Food Security and the COVID-19 Employment Shock in Nigeria: Any Ex-Ante Mitigating Effects of Past Remittances?

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Abstract

This paper examines the role of past remittances in mitigating the adverse effects of COVID-19 employment shocks on food security in Nigeria. We formally define the mitigating effects parameter as the difference in the shock impact between households that received remittances and those that did not. Leveraging pre- and post-COVID-19 surveys, we employ a triple-difference strategy to estimate the mitigating effects parameter. Our results suggest that past remittances can alleviate the negative consequences of COVID-19 employment shocks, particularly in the short term. However, the mitigation effect is limited to the early stages of the pandemic, as the negative effects of the shock persist over time. Additionally, we find that the impact of remittances on mitigating the shock varies based on the origin of remittances, recipients' area of residence, and poverty status. Furthermore, our study highlights the importance of the capital channel in explaining the mitigating role of past remittances. Our findings demonstrate that formal financial inclusion, capital ownership such as livestock, and rental earnings amplify the impact of remittances in mitigating the negative consequences of COVID-19 employment shocks on food security.

JEL Classification: E21, E24, I12, O12, O55.

Keywords: COVID-19; Remittances; Employment Shock; Food Insecurity; Insurance; Africa.

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1 Introduction

In Sub-Saharan Africa (SSA), households are particularly exposed to the severe economic issues brought about by the COVID-19 pandemic (Arezki et al., 2021). These households encounter challenges stemming from lack of social protection, market imperfections, and credit constraints (Kansiime et al., 2020). Against a backdrop of market failures and weak social protection, households tend to rely on private insurance for risk-sharing based on informal mechanisms, including remittances from relatives. The insurance-related migration literature suggests that remittances can function as insurance through two mechanisms. First, remittances can function as an ex-post shock-mitigating mechanism. Households may receive remittances immediately following a shock which helps the household to attenuate subsequent adverse effects. There is evidence of an increase in remittances following shocks such as natural disasters or weather events (Gubert, 2002; Yang and Choi, 2007; David, 2011; Lara, 2016). Second, remittances can function as an ex-ante shock-mitigating mechanism. Remittances may allow households to increase their savings and subsequently cope with the shock by easing budgetary constraints. There is evidence of remittances stimulating financial services, such as savings and credit (Anzoategui et al., 2014; Ambrosius and Cuecuecha, 2016), and even substituting for credit in the case of a health shock (Ambrosius and Cuecuecha, 2013).

Despite the rapidly growing body of COVID-19-related literature, the scope of studies on the insurance function of private transfers like remittances appears limited. Existing evidence on the insurance function of remittances cannot necessarily be inferred from the context of the COVID-19 shock, which is of a different nature in many aspects, including its mechanisms and magnitude. For instance, the ex-post mechanism is not expected to operate in the case of the COVID-19 shock, or at least to have a limited role, as remittance flows to Sub-Saharan Africa have fallen by 12.5% during the pandemic, driven by a 27.7% decline in Nigeria (Ratha et al., 2021).[1] This drop in remittances may be the consequence of adverse employment conditions at the destination, as illustrated by Ambrosius et al. (2021) in the context of Mexico. They also provide evidence that support the limited ex-post mechanism during the pandemic in Mexico while remittances surprisingly increased during the pandemic. Yet, the insurance function of remittances cannot be ruled out as the ex-ante mechanism may be at work during the pandemic. Coping strategies of households during the pandemic mostly consisted of relying on savings or selling assets to cover basic living expenses,[2] which represent important channels of the ex-ante risk-mitigating mechanism of remittances. Consequently, remittances received before the pandemic may possibly contribute to reinforcing household savings or assets and subsequently mitigate the adverse effects of the shock.

This paper aims to assess the role of remittances received in 2019 in mitigating the adverse effects of COVID-19 employment shocks on food security in Nigeria. Our paper makes a number of contributions to the rapidly expanding body of COVID-19-related literature that has not sufficiently

[1]Results of high-frequency surveys in SSA show that 61% of remittance receiving households on average report a decrease in remittances since the beginning of the outbreak.[2]

[2]See The World Bank, "COVID-19 Household Monitoring Dashboard,"https://www.worldbank.org/en/data/interactive/2020/11/11/covid-19-high-frequency-monitoring-dashboard.

explored the mitigating effects of private transfers such as remittances (Tapsoba, 2021; Balde et al., 2020). We elaborate on the rich literature on the difference-in-difference method (Olden and Møen, 2022; Callaway and Karami, 2023) to formally introduce a novel parameter that quantifies the mitigating impact of remittances. This parameter is measured as the difference in the impact of the shock between two sub-samples: households that received remittances in 2019 and those that did not.

We deploy an empirical strategy that addresses potential endogeneity issues originating from time-invariant heterogeneity of shocked and remittance-receiving households, contrary to Tapsoba (2021) and Balde et al. (2020). Their approach involves cross-sectional probit regression or using instruments, which exogeneity is questionable as COVID-19 affects the migrant destination as well as the home location.[3] Specifically, we follow Olden and Møen (2022) by adopting a triple difference-in-difference (DiD) approach using a Two-Way Fixed Effects (TWFE) model. However, the TWFE DiD identifying assumption of a common parallel trend is unlikely to hold in the presence of time-varying heterogeneity. Hence, we check the robustness of our estimates to the presence of a potential time-varying heterogeneity under the form of an Interactive Fixed Effects (IFE) Callaway and Karami (2023). The IFE approach accommodates the violation of the parallel trend due to time-varying effects of some unit-specific unobserved characteristics. Moreover, using remittances before the shock limits the potential confounding effects related to the association between the shock and contemporaneous remittances received during the pandemic. Yet, the presence of households receiving remittances during the pandemic threatens the identification of the TWFE and may confound the ex-ante mechanism with other factors, including the ex-post mechanism. Another potential source of confounding is households that may have received assistance in cash or in-kind from institutions such as governments, NGOs, etc. To address this concern, we conducted sensitivity tests on a reduced sample that excluded all households receiving remittances during the pandemic or any institutional support during the shock.[4]

We also contribute to the literature as we document the pathway to the mitigating effects of remittances. We conduct a formal test of the ex-ante mechanism which is, so far, ignored in the literature. Yet, this mechanism is also a key to understanding the attenuating role of remittances against a shock of that magnitude. We analyze whether household capital ownership amplifies the mitigating effect of remittances. In this paper, household capital ownership refers to two situations. The first comprises households that have an account with a financial institution. We reasonably assume that these households are likely to have access to savings or credit. This is consistent with the evidence that remittances stimulate financial services that help households cope with shocks (Anzoategui et al., 2014; Ambrosius and Cuecuecha, 2016). The second includes households that own livestock or receive rental earnings. Therefore, we adopt a broad definition of capital that includes savings/credit, livestock, and rental earnings to account for the Sub-Saharan context. Evidence that poor and rural households rely more on such assets than on savings as a coping mechanism (Nikoloski et al., 2018) motivates our decision to include livestock and rental earnings

[3] Two instruments are used. The first instrument is the percentage of migrants reporting a job loss because of xenophobia. The second is the percentage of migrants with identity document issues.

[4] See subsection 4.3 for further discussion.

in the capital mechanism test. Livestock can attenuate the deterioration of a household's food security through their sale (Fafchamps et al., 1998). Some types of livestock can also provide food for households, especially during hard times. For instance, poultry and cattle can provide meat, milk, and eggs. As remittances ease budgetary constraints, some households might theoretically acquire more goods, including livestock. Consequently, livestock and other assets that generate rental earnings are worth considering, given their potential contribution to the ex-ante mechanism.

Nigeria arguably offers an appealing context in which to investigate the mitigating role of remittances on the COVID-19 shock. On the one hand, the Nigerian economy is expected to be hardly affected because of economic vulnerabilities that prevailed even before the shock. The country faces critical challenges in terms of food security, as illustrated by its low food consumption score and high-calorie deficiency.[5] On the other hand, Nigeria ranks among the top 10 remittance-recipient countries in SSA.[6] There is evidence that remittances may stimulate financial inclusion, which constitutes a potential channel through which the ex-ante mitigating mechanism of remittances may be fueled (Ajefu and Ogebe, 2019).

We find that remittances mitigate the adverse consequences of the COVID-19 employment shock on food insecurity in Nigeria. Households that receive remittances seem to experience less food security deterioration than non-beneficiary households in the short term. The dramatic rise in food insecurity associated with the shock appears to be 100% offset by remittances received. The results are reinforced by several robustness checks, including sensitivity tests of the findings in relation to the definition of food insecurity. Furthermore, we provide evidence of a decline in the mitigating effect of remittances over time, whereas the adverse impact of the shock persists. Interestingly, our results indicate that the mitigating effect may operate through the capital mechanism, particularly financial inclusion, rental earnings, or livestock ownership. We find that the mitigating effect of remittances is significantly amplified when households have access to or own capital. The heterogeneity of remittances' mitigating effect by the origin of remittances and beneficiary households' area of residence and poverty status is also worth highlighting. Foreign remittances have a greater cushioning effect than domestic ones, as those from abroad are considerably larger. Our results suggest that remittances mitigate adverse shocks mainly in rural and non-poor households. As for poor households, evidence indicates that beneficiaries of international remittances see a mitigating effect. In urban areas, our findings show that only households in capital cities (Lagos/Abuja) that receive international remittances experience a mitigating effect.

The remainder of this paper is organized into four sections as follows. Section 2 presents our data sources and variables. Section 3 describes our methodology, and Section 4 discusses our results and robustness tests. Section 5 provides conclusions arising from our findings.

[5] https://ebrary.ifpri.org/digital/collection/p15738coll16/id/1248

[6] World Bank Group, KNOMAD, https://www.knomad.org/sites/default/files/2019-04/Migrationanddevelopmentbrief31.pdf

2 Data sources and variables

2.1 Data and representativeness

This paper combines data from a pre-COVID-19 face-to-face survey and a post-COVID-19 phone survey that are part of the World Bank's Living Standards Measurement Study: Integrated Surveys on Agriculture (LSMS-ISA). The LSMS-ISA data for Nigeria include a General Household Survey (GHS) conducted in 2018-2019 right before the pandemic. The GHS panel is basically based on a nationally representative sample of 4,976 households interviewed in two waves: during the post-planting period from July to September 2018 and during the post-harvest period in January-February 2019.

To track the impact of the pandemic, the National Bureau of Statistics subsequently conducted the Nigeria COVID-19 National Longitudinal Phone Survey (COVID-19 NLPS 2020) on a nationally representative sample of households drawn from those interviewed in wave 4 of the 2018-2019 GHS. The extensive information collected in the GHS panel just over a year before the pandemic provides abundant background information on COVID-19 NLPS 2020 households that have been leveraged to assess the differential effects of the pandemic across the country. COVID-19 NLPS 2020 began in April-May 2020, early in the pandemic, and included additional following-up rounds.

Of the 4,976 households interviewed in the 2019 post-harvest period (January-February 2019), 4,934 (99.2%) had provided at least one telephone number. From the full sample of households with phone numbers, 3,000 households were randomly selected for COVID-19 NLPS 2020. Of those contacted, 1,950 households completed the phone interviews and constituted the households in the final successful sample that were contacted in subsequent survey rounds. Our preferred sample (hereafter "short panel") is a three rounds balanced panel obtained after merging the households in the 2018-2019 GHS that had complete information in round 1 of the phone survey (N = 1,950): July-September 2018, January-February 2019, and April-May 2020.

We primarily rely on the short panel to limit confounding effects related to some government measures during the pandemic. Firstly, the Nigerian government has implemented a range of social safety net programs to support households in dealing with the adverse consequences of COVID-19. The Nigerian government first announced the delivery of up to 70,000 tons of grain on May 12, 2020. Hence, the use of the short panel helps minimize the influence of relief programs. Secondly, movement restrictions have been gradually eased over time, starting in June, 2020.[7] Table B.7 shows the proportion of shocked households decreased from 37% in May 2020 to only 2% in August 2020. This short timeframe coincided with the period of most stringent movement restrictions, thereby reducing heterogeneity arising from the variations in lockdown enforcement levels over time. While having this potential bias in mind, we also extent the analysis to the whole unbalanced panel in the section 4.4 to explore persistence effects over time. [8]

[7] International Food Policy Research Institute (IFPRI), "COVID-19 Policy Response (CPR) Portal," [https://www.ifpri.org/project/covid-19-policy-response-cpr-portal.].

[8] Including round 2 (June 2020), 3 (July 2020), 4 (August 2020) and 7 (November 2020).

To manage selection bias associated with non-response and potential attrition in the phone survey and to construct nationally representative statistics, appropriate sampling weights had to be chosen and applied. The LSMS-ISA team determined their sampling weights based on the weights used for the GHS panel, with further adjustment for attrition in the phone survey. The weights for the final sample of households from the phone survey were calculated in several stages (see NBS and WB (2020) for details).

Table B.1 compares the weighted and unweighted summary statistics of the selected household characteristics in both sample (pre- and post-COVID sample) during the harvest wave in January-February 2019. Such an analysis shows how attrition and non-response could affect the statistics on household characteristics. The values in the unweighted NLPS 2020 column suggest that more households with a higher standard of living responded to the phone survey. These households were more likely to own certain goods, such as regular mobile phones, smartphones, televisions, cars, and generators. Weighting markedly reduces the differences in unweighted values for the observable characteristics of the GHS panel and phone survey samples. Overall, the weighted values obtained from the GHS panel (Column 2 - Table B.1) and NLPS samples (Column 4 - Table B.1) match very closely across all dimensions. In line with Wooldridge (2007) and Korinek et al. (2007), weighting reduces attrition bias and provides appropriate and representative statistics. While this is promising, the adjustment for attrition might only partially address this bias due to substantial attrition between the Pre and Post COVID-19 samples.

2.2 Variable definition and descriptive statistics

COVID-19 employment shock

The variable used to measure the COVID-19 employment shock is extracted from the employment section of the COVID-19 NLPS 2020 baseline household questionnaire. In particular, we focus on: (1) whether the respondent was working before mid-March and, if not, (2) the main reason why the respondent stopped working. For all individuals responding no to the first question—they were working before mid-March—we consider the following two reasons as representing an employment shock: (1) business/office closed because of coronavirus legal restrictions and (2) unable to go to the farm because of movement restrictions. This approach enables us to account for differences in the way households are affected by the COVID-19 employment shock. Accordingly, our COVID-19 employment shock variable has a value of 1 if any household member stopped working because his/her business/office closed due to legal restrictions or he/she was unable to go to the farm due to movement restrictions (shocked household) or 0 otherwise (non-shocked household).

Table 1 presents the characteristics of the two groups of households. Unsurprisingly, shocked households are more likely than non-shocked households to live in urban areas (Lagos/FCT or other urban areas). This is expected as the COVID-19 pandemic, and movement restrictions started in urban areas. In line with the literature, we find that households involved in non-farm family enterprises or wage work experience more shocks than those working in the agricultural sector. More-

Table 1: Household characteristics at baseline (Post-harvest wave: 2018/2019)

	Shocked (1)	**Non-shocked** (2)	**Difference** (1) - (2)	**t-test**
Residence area				
Lagos/FCT	3.9	2.4	1.5	2.0**
Other urban	35.7	24.4	11.3	5.4***
Rural	60.4	73.4	-13.0	-6.1***
Socio-demographic characteristics				
Average household size	5.6	5.5	0.1	1.2
Female head (%)	14.8	20.9	-6.1	-3.3***
Age of head (years)	46.5	50.7	-4.2	-6.1***
Literate (%)	80.5	77.3	3.2	4.8***
Education level of head (%)				
None (or no school)	31.2	40.3	-9.1	-4.0***
Primary	20.2	26.3	-6.1	-3.1***
Secondary	29.8	19.1	10.7	5.5***
Tertiary	18.7	14.3	4.4	2.6***
Asset ownership (%)				
Regular mobile phone	77.1	75.3	1.8	0.9
Television	48.6	47.8	0.8	0.4
Refrigerator	23.3	16.1	7.2	4.0***
Car	11.2	8.3	2.9	2.1**
Generator	23.9	24.6	-0.7	-0.3
Working status (% Adults)				
Agricultural activities	20.5	32.5	-12.0	-7.1***
Non-farm family enterprise	36.2	31.1	5.1	3.0***
Wage work	14.7	12.0	2.7	2.2**
Consumption quintile (%)				
Q1	19.6	19.9	-0.3	-0.2
Q2	20.4	19.7	0.7	0.4
Q3	16.7	21.7	-5.0	-2.7***
Q4	19.5	20.2	-0.7	-0.4
Q5	23.8	18.4	5.4	2.8***
Observations	725	1225	1950	

$^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.001$

Source : GHS-Panel wave 4 (2018/2019), and authors' calculations.

Note: Estimates are adjusted by the weights accounting for non-contact and non-response.

over, the results indicate that shocked households are better endowed in terms of living standards and education than non-shocked ones. There is a more significant proportion of shocked households (23.8%) than non-shocked households (18.4%) in the top consumption quintile. On average, shocked households own more assets, particularly refrigerators and cars, than non-shocked ones. Also, shocked households have a proportionally higher literacy rate and more household heads with secondary and tertiary education than non-shocked households. Overall, these findings are consistent with the new profile of the poor population induced by COVID-19 (Freije-Rodriguez and Woolcock, 2020).

Remittances in 2019 before the pandemic

To create the remittance measurement variable, we use wave 4 of the GHS panel and consider the post-harvest data collected in January-February 2019 before the pandemic. The survey section on remittances is intended to capture remittances issued to household members aged 10 or older. We focus on the questions asking whether the respondent received the following types of assistance from a non-household member in the past 12 months: monetary assistance and/or in-kind assistance. It should be noted that these two types of assistance are further subdivided in the questionnaire based on their origin: "from abroad" and "from within Nigeria." Therefore, the remittance variable has a value of 1 if the individual received any assistance in the past 12 months from abroad (international remittances) or from within Nigeria (domestic remittances) and 0 otherwise. We aggregate this individual-level information at the household level and define three groups. First, the "no remittance" group includes households where no one received a remittance. Second, the "international remittance" group includes households with at least one member who received an international remittance. Third, the "domestic remittance" group includes households in which at least one member received a remittance originating from within Nigeria only. Households with members who received international and domestic remittances are included in the "international remittances" group.

Figure B.1 presents the remittance distribution by the origin of the remittance and is consistent with other data sources. This gives us confidence that our data are reliable despite the previously highlighted attrition and non-response issues. The results indicate that most of the households did not receive any remittances (68%).[9] This percentage is similar to the proportion of households reporting in the Afrobarometer survey having never received remittances.[10] Furthermore, our findings show that households' likelihood of receiving domestic remittances (27.9%) is significantly higher than international remittances (4%). However, the average international remittance is overwhelmingly (roughly 2.5 times) larger than the average domestic one. The likelihood of receiving international remittances is conditional on the international migration rate, which is relatively low (0.6% in 2013).[11] If we change the scale from the household level to the individual level, we find a similar proportion when computing the likelihood of receiving remittances. The ratio of the number of international beneficiaries to the whole population is estimated to be 0.7% based on the data.

Food insecurity

The food insecurity variable is constructed from a module collected consistently across rounds based on the same recall period of 30 days (see table B.10 for further details).[12] This variable reflects household food shortage situations based on three yes/no questions, commonly used to capture the household Food Insecurity Experience Scale developed by Cafiero et al. (2018). These questions are whether any individual in the household: (1) skipped a meal because there was not enough money or other resources to get food, (2) ran out of food because of a lack of money or other resources, and (3) went without eating for a whole day because of a lack of money or other resources. To construct the variable, we took the following two steps: (1) we transformed each of

[9]Of the final sample of 1,950 households.

[10]The Afrobarometer number is computed using the online data analysis tool.

[11]The World Bank, "Migration and Remittances Factbook 2016".

[12]Our analysis excludes the previous waves of 2015, 2012, and 2010 because of the inconsistency in the recall period.

the yes/no responses into a dummy variable and (2) we took the sum, for each household, of the three dummy variable values from step (1). This procedure yielded our preferred food insecurity variable with a score of 0, 1, 2, or 3. In the case of a household that replies no to all three questions, the total is 0. If a household responds yes to only one of the questions, the total is 1; if a household responds yes to two of the questions, the total is 2; and if a household responds yes to all three questions, the total is 3. Consequently, the higher a household's score, the greater the food shortage the household faces. Amare et al. (2021) use the same three questions to measure food insecurity using Principal Component Analysis (PCA). For robustness check, we also consider alternative definitions of food insecurity using PCA or the three indicators separately (see section 4.3)

Although our preferred food insecurity variable (hereafter reduced FIES) is constructed following the COVID-19 literature (Amare et al., 2021; Jr. Tabe-Ojong et al., 2023), its computation may raise some concerns about its interpretation. First, this variable is computed using a subset of three questions given the available data, out of the eight questions of the Food Experience Insecurity scale framework, contrary to other works like Adjognon et al. (2021) or Rudin-Rush et al. (2022). In spite of the distinction between our variable and the standard measure in the literature, our reduced FIES reasonably captures household food insecurity concerns. This is supported by the noticeable correlation with the comprehensive eight indicators-based FIES (full FIES).[13] [14] Thus, we anticipate that both measures will yield consistent results (Figures B.2, B.3). Second, our reduced FIES is consistent with the traditional food insecurity classification applied in the literature (Smith et al., 2017; Adjognon et al., 2021; Rudin-Rush et al., 2022). Mapping the reduced FIES score with the food insecurity classification makes its interpretation easy (Figure B.4). For instance, the group of households with a reduced FIES score of 0 is roughly equivalent to the category spared by food insecurity.

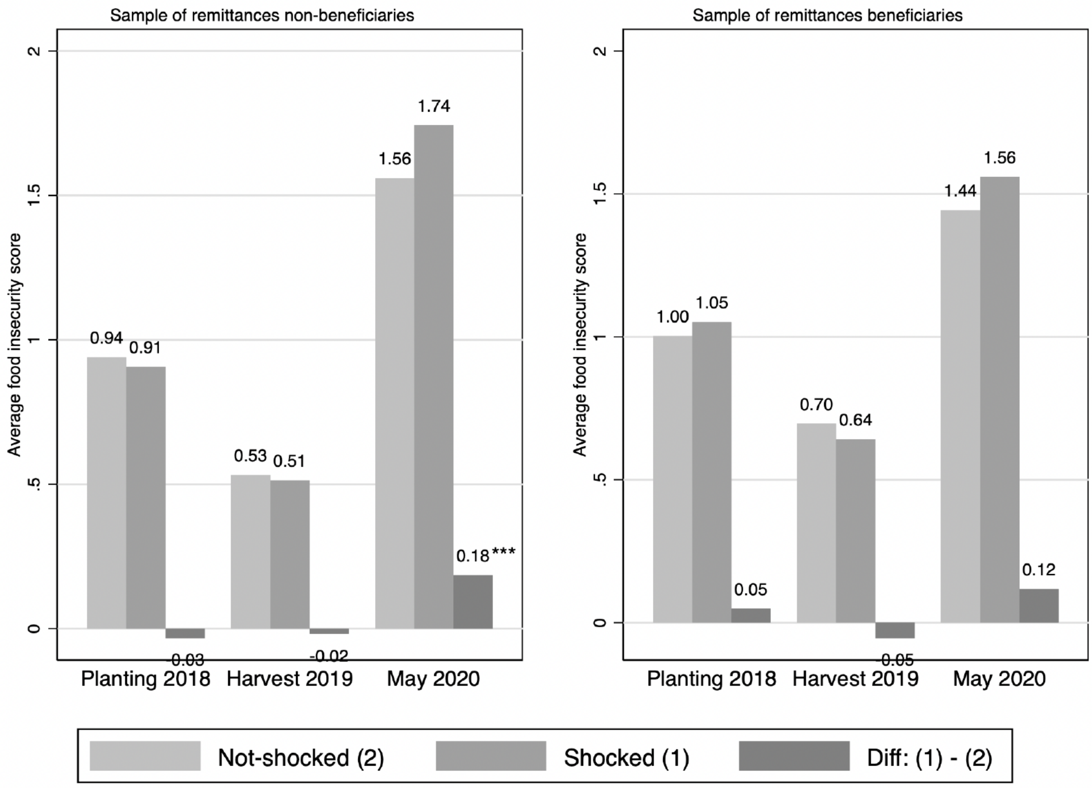
Figure 1 presents the average food insecurity scores of the survey waves covering the period before the shock (2018 plantation and 2019 harvest) and after it (May 2020). Before proceeding to formal estimation in the following section, we present simple differences in food insecurity between shocked and non-shocked households within each sub-sample. Overall, the food insecurity scores increased sharply after the initial shock of COVID-19 in May 2020 for both household sub-samples – those that received remittances and those that did not. Both shocked and non-shocked groups experienced a significant increase in food insecurity following the pandemic. Nonetheless, the average difference in food insecurity between shocked and non-shocked is statistically significant (0.18***) for the sub-sample of remittance non-beneficiaries, while this difference is statistically insignificant for remittance beneficiaries (0.12). These differences provide, at best, suggestive evidence that remittance non-beneficiaries are more affected by the shock than the beneficiaries. They potentially underestimate the shock effects because shocked and non-shocked households are statistically non-comparable. Non-shocked households are likely to overestimate the counterfactual food insecurity based on both groups' characteristics highlighted previously. Subsequently, the

[13] Correlation between the two food insecurity measures is estimated at 0.91 and statistically significant at 1% threshold.

[14] See Table B.13 for more details on the questions used to construct this indicator.

simple difference in average food insecurity between the two groups is probably downward biased. Considering the substantial fluctuation in food insecurity from planting in 2018 to the harvest in 2019, seasonality could potentially introduce bias. The concern is particularly relevant if remittance groups follow divergent trajectories of food insecurity over time.

Figure 1: Average food insecurity score over time



* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: Wave 4 of the 2018-2019 GHS panel, COVID-19 NLPS 2020, and authors' calculations.

Note: Estimates are weighted to account for non-contact and non-response.

3 Methodology

3.1 Notation and parameter of interest

To examine the mitigating role of past remittances, our approach assesses the difference in the impact of the shock on food security between households that received remittances before the pandemic in 2019 ($R = 1$) and those that did not ($R = 0$). Therefore, we are primarily interested in the difference in the average treatment effect on the treated between the sub-sample of remittance beneficiaries ($ATET^{R=1}$) and non-beneficiaries ($ATET^{R=0}$):

$$\beta_1 = ATET^{R=1} - ATET^{R=0} \tag{1}$$

where $ATET^{R=1} = E\left[y^1_{Post} - y^0_{Post} \mid Shock = 1, R = 1\right]$ measure the average causal effect of the shock, which is our treatment here, on shocked households within the sub-sample of remittance beneficiaries. Conceptually, it is average effect of the shock on remittance beneficiaries. Equivalently, the impact of the shock within the sub-sample of households that did not receive any remittances is $ATET^{R=0} = E\left[y^1_{Post} - y^0_{Post} \mid Shock = 1, R = 0\right]$.

The difference in two DiDs ($DiD^{R=1} - DiD^{R=0}$), which can also be considered as a triple difference estimator (Olden and Møen, 2022), appears to be a good candidate to estimate β_1. Indeed, this estimator is identified from the data sampling process and equals the target parameter β_1 under the two assumptions presented below (Theorem 1 in the appendix A):

$$\begin{aligned}
\beta_1 = {} & DiD^{R=1} - DiD^{R=0} + \\
& \underbrace{\left(E\left[\Delta y^0 \mid Shock = 1, R = 0\right] - E\left[\Delta y^0 \mid Shock = 0, R = 0\right]\right)}_{\text{Non-parallel trends bias for the sub-sample } (R=0) := NPT^{R=0}} - \\
& \underbrace{\left(E\left[\Delta y^0 \mid Shock = 1, R = 1\right] - E\left[\Delta y^0 \mid Shock = 0, R = 1\right]\right)}_{\text{Non-parallel trends bias for the sub-sample } (R=1) := NPT^{R=1}} + \\
& \underbrace{E\left[y^1_{Pre} - y^0_{Pre} \mid Shock = 1, R = 1\right]}_{\text{Anticipation bias for the sub-sample } (R=1) := A^{R=1}} - \underbrace{E\left[y^1_{Pre} - y^0_{Pre} \mid Shock = 1, R = 0\right]}_{\text{Anticipation bias for the sub-sample } (R=0) := A^{R=0}}
\end{aligned} \tag{2}$$

where $DiD^{R=j} = E\left[\Delta y^1 \mid Shock = 1, R = j\right] - E\left[\Delta y^0 \mid Shock = 0, R = j\right], j \in \{0, 1\}$ represent the difference-in-difference of population means for each sub-sample.

Assumption 1: (Parallel trends - NPT)

$$\begin{aligned}
& E\left[\Delta y^0 \mid Shock = 1, R = 1\right] - E\left[\Delta y^0 \mid Shock = 0, R = 1\right] = \\
& \quad E\left[\Delta y^0 \mid Shock = 1, R = 0\right] - E\left[\Delta y^0 \mid Shock = 0, R = 0\right]
\end{aligned} \tag{3}$$

Assumption 1 requires the non-parallel trends (NPT) bias to be equal between the sub-samples, which is equivalent to stating that the trend bias is mean independent of prior remittances. Olden and Møen (2022) find the same result.[15] This assumption means that the untreated potential outcomes for shocked and non-shocked households are allowed to not evolve in tandem after the pandemic within each sub-sample as long as the difference in trends in untreated potential outcomes is the same for both sub-samples.

In our context, two primary sources of heterogeneity may threaten the validity of assumption 1. The first source is a placement bias, which might arise from the authorities' decision to selectively implement lockdown measures in areas with a greater risk of pandemic transmission. The second source pertains to a self-selection bias of households that might choose to comply with restrictions based on their own characteristics (such as poverty status, trust in government, financial support, etc.) as discussed in the literature (Bargain and Aminjonov, 2021, 2020; Akim and Ayivodji, 2020). Both sources of heterogeneity also correlate with remittance receipt, which consequently motivates our adoption of a two-way fixed effects model (TWFE) for DiD to account for time-invariant heterogeneities. Such a model has additionally the advantage, over the ones used by Balde et al.

[15] One could temptingly impose the parallel trend hypothesis within each sub-sample. As discussed in Olden and Møen (2022), two parallel trend assumptions are stronger conditions than what is required for identifying the parameter. This case can be thought of as a special case of assumption 2 when the bias within each sub-sample is null.

(2020) and Tapsoba (2021), to address concerns related to time-invariant systematic differences between households that received remittances and those that did not. However, the TWFE fails to identify our target parameter in the presence of time-varying heterogeneity (Olden and Møen, 2022). Therefore, we also utilize an interactive fixed effects (IFE) specification based on Callaway and Karami (2023), which generalizes the TWFE as it allows for time-varying trends of untreated potential outcomes arising from unit-specific unobserved characteristics. We elaborate more on this alternative IFE approach in the empirical strategy section.

Assumption 2: (No anticipation effects)

$$E\left[y^1_{Pre} - y^0_{Pre} \mid Shock = 1, R = 1\right] = E\left[y^1_{Pre} - y^0_{Pre} \mid Shock = 1, R = 0\right] \tag{4}$$

Assumption 2 states that the outcome of shocked households in the pre-period, either remittance beneficiaries or not, is not affected by the upcoming shock. In other words, shocked households are unable to foresee the shock and adopt an anticipatory response that would affect their food security. Similarly to the traditional DiD (Roth et al., 2023; Wing et al., 2018), no anticipation assumption is necessary to identify each parameter $DiD^{R=j}, j = 0, 1$. While Olden and Møen (2022) highlight the importance of assumption 1, we extend further as we showcase that the no anticipation assumption is also required for identifying the parameter. This assumption is plausible in our context as it seems unlikely that households anticipate such a shock during the 2018 planting and 2019 harvest seasons, while the first cases of COVID-19 worldwide were registered much later in January 2020.[16] Even at that time, no one predicted that the virus could become a global pandemic as illustrated by the late World Health Organization (WHO) statement in March 2020.

3.2 Empirical strategy

Although we could replace the expectations with their sample analogs to estimate the mitigating effects (β_1), we prefer to rely on the two-way fixed effects specification in Equation (5). Olden and Møen (2022) demonstrate that the parameters from this regression are equivalent to the previous difference-in-difference parameters of interest. All estimates are weighted to account for non-contact and non-response. Consistent with Wooldridge (2007) and Korinek et al. (2007), using the corrected sampling weight limits attrition bias based on the assumption that data are randomly missing conditional on the observables used to compute the weights:

$$y_{ht} = \alpha_h + \mu_t + \beta_0 \; shock_h \times post_t + \gamma_1 \; shock_h \times post_t \times \mathbb{1}_{R=1} + \epsilon_{ht} \tag{5}$$

where y_{ht} represents the food insecurity outcome of household h in period t. α_h are household fixed effects to control for time-invariant unobserved characteristics that may drive bias selection concerns associated with the shock. They also absorb any initial systematic differences between

[16] https://www.who.int/news/item/27-04-2020-who-timeline---covid-19

remittances and non-remittances households.[17] $post_t$ is a dummy variable with a value of 1 for post-COVID-19 rounds or 0 for pre-COVID-19 rounds. The government initiated a partial lockdown, starting with Lagos, Abuja, and Ogun on March 30th, 2020.[18] μ_t captures time-fixed effects to account for trend-associated omitted confounding factors that are common across groups. Such factors include, for instance, seasonal changes within a year, outside the pandemic, that affects occupation as well as food security.

$Shock_h$ is a dummy variable that indicates whether any household member stopped working due to coronavirus legal restrictions or was unable to farm due to movement restrictions. The household-level definition of shock is more precise than exposure to COVID-19 or state-level lockdown, as is used by Amare et al. (2021).[19] Households in a given area are not all exposed to the COVID-19 shock in the same way, as they do not necessarily comply with lockdown measures. Compliance with lockdown measures depends on poverty status, trust in government, and economic/fiscal support measures (Bargain and Aminjonov, 2021, 2020; Akim and Ayivodji, 2020). However, the exposure to COVID-19 is more likely exogenous than our preferred employment shock. We also consider this alternative definition of the shock in the analysis for the sake of the comparison with the literature as well as a robustness check of our estimates.[20]

The coefficient γ_1 in the regression (eq. 5) is our parameter of interest that quantifies the mitigating effect of past remittances on adverse shocks on food insecurity. Under Assumptions 1 and 2, it is the difference in DiD parameter between households that benefited from remittances ($DiD^{R=1}$) and those that did not ($DiD^{R=0}$) (Olden and Møen, 2022):

$$\gamma_1 = DiD^{R=1} - DiD^{R=0} = \beta_1 \tag{6}$$

The hypothesis can be formally framed as a one-sided statistical test of the null $Ho : \gamma_1 = 0$ against the alternative $Ha : \gamma_1 < 0$. Intuitively, the mitigating role of remittances implies that households that did not receive any remittances experience at least an equal impact of the shock to their beneficiary counterparts.

We focus primarily on remittances received before the COVID-19 shock, considering the ex-ante mechanism and being mindful of identification concerns. The DiD method requires avoiding any potential explanatory variables that are affected by the shock. The COVID-19 shock and subsequent government lockdown measures will likely affect current remittances received during the shock, contrary to 2019 remittances. The COVID-19 shock and subsequent government lockdown measures will likely affect remittances received during the shock. Officially recorded remittance inflows in SSA in 2020 are estimated to be 12.5% lower than in 2019, mainly due to the COVID-19 shock and movement restrictions such as border closures (Ratha et al., 2021). Due to the COVID-19

[17] Eq. 5 can be rewritten as $y_{ht} = \alpha_h + \mu_t + \rho \mathbb{1}_{R=1} + \omega \mathbb{1}_{shock=1} + \beta_0\ shock_h \times post_t + \gamma_1\ shock_h \times post_t \times \mathbb{1}_{R=1} + \epsilon_{ht}$ where ρ captures differences between remittances and non-remittances households. The differences in shocked and non-shocked households are captured in the ω coefficient. As $\mathbb{1}_{R=1}$ and $\mathbb{1}_{shock=1}$ are time-invariant, ρ and ω are absorbed in the household fixed effects α_h.

[18] The announcement was featured on Al jazeera.

[19] Exposure to COVID-19 is measured in terms of the number of cases per state.

[20] Results are qualitatively the same (see table C.2)

shock, migrants will likely experience earning losses in their destination location, which may negatively affect their ability to send money home. Government measures enacted in both destination and origin locations, such as the shutdown of businesses and travel bans, are also likely to affect remittances.[21] Evidence from high-frequency household surveys supports these forecasts. Among Nigerian households, 72% of remittance beneficiaries report experiencing a decrease in their remittances in 2020.[22] Similarly, Ratha et al. (2020) find that Nigerian remittance inflows were down by more than 45% in 2020 compared to 2019.

The identification of parameters relies on the aforementioned assumption 1. Although this assumption cannot be empirically tested, a commonly used validity check in the DiD literature enables us to evaluate its plausibility. As such, we conducted a test of assumption 1 prior to the occurrence of the shock, particularly during the planting season of 2018 and the harvest season of 2019. First, we provide graphical evidence supporting the validity of the common trends assumption in the overall sample before the pandemic (figure 2). This graphical visualization is confirmed with a statistical test using a regression framework that shows zero effect of the shock under the pre-shock period (Table B.3, column 1). Second, we test whether the trend deviation from common trends is mean independent from 2019 remittances over the period preceding the shock (Table B.2). This test is formally framed as the following two-sided hypothesis test: $Ho : \gamma_1 = 0$ during the 2018 planting and 2019 harvest seasons. Specifically, we re-estimate the regression as specified in Equation 5 over this pre-pandemic period. The test is also conducted over a longer period (2010-2016) using a different sample and an alternative measure of food insecurity (Table B.4). Failing to reject H_0 would indicate that the deviation from the common trend is independent of 2019 remittances, thereby providing support for the plausibility of assumption 1.

We discuss two sources of potential bias in the DiD design that may threaten our identification. First, the presence of contemporaneous remittances or social safety nets received during the pandemic may violate our assumption 1. One may argue that shocked households may solicit more remittances to overcome the consequences of the shock conflicting with the idea of the ex-ante mitigating effect of remittances. Although that possibility exists, we rather observe a decline in remittances during the pandemic in Nigeria, which is documented by some works (Ratha et al., 2020) and also supported by our data (figure B.5). Yet, those households still receiving remittances can use ex-post mitigation strategies, which may confound with the ex-ante mechanism we intend to assess. We test the sensitivity of our results regarding this potential bias by controlling for remittances received in May 2020. To be more precise, we remove all households that get remittances in May 2020 and re-estimate the mitigating effects on this reduced sample (see section 4.3 - Table B.8). Moreover, estimates are also subject to a bias when households receive social safety nets to support them during the pandemic. There are 309 households (18.8% of the sample) that received assistance (cash, food, and any other forms) from the Government or NGO in mid-March, around the time of the lockdown enforcement. We assess the robustness of the results by examining a reduced sample that excludes safety net beneficiaries, deploying a strategy similar to that used for

[21] Businesses include remittance providers.

[22] The World Bank. "COVID-19 Households High-Frequency Monitoring Dashboard". World Bank Group. Washington, DC.

addressing the contemporaneous remittances issue (see Table B.9).

Second, assumption 1 is unlikely to hold in the presence of unobserved heterogeneity varying over time. Callaway and Karami (2023) point out the TWFE weaknesses when the untreated potential outcomes are rather generated by an interactive fixed effects model (IFE) allowing some of the components of the unit-specific unobserved heterogeneity to vary over time. The IFE model assumes that the time-invariant unobserved heterogeneity α_h (eq. 5) splits into two components ψ_h and λ_h:

$$y_{ht} = \psi_h + \mu_t + \lambda_h F_t + \beta_0 \; shock_h \times post_t + \gamma_1 \; shock_h \times post_t \times \mathbb{1}_{R=1} + \epsilon_{ht} \tag{7}$$

where ψ_h, λ_h are unobserved, time-constant household characteristics and F_t the time-varying effects of λ_h. We borrow from Callaway and Karami (2023) to derive the expression of the NPT bias (eq. 3) in our setting of triple difference, using the IFE model:[23]

$$\begin{aligned} NPT^{R=1} - NPT^{R=0} = (F_1 - F_0)\{(&E[\lambda_h \mid shock = 1, R = 1] - E[\lambda_h \mid shock = 0, R = 1])- \\ &(E[\lambda_h \mid shock = 1, R = 0] - E[\lambda_h \mid shock = 0, R = 0])\} \end{aligned} \tag{8}$$

Equation 8 implies that assumption 1 is violated when the effects of unit-specific unobserved household characteristics vary over time ($F_1 \neq F_0$). Moreover, the direction and magnitude of the bias are unclear as the mean disparity between shocked and non-shocked households in terms of unobserved factors ($E[\lambda_h \mid shock = 1, R = j] - E[\lambda_h \mid shock = 0, R = j], j = 1, 0$) within both subsamples also matters.

The features of the IFE model are particularly appealing for testing the sensitivity of our TWFE estimates. The interactive effects structure captures time-varying unobservables of the form $\lambda_h F_t$. It generalizes individual-specific linear trend models ($F_t = t$) that are commonly employed in the applied literature to address concerns of non-parallel trends (Wooldridge, 2005; Mora and Reggio, 2019). Following Callaway and Karami (2023) approach, the identification of each individual $ATET^{R=j}$, where $j = 1, 0$, proceeds as follows:

$$\begin{aligned} ATET_t^{R=j} = {} & E[Y_t - Y_{t^*-2} \mid shock = 1, R = j] - \\ & \left(E\left[X' \mid shock = 1, R = j\right] \beta^*_{jt} + F^*_{jt} E[Y_{t^*-1} - Y_{t^*-2} \mid shock = 1, R = j]\right) \end{aligned} \tag{9}$$

where $t = t^* = 3$ is the period when the shock occurs i.e in April-May ($t = 3$) within our setting. X includes time-fixed effects and observed covariates with time-varying effects on food insecurity. The covariates comprise pre-period measured variables, such as residence area and household sociodemographic characteristics, including members' education and gender, as well as owned land area to capture household wealth. These variables are included to account for potential time-varying differential trends in the untreated potential outcomes due to any initial systematic disparities in those characteristics. As we estimate $ATETs$ separately, we allow the potential non-shocked outcomes of the remittance groups to follow distinct time-varying unobserved heterogeneity.

[23] The proof is straightforward and can be made available upon request.

The main challenge to identify the $ATET_t^{R=j}$ is to correctly recover the parameters β_{jt}^* and F_{jt}^* while the others are directly identified from the sampling process. Conditional on household remittances status $j = 1, 0$, the parameters β_{jt}^* and F_{tj}^* are estimated through the model (eq. 10) by exploiting moment conditions and using a covariate W_{ij} as an instrument for $Y_{ijt^*-1} - Y_{ijt^*-2}$:

$$Y_{ijt} - Y_{ijt^*-2} = X_{ij}'\beta_{jt}^* + F_{jt}^*(Y_{ijt^*-1} - Y_{it^*-2}) + V_{ijt} \tag{10}$$

The key requirement of this approach is that W_{ij} has a time-invariant effect on untreated potential outcomes. We use the education level of the household head's father as an instrument, justifying our choice based on the intergenerational mobility literature (Becker and Tomes, 1979; Daude and Robano, 2015; Becker et al., 2018). This body of work notably underscores the influence of parental background (income, endowments) on achieving elevated socio-economic outcomes (income, education, occupation) in adulthood. [24] In our case, the father's education serves as our proxy for the family background of the household head. Consistent with this literature, we reasonably anticipate that the instrument positively correlates with the household head income, which subsequently reinforces the household's food security in the absence of the COVID-19 shock. Importantly, we expect the effect of the father's education (also called intergenerational transmission) on food security to be time-invariant over our period of interest. Our reasoning is based on the theoretical argument that intergenerational transmission functions through long-term mechanisms (Becker and Tomes, 1979; Becker et al., 2018). These mechanisms encompass the propensity to invest in children, primarily influenced by parental preferences, as well as family reputation and connections inherited from parental endowments. They can reasonably be assumed to remain relatively stable within the relatively short time frame considered in this study.

We believe that the main channel through which the mitigating role of past remittances may operate is the capital channel, including savings/credit, livestock, and rental earnings. As remittances relax budgetary constraints, households that have bought more assets, such as livestock, equipment, or land, and generate rental earnings may be less likely to suffer from food insecurity during the COVID-19 shock. Our reasoning is based on the following arguments. First, the data show that relying on savings represents the second most reported coping mechanism (29% of households).[25] This highlights the importance of savings as a coping strategy. Second, findings in the literature suggest that remittances can stimulate financial services (savings or credit) by relaxing household budgetary constraints (Anzoategui et al., 2014; Ambrosius and Cuecuecha, 2016; Ajefu and Ogebe, 2019). Instead of using savings or asking for credit, rural households may also rely on their assets as a mechanism to cope with the COVID-19 shock (Nikoloski et al., 2018). To corroborate the existing evidence, we find a significant positive association between capital ownership and remittances received in 2018-2019. This correlation remains robust even after considering household socio-demographic characteristics and state-fixed effects (Table B.12). We formally investigate the capital mechanism using the following equation:

[24] Endowments can be determined by reputation, family connections (Becker and Tomes, 1979).

[25] Nigeria National Bureau of Statistics, The World Bank, "COVID-19 Impact Monitoring", Baseline Report, 2020. https://microdata.worldbank.org/index.php/catalog/3712/download/48362 First coping mechanism is reducing food consumption.

$$y_{ht} = \tilde{\alpha_h} + \tilde{\mu_t} + \tilde{\beta}_0 \; shock_h \times post_t + \sum_{j=1}^{3} \tilde{\gamma_j} \; shock_h \times post_t \times \mathbb{1}_{group\,=\,j} + \tilde{\epsilon}_{ht} \tag{11}$$

where $j = 0, 1, 2, 3$ represents three subgroups of households. The first group represents the reference group and comprises households with no remittances capital or remittances before the pandemic ($j = 0$). This group is supposed to be the most vulnerable to shock. The coefficient $\tilde{\beta}_0$ is expected to be positive ($\tilde{\beta}_0 > 0$) as it captures the impact of the shock on the most vulnerable household. The second group, which is our primary interest group, includes households that simultaneously owned or had access to capital and received remittances ($j = 1$). The coefficient associated with this group, $\tilde{\gamma_1}$, is the parameter that tests the capital mechanism hypothesis of the mitigation effect of remittances. The intuition is that the attenuating role of remittances operates through capital if accessing or owning capital amplifies their mitigating effect, which is operationalized by a negative coefficient ($\tilde{\gamma_1} < 0$). In other words, the mitigating effect is even higher for remittance households with capital than the third group ($j = 2$), which comprises households that received remittances and did not own or have access to capital. This group accounts for other potential confounding mechanisms of the mitigating effect of remittances that are distinct from the capital mechanism. For instance, households may have used part of their remittances to buy inputs instead of investing in physical capital such as machinery. Household productivity may then increase so that when a shock occurs, they may have more staple food and be better able to cope with it. Hence, this group will allow us to rule out such mechanisms that would contribute to the mitigation effect of past remittances and do not necessarily operate through the capital channel. The coefficient associated with this group, $\tilde{\gamma_2}$, is hypothesized to be negative ($\tilde{\gamma_2} < 0$). Finally, households that owned or had access to capital and did not receive remittances constitute the fourth group ($j = 3$). The coefficient $\tilde{\beta}_3$ captures the potential mitigating effects related solely to capital, not remittances ($\tilde{\beta}_3 < 0$).

4 Results

4.1 Overall mitigating effect of remittances amid COVID-19 employment shock

Table 2 shows the mitigating effect of remittances amid the COVID-19 employment shock on food insecurity. The results indicate that households that received remittances experienced less food insecurity. While the COVID-19 shock tends to increase food insecurity scores, remittances of any origin mitigate the shock's adverse effects (column 2). Following the shock, the food insecurity score for non-beneficiary households increased by 0.29. However, the shock appears to be offset entirely or absorbed when households receive remittances, as the food insecurity scores are roughly zero (0.29-0.32) for remittance beneficiaries. The literature on migration insurance tends to support remittances having a mitigation effect of this magnitude. For instance, Beuermann et al. (2016) find similar magnitudes in Jamaica. Although they look into an entirely different shock, they indicate that remittances absorb 100% of the adverse effect of a health shock impact on household consumption. The remittances' mitigation effect is also relatively sizable in the Philippines. Yang and Choi (2007) find that international remittances offset 60% of the decline in household income resulting from a rainfall shock. Furthermore, our findings highlight the heterogeneity of the mitigation effects of remittances in terms of their origin (domestic or international). While the mitigating impact of domestic remittances enables households to completely offset the impact of the adverse shock (-0.28 + 0.29; column 2), the international remittances more than double that of domestic remittances (column 3). The high average amount of international remittances versus domestic ones might explain this.

Our results are also in line with the COVID-19-related literature, especially regarding the mitigating effects of remittances. The results in Tapsoba (2021) suggest that remittance-receiving households are less likely to report being negatively affected by the pandemic. Focusing on informal workers, Balde et al. (2020) find similar results in Senegal but not in Mali or Burkina Faso. In Nigeria, Amare et al. (2021) study the differential impact of lockdown measures on various means of livelihood, including receiving remittances and assistance. Their findings indicate that households that rely on remittances and government assistance experience a milder adverse lockdown effect on food insecurity. However, the mitigation effects specific to remittances cannot be disentangled in their study because they pool remittances and government assistance.

Table 2: Mitigating effect of remittances

Dependent variable Food insecurity score	(1)	(2)	(3)
Lockdown from business closure	0.19**	0.29***	0.29***
	(0.08)	(0.10)	(0.10)
All remittances 2018-2019 × Lockdown from business closure	–	-0.32*** (0.12)	–
International remittances 2018-2019 × Lockdown from business closure	–	–	-0.69*** (0.26)
Domestic remittances 2018-2019 × Lockdown from business closure	–	–	-0.28** (0.13)
Time fixed effects	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes
Constant	0.96***	0.96***	0.96***
	(0.02)	(0.02)	(0.02)
Observations	5850	5850	5850
Adjusted R^2	0.243	0.245	0.245
Food insecurity score baseline mean	0.76		

Robust standard errors in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$;
Note: Food insecurity score baseline mean corresponds to the weighted average over the 2018 planting and 2019 harvest seasons.

4.2 Heterogeneous effects

The heterogeneous impact of the COVID-19 shock that is documented in the literature raises the question of whether the mitigation effect of remittances is also heterogeneous (Jr. Tabe-Ojong et al., 2023). The effect of the COVID-19 shock on food insecurity is notably more pronounced among poor populations (Amare et al., 2021). In urban areas, the results depend on the country. Adjognon et al. (2021) find a sharp increase in food insecurity in Bamako (Mali). In contrast, Amare et al. (2021) suggest that the shock had no differential effect on food security between urban and rural areas in Nigeria. In other words, the impact of the shock on food insecurity in that country was similar in rural and urban areas, unlike in Mali.[26] To examine this question in Nigeria, we investigate the heterogeneity of the mitigation effects of remittances in rural and urban residential areas and across poverty status.

Table 3 presents the heterogeneity of the mitigating effect of remittances on households by area of residence. We operationalize the heterogeneity analysis with an interaction between the shock variable, the receipt of remittances, and a household's area of residence. We consider households that live in rural areas and did not receive remittances as the reference group. Our results suggest that remittances have a solid mitigating effect in rural areas. We find a significant overall increase in food insecurity among households in rural areas that did not receive remittances (0.28; column 1). However, this adverse shock seems to be considerably attenuated by remittances in those areas (-0.39; column 1). Unsurprisingly, the cushioning effect of international remittances (-1.26; Column 2) is greater than that of domestic remittances (-0.32; column 3). Estimates fail to validate the mitigating effect of remittances in urban areas apart from Lagos, where we see that international remittances have a mitigating effect.

The weak mitigating effect observed in urban areas is probably a result of these residents having more underlying resilience or better access to other coping mechanisms that make them less reliant on remittances. For instance, market imperfections such as credit constraints are likely to be more pronounced in rural areas than in urban ones. Consequently, we can reasonably expect remittances to mitigate the impact of the shock in more financially constrained environments, such as rural areas, than in urban areas. Urban households are likely to have access to financial services, such as credit and savings, independent of whether they receive remittances. They are then better able to smooth their consumption without relying on remittances. In rural areas, on the contrary, credit constraints are more pronounced, and we expect households to rely on remittances. To test this potential explanation, we perform a sensitivity test by excluding all households that reported an increase or no changes in income since mid-March. We assume that these households were partly able to utilize various mechanisms to cope with the shock (see Table C.11). The mitigating effect becomes more pronounced and statistically significant in urban areas, especially for domestic remittances.

Table 4 presents heterogeneity results regarding households' poverty status measured in 2018-2019. We use a triple interaction between the shock variable, the receipt of remittances, and poverty status to investigate the poverty differential effects of the mitigating role of remittances.[27] Our reference group comprises poor households that did not receive remittances. The results indicate that remittances mitigate the negative effects of the shock, mainly for non-poor households.

[26] We find similar results that we can provide upon request.

[27] Households in the first two consumption quintiles, which represent the bottom 40% of the consumption distribution, are considered poor.

Table 3: Mitigating effect of remittances: heterogeneity in terms of area of residence

	Type of remittances		
	Pooled remittances (1)	International remittances (2)	Domestic remittances (3)
Lockdown from business closure	0.28**	0.23*	0.26**
	(0.12)	(0.12)	(0.12)
Lockdown from business closure x Area of residence x Remittances (Ref: Remittances = No, Rural = Yes)			
Closure = Yes × (Remittances = Yes, Lagos/FCT = Yes)	-0.30	-0.55*	-0.19
	(0.24)	(0.30)	(0.30)
Closure = Yes × (Remittances = No, Lagos/FCT = Yes)	-0.05	-0.05	-0.05
	(0.36)	(0.36)	(0.36)
Closure = Yes × (Remittances = Yes, Other urban = Yes)	-0.21	-0.23	-0.21
	(0.18)	(0.41)	(0.19)
Closure = Yes × (Remittances = No, Other urban = Yes)	0.02	0.02	0.02
	(0.17)	(0.17)	(0.17)
Closure = Yes × (Remittances = Yes, Rural = Yes)	-0.39**	-1.26***	-0.32*
	(0.16)	(0.28)	(0.17)
Time fixed effects	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes
Constant	0.96***	0.93***	0.95***
	(0.02)	(0.03)	(0.02)
Observations	5850	4200	5559
Adjusted R^2	0.245	0.273	0.252
Sample	1950 households	1303 non-benef + 97 intl. remit.	1303 non-benef + 550 dom. remit.

Robust standard errors in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
FCT = Federal Capital Territory.

The mitigating effect of pooled remittances is estimated to be -0.46 (column 1). Consistent with the previous results, we find that international remittances have a larger mitigating effect than domestic ones. Regarding poor households, we find evidence of only international remittances having a mitigating effect (-0.93; column 2); domestic remittances have almost zero effect. This indicates that domestic remittances are likely to mitigate shocks only for well-off households. In contrast, international remittances can mitigate the negative consequences of a shock on food insecurity for both groups (poor and non-poor households).

Table 4: Mitigating effect of remittances: heterogeneity in terms of poverty status in 2018-2019

	Type of remittances		
	Pooled remittances (1)	International remittances (2)	Domestic remittances (3)
Lockdown from business closure	0.36**	0.31**	0.34**
	(0.14)	(0.14)	(0.14)
Lockdown from business closure x Poor status (2018/2019) x Remittances (Ref: Remittances = No, Poor = Yes)			
Closure = Yes × (Remittances = Yes, Poor = Yes)	-0.14	-0.93***	-0.08
	(0.23)	(0.24)	(0.24)
Closure = Yes × (Remittances = No, Poor = Yes)	-0.14	-0.14	-0.14
	(0.17)	(0.17)	(0.17)
Closure = Yes × (Remittances = Yes, Poor = No)	-0.46***	-0.73**	-0.43**
	(0.17)	(0.31)	(0.17)
Time fixed effects	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes
Constant	0.96***	0.93***	0.95***
	(0.02)	(0.03)	(0.02)
Observations	5850	4200	5559
Adjusted R^2	0.246	0.273	0.253
Sample	1950 households	1303 non-benef + 97 intl. remit.	1303 non-benef + 550 dom. remit.

Robust standard errors in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
Households in the first and second quintile of consumption are considered poor.

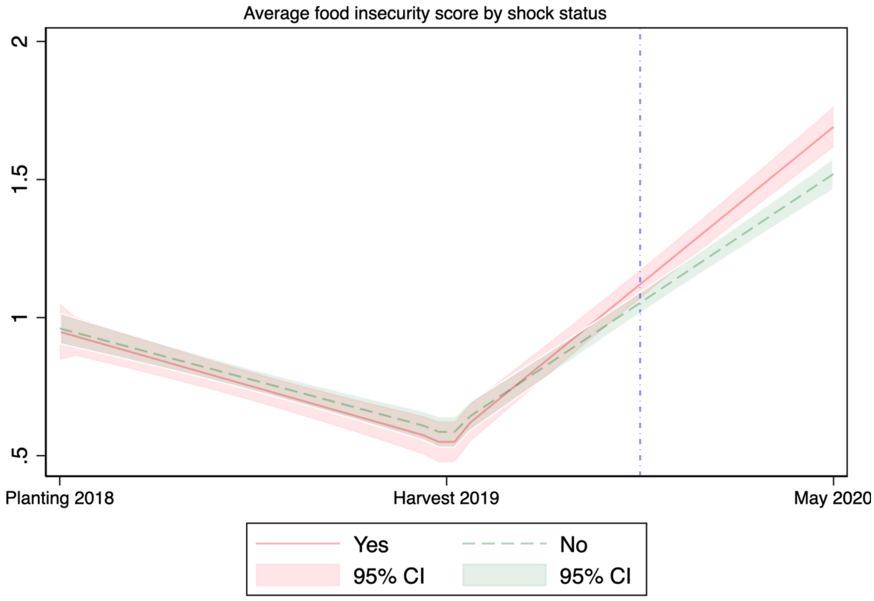
4.3 Parallel trends and robustness checks

Parallel trends

We test the plausibility of a parallel trends assumption on the overall sample and within the subsamples. Figure 2 provides graphical evidence of the plausibility of the parallel trends hypothesis overall. Food insecurity in both groups of households (shocked and non-shocked) seemed to have evolved in tandem during the 2018 planting and 2019 harvest seasons i.e. before the COVID-19 shock occurred.

We complete the visual comparison with two statistical tests using regression analysis that confirm the parallel trends assumption before the shock occurs (Table B.3). We evaluate the impact of the shock during the pre-COVID-19 period (column 1). As expected, the shock is observed to have a statistically zero effect (-0.02) in this period. Then, we exploit the panel structure of the GHS sur-

Figure 2: Parallel trends hypothesis: visual test



Source: Wave 4 of the 2018-2019 GHS panel, COVID-19 NLPS 2020, and authors' calculations.
Note: The dash-dot line represents March 2020, when Nigeria government implemented Lockdown measures. Estimates are weighted to account for non-contact and non-response.

veys to test the parallel trends over a longer period of time from 2010 to 2016 (column 2). Because of attrition issues, the test is conducted on a smaller sample size of 493 households, including 184 shocked and 309 non-shocked. The measure of food insecurity (hereafter alternative FIES) also differs from our preferred reduced FIES. The alternative FIES is a score varying on a scale from 0 to 9 (score = 9 being the most severe) computed on different questions, which are consistently asked on a recall period of 7 days and are phrased similarly over the period 2010-2016.[28] Remarkably, the regression findings still support the parallel trends hypothesis despite the differences in the sample and the food insecurity measure. The interaction term between the shock and the times is statistically insignificant in the whole period (2010 - 2016).

The results of the regression testing the plausibility of assumption 1 are presented in Table B.2. As expected, there is no evidence of remittances having any mitigating impact during the 2018 planting and 2019 harvest seasons across the various specifications. A similar test is conducted in the period (2010 - 2016) using the alternative FIES, and the findings still support the absence of any mitigating effect before the pandemic (Table B.4). These results support the plausibility of the common trends and non-anticipation assumptions.

Robustness checks

Despite evidence of plausible parallel trends, the receipt of remittances following the shock may threaten the parallel trends assumption. While the likelihood of getting remittances declines on the whole, some are still receiving remittances when the shock occurs. Table B.5 shows that 24% of the

[28] Questions are individually turned into dummies and then summed up to provide the alternative FIES score (see Table B.14 for details).

households sample got remittances in May 2020, which means they can also use ex-post mitigation strategies. Hence, identification concerns may arise whether the potential ex-post strategy upward biases our estimates of the ex-ante mitigating effect. To test this possibility, we re-estimate the mitigating effect while accounting for remittances received in May 2020 by removing beneficiary households in May 2020 from the sample (Table B.8). The magnitude of the mitigating effects, especially for international remittances (-0.50), is lower compared to previous estimates on the whole sample (-0.60 in table C.1). Unexpectedly, the bias seems mostly driven by households receiving international remittances as the majority (50.5%) keep benefiting from these transfers. In comparison, a lower proportion of beneficiaries from domestic transfers (only 33%) are still receiving remittances. Although the decline in remittances concerns mostly domestic remittances, the associated mitigating effect (-0.23 against -0.24 in table C.1) appears surprisingly robust to the control for remittances received in May 2020. In sum, the results remain qualitatively the same after accounting for the bias related to the potential ex-post mechanism of remittances. Findings also pass the robustness check to contemporaneous safety nets (Table B.9).

Results remain qualitatively similar when using the interactive fixed-effects model (table 5). We find that the impact of the shock on remittance beneficiary households is significantly lower (-0.17) than on non-beneficiary households. Furthermore, the mitigating effects are more pronounced for international remittances (-0.42) compared to domestic ones (-0.18). However, the magnitudes of the effects are relatively lower than previously reported. This discrepancy may suggest potential upward bias in the Time-Weighted Fixed Effects (TWFE) model estimates. Alternatively, the Interactive Fixed Effects (IFE) estimates might also be affected by weak instrument (Weak-IV) issues, which could exacerbate the TWFE bias (table B.15). Addressing the Weak-IV problem would necessitate further investigations beyond the scope of this study. Nevertheless, the robustness of our findings in the presence of this form of time-varying unobserved heterogeneity, despite potential precision concerns, is noteworthy.

Table 5: Mitigating effects of remittances using the interactive fixed effects (IFE) model

	Remittance beneficiary			Remittance non beneficiary			Remittance Mitigating effects		
	$ATET^{R=1}$ (1)	95 % Conf. interval		$ATET^{R=0}$ (2)	95 % Conf. Interval		(1) - (2)	95 % Conf. Interval	
		Lower	Upper		Lower	Upper		Lower	Upper
All remittances	0.10**	0.07	0.14	0.27**	0.25	0.29	-0.17**	-0.20	-0.12
—International	-0.15	-0.44	0.14	0.27**	0.25	0.29	-0.42**	-0.71	-0.13
—Domestic	0.09**	0.05	0.13	0.27**	0.25	0.29	-0.18**	-0.22	-0.14

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$;

Note: Confidence interval is computed using 999 bootstrap replications.

We conduct additional sensitivity tests on key choices made throughout the empirical strategy (see Online Appendix C). Our findings align with the standard definitions of food insecurity and COVID-19 shocks as employed in the literature (Amare et al., 2021).[29] Furthermore, there are no significant differences in the findings when we include control variables like time-varying observables (see Table C.7) or when using an extended panel (see Table C.9).

[29] Online Appendix C.1

4.4 Persistent effects of both shock and mitigating role of remittances

We take advantage of the extended panel sample to investigate the persistence of the COVID-19 employment shock over time and the lasting mitigation effect of remittances. Figure 3 shows the regression coefficients estimating the impacts of the shock and the mitigation effect of remittances over time. The results show that the adverse shock effects are likely to persist over the period considered, while the mitigating role of remittances seems effective only in the early stages of the shock. We find that the COVID-19 employment shock increased food insecurity in May 2020 (time = 0) and it remains quite high over the following periods, from June 2020 (time = 1) to November 2020 (time = 3). Remittances appear to significantly cushion the adverse effect during the three rounds from May 2020 (time = 0) to August 2020 (time = 2). The mitigation effect of remittances became insignificant in November 2020, while the adverse effect persisted over the entire period (from time = 0 through time = 3). The downward pattern of the mitigation effect is expected because household capital, especially savings, may be insufficient to hold out in the long run. Indeed, household savings are likely to decline over time because of the employment shock, preventing a recovery of savings.

Considering the extended panel raises additional identification concerns that suggest alternative explanations of the downward mitigating effects over time. Governments worldwide, including the Nigerian government, have rolled out many social safety net programs to help households cope with the negative consequences of COVID-19. This support may help households recover their businesses. Governments also eased movement restrictions over time.[30] Table B.7 in Appendix C shows the proportion of shocked households decreased from 37% in May 2020 to only 2% in August 2020. The measures enacted (safety net programs and restriction easing) may raise some identification issues. For instance, our estimates may be biased downward because the impact of the shock could be more critical in the absence of any support programs.

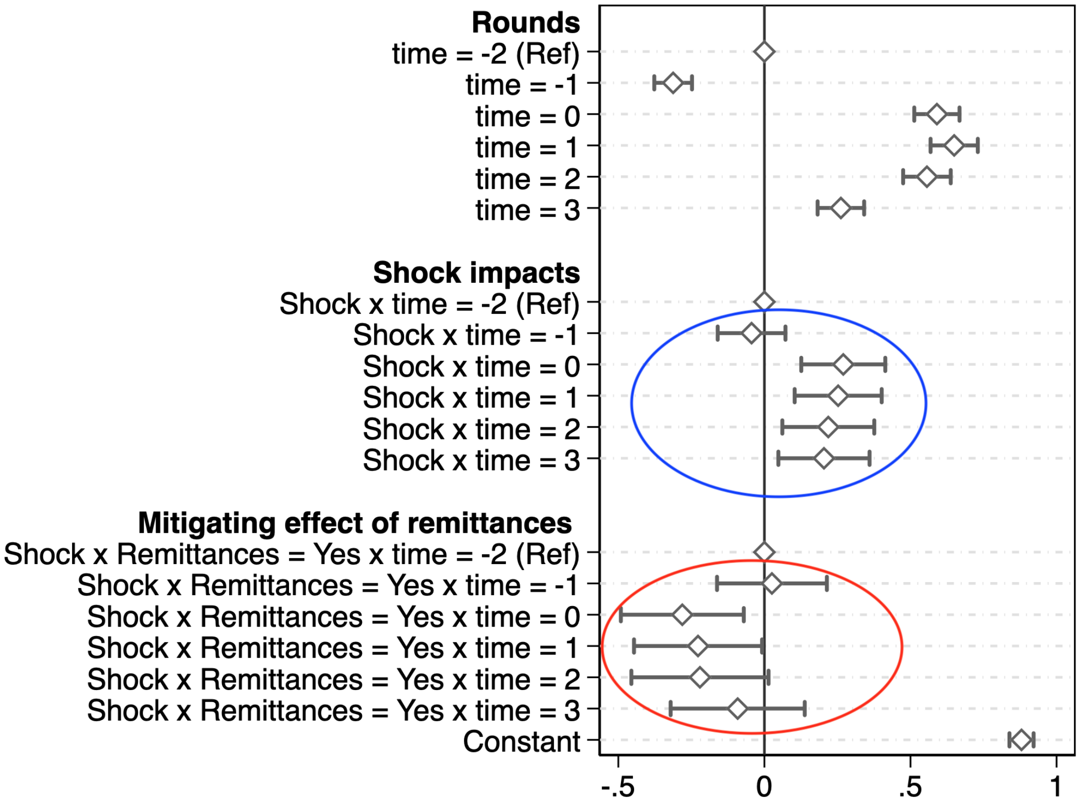
4.5 Pathway to the mitigating role of past remittances: the capital channel

The capital mechanism is tested by considering the broad definitions of household capital, including three dimensions. The first dimension is ownership of an account with a financial institution.[31] We assume that households holding an account will likely have access to formal financial services such as savings or credit, making them less capital-constrained. They are subsequently more likely to smooth their consumption through access to such services relative to households without access to any formal financial services. The second dimension is informal financial services through participation in rotating savings and credit associations. The third dimension is ownership of livestock or assets that generate rental earnings. Indeed, households may hold capital in forms other than money and may even receive non-labor income, protecting them from food insecurity. For instance, households may hold assets such as livestock that they can sell or consume during the COVID-19

[30] See Abiola Odutola, "Full Speech of President Buhari on COVID-19 Pandemic," Nairametrics, April 27, 2020, [https://nairametrics.com/2020/04/27/fill-speech-of-president-buhari-on-covid-19-pandemic/].

[31] Like a commercial bank, micro-finance institution, or cooperative.

Figure 3: Lasting effects of the shock and the mitigating effect of remittances over time



Source: Wave 4 of the 2018-2019 GHS, COVID-19 NLPS 2020, and authors' calculations.
Note: The sample includes the additional waves of June, August and November 2020. Confidence intervals are estimated at 95%.

shock. Some households may earn non-labor income from land or other productive assets, such as tractors and trailers that they rent out.

Table 6 presents the results of the capital mechanism hypothesis test based on Equation 11. The findings support the assumption that capital represents a channel through which the mitigating effect of remittances can operate. The effect appears to be significantly amplified when households have access to any form of capital considered (-0.44; column 1). In contrast, households receiving remittances but lacking ownership or access to capital appear unable to cope significantly with the shock (-0.39). The capital mechanism seems driven mainly by formal financial inclusion, defined as having an account with a financial institution, livestock ownership, or rental earnings. This finding still stands when remittances are accounted for using a reduced sample excluding beneficiaries of remittances in May 2020 (Table C.10). The interaction effect of informal financial services and remittances is insignificant and fails to validate the capital hypothesis mechanism for this type of capital. The capital hypothesis mechanism remains valid when considering the origin of remittances (Table B.6). Overall, the results indicate that the cushioning effects of both international and domestic remittances are more pronounced for households with capital ownership or access.

To strengthen the plausibility of the capital channel hypothesis, we perform a falsification test to verify whether any spurious correlations or random occurrences drive the results (see Table B.11). If the remittance mitigating effects operate solely through the access-to-capital mechanism, there should be no differential effects in the absence of shocks. Typically, we estimated the same regression (Equation 11) over the period preceding the shock, specifically during planting in 2018 and harvest in 2019. Our results successfully pass this falsification test, as we found insignificant coefficients associated with households that received remittances and had access to capital.

Table 6: Capital channel hypothesis test of the mitigating effect of pooled remittances

	Type of capital			
	Pooled capital	Formal financial services	Informal financial services	Livestock ownership, rental earnings
	(1)	(2)	(3)	(4)
Lockdown from business closure	0.40*	0.48**	0.44*	0.49**
	(0.22)	(0.22)	(0.22)	(0.23)
Business closure x Remittances group (Ref: Closure = No; Capital = No; Remittances = No)				
Closure = Yes × (Capital = Yes, Remittances = Yes)	-0.44*	-0.54**	-0.10	-0.91***
	(0.23)	(0.24)	(0.26)	(0.27)
Closure = Yes × (Capital = Yes, Remittances = No)	-0.15	-0.26	0.01	-0.03
	(0.23)	(0.24)	(0.24)	(0.29)
Closure = Yes × (Capital = No, Remittances = Yes)	-0.39	-0.39	-0.39	-0.39
	(0.38)	(0.38)	(0.38)	(0.38)
Time fixed effects	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes
Constant	0.96***	0.97***	0.92***	1.02***
	(0.02)	(0.03)	(0.03)	(0.04)
Observations	5850	4671	3132	1995
Adjusted R^2	0.245	0.213	0.253	0.217

Robust standard errors in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

5 Conclusion

This paper assesses the mitigation effect of past remittances against the COVID-19 employment shock on food insecurity in Nigeria using a difference-in-difference approach. The results indicate that past remittances mitigate the adverse effects of the COVID-19 employment shock, especially in the short term. Households that received remittances appear to experience significantly less deterioration in food security in the early stages of the shock. The findings also highlight some heterogeneity regarding the origin of remittances. Overall, international remittances have a more substantial mitigating effect than domestic ones. Furthermore, the mitigating effect of remittances appears to have the most significant impact on rural and non-poor households. For urban and poor populations, we find that only international remittances cushion the adverse shock of food insecurity. Interestingly, we find evidence that the mitigating effect of remittances is likely to operate through the capital mechanism. The impact seems amplified when a household holds a bank account with a financial institution or owns or has access to capital in the form of livestock or rental earnings.

Our results highlight the lifeline role that remittances might play in mitigating the adverse consequences of an employment shock of a magnitude similar to the COVID-19 pandemic, especially in the early stages. Before the government enacts any relief measures, remittances are readily available resources that help households cope with the shock through the capital mechanism. This result is striking because remittances had been anticipated to play a small role during the COVID-19 pandemic. Due to the pandemic outbreak in migration destination countries or locations, they are expected to decrease sharply. Consequently, a significant policy implication in the post-pandemic context arising from our findings is that remittances may still represent a crucial insurance source worth considering through the ex-ante mechanism.

Governments worldwide and the international community are likely to rethink and revise national social protection strategies to provide more support to households and increase their resilience to adverse shocks. These strategies should consider the capital mechanism insurance of remittances through policies incentivizing households that receive remittances to channel them toward raising household capital. Furthermore, remittance protection should be considered complementary to existing social protection systems. Our findings support that remittances likely protect only part of the population, mainly rural and non-poor households. Even that population may need complementary social safety nets over the long term that would target the most affected households living in urban areas and poor. Indeed, the attenuating role of remittances seems to operate only in the short term and households are still exposed to subsequent shocks as they mainly rely on their savings, which are limited, to cope with the shock.

Nonetheless, our study has certain limitations. Firstly, our reliance on self-reported food insecurity indicators, though comprehensive, suggests the need for further exploration into objective measurements to mitigate reporting bias. Secondly, while we predominantly concentrate on remittances preceding the shock, post-shock remittances merit deeper investigation for their potential contributions to recovery and reconstruction post-COVID-19. Lastly, the estimates based on the interactive fixed effects model may suffer from imprecision due to the weak instrument problem. These avenues pose both challenges and opportunities that warrant dedicated investigation in future research.

References

Adams-Prassl, Abi, Teodora Boneva, Marta Golin, and Christopher Rauh, "Inequality in the impact of the coronavirus shock: Evidence from real time surveys," *Journal of Public Economics*, 2020, *189*, 104245.

Adjognon, Guigonan Serge, Jeffrey R Bloem, and Aly Sanoh, "The coronavirus pandemic and food security: Evidence from Mali," *Food Policy*, 2021, *101*, 102050.

Ajefu, Joseph Boniface and Joseph O. Ogebe, "Migrant remittances and financial inclusion among households in Nigeria," *Oxford Development Studies*, 2019, *47* (3), 319–335.

Akim, Al-Mouksit and Firmin Ayivodji, "Interaction effect of lockdown with economic and fiscal measures against COVID-19 on social-distancing compliance: Evidence from Africa," *Available at SSRN 3621693*, 2020.

Amare, Mulubrhan, Kibrom A. Abay, Luca Tiberti, and Jordan Chamberlin, "COVID-19 and food security: Panel data evidence from Nigeria," *Food Policy*, May 2021, *101*, 102099.

Ambrosius, Christian and Alfredo Cuecuecha, "Are Remittances a Substitute for Credit? Carrying the Financial Burden of Health Shocks in National and Transnational Households," *World Development*, 2013, *46*, 143 – 152.

_ **and** _ , "Remittances and the Use of Formal and Informal Financial Services," *World Development*, 2016, *77*, 80 – 98.

_ **, Raymundo M. Campos Vázquez, and Gerardo Esquivel**, "What drives remittances during a global shock? Evidence from the COVID-19 pandemic in Mexico," Working Paper 2021/13, Discussion Paper 2021.

Anzoategui, Diego, Asli Demirgüç-Kunt, and María Soledad Martínez Pería, "Remittances and Financial Inclusion: Evidence from El Salvador," *World Development*, 2014, *54*, 338 – 349.

Arezki, Rabah, Amadou Boly, and Amah Koffi, "African Economic Outlook 2021: From Debt Resolution to Growth: The road Ahead for Africa," African Development Bank report, African Development Bank 2021.

Balde, Racky, Mohamed Boly, and Elvis Avenyo, "Labour market effects of COVID-19 in sub-Saharan Africa: An informality lens from Burkina Faso, Mali and Senegal," MERIT Working Papers 2020-022, United Nations University - Maastricht Economic and Social Research Institute on Innovation and Technology (MERIT) 2020.

Bargain, Olivier and Ulugbek Aminjonov, "Trust and compliance to public health policies in times of COVID-19," *Journal of Public Economics*, December 2020, *192*, 104316.

_ **and** _ , "Poverty and COVID-19 in Africa and Latin America," *World development*, 2021, *142*, 105422.

Becker, Gary S. and Nigel Tomes, "An Equilibrium Theory of the Distribution of Income and Intergenerational Mobility," *Journal of Political Economy*, 1979, *87* (6), 1153–1189. Publisher: University of Chicago Press.

_ **, Scott Duke Kominers, Kevin M. Murphy, and Jörg L. Spenkuch**, "A Theory of Intergenerational Mobility," *Journal of Political Economy*, October 2018, *126* (S1), S7–S25. Publisher: The University of Chicago Press.

Beuermann, Diether W., Inder J. Ruprah, and Ricardo E. Sierra, "Do remittances help smooth consumption during health shocks?: Evidence from Jamaica," *The Journal of Developing Areas*, 2016, *50* (3), 1–19.

Cafiero, Carlo, Sara Viviani, and Mark Nord, "Food security measurement in a global context: The food insecurity experience scale," *Measurement*, February 2018, *116*, 146–152.

Callaway, Brantly and Sonia Karami, "Treatment effects in interactive fixed effects models with a small number of time periods," *Journal of Econometrics*, March 2023, *233* (1), 184–208.

Daude, Christian and Virginia Robano, "On intergenerational (im)mobility in Latin America," *Latin American Economic Review*, December 2015, *24* (1), 1–29. Number: 1 Publisher: SpringerOpen.

David, Antonio C., "How do international financial flows to developing countries respond to natural disasters?," *Global Economy Journal*, 2011, *11* (4).

Fafchamps, Marcel, Christopher Udry, and Katherine Czukas, "Drought and saving in West Africa: are livestock a buffer stock?," *Journal of Development economics*, 1998, *55* (2), 273–305. Publisher: Elsevier.

Freije-Rodriguez, Samuel and Michael Woolcock, *Poverty and Shared Prosperity: reversals of fortune* 2020.

Gubert, Flore, "Do migrants insure those who stay behind? Evidence from the Kayes area (Western Mali)," *Oxford Development Studies*, 2002, *30* (3), 267–287.

Kansiime, Monica K., Justice A. Tambo, Idah Mugambi, Mary Bundi, Augustine Kara, and Charles Owuor, "COVID-19 implications on household income and food security in Kenya and Uganda: Findings from a rapid assessment," *World development*, 2020, *137*, 105199. Publisher: Elsevier.

Korinek, Anton, Johan A. Mistiaen, and Martin Ravallion, "An econometric method of correcting for unit nonresponse bias in surveys," *Journal of Econometrics*, January 2007, *136* (1), 213–235.

Lara, Jaime, "Remittances as an Insurance Mechanism in the Labor Market," *Journal of Labor Research*, 2016, *37* (3), 368–387.

Mora, Ricardo and Iliana Reggio, "Alternative diff-in-diffs estimators with several pretreatment periods," *Econometric Reviews*, May 2019, *38* (5), 465–486. Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/07474938.2017.1348683.

NBS and WB, "Nigeria COVID-19 National Longitudinal Phone Survey (COVID-19 NLPS) Baseline," 2020.

Nikoloski, Zlatko, Luc Christiaensen, and Ruth Hill, "Household shocks and coping mechanism: evidence from Sub-Saharan Africa," *Publisher: World Bank*, 2018.

Olden, Andreas and Jarle Møen, "The triple difference estimator," *The Econometrics Journal*, September 2022, *25* (3), 531–553.

Ratha, Dilip K., Eung Ju Kim, Sonia Plaza, and Ganesh Seshan, "Resilience: COVID-19 crisis through a migration lens," *Migration and Development Brief*, 2021, *34*.

—, **Supriyo De, Eung Ju Kim, and Nadege Desiree Yameogo**, "Phase II: COVID-19 crisis through a migration lens," *Migration and Development Brief*, 2020, *33.*

Roth, Jonathan, Pedro H. C. Sant'Anna, Alyssa Bilinski, and John Poe, "What's trending in difference-in-differences? A synthesis of the recent econometrics literature," *Journal of Econometrics*, August 2023, *235* (2), 2218–2244.

Rudin-Rush, Lorin, Jeffrey D. Michler, Anna Josephson, and Jeffrey R. Bloem, "Food insecurity during the first year of the COVID-19 pandemic in four African countries," *Food Policy*, 2022, *111*, 102306.

Smith, Michael D., Matthew P. Rabbitt, and Alisha Coleman-Jensen, "Who are the World's Food Insecure? New Evidence from the Food and Agriculture Organization's Food Insecurity Experience Scale," *World Development*, May 2017, *93*, 402–412.

Tabe-Ojong, Martin Paul Jr., Emmanuel Nshakira-Rukundo, and Bisrat Haile Gebrekidan, "COVID-19 and food insecurity in Africa: A review of the emerging empirical evidence," *European Review of Agricultural Economics*, July 2023, *50* (3), 853–878.

Tapsoba, Tebkieta Alexandra, "Remittances and households' livelihood in the context of Covid-19: Evidence from Burkina Faso," *Journal of International Development*, 2021, *n/a* (n/a).

Wing, Coady, Kosali Simon, and Ricardo A. Bello-Gomez, "Designing Difference in Difference Studies: Best Practices for Public Health Policy Research," *Annual Review of Public Health*, 2018, *39* (1), 453–469. _eprint: https://doi.org/10.1146/annurev-publhealth-040617-013507.

Wooldridge, Jeffrey M., "Fixed-Effects and Related Estimators for Correlated Random-Coefficient and Treatment-Effect Panel Data Models," *The Review of Economics and Statistics*, May 2005, *87* (2), 385–390. _eprint: https://direct.mit.edu/rest/article-pdf/87/2/385/1614013/0034653053970320.pdf.

—, "Inverse probability weighted estimation for general missing data problems," *Journal of Econometrics*, December 2007, *141* (2), 1281–1301.

Yang, Dean and HwaJung Choi, "Are remittances insurance? Evidence from rainfall shocks in the Philippines," *The World Bank Economic Review*, 2007, *21* (2), 219–248.

Appendices

A Proofs

A.1 Identification of the target parameter β_1

Theorem 1 *Under assumptions 1 and 2, the target parameter $\beta_1 = ATET^{R=1} - ATET^{R=0}$ is identified.*

Proof.

Recall that the target parameter is $\beta_1 = ATET^{R=1} - ATET^{R=0}$. Starting from the definition, each $ATET^{R=j}, j = 0, 1$ can be expressed as function of DiD and the two sources of bias. For the sake of the presentation, we drop the household subscript h in the following:

$$\begin{aligned}
ATET^{R=1} &= E\left[y^1_{Post} \mid shock = 1, R = 1\right] - E\left[y^0_{Post} \mid shock = 1, R = 1\right] \\
&= E\left[y^1_{Post} - y^0_{Pre} \mid shock = 1, R = 1\right] - E\left[y^0_{Post} - y^0_{Pre} \mid shock = 1, R = 1\right] \\
&= E\left[y^1_{Post} - y^0_{Pre} + y^1_{Pre} - y^1_{Pre} \mid shock = 1, R = 1\right] - E\left[y^0_{Post} - y^0_{Pre} \mid shock = 1, R = 1\right] \\
&= E\left[y^1_{Post} - y^1_{Pre} \mid shock = 1, R = 1\right] + E\left[y^1_{Pre} - y^0_{Pre} \mid shock = 1, R = 1\right] - \\
&\quad E\left[y^0_{Post} - y^0_{Pre} \mid shock = 1, R = 1\right] \\
&= E\left[y^1_{Post} - y^1_{Pre} \mid shock = 1, R = 1\right] + E\left[y^1_{Pre} - y^0_{Pre} \mid shock = 1, R = 1\right] - \\
&\quad E\left[y^0_{Post} - y^0_{Pre} \mid shock = 1, R = 1\right] + E\left[y^0_{Post} - y^0_{Pre} \mid shock = 0, R = 1\right] - \\
&\quad E\left[y^0_{Post} - y^0_{Pre} \mid shock = 0, R = 1\right] \\
&= E\left[y^1_{Post} - y^1_{Pre} \mid shock = 1, R = 1\right] - E\left[y^0_{Post} - y^0_{Pre} \mid shock = 0, R = 1\right] - \\
&\quad \left(E\left[y^0_{Post} - y^0_{Pre} \mid shock = 1, R = 1\right] - E\left[y^0_{Post} - y^0_{Pre} \mid shock = 0, R = 1\right]\right) + \\
&\quad E\left[y^1_{Pre} - y^0_{Pre} \mid shock = 1, R = 1\right] \\
&= DiD^{R=1} - \underbrace{\left(E\left[\Delta y^0 \mid shock = 1, R_{2019} = 1\right] - E\left[\Delta y^0 \mid shock = 0, R_{2019} = 1\right]\right)}_{\text{Non-parallel trends bias } (R=1)} + \\
&\quad \underbrace{E\left[y^1_{Pre} - y^0_{Pre} \mid shock = 1, R = 1\right]}_{\text{Anticipation bias } (R=1)}
\end{aligned} \tag{12}$$

Analogously, we get a similar expression of the $ATET$ for the sub-sample of households not receiving any remittances:

$$\begin{aligned}
ATET^{R=0} = DiD^{R=0} &- \underbrace{\left(E\left[\Delta y^0 \mid shock = 1, R = 0\right] - E\left[\Delta y^0 \mid shock = 0, R = 0\right]\right)}_{\text{Non-parallel trends bias } (R=0)} + \\
&\underbrace{E\left[y^1_{Pre} - y^0_{Pre} \mid shock = 1, R = 0\right]}_{\text{Anticipation bias } (R=0)}
\end{aligned} \tag{13}$$

Combining 12 and 13 yields:

$$\begin{aligned}
\beta_1 = DiD^{R=1} - DiD^{R=0} &- \underbrace{\left(E\left[\Delta y^0 \mid Shock = 1, R = 1\right] - E\left[\Delta y^0 \mid Shock = 0, R = 1\right]\right)}_{\text{Non-parallel trends bias for the sub-sample } (R=1)} + \\
&\underbrace{\left(E\left[\Delta y^0 \mid Shock = 1, R = 0\right] - E\left[\Delta y^0 \mid Shock = 0, R = 0\right]\right)}_{\text{Non-parallel trends bias for the sub-sample } (R=0)} + \\
&\underbrace{E\left[y^1_{Pre} - y^0_{Pre} \mid Shock = 1, R = 1\right]}_{\text{Anticipation bias for the sub-sample } (R=1)} - \underbrace{E\left[y^1_{Pre} - y^0_{Pre} \mid Shock = 1, R = 0\right]}_{\text{Anticipation bias for the sub-sample } (R=0)}
\end{aligned} \tag{14}$$

$DiD^{R=1} - DiD^{R=0}$ is identified from the data sampling process. Thus, β_1 is identified if assumptions 1 and 2 hold, i.e. both biases are zero.

■

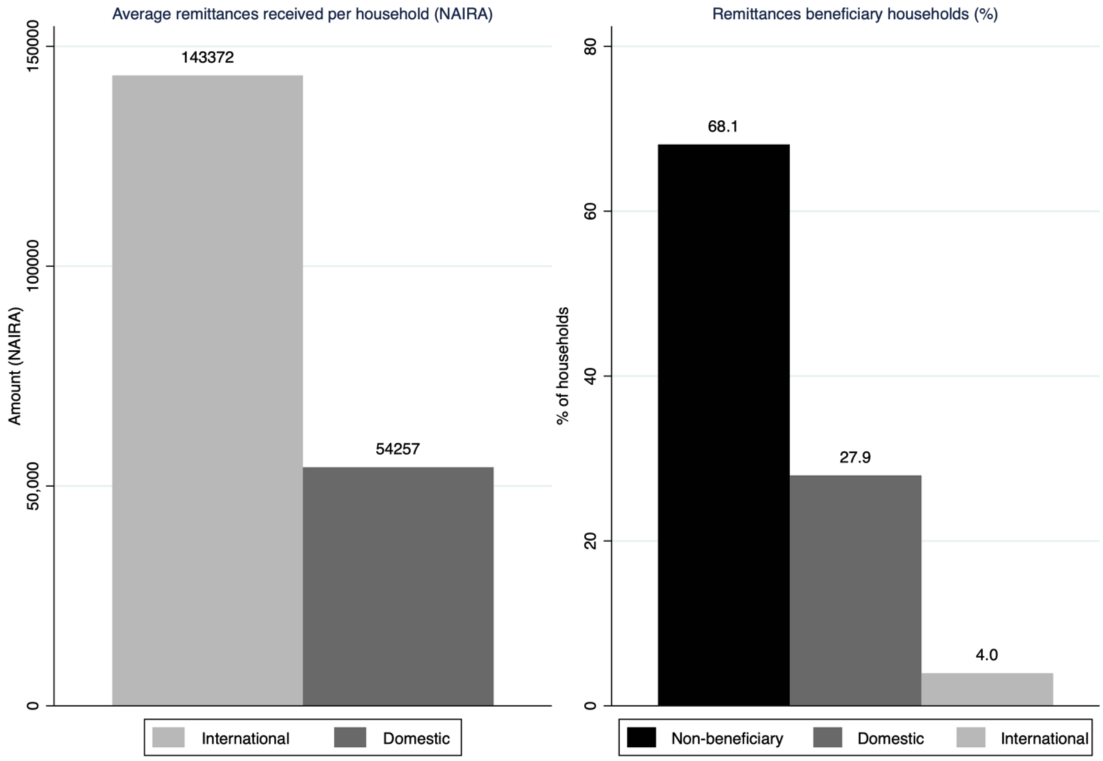
B Supplemental tables and graphs

Table B.1: Pre-COVID-19 versus Post-COVID-19 sample: non-response bias and representativeness

Characteristic	**Pre-COVID-19 sample**		**Post-COVID-19 sample**	
	Unweighted	Weighted	Unweighted	Weighted
	(1)	(2)	(3)	(4)
Sample size (successful interviews)	4976.0	-	1950.0	-
Average household size (family size)	5.3	5.5	5.5	5.5
Household head characteristics				
Female head (%)	20.1	18.6	19.1	18.6
Age of head (years)	49.8	48.8	49.4	49.2
Literate (%)	72.8	74.4	79.4	74.4
Education level of head (%)				
None (or no school)	22.2	20.5	15.8	20.6
Primary	24.6	24.1	24.6	24.1
Junior secondary	4.3	4.0	4.4	4.0
Senior secondary	23.3	23.9	26.7	23.9
Tertiary	16.7	16.0	21.7	16.0
Asset ownership (%)				
Regular mobile phone (Yes/No)	66.1	65.4	71.1	66.0
Smartphone (Yes/No)	26.5	26.7	32.9	26.8
Television (Yes/No)	45.5	45.1	55.3	48.1
Refrigerator (Yes/No)	18.0	17.3	23.4	18.7
Car (Yes/No)	9.8	9.6	12.5	9.4
Power generator (Yes/No)	26.3	24.6	32.4	24.4

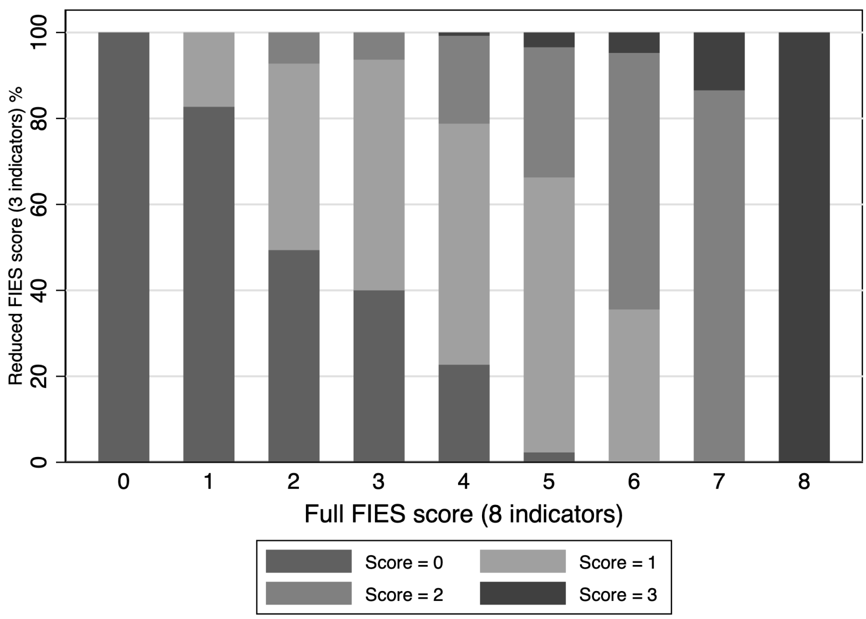
Source : GHS-Panel wave 4 (2018/2019), COVID-19 NLPS 2020, and authors' calculations.
Note: All variables are measured in harvest time (Jan - Fab 2019)

Figure B.1: Remittance distribution by origin (2018-2019)



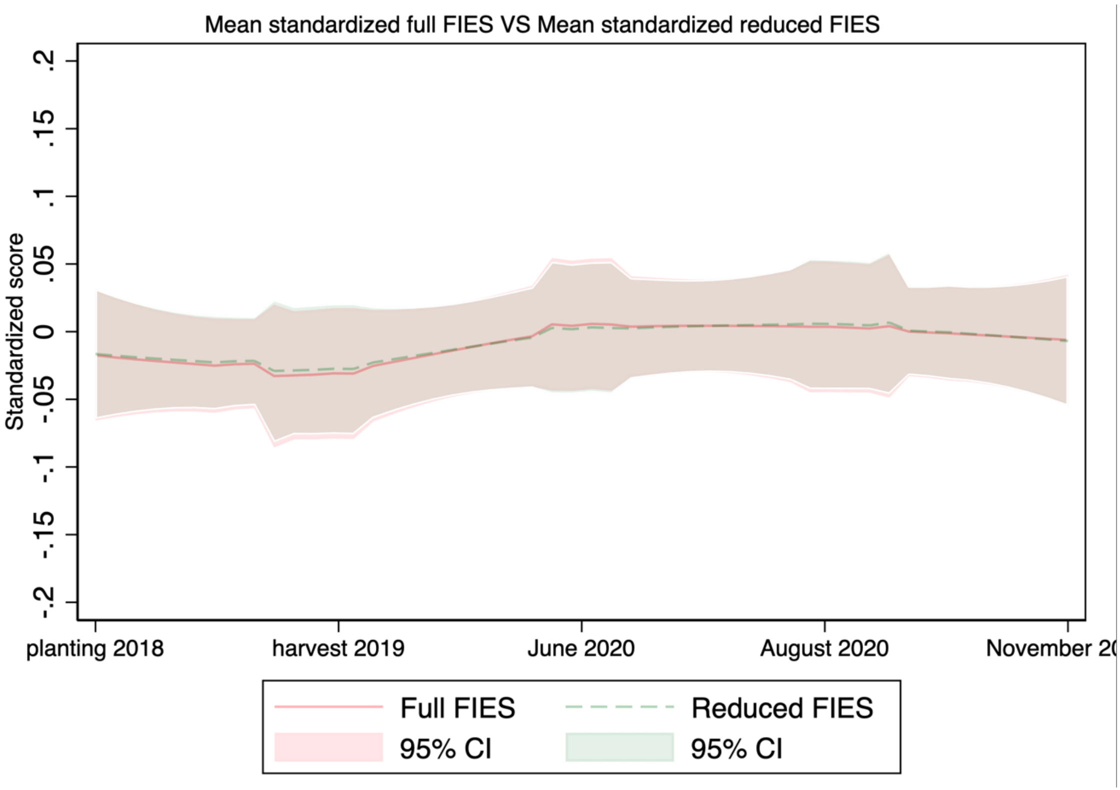
Source: Wave 4 of the 2018-2019 GHS panel, and authors' calculations.
Note: Estimates are weighted to account for non-contact and non-response.

Figure B.2: Correlation between the reduced FIES with the full FIES



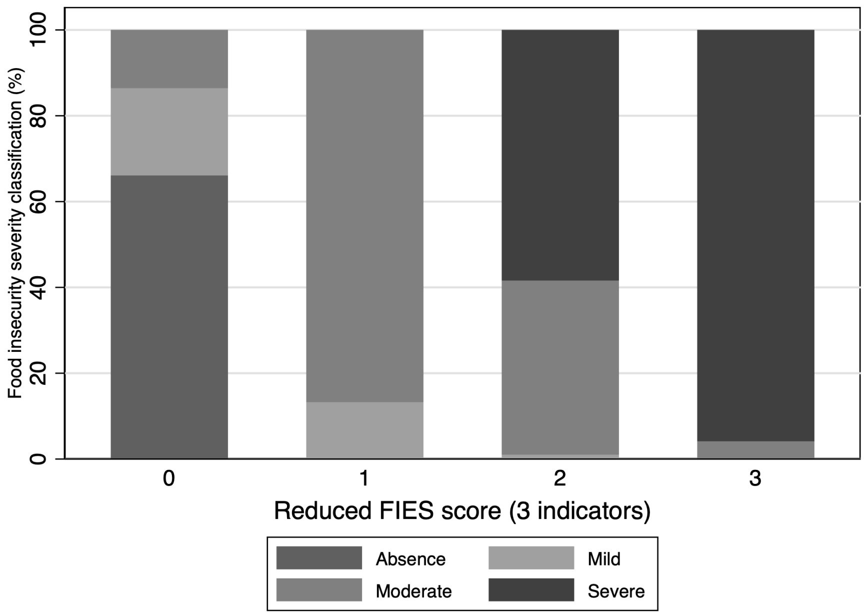
Source: Authors' calculations based on round 2 of COVID-19 NLPS 2020 (June 2020).
Note: Reduced FIES represents our preferred 3-indicators-based food insecurity variable, while the full FIES is the 8-indicators-based food insecurity measure. A score of 0 means the absence of food insecurity, while a score of 8 indicates the highest degree of severity for the full FIES. Most households with a lower score of the reduced FIES fall at the bottom of the full FIES distribution, and the other way around with the households with a higher score which are rather concentrated at the top FIES distribution.

Figure B.3: Comparison between full FIES and reduced FIES



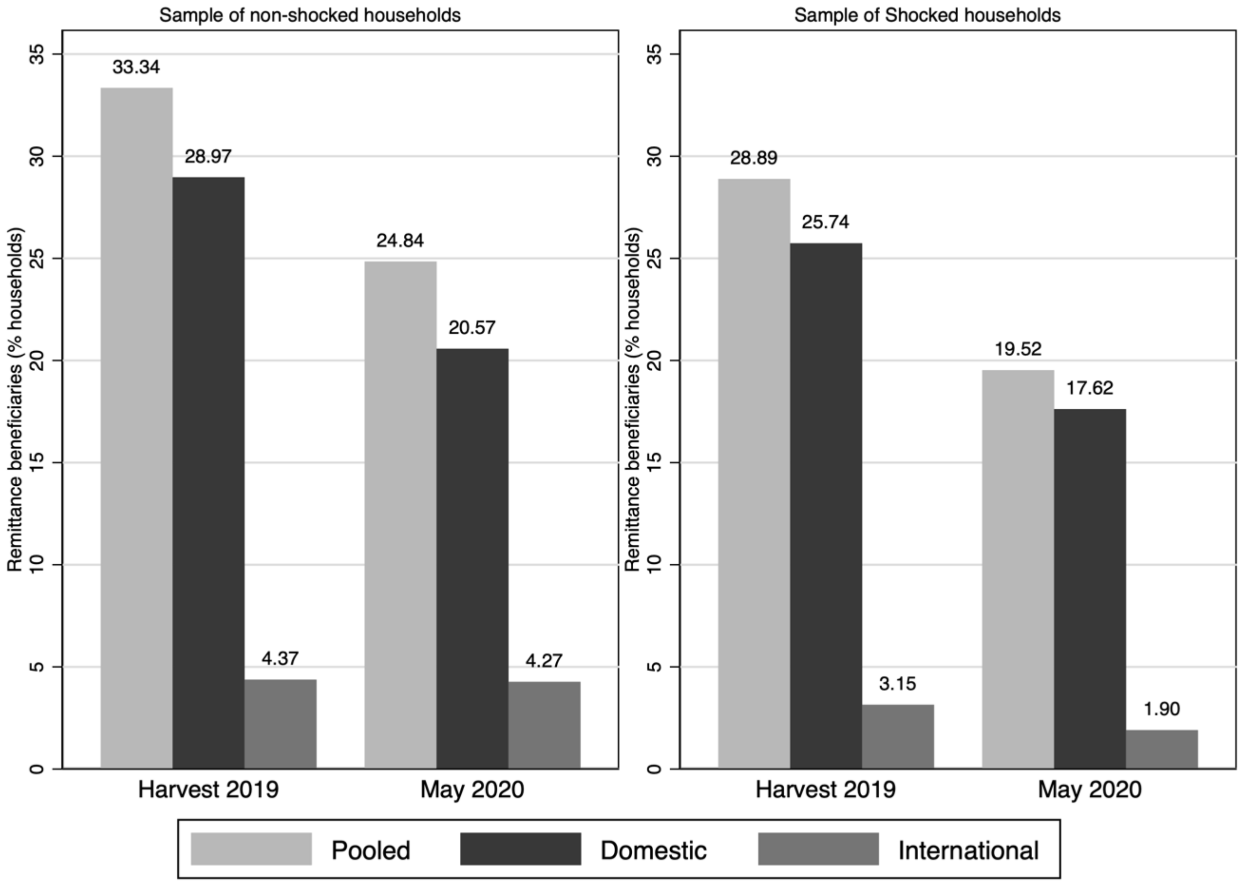
Source: Wave 4 of the 2018-2019 GHS, COVID-19 NLPS 2020, and authors' calculations.
Note: April-May 2020 is missing because the food security module lacks information to compute the full FIES. We proceed to a mean standardization of both variables that accounts for differences in scale. Such a normalization allows a comparison of both measures over time in terms of deviation from the mean and confirms the correlation between the two variables.

Figure B.4: Mapping the reduced FIES score with the food insecurity classification following (Cafiero et al., 2018)



Source:Authors' calculations based on round 2 of COVID-19 NLPS 2020 (June 2020).
Note: Reduced FIES represents our preferred 3-indicators-based food insecurity variable. Based on the raw full FIES score, households with a score of 0 are classified as not concerned by any food insecurity issues. They are experiencing mild food insecurity if they have a score between 1 and 3. Households are considered "moderate food insecurity" when the score falls between 4 to 6 and "severe food insecurity" in case the score is above 7.

Figure B.5: Likelihood of receiving remittances before and after the shock



Source: Wave 4 of the 2018-2019 GHS panel, COVID-19 NLPS 2020, and authors' calculations.
Note: Estimates are weighted to account for non-contact and non-response.

Table B.2: Plausibility of assumption 1: statistical tests using the reduced FIES

Dependent variable Food insecurity score	(1)	(2)
Lockdown from business closure	-0.02 (0.09)	-0.02 (0.09)
All remittances 2018 - 2019 × Lockdown from business closure	-0.01 (0.13)	–
International remittances 2018 - 2019 × Lockdown from business closure	–	-0.56 (0.34)
Domestic remittances 2018 - 2019 × Lockdown from business closure	–	0.06 (0.14)
Time fixed effects	Yes	Yes
Household fixed effects	Yes	Yes
Constant	0.96*** (0.02)	0.96*** (0.02)
Observations	3900	3900
Adjusted R^2	0.097	0.100

Robust standard errors in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$;
Note: The food insecurity score baseline Mean corresponds to
the weighted average over the 2018 planting and 2019 harvest seasons.

Table B.3: Parallel trend hypothesis in the overall sample: statistical tests using regression analysis

Dependent variable: Food insecurity score	Reduced FIES	Alternative FIES
	Non-Shocked: N = 1225; Shocked: N = 725	Non-Shocked: N = 309; Shocked: N = 184
	(1)	(2)
	Time (Ref = Planting 2018)	Time (Ref = Planting 2010)
Harvest 2011	_	-0.59*** (0.14)
Planting 2012	_	0.21 (0.21)
Harvest 2013	_	0.11 (0.20)
Planting 2015	_	0.82*** (0.25)
Harvest 2016	_	0.38* (0.20)
Harvest 2019	-0.37*** (0.05)	_
Business closure (Yes/No) × Time	Ref: Business closure = No; Time = Planting 2018	Ref: Business closure = No; Time = Planting 2010
Yes × Harvest 2011	_	-0.24 (0.20)
Yes × Planting 2012	_	0.18 (0.35)
Yes × Harvest 2013	_	-0.04 (0.33)
Yes × Planting 2015	_	-0.44 (0.36)
Yes × Harvest 2016	_	-0.10 (0.32)
Yes × Harvest 2019	-0.02 (0.08)	_
Constant	0.96*** (0.02)	1.56*** (0.11)
Observations	3900	2958
Adjusted R^2	0.098	0.059
Sample	Planting 2018, Harvest 2019.	Planting 2010, Harvest 2011, Planting 2011, Harvest 2012, Planting 2015, Harvest 2016.

Robust standard errors in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table B.4: Plausibility of assumption 1: statistical tests using the alternative FIES

Dependent variable: Food insecurity score	Alternative FIES
	Non-Shocked: N = 309; Shocked: N = 184
Business closure (Yes/No) × Time	Ref: Business closure = No; Time = Planting 2010
Yes × Harvest 2011	-0.16
	(0.22)
Yes × Planting 2012	0.32
	(0.38)
Yes × Harvest 2013	0.06
	(0.34)
Yes × Planting 2015	-0.29
	(0.38)
Yes × Harvest 2016	-0.00
	(0.35)
Business closure (Yes/No) × All Remittances 2018-2019 × Time	Ref: Business closure = No; All Remittances = No; Time = Planting 2010
Business closure = Yes × All Remittances = Yes × Harvest 2011	-0.29
	(0.31)
Business closure = Yes × All Remittances = Yes × Planting 2012	-0.48
	(0.69)
Business closure = Yes × All Remittances = Yes × Harvest 2013	-0.35
	(0.67)
Business closure = Yes × All Remittances = Yes × Planting 2015	-0.54
	(0.63)
Business closure = Yes × All Remittances = Yes × Harvest 2016	-0.33
	(0.58)
Constant	1.56***
	(0.11)
Observations	2958
Adjusted R^2	0.058
Sample	Planting 2010, Harvest 2011, Planting 2011, Harvest 2012, Planting 2015, Harvest 2016.

Robust standard errors in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table B.5: Remittances status matrix transition between harvest 2019 and May 2020

	Remittance status in May 2020			
Remittance status in harvest 2019	No remittances	International	Domestic	Pooled
No remittances	1066	28	209	1303
	81.8%	2.1%	16.0%	100.0%
International	48	30	19	97
	49.5%	30.9%	19.6%	100.0%
Domestic	368	25	157	550
	66.9%	4.5%	28.5%	100.0%
Pooled	1482	83	385	1950
	76.0%	4.3%	19.7%	100.0%

Table B.6: Capital channel hypothesis test by origin of remittances

	Type capital			
	Pooled capital	Formal financial services	Informal financial services	Livestock ownership, rental earnings
	(1)	(2)	(3)	(4)
Lockdown business from closure	0.29***	0.29***	0.27***	0.25**
	(0.10)	(0.10)	(0.10)	(0.10)
Business closure x Remittances group (Ref: Closure = No; Remittance = No)				
Closure = Yes × (Capital = Yes, Intl remit. = Yes)	-0.70***	-0.90***	0.34	-0.96***
	(0.27)	(0.21)	(0.40)	(0.28)
Closure = Yes × (Capital = Yes, Dom. remit. = Yes)	-0.28**	-0.35**	-0.01	-0.78***
	(0.13)	(0.14)	(0.18)	(0.20)
Closure = Yes × (Capital = No, Intl remit. = Yes)	-0.03	-0.03	-0.03	-0.03
	(0.08)	(0.08)	(0.08)	(0.08)
Closure = Yes × (Capital = No, Dom. remit. = Yes)	-0.28	-0.28	-0.28	-0.28
	(0.34)	(0.34)	(0.34)	(0.34)
Time fixed effects	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes
Constant	0.96***	0.94***	0.93***	0.94***
	(0.02)	(0.02)	(0.03)	(0.03)
Observations	5850	5457	4866	4587
Adjusted R^2	0.245	0.245	0.261	0.261

Robust standard errors in parentheses;
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table B.7: Sample distribution over rounds

Round	Non-shocked	Shocked	Total
May-20	1233	730	1963
%	63	37	100
Jun-20	1656	174	1830
%	90	10	100
Jul-20	1728	66	1794
%	96	4	100
Aug-20	1762	36	1798
%	98	2	100

Table B.8: Robustness of mitigating effect of remittances to the control for current remittances

Dependent variable Food insecurity score	(1)	(2)	(3)
Lockdown from business closure	0.20***	0.28***	0.28***
	(0.06)	(0.07)	(0.07)
All remittances 2018-2019 × Lockdown from business closure	–	-0.27**	
		(0.11)	
International remittances 2018-2019 × Lockdown from business closure	–	–	-0.50**
			(0.23)
Domestic remittances 2018-2019 × Lockdown from business closure	–	–	-0.23**
			(0.11)
Time fixed effects	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes
Constant	0.89***	0.89***	0.89***
	(0.02)	(0.02)	(0.02)
Observations	4446	4446	4446
Adjusted R^2	0.255	0.257	0.257

Robust standard errors in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$;
Note: Regression is based on a reduced sample excluding
households receiving remittances in May 2020.
Estimates are unweighted.

Table B.9: Robustness of mitigating effect of remittances to the control for current safety nets

Dependent variable Food insecurity score	(1)	(2)	(3)
Lockdown from business closure	0.20**	0.31***	0.31***
	(0.09)	(0.10)	(0.10)
All remittances 2018-2019 × Lockdown from business closure	–	-0.39***	–
		(0.13)	
International remittances 2018-2019 × Lockdown from business closure	–	–	-0.78***
			(0.28)
Domestic remittances 2018-2019 × Lockdown from business closure	–	–	-0.34**
			(0.14)
Time fixed effects	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes
Constant	0.92***	0.92***	0.92***
	(0.03)	(0.03)	(0.03)
Observations	4923	4923	4923
Adjusted R^2	0.253	0.256	0.257

Robust standard errors in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$;
Note: Regression is based on a reduced sample excluding
households receiving remittances in May 2020.
Estimates are unweighted.

Table B.10: Details about questions used to construct our primary variables

Variables	Questionnaire used	Questions considered
COVID-19 employment shock	*COVID-19 NLPS 2020 baseline household questionnaire*	**1. Were you working before mid-March?** (Yes/No) **2. What was the main reason you stopped working?** • Business/Office closed due to coronavirus legal restrictions • Not able to go to farm due to movement restrictions
Remittances	*Nigeria General Household Survey - Panel Wave 4, 2018-2019, Post-Harvest Community Questionnaire*	**1. In the past 12 months, did [NAME] receive any of the following assistance from a non-household member?** (Yes/No) • FROM ABROAD A. Monetary assistance B. In-kind assistance • FROM WITHIN NIGERIA A. Monetary assistance B. In-kind assistance
Food insecurity	• *COVID-19 NLPS 2020 baseline household questionnaire* • *Nigeria General Household Survey - Panel Wave 4, 2018-2019, Post-Harvest Community Questionnaire*.	**1. You, or any other adult in your household, had to skip a meal because there was not enough money or other resources to get food?** (Yes/No) **2. Your household ran out of food because of a lack of money or other resources?** (Yes/No) **3. You, or any other adult in your household, went without eating for a whole day because of a lack of money or other resources?** (Yes/No)

Table B.11: Capital channel hypothesis before the pandemic: A falsification test

	Type of capital			
	Pooled capital	Formal financial services	Informal financial services	Livestock ownership, rental earnings
	(1)	(2)	(3)	(4)
Lockdown from business closure	-0.01	-0.06	-0.01	0.01
	(0.15)	(0.15)	(0.16)	(0.16)
Business closure x Remittances group (Ref: Closure = No; Capital = No; Remittances = No)				
Closure = Yes × (Capital = Yes, Remittances = Yes)	-0.07	-0.05	-0.09	0.14
	(0.19)	(0.21)	(0.23)	(0.30)
Closure = Yes × (Capital = Yes, Remittances = No)	-0.01	0.02	-0.01	-0.05
	(0.16)	(0.17)	(0.18)	(0.21)
Closure = Yes × (Capital = No, Remittances = Yes)	0.34	0.34	0.34	0.34
	(0.22)	(0.22)	(0.22)	(0.22)
Time fixed effects	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes
Constant	0.96***	0.97***	0.92***	1.02***
	(0.02)	(0.02)	(0.02)	(0.03)
Observations	3900	3114	2088	1330
Adjusted R^2	0.098	0.082	0.097	0.098

Robust standard errors in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B.12: Correlation between capital ownership and remittances in 2019

	(1) Pooled capital	(2) Formal financial services	(3) Informal financial services	(4) Livestock ownership, rental earning
Remittances in 2018 - 2019 (Ref = No)				
International remittances = Yes	0.08***	0.10***	-0.03	0.12**
	(0.03)	(0.03)	(0.04)	(0.05)
Domestic remittances = Yes	0.04**	0.00	0.04*	0.05**
	(0.02)	(0.02)	(0.02)	(0.02)
Household head demographic characteristics				
Age	-0.00	-0.00	-0.00	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Male	-0.05	0.01	-0.07*	-0.00
	(0.04)	(0.04)	(0.04)	(0.03)
Married	0.07**	0.03	0.07**	0.03
	(0.03)	(0.04)	(0.03)	(0.03)
Household head education level (Ref = None)				
Primary	0.08**	0.12***	0.00	0.07***
	(0.03)	(0.03)	(0.04)	(0.03)
Secondary	0.17***	0.34***	-0.08**	0.03
	(0.03)	(0.03)	(0.04)	(0.03)
Higher	0.25***	0.53***	-0.22***	0.04
	(0.03)	(0.04)	(0.04)	(0.04)
Other	0.15***	0.30***	-0.12***	-0.00
	(0.04)	(0.04)	(0.04)	(0.03)
Household demographic composition				
Number of children aged 0 - 15	0.01	0.01	0.01**	-0.00
	(0.00)	(0.00)	(0.01)	(0.00)
Number of people aged 16-65	0.03***	0.05***	0.02**	0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Number of people aged 65 and over	0.05	0.09**	0.04	0.03
	(0.03)	(0.04)	(0.04)	(0.04)
Area of residence (Ref= Urban)				
Rural	-0.10***	-0.20***	0.01	0.04*
	(0.02)	(0.02)	(0.03)	(0.02)
State fixed effects	Yes	Yes	Yes	Yes
Constant	0.67***	0.47***	0.23***	-0.13**
	(0.07)	(0.07)	(0.07)	(0.06)
Observations	1950	1950	1950	1950
Adjusted R^2	0.120	0.286	0.103	0.033

Robust standard errors in parentheses;
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table B.13: Details about the construction of the 8 indicators-based FIES (full FIES)

<table>
<tr><th>Question considered:
During the last 30 days, was there a time when:</th><th>Dummy variable created</th><th>Eight indicators-based FIES (full FIES)</th></tr>
<tr><td>Question A: You, or any other adult in your household were worried about not having enough food to eat because of lack of money or other resources? (Yes/No)</td><td>Dum A= 1 if Question A=Yes and 0 otherwise</td><td rowspan="8">Full FIES obtained by aggregating Dum A to Dum I.

No food insecurity if Full FIES=0

Mild food insecurity if Full FIES ranges between 1 and 3.

Moderate food insecurity if Full FIES ranges between 4 and 6.

Severe food insecurity if Full FIES is greater than 7.</td></tr>
<tr><td>Question B: You, or any other adult in your household, were unable to eat healthy and nutritious/preferred foods because of a lack of money or other resources? (Yes/No)</td><td>Dum B= 1 if Question A=Yes and 0 otherwise</td></tr>
<tr><td>Question C: You, or any other adult in your household, ate only a few kinds of foods because of a lack of money or other resources? (Yes/No)</td><td>Dum C= 1 if Question A=Yes and 0 otherwise</td></tr>
<tr><td>Question D: You, or any other adult in your household, had to skip a meal because there was not enough money or other resources to get food? (Yes/No)</td><td>Dum D= 1 if Question A=Yes and 0 otherwise</td></tr>
<tr><td>Question E: You, or any other adult in your household, ate less than you thought you should because of a lack of money or other resources? (Yes/No)</td><td>Dum E= 1 if Question A=Yes and 0 otherwise</td></tr>
<tr><td>Question F: Your household ran out of food because of a lack of money or other resources? (Yes/No)</td><td>Dum F= 1 if Question A=Yes and 0 otherwise</td></tr>
<tr><td>Question G: You, or any other adult in your household, were hungry but did not eat because there was not enough money or other resources for food? (Yes/No)</td><td>Dum G= 1 if Question A=Yes and 0 otherwise</td></tr>
<tr><td>Question H: You, or any other adult in your household, went without eating for a whole day because of a lack of money or other resources? (Yes/No)</td><td>Dum H= 1 if Question A=Yes and 0 otherwise</td></tr>
</table>

Table B.14: Details about the construction of the alternative FIES

Question considered: *In the past 7 days, how many days you or someone in your household had to: (if no days, write "0")*	**Dummy variable created**	**Alternative FIES**
Question A: Rely on less preferred foods ?	Dum A= 1 if Question A≥1 and 0 otherwise	Alternative FIES obtained by summing up Dum A to Dum I. Alternative FIES varies between 0 and 9, with the score 9 being the most severe.
Question B: Limit the variety of foods eaten?	Dum B= 1 if Question B≥1 and 0 otherwise	
Question C: Limit portion size at meal-times?	Dum C= 1 if Question C≥1 and 0 otherwise	
Question D: Reduce number of meals eaten a day?	Dum D= 1 if Question D≥1 and 0 otherwise	
Question E: Restrict consumption by adults in order for small children to eat?	Dum E= 1 if Question E≥1 and 0 otherwise	
Question F: Borrow food or rely on help from a friend relative?	Dum F= 1 if Question F≥1 and 0 otherwise	
Question G: Have no food any kind in your household?	Dum G= 1 if Question G≥1 and 0 otherwise	
Question H: Go to sleep at night hungry because there is not enough food?	Dum H= 1 if Question H≥1 and 0 otherwise	
Question I: Go a whole day and night without eating anything?	Dum I= 1 if Question I≥1 and 0 otherwise	

Table B.15: Results of the IFE model for untreated potential outcomes

	No remittances ($R = 0$)	Remittance beneficiaries ($R = 1$)		
		All	International	Domestic
IFE	0.64**	0.99*	0.28	1.08**
	0.30	0.57	1.31	0.51
Tertiary educated adult (%)	-0.23	-0.06	0.24	-0.08
	0.23	0.30	0.59	0.36
Male adult (%)	0.15	-0.67*	-0.94	-0.72
	0.18	0.40	0.75	0.45
Rural (dummy)	-0.01	0.02	-0.26	0.04
	0.11	0.15	0.43	0.17
Land area (ha)	0.09***	0.14*	0.02	0.13*
	0.03	0.07	0.43	0.08
Constant	0.74***	0.94***	0.98**	0.88***
	0.11	0.27	0.37	0.29
N	788.00	403.00	60	343
Weak IV F-stat	3.80	1.50	0.21	1.9

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$;

Note: IFE reports the estimated value of $F^*_{j3}, j = 1, 0$.

Weak IV F-stat reports the F-statistic from the first stage regression.

C Online appendix: additional robustness checks

C.1 Robustness to definitions and weights

We test the robustness of our results to the correction of attrition using sampling weights. We estimate the mitigating effect of remittances without weighting (Table C.1). The coefficients are roughly the same, although small differences in their expected direction are noted. We find that the mitigation effect of remittances is slightly less pronounced than in weighted estimates (Table 2). For instance, we find that the mitigating impact of international remittances is -0.60 (Table C.1, column 3) when sampling weights are ignored versus -0.69 when they are accounted for (Table 2, column 3). This result suggests that the mitigating effect of remittances is likely to be biased downward when attrition is not corrected, which is expected. As previously mentioned, attrition is likely to be driven by positive selection. Table B.1 indicates that more educated and wealthier households are more likely to have been contacted and included in the post-COVID-19 survey sample. The mitigating effect of remittances is likely to be underestimated based on a sample of wealthier households because those households are expected to be better able to cope with adverse shocks. Although our results seem robust to the correction of attrition, potential unobservables may be in play. However, we are confident that our results remain unchanged, given that our estimates represent a lower bound.

Table C.1: Mitigating effect of remittances: Robustness to sampling weights

Dependent variable Food insecurity score	(1)	(2)	(3)
Lockdown from business closure	0.20^{***}	0.29^{***}	0.29^{***}
	(0.06)	(0.06)	(0.06)
All remittances 2018 - 2019 × Lockdown from business closure	–	-0.29^{***}	
		(0.09)	
International remittances 2018 - 2019 × Lockdown from business closure	–	–	-0.60^{***}
			(0.19)
Domestic remittances 2018 - 2019 × Lockdown from business closure	–	–	-0.24^{**}
			(0.10)
Time fixed effects	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes
Constant	0.88^{***}	0.88^{***}	0.88^{***}
	(0.02)	(0.02)	(0.02)
Observations	5850	5850	5850
Adjusted R^2	0.237	0.239	0.240

Robust standard errors in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
Note: Estimates are unweighted.

We run two additional sensitivity tests of our findings to the food insecurity definition using alternative ways of measuring it. The three indicators used to compute food insecurity scores are likely to be strongly correlated. Similarly to Amare et al. (2021), we compute food insecurity scores using the principal component analysis (PCA) method accounting for this correlation while providing different weights to each indicator. Then, instead of computing an aggregate score, we consider the three indicators separately (Tables C.3 and C.4 in Appendix C). Overall, our results remain qualitatively similar, suggesting remittances have a strong mitigating effect following the shock.

Table C.2: Mitigating effect of remittances: Robustness to shock definition

Dependent variable Food insecurity score	(1)	(2)	(3)	(4)	(5)	(6)
Confirmed cases (log scale)	0.04 (0.03)	0.06*** (0.02)	0.06*** (0.02)	–	–	–
COVID-19 exposure (**Ref = Low**) High	–	–	–	0.15* (0.09)	0.26*** (0.10)	0.26*** (0.10)
Remittances × Confirmed cases						
All remittances 2018 - 2019 × **Confirmed cases (log scale)**	–	-0.07*** (0.02)	–	–	–	–
International remittances 2018 - 2019 × **Confirmed cases (log scale)**	–	–	-0.10*** (0.03)	–	–	–
Domestic remittances 2018 - 2019 × **Confirmed cases (log scale)**	–	–	-0.06*** (0.02)	–	–	–
Remittances × COVID-19 exposure (Ref = Low)						
All remittances 2018 - 2019 × **COVID-19 exposure = High**	–	–	–	–	-0.33*** (0.10)	–
International remittances 2018 - 2019 × **COVID-19 exposure = High**	–	–	–	–	–	-0.46*** (0.16)
Domestic remittances 2018 - 2019 × **COVID-19 exposure = High**	–	–	–	–	–	-0.30*** 0.10
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.96*** (0.02)	0.96*** (0.02)	0.93*** (0.03)	0.95*** (0.02)	0.96*** (0.02)	0.96*** (0.02)
Observations	5850	5850	5850	5850	5850	5850
Adjusted R^2	0.241	0.248	0.248	0.241	0.246	0.246

Robust standard errors in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table C.3: Mitigating effect of remittances: Robustness to food security definition (using PCA method)

Dependent variable Food insecurity score	(1)	(2)	(3)
Lockdown from business closure	0.24**	0.36***	0.36***
	(0.10)	(0.12)	(0.12)
All remittances 2018 - 2019 × Lockdown business closure	–	-0.40***	–
		(0.15)	
International remittances 2018 - 2019 × Lockdown business closure	–	–	-0.85***
			(0.31)
Domestic remittances 2018 - 2019 × Lockdown business closure	–	–	-0.35**
			(0.16)
Time fixed effects	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes
Constant	-0.31***	-0.31***	-0.31***
	(0.03)	(0.03)	(0.03)
Observations	5850	5850	5850
Adjusted R^2	0.241	0.244	0.244
Food Insecurity Score Baseline Mean		-0.59	

Robust standard errors in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Note: The food insecurity score baseline mean corresponds to the weighted average over the planting 2018 and harvest 2019 periods.

Table C.4: Mitigating effect of remittances: Robustness to food insecurity definition

Dependent variable	Likelihood to skip a meal		Likelihood to run out of food		Likelihood to not eat for a whole day	
	(1)	(2)	(3)	(4)	(5)	(6)
Lockdown from business closure	0.11***	0.11***	0.07*	0.07*	0.10**	0.10**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
All remittances 2018 - 2019 × Lockdown business closure	-0.10*	–	-0.11*	–	-0.13**	–
	(0.05)		(0.06)		(0.06)	
International remittances 2018 - 2019 × Lockdown business closure	–	-0.24*	–	-0.29	–	-0.16
		(0.12)		(0.20)		(0.15)
Domestic remittances 2018 - 2019 × Lockdown business closure	–	-0.08	–	-0.09	–	-0.12**
		(0.06)		(0.06)		(0.06)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.43***	0.43***	0.39***	0.39***	0.14***	0.14***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	5850	5850	5850	5850	5850	5850
Adjusted R^2	0.255	0.256	0.136	0.137	0.090	0.090

Robust standard errors in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

C.2 Robustness to additional control variables

The literature reports the differential impact of the shock by sector of activity, which may raise some identification concerns. Wage workers seem to be less affected by the COVID-19 shock and lockdown measures (Adams-Prassl et al., 2020; Balde et al., 2020; Amare et al., 2021). One potential explanation for this is that wage workers, especially those working in the formal employment sector, may continue to receive their salary even when businesses are shut down during the pandemic. Wage-related activities are also likely to be performed remotely. In Nigeria, Amare et al. (2021) find that most wage workers are employed in the public sector and non-governmental organizations. Such individuals tend to have long-term contracts, making it easier to access financial services, such as savings and credit, and subsequently more capital. Evidence in the literature also indicates that farmers are less likely to experience a deterioration in food security than workers in other sectors (Kansiime et al., 2020), mostly because farmers rely less on market sources for food. The correlation between these underlying employment factors and capital may represent confounding factors for the capital mechanism test.

We check the robustness of the capital mechanism by controlling for employment activity heterogeneity prior to COVID-19 (Table C.5). We revisit the capital mechanism test by interacting the time variable with three dummy variables that capture household employment activities during the 2019 harvest period. The coefficients associated with the capital mechanism test decrease when accounting for employment heterogeneity. This finding is particularly driven by formal financial services. The interaction effect between capital and remittances declines by approximately 0.04 in absolute value (from -0.42 to -0.38). This may suggest a potential upward bias in the capital mechanism test if employment heterogeneity trends are not accounted for. As anticipated, this decline in coefficients seems to be driven by wage employment. However, the findings remain robust, which validates the capital mechanism.

Table C.5: Capital channel hypothesis test: robustness to control for employment activities

	Type of capital			
	Pooled capital	Formal financial services	Informal financial services	Livestock ownership, rental earnings
	(1)	(2)	(3)	(4)
Lockdown from business closure	0.37*	0.44**	0.41*	0.49**
	(0.22)	(0.22)	(0.22)	(0.23)
Business closure x Remittances group (Ref: Closure = No; Remittances = No)				
Closure = Yes × (Capital = Yes, Remittances = Yes)	-0.39*	-0.48**	-0.12	-0.86***
	(0.23)	(0.24)	(0.26)	(0.27)
Closure = Yes × (Capital = Yes, Remittances = No)	-0.09	-0.19	0.03	0.01
	(0.23)	(0.24)	(0.24)	(0.29)
Closure = Yes × (Capital = No, Remittances = Yes)	-0.41	-0.40	-0.40	-0.42
	(0.38)	(0.38)	(0.37)	(0.38)
Round x Employment activities in 2019 (Ref: Round = Planting 2018, Farm Activities = No)				
Round = Harvest 2019 × Farm activities = Yes	-0.02	-0.09	0.01	-0.07
	(0.07)	(0.09)	(0.10)	(0.13)
Round = May 2020 × Farm Activities = Yes	-0.00	-0.03	-0.06	0.02
	(0.10)	(0.11)	(0.13)	(0.16)
Round = Harvest 2019 × Non-farm Business = Yes	0.06	-0.01	0.01	-0.05
	(0.07)	(0.08)	(0.10)	(0.12)
Round = May 2020 × Non-farm Business = Yes	0.08	0.02	0.02	-0.00
	(0.09)	(0.10)	(0.13)	(0.16)
Round = Harvest 2019 × Wage employment = Yes	-0.14	-0.18*	-0.01	-0.17
	(0.09)	(0.09)	(0.15)	(0.17)
Round = May 2020 × Wage employment = Yes	-0.37***	-0.29**	-0.49***	-0.45**
	(0.11)	(0.11)	(0.17)	(0.23)
Time fixed effects	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes
Constant	0.96***	0.97***	0.92***	1.02***
	(0.02)	(0.03)	(0.03)	(0.04)
Observations	5850	4671	3132	1995
Adjusted R^2	0.251	0.216	0.260	0.221

Robust standard errors in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.6: Sector of activity by shock status (% adults)

Sector	Shocked (1)	Non-shocked (2)	Difference (1) - (2)	t-stat
Agriculture	0.31	0.68	-0.37	-1.32
Mining	0.22	0.01	0.21	2.58***
Manufacturing	0.84	0.64	0.20	0.75
Professional/scientific/technical	0.30	0.52	-0.22	-0.95
Electricity/water/gas/waste	0.81	0.06	0.75	2.92***
Construction	0.88	0.75	0.13	0.43
Transportation	0.40	0.72	-0.32	-1.34
Buying and selling	0.54	0.67	-0.13	-0.58
Financial/insurance/real estate	0.23	0.29	-0.05	-0.27
Personal services	2.43	1.00	1.43	3.30 ***
Education	4.55	2.31	2.25	3.61***
Health	1.29	0.64	0.65	2.05***
Public administration	1.90	2.27	-0.36	-0.77
Other	0.27	0.41	-0.14	-0.71
Observations	725	1225	1950	

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.001$.

We exploit the data at-hand to control for time-varying variables that may be less directly affected by the shock to limit "bad control" issues. To be specific, we introduce controls for changes in socio-demographic characteristics and the education level of the household head, intentionally avoiding variables related to labor market outcomes. Our results remain consistent even after incorporating these additional controls (see Table C.5 in the online appendix). This is expected, given the relatively minor changes in household characteristics observed over such a short time frame (refer to Table C.6 in the online appendix).

Table C.7: Mitigating effect of remittances: control for time-varying observables

Dependent variable Food insecurity score	(1)	(2)	(3)
Lockdown from business closure	0.19**	0.29***	0.29***
	(0.08)	(0.10)	(0.10)
All remittances 2018-2019 × Lockdown from business closure	–	-0.33***	
		(0.12)	
International remittances 2018-2019 × Lockdown from business closure	–	–	-0.72***
			(0.23)
Domestic remittances 2018-2019 × Lockdown from business closure	–	–	-0.29**
			(0.13)
Education of the head (REf= None)			
— Primary	Yes	Yes	Yes
— Secondary	Yes	Yes	Yes
— Vocational education	Yes	Yes	Yes
— University degree	Yes	Yes	Yes
Male (%)	Yes	Yes	Yes
Group age			
— 0 - 5 years	Yes	Yes	Yes
— 6 - 15 years	Yes	Yes	Yes
— 16 - 65 years	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes
Constant	0.10	0.08	0.07
	(0.30)	(0.30)	(0.30)
Observations	5850	5850	5850
Adjusted R^2	0.248	0.250	0.251
Food insecurity score baseline mean		0.76	

Robust standard errors in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$;
Note: Food insecurity score baseline mean corresponds to
the weighted average over the 2018 planting and 2019 harvest seasons.

Table C.8: Household characteristics before and after the pandemic

Household Characteristics	July-Sept 2018 (1)	January-February 2019 (2)	April-May 2020 (3)
Average household size (family size)	5.6	5.5	6.1
Male (%)	31.5	30.7	31.3
Household members age (%)			
—- 0 - 5 ans	13.6	13.1	12.6
—- 6 - 15 ans	23.8	24.5	25.0
—- 16 - 65 ans	55.8	55.4	55.3
—- 66 and over	6.8	7.1	7.1
Education level of head (%)			
None (or no school)	31.5	31.6	31.3
Primary	24.1	24.1	24.3
Junior secondary	26.8	26.8	26.8
Vocational Education	5.4	5.5	5.5
Tertiary	12.0	11.9	12.0
Observations	1950	1950	1950

Source : GHS-Panel wave 4 (2018/2019), COVID-19 NLPS 2020, and authors' calculations.

C.3 Robustness to the study sample

We conduct a robustness check by expanding our sample (hereafter "extended panel") and including additional waves—June, August, and November 2020 (Table C.9). The results remain qualitatively consistent with previous findings based on the short panel (Table 2). The employment shock significantly increases household food insecurity, and remittances can mitigate this adverse effect. However, the magnitude of the coefficients is smaller in the extended panel. The impact of the shock on households that received no remittances is lower in the extended panel estimates (coefficients ranging from 0.19 to 0.26) than in the short panel estimates (coefficients ranging from 0.20 to 0.30). The mitigation effect of remittances is also lower in the extended panel. For instance, the magnitude of the mitigation effect of pooled remittances is estimated to be -0.22 in the extended panel (Table C.9) versus -0.30 in the short panel (Table 2). While these results may suggest a potential downward bias in our estimates resulting from government relief programs, the results remain unchanged overall.[32] The results confirm our strategy of focusing on the early period of the shock, which corresponds to the first round of the COVID-19 survey in May 2020.

Table C.9: Mitigating effect of remittances (extended panel)

Dependent variable Food insecurity score	(1)	(2)	(3)
Lockdown from business closure	0.19*** (0.05)	0.26*** (0.06)	0.26*** (0.06)
All remittances 2018-2019 × Lockdown business closure	– –	-0.22*** (0.08)	– –
International remittances 2018-2019 × Lockdown from business closure	– –	– –	-0.42** (0.17)
Domestic remittances 2018-2019 × Lockdown from business closure	–	–	-0.19** (0.09)
Time fixed effects	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes
Constant	0.88*** (0.02)	0.88*** (0.02)	0.88*** (0.02)
Observations	11213	11213	11213
Adjusted R^2	0.185	0.186	0.186

Robust standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Note: The sample includes the additional waves of June, August and November 2020.
Estimates are unweighted.

[32] All estimates with the extended panel are unweighted and are more likely to be subject to attrition bias. Hence, the results must be taken cautiously and can provide only suggestive evidence.

Table C.10: Capital channel hypothesis test: robustness to the control for current remittances

	Type of capital			
	Pooled capital	Formal financial services	Informal financial services	Livestock ownership, rental earnings
	(1)	(2)	(3)	(4)
Lockdown from business closure	0.49**	0.57**	0.50**	0.63**
	(0.24)	(0.24)	(0.24)	(0.25)
Business closure x Remittances group (Ref: Closure = No; Capital = No; Remittances = No)				
Closure = Yes × (Capital = Yes, Remittances = Yes)	-0.45*	-0.59**	-0.02	-0.88***
	(0.25)	(0.27)	(0.28)	(0.29)
Closure = Yes × (Capital = Yes, Remittances = No)	-0.33	-0.46*	-0.15	-0.04
	(0.25)	(0.26)	(0.27)	(0.34)
Closure = Yes × (Capital = No, Remittances = Yes)	-0.59	-0.59	-0.59	-0.59
	(0.41)	(0.41)	(0.41)	(0.41)
Time fixed effects	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes
Constant	0.95***	0.97***	0.89***	1.01***
	(0.03)	(0.03)	(0.04)	(0.05)
Observations	4446	3537	2412	1470
Adjusted R^2	0.259	0.223	0.277	0.237

Robust standard errors in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table C.11: Heterogeneity in terms of area of residence: sample of households reporting a decrease in income since Mid-March

	Type of remittances		
	Pooled remittances	International remittances	Domestic remittances
	(1)	(2)	(3)
Lockdown from business closure	0.31**	0.26**	0.29**
	(0.13)	(0.13)	(0.13)
Lockdown from business closure x Area of residence x Remittances (Ref: Remittances = No, Rural = Yes)			
Closure = Yes × (Remittances = Yes, Lagos/FCT = Yes)	-0.37	-0.59*	-0.21
	(0.32)	(0.33)	(0.48)
Closure = Yes × (Remittances = No, Lagos/FCT = Yes)	0.37	0.37	0.37
	(0.29)	(0.29)	(0.29)
Closure = Yes × (Remittances = Yes, Other urban = Yes)	-0.40**	0.16	-0.47**
	(0.18)	(0.45)	(0.19)
Closure = Yes × (Remittances = No, Other urban = Yes)	-0.17	-0.17	-0.17
	(0.19)	(0.19)	(0.19)
Closure = Yes × (Remittances = Yes, Rural = Yes)	-0.38**	-1.05***	-0.34*
	(0.19)	(0.17)	(0.19)
Time fixed effects	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes
Constant	1.01***	1.00***	1.00***
	(0.03)	(0.03)	(0.03)
Observations	4377	3147	4185
Adjusted R^2	0.267	0.299	0.273

Robust standard errors in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
FCT = Federal Capital Territory.