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Targeting vulnerability hotspots along the agrifood system

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Contents

Tables

Figures

Abstract

We leverage the multi-stressor nature of the COVID-19 generalized disruption as an opportunity to test the out-of-sample forecasting accuracy of both theory-based and data-driven vulnerability prediction models for the *ex ante* targeting of preventive interventions. Taking advantage of the World Bank multitopic surveys for Ethiopia and Nigeria, the two most populous African countries, our retrospective evaluation assesses the models' ability to anticipate households and agrifood system actors experiencing food insecurity and income losses during the COVID-19 pandemic. The results are disappointing: we document that, despite considerable heterogeneity across data and methods, both models do not achieve satisfactory out-of-sample forecasting performances. Our findings are robust to the use of different data, estimation methods, and several heterogeneity analyses and sensitivity checks. This evidence calls for a refinement of current profiling methodologies and for interoperability efforts to close existing microdata gaps. Such efforts would enable policymakers to implement more effective early-warning systems of vulnerability hotspots and improve the cost-effectiveness of development interventions aimed at targeting groups vulnerable to future food crises.

Keywords: vulnerability, food insecurity, forecasting, policy targeting, COVID-19.

JEL codes: C53, I10, Q12, O12.

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1 Introduction

Much has been written about the severe impacts of the COVID-19 pandemic crisis on the welfare and food security of poor people in developing contexts (Amare *et al.*, 2021; Béné, 2020; Béné *et al.*, 2021; Bundervoet, Dávalos and Garcia, 2022; Egger *et al.*, 2021; Huss *et al.*, 2021; Upton, Constenla-Villoslada and Barrett, 2022). Less empirical effort has been devoted to understanding if it was possible to anticipate the identification of the socioeconomic groups most at risk before the COVID-19 shock took place. In this work, we carry out a retrospective empirical analysis to shed light on this issue.

Overall, international agencies confirm that food security indicators have continued to deteriorate globally despite social protection interventions and extensive measures by national and international actors (FAO *et al.*, 2021). The rising trends of chronic hunger, acute food insecurity, and malnutrition can be attributed to a complex mix of factors including ongoing conflicts, climate variability, extreme weather conditions, dwindling resources, economic challenges, and socio-political instability. These issues are often exacerbated by underlying conditions such as poverty and inequality, which are sometimes aggravated by ineffective policies. These factors collectively undermine efforts to enhance food security and nutrition (FAO, 2023). The role of vulnerability in this context is central: vulnerable households determine the fragility of the entire agrifood system (as producers, processors, retailers, vendors, and consumers), and it is, therefore, critical to provide targeted and timely social protection assistance and insurance mechanisms to all vulnerable groups (FAO, 2021).

Governments face the challenge of rebalancing exposure to various shocks in real time when developing timely policy responses (Barrett *et al*., 2021). In order to enhance the resilience of supply chains and local agrifood systems, it is crucial to identify vulnerability hotspots across the agrifood system and to understand how they respond to different shocks (Reddy, Singh and Anbumozhi, 2016). In conclusion, the literature suggests that a better understanding of vulnerability to food insecurity, and a mapping of the different sources of vulnerability that affect particular actors and categories, should be considered as policy priorities to increase resilience to future shocks (Béné *et al*., 2021; Bundervoet, Dávalos and Garcia, 2022).

The aim is to assess the current state of profiling mechanisms and targeting models in anticipation of the next major food insecurity crisis. To this end, we made two main amendments to the vulnerability literature: first, we adapt the existing measures of vulnerability to poverty to assess *ex ante* food security; second, in the absence of a unified framework for a risk-sensitive and theory-based measure of vulnerability, we explore the predictive performance of different approaches: the widely adopted “vulnerability as expected poverty” (VEP) (Chaudhuri, Jalan and Suryahadi, 2002), the “risk-sensitive” measure of “vulnerability as the threat of future poverty” (VTP) (Calvo and Dercon, 2005), and a simple machine-learning model, namely a classification tree (Hastie, Tibshirani and Friedman, 2009). Due to the chronic scarcity of panel data in developing countries, the first approach offers a viable alternative to food security assessment, already widely implemented in the empirical poverty literature (Celidoni, 2015; Chaudhuri, Jalan and Suryahadi, 2002; Imai, Gaiha and Kang, 2011; Subbarao and Christiaensen, 2004) based on cross-sectional data. The second approach is risk-sensitive and specifically suited for panel data. The third approach is based on recent advances in data-driven methodologies and exploits an intuitive classification tree to predict the food insecurity status out-of-sample.

While employing three different methods, the common goal is to bring an empirical validation mindset based on out-of-sample tests and forecasting performance assessments into the toolbox of empirical vulnerability analysis. In doing so, we answer the recent call to care about whether measurements at our disposal exhibit skill in predicting development outcomes out-of-sample and provide empirical validation of predictive models by testing their forecasting accuracy using the available data (Upton, Constenla-Villoslada and Barrett, 2022). Although conventional poverty and food security measurements often work reasonably well to target the chronically poor or food-insecure people, they perform far worse in identifying transitory deprivation and thus are least helpful in responding to major shocks when they are most needed. In contrast, vulnerability assessments can be seen as an *ex ante* targeting criterion that makes it possible to detect the individuals most in need before the occurrence of shocks.

Taking advantage of household microdata taken from multi-purpose household pre- and post-COVID-19 surveys collected by the World Bank[1] in Ethiopia[2] and Nigeria,[3] we conduct a retrospective evaluation of the accuracy of both theory-based and data-driven vulnerability targeting models in predicting households vulnerable to food insecurity prior to the COVID-19 shock. Thus, we test how accurate our *ex ante* out-of-sample forecasts are in anticipating the *ex post* realizations of food insecurity conditions observed in the post-shock data.

The results of our predictive exercise document that, for both countries, all the models perform quite poorly in identifying *ex ante* households suffering income losses and food insecurity conditions during the COVID-19 pandemic crisis without relevant heterogeneities across different agrifood system actors and livelihoods. The machine-learning model implemented for Nigeria fares better at identifying food-insecure households – but its performance is still far from ideal, mainly due to the limited amount of available data. Our findings of imperfect targeting suggest that a revision of current targeting mechanisms, better profiling methodologies, and more empirical validation of predictive models of development outcomes are urgently needed. This issue is particularly severe in developing countries where data are generally scarce and do not include informal activities (Aiken *et al.*, 2022). These efforts would enable policymakers to take action before rather than after the occurrence of shocks and to implement early-warning systems of vulnerability hotspots in anticipation of future food insecurity crises, such as current severe exogenous shocks induced by geopolitical tensions in Eastern Europe.[4] Besides, strengthening *ex ante* targeting would also improve the cost-effectiveness and efficacy of resilience-building programmes. Lastly, considering the data-poor environments in which current methodologies operate, more investment in scaling up survey instruments, especially their interoperability with non-conventional data sources, is essential to maximize the potential of *ex ante* targeting.

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[1] In supporting the design and implementation of the Ethiopia Socioeconomic Survey (ERSS) for Ethiopia and the General Household Survey (GHS) for Nigeria.

[2] Pre-COVID-19: Ethiopia Socioeconomic Survey (ESS). Post-COVID-19: COVID-19 High Frequency Phone Survey of Households 2020.

[3] Pre-COVID-19: Nigeria General Household Survey – Panel. Post-COVID-19: National Longitudinal Phone Survey (NLPS) 2021–2022.

[4] The war in Ukraine is already causing an increase in the price of wheat by 26.4 percent. This will primarily hurt sub-Saharan African countries with a diet mainly based on wheat, corn, and sorghum and where food represents a large share of consumption. These factors will negatively affect consumers' purchasing power and jeopardize their fragile food security (IMF, 2022).

Two preliminary clarifications are important. First, we are not interested in the effects of the COVID-19 pandemic per se. Instead, we use it merely as a “stress test” for the empirical out-of-sample validation of current profiling methodologies. Second, we know that *ex ante* vulnerability predictions and *ex post* observed outcomes are different metrics. Indeed, the concept of vulnerability, an inherently forward-looking construct, is neither directly observable nor linked to the actual manifestation of shocks (Imai, Gaiha and Kang, 2011; Magrini, Montalbano and Winters, 2018). Hence, naïve comparisons between these two statistics should be taken with a grain of salt. We are also aware that our work is subject to several other methodological caveats (measurement error, data scarcity, absence of *ex ante* identification of the characteristics and probabilities associated with the COVID-19 pandemic “state of the world”). We take all these caveats into careful consideration.

From a methodological viewpoint, our work speaks to both the well-established theoretical and empirical literature on vulnerability to poverty and food insecurity and adverse shocks (Bogale, 2012; Calvo and Dercon, 2005, 2013; Chaudhuri, Jalan and Suryahadi, 2002; Gallardo, 2018; Hoddinott and Quisumbing, 2003; Magrini, Montalbano and Winters, 2018; Povel, 2015; Sileshi *et al.*, 2019), as well as to the flourishing strand of works that leverage data-driven and cross-validation methods coupled with survey information and non-conventional data sources (especially in data-scarce environments) in the service of poverty and food insecurity targeting, mapping, and monitoring (Aiken *et al.*, 2022; Browne *et al.*, 2021; Garbero and Letta, 2022; McBride *et al.*, 2022; Zhou *et al.*, 2022). Specifically, our methodological contribution is to make theory-based, and data-driven literature meet by bringing the classic theory-based models of vulnerability analysis into the “train-test-compare” cultural mindset typical of the machine-learning community based on out-of-sample validation. At the same time, we are advocating for a forecasting culture based on interpretability, domain knowledge, and economic intuition.

The rest of this paper is arranged as follows: the next section reviews the relevant literature, Section 3 describes the context and data, Section 4 illustrates the empirical strategy and the different predictive models, Section 5 presents the results of the empirical analysis, Section 6 disaggregates the analysis by agrifood system actors and livelihood categories to look for heterogeneities in targeting accuracy, and Section 7 concludes and provides policy guidelines and recommendations.

2 Literature review

To place our contribution into proper context, it is first necessary to review the related strands of the scientific literature. To this end, we first briefly review in this section the two currents of scientific literature on *ex ante* profiling methodologies we draw from, namely the traditional vulnerability literature, strongly rooted in standard economic theory, and the new research strand leveraging machine learning for poverty and food insecurity mapping, monitoring, and targeting. We then summarize the literature on the agrifood system impacts of the COVID-19 pandemic on the welfare of poor people in developing countries.

2.1 The vulnerability literature

Measuring and addressing vulnerability is of great relevance for governments and policymakers in improving the targeting of social protection interventions. In the context of developing countries, vulnerability to poverty is the area that has been primarily explored. The concept of vulnerability to poverty refers to the likelihood that an individual or a household will be poor in the future, which means that they will have a level of welfare – generally the level of consumption – below some benchmark, usually the poverty line (Hoddinott and Quisumbing, 2003).

Although vulnerability is strictly linked to poverty, the two concepts are different. Vulnerability is a dynamic concept that is unobservable at any point in time (Chaudhuri, Jalan and Suryahadi, 2002). It is said to be *ex ante* and forward-looking because it is measured at time *t* before the shock occurs (*ex ante*) and refers to the probability of being poor at time *t+1* (forward-looking). In other words, being vulnerable today, before a major shock, means having a high likelihood of being poor if an adverse event happens tomorrow.

Conversely, poverty is an effective outcome that is observable at time *t*. It refers to the *ex post* static status in which the individual lives at the exact moment it is observed and measured (Gallardo, 2018). Correlates of vulnerability may differ from those of poverty. This distinction plays a crucial role in designing policies and targeting only the poor could exclude a significant group of individuals who risk experiencing a welfare loss (Montalbano, 2011).

One of the most popular vulnerability measurements is the so-called "vulnerability as expected poverty" (VEP) (Chaudhuri, Jalan and Suryahadi, 2002). Much of the popularity of this approach comes from the fact that VEP intuitively provides results in terms of expected values of the Foster-Greer-Thorbecke (FGT) measurement of poverty as well as the possibility of implementing it using cross-sectional data, which are more frequently available for developing countries compared to panel data. proposed a measurement of vulnerability as low expected utility (VEU), which is, as suggested by its name, based on expected utility. This measure is also "risk-sensitive" and built on solid theoretical underpinnings. However, the expected utility focus makes it harder to interpret the outcomes of this approach for policymaking. In the presence of panel data, a better option is relying on a "risk-sensitive" approach. In this respect, one of the most robust vulnerability measures is the so-called "vulnerability as the threat of future poverty" (VTP) (Calvo and Dercon, 2013; Ligon and Schechter, 2003). In the VTP approach, vulnerability is defined as a probability-weighted average of future indices of deprivation in different states of the world. This measurement combines households' deprivation and shortfalls in welfare indicators capturing exposure to risks. Unlike VEP, VTP is risk-sensitive and satisfies the so-called focus axiom, according to which the burden of future poverty will not be compensated by possible positive outcomes.

Following on from a seminal work (Christiaensen and Boisvert, 2000), vulnerability measurements have recently been adapted to the field of food insecurity (Bogale, 2012; Das, 2021; Ibok, Osbahr and Srinivasan, 2019; Mutabazi *et al.*, 2015; Ozughalu, 2016; Scaramozzino, 2006; Sharaunga, Mudhara and Bogale, 2015; Sileshi *et al.*, 2019) to potentially overcome the limitations of traditional food insecurity indicators. As with poverty, it is essential to distinguish between food insecurity and vulnerability to food insecurity. Food insecurity indicators are static measurements that refer to the shortage of food for a household at a specific moment in time. In contrast, vulnerability to food insecurity is a dynamic computation embedding risks and shocks that the household might face and that potentially affect food consumption levels (Sileshi *et al.*, 2019). In this framework, vulnerability refers to the household's probability of falling below the food poverty line (Capaldo *et al.*, 2010; Løvendal and Knowles, 2007; Sileshi *et al.*, 2019). Specifically, in the case of Ethiopia, we implement the approach based on vulnerability as expected poverty with a focus on food insecurity, as was done by Bogale (2012) and Sileshi *et al.* (2019). However, while they aim to identify the determinants of vulnerability, distinguishing between chronic and transitory food insecurity, we are interested instead in assessing and validating the model in terms of forecasting accuracy. Conversely, the availability of a panel dataset for Nigeria allows us to explore vulnerability as the threat of food insecurity using a hybrid threshold as proposed by Povel (2015).

2.2 The new machine-learning literature for poverty and food insecurity targeting

In the last few years, in the wake of the increasing use of data science and artificial intelligence techniques in economics, as well as due to the recent availability of large amounts of information in the form of big and non-conventional data sources requiring computationally-intensive tools, a new body of research has focused on the leveraging of machine- and deep-learning predictive algorithms for the mapping, targeting and monitoring of a variety of well-being outcomes.

Among the first to apply these tools in development economics, Blumenstock, Cadamuro and On (2015) use anonymized mobile phone data from Rwanda to show the potential of feature engineering and elastic net regularization techniques in predicting poverty and wealth status and generating high-resolution maps of poverty and wealth from call records. Jean *et al.* (2016) instead couple high-resolution daytime satellite imagery from five African countries with convolutional neural networks to predict local-level poverty. McBride and Nichols (2016) employ United States Agency for International Development (USAID) poverty assessment tools and data to re-calibrate Proxy Means Test poverty-targeting tools towards the prioritization of out-of-sample performance, in place of the traditional in-sample focus, through cross-validation and stochastic ensemble methods.

But poverty is not the only measure of well-being targeted by this literature, which has also focused on food security and resilience outcomes. Hossain, Mullally and Asadullah (2019) employ machine-learning routines, such as random forest and extreme gradient boosting, as well as traditional methods on survey data from Bangladesh to predict household food insecurity measured through caloric intake. Lentz *et al.* (2019) combine high-resolution market data, remote sensing information and survey data to forecast household-level food security status in Malawi using Least Absolute Shrinkage and Selection Operator (LASSO) and logit models. Zhou *et al.* (2022), emphasizing the need for interpretability and transparency of predictive models for policy targeting, leverage gradient boosting and random forest to predict household food insecurity in villages from three African countries. As for resilience, Knippenberg, Jensen and Constas (2019) apply LASSO and random forests to identify the best predictors of a resilience measure based on the Coping Strategy Index of Malawian households, while Garbero and Letta (2022) use a cross-country survey dataset and a battery of machine-learning algorithms to predict household resilience to shocks. More recently, Haushofer *et al.* (2022) employ machine learning – specifically, generalized random forests – on data from an NGO Cash Transfer programme implemented in Kenya to show that households that are social welfare maximizing to target, namely those delivering the largest treatment effects, are not those predicted to be most deprived.

Other recent works in this tradition include the contribution by Tang, Liu and Matteson (2022), who predict poverty at community level in Malawi, Nigeria, United Republic of Tanzania and Uganda through the use of convolutional neural networks applied to data on a popular vegetation index, Browne *et al.* (2021), who apply an interpretable multivariate random forest approach on clustered household-level outcome information and remote sensing feature data to map poverty and malnutrition areas, and, finally, Aiken *et al.* (2022), who develop a new approach to targeting humanitarian assistance and social protection interventions based on a combination of machine-learning algorithms and satellite and mobile phone data, and evaluate this by studying a cash transfer programme implemented by Togo in response to the COVID-19 emergency. Notably, this study is among the first data-driven approaches that have been applied to target COVID-19 response policies. Finally, a recent study (Huang, Hsiang and Gonzalez-Navarro, 2021) provides the first example of the application of deep-learning methods and satellite data to evaluate the impact of anti-poverty programmes, opening the door to an extension of these methodologies towards the estimation of treatment effects and programme evaluation other than policy targeting.

In a recent overview (McBride *et al.*, 2022) the authors advocate the use of machine learning for poverty and food insecurity targeting, mapping, and monitoring, to fine-tune policy efforts on the ground and improve the design of effective early-warning mechanisms. At the same time, the authors warn about several important caveats regarding a wise policy-oriented use of these powerful tools. For instance, while the sudden availability of big data may seem to free researchers and agencies from the chronic microdata gaps in developing contexts, most of the approaches cited above still depend on traditional survey data for ground-truthing and validation of the models developed using remote sensing or other non-conventional information. McBride *et al.* (2022) also note that it is only possible to predict with accuracy states and processes that have been previously observed in data, and this presents a challenge for the development of early-warning systems and suggests that research should also focus on running simulations of extreme scenarios in the development of targeting models and prevention tools. Another crucial point is the distinction between contemporaneous and sequential prediction. While contemporaneous prediction is useful for poverty and malnutrition mapping, *sequential* prediction, which we call forecasting, is the analytical tool necessary for early-warning and targeting purposes (Browne *et al.*, 2021; Tang, Liu and Matteson, 2022). Finally, and differently from other domains, the importance of some degree of interpretability of model outputs should not be understated when it comes to the application of machine-learning routines in the service of policy targeting. In this respect, the well-known trade-off between accuracy and transparency could lean more in favour of the latter, at the expense of a loss in predictive accuracy (Browne *et al.*, 2021; McBride *et al.*, 2022).

2.3 The food security impacts of the COVID-19 crisis

Barrett *et al.* (2021) highlight that the COVID-19 pandemic is only a seemingly unique event. Indeed, it has merely exposed the systemic and pre-existing vulnerabilities of rural populations situated within complex agrifood systems in developing countries. As such, the COVID-19 pandemic-induced food security dynamics reflect the broader issues facing vulnerable rural populations confronting structural deprivation in the midst of myriad shocks and stressors (Béné *et al.*, 2016). In sum, the COVID-19 pandemic acted as a threat amplifier and multiplier of shocks that are neither new nor rare to poor households in developing countries.

Similarly, in a systematic review of the resilience capacity of local agrifood systems, Béné (2020) emphasizes that the major direct impacts of COVID-19 on the agrifood system have been brought about by its effects on the income and purchasing power levels for all agrifood system actors caused by non-pharmaceutical interventions (for example, mobility restrictions and lockdowns), and the subsequent negative effect this had on their access to food. Income losses and food insecurity are thus strictly interconnected, and their joint dynamics are key in explaining the COVID-19 pandemic's direct and indirect effects on the agrifood system. While the major effect of COVID-19 on food security is mediated by income losses, it is also reasonable to assume that when experiencing income losses induced by mobility restrictions, loss of job or death of a household member, households may also, in turn, reduce their levels of food consumption (Béné, 2020), especially in the presence of severe liquidity constraints preventing the adoption of consumption-smoothing strategies. Barrett *et al.* (2021) also highlight how rural households are exposed to agrifood system shocks, particularly the shock produced by the COVID-19, not just as food producers but equally in their roles as food consumers or as workers within the broader agrifood value chain, hinting at the importance of disaggregating impact evaluations of COVID-19 effects on welfare for different agrifood system actors and livelihoods categories.

In a study on nine countries from Africa, Asia, and Latin America with phone-survey data on more than 30 000 respondents, Egger *et al.* (2021) document a generalized decline in income, employment, and food security (captured using self-reported missing or reduced meals) that began with the outset of the COVID-19 pandemic (March 2020). Because households were unable to implement coping strategies in response to these losses, the result was widespread food insecurity among the affected populations, far exceeding the levels of food insecurity generally experienced at the time of year in which interviews were implemented. Using representative and high-frequency phone-survey data on more than 41 000 households from 31 countries (collected by the World Bank), a recent study (Bundervoet, Dávalos and Garcia, 2022) finds that more than one-third of respondents lost their jobs and around two-thirds suffered income losses. The critical point for our purposes is that they also document that job and income losses are strongly associated with increased food insecurity for affected households. Lastly, their analysis suggests that COVID-19 pandemic-induced impacts have been regressive and disproportionately affected segments of the population who were already most vulnerable before the sudden arrival of COVID-19. Pre-existing vulnerabilities interacted with the disruption of ordinary economic activity brought about by the COVID-19 pandemic. Similar insights for geographic areas can be drawn from a recent study for Viet Nam (Vu *et al.*, 2022): using a Bartik-type IV shift-share instrument approach, the authors find small changes in food insecurity risk at the national level during the COVID-19 pandemic, but substantial heterogeneity at a more granular district level, with a subsample of more vulnerable districts severely affected.

3 Context and data

3.1 Context

Ethiopia and Nigeria are the two most populous countries in Africa. The first COVID-19 case in Ethiopia was reported on 13 March 2020, in Addis Ababa. In April, the Ethiopian Government declared a state of emergency, closing land borders and restricting cross-country transportation. However, unlike Nigeria, Ethiopia never went into a complete national lockdown[5]. Despite the high rates of economic growth experienced since 2005, studies reveal that levels of poverty and vulnerability remain very high (Dercon and Christiaensen, 2011; Dercon, Hoddinott and Woldehanna, 2012; IFPRI, 2017), with 26 percent of the rural population living below the poverty line in 2016 (UNDP, 2018). After the COVID-19 pandemic, Abay *et al.* (2020) found that half of the sample of households interviewed reported worse food security conditions compared to the pre- COVID-19-pandemic period, mainly due to food price increases, losses of income, and market closures. The primary social protection response to COVID-19 in Ethiopia has been through the Productive Safety Net Programme (PSNP), which provides food assistance and cash transfers in selected urban and rural areas. The available evidence suggests that the PSNP has at least partially mitigated the impact of the COVID-19 pandemic on food security, with beneficiaries faring better compared to non-beneficiaries (Abay *et al.*, 2020).

Nigeria was one of the first African countries affected by the COVID-19 pandemic, registering the first confirmed case on 27 February 2020, and among the first to introduce non-pharmaceutical restrictions to control the spread of the virus. The COVID-19 pandemic and the collapse of international oil prices that followed threatened Nigeria's already unstable economy (World Bank, 2020). Before the COVID-19 pandemic outbreak, Nigeria was slowly recovering from the 2016 recession. The country remains characterized by extremely high poverty rates and is heavily exposed to local and global food price volatility (Benson, Amare and Ogunniyi, 2020), which significantly amplified the impacts of the COVID-19 pandemic. Moreover, weather shocks to agricultural production exacerbate the adverse effects on household consumption, especially for rural and asset-poor households (Amare *et al.*, 2018). By matching the World Bank's LSMS-ISA pre-COVID-19 data with post-COVID-19 data (taken from high-frequency phone surveys) for Nigeria, the study by Amare *et al.* (2021) shows a 50 percent increase in household food insecurity compared to the pre-COVID-19 pandemic period. Moreover, 79 percent of households reported having suffered a reduction in total income since the start of the COVID-19 pandemic. Further, by carrying out an *ex post* impact evaluation through a difference-in-differences identification strategy, the authors find that mobility restrictions had significant adverse effects on food security outcomes, with disproportionate impacts on poor households and those living in conflict-ridden areas.

[5] This is the reason why we cannot explore the impact of lockdown measures on the outcomes of interest as we do for Nigeria. Instead, along the lines of Bundervoet, Dávalos and Garcia (2022), we estimate the main correlates of food insecurity experienced during the COVID-19 pandemic through a logistic regression, whose results are presented in Table A9 of Annex 2.

3.2 Data

Our research is carried out using combined datasets that include data collected before the COVID-19 pandemic using standard face-to-face surveys – which are employed to predict vulnerable households in the vulnerability analysis – and phone-survey data collected after the COVID-19 pandemic – which are used to compare *ex ante* predictions with post-COVID-19 observed outcomes in the targeting test.

Vulnerability prediction analysis (pre-COVID-19 data)

For the vulnerability analysis through which we predict the households vulnerable to food insecurity and income loss, we use the Living Standard Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) for Ethiopia and Nigeria. These data are nationally representative surveys collected by the World Bank in cooperation with national governments.

For Ethiopia, the analysis is carried out on the cross-sectional dataset covering the time span between 2018 and 2019. This wave does not represent a follow-up of the previous three waves, but it does constitute the baseline for a new panel survey that is not only nationally representative but also representative for each of Ethiopia's 11 regions and for rural and urban areas. For this reason, we could not replicate the longitudinal dataset that we will construct for Nigeria. In total, 7 527 households were interviewed. However, the data have been cleaned and merged in line with the purpose of our study, resulting in a final sample of 6 650 households.

For Nigeria, we use the panel dataset consisting of four waves (2010–2011, 2012–2013, 2015–2016, and 2018–2019), which supports the redesign and implementation of the General Household Survey (GHS). The GHS-Panel sample includes 5 000 households, which is a subsample of the GHS core survey of 22 000 households. A partial refresh of the GHS-Panel sample was implemented in the fourth wave of the panel to maintain the integrity and representativeness of the sample.

Regarding the sample size, a distinction must be made between theory-based and data-driven approaches. For the former, we need longitudinal data, so we only kept households re-interviewed in all the following waves, for which we have a complete set of information. This selection process led to a sample of 1 250 households per wave, with a full sample of 5 000 observations. For the latter, we can apply a larger sample size. In fact, machine-learning models can be estimated without longitudinal information. The only requirement is that households in the post-COVID-19 data also appear in the last pre-COVID-19 survey so we can match pre-COVID-19 input variables to the post-COVID-19 outcomes for each household. As explained in more detail below, we train a machine-learning model on the pre-COVID-19 data (the training set) and use it to predict post-COVID-19 outcomes (the testing set) and assess its forecasting performance. The total sample size is 3 715 household observations in the pre-COVID-19 data.

Targeting test (post-COVID-19 data)

For the targeting test, we use data from the LSMS-Supported High-Frequency Phone Surveys on COVID-19 implemented in 2020 for both Ethiopia and Nigeria. The samples from this survey were selected from the sample of households interviewed in 2018/2019. The interviews consist of a 15-minute questionnaire covering topics like employment status, household livelihoods, income losses, and coping strategies, access to basic needs, and knowledge of COVID-19 and mitigation measures.

Ethiopia's phone survey consists of 12 series collected between April 2020 and June 2021. For our study, we use the first series collected between April and May 2020, which contains information on the two outcomes of interest used in the analysis, namely food insecurity and reduction of food consumption, as explained in the following subsection. Accordingly, we have two different sample sizes: 3 201 households for the first outcome and 1 797 households for the second.

For Nigeria, we use the first round of the phone survey, carried out between April and May 2020, since it contains information on self-reported income losses. For the theory-based approach, the dataset is combined with the panel of pre-COVID-19 data to allow a comparison between pre- and post-COVID-19 outcomes, leading to a final sample for the targeting test of 316 households. The sample size is small because there is a need to use longitudinal data to compute the vulnerability measure implemented. For this reason, we can implement the COVID-19 vulnerability-based targeting test only for households interviewed in all four waves before the COVID-19 pandemic and in the post-COVID-19 period. For the data-driven approach, we do not have these limitations for the reasons explained in Section 3.2.1. We can therefore use a larger sample size of 1 311 observations in the post-COVID-19 dataset.

Outcome variables

Based on the availability of the data and the different methodologies used, we explore different outcome variables for Ethiopia and Nigeria.

For Ethiopia, the analysis of vulnerability is conducted using a dependent variable represented by the logarithm of household per capita food consumption expenditure expressed in the Ethiopian currency, the Birr, which is spatially and temporarily deflated to make it comparable across space and over time.[6] The food consumption variable includes annual values for food consumed both at home and in other contexts. Households estimated as vulnerable to food insecurity in the vulnerability analysis on the pre-COVID-19 data are then compared with households classified as experiencing food insecurity or food deprivation post-COVID-19. In the phone survey, households were asked whether they were able to access basic needs like medicines and the most important food items during the week preceding the interview. According to the 2018-19 ESS, these items are edible oil, teff, wheat, and maize as grain or as flour or cooked.[7] We, therefore, construct a variable for food insecurity that takes value 1 if the household was unable to access at least one of these most essential food items. In addition, the target is tested on a second outcome indicating food deprivation. In fact, the dataset also contains information on income loss and coping strategies, among which a reduction in food consumption was the most frequent. Thus, the second outcome takes value 1 if the household sees itself forced to reduce food consumption to handle income loss. We also extract information from the phone-survey data to reconstruct proxy variables to capture different agrifood system actors and groups. In the questionnaire, households were asked which sources were means of livelihood for the household in the past 12 months. For our analysis, we use two main categories: farm activities that include any activity of farming,

[6] The data were already spatially deflated. To account for inflation, we temporarily deflated all monetary values using the Consumer Price Index for Ethiopia (2010=100).

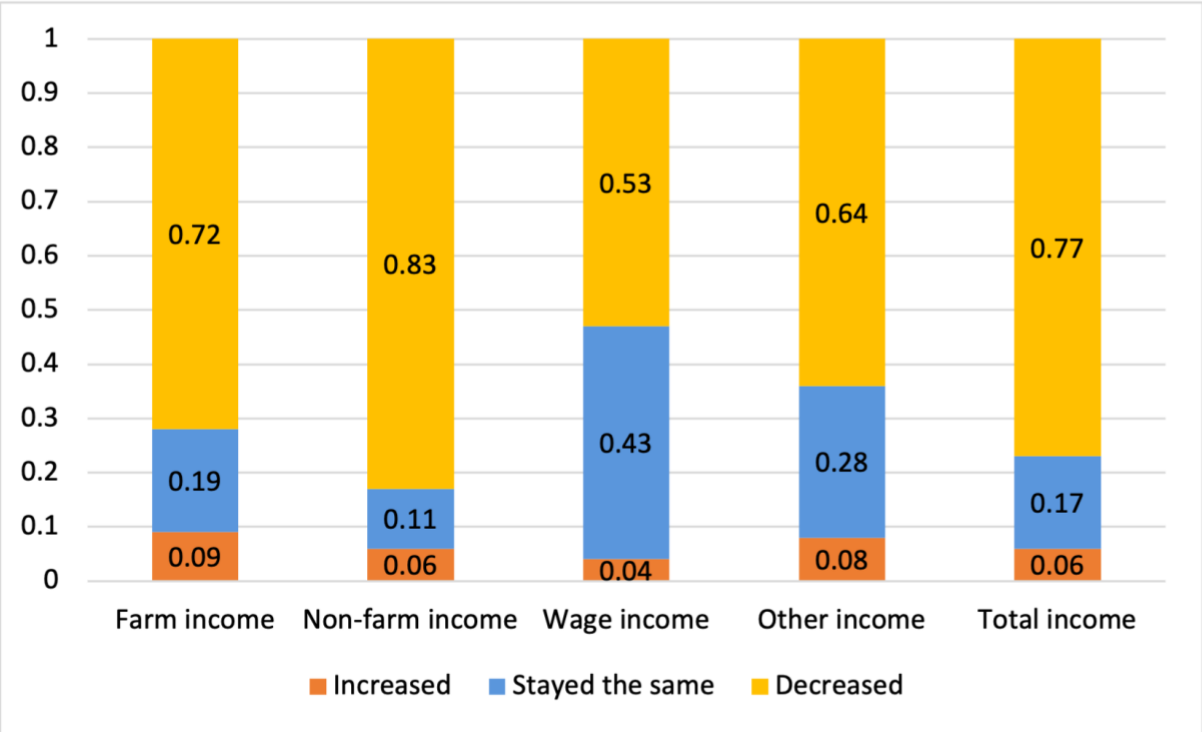
[7] See also Wieser *et al*. (2020).

livestock, or fishing and non-farm business. The construction of these categories will be useful to disaggregate targeting performance for each agrifood system group.

For Nigeria, we implement both a theory-based and a data-driven approach. For the former, the dependent variables used are total income figures and separate income values coming from two mainsources of livelihoods, namely farm activity and non-farm business. All the income figures are expressed in the Nigerian currency Naira and have been spatially and temporarily deflated as for Ethiopia. The total income is given by the sum of farm and non-farm income. The farm income variable includes the gross value of the crop harvested and the value of livestock products and animals sold for that season. Non-farm income refers to self-employment job earnings from activities that differ from agricultural production. This non-farm income variable is constructed by multiplying the monthly reported average value of sales by the months of business activity in the previous 12 months. The total income variable includes the sum of the two categories of income described above, and all the income variables are expressed as logarithmic values. The outcome variables used to evaluate vulnerability predictions via confusion matrices are the self-reported income losses since the COVID-19 pandemic's beginning. Households were asked whether the income from their major sources of livelihood has reduced, stayed the same, or increased.

Figure 1 shows the changes in four major categories of income and the total income. Overall, 77 percent of households in the sample experienced a reduction in total income in Nigeria.

Figure 1. Changes in income sources



Source: Authors' own elaboration based on data from World Bank. 2023. Living Standards Measurement Study. In: *World Bank.* [Cited 4 April 2023]. www.worldbank.org/en/programs/lsms/initiatives/lsms-ISA#2

The lowest losses have been registered for wage income, while 84 percent of the households reported a reduction in income figures deriving from non-farm activities. This discrepancy could be explained by the fact that wage employment provides at least some degree of insurance through formal agreements compared to self-employment non-farm activities.

Income losses represented the main driver of the impact of the COVID-19 pandemic on agrifood systems through their direct effects on food security in Nigeria (Amare *et al.*, 2021) and, more generally, in developing countries (Béné, 2020; Bundervoet *et al.*, 2022; Egger *et al.*, 2021). Since our ultimate focus is on food insecurity through the income loss mechanism, we generate an outcome variable taking value 1 if the household experienced both income losses and food insecurity and zero otherwise. Food insecurity in Nigeria is measured through households' self-reported responses to the Food Insecurity Experience Scale (FIES) questions. The questionnaire contains the last three of the eight questions that are part of the standard FIES module,[8] capturing the more severe aspects of food insecurity. We consider a household as food insecure if it reports having experienced at least one of the food insecurity conditions asked about in the FIES module. Subjective food security metrics like FIES have become the standard for identifying food security conditions in the aftermath of COVID-19. For instance, FIES questions have been used as an indicator of food insecurity by a recent cross-country work (Bundervoet, Dávalos and Garcia, 2022), and very similar self-reported measures (such as skipped or reduced meals) have also been employed as a food security outcome by Egger *et al.* (2021).

For the data-driven approach, as explained in more detail below, we train a machine-learning model on the pre-COVID-19 data (the training set) and use it to predict post-COVID-19 outcomes (the testing set) and assess its forecasting performance. Unlike vulnerability models that are estimated using continuous variables for income or consumption, the machine-learning routine we employ – a classification tree – only needs data on the same binary outcome variable for the training and testing sets to be employed. Moreover, the phone-survey post-COVID-19 data include only basic information and a much more limited set of essential variables compared to the pre-COVID-19 face-to-face surveys. For these reasons, we employ an outcome variable represented by a simple composite indicator of food insecurity using the available household-level FIES questions, namely a dummy variable taking value 1 if a household experienced at least one of the three food insecurity conditions and zero otherwise. This is possible because we have data for this variable in both the pre- and post-COVID-19 surveys. Lastly, for the subsample analysis, we generated two different sets of training and test data for, respectively, farming households, who are identified as those whose primary sourceof income comes from farming and livestock activities, and non-farming households, whose primary income is generated from non-farm businesses.

[8] These three questions form part of the broader Food Insecurity Experience Scale (FIES), frequently used in extensive surveys to assess food insecurity (Cafiero, Viviani and Nord, 2018). For the specific rounds utilized in the LSMS-ISA survey in Nigeria, only these indicators are included, selected for their significance in indicating severe food insecurity. Although they do not cover every aspect of food security, such as food quality, these indicators are crucial for understanding shifts in food security, particularly in environments like Nigeria where food availability and shortages are significant concerns.

Explanatory variables

For Ethiopia, the independent variables refer to a set of standard household characteristics, including dummies for the age and gender of the head of the household, household size, and several variables capturing welfare aspects such as education levels, asset resources, and distances from major roads. Tables A1 and A2 in Annex 1 report the description and summary statistics of the main variables used in the analysis and additional information on the sample characteristics. For instance, almost half of the sample resides in rural areas, only 30 percent of the households are headed by a woman, and nearly 60 percent of the heads of household are illiterate.

For Nigeria, the main explanatory variables included in the theory-based vulnerability model are basic household demographics, education characteristics, and idiosyncratic and rainfall shocks. For our analysis, we use five different potential shocks, namely the three idiosyncratic shocks reported as the most severe by the households and two weather shocks. These are i) the death of a working member of the household, ii) the illness of an income-earning member of the household, iii) the rise in the price of major food items consumed, iv) drought, and v) flood. The dataset also includes a set of georeferenced variables, which are used to construct negative and positive values of rainfall anomalies from which the dummies for drought and flood are constructed.[9] Table A3 in Annex 1 reports the description of the entire set of variables used for the vulnerability analysis, while Table A4 displays their descriptive statistics.

On the other hand, we use lagged input variables in the machine-learning prediction task, with the only exception being the shock variables. This means that, for each wave, the outcome variable is at time *t*, whereas all the input variables, except contemporaneous shock dummies, are at time *t-1* and thus are taken from the previous wave. In this way, we can use the entire set of household characteristics available from the last pre-COVID-19 LSMS-ISA survey (2018–2019) as inputs employed,[10] jointly with simulated shock dummies (more information on this is provided in the methodology section), to predict the post-COVID-19 food insecurity outcome variable. Precisely, because of the need to have at least two pre-COVID-19 survey waves for the same set of households, we cannot run the machine-learning exercise on the Ethiopian data since, as explained above, a new panel was started in the last pre-COVID-19 wave.

Food insecurity line

As is often the case for poverty and resilience assessments (Barrett and Constas, 2014; Calvo and Dercon, 2005, 2013; Chaudhuri, Jalan and Suryahadi, 2002; Cissé and Barrett, 2018; Constas, Frankenberger and Hoddinott, 2014; Ligon and Schechter, 2003; Povel, 2015), our analyses make use of thresholds to discriminate vulnerable and non-vulnerable households. The thresholds also change based on the analysis implemented. For the vulnerability analysis in Ethiopia – which, in the case of poverty assessments, implies the use of the well-known poverty line – the food poverty line represents the threshold since we are ultimately interested in vulnerability to food insecurity. To calculate this, we apply the estimate proposed by the Ethiopian Government in 2016. According to the Ethiopian Government, the minimum acceptable level of per capita calorie intake per day is 2 200 Kcal (MoFED, 2002). The food poverty line is thus estimated based on the cost of a bundle of food that satisfies the minimum

[9] For more details on variable construction, see Annex 1.

[10] See Table A1 in the Annex 1 for the list and description of these variables (the same ones used in the VTFI model).

acceptable level of per capita calorie intake per day, set at 3 772 Birr per year per person in 2016 (NPC, 2017).[11] For the vulnerability approach in Nigeria, inspired by Povel (2015), who uses a hybrid threshold composed of both the poverty line and the initial level of welfare of each individual, focusing on food insecurity, we replace the poverty line with the FIES indicators. This decision stems from our willingness to predict individuals who feel food insecure but also experienced an objective loss of welfare.

[11] All monetary values are temporarily deflated using the Consumer Price Index for Ethiopia (2010=100).

4 Empirical strategy

To provide a comprehensive retrospective evaluation of the accuracy of theory-based vulnerability models and data-driven methodologies in predicting households affected by the COVID-19 shock, we apply the following methodological steps: i) we first develop forecasts of vulnerable households using data from the pre-COVID-19 face-to-face surveys; ii) we then generate confusion matrices to carry out an out-of-sample validation of the forecasts using post-COVID-19 data from the phone surveys.

For the vulnerability analysis, while we can take advantage of the full longitudinal LSMS-ISA dataset from the pre-COVID-19 surveys for Nigeria, this is not possible for Ethiopia since, as previously stated, a new panel was started in the 2018–2019 wave of data collection and follow-up phone surveys were based on this new sample. The implication in terms of methodology is that the VTP approach cannot be employed, as it requires panel data for the pre-COVID-19 period. We will thus rely on VEP to predict vulnerable households in Ethiopia since this methodology also works for cross-sectional data, as we explain below.

4.1 Ethiopia – Vulnerability as expected food insecurity (VEFI)

The methodology used for the Ethiopia analysis is an adaptation of the measure of vulnerability as expected poverty (VEP) (Chaudhuri, Jalan and Suryahadi, 2002), which we call vulnerability as expected food insecurity (VEFI) in the remainder of this paper. This measure identifies vulnerability as the probability that household well-being will fall below a given threshold. For the purpose of this study, well-being is measured using the logarithm of household per capita food consumption expenditure, and the threshold is the food poverty line. Specifically, VEFI is expressed as:

$$V_{ht} = P\left(c_{h,t+1} < z\right) \tag{1}$$

where the vulnerability of the household *h* during the current time *t* (V_{ht}) is given by the probability that the logarithm of household food consumption expenditure at a future time ($c_{h,t+1}$) will be lower than the food poverty line (z) representing the threshold.

Estimating vulnerability requires a determination of the probability distribution of consumption. If we assume that log consumption is normally distributed, we can capture the entire consumption distribution by simply estimating the mean and variance of future consumption. We empirically estimate VEFI using the ordinary least square (OLS):

$$ln\ c_{ht} = x_{ht}\beta + \varepsilon_{ht} \tag{2}$$

where $ln\ c_{ht}$ represents the logarithm of household *h* per capita food consumption expenditure in the current period *t*, x_{ht} is a set of household and community characteristics, and β is a vector of parameters. ε_{ht} is the disturbance term that captures idiosyncratic shocks, and it thus has a mean of zero and is heteroscedastic. This is the primary assumption of this approach, namely that the unexplained variance of outcomes in our cross-sectional regression is not equal across households. The second assumption is that this cross-sectional variance proxies longitudinal distribution. This latter assumption allows us to make up for the absence of a longitudinal component in the Ethiopian survey data. To address the issue of inefficient estimates, we use the three-step feasible generalized least squares (FGLS) econometric procedure proposed by Amemiya (1977). First, we regress the squared residuals on a set of household characteristics x_{ht} as follows:

$$\hat{\varepsilon}^2{}_{OLS,ht} = x_{ht}\theta + \eta_{ht} \tag{3}$$

where θ is the vector of parameters and η represents the error term. The predictions of Equation (3) are used to obtain an asymptotically efficient FGLS estimate of θ and weight the previous equation (after weighting each residual by $x_{ht}\theta$):

$$\frac{\hat{\varepsilon}^2_{OLS,ht}}{x_{ht}\hat{\theta}_{OLS}} = \left(\frac{x_{ht}}{x_{ht}\hat{\theta}_{OLS}}\right)\theta + \frac{\eta_{ht}}{x_{ht}\hat{\theta}_{OLS}} \tag{4}$$

Then the standard deviation of the variance is computed as:

$$\hat{\sigma}_{\varepsilon,ht} = \sqrt{x_{ht}\hat{\theta}_{FGLS}} \tag{5}$$

Finally, once we get an efficient estimate of the variance, Equation (2) is transformed as follows to obtain an asymptotically efficient estimate of β:

$$\frac{ln\ c_{ht}}{\hat{\sigma}_{\varepsilon,ht}} = \left(\frac{x_{ht}}{\hat{\sigma}_{\varepsilon,ht}}\right)\beta + \frac{\varepsilon_{ht}}{\hat{\sigma}_{\varepsilon,ht}} \tag{6}$$

We are now able to estimate the expected log consumption and its variance as in Equations (7) and (8), respectively:

$$\hat{E}[ln\ c_{ht}/x_{ht}] = x_{ht}\hat{\beta} \tag{7}$$

$$\hat{V}[ln\ c_{ht}/x_{ht}] = x_{ht}\hat{\theta} \tag{8}$$

We can finally measure the probability that household *h* will be food insecure in the future as follows:

$$\hat{V}_{ht} = Pr[(ln\ c_{ht} < ln\ z) \mid X_{ht}, V_t] = \Phi\left(\frac{ln\ z - \hat{E}(ln\ c_{ht})}{\sqrt{V\hat{a}r(ln\ c_{ht})}}\right) \tag{9}$$

This represents our measure of vulnerability. Specifically, vulnerable households are those with a probability higher than 50 percent that their per capita food consumption will fall below the food consumption threshold. A sensitivity check with a probability higher than 25 percent will also be run. We also apply a refinement of this measurement in the form of a decomposition of the risk-induced component of vulnerability, namely the sub-component of the overall measurement associated with a high estimated variance of consumption but expected consumption above the poverty line.

4.2 Nigeria – Vulnerability as the threat of food insecurity (VTFI)

The approach outlined above for Ethiopia is necessary to estimate vulnerability in a constrained data environment in which repeated information about households is not available. However, should the forecasting test for VEFI point to bad targeting performances, it would be obvious to attribute such modest results to the lack of panel data and a vulnerability estimation method based on them. To rule out such concerns, we also deploy, for Nigeria (which also features LSMS-ISA data harmonized with the Ethiopian ones, but in which panel data are available), a vulnerability estimation approach explicitly based on panel information.

Specifically, to assess vulnerable households in Nigeria, we implement the "vulnerability as the threat of poverty" (VTP) measurement, applying the extension proposed by Povel (2015), and adapt it to a food insecurity focus: vulnerability as the threat of food insecurity (VTFI) for the remainder of this paper. This approach allows us to estimate household-specific vulnerability measurements that consider the possible "states of the world" that households could face, coupled with their respective probabilities. Using information about the occurrence of the shocks and estimating the related loss of income, we can predict the deprivation indexes associated with all the different states of the world considered, which are represented by the different combinations of shocks listed in Section 3.2.4 that a household might potentially face. This provides us with an *ex ante* measurement of household vulnerability to downside risks. Precisely, vulnerability is measured as:

$$VTFI_i = \sum_{j=1}^{N_i} \left(p_{ij} \times x_{ij}^{\alpha}\right) \tag{10}$$

where $N_i = \sum_{k=0}^{K_i} \frac{K_i!}{(K_i-k)!k!}$ represents the number of possible states of the world. In our case, we consider five shocks $N_i = \sum_{k=0}^{5} \frac{5!}{(5-k)!k!}$ = 32 states of the world. p_{ij} represents the probability of the state of the world j will occur and ranges between zero and one. It is measured as:

$$p_{ij} = \prod_{q=1}^{Q_{ij}} p_{ijq} \times \prod_{l=1}^{L_{i,i\neq q}} \left(1 - p_{ijl}\right) \tag{11}$$

where $\prod_{q=1}^{Q_{ij}} p_{ijq}$ yields the probability that Q_i risks will occur in state of the world j while $\prod_{l=1}^{L_{i,i\neq q}} \left(1 - p_{ijl}\right)$ represents the probability that L_i other shocks will not occur in the same situation. x_{ij}^{α} denotes the deprivation index and is measured as $x_{ij} = \sum_{q=1}^{Q_{ij}} \frac{s_{ijq}}{y_i}$ where s_{ijq} represents the severity of shock q in state of the world j, namely the loss of income (log) in that state of the world, and y_i is the threshold and represents the (logged) household income – unlike Calvo and Dercon (2013), who use the poverty line. To distinguish between households vulnerable to income losses but not experiencing food insecurity and those that experience both, inspired by the hybrid method proposed by Povel (2015), we use a food insecurity line constructed using FIES data.[12] To estimate income losses, assuming that shocks are independent, we calculate the elasticities of income to each shock separately, as follows:

$$y_{it} = \alpha_i + \beta_1 \, shock_{it} + \beta_2 X'_{it-1} + \varepsilon_{it} \tag{12}$$

y_{it} refers to the household i log of total income at time t (we also carry out the same analysis separately for farm and non-farm income). α_i captures household fixed effects that absorb

[12] Unfortunately, we do not have information on income or consumption figures in the post-COVID-19 phone survey data from Nigeria.

many potential time-invariant confounders, and $shock_{it}$ indicates the shocks that enter the regression separately. X'_{it-1} is a set of household characteristics, including age and sex of the head of household and household size and a set of welfare indicators (Tropical Livestock Units and an index for the non-agricultural assets held by the household) at time *t-1* that enable an *ex ante* computation of the outcome variable. The coefficient β_1 captures the percentage change in the log income given by each shock. To obtain a household-specific value for the loss experienced, we multiply the coefficients by household income values:

$$loss_{it} = \beta_{1i} \times y_{it} \tag{13}$$

To control for household-specific characteristics, we re-estimate the predicted loss using the following regression:

$$loss_{it} = \alpha_i + \beta_1 X'_{it-1} + \varepsilon_{it} \tag{14}$$

As in Equation (12), α_i captures household fixed effects. X'_{it-1} includes the same variables as Equation (10).

To satisfy the focus axiom (defined in subsection 2.1), we divide each predicted household-specific loss s_{ijq} by household total income y_i and replace negative losses (gains) with zeros. Finally, we sum all the different losses to get an overall index of deprivation x_{ij} that household i faces in the different states of the world as follows:

$$x_{ij} = \sum_{q=1}^{Q_{ij}} \frac{s_{ijq}}{y_i} \tag{15}$$

As we assume that households are risk-averse, we set the parameter α=2 so that we take the square of x_{ij} .[13] Once we have state- and household-specific deprivation indexes, we calculate the household-specific probability of experiencing shocks in the state of the world j. To this end, in line with the vulnerability literature (Calvo and Dercon, 2013; Povel, 2015), we assume independent probabilities. A logit model is then used to predict the probability that the household will be affected by each shock:

$$Pr(shock_{it}) = F(X'_{it-1}) \tag{16}$$

$shock_{it}$ at time *t* is predicted using explanatory variables from time *t-1* and X'_{it-1} includes age and sex of the head of the household and household size, and a set of welfare variables as in Equation (12). The household- and state-specific probabilities are then computed as in Equation (11) and multiplied by the household- and state-specific index of deprivation previously calculated in Equation (15).

The measurement of vulnerability as the threat of food insecurity is then calculated using Equation (10). Vulnerable households are identified as those above the median value of the vulnerability distribution. To identify vulnerable and non-vulnerable households, we use the same cutoff used for the previous model specification, which represents a "normal world" in

[13] The parameter $\boldsymbol{\alpha}$ regulates the strength of risk sensitivity. It emphasizes the sensitivity to risk of the vulnerability measurement where 1 means risk neutrality (Povel, 2015).

which different states of the world can happen with a given probability. Furthermore, since the COVID-19 pandemic represents a rare event in the form of a major exogenous shock, we also separately consider the worst-case scenario, which refers to the state of the world in which all the shocks occur simultaneously, and we assign this a probability of occurrence equal to one, for reasons that will be explained in detail in the next section. Because we are interested in the link between income losses and food insecurity, the final sample of vulnerable households is represented by those households that are vulnerable to income losses and that also reported having experienced food insecurity conditions. In the targeting test, we will then compare these food-insecure households predicted as vulnerable by our models with households actually experiencing income losses and food insecurity during the COVID-19 pandemic, in line with the recent cross-country evidence provided in relation to the close link between the COVID-19 pandemic-induced income losses and heightened food insecurity at household level (Bundervoet, Dávalos and Garcia, 2022; Egger *et al.*, 2021).

4.3 Nigeria – Machine learning

As a third forecasting model, we employ a simple and straightforward machine-learning predictive routine, classification trees (Hastie, Tibshirani and Friedman, 2009). Unlike the previous vulnerability models, which are strongly rooted in standard economic theory, classification trees are purely data-driven predictive techniques aimed at maximizing the out-of-sample predictive performance of a given outcome of interest. In this way, we can test the differences in performance between theory-based and data-driven forecasting methodologies for this task.

At the core of the machine-learning mindset lies the "firewall" principle: none of the data involved in generating the predictive model should be used to evaluate its predictive performance (Mullainathan and Spiess, 2017). In this spirit, we use pre-COVID-19 data to tune our classification tree and select the best model and then use it to predict the food insecurity outcome for the unseen observations in the post-COVID-19 dataset.

Classification trees are particularly suited for applications in which the decision rule needs to be transparent and must be communicated (Lantz, 2019), which is in line with recent calls for interpretability in the use of machine learning for policy targeting (Browne *et al.*, 2021; McBride *et al.*, 2022). Indeed, the output of a decision tree is intuitive and can also be easily understood by someone without strong statistical skills, such as decision-makers, which makes this technique appealing for policy targeting purposes. From a technical point of view, classification trees are based on a process called recursive binary splitting: the algorithm divides the data into progressively smaller subsets to identify recurring patterns that can be used for predicting a specific binary output. Trees are considered highly flexible methods because non-linearities and interactions are automatically captured by the sequence of splits in the tree. A drawback of classification trees is that they tend to be prone to overfitting on the training data: a high number of branches and leaves in a tree is likely to overfit the data, leading to a final model which performs very well in-sample but poorly out-of-sample. The solution to this issue is to reduce the size and complexity of the tree by "pruning" the tree. Pruning means setting a penalization cost for flexibility, which is referred to as a "complexity parameter" (cp). In order to select the optimal value of cp, which maximizes the out-of-sample accuracy of our model, we run ten-fold cross-validation on the full set of pre-COVID-19 data, compare the ten-resulting cross-validation errors, and apply the complexity parameter associated with the lowest cross-validation error. This cp is then selected for the model used to predict unseen observations belonging to the held-out post-COVID-19 data.

Besides transparency, another critical reason why we select classification trees from many available machine-learning techniques is that we have substantial missing data in our samples. Just like traditional econometric approaches, most machine-learning routines do not handle missing data unless they are imputed. In our case, given the numerous cases where values for several variables are missing for many observations, this would imply either accepting a drastic loss in sample size (which is already limited) or opting for massive imputation of missing values, which would very likely result in data distortion. Unlike other methods, classification trees automatically handle missing data using surrogate splits in the case of missing observations (Lantz, 2019).

Before performing our classification exercise, we must tackle the challenge of data imbalance of the primary outcome of interest, food insecurity. In fact, in the pre-COVID-19 sample, food insecurity (as measured using the composite FIES indicator described above) is, from a statistical point of view, a “rare” event, meaning that there are many more food-secure households than food-insecure ones. When facing data imbalance issues like this, machine-learning routines simply tend to predict the over-represented class (y = 0 in our case). This happens because the algorithms aim to maximize overall accuracy and provide the lowest total error rate, irrespective of which class the errors come from. Clearly, a model that predicts all households as food secure would be useless. To prevent this from happening, we use a popular data rebalancing technique, the synthetic minority oversampling technique (SMOTE) routine by Chawla *et al.* (2002). Using SMOTE, we can rebalance the frequency of two classes of our outcome variable, food insecurity, in the pre-COVID-19 sample. Specifically, SMOTE oversamples the under-represented cases and undersamples the majority class, leading to a smaller but rebalanced dataset. Crucially, we run SMOTE only on the pre-COVID-19 dataset, leaving the post-COVID-19 data untouched. This means that while the pre-COVID-19 dataset is artificially rebalanced, the forecasting performance of the classification tree is evaluated on the original post-COVID-19 data.

As we want to assess how accurate, given available pre-shock information, machine learning is in identifying vulnerable households before a food security crisis occurs, we need to simulate the occurrence of the shock in the covariate space of the post-COVID-19 dataset. We do so by adopting a “trick” that leads the algorithm to “believe” that a massive sequence of shocks has taken place in the post-COVID-19 data: we take all the shock dummies available in the last pre-COVID-19 wave (food price spikes, droughts, floods, illnesses, and deaths of household members) and artificially switch them to one for all the observations in the sample. Through this technique, the algorithm, which has previously learned from the pre-COVID-19 data that shocks tend to be associated with food insecurity status, “recognizes” the abrupt change in the patterns of key features and consequently also takes its decisions on the classification of observations based on this change. It should be noted that a need for the simulation of unobserved events and large-scale shocks has recently been emphasized in the specialized literature (McBride *et al.*, 2022).

Conceptually, by doing this, we are mimicking the occurrence of the COVID-19 generalized disruption by simulating, for the entire sample, the simultaneous occurrence of all the shocks and stressors that most households reported facing at various points in time across all waves. This simulation relies on a reasoning analogous to that behind the worst-case scenario in the

VTFI model and draws heavily on the argument advanced by Barrett *et al.* (2021), already reported above, that the COVID-19 shock is less a new shock or unique event than a dramatic, recent manifestation of familiar shocks, stressors, and uncertainties that burden poor populations in developing contexts.

4.4 Targeting evaluation

As Upton, Constenla-Villoslada and Barrett (2022) explain, a key performance test of any measurement, especially one estimated in a population-representative sample, is how well it estimates out-of-sample, namely when applied to observations not from the original estimation sample. Therefore, after developing the various predictive models, we compare the predictions with actual outcome data from the COVID-19 phone surveys to evaluate the out-of-sample performance of the models considered. This comparison is carried out using confusion matrices (Hastie, Tibshirani and Friedman, 2009; Lantz, 2019). A confusion matrix is a straightforward tool widely employed to evaluate predictive performance. In the case of classification problems with a binary outcome variable (such as ours), it consists of a simple two-way table such as Table 1.

Table 1. Example of a confusion matrix for a binary classification problem

<table>
<tr><td colspan="2"></td><td colspan="2">Real status</td><td></td></tr>
<tr><td colspan="2"></td><td>Y = 0</td><td>Y = 1</td><td></td></tr>
<tr><td rowspan="2">Predicted status</td><td>Y = 0</td><td>True negatives</td><td>False negatives (type II error)</td><td></td></tr>
<tr><td>Y = 1</td><td>False positives (type I error)</td><td>True positives</td><td></td></tr>
<tr><td colspan="2"></td><td>Specificity:
True negatives/total negatives</td><td>Sensitivity:
true positives/total positives</td><td>Accuracy:
(true negatives + true positives)/total observations</td></tr>
</table>

Source: Authors' own elaboration.

The true negatives cell contains those negative cases (Y = 0) that were correctly identified. The true positives cell includes the positive cases (Y = 1) correctly identified. The other two cells contain the observations erroneously classified by the model: False negatives (type II error) in which households are predicted to be non-vulnerable to food insecurity before the shock but proved to be food insecure after the shock, and false positives (type I error) in which households are predicted to be vulnerable to food insecurity before the shock but proved to be food secure after the shock. The total accuracy of the predictive model is given by the sum of the true negatives and true positives cells, divided by the total number of observations.

The specificity of the model, and thus its ability to correctly classify negative cases, is given by the number of observations in the true negatives cell divided by the number of negative observations. In the same way, the sensitivity of the model, its ability to correctly predict positive cases only, is the number of units in the true positive cells divided by the total number of positive cases.

To determine if our models are effective at identifying and targeting households likely to become food insecure after a significant shock, we are particularly interested in the sensitivity performance of the models.

5 Empirical results

This section contains the resulting estimates of the vulnerability-based targeting analysis, divided into different subsections for Ethiopia and Nigeria.

5.1 Ethiopia

Tables 2 and 3 below show the main results for Ethiopia comparing households predicted as vulnerable to food insecurity by the VEFI model using data before the COVID-19 pandemic outbreak with those households that experienced an actual status of food insecurity (Table 2) or a reduction in food consumption (Table 3) during the COVID-19 pandemic. In Table 2, the model shows overall accuracy of 79 percent, and an even higher specificity (Y = 0), managing to predict 94 percent of households that did not experience food insecurity after the COVID-19 shock. If we limited our judgement to these metrics, we would conclude that theory-based targeting performed quite well in pre-COVID-19 settings. We should note, however, that this model performs spectacularly poorly in predicting positive instances (Y = 1): the sensitivity metrics show an accuracy value of 11 percent.

Table 2. Vulnerability targeting performance for Ethiopia – food insecurity

		Real status		
		Y = 0	Y = 1	Total
Predicted status	Y = 0	2 485	486	2 971
	Y = 1	171	59	230
	Total	2 656	545	3 201
	Correctly predicted	**94%**	**11%**	**79%**

Notes: The predicted status refers to the vulnerability to food insecurity. The real status represents the observed food insecurity outcome.

Source: Authors' own elaboration.

Table 3. Vulnerability targeting performance for Ethiopia – reduction in food consumption

		Real status		
		Y = 0	Y = 1	Total
Predicted status	Y = 0	1 432	252	1 684
	Y = 1	90	23	113
	Total	1 522	275	1 797
	Correctly predicted	**94%**	**8%**	**81%**

Notes: The predicted status refers to the vulnerability to food insecurity. The real status represents the observed reduction in food consumption outcome.

Source: Authors' own elaboration.

This value is only slightly higher (23 percent) if we consider the alternative vulnerability cutoff at 25 percent ($\hat{V}_{ht}$>0.25) as reported in Table A5 in Annex 2. Since, from a policy-targeting standpoint, we are most interested in correctly predicting the individuals who are most in need, the model's performance can be considered as highly questionable.

In Table 3, although the overall accuracy is slightly higher (81 percent) compared to the previous outcome, the model performs even more poorly in predicting positive instances (8 percent). In this case too, as above, the sensitivity value is slightly higher if the vulnerability threshold is set at 25 percent ($\hat{V}_{ht}$>0.25) as reported in Table A6 in Annex 2.

Risk–vulnerability results

In this section we look at the subsample of risk-induced vulnerability. This includes households that register a probability higher than the probability threshold, that will fall below the food security threshold because of an extreme fluctuation of their food security well-being. In this respect, they can be seen as pure vulnerable cases since their vulnerability depends entirely on risk exposure and does not depend in any way on lower food security prospects in an environment of full certainty.

However, in their case also, the overall accuracy of our vulnerability measurement remains very disappointing, especially the prediction of positive instances. This outcome holds for both metrics (food insecurity and reduction in food consumption) (see Tables 4 and 5).

Table 4. Risk-vulnerability targeting performance for Ethiopia – food insecurity

		Real status		
		Y = 0	Y = 1	Total
Predicted status	Y = 0	136	45	181
	Y = 1	35	14	49
	Total	171	59	230
	Correctly predicted	**80%**	**24%**	**65%**

Notes: The predicted status refers to the risk-vulnerability to food insecurity. The real status represents the observed food insecurity outcome.

Source: Authors' own elaboration.

Table 5. Risk-vulnerability targeting performance for Ethiopia – reduction in food consumption

		Real status		
		Y = 0	Y = 1	Total
Predicted status	Y = 0	67	20	87
	Y = 1	23	3	26
	Total	90	23	113
	Correctly predicted	**74%**	**13%**	**62%**

Notes: The predicted status refers to the risk-vulnerability to food insecurity. The real status represents the observed reduction in food consumption outcome.

Source: Authors' own elaboration.

As above, the sensitivity metrics look higher in both cases if the vulnerability threshold is set at 25 percent ($\hat{V}_{ht}$>0.25), as reported in Tables A7 and A8 in Annex 2. This seems a potential route for targeting food secure households that are indeed more exposed to risk even when associated with occurrences characterized by low probabilities.

5.2 Nigeria

Vulnerability model – Vulnerability as the threat of food insecurity

The empirical test carried out above for Ethiopia points to extremely disappointing performances. However, the reader may legitimately attribute such failure to the constrained data environment we have to use for Ethiopia, where only cross-sectional data, and a vulnerability methodology based on them (Chaudhuri, Jalan and Suryahadi, 2002), can be deployed. Therefore, we now turn to the empirical results for Nigeria, where panel data and longitudinal vulnerability prediction models have been employed.

Table 6 below shows the baseline model results comparing the predicted vulnerable households in the scenario in which we consider all the different states of the world pre-COVID-19 (Equation [10]) with the real status of households that experienced both income losses and food insecurity in the post-COVID-19 period. Using this model, we manage to predict 88 percent of the households that did not experience an income loss coupled with a situation of food insecurity in the immediate aftermath of the COVID-19 pandemic. Thus, our model has a specificity, namely the ability to detect negative cases (Y = 0), equal to 88 percent.

However, this model also clearly fails to predict vulnerable households, with a sensitivity value, and thus the ability to correctly classify positive cases (Y = 1) of 16 percent, a very disappointing performance. This failure to predict vulnerable households results in low overall accuracy for the predictive model (39 percent), as most households (212 out of 316) in the phone-survey data reported having experienced both income losses and food insecurity. Vulnerability-based targeting seems unable to predict that a large proportion of households would have been vulnerable to income losses and food insecurity in the case of a major covariate shock such as the COVID-19 crisis.

Table 6. Vulnerability targeting performance for Nigeria (all states of the world)

<table>
<tr><td></td><td></td><td colspan="3">Real status</td></tr>
<tr><td></td><td></td><td>Y = 0</td><td>Y = 1</td><td>Total</td></tr>
<tr><td rowspan="3">Predicted status</td><td>Y = 0</td><td>91</td><td>178</td><td>269</td></tr>
<tr><td>Y = 1</td><td>13</td><td>34</td><td>47</td></tr>
<tr><td>Total</td><td>104</td><td>212</td><td>316</td></tr>
<tr><td></td><td>Correctly predicted</td><td>88%</td><td>16%</td><td>39%</td></tr>
</table>

Notes: The predicted status refers to combined vulnerability to income losses and food insecurity calculated considering all the states of the world. The real status represents the observed income losses and food insecurity outcome.

Source: Authors' own elaboration.

Table 7. Vulnerability targeting performance for Nigeria (worst-case scenario)

		Real status		
		Y = 0	Y = 1	Total
Predicted status	Y = 0	78	152	230
	Y = 1	26	60	86
	Total	104	212	316
	Correctly predicted	**75%**	**28%**	**44%**

Notes: The predicted status refers to combined vulnerability to income losses and food insecurity calculated considering only the worst-case scenario. The real status represents the observed income losses and food insecurity outcome.

Source: Authors' own elaboration.

This failure could be since an extreme scenario, such as the occurrence of a pandemic, which could be mimicked by the simultaneous occurrence of the many idiosyncratic and covariate shocks that plague households' welfare in developing contexts (Barrett *et al.*, 2021), is by design assigned a very low probability by the estimated vulnerability model, being a "fat-tail risk", namely a devastating but extremely rare event. We, therefore, amend the standard model to carry out a sensitivity analysis on the pre-COVID-19 data and replace the vulnerability measurement with one calculated in a single hypothesized scenario in which all the shocks occur simultaneously to mimic the real-world COVID-19 scenario. In this way, the model is trained to consider a rare event as certain (probability assigned = 1) and could be better able to identify vulnerable households.

Table 7 displays the results using the model in which the vulnerable households are identified only considering this worst-case scenario. Although this model specification seems to perform slightly better in terms of sensitivity and accuracy, the results are still very disappointing, meaning that the targeting failures are not due to an inherent inability of standard vulnerability models to spot and properly consider extreme scenarios and catastrophic disasters.

One may be concerned that models' forecasting failures occur because of the discontinuity in data collection methods between the pre- and post-COVID-19 surveys. We acknowledge that there is room for measurement errors of some variables, which stems from the lack of complete harmonization between the phone surveys implemented in response to the emergency and the standard pre-COVID-19 field surveys. In any case, to gauge the magnitude of this concern, we also ran the same analysis for Nigeria using only the pre-COVID-19 data for both the prediction and the test sets: the former is composed of the first three waves of the panel, and the latter is tested using the fourth wave. This test thus uses a fully harmonized pre-COVID-19 pandemic dataset of standard field surveys. Our main conclusions are not overturned by this check, and the results, summarized in Table A10 of Annex 2, still report very disappointing performance in terms of predictive accuracy, suggesting that the measurement error issue regarding post-COVID-19 phone-survey data should not be seen as the primary concern for the Nigeria analysis (and, albeit we cannot test it, for Ethiopian data likewise).

Model without hybrid food security threshold

As explained in the methodological section, a vulnerability measurement not associated with a food insecurity threshold, in the absence of a clear income loss threshold to establish deprivation (as is the case for the post-COVID-19 phone survey data, for which we only observe whether the household experienced a loss), will tend to overpredict most, if not all, the observations as vulnerable. In such a case it is sufficient to have experienced a loss to be classified as vulnerable, irrespective of baseline income. A naïve model like this is designed to perform very well in the case that a major covariate shock (such as the COVID-19 pandemic) causes income losses to almost all the households in the sample.

Indeed, this is the case: Tables A11 and A12 in Annex 2 report the results of the targeting exercise conducted in this way. As the reader can see, the results are different from our benchmark estimates: both in the baseline scenario with all the states of the world as well as in the worst-case scenario, the total accuracy of the models is 50 percent or higher and, more importantly, sensitivity is much higher than the previous model, reaching the 100 percent in the worst-case scenario. This is a very good but misleading performance, as explained above. The model needs to be linked to a food insecurity threshold (even a subjective one such as the FIES) to mimic the poverty line used for standard empirical models in the vulnerability literature.

Treatment vs control samples in post-COVID-19 data

The reader may object that targeting based on the different vulnerability models all fail because we are considering the full sample size of households that were re-interviewed in the phone surveys after the COVID-19 shock, without distinguishing between those exposed to the non-pharmaceutical interventions (lockdowns, mobility restrictions, etc.) and those merely experiencing the spread of the contagion and the spillovers of the global COVID-19 pandemic. We did take that into account, however, and we present here the reason why we included the full sample in the baseline analysis instead of only households experiencing lockdowns.

We followed Amare *et al.* (2021) and used the same variable they employed as the treatment effect in their *ex post* assessment using phone surveys: a dummy taking value 0 for households living in lockdowns in which non-pharmaceutical interventions were implemented, and 0 otherwise.[14] Similarly to the spirit of their exercise, we then carried out a difference-in-difference analysis of the impact of this lockdown variable on our outcome variable for different categories of income sources as well as for total income. Remember that our variable is built to get value 1 only if the household experienced an income loss (total income or a single category) and also experienced at least a situation of food insecurity according to the FIES variable. In all other cases, the dummy outcome variable is assigned value 0.

The results are presented in Table A13 in Annex 2. Differently from Amare *et al.* (2021), we always find insignificant impacts of the lockdowns on our outcomes of interest. While this difference with respect to their findings is due to several reasons (different samples, different outcome, different controls), we think our results make sense in that it is arbitrary to consider only the incomes and food security levels of households directly exposed to lockdowns as hit by the shock at hand: the COVID-19 pandemic is global, and determined a black-out of within-country and international supply chains, triggering a deep recession that left no communities unaffected, especially in developing contexts. Indeed, as reported in the data section, even the questions of the phone surveys themselves make explicit reference to the arrival of the COVID-19 pandemic in asking interviewed households whether they had experienced income losses or food insecurity, regardless of whether they were exposed to lockdowns or not.

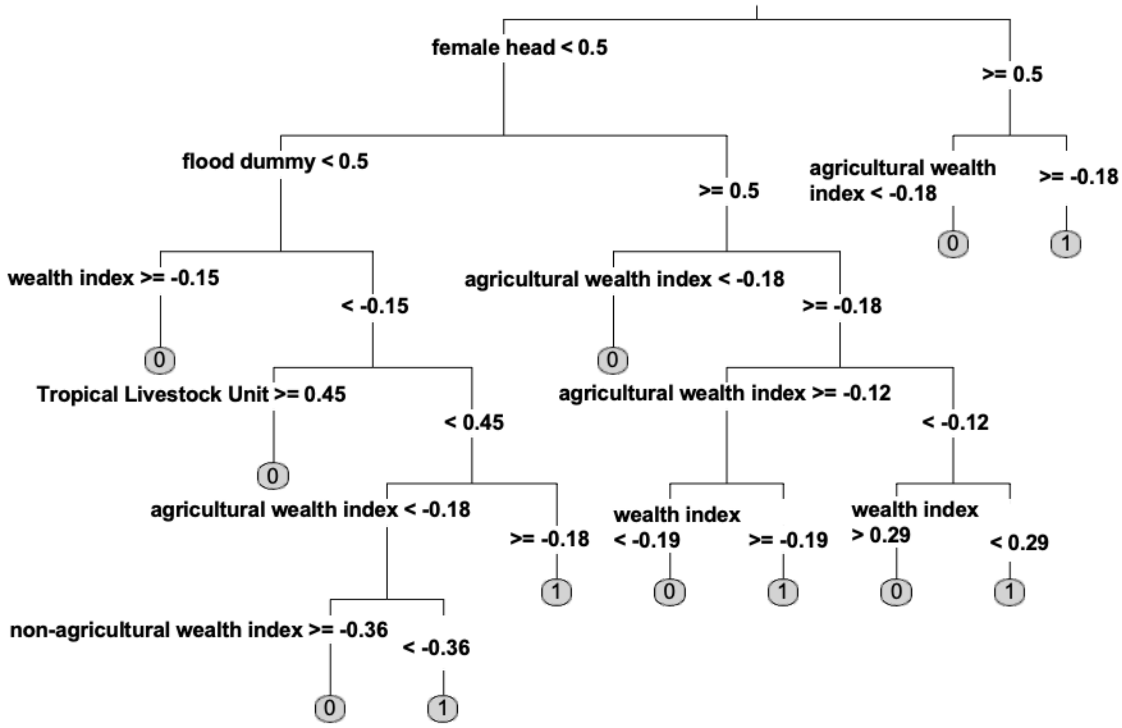
[14] The authors are grateful to Luca Tiberti for sharing data referring to this variable.

We conclude that all households in the post-COVID-19 sample are "treated" in the sense of being exposed to the COVID-19 crisis, and that all of them should be included in the targeting analysis, all the more so as we do not find any significant additional impact of the lockdown on households living in areas where mobility restrictions were implemented. In any case, we also conducted a subsample analysis of the targeting performance for each of the two separate samples of the "lockdown" variable used by Amare *et al.* (2021). These results are reported in Annex 2 in Tables A14 and A15 for households exposed to lockdowns; and in Tables A16 and A17 for those not exposed to mobility restrictions. The estimates are not significantly different and all point to a failure of targeting models to identify the hardest-hit households.

Machine-learning model

Figure 3 below shows the classification tree constructed using pre-COVID-19 information from the LSMS-ISA face-to-face surveys. The tree is composed of those variables that have been automatically selected by the algorithm as the ones more correlated with the outcome variable, the FIES food security indicator: a dummy referring to the female gender of the household head, a dummy capturing flood shocks, a variable indicating the value of Tropical Livestock Units for small ruminants, and three asset measurements, namely the agricultural and non-agricultural wealth indices, and the overall wealth index (combining both productive and non-productive assets).

Figure 2. Classification tree of food-insecure households in Nigeria



Source: Authors' own elaboration.

These variables interact with each other and, depending on whether the value of each variable is below or above the reported thresholds, the tree classifies each observation in the pre-COVID-19 training set as food insecure (Y = 1) or not (Y = 0). It is interesting to note that although the relationships depicted in the tree only signal correlation and not causation, the variables selected by the algorithm are consistent with the findings on the drivers and determinants of poverty traps highlighted by the well-established poverty trap literature (Barrett and Carter, 2013; Carter and Barrett, 2006; Carter *et al.*, 2008). This means that, despite being quite simple, the tree can detect critical recurring patterns embedded in the fabric of the data.

Table 8. Tree-based targeting performance for Nigeria

		Real status		
		Food insecurity = 0	Food insecurity = 1	Total
Predicted status	Food insecurity = 0	82	202	284
	Food insecurity = 1	205	822	1 027
	Total	287	1 024	1 311
	Correctly predicted	**29%**	**80%**	**69%**

Notes: the predicted status refers to the predicted out-of-sample food-insecure households using the train set (before the COVID-19). The real status represents the observed food-insecure households of the test set (after the COVID-19). FIES is a binary outcome that takes value 1 if the household is predicted (predicted status) or reported (real status) to be food insecure and 0 otherwise.

Source: Authors' own elaboration.

How accurate is this tree in forecasting households that have experienced food insecurity conditions during the COVID-19 pandemic? The answer can be found in the confusion matrix shown in Table 8 above: 80 percent of food-insecure households during the COVID-19 crisis have been correctly predicted by the algorithm, thanks to the "multiple-shock" simulation that we artificially introduced into the post-COVID-19 shock data. The tree is, however, much less accurate in identifying non-food-insecure households, with a specificity of only 29 percent. For this reason, the overall forecasting accuracy of the model is good, 69 percent, but not high.

Despite operating in a relatively data-poor environment, a simple machine-learning model like the one shown in Figure 3 can anticipate more than three out of four households experiencing food insecurity due to the COVID-19 shock. This gives an idea of the significant potential of machine-learning techniques in identifying poverty, food insecurity, and vulnerability hotspots, in line with the findings of other recent contributions (Aiken *et al.*, 2022; Garbero and Letta, 2022; McBride *et al.*, 2021; Zhou *et al.*, 2021). However, the targeting performance of the classification tree is still imperfect and, overall, unsatisfactory, as the tree tends to overpredict food insecurity and maximize sensitivity at the expense of specificity and overall accuracy. This pattern seems to be the opposite of the performance of vulnerability-based targeting models, which instead identify food-secure households very well but fail to spot food-insecure ones.

6 Subsample analysis by agrifood system categories

6.1 Ethiopia

The following tables show the results from the VEFI analysis carried out separately for differentlivelihoods sources and for both the outcomes of interest. Unsurprisingly, given the main model's failure to identify food-insecure people and those that reduced their food consumption, no significant heterogeneity emerges from the livelihood decomposition exercise.

Table 9. Vulnerability targeting performance for Ethiopia – food insecurity – farm activity

		Real status		
		Y = 0	Y = 1	Total
Predicted status	Y = 0	631	186	817
	Y = 1	136	41	187
	Total	767	237	1 004
	Correctly predicted	**82%**	**22%**	**68%**

Notes: The predicted status refers to vulnerability to food insecurity. The real status represents the observed food insecurity outcome. Analysis calculated on the subsample of farm activity.

Source: Authors' own elaboration.

Table 10. Vulnerability targeting performance for Ethiopia – reduction in food consumption – farm activity

		Real status		
		Y = 0	Y = 1	Total
Predicted status	Y = 0	367	90	457
	Y = 1	75	19	94
	Total	442	109	551
	Correctly predicted	**83%**	**17%**	**70%**

Notes: The predicted status refers to vulnerability to food insecurity. The real status represents the observed reduction in food consumption outcome. Analysis calculated on the subsample of farm activity.

Source: Authors' own elaboration.

The VEFI model performs only slightly better at identifying food- insecure people and households that reduced their food consumption in the subsample of farm activities (Tables 9 and 10) compared to the almost-zero ability to do so for the non-farm business (Tables 11 and 12). The VEFI model was not able to anticipate who would have been food-insecure during the COVID-19 emergency, neither for the sample as a whole nor for specific actors situated in different segments of the agrifood system.

Table 11. Vulnerability targeting performance for Ethiopia – food insecurity – non-farm business

		Real status		
		Y = 0	Y = 1	Total
Predicted status	Y = 0	642	100	742
	Y = 1	22	6	28
	Total	664	106	770
	Correctly predicted	**97%**	**6%**	**84%**

Notes: The predicted status refers to vulnerability to food insecurity. The real status represents the observed food insecurity outcome. Analysis calculated on the subsample of non-farm business.

Source: Authors' own elaboration.

Table 12. Vulnerability targeting performance for Ethiopia – reduction in food consumption – non-farm business

		Real status		
		Y = 0	Y = 1	Total
Predicted status	Y = 0	569	62	631
	Y = 1	19	2	21
	Total	588	64	652
	Correctly predicted	**97%**	**3%**	**88%**

Notes: The predicted status refers to vulnerability to food insecurity. The real status represents the observed reduction in food consumption outcome. Analysis calculated on the subsample of non-farm business.

Source: Authors' own elaboration.

6.2 Nigeria

Vulnerability model

Table 13 below reports the results of the baseline model (with all the states of the world considered); Table 14 for the worst-case scenario with the simulated simultaneous occurrences of all shocks. For non-farm income, both targeting performances are even worse than the benchmark results.

Table 13. Vulnerability targeting performance for Nigeria (all states of the world) – non-farm income

		Real status		
		Y = 0	Y = 1	Total
Predicted status	Y = 0	41	89	130
	Y = 1	9	13	22
	Total	50	102	152
	Correctly predicted	**82%**	**13%**	**36%**

Notes: The predicted status refers to the combined vulnerability to income losses and food insecurity computed considering all the states of world for the subsample of non-farm income. The real status represents the observed non-farm income losses and food insecurity outcome.

Source: Authors' own elaboration.

Table 14. Vulnerability targeting performance for Nigeria (worst-case scenario) – non-farm income

		Real status		
		Y = 0	Y = 1	Total
Predicted status	Y = 0	37	78	115
	Y = 1	13	24	37
	Total	50	102	152
	Correctly predicted	**74%**	**24%**	**40%**

Notes: The predicted status refers to the combined vulnerability to income losses and food insecurity computed considering only the worst-case scenario for the subsample of non-farm income. The real status represents the observed non-farm income losses and food insecurity outcome.

Source: Authors' own elaboration.

Tables 15 and 16 below do the same for farm incomes and confirm that even for this second agrifood system category there is no ability of the models to anticipate households that would have proved vulnerable to the pandemic in terms of income losses and food insecurity.

In sum, a disaggregation of the analysis by different livelihoods categories and agrifood system actors shows no systematic heterogeneity in the predictive ability of the VTFI model: the failure of targetingmodels to anticipate which households would have been hardest-hit by COVID-19 seems to be a common feature for the full sample, regardless of the source of income and category considered.

Table 15. Vulnerability targeting performance for Nigeria (all states of the world) – farm income

		Real status		
		Y = 0	Y = 1	Total
Predicted status	Y = 0	72	106	178
	Y = 1	17	36	53
	Total	89	142	231
	Correctly predicted	**81%**	**25%**	**47%**

Notes: The predicted status refers to the combined vulnerability to income losses and food insecurity computed considering all the states of world for the subsample farm income. The real status represents the observed farm income losses and food insecurity outcome.

Source: Authors' own elaboration.

Table 16. Vulnerability targeting performance for Nigeria (worst-case scenario) – farm income

		Real status		
		Y = 0	Y = 1	Total
Predicted status	Y = 0	67	103	170
	Y = 1	22	39	61
	Total	89	142	231
	Correctly predicted	**75%**	**27%**	**46%**

Notes: The predicted status refers to the combined vulnerability to income losses and food insecurity computed considering only the worst-case scenario for the subsample of farm income. The real status represents the observed farm income losses and food insecurity outcome.

Source: Authors' own elaboration.

Machine-learning model

Lastly, for the machine-learning model, the decomposition results for farm-income livelihoods and non-farm income businesses are reported in Tables 17 and 18, respectively.

The pattern is qualitatively consistentwith the whole sample results: the sensitivity metrics is high, the specificity one is low, the overall accuracy is acceptable. There are, in sum, no discrepancies in the performance of the classification tree routine across the two categories of agrifood system actors.

Table 17. Tree-based targeting performance for Nigeria – farm income

		Real status		
		Y = 0	Y = 1	Total
Predicted status	Y = 0	35	107	142
	Y = 1	57	219	276
	Total	92	326	418
	Correctly predicted	**38%**	**67%**	**61%**

Notes: The predicted status refers to the predicted food insecure households. The real status represents the observed food insecure households in the subsample of farm income.

Source: Authors' own elaboration.

Table 18. Tree-based targeting performance for Nigeria – non-farm income

		Real status		
		Y = 0	Y = 1	Total
Predicted status	Y = 0	27	65	92
	Y = 1	84	407	491
	Total	111	472	583
	Correctly predicted	**24%**	**86%**	**74%**

Notes: The predicted status refers to the predicted food insecure households. The real status represents the observed food insecure households in the subsample of non-farm income.

Source: Authors' own elaboration.

7 Policy implications and conclusions

In developing emergency interventions in response to large-scale shocks, governments face the challenge of rebalancing exposure to myriad shocks in real time (Barrett *et al.*, 2021). On the other hand, knowing in advance which groups and communities are most at risk in case of a future shock would enable *ex ante* preventive policies and resilience-building efforts aimed at minimizing exposure before the shock occurs. This is even more urgent in this historical period, where new economic and political tensions are emerging, increasing the overall risk exposure of the most vulnerable households and their liquidity and behavioural constraints. For instance, the recent war in Ukraine caused a rise in food prices and fossil fuels, which are predicted to increase even further, compromising access to food and food production for low-income countries and vulnerable groups (IMF, 2022). Due to its unpredictable nature, the COVID-19 pandemic caught most governments unprepared and revealed a shortage of both preventive and absorptive policies.

Readers may be concerned that models' forecasting failures are not due to their intrinsic shortcomings in out-of-sample performances but to the "black swan" nature of the COVID-19 crisis. Thus, we stress again that the development literature agrees that, while unique in its causes, the pandemic shock is akin to a multi-stressor shock whose consequences have merely amplified the pre-existing vulnerabilities to different risk factors to which rural populations living in poor countries are routinely exposed (Barrett *et al.*, 2021).

Our COVID-19 stress test leverages this large-scale shock not to assess *ex post* its well-documented welfare impacts but to retrospectively evaluate the *ex ante* forecasting ability of several approaches currently available as predictive tools for policy targeting. Results have provided evidence of heterogeneous and overall disappointing performances. While standard vulnerability models largely failed to anticipate hardest-hit groups and food-insecure households during the COVID-19 pandemic, a simple machine-learning routine fared better. The downside, however, is that it overpredicted food-insecure households, resulting in modest accuracy overall.

This hampers the ability of the predictive tool to be cost-effective. The absence of a satisfactory forecasting model among the ones employed is a worrisome finding, given that vulnerable households are the nodes that determine the fragility of the entire agrifood system chain (producers, processors, retailers, vendors, and consumers) (FAO, 2021). From a methodological perspective, the results are in line with the evidence recently provided by Upton *et al.* (2022) on the disappointing out-of-sample performance of popular resilience metrics, and reinforce the view that predictive models of poverty, vulnerability, resilience, and other development outcomes should always be subject to rigorous empirical validation of their forecasting ability on held-out, unseen data.

These findings are subject to a number of caveats: i) the presence of non-trivial data issues (for example, the focus on income losses rather than consumption behaviour due to the lack of consumption data in the post-COVID-19 surveys, the use of subjective measures of food insecurity, measurement errors in comparing different datasets) and the fact that all the methodologies were employed in data-poor environments with small sample sizes, which is especially penalizing for data-driven routines; ii) the decision to proxy shock probabilities and corresponding severities using relatively limited panel data; iii) the lack of a rigorous identification of all the potential mechanisms at play in the vulnerability framework (for example, the hypothesis of non-transferability across states of the world of insurance mechanisms, whereby households can smooth away variations in outcomes over states of the world); and iv) the assumption underlying the simulations whereby the COVID-19 shock can be approximated as a simultaneous occurrence of all the food insecurity and income shocks households routinely face in rural developing contexts.

Despite these caveats, through careful analytical elaborations, we highlight a lack of appropriate forecasting and prevention tools, at least when using exclusively traditional surveys and publicly available data. While mapping and targeting subnational vulnerability hotspots and food insecurity pockets is a clear policy priority, standard models failed to address this need in the case of the COVID-19 shock and are likely to do so again soon. Our goal was to provide a forward-looking assessment of current predictive models using standard microdata in anticipation of the next major agrifood system crisis. In this respect, we emphasize three main insights: i) targeting vulnerable people is a fundamental prevention tool and can ensure not only *ex ante* resilience building, but also timely *ex post* assistance in the immediate aftermath of a shock; ii) simulations of forecasting abilities of current models in anticipation of large-scale shocks are still underdeveloped and should become mainstream practice (McBride *et al.*, 2021); and iii) a promising route for investigation is the integration of the “philosophy” of the machine-learning field with the interpretability, domain knowledge and theoretical insights underlying standard vulnerability models, so as to develop new and better targeting tools that combine the predictive power of machine learning with the economic guidance of traditional models.

Therefore, efforts should be devoted to promoting a refinement of targeting mechanisms and the development of better profiling methodologies underlying preventive interventions. These efforts would enable policymakers to act before, rather than after, the occurrence of shocks and to implement early-warning systems of vulnerability hotspots in anticipation of future agrifood system crises. In turn, all this would also improve the cost-effectiveness and efficacy of resilience-building programmes aimed at strengthening absorption capacity within local agrifood systems. From a data-oriented perspective, our work highlights the fact that, no matter how theoretically sound or computationally powerful they are, predictive models cannot do much if they operate in data-scarce environments. Lastly, and more generally, improving the interoperability of traditional survey data with non-conventional data sources (big data, crowdsourced data, citizen-generated information) appears a promising route. Considering all this, more investment in closing data gaps in rural developing contexts should be considered a critical priority for policy practitioners, donors, and stakeholders to maximize the potential of predictive models for *ex ante* targeting.

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Annex 1. Variables

Details about variables' construction

Ethiopia

Asset index

The variable asset index has been created using factor analysis. It includes a set of 35 non-agricultural durable assets (such as for example televisions, radios, water pumps, private car) held by the household.

Nigeria

Rainfall anomalies and weather shocks

First, following Dell, Jones and Olken (2014), we construct the measure of rainfall anomalies as a deviation of the level of rainfall in the previous twelve months from the historical average as follows:

$$\text{Rainfall anomalies: } \left(\frac{R_{it}-R_i}{R_{it}^{SD}}\right)$$

where R_{it} indicates the last twelve months rainfall at the location of household *i* for year *t*. R_i is the historical average rainfall at the location of household *i,* calculated based on the local government area (lga)*.* R_{it}^{SD} is the standard deviation of rainfall at the location of household *i.* Second, we identify as droughts rainfall anomalies under the 25th percentile of the total distribution and as heavy rains/floods values of anomalies over the 75th percentile of the distribution. Third, dummy variables for droughts and flood are created; the first takes value one if the household experienced drought anomalies, and the second takes value one if the household experienced heavy rains/flood rainfall anomalies.

Non-agricultural wealth index

Also in this case, a factor analysis has been used to construct the variable indicating non-agricultural wealth index. As for the variable asset index for Ethiopia, it includes 34 durable assets held by the household.

Variable description and statistics

Ethiopia

Table A11. Definition of the variables included in the analysis – Ethiopia

Variable name	Definition	Time period	Source
Vulnerability analysis (VEFI) – Ethiopia			
Food consumption (log)	Log of per capita food consumption (spatially and temporally deflated)	2018–2019	LSMS - ISA
Age of the household head	Age of the household head (years)	2018–2019	LSMS - ISA
Female household head	= 1 if the household head is female	2018–2019	LSMS - ISA
Household size	Number of members of the household	2018–2019	LSMS - ISA
Number of infants	Number of household members with less than 5 years old	2018–2019	LSMS - ISA
Number of children	Number of household members with less than 15 years old	2018–2019	LSMS - ISA
Married household head	= 1 if the household head is married	2018–2019	LSMS - ISA
Household head can read and write	= 1 if the household head can read and write	2018–2019	LSMS - ISA
Primary education	= 1 if the household head has completed primary education	2018–2019	LSMS - ISA
Secondary education	= 1 if the household head has completed secondary education	2018–2019	LSMS - ISA
Upper education	= 1 if the household head has a higher level of education	2018–2019	LSMS - ISA
Rural households	= 1 if the household lives in a rural area	2018–2019	LSMS - ISA
Number of rooms	Number of rooms in the house	2018–2019	LSMS - ISA
Asset index	Index of durable assets owned by the households	2018–2019	LSMS - ISA
Region dummies	Tigary, Afar, Amhara, Oromia, Somali, Benishangul Gumuz, Southern Nations, Nationalities, and People's Region (SNNP), Gambela, Harar, Addis Ababa, Dire Dawa	2018–2019	LSMS - ISA
Distance to the main road	Household distance in kilometers to the nearest major road	2018–2019	LSMS - ISA

Source: Authors' own elaboration.

Table A2. Descriptive statistics – Ethiopia

Variable name	Obs	Mean	SD	Min	Max
Vulnerability analysis (VEFI) – Ethiopia					
Food consumption (log)	6 650	8.053	0.791	5.136	11.688
Age of the household head	6 650	42.202	15.067	13	98
Female household heads	6 650	0.316	0.465	0	1
Household size	6 650	4.237	2.281	1	19
Number of infants	6 650	0.55	0.758	0	6
Number of children	6 650	1.763	1.745	0	14
Married household head	6 650	0.786	0.41	0	1
Household head can read and write	6 647	0.587	0.492	0	1
Primary education	6 650	0.42	0.494	0	1
Secondary education	6 650	0.212	0.409	0	1
Upper education	6 650	0.15	0.357	0	1
Rural households	6 650	0.465	0.499	0	1
Number of rooms	6 650	1.808	1.445	1	50
Asset index	6 650	0.003	0.499	-1.197	9.526
Regions					
Tigary	6 650	0.101	0.302	0	1
Afar	6 650	0.079	0.269	0	1
Amhara	6 650	0.111	0.314	0	1
Oromia	6 650	0.111	0.314	0	1
Somali	6 650	0.089	0.285	0	1
Benishangul Gumuz	6 650	0.05	0.218	0	1
Southern Nations, Nationalities, and People's Region (SNNP)	6 650	0.101	0.301	0	1
Gambela	6 650	0.072	0.258	0	1
Harar	6 650	0.082	0.275	0	1
Addis Ababa	6 650	0.117	0.321	0	1
Dire Dawa	6 650	0.087	0.282	0	1
Distance to the main road	6 650	14.478	25.882	0	309.8
Targeting analysis – Ethiopia					
Food Insecurity	3 201	0.17	0.376	0	1
Food insecurity – farm activity	1 004	0.236	0.425	0	1
Food insecurity – non-farm business	770	0.138	0.345	0	1
Reduction in food consumption	1 797	0.153	0.36	0	1
Reduction in food consumption – farmactivity	551	0.198	0.399	0	1
Reduction in food consumption – non-farm business	652	0.098	0.298	0	1

Source: Authors’ own elaboration.

Nigeria

Table A3. Definition of the variables included in the analysis – Nigeria

Variable name	Definition	Time period	Source
Vulnerability analysis (VTFI) – Nigeria			
Total income	Log of the total household gross income (non-farm, wage, farm, and other income)	2011–2019	LSMS - ISA
Non-farm income	Log of the value of sales coming from non-farm activities	2011–2019	LSMS - ISA
Farm income	Log of the household gross value of crop production and livestock production	2011–2019	LSMS - ISA
Death shock	= 1 if the household has been affected by the death of a working member of the household	2011–2019	LSMS - ISA
Illness shock	= 1 if the household has been affected by the illness of an income earning member of the household	2011–2019	LSMS - ISA
Food price shock	= 1 if the household experienced an increase in the price of major food items consumed	2011–2019	LSMS - ISA
Drought shock	= 1 if the household experienced a drought shock	2011–2019	LSMS - ISA
Heavy rains/flood shock	= 1 if the household experienced a flood shock	2011–2019	LSMS - ISA
Age of the household head	Age of the household head, in years	2011–2019	LSMS - ISA
Female household heads	= 1 if the household head is female	2011–2019	LSMS - ISA
Household head can read and write	= 1 if the household head can read and write	2011–2019	LSMS - ISA
Household size	Number of members of the household	2011–2019	LSMS - ISA
Urban households	= 1 if the household live in an urban area	2011–2019	LSMS - ISA
Non-agricultural wealth index	Index of non-agricultural assets held by the household	2011–2019	LSMS - ISA
TLU large ruminants	Tropical Livestock Unit - large ruminants held by the household	2011–2019	LSMS - ISA
TLU small ruminants	Tropical Livestock Unit - small ruminants held by the household	2011–2019	LSMS - ISA
TLU other animals	Tropical Livestock Unit - other animals held by the household	2011–2019	LSMS - ISA
Year of the interview	Year in which the household has been interviewed	2011–2019	LSMS - ISA

Source: Authors' own elaboration.

Table A4. Descriptive statistics – Nigeria

Variable name	Obs	Mean	SD	Min	Max
Vulnerability analysis (VTFI) – Nigeria					
Total income (log)	4 973	7.599	2.92	0	13.802
Non-farm income (log)	4 973	4.597	4.126	0	13.159
Farm income (log)	4 973	4.422	3.939	0	12.269
Death shock	5 000	0.072	0.258	0	1
Illness shock	5 000	0.044	0.204	0	1
Food-price shock	5 000	0.099	0.299	0	1
Drought shock	5 000	0.211	0.408	0	1
Heavy rains/flood shock	5 000	0.242	0.429	0	1
Age of the household head	5 000	52.33	14.272	18	100
Female household head	5 000	0.182	0.386	0	1
Household head can read and write	5 000	0.675	0.469	0	1
Household size	5 000	6.834	3.497	1	33
Urban household	5 000	0.293	0.455	0	1
Non-agricultural wealth index	4 986	0.044	0.544	-0.647	5.127
Tropical Livestock Unit (TLU) large ruminants	4 648	0.015	0.91	-2.195	20.534
Tropical Livestock Unit (TLU) small ruminants	5 000	0.42	3.274	0	163.75
Tropical Livestock Unit (TLU) other animals	5 000	0.223	0.636	0	14.4
Year of the interview	5 000	0.058	0.779	0	50
Targeting analysis – Nigeria					
Total income loss and food insecurity	316	0.671	0.47	0	1
Machine learning analysis – Nigeria					
Training sample (pre-COVID-19)					
Food Insecurity Experience Scale (FIES) (whole sample)	3 715	0.14	0.352	0	1
Food Insecurity Experience Scale (FIES) (farming households subsample)	1 440	0.13	0.338	0	1
Food Insecurity Experience Scale (FIES) (non-farming householdssubsample)	1 352	0.16	0.365	0	1
Test sample (post-COVID-19)					
Food Insecurity Experience Scale (FIES) (whole sample)	1 311	0.78	0.413	0	1
Food Insecurity Experience Scale (FIES) (farming households subsample)	418	0.78	0.42	0	1
Food Insecurity Experience Scale (FIES) (non-farming householdssubsample)	583	0.81	0.393	0	1

Source: Authors' own elaboration.

Annex 2. Additional results

Ethiopia

Sensitivity analysis for vulnerability targeting performances

Table A5. Vulnerability targeting performance for Ethiopia ($\widehat{V}_{ht}$>0.25) – food insecurity

		Real status		
		Y = 0	Y = 1	Total
Predicted status	Y = 0	2 293	418	2 711
	Y = 1	363	127	490
	Total	2 656	545	3 201
	Correctly predicted	**86%**	**23%**	**76%**

Notes: The predicted status refers to the vulnerability to food insecurity. The real status represents the observed food insecurity outcome.

Source: Authors' own elaboration.

Table A6. Vulnerability targeting performance for Ethiopia ($\widehat{V}_{ht}$>0.25) – reduction in food consumption

		Real status		
		Y = 0	Y = 1	Total
Predicted status	Y = 0	1 306	212	1 518
	Y = 1	216	63	279
	Total	1 522	275	1 797
	Correctly predicted	**86%**	**23%**	**76%**

Notes: The predicted status refers to the vulnerability to food insecurity. The real status represents the observed reduction in food consumption outcome.

Source: Authors' own elaboration.

Sensitivity analysis for risk-vulnerability targeting performances

Table A7. Risk-vulnerability targeting performance for Ethiopia ($\widehat{V}_{ht}$>0.25) – food insecurity

		Real status		
		Y = 0	Y = 1	Total
Predicted status	Y = 0	136	45	181
	Y = 1	227	82	309
	Total	363	127	490
	Correctly predicted	**37%**	**65%**	**44%**

Notes: The predicted status refers to the vulnerability to food insecurity. The real status represents the observed food insecurity outcome.

Source: Authors' own elaboration.

Table A8. Risk-vulnerability targeting performance for Ethiopia ($\widehat{V}_{ht}$>0.25) – reduction in food consumption

		Real status		
		Y = 0	Y = 1	Total
Predicted status	Y = 0	67	20	87
	Y = 1	149	43	192
	Total	216	63	279
	Correctly predicted	**31%**	**68%**	**39%**

Notes: The predicted status refers to the vulnerability to food insecurity. The real status represents the observed reduction in food consumption outcome.

Source: Authors' own elaboration.

Correlates of food insecurity experienced during the COVID-19 pandemic

Table A9. Logistic regression results – Ethiopia

Dependent variables	(1) Food insecurity	(2) Reduction of food consumption
Age of the household head	-0.00514**	-0.00416
	(0.00226)	(0.00273)
Age squared	5.11e-05**	3.40e-05
	(2.24e-05)	(2.74e-05)
Female head of household	0.0113	-0.0104
	(0.0147)	(0.0177)
Household size	0.00401	-0.000780
	(0.00291)	(0.00377)
Rural	0.0418***	0.0532***
	(0.0151)	(0.0196)
Literacy rate	-0.0270*	0.00696
	(0.0158)	(0.0190)
Total income reduced	0.0623***	0.0320
	(0.0128)	(0.0277)
Region dummies	YES	YES
Pseudo R-squared	0.12	0.19
Observations	3 203	1 797

Notes: The dependent variables are dummies taking value 1 if the household was food insecure in the sense that it was not able to access the most important goods (1) or if the household reduced its food consumption in response to an income loss (2). Results are marginal effects for discrete variables and semi-elasticities for continuous variables. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' own elaboration.

Nigeria

Theory-based vulnerability model results using only pre-COVID-19 data

Table A10. Vulnerability targeting performance for Nigeria (only using pre-COVID-19 data)

		Real status		
		Y = 0	Y = 1	Total
Predicted status	Y = 0	833	260	1 093
	Y = 1	63	42	105
	Total	896	302	1 198
	Correctly predicted	**93%**	**14%**	**73%**

Notes: The predicted status refers to the combined vulnerability to income losses and food insecurity. The real status represents the observed non-farm income losses and food insecurity outcome. Both status are from pre-COVID-19 data.

Source: Authors' own elaboration.

Vulnerability model benchmark results without hybrid food insecurity threshold

Table A11. Vulnerability targeting performance for Nigeria (all states of the world) – benchmark

		Real status		
		Y = 0	Y = 1	Total
Predicted status	Y = 0	50	104	154
	Y = 1	54	108	162
	Total	104	212	316
	Correctly predicted	**48%**	**51%**	**50%**

Notes: The predicted status refers to the combined vulnerability to income losses and food insecurity computed considering all the states of world. The real status represents the observed income losses and food insecurity outcome.

Source: Authors' own elaboration.

Table A12. Vulnerability targeting performance for Nigeria (worst-case scenario) – benchmark

		Real status		
		Y = 0	Y = 1	Total
Predicted status	Y = 0	0	0	0
	Y = 1	104	212	316
	Total	104	212	316
	Correctly predicted	**0%**	**100%**	**67%**

Notes: The predicted status refers to the combined vulnerability to income losses and food insecurity computed considering only the worst-case scenario. The real status represents the observed income losses and food insecurity outcome.

Source: Authors' own elaboration.

Difference-in-difference analysis of the impact of lockdown and mobility restrictions on income-food security outcomes

Table A13. Diff-in-diff of lockdown impacts on post-COVID-19 phone survey data

Dependent variable	(1) Total income loss and experienced food insecurity	(2) Non-farm income loss and experienced food insecurity	(3) Farm income loss and experienced food insecurity
Post (2020)	-0.183***	0.205***	0.0809*
	(0.0255)	(0.0611)	(0.0473)
Lockdown*post	0.0332	0.0386	0.0191
	(0.0513)	(0.0584)	(0.0744)
Constant	0.970***	0.594***	0.629***
	(0.0106)	(0.0525)	(0.0479)
Observations	723	601	706
Number of households	373	367	372
Household fixed effect	Yes	Yes	Yes

Notes: The dependent variables are dummies taking value 1 if the household experienced both an income loss (for each corresponding category) and a food insecurity experience or at least one of the three FIES questions; and 0 otherwise. Variable "Post (2020)" is a dummy for 2020. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' own elaboration.

Subsample analysis by treatment (lockdown) status

a. Treated (exposed to lockdowns and mobility restrictions)

Table A14. Vulnerability targeting performance for Nigeria (all states of the world) – treated

		Real status		
		Y = 0	Y = 1	Total
Predicted status	Y = 0	20	40	60
	Y = 1	2	7	9
	Total	22	47	69
	Correctly predicted	**91%**	**15%**	**39%**

Notes: The predicted status refers to the combined vulnerability to income losses and food insecurity computed considering all the states of world. The real status represents the observed income losses and food insecurity outcome in the treated group.

Source: Authors' own elaboration.

Table A15. Vulnerability targeting performance for Nigeria (worst-case scenario) – treated

		Real status		
		Y = 0	Y = 1	Total
Predicted status	Y = 0	20	36	56
	Y = 1	2	11	13
	Total	22	47	69
	Correctly predicted	**91%**	**23%**	**45%**

Notes: The predicted status refers to the combined vulnerability to income losses and food insecurity computed considering only the worst-case scenario. The real status represents the observed income losses and food insecurity outcome in the treated group.

Source: Authors' own elaboration.

b. Untreated (not exposed to lockdowns and mobility restrictions)

Table A16. Vulnerability targeting performance for Nigeria (all states of the world) – untreated

		Real status		
		Y = 0	Y = 1	Total
Predicted status	Y = 0	71	138	209
	Y = 1	11	27	38
	Total	82	165	247
	Correctly predicted	**87%**	**16%**	**40%**

Notes: The predicted status refers to the combined vulnerability to income losses and food insecurity computed considering all the states of world. The real status represents the observed income losses and food insecurity outcome in the untreated group.

Source: Authors' own elaboration.

Table A17. Vulnerability targeting performance for Nigeria (worst-case scenario) – untreated

		Real status		
		Y = 0	Y = 1	Total
Predicted status	Y = 0	58	116	174
	Y = 1	24	49	73
	Total	82	165	247
	Correctly predicted	**71%**	**30%**	**43%**

Notes: The predicted status refers to the combined vulnerability to income losses and food insecurity computed considering only the worst-case scenario. The real status represents the observed income losses and food insecurity outcome in the untreated group.

Source: Authors' own elaboration.

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