CHAPTER 5

Assessing the Vulnerability of West and Central African Countries to COVID-19

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Introduction

As of October 2021, the effects of the COVID-19 pandemic in African countries are still unfolding. The early stages of the pandemic were characterized by apparent lower illness and mortality rates in Africa compared to the other world regions, although significant underreporting of COVID-19 cases and deaths in Africa is likely. [1] However, the economic effects of the pandemic and the measures taken to combat it were expected to impact African countries severely, worsening poverty and hunger and erasing recent economic gains (Bouët, Laborde, and Seck 2021). A "third wave" of the pandemic in mid-2021 saw rapidly escalating health effects and a return to lockdowns and other mitigation efforts in many countries (Mwai 2021). The crisis is expected to have severe impacts on food security in Africa as in other regions, due to food supply chain disruptions, income loss, school closures, and other factors (HLPE 2020).

The health, economic, and food security effects of the pandemic vary greatly between and within countries. Underlying characteristics of households and regions influence their vulnerability to shocks and ultimately determine the severity of the impacts they experience from the crisis. Due to limited national resources, pandemic responses must prioritize the locations where the effects are likely to be particularly devastating. Therefore, efforts to identify the most vulnerable households and communities are essential to targeting those most in need of assistance.

In the literature, vulnerability has emerged as a development concept because of the recognition that poverty and food insecurity are dynamic in nature and reflect the exposure of households, communities, and countries to risk (Naudé, Santos-Paulino, and McGillivray 2009). Vulnerability is generally defined as the susceptibility of an individual, household, community, or country to fall below a threshold welfare level in response to an adverse shock (Naudé, Santos-Paulino, and McGillivray 2009; Barrett and Constas 2014; Moret 2018). Therefore, vulnerability is related to the concept of resilience but can be differentiated as a measure more focused on short-term reactions to specific hazards than on longer-term capacity to maintain or improve well-being (Barrett and Constas 2014). Efforts to assess vulnerability incorporate both exposure to shocks or hazards and ability to respond to these shocks—as stated by Moret (2017, 7), "Risk + Response = Vulnerability." The literature emphasizes that vulnerability must be considered in relation to a particular outcome—for example, economic vulnerability, vulnerability to negative impacts of climate change, etc. Vulnerability measurements cannot be standardized; rather, vulnerability assessments should be appropriate to the context (Nkonde, Masuku, and Manyatsi 2014; Moret 2018).

In this chapter, we examine vulnerability to the negative effects of COVID-19 among select West and Central African countries at the community level and assess the impact of COVID-19 vulnerability on food security at the household level. In the following section, we describe subnational vulnerability hot spots in 10 West and Central African countries by examining the underlying conditions at the first administrative division level that are expected to render these areas particularly vulnerable to the pandemic. In the third section, we examine the impact of vulnerability to COVID-19 on food security at the household level in Mali using five rounds of COVID-19-specific Living Standards Measurement Study (LSMS) surveys from the World Bank (World Bank 2020). The final section discusses the implications and presents key recommendations.

Identification of Vulnerability Hot Spots

Methodology and Data

To identify areas at particular risk for food insecurity and negative health effects arising from the COVID-19 crisis, we developed a vulnerability index based on multiple indicators. We classify subnational areas—usually at the level of the first administrative division—according to their vulnerability with respect to two sub-indexes grouping similar indicators, as well as to the combined index. Our basic approach is similar to the approaches followed in other studies; these include the Household Vulnerability Index developed by the Food, Agriculture and Natural Resources Policy Analysis Network (FANRPAN) to measure vulnerability to shocks and stressors such as climate change and the effects of HIV/AIDS based on the households' access to different types of assets and services (Nkonde, Masuku, and Manyatsi 2014). The Local Vulnerability Index developed

1 For example, *The Economist* estimates that Africa's cumulative COVID-19 fatalities as of October 2021 may be up to 800 percent higher than official counts—a greater level of underreporting than that of any other continent. However, Africa's mortality rates including estimated deaths are still lower than estimated mortality rates in most other continents (*Economist* 2021).

by Naudé, McGillivray, and Rossouw (2009) for magisterial districts of South Africa similarly assesses each district's vulnerability in different domains, including economic, environmental, and demographic and health vulnerability, before deriving a composite index.

Several COVID-19-specific subnational vulnerability analyses have been carried out for the United States. Nayak et al. (2020) and Neelon et al. (2021) examine associations between COVID-19 infection and death rates and the US Centers for Disease Control and Prevention's (CDC) Social Vulnerability Index, a composite index based on four subthemes (socioeconomic status, household composition and disability, minority status and language, and housing type and transportation). A notable initiative to create a COVID-19-specific subnational vulnerability index for African countries was carried out by Surgo Ventures, using indicators reflecting seven themes, including socioeconomic status, population density, and epidemiological and health system factors, to develop theme scores and overall vulnerability scores for each area (Surgo Ventures 2021). Our index differs from other efforts in that we include a food security theme, incorporating a food security sub-index to capture vulnerability to the deterioration of food security due to the pandemic, in addition to examining vulnerability to health-related impacts.

Similar analyses can be carried out for individual countries or for regions; here we examine a group of 10 West and Central African countries [2] for which sufficient data are available. All localities are classified into vulnerability categories based on their relationship to the regional average; thus, we rely on relative vulnerability benchmarks as opposed to absolute levels of vulnerability.

Our vulnerability index attempts to identify areas at highest risk for negative health and food security impacts induced by COVID-19. We generate sub-indexes that reflect two dimensions of vulnerability: (1) an area's ability to care for infected people, as reflected by the quality of health systems, and (2) its susceptibility to negative food security impacts from the crisis. Under (1), we include two indicators of access to healthcare—the share of women receiving assistance from a medical professional during their last childbirth and the share of women reporting that distance to a medical facility constitutes a major obstacle. Indeed, limited access to healthcare can exacerbate the health impacts of the COVID-19 crisis. Under (2), we use the prevalence of stunting in children under the age of five, an indicator of chronic food insecurity, as well as average food expenditure per capita (in purchasing power parity). Communities and households suffering from chronic food insecurity are likely to have fewer resources to withstand additional shocks.

Notably, the index does not attempt to predict which locations will experience higher infection rates. For countries or regions with sufficient data, a third sub-index could be developed to identify areas with higher susceptibility to infection; based on emerging knowledge about risk factors related to COVID-19 infection rates, this sub-index would likely include variables related to density, connectivity, and population mobility (Rice et al. 2021; Zhang et al. 2021; Matheson et al. 2020). We cannot implement this type of analysis in the current study due to the lack of relevant data at the subnational level (with the exception of population density).

Data sources include Demographic and Health Surveys (DHS), Living Standards Measurement Study (LSMS) surveys, and other national household budget surveys. Data available for the most recent year were used; years range from 2013 to 2018. A complete list of data sources for each country is provided in

TABLE 5.1—SUMMARY STATISTICS, FOOD SECURITY AND HEALTH SYSTEMS SUB-INDEX VARIABLES

Variable	Obs.	Mean	Standard deviation	Min.	Max.
Food security sub-index					
Average food expenditure per capita (PPP)	139	984.53	511.02	367.00	3,316.50
Stunting rate in children under five (percent)	139	0.32	0.13	0.11	0.66
Health systems sub-index					
Share of women 15–49 receiving assistance from a doctor, nurse/midwife, etc., at last birth (percent)	139	0.55	0.30	0.04	1.00
Share of women 15–49 for whom distance to a health facility is a major problem (percent)	139	0.38	0.19	0.02	0.84

Source: Authors' construction based on national data sources (see Appendix Table 5.A1).
Note: Max. = maximum; min. = minimum; obs. = number of observations; PPP = purchasing power parity.

2 Benin, Burkina Faso, Cameroon, Chad, Ghana, Mali, Niger, Nigeria, Senegal, and Togo.

Appendix Table 5.A1. Table 5.1 presents summary statistics of the indicators used to construct the two sub-indexes.

The regional analysis shown in this chapter relies on indicators that were available for all countries in the region, which significantly limits the number of indicators used. Analysis carried out at the country level could potentially include other indicators available for the country—for example, the food security and health systems sub-indexes could be enriched with additional indicators, and data on age structure and preexisting medical conditions such as diabetes and high blood pressure could be used to construct another sub-index on factors related to more severe health outcomes of COVID-19.

Based on the indicators listed above, we use principal component analysis (PCA) to generate scores for each location for the strength of health systems and severity of food insecurity. Vulnerability sub-indexes are then constructed by assigning each score to one of four categories, with thresholds based on the mean and standard deviation of scores for all locations. The thresholds are designed such that approximately 25 percent of observations fall into each category, assuming a normal distribution. Prior to PCA, indicators are transformed such that higher values correspond to greater vulnerability (for example, lower levels of healthcare access and food security). Categories are constructed as follows:

$$
\begin{array}{ll}
I_{ik} \geq \bar{I}_k + 0.67 * std(I_k) & :3 = \textit{Much more vulnerable,} \\
\bar{I}_k + 0.67 * std(I_k) \leq I_{ik} < \bar{I}_k & :2 = \textit{More vulnerable,} \\
\bar{I}_k \leq I_{ik} < \bar{I}_k - 0.67 * std(I_k) & :1 = \textit{Less vulnerable, and} \\
I_{ik} < \bar{I}_k - 0.67 * std(I_k) & :0 = \textit{Much less vulnerable,}
\end{array}
$$

where $\bar{I}_k$ represents the mean and $std(I_k)$ represents the standard deviation over all countries of the k^{th} indicator, and I_{ik} represents the i^{th} observation of the k^{th} indicator. A category score of 3 indicates the highest level of vulnerability relative to the regional average, and a category score of 0 represents the lowest level of vulnerability.

Following the classification of scores to generate sub-indexes for health systems and food insecurity, a composite vulnerability score for each location is calculated by averaging the score for each indicator. The composite vulnerability score is then classified into one of the same four categories according to the first method outlined above.

It should be noted that assigning weights to indicators with respect to their respective contribution to vulnerability is not obvious. Our approach is based on other similar indexes (for example, the CDC index) that involve grouping similar indicators into sub-indexes and then combining sub-indexes with equal weight into a composite index. This composite index should be viewed as an initial ex ante attempt to identify areas with the potential to be particularly vulnerable, but it needs to be refined as more analysis becomes available on the importance of different drivers of vulnerability. The composite index provides a summary of performance in different dimensions of vulnerability but may mask differences in vulnerability with regard to food insecurity versus vulnerability with regard to health systems. Thus, for targeting purposes, the sub-indexes may be more informative than the combined index.

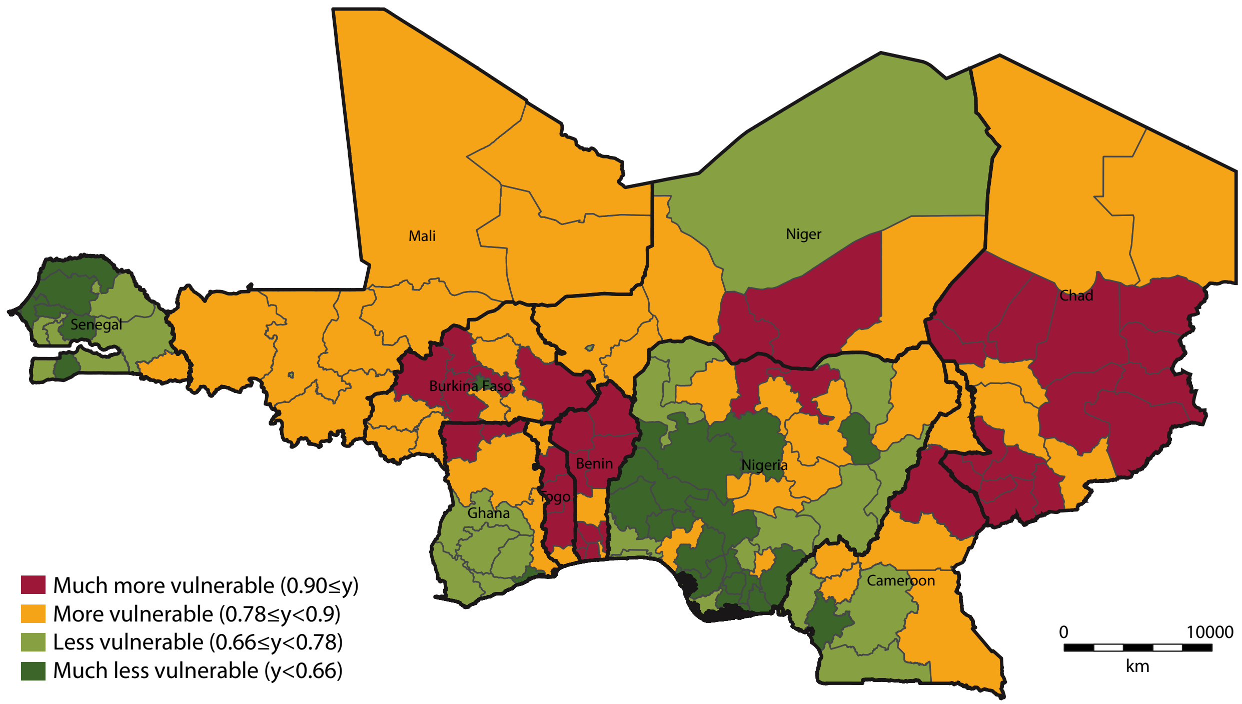
Another important limitation of the index is its silence regarding which areas are likely to suffer from high COVID-19 caseloads. Higher infection rates are clearly likely to affect vulnerability with respect to health outcomes; they can also plausibly influence vulnerability to food insecurity, although even areas with low infection rates are likely to suffer from food insecurity resulting from lockdowns and other measures taken to prevent the spread of the virus. However, the relationship between COVID-19 infection rates and outcomes is likely to be complex, as areas suffering from high infection rates also tend to be those with stronger health systems (Zhang et al. 2021; Muchangi 2021).

Results

Subnational Vulnerability in West and Central Africa

In this section we present the results of the vulnerability classification for select West and Central African countries for the two sub-indexes as well as for the combined vulnerability index. Figure 5.1 shows the food security sub-index, constructed from the prevalence of stunting in children under age five and household food expenditures per capita (purchasing power parity). Northern Nigeria, southern Niger, northern Chad, and several regions of Burkina Faso and Cameroon have the highest stunting rates in the region, while per capita food expenditures are lowest in Togo and Benin as well as areas of Burkina

FIGURE 5.1—FOOD SECURITY VULNERABILITY SUB-INDEX



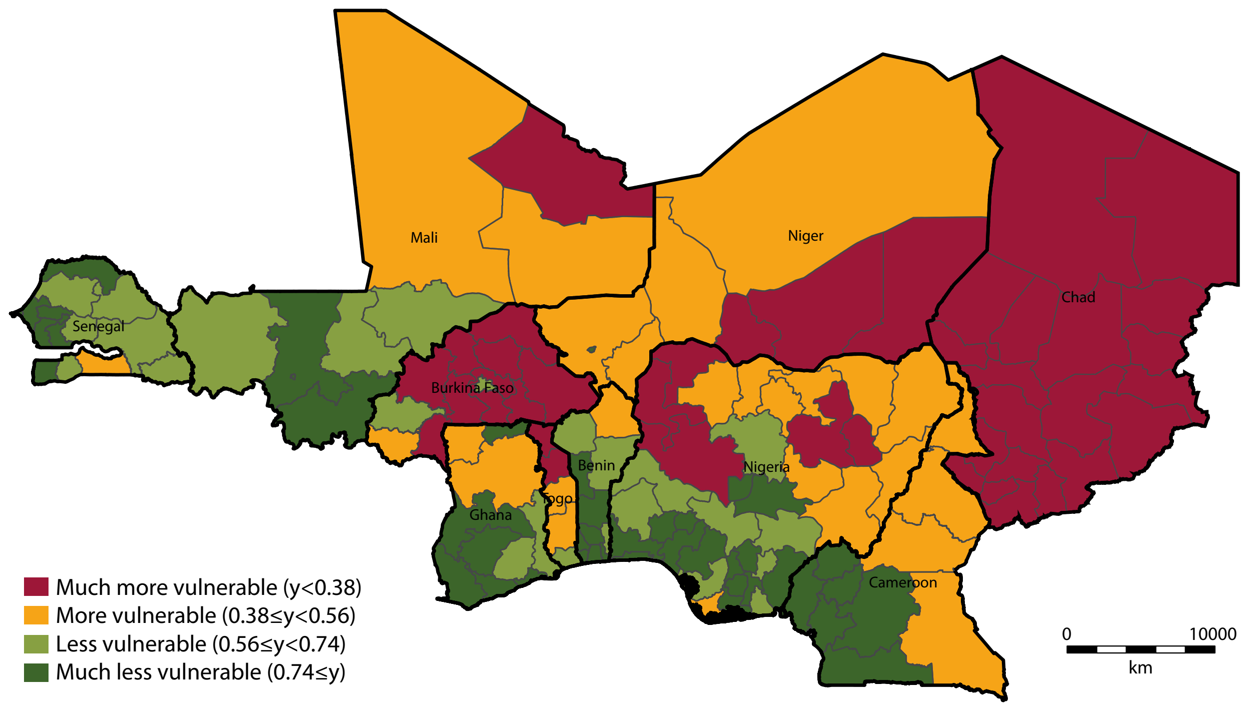
Source: Authors' construction based on national data sources (see Appendix Table 5.A1).

Faso, Ghana, Niger, Nigeria, Cameroon, and Chad. The sub-index suggests that vulnerability with respect to food insecurity is highest in some Sahelian areas—parts of Burkina Faso, northern Ghana, northern Nigeria, southern Niger, northern Cameroon, and Chad—as well as Togo and Benin. Senegal and southern and central Nigeria show the lowest vulnerability.

Figure 5.2 presents the classified health systems sub-index, based on indicators of access to medical services: the share of women receiving assistance from a medical professional during childbirth and the share of women reporting that distance to a health facility presents major problems. For both indicators, access to health services is generally higher in the western and southern areas of the West and Central Africa region. For the combined health systems sub-index, areas in the highest vulnerability category include nearly all regions of Chad (except for the capital, N'Djamena); most regions of Burkina Faso; and parts of southern Chad, northern Nigeria, northern Mali, and northern Togo.

Figure 5.3 shows the composite vulnerability index for the selected countries. Most regions of Chad as well as parts of Burkina Faso and southern Niger are classified as much more vulnerable than the regional average, reflecting

FIGURE 5.2—HEALTH SYSTEMS VULNERABILITY SUB-INDEX

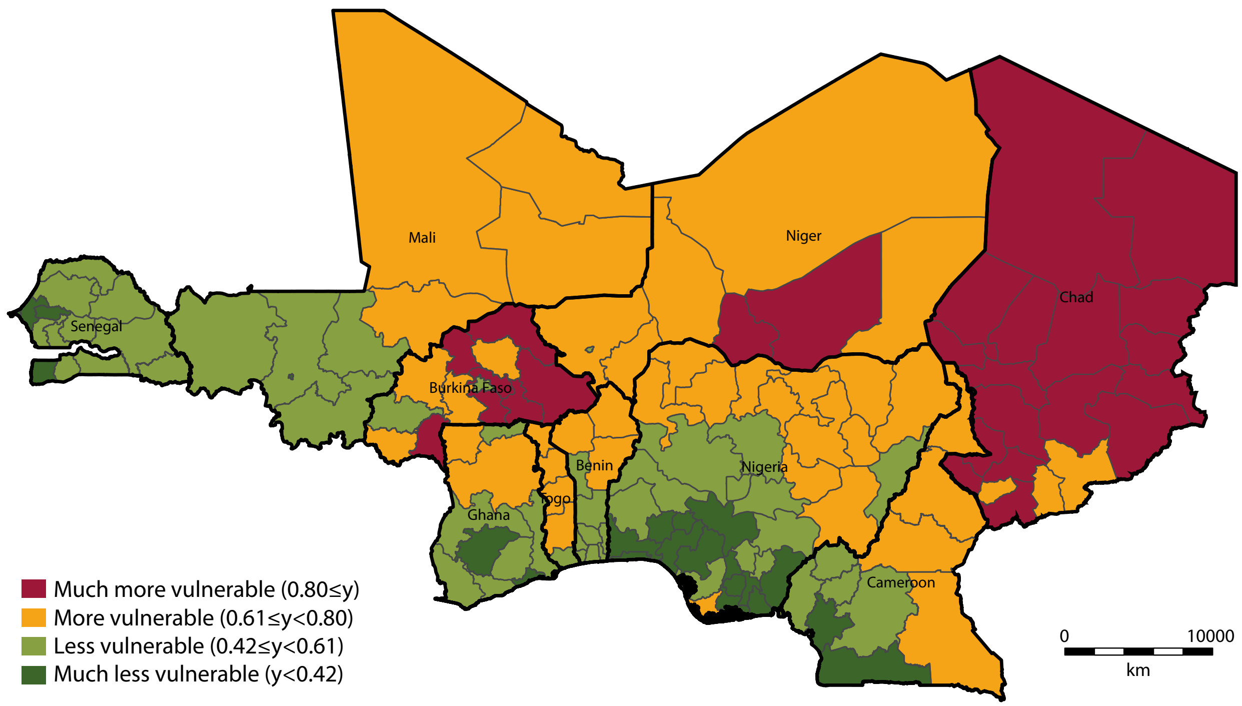


Source: Authors' construction based on national data sources (see Annex Table 5.A1).

their lower performance on both health systems and food security indicators. The lowest levels of vulnerability are found in Senegal as well as in southern areas of Mali, Ghana, Togo, Benin, Nigeria, and Cameroon. Most countries in the region have fairly low intra-country variations in vulnerability levels with respect to the regional average, while Burkina Faso, Cameroon, Ghana, and Nigeria have at least two regions or states in each of three vulnerability categories.

There are some commonalities across the indicators, with eastern and southern areas of the region performing better on most indicators as well as on the composite vulnerability index. Chad and Burkina Faso stand out as the countries with the largest share of regions in the highest vulnerability category, while Senegal is the only country with no regions in the two highest categories. Differences between countries and areas within the region seem to be associated with overall levels of development. The areas identified as more vulnerable than the regional average have fewer resources to absorb shocks. It bears repeating that these areas are not necessarily those more likely to experience high COVID-19 infection rates; however, infected people in vulnerable regions may experience more severe health impacts due to lower access to healthcare,

FIGURE 5.3—COMPOSITE VULNERABILITY CLASSIFICATION



Source: Authors' construction based on national data sources (see Appendix Table 5.A1).

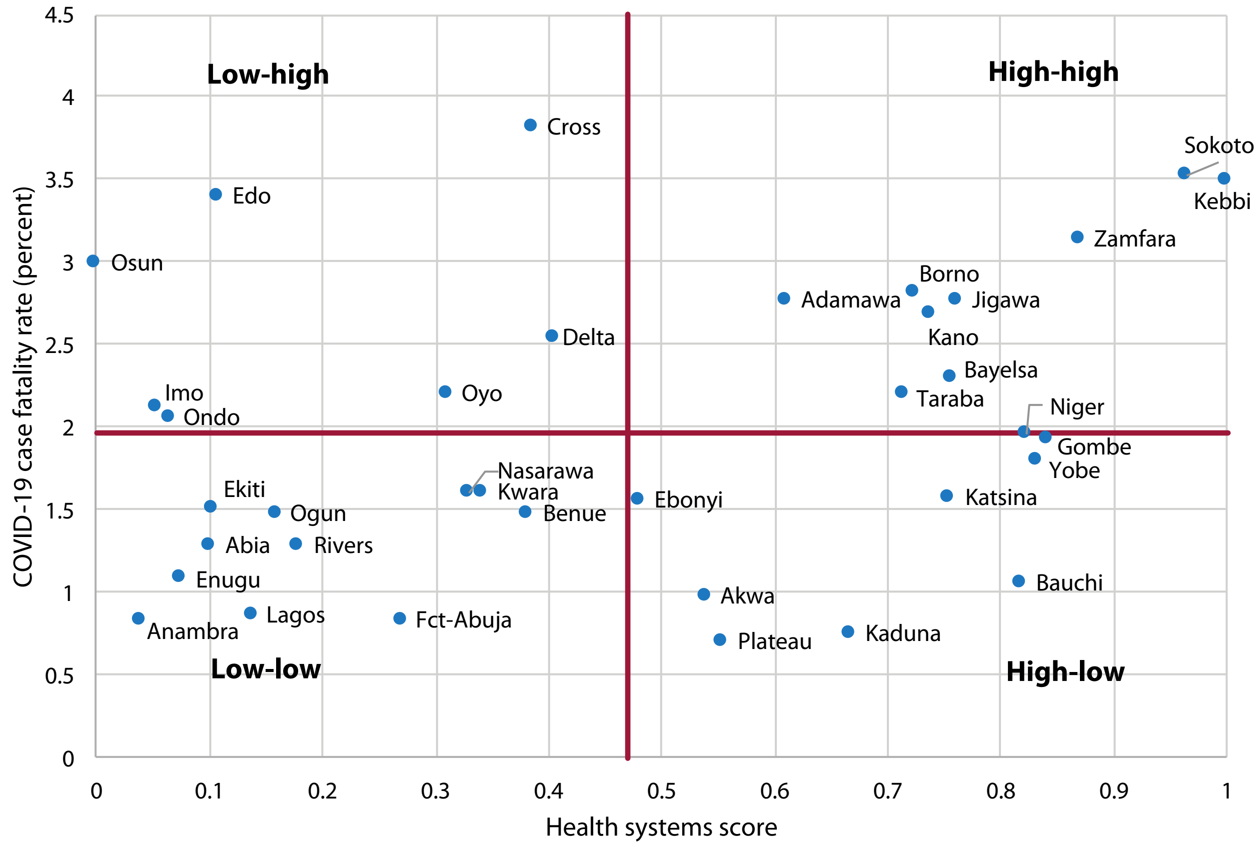
and the populations of these regions may be more severely affected by the economic impacts of lockdowns, movement restrictions, and other measures taken to limit the spread of the disease.

Outcomes of Vulnerability

An important next step for the analysis would be to validate the vulnerability index with outcome data. While updated subnational data reflecting the period after the onset of COVID-19 are not yet available in most cases, in this subsection we explore simple correlations between the vulnerability index and selected outcome data for illustrative purposes. By design, the vulnerability index is developed to identify areas most at risk for severe impacts of COVID-19. Data on COVID-19-related hospitalizations and deaths would be relevant to assess the severity of health impacts, while data on changes in food security status would be required to evaluate impacts on food security.

Unfortunately, data on COVID-19 hospitalization or mortality rates are not available at the subnational level for most of the countries of analysis. An exception is Nigeria, which releases weekly reports on COVID-19 cases and deaths by state. COVID-19 case fatality rates are expected to be correlated with the quality of health systems, preexisting health conditions, and, potentially, food security to the extent that undernutrition is linked to lower immune system function and worse health outcomes (Kurtz et al. 2021). Unfortunately, subnational data on preexisting conditions are unavailable for Nigeria. We find that case fatality rates for Nigerian states as of late September 2021 are moderately positively correlated with the health systems score (0.311), but uncorrelated with the food security score (0.028). In Figure 5.4, we compare health systems sub-index scores for Nigerian states with data on COVID-19 case fatality rates.[3] The vertical and horizontal lines indicate the average health systems score and mortality rate, respectively. The majority of Nigerian states fall into either the lower left-hand quadrant, with lower than average vulnerability scores and fatality rates, or the upper right-hand quadrant, with higher than average vulnerability and fatalities. This association suggests that areas with poorer health systems may have experienced greater mortality impacts; however, more rigorous analysis would be required to establish causality, and any findings should be treated with caution, given likely significant underreporting of COVID-19 cases and deaths.

FIGURE 5.4—HEALTH SYSTEMS VULNERABILITY AND COVID-19 CASE FATALITY RATES, NIGERIA



Source: Authors' construction based on NCDC 2021 (COVID-19 case fatality rates) and other national data (health systems score—see Appendix Table 5.A1).

Note: Case fatality rates are cumulative as of September 26, 2021. Kogi state is not shown due to very low recorded COVID-19 cases. FCT = Federal Capital Territory.

Comparable data on food security at the subnational level prior to and during the COVID-19 crisis are very limited. However, data based on the Cadre

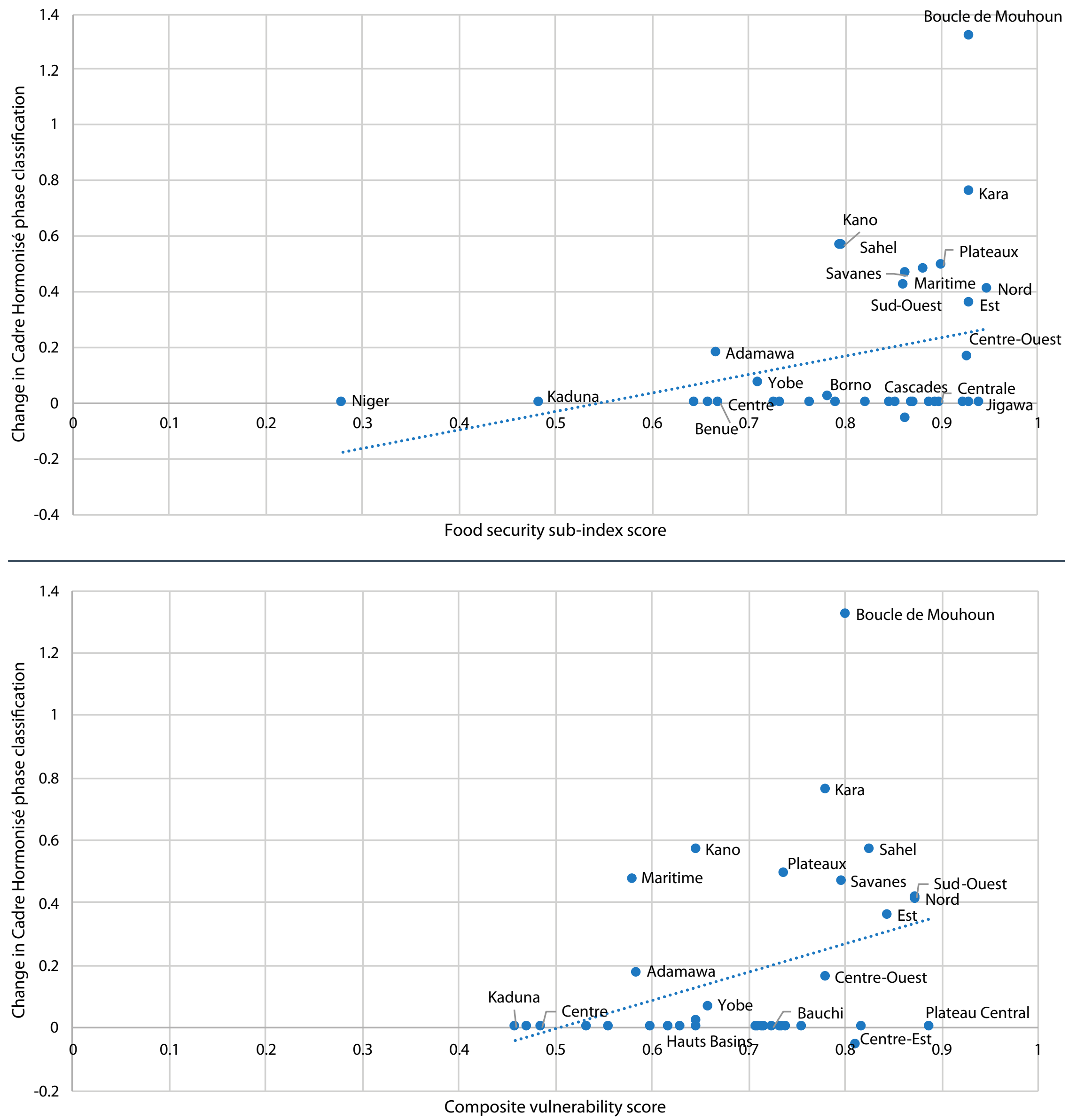
3 The health systems scores are shown before classification into four categories in order to preserve variation between states.

Harmonisé (CH, Harmonized Framework) indicator developed for select West African countries can provide important insight into changes in food security at the subnational level during the COVID-19 period. The CH phase classification is a composite indicator developed by the Permanent Interstate Committee for Drought Control in the Sahel (CILSS) and its technical partners[4] to monitor the current and projected food and nutrition security situation in the Sahel and West Africa. It includes indicators related to dietary diversity, livelihood strategy changes, observed coping strategies, nutrition status, and mortality (CILSS 2019).

In March 2020, CH projections were carried out for a number of West African countries for the period of June–August 2020. Updated estimations for the same period were completed in July 2020 for Burkina Faso, Togo, and 17 northern and central Nigerian states, taking into account the current effects of the COVID-19 crisis. Differences between the March 2020 projections and the July 2020 updates reflect the impact of current events on food security, including the pandemic and related lockdown measures. Of the 35 subnational areas covered, 14 showed increases in the CH phase classification, indicating

4 Partners include Action Against Hunger, the Food and Agriculture Organization of the United Nations, the Famine Early Warning Systems Network, the Integrated Food Security Phase Classification Global Support Unit, the International Federation of Red Cross and Red Crescent Societies, the Joint Research Centre of the European Commission, Oxfam, Save the Children, UNICEF, and the World Food Programme.

FIGURE 5.5—CHANGE IN FOOD INSECURITY VERSUS VULNERABILITY (FOOD SECURITY SUB-INDEX AND COMPOSITE INDEX), BURKINA FASO, TOGO, AND NORTHERN NIGERIA, MID-2020



Source: Authors' construction based on FSNWG–West Africa 2021 (Cadre Harmonisé data) and national sources (vulnerability index—see Appendix Table 5.A1).

Note: The y-axis shows the difference between the March 2020 Cadre Harmonisé (CH) projections for June–August 2020 and the July 2020 updates. Increases in the CH phase classification indicate decreases in food security. CH data at the second administrative division level were aggregated to the first administrative division level using population-weighted averages. Increases in food security sub-index and composite vulnerability scores (measured on the x-axes) correspond to greater vulnerability. Some data labels were omitted for legibility.

declines in food security; only 1 area showed a (small) improvement in food security. Nearly all (12 out of 14) of the areas showing declines in food security were classified as "more" or "much more" vulnerable than the regional average on the food security sub-index. Areas with larger declines in food security, as measured by the CH, also tended to have higher vulnerability levels, as measured by both the food security sub-index and the composite vulnerability index. Figure 5.5 compares changes in CH classification with vulnerability scores prior to classification into the four categories.

These findings are suggestive of an association between higher levels of vulnerability and food insecurity during the early months of the pandemic. However, more rigorous analysis is required to establish causality, pending data availability.

Impact of Vulnerability to COVID-19 on Food Security at the Household Level

LASSO Model

In this section, we turn to the household-level analysis of the impact of vulnerability to the pandemic on food security. Given the number of variables involved and the lack of consensus on an exhaustive list of COVID-19 determinants affecting food security, we decided to use the LASSO (least absolute shrinkage and selection operator) algorithm. To illustrate the impact of vulnerability to COVID-19 on food security, we implement a double selection model at the household level using the LASSO machine learning algorithm. In other words, we assume that the probability of being food insecure is a function of a set of vulnerability variables that are themselves determined by household and location characteristics. Following Belloni, Chernozhukov, and Wei (2016), the model takes the following form:

$$\mathrm{E}[y|\boldsymbol{d}, x] = G(\boldsymbol{d}\alpha' + \beta_0 + x\beta'), \quad (1)$$

where $G(a) = \exp(a)/\{1 + \exp(a)\}$, $\boldsymbol{d}$ contains the J covariates of interest, and x is the p controls.

Initially introduced by Tibshirani (1996), LASSO estimates the parameters by finding the minimum of a cost function of the following form:

$$Q_L = \frac{1}{N}\sum_{i=1}^{N} w_i f(y_i, \beta_0 + x_i\beta') + \lambda \sum_{j=1}^{p} \theta_j |\beta_j|, \quad (2)$$

where N is the number of observations, w_i are observation-level weights, $f(\cdot)$ is the model likelihood contribution, $\lambda \geq 0$ is the LASSO penalty parameter, and θ_j are coefficient-level weights.

Data Description

This section is based on longitudinal household data from the World Bank's LSMS-supported High-Frequency Phone Survey on COVID-19 in Mali. The dataset includes five rounds collected in May, June, July, September, and October 2020. The survey period corresponds to the pastoral lean season (April–June) and the agricultural lean season (July–October) (FEWS NET 2013). These data were designed to be representative at the country and regional levels as well as at the urban and rural levels. The survey covers 12 topics that provide detailed and relevant information on prices and food security, income, and socioeconomic indicators to assess the welfare impact of the pandemic. The survey also includes variables related to employment, access to basic services, shocks and coping strategies, income loss, behavior, and social distancing. Data on governance and sociopolitical crisis cover the period up to July. As presented in Table 5.1, data sample sizes range between 1,718 and 1,935 households.

In Mali, the first cases of COVID-19 were reported on March 25, 2020, in a context marked by a worsening security crisis. As of October 25, 2020, the country had recorded 3,490 positive cases, with peaks of over 80 and 50 confirmed cases per day in June and October, respectively (Mali, Ministry of Health and Social Affairs 2020). After the survey period, the COVID-19 situation worsened, intensifying during November 2020–January 2021 and again in March–April 2021, when daily cases reached a new peak of 413. Infection rates had declined again by June 2021, with daily average new cases in the single digits (HERA 2021).

We carry out two versions of the analysis. In the first estimation, y is a binary variable equal to 1 if the household reported having experienced food insecurity due to COVID-19; in the second, the dependent variable is reported food insecurity not due to COVID-19. Vector $\boldsymbol{d}$ includes variables (poverty status, access to health services, access to the Internet, population density, and negative shocks) that capture household vulnerability to the pandemic. Finally, the controls (x) include household demographics (age, gender, size, location), governance, perception of government responses to the pandemic, and political environment. The vector $\boldsymbol{d}$ variables were selected based on their potential to reflect households' vulnerability to negative effects of COVID-19 on food security.

Table 5.2 reports summary statistics of variables of interest used in our analysis. Poverty status, which is defined here by households' subjective assessments of their status, varies between 25.5 percent at the beginning of the pandemic and 26.6 percent in October 2020. As mentioned above, following Carletto, Zezza, and Banerjee (2013) and Bellemare and Novak (2017), we defined COVID-19-related food insecurity by using variables related to the households' self-reported ability to eat nutritious or healthy food.[5] In the questionnaire, households that reported not being able to eat nutritious or healthy food were asked whether this was specifically due to the COVID-19 crisis. Households that replied affirmatively are considered to be food insecure due to COVID-19, while households that reported food insecurity but answered that it was not due to COVID-19 are considered to have been food insecure in the absence of the COVID-19 crisis.

Over the five rounds of the survey, the results show a significant decrease in households considered to be food insecure both in the absence of COVID-19 and due to the COVID-19 crisis. Indeed, household food insecurity was the highest at the beginning of the pandemic (just over 43 percent

TABLE 5.2—DESCRIPTIVE STATISTICS OF VARIABLES OF INTEREST

Variable	Round 1 (N = 1,718)	Round 2 (N = 1,935)	Round 3 (N = 1,897)	Round 4 (N = 1,792)	Round 5 (N = 1,761)
Food insecurity due to COVID-19 (1 if food insecure because of COVID-19, 0 if no)	43.3 (0.496)	36.0 (0.480)	27.5 (0.447)	28.0 (0.449)	28.2 (0.450)
Food insecurity in the absence of COVID-19 (1 if food insecure, 0 if no)	43.6 (0.496)	39.9 (0.490)	31.1 (0.463)	31.6 (0.465)	31.9 (0.467)
Poverty (1 if poor, 0 if no)	25.5 (0.436)	26.7 (0.442)	26.4 (0.441)	26.2 (0.439)	26.6 (0.442)
Illness of an income-earning household member (1 if yes, 0 if no)	10.1 (0.301)	10.0 (0.300)	10.3 (0.304)	10.1 (0.301)	10.2 (0.303)
Loss of employment (1 if yes, 0 if no)	11.9 (0.324)	11.9 (0.324)	12.2 (0.327)	12.5 (0.331)	12.5 (0.330)
Bankruptcy of a nonfarm family business (1 if yes, 0 if no)	6.7 (0.254)	6.7 (0.251)	7.0 (0.254)	6.8 (0.251)	6.9 (0.253)
Increase in price of major food items consumed (1 if yes, 0 if no)	25.7 (0.437)	25.8 (0.438)	25.6 (0.437)	25.0 (0.433)	25.0 (0.433)
Need access to COVID-19-related services (1 if yes, 0 if no)	2.2 (0.148)	2.4 (0.154)	2.5 (0.155)	2.5 (0.155)	1.1 (0.106)
Need access to maternal health services (1 if yes, 0 if no)	15.2 (0.359)	15.1 (0.358)	15.1 (0.358)	15.1 (0.358)	14.4 (0.351)
Need access to child health services other than COVID-19 (1 if yes, 0 if no)	32.6 (0.469)	34.1 (0.474)	34.0 (0.474)	33.9 (0.474)	38.0 (0.486)
Need access to adult health services other than COVID-19 (1 if yes, 0 if no)	31.0 (0.463)	32.0 (0.467)	31.8 (0.466)	31.9 (0.466)	35.6 (0.479)
Access to the Internet (1 if yes, 0 if no)	74.7 (0.435)	74.2 (0.438)	74.0 (0.439)	73.9 (0.439)	74.0 (0.438)
Sample weight (used as proxy for population density)	1,405.44	1,243.72	1,242.74	1,298.27	1,310.97

Source: Authors' calculations based on Mali Living Standards Measurement Study–Integrated Surveys on Agriculture High-Frequency Phone Survey 2020 rounds (World Bank 2020).

Note: The first values listed are means, and the values in parentheses are standard deviations.

5 The question used to assess food insecurity is "You or other members of your household, have you been in a situation where you could not eat foods that are nutritious and good for your health because you did not have enough money or other ways to get food?" The same question format was used consistently in the first four rounds of the panel survey. For the final cycle, we assume that the numbers do not change between rounds four and five.

in May for both categories) but decreased in October to 31.9 percent for those insecure prior to COVID-19 and 28.2 percent for those insecure due to the pandemic.

Our findings suggest that more than 30 percent of the population had access to child health services, compared to 15 percent for maternal health services. Less than 3 percent of households had access to health services related to COVID-19. There was a slight increase in access to child health services (vaccination) during the period under consideration.

Between 10 and 12 percent of households have experienced the loss of either employment or an income-earning family member due to the COVID-19 pandemic. The proportion of households negatively affected by the bankruptcy of a nonfarm family business, an increase in the price of major food items consumed, or the illness of an income-earning household member was roughly stable over the five survey rounds. In terms of health services, the proportion of households with access to child or adult health services (other than COVID-19) and COVID-19-related services (testing, diagnosis, treatment) remained more or less the same throughout the period under consideration. The results also indicate that more than 7 in 10 Malian households have access to the Internet. This proportion remained stable over the period under consideration.

Table 5.3 presents a summary of unconditional transition probabilities from one state of food security to the other between survey rounds. Overall, the probability of staying in the same state is approximately 59–70 percent for food secure households, as compared to 34–43 percent for food insecure households. However, it is worth noting that the dynamics are different from one round to another. In future analysis, it will be interesting to explore the relationship between household characteristics and food security transition probabilities. In the current study, we account for only household and location attributes that ultimately determine the negative effects of COVID-19 on food security at the household level and that may be more complex than one would expect.

TABLE 5.3—UNCONDITIONAL TRANSITION PROBABILITIES FOR FOOD SECURITY

Food security status	From round 1 to 2		From round 2 to 3		From round 3 to 4		From round 4 to 5	
	Food secure	Food insecure	Food secure	Food insecure	Food secure	Food insecure	Food secure	Food insecure
Food secure	0.593	0.407	0.656	0.345	0.656	0.345	0.697	0.303
Food insecure	0.567	0.433	0.623	0.377	0.623	0.377	0.656	0.344

Source: Authors' calculations based on World Bank 2020.

Note: Unconditional transition probabilities refer to probabilities of entering a different food security status, independent of any other factors. The row categories represent status in the first of two subsequent rounds, and the column categories represent status in the second of the subsequent rounds. For example, 0.593 is the share of households that were food secure in round 1 that also reported being food secure in round 2.

Results

Estimation results are reported in Table 5.4. For the sake of parsimony, we discuss only the results of variables of interest (matrix d in equation 1). In total we had 40 control variables, but the LASSO algorithm selected only 23.[6] The first two columns of Table 5.4 present the results for food insecurity as aggravated by COVID-19, while the last two focus on food insecurity in the absence of COVID-19.

Overall, the results between the two specifications are qualitatively the same, which is probably due to the short period of time examined (five months). As expected, poverty status, negative shocks, access to the Internet, and population density have significant impacts on household food security.

In the literature, as pointed out by Naudé, Santos-Paulino, and McGillivray (2009), poverty status is often included in assessments of resilience and vulnerability; indeed, poverty status has a strong relationship with food and nutrition insecurity (see, for example, Siddiqui et al. 2020; Wight et al. 2014). Health variables such as access to maternal, child, and COVID-19-related health services are included to reflect households' access to medical services. Access to health services is an important factor in households' ability to respond to health shocks (FAO 2016), with medical services being particularly relevant for resilience to

6 We tested for overspecification by implementing the elastic net (Zou and Hastie 2005), which includes a penalty whenever covariates are correlated. More specifically, coefficient estimates from the elastic net are more robust to the presence of highly correlated covariates than are LASSO solutions. Results from the elastic net did not suggest overspecification or redundancy and indicated that variables are not correlated enough to require a robust estimation.

TABLE 5.4—ESTIMATION RESULTS, DRIVERS OF FOOD INSECURITY

Variable	Food insecurity exacerbated because of COVID-19		Food insecurity in the absence of COVID-19	
	Coefficient	Robust standard error	Coefficient	Robust standard error
Poverty (1 if poor, 0 if no)	0.4901***	0.0761	0.5072***	0.0759
Illness of an income-earning household member (1 if yes, 0 if no)	0.6989***	0.1004	0.6852***	0.1004
Loss of employment (1 if yes, 0 if no)	0.7997***	0.0882	0.7801***	0.0883
Bankruptcy of a nonfarm family business (1 if yes, 0 if no)	-0.0420	0.1288	-0.0072	0.1276
Increase in price of major food items (1 if yes, 0 if no)	0.1279*	0.0728	0.1196*	0.0728
Access to the Internet (1 if yes, 0 if no)	-0.4403***	0.0744	-0.4580***	0.0742
Assess to COVID-19-related services (1 if yes, 0 if no)	-0.0295	0.1906	-0.0451	0.1911
Assess to maternal health services (1 if yes, 0 if no)	0.0512	0.0859	0.0816	0.0856
Assess to child health services other than COVID-19 (1 if yes, 0 if no)	0.0613	0.0659	0.0687	0.0658
Population density	0.0455**	0.0235	0.0510**	0.0234
Number of observations	5,288		5,288	
Number of controls	40		40	
Number of selected controls	23		23	
Wald chi-squared (10)	221.6		224.9	
P-value	0.00		0.00	

Source: Authors' estimation results.
Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

health shocks such as COVID-19. However, in our results these variables are not significant. Most of the health access variables are too general[7] to capture the impact of COVID-19 in the short term. For example, for the COVID-19-related health services variable, only symptomatic respondents answered this question; however, they represent less than 3 percent of surveyed individuals.

Access to the Internet is expected to reflect households' ability to access information and overcome the effects of social distancing; in some cases, Internet access can permit household members with formal employment to protect their income sources by working from home during lockdowns. Our results suggest that the probability of being food insecure is much lower for households with Internet access compared to those without access to the Internet. While access to the Internet is higher among the non-poor (79 percent) than the poor (58 percent), the community at large is rather well serviced, with at least 75 percent of surveyed individuals having Internet access. This may be due to Mali's high mobile connectivity rate, with 125 mobile cellular subscriptions per 100 people as of 2020 (World Bank 2021).

Negative shocks such as illness of an income-earning household member, job loss, bankruptcy of a nonfarm family business, and increase in the price of a major food item increase the probability of households depleting their assets to cope, which ultimately threatens their food security standings. We found that households hit by illness of an income-earning family member, loss of employment, or increase in the price of a major food item consumed have a higher probability of becoming food insecure.

7 They are not specifically related to health conditions that put an individual at greater risk of contracting COVID-19 or of experiencing worse outcomes, such asthma, blood disorders, cancer, cerebrovascular disease, chronic obstructive pulmonary disease, chronic kidney disease, cystic fibrosis, diabetes, Down syndrome, heart disease, hypertension, use of corticosteroids or other immunosuppressive medications, solid organ or blood stem cell transplantation, neurological conditions, and obesity.

Finally, we include sample weight as a proxy for population density as an additional vulnerability variable that captures the level of social interaction with respect to social distancing measures. Higher population density is expected to increase the speed of COVID-19 contagion, therefore contributing to negative impacts on food security. Our findings confirm that higher population density is associated with negative impacts of COVID-19 on food security.

Conclusion and Recommendations

In this chapter we present two types of vulnerability analysis: we examine the vulnerability of subnational regions to the health and food security effects of COVID-19, and the vulnerability of households to the negative impacts of COVID-19 on food security. The subnational analysis suggests that while there are major differences in vulnerability between West and Central African countries, vulnerability can also vary markedly within countries, underlining the need for decision-makers to monitor local effects closely and be prepared to intervene in areas with high levels of vulnerability. While the impacts of COVID-19 are still unfolding, we find some evidence that higher levels of vulnerability may be associated with larger reductions in food security due to the pandemic. The household-level analysis examines the impact of drivers of vulnerability to COVID-19 on food security. Findings suggest that preexisting poverty, lack of access to the Internet, greater population density, and negative income and price shocks increase susceptibility to negative food security impacts.

Both types of analysis point to the importance of programs to help households absorb negative shocks. The effects of crises are not uniform; therefore, resource limitations require governments and donors to allocate assistance to the most vulnerable locations, households, and individuals. In cases of sudden and widely shared crises, geographic targeting may be the most efficient and effective approach.

As post-COVID-19 crisis data become more widely available, ex post analyses should be carried out to refine subnational vulnerability analyses to identify the areas or households at highest risk. This would help to inform regular and ongoing monitoring of vulnerability to future crises. Ongoing vulnerability monitoring efforts could include multiple indexes customized to different types of shocks. While many drivers of vulnerability are not dependent on the type of shock, other drivers may differ. For example, population density is often associated with better access to health systems and other services that help households adapt to shocks, but in the case of COVID-19, density increases household members' risk of contracting the disease through social interactions, which in turn may exacerbate the negative impact on food security and health.

Appendix

Table 5.A1—Data sources for subnational vulnerability analysis		
Country	**Indicator**	**Source**
Benin	Stunting, medical assistance, distance to health facility	DHS 2017–2018
Benin	Per capita food expenditure	EMICOV 2015 (PPP from WDI 2015)
Burkina Faso	Stunting, medical assistance, distance to health facility	DHS 2017
Burkina Faso	Per capita food expenditure	LSMS 2014 (PPP from WDI 2015)
Cameroon	Stunting, medical assistance, distance to health facility	DHS 2018
Cameroon	Per capita food expenditure	ECAM4 2014 (PPP from WDI 2014)
Chad	Stunting, medical assistance, distance to health facility	DHS 2018
Chad	Per capita food expenditure	ECOSIT4 2018 (PPP from WDI 2014)
Ghana	Stunting	Micronutrient survey 2017
Ghana	Medical assistance, distance to health facility	DHS 2014
Ghana	Per capita food expenditure	GLSS 7 2017 (report) (PPP from WDI 2017)
Mali	Stunting, medical assistance, distance to health facility	DHS 2018
Mali	Per capita food expenditure	ENSAN 2016 (PPP from WDI 2016)
Niger	Stunting, medical assistance, distance to health facility	DHS 2012
Niger	Per capita food expenditure	LSMS 2014 (PPP from WDI 2014)
Nigeria	Stunting, medical assistance, distance to health facility	DHS 2018
Nigeria	Per capita food expenditure	LSMS 2014 (PPP from WDI 2014)
Senegal	Stunting, medical assistance, distance to health facility	DHS 2017
Senegal	Per capita food expenditure	PAPA 2017 (PPP from WDI 2017)
Togo	Stunting	MICS 2017
Togo	Medical assistance, distance to health facility	DHS 2013
Togo	Per capita food expenditure	QUIBB 2015 (PPP from WDI 2015)

Note: DHS = Demographic and Health Surveys; ECAM4 = Quatrième Enquête Camerounaise auprès des Ménages; ECOSIT4 = Enquête sur les Conditions de Vie des Ménages et la Pauvreté au Tchad; EMICOV = Enquête Modulaire Intégrée sur les Conditions de Vie des Ménages; ENSAN = Enquête Nationale sur la Sécurité Alimentaire et Nutritionnelle; GLSS 7 = Ghana Living Standards Survey–Round Seven; LSMS = Living Standards Measurement Study; MICS = Multiple Indicator Cluster Surveys; PAPA = Projet d'Appui aux Politiques Agricoles; PPP = purchasing power parity; QUIBB = Questionnaire Unifié des Indicateurs de Base du Bien-être; WDI = World Bank World Development Indicators.