Indicator	*Share of households deprived*
Non-attendance rate	10.2
Educational delays	1.7
Inadequate care of young children	14.2
Low adult education level	77.5
Inadequate materials (roof)	5.2
Inadequate materials (floor and walls)	18.3
Overcrowding	40.5
Insecurity of tenure	9.9
Vulnerable employment	61.3
Unemployment	14.2
Lack of Social Security	69.1
Child labor	4.8
Lack of health services	9.8
Lack of drinking water	19.6
Lack of sanitation	41.5
Food insecurity	16.0
Lack of public spaces	38.6
Crime	7.6
Insecurity	42.8
Environmental risk factors	5.2
MPI	**28.1**

Source: DIGESTYC estimates based on EHPM (2019).

The figure below shows the small area estimates of multidimensional poverty. Multidimensional poverty varies between 0.0 and 77.6 percent. There is significant variation at the municipality level with respect to the share of households affected by multidimensional poverty. This is in line with what is observed for monetary poverty estimates. Like monetary poverty, there is a large concentration of multidimensional poverty in the Northeast and Southwest of the country. Contrary to the income-based measure of poverty, certain municipalities on the country's southern border are significantly affected by a high share of households being multidimensionally poor. The map below can serve as a complementary measure to the poor income-based poverty maps and can draw additional insights into the underlying drivers. It can also generate a broader perspective on poverty without solely relying on monetary measures.

FIGURE 7: SMALL-AREA ESTIMATES OF MULTIDIMENSIONAL POVERTY (2019)



Notes: The map plots the multidimensional poverty indicator at the subnational level in El Salvador. We follow the national definition of multidimensional poverty. Source: World Bank estimates based on EHPM (2019) and Census (2007). The poverty rate is measured at the household level and reported in percent.

There is considerable spatial variation in the five dimensions of the MPI. Figure 5 to 9 plot the five dimensions of the MPI. These graphs reveal that there is significant heterogeneity across municipalities in all dimensions. The spatial dimension of the overall MPI seems to be most aligned with the educational, housing, and health dimension, while the labor and living condition dimension reveal a slightly different spatial pattern. Investments in education, health and housing of the poorest might be most effective in decreasing multidimensional poverty.

FIGURE 5: MPI - EDUCATIONAL DIMENSION

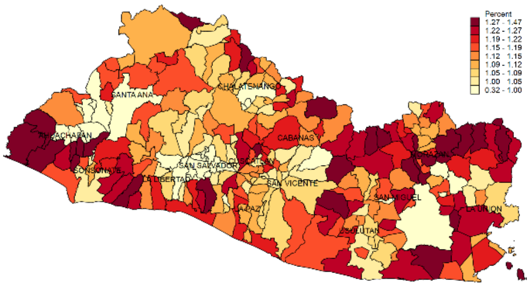


FIGURE 6: MPI - HOUSING DIMENSION

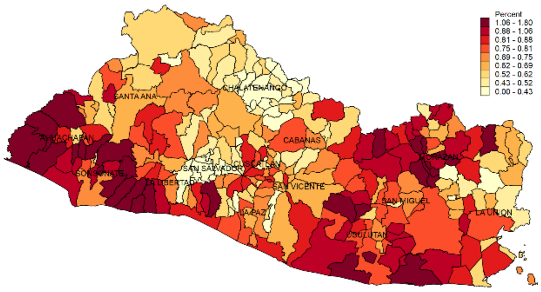


FIGURE 7: MPI - LABOR DIMENSION

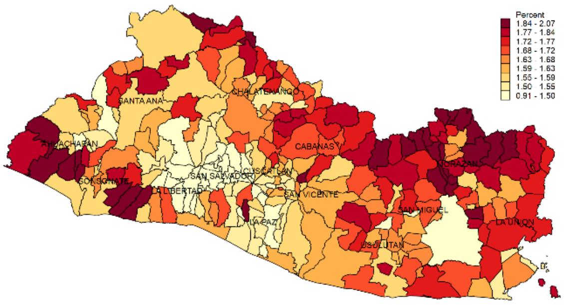


FIGURE 8: MPI - HEALTH DIMENSION

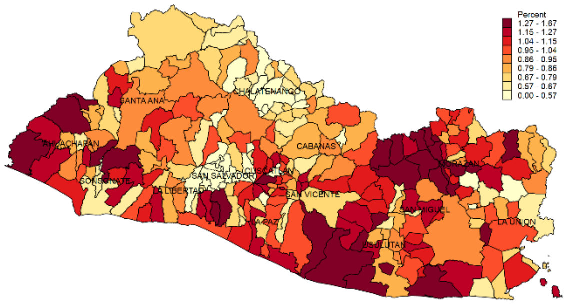
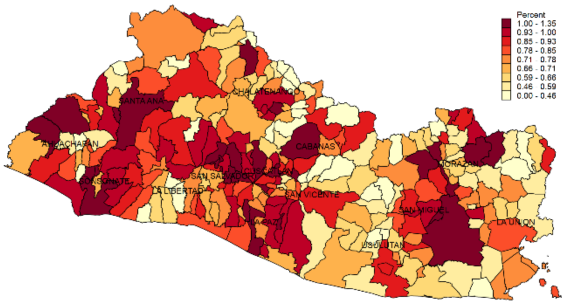


FIGURE 9: MPI - LIVING CONDITIONS DIMENSION



Notes: The maps plot the 5 main dimensions of the MPI, following the national methodology. Source: *World Bank estimates based on EHPM (2019) and Census (2007). The poverty rate is measured at the household level and reported in percent.*

How could these updated maps be used to improve the targeting of social programs and inform the poverty eradication strategy?

The "Poverty Eradication Strategy" was established by the previous government in 2017, with the signature of the Executive Decree No. 28. The Strategy is defined as a set of programs and policies designed for the eradication of extreme poverty in the period 2017-2030. This is done through the social protection system and policies supporting skill development and income improvements among families living in extreme poverty in the 262 municipalities.

The government of El Salvador currently identifies municipalities with high extreme poverty using information from the 2007 Population Census as well as the unique participant registration system (RUP). The RUP comes along with a household questionnaire, allowing insights into each household's socioeconomic condition. The identification of poor municipalities and households is based on four different dimensions of this questionnaire: household wealth, access to public services, education, and each household's social capital. [25] Eligible municipalities are those part of strata 1 to 7, according to the RUP. This ranking of municipalities is currently the basis for geographic targeting mechanisms forming part of El Salvador's poverty eradication strategy 2020, such as the "Familias Sostenibles" program. In a second stage, the prioritization of households in each municipality is based on the score of the Quality-of-Life Index based on the Single Registry of Participants (IRUP).

When comparing the ranking of municipalities based on the updated poverty maps to the ranking of municipalities currently used in the current poverty reduction strategy, there are significant differences. To evaluate this, we look at a number of example municipalities and compare their ranking from the RUP to the estimates of moderate monetary poverty from the Fay-Herriot model. The poorest municipality in the previous maps is San Isidro. In contrast, this municipality only ranks 49th when looking at the Fay-Herriot estimates. Similarly, the municipality with the lowest poverty rate on the previous maps (San Salvador) ranks at 219th in the Fay-Herriot maps. For a full comparison of the ranking of all municipalities, see Annex 6. This reranking suggests that there is scope for efficiency savings to reduce poverty by using more updated poverty information at a subnational level (Fay-Herriot Poverty maps) to identify poor municipalities.

There are several possible reasons for the reranking of municipalities between the old and new poverty maps. First, there could be methodological reasons for the change in rankings. As detailed in the methodological section of this report, Fay-Herriot estimation techniques have important empirical advantages over alternative small-area poverty estimations. The Fay-Herriot model accounts for lack of precision and representativeness at disaggregated geographical levels. In addition, it allows to combine survey data with alternative data sources, drawing from additional information. Second, the reranking could be due to different data sources at use for the estimation of old and news maps. While our updated maps draw from a combination of updated household surveys, population estimates and the Census from 2007, the previous maps rely on data from the RUP Lastly, poverty stories could indeed have changed for municipalities. These changes could be due to the large emigration from El Salvador, urban-rural migration patterns, natural disasters, the development of criminal activity at the subnational level, or spatial patterns of corruption and fraud. We leave a detailed analysis of these potential drivers to future research.

[25] El Salvador 2020. Manual Operativo. Estrategia de Erradicación de la Pobreza. Familias Sostenibles."

Caveats and limitations

Although the Fay-Herriot model has many advantages over alternative small-area poverty estimation techniques, it is subject to important caveats and limitations.[26] The most important limitation is that estimates rely on a model, which relies on model assumptions. These assumptions, on the other hand, might be difficult to check or not aligned with the true underlying data distribution.[27] Another important caveat is that the model assumes that sampling variances are known, which is not true in empirical applications. Therefore, the model relies on estimates of these variances. This estimation could introduce potential errors for estimated MSEs. Lastly, the model relies on information gathered from sampled areas. Consequently, imprecision might still be an issue in area-level models.

Given that the resulting poverty estimates rely on empirical estimation techniques, the municipal moderate poverty rate is not always larger than the municipal extreme poverty rate. When comparing the resulting EBLUPs of moderate and extreme poverty rates to each other, there are 7 municipalities, for which the model estimates a larger extreme poverty rate than a moderate poverty rate. This is the case for the municipalities of San Fernando, Delicias de Concepción, Santa Rita, Santiago de la Frontera, Arambala, Masahuat, and Comalapa.

3. Conclusion

In this paper, we derive small-area poverty estimates at the municipality level by applying the Fay-Herriot model for small area estimations, using household data from 2019 and the Population Census from 2007. We estimate several model specifications and choose the one with the highest precision and lowest number of outbound predictions: the non-transformed model specification with an *ampl* correction of the variance.

We find that poverty rates vary significantly at the municipality level in El Salvador. All poverty indicators shown in this report point towards the concentration of poverty in certain areas. While there are certain variations in the ranking of poverty across the different indicators at use, the poorest municipalities are concentrated in the Northeast and West of El Salvador.

[26] Corral, Paul; Molina, Isabel; Cojocaru, Alexandru; Segovia, Sandra. 2022. Guidelines to Small Area Estimation for Poverty Mapping. Washington, DC : World Bank. © World Bank. https://openknowledge.worldbank.org/handle/10986/37728 License: CC BY 3.0 IGO.

[27] These assumptions are the linearity assumption as well as the normality assumption of the Fay-Herriot model.

The poverty maps are an important contribution to El Salvador's agenda to eliminate poverty. The maps presented in this report can serve as an input for geographic targeting programs. The maps can also be combined with complementing targeting strategies in the design and application of public policies. The maps shed light on important poverty drivers in the country's development agenda. Small-area poverty estimates of multidimensional poverty and its dimensions are especially useful to detect investment needs for education, health, housing, or labor markets. Our methodology considers the data environment in El Salvador and therefore makes an important contribution to the country's agenda to eliminate poverty.

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Annex

Annex 1 – Choosing the best model among several model specifications

To estimate the Fay-Herriot model, we apply the Stata ado command Fayherriot developed by Halbmeier et al. (2019). [28] The Fayherriot command is the most up-to-date command for an empirical analysis of the Fay-Herriot model and the most precise one. It allows:

- To produce out-of-sample predictions.
- Adjust non-positive random-effects variance estimates.
- Deal with the violation of model assumption.

The Fay-Herriot model is estimated at the municipality level and requires datasets at the domain level of interest with one observation per domain. We, therefore, first, aggregate the household data at our domain level of interest, the municipality level. Due to its mixed nature, the Fay-Herriot model requires a pre-specified estimation of the sampling error variance. We base our estimates of the sampling error variance on the direct estimates of the poverty indicators of interest. We also account for the survey design of the national household survey.

We estimate several specifications of the Fay-Herriot model and then choose the one with the highest precision. A rule of thumb often applied by statistical offices is that the CV should not be larger than 20 percent. An additional selection criteria is the number of outbound estimates (e.g. the number of negative estimates).

We implement the stata command *fayherriot*. Using this command allows for an out-of-sample estimation based on the in-sample observations. The first model specification is a simple linear mixed model, depending on direct estimates of the national poverty indicator at the household level and regressed on the municipality explanatory variables and the sampling error variance. The gamma option specifies the display of summary statistics of the shrinkage factor[29], and *nolog* suppresses the iteration log of the optimization algorithm. The variance of the random effects is estimated through the reml estimation method. Table A1 shows the results of this specific Fay-Herriot model. While the CV and MSE of our estimator is low, all estimates are outbound (above 1).

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28 Halbmeier et al. (2019). The fayherriot command for estimating small-area indicators. The Stata Journal (2019). 19, Number 3, pp. 626–64. DOI: 10.1177/1536867X1987423.

29 The shrinkage factor shows how direct estimates and model predictions are weighted when calculating the EBLUP. Large values off γd mean that a large weight is given to the direct estimate θd.

TABLE A1: FH MODEL - POVERTY RATE (2019)

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	226	20.87	9.87	0	66.62
CV (Direct estimator)	226	315.38	283.12	0	1479.23
EBLUP estimator	262	124.13	11.74	100	194.69
CV (FH Model)	262	342.75	265.22	0	962.88
MSE EBLUP	262	.37	.52	0	2.07

Notes: The table reports results from a Fay-Herriot estimation for moderate poverty rates using a simple linear mixed model. The first row reports the direct estimator (in %), which relies on direct observations from survey data. The indicator is only reported for 226 municipalities included in the survey. The second row presents the coefficient of variation (CV) multiplied by 100 of the direct estimator. Row 3 reports the empirical best linear unbiased predictor (EBLUP) (in %) at the municipality level generated from a Fay-Herriot model. In this case, we perform out-of-sample predictions and estimate poverty estimates for all 262 municipalities in El Salvador. Row 4 presents the respective CV of the EBLUPs as well as its mean squared error (MSE) multiplied by 100. Source: EHPM (2019) and Census (2007).

To account for the occurrence of zero variances, we apply the *ampl* estimation. In this case, the random effect variance is estimated via the adjusted maximum-likelihood method (Li and Lahirini, 2010).[30] Table A2 shows the results. The mean squared error is lower for this model, and the CV is below 20 percent. There are also no outbound estimates. This model specification is therefore a good option for small-area estimations in El Salvador.

TABLE A2: FH MODEL WITH AMPL ESTIMATION - POVERTY RATE (2019/20)

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	226	20.87	9.87	0	66.62
CV (Direct estimator)	225	1768.8	1722.97	0	9018.58
EBLUP estimator	262	21.09	8.87	0	66.62
CV (FH Model)	261	1878.94	1597.07	0	11243.48
MSE EBLUP	262	.22	.29	0	1.12

Notes: The table reports results from a Fay-Herriot estimation for moderate poverty rates using a ampl estimation technique for the variance. The first row reports the direct estimator (in %), which relies on direct observations from survey data. The indicator is only reported for 226 municipalities included in the survey. The second row presents the coefficient of variation (CV) multiplied by 100

[30] Li, H., and P. Lahiri. 2010. An adjusted maximum likelihood method for solving small area estimation problems. Journal of Multivariate Analysis101: 882–892.

of the direct estimator. Row 3 reports the empirical best linear unbiased predictor (EBLUP) (in %) at the municipality level generated from a Fay-Herriot model. In this case, we perform out-of-sample predictions and estimate poverty estimates for all 262 municipalities in El Salvador. Row 4 presents the respective CV of the EBLUPs as well as its mean squared error (MSE) multiplied by 100. Source: EHPM (2019) and Census (2007).

An alternative estimation method to account for zero variances is the aryl estimation. Table A3 shows the result of this estimation. The CV is larger than the one in Table A2.

TABLE A3: FH MODEL WITH ARYL ESTIMATION – POVERTY RATE (2019/20)

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	226	20.87	9.87	0	66.62
CV (Direct estimator)	225	1768.8	1722.97	0	9018.58
EBLUP estimator	262	21.09	8.9	0	66.62
CV (FH Model)	261	1920.76	1679.07	0	11865.86
MSE EBLUP	262	.24	.33	0	1.27

Notes: The table reports results from a Fay-Herriot estimation for moderate poverty rates using an aryl transformation. The first row reports the direct estimator (in %), which relies on direct observations from survey data. The indicator is only reported for 226 municipalities included in the survey. The second row presents the coefficient of variation (CV) multiplied by 100 of the direct estimator. Row 3 reports the empirical best linear unbiased predictor (EBLUP) (in %) at the municipality level generated from a Fay-Herriot model. In this case, we perform out-of-sample predictions and estimate poverty estimates for all 262 municipalities in El Salvador. Row 4 presents the respective CV of the EBLUPs as well as its mean squared error (MSE) multiplied by 100. Source: EHPM (2019) and Census (2007).

Next, we estimate an *arcsin* transformation of the model. An *arcsin* transformation of the Fay-Herriot model is beneficial when the outcome of interest lies within a range of 0 and 1, as is the case for poverty rates. We first take the direct estimator's arcsin square root from the household survey to apply the arcsin transformation. We then estimate the *arcsin* variance from the effective sample size based on the actual sample size and the survey design's design effect (Results in Table A4). The *arcsin* method sets an upper- and lower bound for the estimated poverty rate (0 and 1) but does not report the Mean-Squared-Error or coefficients of variation. It is, therefore, difficult to compare the performance of this model to the other model specifications.

TABLE A4: FH MODEL WITH *ARCSIN* TRANSFORMATION

Variable	Obs	Mean	Std. Dev.	Min	Max

Direct estimator	226	20.87	9.87	0	66.62
EBLUP estimator	262	20.4	6.26	5.23	38.41

Notes: The table presents results from a model specification of the Fay-Herriot model using an arcsin transformation. Under this specification, it is not possible to compute the coefficients of variation (CVs) nor mean-squared errors (MSEs). Source: EHPM (2019) and Census (2007)

We then estimate a log transformation of the classical Fay-Herriot model for in-sample municipalities. The log transformation can help with analyses in which not all domains are sampled. We, therefore, log-transform equivalent incomes and the variances of the sampling error. For the back-transformation of the EBLUP and MSE to its original scale, we once applied the bias correction developed by Slud and Maiti (2006)[31] and the crude bias correction by Neves et al. (2013) and Rao and Molina (2015)[32]. The results are shown in table A5 and table A6. Only under the crude bias correction method, out-of-sample predictions are possible.

TABLE A5: FH LOG-TRANSFORMED MODEL - POVERTY RATE (2019)

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	226	20.87	9.87	0	66.62
CV (Direct estimator)	225	1768.8	1722.97	0	9018.58
EBLUP estimator	225	21.43	9.17	5.26	66.62
CV (FH Model)	225	1766.4	1530.39	0	6199.38
MSE EBLUP	225	.19	.27	0	1.53

Notes: The table reports results from a Fay-Herriot estimation for moderate poverty rates using a log transformation. The first row reports the direct estimator (in %), which relies on direct observations from survey data. The indicator is only reported for 226 municipalities included in the survey. The second row presents the coefficient of variation (CV) multiplied by 100 of the direct estimator. Row 3 reports the empirical best linear unbiased predictor (EBLUP) (in %) at the municipality level generated from a Fay-Herriot model. In this case, we perform out-of-sample predictions and estimate poverty estimates for all 262 municipalities in El Salvador. Row 4 presents the respective CV of the EBLUPs as well as its mean squared error (MSE) multiplied by 100. Source: EHPM (2019) and Census (2007).

31 Slud, E. V., and T. Maiti. 2006. Mean-squared error estimation in transformed Fay–Herriot models. Journal of the Royal Statistical Society, Series B 68: 239–257.

32 Neves, A., D. Silva, and S. Correa. 2013. Small domain estimation for the Brazilian service sector survey. Estadística 65: 13–37. Rao, J. N. K., and I. Molina. 2015. Small Area Estimation. 2nd ed. Hoboken, NJ: Wiley.

TABLE A8: FH LOG-TRANSFORMED MODEL WITH CRUDE BACK-TRANSFORMATION - POVERTY RATE (2019)

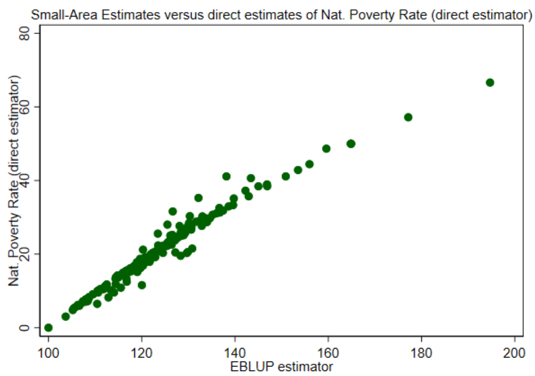
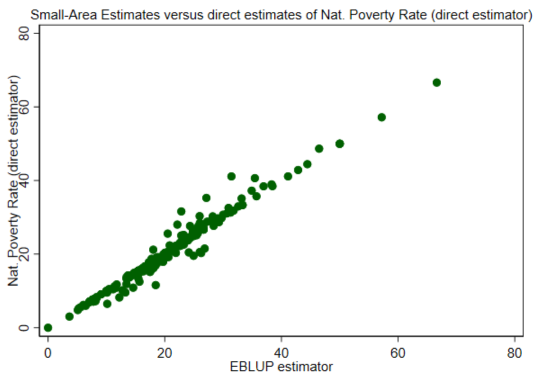
Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	226	20.87	9.87	0	66.62
CV (Direct estimator)	225	1768.8	1722.97	0	9018.58
EBLUP estimator	262	21.63	8.68	5.26	66.62
CV (FH Model)	262	4272.51	7439.44	0	39927.3
MSE EBLUP	262	.24	.35	0	2.06

Notes: The table reports results from a Fay-Herriot estimation for moderate poverty rates using a log transformation with crude-bias-correction and out-of-sample predictions. The first row reports the direct estimator (in %), which relies on direct observations from survey data. The indicator is only reported for 226 municipalities included in the survey. The second row presents the coefficient of variation (CV) multiplied by 100 of the direct estimator. Row 3 reports the empirical best linear unbiased predictor (EBLUP) (in %) at the municipality level generated from a Fay-Herriot model. In this case, we perform out-of-sample predictions and estimate poverty estimates for all 262 municipalities in El Salvador. Row 4 presents the respective CV of the EBLUPs as well as its mean squared error (MSE) multiplied by 100. Source: EHPM (2019) and Census (2007).

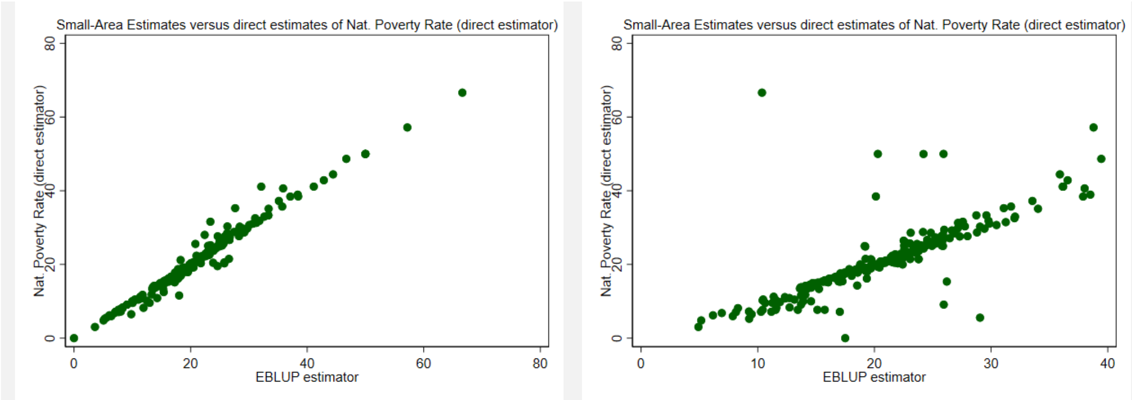
We choose the model version with the highest precision to estimate the poverty rate at the municipality level. Comparing the mean-squared errors and coefficients of variation among all model specifications shows that the model specification using an *ampl* estimation method for the random error variance is the best performing model.

As an additional indication for the performance of our model we plot the EBLUPs against the direct estimators. Figure A1 shows the results. Under the ideal setting, we would see a symmetric allocation of the points around a imaginary diagonal straight line. The *ampl* specification fairs quite well when comparing the different model specifications, based on these images.

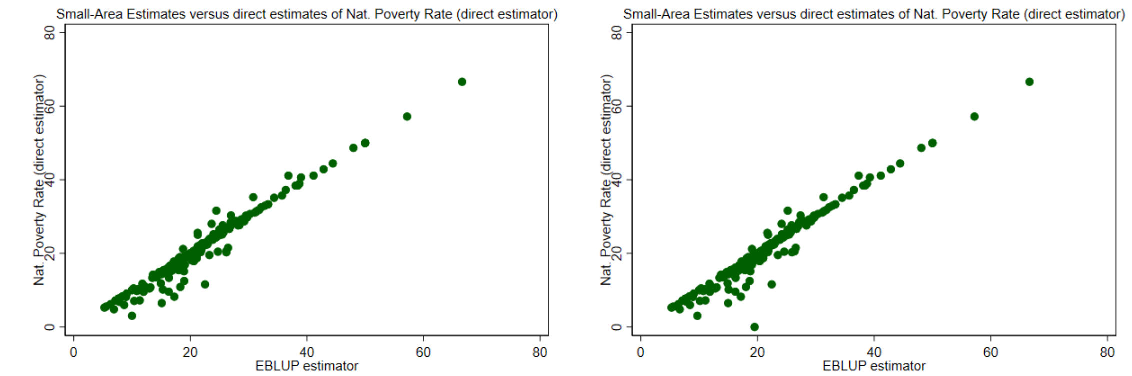
FIGURE A1: THE PRECISION OF DIFFERENT MODEL SPECIFICATIONS

Direct estimator	***Direct estimator with ampl estimation***
	

Direct estimator with aryl estimation	***Arcsin transformation***



Log transformation ***Log transformation (out-of-sample)***

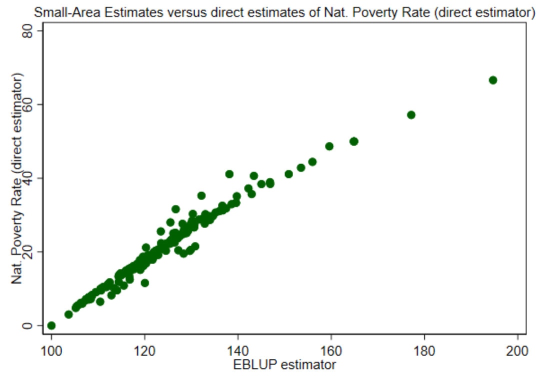


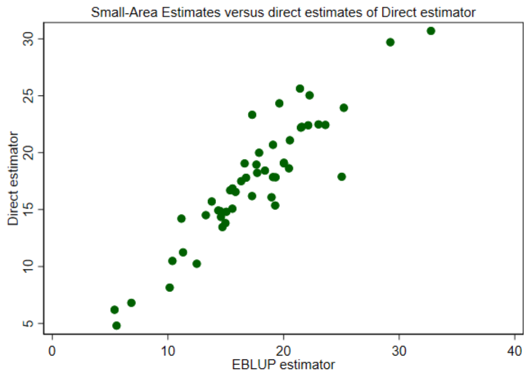
Notes: The figure shows scatter plots of the direct estimator observed from the household survey (on the y-axis) and the estimated small-area estimators from different Fay-Herriot model specifications (on the x-axis). Source: EHPM (2019) and Census (2007).

The advantage of the national household survey in El Salvador is that it includes 50 municipalities, for which the data at hand is self-representative. We therefore restrict our evaluation of the goodness of fit to these 50 municipalities. Figure A2 plots the FH-estimators against the direct estimators of these municipalities. We also report our results in the tables to follow. These analyses are only robustness checks and not the main decision criteria, as we need to consider the full information feeding into our model to make a final decision. It therefore only serves to validate if our chosen model specification is completely off, which is not the case. The mean-squared error and coefficient of variation of our chosen model is low and there are no outliers in the EBLUPs.

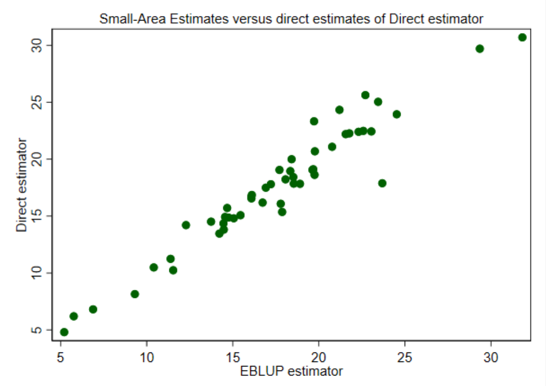
FIGURE A2: THE PRECISION OF DIFFERENT MODEL SPECIFICATIONS (50 SELF-REPRESENTATIVE MUNICIPALITIES)

Direct estimator ***Direct estimator with ampl estimation***

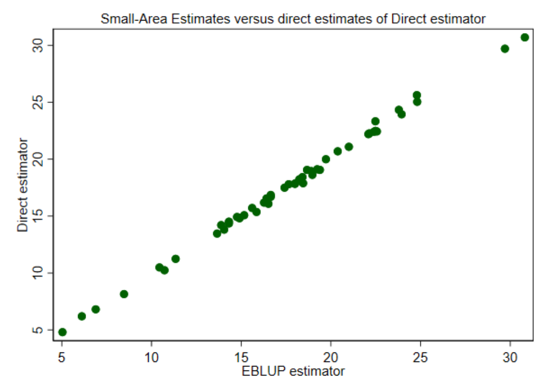




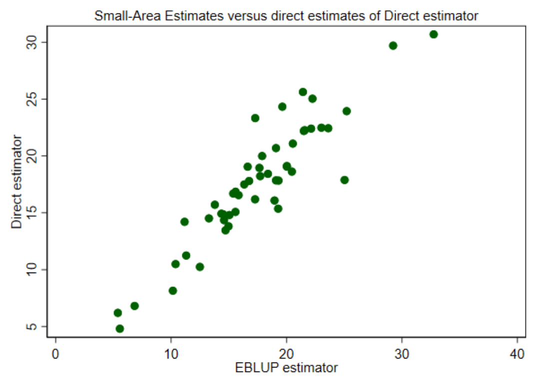
Direct estimator with aryl estimation



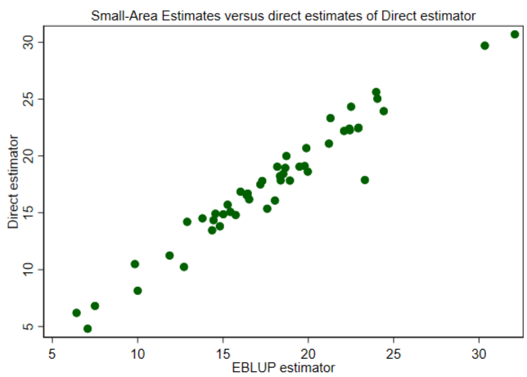
Arcsin transformation



Arcsin transformation with ampl



Log transformation (out-of-sample)



Source: EHPM (2019) and Census (2007)

Table A9: FH Model - Direct estimator - 2019

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	50	4.06	2.52	.35	10.41
CV (Direct estimator)	50	122.66	46.28	35.25	271.7
EBLUP estimator	50	103.97	2.31	100.42	110.11
CV (FH Model)	50	108.34	33.08	34.88	196.76

MSE EBLUP	50	.01	.01	0	.05

Notes: The table reports results from a Fay-Herriot estimation for moderate poverty rates using a simple linear mixed model. In this case, we restrict our sample to the 50 auto-representative municipalities. The first row reports the direct estimator (in %), which relies on direct observations from survey data. The indicator is only reported for 226 municipalities included in the survey. The second row presents the coefficient of variation (CV) multiplied by 100 of the direct estimator. Row 3 reports the empirical best linear unbiased predictor (EBLUP) (in %) at the municipality level generated from a Fay-Herriot model. Row 4 presents the respective CV of the EBLUPs as well as its mean squared error (MSE) multiplied by 100. Source: EHPM (2019) and Census (2007).

TABLE A10: FH MODEL WITH AMPL ESTIMATION - DIRECT ESTIMATOR - 2019

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	50	4.06	2.52	.35	10.41
CV (Direct estimator)	50	3768.1	1681.57	1764.71	10036.85
EBLUP estimator	50	3.68	2.05	.52	9.44
CV (FH Model)	50	3833.67	2497.08	1697.9	12217.02
MSE EBLUP	50	.01	.01	0	.03

Notes: The table reports results from a Fay-Herriot estimation for moderate poverty rates using an ampl estimation technique for the variance. In this case, we restrict our sample to the 50 auto-representative municipalities. The first row reports the direct estimator (in %), which relies on direct observations from survey data. The indicator is only reported for 226 municipalities included in the survey. The second row presents the coefficient of variation (CV) multiplied by 100 of the direct estimator. Row 3 reports the empirical best linear unbiased predictor (EBLUP) (in %) at the municipality level generated from a Fay-Herriot model. Row 4 presents the respective CV of the EBLUPs as well as its mean squared error (MSE) multiplied by 100. Source: EHPM (2019) and Census (2007).

TABLE A11: FH MODEL WITH ARYL ESTIMATION - DIRECT ESTIMATOR - 2019

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	50	4.06	2.52	.35	10.41
CV (Direct estimator)	50	3768.1	1681.57	1764.71	10036.85
EBLUP estimator	50	3.86	2.2	.41	9.62
CV (FH Model)	50	3509.64	1714.68	1705.14	8673.9
MSE EBLUP	50	.01	.01	0	.04

Notes: The table reports results from a Fay-Herriot estimation for moderate poverty rates using an aryl transformation. In this case, we restrict our sample to the 50 auto-representative municipalities. The first row reports the direct estimator (in %), which relies on direct observations from survey data. The indicator is only reported for 226 municipalities included in the survey. The second row presents the coefficient of variation (CV) multiplied by 100 of the direct estimator. Row 3 reports the empirical best linear unbiased predictor (EBLUP) (in %) at the municipality level generated from a Fay-Herriot model. Row 4 presents the respective CV of the EBLUPs as well as its mean squared error (MSE) multiplied by 100. Source: EHPM (2019) and Census (2007).

TABLE A12: FH MODEL WITH ARCSIN TRANSFORMATION

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	50	4.06	2.52	.35	10.41
EBLUP estimator	50	4.04	2.46	.49	10.3

Notes: The table reports results from a Fay-Herriot estimation for moderate poverty rates using an arcsin transformation. In this case, we restrict our sample to the 50 auto-representative municipalities. The first row reports the direct estimator (in %), which relies on direct observations from survey data. The indicator is only reported for 226 municipalities included in the survey. The second row presents the coefficient of variation (CV) multiplied by 100 of the direct estimator. Row 3 reports the empirical best linear unbiased predictor (EBLUP) (in %) at the municipality level generated from a Fay-Herriot model. Row 4 presents the respective CV of the EBLUPs as well as its mean squared error (MSE) multiplied by 100. Source: EHPM (2019) and Census (2007).

TABLE A13: FH MODEL WITH ARCSIN TRANSFORMATION AND AMPL ESTIMATION - DIRECT ESTIMATOR - 2019

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	50	4.06	2.52	.35	10.41
EBLUP estimator	50	4.02	2.39	.68	10.19

Notes: The table reports results from a Fay-Herriot estimation for moderate poverty rates using an arcsin transformation and ampl estimation technique for the variance. In this case, we restrict our sample to the 50 auto-representative municipalities. The first row reports the direct estimator (in %), which relies on direct observations from survey data. The indicator is only reported for 226 municipalities included in the survey. The second row presents the coefficient of variation (CV) multiplied by 100 of the direct estimator. Row 3 reports the empirical best linear unbiased predictor (EBLUP) (in %) at the municipality level generated from a Fay-Herriot model. Row 4 presents the respective CV of the EBLUPs as well as its mean squared error (MSE) multiplied by 100. Source: EHPM (2019) and Census (2007).

TABLE A14: FH LOG-TRANSFORMED MODEL - DIRECT ESTIMATOR - 2019

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	50	4.06	2.52	.35	10.41
CV (Direct estimator)	50	3768.1	1681.57	1764.71	10036.85
EBLUP estimator	50	4.21	2.23	.78	10.64

CV (FH Model)	50	4026.75	603.73	3360.12	6481.88
MSE EBLUP	50	.03	.03	0	.15

Notes: The table reports results from a Fay-Herriot estimation for moderate poverty rates using a log transformation. In this case, we restrict our sample to the 50 auto-representative municipalities. The first row reports the direct estimator (in %), which relies on direct observations from survey data. The indicator is only reported for 226 municipalities included in the survey. The second row presents the coefficient of variation (CV) multiplied by 100 of the direct estimator. Row 3 reports the empirical best linear unbiased predictor (EBLUP) (in %) at the municipality level generated from a Fay-Herriot model. Row 4 presents the respective CV of the EBLUPs as well as its mean squared error (MSE) multiplied by 100. Source: EHPM (2019) and Census (2007).

TABLE A15: FH LOG-TRANSFORMED MODEL WITH CRUDE BACK-TRANSFORMATION - DIRECT ESTIMATOR - 2019

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	50	4.06	2.52	.35	10.41
CV (Direct estimator)	50	3768.1	1681.57	1764.71	10036.85
EBLUP estimator	50	4.3	2.31	1.06	10.51
CV (FH Model)	50	2914.74	767.78	1764.17	5154.36
MSE EBLUP	50	.01	.01	0	.06

Notes: The table reports results from a Fay-Herriot estimation for moderate poverty rates using a log transformation with a crude-back-transformation and out-of-sample predictions. In this case, we restrict our sample to the 50 auto-representative municipalities. The first row reports the direct estimator (in %), which relies on direct observations from survey data. The indicator is only reported for 226 municipalities included in the survey. The second row presents the coefficient of variation (CV) multiplied by 100 of the direct estimator. Row 3 reports the empirical best linear unbiased predictor (EBLUP) (in %) at the municipality level generated from a Fay-Herriot model. Row 4 presents the respective CV of the EBLUPs as well as its mean squared error (MSE) multiplied by 100. Source: EHPM (2019) and Census (2007).

Annex 2 – FH Estimates of Extreme Poverty Indicators

The tables below shows the results of the different model specification for the small-area estimation of extreme poverty. The first row reports the direct estimator (in %), which relies on direct observations from survey data. The indicator is only reported for 226 municipalities included in the survey. The second row presents the coefficient of variation (CV) multiplied by 100 of the direct estimator. Row 3 reports the empirical best linear unbiased predictor (EBLUP) (in %) at the municipality level generated from a Fay-Herriot model. In this case, we perform out-of-sample predictions and estimate poverty estimates for all 262 municipalities in El Salvador (with exception of the log-transformed model). Row 4 presents the respective CV of the EBLUPs as well as its mean squared error (MSE) multiplied by 100.

TABLE A16: FH MODEL - DIRECT ESTIMATOR - 2019

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	226	6.54	6.6	0	38.46
CV (Direct estimator)	226	169.76	196.67	0	1132.33
EBLUP estimator	262	106.92	6.7	98.56	146.9
CV (FH Model)	262	196.81	187.43	0	676.56
MSE EBLUP	262	.1	.15	0	.61

Source: EHPM (2019) and Census (2007)

TABLE A17: FH MODEL WITH AMPL ESTIMATION - DIRECT ESTIMATOR - 2019

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	226	6.54	6.6	0	38.46
CV (Direct estimator)	187	3720.77	2743.43	0	10385.96
EBLUP estimator	262	6.45	5.92	-1.67	38.46
CV (FH Model)	223	3749.25	10325.05	-119066.39	62830.85
MSE EBLUP	262	.08	.11	0	.4

Source: EHPM (2019) and Census (2007)

TABLE A18: FH MODEL WITH ARYL ESTIMATION - DIRECT ESTIMATOR - 2019

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	226	6.54	6.6	0	38.46
CV (Direct estimator)	187	3720.77	2743.43	0	10385.96
EBLUP estimator	262	6.47	5.94	-1.62	38.46
CV (FH Model)	262	3182.78	10654.79	-136246.7	65948.95
MSE EBLUP	262	.08	.12	0	.46

Source: EHPM (2019) and Census (2007)

TABLE A19: FH MODEL WITH ACRSIN TRANSFORMATION

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	226	6.54	6.6	0	38.46
EBLUP estimator	262	7.76	4.79	.44	27.14

Source: EHPM (2019) and Census (2007)

TABLE A20: FH MODEL WITH ACRSIN TRANSFORMATION AND AMPL ESTIMATION - DIRECT ESTIMATOR - 2019

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	226	6.54	6.6	0	38.46
EBLUP estimator	262	7.67	4.64	.46	26.66

Source: EHPM (2019) and Census (2007)

TABLE A21: FH LOG-TRANSFORMED MODEL - DIRECT ESTIMATOR - 2019

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	226	6.54	6.6	0	38.46
CV (Direct estimator)	187	3720.77	2743.43	0	10385.96
EBLUP estimator	187	8.38	5.77	1.15	38.46
CV (FH Model)	187	3182.42	2003.28	0	6659.05
MSE EBLUP	187	.07	.11	0	.9

Source: EHPM (2019) and Census (2007)

TABLE A22: FH LOG-TRANSFORMED MODEL WITH CRUDE BACK-TRANSFORMATION - DIRECT ESTIMATOR - 2019

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	226	6.54	6.6	0	38.46
CV (Direct estimator)	187	3720.77	2743.43	0	10385.96
EBLUP estimator	262	9.25	6.01	1.28	38.46

CV (FH Model)	262	17586.62	27935.74	0	174622.73
MSE EBLUP	262	.13	.27	0	2.23

Source: EHPM (2019) and Census (2007)

Annex 3 – FH Estimates of Poverty Gaps

The tables below shows the results of the different model specification for the small-area estimation of moderate poverty gaps. The first row reports the direct estimator (in %), which relies on direct observations from survey data. The indicator is only reported for 226 municipalities included in the survey. The second row presents the coefficient of variation (CV) multiplied by 100 of the direct estimator. Row 3 reports the empirical best linear unbiased predictor (EBLUP) (in %) at the municipality level generated from a Fay-Herriot model. In this case, we perform out-of-sample predictions and estimate poverty estimates for all 262 municipalities in El Salvador (with exception of the log-transformed model). Row 4 presents the respective CV of the EBLUPs as well as its mean squared error (MSE) multiplied by 100.

TABLE A23: FH MODEL - DIRECT ESTIMATOR - 2019

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	226	5.07	4.06	0	22.95
CV (Direct estimator)	226	109.82	121.4	0	921.32
EBLUP estimator	262	105.22	3.95	100	125.8
CV (FH Model)	262	129.42	119.88	0	431.83
MSE EBLUP	262	.04	.06	0	.22

Source: EHPM (2019) and Census (2007)

TABLE A24: FH MODEL WITH AMPL ESTIMATION - DIRECT ESTIMATOR - 2019

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	226	5.07	4.06	0	22.95
CV (Direct estimator)	217	2771.69	2379.64	0	10906.5
EBLUP estimator	262	5	3.62	0	22.95
CV (FH Model)	253	3769.34	7463.48	0	80769.03

MSE EBLUP	262	.03	.04	0	.17

Source: EHPM (2019) and Census (2007)

TABLE A25: FH MODEL WITH ARYL ESTIMATION - DIRECT ESTIMATOR - 2019

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	226	5.07	4.06	0	22.95
CV (Direct estimator)	217	2771.69	2379.64	0	10906.5
EBLUP estimator	262	5.01	3.63	0	22.95
CV (FH Model)	253	3834.65	7598.93	0	81750.99
MSE EBLUP	262	.03	.05	0	.19

Source: EHPM (2019) and Census (2007)

TABLE 26: FH MODEL WITH ACRSIN TRANSFORMATION

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	226	5.07	4.06	0	22.95
EBLUP estimator	262	4.91	2.34	.87	14.33

Source: EHPM (2019) and Census (2007)

TABLE A27: FH MODEL WITH ACRSIN TRANSFORMATION AND AMPL ESTIMATION - DIRECT ESTIMATOR - 2019

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	226	5.07	4.06	0	22.95
EBLUP estimator	262	4.85	2.22	.92	13.55

Source: EHPM (2019) and Census (2007)

TABLE A28: FH LOG-TRANSFORMED MODEL - DIRECT ESTIMATOR - 2019

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	226	5.07	4.06	0	22.95
CV (Direct estimator)	217	2771.69	2379.64	0	10906.5

EBLUP estimator	217	5.39	3.74	.01	22.95
CV (FH Model)	217	4237.61	4100.38	0	20765.56
MSE EBLUP	217	.05	.08	0	.68

Source: EHPM (2019) and Census (2007)

TABLE A29: FH LOG-TRANSFORMED MODEL WITH CRUDE BACK-TRANSFORMATION - DIRECT ESTIMATOR - 2019

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	226	5.07	4.06	0	22.95
CV (Direct estimator)	217	2771.69	2379.64	0	10906.5
EBLUP estimator	262	5.82	4.04	.01	24.2
CV (FH Model)	262	25791.81	60792.3	0	350094.63
MSE EBLUP	262	.06	.2	0	2.1

Source: EHPM (2019) and Census (2007)

Annex 4 – FH Estimates of Poverty Severity

The tables below shows the results of the different model specification for the small-area estimation of moderate poverty severity. The first row reports the direct estimator (in %), which relies on direct observations from survey data. The indicator is only reported for 226 municipalities included in the survey. The second row presents the coefficient of variation (CV) multiplied by 100 of the direct estimator. Row 3 reports the empirical best linear unbiased predictor (EBLUP) (in %) at the municipality level generated from a Fay-Herriot model. In this case, we perform out-of-sample predictions and estimate poverty estimates for all 262 municipalities in El Salvador (with exception of the log-transformed model). Row 4 presents the respective CV of the EBLUPs as well as its mean squared error (MSE) multiplied by 100.

TABLE A30: FH MODEL - DIRECT ESTIMATOR - 2019

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	226	2.14	2.01	0	11.2

CV (Direct estimator)	226	54.21	69.25	0	602.43
EBLUP estimator	262	102.11	1.84	99.89	111.85
CV (FH Model)	262	62.27	60.58	0	208.59
MSE EBLUP	262	.01	.01	0	.05

Source: EHPM (2019) and Census (2007)

TABLE A31: FH MODEL WITH AMPL ESTIMATION - DIRECT ESTIMATOR - 2019

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	226	2.14	2.01	0	11.2
CV (Direct estimator)	217	3280.47	2597.42	0	10906.5
EBLUP estimator	262	2.06	1.77	-.15	11.2
CV (FH Model)	253	3124.12	15445.86	-134209.7	150595.84
MSE EBLUP	262	.01	.01	0	.04

Source: EHPM (2019) and Census (2007)

TABLE A32: FH MODEL WITH ARYL ESTIMATION - DIRECT ESTIMATOR - 2019

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	226	2.14	2.01	0	11.2
CV (Direct estimator)	217	3280.47	2597.42	0	10906.5
EBLUP estimator	262	2.07	1.77	-.13	11.2
CV (FH Model)	253	2942.09	17462.22	-164864.92	148287.67
MSE EBLUP	262	.01	.01	0	.04

Source: EHPM (2019) and Census (2007)

TABLE A33: FH MODEL WITH ACRSIN TRANSFORMATION

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	226	2.14	2.01	0	11.2
EBLUP estimator	262	1.94	1.01	.4	5.87

Source: EHPM (2019) and Census (2007)

Table A34: FH Model with ACRSIN transformation and AMPL estimation - Direct estimator - 2019

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	226	2.14	2.01	0	11.2
EBLUP estimator	262	1.91	.96	.38	5.47

Source: EHPM (2019) and Census (2007)

Table A35: FH Log-Transformed Model - Direct estimator - 2019

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	226	2.14	2.01	0	11.2
CV (Direct estimator)	217	3280.47	2597.42	0	10906.5
EBLUP estimator	217	2.28	1.93	0	11.2
CV (FH Model)	214	14746.64	22601.62	0	178691.44
MSE EBLUP	217	.07	.13	-.01	.87

Source: EHPM (2019) and Census (2007)

Table A36: FH Log-Transformed Model with crude back-transformation – Direct estimator – 2019

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	226	2.14	2.01	0	11.2
CV (Direct estimator)	217	3280.47	2597.42	0	10906.5
EBLUP estimator	262	2.89	3.74	0	44.59
CV (FH Model)	262	82685.79	229534.48	0	1455918.3
MSE EBLUP	262	.05	.33	0	5.09

Source: EHPM (2019) and Census (2007)

Annex 5 – FH Estimates of Multidimensional Poverty

The tables below shows the results of the different model specification for the small-area estimation of multidimensional poverty. The first row reports the direct estimator (in %), which relies on direct observations from survey data. The indicator is only reported for 226 municipalities included in the survey. The second row presents the coefficient of variation (CV) multiplied by 100 of the direct estimator. Row 3 reports the empirical best linear unbiased predictor (EBLUP) (in %) at the municipality level generated from a Fay-Herriot model. In this case, we perform out-of-sample predictions and estimate poverty estimates for all 262 municipalities in El Salvador. Row 4 presents the respective CV of the EBLUPs as well as its mean squared error (MSE) multiplied by 100.

TABLE A37: FH MODEL WITH AMPL ESTIMATION - DIRECT ESTIMATOR - 2019

Variable	Obs	Mean	Std. Dev.	Min	Max
Direct estimator	226	32.9	16.8	0	81.1
CV (Direct estimator)	223	166.8	81.1	48.3	525.8
EBLUP estimator	262	25.6	16	-22	77.6
CV (FH Model)	259	125.2	546.1	-523.5	6626.9
MSE EBLUP	262	204.2	149.8	0	1411.8

Source: EHPM (2019) and Census (2007)

Annex 6 – Comparison of municipality rankings of old and new maps (From highest to lowest poverty incidence)

TABLE A38: COMPARISON OF OLD AND NEW MUNICIPALITY RANKING (FROM POOREST TO LEAST POOR)

Old Ranking[33]	New Ranking
San Isidro	Potonico
San Antonio	Estanzuelas

33 We do not dispose of the old poverty estimates at the municipality level. Alternative measures of previous estimates can be found here: https://esri-sv.maps.arcgis.com/home/item.html?id=0bc142780f3e44f39d8bbdf7ed9f9116

Cualococti	Santo Domingo De Guzman
Cuisnahiat	Meanguera Del Golfo
Guaymango	Berlin
San Simon	Jucuapa
Torola	Nuevo Eden De San Juan
Lislique	Gualococti
Cacaopera	Mercedes La Ceiba
Cancasque	Santo Domingo
Monte San Juan	San Simon
San Fernando	Cacaopera
Guatajiagua	San Antonio
Yamabal	Yamabal
Jucuaran	San Emigdio
San Fernando	Santa Isabel Ishuatan
Jutiapa	Santa Catarina Masahuat
Jicapala	El Rosario
San Francisco Javier	Corinto
El Rosario	Guaymango
Joateca	Ojos De Agua
Nuevo Eden San Juan	San Jorge
San Cristobal	Jicalapa
San Pedro Puxtla	Guatajiagua
San Antonio de la Cruz	Paraiso De Osorio
Caluco	Candelaria
Tacuva	San Julian
Santa Isabel Ishuatan	Jujutla
Teotepeque	Santa Elena
Santa Clara	San Pedro Puxtla
San Dionisio	Lislique
Chilango	San Francisco Menendez
Arambala	El Triunfo
Jujutla	San Lorenzo
Sensembra	Yoloaiquin

El Carmen	Chilanga
San Francisco Morazan	San Pedro Masahuat
Alegria	San Cristobal
Mercedes la Ceiba	San Fernando
Santa Catarina Masahuat	Caluco
San Fransico Chinameca	Zaragoza
San Lorengo	San Ramon
Santon Domingo de Guzaman	El Rosario
Chiltiupan	San Miguel De Mercedes
Nueva Granda	Cuisnahuat
Victoria	Nahulingo
Carolina	San Gerardo
Perquin	Mercedes Umaña
Huizucar	San Isidro
Lolotiquillo	Poloros
San Idefonso	Tacuba
Comasagua	San Antonio Los Ranchos
Oratorio de Concepción	El Congo
San Gerardo	Perquin
Cinquera	El Paraiso
Tecoluca	San Luis De La Reina
Masahuat	Tepecoyo
Corinto	San Luis Del Carmen
Jocoatique	Nueva Guadalupe
San Emigdio	Alegria
Mercedes Umaña	Santa Cruz Michapa
El Rosario	Nombre De Jesus
Lolotique	Cinquera
Sesori	Santa Cruz Analquito
San Pedro Nonualco	Concepcion Batres
El Porvernir	San Lorenzo
Santa Maria Ostuma	Bolivar
Nahuizalco	Tejutla
Dolores	Santo Tomas

San Jorge	San Francisco Morazan
Santa Cruz Analquito	Sacacoyo
Tapaluaca	Ilobasco
Nueva Trinidad	San Buena Ventura
Estanzuelas	Sociedad
San Micuel Tepezontes	San Rafael Cedros
Rosario de Mora	Verapaz
San Rafael Oriente	Yucuaiquin
Jiquilisco	San Francisco Chinameca
Paraiso de Osorio	San Agustin
San Antonio Masahuat	Ahuachapan
San Pedro Masahuat	Santa Maria Ostuma
Osicala	Tenancingo
Ozatlan	Torola
Apastepeque	El Divisadero
Tecapan	Jerusalén
San Juan Tepezaontes	San Antonio Masahuat
Yucuaiquin	Dolores
Jerusalen	Las Flores
Las vueltas	Salcoatitan
Suchitoto	Juayua
Ojos de Agua	San Ildefonso
La Laguna	San Luis La Herradura
Sociedad	Joateca
San Ramon	Ciudad Barrios
San Julian	Nahuizalco
San Matias	San Antonio Pajonal
San Pedro Perulapan	Concepcion De Ataco
San Fransicco Menendez	Ozatlan
Chinameca	Colon
Delicias de Concepcion	Tamanique
Moncagua	Nueva Trinidad
Ciudad Barrios	San Antonio Del Monte
Concepcion Matres	Santiago Texacuangos
Comalapa	Suchitoto

El Carrizal	Jiquilisco
Santiago Nonualco	Coatepeque
Candelaria	San Juan Tepezontes
Meanguera	San Fernando
San Carlos	Cancasque
Tenanciango	Jocoaitique
Cuirilagua	Nueva Esparta
Yoloaiquin	Zacatecoluca
San Luis la Herradura	California
San Agustin	Carolina
San Jose	San Sebastian
San Antonio Los Ranchos	Tepetitan
San Luis la Reina	Citala
Yayantique	Tecoluca
Panchimalco	San Pablo Tacachico
Tejuteque	El Carrizal
Arcatao	San Francisco Javier
Santa Elena	Intipuca
San Luis del Carmen	Lolotique
Anamoros	El Transito
Santa Rosa Guachipilin	San Jose Guayabal
Concepción de Ataco	Ereguayquin
Berlin	San Alejo
San Buena Ventura	La Libertad
Potonico	San Isidro
Tamanique	Nueva Granada
San Esteban Catarina	Moncagua
Izalco	San Luis Talpa
San Luis Talpa	Sesori
San Jose Guyabal	El Porvenir
El Carmen	San Vicente
Poloros	San Juan Nonualco
El Paisanl	San Cayetano Istepeque
Coatepeque	Acajutla

Santiango de la Frontera	Guadalupe
El Transito	El Paisnal
San Isidro	Turin
Conchagua	Chiltiupan
La Reina	Victoria
Agua Caliente	Texistepeque
Nueva Esparta	Oscicala
Ereguyquin	Azacualpa
San Pablo Tacachico	Guazapa
Apaneca	Izalco
San Cayetano Istepque	Puerto El Triunfo
El Divididero	Santa Clara
Comacaran	Huizucar
Talnique	Arcatao
Puerto el Triunfo	San Pedro Perulapan
Intipuca	Panchimalco
Quelepa	San Rafael Obrajuelo
San Ignacio	Talnique
El Triunfo	Conchagua
Uluazapa	Candelaria De La Frontera
Tepetitan	Lolotiquillo
San Alejo	San Ignacio
Santa Cruz Michapa	Chalchuapa
Ilobasco	Santa Rosa Guachipilin
Santo Domingo	Jutiapa
Guadalupe	Monte San Juan
Guacotecti	Concepcion De Oriente
Chapeltique	San Sebastian Salitrillo
Atiquizaya	San Juan Opico
La Palma	La Palma
Salcoatitan	San Martin
Santa Rita	Las Vueltas
Las Flores	Comacaran
Verapaz	Ciudad Arce

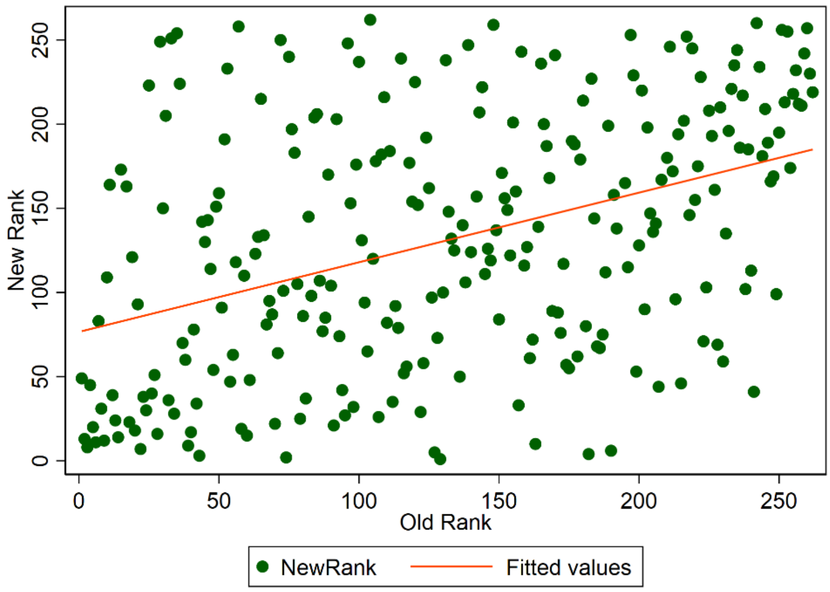
Citala	Jucuaran
Tepecoyo	Apopa
El Paraiso	San Juan Talpa
nueva Concepcion	Chinameca
Sensutepeque	Yayantique
Nombre de Jesus	Santiago Nonualco
San Isidrio Labrador	San Isidro Labrador
El Sauce	Santa Maria
Ahuachapan	Aguilares
Meanquera del golfo	Meanguera
San Jose Villanueva	San Rafael Oriente
Texistepeque	Chirilagua
Tejutal	Cojutepeque
Bolivar	San Francisco Gotera
San Rafael Cedros	Atiquizaya
Zacatecoluca	Sensuntepeque
Nejapa	Santa Ana
Jucuapa	Nueva Concepcion
Candearia de la Frontera	Comasagua
Acajutal	Anamoros
San Rafael Cedros	Metapan
San Lorenzo	Olocuilta
Concepcion de Oriente	Ciudad Delgado
San Sebastian	Sonsonate
Dulce Nombre de Maria	Rosario De Mora
Armenia	Concepcion Quezaltepeque
El Congo	Nejapa
La Libertad	Chapeltique
Cuyultitlan	Quelepa
Juayua	Jayaque
Concepcion Quezaltepeque	La Laguna
Guazapa	Apastepeque
San Juan Nonualco	San Dionisio
Turin	Tecapan

San Miguel de Mercedes	La Reina
San Juan Opico	Usulutan
El Rosario	San Francisco Lempa
Santa Maria	La Union
Jocoro	Cuscatancingo
Ciudad Arce	Ilopango
San Antonio Pajonal	Tonacatepeque
Olocuitla	El Sauce
Nahuilingo	San Pedro Nonualco
Jayaque	San Carlos
San Bartolome	Quezaltepeque
Azacualpa	San Marcos
Pasaquina	San Salvador
San Rafel Obrajuelo	Cuyultitan
San Juan Talpa	Santa Rosa De Lima
El Refugio	Agua Caliente
Sacacoyo	San Antonio De La Cruz
Santiango Texacuangos	El Carmen
Usulutan	Tejutepeque
Metapan	El Rosario
Chalchupa	San Jose Villanueva
Santo Tomas	El Refugio
La Union	Armenia
Nueva Gadaupe	Soyapango
San Vicente	El Carmen
Sonsonate	Santa Tecla
Santa Rosa de Lima	Oratorio De Concepcion
Santiango de Maria	San Miguel
Nuevo Cuscatlan	Santiago De Maria
San Francisco Gotera	Guacotecti
Quezalpeque	Delicias De Concepcion
San Antonio del Monte	San Esteban Catarina
Cojuteque	San Jose
California	San Miguel Tepezontes

Zaragoza	Santa Rita
Chalatenango	Mejicanos
San Miguel	Uluazapa
Aquilares	Nuevo Cuscatlan
San Francisco Lempa	Pasaquina
Santa Ana	Jocoro
San Sebastian Salitrillo	Santiago De La Frontera
San Martin	San Matias
Colon	Teotepeque
Cuidad Delgado	Tapalhuaca
Sonzacate	Arambala
Tonacateque	San Bartolome Perulapia
Ayutuxtepeque	Dulce Nombre De Maria
Apopa	Sensembra
San Marcos	Ayutuxtepeque
San Tecla	Sonzacate
Ilopango	Antiguo Cuscatlan
Cuzcatancingo	Masahuat
Mejicanos	Apaneca
Antiguo Cuscatlan	Chalatenango
Soyapango	San Rafael
San Salvador	Comalapa

Notes: The table reports the ranking of municipalities on national poverty rates for old and new poverty maps. The highest rank (1) is the poorest municipality Source: World Bank estimates based on EHPM 2019 and the Population Census, and El Salvador 2020 Manual operativo Estrategia de Erradicacion de Pobreza

FIGURE A4: SCATTER PLOT OF NEW AND OLD MUNICIPALITY RANKINGS



Notes: The graph plots the old municipality ranking in municipal poverty estimates against the new ranking. The orange line represents the fitted line. Source: World Bank estimates based on EHPM 2019 and the Population Census, and El Salvador 2020 Manual operativo Estrategia de Erradicacion de Pobreza

Annex 7 – Small area estimates of poverty (Fay-Herriot)

The below table presents small-area poverty estimates at the municipality level. We consider the national poverty line for moderate poverty and household estimates. Column 1 presents the name of the respective municipality, Column 2 poverty estimates from the Fay-Herriot model, Column 3 the related MSE (multiplied by 100) and Column 4 the related CV (multiplied by 100).

TABLE A39: SMALL-AREA POVERTY ESTIMATES (FAY-HERRIOT)

Municipality	Moderate poverty estimates (%)	MSE	CV
Potonico	66.62	0	0
Estanzuelas	57.18	0	0
Santo Domingo De Guzman	50.00	0	0
Meanguera Del Golfo	50.00	0	0
Berlin	49.98	0	0
Jucuapa	46.46	0.06	538.49

Nuevo Eden De San Juan	44.44	0	0
Gualococti	42.86	0	0
Mercedes La Ceiba	41.13	0	0
Santo Domingo	38.46	0	0
San Simon	38.31	0.11	851.56
Cacaopera	36.93	0.12	943.52
San Antonio	35.71	0	0
Yamabal	35.44	0.36	1697.56
San Emigdio	34.90	0.19	1253.88
Santa Isabel Ishuatan	33.39	0.93	2891.31
Santa Catarina Masahuat	33.33	0	0
El Rosario	33.33	0	0
Corinto	33.17	0.17	1228.64
Guaymango	32.59	0.05	660.45
Ojos De Agua	31.80	0	183.61
San Jorge	31.43	0.4	2010.22
Jicalapa	31.30	0	0
Guatajiagua	31.18	0.06	756.22
Paraiso De Osorio	31.06	0.87	2995.19
Candelaria	30.93	0.27	1664.83
San Julian	30.66	0.09	986.62
Jujutla	30.00	0.17	1390.04
Santa Elena	29.72	0	230.38
San Pedro Puxtla	29.41	0	0
Lislique	29.29	0.09	997.17
San Francisco Menendez	29.05	0.12	1194.37
El Triunfo	28.60	0	0
San Lorenzo	28.57	0	0
Yoloaiquin	28.57	0	0
Chilanga	28.38	0.22	1639.04
San Pedro Masahuat	28.21	0.18	1522.45
San Cristobal	28.04	0.08	1037.53
San Fernando	27.58	1.01	3635.03
Caluco	27.30	0.8	3285.41

Zaragoza	27.26	0.09	1069.47
San Ramon	27.15	0.82	3331.39
El Rosario	27.13	0.46	2511.01
San Miguel De Mercedes	27.09	0.92	3536.05
Cuisnahuat	26.84	0.56	2782.51
Nahulingo	26.67	0	0
San Gerardo	26.67	0	0
Mercedes Umaña	26.62	0.07	1010.14
San Isidro	26.41	0.9	3598.76
Poloros	26.24	0.2	1720.13
Tacuba	26.24	0.37	2324.98
San Antonio Los Ranchos	26.09	0.81	3453.11
El Congo	26.01	0.15	1506.73
Perquin	26.00	0.69	3184.48
El Paraiso	25.97	0.33	2200.28
San Luis De La Reina	25.76	0.59	2979.83
Tepecoyo	25.67	0	218.9
San Luis Del Carmen	25.55	0.88	3681.56
Nueva Guadalupe	25.49	0.04	746.14
Alegria	25.46	0.06	961.09
Santa Cruz Michapa	25.24	0.16	1569.17
Nombre De Jesus	25.05	0.17	1633.39
Cinquera	25.02	0.08	1143.79
Santa Cruz Analquito	25.00	0	0
Concepcion Batres	25.00	0	0
San Lorenzo	24.94	0.66	3251.92
Bolivar	24.88	0.02	596.23
Tejutla	24.86	0	0
Santo Tomas	24.81	0.09	1225.43
San Francisco Morazan	24.81	0.85	3712.89
Sacacoyo	24.81	0.15	1586.4
Ilobasco	24.64	0.05	898.87
San Buena Ventura	24.51	0.81	3661.53
Sociedad	24.35	0.07	1073.54

San Rafael Cedros	24.33	0.22	1938.82
Verapaz	24.32	0.02	541.36
Yucuaiquin	24.22	0	268.4
San Francisco Chinameca	24.19	0.8	3700.44
San Agustin	24.17	0.81	3724.2
Ahuachapan	24.16	0.09	1271.73
Santa Maria Ostuma	24.13	0.39	2600.39
Tenancingo	24.12	0.79	3681.28
Torola	23.97	0.07	1138.74
El Divisadero	23.93	0.04	784.61
Jerusalen	23.90	0.85	3860.43
San Antonio Masahuat	23.65	0.84	3872.35
Dolores	23.47	0.16	1709.73
Las Flores	23.41	0.83	3880.89
Salcoatitan	23.29	0.06	1057.2
Juayua	23.27	0.43	2814.58
San Ildefonso	23.25	0.46	2907.78
San Luis La Herradura	23.25	0.25	2129.57
Joateca	23.08	0	0
Ciudad Barrios	23.07	0.13	1549.91
Nahuizalco	22.92	0.05	947.47
San Antonio Pajonal	22.84	0.47	3009.31
Concepcion De Ataco	22.83	0.41	2791.82
Ozatlan	22.80	0.79	3905.35
Colon	22.77	0.06	1039.59
Tamanique	22.72	0.79	3918.33
Nueva Trinidad	22.66	0.84	4035.22
San Antonio Del Monte	22.54	0.12	1560.96
Santiago Texacuangos	22.53	0.21	2044.23
Suchitoto	22.52	0.1	1400.03
Jiquilisco	22.41	0.05	974.12
Coatepeque	22.28	0.06	1072.29
San Juan Tepezontes	22.25	0.88	4213.72
San Fernando	22.22	0	0
Cancasque	22.18	0.95	4391.26

Jocoaitique	22.16	0.59	3468.21
Nueva Esparta	21.91	0.37	2784.65
Zacatecoluca	21.87	0.05	1057.49
California	21.83	1.11	4820.92
Carolina	21.77	0.06	1161.72
San Sebastian	21.75	0.22	2167.56
Tepetitan	21.74	0.09	1412.57
Citala	21.70	0.02	697.56
Tecoluca	21.66	0.22	2157.34
San Pablo Tacachico	21.52	0.14	1719.26
El Carrizal	21.51	0	0
San Francisco Javier	21.43	0	0
Intipuca	21.43	0	0
Lolotique	21.32	0.24	2298.25
El Transito	21.22	0.16	1871.22
San Jose Guayabal	21.20	0.32	2674.21
Ereguayquin	21.14	0.79	4217.07
San Alejo	21.12	0.13	1721.35
La Libertad	21.06	0.04	967.35
San Isidro	21.01	0.1	1526.91
Nueva Granada	20.95	0.8	4282.06
Moncagua	20.85	0.19	2096.52
San Luis Talpa	20.71	0.09	1430.77
Sesori	20.63	0.21	2243.83
El Porvenir	20.62	0.04	919.42
San Vicente	20.59	0.05	1056.03
San Juan Nonualco	20.51	0.47	3347.53
San Cayetano Istepeque	20.25	0.03	812.24
Acajutla	20.22	0.12	1734.46
Guadalupe	20.12	0.15	1935.05
El Paisnal	20.04	0.2	2227.36
Turin	20.00	0	0
Chiltiupan	20.00	0	0
Victoria	19.97	0.15	1922.88
Texistepeque	19.89	0.02	698.64

Oscicala	19.86	0.17	2058.64
Azacualpa	19.84	0.9	4776.82
Guazapa	19.77	0.08	1435.85
Izalco	19.71	0.18	2135.38
Puerto El Triunfo	19.68	0.18	2148.04
Santa Clara	19.65	0.87	4758.2
Huizucar	19.64	0.79	4525.09
Arcatao	19.59	1.04	5212.5
San Pedro Perulapan	19.53	0.24	2525.96
Panchimalco	19.51	0.06	1210.18
San Rafael Obrajuelo	19.35	0.78	4560.99
Talnique	19.15	0.86	4833.91
Conchagua	19.13	0.04	1092.79
Candelaria De La Frontera	19.10	0.03	872.61
Lolotiquillo	18.83	0.24	2596.62
San Ignacio	18.80	0.22	2502.43
Chalchuapa	18.79	0.07	1402.31
Santa Rosa Guachipilin	18.71	0.17	2175.34
Jutiapa	18.49	0.28	2864.67
Monte San Juan	18.45	0.44	3585.69
Concepcion De Oriente	18.41	0.32	3073.36
San Sebastian Salitrillo	18.28	0.24	2674.73
San Juan Opico	18.27	0.07	1494.3
La Palma	18.23	0.14	2064.86
San Martin	18.21	0.06	1328.26
Las Vueltas	18.18	0	0
Comacaran	18.18	0	0
Ciudad Arce	18.13	0.07	1494.89
Jucuaran	18.07	0.19	2386.75
Apopa	18.05	0.07	1435.17
San Juan Talpa	18.03	0.35	3291.5
Chinameca	17.98	0.14	2079.15
Yayantique	17.89	0.03	909.83
Santiago Nonualco	17.85	0.05	1189.06
San Isidro Labrador	17.75	1.05	5781.15

Santa Maria	17.73	0.17	2338.84
Aguilares	17.72	0.02	866.65
Meanguera	17.57	0.34	3341.13
San Rafael Oriente	17.56	0.23	2702.57
Chirilagua	17.48	0.29	3107.79
Cojutepeque	17.44	0.07	1498.15
San Francisco Gotera	17.27	0.05	1337.43
Atiquizaya	17.05	0.06	1462.68
Sensuntepeque	16.96	0.05	1299.91
Santa Ana	16.71	0.07	1540.87
Nueva Concepcion	16.66	0.09	1806.93
Comasagua	16.59	0.32	3429.01
Anamoros	16.33	0.13	2233.02
Metapan	16.21	0.02	966.2
Olocuilta	16.11	0.06	1490.57
Ciudad Delgado	15.90	0.11	2127.08
Sonsonate	15.72	0.07	1678.74
Rosario De Mora	15.66	0.27	3294.92
Concepcion Quezaltepeque	15.61	0.02	909.98
Nejapa	15.59	0.13	2300.98
Chapeltique	15.48	0.24	3172.32
Quelepa	15.39	0.83	5920.96
Jayaque	15.38	0	0
La Laguna	15.38	0	0
Apastepeque	15.37	0.21	3006.43
San Dionisio	15.36	0	0
Tecapan	15.34	0	0
La Reina	15.29	0	413.2
Usulutan	15.24	0.07	1763.51
San Francisco Lempa	15.22	1.12	6954.45
La Union	14.91	0.05	1531.11
Cuscatancingo	14.88	0.1	2083.72
Ilopango	14.74	0.05	1580.26
Tonacatepeque	14.65	0.07	1783.97
El Sauce	14.58	0.31	3801.39

San Pedro Nonualco	14.29	0	0
San Carlos	13.97	0.05	1625.19
Quezaltepeque	13.70	0.04	1514.01
San Marcos	13.70	0.04	1513.15
San Salvador	13.69	0.12	2544.27
Cuyultitan	13.48	0.81	6686.2
Santa Rosa De Lima	13.47	0.06	1887.03
Agua Caliente	13.44	0.25	3713.86
San Antonio De La Cruz	13.43	0	494.04
El Carmen	13.26	0.34	4429.84
Tejutepeque	12.73	0.2	3504.05
El Rosario	12.22	0.33	4695.48
San Jose Villanueva	11.76	0	0
El Refugio	11.55	0.12	2982.17
Armenia	11.44	0.03	1621.58
Soyapango	11.41	0.07	2294.01
El Carmen	11.15	0.07	2373.6
Santa Tecla	10.46	0.06	2367.25
Oratorio De Concepcion	10.35	0.05	2102.69
San Miguel	10.33	0.03	1727.88
Santiago De Maria	10.14	0.25	4942.99
Guacotecti	10.10	0.11	3248.53
Delicias De Concepcion	10.06	0.03	1816.73
San Esteban Catarina	10.00	0	0
San Jose	10.00	0	0
San Miguel Tepezontes	9.11	0	0
Santa Rita	9.09	0	0
Mejicanos	8.37	0.04	2409.41
Uluazapa	8.33	0	0
Nuevo Cuscatlan	8.18	0.85	11243.48
Pasaquina	8.13	0.09	3738.2
Jocoro	7.75	0.07	3476.52
Santiago De La Frontera	7.69	0	0
San Matias	7.69	0	0
Teotepeque	7.69	0	0

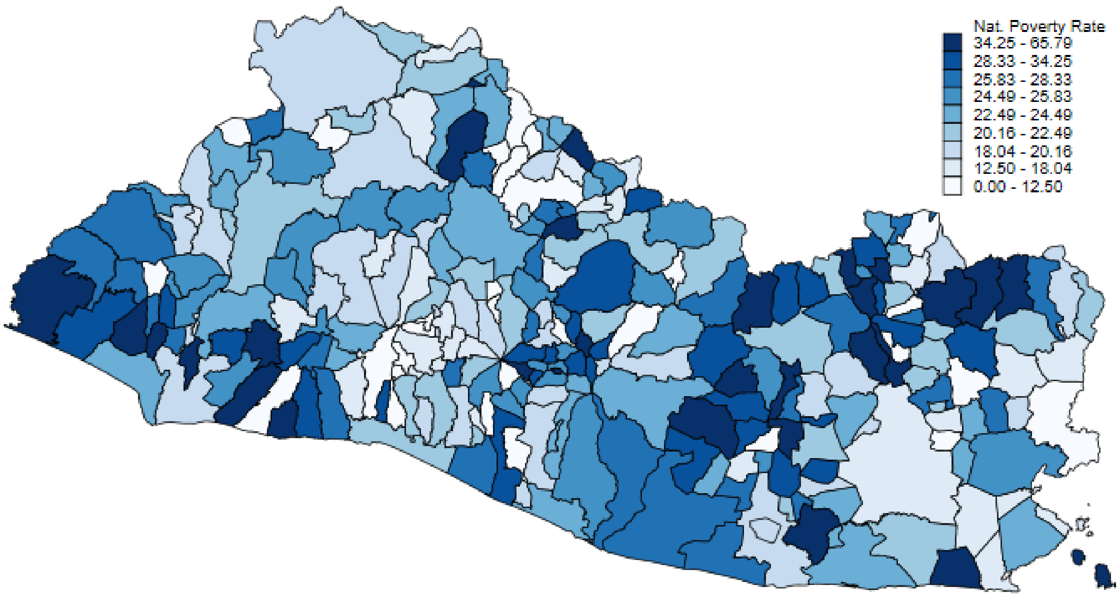
Tapalhuaca	7.69	0	0
Arambala	7.69	0	0
San Bartolome Perulapia	7.17	0	0
Dulce Nombre De Maria	7.16	0	0
Sensembra	7.14	0	0
Ayutuxtepeque	6.97	0.05	3150.42
Sonzacate	6.44	0.04	2999.35
Antiguo Cuscatlan	6.06	0.05	3724.27
Masahuat	5.56	0	0
Apaneca	5.26	0	0
Chalatenango	5.09	0.02	2436.89
San Rafael	3.66	0.05	5989.92
Comalapa	0.00	0	0

Notes: The table presents results from a Fay-Herriot model using an ampl estimation technique ofr variances. Column 1 reports the estimated moderate poverty rate per municipality, Column 2 the related mean-squared errors (MSE) and Column 3 the coefficients of variation (CVs). Source: World Bank estimates based on EHPM (2019). Source: Census (2007) and EHPM (2019).

Annex 8 – Poverty Maps using Poverty Headcount Ratios

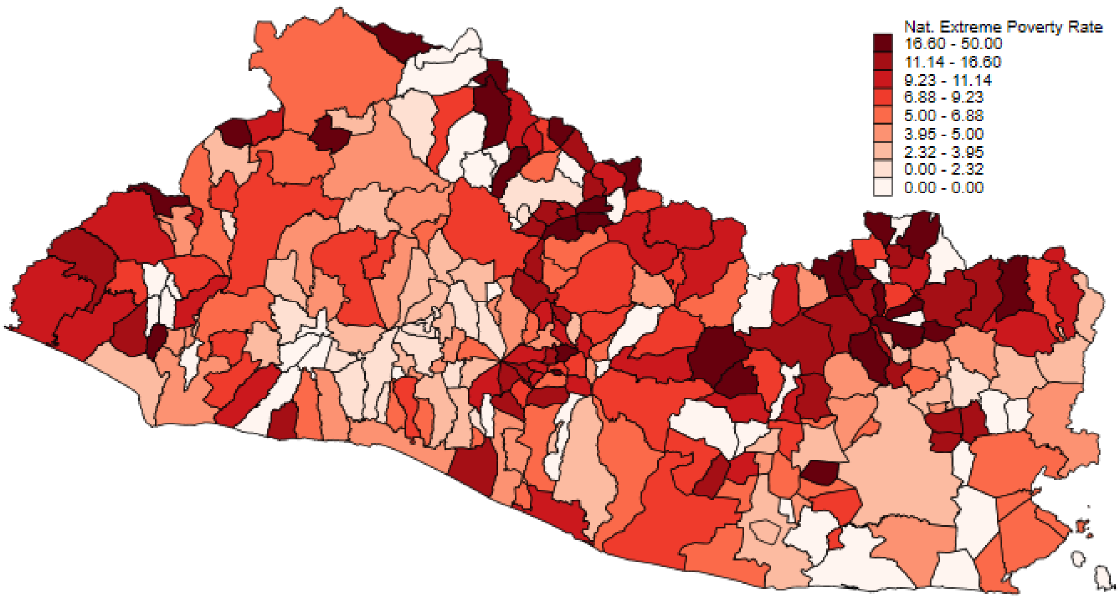
The following presents municipal poverty maps relying on poverty headcount ratios. While the previous maps rely on household estimates, these maps rely on population estimates.

FIGURE A5: SMALL AREA ESTIMATES OF THE MODERATE POVERTY HEADCOUNT RATE AT THE MUNICIPALITY LEVEL (2019)



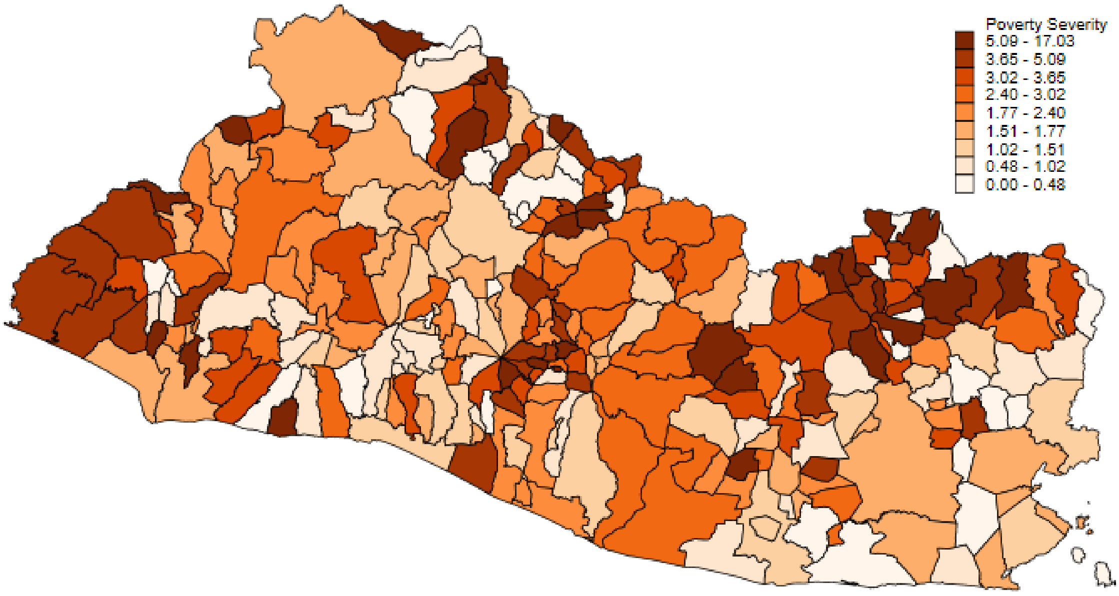
Source: EHPM (2019) and Census (2007). Poverty is measured at the population level and using national poverty lines.

FIGURE A6: SMALL AREA ESTIMATES OF THE EXTREME POVERTY HEADCOUNT RATE AT THE MUNICIPALITY LEVEL (2019)



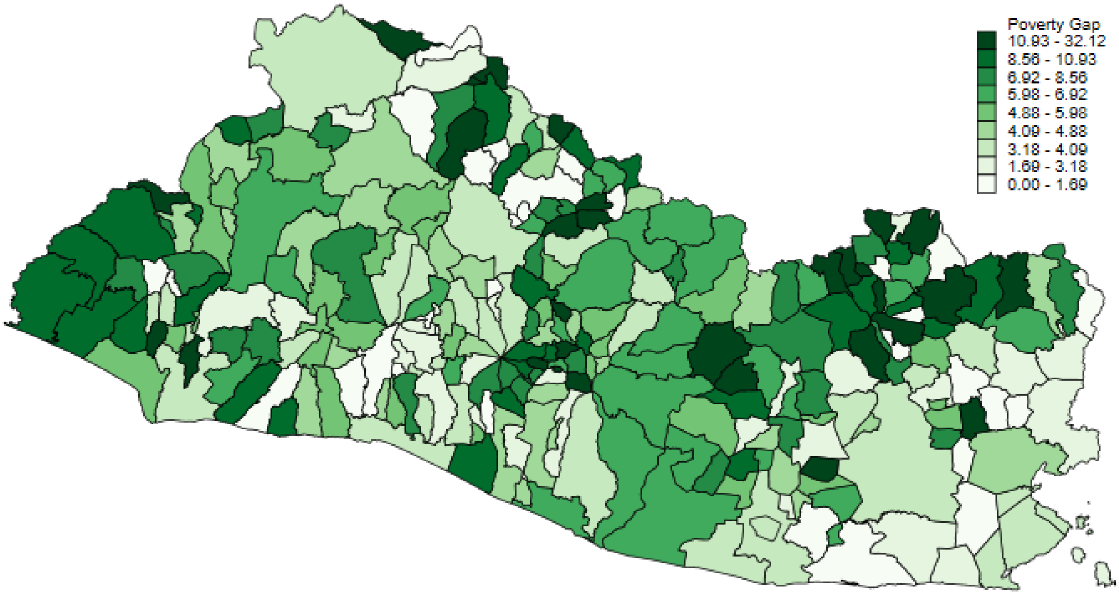
Source: EHPM (2019) and Census (2007). Extreme poverty is measured at the population level and using national poverty lines.

FIGURE A7: SMALL AREA ESTIMATES OF THE POVERTY SEVERITY AT THE MUNICIPALITY LEVEL (2019)



Source: EHPM (2019) and Census (2007). Poverty severity is measured at the population level and using national poverty lines.

FIGURE A8: SMALL AREA ESTIMATES OF THE POVERTY GAP AT THE MUNICIPALITY LEVEL (2019)



Source: EHPM (2019) and Census (2007). Poverty gaps are measured at the population level and using national poverty lines.