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ABSTRACT

Sustaining Poverty Gains: A Vulnerability Map to Guide Social Policy*

Poverty maps are a useful tool for the targeting of social programs on areas with high concentrations of poverty. However, a static focus on poverty ignores the temporal dimension of poverty. Thus, current nonpoor households still face substantial welfare volatility and are at risk of becoming poor in the face of shocks. We combine the methods of poverty mapping and vulnerability estimation to create highly disaggregated vulnerability maps. The maps include predictions of the share of chronically poor households (poverty-induced vulnerability)—the focus of traditional poverty maps—and the share of households showing a significant probability of falling into poverty (risk-induced vulnerability). As an application of the method, we estimate a vulnerability map Senegal that provides quotas for the expansion of the social registry. Accounting for the poor and the population at risk of poverty implies, in practice, the expansion of coverage into urban and periurban areas that tend to experience lower poverty rates. Also, the inclusion of nonpoor households serves as a first step toward supporting a dynamic social registry.

JEL Classification: C15, R11, I32

Keywords: poverty, vulnerability, poverty maps, targeting, social protection

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1. Introduction

Most social programs in developing countries are based on the explicit objective of reducing poverty (Elbers et al. 2007). Targeting is centered on successfully identifying poor households. However, this prioritization ignores the intertemporal dimension of poverty. Nonpoor households are also at risk of becoming poor. The exposure to natural shocks, pandemics, economic crises, and climate change means there is a need to rethink social assistance to cover both the poor (improving incomes and therefore reducing poverty) and providing insurance against risks (reducing the likelihood of falling into poverty). As an integral part of designing a new generation of social assistance programs that aim to sustain previous poverty gains, it is necessary to develop new targeting mechanisms that cover currently poor household and those that are vulnerable to poverty.

We develop a novel method for producing vulnerability maps for small administrative areas combining information from a household survey and a national census. The approach integrates insights and techniques from the literature on small area estimation and the vulnerability to poverty. While conventional poverty mapping focuses on estimating the share of households that are currently poor (poverty-induced vulnerability), the proposed method also enables the estimation of the share of nonpoor households that are highly likely to fall into poverty (risk-induced vulnerability). Following the vulnerability literature, the analysis relies on a definition whereby households are considered at risk of poverty if the predicted probability that a household will become poor in the next two periods is above 0.5. A complete description of poverty and risk-induced vulnerability is provided in Günther and Harttgen (2009); implementation details can be found in the methodological section.

The application of the method described here involved the creation of a comprehensive poverty and vulnerability map of Senegal. The map offers a detailed spatial analysis of poverty-induced and risk-induced vulnerability across the country. The overarching findings indicate elevated poverty rates in rural areas and the southeastern regions. However, the results also reveal a more nuanced picture of poverty and vulnerability. Specifically, though they exhibit lower poverty rates, urban communes account for most of the households that face a considerable risk of falling into poverty.

The ability of the method to identify not only pockets of poverty, but also concentrations of highly vulnerable populations means that the method can be used as the basis for determining commune-level eligibility quotas for the expansion of the national social registry, the *Registre National Unique* (RNU). Taking advantage not only of poverty rates, but also vulnerability rates allowed the RNU to support a safety net that protects previous gains in reducing poverty. The aim of targeting the program on the population that is currently experiencing poverty is to reduce deprivation now. However, risk-induced vulnerability involves fluctuations in welfare, that is, the likelihood of households currently above the poverty line to fall into poverty after exposure to unforeseen shocks. In the realm of social assistance, this means the method described here can help enhance the targeting of the RNU to contribute more effectively to the ability of households to cope with risks, a crucial step toward increasing the resilience of the population to risks and shocks (Skoufias, Vinha, and Beyene 2024).

Accounting not only for poor households, but also for households at risk of becoming poor reflects a recognition that expanding the safety net to cover a portion of nonpoor households is essential to sustaining the gains of past spells of poverty reduction during economic downturns and shocks. In practice, using vulnerability rates along with poverty rates, instead of poverty rates alone, increases program eligibility among households in urban and periurban communes. For instance, urban Dakar's eligibility rises by 84 percent with respect to the eligibility rate if only the poverty rate is considered. Nonetheless, rural areas still exhibit consistently higher program eligibility rates because of their comparatively high poverty rates. Taking risk-induced vulnerability into account broadens the scope of social protection to encompass households that, in the face of a shock, could slip into poverty, a scenario that the current targeting mechanism may not address sufficiently.

The paper is structured as follows. Section 2 explains the use of poverty maps in support of the targeting of social programs, and a discussion of the concept of the vulnerability to poverty. Section 3 describes the data and the methods used in estimating poverty and vulnerability and clarifies the assumptions involved in adding vulnerability to the concepts behind poverty mapping. Section 4 provides estimates of poverty and vulnerability using data on Senegal, the distribution of communes by poverty- and risk-induced vulnerability rates, and several robustness checks. Section 5 provides background on the RNU, the recent expansion of the registry, and the operational implications of using vulnerability as part of the eligibility quota system. The last section concludes.

2. Expanding poverty mapping to measure vulnerability

Targeting in social programs

The use of targeting in antipoverty programs in the context of limited resources has been widely studied, and there is a general consensus on the positive relationship between effective targeting and a program's impact (Alatas et al. 2012; Brown, Ravallion, and van de Walle 2016; Coady, Grosh, and Hoddinott 2004).

However, targeting is expensive in monetary, administrative, and political terms. The production of data is costly; the collection of data takes time; and the exclusion of some applicants may have political and social consequences. Therefore, targeting always involves a trade-off between errors of inclusion, errors of exclusion higher implementation costs (Morley and Coady 2003). Among the strategies in social program targeting, geographical targeting exploits information on variations in poverty rates by location to channel resources toward regions with the highest poverty rates.

Nonetheless, the implementation of geographical targeting is not a trivial endeavor because household surveys alone do not usually provide information to support accurate poverty estimates across small administrative units. Poverty measures derived from survey data are usually either too noisy or lack adequate coverage. Small area estimation techniques have been developed as a way to produce highly disaggregated poverty rates by imputing poverty into a population census.[1] The poverty maps created through these techniques provide relatively precise estimates of poverty and have been used in several countries to channel resources toward localities in which poverty is more concentrated.

There are two main approaches to the application of poverty maps in social program targeting. In the single-step approach, localities with the highest poverty rates are identified and prioritized in the disbursement of resources.[2] Evidence shows that the effectiveness of this process increases in cases where poverty is more spatially concentrated (Elbers et al. 2007). An alternative approach, which is used in the case of the national social registry (RNU) in Senegal, consists of two steps. First, the information supplied through the poverty map is used to develop eligibility quotas by location. These quotas are then processed using additional tools to identify program recipients. Including vulnerability on the targeting raises program's effectiveness because the share of the population living above the poverty line that may be only a shock away from becoming poor. Moreover, this share is likely to increase if the poverty rate has recently declined.

The analysis incorporated the notion of vulnerability to poverty into the estimation of poverty maps by combining small area estimation techniques with methods derived from the literature on vulnerability to poverty. Among the many approaches available for estimating vulnerability, the analysis drew on the approach of Günther and Harttgen (2009), which enables the calculation of welfare variability based solely on cross-sectional data. This approach divides vulnerable households into two groups: first, poverty-

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[1] For a complete review of the relevant literature, see Rao and Molina (2015). See Molina, Corral Rodas, and Nguyen (2022) for a review of the application to poverty measurement.
[2] Targeting areas where poverty rates are highest helps minimize errors of inclusion—that is, some households that are not poor are included in a program by error—because these areas have smaller shares of nonpoor households.

induced vulnerability, which encompasses chronically poor households, and, second, risk-induced vulnerability, which covers households that are not now poor, but that face a substantial risk of falling into poverty. The approach is widely favored among practitioners because it facilitates the generation of vulnerability estimates in the absence of panel data. Notable instances of such an application are described by Atamanov, Mukiza, and Ssennono (2022), Rude and Robayo-Abril (2023), and Skoufias, Vinha, and Beyene (2024).

While the Günther and Harttgen (2009) method offers the advantage of requiring only a single cross-sectional household survey, the vulnerability estimates are representative at the same geographical level as the household survey. The method thus does not provide vulnerability rates at the spatial resolution necessary to implement the effective, highly disaggregated targeting sought for social programs. The proposed approach overcomes this limitation by recovering poverty rates and the shares of households at risk of becoming poor from welfare indicators imputed from census data. This information is then used to create a highly spatially disaggregated vulnerability map. As in Günther and Harttgen (2009), a household is considered vulnerable if it exhibits a probability of falling into poverty of more than 50 percent over the next two years. Methodological details are provided in the data and methods section.

The concept of vulnerability

According to Dercon (2005, 2010), vulnerability is often defined as "the risk of households falling into or remaining in poverty because of either idiosyncratic hazards (due to characteristics of the individual household) or covariate aggregate hazards (external to the household)." This definition highlights several characteristics of vulnerability. First, both poor and nonpoor households can be vulnerable. Second, risk is a critical component of vulnerability. Third, risk is related to household- and community-specific characteristics.

Transforming this general definition into measurable concepts requires a precise understanding and the modeling of the income-generating function of households, particularly the expected mean and variance of income and consumption under different realizations of the potential shocks. Overall, there are three common empirical approaches to the measurement of vulnerability. These are known as the vulnerability to expected poverty, the vulnerability to expected utility, and the uninsured exposure to risk. Pritchett, Suryahadi, and Sumarto (2000) were among the first to introduce the concept of vulnerability to expected poverty, which defines vulnerability as the probability that a household will fall below a specific threshold, often the poverty line.[3] Vulnerability to expected utility estimates the intensity of vulnerability by measuring the gaps between the utility attained under conditions of certainty and the expected utility (Calvo and Dercon 2013; Gallardo 2020; Günther and Maier 2014; Ligon and Schechter 2003; Magrini, Montalbano, and Winters 2018). Lastly, vulnerability as uninsured exposure to risk estimates the degree to which exogenous shocks reduce household consumption (Amin, Rai, and Topa 2003; Cafiero and Vakis 2006; Cochrane 1991; Dutta, Foster, and Mishra 2011; Jalan and Ravallion 1999; Povel 2015; Townsend 1994). Despite their methodological differences and various data requirements, all these methods aim to estimate expected household consumption and its variance.[4]

Estimating the mean and variance of household consumption is challenging because of the intertemporal nature of vulnerability. Long panel data at the household level are necessary to obtain accurate estimates, but such data are often unavailable in developing countries. If panel data are not available, household-specific mean consumption and its variance may be estimated from cross-sectional data under certain restrictions. Chaudhuri, Jalan, and Suryahadi (2002) propose a method for estimating the mean and variance of household consumption on cross-sectional data by assuming that the variance of consumption can be modeled as a function of observable household and community characteristics, while the error term in a consumption regression captures the unexplained variability caused by household- and community-specific income variance. Given the low availability of panel data, it is not surprising that a large number of published studies rely on cross-sectional data to estimate vulnerability (Chaudhuri 2003; Christiaensen and Subbarao 2005; Dang and Lanjouw 2014; Günther and Harttgen 2009; Kamanou and Morduch 2002; Suryahadi and Sumarto 2003; Tesliuc and Lindert 2004).[5]

3. Data and methods

Estimating a map of poverty and vulnerability requires a household survey and a population census. In the case here, the map is constructed using the Harmonized Survey on Household Living Standards 2018–

[3] This measure of vulnerability has an intuitive interpretation: the probability of falling into poverty. However, its simplicity comes at the cost of violating desirable axiomatic properties (see Calvo and Dercon 2005).
[4] See Gallardo (2018) for an in-depth review of the literature.
[5] Following Günther and Harttgen (2009), various studies apply multilevel models to estimate the vulnerability to poverty in various countries. Examples include Échevin (2014), who applies a two-level model to study idiosyncratic and covariance shocks in Haiti; Mina and Imai (2017) and Pham, Mukhopadhaya, and Vu (2021), who apply a three-level model in the Philippines and Viet Nam, respectively, and Skoufias, Vinha, and Beyene (2024), who examine the vulnerability to poverty in the drought-prone regions of Ethiopia.

2019.[6] The survey collected information on household and dwelling characteristics, educational attainment, asset ownership, and access to services. It forms the basis for constructing a household consumption aggregate and estimating the country's official poverty rate. The survey is representative at the regional (14 regions) and the national level. It contains information on 7,156 households (66,120 individuals) distributed across rural (55 percent) and urban areas (45 percent).

For the population census, the analysis relies on the 2013 Population and Housing Census.[7] The census questionnaire includes information on household characteristics and living conditions, but does not cover household expenditures, which are necessary for the calculation of poverty. Appendix A, table A.1 compares the variables available in the census and the household survey. The comparison is critical because a fundamental assumption of small area estimation is that the survey used to model welfare is representative of the entire population. Consequently, the objective is to ensure that the data in both the survey and census bear a close resemblance. The next subsections explain vulnerability estimation in the context of small area estimation techniques. The paper then describes how this compares with the Günther and Harttgen (2009) method, which relies solely on survey data.

Estimation of vulnerability: adding vulnerability to poverty map

The first step is to estimate a function of the household income-generating function in the survey data. The regression uses a multilevel model because this allows the decomposition of the unexplained variance of the dependent variable—expenditure per capita in the case here—into a household (idiosyncratic) and a community (covariate) component. To illustrate the estimation formally, suppose $h = 1, \ldots ; I$ represents households, while $c = 1, \ldots ; C$ represents communes; and every household h is nested withing a community c. Equation 1 summarizes the model for the log of household per capita expenditure $ln\ (y_{ch})$ as a function of covariates x_{ch}, which vary by household h in community c.[8]

[6] EHCVM (Enquête Harmonisée sur le Conditions de Vie des Ménages 2018–2019, Harmonized Survey on Household Living Standards 2018–2019), Living Standards Measurement Study, World Bank, Washington, DC, https://microdata.worldbank.org/index.php/catalog/4292.
[7] RGPHAE 2013 (2013 Recensement Général de la Population et de l'Habitat, de l'Agriculture et de l'Elevage; Population and Housing Census, 2013) (dashboard), National Agency of Statistics and Demography, Dakar, Senegal, https://www.ansd.sn/enquete-et-etude/recensement-general-de-la-population-et-de-lhabitat-de-lagriculture-et-de-lelevage.
[8] Even though it is popular, the logarithmic transformation is not always ideal, especially for small values of welfare where it can produce left skewed distributions. The analysis implemented a data-driven approach to transformations by Box-Cox tests and a log-shift transformation, with the objective of selecting one that reduces departures from normality (see Corral Rodas et al. 2022). Simulation studies show that data-driven transformations may reduce bias and noise caused by departures from normality (see Corral Rodas et al. 2022; Tzavidis et al. 2018).

$$ln\,(y_{ch}) = \beta_{0c} + \beta_1 x_{ch} + \eta_c + \varepsilon_{ch}\ with\ \ h = 1, \ldots, N_c\,; c = 1, \ldots, C\,(1)$$

The error component, η_c, represents a community-level random effect that shifts the intercept of the regression up or down for each commune, while the household idiosyncratic error within communes (ε_{ch}) is assumed to be independent across all households in the sample. Both η_c and ε_{ch} are assumed to be normally distributed as in $\eta_c \sim N(0, \sigma_\eta^2)$, and $\varepsilon_{ch} \sim N(0, \sigma_\varepsilon^2)$.

In the poverty mapping literature, multilevel models are often called nested-error models. Among several estimation strategies, Empirical Best (EB) methods are preferred as they provide accuracy and efficiency gains over previous applications, such as Elbers, Lanjouw, and Lanjouw (2003), allow for the inclusion of random location effects and the recovery of location and household-specific idiosyncratic errors (Corral Rodas, Molina, and Nguyen 2021). In the nested-error model (Battese, Harter, and Fuller 1988), welfare (and poverty) are imputed into census data by using the census empirical best approach of Corral Rodas, Molina, and Nguyen (2021).

In the application here, model fitness is maximized by estimating equation 1 independently for each region in Senegal. For each region, the estimation steps detailed in Corral Rodas et al. (2022) are followed, in particular: (1) using the variance inflation factor (VIF) to remove highly collinear variables, (2) estimating a separate regression for each region, (3) dropping high-leverage observations, and (4) avoiding overfitting by limiting the set of right-hand-side variables using a Lasso regression.[9] The model parameters and error terms allow the consumption and probability of falling into poverty ($\widehat{v_{ij}}$) of every household in the 2013 census to be predicted using equation (2). The predicted probability decreases with the predicted household consumption and increases on the variance of the errors.[10] As in Günther and Harttgen (2009), households exhibiting a probability of becoming poor above 50 percent (at least once) in the next two years are considered vulnerable, and the group of vulnerable households includes those households predicted to be poor (poverty-induced vulnerability) and those households that are nonpoor, but are at risk of poverty (risk-induced vulnerability).

[9] Leverage measures the influence on the fitted values of a given observation. Following Corral Rodas et al. 2022, the analysis here controls for high-leverage observations by eliminating observations with leverage above $(2k + 2)/n$. Because this incurs a loss of information, the predicted poverty rates in the new sample are checked to ensure they are similar to the original data. The census and survey questionnaires had 43 variables in common. The lasso selection process yields a selected set of covariates, although some of the included covariates may be nonsignificant. Reducing the number of variables avoids situations where the number of right-hand-side variables is large relative to the number of observations in a region, especially in regions with smaller populations.

[10] See Corral Rodas, Molina, and Nguyen (2021) for the estimation of $\widehat{\eta_c}$.

$$\widehat{v_{\iota c}} = P(lny_{ch} < lnz \mid X, Z) = \phi\left(\left(lnz - \left(\widehat{\beta_{0c}} + \widehat{\beta_1}x_{ch} + \widehat{\eta_c}\right)\right) \Big/ \sqrt{\hat{\sigma}^2_{\eta_c} + \hat{\sigma}^2_{\varepsilon_{ch}}}\right) \qquad (\mathbf{2})$$

There are several assumptions embedded in the model. First, it is assumed that equation (1) represents the true household welfare-generating function and is stable over time, that is, the returns to characteristics and the distribution of unobservable factors are time invariant. Second, the intertemporal variance in consumption can be recovered from the cross-sectional variation across households with the same characteristics.[11] Third, measurement errors are not driving the consumption variance estimates. Fourth, the model calibration maximizes the model's fit (measured by the R-squared), and the precision of coefficients.[12] Finally, the model assumes that the probability of falling into poverty depends on a covariate and idiosyncratic component of the predicted variances. However, the model does not identify shocks directly, and it is assumed that covariate effects are not correlated across communities.[13]

Estimation of vulnerability: comparison with the Günther-Harttgen approach

The Günther and Harttgen (2009) model uses only household survey data and estimates a model that includes household composition, education of the household head, asset ownership, access to services, dwelling characteristics, and labor market information. Because our estimation is restricted to the variables available in the survey and census data, the analysis relies on a smaller set of variables that, in particular, exclude labor market information.

The main difference in terms of econometric modeling is that the original Günther and Harttgen (2009) method is a two-level model that, in addition to a random intercept, also includes a random slope. This produces three error terms: a household-level error that captures idiosyncratic variance (ε_{ch}) and two community-level errors, $u_{1c}X_{ch}$ and u_{0c}, for covariate variance. In practice, this implies an equation system whereby both β_{0c} and β_{1ch} have a fixed component (γ_{00} and γ_{10}) that varies across communities

[11] As explained by Skoufias, Vinha, and Beyene (2024), the validity of this assumption can only be assessed empirically through multiple rounds of panel data and a comparison of the cross-sectional estimates of the variability of consumption among households with the same characteristics.

[12] Günther and Harttgen (2009) carry out simulations on alternative measurement error assumptions. The approach here in variable selection and fitting models at the lowest level of representativity of the household survey data is considered a best practice.

[13] As noted by Skoufias, Vinha, and Beyene (2024), community-level errors are likely to be correlated. For instance, in the case of climatic or large-scale shocks impacting large geographic areas, it is reasonable to assume that there are spatial clusters in which community errors are correlated. It is possible to impose additional structure in the model's estimation to include this correlation structure in a correlated random coefficient estimation. For the implementation of the correlated random coefficient model, see Barriga-Cabanillas et al. (2018).

and are interacted with community characteristics Z_c. The system of equations used in the original Günther and Harttgen (2009) implementation is described by equations 3, 4, and 5.

$$ln(y_{ch}) = \beta_{0c} + \beta_{1c}X_{ch} + \varepsilon_{ch}, h = 1, \ldots, N_c; c = 1, \ldots, C \quad (3)$$

$$\beta_{0c} = \gamma_{00} + \gamma_{01}Z_c + u_{0c} \quad (4)$$

$$\beta_{1c} = \gamma_{10} + \gamma_{11}Z_c + u_{1c} \quad (5)$$

Substituting equations 4 and 5 into equation 3 yields equation 6 in which the constant and slope terms vary with community characteristics ($\gamma_{11}Z_cX_{ch}$) and community unobserved factors ($u_{1c}X_{ch}$). However, if u_{1c} and γ_{11} are assumed to be zero and no commune-level characteristics are included, the system reduces to equation 1.[14]

$$ln(y_{ch}) = \gamma_{00} + \gamma_{01}Z_c + \left(\gamma_{01} + \gamma_{11}Z_c\right)X_{ch} + u_{0c} + u_{1c}X_{ch} + \varepsilon_{ch} \quad (6)$$

A comparison of equations 1 and 6 provides useful insights. First, although the specification does not include random slopes, the estimation of region-specific models allows, in practice, coefficients to vary entirely across regions, equivalent to interacting every coefficient with a regional dummy.[15] Second, the estimated variance of expenditure across households and communities in Günther and Harttgen (2009) is modeled as a function of household and community characteristics using a linear model described in equation (7).[16]

$$\left(u_{0c} + \varepsilon_{ch}\right)^2 = \theta_0 + \theta_1X_{ch} + \theta_2Z_c + \theta_3X_{ch}Z_c, \quad (7)$$

Third, when imputed to the census, the area-level effects are only available for those geographical areas included in the sampling of the household survey.[17] Considering these points, the robustness check section compares the variance estimates in both models showing that, despite the estimated differences, both methods provide comparable results on the share of the vulnerable population and the ranking of the country's departments.

[14] It is possible to include (commune-level) characteristics interacted with household characteristics in the empirical best models to recover (Z_cX_{ch}). Including commune-level characteristics (Z_c) is optional because it is subject to the availability of statistically representative commune-level variables, which are usually derived from the census.

[15] Even if the same covariates are used as candidates in the Lasso regression, model selection is implemented independently, which might lead to region-specific models.

[16] The analysis obtains empirical best estimates of the random location effects, (u_{0c}) (Rao and Molina 2015). It also modeled for heteroskedasticity in the idiosyncratic portion of the residuals (Elbers, Lanjouw, and Lanjouw 2003).

[17] Estimates for the idiosyncratic and covariate shocks are modeled based on the equations $u_{0c}^2 = \tau_0 + \tau_1Z_c$ and $\varepsilon_{ch}^2 = \theta_0 + \theta_1Z_c + \theta_3X_{ch}Z_c$. In the case of the vulnerability map, an alpha model was implemented for the variance of the idiosyncratic errors because the literature suggests this helps reduce bias and noise in the estimates.

4. Estimating a vulnerability map of Senegal

A vulnerability map is estimated at the commune level. To achieve this, the steps outlined in section 3 were followed, and an individual model was developed to predict household expenditures in each of the country's 14 regions. Appendix A, table A.1 compares the variables available in the census and the household survey, while regressions for each region are illustrated in appendix B, table B.1. The variables used for each of the regions vary, but present consistent coefficients, such as a negative relationship with household expenditure in the case of household size, the dependency ratio, and rural location, a positive correlation with higher educational attainment and asset ownership, and a positive relationship with dwelling conditions and better access to public services, such as piped water. Another measure of the model's performance is how closely poverty estimates in the census data match the poverty rates observed in the household survey. The difference between the observed and predicted poverty rates is less than 1 percent at the national level while in 10 of the 14 regions it is below 5 percent. Yet, all estimates fall within the survey's poverty estimate 95 percent confidence interval (table 1).

Table 1. The observed poverty rate and small area estimation predictions, by region

Region	*Survey*		*Census*	
	Poverty rate (observed)	*Vulnerability (predicted)*	*Poverty rate (predicted)*	*Vulnerability (predicted)*
Dakar	9.0	11.0	9.4	16.0
Diourbel	43.9	60.6	44.7	61.4
Fatick	49.2	74.7	52.6	77.3
Kaffrine	53.0	78.0	54.5	74.0
Kedougou	61.9	82.5	69.0	82.0
Koalack	41.5	58.9	40.6	60.4
Kolda	56.6	83.3	57.2	82.0
Louga	43.4	66.1	45.0	67.0
Matam	47.7	88.1	44.6	89.0
Saint-Louis	40.1	56.0	41.5	55.3
Sedhiou	65.6	89.5	73.0	90.1
Tambacounda	61.9	84.0	60.6	79.4
Thies	34.1	45.7	33.2	51.0
Ziguinchor	51.1	83.0	55.0	72.0
National	37.8	55.9	38.2	55.7

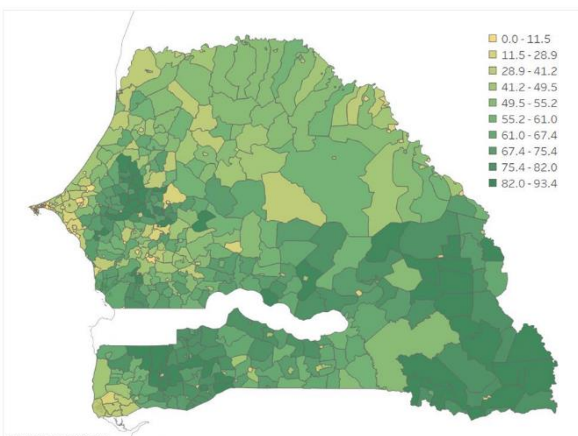
Sources: Calculations using EHCVM (Enquête Harmonisée sur le Conditions de Vie des Ménages 2018–2019; Harmonized Survey on Household Living Standards 2018–2019), Living Standards Measurement Study, World Bank, Washington, DC, https://microdata.worldbank.org/index.php/catalog/4292; RGPHAE 2013 (2013 Recensement Général de la Population et de l'Habitat, de l'Agriculture et de l'Elevage; Population and Housing Census, 2013) (dashboard), National Agency of Statistics and Demography, Dakar, Senegal, https://www.ansd.sn/enquete-et-etude/recensement-general-de-la-population-et-de-lhabitat-de-lagriculture-et-de-lelevage.

Based on the imputed model in the census, the national vulnerability rate is 55.7 percent. This includes 38.2 percent of individuals who are vulnerable because of poverty (poverty-induced vulnerability) and 17.5 percent who are nonpoor but exhibit a high probability of falling into poverty (risk-induced vulnerability). Survey estimates of vulnerability are consistent with the small area estimates, with a predicted aggregate vulnerability rate of 55.9 percent. While there are some differences in the point estimates of regional vulnerability, the census and survey estimates show a similar ranking across regions.

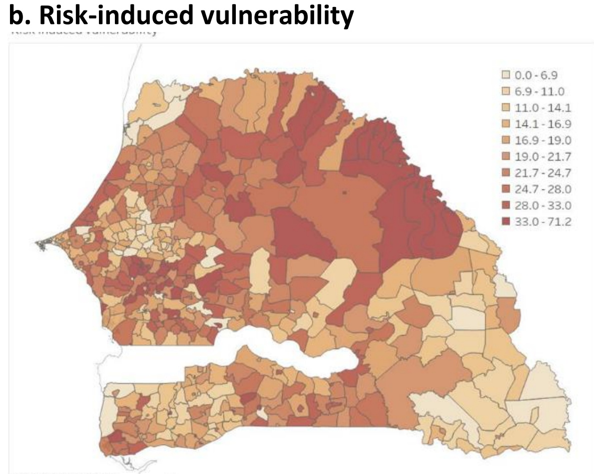
Map 1 displays the poverty-induced vulnerability (panel a) and risk-induced vulnerability (panel b) for all 552 communes in the country. Panel a reveals the spatial concentration of communes with high levels of poverty-induced vulnerability in the southeast and the heterogeneity in the region surrounding Dakar. For instance, poverty incidence ranges from less than 2 percent in the communes of Fann-Point E-Amitié and Mermoz-Sacre-Coeur in the department of Dakar to 37 percent in Yène in the department of Rufisque. Meanwhile, communes with greater risk-induced vulnerability are concentrated in the north of the country. Panel c shows aggregate commune vulnerability.

Map 1. Small area estimates of poverty and risk-induced vulnerability

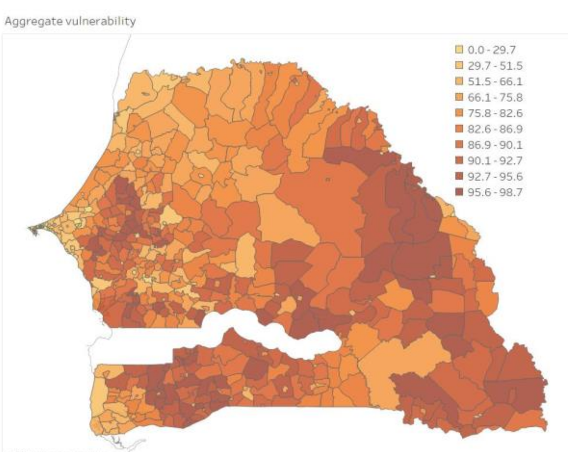
a. Poverty-induced vulnerability



b. Risk-induced vulnerability



c. Total vulnerability

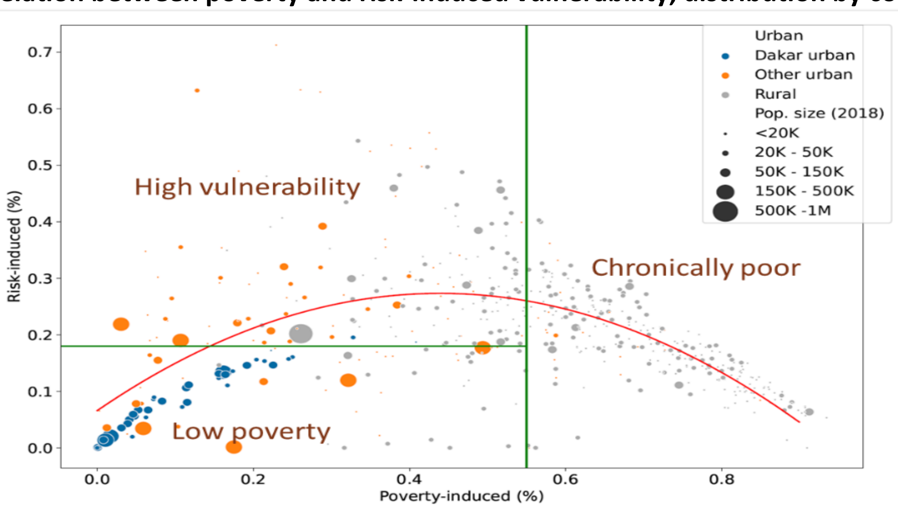


Source: Calculations using EHCVM (Enquête Harmonisée sur le Conditions de Vie des Ménages 2018–2019; Harmonized Survey on Household Living Standards 2018–2019), Living Standards Measurement Study, World Bank, Washington, DC, https://microdata.worldbank.org/index.php/catalog/4292.

Classifying communes according to poverty and vulnerability across Senegal

To illustrate the distribution of vulnerability across the country, the analysis classified communes into three groups according to poverty- and risk-induced vulnerability rates relative to the unweighted national median across communes: low poverty, high vulnerability, and chronically poor. Figure 1, panel a, shows the distribution of poverty and risk-induced vulnerability across communes by population size and urban or rural location. The low-poverty group consists of communes with low poverty-induced and low risk-induced vulnerability (bottom left quadrant). The high-vulnerability group consists of communes with low poverty-induced vulnerability rates, but high rates of risk-induced vulnerability (top left quadrant). Chronically poor communes (right quadrants) exhibit high poverty rates. By construction, this last group includes few households that are at risk of poverty.

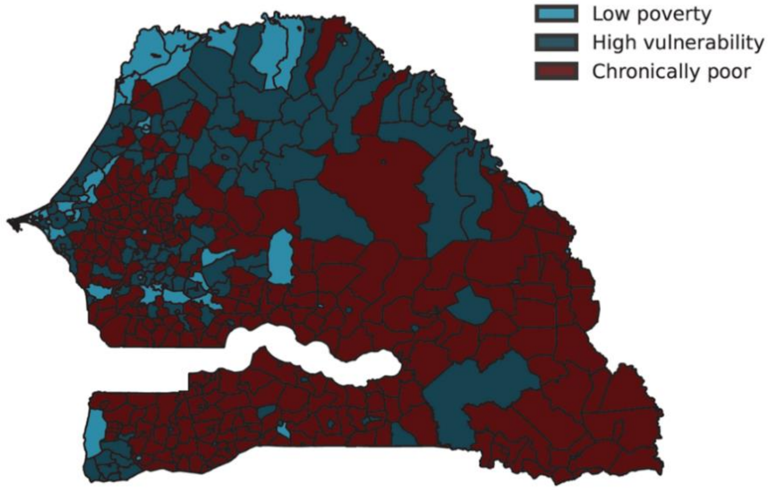
Figure 1. Relation between poverty and risk-induced vulnerability, distribution by commune



Sources: Calculations using EHCVM (Enquête Harmonisée sur le Conditions de Vie des Ménages 2018–2019; Harmonized Survey on Household Living Standards 2018–2019), Living Standards Measurement Study, World Bank, Washington, DC, https://microdata.worldbank.org/index.php/catalog/4292; RGPHAE 2013 (2013 Recensement Général de la Population et de l'Habitat, de l'Agriculture et de l'Elevage; Population and Housing Census, 2013) (dashboard), National Agency of Statistics and Demography, Dakar, Senegal, https://www.ansd.sn/enquete-et-etude/recensement-general-de-la-population-et-de-lhabitat-de-lagriculture-et-de-lelevage. *Note:* A household is considered vulnerable if it has a probability of falling into poverty above 29 percent in one year (50 percent in two years). Regions are classified using the median, unweighted values of poverty and risk-induced vulnerability across communes. Low-poverty communes show low poverty rates and low vulnerability rates. High-vulnerability communes have low poverty rates, but high risk-induced vulnerability rates. Chronically poor communes have high poverty-induced vulnerability.

Communes in the low-poverty group tend to have larger populations and are more likely to be located in urban areas, while small rural communes account for almost all the communes in the chronically poor group. Map 2 shows the distributions of these three groups across the country. Urban areas around Dakar have low poverty levels, while urban communes in the periphery of the country combine low poverty and high vulnerability levels (labeled 'other urban group'). Communes that are predominantly rural are more likely to fall in the chronically poor category, with the highest levels of poverty-induced vulnerability.

Map 2. The spatial distribution of communes, by vulnerability classification



Sources: Calculations using EHCVM (Enquête Harmonisée sur le Conditions de Vie des Ménages 2018–2019; Harmonized Survey on Household Living Standards 2018–2019), Living Standards Measurement Study, World Bank, Washington, DC, https://microdata.worldbank.org/index.php/catalog/4292; RGPHAE 2013 (2013 Recensement Général de la Population et de l'Habitat, de l'Agriculture et de l'Elevage; Population and Housing Census, 2013) (dashboard), National Agency of Statistics and Demography, Dakar, Senegal, https://www.ansd.sn/enquete-et-etude/recensement-general-de-la-population-et-de-lhabitat-de-lagriculture-et-de-lelevage. *Note:* A household is considered vulnerable if it has a probability of falling into poverty above 29 percent in one year (50 percent in two years). Regions are classified using the median, unweighted values of poverty and risk-induced vulnerability across communes. Low-poverty communes show low poverty rates and low vulnerability rates. High-vulnerability communes have low poverty rates, but high risk-induced vulnerability rates. Chronically poor communes have high poverty-induced vulnerability.

To investigate whether there are systematic differences among communes that vary by poverty rate and risk-induced vulnerability, the analysis combined data from the census, administrative records, and satellite-based measures. It examined the correlation between commune characteristics and the capacity to promote income generation, intergenerational mobility, and lower risk of flooding. Low- and high-vulnerability communes differ in access to services, exposure to flood risk, and asset ownership (table 2). Households in high-vulnerability communes face a high risk of income loss, present lower educational attainment, access to services, and asset ownership. [18] Underlining the importance of including disaster risk management within a strategy for poverty reduction, lower asset ownership reflects not only a constrained capacity to generate income, but also the lack of a traditional buffer to insure against shocks that the data indicate are more likely to occur in these communes (Carter and Barrett 2006).

[18] Calculated as the first component from a principal component analysis using the assets owned by the household.

Table 2. Comparison: commune-level characteristics

Indicator	Risk-induced vulnerability (poverty-induced vulnerability = low)		Chronically poor
	Low	*High*	
Household characteristics			
No formal education, household head	0.50	0.77	0.85
More than secondary education, head	0.19	0.06	0.02
Dependency ratio	0.40	0.50	0.55
Rural	0.12	0.62	0.96
Employment, head			
Employed	0.22	0.10	0.04
Self-employed	0.36	0.46	0.56
Unemployed	0.31	0.34	0.35
Assets			
Wealth index	0.92	-0.36	-1.30
Mobile phone	0.87	0.78	0.75
Computer	0.21	0.07	0.02
Car	0.13	0.07	0.02
Fridge	0.38	0.16	0.03
TV	0.79	0.47	0.16
Dwelling characteristics (improved)			
Walls	0.93	0.73	0.40
Floor	0.86	0.73	0.54
Roof	0.80	0.45	0.54
Electricity	0.86	0.50	0.14
Sewer	0.54	0.14	0.03
Flush toilet	0.31	0.04	0.16
Running water	0.56	0.29	0.12
Administrative data measures			
Coverage 3G mobile network (pop. shares)	0.98	0.92	0.78
Average nighttime light luminosity (2018)	15.00	1.30	0.03
Exposed to fluvial flood risks (pop. shares)	0.02	0.05	0.03
Exposed to pluvial flood risks (pop. shares)	0.02	0.03	0.52

Sources: Calculations using commune vulnerability rates from the poverty mapping exercise; RGPHAE 2013 (2013 Recensement Général de la Population et de l'Habitat, de l'Agriculture et de l'Elevage; Population and Housing Census, 2013) (dashboard), National Agency of Statistics and Demography, Dakar, Senegal, https://www.ansd.sn/enquete-et-etude/recensement-general-de-la-population-et-de-lhabitat-de-lagriculture-et-de-lelevage.
Note: Low and high poverty- and risk-induced vulnerability are defined by national medians. Variables are population weighted.

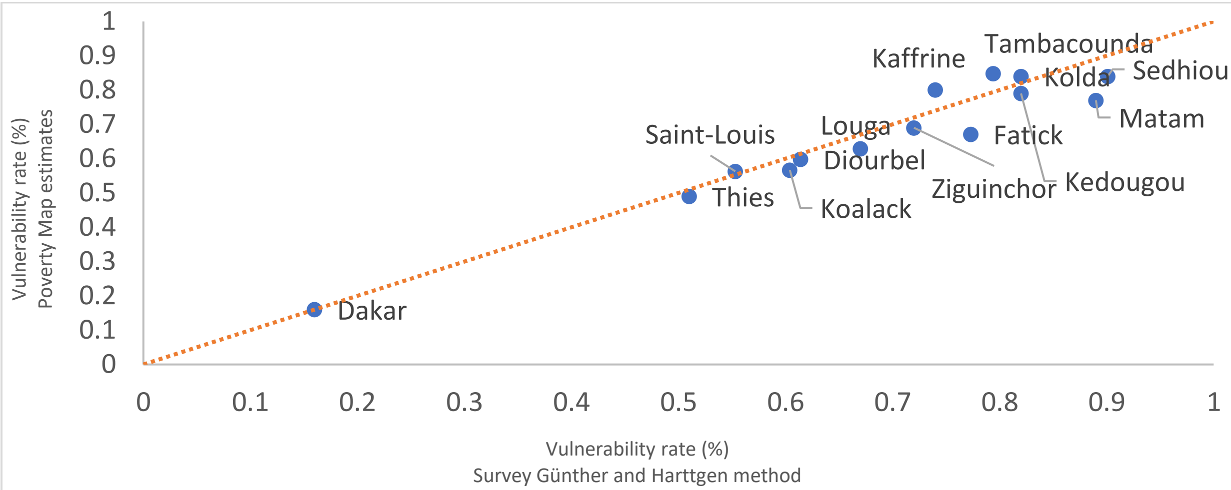
Robustness checks

This subsection assesses the difference in the variance estimations and the associated implications for the predicted vulnerability rates between the Günther and Harttgen (2009) approach and the small area estimation method. To render the results comparable between survey estimates and imputations into the census, the vulnerability predictions across communes are aggregated by the department and nationwide rates.

Despite the use of a slightly different econometric technique and the limitation in the covariates available in the census and household survey, the results of the analysis closely matches the estimates based directly on the household survey. In the analysis, the vulnerability predictions by department from the small area estimations in the census were aggregated and compared with the results of the Günther and

Harttgen (2009) model implemented on the household survey. The predicted rates and the rankings by department produced by both methods are comparable, providing confidence in the robustness of the small area application to vulnerability (figure 2).

Figure 2. Vulnerability estimates of survey implementation using two methods, by department



Sources: Calculations using EHCVM (Enquête Harmonisée sur le Conditions de Vie des Ménages 2018–2019; Harmonized Survey on Household Living Standards 2018–2019), Living Standards Measurement Study, World Bank, Washington, DC, https://microdata.worldbank.org/index.php/catalog/4292; RGPHAE 2013 (2013 Recensement Général de la Population et de l'Habitat, de l'Agriculture et de l'Elevage; Population and Housing Census, 2013) (dashboard), National Agency of Statistics and Demography, Dakar, Senegal, https://www.ansd.sn/enquete-et-etude/recensement-general-de-la-population-et-de-lhabitat-de-lagriculture-et-de-lelevage.

Note: A household is considered vulnerable if it exhibits a probability of falling into poverty above 29 percent in one year (50 percent in two years). This applies to both census- and survey-based estimations.

Table 3 illustrates the predicted variance component of the survey and census data. In the household survey, the data included 540 of the 551 communes in Senegal, representing about 98 percent of the population. Table 3, columns 1 and 2 show that the mean and overall distribution of the predicted variances in the Günther and Harttgen (2009) approach and the small area estimation approach are similar across these communes. Table 3, column 3 shows the variance in the small area estimations imputed into the census, only including those communes sampled in the household survey, while column 4 presents the estimates for communes not sampled in the household survey. In general, the variance shown in table 3, column 4 is slightly lower, but is aligned well with the estimates in the overall sample even if their estimates do not include area effects.

Table 3. Variance predictions across estimation methods

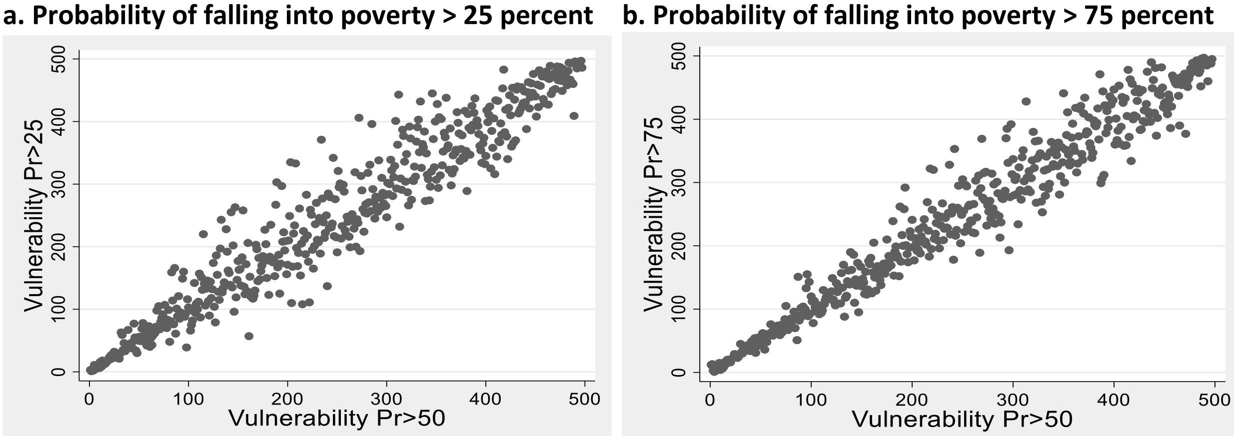
Indicator		Household survey		Census	
		Günther and Harttgen (2009)	*SAE*	*SAE*	*SAE*
		Total sample	*Total sample*	*Communes in household survey*	*Communes not in household survey*
		(1)	*(2)*	*(3)*	*(4)*
Communes, number		540		540	11
	Sample mean	0.346	0.349	0.343	0.336
Predicted	5	0.217	0.277	0.259	0.292
variance,	25	0.305	0.312	0.328	0.333
selected	50	0.354	0.348	0.344	0.334
percentiles	75	0.395	0.375	0.357	0.334
	95	0.447	0.424	0.426	0.395

Sources: Calculations using EHCVM (Enquête Harmonisée sur le Conditions de Vie des Ménages 2018–2019; Harmonized Survey on Household Living Standards 2018–2019), Living Standards Measurement Study, World Bank, Washington, DC, https://microdata.worldbank.org/index.php/catalog/4292; RGPHAE 2013 (2013 Recensement Général de la Population et de l'Habitat, de l'Agriculture et de l'Elevage; Population and Housing Census, 2013) (dashboard), National Agency of Statistics and Demography, Dakar, Senegal, https://www.ansd.sn/enquete-et-etude/recensement-general-de-la-population-et-de-lhabitat-de-lagriculture-et-de-lelevage. *Note:* The Günther and Harttgen (2009) variance estimations follow equation (7). SAE = small area estimation.

The analysis also tested for the sensitivity of the results to changes in the cutoff used to define vulnerability. The commune ranking is consistent no matter the cutoff used (figure 3). For instance, the rank correlation between the baseline result and using a vulnerability threshold of 13 percent in one year (25 percent in two years) is 0.97. In a similar manner, the correlation is 0.96 when a threshold of 50 percent in one year (75 percent in two years) is used.

Figure 3. Testing commune reranking under different probability cut-offs

a. Probability of falling into poverty > 25 percent **b. Probability of falling into poverty > 75 percent**



Sources: Calculations using EHCVM (Enquête Harmonisée sur le Conditions de Vie des Ménages 2018–2019; Harmonized Survey on Household Living Standards 2018–2019), Living Standards Measurement Study, World Bank, Washington, DC, https://microdata.worldbank.org/index.php/catalog/4292; RGPHAE 2013 (2013 Recensement Général de la Population et de l'Habitat, de l'Agriculture et de l'Elevage; Population and Housing Census, 2013) (dashboard), National Agency of Statistics and Demography, Dakar, Senegal, https://www.ansd.sn/enquete-et-etude/recensement-general-de-la-population-et-de-lhabitat-de-lagriculture-et-de-lelevage.

Note: In the baseline results, a household is considered vulnerable if it has a probability of falling into poverty above 29 percent in one year (50 percent in two years). This applies to both census- and survey-based estimations. Additional cutoffs consider a household as vulnerable if the probability of falling into poverty is above 13 percent in one year (25 percent in two years) (panel a) or 50 percent in one year (75 percent in two years) (panel b).

5. Using poverty and vulnerability maps to update RNU quotas

The Government of Senegal began developing the first RNU in 2015. The goal was to provide a unified information database to coordinate the various social projects and programs and serve as the foundation for targeting beneficiaries. The identification of households entering the RNU database relied on the poverty rates from the 2015 poverty map to provide commune eligibility quotas. Subsequently, communities provided lists of local households considered among the poorest in the area. Then, one by one, households with the lowest score in a proxy mean test were granted access to social programs until the commune quotas were met. Between 2015 and 2022, the RNU collected socioeconomic information on 550,000 households, representing nearly 29 percent of all households in the country. Because of the lower poverty rates in urban areas and in Dakar Region, the RNU includes a larger share of rural households.[19]

In 2022, the government planned an expansion of the RNU to reach one million households. Recognizing that households are exposed to recurrent and severe shocks, one of the goals was to include households that were vulnerable though they might not be poor. Expanding the eligibility criteria to cover the poor, but also the vulnerable presents data and methodological challenges. Most methods for estimating vulnerability rely on household panel data, which are not available in Senegal. Furthermore, even if methods to estimate vulnerability from cross-sectional data exist, they fail to provide estimates at the level of geographical disaggregation necessary for targeting RNU regional eligibility quotas. The methodology described here represents a solution because it provides eligibility quotas that account for commune poverty rates as well as the probability that poverty rates will rise in the face of shocks.

How does the use of a vulnerability map affect the expansion of the RNU? While the implementation of the first RNU relied on commune poverty rates, the expansion of the RNU relies on commune vulnerability rates to determine the number of households in each commune that may be registered. Commune vulnerability includes the poverty rate as in the previous RNU, plus an estimate of the share of the nonpoor at risk of becoming poor. The new quotas will therefore shift depending on the distribution of risk-induced vulnerability rates across communes. This implies that, under the new system, a commune with a low poverty rate, but high overall vulnerability will benefit similarly to a commune with a high poverty rate. In the past, the former was not considered in RNU registrations. Accounting for the poor, but also for

[19] The RNU includes 66 percent of households as rural though only 55 percent of the population is rural. Similarly, Dakar represents 31 percent of all households, but only 14 percent of the RNU. Kolda and Ziguinchor regions are overrepresented. They account for 18 percent of the RNU, but only 9 percent of the population.

households at risk of becoming poor recognizes that safety net expansion to nonpoor households is crucial to sustaining progress in poverty reduction even during economic downturns and shocks.

In practice, using vulnerability rates boosts eligibility among households in urban and periurban communes. While rural communes are, on average, poorer, urban and periurban communes exhibit lower than average poverty rates, but account for a relatively larger share of all nonpoor households at risk of poverty. Thus, most rural communes exhibit poverty rates that are higher than the national median poverty rate, that is, they are more likely to count among the chronically poor (table 4, panel a). Meanwhile, urban communes in Dakar show poverty rates below the national median, indicating a lower incidence of poverty. Similarly, other urban areas generally show low poverty rates, but risk-induced vulnerability rates that surpass the national median. This also has implications on the type of benefits for different localities, where a stronger focus on social insurance versus social protection should be the case for areas with higher risk-induced vulnerability.

Table 4. Commune vulnerability rates, by urban or rural location

	Dakar urban	*Other urban*	*Rural*	*National*
Communes, by vulnerability rate, number				
Low poverty	47	35	28	110
High vulnerability	1	63	101	165
Chronically poor	0	20	256	276
Census predictions: population averages, %				
Poverty-induced	8.2	22.5	56.8	38.2
Risk -induced	6.9	18.8	21.5	17.5
Risk/poverty ratio	83.9	83.2	37.9	45.8
Census predictions: commune average, %				
Poverty-induced	9.5	32.6	63.0	51.8
Risk -induced	7.3	24.4	20.5	20.2
Risk/poverty ratio	77.6	75.0	32.5	39.0
Estimated population, 2018				
Total, million	3.3	3.6	8.7	15.5
Share of total, %	21.3	23.2	56.1	100

Sources: Calculations using commune vulnerability rates from the poverty mapping exercise; RGPHAE 2013 (2013 Recensement Général de la Population et de l'Habitat, de l'Agriculture et de l'Elevage; Population and Housing Census, 2013) (dashboard), National Agency of Statistics and Demography, Dakar, Senegal, https://www.ansd.sn/enquete-et-etude/recensement-general-de-la-population-et-de-lhabitat-de-lagriculture-et-de-lelevage.

To evaluate the effect of vulnerability rates on the allocation of eligibility quotas to urban and periurban communes, we computed the ratio of risk-induced vulnerability to poverty-induced vulnerability. A higher ratio indicates that risk-induced vulnerability is more important in the total quota. This ratio is highest in urban Dakar and other urban areas (see table 4). For instance, urban Dakar shows poverty- and risk-induced vulnerability rates of 8.2 and 6.9 percent. This produces a ratio of risk-induced vulnerability rate to poverty-induced vulnerability that indicates the quota of urban Dakar is 84 percent higher than it would have been under the old RNU system. Rural areas are still assigned consistently higher quotas because of their higher poverty rates (56.8 percent of the population). However, the effect of accounting for risk-induced vulnerability in the total quota in rural areas, which represent more than half the country's population, is marginal compared with the effect in urban areas. These results hold if the analysis is based on communes instead of population averages.

6. Conclusions

About 55 percent of the population in Senegal was vulnerable in 2018/19. Of the vulnerable, two-thirds were poor (poverty-induced vulnerability), while the remaining one-third were people with expenditures above the poverty line, but facing a high probability of becoming poor (risk-induced vulnerability). Relying only on the information from the latest household survey provides valuable insights into the characteristics and regional distribution of the poor and vulnerable. However, it cannot provide highly detailed spatial information that is crucial for supporting the implementation of targeted social programs. This paper addresses the related knowledge gap by combining two separate, but linked strands in the pertinent literature: the small area estimation of poverty and the estimation of vulnerability. The combination enables the estimation of highly disaggregated poverty rates and the determination of the share of nonpoor households at risk of falling into poverty.

Poverty- and risk-induced vulnerability underline different economic challenges: deprivation versus variations in welfare. From a public policy perspective, it is crucial to understand how overlapping factors contribute to (or limit) the capacity of households to increase their incomes and improve their resilience to adverse shocks. If structural poverty is the primary concern, the most suitable interventions are likely to involve cash transfer programs or initiatives that improve the delivery of basic services and facilitate investments in physical and human capital. In contrast, if vulnerability is predominantly risk induced, then implementing a program that addresses the risk may be essential (Skoufias, Vinha, and Beyene 2024). For example, if the risk is caused by wide uninsured income fluctuations, then implementing an insurance-based program may be required to reduce vulnerability.

The analysis described in this paper involved the application of this proposed method to the generation of a poverty and vulnerability map for Senegal. Unlike the previous quotas, which relied on commune poverty rates, the new method is based on a recognition of the dynamic nature of poverty. Nonpoor households experience shocks and may therefore be at risk of falling into poverty. This extension of the registry to collect information on nonpoor households is a first step toward making the RNU dynamic and enable an expansion of the RNU to respond effectively in times of crisis.

What are the implications of accounting for vulnerability in allocating RNU eligibility quotas across communes? Poverty- and risk-induced vulnerability are not equally distributed across communes. Relative to urban communes, rural communes tend to present higher poverty rates. However, a considerable share of the population in urban areas is susceptible to falling into poverty. The revised quotas therefore increase the participation of urban households in the registry.

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Appendix A. Variables: the 2013 census and 2018/19 household survey

Table A.1. Observed poverty rate and small area estimation predictions at the regional level

	ECVHM 2018/19		Census 2013	
	Mean	**Variance**	**Mean**	**Variance**
HH age	51.58	199.17	48.28	209.47
HH size	8.93	33.81	8.20	35.36
HH male	0.72	0.20	0.78	0.17
Dependency ratio	0.47	0.05	0.42	0.06
No education	0.66	0.23	0.64	0.23
Primary education	0.15	0.13	0.15	0.13
Secondary education	0.12	0.11	0.15	0.12
Tertiary education	0.07	0.06	0.06	0.06
Rural	0.47	0.25	0.46	0.25
TV	0.57	0.24	0.53	0.25
Iron	0.04	0.04	0.03	0.03
Car	0.05	0.05	0.08	0.07
Computer	0.11	0.10	0.12	0.11
Refrigerator	0.32	0.22	0.23	0.18
Electricity (grid)	0.59	0.24	0.58	0.24
Water access: Yard	0.22	0.17	0.20	0.16
Water access: Tap	0.45	0.25	0.38	0.23
Water access: Public fountain	0.12	0.11	0.19	0.16
Water access: Well	0.07	0.06	0.07	0.07
Water access: nonprotected	0.14	0.12	0.15	0.13
Water disposal: Protected	0.26	0.19	0.30	0.21
Toilet: Improved	0.12	0.11	0.16	0.13
Toilet: Not Improved	0.47	0.25	0.32	0.22
Soil: improved	0.77	0.18	0.76	0.18
Roof: Concrete	0.36	0.23	0.32	0.22
Roof: Straw	0.14	0.12	0.20	0.16
Roof: Tile	0.11	0.10	0.11	0.10
Walls: Improved	0.82	0.15	0.74	0.19
Garbage picked up	0.51	0.25	0.52	0.25
Dakar	0.28	0.20	0.31	0.21
Ziguinchor	0.05	0.05	0.05	0.05
Diourbel	0.10	0.09	0.10	0.09
Saint-Louis	0.06	0.06	0.07	0.06
Tambacounda	0.04	0.04	0.04	0.04
Koalack	0.06	0.06	0.06	0.06
Thies	0.13	0.11	0.12	0.11
Louga	0.06	0.05	0.06	0.06
Fatick	0.05	0.05	0.05	0.04
Kolda	0.05	0.04	0.04	0.04
Matam	0.04	0.04	0.03	0.03
Kaffrine	0.04	0.04	0.03	0.03
Kedougou	0.01	0.01	0.01	0.01
Sedhiou	0.03	0.03	0.03	0.02

Sources: Calculations using EHCVM (Enquête Harmonisée sur le Conditions de Vie des Ménages 2018–2019; Harmonized Survey on Household Living Standards 2018–2019), Living Standards Measurement Study, World Bank, Washington, DC, https://microdata.worldbank.org/index.php/catalog/4292; RGPHAE 2013 (2013 Recensement Général de la Population et de l'Habitat, de l'Agriculture et de l'Elevage; Population and Housing Census, 2013) (dashboard), National Agency of Statistics and

Demography, Dakar, Senegal, https://www.ansd.sn/enquete-et-etude/recensement-general-de-la-population-et-de-lhabitat-de-lagriculture-et-de-lelevage.

Appendix B. Model regressions

Table B.1. Model regressions

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Variables	Dakar	Ziguinchor	Diourbel	Saint-Louis	Tambacounda	Koalack	Thies
Household	HH size (logs)	-0.433***	-0.564***	-0.437***	-0.498***	-0.324***	-0.423***	-0.362***
Demographics	Dependency ratio	-0.454***	-0.231**	-0.302***	-0.376***	-0.514***	-0.256**	-0.310***
Household	Age							
Head	Male	-0.0486*					-0.0545	-0.0540*
	Tv	0.0867*	0.199***		0.0707			0.192***
	Car	0.489***	0.586***	0.354***	0.256**		0.515***	0.383***
Assets	Computer	0.116***	0.226***	0.215***	0.219***	0.213**	0.247***	0.235***
	Refrigerator	0.204***			0.247***			0.139***
	Iron	0.163***			0.104			
	Walls: Improved		0.180***	0.189***				
	Roof: improved	0.0654	0.147**	0.118***	0.115***	0.157***		
	Garbage picked up	0.0899	0.106**	0.0845**	0.0795*	0.136***	0.154***	0.0617
	Soil: improved		0.127**	0.0232	0.175***	0.131***	0.0964**	0.146***
	Water disposal: Protected	0.0876***	0.197***	0.347***	-0.0392	0.184***	0.0562	0.0540
Service access	Water access: Public fountain						-0.212***	
	Water access: Tap	-0.141***		-0.0608			-0.125**	
	Water access: Other nonprotected	-0.389***			0.00937	-0.106*		
	Toilet: Improved				0.176**	0.383**		0.183***
	Toilet: Not Improved	-0.112***	0.255***					
	Electricity					0.0566	0.123***	
Location	Rural	-0.136**	0.0679					
	Constant	14.21***	13.57***	13.76***	13.95***	13.59***	13.86***	13.63***
Model Fit	Observations	939	466	535	486	422	507	552
	R2	0.713	0.633	0.536	0.587	0.448	0.622	0.602

Table B.1 Model regressions (continued)

	Vd	(8) Louga	(9) Fatick	(10) Kolda	(11) Matam	(12) Kaffrine	(13) Kedougou	(14) Sedhiou
Household Demographics	HH size (logs)	-0.451***	-0.461***	-0.370***	-0.480***	-0.554***	-0.443***	-0.396***
	Dependency ratio	-0.413***	-0.459***	-0.746***	-0.474***	-0.652***	-0.642***	-0.497***
Household Head	Age		0.00304**	-0.002				
	Male		-0.0994**		-0.0720	-0.0712		
	Secondary education					0.122	0.157*	
Assets	Tv			0.140*	0.193***			0.257***
	Car	0.340***		0.407*		0.493***		0.765***
	Computer	0.242***	0.339***		0.481***	0.277***	0.464***	0.231**
	Refrigerator	0.216***						
	Iron		0.128	0.339				
Service access	Walls: Improved		0.0918	-0.332***		-0.00411		
	Roof: improved	0.168***	0.0699	0.192*	0.137**			0.313**
	Garbage picked up		0.124***			0.164***	0.222***	
	Soil: improved	0.102**	0.176***		0.236***	0.207***		0.0388
	Water disposal: Protected	0.0768**		0.206			0.127*	0.121
	Water access: Public fountain			0.173		-0.159***		
	Water access: Tap		0.0320		0.0467			
	Water access: Other nonprotected			-0.123***				
	Toilet: Improved			0.330*				0.312*
	Electricity							0.0697
Location	Rural				0.162***		-0.134	
Model Fit	Constant	13.93***	14.01***	13.991	13.83***	14.36***	14.02***	13.71***
	Observations	468	443	418	391	417	442	393
	R2	0.632	0.463	0.378529	0.482	0.525	0.529	0.474

Sources: Calculations using EHCVM (Enquête Harmonisée sur le Conditions de Vie des Ménages 2018–2019; Harmonized Survey on Household Living Standards 2018–2019), Living Standards Measurement Study, World Bank, Washington, DC, https://microdata.worldbank.org/index.php/catalog/4292; RGPHAE 2013 (2013 Recensement Général de la Population et de l'Habitat, de l'Agriculture et de l'Elevage; Population and Housing Census, 2013) (dashboard), National Agency of Statistics and Demography, Dakar, Senegal, https://www.ansd.sn/enquete-et-etude/recensement-general-de-la-population-et-de-lhabitat-de-lagriculture-et-de-lelevage.