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Agricultural risks, the COVID-19 pandemic, and farm household welfare and diversification strategies in Africa

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Abstract: Agricultural activities in many African countries are bedevilled by a range of risk factors. Using micro-level household datasets from a range of countries in Africa, we examine the drivers of agricultural risks, while exploring the role of context as well as the impact of the COVID-19 pandemic on household welfare, with a focus on farm households relative to their non-farm counterparts. We demonstrate that the probability of experiencing risks related to agriculture is significantly influenced by a range of individual- and farm-level/contextual factors, with these effects showing considerable variations across contexts and countries in Africa. We also find that farm households witnessed important reductions in their incomes during the COVID-19 period in Uganda. The study contributes to the design of evidence-based approaches to reducing farmers' vulnerabilities to agricultural risks and pandemic-related shocks.

Key words: agricultural risk, COVID-19 pandemic, farm households, welfare, Africa

JEL classification: I31, O55, Q15, R14

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1 Introduction

In most African countries, the agricultural sector continues to play a significant role in employment and GDP growth. In 2019, for instance, about 53 per cent and 16 per cent of total employment and GDP, respectively, in sub-Saharan Africa (SSA) was accounted for by the agricultural sector (World Bank 2022). In spite of the important developmental benefits of the agricultural sector, especially in Africa, the majority of people engaged in the sector are peasants/smallholders (Herrero et al. 2017; Osabuohien 2020; Ruml et al. 2022), who are usually exposed to myriad risk factors including attacks by pests and diseases, market price uncertainties, and unstable weather conditions. Agricultural risks can be covariant/systematic (i.e. affecting a group of individuals or community) or idiosyncratic (i.e. affecting an individual farmer or household) and they may impact individuals or groups differently (PARM 2017).

Agricultural risks are said to fall into different categories, such as price- or market-related risks (price fluctuations), financial risks (lack of credit/loans), production risks (weather, pests and diseases, technology change), institutional risks (regulations), and human resources risks (physical and mental) (Hardaker et al. 2015; Harwood et al. 1999). Farmers' socioeconomic backgrounds (e.g., education, religion, age, gender, and farming practice) may influence their risk perceptions and the coping strategies they adopt (Ahsan 2011; Bergfjord 2013). Recent studies have discussed farmers' perceptions of agricultural risk and response strategies (Legesse and Drake 2005; Tzouramani et al. 2013), the factors affecting those perceptions (Oo et al. 2017; Winsen et al. 2014), and the barriers to risk management (Ejemeyovwi et al. 2022; Ochieng et al. 2017).

Farmers' exposure to or experience of agricultural risks may vary across farms and localities as well as contexts. For instance, Duong et al. (2019) observed that weather-related risks are the most cited in developing countries, while biosecurity threats are the most cited in developed countries. Consequently, in designing agricultural risk management policies, there is a need to consider context-specific risk experiences. Any approach to risk management in agriculture needs to be adapted to the particular circumstances of the country, supply chain, socioeconomic context, and locality. For example, tackling the risk of post-harvest losses might require an understanding of the crop type cultivated, distance from farm to market, climate effect on crop, storage availability and type, and farmers' characteristics, as well as national policies.

Previous studies on agricultural risk and farmers' coping strategies have focused on farmers' risk perceptions and how they respond to perceived risks: factors affecting farmers' risk perceptions and coping strategies (Dasmani et al. 2020; Legesse and Drake 2005; Tzouramani et al. 2013) and the barriers to risk management and coping strategies (Ochieng et al. 2017). These studies are limited in their approach to the issue of identifying the drivers of agricultural risks as they use only a small sample of farmers or single-country case studies. In this study, we contribute to the literature by utilizing micro-level smallholder farm household data from multiple countries (each country's data being nationally representative) to examine the following research questions: (i) What factors determine farmers' exposure to agricultural risks and do they vary by the type of risk? (ii) How does context mediate the effect of various individual-level factors on agricultural risks? (iii) How do the drivers of agricultural risks differ across countries in Africa?

Further, the outbreak of the COVID-19 pandemic and the related containment measures, including the imposition of national lockdowns and border closures, undeniably slowed economic activity in most African countries and worsened the plight of many low-income and vulnerable households, most of whom are engaged in agricultural activities (Osabuohien et al. 2022). There are perceptions that farm households were more adversely impacted by the pandemic than non-farm households, partly due to their already low levels of income and limited diversification. However, there is little empirical evidence on this issue, especially from Africa. Studies have noted that climate change, pests and crop diseases, and the outbreak of human diseases such as Swine Flu and Ebola in Africa contributed to low food production and distribution, thereby affecting agricultural activities, in SSA prior to the emergence of COVID-19 (Gralek et al. 2020; Pais et al. 2020; World Health Organization 2020). The fact that smallholder farming systems in Africa are generally labour-intensive and rainfall-dependent, and have weak linkages between input and output markets as well as limited post-harvest technologies and infrastructure increased their vulnerability to the adverse effects of the COVID-19 pandemic (Nhemachena and Murwisi 2020), as it came with the enforcement of social distancing, working from home, restricted transportation, and lockdowns (Osabuohien et al. 2022; Ufua et al. 2021). The imposition of movement restrictions would necessarily adversely affect labour-dependent farm operations such as planting, harvesting, threshing, and storage in Africa (Nassary et al. 2020).

There were immediate measures to mitigate the effects of COVID-19 on the agricultural sector. For example, at the time when some local markets were closing down due to travel restrictions, the International Fund for Agricultural Development (IFAD) helped connect farmers to buyers and provided seeds and fertilizer to farms in several countries in SSA (Rural21 2020). Nevertheless, African farmers may struggle more to access and obtain quality seeds as a result of the pandemic than they did before it (Ojiewo and Pillandi 2020). Thus, there is a need for an assessment of the impact of COVID-19 on Africa's agriculture.

To this effect, we ask the following additional questions: (iv) What was the effect of the COVID-19 pandemic on the welfare of farm versus non-farm households? and (v) What mitigating measures or diversification strategies were adopted by farm households amidst the crisis? Unpacking these issues will contribute to our understanding of the impacts of the COVID-19 pandemic on different types of households and the related mitigating measures.

The rest of the paper is structured as follows. The next section highlights the theoretical and empirical literature, including the conceptual framework of the study, while Section 3 presents a brief note on contextual issues related to the agricultural risks and diversification strategies and COVID-19 containment measures implemented in the five countries considered in this study. Sections 4 and 5 present the data and methods of analysis, and the discussion of the empirical results, respectively. Section 6 concludes.

2 Insights from related literature

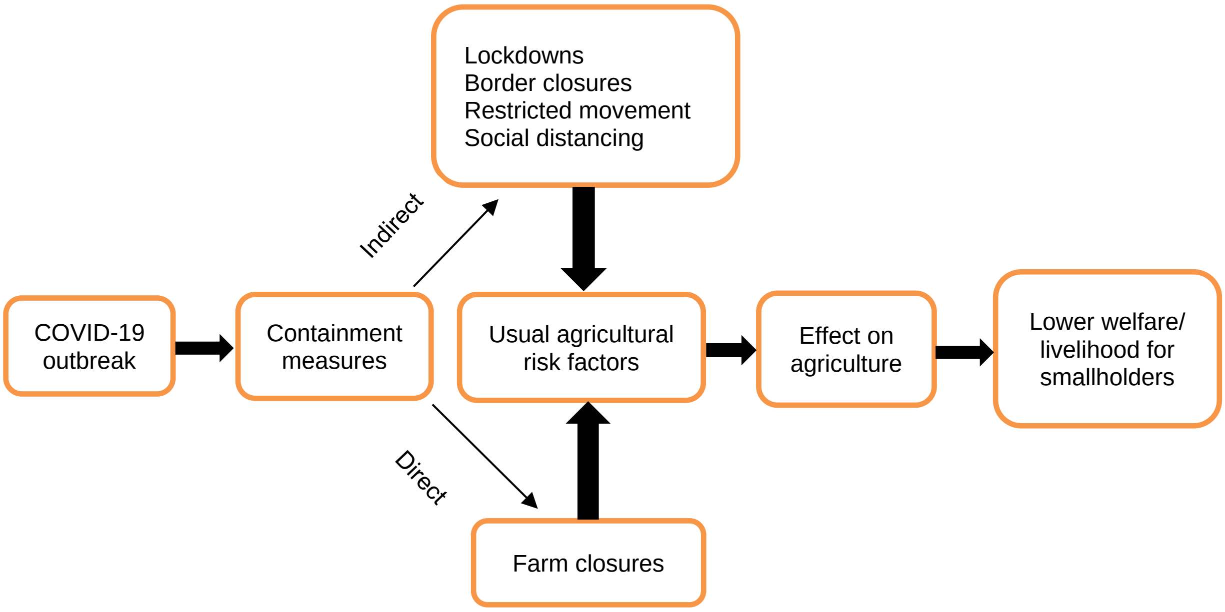
2.1 Theoretical underpinnings and conceptual framework

A number of health-related crises have disrupted economic activities in Africa in recent years, including the outbreaks of Swine Flu, Ebola, and SARS. These crises prompted scholars to study the impact of diseases on a global, national, or regional scale. Brahmbhatt and Dutta (2008), for example, described the dynamics of SARS—behavioural responses and economic impacts as well as numbers of cases and deaths—using an economic epidemiological approach. In another study, Barratt et al. (2019) accounted for the indirect cost implications of the outbreak and spread of animal diseases—in particular the cost to smallholders and the agricultural value chain, especially with regard to livestock production.

There is no doubt, however, that the outbreak and spread of COVID-19 and its containment measures had the greatest impact on economic activities across the globe (CCAFS 2020), and these shocks have been found to be complex in their effects due to both inter- and intra-sector transmission (Amjath-Babu et al. 2020). Due to government-imposed COVID-19 restrictions, economic hardships were witnessed in terms of reduced earnings and economic activities. These impacts are considered to be more severe on the poor (who are mostly rural smallholder farmers) than on the rich, since smallholders already facing agricultural risks that are known to them and adopting coping strategies to mitigate these will be hard hit by the unexpected pandemic outbreak, which will affect both their farming activities and their livelihoods/welfare.

Our study focuses on how the pandemic has affected smallholder farmers in Africa. In our conceptualization, we hypothesize that the impact of COVID-19 on agricultural activities is twofold: direct and indirect. The direct impact is related to the closure of farms and the interruption of the agricultural value chain, since any curtailment of agricultural activities will necessarily have a direct impact on farm production (Devereux et al. 2020). The indirect aspect is related to other COVID-19 restrictions/containment measures that restricted agricultural activities. These include lockdowns that reduced farm working days and hours, border closures that affected fertilizer access, restricted transport that limited access to extension officers, social distancing that affected the number of labourers on farms, and other measures that affected farming activities in general (Figure 1).

Figure 1: COVID-19 effect on agriculture and farmers' welfare



Source: authors' construction.

The outbreak of COVID-19 and its containment measures would therefore have had both direct and indirect effects on farm household welfare.[1] As shown in Figure 1, direct containment measures like farm closures and indirect measures like lockdowns and restricted movement/ transportation would add to the agricultural risks farmers usually faced. With restricted transportation, farmers may not get fertilizer on time or at all, extension services would be limited, labour would be reduced, products due for harvest might not be harvested, land might not be cleared, and planting may be ceased. All these factors would directly affect food production and

[1] See Hoddinott and Quisumbing (2003) for a detailed discussion on how risks/shocks can affect household welfare.

consequently welfare, since reductions in farm production mean lower earnings for smallholders, who are already poor and have no alternative income. Low earnings would translate to a decline in livelihood and welfare for the smallholder.

2.2 Empirical literature

There is an extensive empirical literature on agricultural risk and farmers' coping strategies across the globe. Our thematic review of the literature (agricultural risk and/or COVID-19 risk) revealed mixed results. In this sub-section we present these results in two parts: first those related to the drivers of agricultural risk and second to COVID-19 as a risk factor in agricultural activity.

Drivers of agricultural risk

Various studies have been carried out on factors that influence farmers' risk-facing and -coping strategies across the globe. Aminu et al. (2019) examined farm risks and the management strategies adopted by arable crop farmers in Ogun State, Nigeria. The authors found that erratic rainfall, pests, and diseases are the major production risks encountered by farmers but that they also face other types of agricultural risk, including personal risk (ill-health), marketing risk (market price fluctuations), financial risk (lack of insurance and access to credit), and institutional risk (lack of access to government subsidies). The most common coping strategies employed by farmers are diversification, on-farm sales, cooperative membership, selling at reduced prices, off-farm activities, and borrowing. The authors further asserted that the socioeconomic characteristics of farmers influence their attitude towards risk.

Duong et al. (2019) carried out a systematic literature review of farmers' perceptions of and responses to agricultural risks. Using a data reduction method (factor analysis) and descriptive statistics, they analysed 197 studies and found that weather-related risk (55 per cent), biosecurity threats (48 per cent), and human risk (35 per cent) are the significant risks perceived by farmers to their agricultural activities. They found that diversification of crop and animal production (28 per cent) and pest and disease monitoring and prevention (20 per cent) were the preferred agricultural risk management strategies employed by farmers. They also found a mismatch between perceived risk sources and risk management strategies, highlighting a need to improve understanding of why particular management responses are chosen to address the various risks.

Senapati (2020) examined farmers' attitudes towards risk and the effect of specific demographic and socioeconomic characteristics on farmers' risk attitudes. The author found that most farmers are risk-averse and that there is an inverse relationship between household size and risk averseness, as there is between off-farm income and risk averseness. The coping strategies of farmers included stocking food grains, saving money, selecting suitable crops (e.g. drought- or flood-resistant crops), and mixed cropping.

Mathithibane (2021) studied the climate-risk-coping strategies of maize farmers in South Africa and found that reducing crop production in times of uncertainty is the preferred coping mechanism adopted by farmers. He also found that farmers with crop insurance are best prepared to manage weather risk and thus demonstrate lower levels of crop loss.

Adnan et al. (2020) revealed that social and farm features influence the choice of risk management strategies. They concluded that age, educational level, extension experience, household income, farming area, land ownership, and risk-aversion are the most important factors affecting risk management strategy adoption. Again, floods, rainfall, pests, and diseases are the major production risks that farmers experience.

Nazir et al. (2018) studied farmers in Pakistan to understand the links between socioeconomic attributes, perceived risk sources, and coping strategies. The authors indicated that a change in agricultural machinery is a risk source and the promotion of products internationally is the principal strategy adopted by farmers to mitigate farm risk pressures. Other important coping strategies are crop insurance, precautionary saving, off-farm activities, and crop diversification. The most common agricultural risks encountered by farmers in Pakistan are insufficient machinery, crop disease, and production uncertainty.

In sum, the above studies demonstrate a wide range of agricultural risks encountered by farmers and related coping strategies, as well as variations in these across jurisdictions.

COVID-19 as an agricultural risk

There is a growing literature on the effects of the COVID-19 pandemic on the welfare of farm households; again, however, the evidence therein is mixed. Hammond et al. (2022) examined how farmers perceive the effects of the pandemic and the related containment measures on their livelihood and agricultural activities, as well as the coping strategies farm households adopted during the pandemic. They interviewed 9,201 smallholder farmers in seven countries (Burundi, Kenya, Rwanda, Tanzania, Uganda, Viet Nam, and Zambia) and found varied effects. They found that food purchase, off-farm income, sale of farm produce, and access to crop inputs were all affected. The effects attributed to government restrictions were widespread and severe, as off-farm and farm-based incomes were reduced, worsening economic and food security outcomes. In locations subject to more stringent restrictions, up to 80 per cent of households had to reduce food consumption. Almost all households with off-farm incomes reported reductions and half to three-quarters of households (depending on the location) with income from farm sales reported losses compared with the pre-pandemic period. In locations with more relaxed containment measures in place, less frequent and less severe economic and food security outcomes were perceived by the respondents. The authors found that between 30 per cent and 90 per cent of households applied coping strategies in response to the pandemic during 2020.

In a similar vein, Siche (2020) concluded that there is sufficient evidence to affirm that the COVID-19 pandemic has had an important effect on agriculture and the food supply chain, mainly affecting food demand and consequently food security, with an especially great impact on the most vulnerable population.

Andrieu et al. (2021) analysed the impact of the COVID-19 pandemic on agricultural systems and the decisions taken by policy-makers to handle its direct and indirect effects in Burkina Faso, Columbia, and France. Their study was based on surveys conducted with farmers, traders, and extension staff. They identified contrasting state responses to the pandemic. In Burkina Faso, crop farmers and pastoral farmers in rural areas were not affected in their productive activities by COVID-19 lockdown measures, but their product marketing was affected as the demand from traders decreased during lockdown. In contrast, in Colombia, the initial on-farm effects of COVID-19 resulted in the reorganization of labour. For instance, organic vegetable producers near Cali had to reorganize their farm activities and labour to respond to a higher demand for quality and coffee farmers also reported a reorganization of farm activities linked to decreased contacts with the city (for off-farm activities or leisure) and more time available to farm activities. In France, the pandemic impacted on wine merchants as wine exports to Asia declined and, although in the short-term there were no visible impacts of the pandemic on labour demand, cereal stocks, or marketing (except for cereals grown for fuel), vegetable production and sales were affected in the short term and vineyards in the medium term. The authors added that in Colombia, despite the selling price of coffee being exceptionally high, only a 7 per cent decrease in coffee production was reported. Thus, the authors concluded that the measures implemented in response to the COVID-19 crisis did not lead to a drastic change in agricultural or farming systems.

Amankwah and Gourley (2021) studied outcomes in five African countries and concluded that, in general, the share of households that had entered agriculture since the start of the pandemic was higher than those exiting. They also asserted that many households entered agriculture after the pandemic. In Malawi, for example, about 9 per cent of households that were not involved in agriculture (either crop or livestock farming) before the pandemic began to be afterwards, compared with less than 2 per cent that were involved in agriculture pre-pandemic who ceased to be. In Nigeria, the number of households that had gone into agriculture since the start of the pandemic was also higher (12 per cent) than the number of those exiting (4 per cent). The authors further found that 41 per cent of households in Ethiopia, and 73 per cent in Malawi, that had received income from agriculture in the last 12 months reported loss of income due to the pandemic.

Goswami et al. (2021) explored the multiple pathways of present and future impact on smallholder agricultural systems created by the COVID-19 pandemic. The authors found that the pandemic has affected farming in the areas of input availability, credit access, produce marketing, and labour availability, among others. Coping strategies adopted by farmers included engaging family as labourers, exchanging labourers with neighbouring farmers, borrowing money from relatives, accessing food hand-outs, replacing dead livestock, early harvesting, and reclaiming water bodies.

3 Agricultural risks and COVID-19 containment efforts in the studied countries

The first measures taken by African governments in response to the outbreak of COVID-19 were to restrict cross-border movement and limit foreign air travel (Medinilla et al. 2020). Between 13 and 24 March 2020, 25 African countries imposed such restrictions. Almost all these countries also suspended the arrival of international flights, at least from countries particularly affected by the virus. Stricter (sanitary) border controls usually increase trading costs (Bao et al. 2020), and intra-African trade of agricultural products duly slowed (Bouët et al. 2021). In fact, the COVID-19 pandemic sparked an unprecedented decline in world trade (down by 15.5 per cent in volume between the fourth quarter of 2019 and the second quarter of 2020), but an even more pronounced drop for Africa as a whole: down 17.7 per cent.

3.1 Côte d'Ivoire

Côte d'Ivoire recorded its first case of the COVID-19 virus on 12 March 2020. The government quickly adopted containment measures such as a curfew from 9 pm to 5 am; bans on international travel and public gatherings; closures of schools, restaurants, bars, and other recreational facilities; restrictions on public transport and movements within the country; and the wearing of masks. These containment measures started to be relaxed on 7 May 2020 and were further eased on 14 May 2020. Schools reopened on 25 May 2020, domestic flights resumed on 26 June 2020 and international flights on 1 July 2020, and the prohibition on public gatherings was lifted on 30 July 2020.

Other actions taken to tackle the socioeconomic effects of the spread of the disease included a package of economic measures designed to maintain the income of the most vulnerable through agricultural inputs support and the expansion of the cash transfer scheme announced by the government on 31 March 2020. Despite these measures, however, smallholders were relatively hard hit by the pandemic. Hodey and Dzanku (2021) showed that about 56 per cent of respondents sampled from eight African countries (including Nigeria, Tanzania, and Zambia) decreased their farming activities during the pandemic.

3.2 Mozambique

COVID-19 containment measures in Mozambique followed a similar pattern to those in other African countries. Public events were cancelled on 19 March 2020 and international travel controls introduced on 20 March. Public information campaigns started on 22 March and schools were closed on 23 March. Further restrictions followed: public gathering restrictions and workplace closures on 30 March, and the closure of public transport, a stay-at-home order, and restrictions on internal movement on 1 April (Ask About 2020). The government also closed international borders, though allowing limited food imports (Paganini et al. 2020).

These measures impacted the agricultural value chain, with important implications for food security. For instance, poultry farmers experienced significant delays in the supply of key inputs such as veterinary products and chicken feed during the pandemic. This led to a rise in the price of agricultural inputs (Nhemachena and Murwisi 2020). Since Mozambique relies heavily on small-scale family farming in rural areas, disruptions to supply and access to key farm inputs led to low on-farm productivity and limited food availability (Paganini et al. 2020). Paganini et al. (2020) indicated that people in the capital city, Maputo, a major trans-shipment port highly dependent on food imports, faced especially severe food insecurity.

3.3 Nigeria

Nigeria's Federal Ministry of Health confirmed the first COVID-19 case on 27 February 2020 in Ogun State, making it the third country in Africa to report a COVID-19 case, after Egypt and Algeria. Before the first case was even confirmed, however, the Nigerian government formed an inter-ministerial, multisectoral technical working group to prepare for any possible outbreak of the disease. Subsequently, the National Coronavirus Preparedness Group was tasked with strengthening in-country diagnostic capacity for the testing of COVID-19 (Arowosafe et al. 2022; Kapata et al. 2020).

Measures taken to contain the spread of the disease included the closure of land borders, a ban on international flights, and mandatory institutional quarantine (on 23 March 2020) and a stay-at-home order and cessation of non-essential movements (lockdown) on 30 March (Dan-Nwafor et al. 2020). The lockdown involved the closure of schools and workplaces, a ban on religious activities and social gatherings, and the cancellation of public events. These containment measures came with significant social and economic costs. Many people were unable to carry on their usual income-generating activities, which most affected the vulnerable and poor (Nigeria National Bureau of Statistics and the World Bank 2020), i.e. mainly smallholder farmers. As indicated by Daudu et al. (2021), COVID-19 was a major cause of food insecurity during lockdown at rural household level in southwestern Nigeria, the region declared to be epicentre of the disease. Balana et al. (2020) further observed that the COVID-19-induced travel and movement restrictions caused smallholder farmers to plant fewer crops and reduce cropping area and fertilizer application, and that 88 per cent of smallholder households lost half or more of their income as a result of the pandemic.

3.4 Tanzania

The Tanzanian government began rolling out its COVID-19 containment measures by closing schools and banning public gatherings on 17 March 2020. People were advised to avoid non-essential movement, though no formal internal movement restrictions were put in place.

Restrictions on air travel and inter-country public bus services were imposed on 25 March and tightened on 11 April; these were, however, relaxed on 14 May and lifted completely on 18 May. Tanzania closed its Kenya border on 17 May (Kell 2020; UN Migration Agency 2020).

Despite Tanzania's relatively relaxed COVID-19 restrictions, the country was hit hard by the pandemic. Most agricultural inputs in Tanzania are imported—for example, about 80 per cent of fertilizers, 60 per cent of seeds, and almost all agrochemicals used by farmers (Nhemachena and Murwisi 2020). Thus, even the limited pandemic-related disruptions exerted significant negative effects on the supply of and access to farm inputs.

3.5 Uganda

In order to contain the COVID-19 pandemic in Uganda, the government imposed a nationwide lockdown and closed non-food-selling businesses on 31 March 2020. Restrictions on transport were imposed on the same date and tightened on 10 April, when social distancing and mandatory mask-wearing were also introduced (Anadolu Agency 2020; UN Migration Agency 2020). These measures impacted on economic activities, as witnessed in other jurisdictions. Even though Uganda recorded fewer COVID-19 cases than its comparator countries in the sub-region, the effect of the pandemic-related restrictions on economic activity and livelihoods was not inconsequential. Bouët et al. (2021) estimated an income loss of about US$184 million (9.1 per cent of monthly GDP) due to the slowdown in economic activities and job losses. The authors further suggested that about 65 per cent of the total population experienced either partial or full loss of income. Thus, the pandemic had a severe impact on the economy, and consequently on living conditions and livelihoods, particularly in terms of agricultural activities.

As in other countries, Uganda's COVID-19-related restrictions had an adverse effect on the supply of agricultural inputs such as seeds, fertilizers, and agrochemicals. In particular, the closure of public transport services limited access to these inputs, since farmers (who mainly live in rural areas) could not collect supplies from the cities and towns, where most agricultural inputs are sold (Nhemachena and Murwisi 2020; Palladium 2020).

4 Data and empirical estimation approach

4.1 Data

In our quest to empirically examine, on the one hand, the drivers of agricultural risks and their variation across contexts and, on the other, the impact of the COVID-19 pandemic on the welfare of farm versus non-farm households, we used two types of micro-level data.

First, in our attempt to answer research questions (i)–(iii), we used a nationally representative smallholder household survey dataset collected by the World Bank for five African countries (Côte d'Ivoire, Mozambique, Nigeria, Tanzania, and Uganda). The Mozambique and Uganda data were collected in 2014/15 and 2015, respectively, while those for Côte d'Ivoire, Nigeria, and Tanzania were collected in 2016.

The dataset contains detailed information on a range of household demographic characteristics, farming practices, and types of agricultural risks encountered by farmers. Importantly, the instruments used in collecting the five sets of data broadly followed the same structure, especially in terms of the definition of the key variables used in this paper, thus making them largely comparable. In each dataset, for instance, respondents were asked to indicate whether they had experienced any form of agricultural risk, both broadly and specific to identified types of agricultural risks, such as weather-related risk, pest attacks, and accidents. Using this information, we constructed an aggregate measure of agricultural risk and a host of specific agricultural risks. These variables are used as dependent variables in our model of the determinants of agricultural risks.

Table 1 presents the summary statistics of the dependent variables employed in the agricultural risk model. In the aggregate sample, over 88 per cent of farmers experienced at least one form of agricultural risk, though there are important variations across specific risk types; for instance, while 21 per cent of farmers experienced risk related to unexpected price change, 58 per cent of farmers experienced pest-related risk, and more than 68 per cent experienced risk related to poor weather conditions.

Table 1: Summary statistics of main dependent variables (agricultural risk model)

Variable		Mean	Std. dev.	Range
Agr_risk_b	Binary: measures whether or not the individual faced any form of agricultural risk. Assumes a value of 1 if 'Yes' and zero otherwise.	0.885	0.319	0–1
weather	Binary: measures whether or not the individual faced weather-related agricultural risk. Assumes a value of 1 if 'Yes' and zero otherwise.	0.678	0.467	0–1
pest	Binary: measures whether or not the individual faced pest-related agricultural risk. Assumes a value of 1 if 'Yes' and zero otherwise.	0.581	0.493	0–1
accident	Binary: measures whether or not the individual faced accident-related agricultural risk. Assumes a value of 1 if 'Yes' and zero otherwise.	0.145	0.352	0–1
price_change	Binary: measures whether or not the individual faced an unexpected price change-related agricultural risk. Assumes a value of 1 if 'Yes' and zero otherwise.	0.208	0.406	0–1
contract_disease	Binary: measures whether or not the individual faced a crop disease-related agricultural risk. Assumes a value of 1 if 'Yes' and zero otherwise.	0.020	0.138	0–1
mkt_downturn	Binary: measures whether or not the individual faced a market downturn-related agricultural risk. Assumes a value of 1 if 'Yes' and zero otherwise.	0.082	0.275	0–1
breakdown_equipment	Binary: measures whether or not the individual faced a breakdown of equipment-related agricultural risk. Assumes a value of 1 if 'Yes' and zero otherwise.	0.077	0.266	0–1
p_unrest	Binary: measures whether or not the individual faced a political unrest-related agricultural risk. Assumes a value of 1 if 'Yes' and zero otherwise.	0.039	0.195	0–1

Source: authors' construction.

Second, to seek responses to questions (iv) and (v), we drew on six rounds of the World Bank's 'High-Frequency Phone Survey (HFPS) on COVID-19' dataset for Uganda.[2] The HFPS contains detailed information on households' economic activities before and during the pandemic—earnings and income—as well as detailed individual and contextual characteristics. In the immediate post-COVID round of the survey, respondents were asked the following questions:

[2] Round 1 June 2020; Round 2 July/August 2020; Round 3 September/October (1st–2nd) 2020; Round 4 October (27th–31st)/November 2020; Round 5 February 2021; Round 6 March/April 2021; Round 7 October/November 2021.

Q1: 'Since March 20, 2020, the day that schools were closed, has income from the activity increased, stayed the same, reduced, or become a total loss (no earnings)?'

Q2: 'Compared with the average monthly income during the 12 months prior to COVID, is the household monthly income at the same level as before COVID, above the pre-COVID level, or below the pre-COVID level?'

However, in the subsequent rounds, question 1 was rephrased to reflect respondents' perceived level of income loss in the month of the survey relative to the preceding month, as captured below:

Q1a: 'Since the last call, has income from activity increased, stayed the same, reduced, or become a total loss (no earnings)?'

Using the responses to these questions, we create two alternative measures of income loss due to the COVID-19 pandemic. Our first measure of income loss (inc_loss1) is binary and assumes a value of 1 if the household indicates that their income has reduced, or they have experienced a total loss in income or earnings, and 0 if otherwise. The second measure of income loss (inc_loss2) is binary and takes a value of 1 if the household indicates that their current monthly income is below the pre-COVID level and 0 if otherwise. Table 2 presents the summary statistics for these variables and those for other key independent variables employed in the model of determinants of COVID-related income loss.

Table 2: Summary statistics of key variables (COVID-related income loss model)

Variable		**Mean**	**Std. dev**	**Range**
Inc_loss1	Binary: measures whether or not a household experienced a reduction in income or a total loss in income during the post-COVID period. Assumes a value of 1 if 'Yes' and zero otherwise.	0.938	0.241	0–1
Inc_loss2	Binary: measures whether or not a household's current monthly income is below the pre-COVID level. Assumes a value of 1 if 'Yes' and zero otherwise.	0.671	0.470	0–1
Farm	Binary: measures whether or not the household's main economic activity is farming. Assumes a value of 1 if 'Yes' and zero otherwise.	0.863	0.343	0–1
Educ	Categorical: measures the highest level of educational attainment of the head of the household. Assumes a value of 0 if the head has No education, 1 if Primary, 2 if Secondary, and 3 if Tertiary.	1.401	0.802	0–3
Male	Binary: measures the gender of the head of the household. Assumes a value of 1 if male and 0 if female.	0.688	0.463	0–1
Age	Continuous: measures the age of the head of the household.	48.341	15.257	18–96

Source: authors' construction.

Over 94 per cent of households experienced either a reduction in income or a total loss in income during the post-COVID period, while close to 68 per cent of households had monthly incomes below the pre-COVID level. About 86 per cent of households in the sample are engaged in agricultural activities as their main economic activity.

4.2 Empirical estimation approach

To estimate the determinants of agricultural risks and of COVID-induced income reduction, we employ the binary probit model, since the dependent variable in both cases is binary. Consequently, we follow the specification in equation (1) below:

$$A_i^* = \gamma + \alpha_i Ind_i + \beta_i Z_i + \varepsilon_i \quad (1)$$

Equation (1) is the index function model and A_i^* is the latent continuous response variable that indicates whether household i encountered an agricultural risk (be it broad or specific) or experienced a reduction in income due to COVID-19. Ind_i and Z_i denote vectors of household- and farm-level/contextual factors, respectively, related to household *i*. The household-level covariates included in the estimations are: the educational attainment of the household head, the head's gender and age, the size of the household, and whether the household's main economic activity is farming.[3] The farm/contextual variables are: locality (rural versus urban), region, type of crop cultivated, nature of land ownership, and whether the farm is treated as a family business. Ownership of livestock and country dummies are included in the agricultural risk model. α_i and β_i are vectors of coefficients to be estimated and γ is the intercept term. ε_i is the standard error term. The dependent variable, A_i, is observed as follows:

$$A_i = \begin{cases} 1 & if \ A_i^* > 0 \\ 0 & if \ A_i^* \leq 0 \end{cases} \tag{2}$$

We apply the probit regression estimation technique given the binary nature of the dependent variable; the related model is stated as follows:

$$\Pr\left(A_i = 1 | X_i\right) = \Phi(\gamma + \alpha_i Ind_i + \beta_i Z_i) \tag{3}$$

where Φ is a cumulative standard normal distribution function while all other elements of Equation (3) maintain their usual meaning.

To estimate agricultural risk, we employ a simple probit model, since we do not find any concerns over potential endogeneity bias in the underlying relationship. More importantly, our goal is to illustrate the presence or otherwise of an association between the dependent variable and the regressors; thus, we refrain from making inferences of causality from the findings. However, in the COVID-19-induced income loss models, our goal is to show the causal effect of the pandemic on farm household incomes. Due to the lack of suitable external instruments, we adopt the Propensity Score Matching (PSM) approach to shed light on the effect of being a farm household on the probability of reporting a reduction or total loss of income due to the COVID-19 pandemic.

The PSM approach allows us to deal with the potential endogeneity bias problem and the sample selection issue[4] in the underlying relationship by matching treated groups to their non-treated counterparts based on a set of observable baseline characteristics (Iddrisu and Danquah 2021). In this study, we include the following regressors in the estimation of the propensity scores: age and sex of the household head, educational attainment of the household head, household size and locality (rural versus urban dummy and regional dummies). Following the precedence of earlier scholars (e.g. Zhang and Posso 2019), we employ conventional matching methods such as Nearest-Neighbour Matching (with or without calliper and with or without replacement) to match treated households with comparable untreated counterparts, conditional on the estimated propensity scores. The suitability of the PSM approach depends, however, on the presence of a common support between treated and non-treated households. Figure A1 (in the Appendix) illustrates the extent to which the treated households are matched with their untreated counterparts based on the propensity scores. The summary statistics of the main independent variables in the agricultural risk- and COVID-induced income reduction models are presented in Tables A1 and A2 in the Appendix, respectively.

[3] Given our interest in demonstrating whether farm households are hurt more than their non-farm counterparts by the COVID-19 pandemic, this variable is included only in the COVID-19-induced income loss models.

[4] This issue arises because households decide whether to participate in farm activities or not, and this decision may be influenced by observable and/or unobservable factors that are peculiar to these households.

5 Results

In this section, we present the main results of the study in relation to our five research questions. First, we present evidence on the determinants of agricultural risk and whether they vary by the type of risk; second, we assess the role of context (focusing on whether a farmer is located in either a rural or an urban area) in the effect of the various individual-level factors (such as age, educational attainment, and gender); third, we discuss how the determinants of farmers' exposure to agricultural risks varies across countries in Africa; fourth, we present the results of our estimation of the effect of the COVID-19 pandemic on the welfare of farm versus non-farm households; finally, we discuss the coping—mitigating or diversification—strategies adopted by farm households during the pandemic.

5.1 What factors determine farmers' exposure to agricultural risks and do they vary by the type of risk?

Farmers' exposure to agricultural risks is influenced by a range of individual and contextual as well as farm-level factors (Table 3). For instance, having a tertiary-level educational qualification reduces the chance of experiencing agricultural risk by close to 14 per cent relative to having no educational record, while farm households whose head is male are around 2 per cent less likely to experience agricultural risk than female-headed households; this is consistent in the locality-disaggregated estimations. Context and the type of crop cultivated by the farmer are both found to have a significant effect on the probability of agricultural risk exposure. Indeed, rural households are more likely to experience agricultural risks than their urban counterparts, whereas farmers cultivating maize as their main crop are also more susceptible to agricultural risks than those cultivating other crops. Further, we find that farm households that consider farming as a business have a higher chance of experiencing agricultural risks; this is perhaps driven by rural households.[5] Compared with farmers in Côte d'Ivoire, farmers in Mozambique and Uganda are less likely to experience agricultural risks; this is not the case for farmers in Tanzania. The ownership of livestock reduces the probability of experiencing agricultural risks but only among urban households, while farmers with customary land tenure securities exhibit lower probabilities of experiencing agricultural risks than those without such security.

Additionally, we find important variations in the effect of the various factors on specific types of agricultural risk; these variations are found not only in terms of the significance of the covariates across risk types but also in terms of the signs of these covariates (Table 4). For example, whereas having a tertiary level of educational attainment increases the chance of experiencing risks related to uncertain price change and market downturn, it reduces the probability of experiencing risk related to political unrest in comparison with having no educational experience. These effects are significant at the conventional levels of statistical significance. Being a male is associated with an increase in the probability of experiencing risk related to the breakdown of equipment, while ownership of livestock raises the likelihood of experiencing risk related to pest attacks. Interestingly, individuals who consider farming as a business are less likely to encounter weather-related agricultural risk than those who do not; this might be due to the fact that those who see farming as a business are able to invest intensively in their agricultural activities, including the setting-up of irrigation facilities, thus reducing their reliance on natural rainfall.

Further, we find important variations in the effect of the various country dummies across risk types. As an example, while farmers in Tanzania are more likely to report experiences of risks

[5] The coefficient of the farm_bus variable is significant in the full sample and only in the rural sub-sample estimations.

related to weather and pest attacks than those in Côte d'Ivoire, the opposite is the case for risks associated with accidents and political unrest. These differences point to the fact that, although they share a lot of characteristics, farmers in different countries within Africa are exposed to different challenges related to their farming activities.

Table 3: Determinants of agricultural risk (marginal effects); baseline estimates and disaggregation by locality

Dependent var: Agricultural risk (binary)	**Baseline**	**Baseline+**	**Baseline++**	**Locality-disaggregated estimations**	
	I	**II**	**III**	**Urban sub-sample**	**Rural sub-sample**
Covariates					
Educational attainment (Base: None)					
Primary	0.019	0.013	-0.010	-0.007	-0.002
	(0.014)	(0.012)	(0.011)	(0.016)	(0.022)
Secondary	0.018	0.039***	-0.038**	-0.074**	-0.003
	(0.015)	(0.013)	(0.017)	(0.036)	(0.024)
Tertiary	-0.018	0.057***	-0.135***	-0.160**	-0.069
	(0.025)	(0.016)	(0.050)	(0.077)	(0.062)
Male (Base: Female)	0.012*	-0.011*	-0.022***	-0.030***	-0.016**
	(0.007)	(0.006)	(0.007)	(0.012)	(0.008)
Age	0.005***	0.002*	-0.001	0.003	-0.003**
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Age2	-0.000***	-0.000	0.000	-0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Livestock_own		-0.006	-0.010	-0.023*	0.001
		(0.006)	(0.007)	(0.012)	(0.009)
Customary_landown		-0.008	-0.002	0.007	-0.014*
		(0.006)	(0.007)	(0.011)	(0.008)
Rural (Base: Urban)		0.053***	0.010	-	-
		(0.006)	(0.009)		
Farm_bus			0.017**	0.016	0.014*
			(0.007)	(0.012)	(0.008)
Crop_maize			0.017*	0.016	0.015
			(0.010)	(0.015)	(0.011)
Country dummy (Base: Côte d'Ivoire)					
Tanzania			0.005	0.008	0.003
			(0.005)	(0.013)	(0.005)
Mozambique			-0.154***	-0.200***	-0.148***
			(0.012)	(0.031)	(0.013)
Uganda			-0.135***	-0.120***	-0.185***
			(0.012)	(0.016)	(0.022)
Prob > chi2	0.000	0.000	0.000	0.000	0.000
Pseudo R-squared	0.005	0.028	0.123	0.068	0.175
Observations	9,102	8,562	6,841	3,109	3,732

Note: the dependent variable is an aggregate measure of agricultural risk. It assumes a value of 1 if the farmer faced any form of agricultural risk and zero otherwise; models I–III present the baseline estimation for the full sample; in model I, we estimate the determinants of agricultural risk, accounting for only individual-level covariates, while model II presents the same type of results but with the incorporation of both individual- and farm-level/locality covariates and model III includes two additional covariates (farm_bus and crop_maize) and country dummies; standard errors clustered at the household level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' construction.

Table 4: Determinants of agricultural risk (marginal effects): specific risk elements

Dependent var:	**Weather**	**Pest**	**Accident**	**Price change**	**Crop disease**	**Market downturn**	**Equipment breakdown**	**Political unrest**
Covariates	**I**	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**
Educational attainment (Base: None)								
Primary	-0.022	0.024	0.012	0.059***	0.007	0.011	0.004	-0.080***
	(0.019)	(0.022)	(0.015)	(0.016)	(0.005)	(0.012)	(0.012)	(0.023)
Secondary	-0.034	0.049*	0.050***	0.058***	0.007	0.031**	0.001	-0.080***
	(0.023)	(0.026)	(0.018)	(0.020)	(0.006)	(0.014)	(0.014)	(0.023)
Tertiary	-0.008	0.054	0.047	0.084***	0.019**	0.048**	0.008	-0.063**
	(0.032)	(0.036)	(0.029)	(0.031)	(0.010)	(0.022)	(0.019)	(0.025)
Male (Base: Female)	0.012	-0.008	-0.006	0.008	0.002	0.004	0.013**	0.008
	(0.010)	(0.011)	(0.008)	(0.010)	(0.003)	(0.007)	(0.006)	(0.006)
Age	0.000	0.001	0.001	0.002	0.000	0.001	0.000	-0.001
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Age2	-0.000	0.000	-0.000	-0.000*	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Livestock_own	0.004	0.027**	-0.005	0.013	-0.002	0.010	0.006	0.006
	(0.010)	(0.011)	(0.009)	(0.009)	(0.003)	(0.006)	(0.006)	(0.006)
Cust_landown	0.007	0.057***	0.017**	0.005	-0.009***	-0.013**	-0.007	0.009
	(0.010)	(0.011)	(0.008)	(0.010)	(0.003)	(0.006)	(0.006)	(0.006)
Rural (Base: Urban)	-0.010	0.013	-0.005	-0.029**	-0.006	0.013	-0.005	-0.008
	(0.014)	(0.012)	(0.010)	(0.012)	(0.004)	(0.009)	(0.009)	(0.007)
Farm_bus	-0.032***	0.039***	0.006	0.088***	0.014***	0.034***	0.009	0.023***
	(0.011)	(0.012)	(0.009)	(0.012)	(0.005)	(0.008)	(0.007)	(0.008)
Crop_maize	0.046***	0.075***	0.028***	0.028**	0.006	0.029***	0.013	-0.007
	(0.012)	(0.014)	(0.010)	(0.012)	(0.004)	(0.009)	(0.009)	(0.006)
Country dummy (Base: Côte d'Ivoire)								
Tanzania	0.072***	0.272***	-0.048***	0.223***	0.002	0.119***	0.100***	-0.013*
	(0.018)	(0.021)	(0.015)	(0.012)	(0.005)	(0.010)	(0.009)	(0.007)
Mozambique	0.003	0.140***	0.033*	0.042***	0.001	0.021***	0.016**	
	(0.021)	(0.023)	(0.018)	(0.012)	(0.006)	(0.008)	(0.007)	
Uganda	0.058***	0.384***	0.000	0.297***	-0.006	0.050***	0.031***	
	(0.021)	(0.022)	(0.017)	(0.016)	(0.005)	(0.009)	(0.008)	
Nigeria	-0.297***	0.221***	0.022	0.249***	0.031***	0.112***	0.140***	0.036***
	(0.021)	(0.021)	(0.016)	(0.015)	(0.007)	(0.011)	(0.012)	(0.010)
Prob > chi2								
Pseudo R-squared								
Observations	7,702	7,702	7,702	7,702	7,702	7,702	7,702	4,426

Note: the dependent variables used in each of the estimations here are binary, assuming a value of 1 if the specific risk type is experienced by the farmer and zero otherwise; 'Weather' refers to a situation where agricultural activities have been seriously affected by poor weather conditions; 'Pest' refers to a situation where agricultural activities have been seriously affected by pests; 'Accident' refers to a situation where agricultural activities have been seriously affected by an accident; 'Price change' refers to a situation where the farmer is hit by an unexpected price change; 'Market downturn' refers to a situation where the farmer is hit by an unexpected fall in demand; and 'Equipment breakdown' refers to a situation where farming equipment breaks down unexpectedly; standard errors clustered at the household level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' construction.

5.2 How does context mediate the effect of various individual-level factors on agricultural risks?

In column I of Table 5, we report the marginal effects of the interaction of each of the covariates in Table 3 with the rural dummy, while column II presents our baseline estimates (as in Table 3) for purposes of comparison. Surprisingly, context (that is, whether a farmer lives in a rural versus urban area) moderates the effect of the various individual-level factors on the probability of experiencing agricultural risks. In particular, conditional on living in a rural area vs an urban area, there is no difference in the probability of experiencing agricultural risks between males and females or among farmers with different levels of educational attainment; this contrasts sharply with our baseline estimates. Thus, context diminishes the importance of the various individual-level factors in explaining the probability of experiencing agricultural risks.

Table 5: Marginal effects of interaction terms (with rural dummy)

Dependent var: Agricultural risk (binary)	**Contrast (dy/dx)**	**Baseline++ (dy/dx)**
	I	**II**
Covariates		
Educational attainment (Base: None)		
Primary	-0.001	-0.010
	(0.031)	(0.011)
Secondary	0.057	-0.038**
	(0.045)	(0.017)
Tertiary	0.44	-0.135***
	(0.102)	(0.050)
Male (Base: Female)	0.004	-0.022***
	(0.015)	(0.007)
Age	-0.000	-0.001
	(0.000)	(0.001)
Prob > chi2	0.000	0.000
Pseudo R-squared	0.124	0.123
Observations	6,841	6,841

Note: the dependent variable is an aggregate measure of agricultural risk. It assumes a value of 1 if the farm faced any form of agricultural risk and zero otherwise; other covariates included in the models but not reported here are: Livestock_own, Customary_landown, Farm_bus and the various country dummies; standard errors clustered at the household level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

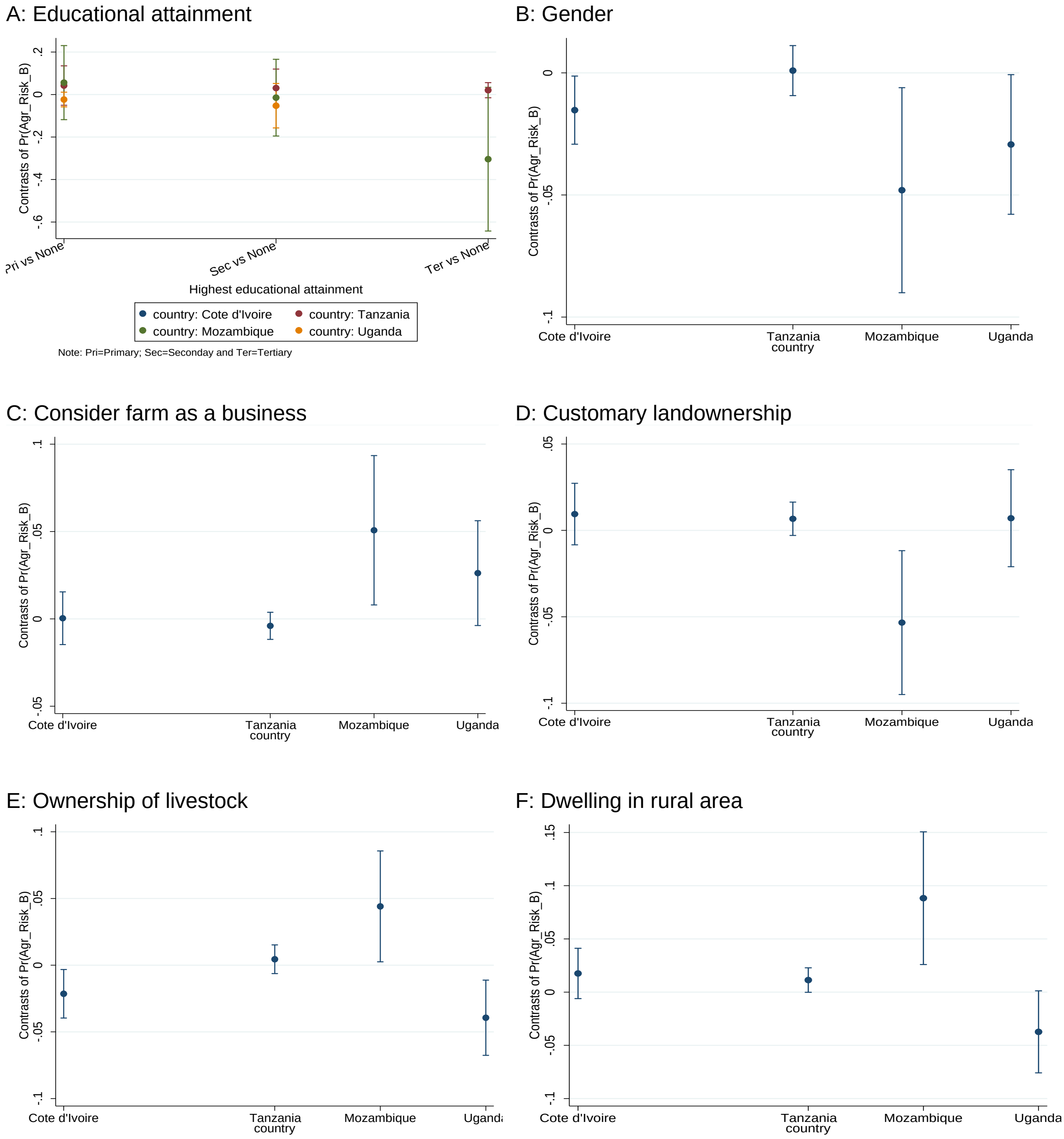
Source: authors' construction.

5.3 How do the drivers of agricultural risks differ across countries in Africa?

As mentioned earlier, African farmers likely share a number of characteristics, mostly in terms of the nature of land ownership for farming practices and their acute over-reliance on natural rainfall. However, there might be reasons that farmers in the various countries in Africa have different experiences; these might relate to the effect of the various individual- and farm-level/contextual factors on their likelihood of experiencing risks related to farming.

Figure 2 presents the differences in the predictive margins of differences in these predictor variables. Educated farmers do not show a significant chance of experiencing (or otherwise) agricultural risks in comparison with their uneducated counterparts in most of the sampled countries; tertiary-level educated farmers, however, exhibit a lower chance of experiencing agricultural risks in Mozambique than farmers with no schooling record. Also, while the gender of the farmer matters in predicting the probability of experiencing (or otherwise) agricultural risks in Côte d'Ivoire and Mozambique, this is not the case in Tanzania. Variations are also observed in the effects of other factors, such as locality and nature of landownership, with Mozambique standing out as a case where these contextual factors play a significant role in influencing the likelihood of experiencing agricultural risks. These findings point to the fact that policies aimed at reducing farmers' exposure to agricultural risks must be context-specific.

Figure 2: Contrasts of predictive margins of key individual- and farm-level/contextual factors (by country)



Note: results based on estimation of the determinants of agricultural risks, disaggregated by country (see Table A3 in the Appendix); 95% confidence intervals are plotted.

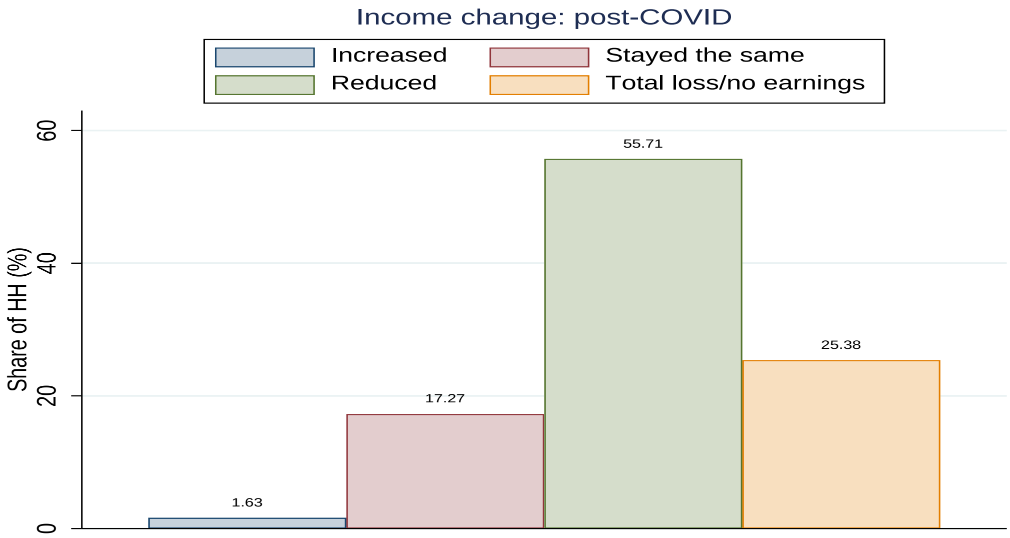
Source: authors' construction.

5.4 What was the effect of the COVID-19 pandemic on the welfare of farm versus non-farm households?

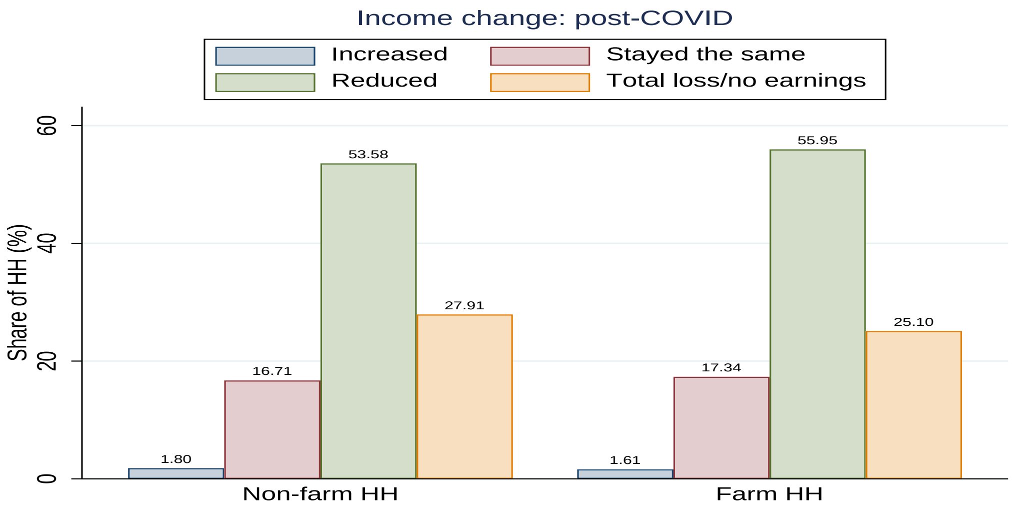
Figure 3 plots responses to the question of whether individuals witnessed a change in their incomes relative to the month preceding the month of the survey round. Uganda imposed a COVID-19-related lockdown and school closures on 20 March 2020. In the month following the imposition of the lockdown, over 55 per cent of households reported a reduction in income compared with the pre-COVID level, while more than a quarter of households reported experiencing a total loss in income or earnings. Only 1.6 per cent of households reported an increase in their income during the month immediately after the lockdown and school closures were introduced.

Figure 3: Post-COVID income change (% share of households); income concept 1

Panel A: Full sample



Panel B: Farm vs non-farm households



Note: responses are in answer to the question: 'Since March 20, 2020, the day that schools were closed, has income from the activity increased, stayed the same, reduced, or become a total loss (no earnings)?'

Source: authors' construction.

Considering the differences in these responses across household types (i.e. farm versus non-farm —Panel B), we find a marginal difference across household types in the share of households reporting either a reduction in income or a total loss. For instance, about 56 per cent and 54 per cent of farm and non-farm households, respectively, reported a fall in income during the immediate post-COVID lockdown period. However, there are important variations in responses to the question whether the household's income is above, below, or the same as the pre-COVID level (Figure A2 in the Appendix). In particular, 58 per cent and 45 per cent of farm and non-farm households, respectively, reported that their current income is below its pre-COVID level.

Although these descriptive primary data provide insight into the differential effects of the pandemic on the welfare of farm versus non-farm households, they are nevertheless short of providing rigorous evidence of an underlying relationship. Consequently, we estimate the effect of being a farm household on the probability of reporting a reduction or total loss of income after the imposition of COVID-19-related restrictions and see that farm households are about 3.2 per cent more likely to report a reduction/loss in income during the COVID period relative to their non-farm counterparts (Table 6).

Among farm households, however, there are differences across our different covariates. For example, households headed by males have a lower probability of reporting a reduction/loss in income during the COVID period than female-headed households, while households in the Western region are 5–10 per cent less likely to report a reduction/loss in income during the COVID period. These results are, however, not entirely consistent when we disaggregate the sample across rounds of the surveys (see Tables A4 and A5 in the Appendix) but are broadly maintained when we use a potential endogeneity bias-corrected estimation strategy, that is, the PSM approach (Table 7).

The findings from the survey round-disaggregated analysis indicate that in the month immediately following the imposition of pandemic-related restrictions in Uganda, farm households were not disproportionately affected by those restrictions compared with non-farm households; this story, however, changed over time, with farm-households witnessing significant reductions in income during the post-pandemic period compared with non-farm households.

Table 6: Determinants of income loss (marginal effects)

Dependent var: income_loss	Inc_loss1	Inc_loss2
	I	II
Covariates		
Farm	0.032*	0.036
	(0.017)	(0.031)
Male	0.008	-0.035*
	(0.011)	(0.020)
Educational attainment (Base: None)		
Primary	0.011	0.025
	(0.017)	(0.034)
Secondary	0.003	-0.009
	(0.019)	(0.037)
Tertiary	-0.033	-0.032
	(0.021)	(0.043)
age	-0.001***	-0.001
	(0.000)	(0.001)
hhsize	0.001	0.000
	(0.002)	(0.003)
Asset_moto	0.014	0.044*
	(0.015)	(0.027)
Asset_tv	0.015	-0.032
	(0.015)	(0.023)
Own_comp	-0.048**	-0.043
	(0.022)	(0.054)
Locality (Base: Urban)		
Other urban	-0.084	-0.244
	(0.052)	(0.160)
Rural	-0.014	-0.036
	(0.013)	(0.023)
Region (Base: Central)		
Eastern	0.022	0.364***
	(0.019)	(0.030)
Kampala	-	-0.469***
		(0.062)
Northern	-0.042***	0.184***
	(0.016)	(0.026)
Western	-0.055***	-0.101***
	(0.015)	(0.022)
Prob > chi2	0.000	0.000
Pseudo R-squared	0.086	0.237
Observations	1,888	1,973

Note: table shows the probabilities of reporting an income fall or total loss of income during the post-COVID period. The dependent variable used here is based on two measures of income loss: the first is responses to the question whether a household witnessed a reduction or a total loss of income due to the COVID-19 pandemic and it assumes a value of 1 if yes and 0 otherwise (the evidence for this is presented in model I); the second measure is responses to the question whether a household's post COVID-19 income is below the level it was prior to COVID and it assumes a value of 1 if yes and 0 otherwise (the evidence for this is presented in model II); standard errors clustered at the household level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' construction.

Table 7: Effect of farm household on COVID-related income loss: propensity score-matching estimates

	Full sample		Wave 4		Wave 5		Wave 6	
	ATE	**Std. err.**	**ATE**	**Std. err.**	**ATE**	**Std. err.**	**ATE**	**Std. err.**
Farm (farm HH vs non-farm HH)	0.175*	0.093	0.102*	0.061	0.289***	0.049	0.106	0.093

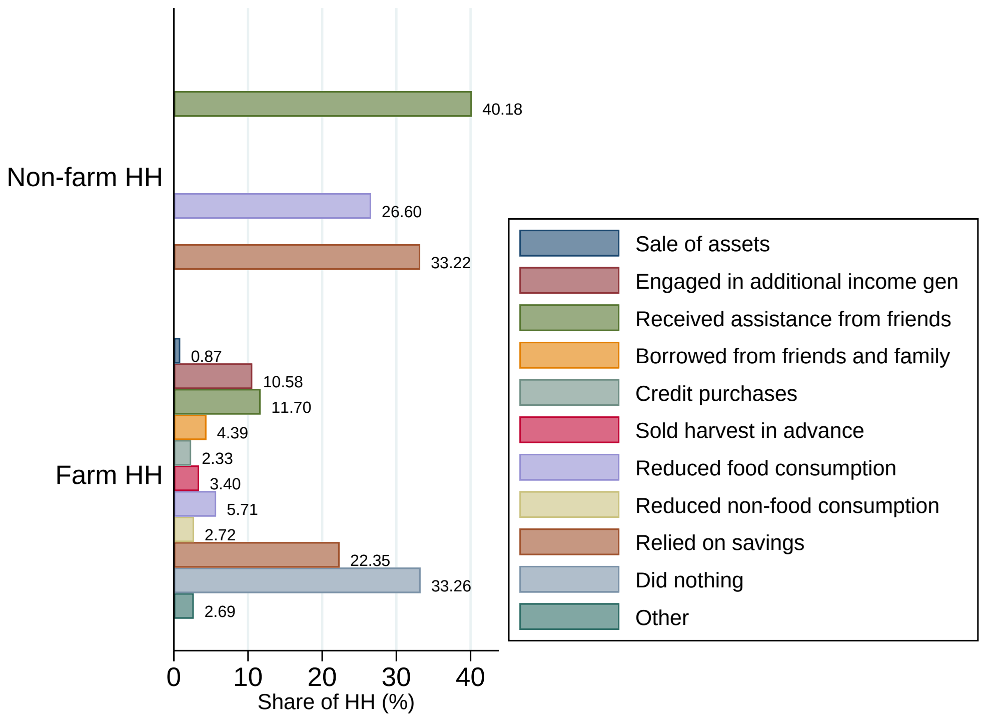
Note: number of observations is 2,151 and robust standard errors are reported; *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' construction.

5.5 What mitigating measures or diversification strategies were adopted by farm households amidst the crisis?

In Figure 4, we show that, unlike non-farm households, farm households adopted a wide range of measures to mitigate the effects of shocks on their welfare. The most common coping strategies adopted by households amidst the COVID-19 crisis were reliance on savings, receiving assistance from friends, and reducing food consumption. However, around a third of farm households responded to the crisis by doing nothing. Among farm households, reliance on savings, engaging in additional income-generating activities, receiving assistance from friends, and reducing food consumption were the top five risk-coping strategies.

Figure 4: Risk-coping strategies adopted by farm and non-farm households



Source: authors' construction.

6 Conclusion

Agricultural activities in many African countries are bedevilled by a range of risk factors. Exposure to or experience of such risks may vary across farmers and localities as well as contexts. This issue has, however, received limited attention in the literature. Therefore, this study examined the drivers of agricultural risks and their variations across locality and countries in Africa as well as the effect of the COVID-19 pandemic-related restrictions on the welfare of farm households. Using two types of micro-datasets, namely, smallholder household survey data from five African countries and the High-Frequency Phone Survey (HFPS) on COVID-19 datasets for Uganda, we observe that the probability of experiencing risks related to agriculture is significantly influenced by a range of individual- and farm-level/contextual factors, these effects showing considerable variations across contexts and countries in Africa.

In addition, we show that farm households witnessed important reductions in their incomes during the COVID-19 period in Uganda. In terms of the coping strategies adopted by households amidst the crisis, we find that, unlike non-farm households, farm households adopt a range of risk-coping mechanisms, including reliance on savings, engaging in additional income-generating activities, receiving assistance from friends, and reducing food consumption. These findings point towards the need to incorporate individual-level and farm-level/contextual factors into approaches aimed at reducing farmers' vulnerability to agricultural risks, thereby contributing to improvements in on-farm productivity and farmer welfare in Africa and elsewhere.

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Appendix

Table A1: Summary statistics of the main independent variables (agricultural risk model)

Variable	Description	Mean	Std. Dev.
Educ	Categorical: represents the educational attainment of the individual. Assumes a value of 0 if 'no education', 1 if 'primary' is the highest educational attainment of the respondent, 2 if 'secondary', and 3 if 'tertiary'.	1.178	0.613
Male	Binary: captures the gender of the individual and assumes a value of 1 if male and 0 if female.	0.540	0.499
Age	Continuous: captures the age of the individual.	39.823	15.394
Rural	Binary: captures the locality of the individual and assumes a value of 1 if rural and zero otherwise.	0.684	0.465
Customary_landown	Binary: captures the nature of land ownership related to the individual's farmland. Assumes a value of 1 if 'customary' and zero otherwise.	0.444	0.497
Livestock_own	Binary: captures whether or not the individual owns livestock. Assumes a value of 1 if 'Yes' and zero if 'No'.	0.514	0.500
Farm_bus	Binary: captures whether the individual considers his/her farm as a business. Assumes a value of 1 if 'Yes' and zero if 'No'.	0.624	0.485
Crop_maize	Binary: refers to the type of crop cultivated by the individual. Assumes a value of 1 if maize and zero otherwise.	0.769	0.422
Country	Categorical: captures the country of the individual.	17.149	8.653

Source: authors' construction.

Table A2: Summary statistics of the main independent variables (COVID-related income loss model)

Variable	Description	Mean	Std. Dev.
Educ	Categorical: represents the educational attainment of the individual. Assumes a value of 0 if 'no education', 1 if 'primary' is the highest educational attainment of the respondent, 2 if 'secondary', and 3 if 'tertiary'.	1.40	0.802
Male	Binary: captures the gender of the individual and assumes a value of 1 if male and 0 if female.	0.688	0.463
Age	Continuous: captures the age of the individual.	48.34	15.257
Urban	Categorical: captures the locality of the individual and assumes a value of 1 if 'urban', 2 if 'other urban', and 3 if 'rural'.	2.47	0.88
hhsize	Continuous: captures the size of the household.	5.39	2.75
own_comp	Binary: captures whether or not the household owns a computer. Assumes a value of 1 if 'Yes' and zero if 'No'.	0.030	0.170
Asset_tv	Binary: captures whether or not the household owns a TV set. Assumes a value of 1 if 'Yes' and zero if 'No'.	0.242	0.428
Asset_moto	Binary: captures whether or not the household owns a motorcycle. Assumes a value of 1 if 'Yes' and zero if 'No'.	0.13	0.336
region	Categorical: captures the region of the household. Assumes a value of 1 if Central, 2 if Eastern, 3 if Kampala, 4 if Northern, and 5 if Western.	3.047	1.539

Source: authors' construction.

Table A3: Determinants of agricultural risk (marginal effects); disaggregated by country

Dependent var: Agricultural risk (binary)	Côte D'Ivoire I	Tanzania II	Mozambique III	Uganda IV
Covariates				
Educational attainment (Base: None)				
Primary	-	0.056	0.051	-0.020
		(0.056)	(0.089)	(0.019)
Secondary	-	0.051	-0.001	-0.033
		(0.055)	(0.092)	(0.052)
Tertiary	-	0.035	-0.221	
		(0.024)	(0.171)	
Male (Base: Female)	-0.022	0.001	-0.051**	-0.029**
	(0.013)	(0.005)	(0.022)	(0.014)
Age	-0.000	0.001	-0.009**	0.001
	(0.002)	(0.001)	(0.004)	(0.002)
Age2	-0.000	-0.000	0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Livestock_own	-0.023**	0.002	0.038*	-0.038***
	(0.009)	(0.005)	(0.022)	(0.015)
Cust_landown	0.009	0.006	-0.056***	0.005
	(0.008)	(0.005)	(0.021)	(0.014)
Rural (Base: Urban)	0.020**	0.007	0.069**	-0.032*
	(0.010)	(0.004)	(0.028)	(0.017)
Farm_bus	0.002	-0.006	0.041*	0.028*
	(0.009)	(0.004)	(0.022)	(0.014)
Crop_maize	0.005	0.012	0.026	0.017
	(0.008)	(0.007)	(0.031)	(0.019)
Prob > chi2	0.001	0.000	0.000	0.009
Pseudo R-squared	0.10	0.054	0.041	0.010
Observations	1,022	1,942	1,249	2,626

Note: the dependent variable is an aggregate measure of agricultural risk. It assumes a value of 1 if the farm faced any form of agricultural risk and zero otherwise; standard errors clustered at the household level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' construction.

Table A4: Determinants of income loss (marginal effects)

Dependent var: income_loss	**Post-COVID income loss**		
	I	**II**	**III**
Farm	0.013	0.128***	-0.010
	(0.038)	(0.037)	(0.036)
Male	-0.052**	-0.049**	-0.044**
	(0.023)	(0.023)	(0.022)
Educational attainment (Base: None)			
Primary	0.004	-0.023	-0.045
	(0.039)	(0.037)	(0.035)
Secondary	-0.021	-0.078*	-0.063
	(0.044)	(0.042)	(0.039)
Tertiary	-0.075	-0.082*	-0.119***
	(0.050)	(0.048)	(0.044)
age	-0.001	-0.001	-0.000
	(0.001)	(0.001)	(0.001)
hhsize	-0.001	0.002	0.007*
	(0.004)	(0.004)	(0.004)
Asset_moto	0.091***	0.009	0.028
	(0.031)	(0.030)	(0.029)
Asset_tv	-0.038	0.042	0.043
	(0.028)	(0.028)	(0.026)
own_comp	-0.019	-0.026	-0.029
	(0.064)	(0.060)	(0.058)
Locality (Base: Urban)			
Other urban	-0.166	-0.342***	-0.307**
	(0.194)	(0.124)	(0.128)
Rural	-0.068***	-0.026	-0.005
	(0.026)	(0.026)	(0.025)
Region (Base: Central)			
Eastern	0.380***	0.398***	0.474***
	(0.030)	(0.031)	(0.030)
Kampala	-0.442***	-0.375***	-0.369***
	(0.033)	(0.039)	(0.027)
Northern	0.142***	0.200***	0.337***
	(0.036)	(0.035)	(0.034)
Western	-0.083**	-0.175***	-0.156***
	(0.034)	(0.032)	(0.031)
Prob > chi2	0.000	0.000	0.000
Pseudo R-squared	0.046	0.079	0.060
Observations	1,973	1,973	1,973

Notes: table reports the probabilities of reporting an income fall or total loss of income during the post-COVID period. The dependent variable is based on the question whether a household's post-COVID-19 income is below the level it was prior to COVID and it assumes a value of 1 if yes and 0 otherwise; models I–III represent the results for the three waves of the survey wherein the information was collected on this issue; standard errors clustered at the household level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' construction.

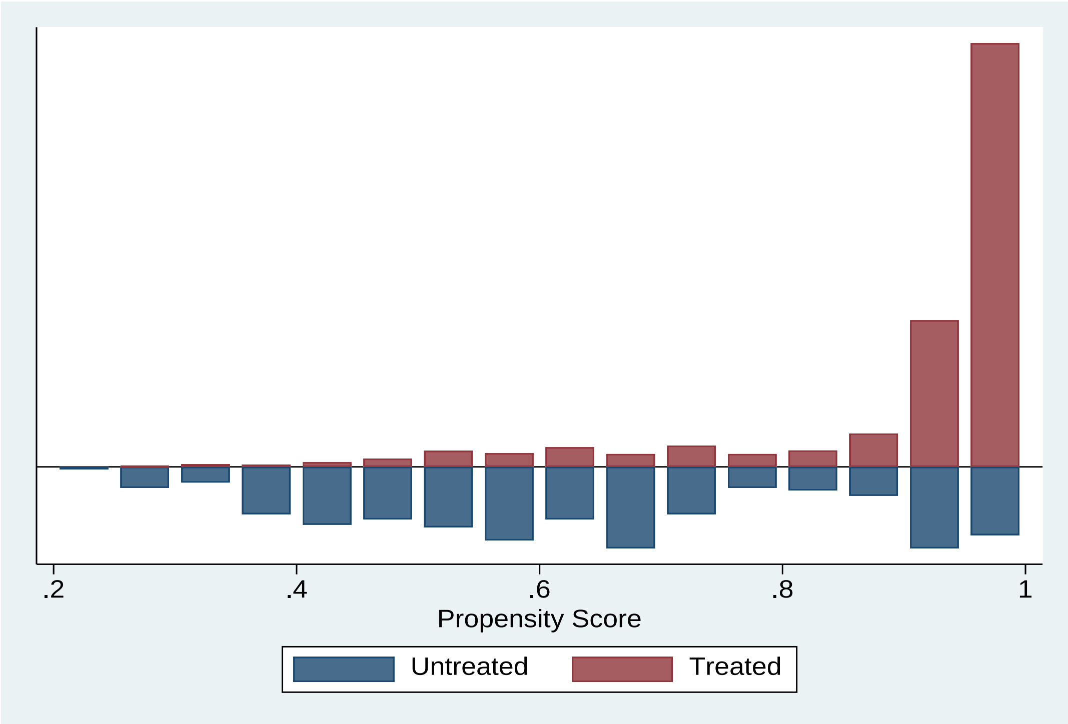
Table A5: Determinants of income loss (marginal effects)

Dependent var: income_loss	**Post-COVID income loss**				
	I	**II**	**III**	**IV**	**V**
Farm	0.037	0.072*	0.051	0.103***	0.019
	(0.037)	(0.040)	(0.042)	(0.040)	(0.040)
Male	-0.038*	0.006	-0.040	-0.058**	-0.063***
	(0.020)	(0.024)	(0.025)	(0.025)	(0.024)
Educational attainment (Base: None)					
Primary	0.012	0.070*	0.099**	0.102**	0.048
	(0.034)	(0.042)	(0.042)	(0.041)	(0.041)
Secondary	0.049	0.047	0.025	0.064	0.021
	(0.037)	(0.046)	(0.047)	(0.046)	(0.045)
Tertiary	-0.029	0.061	0.047	0.088*	-0.002
	(0.044)	(0.053)	(0.053)	(0.052)	(0.051)
age	-0.001*	0.001	-0.001	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
hhsize	0.003	0.004	-0.002	-0.003	0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Asset_moto	0.072***	0.007	0.062*	-0.023	0.027
	(0.028)	(0.034)	(0.034)	(0.034)	(0.033)
Asset_tv	0.024	0.005	-0.051*	0.005	-0.050*
	(0.025)	(0.030)	(0.030)	(0.030)	(0.030)
own_comp	-0.024	-0.038	0.050	-0.090	-0.051
	(0.049)	(0.066)	(0.067)	(0.069)	(0.065)
Locality (Base: Urban)					
Other urban	-0.220	-0.375***	-0.102	-0.150	-0.154
	(0.177)	(0.119)	(0.200)	(0.157)	(0.163)
Rural	-0.039*	-0.014	-0.003	0.034	0.003
	(0.023)	(0.029)	(0.029)	(0.029)	(0.029)
Region (Base: Central)					
Eastern	-0.054**	0.193***	0.153***	0.179***	0.209***
	(0.025)	(0.033)	(0.033)	(0.034)	(0.034)
Kampala	0.050	0.056	0.155***	-0.096	-0.101
	(0.035)	(0.065)	(0.057)	(0.068)	(0.067)
Northern	-0.157***	-0.098***	-0.084**	-0.047	0.033
	(0.028)	(0.036)	(0.036)	(0.036)	(0.036)
Western	-0.019	-0.230***	-0.193***	-0.227***	-0.224***
	(0.023)	(0.033)	(0.033)	(0.032)	(0.033)
Prob > chi2	0.000	0.000	0.000	0.000	0.000
Pseudo R-squared	0.046	0.079	0.060	0.080	0.089
Observations	1,973	1,973	1,973	1,973	1,973

Note: table reports the probabilities of reporting an income fall or total loss of income during the post-COVID period. The dependent variable is based on the question whether a household witnessed a reduction or a total loss of income due to the COVID-19 pandemic and it assumes a value of 1 if yes and 0 otherwise; models I–V represent the results for the five waves of the survey wherein information was collected on this issue; standard errors clustered at the household level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' construction.

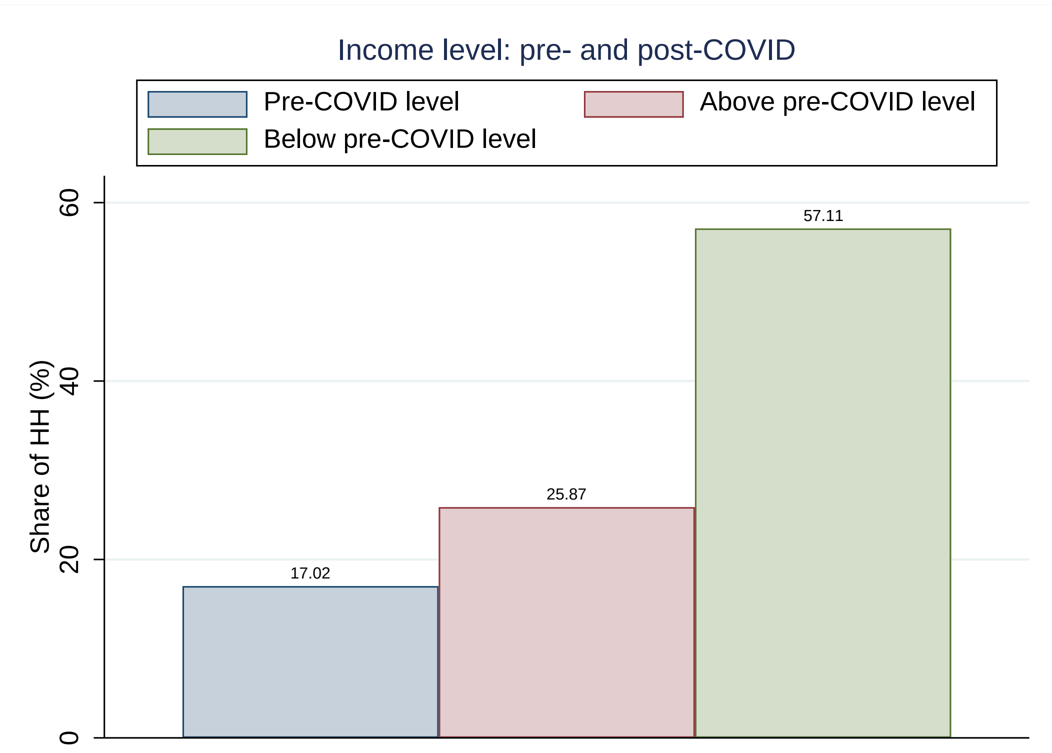
Figure A1: Propensity score



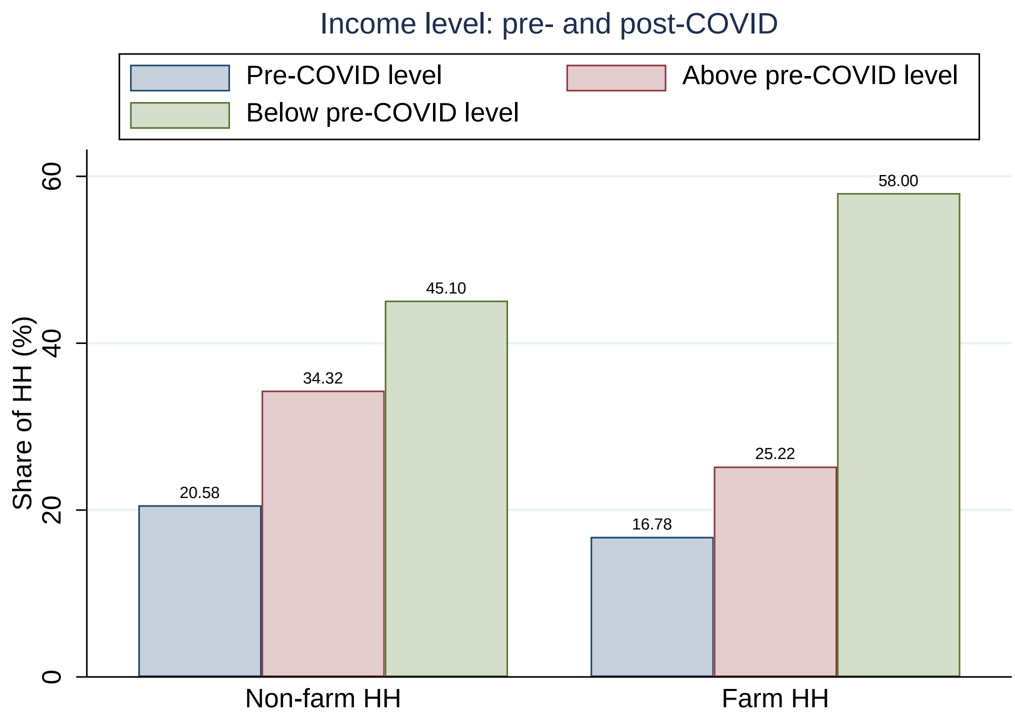
Source: authors' construction.

Figure A2: Post-COVID income change (% share of households); income concept 2

Panel A: Full sample



Panel B: Farm vs non-farm households



Note: responses are in answer to the question: 'Since March 20, 2020, the day that schools were closed, has income from the activity increased, stayed the same, reduced, or become a total loss (no earnings)?'

Source: authors' construction.