# The effect of invasive pests on food security: An understudied effect of climate change

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**Abstract**

Insect pest invasions have been exacerbated by climate change, threatening global agricultural production and food security. While the direct effect of climate change on agricultural production has received a lot of attention in the literature, less work estimates the indirect effect of climate change on agricultural production and food security through insect pests. In this paper, we use the example of the introduction of Fall armyworms (FAW) to Africa to study the effect of insect pests on agricultural production and food security in the face of climate change. We use a panel of primary farmer data to evaluate the effect of this pest and analyze which characteristics make farmers more vulnerable to food insecurity in the face of an FAW invasion. We find that an increase in FAW severity decreases maize yield by 43.3 percent and can increase food insecurity by up to 9 percent, similar in magnitude of a drought in a 30 year time period. Further, we find that increased temperatures are related to a higher incidence of FAW. When we include this effect, we find that increased pest pressure magnifies the effect of climate change on yield by 5.4 percent. Farmers can mitigate the effects of both FAW and higher temperatures associated with climate change by using early maize varieties and hybrids. Our work points to the importance of considering the indirect effect of climate change on agriculture through insect pests when evaluating both the costs of and adaptation to climate change.

**Keywords:** sub-Saharan Africa, fall army worms, food security, climate change.

**JEL Classification:** Q5, Q1, Q54, Q57

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# 1. Introduction

As highlighted by the barren fields left in East Africa after the recent locust invasion (Kassegn and Endris, 2021), insect pests are a threat to global agricultural production and food security. This threat is amplified by climate change, as temperatures increase both the range and appetite of insect pests (Gregory et al., 2009; Paini et al., 2016; Deutsch et al., 2018). And these pest invasions can have substantial impacts on food security (Devi, 2018; Tambo et al., 2021b; Kabwe et al., 2018). In this article, we use the recent introduction of fall armyworms (FAW) to Sub-Saharan Africa (SSA) to study the effect of a pest invasion on crop production and the subsequent impacts on welfare (as measured by household food security). We also estimate the effect of temperature on FAW pressure and calculate future damage from FAW that is expected to come from climate change.

Endemic to the Americas, FAW are new to Africa. They were first reported in Central and Western Africa in 2016. By September of that same year, they had spread to almost all the parts of SSA. The incredibly rapid spread of the FAW in SSA is attributed to the region's predominant warm and wet climate which provides abundant forage (Nurzannah et al., 2020; Njuguna et al., 2021). As a result, FAW are predicted to continue as a threat to agricultural production and food security in SSA (Gregory et al., 2009).

FAW can attack several hectares of crop in a single night. While they can survive on a wide range of plants, they prefer to infest maize, substantially threatening local maize production (Chormule et al., 2019; Midega et al., 2018; Andrews, 1980). In most parts of Africa, maize is the most important food and cash crop for farm households (Cairns et al., 2013). Most rural households in Zambia cultivate less than a hectare of maize with yields of about 2,400 kg/ha against an average of 3,600 kg/ha (Hichaambwa and Jayne, 2012; Franzel et al., 2002). With small cultivated land areas and low yields, most smallholder farm households barely produce enough maize to last until the next harvest (Mason et al., 2015). FAW, therefore, poses an important threat to food insecurity.

Climate change has heightened pest pressure, leading to increased crop damage, reduced production and productivity, and greater food insecurity (Skendžic et al., 2021; Matzrafi, 2019; Fand et al., 2012). For some insects, such as green and black stink bugs which cause damage to several crops, a 1 °C increase in temperature would result in a 15 percent increase in their population (Karuppaiah and Sujayanad, 2012). Temperature increases driven by climate change increase pest metabolic rates—typically doubling for every 10 °C rise—which also leads to significant increases in their population and geographic range (Skendžic et al., 2021).

According to Deutsch et al. (2018), if temperatures increase by 2 °C due to climate change, the median increase in yield losses due to pest pressure is 46%, 19%, and 31% for wheat, rice, and maize, respectively, resulting in estimated total losses of 59, 92, and 62 metric megatons per year. Lobell and Field (2007) projected that a 1 °C rise in temperature over a 30-year period would result in approximately a 3% decline in global maize yields. A more significant impact of 6.84% yield loss was projected for Sub-Saharan Africa over the same period by Lobell et al. (2011a)[1][2].

To measure this effect, we first estimate the effect of climate change-driven temperature increases on crop yields, and then assess the additional impact through increased Fall Armyworm (FAW) pressure.

While recent work by Davis et al. (2018), Baudron et al. (2019), and Pedigo et al. (1986) establish the correlation between FAW and maize yields, little research estimates the impact of insect pests on food security (Devi, 2018; Tambo et al., 2021b). Second, studies that have estimated the relationship between pests and food security often use cross-sectional data and rely on self-reported estimates of FAW infestations and other insect pests (Tambo et al., 2021b; Bannor et al., 2022; Abro et al., 2021). Given that the climate conditions suitable for maize are also conducive to FAW presence (Davis et al., 2018), using only cross-sectional data, may result in biased estimates of the damage caused by FAW. In this paper, we estimate the effect of FAW on maize yields and how they affect food security. Further, we identify climate change adaptation strategies and characteristics associated with farmers' ability to weather these pest shocks. Finally, we compare the projected yield and welfare losses from climate change and those from climate change through insect pest shocks.

Our contributions are fourfold. First, this study is one of the first situated in SSA that makes use of a primary panel of household data to empirically quantify the effect of FAW on maize yield and food security. These data allow us to control for time-invariant household characteristics which might otherwise bias our estimates. Second, the study controls for measurement errors resulting from farmers' self-reporting of FAW. Third, this is one of the first papers to estimate the indirect effect of climate change on yield due to increased pest pressure. Finally, we also explore the effectiveness of various adaptation strategies to FAW and highlight their interactions with adaptation to higher temperatures from climate change.

Our results indicate that compared to households who had no nearby FAW infestations, households who had FAW infestations in their surrounding villages (called a 'camp') experienced an average yield loss of 10.5 percent. If they themselves also report FAW infestations, the damage increases to 43.3 percent. Using three different food security metrics, we find the effects of FAW on food security that are similar to that of a drought in a 30 year time period.

Lastly, we estimate the potential increased effect of FAW on crop yields due to climate change. We

[1]Under optimal rain-fed conditions but could be greater than 10 percent yield loss per 1 °C warming in hotter regions.

[2]In SSA, it is projected that the temperature will increase by 0.6 °C per decade, amounting to a total increase of 1.8 °C over a 30-year period.

first estimate the direct effect of temperature increases on maize yield. We find that the predicted 1.8 °C temperature increase over the next 30 years from climate change is estimated to result in a 5.4 percent decline in maize yields. This estimate is consistent with the 6.84 percent yield loss projected by the model used in Lobell et al. (2011a) for Sub-Saharan Africa, and aligns closely with the findings of Xu et al. (2016), who report similar losses from a 1 °C temperature increase over a 30-year period in the United States in a region with idea conditions for maize production. We next estimate the effect of the same temperature increase on pest pressure and find that a 1.8 °C increase is expected to increase FAW pressure by 14.2 percent. When we incorporate the effect of higher FAW (insect pests) damage from increasing temperatures in our climate change and crop yields model, our results suggest that rising temperatures will generate a further 0.8 percent decline in yields increasing the total effect to an expected yield loss of 6.2 percent, an increase of almost 13 percent. With regards to food security, including the effect of climate change on FAW increases expected food security losses from climate change by 1.3 - 9 percent depending on the metric used. Thus, we find that increased pest pressure contributes a substantial fraction of the costs of climate change to agriculture and food security.

The structure of this paper is as follows. Section 2 outlines the global context of FAW infestations and summarizes the damage estimates reported in various studies. Section 3 describes the data and the empirical strategy employed in the analysis. The findings from the main specification are presented in Section 4. A discussion of these results is provided in Section 5, and Section 6 offers concluding remarks.

## 2. Background

Fall armyworm (Spodoptera frugiperda J.E Smith) is a pest native to subtropical tropical America, where it is considered the most damaging pest for maize (Andrews, 1980). FAW can cause serious damage to about 100 different crops, although they tend to prefer the gramineous (grass) family such as maize, sorghum, and millet (Pogue, 2002; Buntin et al., 2001).

It is believed that FAW reached Africa through commercial aircraft or in cargo containers and then spread via wind and flight (Day et al., 2017). As of September 2016, FAW were reported to have reached almost all SSA, with 44 countries reporting infestations. They were further reported to have reached India by May 2018, and Thailand and China by January 2019 (Davis et al., 2018; Li et al., 2020). In Zambia, the first infestations were reported in November and early December 2016, affecting over 100 out of 116 districts in all provinces with varying degrees of severity (Chormule et al., 2019; Kabwe et al., 2018). In 2017, fifty-eight percent of farmers reported having been affected by the FAW infestation, which resulted in huge losses in maize yield (Chormule et al., 2019). According to the report by the Zambian Disaster Management and Mitigation Unit (DMMU), more than 172,000 hectares of maize were destroyed by the FAW during the 2016/17 agricultural season when the pest was first reported, leading the government to spend millions of dollars on pesticides and other control measures.

Maize is one of the most important foods and cash crops for smallholder and commercial farming families in Africa (Cairns et al., 2013). It is also the primary host crop for FAW, with some reports of FAW in sorghum. In SSA, FAW are estimated to have caused about 15-21 percent losses in annual maize production over the period of three years, with the damage valued at approximately 6.19 billion dollars (Davis et al., 2018). Therefore, the damage from FAW seriously threatened agricultural production and the food security of the region (Westhuizen et al., 2011).

Previous research on the effect of FAW on maize and food security largely uses either agronomic field experiments or cross-sectional, survey-based estimates. The use of agronomic field experiments raises the concern of whether these controlled settings are representative of the situation faced by farmers. On the other hand, survey-based approaches raise the concern that self-reports of infestation may lead more attentive and productive farmers to report higher levels of infestation, biasing the estimate of the effect of FAW. Table 1 gives a summary of the location, date, method used, and yield estimates of some of the studies that have quantified the effect of FAW on maize yields.

Table 1: Studies done on FAW date, location, method and yield damage estimates

| Author | Location | Date | Method | Yield damage estimates |
|---|---|---|---|---|
| Tambo J., et al. | Zimbabwe | 2017 - 18 | Recall method | 43-57 perc |
| Makgoba, Mankwana C., et al. | South Africa | 2021 | Recall method | 43-57 perc |
| Chimweta, Moreblessing, et al. | Zimbabwe | 2019 | Field measurements | 25-50 perc |
| De Groote, Hugo, et al | Kenya | 2018 | Recall method | ¿ 50 perc |
| Chimweta et al | Zimbabwe | 2019 | Recall method | 58 perc |
| Day et al | Zimbabwe | 2017 | Recall method | 25 - 50 perc |
| CABI | Zambia | 2017-18 | Recall method | 26 perc |
| CABI | Ghana | 2017-18 | Recall method | 35 perc |
| CABI | Namibia | 2017-18 | Recall method | 17 perc |
| CABI | Ghana | 2017-18 | affected vs not affected farmers yields | 17 perc |
| Baudron et al | Zimbabwe | 2018 | Structural model eq and Image J to grain wgt | 26 - 55 perc |
| Kumela et al | Kenya | 2017-18 | Recall method (Socio-economic surveys) | 47 perc |
| Kumela et al | Ethiopia | 2017-18 | Recall method (Socio-economic surveys) | 32 perc |
| Cruz and Turpin | USA (Indiana) | 1983 | Green house | 19 perc |
| McMillan and Shark | USA | 1967 | Field trials | 18 perc |
| Henderson et al | USA | 1966 | Field trials | 5 - 22 perc |
| Evan and Stansly | Ecuador | 1986 | Field trials | 11 - 42 perc |
| Foster R.E | USA (Florida) | 1989 | Field trials | 35 perc |

# 3. Data and methods

Our study site includes 12 districts in Zambia which were randomly selected to cover the three primary rainfall zones in the country (see Figure A.1 in the appendix which illustrates where the study regions are shaded). These districts are Mkushi, Mumbwa, Mpongwe, Masaiti, Lundazi, Petauke, Mbala, Mungwi, Chinsali, Mufumbwe, Solwezi, Choma, and Namwala.We then randomly selected four camps in each district. We then randomly selected households from random villages within the camps. Twenty-five households were randomly selected within the chosen camps [3].

The data come from a large panel household survey of smallholder farmers across Zambia conducted in June and July of 2016, 2017, 2018, and 2019 covering 2015/16, 2016/17, 2017/18 and 2018/19 agricultural seasons. The survey sample includes about 1,200 smallholder households in 12 districts of Zambia with data on socioeconomic, and demographic characteristics, production activities, income sources and insect pest infestation, household consumption, and weekly dietary questions.

After the arrival of FAW in late 2016, we asked farmers about the proportion of their crops that FAW damaged. Based on responses, enumerators categorized the severity of infestation into three categories: less than 25 percent was labeled as low, 25-50 percent was moderate, and more than 50 percent of crop damage was severe. All four years of the survey collect maize yield and several measures of food security: the Food Consumption Score (FCS), Household Dietary Diversity Score (HDDS), and the reduced Coping Strategy Index (rCSI).

Because weather affects both the prevalence of FAW and yield, we control for rainfall and temperature.

[3] An agricultural camp is defined as a small unit within the agricultural sector where farmers are grouped around agricultural extension service provision in groups called cooperatives (Alamu et al., 2019). An agricultural camp. An average camp is approximately about 20 km in radius (Dube et al., 2016)

The rainfall data come from the Climate Hazards Center InfraRed Precipitation with Station data (CHIRPS) repository. CHIRPS uses a high-resolution background climatology with estimations of precipitation means and variations which are more accurate. The temperature data is from the Moderate Resolution Imaging Spectroradiometer (MODIS). To extract both the temperature and rainfall data, we created a 4 km buffer around the household that covers the maximum distance from the household to their fields and used that buffer to extract both gridded temperature and rainfall measures. All of the processing and analysis was completed using the software R.

## 3.1. Variable construction

**Dependent variables**

The outcomes of interest in this study are maize yields and food security as measured by the FCS, HDDS, and rCSI. Maize yield was calculated directly from survey data. With regards to the FCS, we recorded the frequency of all foods the households reported to have consumed in the 24 hours before the interview. Foods that are in the same group were aggregated and multiplied with a value according to the food group's nutritional weight to obtain a score. We then used this metric, following a range of 0-21, to categorize an aspect of each household's food security as follows; FCS $\leq 10$ is considered poor; FCS 28 - 42 was borderline and FCS $> 42$ the score was considered acceptable. If the FCS is $< 35$ that household would be considered food insecure. This assessment is based on Project (2018) (the International Dietary Data Expansion Project).

With HDDS, we defined dietary diversity as the number of unique food groups that any member of a household consumed in the past 7 days instead of 24 hours. The HDDS is a measure that focuses on the quality of diet by calculating the number of different food groups consumed, instead of the quantity of different food groups consumed. Our panel dataset captured 12 HDDS food categories: cereals, root and tubers, vegetables, fruits, meat and poultry, eggs, fish and seafood, pulses and legumes, milk/dairy products, fat and oil, sugar, and other miscellaneous foods, similar to the study by Swindale and Bilinsky (2006). The interview is based on farmer recall and the data is self-reported. While bias due to self-reported is a legitimate concern, in a study by Gupta et al. (2020), the authors show that the HHDS recall results are consistent regardless of the recall period (24 hours or 7 days).

We computed the rCSI following the guidelines from El-Rhomri and Domínguez-Serrano (2019). rCSI measures the number of times a household engaged in coping behaviors to mitigate food insecurity and the severity of those behaviors. To compute the rCSI, the enumerators asked the households questions about a list of coping strategies that they used in the last week. We then computed the rCSI after categorizing the access to food as follows; rCSI 0 - 3 is No or low coping strategies; rCSI 4 - 9 was medium coping strategies and rCSI $\geq 10$ High coping strategies (El-Rhomri and Domínguez-Serrano, 2019; Project, 2018).

### 3.2. Econometric model

To estimate the effects of FAW on Maize yields, we employ a difference-in-differences model with household and year-fixed effects Equation 1:

$$Y_{it} = \sigma_t + \beta FAW_{it} + \gamma \mathbf{X}_{it} + \lambda gdd_{it} + \omega kdd_{it} + \rho Rain_{it} + \Omega Rain_{it}^2 + \alpha_i + \theta_t + \varepsilon_{it} \quad (1)$$

The dependent variable, $Y_{it}$, is the natural log of maize yields (kg/ha) or food security [4] for the *ith* household at time $t$, $\beta$ measures the effect of FAW intensity, $\gamma$ capture the effect of agricultural inputs, $gdd$ is the growing degree days (GDD), representing the heat units that enable plant growth, $kdd$ is killing degree days (KDD), $Rain$ is the seasonal rainfall and its square. We log yields to mitigate the effect of outliers which allows us to interpret the effects in terms of the percentage change. With hyperbolic sine transformations, the coefficients represent the elasticities of output with respect to the individual inputs. We include household fixed effects, $\alpha_i$ for household $i$, common shocks ($\theta_t$), and lastly $\varepsilon_{it}$ is the error term. In all of our specifications, we cluster the standard errors at the camp level.

In some specifications, we include production inputs $\mathbf{X}_{it}$, namely the quantity of maize seed planted, the quantity of fertilizer applied, total land cultivated (ha), household size as a proxy for labor, capital, temperature, and amount of precipitation which are all transformed using the hyperbolic sine. Since FAW are typically observed only mid-season, most input decisions would have been made before the severity of FAW is known. However, there is a possibility that farmers may adjust their input use, such as reducing fertilizer, in response to the perceived threat of FAW. Therefore, we wanted a specification that controls for these inputs to avoid confounding the farmers' responses with the presence of FAW.

The primary criticism of the two-way fixed effects (TWFE) estimator is that it calculates a weighted average of all possible 2x2 differences-in-differences (DiD) estimates, with weights determined by group sizes and treatment variances (Borusyak et al., 2024; Goodman-Bacon et al., 2019). This effectively means that the TWFE estimator represents a variance-weighted average treatment effect on the treated (ATT) under the assumption of common trends and time-invariant treatment effects. However, recent research by Callaway and Sant'Anna (2021) highlights that the TWFE estimator can be biased in the presence of time-varying treatment effects, particularly in designs with differential timing of treatment adoption. The strength of their approach lies in their proposed estimators, which eliminate 2x2 DiD comparisons between newly-treated and already-treated units, ensuring consistency even with heterogeneous treatment effects across time and treated units.

As shown in Table A.3, the robust estimators proposed by Callaway and Sant'Anna (2021) yield estimates

[4] We assume that the effect of FAW on food security occurs within the same year as the affected harvest

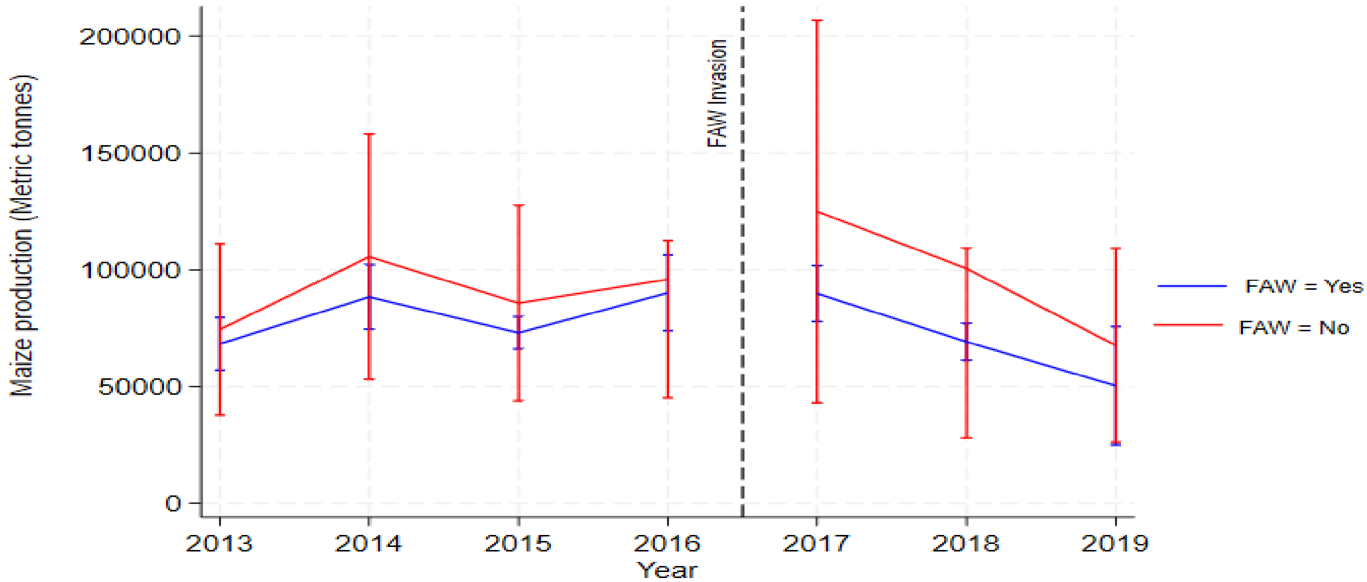


Figure 1: Maize production trends from 2013 - 2019.

that are similar to our TWFE estimates when we apply the intent-to-treat (ITT) approach. This consistency aligns with findings by Wooldridge (2021), where the Two-Way Mundlak Regression (TWM) was applied, providing the necessary tools for analyzing staggered treatment designs. Moreover, the flexibility of the TWM estimator can be particularly useful when there is a concern that the common trends assumption may be violated, as it allows for suitably heterogeneous treatment effects. In Table A.3, the results from the TWM regression using the ITT approach are consistent with those from the TWFE model.

We measure FAW damage both discretely and by reported level linearly: (0 = No infestations, 1 = Low levels, 2 = Medium, 3 = Severe) - see Section 3 to see how the levels are generated.

For the difference-in-differences approach to be valid, the parallel trend assumption needs to hold: that in the absence of FAW, yields would have evolved in the same way for households who were and were not affected by FAW. We are unable to formally test parallel trends since we only have one year of data before the outbreak. However, we first compare the characteristics of farmers who later report FAW to those who don't to test for systemadic differences. Second, we plot the trend using the Crop Forecast Survey (CFS), which provides nationally representative district-level maize production forecasts. We compare districts with high FAW intensity to those with low intensity, grouping districts based on the number of farmers reporting FAW. Districts with a high number of reports are considered treated (high FAW), while those with fewer reports are considered controls (low FAW). We use maize production forecasts from 2013 to 2019. Figure 1 shows that production trends in high FAW districts vs. low FAW districts were similar until the FAW invasions.

As a robustness check for the parallel trend assumption, we carry out a leads test in our main regressions following the approach used by Autor (2003).

To estimate the effect of FAW intensity on food security outcomes, we employ the following Tobit model specification:

$$Q_{it}^{*} = \beta' \mathrm{FAW}_{it} + \lambda \mathrm{gdd}_{it} + \omega \mathrm{kdd}_{it} + \rho \mathrm{Rain}_{it} + \Omega \mathrm{Rain}_{it}^{2} + \Phi_t + \zeta_{it} \tag{2}$$

$$Q_{it} = \begin{cases} Q_{it}^{*} & \text{if } Q_{it}^{*} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

Here, subscript $i$ refers to the household and $t$ to time. $Q_{it}$ is the observed value of the outcome variable (food security outcome) for household $i$ at time $t$, while $Q_{it}^{*}$ denotes the latent (uncensored) outcome [5]. The parameter vector $\beta'$ captures the effect of FAW intensity. Climatic controls include growing degree days (GDD), killing degree days (KDD), rainfall, and its square term, as described in Equation 1. The term $\Phi_t$ represents year fixed effects, accounting for time-specific shocks common to all households.

The model assumes a random effects structure, with the composite error term defined as:

$$\zeta_{it} = \lambda_i + u_{it} \tag{4}$$

In this, $\lambda_i$ captures unobserved household-specific random effects, while $u_{it}$ is the idiosyncratic error term. The random effects $\lambda_i$ are assumed to follow a normal distribution and to be independent of the explanatory variables, consistent with standard assumptions Kaya Samut and Cafrı (2016).

#### 3.2.1. Correcting for self-reporting bias

Our measure of FAW intensity is based on self-reporting, which might lead our results to suffer from selection or classical measurement error. Observant farmers may be more likely to report FAW and may also have higher yields. If they only have higher yields on average, the household fixed effects should capture that variation. More problematic would be if unobserved characteristics of these farmers could make them more likely to undertake mitigation measures if their yield is under threat, or if their yields vary in other time-varying ways not captured in the survey from farmers who do not report FAW. Even if there is no systematic bias in reporting, measurement error of FAW would bias the estimate of FAW toward zero.

[5] Given that the outcome is continuous but has a large mass at zero, we employ a Tobit model to account for censoring at zero. This approach allows us to model both the probability of observing a positive outcome and the intensity of the outcome when it is positive, addressing the limitations of standard linear regression in the presence of censoring.

We test the correlation between most characteristics and the local deviation in reporting FAW (see the subsubsection A.1.1).

To address this concern, we assume that the true FAW intensity for a specific farm is correlated with the presence of FAW in the nearby region. Thus, to control for the previously discussed possible limitations in the measurement of FAW intensity, we use the camp level average of the summed farmer response on FAW intensity at their camp subtracting the intensity reported by the observed household (Equation 5). We then use this camp-level measure as an instrument for the individual household's FAW exposure. [6] Further, we estimate the effect of FAW on our food security outcomes using the same specifications used in Equation 1 for the FE, Equation 6 for the ITT and Equation 7 for IV (See subsection A.1 for details of the instrument).

To estimate the effect of climate change on yields, we regress weather variables on maize yields following Equation 1: We then use these coefficients to estimate the effect of increasing temperatures from 30 years of future climate change in Zambia on yield. We compare these results against the estimates of the effect of temperature on FAW intensity and the estimates of FAW intensity on yield.

[6] The results of this regression should be seen as a local average treatment effect (LATE) where it reflects the yield loss associated with farmer '$i$' reporting FAW where that reporting is correlated with having a higher level of infestation at the camp level.

# 4. Results

The results section is structured as follows: we begin by testing for differences in characteristics using normalized differences, as shown in subsection 4.1. Next, we examine the leads in subsection 4.2. We then analyze the effects of FAW on maize yields in subsection 4.3. Following this, we explore the impact of FAW on food outcomes. We also compare the direct effects of climate change on yield with the effects mediated through FAW in subsection 4.5. Finally, we investigate planting timing and the use of maize hybrids as climate adaptation strategies in subsection 4.6.

## 4.1. Balance table

To explore whether farmers who report FAW are systematically different from those who do not, in Table 2 we present summary statistics for both groups from 2016, the year before FAW arrived in SSA. We formally test for differences in these characteristics using the normalized differences similar to the approach of Friedman et al. (2016). Table 2 reveals that reports of FAW are not strongly correlated with most farmer or location characteristics. However, small but significant differences exist in age and rainfall between farmers who later report FAW and those who do not. We find that during the 2015/16 agricultural season, farming households with FAW infestations were headed by marginally older household heads, with an average age of 46 years, compared to households with no FAW with an average age of 45 years. With regards to rainfall, we find that farming households with FAW infestations received slightly less rainfall, with an average of approximately 931 mm, compared to households with no FAW 961 mm. Note that these differences are only significantly different from zero at the 10 percent and we control for them in our regression.

Table 2: Baseline characteristics with the (2015/16 agricultural season) Means and Balance

| | Means (SD) | | Normalized differences |
|---|---|---|---|
| | Control | FAW | Control vs treatment |
| Age (years) | 46.6 | 45.319 | 0.018* |
| | (15.589) | (14.592) | |
| Gender (1 = male) | 0.835 | 0.808 | 0.0142 |
| | (0.371) | (0.393) | |
| Education | 3.313 | 3.116 | 0.107 |
| | (1.827) | (1.489) | |
| Charcoal | 0.166 | 0.224 | -0.0391 |
| | (0.372) | (0.417) | |
| Total landholding | 4.46 | 4.77 | -0.115 |
| | (9.74) | (6.049) | |
| Cultivated land | 2.334 | 2.464 | -0.134 |
| | (2.402) | (2.414) | |
| Maize yield | 1515.577 | 1601.981 | 0.218 |
| | (1797.449) | (1508.622) | |
| Total income | 7129.986 | 7436.039 | 0.178 |
| | (13891.93) | (13897.2) | |
| Rainfall | 931.291 | 960.517 | 0.401* |
| | (141.141) | (159.616) | |
| Access to credit | 0.722 | 0.73 | 0.00947 |
| | (0.448) | (0.444) | |
| Asset index | 117.305 | 77.842 | 0.069 |
| | (530.63) | (4.122) | |

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

## 4.2. Test for leads

Because we have only one data point from before the infestation and therefore cannot show parallel trends, we carry out a leads test following the approach used by Autor (2003). We use leads in all of our OLS, ITT and LATE specifications, presented in Table 3. These results indicate that the effect of FAW on maize yields are only significant in the years in which FAW were experienced, not the years before, suggesting that there is not something systematically different in our treatment and control groups before the pest infestations.

## 4.3. Effect of FAW on crop yields

We next explore the effect of FAW severity on maize yields using estimates from the difference-in-differences regression with two-way fixed effects (Table 4). As noted in the methods, we instrument for reported FAW infestation rates using camp-level averages in an instrumental variables framework to address potential measurement error. We find a negative and significant effect of FAW on agricultural productivity. In columns 1 and 4 we present the effect of the self-reported FAW intensity on maize yields where we find that a one-unit increase in FAW severity decreases yield by 2-5 % and in columns 2 and 5 we regress the instrument (FAW intensity at the camp level excluding the observed household) with all the exogenous variables and household and year fixed effects. This result can be thought of as the effect of an increase in village average levels of FAW on a household's maize yield. In column 6, we present the instrument variable

Table 3: Effects of FAW on Maize yields

| VARIABLES | (1) lyield | (2) lyield | (3) lyield | (4) lyield | (5) lyield | (6) lyield |
|---|---|---|---|---|---|---|
| | OLS | ITT | IV | OLS | ITT | IV |
| FAW | -0.042 | -0.086* | -0.351* | -0.033*** | -0.105*** | -0.434*** |
| | (0.025) | (0.053) | (0.231) | (0.025) | (0.049) | (0.227) |
| Lead FAW | -0.019 | 0.009 | -0.048 | -0.014 | 0.021 | -0.171 |
| | (0.037) | (0.037) | (0.107) | (0.034) | (0.035) | (0.156) |
| gdd | 0.0002 | 0.0006 | 0.0008* | 0.0007 | 0.0007* | 0.0011 |
| | (0.0010) | (0.0011) | (0.0012) | (0.0009) | (0.0007) | (0.0011) |
| kdd | -0.0017*** | -0.0019 | -0.0026*** | -0.0004 | -0.0023 | -0.0031*** |
| | (0.0009) | (0.0010) | (0.0012) | (0.0009) | (0.0010) | (0.0010) |
| rainfall | 0.0060*** | 0.0062*** | 0.0059*** | 0.0063*** | 0.0062*** | 0.0065*** |
| | (0.0012) | (0.0012) | (0.0013) | (0.0013) | (0.0012) | (0.0007) |
| square of rainfall | -2.53e-06*** | -2.61e-06*** | -2.48e-06*** | -2.49e-06*** | -2.81e-06*** | -2.56e-06*** |
| | (4.90e-07) | (5.35e-07) | (5.57e-07) | (4.59e-07) | (5.03e-07) | (3.76e-07) |
| Controls | No | No | No | Yes | Yes | Yes |
| HHFE FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,725 | 2,520 | 2,520 | 2,742 | 2,537 | 2,537 |

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

specification where intensity is instrumented using the FAW intensity at a camp. We find that FAW reduce maize yields. As the intensity of FAW worsens, we find that households who moved from moderate to severe intensity of FAW in their surrounding camp experienced an average of 39.8 percent lower maize yields than households with no FAW infestations.

Table 4: Effects of FAW on Maize yields

| VARIABLES | (1) lyield | (2) lyield | (3) lyield | (4) lyield | (5) lyield | (6) lyield |
|---|---|---|---|---|---|---|
| | OLS | ITT | IV | OLS | ITT | IV |
| FAW | -0.022 | -0.097*** | -0.328*** | -0.055* | -0.116* | -0.398*** |
| | (0.021) | (0.047) | (0.163) | (0.019) | (0.045) | (0.156) |
| gdd | 0.0001 | 0.00004 | 0.0006 | -0.0005 | 0.0005* | 0.0011* |
| | (0.0007) | (0.00086) | (0.0003) | (0.0007) | (0.0007) | (0.0009) |
| kdd | -0.0004 | -0.0002 | -0.0009 | -0.0019*** | -0.0009 | -0.0018** |
| | (0.0008) | (0.0009) | (0.0010) | (0.0007) | (0.0008) | (0.0010) |
| rainfall | 0.0066*** | 0.0067*** | 0.0066*** | 0.0066*** | 0.0067*** | 0.0065*** |
| | (0.0007) | (0.0008) | (0.0008) | (0.0006) | (0.0008) | (0.0008) |
| square of rainfall | -2.78e-06*** | -2.86e-06*** | -2.74e-06*** | -2.75e-06*** | -2.81e-06*** | -2.66e-06*** |
| | (3.44e-07) | (3.69e-07) | (3.78e-07) | (3.29e-07) | (3.56e-07) | (3.42e-07) |
| Controls | No | No | No | Yes | Yes | Yes |
| HH FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,520 | 2,520 | 2,520 | 2,742 | 2,537 | 2,537 |

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

## 4.4. Effects of FAW on Food security outcomes

We next estimate the effect of FAW severity on three common measures of food security: FCS, HDDS, and rCSI. To put these effects in context, we compare the effect of FAW on food security to that of a drought in a 30 year time period. [7]. The estimates from Table 5 column 4 indicate that compared to households that had no FAW infestation in their area, households that faced severe FAW in their camp experienced an average of 9.88 percent drop in food consumption score (FCS) which is notably higher than the estimated effect of a drought in a 30 year time period on FCS (6.12 percent drop).

With regards to the HDDS, the results in column 6 of Table 5 indicate that compared to households that had no FAW infestation in their area, households facing severe FAW in their camp experienced an average of 14.92 drop in dietary diversity which is somewhat similar to the effect of drought in the last 30 years (16.14 percent).

Finally, the results for the reduced coping strategy index (rCSI) in column 6 of Table 5 indicate that compared to households who had no FAW infestation in their area, households who faced severe FAW in their camp experienced an average of 67.25 percent increase in the coping strategy index, which is higher than the effect of drought in the last 30 years which increased the coping strategy index by 42.13 percent.

[7] To estimate the effects of drought using a 30 year time period, we start by calculating the mean ($\mu$) and standard deviation ($\sigma$) for the 30 years of precipitation data. We then determine the drought threshold as $\mu - 2\sigma$, representing the amount of precipitation considered to indicate drought conditions. Next, we identify the years in our dataset where precipitation was low enough to be classified as drought years. In our dataset, the agricultural seasons of 2015/16 and 2018/19 are examples of such drought years.

We calculate the average Food Consumption Score (FCS) during these drought years to understand the historical impact of drought conditions on FCS. We then calculate the baseline average FCS during non-drought years. To quantify the reduction in FCS due to drought, we present the calculations as follows:

$$\text{Percentage Reduction} = \left( \frac{Y_{\text{baseline FCS}} - Y_{\text{drought FCS}}}{Y_{\text{baseline FCS}}} \right) \times 100\%$$

One may be concerned that the data we have may not be sufficient. To ensure robustness, we extend these calculations by using data from the Food Security Research Project (FSRP), which covers the 1999/2000, 2002/2003, and 2006/2007 agricultural years, and from the Rural Agricultural Livelihood Survey (RALS), which covers the 2010/2011, 2013/2014, and 2018/19 agricultural years—a period closer to 30 years. We find that the results are consistent with the calculations using our dataset.

Table 5: Effects of FAW on Food security outcomes

| VARIABLES | (1) FCS | (2) FCS | (3) FCS | (4) HDD | (5) HDD | (6) HDD | (7) rCSI | (8) rCSI | (9) rCSI |
|---|---|---|---|---|---|---|---|---|---|
| | OLS | ITT | IV | OLS | ITT | IV | OLS | ITT | IV |
| FAW | 0.0047 | -0.0483*** | -0.0988*** | -0.0058 | -0.0730*** | -0.1492*** | 0.1284*** | 0.3290*** | 0.6725*** |
| | (0.0082) | (0.0158) | (0.0317) | (0.0093) | (0.0196) | (0.0381) | (0.0189) | (0.0423) | (0.0845) |
| gdd | 0.0008*** | 0.0006*** | 0.0003 | 0.0004 | 0.0001 | -0.0003 | -0.0063*** | -0.0052*** | -0.0032*** |
| | (0.0002) | (0.0003) | (0.0004) | (0.0003) | (0.0003) | (0.0004) | (0.0006) | (0.0006) | (0.0007) |
| kdd | -0.0007*** | -0.0009*** | -0.0009*** | 0.0001 | -0.00004 | -0.00006 | 0.0034*** | 0.0036*** | 0.0036 |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.00034) | (0.00034) | (0.0007) | (0.0006) | (0.0006) |
| rainfall | 0.0007*** | 0.0003** | 0.00006 | 0.0019*** | 0.0014*** | 0.0010*** | -0.0056*** | -0.0044*** | -0.0023 |
| | (0.0001) | (0.0002) | (0.0003) | (0.0002) | (0.0002) | (0.0003) | (0.0003) | (0.0004) | (0.0007) |
| square of rainfall | -1.80e-07*** | -2.78e-08 | 1.08e-07 | -6.17e-07*** | -4.33e-07 | -2.27e-07* | 2.40e-06*** | 1.85e-06*** | 9.24e-07 |
| | (7.94e-08) | (9.40e-08) | (1.22e-07) | ( 8.16e-08) | (1.02e-07) | (1.37e-07) | (1.64e-07) | (2.01e-07) | (2.99e-07) |
| HHFE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,980 | 2,760 | 2,760 | 2,922 | 2,756 | 2,756 | 2,922 | 2,756 | 2,760 |

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

## 4.5. Comparing the direct effects of climate change on yield to the effects of climate change on yield through FAW

In this section, we begin by estimating the effect of temperature on yield and then using those estimates to calculate how much climate-change-driven temperature increases are expected to affect yields over the next 30 years (Equation 13 in the appendix). According to Jain (2007) the temperature in Zambia during the growing season is increasing at a rate of 0.6°C per decade, meaning we should experience a temperature increase of 1.8°C in 30 years if temperatures increase linearly. This temperature increase would lead to an increase of 327°C GDD and 170°C KDD over the growing season. Multiplying each increase by their estimated coefficients, we find that 30-years of climate change would generate a 5.4 percent decrease in yields (see Equation 13 in the appendix for details). Our estimates are roughly similar to estimates reported by Lobell et al. (2011a) who found a 6.84 percent [8] decline in maize yields for a 30-year climate change.

To show the effect of climate change on yields through increased FAW pressure, we first obtain coefficient estimates of GDD and KDD (climate change) (from Table 6). We then multiply with the predicted change in temperature for the next 30 years and find that the expected increase in FAW pressure coming from increased temperatures would lead to a further 0.8 percent reduction in yield. Added to the earlier estimated direct effect of increased temperatures on yields, the additional effect of temperature on FAW would imply that climate change would decrease yields by approximately 5.4 percent over the next 30 years [9]. Thus, an increase in the cost of climate change of 13 percent. The estimates of the direct effect of climate change on yield compared to the estimates that incorporate the effect of climate change on yield through insect pests

[8] Under optimal rain-fed conditions but could be greater than 10 percent yield loss per 1°C warming in hotter regions
[9] The total effect is 6.2%, which represents 13% of the cost of climate change.

(FAW).

Table 6: Effect of temperature (GDD and KDD) on FAW

| VARIABLES | (1) FAW |
|---|---|
| GDD | 0.0014*** |
| | (0.0004) |
| KDD | -0.0019*** |
| | (0.0005) |
| Controls | Yes |
| HH FE | Yes |
| Year FE | Yes |
| R-squared | 0.35 |
| Observations | 2,542 |

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

To estimate the effect of climate change on food security through the FAW, we follow the steps highlighted above when we show the effect of climate change on maize yield through FAW infestations. Our results indicate that a 1.8 °C climate change from a 30-year climate change when we incorporate FAW shows a further 1.31 percent reduction in FCS compared to the direct 30-year effect of climate change on food security. About HDD, our results show that by incorporating FAW in the climate change forecast, we find that a 30-year climate change further 1.97 percent reduction in HDD compared to a direct effect of a 30-year climate change on HDD. Lastly, we find that by incorporating the effect of FAW in the climate change forecasts, our results indicate a further 8.9 reduction in rCSI for a 30-year climate change compared to a direct effect of a 30-year climate change on rCSI.

## 4.6. Planting timing and the use of maize hybrids as climate adaptation strategies climate change adaption

Finally, we explored whether there are any actions that farmers can take to mitigate the effects of FAW and whether these same actions are helpful or harmful in the face of climate-change induced temperature increases. We evaluate the effect of planting timing and the use of maize hybrid seeds on the subsequent damage farmers reported from FAW and how they react to higher temperatures. Column 2 of Table 7 presents the effect of climate change on maize yields and how planting timing can mitigate the effects of climate change. Our results that planting early can increase yields by 11.7 percent compared with farmers who planted late. Further, our results suggest that early planting can mitigate the effect of a 1.8 °C increase in temperature, increasing the yield by 10.9 percent compared to those who planted late [10].

[10]Typically the farmers start planting in the fourth week of November (Waldman et al., 2019)

Hybrid seeds, some of which may be drought tolerant, are another agricultural technology that can mitigate the effect of heat and may affect the damage done by FAW. The estimates in column 3 of Table 7 indicate that farmers who plant hybrid maize are more likely to have 3.7 percent more yield than their counterparts who planted self-pollinated (traditional) maize. Further, planting hybrids can mitigate the effect of a 1.8 °C increase in temperature, by increasing the yield by 16 percent.

We also find that the use of hybrids and early planting is effective in mitigating the yield losses caused by FAW. We find that farmers who planted earlier are likely to have 36.6 percent more yield compared to counterparts who planted late when both faced attack by FAW. Thus, our results suggest that these technologies can both mitigate increased temperatures and increased pest pressure resulting from climate change.

Table 7: Using planting timing and the use of Maize hybrids as climate adaptation

| VARIABLES | (1)<br>Yield | (2)<br>Yield |
|---|---|---|
| FAW | -0.443** | -0.851** |
| | (0.196) | (0.376) |
| Early planting | 0.117 | |
| | (0.332) | |
| FAW * Early planting | 0.376* | |
| | (0.217) | |
| GDD | 0.00177* | 0.00287* |
| | (0.000994) | (0.00153) |
| KDD | -0.00207* | -0.00432* |
| | (0.00123) | (0.00248) |
| Early planting * GDD | -0.00017 | |
| | (0.00051) | |
| Early planting * KDD | 0.00062 | |
| | (0.00091) | |
| Early planting * rainfall | 1.19e-09 | |
| | (1.27e-08) | |
| Early planting * square of rainfall | -1.28e-08 | |
| | (1.33e-08) | |
| Hybrid | | 0.037 |
| | | (0.468) |
| FAW * Hybrid | | 0.729** |
| | | (0.336) |
| Hybrid * GDD | | -0.00106 |
| | | (0.00099) |
| Hybrid * KDD | | 0.00247* |
| | | (0.00211) |
| Hybrid * rainfall | | 0.507 |
| | | (0.535) |
| Hybrid * square of rainfall | | -1.58e-07 |
| | | (2.89e-07) |
| Rainfall | 0.00448*** | 2.38e-09*** |
| | (0.00121) | (3.56e-9) |
| Square of rainfall | -1.28e-08 | -1.71e-10*** |
| | (1.33e-08) | (2.61e-11) |
| Controls | Yes | Yes |
| HH FE | Yes | Yes |
| Year FE | Yes | Yes |
| Observations | 2,713 | 2,520 |
| R-squared | 0.374 | 0.369 |

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

# 5. Discussion

FAW pose a growing global threat to maize production and are exacerbated by increased temperatures driven by climate change (Rwomushana et al., 2018). Our study uses both the introduction of FAW and their varying intensity across years and districts (refer to Figure A.2 in the appendix) to identify their effect on yield and food security, and how their intensity is affected by temperature. We then compare these indirect damages of higher temperatures to their direct effect on yield and food security to calculate the damages associated with this understudied effect of climate change.

Using nationally representative panel data, we find that FAW reduced yields by 43.3 percent. Our findings align with those of previous cross-sectional and experimental field studies such as Marenco et al. (1992), Evans and Stansly (1990), and Davis et al. (2018), which identified that fall armyworm infestations lead to yield reductions ranging from 11 - 42 percent.

Smallholder farmers, primarily producing for home consumption, are particularly vulnerable to agricultural shocks such as FAW (Mendoza et al., 2017; Zuma et al., 2018; Mwalwayo and Thole, 2016). In Figure 2, we observe the distribution of FCS measures for our sample, with the classification cutoffs for borderline and poor food security illustrated in the red dashed lines. For households reporting FAW in their camps, damage increases by 9.88 percent (refer to Table 5). This effect places 13 percent of households at risk of falling below acceptable FCS levels due to FAW.

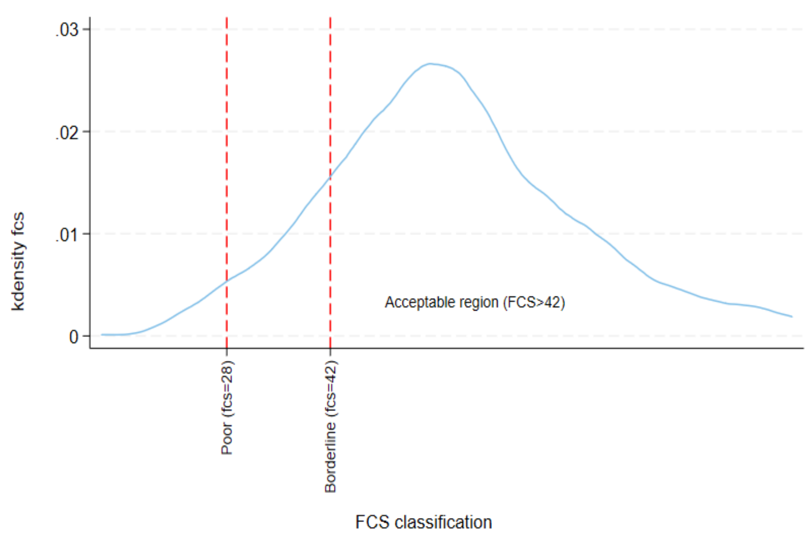


Figure 2: FCS classifications in the baseline year (2016).

Our HDDS analysis, similar to Figure 2, indicates that for households experiencing FAW damage in their camps, coupled with reported FAW infestations, damage increases by 14.92 percent (see Table 5).

Consequently, 8 percent of households are at risk of falling below medium dietary diversity levels due to FAW. This heightened risk may stem from income loss and crop failure caused by FAW, leading households to substitute staple foods like maize with less affected alternatives such as cassava. Specifically, in low-income countries, households typically reduce their consumption of relatively expensive foods, such as beef, fish, or fruits, during production shocks (Erokhin et al., 2021). Our findings align with those of Jensen and Miller (2010), suggesting that instead of reducing their food variety during income shocks, households prioritize ensuring that their caloric needs are met by consuming the staple crop first, before considering any other dietary requirements. Consequently, they may adjust their consumption habits to focus more on the staple crop, potentially reducing dietary diversity.

The Coping Strategy Index (rCSI) captures the degree to which households are using coping mechanisms during food scarcity (Maxwell et al., 2003). We observe households have a 67.25 percent increase in reliance on coping strategies when they live in their camps with reported FAW infestations (see Table 5). To put these numbers in context, almost half (49 percent) of households risk falling below medium food security levels due to FAW. This heightened risk during FAW invasions prompts farmers to adopt various coping strategies, including meal reduction, foraging, and charcoal production (Hadunka and Baylis, 2022; Benfica and Kilic, 2015; Tambo et al., 2021a).

Forecasting the effect of climate change has become increasingly important, especially in recent years, where the effects can be seen in changes to forage, biodiversity, and the occurrence and severity of disasters (Yerlikaya et al., 2020; Urban et al., 2016; Chown et al., 2010). Many studies that forecast the effect of climate change on crop yields, however, do not incorporate the effect of crop pests. Our results without incorporating the effects pests are similar to results by Lobell et al. (2011b) [11] but when we incorporate the effect of pests our results are slightly higher indicating that without incorporating the effects of pests projects on the effect of climate change on crop yield would be biased [12]. This underscores the importance of integrating factors like pest shocks into climate change prediction models for crop yields and/or food security to enhance prediction accuracy.

Climate change has led to moisture stress and shortened growing seasons (Connolly-Boutin and Smit, 2016). Our findings indicate that adopting early planting and hybrid maize varieties are effective mitigation strategies for both FAW and increased temperatures associated with change, consistent with studies by Campos et al. (2004) and Fisher et al. (2015). [13]. This finding suggests that the benefits of some climate

[11] Note that Schlenker and Lobell (2010) mention that countries with relatively low yields have the highest projected yields losses and Zambia has yields that are above average (Cairns et al., 2013).

[12] When we incorporate the effect of insect pests (FAW), we find a 1.31 percent further loss in yields. While some farmers respond with increased use of insecticides, this increases their costs. Farmers cannot completely mitigate the effect of increased pests, and therefore, projections that do not account for the effect of crop pests could be biased.

[13] Most smallholder farmers in Zambia are on the Fertilizer Input Subsidy Program (FISP) where farmers decide when to plant-primarily based on the timing of when they receive the inputs. Most farmers receive their packages after the fourth week

mitigation strategies may be undervalued if they do not include the benefits associated with mitigating pest damage.

of November, which is when the rains begin (Waldman et al., 2019). In some cases, the inputs are distributed as late as January, so the planting time may be restricted Namonje-Kapembwa et al., 2015

# 6. Conclusion

The effect of climate change intertwined with crop pests has largely gone understudied. Rising temperatures means pests will continue ravaging crops, posing a serious threat to food security, especially in SSA (Gregory et al., 2009; Paini et al., 2016; Deutsch et al., 2018). In particular, evidence from Deutsch et al. (2018) suggests that the changing climate has facilitated the spread and appetite of FAW in many parts of the world.

Our findings align with Marenco et al. (1992), Evans and Stansly (1990), and Davis et al. (2018), which report yield reductions due to fall armyworm infestations ranging from 11 to 42 percent. However, many studies are limited by their reliance on experimental field trials, which may not reflect the real-world impact on farmers, or by cross-sectional data and self-reporting errors in non-experimental settings.

These pest outbreaks have significant implications for future food security. We show that the effect of severe FAW outbreaks, such that as experienced by 74 percent of farmers in our geographically diverse sample in Zambia, have an effect on households' food security that, depending on the food security measure, ranges from 1 to 1.5 times larger than that of a drought in a 30 year time period.

Forecasting the impact of climate change on crop yields is crucial, especially given its observable effects on forage, biodiversity, and disaster severity. However, many studies overlook the influence of crop pests. Our findings, excluding pest effects, align with Lobell et al. (2011b). Incorporating pest impacts, however, yields slightly higher results, suggesting that omitting pests biases climate change projections on crop yields.

Our results also point to a few strategies that can mitigate the effects of FAW. First, the current approach that governments use involves providing relief food whenever there is a crop production shock. However, with FAW invasions, providing food relief is costly and unsustainable.

Our findings provide new insight into the impact of FAW on food security. We contribute towards understanding how to provide sustainable and less costly interventions. In cases of FAW infestations, increasing capital, landholding, and seeking off-farm income is likely more effective in ensuring household food security. Finally, we suggest that the Ministry of Agriculture educate farmers on the positive effects of early planting and the use of drought-tolerant hybrid seeds that can cushion the effects of climate change on yields.

# Declaration

The authors declare that they have no conflict of interest.

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# A. Appendix

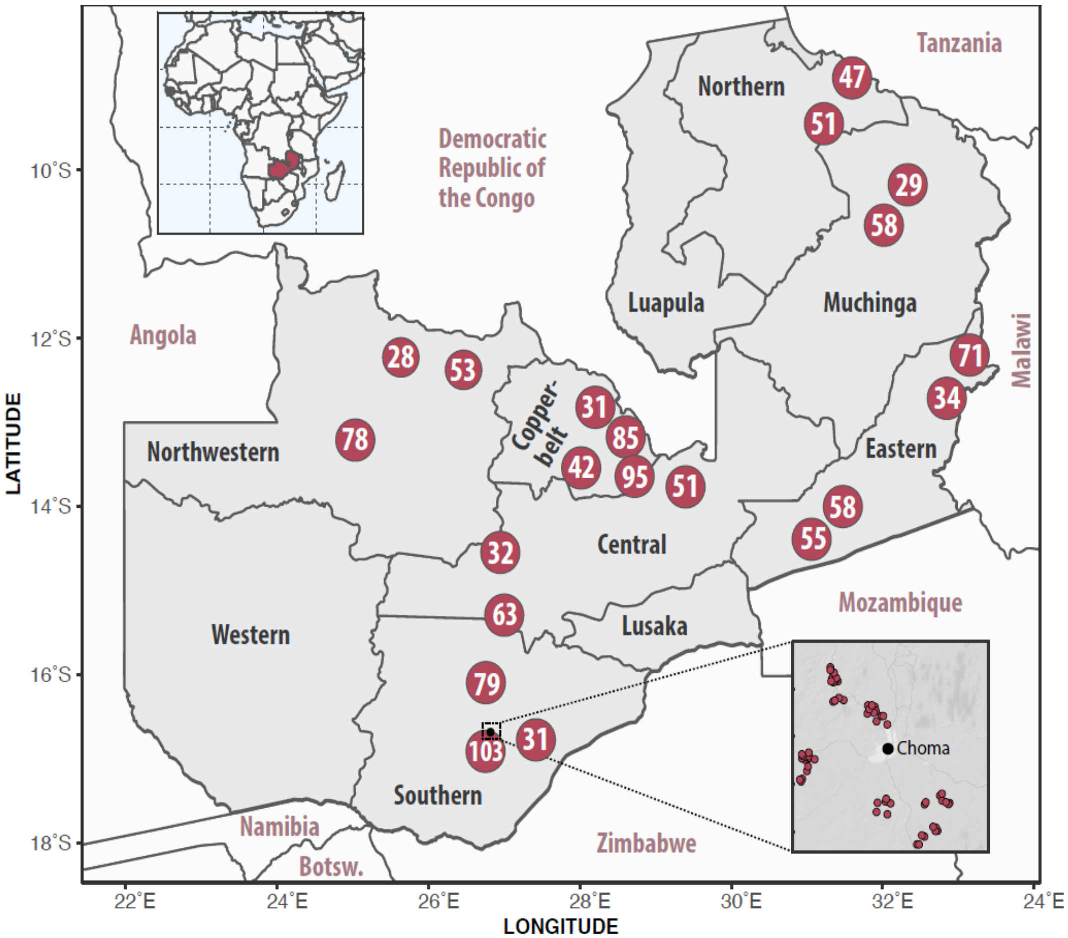


Figure A.1: The map shows the sample sizes across the districts we sampled.

## A.1. Instrumental variables

For the instrument to be valid, the errors in reporting across the camps need to be randomly distributed across space and the camp level average response and should not be correlated with the maize yields (exogenous) but should be correlated with the household level reported infestations through spatial spillovers while controlling for household fixed effects (See results in the appendix). We test for weak instruments on both the intensity and binary instrument and from the first stage regression to assess if the instrument is strong and the household's stated infestation intensities are correlated with the FAW intensities of the neighboring farms in the camp. In terms of external validity, if the probability of correctly reporting FAW in one's field is randomly distributed over space, the average camp infestation level should only determine the maize yields of an individual household by affecting that household's likelihood of being infested itself. If instead errors in reporting are correlated over space (and are, say, driven by having different quality FAW training from the local camp or district extension officer), one might worry that our instrument is itself correlated with time-varying unobserved characteristics at the camp level, and therefore fails the exclusion restriction. To explore the validity of the assumption that misreporting is not correlated over space, we first estimate the spatial correlation of the camp-level sum of deviations between farmers reported and camp average FAW levels using a Moran's I. We dropped the camps with no FAW since one would expect those households to have zero deviation and spatially correlated. Beyond spatial correlation, one might worry that misreporting is correlated with farmer (and camp) characteristics. We test this probability by estimating the household deviation from camp average in stated FAW levels against the deviations in household characteristics from camp average. Second, we estimate the sum of deviations per camp against camp-level average characteristics. We first employ a standard difference-indifferences for the deviation between the infestations $i's$ reporting and the camp average responses in reporting. The control variables we use include deviations between the farmer $i$'s characteristics and the average camp level characteristics reported such as age, education, sex, household size, quantity of fertilizer used, quantity of seeds used, land cultivated (ha), and amount of precipitation which are all deviations in farmer $i's$ reporting and the camp average level FAW reporting for the $i^th$ household. The dependent variable is the lag of maize yields since households with higher maize yields are more likely to be concerned about FAW infestations than households with lower maize yields and as such are more likely to report FAW infestation cases than households who had less yield (See equations and detailed explanations in the appendix).

The instrument we use in this study for all the equations above is the average of the sum farmer response on FAW intensity at camp level for the household in a particular camp minus the observed household. We specify the instrument as follows;

$$CA_{ic} = \left[\sum_{i=1}^{n} FAW_{it}\right] / n - 1 \quad (5)$$

Where $CA_{it}$ is the average of the sum of the responses of the farmers in camp $i$ at time $t$ divided by the number of households in the camp where the observed household is located.

Sum of camp-level average response (IV) is an exogenous variable and highly correlated with the household-level reported infestations through spatial spillover. The household's infestation intensities are dependent on the FAW intensities of the neighboring farms in the camp. If the infestations in the camp are high, it is likely that it will affect the observed household's infestation intensities. However, our IV is uncorrelated with the maize yields and other unobserved variables. The average camp level infestations only determine the maize yields through the spillovers to the households in the camp and does not directly determine the effects of the intensity on maize yields for the households in the camp and thus meeting the exclusion requirement and making it a good IV.

We estimate the two stage as follows; in the first stage, I estimate the FAW function (the reduced form model) by regressing FAW on all the exogenous explanatory variables and the instrument. In the first stage, I regress the FAW presence variable on the instrument with all the exogenous variables and household fixed effects which is written as;

$$FAW_{it} = CA_{ic} + \beta_1 \boldsymbol{X_{it}} + \alpha_i + \xi_{it} \quad (6)$$

Where $CA_{ic}$ is the instrument $i^{th}$ household in camp $c$, $\boldsymbol{X_{it}}$ is a vector of all exogenous explanatory variables.

In the second stage, I obtain the predicted intensity $FA\hat{W}_{it}$ for the $i^{th}$ household from (7), which is now part of the vector $\boldsymbol{X_{it}}$ as follows;

$$\log Y_{it} = FA\hat{W}_{it} + \boldsymbol{\beta}_1 \boldsymbol{X}_{idt} + \alpha_i + \tau_{idt} \quad (7)$$

We then carry out statistical tests from the reduced form regression to assess if the instrument is good. Using the statistical results from the reduced form regression, the F-statistics from the first regression was 51.64 for Equation 6 and 59.02 for Equation 7, which both were higher than the threshold of 23.63 for the reliability of the t-test test based on the IV estimates reliable according to Stock and Yogo (2002). The probability level in both cases was less than 5 percent indicating low probability of the IV being biased. I conducted a test for weak instruments on both regressions Equation 6 and Equation 7.

### A.1.1. The errors are random

One of the major concerns one may have is that the measurement error in reporting may not be random; more observant farmers may be more likely to report FAW. The results from (Table A.1) show that generally there is a low correlation between most characteristics and the deviation in reporting FAW. The estimates indicate that age, income, household size education, and quantity of seed used one the factors that might be causing the deviation between the farming household 'i' and the average sum of the responses at camp level minus the household being observed. Farming households with a household head younger than 45 years are less likely to report FAW infestations. In terms of education, the results indicate that household heads with less than the camp average education are likely not to report infestations as compared to people with average education in the camp and this may cause deviations in reporting. The results also indicate that households with a smaller number of family members tend to report FAW infestations more than on average than the camp average (see Table A.1).

We estimate the household deviation from camp average in stated FAW levels against the deviations in household characteristics from camp average. Second, we estimate the sum of deviations per camp against camp-level average characteristics. We first employ a standard difference-in-differences for the deviation between the infestations i's reporting and the camp average responses in reporting.

$$dFAW_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 Y_{it-1} + \alpha_i + \varepsilon_{it} \tag{8}$$

Where $dFAW_{it}$ is the deviation in farmer i's reporting and the camp average level FAW reporting for the $i^t h$ household at time $t$ ($t$=1, 2, 3 and 1= 2016, 2=2017, 3=2018). The controls, $X_{it}$, are a vector are the deviations between the farmer i's characteristics and the average camp level characteristics reported such as age, education, sex, household size, quantity of fertilizer used, quantity of seeds used, land cultivated (ha), and amount of precipitation which are all deviations in farmer i's reporting and the camp average level FAW reporting for the $ith$ household $t$. The variable $Y_{it-1}$ is the lag of maize yields since households with higher maize yields are more likely to be concerned about FAW infestations than households with lower maize yields and as such are more likely to report FAW infestation cases than households who had less yield yields. W then plotted a map showing the misreporting of FAW across all the camps that were surveyed to understand if the mis-reporting was random (Figure A.2).

For the estimates to be unbiased, the errors had to be randomly distributed. Figure A.2 shows the distribution of the deviation in reporting (mis-reporting) is random. The Moran's I test results in Figure A.3 show that the distribution in reporting is random across camps (no spatial autocorrelation). This result

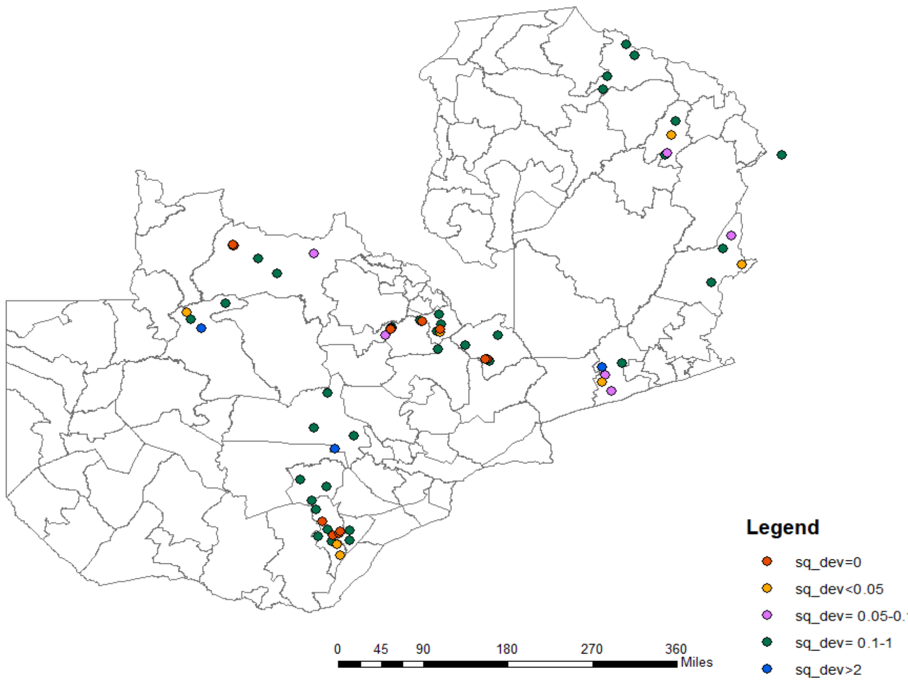


Figure A.2: Distribution of the deviations in farming households and average camp responses in FAW reporting.

implies the errors in reporting are randomly distributed. One of the concerns we had in this paper is that farmer self-reporting error might worry that this measurement error is not random as more observant farmers may be more likely to report FAW and may also likely have higher yields and this may bias the results towards zero.

The other cardinal issue that the paper addresses is possible errors resulting from farmers reporting their own infestations (self-reporting). This possible mis-measurement error may not be random because more observant farmers could be more likely to report FAW. The results from Table A.1 (Appendix) indicate that generally there is a low correlation between most characteristics and the deviation in reporting of FAW. The estimates indicate that age, income, household size education, and quantity of seed used as some of the factors that might be causing the deviation between the farming household $i$ and the average sum of the responses at camp level minus the household being observed. Farming households with household heads younger than 45 years are less likely to report FAW infestations. In terms of education, the results suggest that household heads with less than the camp average education are less likely to report infestations compared to people closer to or above the average education in the camp, which may have led to the deviations in reporting. The results also indicate that households with a smaller number of family members tend to report FAW infestations more than the camp average. This is important because it shows that perceptions that farmers

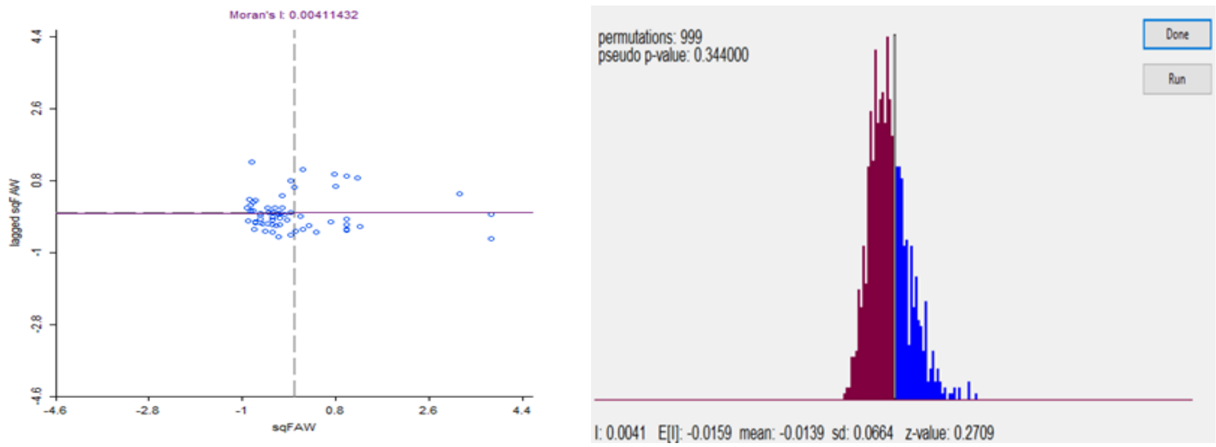


Figure A.3: Moran's I of the deviations in farming households and average camp responses in FAW reporting

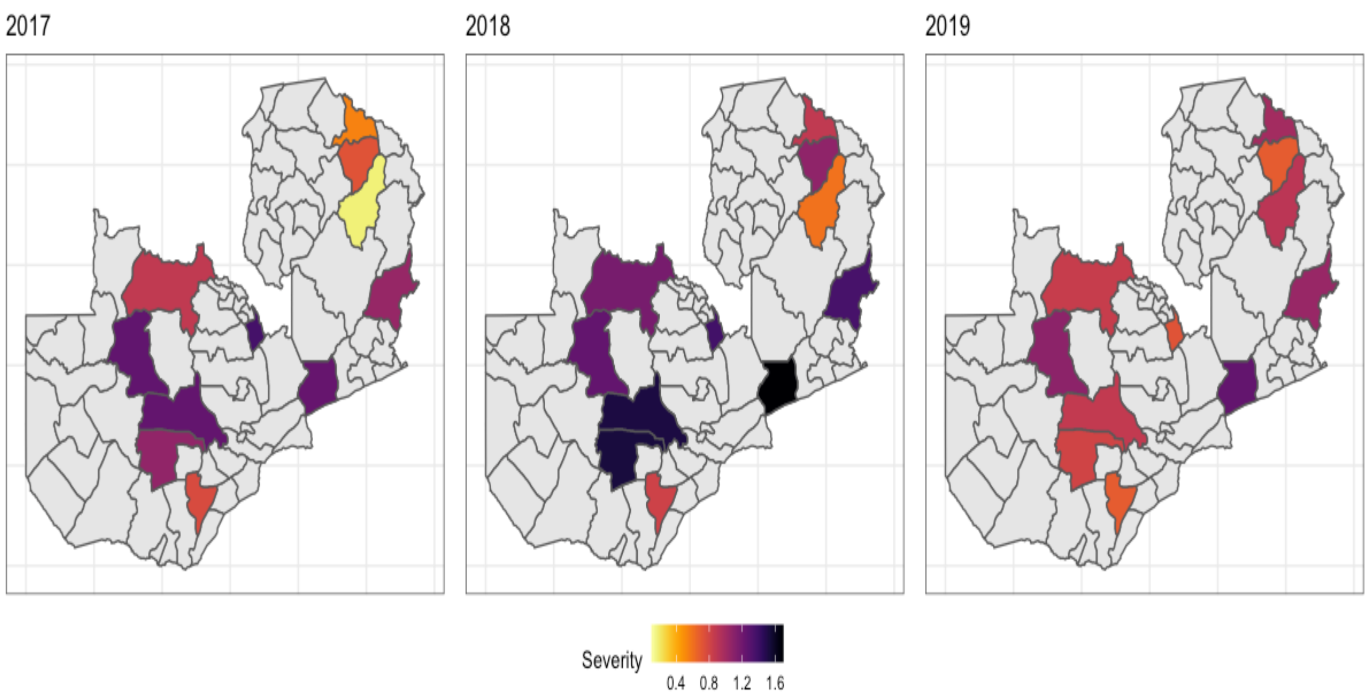


Figure A.4: FAW infestations intensity across years and district.

such as identifying FAW are not very far off. Farmers usually understand what they are observing.

Table A.1: Deviation in reporting between the household and the camp average

| Variables | FAW-camp average for FAW of HHs |
|---|---|
| Yield - yield camp average (prior year yields) | -0.0130 |
| | (0.0370) |
| Age of HH - camp average age of HHs | -0.00359* |
| | (0.00201) |
| Sex of HH - camp average for sex of HHs | -0.0210 |
| | (0.0824) |
| Education of HH - camp average Education of HHs | -0.0312* |
| | (0.0193) |
| Income of HH - camp average Income of HHs | -4.22e-06* |
| | (2.37e-06) |
| Access to credit - camp average access to credit | -0.0456 |
| | (0.0700) |
| Household size - camp average Household size | 0.210*** |
| | (0.0698) |
| Total landholding - camp average total landholding | -0.0743 |
| | (0.0751) |
| Fertilizer application rate - camp average application | 0.00821 |
| | (0.0144) |
| Quantity of seed used - camp average quantity of seed used | 0.123** |
| | (0.0529) |
| Rainfall - camp average quantity used | 0.0204 |
| | (0.0729) |
| Capital - camp average capital of HHs (Monetary) | 0.0121 |
| | (0.0327) |
| HH × Camp FE | Yes |
| Year × Camp FE | Yes |
| District × Camp FE | Yes |
| Observations | 832 |
| R-squared | 0.12 |

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

## A.2. Robustness checks

We then analyze the effects of regressing maize yields using the district-fixed effects as a robustness test. In Table A.2, we present estimates of the factors that help explain the effects of FAW on maize yields. The household-by-year fixed effects estimates were lower than the household fixed effects with year interactions. Column 2 presents the FAW intensity with district fixed effects analysis of maize yields. Column 3 presents the results of the ITT and column 4 presents the second stage IV with the household-by-year fixed effects interactions from regressing maize yields on FAW intensity and the production factors that affect influence maize yields. The results from the fixed effects estimates indicate that as the intensity of FAW increases from

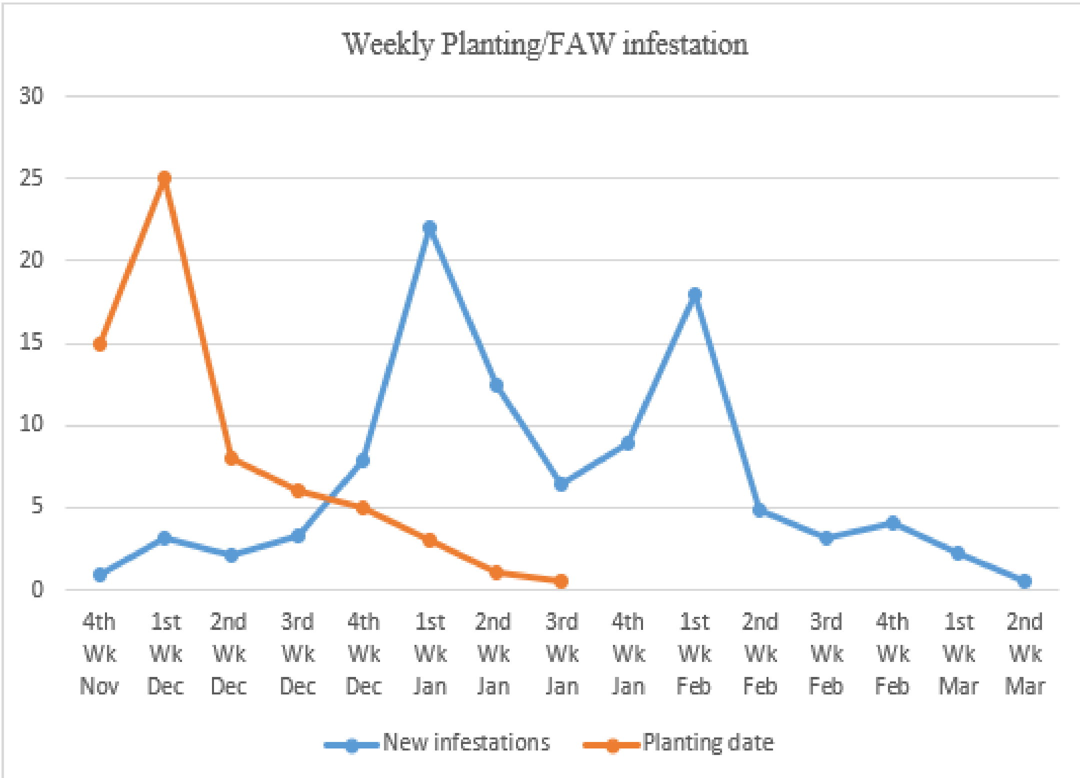

Figure A.5: Changes in total infestations across time and planting dates for 2016/17 Agricultural season

a lower level to a higher level of FAW infestation intensity, farming households are more likely to experience 4.7 percent maize yield loss, which is not significantly different from zero. With regards to the ITT results, it is reported that farmers that are in camps with FAW on average, maize yields were 11 percent lower. The IV estimates indicate that compared to households that had no FAW infestation cases, households that had the severe intensity of FAW in their surrounding camp experienced an average of 24.8 percent lower maize yields. With regards to the impact of FAW, the fixed effects estimate in column 5 indicates that as the intensity of FAW increased from low to medium levels on average, maize yields were 4.7 percent lower. Furthermore, the ITT estimates in column 6, with the household fixed effects indicate that households who had severe intensity of FAW nearby and are more likely to have and report FAW on average experienced 21 percent lower maize yields. On the other hand, the IV estimates in column 7 indicate that compared to households that had no FAW infestation cases, households that had the severe intensity of FAW in their surrounding camp experienced an average of 54.4 percent lower maize yields. The household fixed effects estimates are consistent with those from the district fixed effects.

The results from the weak instrument test using household fixed effects and year fixed effects indicate that the F-statistics from the first regression was 56.35 for equation Equation 6 which uses the intensity in creating the instrumental variable and 34.43 for Equation 7 which uses the binary FAW variable in creating the instrumental variable. My statistical tests for both my regressions from the first regressions are higher than the threshold cut 22 by Stock and Yogo (2002) of 23.63 which is the t-test based on the IV estimates. The Wald test indicates that the maximum amount that the instruments might be biased from weak instruments is 4 percent. Given this maximum amount of bias is relatively low, thus we can reject the null hypothesis of weak instruments. With such high F-statistics, the choice of the instrument is statistically valid and strong as it is in line with the literature.

With regards to district-by-year fixed effects, the statistical results from the first stage regression, the F-statistics from the first regression was 46.33 for Equation 6 and 34.33 for Equation 7, which both were higher than the threshold of 23.63 for the reliability of the t-test test based on the IV estimates reliable according to Stock and Yogo (2002). The Wald the test indicates that the maximum amount that the instruments might be biased from weak instruments were 3 percent thus, which is sufficiently low. Given the F-statistic was higher than the threshold cut-off provided by Stock and Yogo (2002) and the maximum amount of bias is relatively low, we, therefore, fail to reject the null hypothesis that the instruments are weak.

Table A.2: Effects of FAW on Maize yields

| VARIABLES | (1) Yield | (2) Yield | (3) Yield | (4) Yield | (5) Yield | (6) Yield |
|---|---|---|---|---|---|---|
| | FE | ITT | IV | FE | ITT | IV |
| FAW | -0.0473** | -0.110*** | -0.248*** | -0.0474 | -0.0210 | -0.5441 |
| | (0.0213) | (0.0407) | (0.0880) | (0.0399) | (0.0820) | (0.212) |
| Labor (Household size) | 0.0633** | 0.0276 | -0.0495 | 0.0753*** | 0.0834** | 0.0730 |
| | (0.0264) | (0.0322) | (0.0520) | (0.0276) | (0.0359) | (0.0700) |
| Landholding size (total cultivated land) (ha) | -0.269*** | -0.284*** | -0.286*** | -0.269*** | -0.286*** | -0.284*** |
| | (0.0571) | (0.0606) | (0.0600) | (0.0571) | (0.0605) | (0.0599) |
| Fertilizer Application rate (kg) | 0.116*** | 0.112*** | 0.115*** | 0.116*** | 0.113*** | 0.113*** |
| | (0.0114) | (0.0118) | (0.0119) | (0.0115) | (0.0117) | (0.0121) |
| Quantity of seed (kg) | 0.378*** | 0.399*** | 0.408*** | 0.377*** | 0.395*** | 0.395*** |
| | (0.0465) | (0.0488) | (0.0487) | (0.0466) | (0.0489) | (0.0490) |
| Capital | 0.125*** | 0.122*** | 0.122*** | 0.126*** | 0.122*** | 0.122*** |
| | (0.0120) | (0.0124) | (0.0118) | (0.0120) | (0.0124) | (0.0122) |
| Weather controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| District FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,668 | 2,512 | 2,512 | 2,668 | 2,512 | 2,512 |
| R-squared | 0.646 | 0.655 | 0.295 | 0.647 | 0.654 | 0.349 |

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

Table A.3: Alternative Difference-in-Differences Estimators - Robustness Check

| | Point Estimate | Standard Error |
|---|---|---|
| Callaway-Sant'Anna | -0.0977** | 0.1409 |
| Two-Way Mundlak Regression (TWM) | -0.0935* | 0.0511 |

Note: All these models include weather controls

## A.3. Climate change calculations

To understand the effect of climate on crop yields, we first estimate the effect of GDD on maize yields. We then multiply the coefficient on GDD by the average change in GDD resulting from the predicted increase in temperature from climate change in Zambia after 30 years., $\frac{\partial gdd}{\partial Temp}$ is the change in GDD temperature change in Zambia in 30 years ( $0.6° * 30 = 1.8°$ compared to GDD at the current temperature (original temperature) which is ($gdd$ (at temp + 0.6°) - ($gdd$ (at original temp)). We then add these estimates from the effect of KDD on maize yields from the regressions, and we multiply this with the changes in KDD in as in Zambia as the temperature changes for 30 years. Which is $\frac{\partial kdd}{\partial Temp}$ ($kdd$ (at temp + 0.6°) - ($kdd$ (at original temp)), See Equation 13 in the appendix

$$\frac{\partial LnYield}{\partial \boldsymbol{Temp}} = \frac{\partial LnYield}{\partial gdd} * \frac{\partial gdd}{\partial Temp} + \frac{\partial LnYield}{\partial kdd} * \frac{\partial kdd}{\partial Temp} \tag{9}$$

[14]

We estimate the effect of climate change on yields via climate change's effect on FAW. To achieve this, we multiply the effect of climate change on yields by the effect of FAW on yields and then multiply this by the predicted temperature change in Zambia as follows in Equation 7:

We multiply all these as follows;

$$\left(\frac{\partial Yield}{\partial \boldsymbol{FAW}}\right) * \left(\frac{\partial FAW}{\partial \boldsymbol{Temp}}\right) * \partial PredTemp \tag{10}$$

= (0.0013859 * 327.481) + (-0.0018894 *170.1873) * (-0.05223559) = -0.00717436.

$$\left(\frac{\partial Yield}{\partial \boldsymbol{FAW}}\right) * \left(\frac{\partial FAW}{\partial \boldsymbol{Temp}}\right) * \partial PredTemp \tag{11}$$

[15]

[14]( $0.6° * 40 = 1.8°$ compared to GDD at the current temperature (original temperature) which is ($gdd$ (at temp + 0.6°) - ($gdd$ (at original temp))

[15]Which is $\frac{\partial kdd}{\partial Temp}$ ($kdd$ (at temp + 0.6°) - ($kdd$ (at original temp))

[16]

## A.4. Climate change calculations: Early planting and hybrids

$$\frac{\partial Yield}{\partial \boldsymbol{Temp}} = \frac{\partial Yield}{\partial gdd} * \frac{\partial gdd}{\partial Temp} + \frac{\partial Yield}{\partial kdd} * \frac{\partial kdd}{\partial Temp} \tag{12}$$

$\frac{\partial kdd}{\partial Temp}$ = (0.0004869 * 327.481) + (-0.0013987 *170.1873) = -0.07859006

[17]

$$\frac{\partial Yield}{\partial \boldsymbol{Temp}} = \frac{\partial Yield}{\partial plant.gdd} * \frac{\partial gdd}{\partial Temp} + \frac{\partial Yield}{\partial kdd} * \frac{\partial plant.gkdd}{\partial Temp} \tag{14}$$

$\frac{\partial kdd}{\partial Temp}$ = (0.0001569 * 327.481) + (-0.000224 *170.1873) = 0.01325988

## A.5. Controlling FAW

FAW are difficult to control due to their propensity to attack a wide range of crops, and their ability to spread quickly (Midega et al., 2018). First, the female moth can lay hundreds of eggs on the upper layer of the leaves. Adult moths can also migrate over long distances, such as traveling over 100 km in a single night (Rose et al., 1975; Devi, 2018; Prasanna et al., 2018). Second, the ideal climatic conditions for maize are also conducive to the FAW. A large proportion of Zambia covers agro-climatic areas that are suitable for FAW, especially the high maize-producing regions (Davis et al., 2018).

The two main approaches for controlling FAW include reducing the likelihood of crop damage, such as the use of resistant crop varieties and habitat management; and intervening when crops are already infested, including spraying leaves with pesticides, releasing natural enemies, or picking off the insects by hand. In Zambia, farmers primarily intervene once FAW are already in the field, such as through the use of pesticides (Davis et al., 2018; Bateman et al., 2018). In terms of pesticide use, there was a drastic reduction in synthetic pesticide use in Zambia in 2018 compared to previous years (2017), because when the FAW farmers found the synthetic pesticides to be ineffective whether this was due to farmers not having been trained on how to effectively use pesticides especially that it was the first agricultural season that they were being exposed to pesticides still remains unclear. The other reason could be due to the government's increasing recommendation of bio-pesticide use due to their reduced environmental impact and thus their

[16] $(0.6° * 3 = 1.8°\text{C})$

[17]

$$\frac{\partial LnYield}{\partial \boldsymbol{Temp}} = \frac{\partial LnYield}{\partial gdd} * \frac{\partial gdd}{\partial Temp} + \frac{\partial LnYield}{\partial kdd} * \frac{\partial kdd}{\partial Temp} \tag{13}$$

$\frac{\partial kdd}{\partial Temp}$ = (0.0007554 * 327.481) + (-0.0017605 *170.1873) = -0.05223559 increased availability (in agro-shops) in place of synthetic pesticides (Davis et al., 2018). The widespread lack of availability of synthetic pesticides was also a huge problem (especially in 2017). Most of the agricultural camps and agro-shops did not have pesticides. At the time, the pest was new and the government had not yet decided which pesticides to encourage farmers to use without harming the environment. The reduction in synthetic pesticides could also be attributed to the increase in the number of farmers deploying a wider range of control methods as well as Zambian smallholder farmers using traditional, non-chemical approaches in maize cultivation (Davis et al., 2018).

In our interviews, smallholder farmers in Zambia reported that some synthetic pesticides were ineffective in eliminating the pest, particularly in the first year of infestation. Some researchers argue this was largely an issue of false pest identification which was a problem among smallholders who had little training by the government and the private sector, and a lack of FAW early warning (Kabwe et al., 2018). The early warning systems for FAW were not functional in Zambia during the first year of the FAW infestation. For this reason, most of the farmers had minimal knowledge of the appropriate control measures they could employ (Kabwe et al., 2018). Thus, farmers used household items such as detergent paste as a pesticide, which allowed the infestation to grow unchecked.

Studies show that well-planned maize planting dates can be an important coping strategy against weather-related shocks in agriculture, and some evidence shows that it is also important for deterring FAW from attacking crops (Baudron et al., 2019; Bosque et al., 2011). Some studies suggest that the relationship between planting date and FAW infestation is based on the stage of growth at which the plant is attacked by FAW. Plants vary in their susceptibility to stress according to the stages of their growth and thus there seems to be a strong correlation between the stage of growth when the crop gets injured or damaged by pests and the resulting yield losses (Buntin, 1986; Gross Jr et al., 1982). Morrill and Greene (1974) found that greater reductions in yields occurred when the maize crop is infested during the early and mid-whorl stages instead of the late whorl or tasseling stages. Thus, early planting timing is one way in which farmers can minimize their yield losses from FAW. Several studies have that reported maize hybrids have shown some resistance to FAW compared to self-pollinated varieties (Baudron et al., 2019; Bosque et al., 2011). Baudron et al. (2019) reported that maize hybrids that have been used in field trials in the Americas seem to have a higher resistance to FAW infestations than those in other parts of the world. These studies report that the resistance of these specific hybrids to FAW infestations is due to some genes that these maize hybrids may possess (Berg et al., 2021). Thus, some maize hybrids with these specific proteins are relatively less likely to be seriously damaged by FAW compared to those that do not have such proteins in their genes (Kumar, 2002). However, a study by Davis et al. (2018) found that most of the hybrids in Zambia do not show resistance to FAW.

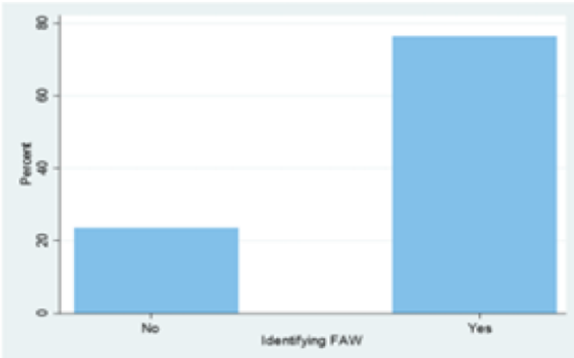


Figure A.6: Identification of FAW

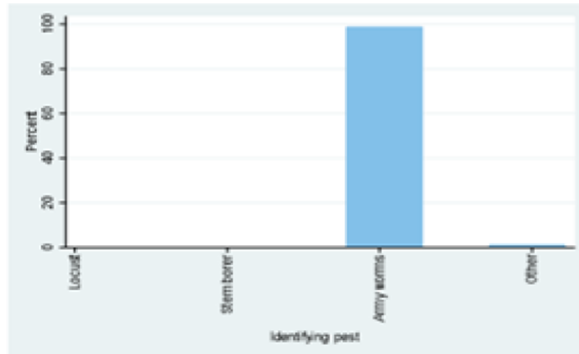


Figure A.7: Identification of insect pests

## A.6. Farmer FAW control

We find that through the 3 years of FAW invasion, most farmers (76 percent) in the sample reported that they were able to identify FAW (Figure A.6). When farmers were asked which insect pests they saw in their fields, the majority of the farmers (74 percent) mentioned FAW while 11 percent mentioned stem borers and 12 percent were unsure of the pests they saw (Figure A.7). Misidentification is the biggest challenge that farmers face when trying to identify pests. Only well attuned farmers can tell the difference between FAW and stem borers as they look highly similar, with only a few distinct features (Devi, 2018; Chormule et al., 2019). We also carried out a separate experiment in Zambia where we asked the farmers to identify the FAW in a picture of grain borers and FAW, which look very similar as well. We discovered that over 80 percent of the farmers were able to correctly identify FAW. According to the question posed to farmers about their view on the crop mostly attacked by FAW, 93 percent of the farmers in our sample indicated that FAW attacked their maize more than other crops (Figure A.8). This result is in agreement with findings by many studies that state maize is the primary host of FAW (Goergen et al., 2016; Pogue, 2002). The results in Figure A.9 show that 45 percent of the farmers reported that camp extension officers were the main source of information on FAW. This is consistent with findings by Kumela et al. (2019) in Ethiopia and Kenya where the government extension agents were the main source of information about FAW.

Climatic conditions suitable for maize are also conducive to FAW invasions (Asare-Nuamah, 2021; Davis et al., 2018). Figure A.10 (Appendix) reveals the percentage of households that experienced invasions along with the yields (total kg of maize/hectare) by the district. The districts that had high maize yields also had a high percentage of households that reported cases of FAW infestation which is consistent with Davis et al. (2018).

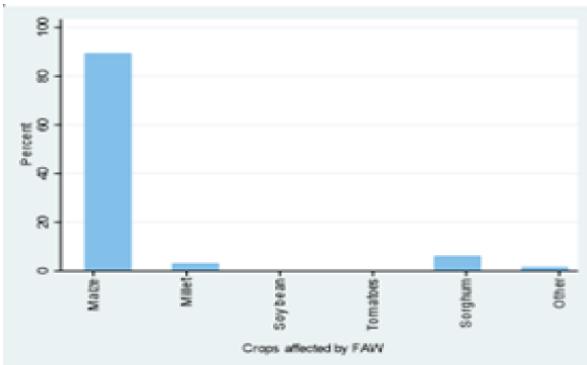


Figure A.8: Crops attacked

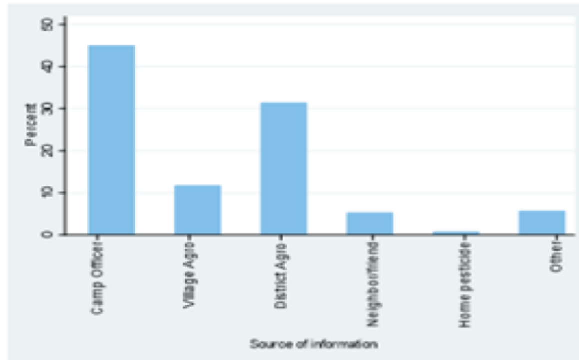


Figure A.9: Source of information

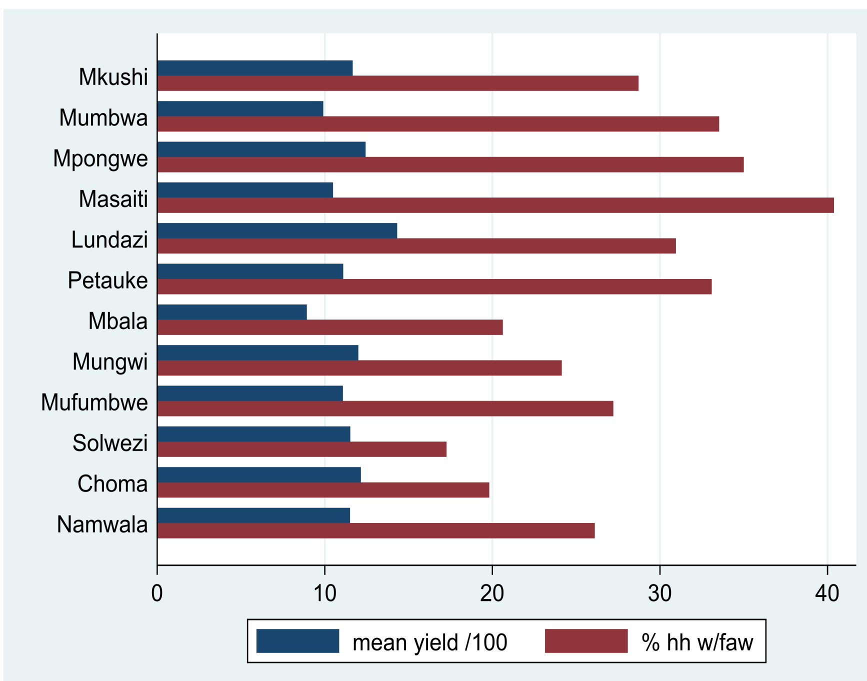


Figure A.10: Maize yields for 2017/18 agricultural season and proportion of household that reported FAW infestations by districts. **Source: Author's work from the field work**

## A.7. Farmer heterogeneous effects

To explore the farmers' heterogeneous effects on food security, we regress farmer characteristics on food security outcomes such as capital, capital, and landholding size. Additionally, we examine the interaction between farmer characteristics and reported FAW severity using the difference-in-differences framework as specified in Equation 1.

In this section of the results, we focus on understanding how farmers can respond to a shock caused by FAW. We find that income is positively related to FCS and HDDS and is even more important in the face of FAW. To explore the effect of FAW across households, we interact FAW with various farmer characteristics that may be associated with being more or less vulnerable to agricultural shocks. In particular, we consider off-farm income, cultivated land, and capital.

Table A.4: Farmer heterogeneous effects

| VARIABLES | (1) FCS | (2) HDD | (3) rCSI | (4) FCS | (5) HDD | (6) rCSI | (7) FCS | (8) HDD | (9) rCSI |
|---|---|---|---|---|---|---|---|---|---|
| FAW | -0.0243 | -0.00641 | 0.110*** | -0.00313 | -0.0193*** | 0.00998 | -0.00354 | -0.0199*** | 0.243*** |
| | (0.0233) | (0.0207) | (0.03) | 0.00688) | (0.00689) | 0.00976) | (0.00689) | (0.00689) | (0.0141) |
| Income | 0.0159*** | 0.0234*** | -0.00621 | | | | | | |
| | (0.0036) | (0.00313 ) | (0.00455) | | | | | | |
| FAW*Income | 0.00267 | 0.00367* | -0.0124*** | | | | | | |
| | (0.00275) | (0.00239) | (0.00348) | | | | | | |
| Capital | | | | 0.0286*** | 0.0210** | -0.0294*** | | | |
| | | | | (0.0083) | (0.0038) | (0.0105) | | | |
| FAW*Capital | | | | 0.00399* | 0.00568 | -0.0260*** | | | |
| | | | | (0.00366) | 0.00343) | (0.00459) | | | |
| Land | | | | | | | 0.00268 | 0.00227 | -0.0018 |
| | | | | | | | (0.00163) | (0.00163) | (0.00334) |
| FAW*Land | | | | | | | 1.86e-05 | -2.32e-06 | -2.62e-06 |
| | | | | | | | (1.18e-05) | (1.45e-06) | (2.42e-05) |
| Weather controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| HHFE FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| District FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,922 | 2,922 | 2,922 | 2,904 | 2,904 | 2,904 | 2,920 | 2,920 | 2,920 |

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

In the presence of FAW, income has a negative effect on FCS and HDD. We would expect that some households would be better able to respond to a shock by FAW than others. To explore the effect of FAW across households, we interact various characteristics with household characteristics that may be associated with being more or less vulnerable to agricultural shocks. In particular, we consider off-farm income, cultivated land and capital. The results from Table A.4 indicate that in the presence of FAW, off-farm income still results in positive FS outcomes even though the FAW effect is reduced. In the presence of FAW, income has a negative effect on FCS and HDD. This could be due to the fact that income obtained from off-farm activities is usually diverted towards purchasing pesticides and labor for handpicking the FAW, thus tightening the household liquidity, meaning households are not able to afford an adequate number of quality meals in a day. This is consistent with the findings from a study by Tambo et al. (2020) which found that households that were affected by FAW spend a good proportion of their income on controlling for FAW at the expense of other household needs such as food. The caveat is that this off-farm income is from the same years as the FAW infestation, and we as one might rightly point out that they could be some endogeneity concerns. We acknowledge the endogeneity concerns.

However, in the presence of FAW, we find that income improves the households' CSI. This could be because when households are faced with agricultural/food shocks, they use the off-farm income to protect their food consumption and their means of coping is through self-insurance through precautionary savings and sometimes through a food-sharing mechanism. In the baseline (before FAW infestations were reported), off-farm income had a positive effect on all the FS outcomes prior to FAW infestation. Households with off-farm income are more likely to afford food with higher calories as well as better dietary quality and micronutrient supply. Additionally, even though coping strategies may sometimes have negative effects such as deforestation in the cases of charcoal production (Mulenga et al., 2017), off-farm income enables the households to pay for the basics which include food, farming input, and school fees to ensure the households maintain their society's level of welfare, which is consistent with the findings by Babatunde and Qaim (2010) and Mjonono et al. (2009).

With regards to capital, households use their liquidity to smooth the effects of a crop failure or production shock caused by FAW to protect their household against potential food insecurity. Households may engage in off-farm businesses, such as increasing the amount of charcoal they produce, which may better equip them by not only increasing the household CSI but the FCS and HDD as well.

We find that farmers with larger land for cultivation had worse FCS and HDD but better CSI outcomes. These effects are relatively smaller compared to the baseline effect of capital on all the FS outcomes. A plausible explanation for this, which is also consistent with a study by Tambo et al. (2020), is that as a household's cultivated land increases, they are more likely to be affected by FAW and to lose their crop. Thus the households are more likely to seek more strategies that help them manage FAW effectively. This will require investing in pesticides and other control methods, which in turn will change feeding habits by reducing the amount, frequency, and quality of food intake.

On the other hand, households with large cultivated land are likely to have better CSI because a larger land area promotes coping mechanisms such as charcoal production, mushroom picking, wild fruits, etc. However, in the presence of FAW infestations, households will focus on mainly coping strategies that can generate income that can be used as a safety net during this agricultural shock, and thus charcoal becomes the major coping strategy (Tsegaye et al., 2018; Kalaba et al., 2013; Ndegwa et al., 2016). At the baseline, the results indicate that capital plays a significant role in increasing all the households' FS outcomes. In short, capital enables households to buy inputs such as certified seeds and fertilizers which enhance agricultural productivity and also provide the household with liquidity.