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Abstract

The COVID-19 pandemic is having disruptive consequences on many people's livelihoods around the world, projecting 150 million people into extreme poverty. In many developing countries, where economies still rely on agriculture, domestic food supply chains have been severely affected due to internal mobility restrictions, resulting in income reduction and job loss. In this context, the ability to adapt to the "new normal" is crucial in ensuring market inclusion, but it is often limited by many constraints that participants at different levels of the chain face. Understanding the main constraints and the possible ways in which the agri-food system participants can adapt is then key for targeting appropriate responses. Using Ethiopia as a case study, this paper aims to identify different impacts at various stages along the agri-food value chain, assessing the impact of COVID-19 on household employment and income and identifying the main determinants that mediate those impacts. Using both longitudinal and cross-sectional econometric models over a panel sample composed of a pre- COVID face-to-face interview and 6 follow-up phone-based surveys, the paper shows that the crisis has reduced both employment and income, with worsening trends over time. The study shows that farming, which had initially been relatively less affected, reported highly negative impacts in subsequent rounds, making it the most affected stage in the agri-food value chain. Access to formal institutions, such as formal insurance, credit, formal contract, and land ownership title, played a key role in reducing the likelihood of income loss.

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

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1. Introduction

The COVID-19 outbreak has some peculiarities that make it different from other shocks that affected the world economy, such as the great recession of 2007-08 (Schimdhuber and Qiao, 2020). Indeed, while the latter can be qualified as a demand asymmetric (idiosyncratic) shock, the former is both a demand (recession) and supply (value chain disruption) shock determining a symmetric (systemic) shock.[1] More precisely, from the macroeconomic viewpoint, the COVID-19 crisis is a typical Keynesian supply shock (Guerrieri et al., 2020), that is a supply shock that triggers changes in aggregate demand larger than the shock itself. In a globalized economy, characterized by multiple, interlinked value chains and incomplete markets, a Keynesian supply shock is more likely to happen and this has been the case of the current crisis.

Therefore, there is no doubt that value chain disruption is one of the main transmission channels of the crisis and agri-food value chains (AFVCs) are no exception in this regard. Although some segments of the chain such as the upstream and specifically farming have been initially less affected by restrictions decisions, other segments especially downstream such as food services, restaurants, and retail, and midstream such as processing, logistics, and transportation have been impacted form the real onset of the crisis. Indeed, it has been reported 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). 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 of the value chain (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 capacity– is often limited by many constraints they face, such as access to technology, financial services, or social safety nets. Many of them have limited options to cope with the COVID-19 shock, resulting in income reduction or job loss, with consequent effects on poverty and food security. Understanding what are the constraints faced by

[1] Furthermore, while in the case of the "great recession" there was relatively little level of uncertainty around its economic impact, in the case of the "great lockdown" there is the highest level of uncertainty due to its unprecedented nature.

participants in the AFVC and their available options to adapt to the "new normal" is then crucial for targeting appropriate food security and poverty responses.

This study aims at investigating what has been the differentiated impact of COVID-19 on different segments of AFVCs. Specifically, the research questions are the following:

a) Which segments of the AFVC (such as production, distribution, retail) have been most affected by the crisis, in terms of labor participation and income change, compared to other economic activities?
b) Which determinants at the household level have most influenced the impact of COVID-19 on income, and specifically on farm income?

Ethiopia has been selected as a case study. This country is an interesting case for several reasons. Its economy is mainly based on agriculture that accounts for 34% of GDP[2], with smallholder farming accounting for 95% of agricultural production and 85% of all employment (FAO 2020). 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, compounding with the already exiting constraints (Croppenstedt et al., 2003; Bryan et al., 2009; Asfaw et al., 2011; Haverst SA, 2012). In such a situation, the COVID-19 outbreak could force additional family farmers and small and medium enterprises out of the market.

The first case of COVID-19 in the country was reported on March 13th, 2020[3]. In the same month, the national government implemented a set of containment measures, such as schools' closure, social 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. The virus spread differently across regions. In particular, the Addis Ababa region reported the highest proportion of cases per million of population, followed by Harar and Dir Dawa.

Although farmers could continue working, they faced many challenges. With borders shut, imported inputs were not available in the country. Moreover, domestic travel restrictions made it almost impossible for farmers to reach the markets. This would likely lead to a heavy drop in production and sales, particularly of some vegetables such as tomato, papaya, and watermelon (Molla, 2020). The travel restrictions also doubled transport costs, with a further

[2] Source: https://data.worldbank.org/indicator/NV.AGR.TOTL.ZS?locations=ET accessed on 29/08/2020
[3] https://www.afro.who.int/news/first-case-covid-19-confirmed-ethiopia

domino effect on production. Additionally, since many farmers could not store their goods – particularly perishable produce – they were forced to accept the low prices set by buyers. Hired labor was also an issue. Many rural labor workers returned to their homes, and the few workers that remained available 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. 2020a; Tamru et al. 2020).

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 still few. Amare et al. (2020) used panel data household survey to quantify the overall and differential impacts of COVID-19 on household food security, labor market participation, and local food prices in Nigeria. They found that households located in areas affected by higher cases or by more stringent mobility lockdowns experienced a significant increase in food insecurity, a reduction in labor market participation, and an increase in food prices.

In Ethiopia, Hirvonen et al. (2020a) conducted a phone-based sample of nearly 600 households in Addis Ababa in May 2020 (i.e. two months after the pandemic onset), to assess changes in income and food and nutrition security status during the COVID-19 pandemic. They found that less-wealthy households were more likely to report income losses, with 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., 2020a). Tamru et al. (2020) and Hirvonen et al. (2020b) analyzed the impact of COVID-19 on the Ethiopian vegetable value chain, findings that 60% of the smallholder farmers reported that they received less income than usual. They also found that the pandemic in Ethiopia disrupted trade not only between neighboring countries but also among sub-national regions, thus determining high volatility in agricultural prices.

Although these studies provide important early estimates on the effects of the pandemic on relevant indicators of welfare, they present some limitations. Some of them are based on a limited and nonrepresentative sample. The majority of the existing studies only focus 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 in Khamis et al. (2021), but they do not specifically consider the different segments of the food value chain. This paper addresses both limitations contributing to estimating the magnitude of food supply chain disruption caused by the COVID-19 outbreak in Ethiopia over a relatively longer time (seven months from the pandemic onset) and looking specifically at differentiated impacts on various AFVC segments.

It will also help to identify the main constraints faced by AFVC participants, which prevent them to ensure adequate levels of income. These findings are relevant not only because they provide policy insights for the current crisis, but also because they contribute to building evidence for managing future possible crises.

The paper is organized as follows: the next section describes the data used and presents some descriptive statistics of relevant variables, in particular, related to employment and income; section 3 describes the empirical strategy adopted; section 4 presents the results of the analysis; section 5 concludes.

2. Data and descriptive statistics

The analysis uses longitudinal data over seven rounds, which include a pre-pandemic face-to-face survey, used as the baseline, and six follow-up phone surveys. The availability of this longitudinal data that capture information before and after the start of the pandemic makes Ethiopia an ideal case for an early empirical examination of COVID-19's impacts.

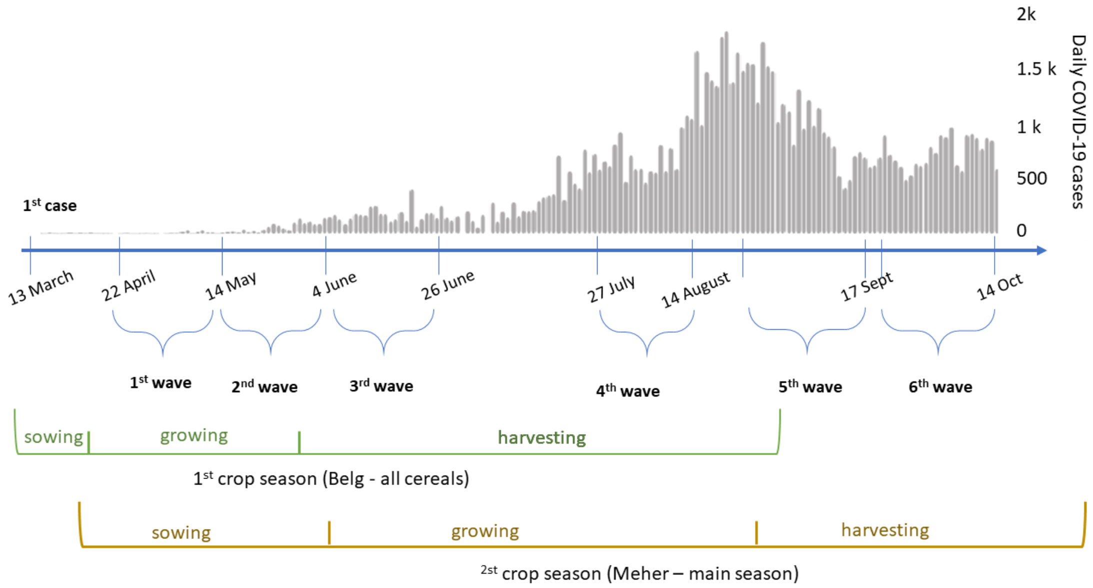
Pre-COVID data are taken from the 2018/19 Ethiopia Socioeconomic Survey (ESS), which is part of the World Bank's Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA). It covers all regions of the country and is representative at national, urban/rural, and regional levels. The other six rounds of data are part of the COVID-19 High-Frequency Phone Survey of Households (HFPSH) 2020. This phone-based survey is a 15-minute questionnaire submitted to a subsample of the ESS 2018/19 households with access to a phone every month, from April to September. The World Bank team attempted to interview the same households in each round. This allowed tracking the same set of households from 2019 to September 2020, leading to a balanced dataset of 2,347 households[4]. To obtain unbiased estimates, sampling weights at the household level have been constructed, following Himelein, K. (2014), to have a sample that is representative at the national and urban/rural levels. A major problem with the HFPSH surveys is that the phone penetration in rural Ethiopia is still low. Indeed about only 40% of rural households have access to a phone, compared to over 90% of urban households, and they are systematically different from those without

[4] 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

(Ambel et al. 2020). The sample of the HFPSH is therefore representative only of those households that have access to phones in urban and rural Ethiopia. Additionally, only one member per household, typically the household head or the spouse, has been interviewed. Household heads could systematically differ from the rest of the population, undermining the representativeness of the sample at the individual level. Further discussion about this issue is presented in section 4.3.

Figure 2 combines daily cases of COVID-19, the dates of data collection of the HFPSH, and the crop seasons over a timeline.

Figure 2. 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

Seasonality could represent an issue, especially for agricultural-related activities. The pre-COVID survey considers the employment activities over a year, including both planting and harvesting seasons. Questions on employment in the post-COVID rounds instead consider only the last 7 days. There could be then an underestimation of the farming-related employment rate. However, the months under analysis coincide with a sowing or a harvesting period of the two main crop seasons, as reported in Figure 2. Looking at the crop calendar in the country[5], only two crops report neither planting nor harvesting in the period under analysis, which are sugarcane and taro. Therefore, although it is not possible to completely exclude problems of seasonality, we can state that the problem is minimal.

Another factor to consider in the analysis is the desert locusts invasion. The desert locusts are the most destructive migratory pests in the world (Cressman et al., 2016; Lazar et al., 2016). They arrived in the Horn of Africa in summer 2019, when numerous swarms from Yemen invaded Ethiopia, Djibouti, and northern Somalia.

In the fourth[6] round of data, 45% of farmers self-reported to have experienced desert locusts in their farm, and 41% of households experienced locusts in their kebele. 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.

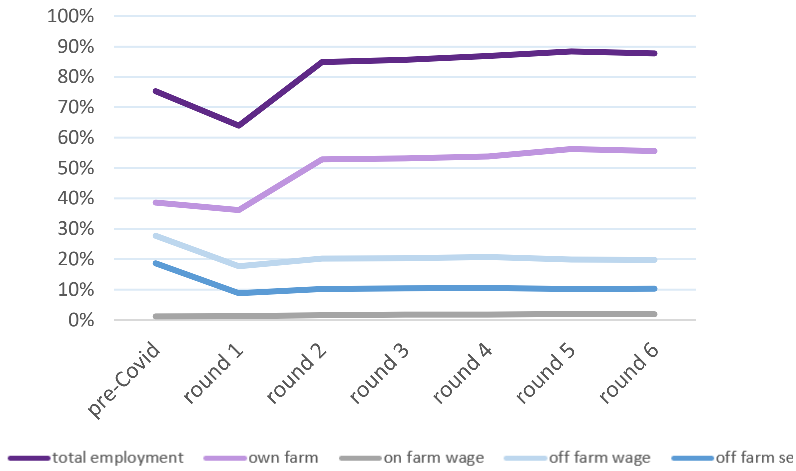
Employment

As shown in Figure 4, the employment rate experienced a significant reduction in the aftermath of the COVID-19 outbreak. Considering overall employment, there has been a reduction of 11 percentage points. However, after the initial outbreak, it seems that labor activities recovered quickly, exceeding the employment rate before COVID-19. This increase seems to be driven by own farming activity.

[5] Source : http://www.fao.org/agriculture/seed/cropcalendar/welcome.do;jsessionid=62FFB1AC3CB6FA74244A91586E5E1758

[6] 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.

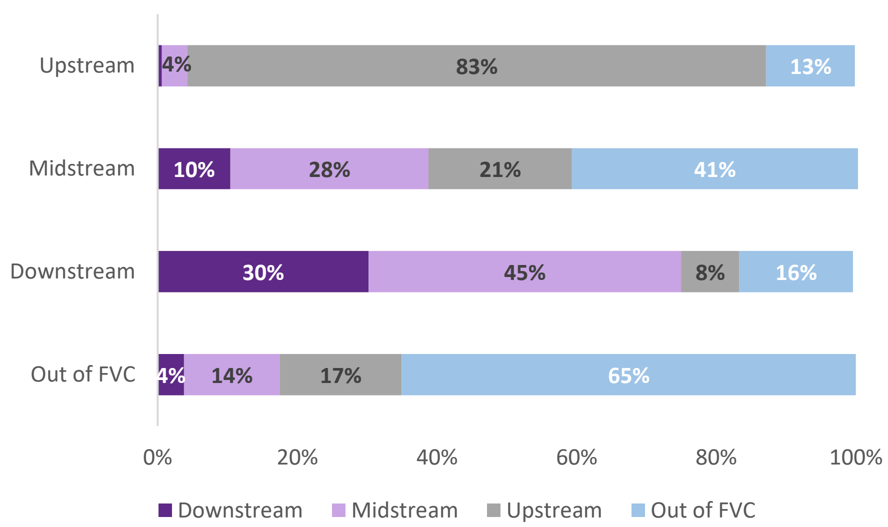
Figure 4. Employment trends



Source: Own elaboration from ESS 2018/2019 and HFPSH 2020

It is interesting to see the dynamics of labor mobility within the AFVC. The upstream segment remained quite stable, with 83% of people that did not change occupation on average. Among those that changed, the majority preferred to move out of the AFVC. A different scenario is presented for people who whose employed in the midstream. In this case, only 28% remained in the same segment, while 41% moved out of the chain, and 21% moved to upstream. A similar situation can be found in the downstream, with only 30% on average that did not change the segment of the AFVC. Here however people preferred to move to midstream. Finally, 65% of who was out of the chain remained out, and the rest split mainly between midstream and upstream.

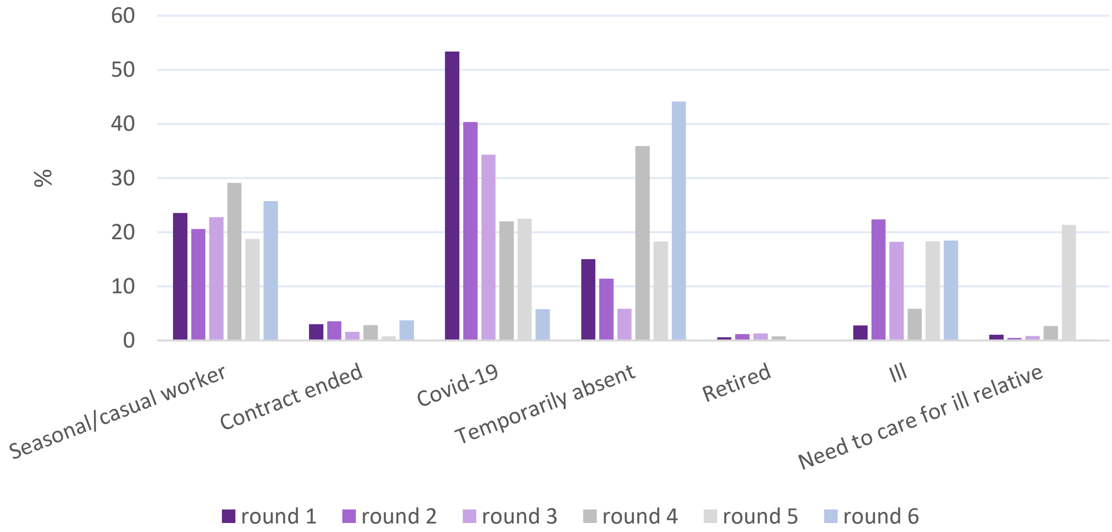
Figure 5. Labor mobility along with segments of AFVC



Source: Own elaboration from ESS 2018/2019 and HFPSH 2020

As expected, the main reason to stop working, especially in the first rounds, is COVID-19. Between April and May, more than half of individuals declared that the pandemic-related crisis caused their employment loss. In the last rounds instead, being "temporarily absent" is the main reason to stop working. This can be indirectly associated with the crisis because probably people temporarily left their job in the city to migrate to rural areas.

Figure 6. Reason to stop working, percentage.



Source: Own elaboration from HFPSH 2020

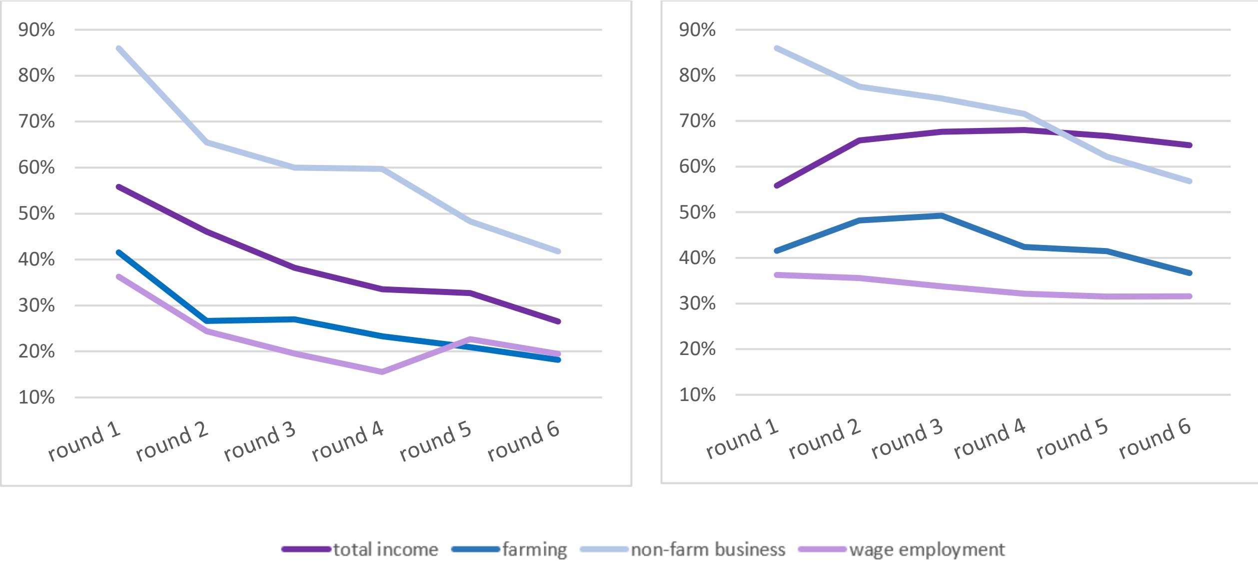
Income

In the phone-based surveys, respondents were asked to assess the income change the household has experienced, compared to the situation before the COVID-19 outbreak in the first round, and compared to the last call in the other rounds. The possible answers ranged from total loss to increase. The categorical nature of the question does not allow to compute precise estimates of the impact of COVID-19 on income, limiting the analysis to its incidence, but with few possibilities to look at its magnitude and severity (De Weerdt, 2008). If we look at the percentage of households that reported a reduction or a total loss between each round, we can see a decreasing trend for all sources of income. However, if we compare the income change to the situation before the COVID-19 outbreak, the trend is substantially different. The percentage of households indeed increased, up to 9 percentage points. Comparing the two figures, it is evident how COVID-19 has drastically affected the livelihood of Ethiopian households.

Figure 7. Percentage of HHs with income reduction or total loss, wave by wave and compared to the pre-COVID situation

a) % of HHs with income reduction or total loss, from round to round

b) % of HHs with income reduction or total loss compared to the pre-COVID situation



Source: Own elaboration from ESS 2018/2019 and HFPSH 2020

3. Empirical strategy

To assess the impact of COVID-19 on income and employment we ran a longitudinal model with household fixed effects and a continuous treatment variable, adapting the approach implemented in Amare et al. (2020). The dependent variables analyzed are two: participating in labor activities, considering any type of activity and specific sectors; and income change, looking at total income and different sources. Regarding employment, labor activities are grouped into own farm, on-farm wage employment, off-farm self-employment, and off-farm wage employment. Occupations can be also divided in terms of segments of AFVC, distinguishing between downstream, midstream, and upstream. Upstream includes labor activities related to direct production, namely own farm activities and agricultural workers. Midstream refers to those activities in the middle of the chain, such as manufacturing of food products, wholesale and retail trade, transportation, and distribution. Upstream instead concerns those activities where the food product is in its final form and it is ready to be sold, such as restaurants and bars. For each labor activity, we computed a dummy equal to 1 if the individual operated in that activity, and zero otherwise.

A major issue is that the information is provided only for one member of the household, the respondent. This implies that the individual sample could not be representative of the entire individual population. Looking at the descriptive statistics of some individual characteristics, some differences between the entire individual sample at baseline and the phone-based subsample, as reported in Table 1, emerge. Individuals belonging to the HFPS subsample are mainly located in urban areas, the majority are male, and the employment rate is higher. They are older, more educated and a higher share has a formal job contract. The rate of non-farm employment activities is higher compared to the baseline population, however, the rate of farm-related activities is similar. The same for the employment rate along the food value chain.

Table 1. Comparison of individual characteristics between baseline population and phone-based subsample

Variable	Baseline population	Phone-based sample
Rural	0.72	0.64
	(0.45)	(0.48)
Sex=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)
NEET	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: sample weights are applied. Standard deviation in parenthesis. Children below 11 years old are excluded.

Given these differences, the results of the analysis could not be generalized to the entire Ethiopian population. To check this issue, in section 4.3 we ran a robustness check using adjusted individual weights.

Regarding household income change, we consider total income and specific generating-income 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 (reduction), 0 (no change) and 1 (increase).

The main variable of interest is the 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[7] and weekly governmental bulletins[8]. This variable captures the evolution and the spread of the virus around the country. It also allows capturing behavioral effects associated with the fear of contagion. 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 for the log transformation (Johnson, 1949; Burbidge et al., 1988).

The variable presents some limitations: firstly, the number of confirmed cases probably underestimates the real infection level due to the limited testing capacity of the country. Reporting the cases over the population can help to reduce the bias, assuming the testing capacity is equally proportional among regions. Secondly, this variable does not completely reflect the real variation in terms of access to the market and restrictions imposed by the government, which in turn affect labor participation. However, it is reasonable to assume that as long as the number of confirmed cases increases in a region, both the restrictions imposed by the government and the self-imposed restrictions of individuals will increase. In Amare et al. (2020), variables of COVID-19 cases and government restrictions produced the same results, confirming that the two variables are interchangeable. Thirdly, it does not capture spillover effects that occurred at the national level. Indeed each region is treated as an independent entity, assuming that each one does not have any interaction with the rest of the country and that no aggregate impacts occurred.

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[7] Available at this link: https://www.covid19.et/covid-19/

[8] See https://www.ephi.gov.et/

The baseline model is the following:

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

Where y_{hrt} is the outcome variable, either labor or income, defined for each individual/household h in region r and round t. α_{hr} captures individual/household fixed effects, allowing to control for unobserved time-invariant heterogeneity among individuals/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 COVID-19 shock, equal to 1 for the post-COVID round and 0 for the pre-COVID round. The parameter associated with this dummy captures aggregate time trends in the labor market and income composition. The interaction term between time and the number of cases allows capturing the differential impact of COVID-19 on labor participation and income change across regions with different exposure to the virus. ε_{hrt} is the error term. Given that the virus spread differently among regions over time, we need to control for this time. Regions that experienced the virus earlier are indeed more likely to report more cases than the other regions. A first specification of the baseline equation introduces the variable Day_{1_r}, 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.

The equation is the following:

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

To differentiate the impact of the isolated interactions and the impact of the combined spatial and temporal variabilities, we introduce an additional specification of the model, which includes the interaction between the dummy of time, the number of confirmed cases per million of population, and the variable Day_{1_r}.

The corresponding specification of the model is the following:

$$\begin{aligned} y_{hrt} = \alpha_{hr} + \beta_0 Time_t + \beta_1 (Cases_r * Time_{t)} + \beta_2 (Day_{1_r} * Time_t) + \\ + \beta_3 \left(Cases_r * Day_{1_r} * Time_t\right) + \varepsilon_{hrt} \qquad (3) \end{aligned}$$

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 that lost the 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 wave, comparing it with the baseline. In this way, it is possible to observe a possible 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 with the intensification of the crisis over time. We also estimated the impact of COVID-19 from wave to wave, comparing the outcome with the previous interview. Results still hold and they are available in the appendix. The analysis is undertaken over the balanced sample. However, given some attrition rates, we replicated the analysis over the unbalanced sample, finding consistent results, as reported in the appendix.

To estimate the regression we used the linear probability model with fixed effects. The advantage of this model compared to a logit or conditional logit model with fixed effects is the inclusion of all observations. Logit model with fixed effects drops the units which show no variability in the dependent variable (Beck 2018), drastically reducing the number of observations in case of small variability.

To investigate what are the main determinants that influenced changes in income in the presence of COVID-19, 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 in the presence of the pandemic. The probability that the outcome variable takes a certain value is given by

$$Prob(y_{ht+1} = j) = x_{ht}^{T}\beta + u_{ht+1} \tag{4}$$

Where h is the household, x is a column vector of observable variables, namely the attributes and factors in time t, and u_{ht+1} is the error term. j takes the value 1 if the outcome is dichotomous, or multiple values if it is categorical.

The regressors include household characteristics, water and sanitation conditions of the dwelling, level of infrastructure and variables at the community level, employment and economic related variables, and agricultural-related variables when considering farm income.

The dependent variable is the change in income at the household level. We have decided to not consider the employment status because there could be problems of endogeneity caused by omitted variable bias. This could occur mainly by external factors, for which information is not provided in the survey and which could affect the status of employment. An example could be the loss of an employee's job due to the closure of the company where he/she worked.

The estimation has been conducted through the maximum likelihood method, and 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.

4. Results

4.1 Impact of COVID-19 cases

Tables 2 and 3 report the different model specifications, 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. Driven by theoretical considerations, the R-square, and the level of completeness, we selected the last model for the analysis. Results in the tables refer to wave 1, used as an example.

Table 2. Regression results over different models, employment – wave 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

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

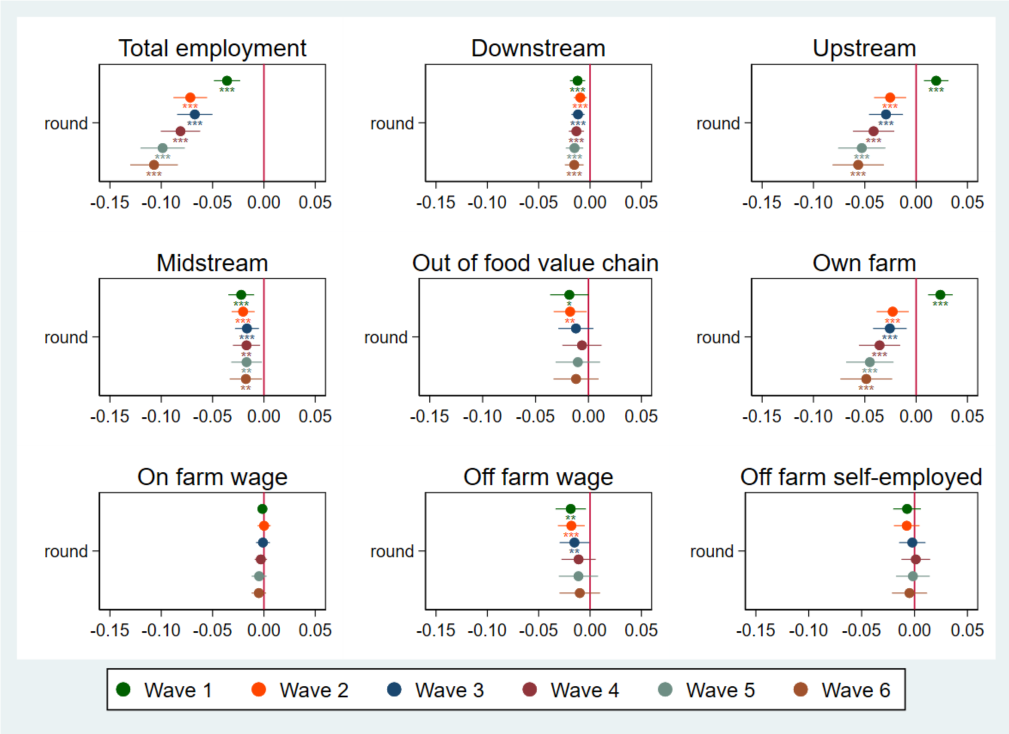
Table 3. Regression results over different models, income – wave 1

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

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Figure 8 the coefficient of the interaction term between the time trend and the COVID-19 cases is reported 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. Decomposing the impact along the AFVC, we can state that the segment most affected is the upstream. Although it had initially been relatively less affected, reported highly negative impacts in subsequent rounds. Downstream and midstream segments have also been negatively affected, but in this case, the impact remained constant over time. For those working out of the 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 did no longer have an impact, or that different occupations within this category experienced a contrasting effect. Among the off-farm self-employment occupations, for instance, construction and manufacturing reported a positive effect, while trade and restaurants, hotels, and bars showed negative coefficients.

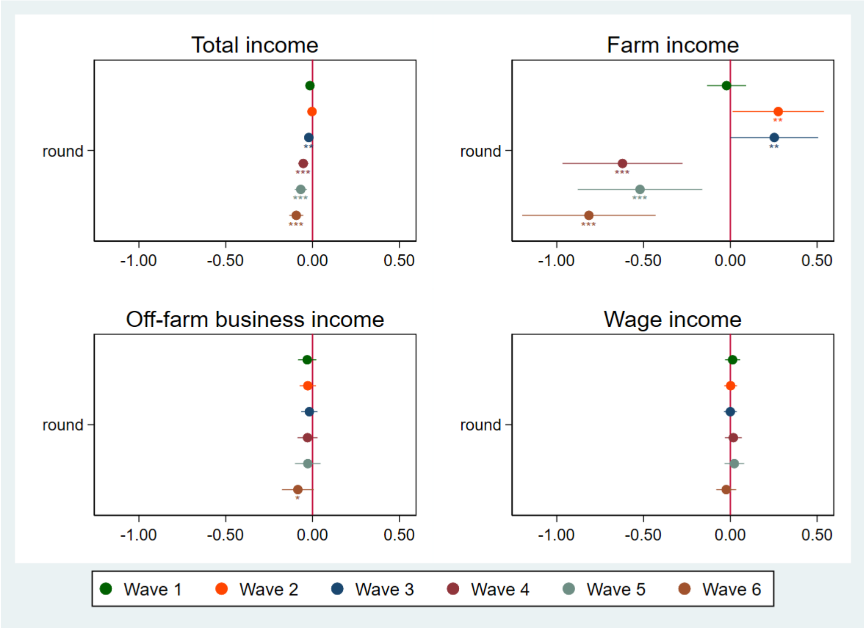
Figure 8. Impact of COVID-19 cases on employment over time



Source: Own calculation from ESS 2018/2019 and HFPSH 2020.
Note: Dots are coefficients estimated from a linear probability regression. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals.

In the case of income, the impact takes more time to occur, as expected. 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 the effect, as seen for employment, 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 in the cities, safeguarding farmers living in rural areas. But then the virus expanded all around the country, affecting also people located in 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, because of the limited coping mechanisms available.

Figure 9. Impact of COVID-19 cases on income over time



Source: Own calculation from ESS 2018/2019 and HFPSH 2020.
Note: Dots are coefficients estimated from a linear probability regression. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals.

In the same period, some regions of the country were invaded by desert locusts, with drastic consequences on production. For this reason, it is important to take into account also the presence of locusts in the farm. This information in the HFPH surveys is available only in the 4th wave. The inclusion of the dummy of having experienced desert locusts in the farm in the regression has a significant impact in changing the coefficients associated with the number of COVID-19 cases. Results are reported in Table 4. For employment, the coefficient of the COVID-19 cases loses significance, while having locusts in 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 significant at -0.621, the inclusion of desert locusts moves the coefficient to -1.103, with the same level of significance, increasing in this way 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.

Table 4. Simultaneous impact of self-reported locusts and COVID-19 on own farm employment activities and farm income change, 4th wave

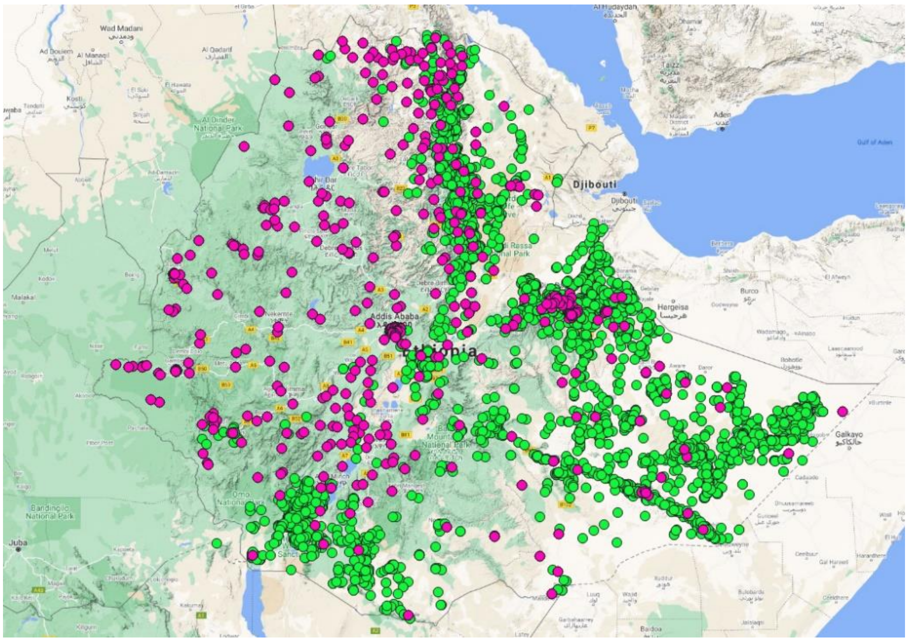
	Employed in own farm activities	Farm income change
Time	0.0489	5.242***
	(0.504)	(1.893)
Cases*Time	0.0216	-1.103***
	(0.0938)	(0.372)
Days*Time	-0.0237**	-0.0998***
	(0.0115)	(0.0350)
Days*Time*Cases	0.00333*	0.0194***
	(0.00200)	(0.00671)
Locusts in the farm	0.134*	-0.0244
	(0.0685)	(0.110)
Constant	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

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

For more complete information on locusts, we retrieved GIS data on desert locusts from the FAO Locusts Hub[9] and merged it with the households' location. Given that the households coordinates refer to the dwelling, and not to the parcel, and that they have been 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 11 reports the location of households (in purple) and where the desert locusts have been observed (in green) over the year 2020.

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

Figure 11. Map of households' location (in purple) and locusts sites (in green) in 2020



Source: own elaboration using data from FAO Locusts Hub and ESS 2018/2019

When using the georeferenced data, locusts do not show to have a significant impact on own farm labor activities. Instead, the impact is significant and negative for farm income. As reported in Table 5, having experienced locusts is negatively associated with income increase. The effect seems higher in the 4th wave, which corresponds to the more damaging period for crops caused by locusts, given their level of maturity and aggregation. The inclusion of the locusts' data over all the six waves does not seem to have affected the impact of COVID-19 cases on farm income. Coefficients indeed remained almost the same.

Although GIS data are usually more precise and reliable, in this case, many data gaps undermine the quality of the information. Firstly, households coordinates have been slightly modified, and although this change is minimal, it introduces some measurement bias. Secondly, the parcel could be far from the dwelling, and given that only the distance is available, and 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 movements that locusts have done from one point to the other over time, excluding crossed areas. For these reasons, although results from GIS data on locusts are consistent and support previous findings, self-reported information could be more reliable to measure the effect of these pests on farm crops.

Table 5. Simultaneous impact of locusts (using 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)
Locusts 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

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.2 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 four categories: household characteristics, infrastructures, WASH variables, and economic related variables. As dependent variables, we considered a change in total and in farm incomes. For illustrative reasons we only report the results of the models where the dependent variable is dichotomous[10].

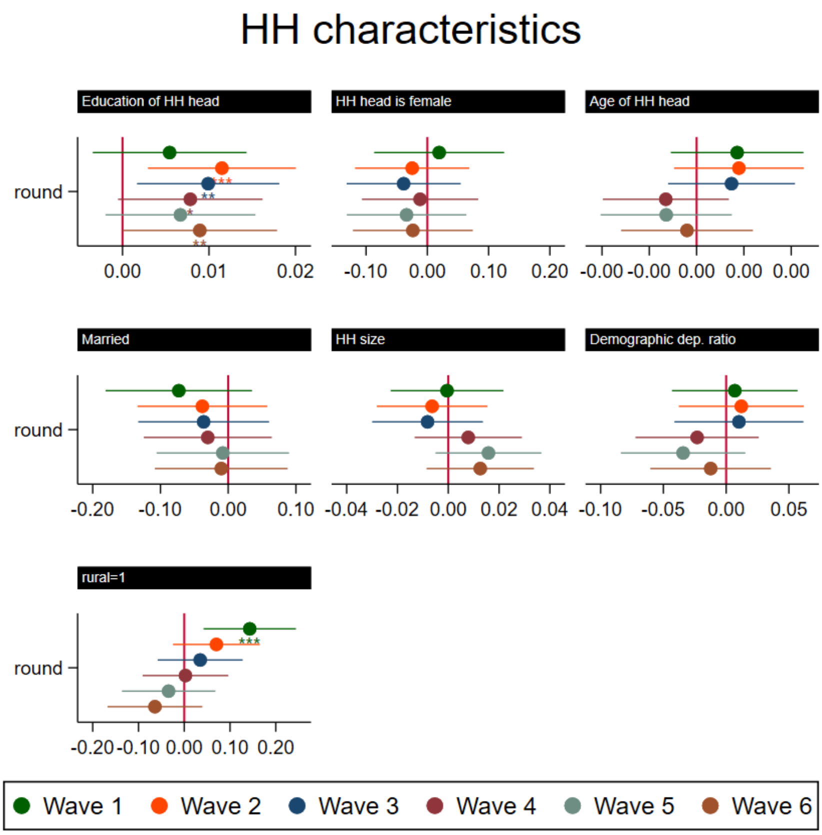
Total income change

Figure 12 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 having income

[10] For space constraints, estimates of the ordered probit model are not reported in the paper, but they are available under request.

increase or unchanged. Living in rural areas shows a positive and significant coefficient only in the first round. Indeed in the beginning rural areas were advantaged.

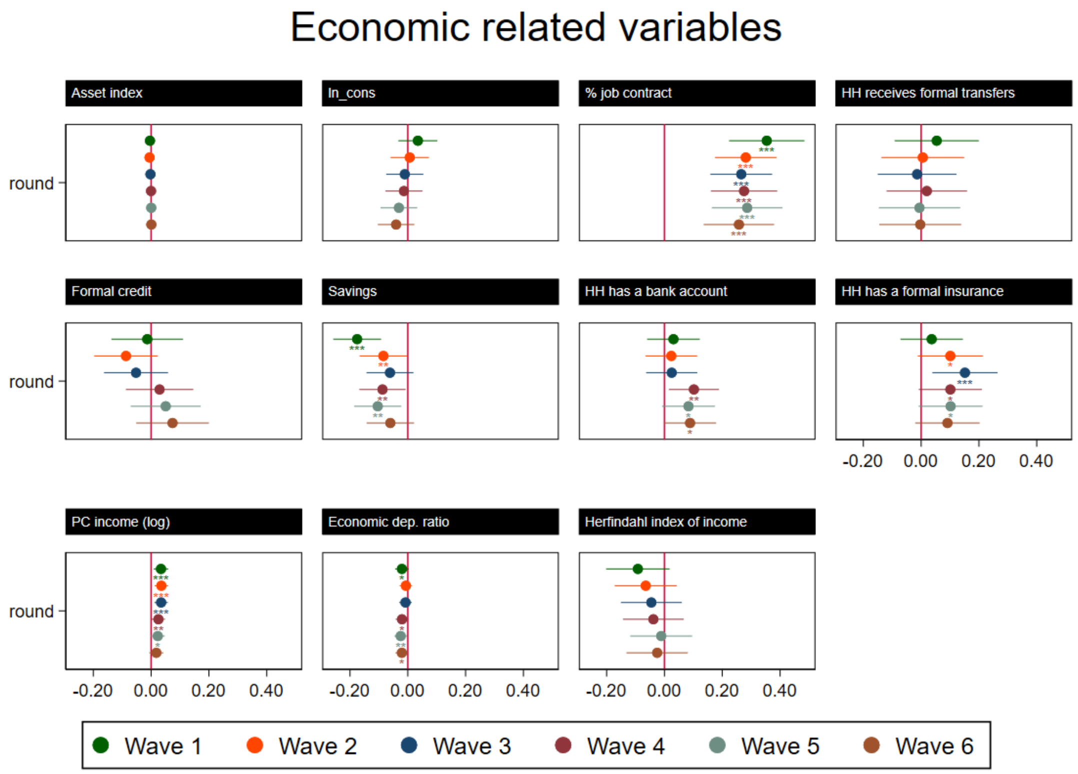
Figure 12. Effects of households characteristics on total income change over rounds



Source: Own calculation from ESS 2018/2019 and HFPSH 2020.
Note: Dots are average marginal effects from a probit regression. Each post-Covid round is compared with the baseline. Bars are 95% confidence intervals.

For what concerns economic-related variables, Figure 13 shows some interesting patterns. Having a formal job contract is associated with a higher probability of income increase or unchanged. A similar relationship can be found with having a bank account and formal insurance, although the magnitude and the level of significance are lower. These results show that access to formal institutions is a winning strategy to contrast the negative consequences caused by the crisis. Savings instead show an opposite trend. Per capita household income reports a positive relationship, meaning that as per capita income increases also 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.

Figure 13. Effects of economic-related variables on total income change over rounds



Source: Own calculation from ESS 2018/2019 and HFPSH 2020.
Note: Dots are average marginal effects from a probit regression. Each post-Covid round is compared with the baseline. Bars are 95% confidence intervals.

Regarding infrastructure and WASH-related variables, none of them report a substantial effect on total income. 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, to the probability of income increase or unchanged. However, the coefficient is lower than 1%. The graphs of these two categories of variables are reported in the appendix.

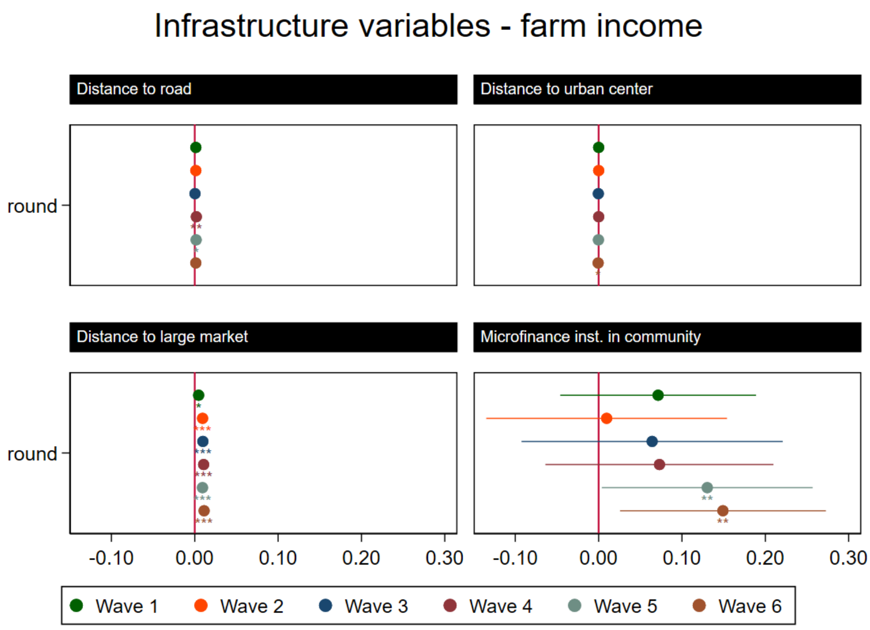
Farm income change

The same variables considered in the previous section show in part different patterns when considering farm income. Looking at the household characteristics, 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 ways.

Even in the case of farm income, variables of distance do not show significant patterns, except for distance to a large market, where it seems that the more distant the household is to the market and the higher is the probability of farm income unchanged or increase. The explanation could be that farther households had already put in place some strategies to account for the distance, so they were advantaged than those farmers that 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 could have directly bought products from the closest farmers instead of going to the 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 is important in supporting farm livelihood in situations of crisis.

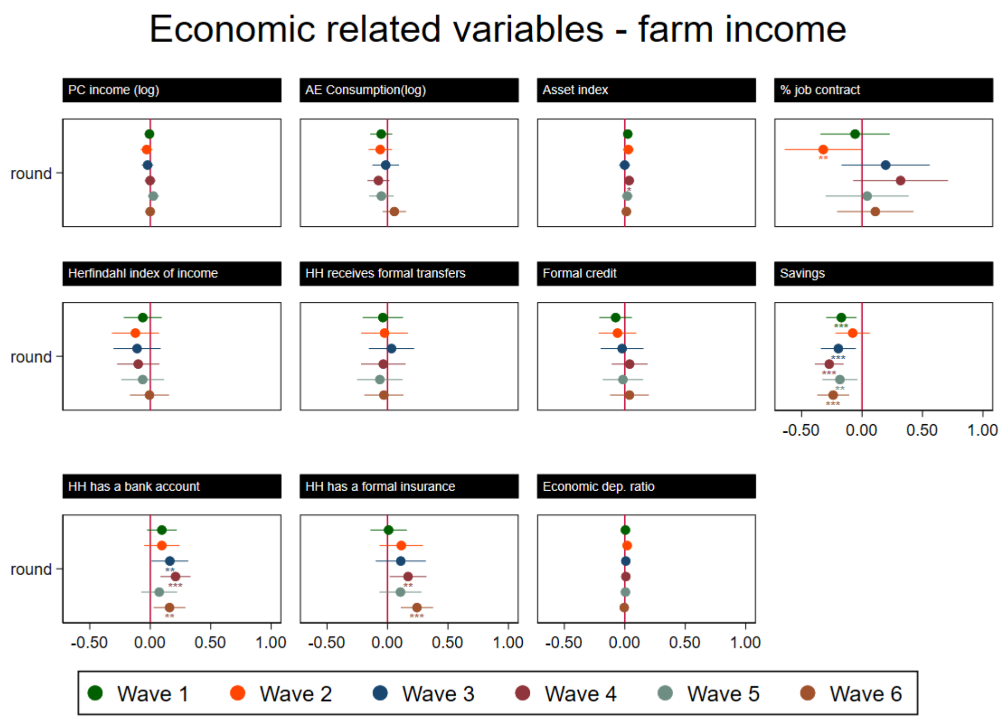
Figure 14. Effects of infrastructure variables on farm income change over rounds



Source: Own calculation from ESS 2018/2019 and HFPSH 2020.
Note: Dots are average marginal effects from a probit regression. Each post-Covid round is compared with the baseline. Bars are 95% confidence intervals.

For what concerns economic-related variables, estimates for farm income are similar to the ones for total income, with few exceptions. Even in this case having a bank account and formal insurance rise the probability of income increase, while savings increases the probability of income loss. A different result regards having a formal job contract, where here it does not have a clear and significant effect. This is comprehensible given that the majority of households in Ethiopia run family farming on their land, so they do not participate in the labor market, although they conduct labor activities.

Figure 15. Effects of economic-related variables on farm income change over rounds

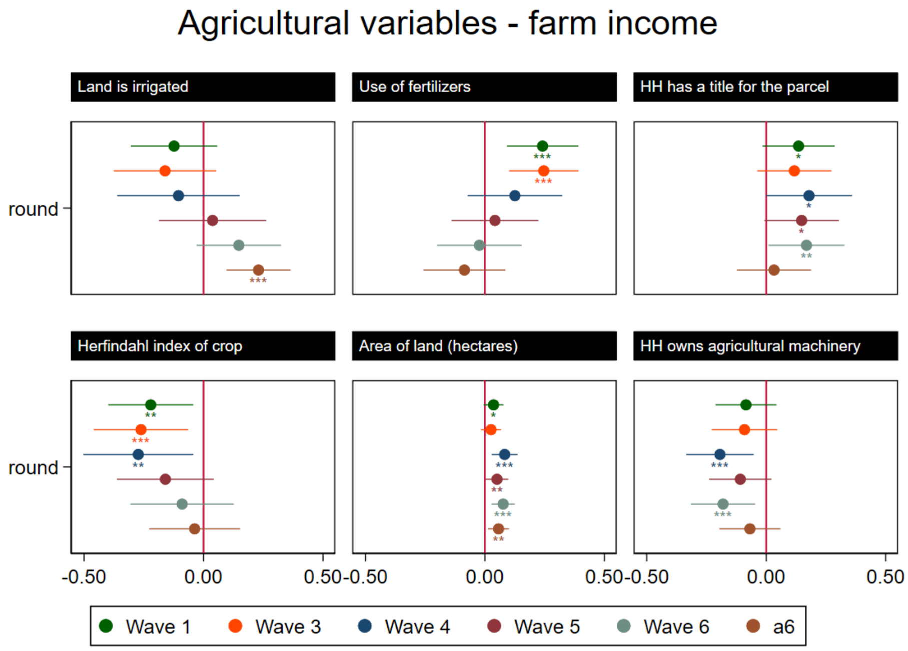


Source: Own calculation from ESS 2018/2019 and HFPSH 2020.
Note: Dots are average marginal effects from a probit regression. Each post-Covid round is compared with the baseline. Bars are 95% confidence intervals.

Regarding the agricultural-related variables, reported in Figure 16, results seem to suggest that farmers with larger areas of land and those with low crop diversification have a higher probability of success compared to smallholders with a higher Herfindahl index of crop. The marginal effects of land size on the probability of farm income change being equal to 1, reported in Figure 17, confirm previous findings. In all six rounds indeed the probability of not having an income reduction increases with land size.

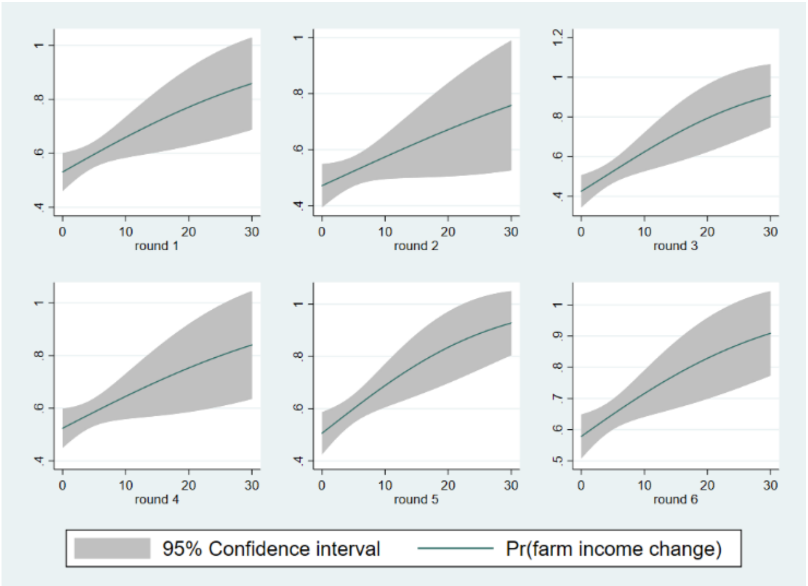
Having a title of ownership or holding the rights of use of the parcel is particularly relevant during the COVID-19 crisis, as they guarantee a greater probability of avoiding an income reduction. Households that use fertilizers and those that have agricultural machinery, although they initially experience a positive or insignificant effect, are subsequently negatively affected. This result can be the consequence of the mobility and trade restrictions, which increased prices and decreased the availability of inputs.

Figure 16. Effects of agricultural-related variables on farm income change over rounds



Source: Own calculation from ESS 2018/2019 and HFPSH 2020.
Note: Dots are average marginal effects from a probit regression. Each post-Covid round is compared with the baseline. Bars are 95% confidence intervals.

Figure 17. 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.

4.3 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 6 reports the results of the test, applied for the change of total income at the household level and the variable of 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, as reported in 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. Introducing regional income indeed leads the variable of COVID-19 cases to lose its significant effect.

Table 6. 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

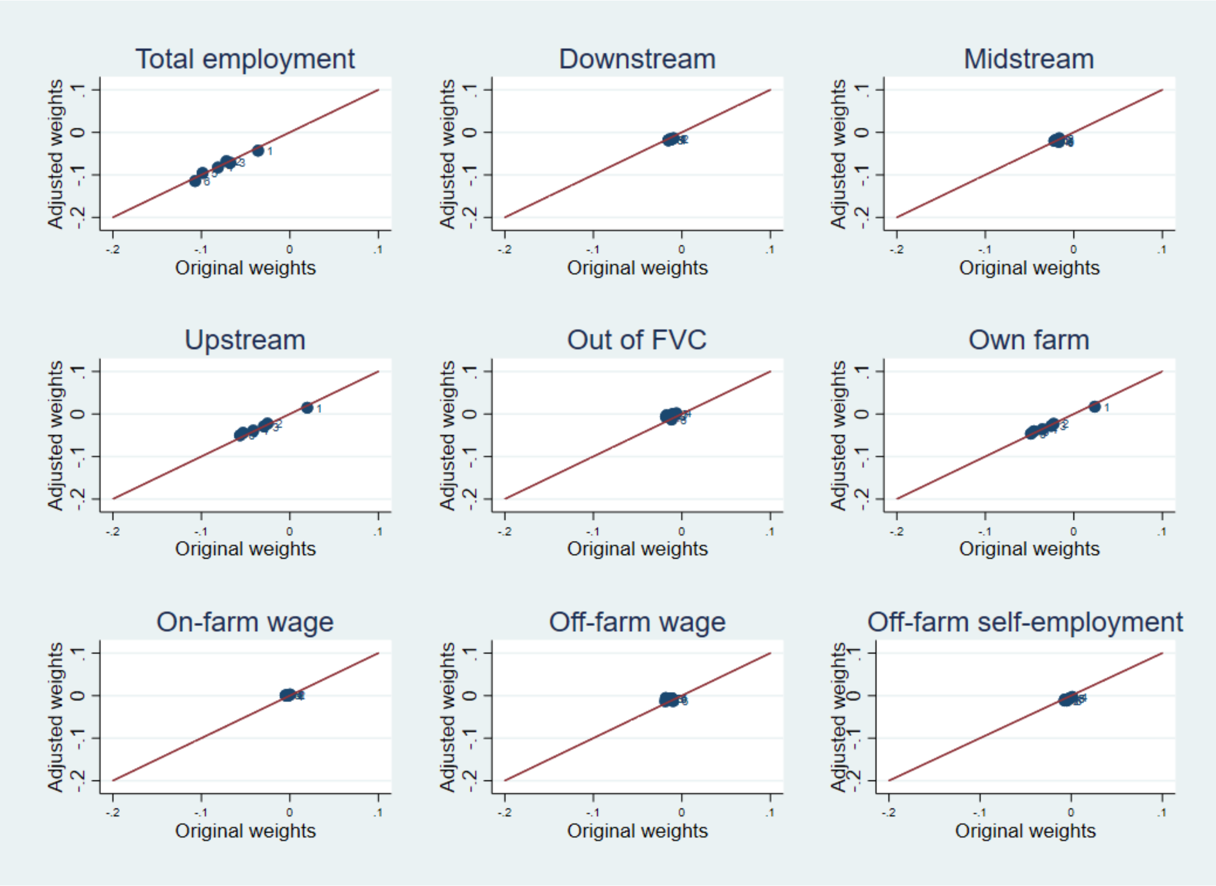
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Inverse probability weights

To address the problem of representativeness of the individual sample, as a robustness check we created individual-level adjusted weights using the inverse probability based on the ESS 2018/2019, and we compared the outcomes using these weights with the estimates previously presented. A similar check has been implemented in Khamis et al. (2021), where the authors rely 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 this 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.

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 considered include age, gender, years of completed education, living in rural areas, income quintile, being employed, working in own farm activities, and 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 18 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, corresponding to 98%. This result is rather robust, suggesting that the labor market outcomes of the subsample of individuals are generally consistent with the outcomes of the entire working population.

Figure 18. Comparison of weighting methods



Source: own elaboration from ESS 2018/2019 and HFPSH 2020

5. 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 onset. Upstream, and specifically own farm activities, 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 part is in line with previous studies that arose in the immediate aftermath of the pandemic, such as Bundervoet and Finn (2020) and Reardon et al. (2020), which stated that farming was the less affected sector. However, tracking the impact over time allowed to gain a more complete picture, where farming, after an initial advantage, has been affected by the disruption of the food value chain. This highlights the importance to monitor 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.

The analysis also showed that the most vulnerable farmers have been hit hardest. Small family-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 access specific tools that allow them to overcome the constraints they currently face. 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 opportunities to access financial services as well as formal institutions also individuals located in remote areas of the country.

Last but not least, multiple shocks dramatically change the picture. This is the case of the desert locusts outbreak, that compounded the already difficult situation created by COVID-19. Therefore, policy makers should consider the effects of simultaneous shocks when designing policy responses to the crisis. The long-term impact of the crisis is still uncertain, so it is recommended to closely monitor the effects of the crisis and to quickly respond with appropriate policies.

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Appendix

Figure A.1 Impact of COVID-19 cases on income change, wave by wave.

Note: previous call is considered the baseline.

Figure A.2 Impact of COVID-19 cases on employment over time, unbalanced sample

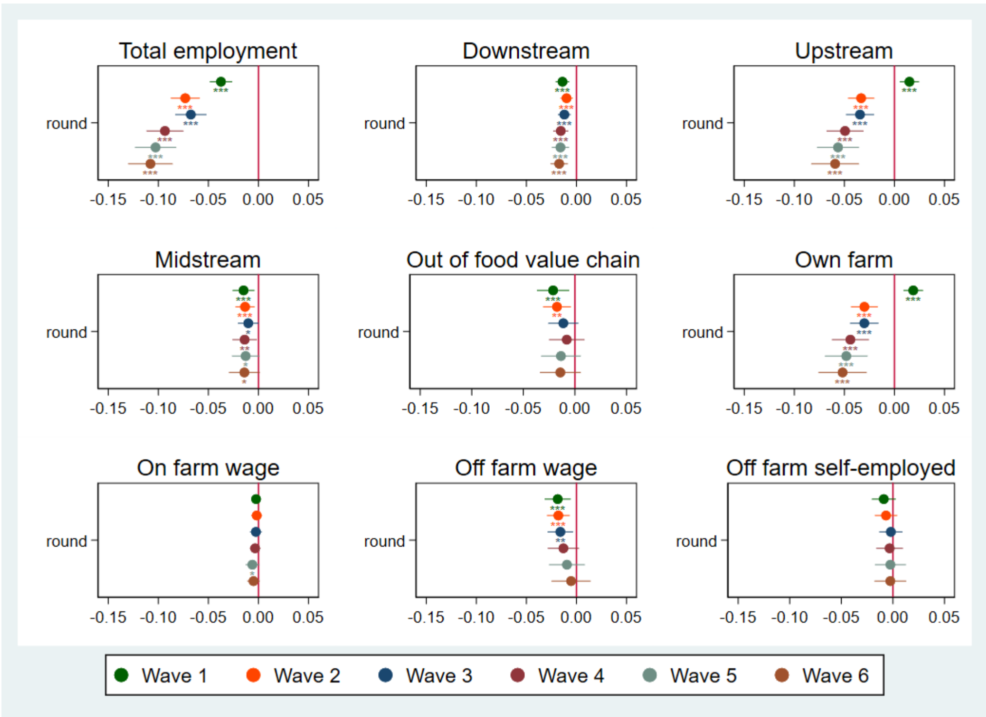

Figure A.3 Impact of COVID-19 cases on total income over time, unbalanced sample

Table A.1 Full regression estimates, total employment, and total income

Total employment

Variables	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5	Wave 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 member 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

Robust standard errors in parentheses

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

Total income

Variables	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5	Wave 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 member 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

Robust standard errors in parentheses

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