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The impact of COVID-19 on household income and participation in the agri-food value chain: Evidence from Ethiopia

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Abstract. The effects of COVID-19 have been highly heterogeneous, crucially depending on household livelihoods. In the context of households reliant on agri-food systems, the extent of these effects significantly depends on their position within the value chain. An assessment of the COVID-19 effects along the agri-food value chain and the identification of pivotal factors influencing these outcomes are key for designing appropriate responses and targeting the population most in need should a crisis akin to COVID-19 emerge in the future. Using a longitudinal dataset from Ethiopia, composed of a pre-COVID baseline and six follow-up phone-based surveys, this paper estimates the COVID-19-induced change in household income and job participation, tracing its evolution throughout seven months after the pandemic onset. Applying both longitudinal and cross-sectional econometric models, we show that the COVID-19 shock reduced both employment and income, with increasingly negative impacts over time. Despite initial resilience in the face of restrictive measures, farming eventually emerged as the most affected segment within the agri-food value chain over the medium term. Access to formal institutions such as insurance and credit services, formal contractual arrangements, and secured land ownership title played a key role in mitigating the likelihood of income loss.

Keywords: COVID-19, food value chain, labor market, income loss, Ethiopia.
JEL Codes: I15, O12, Q12.

1. INTRODUCTION

The COVID-19 pandemic caused unprecedented disruptions in many value chains at domestic as well as global levels (Moosavi et al., 2022), including the bioeconomy and specifically the agri-food value chains (AFVCs) (Devereux et al., 2020), although significant heterogenous effects were reported[1]. Although some segments of AFVC such as farming have

[1] For instance, in the short run the bioeconomy – i.e. the economic activities that depend on the use of biological resources, including agriculture and food processing – showed a level of resil-

been initially less affected by restriction decisions, downstream segments such as food services, restaurants, and retail as well as midstream segments such as processing, logistics, and transportation, have been impacted since the onset of the crisis[2]. The general conclusion of early studies is that the COVID-19 impact is differentiated across different segments of the AFVC as well as within each segment (Diao et al., 2020; Tamru et al., 2020; Tesfaye et al., 2020).

The pandemic and the related restrictions implemented by governments raised many challenges to individuals and households participating in the AFVC. The ability to absorb, adapt, and even transform the way a livelihood is gained by individuals and households – in short, their resilience to the COVID-19 shock – has been often limited by many factors such as access to technology, financial services, or social safety nets[3]. Indeed, many agents had limited options to cope with the COVID-19 shock, resulting in income reduction or job loss and eventually increasing poverty and food insecurity. Assessing COVID-19 impacts across AFVC segments and identifying the main factors that determined those impacts on AFVC participants and their options to adapt to the "new normal" is then crucial for designing appropriate responses and targeting the groups most in need should a shock similar to COVID-19 occur again in the future.

Using Ethiopia as a case study, this study aims at: (i) assessing which segments of the AFVC have been most affected by the pandemic, in terms of labor participation and income loss; and (ii) identifying which factors at the household level have mostly influenced the impact of COVID-19 on income, and specifically on farm income. Ethiopia has been selected for several reasons. Its economy is mainly based on agriculture, which accounts for 34% of GDP (World Bank, 2021), 80% of the population depends on agriculture (Njeru et al., 2016), and smallholder farming accounts for 95% of agricultural production (Tigre and Heshmati, 2022). However, new commercial and gig economy clusters are emerging in the country, as is the case of intensive vegetable cultivation in the central Rift Valley (Minten et al., 2020). These new activities challenge small farmers' and small enterprises' participation in the AFVC, which are compounding with already existing structural constraints such as low access to credit and extension, weak labor market, and high transaction costs (Croppenstedt et al., 2003; Bryan et al., 2009; Asfaw et al., 2011; Harvest SA, 2012). In such a situation, the COVID-19 shock could push smallholder farmers and small and medium enterprises out of the market.

The first case of COVID-19 in the country was reported on March 13^{th,} 2020[4]. In the same month, the federal government implemented a set of containment measures, such as school closure, physical distancing, and restrictions on gathering and transportation (Baye, 2020). In April, a five-month state of emergency was declared, though economic activities continued to operate. Although farmers could keep working, they faced many challenges. With borders shut, imported inputs were more difficult to find and their price increased (Hirvonen et al., 2021b, 2021c, and 2021d). Moreover, restrictions on movement made it almost impossible for farmers to reach the markets. This eventually led to a drop in agri-food sales, particularly of some vegetables such as tomatoes, papaya, and watermelon (Molla, 2020). The travel restrictions also doubled transport costs, with a further domino effect on production, raising the farmgate and retail prices of some products, such as tomatoes (Hirvonen et al. 2021b). Additionally, since many farmers could not store their goods – particularly perishable produce – they were forced to accept the low prices set by buyers (Ababulgu et al., 2022). Hired labor was also affected. Many rural workers returned to their homes and the reduced labor supply pushed up the costs of labor (Agajie, 2020). Effects were driven also by the fear of contagion. People associated raw vegetables with infection, reducing their purchases (Hirvonen et al., 2021a; Tamru et al., 2020). This determined a significant reduction in local market sales as well as exports (Ababulgu et al., 2022).

Although anecdotal evidence exists on the impacts of COVID-19 on AFVC participation and income, rigorous empirical studies based on household-level survey data are few. Josephson et al. (2021) used the World Bank phone-based surveys of Ethiopia, Malawi, Nigeria, and Uganda to document the socioeconomic impacts of the pandemic. They found that 77% of households across the four countries experienced an income loss in the immediate aftermath of the pandemic. However, the authors were not able to measure how much of the loss

ience relatively higher than the overall economy in Europe. However, this result was mainly driven by the technology-intensive sectors of the bioeconomy, such as biochemistry and bioelectricity, which partially offset the negative impact on the more traditional sectors of biomass processing, namely agriculture and food processing (Lasarte-López et al., 2023).

[2] Indeed, it was initially expected that farming experienced less direct effects, except where hired labor was important, although interlinkages with the other segments of the chain may have caused income losses and production disruption (Swinnen, 2020).

[3] For instance, Cesaro et al. (2022) found that financial liquidity and repairment of equipment and machinery were the difficulties most reported by farmers in Italy in the short run.

[4] For details, see https://www.afro.who.int/news/first-case-covid-19-confirmed-ethiopia.

can be directly determined by the pandemic, given the descriptive nature of their analysis. According to this study, Ethiopian households are significantly less likely to experience an income loss compared to those from the other three countries.

More recently, the same dataset has been used by Rudin-Rush et al. (2022) to document trends in food security over the twelve months after the onset of the COVID-19 pandemic. This study reports a sharp increase in food insecurity in the aftermath of the pandemic, with a subsequent gradual decline. Furthermore, rural households were more negatively affected than urban households in terms of food security.

IFPRI conducted a series of monthly phone-based surveys between May and August 2020 (i.e., up to five months after the pandemic onset) interviewing nearly 600 households in Addis Ababa (Hirvonen et al., 2021a). More than half of respondents reported a fall in income relative to their average pre-pandemic income at the same time of the year (Hirvonen et al., 2020), with the proportion of affected households increasing from May to July (Hirvonen et al., 2021a). Poorer households more likely reported income losses, with a significant worsening of household food security and nutritional status. Income loss and unemployment were identified as the most common shocks experienced by the respondents (Abate et al., 2020; de Brauw et al., 2020; Hirvonen et al., 2020). Despite income loss, Zhang et al. (2022) found that the population in Addis Ababa was not affected on average in terms of food security. However, the situation in other regions of the country was much different, especially in rural areas and among vulnerable individuals and households (Abay et al., 2023, Zhang et al., 2022).

Hirvonen et al. (2021b) relied on a large value chain survey administered by IFPRI in February 2020 and follow-up phone interviews collected in May 2020 to analyze the disruption of the vegetable value chain from the main producing areas in the Central Rift Valley to Addis Ababa, including changes in prices and adjustments in the marketing activities of the participants – from farmers to wholesalers and retailers. They found that nearly 60% of the smallholders and more than 60% of the investors reported less income than usual. They also found that the pandemic in Ethiopia disrupted trade not only between neighboring countries but also among subnational geographies, thus determining high volatility in agricultural prices (Hirvonen et al., 2021b). However, they found that the changes in wholesale and retail marketing margins were relatively low, suggesting a resilient response of the domestic food value chains during the pandemic in Ethiopia.

Although these studies provided important early estimates of the effects of the pandemic on relevant indicators of welfare, they present some limitations. Some of them are based on a non-representative sample. The study of Hirvonen et al. (2021d) focuses on the vegetable value chain only, while Hirvonen et al. (2021b) focus only on households living in Addis Ababa. Most of the existing studies focus only on one or a few points in time, failing to capture the evolving impact of COVID-19 over time. Other studies look at the impact on employment, such as Khamis et al. (2021), but they do not specifically disaggregate the analysis across AFVC segments. Our study aims to address these limitations contributing to estimating the magnitude of AFVC disruption caused by the COVID-19 pandemic in Ethiopia over a relatively longer time (seven months from the pandemic onset) and looking specifically at differentiated impacts on various AFVC segments. It also helps to identify the main factors that contributed to offset the negative consequences of COVID-19 shock and to keep adequate levels of income for AFVC participants. Although the data present some limitations in terms of representativeness (cf. Section 2), we think the findings emerging from this study are relevant not only because they provide a better understanding of the COVID-19 impact in Ethiopia, but also because they can contribute to a better management of COVID-19-like crises should they emerge in the future.

The paper is organized as follows. The next section describes the data used. Section 3 presents some descriptive statistics, with specific reference to employment and income. Section 4 describes the empirical strategy adopted. Section 5 presents and discusses the results of the analysis. Section 6 concludes.

2. DATA

The analysis uses a seven-rounds longitudinal dataset, which includes a baseline pre-pandemic face-to-face survey and six follow-up phone surveys. Pre-COVID data come from the 2018/19 Ethiopia Socioeconomic Survey (ESS), which is part of the World Bank's Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA). It covers all regions of the country and is representative at national, urban/rural, and regional levels. The other six rounds of data are part of the World Banks's COVID-19 High-Frequency Phone Survey of Households (HFPSH) 2020. This phone-based survey is a 15-minute questionnaire administered to a subsample of the ESS 2018/19 households from April to mid-October (Figure 1). The World Bank team interviewed the same households in each round, leading to a

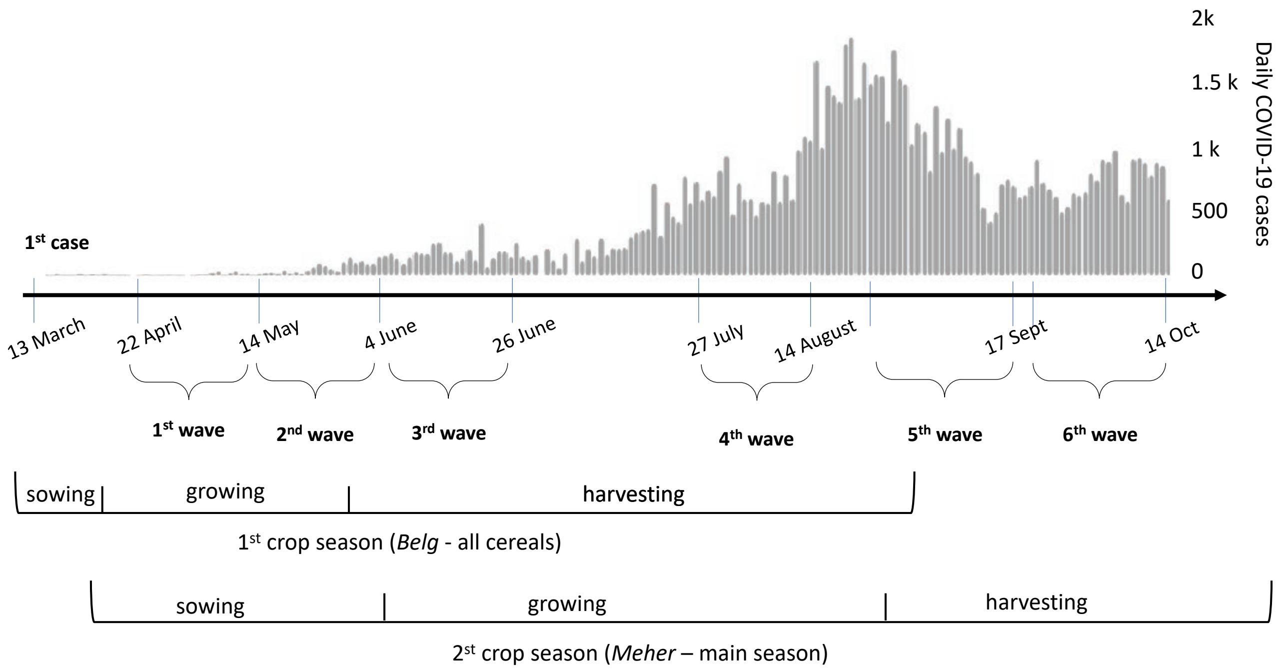

Figure 1. Timeline with daily COVID-19 cases, surveys date, and crop seasons in Ethiopia. Source: data on COVID-19 daily cases retrieved from https://covid19.who.int/region/afro/country/et; information on crop seasons retrieved from https://www.prepdata.org/stories/ethiopia-climate-and-agriculture; date of COVID-19 HFPSH data collection retrieved from https://microdata.worldbank.org/index.php/catalog/3716.

balanced dataset of 2,347 households[5]. To obtain unbiased estimates, sampling weights at the household level have been constructed by the World Bank team following Himelein (2014), thus having a sample that is representative at the national and urban/rural levels.

A major problem with the HFPSH surveys is that phone penetration in rural Ethiopia is still low, with only 40% of rural households having access to a phone. Therefore, data are representative only of those households that have access to phones in urban areas (90% of all urban households) and better-off rural households that have access to mobile phones (Wieser et al., 2020). However, these rural households are systematically different from the majority of rural households (Ambel et al., 2020a). Additionally, only one member per household – typically the household head or the spouse – has been interviewed, but household heads could systematically differ from the rest of the population, undermining the representativeness of the sample at the individual level[6].

A key methodological concern is that factors other than the COVID-19 crisis could drive the evolution of outcomes over time. Specifically, month-to-month seasonality could represent an issue. In principle, it can be controlled by including month fixed effects. However, this could not be done due to the different time reference between the baseline and phone surveys, especially for the employment variable. While the pre-COVID survey considers the employment activities over the preceding twelve months, including both planting and harvesting seasons, questions on employment in the phone surveys consider only the week before the interview. There could be then an underestimation of the farming-related employment rate. Luckily, the phone survey covers the sowing and the harvesting periods of the two main crop seasons (Figure 1)[7]. Therefore, although it is not possible to fully rule problems of seasonality out, it is likely that it does not significantly affect our estimates.

Seasonality can also bias the analysis because of its impact on farm income. There are two rainy seasons over the year: the small rainy season (*belg*), which occurs between March and May, and the main rainy season

[5] Each COVID-19 HFPSH survey has a slightly different number of observations, ranging from 2,704 to 3,249 households. In order to have a balanced panel we reduced the sample to 2,347 observations. For more information on sampling design please visit https://microdata.worldbank.org/index.php/catalog/3716.

[6] Further discussion about this issue is presented in section 4.3.

[7] Only sugarcane and taro are neither planted nor harvested in the period under analysis. Source: http://www.fao.org/agriculture/seed/cropcalendar/welcome.do;jsessionid=62FFB1AC3CB6FA74244A91586E5E1758.

(*meher*), which takes place between June and September[8] (Hirvonen et al., 2016). Around 90% of the total crop production is done during the *meher* season (Taffesse et al., 2013). Farmers usually run out of stock between July and September, which can result in increasing household food insecurity (Dercon and Krishnan, 2000; Hirvonen et al., 2016; Gilbert et al., 2017; Sibhatu and Qaim, 2017; Roba et al., 2019). However, seasonality-induced food shortage is quite homogeneous across farmers, and it is captured by a variable that controls for the aggregate time trend (cf. Section 4.3).

Another factor to consider in the analysis is the desert locusts' outbreak, i.e. the most destructive migratory pests in the world (Cressman et al., 2016; Lazar et al., 2016), that swarmed from Yemen to the Horn of Africa in the summer of 2019. In the fourth round of phone surveys[9], 45% of farmers self-reported that they experienced desert locusts on their farm, and 41% of households experienced locusts in their *kebele*[10]. Desert locusts have negative consequences on income because they destroy the crops and the fodder for livestock. Additionally, labor time is required to spray the chemicals on the area under cultivation.

3. DESCRIPTIVE STATISTICS

3.1. Employment

The first round of the phone-based survey asked if the individual did any work in the seven days before the interview, if the individual was working before the COVID-19 outbreak, and if the current work is the same as before the pandemic. For the other rounds of data, the questions were the same, but using as reference time the previous call. As shown in Figure 2, the employment rate experienced a significant reduction in the aftermath of the COVID-19 outbreak. Overall employment dropped by 11 percentage points. However, labor activities recovered quickly over the next months, exceeding the employment rate before COVID-19 (Ambel et al., 2020b), driven by own farming activity.

The dynamics of labor mobility are somehow different within the various AFVC segments[11] (Table 1).

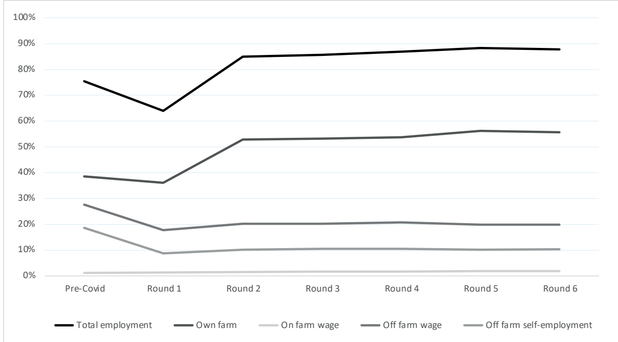

Figure 2. Evolution of employment in Ethiopia, 2018/19 – mid October 2020. Source: Own elaboration from ESS 2018/2019 and HFPSH 2020. Note: Sampling weights applied.

The upstream segment was quite stable, with 83% of people remaining in the same segment of employment and 12% moving towards non-AFVC activities after seven months. In the case of midstream activities, only 26% remained in the same segment, while 39% moved towards non-AFVC activities, 23% moved to upstream activities, and the remaining 12% moved to downstream activities. Similarly, in the downstream segment, only 27% on average did not change the segment of employment, while most of the people who did it, moved to midstream activities (49%). Finally, almost two-thirds of the ones who were not originally working in AFVC activities remained outside the AFVC, while the ones who entered the AFVC split mainly between midstream (14%) and upstream (18%) activities.

Employment changes can be in part driven by seasonality. Indeed, seasonal migration in Ethiopia occurs both from rural to urban areas, used as a coping strategy during the dry season (Asefawu, 2022), and also towards northwest Ethiopia for temporary employment on large-scale agricultural farms during the rainy season (Schicker et al., 2015). However, respondents reported that the main reason for stop working is COVID-19, especially in the early phone rounds. Between April and May (round 1), more than half of individuals stated that they lost their job because of the pandemic (Figure 3). In the last rounds instead, being "temporarily absent" is the main reason to stop working. This can be indirectly associated with the pandemic since many who temporarily left their job in the city migrated to rural areas[12].

[8] This refers to the growing period of the season.

[9] Information on desert locusts is available only in rounds 4 and 6. However, in round 6 very few respondents answered the questions related to locusts, so it is not possible to produce reliable estimates.

[10] The *kebele* is the smallest administrative unit of Ethiopia, i.e. a neighbourhood or a localized and delimited group of people consisting of at least 500 families.

[11] The variable of labor participation in AFVC activities has been decomposed into three segments, namely: a) upstream (primary production, including farming, fishing, forestry and hunting), b) midstream (manufacturing of food products, including processing; wholesale and retail trade; transport; and distribution), and c) downstream (restaurants and bars).

[12] Detailed information on the number of individuals that started to work again in each round, and the reason for having stopped working

Table 1. Labor transition matrix across AFVC segments and non-AFVC, 2018/19 – mid-October 2020.

		N. Obs.	Round 6			
			Downstream	Midstream	Upstream	Non-AFVC
Pre-Covid	AFVC Downstream	145	27.5	48.5	6.2	17.8
	AFVC Midstream	184	12.4	26,0	22.9	38.8
	AFVC Upstream	517	0.6	3.6	83.3	12.1
	Non-AFVC	834	4.0	14.4	17.8	63.9

Source: Own elaboration from ESS 2018/2019 and HFPSH 2020.
Note: Upstream: agricultural production and agricultural employment, including fisheries, forestry, and hunting; Midstream: manufacturing of food products, including processing, trade, and transport; Downstream: restaurants and bars; Non-AFVC: all other employment activities. Sampling weights applied.

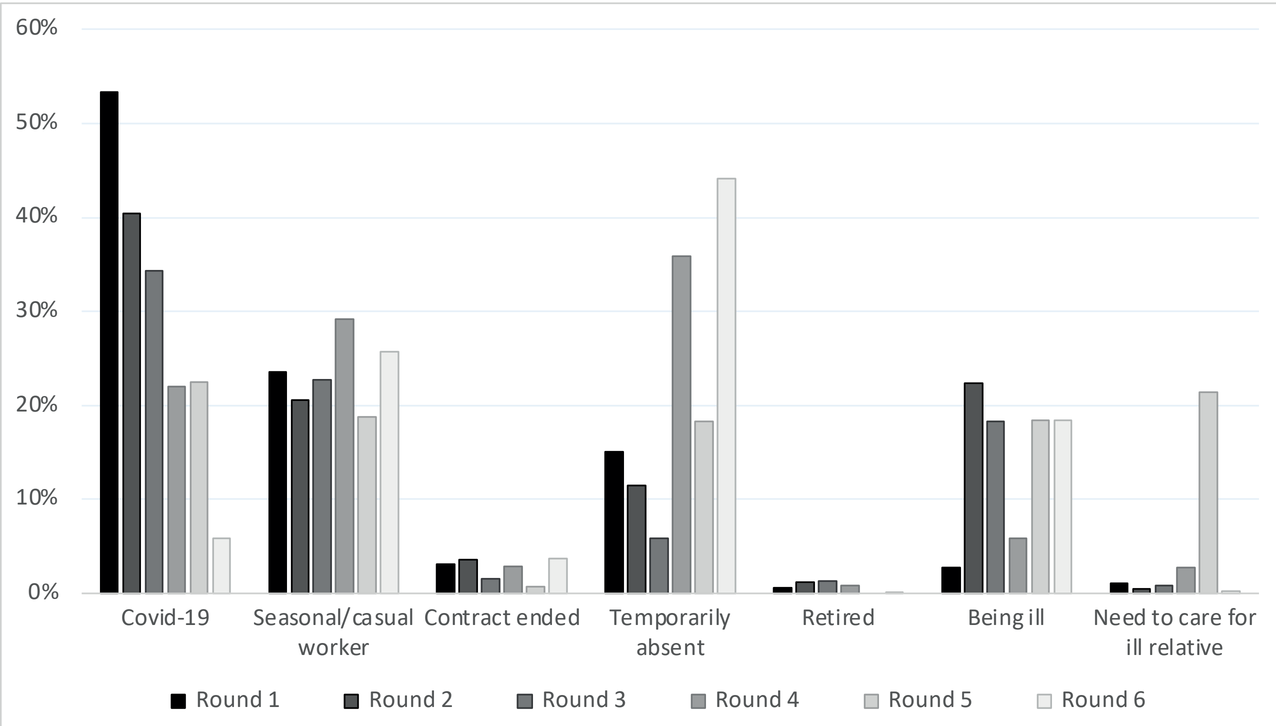

Figure 3. Reason to stop working, share on round total. Source: Own elaboration from HFPSH 2020. Note: sampling weights applied.

3.2. Income

Respondents to the phone-based survey were asked to assess the income change experienced by the household compared to the situation before the COVID-19 outbreak in the first-round interview, and compared to the previous call in the subsequent rounds. The possible answers ranged from "total loss" to "income reduction", "no change" and "income increase". The categorical nature of the question does not allow for computing accurate estimates of the magnitude of COVID-19 impact on income, limiting the analysis to the qualitative incidence of the pandemic (De Weerdt, 2008). In the case of farming income, the answer highly depends on the harvest time of cultivated crops. In fact, the bulk of crop sales occurs between December and February, though April usually records the largest sales (Hirvonen et al., 2016). Figure 4 (panel a) shows a generalized decreasing trend of the share of households that reported a reduction of income or a total loss between rounds, not only for farming income but also for other

in the previous round is reported Table A.1 in the Appendix.

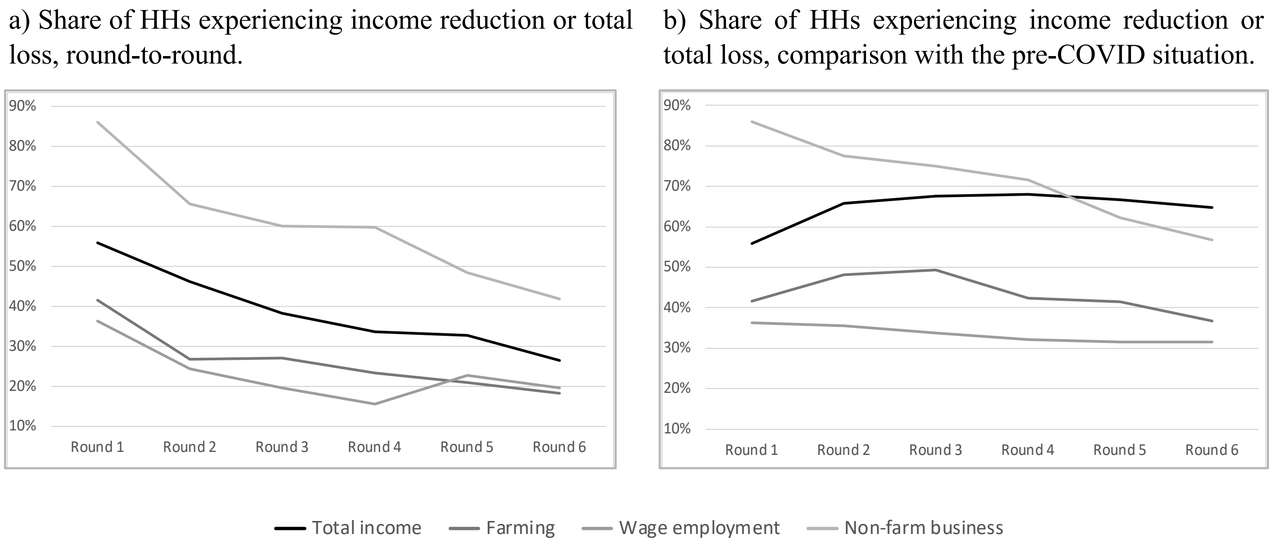

Figure 4. Share of HHs experiencing income reduction or total loss per income source category, share by income source. Source: Own elaboration from ESS 2018/2019 and HFPSH 2020. Note: Sampling weights applied.

sources of income. If we compare the income change to the situation before the COVID-19 outbreak[13] (Figure 4, panel b), the trend is different. The share of households that reported a reduction in income compared to the pre-COVID situation shrank only for non-farm business while it did not change significantly over time for other income sources. In the case of total income, the share of households experiencing a reduction/total loss even increases over time, up to 9 percentage points increase in the sixth round compared to the baseline.

Table 2 reports the descriptive statistics of the outcome variables per each round. Specifically, the employment variables show the rate of people employed in each sector, while the income variables report the share of households that experienced a reduction in income or a total loss compared to the baseline.

There are some differences between the overall baseline sample and the phone-based sub-sample (Table 3). Respondents to the HFPS sample are mainly located in urban areas, the majority of them are males, and their employment rate is higher. They are generally older, more educated, and more employed through a formal job contract. The rate of non-farm employment activities is higher compared to the baseline population. Vice versa, the rate of farm-related activities is similar and the same is true for the employment rate in the upstream segment.

Given these differences, the results of the analysis could not be generalized to the whole Ethiopian population. To check for possible problems of representativeness, we ran a robustness check using individually-adjusted weights (cf. Section 4.3).

4. EMPIRICAL STRATEGY

4.1. Outcome variables

To assess the impact[14] of COVID-19 on income and employment we estimated a household fixed effects model with a continuous treatment variable, adapting the approach implemented by Amare et al. (2020). We use two dependent variables, namely: participating in labor activities, considering any type of activity as well as specific sectors; and income change, looking at both the total income and the different income sources.

Labor activities are grouped into own-farm, on-farm wage employment, off-farm self-employment, and off-farm wage employment. We also consider employment according to segments of AFVC (i.e., downstream, midstream, and upstream activities as defined above) given the expected differentiated impact of COVID-19

[13] The change of income is computed backward up to the baseline. If, for instance, in round 2 income did not change compared to the previous round, and in round 1 it increased compared to the baseline, in round 2 it also increased compared to the baseline. The change is assumed to occur with the same amount, therefore if a household first reports an increase, and then a reduction, the net effect is null. We are aware of the arbitrariness of this methodology. For this reason, the analysis has been also conducted round by round, finding similar results, as reported in the Appendix.

[14] We use the terms "impact" and "effect" throughout the paper, but we acknowledge that we are not able to fully identify a causal mechanism with our estimation strategy due to the limitations described in Section 2.

Table 2. Descriptive statistics of employment and income outcomes.

	Round						
	Baseline	1	2	3	4	5	6
Employment: % of individuals							
Total employment	75%	64%	85%	86%	87%	88%	88%
Downstream	4%	1%	2%	2%	2%	2%	2%
Upstream	40%	37%	55%	55%	56%	58%	57%
Midstream	5%	7%	8%	8%	8%	8%	9%
Out of FVC	25%	18%	20%	21%	21%	20%	20%
Own farm	39%	36%	53%	53%	54%	56%	56%
On-farm wage	1%	1%	2%	2%	2%	2%	2%
Off-farm self-employment	28%	18%	20%	20%	21%	20%	20%
Off-farm wage employment	19%	9%	10%	10%	11%	10%	10%
Income: % of households							
Total income		56%	67%	70%	72%	72%	71%
Farming		42%	50%	51%	47%	45%	41%
Wage employment		36%	36%	34%	35%	36%	33%
Non-farm business		86%	82%	82%	76%	68%	65%

Source: Own elaboration from ESS 2018/2019 and HFPSH 2020.
Note: Employment variables report the share of people employed in each round. Income figures show the share of households that reported income reduction or total loss compared to the baseline. Sampling weights applied.

related restrictions on different stages of the value chain (Reardon et al., 2020b, Swinnen and McDermott, 2020). For each labor activity, we computed a dummy equal to 1 if the individual operated in that activity, and zero otherwise.

We consider total income and specific income-generating activities, namely family farming, non-farm family business, wage employment of household members, and other sources of income (pension, remittances, etc.). The variables take the values -2 (total loss), -1 (income reduction), 0 (no change), and 1 (income increase).

4.2. Treatment variable

The main variable of interest is the number of confirmed cases of COVID-19 over the number of inhabitants in each region. This information has been retrieved from the Ethiopia COVID-19 Monitoring Platform[15] and weekly governmental bulletins[16]. This variable captures the evolution and the spread of the virus across the country. The variable has been transformed using the inverse hyperbolic sine (IHS) transformation, to account for zero cases in the first post-COVID survey. Regression results can be interpreted as the log transformation (Johnson, 1949; Burbidge et al., 1988).

This variable presents some limitations. Firstly, the ratio of confirmed cases over the number of tests would do a better job than using the number of the total population in each region, but unfortunately, data on testing disaggregated at the regional level are not available. Secondly, the number of confirmed cases probably underestimates the real infection level due to the limited testing capacity of the country[17]. Although the testing capacity is presumably unequal across regions, as access to basic health care in Ethiopia is highly unequal (Woldemichael et al., 2019; Alene et al., 2021), the use of fixed effects estimator (cf. Section 4.3) should partially mitigate the issue, controlling for differences across regions that do not vary over time.

Thirdly, the number of confirmed cases does not adequately proxy the treatment variable, i.e. the variation in terms of access to the market and restrictions imposed by the government, which in turn affect labor participation and income. However, we can assume that as the number of confirmed cases increases in a region, both the restrictions imposed by the government and the individually self-imposed restrictions would increase. Indeed, data confirm that the economic and health effects of the pandemic covary in Ethiopia. When using daily data retrieved from the Oxford COVID-19 Government Response Tracker (OxCGRT), the correlation between the COVID-19 cases and the stringency index is positive and significant[18]. Although there could be a time lag between the implementation of the restrictions and the effect in terms of COVID-19 cases, this lag is shorter (7 to 14 days depending on the restriction type and stringency as well as on the rate of infection of the specific COVID-19 variant) than the period analyzed in each round (i.e., one month). Therefore, the average effect of the restrictions over a month should be captured by the number of confirmed cases. It is also important to consider the heterogeneity of the response across the regions. Indeed, although measures were coordinated at the national level, each regional state in Ethiopia tailored policy implementation to the local situation through its own Public Health Emergency Opera-

[15] Available at this link: https://www.covid19.et/covid-19/.
[16] See https://www.ephi.gov.et/.

[17] The virus spread unheavenly across regions. In particular, the Addis Ababa region reported the highest proportion of cases per million population, followed by Harar and Dir Dawa. Factors that can explain this heterogeneity are a different testing capacity, driven by better infrastructure, especially in the capital and in other urban areas, population density, and degree of internal and international connectivity.
[18] Similar results were found in other countries. For instance, Amare et al. (2021) in Nigeria found that the variables of COVID-19 cases and government restrictions produced the same results, confirming that the two variables can proxy each other.

Table 3. Comparison of individual characteristics between the baseline sample and phone-based subsample.

Variable	Baseline population	Phone-based sub-sample	Student's t significance
Rural	0.72	0.64	***
	(0.45)	(0.48)	
Sex: 1=female	0.51	0.27	***
	(0.50)	(0.45)	
Employed in any activity	0.75	0.85	***
	(0.43)	(0.35)	
Age	30.69	38.33	***
	(16.38)	(13.76)	
Not engaged in Education, Employment or Training	0.10	0.11	
	(0.30)	(0.31)	
Literacy rate	0.55	0.63	***
	(0.50)	(0.48)	
Formal job contract	0.04	0.10	***
	(0.19)	(0.30)	
Years of education	3.70	4.75	***
	(4.32)	(5.12)	
Agricultural wage work	0.01	0.01	
	(0.09)	(0.09)	
Non-farm self-employment	0.10	0.15	
	(0.29)	(0.36)	
Non-farm wage work	0.12	0.22	***
	(0.32)	(0.42)	
Own farm work	0.63	0.63	***
	(0.48)	(0.48)	
Upstream of AFVC	0.63	0.64	
	(0.48)	(0.48)	
Midstream of AFVC	0.03	0.04	***
	(0.16)	(0.20)	
Downstream of AFVC	0.01	0.01	**
	(0.10)	(0.12)	
N. of observations	19,910	2,347	

Note: the first column includes all individuals at the baseline. The second column includes only individuals from the baseline who were tracked in the phone-based surveys. Sampling weights applied. Standard deviation in parenthesis. Children below 11 years old dropped from the sample. Mean difference is computed through a linear regression, where the independent variable is a dummy equal to one if the individual belongs to the phone subsample. *** p<0.01, ** p<0.05, * p<0.1.

tions Centre (PHEOC)[19]. This calls for using regionally disaggregated variables.

Fourthly, the number of confirmed cases does not capture spillover effects that may occur across regions. Indeed, each region is treated as an independent entity assuming that each of them does not have interactions with the rest of the country and no aggregate impacts occurred. This assumption does not hold when two or more regions have strong economic relationships. For instance, this may happen when a food value chain crosses over regional boundaries – e.g. a food item is produced in a region and consumed in another – or workers commute between different regions. In these cases, should one region be affected differently than others, this effect would affect not only that specific region, but also other geographically closer or economically linked regions. However, as regions in Ethiopia are quite large and people are mostly working in the local economy (e.g. high share of family farmers), the spillover effect should be limited. Additionally, the Ethiopian political system based on ethnic federalism, where the regions have been identified based on "settlement patterns, identity, languages" (Article 46.2 of the Ethiopian Constitution), makes it easier to conceptualize regions as separate economies. Evidence indeed shows that labor mobility and internal migration in Ethiopia are limited (Bundervoet, 2018) because migration across regional boundaries often creates social tensions and violence (Breines, 2020; Fessha and Dessalegn, 2020).

4.3. Model specification

The base model is the following:

$$y_{hrt} = \alpha_{hr} + \beta_0 Time_t + \beta_1 (Cases_r * Time_t) + \varepsilon_{hrt} \quad (1)$$

where y_{hrt} is the outcome variable – either labor or income – defined for each household h in region r and round t; α_{hr} captures household fixed effects, allowing controlling for unobserved time-invariant heterogeneity among households; $Cases_r$ is the number of confirmed COVID-19 cases per million population in each region; $Time_t$ is a dummy variable representing the time of observation, equal to 1 for the post-COVID round and 0 for the pre-COVID round, whose coefficient captures the aggregate time trend in the labor market and income composition; the interaction term between time and the number of cases captures the differential impact of COVID-19 on labor participation and income change across regions due to different exposure to the virus; ε_{hrt} is the error term.

Considering that the virus spread unevenly across regions over time, we need to control for this. Regions that experienced the virus earlier are indeed more likely to report more cases than the other regions. A first specification of the base model introduces the variable Day_{1r},

[19] Source: https://www.acceleratehss.org/wp-content/uploads/2022/03/Covid-Collaborative-Ethiopia-Case-Study.pdf

which reports the number of days that occurred from the first COVID-19 case at the national level to the first COVID-19 case registered in the region:

$$y_{hrt} = \alpha_{hr} + \beta_0 Time_t + \beta_1(Cases_r * Time_t) + \beta_2(Day_{1r} * Time_t) + \varepsilon_{hrt} \quad (2)$$

To differentiate the impact of the isolated interactions and the impact of the combined spatial and temporal variabilities, we consider also a specification that includes the triple interaction between the time dummy, the number of confirmed cases per million inhabitants, and the variable as follows:

$$y_{hrt} = \alpha_{hr} + \beta_0 Time_t + \beta_1(Cases_r * Time_t) + \beta_2(Day_{1r} * Time_t) + \beta_3(Cases_r * Day_{1r} * Time_t) + \varepsilon_{hrt} \quad (3)$$

As an additional specification, we include in (3) some control variables available in the phone-based post-COVID surveys, which are not captured by the fixed effects. These variables are the presence of another member in the household who lost a job in the aftermath of the pandemic, and if the household received any assistance since the outbreak of the pandemic.

The analysis has been conducted for each post-COVID round, comparing it with the baseline. In this way, it is possible to observe the evolution of the response to the crisis over time. We expect that regions more affected by the pandemic will report a higher reduction in labor participation and income and that the effect will increase the pandemic deepening over time[20].

We used a linear probability model with household fixed effects. The advantage of this model compared to a logit or conditional logit model with fixed effects is the inclusion of all observations. In fact, the logit model with fixed effects drops the units that show no variability in the dependent variable (Beck, 2018), drastically reducing the number of observations in case of small variability. In our data, this would result in an 80% reduction of the sample size.

All analyses have been carried out using the balanced sample. However, given the existence of significant attrition rates, we replicated the analysis also using the unbalanced sample, finding consistent results (cf. Figures A.2 and A.3 in the Appendix).

An important issue that could have affected our estimates is the desert locust outbreak experienced by some regions of the country in the period of analysis, which might have harsh consequences on production[21]. For this reason, it is important to consider this shock on farming employment and income. The HFPH surveys report information on desert locust outbreak only in the 4th wave. We retrieved GIS data on desert locusts from the FAO Locusts Hub[22] and merged it with the households' location. Given that the household coordinates refer to the dwelling, and not to the parcel, and they are slightly modified for privacy reasons, we created a buffer of 3 km around the household centroid to account for these factors (on average the parcel is 1.7 km distant from the dwelling). Regarding the location of locusts, we considered the area surveyed, which is 580 hectares on average. Figure 5 reports the location of households (in purple) and where the desert locusts have been observed (in green) over the year 2020.

Although GIS data are quite accurate and reliable, many data gaps undermine the quality of the information and might represent a limitation of our analysis. Firstly, household coordinates have been slightly modified for privacy reasons and this might determine some measurement bias. Secondly, only the distance of the parcel is available, not the direction: it is not possible to know exactly where it is located. Thirdly, the information provided for locusts does not account for the locust swarm movements over time, excluding areas outside sampled locations. For these reasons, self-reported information could be more reliable to measure the effect of these pests on farm crops. Therefore, we report estimates of the impact of locust outbreak using GIS data as well as self-reported data (cf. Section 5.1).

The second part of the analysis aims at identifying the main determinants influencing changes in income in the presence of COVID-19. In doing this, we use a probability model with regressors in time t (pre-COVID) and the dependent variable in time $t+1$ (post-COVID). In this way, we can estimate which attributes that were in place in normal conditions are more likely to affect the outcome during the pandemic. The probability that the outcome variable takes a certain value is given by

$$Prob(y_{h,t+1} = j) = \mathbf{x}^{T}_{h,t}\boldsymbol{\beta}\mathbf{c} + u_{h,t+1} \quad (4)$$

where h is the household, $\mathbf{x}$ is a column vector of observable variables, namely the attributes and factors in time t, $u_{h,t+1}$ is the error term, and j takes the value 1 if the

[20] We also estimated the impact of COVID-19 from wave to wave, comparing the outcome with the previous interview and results still hold (cf. Figure A.1 in the Appendix).

[21] The desert locust outbreak appeared in Ethiopia in second half of 2019. By January 2020, the outbreak was already significantly affecting the country, peaking around mid 2020 around the harvesting time of the first crop season (*belg*) when most cereals were ready to be harvested (see Figure 1). According to FAO, the outbreak was the worst in 25 years in the country.

[22] https://locust-hub-hqfao.hub.arcgis.com/.

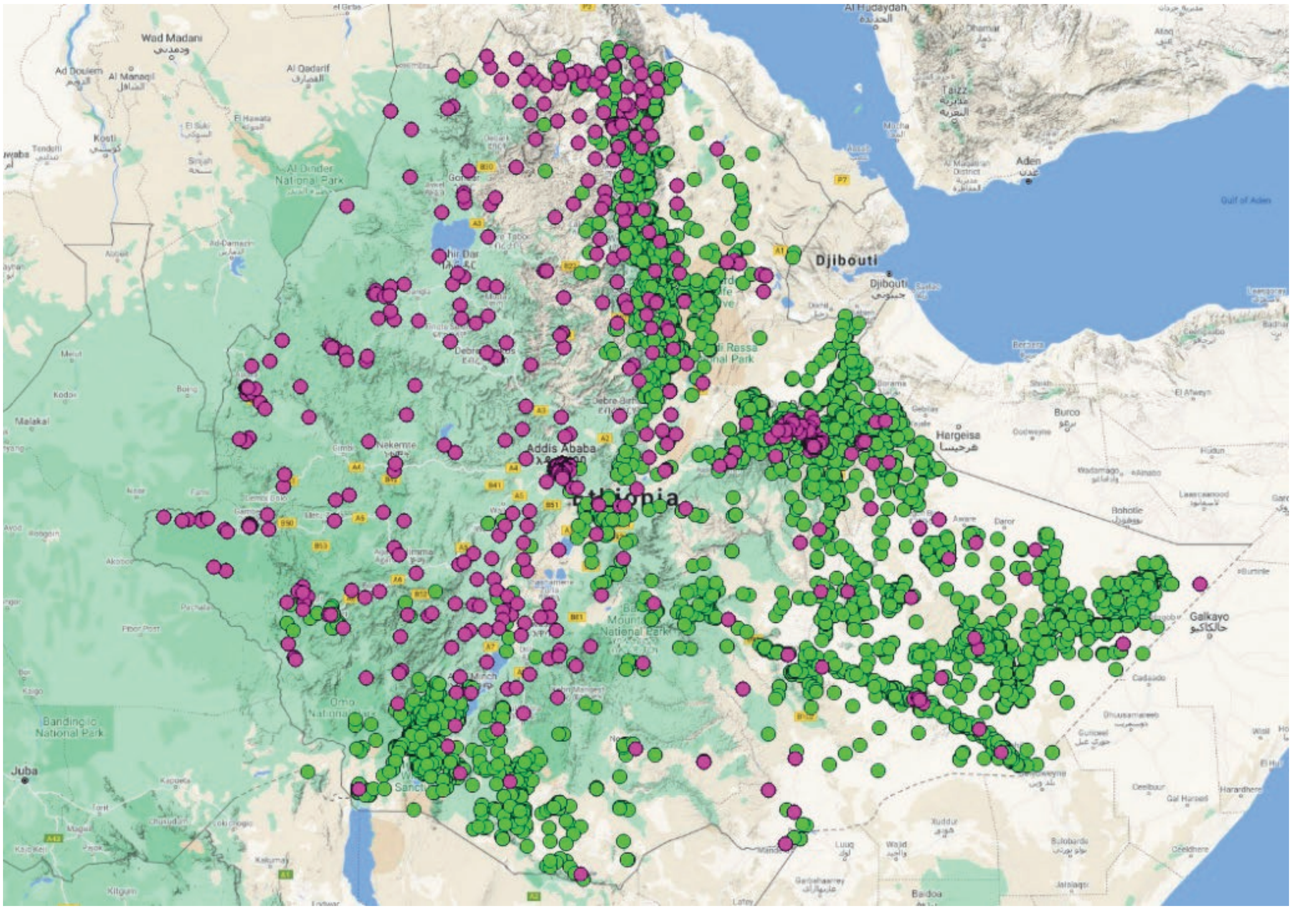

Figure 5. Map of households' location (purple circles) and locust swarm sites (green circles), 2020. Source: own elaboration using data from FAO Locusts Hub and ESS 2018/2019.

outcome is dichotomous, or multiple values if it is categorical. The regressors include household characteristics, level of infrastructure and variables at the community level, economic-related variables, and agricultural-related variables when considering farm income.

The dependent variable is the change in income at the household level. We decided to not consider the employment status because there could be problems of endogeneity because of omitted variable bias. This could occur mainly by external factors, for which information is not provided in the survey. An example could be the loss of job due to the employing company shut-down. In addition to econometric issues, as the job loss mainly depends on factors beyond household or individual control, investigating the household-related determinants of the loss of employment due to the COVID-19 crisis would make little sense.

The estimation has been conducted using a maximum likelihood estimator. We used the ordered probit model to account for the categorical nature of the dependent variable. However, given that the response rate for total loss and income increase was very low, we also created a dummy equal to 1 if income did not change or increase, and 0 otherwise. In this case, we used a probit model.

5. RESULTS

5.1. Impact of COVID-19 cases

The impact on employment

Table 4 reports the impact on employment at round 1 as resulting from the different model specifications[23],

[23] Table 4 reports the estimation for round 1 as an example. Then we provide a visual estimation of our model results (e.g. Figure 5) that makes easier understanding the evolution of the relevant outcomes over the analyzed period. The estimates of each model are available upon request to the authors.

Table 4. Regression results over different models, employment – round 1.

Dependent variable: individual employed in any activity					
Variable	(1)	(2)	(3)	(4)	(5)
Time	-0.0684***	-0.0758***	-0.0657***	-0.0658***	-0.0709***
	(0.0137)	(0.0127)	(0.0185)	(0.0193)	(0.0196)
Cases*Time	-0.0438***	-0.0353***	-0.0362***	-0.0361***	-0.0360***
	(0.00866)	(0.00577)	(0.00607)	(0.00651)	(0.00654)
Days*Time			-0.000395	-0.000386	-0.000364
			(0.000505)	(0.000644)	(0.000640)
Cases*Days*Time				-9.72e-06	-1.53e-06
				(0.000383)	(0.000383)
Constant	0.746***	0.746***	0.746***	0.746***	0.746***
	(0.0163)	(0.00507)	(0.00507)	(0.00507)	(0.00507)
Controls	No	No	No	No	Yes
Fixed effects	No	Yes	Yes	Yes	Yes
Observations	4,694	4,694	4,694	4,694	4,694
R-squared	0.042	0.071	0.082	0.107	0.116
Number of pid		2,347	2,347	2,347	2,347

Note: Estimates are computed using a linear probability model. Sampling weights applied. Standard errors clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1. Data refers to the 1st wave.

starting from model (1), which is a simple OLS over the pooled sample, to model (5), which includes all the variables and their interaction terms, the individual/household fixed effects, and the controls. We consider the last model as the best suited model for the analysis. In fact, from the theoretical viewpoint, the within estimator of the fixed effects model is robust to many types of omitted variable bias[24]. Furthermore, the inclusion of all regressors in model 5 allows controlling for more variables and provides insights on the role of such controls in determining the outcome variables. This also leads to higher adjusted R-square statistics as shown in Table 4.

As expected, our variable of interest, i.e. the interaction term Cases*Time, has a negative sign and is statistically significant, meaning that COVID-19 negatively impacted employment, while the other interaction terms are not statistically significant.

Figure 6 reports the coefficient of the interaction term between the time trend and the COVID-19 cases for each round, firstly considering any labor activities and then looking at specific sectors or segments of the AFVC. These results show how COVID-19 negatively impacted employment activities in Ethiopia. They also show that the severity of the impact increased over time.

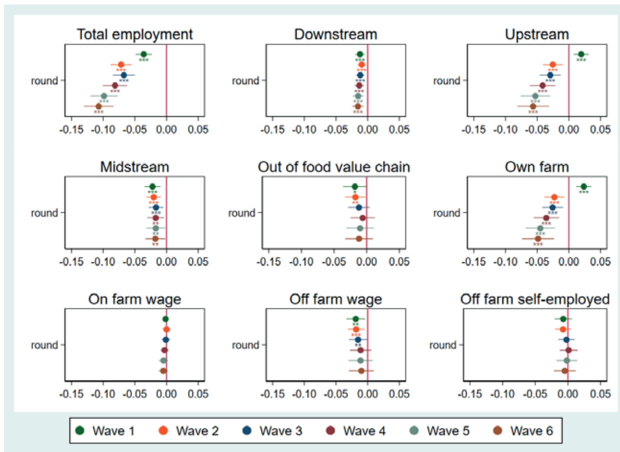

Figure 6. Impact of COVID-19 cases on employment over time. Source: Own calculation from ESS 2018/2019 and HFPSH 2020. Note: Dependent variable = dummy equal to 1 if the individual is employed. Dots are coefficients estimated from a linear probability model with household fixed effects. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals. Sampling weights applied. Standard errors clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

Decomposing the impact along the AFVC, we can see that upstream activities are the most affected. Although this segment had initially been relatively less affected, it shows increasingly negative impacts in subsequent rounds. Downstream and midstream segments have

[24] However, it is more inefficient than an OLS estimator, because it reduces the variation of the independent and dependent variables used for estimation. Indeed, it is more affected by measurement errors and by omitted variables that are not constant within the household.

Table 5. Regression results over different models, income – round 1.

Dependent variable: change in total HH income					
Variable	(1)	(2)	(3)	(4)	(5)
Time	-0.567***	-0.567***	-0.544***	-0.558***	-0.549***
	(0.0274)	(0.0274)	(0.0374)	(0.0404)	(0.0412)
Cases*Time	-0.0246**	-0.0246**	-0.0266**	-0.0157	-0.0148
	(0.0112)	(0.0112)	(0.0114)	(0.0118)	(0.0119)
Days*Time			-0.000879	5.95e-05	1.58e-05
			(0.00110)	(0.00162)	(0.00161)
Cases*Days*Time				-0.000967	-0.000970
				(0.000864)	(0.000864)
Constant	0	-0	-0	-0	0
	(3.08e-10)	(0.0106)	(0.0106)	(0.0106)	(3.08e-10)
Controls	No	No	No	No	Yes
Fixed effects	No	Yes	Yes	Yes	Yes
Observations	4,691	4,691	4,691	4,691	4,691
R-squared	0.336	0.503	0.503	0.504	0.505
Number of pid		2,347	2,347	2,347	2,347

Note: Estimates are computed using a linear probability model. Sampling weights applied. Standard errors clustered at the household level.*** p<0.01, ** p<0.05, * p<0.1. Data refers to the 1st wave.

also been negatively affected, but in this case, the impact did not significantly change over time. In the case of non-AFVC, after an initial negative impact, the coefficients became no longer significant from the third round onwards. This could mean that the COVID-19 cases no longer had an impact or that employment effects within this category offset each other. For instance, among the off-farm self-employment, construction and manufacturing reported a positive effect, while trade and restaurants, hotels, and bars showed negative coefficients.

The impact on income

Table 5 shows the results of the various models estimating the impact of COVID-19 on income change. Again, the interaction term Cases*Time is negative and most of the time statistically significant[25].

The impact of COVID-19 on income (Figure 7), takes more time to occur. Households indeed can rely on savings or other coping strategies in the short run. However, from the third round onwards total income has been negatively affected by COVID-19 cases, and, similarly to employment, the effect increases over time. Wage income and off-farm business income do not seem to have been significantly affected, while it is interesting to see the impact on farm family farming. After an initial positive effect, in the last three rounds COVID-19 cases have significantly and negatively impacted farm income. This can be explained because initially, the virus spread

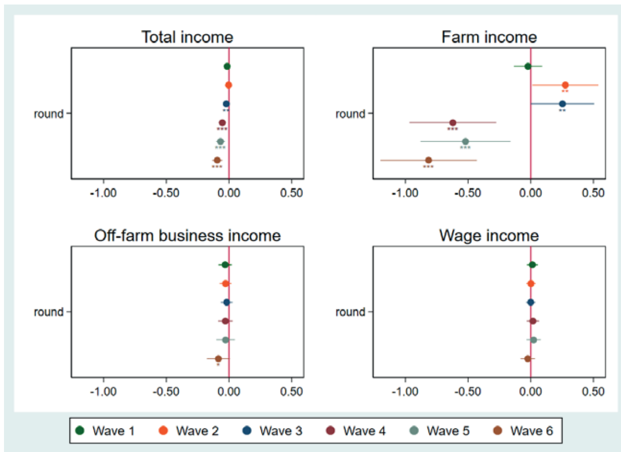

Figure 7. Impact of COVID-19 cases on income over time. Source: Own calculation from ESS 2018/2019 and HFPSH 2020. Note: Dependent variable = categorical variable of income change, ranging from -2 (total loss) to 1 (increase). Dots are coefficients estimated from a linear probability model with household fixed effects. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals. Sampling weights applied. Standard errors clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

[25] The coefficient loses significance when the triple interaction term is added. However, from the third round onwards it is statistically significant.

in the cities, marginally hitting farmers livelihood in rural areas. Then the virus spread across the whole country, affecting also people located in more remote areas. Additionally, if initially smallholders and subsistence farm households were more advantaged against the measures implemented by the government because they relied less on external inputs and markets, this advantage disappeared over time, due to the limited coping mechanisms they had available.

The impact of locust outbreak on farm employment and income

The inclusion of the dummy for respondents who self-reported to have experienced the desert locust shock on the farm has a significant impact on changing the coefficients associated with the number of COVID-19 cases. Results are reported in Table 6. For employment, the coefficient of the COVID-19 cases loses significance, while having locusts on the farm is positively and significantly associated with labor activities. This confirms the additional labor time required to spray the chemicals all over the land. Regarding income, compared to previous results, where the coefficient of COVID-19 cases was -0.621, the inclusion of desert locusts increases the magnitude of the coefficient to -1.103, strengthening the negative impact of COVID-19 cases on farm income. These results show that it is important to consider multiple shocks experienced by individuals and households when assessing the impact of a certain event.

When using the georeferenced data (Table 7), the locust variable loses significance for own farm labor activities. Instead, the impact of locust outbreak is significant and negative in the case of farm income. The effect of the locust dummy is larger in the 4th wave (-0.377), which corresponds to the most damaging period for crops, given the locust life cycle as well as the timing of the crop season (peak harvesting in the first crop season, cf. Figure 1). The inclusion of the locusts' data over all six waves does not significantly affect the impact of COVID-19 cases on farm income, showing only slight changes from the model not including the locust dummy estimates.

Table 6. Simultaneous impact of locusts (self-reported data) and COVID-19 on own farm employment activities and farm income change, 4th round.

	Employed in own farm activities	Farm income change
Time	0.0489	5.242***
	(0.504)	(1.893)
Cases*Time	0.0216	-1.103***
	(0.0938)	(0.372)
Days*Time	-0.0237**	-0.0998***
	(0.0115)	(0.0350)
Days*Time*Cases	0.00333*	0.0194***
	(0.00200)	(0.00671)
Locusts on the farm	0.134*	-0.0244
	(0.0685)	(0.110)
Constant	0.542***	-0
	(0.00927)	(0.0111)
Controls	yes	yes
FE	yes	yes
Observations	2,961	2,639
R-squared	0.088	0.309
Number of pid1	2,347	2,347

Note: Estimates are computed using a linear probability model. Sampling weights applied. Standard errors clustered at the household level.*** p<0.01, ** p<0.05, * p<0.1. Data refers to the 4th wave.

5.2. Determinants of income change

In this section, the results of the regressions aimed to identify the main determinants of income change are presented. Regressors have been grouped into three categories: household characteristics, infrastructures, and economic-related variables. As dependent variables, we considered the change in total and farm incomes. For illustrative reasons, this section reports only the results of the models using a dichotomous dependent variable. The estimates of the ordered probit model are reported in the Appendix (Tables A.4 and A.5).

Total income change

Figure 8 reports the estimated coefficients of household characteristics over the six rounds. The only significant variable here is the level of education of the household head. A higher level of education is positively associated with a higher probability of not experiencing an income reduction/total loss. Living in rural areas shows a positive and significant coefficient only in the first round, consistent with previous analyses that show that rural areas were initially less affected.

Economic-related variables (Figure 9) show some interesting patterns. Having a formal job contract is associated with a higher probability of income increase or unchanged income level. A similar relationship can be found with having a bank account and formal insurance, although the magnitude and the level of significance are lower than in the case of a formal contract. These results

Table 7. Simultaneous impact of locusts (GIS data) and COVID-19 on farm income change.

	wave 1	wave 2	wave 3	wave 4	wave 5	wave 6
Time	-0.377***	-0.981***	-1.163***	2.829***	3.007***	5.228***
	(0.0627)	(0.269)	(0.363)	(0.895)	(1.141)	(1.273)
Cases*Time	-0.0217	0.277**	0.254**	-0.620***	-0.519***	-0.815***
	(0.0564)	(0.134)	(0.129)	(0.174)	(0.182)	(0.196)
Days*Time	0.00110	0.0131**	0.0189**	-0.0531***	-0.0581**	-0.103***
	(0.00267)	(0.00638)	(0.00858)	(0.0169)	(0.0250)	(0.0273)
Cases*Days*Time	-0.00175	-0.00621**	-0.00654**	0.0104***	0.00923**	0.0153***
	(0.00185)	(0.00281)	(0.00272)	(0.00310)	(0.00365)	(0.00393)
Locust dummy	-0.307***	-0.350***	-0.0973	-0.377***	0.0327	-0.00324
	(0.104)	(0.129)	(0.156)	(0.144)	(0.245)	(0.213)
Constant	0.00328	0.00398	0.00131	0.00455	-0.000442	4.29e-05
	(0.0114)	(0.0126)	(0.0111)	(0.0131)	(0.0163)	(0.0139)
Controls	yes	yes	yes	yes	yes	yes
FE	yes	yes	yes	yes	yes	yes
Observations	3,025	2,882	2,850	2,853	2,844	2,843
R-squared	0.386	0.415	0.384	0.225	0.102	0.099
Number of pid1	2,347	2,347	2,347	2,347	2,347	2,347

Note: Dependent variable: categorical variable of income change, ranging from -2 (total loss) to 1 (increase). Estimates are computed using a linear probability model with household fixed effects. Sampling weights applied. Standard errors clustered at the household level.*** p<0.01, ** p<0.05, * p<0.1.

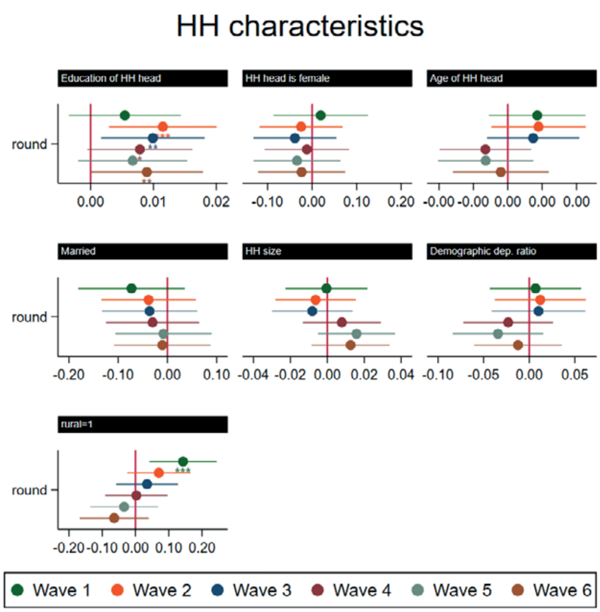

Figure 8. Effects of households' characteristics on total income change over time. Source: Own calculation from ESS 2018/2019 and HFPSH 2020. Note: Dependent variable = dummy equal to 1 if total income did not decrease compared to pre-Covid round. Dots are average marginal effects from a probit regression. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals. Sampling weights applied. Robust Standard errors. *** p<0.01, ** p<0.05, * p<0.1.

show that access to formal institutions is a winning strategy to contrast the negative consequences caused by the crisis. Per capita household income reports a positive relationship, meaning that as per capita income increases the probability of not experiencing an income reduction increases. Richer households are then expected to suffer less from the crisis. However, the magnitude of the coefficient is quite small, suggesting that the differential effect between poorer and richer households is limited.

Regarding infrastructure variables, none of them has a substantial effect on total income (Figure 10). Being distant to the urban center, to the main road, or to the markets seems to be slightly positively associated, sometimes in a significant way, with the probability of income increase or unchanged. However, the coefficient is lower than 1%.

Farm income change

The same variables considered in the previous section show partly different patterns when considering farm income. Looking at the household characteristics (Figure 11), the education of the household head no longer seems to play a relevant role, while the household size and the age of the household head are associated with a higher probability of income reduction, although the effect is statistically significant only in a few rounds.

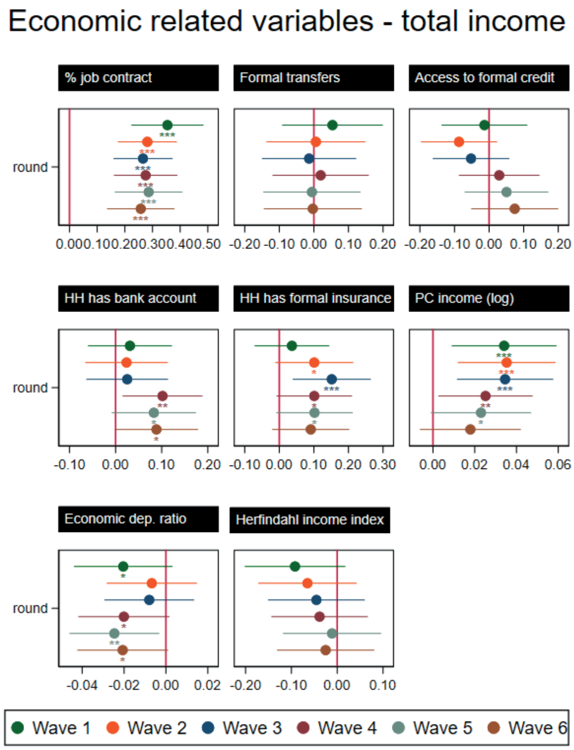

Figure 9. Effects of economic-related variables on total income change over time. Source: Own calculation from ESS 2018/2019 and HFPSH 2020. Note: Dependent variable = dummy equal to 1 if total income did not decrease compared to pre-Covid round. Dots are average marginal effects from a probit regression. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals. Sampling weights applied. Robust Standard errors. *** p<0.01, ** p<0.05, * p<0.1.

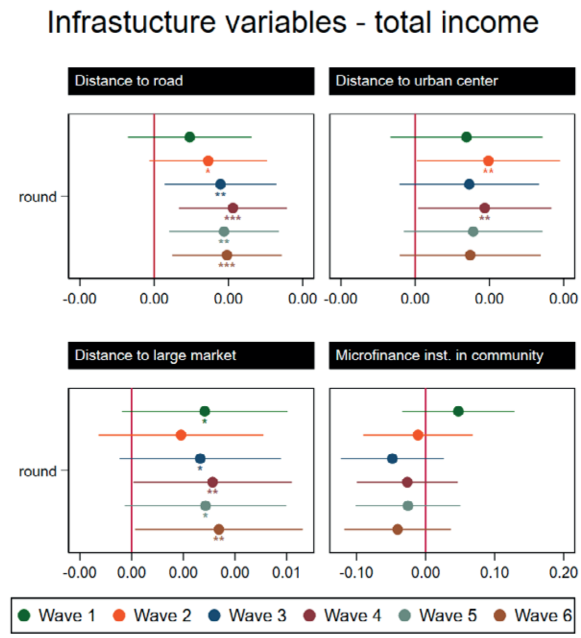

Figure 10. Effects of infrastructure variables on total income change over time. Source: Own calculation from ESS 2018/2019 and HFPSH 2020. Note: Dependent variable = dummy equal to 1 if farm income did not decrease compared to pre-Covid round. Dots are average marginal effects from a probit regression. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals. Sampling weights applied. Robust Standard errors. *** p<0.01, ** p<0.05, * p<0.1.

Even in the case of farm income (Figure 12), distance does not show significant effects, except for distance to a large market, where it seems that the more distant the household the higher the probability of farm income unchanged or increased. This result may look counterintuitive. A possible explanation could be that more (economically) isolated households had already put in place some strategies to account for the distance from large markets, so they were more advantaged relatively to those farmers who were used to relying on markets. Additionally, given the travel restrictions, domestic food value chains could have reshaped to adapt to the new situation, shortening their lengths. In this way, people in remote areas relied more on locally produced agricultural products instead of going to the main urban market.

The role of microfinance institutions in the community is interesting. Indeed, differently from total income, here it shows a positive coefficient, and in the last rounds the effect is also statistically significant. This means that this type of institution matters in times of crisis.

As in the total income case, having a bank account and formal insurance rise the probability of farm income increase (Figure 13). Having a formal job contract does not show a statistically significant effect on agricultural income. This makes sense given that most households in Ethiopia run family farms and do not participate in the formal labor market.

Regarding the agricultural-related variables (Figure 14), results seem to suggest that farmers with larger areas of land have a higher probability of success compared to smallholders, as shown also by the marginal effects of land size on the probability that farm income did not decrease (Figure A.4 in the Appendix). This result is in contrast to findings from other studies conducted in different contexts. Cesaro et al. (2022), for example, found that medium-large farms in Italy expressed greater concern about the negative consequences of COVID-19 in the short term than small farms. Having a land ownership title or holding the right to use it played an important role in cushioning the negative COVID-19 impact. Households that use fertilizers and those that have agricultural machinery, although they initially experienced a positive or insignificant effect, were subsequently nega-

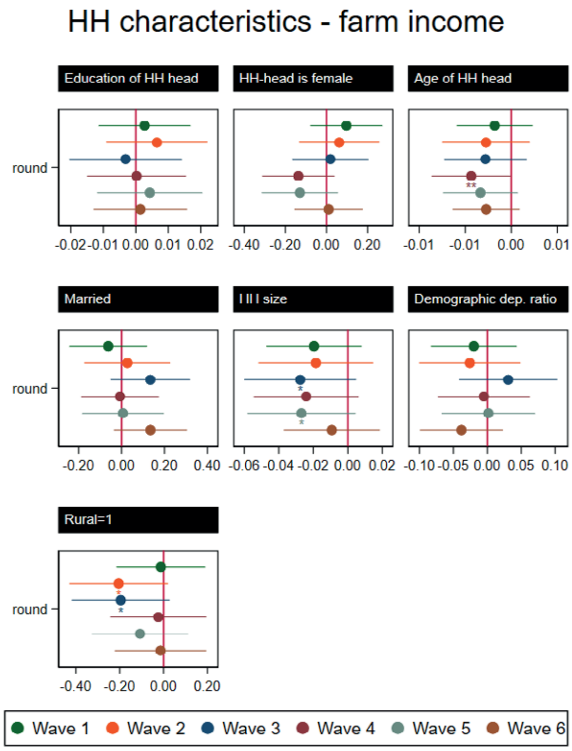

Figure 11. Effects of households' characteristics on farm income change over time. Source: Own calculation from ESS 2018/2019 and HFPSH 2020. Note: Dependent variable = dummy equal to 1 if total income did not decrease compared to pre-Covid round. Dots are average marginal effects from a probit regression. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals. Sampling weights applied. Robust Standard errors. *** p<0.01, ** p<0.05, * p<0.1.

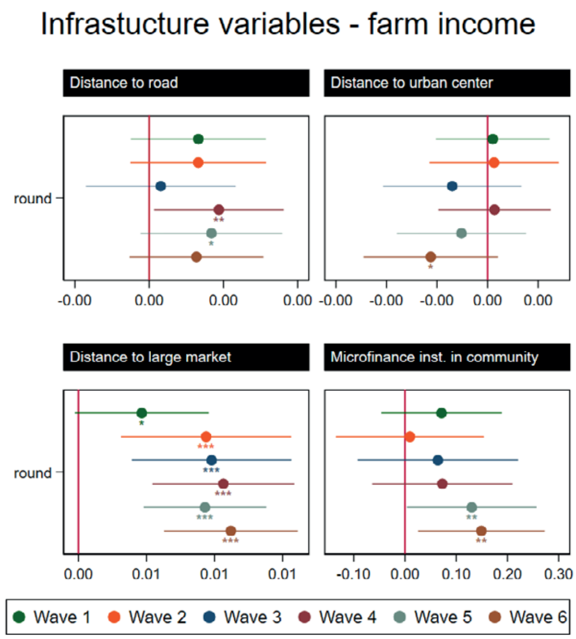

Figure 12. Effects of infrastructure variables on farm income change over time. Source: Own calculation from ESS 2018/2019 and HFPSH 2020. Note: Dependent variable = dummy equal to 1 if farm income did not decrease compared to pre-Covid round. Dots are average marginal effects from a probit regression. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals. Sampling weights applied. Robust Standard errors. *** p<0.01, ** p<0.05, * p<0.1.

tively affected. This result can be the consequence of the mobility and trade restrictions, which decreased inputs availability and increased their prices. A less diversified crop mix was detrimental to farm income increase in early rounds, as shown by the coefficient of the Herfindahl index of crop[26].

5.3. Robustness Checks

Placebo test

To test the validity of the treatment variable used in the analysis, we ran a placebo test, imputing the COVID-19 shock in the prior wave of the ESS, collected in 2015/2016, and considering as baseline the 2012/2014 ESS survey. If the variable of the number of COVID-19 cases correctly captures the impact of the COVID-19 shock, we should not find any significant effect, given that at that time the shock did not occur.

Table 8 reports the results of the test, applied for the change of total income at the household level and total employment at the individual level. The variable is valid when applied to the model of household income, where none of the coefficients related to COVID-19 is significant. Instead, when running the same model on total employment, the coefficient of the interaction between time and COVID-19 cases is significant (column 1). However, the sign is positive, in contrast to the predicted effect that the shock should have. A possible explanation is that the variable of COVID-19 cases is in a way correlated with regional characteristics. For instance, we know that COVID-19 has affected some economic sectors more than others and, if a region is specialized in one sector, this correlation will be significant. If the employment rate was expanding between 2014 and 2016 in that specific sector, the correlation would be positive.

[26] The Herfindahl index is a measure of crop concentration. It is computed as the sum of square of the proportion of individual crop groups in a portfolio. The index decreases with an increase in diversification. It ranges from 0 (complete diversification) to 1 (complete specialization) (Singh et al., 2018).

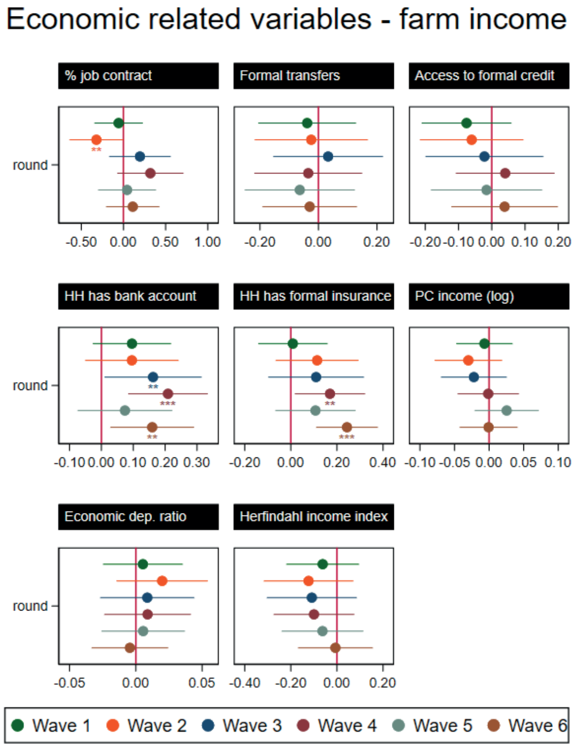

Figure 13. Effects of economic-related variables on farm income change over time. Source: Own calculation from ESS 2018/2019 and HFPSH 2020. Note: Dependent variable = dummy equal to 1 if farm income did not decrease compared to pre-Covid round. Dots are average marginal effects from a probit regression. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals. Sampling weights applied. Robust Standard errors. *** p<0.01, ** p<0.05, * p<0.1.

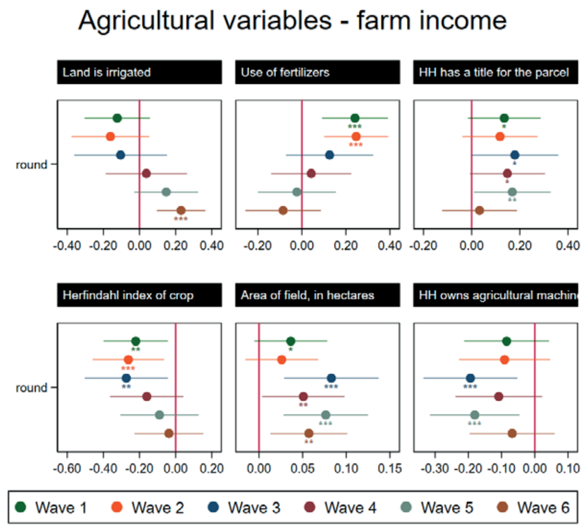

Figure 14. Effects of agricultural-related variables on farm income change over time.cSource: Own calculation from ESS 2018/2019 and HFPSH 2020. Note: Dependent variable = dummy equal to 1 if farm income did not decrease compared to pre-Covid round. Dots are average marginal effects from a probit regression. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals. Sampling weights applied. Robust Standard errors. *** p<0.01, ** p<0.05, * p<0.1.

Introducing regional income (column 2)[27] indeed makes the interaction term not significant.

Inverse probability weights

To address the problem of representativeness of the individual sample, we created individual-level adjusted weights using the inverse probability based on the ESS 2018/2019, and we compared the outcomes using these weights following Khamis et al. (2021)[28]. We ran a logit regression to estimate the probability of being in the HFPS subsample over a set of variables at the individual level, weighted by the household weights of ESS 2019. Variables include age, gender, years of completed education, living in rural areas, income quintile, being employed, working in own farm activities, and being not engaged in education, employment or training (NEET). Children below 12 years old have been excluded. The inverse of the estimated probability is the adjusted weight. This procedure gives greater weight to observations that appeared in the HFPS sample. Figure 15 reports the coefficients estimated with original weights vis-à-vis the adjusted ones. The correlation of the estimates using the two methods is very high, i.e. 98%. This result suggests that the labor market outcomes of the subsample of individuals are generally consistent with the outcomes of the whole working population.

6. CONCLUSIONS

The analysis showed that COVID-19 negatively impacted both household employment and income, the more so the longer the time length from the pandemic

[27] Regional income can capture the level of economic development of the region, which is in turn correlated with other factors, including the economic sector.

[28] Khamis et al. (2021) relied on the World Bank's Global Monitoring Database. Although they found similar results when applying the corrected weights compared to the original ones, they had a limited set of variables available to use for reweighting the estimates, undermining the effectiveness of the weights created. In our case, instead, we can consider more variables, increasing the ability to effectively adjust for the differences between the individuals in the subsample and the rest of the population.

Table 8. Placebo test on ESS 2012/2014 and ESS 2015/2016.

Variables	Total income change	Total employment	
		(1)	(2)
Time	0.0852	-0.294***	-0.363**
	(0.154)	(0.0850)	(0.169)
Time*cases	0.0136	0.0258**	0.0419
	(0.0204)	(0.0113)	(0.0365)
Time*days	0.00274	0.00153	0.00192
	(0.00538)	(0.00295)	(0.00311)
Time*days*cases	-0.000364	-0.000233	-0.000312
	(0.000701)	(0.000386)	(0.000431)
Cases*regional income			-4.31e-07
			(9.34e-07)
Constant	-0.00491	0.601***	0.601***
	(0.0109)	(0.00583)	(0.00584)
Controls	Yes	Yes	Yes
FE	Yes	Yes	Yes
Observations	9,760	21,289	21,289
Number of pid	4,887	11,368	11,368
R-squared	0.023	0.050	0.050

Note: Dependent variables: categorical variable of income change, ranging from -2 (total loss) to 1 (increase) (1st column), and dummy equal to 1 if the individual is employed (2nd column). Income change is computed by comparing the amount of household income earned in each round. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

onset. Upstream activities, and specifically own farming, are the most affected segment of the AFVC. Indeed, despite an initial positive effect, the impact then became negative and increased in magnitude over time. This finding is partly in line with previous studies published in the immediate aftermath of the pandemic (Bundervoet and Finn, 2020; Reardon et al., 2020a) that show that farming was the less affected sector. However, tracking the impact over time allowed gaining a more complete understanding of the evolution of the effect, with farming increasingly severely affected by the disruption of the food value chain. The initial resilience capacity of the Ethiopian food marketing systems, as reported by Hirvonen et al. (2021b) for the vegetable value chain does not seem to persist over time. This highlights the importance of monitoring the evolution of the impact of the shock over time. Indeed, considering only the initial effect could give an incomplete and misleading understanding of the actual situation.

We also showed that the most vulnerable farmers have been hit hardest. Small farming households are more exposed to the negative consequences of the crisis. There is the need then to target specifically this group of AFVC actors, especially in situations of crisis. To do this, AFVC participants need to have access to specific tools that allow them to cope with the shock. Access to formal institutions, such as formal insurance, bank account, formal contract, and land title are all positively associated with a higher probability of income increase. The national government should then increase its effort in providing improved opportunities to access financial services as well as formal institutions.

Last but not least, multiple shocks dramatically worsen the picture. This is the case of the desert locust outbreak, that compounded with an already difficult situation created by COVID-19. Therefore, policymakers should consider the effects of simultaneous shocks when designing policy responses to the crisis.

From our data, it is not possible to identify how the above impacts may affect other important dimensions of well-being such as food security. Abay et al. (2023) found that household food insecurity increased by 11.7 percentage points. The authors did not assess the relationship between a reduction in employment/income and food security. However, there is evidence from other studies that a reduction in employment and income may or may not affect food security. Especially when subjective estimates of income change are used, the relationship is not straightforward. In Hirvonen et al. (2021a), for example, self-reported income shocks did not appear to be associated with changes in the Household Dietary Diversity Score (HDDS). Furthermore, other mechanisms may be in place that can influence food security, depending on the type of household considered, its integration into the food value chain, and the participation in safety net programs[29]. Additional analysis of the mechanisms and close monitoring of the effects of the crisis are then required to respond with appropriate policies as other crises arise.

The main limitations of this work are related to the type of data available, which reduces the internal and external validities of the findings (Abate et al., 2023). Indeed, the fact that data are collected through phone interviews limits the representativeness of the sample, especially considering the low phone penetration in the rural areas of the country. The COVID-19 cases variable is not fully able to capture the infection rate and the economic downturn caused by the policy interventions in the country. Additionally, measurement error could be widespread in self-reported data. This is particularly relevant

[29] Abay et al. (2023), in the same study cited above, showed that participation in the Productive Safety Net Program (SNP) offsets virtually almost all of the COVID-19 induced food insecurity increase (11.7 percentage points): the likelihood of becoming food insecure increased by only 2.4 percentage points for PSNP households. Qualitatively similar results are reported by Maffioli et al (2023) for Myanmar.

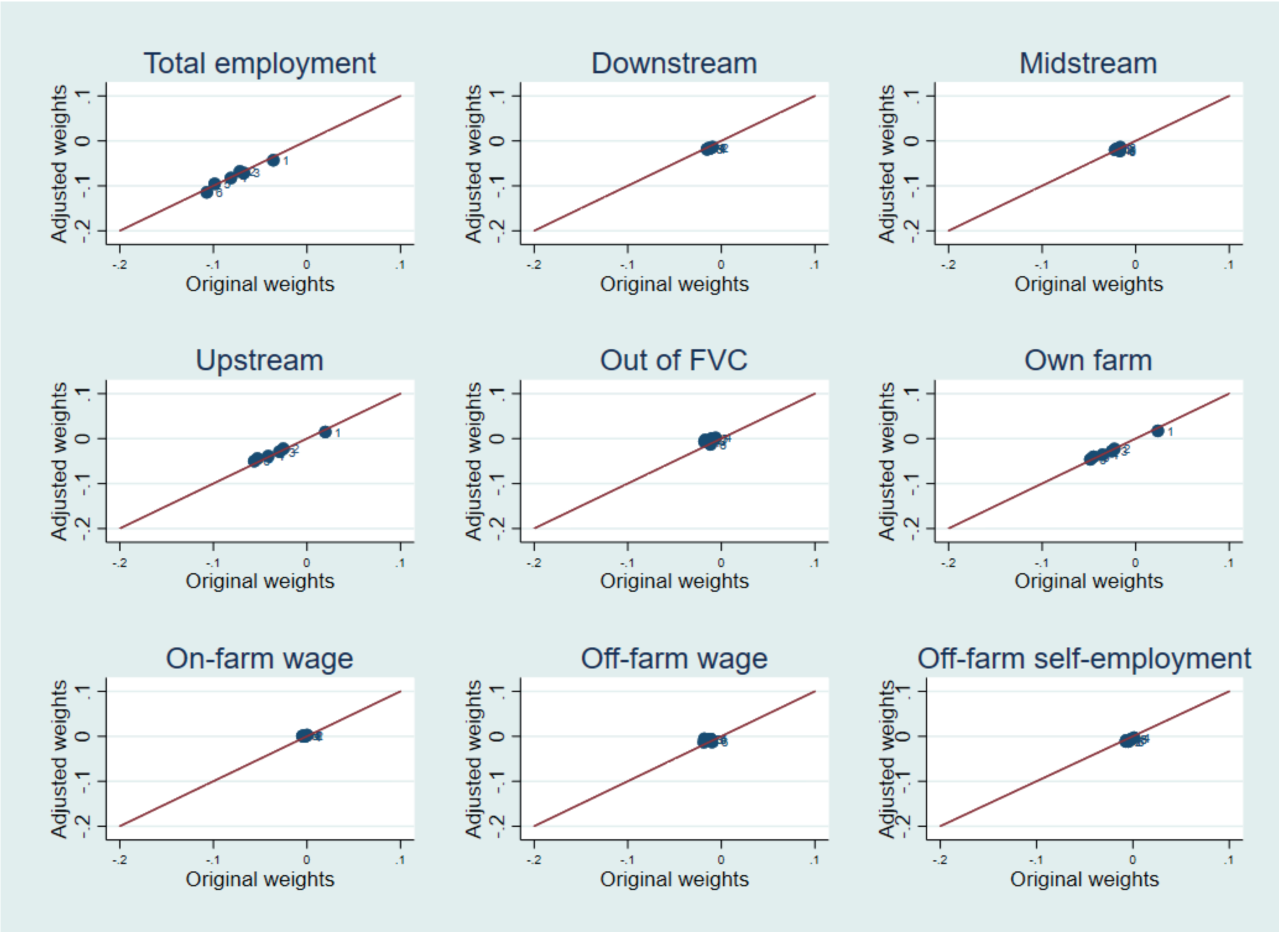

Figure 15. Comparison of weighting methods. Source: own elaboration from ESS 2018/2019 and HFPSH 2020.

for the variable of income change, which is highly subjective to respondents' perception. Income data collected through more reliable measures are then needed to avoid major measurement errors. Finally, data used in this study were not intended to specifically track AFVC participants. Household surveys based on random sampling of the whole economy are typically unable to capture a representative picture of the actors across the different segments of the value chain[30]. Vice versa, information/data retrieved through survey based on representative samples of the main AFVCs[31] coupled with cascading survey of the various AFVC segments would have been better suited to grasp a better understanding of the overall effect of the COVID-19 crisis on the Ethiopian food system.

[30] For instance, less than 100 individuals employed in the downstream segment are surveyed in each post-COVID round.

[31] Studies on specific value chains in Ethiopia have been conducted only for the dairy value chain (see Hirvonen et al., 2021c), and the vegetable value chain (Hirvonen et al., 2021d).

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APPENDIX

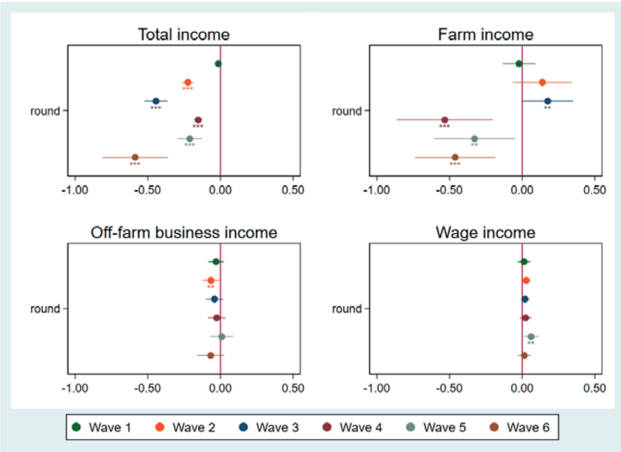

Figure A.1. Impact of COVID-19 cases on income change, wave by wave. Source: Own calculation from ESS 2018/2019 and HFPSH 2020. Note: Dependent variable = categorical variable of income change, ranging from -2 (total loss) to 1 (increase). Dots are coefficients estimated from a linear probability model with household fixed effects. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals. Sampling weights applied. Previous call is considered the baseline. Standard errors clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

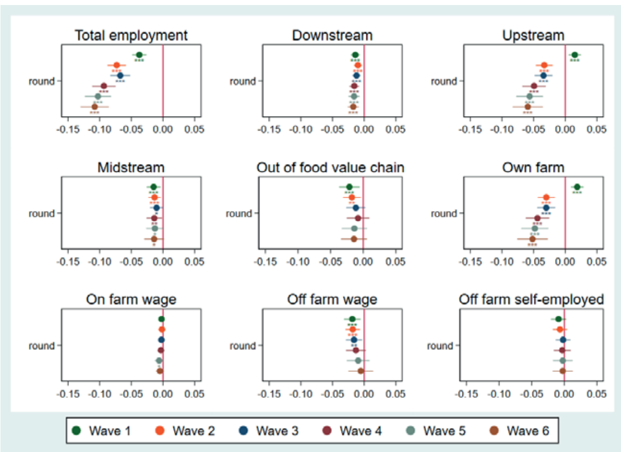

Figure A.2. Impact of COVID-19 cases on employment over time, unbalanced sample. Source: Own calculation from ESS 2018/2019 and HFPSH 2020. Note: Dependent variable = dummy equal to 1 if the individual is employed. Dots are coefficients estimated from a linear probability model with household fixed effects. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals. Sampling weights applied. Standard errors clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

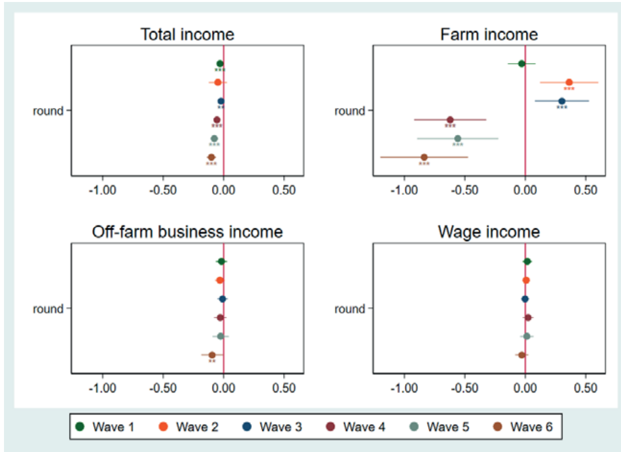

Figure A.3. Impact of COVID-19 cases on total income over time, unbalanced sample. Source: Own calculation from ESS 2018/2019 and HFPSH 2020. Note: Dependent variable = categorical variable of income change, ranging from -2 (total loss) to 1 (increase). Dots are coefficients estimated from a linear probability model with household fixed effects. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals. Sampling weights applied. Standard errors clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

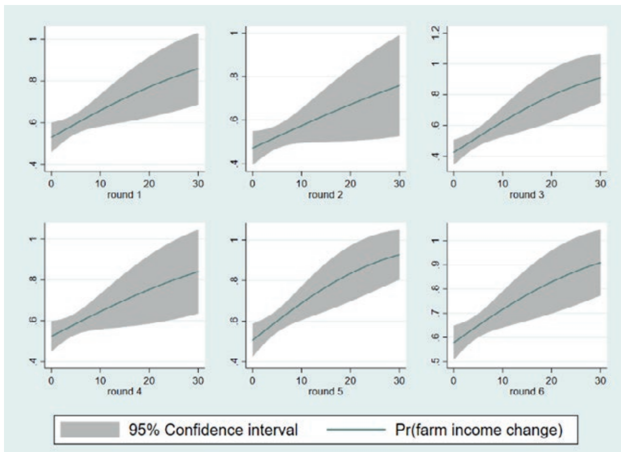

Figure A.4. Marginal effects of land size on the probability that farm income change has not decreased. Source: Own calculation from ESS 2018/2019 and HFPSH 2020.

Table A.1. Number of individuals that started to work again in each round, by reason for stop working in the previous round.

Reason for stop working	N. of individuals that started working again				
	Round 2	Round 3	Round 4	Round 5	Round 6
Seasonal/Casual worker	27	8	8	7	6
Contract ended	3	0	3	2	1
Covid-19	83	22	22	5	6
Temporarily absent	25	8	6	5	9
Retired	0	0	0	1	0
Being ill	2	8	2	1	5
Need to care for ill	1	1	1	0	0
Other	1	0	1	1	0
N/A	329	94	71	54	30
Total	471	141	114	76	57

Table A.2. Full regression estimates, total employment.

Variables	Round 1	Round 2	Round 3	Round 4	Round 5	Round 6
Time	-0.0709***	0.313***	0.368***	0.643***	0.886***	0.961***
	(0.0196)	(0.0463)	(0.0539)	(0.0807)	(0.0975)	(0.107)
Time*Cases	-0.0360***	-0.0717***	-0.0673***	-0.0813***	-0.0987***	-0.107***
	(0.00654)	(0.00837)	(0.00879)	(0.00980)	(0.0110)	(0.0118)
Time*Days	-0.000364	-0.00707***	-0.00792***	-0.0178***	-0.0260***	-0.0296***
	(0.000640)	(0.00134)	(0.00142)	(0.00281)	(0.00377)	(0.00391)
Time*Cases*Days	-1.53e-06	0.00251***	0.00197***	0.00266***	0.00338***	0.00377***
	(0.000383)	(0.000367)	(0.000345)	(0.000434)	(0.000513)	(0.000514)
Other HH members lost job	0.0119	-0.166***	-0.0858	-0.1000	-0.233***	-0.225***
	(0.0412)	(0.0629)	(0.0663)	(0.0647)	(0.0822)	(0.0742)
HH received assistance	0.0449	0.0777	0.0571	0.0223	-0.0219	-0.000938
	(0.0358)	(0.0634)	(0.0537)	(0.0495)	(0.0480)	(0.0459)
Constant	0.746***	0.747***	0.748***	0.749***	0.752***	0.752***
	(0.00507)	(0.00840)	(0.00833)	(0.00853)	(0.00842)	(0.00863)
Observations	4,693	4,694	4,694	4,693	4,694	4,694
R-squared	0.122	0.086	0.079	0.098	0.124	0.116
Number of pid1	2,347	2,347	2,347	2,347	2,347	2,347

Source: Own calculation from ESS 2018/2019 and HFPSH 2020.
Note: Dependent variable = dummy equal to 1 if individual is employed. Coefficients estimated using a linear probability model with household fixed effects. Each post-COVID round is compared with the baseline. 95% confidence intervals in parenthesis. Sampling weights applied. Standard errors clustered at the household level. *** p<0.01, ** p<0.05, * p<0.

Table A.3. Full regression estimates, total income.

Variables	Round 1	Round 2	Round 3	Round 4	Round 5	Round 6
Time	-0.549***	-0.599***	-0.502***	-0.237*	-0.0341	0.203
	(0.0412)	(0.0522)	(0.0685)	(0.124)	(0.160)	(0.186)
Time*Cases	-0.0148	-0.00295	-0.0216**	-0.0533***	-0.0677***	-0.0937***
	(0.0119)	(0.0102)	(0.0110)	(0.0150)	(0.0179)	(0.0206)
Time*Days	1.58e-05	-0.00265	-0.00653**	-0.0154**	-0.0162*	-0.0172*
	(0.00161)	(0.00198)	(0.00311)	(0.00670)	(0.00945)	(0.0102)
Time*Cases*Days	-0.000970	0.000198	0.000921	0.00199**	0.00188	0.00192
	(0.000864)	(0.000564)	(0.000685)	(0.000947)	(0.00119)	(0.00124)
HH received assistance	-0.0774	-0.141**	-0.201***	-0.117	-0.163**	-0.165**
	(0.0808)	(0.0549)	(0.0760)	(0.0768)	(0.0779)	(0.0787)
Other HH members lost job	-0.0758	-0.119	-0.123	-0.0720	-0.128	-0.108
	(0.0871)	(0.0839)	(0.0759)	(0.0823)	(0.0809)	(0.0802)
Constant	-0	-0	0	0	-0	0
	(0.0105)	(0.0107)	(0.0122)	(0.0137)	(0.0151)	(0.0156)
Observations	4,691	4,693	4,694	4,691	4,693	4,685
R-squared	0.505	0.568	0.540	0.472	0.408	0.363
Number of pid1	2,347	2,347	2,347	2,347	2,347	2,347

Source: Own calculation from ESS 2018/2019 and HFPSH 2020.
Note: Dependent variable: categorical variable of income change, ranging from -2 (total loss) to 1 (increase). Estimates are computed using a linear probability model with household fixed effects. Sampling weights applied. Standard errors clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.4. Ordered probit, total income change.

Variables	Round 1				Round 2				Round 3			
	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1
Years of education	-0.00171**	-0.00620**	0.00730**	0.000611*	-0.00211**	-0.00595**	0.00678**	0.00129**	-0.00160	-0.00291	0.00331	0.00119
	(0.000869)	(0.00296)	(0.00348)	(0.000348)	(0.000983)	(0.00283)	(0.00319)	(0.000635)	(0.00130)	(0.00241)	(0.00273)	(0.000968)
HH head is female	-0.00176	-0.00647	0.00759	0.000643	0.0117	0.0304	-0.0358	-0.00640	0.0288	0.0446	-0.0554	-0.0181
	(0.0102)	(0.0381)	(0.0445)	(0.00384)	(0.0118)	(0.0284)	(0.0344)	(0.00587)	(0.0247)	(0.0292)	(0.0416)	(0.0123)
Age of HH head	-0.000461*	-0.00167*	0.00197*	0.000165	-0.000205	-0.000577	0.000657	0.000125	3.79e-05	6.89e-05	-7.85e-05	-2.83e-05
	(0.000276)	(0.000975)	(0.00115)	(0.000103)	(0.000323)	(0.000923)	(0.00105)	(0.000198)	(0.000429)	(0.000779)	(0.000887)	(0.000321)
HH head is married	0.00802	0.0306	-0.0355	-0.00314	0.00925	0.0275	-0.0306	-0.00615	0.0162	0.0319	-0.0347	-0.0134
	(0.00975)	(0.0393)	(0.0449)	(0.00416)	(0.0107)	(0.0337)	(0.0366)	(0.00782)	(0.0184)	(0.0370)	(0.0392)	(0.0163)
HH size	-0.000397	-0.00144	0.00169	0.000141	0.000208	0.000586	-0.000667	-0.000127	0.000337	0.000613	-0.000698	-0.000252
	(0.00206)	(0.00744)	(0.00877)	(0.000733)	(0.00242)	(0.00683)	(0.00777)	(0.00148)	(0.00344)	(0.00626)	(0.00713)	(0.00257)
Asset index	0.00193	0.00699	-0.00823	-0.000689	-0.000412	-0.00116	0.00132	0.000251	-0.00147	-0.00268	0.00305	0.00110
	(0.00164)	(0.00593)	(0.00696)	(0.000620)	(0.00180)	(0.00503)	(0.00574)	(0.00109)	(0.00267)	(0.00469)	(0.00539)	(0.00196)
HH consumption (log)	-0.00901	-0.0326	0.0384	0.00321	0.00215	0.00605	-0.00689	-0.00131	0.00419	0.00761	-0.00867	-0.00313
	(0.00662)	(0.0233)	(0.0276)	(0.00241)	(0.00756)	(0.0212)	(0.0242)	(0.00462)	(0.00975)	(0.0178)	(0.0202)	(0.00731)
% of members with job contract	-0.0635***	-0.230***	0.271***	0.0227***	-0.0634***	-0.178***	0.203***	0.0386***	-0.0686***	-0.125**	0.142**	0.0513**
	(0.0148)	(0.0494)	(0.0580)	(0.00629)	(0.0143)	(0.0367)	(0.0423)	(0.00933)	(0.0248)	(0.0522)	(0.0564)	(0.0203)
HH receives social assistance	-0.0111	-0.0470	0.0530	0.00514	0.00674	0.0174	-0.0205	-0.00370	-0.00351	-0.00662	0.00740	0.00273
	(0.0113)	(0.0549)	(0.0595)	(0.00674)	(0.0188)	(0.0443)	(0.0538)	(0.00927)	(0.0217)	(0.0423)	(0.0465)	(0.0175)
HH has formal credit	-0.00174	-0.00641	0.00751	0.000639	0.0325*	0.0662**	-0.0851**	-0.0136**	0.0414	0.0531**	-0.0723*	-0.0223**
	(0.0113)	(0.0424)	(0.0494)	(0.00428)	(0.0193)	(0.0268)	(0.0401)	(0.00610)	(0.0275)	(0.0221)	(0.0382)	(0.0111)
HH has savings	0.0289***	0.107***	-0.126***	-0.0102***	0.0163*	0.0456*	-0.0520*	-0.00989*	0.00586	0.0106	-0.0121	-0.00437
	(0.00887)	(0.0298)	(0.0354)	(0.00329)	(0.00957)	(0.0258)	(0.0297)	(0.00568)	(0.0125)	(0.0230)	(0.0262)	(0.00940)
HH has bank account	0.000199	0.000722	-0.000850	-7.10e-05	-0.000563	-0.00158	0.00180	0.000343	-0.00125	-0.00227	0.00259	0.000933
	(0.00918)	(0.0333)	(0.0392)	(0.00328)	(0.0106)	(0.0297)	(0.0338)	(0.00642)	(0.0142)	(0.0258)	(0.0294)	(0.0106)
HH has formal insurance	-0.00823	-0.0329	0.0377	0.00343	-0.0199**	-0.0726*	0.0756**	0.0169*	-0.0321***	-0.0817**	0.0793**	0.0346**
	(0.00832)	(0.0360)	(0.0403)	(0.00400)	(0.00835)	(0.0377)	(0.0364)	(0.00978)	(0.0117)	(0.0387)	(0.0328)	(0.0174)
Distance to main road	-0.000181	-0.000657	0.000774	6.47e-05	-0.000246	-0.000693	0.000790	0.000150	-0.000418*	-0.000761*	0.000867*	0.000313*
	(0.000156)	(0.000561)	(0.000660)	(5.67e-05)	(0.000176)	(0.000495)	(0.000566)	(0.000106)	(0.000227)	(0.000405)	(0.000466)	(0.000164)
Distance to urban center	-4.57e-05	-0.000166	0.000195	1.63e-05	-0.000132*	-0.000373**	0.000424**	8.06e-05*	-0.000138	-0.000250	0.000285	0.000103
	(5.15e-05)	(0.000188)	(0.000220)	(1.89e-05)	(6.85e-05)	(0.000187)	(0.000213)	(4.33e-05)	(9.06e-05)	(0.000161)	(0.000183)	(6.77e-05)
Distance to market	-0.000476	-0.00173	0.00203	0.000170	-0.000356	-0.00100	0.00114	0.000217	-0.000705	-0.00128	0.00146	0.000527
	(0.000300)	(0.00108)	(0.00127)	(0.000108)	(0.000345)	(0.000967)	(0.00111)	(0.000207)	(0.000466)	(0.000854)	(0.000972)	(0.000345)

(Continued)

Table A.4. (contd.) Ordered probit, total income change.

Variables	Round 1				Round 2				Round 3			
	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1
Microfinance institution	-0.00341	-0.0124	0.0145	0.00123	0.00690	0.0192	-0.0220	-0.00412	0.0149	0.0265	-0.0306	-0.0108
	(0.00761)	(0.0278)	(0.0326)	(0.00280)	(0.00866)	(0.0239)	(0.0273)	(0.00524)	(0.0118)	(0.0211)	(0.0241)	(0.00870)
Electricity	0.00876	0.0340	-0.0394	-0.00340	-0.00303	-0.00835	0.00957	0.00180	0.00114	0.00208	-0.00237	-0.000857
	(0.00800)	(0.0330)	(0.0376)	(0.00342)	(0.0105)	(0.0281)	(0.0326)	(0.00605)	(0.0140)	(0.0258)	(0.0292)	(0.0106)
Safe water	0.00339	0.0119	-0.0141	-0.00114	0.00513	0.0136	-0.0158	-0.00290	0.0197	0.0298	-0.0373	-0.0122
	(0.00953)	(0.0323)	(0.0388)	(0.00302)	(0.0112)	(0.0280)	(0.0333)	(0.00595)	(0.0156)	(0.0197)	(0.0267)	(0.00846)
Toilet	0.0258*	0.0701**	-0.0901**	-0.00581**	0.0254	0.0522**	-0.0669*	-0.0107**	0.0212	0.0307	-0.0392	-0.0127
	(0.0152)	(0.0299)	(0.0427)	(0.00249)	(0.0164)	(0.0239)	(0.0353)	(0.00505)	(0.0193)	(0.0214)	(0.0314)	(0.00919)
HH income (log)	-0.00805***	-0.0292***	0.0344***	0.00287***	-0.00995***	-0.0280***	0.0319***	0.00606***	-0.0119***	-0.0216***	0.0246***	0.00888***
	(0.00262)	(0.00819)	(0.00973)	(0.00108)	(0.00330)	(0.00805)	(0.00930)	(0.00212)	(0.00388)	(0.00653)	(0.00731)	(0.00299)
Demographic Dependency Ratio	0.000241	0.000873	-0.00103	-8.60e-05	-0.00134	-0.00376	0.00428	0.000814	-0.00581	-0.0106	0.0120	0.00434
	(0.00499)	(0.0180)	(0.0212)	(0.00178)	(0.00546)	(0.0154)	(0.0175)	(0.00335)	(0.00826)	(0.0145)	(0.0167)	(0.00609)
Economic Dependency Ratio	0.00329	0.0119	-0.0140	-0.00117	0.00224	0.00630	-0.00717	-0.00136	0.00438	0.00797	-0.00907	-0.00328
	(0.00223)	(0.00803)	(0.00946)	(0.000806)	(0.00224)	(0.00631)	(0.00714)	(0.00141)	(0.00366)	(0.00636)	(0.00728)	(0.00273)
Income diversification	0.0201*	0.0728*	-0.0857*	-0.00717*	0.0187	0.0527	-0.0600	-0.0114	0.0147	0.0268	-0.0305	-0.0110
	(0.0109)	(0.0379)	(0.0448)	(0.00407)	(0.0121)	(0.0327)	(0.0376)	(0.00723)	(0.0157)	(0.0286)	(0.0327)	(0.0116)
Rural	-0.0297**	-0.0993***	0.120**	0.00883**	-0.0331**	-0.0815***	0.0973***	0.0173***	-0.0239	-0.0402	0.0476	0.0165
	(0.0125)	(0.0382)	(0.0469)	(0.00370)	(0.0139)	(0.0275)	(0.0349)	(0.00655)	(0.0163)	(0.0258)	(0.0311)	(0.0109)
HH received assistance since COVID-19 outbreak	0.0230	0.0653	-0.0827	-0.00563*	0.0269*	0.0575**	-0.0727**	-0.0117**	0.0441*	0.0572***	-0.0779**	-0.0234**
	(0.0193)	(0.0433)	(0.0593)	(0.00335)	(0.0150)	(0.0250)	(0.0349)	(0.00513)	(0.0261)	(0.0205)	(0.0364)	(0.00975)
Observations	2,344	2,344	2,344	2,344	2,346	2,346	2,346	2,346	2,347	2,347	2,347	2,347

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.4. (contd.) Ordered probit, total income change.

Variables	Round 4				Round 5				Round 6			
	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1
Years of education	-0.00165	-0.00310	0.00278	0.00197	-0.000920	-0.00220	0.00151	0.00161	-0.00137	-0.00329	0.00204	0.00262
	(0.00130)	(0.00249)	(0.00222)	(0.00156)	(0.00113)	(0.00273)	(0.00187)	(0.00198)	(0.00117)	(0.00280)	(0.00176)	(0.00220)
HH head is female	0.0102	0.0180	-0.0168	-0.0115	0.0228	0.0477	-0.0357	-0.0347	0.0284	0.0582	-0.0404	-0.0462
	(0.0228)	(0.0366)	(0.0358)	(0.0236)	(0.0225)	(0.0366)	(0.0311)	(0.0279)	(0.0241)	(0.0368)	(0.0297)	(0.0310)
Age of HH head	0.000673	0.00126	-0.00113	-0.000802	0.000735	0.00176*	-0.00121*	-0.00129*	0.000402	0.000965	-0.000599	-0.000768
	(0.000473)	(0.000840)	(0.000754)	(0.000554)	(0.000447)	(0.000954)	(0.000674)	(0.000721)	(0.000400)	(0.000929)	(0.000578)	(0.000749)
HH head is married	0.00689	0.0134	-0.0118	-0.00854	0.00394	0.00963	-0.00651	-0.00707	0.00505	0.0124	-0.00755	-0.00993
	(0.0202)	(0.0398)	(0.0344)	(0.0256)	(0.0180)	(0.0443)	(0.0296)	(0.0328)	(0.0182)	(0.0453)	(0.0270)	(0.0364)
HH size	-0.00296	-0.00555	0.00498	0.00353	-0.00408	-0.00975	0.00669	0.00714	-0.00219	-0.00526	0.00327	0.00419
	(0.00339)	(0.00625)	(0.00564)	(0.00399)	(0.00311)	(0.00714)	(0.00499)	(0.00523)	(0.00301)	(0.00719)	(0.00448)	(0.00571)
Asset index	-0.00126	-0.00237	0.00213	0.00151	-0.00249	-0.00595	0.00408	0.00436	-0.00228	-0.00548	0.00340	0.00436
	(0.00261)	(0.00473)	(0.00430)	(0.00304)	(0.00258)	(0.00564)	(0.00393)	(0.00429)	(0.00259)	(0.00579)	(0.00364)	(0.00474)
HH consumption (log)	0.000210	0.000394	-0.000354	-0.000250	0.00482	0.0115	-0.00792	-0.00844	0.00866	0.0208	-0.0129	-0.0165
	(0.00968)	(0.0181)	(0.0163)	(0.0115)	(0.00852)	(0.0207)	(0.0141)	(0.0151)	(0.00821)	(0.0198)	(0.0121)	(0.0159)
% of members with job contract	-0.0684***	-0.128**	0.115**	0.0815**	-0.0557**	-0.133**	0.0914**	0.0974**	-0.0518**	-0.124*	0.0772**	0.0990**
	(0.0261)	(0.0578)	(0.0491)	(0.0340)	(0.0229)	(0.0663)	(0.0439)	(0.0448)	(0.0231)	(0.0657)	(0.0393)	(0.0490)
HH receives social assistance	-0.00183	-0.00350	0.00311	0.00222	0.00179	0.00420	-0.00292	-0.00307	-0.00323	-0.00804	0.00487	0.00640
	(0.0231)	(0.0449)	(0.0395)	(0.0285)	(0.0206)	(0.0474)	(0.0333)	(0.0347)	(0.0202)	(0.0521)	(0.0309)	(0.0414)
HH has formal credit	0.0165	0.0266	-0.0260	-0.0172	0.00197	0.00462	-0.00321	-0.00339	-0.00502	-0.0127	0.00764	0.0101
	(0.0245)	(0.0322)	(0.0347)	(0.0220)	(0.0204)	(0.0465)	(0.0327)	(0.0342)	(0.0191)	(0.0517)	(0.0300)	(0.0408)
HH has savings	0.0158	0.0289	-0.0260	-0.0186	0.0216*	0.0497*	-0.0343**	-0.0370*	0.0205*	0.0473*	-0.0295*	-0.0383*
	(0.0123)	(0.0229)	(0.0202)	(0.0149)	(0.0113)	(0.0257)	(0.0174)	(0.0194)	(0.0115)	(0.0257)	(0.0157)	(0.0213)
HH has bank account	-0.0313**	-0.0570**	0.0522**	0.0360**	-0.0197	-0.0464	0.0322	0.0339	-0.0264*	-0.0618**	0.0390**	0.0492**
	(0.0156)	(0.0260)	(0.0244)	(0.0169)	(0.0128)	(0.0293)	(0.0204)	(0.0215)	(0.0135)	(0.0292)	(0.0188)	(0.0235)
HH has formal insurance	-0.0165	-0.0365	0.0299	0.0231	-0.0198**	-0.0599*	0.0360*	0.0437*	-0.00828	-0.0216	0.0127	0.0172
	(0.0128)	(0.0334)	(0.0252)	(0.0208)	(0.0100)	(0.0359)	(0.0194)	(0.0264)	(0.0139)	(0.0404)	(0.0224)	(0.0318)
Distance to main road	-0.000559**	-0.00105***	0.000940***	0.000665***	-0.000424**	-0.00101**	0.000696**	0.000742**	-0.000431**	-0.00103**	0.000641**	0.000823**
	(0.000220)	(0.000402)	(0.000359)	(0.000254)	(0.000202)	(0.000491)	(0.000320)	(0.000368)	(0.000210)	(0.000492)	(0.000297)	(0.000398)
Distance to urban center	-0.000160**	-0.000301**	0.000270**	0.000191**	-0.000158**	-0.000377**	0.000259**	0.000276**	-0.000145**	-0.000349**	0.000216**	0.000278**
	(7.91e-05)	(0.000138)	(0.000127)	(8.77e-05)	(7.36e-05)	(0.000148)	(0.000106)	(0.000114)	(7.34e-05)	(0.000152)	(9.85e-05)	(0.000125)
Distance to market	-0.000889**	-0.00167**	0.00150**	0.00106**	-0.000755*	-0.00181*	0.00124*	0.00132*	-0.000951**	-0.00228**	0.00142**	0.00182**
	(0.000451)	(0.000849)	(0.000756)	(0.000533)	(0.000396)	(0.000982)	(0.000663)	(0.000706)	(0.000415)	(0.00101)	(0.000615)	(0.000793)

(Continued)

Table A.4. (contd.) Ordered probit, total income change.

Variables	Round 4				Round 5				Round 6			
	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1
Microfinance institution	0.00552	0.0102	-0.00925	-0.00651	-0.00157	-0.00378	0.00259	0.00277	-0.00132	-0.00318	0.00197	0.00253
	(0.0114)	(0.0211)	(0.0191)	(0.0133)	(0.00940)	(0.0225)	(0.0154)	(0.0165)	(0.0103)	(0.0248)	(0.0153)	(0.0198)
Electricity	-0.000411	-0.000768	0.000691	0.000488	-0.00458	-0.0107	0.00743	0.00783	0.00543	0.0134	-0.00818	-0.0107
	(0.0147)	(0.0274)	(0.0246)	(0.0174)	(0.0135)	(0.0306)	(0.0218)	(0.0224)	(0.0127)	(0.0324)	(0.0193)	(0.0258)
Safe water	0.0306	0.0431**	-0.0455*	-0.0281**	0.0220	0.0421*	-0.0329*	-0.0312*	0.0215	0.0420*	-0.0297*	-0.0338*
	(0.0187)	(0.0193)	(0.0240)	(0.0135)	(0.0149)	(0.0221)	(0.0198)	(0.0170)	(0.0138)	(0.0222)	(0.0176)	(0.0181)
Toilet	0.0213	0.0315	-0.0322	-0.0205	0.0178	0.0344	-0.0266	-0.0255	0.0235	0.0435*	-0.0317	-0.0353*
	(0.0191)	(0.0215)	(0.0257)	(0.0147)	(0.0168)	(0.0249)	(0.0223)	(0.0192)	(0.0168)	(0.0227)	(0.0199)	(0.0193)
HH income (log)	-0.0104***	-0.0194***	0.0174***	0.0123***	-0.00920**	-0.0220***	0.0151***	0.0161***	-0.00762**	-0.0183**	0.0113**	0.0146**
	(0.00394)	(0.00674)	(0.00599)	(0.00452)	(0.00361)	(0.00729)	(0.00508)	(0.00570)	(0.00362)	(0.00767)	(0.00484)	(0.00635)
Demographic Dependency Ratio	-0.000787	-0.00148	0.00133	0.000938	0.00397	0.00948	-0.00651	-0.00694	-7.28e-05	-0.000175	0.000108	0.000139
	(0.00762)	(0.0142)	(0.0128)	(0.00904)	(0.00638)	(0.0160)	(0.0108)	(0.0116)	(0.00654)	(0.0157)	(0.00974)	(0.0125)
Economic Dependency Ratio	0.00640*	0.0120*	-0.0108*	-0.00762*	0.00723**	0.0173**	-0.0119**	-0.0127**	0.00598*	0.0144*	-0.00891*	-0.0114*
	(0.00383)	(0.00674)	(0.00607)	(0.00443)	(0.00336)	(0.00725)	(0.00498)	(0.00554)	(0.00340)	(0.00765)	(0.00471)	(0.00627)
Income diversification	0.0115	0.0215	-0.0193	-0.0136	0.00290	0.00693	-0.00476	-0.00507	0.00715	0.0172	-0.0107	-0.0137
	(0.0160)	(0.0302)	(0.0271)	(0.0191)	(0.0137)	(0.0329)	(0.0226)	(0.0240)	(0.0138)	(0.0332)	(0.0207)	(0.0263)
Rural	-0.0184	-0.0319	0.0298	0.0205	-0.0148	-0.0330	0.0235	0.0243	-0.00540	-0.0127	0.00797	0.0101
	(0.0158)	(0.0256)	(0.0244)	(0.0168)	(0.0137)	(0.0274)	(0.0203)	(0.0207)	(0.0137)	(0.0313)	(0.0199)	(0.0251)
HH received assistance since COVID-19 outbreak	0.00888	0.0155	-0.0145	-0.00989	0.0141	0.0304	-0.0223	-0.0222	0.0133	0.0291	-0.0193	-0.0232
	(0.0183)	(0.0291)	(0.0286)	(0.0188)	(0.0172)	(0.0309)	(0.0249)	(0.0232)	(0.0158)	(0.0297)	(0.0213)	(0.0242)
Observations	2,344	2,344	2,344	2,344	2,346	2,346	2,346	2,346	2,338	2,338	2,338	2,338

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.5. Ordered probit, farm income change.

Variables	Round 1				Round 2				Round 3			
	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1
Years of education	-0.000162	-0.00105	0.00110	0.000115	-0.000382	-0.00382	0.00323	0.000972	2.50e-05	0.000465	-0.000373	-0.000117
	(0.000910)	(0.00591)	(0.00617)	(0.000648)	(0.000635)	(0.00646)	(0.00547)	(0.00163)	(0.000380)	(0.00702)	(0.00563)	(0.00177)
HH income (log)	-0.000180	-0.00116	0.00121	0.000127	0.00277	0.0277	-0.0234	-0.00705	0.00128	0.0238	-0.0191	-0.00601
	(0.00277)	(0.0178)	(0.0186)	(0.00194)	(0.00219)	(0.0192)	(0.0162)	(0.00528)	(0.00140)	(0.0193)	(0.0156)	(0.00513)
HH consumption (log)	0.00915	0.0590	-0.0617	-0.00646	0.00433	0.0433	-0.0366	-0.0110	0.00113	0.0211	-0.0169	-0.00531
	(0.00624)	(0.0365)	(0.0379)	(0.00503)	(0.00442)	(0.0476)	(0.0394)	(0.0127)	(0.00269)	(0.0539)	(0.0427)	(0.0138)
HH head is female	-0.00946	-0.0696	0.0702	0.00881	0.00185	0.0179	-0.0153	-0.00441	-0.00273	-0.0560	0.0433	0.0155
	(0.00817)	(0.0673)	(0.0652)	(0.0105)	(0.00863)	(0.0810)	(0.0703)	(0.0194)	(0.00465)	(0.0969)	(0.0714)	(0.0300)
Age of HH head	0.000362	0.00233	-0.00244	-0.000255	0.000440	0.00441**	-0.00373**	-0.00112*	0.000207	0.00385*	-0.00308*	-0.000970*
	(0.000303)	(0.00173)	(0.00183)	(0.000210)	(0.000312)	(0.00211)	(0.00181)	(0.000643)	(0.000206)	(0.00201)	(0.00166)	(0.000574)
HH head is married	0.00565	0.0395	-0.0405	-0.00464	0.00306	0.0319	-0.0264	-0.00861	-0.0100	-0.134	0.116	0.0283
	(0.00952)	(0.0705)	(0.0712)	(0.00891)	(0.00783)	(0.0831)	(0.0672)	(0.0238)	(0.00957)	(0.0856)	(0.0771)	(0.0174)
HH size	0.00243	0.0157	-0.0164	-0.00171	0.000526	0.00526	-0.00445	-0.00134	0.000362	0.00673	-0.00540	-0.00170
	(0.00182)	(0.0115)	(0.0119)	(0.00143)	(0.00144)	(0.0151)	(0.0127)	(0.00384)	(0.000727)	(0.0149)	(0.0119)	(0.00373)
Asset index	-0.00397	-0.0256	0.0268	0.00280	-0.00481*	-0.0481**	0.0407**	0.0122*	-0.000429	-0.00799	0.00640	0.00201
	(0.00326)	(0.0195)	(0.0201)	(0.00274)	(0.00265)	(0.0211)	(0.0175)	(0.00647)	(0.00117)	(0.0214)	(0.0171)	(0.00547)
Land is irrigated	0.0220	0.105	-0.118	-0.00901	0.0113	0.0908	-0.0827	-0.0193	-0.00132	-0.0267	0.0209	0.00703
	(0.0217)	(0.0730)	(0.0890)	(0.00614)	(0.0139)	(0.0924)	(0.0895)	(0.0170)	(0.00626)	(0.134)	(0.103)	(0.0374)
Organic fertilizer	-0.0535**	-0.221***	0.255***	0.0199**	-0.0385*	-0.216***	0.202***	0.0522***	-0.0131	-0.154**	0.129**	0.0381*
	(0.0244)	(0.0503)	(0.0644)	(0.00981)	(0.0199)	(0.0510)	(0.0505)	(0.0186)	(0.0124)	(0.0758)	(0.0644)	(0.0226)
Title of the land	-0.00855	-0.0525	0.0557	0.00526	-0.0101	-0.0892	0.0781	0.0212	-0.00894	-0.130	0.108	0.0306
	(0.0106)	(0.0627)	(0.0679)	(0.00557)	(0.00907)	(0.0642)	(0.0585)	(0.0150)	(0.00919)	(0.0847)	(0.0744)	(0.0190)
% of members with job contract	0.00606	0.0391	-0.0408	-0.00427	0.0509**	0.509***	-0.430***	-0.129**	-0.0180	-0.335	0.268	0.0843
	(0.0166)	(0.107)	(0.112)	(0.0120)	(0.0229)	(0.193)	(0.164)	(0.0547)	(0.0164)	(0.221)	(0.175)	(0.0616)
HHI_crop	0.0290**	0.187***	-0.196***	-0.0205*	0.0271**	0.271***	-0.229***	-0.0688**	0.0164	0.304***	-0.244***	-0.0767**
	(0.0134)	(0.0712)	(0.0734)	(0.0120)	(0.0126)	(0.0772)	(0.0643)	(0.0275)	(0.0121)	(0.0943)	(0.0743)	(0.0321)
Land size (hectares)	-0.00553**	-0.0357**	0.0373**	0.00390*	-0.00189	-0.0189	0.0160	0.00480	-0.00265	-0.0494**	0.0396**	0.0124**
	(0.00280)	(0.0150)	(0.0157)	(0.00234)	(0.00178)	(0.0159)	(0.0136)	(0.00413)	(0.00209)	(0.0197)	(0.0162)	(0.00562)
Income diversification	0.00666	0.0430	-0.0449	-0.00470	0.00412	0.0412	-0.0348	-0.0105	0.000694	0.0129	-0.0104	-0.00326
	(0.00966)	(0.0613)	(0.0643)	(0.00670)	(0.00738)	(0.0748)	(0.0634)	(0.0189)	(0.00445)	(0.0834)	(0.0670)	(0.0208)
Social assistance	0.00305	0.0188	-0.0199	-0.00195	-0.00407	-0.0437	0.0356	0.0122	-0.00397	-0.0938	0.0698	0.0280
	(0.0123)	(0.0724)	(0.0776)	(0.00705)	(0.00677)	(0.0753)	(0.0586)	(0.0235)	(0.00421)	(0.0890)	(0.0606)	(0.0324)
Agricultural machinery	0.00849	0.0503	-0.0535	-0.00522	0.00483	0.0461	-0.0397	-0.0112	0.0135	0.189***	-0.162***	-0.0402***
	(0.0100)	(0.0544)	(0.0595)	(0.00513)	(0.00725)	(0.0610)	(0.0543)	(0.0140)	(0.0109)	(0.0587)	(0.0558)	(0.0142)

(Continued)

Table A.5 (contd.). Ordered probit, farm income change.

Variables	Round 1				Round 2				Round 3			
	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1
Formal credit	0.0103	0.0580	-0.0626	-0.00568	0.00727	0.0626	-0.0553	-0.0146	0.00299	0.0482	-0.0398	-0.0114
	(0.0124)	(0.0605)	(0.0678)	(0.00530)	(0.00873)	(0.0663)	(0.0605)	(0.0146)	(0.00525)	(0.0726)	(0.0610)	(0.0168)
Savings	0.0155*	0.0973*	-0.103*	-0.00988*	0.00196	0.0194	-0.0164	-0.00491	0.00897	0.138**	-0.113**	-0.0342**
	(0.00934)	(0.0541)	(0.0581)	(0.00595)	(0.00568)	(0.0555)	(0.0473)	(0.0139)	(0.00719)	(0.0582)	(0.0492)	(0.0155)
Bank account	-0.00410	-0.0263	0.0274	0.00296	-0.00637	-0.0652	0.0550	0.0166	-0.00667	-0.128**	0.101**	0.0339*
	(0.00847)	(0.0554)	(0.0575)	(0.00642)	(0.00620)	(0.0604)	(0.0513)	(0.0156)	(0.00549)	(0.0631)	(0.0498)	(0.0188)
Formal insurance	0.00245	0.0153	-0.0161	-0.00162	-0.00740	-0.0878	0.0692	0.0261	-0.00384	-0.0944	0.0709	0.0273
	(0.0100)	(0.0599)	(0.0637)	(0.00627)	(0.00563)	(0.0713)	(0.0523)	(0.0250)	(0.00354)	(0.0870)	(0.0611)	(0.0292)
Distance to road	-0.000101	-0.000653	0.000683	7.14e-05	-3.87e-05	-0.000387	0.000327	9.83e-05	1.52e-05	0.000283	-0.000227	-7.13e-05
	(0.000107)	(0.000695)	(0.000730)	(7.50e-05)	(7.21e-05)	(0.000721)	(0.000616)	(0.000178)	(5.12e-05)	(0.000901)	(0.000722)	(0.000230)
Distance to urban center	1.70e-05	0.000110	-0.000115	-1.20e-05	1.04e-05	0.000104	-8.84e-05	-2.66e-05	1.17e-05	0.000218	-0.000175	-5.50e-05
	(4.00e-05)	(0.000259)	(0.000269)	(2.95e-05)	(2.94e-05)	(0.000287)	(0.000243)	(7.36e-05)	(1.87e-05)	(0.000308)	(0.000248)	(7.81e-05)
Distance to market	-0.000458	-0.00295*	0.00309*	0.000323	-0.000730**	-0.00730***	0.00617***	0.00186***	-0.000470	-0.00874***	0.00701***	0.00220***
	(0.000279)	(0.00175)	(0.00183)	(0.000220)	(0.000349)	(0.00248)	(0.00219)	(0.000701)	(0.000327)	(0.00270)	(0.00221)	(0.000822)
Microfinance institution	-0.00380	-0.0254	0.0263	0.00287	0.00304	0.0292	-0.0250	-0.00723	-0.00241	-0.0492	0.0387	0.0130
	(0.00677)	(0.0467)	(0.0482)	(0.00528)	(0.00612)	(0.0566)	(0.0487)	(0.0140)	(0.00356)	(0.0651)	(0.0506)	(0.0180)
Electricity	-0.0172*	-0.103**	0.109**	0.0111*	-0.00393	-0.0387	0.0329	0.00972	-0.00377	-0.0647	0.0524	0.0160
	(0.00981)	(0.0435)	(0.0485)	(0.00572)	(0.00540)	(0.0517)	(0.0442)	(0.0129)	(0.00393)	(0.0573)	(0.0471)	(0.0139)
Safe water	0.0379**	0.159***	-0.185***	-0.0116**	0.0224	0.152**	-0.144**	-0.0296**	0.00478	0.0723	-0.0610	-0.0161
	(0.0182)	(0.0491)	(0.0621)	(0.00542)	(0.0151)	(0.0643)	(0.0670)	(0.0127)	(0.00644)	(0.0764)	(0.0669)	(0.0157)
Toilet	0.261	0.222**	-0.468***	-0.0145**	0.105*	0.263***	-0.327***	-0.0406***	0.0178	0.168	-0.155	-0.0307
	(0.194)	(0.0929)	(0.107)	(0.00635)	(0.0599)	(0.0393)	(0.0744)	(0.0110)	(0.0339)	(0.169)	(0.180)	(0.0220)
Demographic Dependency Ratio	0.00346	0.0223	-0.0233	-0.00244	0.00151	0.0151	-0.0128	-0.00385	-0.000883	-0.0164	0.0132	0.00414
	(0.00442)	(0.0270)	(0.0284)	(0.00313)	(0.00309)	(0.0303)	(0.0257)	(0.00774)	(0.00181)	(0.0317)	(0.0255)	(0.00804)
Economic Dependency Ratio	0.000186	0.00120	-0.00125	-0.000131	-0.00155	-0.0155	0.0131	0.00395	5.26e-05	0.000978	-0.000784	-0.000247
	(0.00189)	(0.0122)	(0.0127)	(0.00133)	(0.00165)	(0.0149)	(0.0127)	(0.00387)	(0.000836)	(0.0156)	(0.0125)	(0.00396)
Rural	-0.00160	-0.0101	0.0107	0.00108	0.0117*	0.149	-0.109*	-0.0519	0.00456	0.111	-0.0820	-0.0340
	(0.0138)	(0.0855)	(0.0904)	(0.00895)	(0.00699)	(0.0973)	(0.0591)	(0.0463)	(0.00432)	(0.113)	(0.0758)	(0.0408)
HH received assistance since COVID-19 outbreak	0.0550**	0.203***	-0.245***	-0.0136**	0.0533**	0.267***	-0.278***	-0.0419***	0.00494	0.0765	-0.0641	-0.0174
	(0.0253)	(0.0534)	(0.0726)	(0.00607)	(0.0222)	(0.0529)	(0.0590)	(0.0123)	(0.00537)	(0.0617)	(0.0532)	(0.0137)
Observations	678	678	678	678	535	535	535	535	503	503	503	503

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.5 (contd.). Ordered probit, farm income change.

Variables	Round 4				Round 5				Round 6			
	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1
Years of education	8.28e-05	0.000870	-0.000482	-0.000471	-0.000283	-0.00482	0.00156	0.00355	-1.55e-05	-0.00121	0.000287	0.000938
	(0.000613)	(0.00637)	(0.00352)	(0.00346)	(0.000432)	(0.00692)	(0.00221)	(0.00512)	(7.73e-05)	(0.00606)	(0.00144)	(0.00470)
HH income (log)	-0.00103	-0.0108	0.00599	0.00585	-0.00179	-0.0304	0.00981	0.0224	-0.000304	-0.0237	0.00563	0.0184
	(0.00169)	(0.0176)	(0.00969)	(0.00963)	(0.00154)	(0.0199)	(0.00648)	(0.0148)	(0.000317)	(0.0182)	(0.00450)	(0.0142)
HH consumption (log)	0.00504	0.0529	-0.0293	-0.0286	0.00245	0.0417	-0.0135	-0.0307	-0.000217	-0.0169	0.00401	0.0131
	(0.00379)	(0.0436)	(0.0233)	(0.0239)	(0.00272)	(0.0504)	(0.0157)	(0.0373)	(0.000579)	(0.0439)	(0.0105)	(0.0340)
HH head is female	0.00478	0.0460	-0.0273	-0.0236	0.00346	0.0531	-0.0193	-0.0372	-0.000200	-0.0161	0.00361	0.0127
	(0.0114)	(0.0979)	(0.0621)	(0.0472)	(0.00629)	(0.0835)	(0.0338)	(0.0558)	(0.000981)	(0.0817)	(0.0172)	(0.0655)
Age of HH head	0.000545	0.00572***	-0.00317***	-0.00310**	0.000275	0.00468***	-0.00151**	-0.00345**	5.44e-05	0.00424**	-0.00101**	-0.00329**
	(0.000353)	(0.00208)	(0.00114)	(0.00131)	(0.000248)	(0.00180)	(0.000627)	(0.00145)	(4.51e-05)	(0.00182)	(0.000488)	(0.00144)
HH head is married	-0.000763	-0.00791	0.00444	0.00424	-0.00312	-0.0486	0.0175	0.0342	-0.000821	-0.0560	0.0155	0.0413
	(0.00852)	(0.0882)	(0.0500)	(0.0468)	(0.00565)	(0.0818)	(0.0323)	(0.0549)	(0.00137)	(0.0773)	(0.0246)	(0.0542)
HH size	0.000591	0.00621	-0.00344	-0.00336	0.000854	0.0145	-0.00469	-0.0107	8.68e-05	0.00677	-0.00161	-0.00525
	(0.00125)	(0.0139)	(0.00766)	(0.00747)	(0.000731)	(0.0140)	(0.00444)	(0.0103)	(0.000157)	(0.0115)	(0.00275)	(0.00895)
Asset index	-0.00191	-0.0201	0.0111	0.0109	-0.000490	-0.00834	0.00269	0.00614	-3.48e-05	-0.00271	0.000644	0.00210
	(0.00172)	(0.0159)	(0.00905)	(0.00858)	(0.00118)	(0.0194)	(0.00631)	(0.0142)	(0.000239)	(0.0187)	(0.00443)	(0.0145)
Land is irrigated	-0.00461	-0.0564	0.0278	0.0332	-0.00532	-0.131*	0.0221**	0.114	-0.00148	-0.227***	-0.0240	0.252***
	(0.00788)	(0.105)	(0.0454)	(0.0671)	(0.00450)	(0.0783)	(0.00937)	(0.0787)	(0.00106)	(0.0500)	(0.0309)	(0.0763)
Organic fertilizer	-0.00700	-0.0657	0.0388	0.0340	0.000899	0.0156	-0.00490	-0.0115	0.000232	0.0186	-0.00427	-0.0145
	(0.00997)	(0.0746)	(0.0469)	(0.0376)	(0.00448)	(0.0799)	(0.0247)	(0.0597)	(0.000844)	(0.0687)	(0.0155)	(0.0541)
Title of the land	-0.0148	-0.128*	0.0779	0.0647*	-0.00704	-0.108	0.0398	0.0753	9.23e-05	0.00719	-0.00168	-0.00559
	(0.0126)	(0.0726)	(0.0500)	(0.0348)	(0.00723)	(0.0731)	(0.0307)	(0.0488)	(0.000915)	(0.0711)	(0.0164)	(0.0556)
% of members with job contract	-0.0314	-0.330*	0.183*	0.178*	-0.00580	-0.0986	0.0318	0.0726	-0.00167	-0.130	0.0309	0.101
	(0.0205)	(0.170)	(0.0965)	(0.0938)	(0.0113)	(0.182)	(0.0586)	(0.134)	(0.00250)	(0.174)	(0.0411)	(0.136)
HHI_crop	0.0164	0.172*	-0.0955*	-0.0933*	0.00462	0.0787	-0.0254	-0.0579	0.00187	0.146*	-0.0346*	-0.113*
	(0.0119)	(0.0884)	(0.0505)	(0.0500)	(0.00706)	(0.0949)	(0.0306)	(0.0712)	(0.00164)	(0.0774)	(0.0189)	(0.0618)
Land size (hectares)	-0.00138	-0.0145	0.00805	0.00786	-0.00189	-0.0321**	0.0104*	0.0237**	-0.000325	-0.0253*	0.00601	0.0196*
	(0.00131)	(0.0122)	(0.00690)	(0.00655)	(0.00166)	(0.0159)	(0.00573)	(0.0118)	(0.000283)	(0.0150)	(0.00396)	(0.0115)
Income diversification	0.00648	0.0681	-0.0378	-0.0369	-0.00144	-0.0245	0.00789	0.0180	-0.00107	-0.0833	0.0198	0.0646
	(0.00738)	(0.0748)	(0.0413)	(0.0408)	(0.00437)	(0.0703)	(0.0227)	(0.0519)	(0.00112)	(0.0689)	(0.0167)	(0.0539)
Social assistance	-0.00463	-0.0555	0.0278	0.0323	0.00467	0.0672	-0.0254	-0.0464	0.000747	0.0509	-0.0141	-0.0375
	(0.00637)	(0.0797)	(0.0352)	(0.0508)	(0.00633)	(0.0754)	(0.0324)	(0.0489)	(0.00145)	(0.0800)	(0.0255)	(0.0561)
Agricultural machinery	0.00823	0.0785	-0.0463	-0.0404	0.0127	0.173***	-0.0691**	-0.116***	0.00106	0.0728	-0.0201	-0.0538
	(0.00782)	(0.0561)	(0.0360)	(0.0279)	(0.0106)	(0.0566)	(0.0281)	(0.0387)	(0.00115)	(0.0547)	(0.0174)	(0.0388)

(Continued)

Table A.5 (contd.). Ordered probit, farm income change.

Variables	Round 4				Round 5				Round 6			
	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1
Formal credit	-0.00172	-0.0190	0.0103	0.0105	-0.000403	-0.00700	0.00222	0.00518	-0.000362	-0.0309	0.00648	0.0248
	(0.00551)	(0.0622)	(0.0329)	(0.0348)	(0.00408)	(0.0713)	(0.0223)	(0.0531)	(0.000743)	(0.0654)	(0.0121)	(0.0541)
Savings	0.0229**	0.188***	-0.108***	-0.103***	0.0130	0.177***	-0.0605**	-0.129***	0.00347	0.220***	-0.0601***	-0.163***
	(0.0117)	(0.0496)	(0.0305)	(0.0297)	(0.0103)	(0.0614)	(0.0237)	(0.0460)	(0.00272)	(0.0538)	(0.0195)	(0.0402)
Bank account	-0.0173*	-0.176***	0.0928***	0.101***	-0.00623	-0.110	0.0332	0.0828	-0.00233	-0.179***	0.0357***	0.145***
	(0.00953)	(0.0571)	(0.0322)	(0.0359)	(0.00582)	(0.0679)	(0.0208)	(0.0527)	(0.00183)	(0.0528)	(0.0134)	(0.0462)
Formal insurance	-0.00937*	-0.139**	0.0591***	0.0890*	-0.00549	-0.139**	0.0264**	0.118*	-0.00141	-0.200***	0.00292	0.198***
	(0.00516)	(0.0626)	(0.0206)	(0.0490)	(0.00428)	(0.0695)	(0.0103)	(0.0688)	(0.00101)	(0.0569)	(0.0223)	(0.0746)
Distance to road	-6.24e-05	-0.000655	0.000363	0.000355	-7.66e-05	-0.00130*	0.000421	0.000959*	-1.25e-05	-0.000975	0.000232	0.000756
	(7.13e-05)	(0.000726)	(0.000412)	(0.000384)	(6.42e-05)	(0.000783)	(0.000274)	(0.000565)	(1.37e-05)	(0.000873)	(0.000217)	(0.000676)
Distance to urban center	-2.93e-06	-3.08e-05	1.71e-05	1.67e-05	3.12e-05	0.000532*	-0.000172*	-0.000391*	3.54e-06	0.000276	-6.55e-05	-0.000214
	(2.13e-05)	(0.000224)	(0.000125)	(0.000121)	(2.65e-05)	(0.000274)	(8.90e-05)	(0.000209)	(4.90e-06)	(0.000347)	(8.51e-05)	(0.000268)
Distance to market	-0.000617*	-0.00649***	0.00359***	0.00351***	-0.000415	-0.00706***	0.00228***	0.00520***	-0.000101	-0.00785***	0.00186***	0.00609***
	(0.000322)	(0.00163)	(0.00108)	(0.000917)	(0.000302)	(0.00178)	(0.000799)	(0.00128)	(7.01e-05)	(0.00184)	(0.000671)	(0.00140)
Microfinance institution	-0.00583	-0.0674	0.0346	0.0386	-0.00912	-0.194***	0.0324**	0.170***	-0.00131	-0.119**	0.0167**	0.103**
	(0.00515)	(0.0593)	(0.0282)	(0.0362)	(0.00637)	(0.0543)	(0.0149)	(0.0593)	(0.000937)	(0.0524)	(0.00793)	(0.0504)
Electricity	-0.00352	-0.0359	0.0202	0.0192	-0.00618	-0.0924*	0.0313	0.0673*	0.000139	0.0110	-0.00259	-0.00852
	(0.00513)	(0.0503)	(0.0288)	(0.0266)	(0.00510)	(0.0549)	(0.0201)	(0.0393)	(0.000628)	(0.0502)	(0.0118)	(0.0391)
Safe water	0.0279	0.182***	-0.133**	-0.0766***	0.0120	0.140**	-0.0632*	-0.0886**	0.00222	0.133**	-0.0477	-0.0878**
	(0.0189)	(0.0623)	(0.0562)	(0.0237)	(0.00940)	(0.0616)	(0.0338)	(0.0347)	(0.00207)	(0.0659)	(0.0301)	(0.0383)
Toilet	0.00334	0.0320	-0.0189	-0.0164	0.0198	0.179**	-0.0910	-0.107**	0.00825	0.256***	-0.120**	-0.144***
	(0.0118)	(0.104)	(0.0650)	(0.0504)	(0.0176)	(0.0903)	(0.0625)	(0.0425)	(0.00726)	(0.0905)	(0.0612)	(0.0370)
Demographic Dependency Ratio	0.00179	0.0188	-0.0104	-0.0102	-0.000284	-0.00484	0.00156	0.00356	0.000374	0.0292	-0.00693	-0.0226
	(0.00279)	(0.0288)	(0.0158)	(0.0158)	(0.00192)	(0.0322)	(0.0104)	(0.0238)	(0.000450)	(0.0288)	(0.00707)	(0.0223)
Economic Dependency Ratio	-0.000513	-0.00539	0.00299	0.00292	-0.000111	-0.00188	0.000608	0.00139	0.000131	0.0102	-0.00242	-0.00790
	(0.00137)	(0.0139)	(0.00778)	(0.00754)	(0.000771)	(0.0129)	(0.00418)	(0.00953)	(0.000194)	(0.0133)	(0.00314)	(0.0104)
Rural	0.00213	0.0236	-0.0125	-0.0132	0.00105	0.0186	-0.00568	-0.0140	-0.000584	-0.0415	0.0114	0.0307
	(0.00823)	(0.0939)	(0.0479)	(0.0542)	(0.00531)	(0.0980)	(0.0283)	(0.0750)	(0.00155)	(0.0969)	(0.0297)	(0.0688)
HH received assistance since COVID-19 outbreak	-0.00148	-0.0160	0.00871	0.00880	-0.00337	-0.0622	0.0175	0.0481	0.000167	0.0127	-0.00311	-0.00975
	(0.00538)	(0.0601)	(0.0320)	(0.0334)	(0.00397)	(0.0680)	(0.0166)	(0.0553)	(0.000840)	(0.0613)	(0.0155)	(0.0467)
Observations	506	506	506	506	497	497	497	497	496	496	496	496

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1