The Impact of Pest Shocks on Charcoal Production and Deforestation in Zambia

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Abstract

Sub-Saharan Africa (SSA) is home to some of the world's highest rates of deforestation. One driver may be negative agricultural shocks that drive households to consume natural resources as a coping mechanism. This paper uses primary household panel data from Zambia to estimate the effect of a persistent agricultural pest, fall armyworms (FAW), on charcoal production and deforestation. I exploit exogenous variation in the intensity of exposure to FAW across households and years to identify their effect. I find a positive and significant effect of FAW on charcoal production and deforestation. The estimates indicate that having FAW in the village increases the probability of a farmer producing charcoal by 3.48 percentage points, from 22 percent to 25 percent, leading to an increase in deforestation of 13.6 percent. The results also indicate that when methods to mitigate FAW damage are available, farmers are less likely to resort to charcoal production as a coping strategy. Having the ability to reduce the share of maize, diversify the crops produced, use pesticides, or migrate for off-farm employment are associated with a lower propensity to switch to charcoal production in response to FAW. Farmers' coping strategies in response to FAW attacks reduce charcoal production by 15 to 80 kg during an invasion.

Keywords: sub-Saharan Africa, price variability, perennial cash crop, deforestation, charcoal production.

JEL Classification: Q1,Q2,Q5

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1. Introduction

Forests are a vital carbon sink and deforestation is a significant source of Greenhouse Gases (GHGs) (Fearnside, 2000; Houghton et al., 2000). Deforestation is recently on the rise, particularly in sub-Saharan Africa (SSA), largely driven by charcoal production (Sparovek et al., 2012; Bare et al., 2015). Most charcoal producers are maize farmers, who use the income from charcoal production to purchase farm inputs such as seeds, fertilizers, and pesticides for the upcoming agricultural season (Kalipeni et al., 2009). This paper explores whether and when agricultural productivity shocks affect charcoal production and associated deforestation.

The effect of agricultural productivity on deforestation is unclear. While some prior work has found a correlation between low agricultural productivity and consumption of forest products (Mulenga et al., 2014; Noack et al., 2019), other research shows that an increase in agricultural production can lead to increases in deforestation (Sedano et al., 2022; Silva et al., 2019; Pelletier et al., 2021). In as much as charcoal production and its associated deforestation may be a coping strategy, little work estimates the causal effect of agricultural production shocks on charcoal production and how it is affected by the availability of other coping strategies. This is crucial as climate-induced agricultural shocks are expected to increase with climate change, making it essential to identify coping strategies that minimize or avoid deforestation. In this study, I use a specific persistent exogenous agricultural shock - the arrival of fall armyworms (FAW) in Zambia in late 2016 - to estimate the dynamics of agricultural output and charcoal production alongside how they are affected by possible coping mechanisms.[1]

In this study, I leverage a new crop pest to estimate the relationship between agricultural productivity, charcoal production, and deforestation is not unidirectional; rather, it depends on the specific agricultural shock affecting productivity. [2] Fall armyworms were first reported in Zambia

[1] Farmers can employ several coping strategies during a bad agricultural season such as: migration, crop diversification, off-farm employment, and charcoal production (Eriksen et al., 2005; Osei, 2017; Hänke and Barkmann, 2017). Farmers use the income from charcoal production as a safety net during a crop failure or other economic shocks (Brobbey et al., 2019; Ndegwa et al., 2016; Mulenga et al., 2017). Previous studies examining the relationship between charcoal production and agricultural shocks have primarily focused on temporary shocks, such as droughts. Consequently, the coping mechanisms identified are typically short-term responses. Additionally, many of these studies concentrate on shocks that impact both the demand and supply sides of the charcoal market. However, a significant limitation in this literature is the presence of identification flaws, which often result in endogeneity issues within the specifications.

[2] Even with the same shock, the response may vary: one could argue that if people experience a persistent shock during a particular season, they may clear more land in preparation for the next. In this paper, I demonstrate that

in 2016 (Durocher-Granger et al., 2020; Hadunka, 2019). To estimate the effect of FAW exposure on charcoal production, I utilize a panel dataset of 1,200 farmers over four years. Additionally, I analyze the factors that can either exacerbate or mitigate the link between FAW and charcoal production.

First, I develop a single-period model to generate some hypotheses on how FAW would affect the decision to produce charcoal or agricultural goods. The production of each is a function of how much labor the households put into each activity alongside the amount of capital and the availability of trees for charcoal production. All households face two states of the world, one in which they are affected by FAW and one in which they are not. The model predicts that in the event of a FAW infestation, households will increase charcoal production. I test this prediction using empirical estimates, primarily employing a correlated random effects (CRE) probit model proposed by Wooldridge (2021) [3] which is well-suited to my unbalanced and nonlinear panel data and binary dependent variable (household participation in charcoal production) as my preferred method and a linear fixed effects model as a robustness check.

I find that the presence of FAW in a village increases the probability of producing charcoal by 3.49 percentage points, from 22 percent to 25 percent. This result is robust to the linear probability model with household and year-fixed effects. Furthermore, the results indicate that when methods to mitigate FAW damage, such as reducing the share of maize, migrating for off-farm employment opportunities, and chemical spraying, are available, farmers are less likely to resort to charcoal production as a coping strategy. The findings are consistent with previous studies, which suggest that charcoal production is more labor-intensive and less profitable compared to crop production (Hänke and Barkmann, 2017; Mwampamba et al., 2013; Stassen, 2015). As a result, farmers would generally prefer crop production over charcoal during a normal agricultural season.

Additionally, I find that for smallholder farmers who primarily depend on maize production for their income, a negative shock in agricultural productivity leads to an increase in charcoal production, thereby contributing to deforestation [4]. This finding contrasts with existing literature

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the timing of the shock plays a crucial role. A shock can compel individuals to produce charcoal, reducing the labor available for land clearing in the following season. Consequently, land clearing contributes minimally to deforestation, while charcoal production emerges as the primary driver.

[3] In this analysis, I use a Two-way Mundlak framework (Wooldridge, 2021) to address incidental parameter bias in fixed effects models, offering a more robust approach by controlling for unobserved heterogeneity without assuming uncorrelated individual effects.

[4] In Figure 3, we see that prior to FAW infestations, deforestation rates were similar for households that eventually

which finds that an increase in agricultural productivity leads to more deforestation (Hänke and Barkmann, 2017; Stassen, 2015; Abman et al., 2020), which demonstrates a negative relationship between agricultural production and deforestation. I also identify a cyclical and reinforcing relationship between crop pests and deforestation, both of which are intensified by climate change. As climate change increases the range and increases the feeding activity of pests like FAW, it drives higher levels of charcoal production. This leads to further deforestation, which in turn reduces natural pest control by predators such as birds, worsening the severity of FAW infestations. Moreover, the greenhouse gas emissions from charcoal production contribute to climate change, further amplifying the impact of crop pests and perpetuating the cycle. My results indicate that FAW infestation leads to increased deforestation, which accelerates climate change. In turn, this heightens the severity and spread of pests, further driving deforestation. I also find that that proximity to forests increases charcoal production, while perceptions of forest stock have little impact, and traditional land ownership slightly reduces charcoal production, even during FAW shocks.

This study explores how farmers respond to pest shocks and the impact of their coping mechanisms on natural resource management, contributing to the literature on charcoal production, deforestation, and agricultural productivity. Previous research has explored the relationship between agricultural productivity and charcoal production (Doggart et al., 2020; Mulenga et al., 2017; Zulu and Richardson, 2013), but many of these studies suffer from weak causal inference designs, as agricultural productivity is endogenous, potentially leading to biased estimates. This paper is among the few to use a clearly exogenous productivity shock—one unlikely to affect the demand or supply costs of charcoal, except through changes in labor costs. It strengthens the evidence of a negative relationship between agricultural productivity and deforestation.

This study explores how farmers respond to pest shocks and how coping mechanisms impact natural resource management, contributing to the literature on charcoal production, deforestation, and agricultural productivity. Previous research shows mixed results: some studies suggest a positive relationship between agricultural productivity and charcoal production (Abman and Carney, 2020; Chibwana et al., 2013; Doggart et al., 2020), while others find a negative relationship (Mulenga et al., 2017; Labarta et al., 2008; Zulu and Richardson, 2013). However, these studies have some

experienced FAW and those that did not. However, following the shock, deforestation rates increased more for households involved in charcoal production compared to those not engaged in charcoal production.

weak designs for causal inference, as agricultural production/productivity is endogenous, which may lead to biased estimates.[5] This paper is among the few to use an exogenous shock to analyze the impact of negative agricultural shocks on deforestation. It also evaluates how deforestation, driven by coping mechanisms, compares to other strategies.

Given that FAW and other agricultural pests outbreaks are becoming more prevalent with climate change (Gregory et al., 2009; Paini et al., 2016), this study highlights an additional cost of climate change as it drives farmers to consume natural resources as a coping strategy. Second, this paper highlights which other strategies can help mitigate the link between negative agricultural production shocks and deforestation. These findings can help policymakers and resource managers identify and support households that are more likely to produce charcoal when faced with an agricultural production shock. Additionally, policymakers should focus on enhancing the availability of coping mechanisms that most effectively reduce the likelihood of charcoal production.

The remainder of this paper is organized as follows. Section 2 provides the background of the agricultural conditions, charcoal production, and fall armyworm infestation in Zambia. In Section 3, I provide a basic model explaining the relationship between agricultural output, charcoal production, and fall armyworm. In Section 4 I discuss my empirical strategy. Section 5, provides details of the data used. In Section 6, I show the results from the main specification. In Section 7 I discuss some robustness checks and different specifications. Section 8 concludes the paper.

2. Background

2.1. Charcoal dynamics

Africa has the highest deforestation rates in the world (Yalew, 2015). Most of the African countries with high deforestation are in the SSA region. Zambia has one of the highest rates of deforestation and forest degradation in SSA, with most estimates indicating between 250,000 - 300,000 hectares of forest loss per year and a deforestation rate of approximately 6 percent (Zulu and Richardson, 2013; Mabeta et al., 2018; Kalaba, 2016; Ngoma et al., 2021; Phiri et al., 2019). A number of factors have been identified as drivers of deforestation, with charcoal and fuel wood production among the most prominent (Mulenga et al., 2019; Mwitwa and Makano, 2012;

[5] It is much less common for people to sell firewood, while charcoal is widely sold along roadsides and in towns.

Chidumayo et al., 2002).

Households frequently turn to charcoal production as a coping mechanism during periods of production shocks, particularly when crops fail, using it as a way to smooth their income. Charcoal production involves a tedious process of clearing forest or woodland whose trees are converted into charcoal biomass, which can be used as a source of energy (Chidumayo and Gumbo, 2013). The most common way of making a kiln (surface earth mound) is by digging a pit or hole, filling it with wood, and covering it with mud. This way, the surface earth-mound limits the amount of oxygen reaching the burning logs, thus preventing the total burning of the wood to ashes in the process of obtaining the biomass (carbonization) (Girard et al., 2002; Demirbas et al., 2016).

Production shocks often occur after harvests, leading to income shocks that force farmers to turn to charcoal production as a safety net (Kiruki et al., 2020; Brobbey et al., 2019; Mburu et al., 2015). Charcoal is typically produced during the dry season, from September to October, just before the planting season begins. The income from charcoal sales is critical for farmers as it helps them purchase agricultural inputs for the planting season in November (Zackrisson et al., 1996; Jones et al., 2016; Smith et al., 2017). However, this timing creates a labor competition between charcoal production and land preparation for the agricultural season. Charcoal production delays land clearing and gardening, potentially postponing the start of the farming season (Labarta et al., 2008; Zulu and Richardson, 2013).[6]

Charcoal production is likely to remain a major cause of deforestation in many parts of SSA, including Zambia. Increased demand for charcoal is driven by high electricity tariffs, unreliable electricity supply, and the lack of alternative energy sources (Mulenga et al., 2017). On the supply side, charcoal remains a crucial source of income for rural households, especially for smallholder farmers who rely on it during times of negative production shocks (Mulenga et al., 2014; Zulu and Richardson, 2013).

A number of studies have been conducted to understand the relationship between maize production-productivity and charcoal production (Mulenga et al., 2017; Smith et al., 2017). Mulenga et al. (2017) is one of the few studies to address the relationship between agricultural productivity and charcoal production rigorously. The authors find a negative relationship between maize yields and the likelihood of charcoal production in Zambia. However, the results do not attribute yield loss to

[6] See Figure A.2 in the appendix for the production timing.

a particular factor, such as an insect pest shock. A more nuanced understanding of how different production shocks are associated with charcoal production helps identify interventions to address the over-exploitation of natural resources.

2.2. Fall Armyworms in Zambia

Fall armyworms are a voracious pest native to the Americas that can attack a crop at any stage in its development but usually appears in the early stages with the potential to cause complete crop failure (Harrison et al., 2019; Donatelli et al., 2017). Since first being reported in 2016, the pest has ravaged staple maize fields and significantly reduced yields in SSA. According to the Zambia Vulnerability Assessment Report of 2018 by the Disaster Management and Mitigation Unit (DMMU), estimated more than 130,000 hectares of maize were destroyed by the FAWs during the 2016/17 agricultural season, causing the government to spend millions of dollars on pesticides, and other control measures (Province, 2012).

A normal agricultural season in most parts of SSA usually begins in November, and farmers start planting by the end of that month (Umar, 2014; Vorlaufer et al., 2017). The farmers started reporting the FAW invasions on the maize planted in November because, at that time, most of the maize would have emerged, and FAW would have started ravaging them (Babu et al., 2019; Supartha et al., 2021; Prabhakar et al., 2020). Typically, the harvest of crops, especially maize, is done in July, and this is usually done by hand (Adnan et al., 2017; Awal et al., 2006). Depending on the intensity of FAW experienced by farmers who reported FAW, the farmers could possibly experience low crop production or complete crop failure. When farmers experience low yields or crop failure, the incomes of farmers are affected bearing in mind that the major and possibly only source of income for these rural farmers is agriculture.

Huge losses in crops and expected incomes would make farmers who reported FAW infestations to be more likely to engage in other income-generating activities to supplement their crop income in the next agricultural season. Natural resource exploitation, particularly forest-based activities such as harvesting wild fruits, mushrooms, honey, and charcoal, is a readily available option for supplementing farm income. These can either be for home consumption, sale, or both. Charcoal, in particular, remains a common source of forest income among rural smallholder farming households in Zambia (Mulenga et al., 2014; Brobbey et al., 2019; Zulu and Richardson, 2013).

FAW are a possible cause of production shocks as they are likely to continue causing crop damage in the foreseeable future. The magnitude of the FAW shock would shift some of the household's labor and resources toward charcoal production. However, how farmers shift their labor between both types of production is unknown.

This paper analyses this nuance by determining the nature and magnitude of the relationship between FAW infestation of maize fields and smallholder farmers' likelihood of participation in charcoal production. In addition, in the event of an FAW infestation, I assess the strategies that farmers use to mitigate this risk.

3. Charcoal and FAW theoretical model

3.1. Basic Model

To characterize the responses of farmers to productivity shocks from FAW infestations, I consider the problem of a representative, utility-maximizing household. Households have a total production, y_i, and they consume a certain amount, c_i. I start by assuming each household maximizes its utility and that there are no savings such that $y_i = c_i$. Each household is able to produce either an agricultural output or charcoal, with production for each characterized by the production functions f and g, respectively. I also assume that the agricultural good is the numeraire, so it has a price of 1, and the price of the charcoal is p.

There are two states of the world, s_p and s_{np} which the household must consider: one in which a pest infects its crops (state p), which happens with probability α and one without pests (state np) with probability $(1-\alpha)$. The pests affect only the agricultural output and not the production of charcoal.

The household must choose how much labor they will allocate to the production of either charcoal or agricultural goods. I normalize the time they can allocate for labor to be 1, such that the time they spend in agricultural work is l_a and the time they spend in charcoal production is $(1-l_a)$.

Households then maximize the following equation:

$$y = \alpha[f(l_a, k, s_p) + p \cdot g(1-l_a)] + (1-\alpha)[f(l_a, k, s_{np}) + p \cdot g(1-l_a)] \tag{1}$$

The inputs for the production of the agricultural good, in addition to the labor, and the total amount of capital k. In contrast, the production of charcoal requires the total availability of trees, t. I assume that land size is only part of the agricultural production function, while the trees are only part of the charcoal production function. Additionally, I assume diminishing marginal product of labor in both production functions ($f_l < 0, g_l < 0$) and that land inputs and labor are complements in production ($f_{l,k} > 0, g_{l,t} > 0$). Solving for the first-order conditions, I get:

$$\rightarrow \alpha f_l(l_a, k, s_p) + (1-\alpha) f_l(l_a, k, s_{np}) - p \cdot g_l(1-l_a, t) = 0 \tag{2}$$

For simplicity, I also assume that under the bad state, in which the farmer is affected by the FAW, the production of the agricultural good becomes a fraction μ of the production in the good state, such that I have $f(l_a, k, s_p) = \mu \cdot f(l_a, k, s_{np})$. This captures the possible intensity of the pest. This also implies that:

$$\rightarrow \alpha\mu f_l(l_a, \Lambda, k, s_{np}) + (1-\alpha) f_l(l_a, k, s_{np}) - p \cdot g_l(1-l_a, t) = 0$$

$$\rightarrow f_l(l_a, k, s_{np})[(1-\alpha) + \alpha\mu] = p \cdot g_l(1-l_a, t)$$

$$\rightarrow f_l(l_a, k, s_{np}) = \frac{p}{1-\alpha \cdot (1-\mu)} \cdot g_l(1-l_a, t) \tag{3}$$

Therefore, I can see from the equilibrium equation that if the household decides to produce charcoal, it must be the case that the *marginal product of labor in agriculture* is equal to a constant times the *marginal product of labor in charcoal production.* My model predicts the following:

1. If the price of charcoal (p) increases, the right-hand side (RHS) of the equation, the marginal product of labor in the agricultural sector on the left-hand side (LHS) must increase. Since the production functions exhibit diminishing marginal product of labor, that implies that an increase in charcoal price will lead to a **decrease** in the labor supplied in agriculture by the household.

2. If the pest infestation risk (α) increases, then the RHS of the equation becomes larger, which by the same logic implies a smaller amount of labor will be allocated to agricultural production.

3. If the impact of the pests increases (μ), then the RHS of the equation becomes larger, which will result in a decrease in the amount of labor allocated to agricultural production.

4. If the household has more capital (k), then since labor and land are complements, that increases the labor used in the agricultural sector.

5. Similarly, if the household has more access to trees (t), then since labor and trees are complements of the charcoal production, that leads to a decrease in the supply of labor in the

agricultural sector and an increase in the labor supplied to charcoal.

Therefore, the new maximization problem is as follows:

4. Empirical Strategy

The empirical strategy is structured as follows: In subsection 4.1, I present the econometric models used to estimate the impact of FAW on various outcomes. First, I estimate the effects of FAW on household participation in charcoal production using the correlated random effects (CRE) model, following the framework proposed by Wooldridge (2021), which is my preferred approach. I then explain the reasons for its preference. I then conduct robustness checks using a linear probability model (LPM) with fixed effects (FE). For the effect of FAW on the quantity of charcoal produced, I apply a Tobit model. Next, I address potential endogeneity concerns by detailing the instrumental variable (IV) technique used and specifying the instrument. Finally, I employ a two-way fixed effects model to examine the effects of charcoal production on deforestation rates. In subsection 4.2, I outline the identification assumptions. I begin by testing the exogeneity of FAW to farmer characteristics, followed by a spatial autocorrelation test. I then perform a leads test to examine whether differences existed between households that produced charcoal and those that did not before the FAW invasion, and conclude by plotting deforestation trends using leads and lags.

4.1. Econometric model

We employ a CRE probit model to estimate the effects of FAW on household participation in charcoal production. The most common panel probit model with a time-invariant and time-varying error component is the random effects probit model. However, a potential problem with this estimator is the assumption that covariates are independent of the time-invariant error. If one suspects correlation, that can be modeled with the Mundlak device, which models the time-invariant error as a function of the means of time-varying covariates. Through the Mundlak device, the random effects probit estimation will have coefficients that margin out the time-invariant error on the time-varying variables. Additionally, the Mundlak approach avoids the incidental parameter problem that often biases fixed effects estimations in nonlinear models. For these reasons, the random effects probit model with the Mundlak device would be superior for the non-linear models to the linear fixed effects model (Chamberlain, 1982; Wooldridge, 2021). [7]

[7] Wooldridge (2021) extends the use of the Mundlak device, offering a robust solution to the limitations of both fixed and random effects models, and making the estimates from my method comparable to the newer difference-in-difference approaches.

For the full sample, I employ a TWM model, which accounts for the unbalanced nature of I panel data and the non-linearity of the binary dependent variable—taking a value of 1 if the household participates in charcoal or firewood production, and 0 otherwise. In the first year, the charcoal variable is binary but in the subsequent years, the quantity of charcoal production is a continuous variable for the quantity produced. The estimated model is as follows:

$$P\left(y_{it}=1 \mid \mathbf{x}_{it}, FAW_{it-1}\right)=\Phi\left(\beta FAW_{it-1}+\mathbf{x}_{it}^{\prime} \gamma+\overline{\mathbf{x}}_{i}^{\prime} \phi+u_{it}\right), t=1, \ldots, T \tag{4}$$

The coefficient of interest, β, represents the effect of the severity of Fall Armyworm (FAW) on the likelihood of household participation in charcoal production. The FAW variable is lagged by one year, as the decision to produce charcoal is primarily driven by FAW intensity in the previous agricultural season. [8] The reason for lagging the FAW variable is that if a household is severely affected by FAW during one season, leading to crop losses, they are more likely to engage in charcoal production the following year to generate income needed for agricultural inputs. In the model, $\mathbf{x}_{it}$ is a vector of time-varying covariates, including household characteristics, agricultural production, and climatic variables. The term $\overline{\mathbf{x}}_i$ represents the individual-specific mean of these time-varying covariates (Mundlak term), which accounts for potential correlation between the covariates and the time-invariant unobserved individual heterogeneity. The time fixed effects, δ_t, are included to control for common shocks across all households in a given year. Finally, u_{it} represents the idiosyncratic error term, and $\Phi(\cdot)$ is the cumulative distribution function (CDF) of the standard normal distribution, corresponding to the probit model's link function.

As a robustness check, I consider a linear probability model with fixed effects (FE) estimation as specified in Equation 5.

$$Y_{it}=\beta FAW_{it-1}+\gamma \mathbf{X}_{it}+\mu_t+\alpha_i+\varepsilon_{it} \tag{5}$$

The variable Y_{it} is a binary indicator, taking the value of 1 if the household participates in charcoal production, and 0 otherwise. $\mathbf{X}it$ denotes a set of time-varying predictor variables. The term α_i accounts for the combined effect of all unobserved, time-invariant factors, while μ_t controls

[8] I tested for serial correlation due to the annual structure of the data by examining the coefficient on the lagged residuals, following Wooldridge (2010). The coefficient on the lagged residuals was close to -0.5, indicating that serial correlation is not a concern in this case.

for year fixed effects, capturing common shocks across all households. Finally, εit represents the error term. Note: The linear probability model with fixed effects (FE) is consistent with the CRE model. It is also worth noting that the model above suggests that if the marginal value product of labor in charcoal production is less than that in agriculture, the farmer will choose not to produce charcoal.[9]

In the Two-Way Mundlak framework, I estimate the effect of FAW intensity on the quantity of charcoal produced with the following Tobit regression:

$$Q_{it}^* = \beta' FAW_{it-1} + \gamma \mathbf{X}_{it} + \delta \overline{\mathbf{X}}_i + \omega_t + \zeta_{it} \tag{6}$$

$$Q_{it} = \begin{cases} Q_{it}^*, & \text{if } Q_{it}^* > 0 \\ 0, & \text{otherwise} \end{cases}, \quad i = 1, \dots, N \text{ and } t = 1, \dots, T \tag{7}$$

Where i refers to the household and t represents time. Q_{it} is the observed quantity of charcoal produced by household i at time t, while Q_{it}^* is the latent (uncensored) quantity of charcoal produced. The coefficient β' captures the effect of FAW intensity, $\mathbf{X}_{it}$ includes time-varying covariates such as household characteristics and climatic variables, and $\overline{\mathbf{X}}_i$ represents the household-specific averages of the time-varying covariates (Mundlak term), which accounts for potential correlation between the covariates and the unobserved individual heterogeneity. ω_t represents the time fixed effects, which control for common shocks across all households in a given year.

The model assumes a random effects structure, where the error term is defined as:

$$\zeta_{it} = \lambda_i + u_{it} \tag{8}$$

Where λ_i represents the unobserved individual-specific random effects, and u_{it} is the idiosyncratic error term. By including $\overline{\mathbf{X}}_i$, the model accounts for the potential correlation between the time-varying covariates and the individual-specific effects, following the Mundlak approach (Wooldridge, 2010).

The individual-specific effects λ_i are assumed to be randomly drawn from a probabilistic dis-

[9]See the theoretical model in Section 3.

tribution (Samut and Cafrı, 2016).

The CRE Tobit model often provides more efficient estimates compared to fixed-effects Tobit models, which suffer from the incidental parameter problem, especially in non-linear settings.

I then explore heterogeneity in farmers' likelihood of charcoal production. I regress the likelihood of participating in charcoal production on farmer characteristics such as the asset index, access to credit, landholding size etc, and also the interaction of farmer characteristics with FAW severity variable using the CRE framework as specified in Equation 4. Understanding how individual characteristics have an effect on charcoal production is of relevance.

Furthermore, I explore various coping strategies that farmers use when affected by FAW. I regress the FAW_{it} on the various coping mechanisms such as inter-cropping, migration, crop diversification, off-farm jobs (piece-work), and maize share on the outcome variable as specified in Equation 4.

Lastly, I investigate the effect of the coping strategies on the farmer's likelihood to participate in charcoal production using the CRE framework as specified in Equation 4. The problem with this regression is that charcoal production is a coping strategy that farmers use when their crops are afflicted by FAW, which is endogenous. The endogeneity arises from the possible simultaneity when deciding among the available coping strategies to employ. For example, in the instance where the household decides to migrate when affected by FAW, then that household cannot also choose to do piece-works at the same time.

To address the potential endogeneity concern, I employ an instrumental variable (IV) technique. I use the availability of other coping strategies in a camp as the exogenous measure, i.e., the camp level average of the sum of each farmer's coping strategy except the observed household. I follow the procedure by Papke and Wooldridge (2008) where they employ a correlated random effects approach with instrumental variables in both the linear and nonlinear models. I leverage the variation of coping strategies across the agricultural camps in constructing the instrument. I specify the instrument as follows:

$$Z_{it} = \frac{\sum_{j \neq i} CS_{jt}}{n-1} \tag{9}$$

Where CS_{jt} represents the coping strategies available for household j in the camp, and n is the total number of farmers in the camp. The instrument averages the coping strategies of all households except for the observed household, ensuring the instrument is exogenous to the household's own behavior.

I then regress these coping strategy instruments (as specified in Equation 9 on the likelihood of producing charcoal separately as a reduced form using Equation 4. The instrument should not be correlated with the outcome (likelihood to produce charcoal) of the regression other than through the endogenous variable (household coping strategy). For the exclusion criteria, I argue that average coping strategies do not directly affect household outcomes. However, there are challenges to that assumption - i.e., if neighboring coping strategies generate spillovers in economic outcomes (not just in coping strategies), then that would violate the exclusion criterion. For this study, concerns over spillovers arising from neighbors' coping strategies are arguably limited because these coping mechanisms are done on a relatively smaller scale, and the chances of generating spillovers are minimal. One could argue that information spillovers may occur, as farmers have the opportunity to observe the coping mechanisms of their neighbors. However, I contend that these coping mechanisms are already common knowledge, widely understood, and accessible to everyone within the camps. To examine whether coping mechanisms in neighboring areas generate spillover effects on economic outcomes, I regress FAW (Fall Armyworm) intensity on charcoal prices. If such economic spillovers were present, we would expect an increase in FAW intensity to result in significantly lower charcoal prices, as more people might turn to charcoal production as a coping strategy. However, the results in Table A.10 show that the increase in FAW intensity has a small and statistically insignificant effect on charcoal prices. This suggests that the coping mechanisms are not driving any significant economic activity.

Furthermore, for the instrument Z_{it} to be valid, it also needs to be highly correlated with the household coping strategies, i.e., $E\left[Z_{it} \cdot \varepsilon_{it}\right] = 0$. This means household coping strategies must be correlated with the neighboring farms' coping strategies within the camps. I test for weak instruments and whether the household's coping strategies are correlated with the neighboring farms' coping strategies within the camps. To satisfy the exclusion restriction, the likelihood that the household is practicing any of the coping strategies must be randomly distributed over space. The average camp coping strategies should only determine an individual household's likelihood to participate in charcoal production by affecting that household's likelihood of the household using the coping strategies themselves.

One problem with the equations above is that the variable of interest, FAW intensity, is based on self-reporting, which may suffer from measurement error. I specify the instrument the instrument in detail in subsection A.2. Further, one might worry that this measurement error is not random; more observant farmers may be more likely to report FAW and may also likely have higher maize yields. One may be concerned that if I do not instrument for the self-reported FAW infestations, my estimates of the effect of FAW on charcoal production will be biased.

To further address endogeneity concerns, I use the fact that FAW intensity for the i^{th} farm is correlated with the presence of FAW on the neighboring farm, j. As a robustness check, I control for the possible mismeasurement error in reporting by using the average of the sum farmers' responses on FAW intensity at a camp level for the household in a particular camp minus the observed household as specified in Equation 4 (these camps households are from specific camps which are heterogeneous). I then regress the instrument on the likelihood of producing charcoal using the RF approach as in equation 3. The exclusion restriction states that if the probability of detecting FAW in one's field is randomly distributed over space, then the average camp infestation level should only determine the individual's decision to participate in charcoal production by affecting that household's likelihood of being infested itself. I plot the individual deviation from the camp average over space to show that the mismeasurement error is randomly distributed (see Figure A.1). I then test for weak instruments on both the intensity and binary instrument and from the first stage regression to assess if the household's stated infestation intensities are correlated with the FAW intensities of the neighboring farms in the camp.

Finally, in a different specification, I explore the effects of charcoal production on deforestation. To estimate the effects of charcoal production on deforestation rates; I employ the generalized two-way fixed effects model as follows.

$$Deforest_{idt} = \alpha Charc_{idt} + \beta \mathbf{X}_{idt} + \theta_d + \gamma_t + \zeta Camp * t + \tau_d + \omega_{idt} \tag{10}$$

Where $Deforest_{idt}$ is the deforestation rate, $Charc_{idt}$ is the variable of interest, representing the quantity of charcoal produced by the household, and $\mathbf{X}_{jt}$ is a vector of weather regressors

(Growing Degree Days (GDD), Killing Degree Days (KDD) [10]), and rainfall).[11]

θ_d is a time-invariant fixed effect for household i in district d, γ_t is a time effect that is the across households but varies across time $t = 1, \ldots, T$, η_{it} is a household $\times$ time random effect, ζ is the camp $\times$ time fixed effects, and τ_d are the district fixed effects. I control for the district-fixed effects because some farmers are located in districts in an agricultural zone with more rainfall, and as such, they have relatively more access to forests than others, and ω_{idt} are the idiosyncratic errors.

4.2. Identification Assumptions

My analysis exploits the variation in FAW infestations across households to identify the causal effect of FAW on charcoal production. We assume that the infestation of a household to the FAW is truly exogenous to farmers' characteristics. I conduct two specifications to test whether the fall armyworm infestation is exogenous to farmers' characteristics and only dependent on local climate conditions.

While I cannot prove that the FAW infection is truly exogenous to farmers and geographical characteristics, I can test to see whether there are differences in the observables. If the FAW is exogenous in terms of geographical and climatic characteristics, I would expect that the observable characteristics of the farmers who were afflicted by FAW and those who were not are similar. To test the above assumption, I specify the following regression equation:

$$FAW_{it} = \gamma_1 Temp_{it} + \gamma_2 Temp_{it}^2 + \rho_1 Rain_{it} + \rho_2 Rain_{it}^2 + \phi \mathbf{X}_{it} + \lambda_{dt} + \epsilon_{it} \tag{11}$$

Where $Temp_{it}$ represents the growing degree days (temperature) influencing the activity of FAW, and $Temp_{it}^2$ is its square term. Similarly, $Rain_{it}$ represents rainfall, and $Rain_{it}^2$ is its square term. I include the square terms to account for potential nonlinearity in the effects of temperature and rainfall. $\mathbf{X}$ represents a vector of farmer characteristics such as land cultivated, education, household size, and gender. d indicates district, t indicates year, λ_t captures district-by-year fixed effects, and ϵ_{it} denotes the error term. Results can be found on Table 1.

[10] KDD represents the temperatures at which crops can be severely damaged or destroyed. Specifically, KDD occurs when temperatures exceed 29°C.

[11] I use GDD and KDD as controls, following the arguments from the studies by Fraisse and Paula-Moraes (2018) and Lobell et al. (2011), which assert that GDD and KDD are important indicators of the temperatures necessary for tree growth in a forest (GDD) and the temperatures that have the potential to destroy or kill the trees in a forest (KDD).

One may worry that FAW infestations are determined by farmer characteristics and not exogenous factors such as temperature and rainfall. To address this concern, I provide evidence supporting the exogeneity of the relationship by regressing FAW incidence on temperature, which I convert to growing degree-days (GDD) for each household's geographic location. In calculating the GDD, I follow the procedure by Fraisse and Paula-Moraes (2018). The formula is as follows:

$$GDD = \max\left(\left[0, \frac{T_{max} + T_{min}}{2} - T_{base}\right]\right) \tag{12}$$

Where T_{max} is the maximum average temperature for that day, and the T_{min} is the minimum temperature for the particular day. T_{base}, is the base is the optimal temperature in which FAW thrives, which is 10 degrees Celsius (Fraisse and Paula-Moraes, 2018). To understand how much of the variation in infestation severity is determined by the GDD, I check the correlation between the two variables. The motivation for this is to demonstrate that the FAW infestations are possibly determined by weather factors and not farmer characteristics.

In Figure 2, I use Moran's I to demonstrate the absence of spatial autocorrelation in FAW diffusion, indicating that these infestations are driven by exogenous weather variables. Table 1 shows that exogenous weather variables are the primary determinants of FAW infestations, while farmer characteristics have no significant effect on FAW occurrences.

As a robustness check for the parallel trend assumption, I carry out a leads test following the approach used by Autor (2003). I test whether households that produced charcoal and those that did not were different before FAW invasions.

$$Y_{it} = \gamma_s + \lambda_t + \sum_{k=l+1}^{z} \beta_k D_{it}(t = q + k) + X_{it}\delta + \varepsilon_{it} \tag{13}$$

For this, I include the lags and leads(future) of FAW. Where Y_{it} is the likelihood to produce charcoal, l is the 'leads', which is basically the current FAW infestations, which in this study is the 'future FAW' in that it captures FAW in November-April compared to the harvesting of charcoal in October before planting in that same agricultural (planting usually starts in November). For instance, in this year's agricultural season, production begins November 2021- April 2022. For the lead l, the decision to produce charcoal around October 2022 is basically from the FAW infestations in the same agricultural season (April - November). As for the lag, z, which affects the farmers' decisions to produce charcoal in the current year based on the previous year's infestations, the possible crop failure from FAW leads to charcoal production starting October 2022 is from the previous agricultural season, which between November 2020 - November 2021 (see figure Figure A.2 in the appendix). β_k is the coefficient for the kth lead or lag. The assumption for this test is that $\beta_k = 0, \forall k < 0$, which means all the coefficients on all leads of the treatment should be zero (Autor, 2003).

5. Data sources

The data comes from a large panel survey of smallholder farmers across Zambia called the Household Income Consumption and Production Survey (HICPS). The survey was conducted in June and July of 2016, 2017, 2018, and 2019, covering the 2015/16, 2016/17, 2017/18 and 2018/19 agricultural seasons. The HICPS sampled about 1,200 smallholder households in 12 districts of Zambia.[12] The data collected includes socioeconomic, demographic characteristics, production activities, income sources, insect pest infestation, charcoal/firewood production and sales (aggregated monthly), and expenditure from charcoal sales (how the money from charcoal sales was spent).[13]

Respondents were randomly selected across all the districts. On average, the same number of households were sampled from each district. I further randomly selected agricultural camps within the districts. 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., 2018). A cooperative is a small group of farmers living in the same locality (camps) that come together to help each other to have better price bargains, access to resources (agricultural inputs), and extension services. Cooperatives are the best way in which governments can reach farmers and provide inputs and extension services (Bijman and Wijers, 2019; Blekking et al., 2021). Even though the cooperatives are heterogeneous, the members within the same cooperatives usually have access to resources (inputs, pesticides) at similar times. Finally, I randomly selected households within the agricultural camps and villages.

The HICPS defines FAW infestation intensity as the proportion of the farmer's crop in the field that was damaged by FAW. Based on the farmer's responses, enumerators categorized the infestation in three categories: if the farmer reported that the infestations destroyed less than 25 percent of their crop, then that would be categorized as a low level of infestation intensity; reports of crop damage of 25-50 percent were be categorized as severe medium (moderate) infestation intensity; and damages of over 50 percent were regarded as severe infestation intensity. The survey also asked if and when the households produced charcoal during their agricultural production

[12]The selected districts are shaded in Figure 1 of the appendix. The districts include Mkushi, Mumbwa, Mpongwe, Masaiti, Lundazi, Petauke, Mbala, Mungwi, Chinsali, Mufumbwe, Solwezi, Choma and Namwala.

[13]The surveywas conducted in cooperation between researchers at the University of Illinois, Indiana University, Princeton University, the University of Zambia, and the Zambia Agricultural Research Institute.

season.

To plot the pre-trends, I use deforestation rates data from the University of Maryland's Global Forest Change dataset. Additionally, I complement the HICPS data with rainfall information from the Climate Hazards Center InfraRed Precipitation with Station data (CHIRPS) repository, and temperature data from the Moderate Resolution Imaging Spectroradiometer (MODIS).

5.1. Descriptive Statistics

To test whether households affected by FAW infestations are more likely to produce charcoal, I create a map of households that reported severe FAW infestation (those reported more than 50 percent crop loss) and overlay the shapefile layer of the households that reported charcoal production. I concentrate on households that reported severe infestations to avoid having a large number of households on a map, which would make visualizing the relationship between FAW and charcoal production difficult (see Figure A.3). Additionally, households with severe FAW are more likely to produce charcoal compared to those who experienced less severe infestation. Figure A.3 shows that households that produced charcoal also reported having severe FAW infestation. This suggests a correlation between FAW and charcoal production.

Over the years, the charcoal market has provided consumers, especially urban households, with an affordable source of energy at relatively stable prices (Zulu and Richardson, 2013).[14] Production of charcoal is not driven by the demand or prices but instead by other factors. The farmers' decisions to produce charcoal are not influenced by the prices but by the marginal product of labor for the agricultural sector and farmer characteristics. When the marginal productivity of labor in agriculture is low, the farmers will shift their labor to other coping mechanisms, such as charcoal with higher marginal productivity, and this decision is not influenced by the prices of charcoal. [15]

With regards to the pre-trends in Figure 3, I find that the deforestation rates are observably lower in places where FAW is not reported. However, there is no statistical difference in deforestation rates between households that reported having had FAW at least once and those that did not. I observe in Figure 3 that prior to FAW invasions (treatment), there is no discernible difference in

[14] Figure A.4, in the appendix, shows the average prices of charcoal for the 2016-17 and 2017/18 agricultural season. The graph shows that charcoal prices have been somewhat stable within and across years. The consistency of charcoal prices is corroborated in the literature of Ellegård, Nordström, et al. (2003) and Chomitz and Griffiths (2001).

[15] This is discussed in detail in Section 3.

deforestation rates between households that reported encountering FAW at least once and those that did not. [16] [17]

I use the deforestation rate as a proxy for charcoal production as it allows us to show pre-trends before November 2016. It works as deforestation, and charcoal production has a strong correlation (see Table A.1 in the appendix).

The leads test results (see, Table A.2 in the appendix), indicate that the coefficient for the lead of the treatment is zero. This entails that the households that produced charcoal and those that did not were not different before the invasion of FAW. This further supports the differences-in-difference (Diff-in-Diff) parallel trend assumption.

It is also worth noting that at baseline, all of the farmers have access to forests nearby. To show this, I plotted the remaining forests (the level of forests) in the baseline, and it is clear that both farmers who reported FAW infestations and those who did not have access to the forests (see Figure A.5). However, charcoal production as a risk management tool was only available to some farmers in some regions (camps) (see Figure A.3)

The results show that temperature (GDD) and rainfall determine the severity of FAW and not farmer characteristics. From Table 1, I find that GDD and rainfall have significant effects on the intensity of FAW, which is not the case for farmer characteristics. From Table 1, I can also see that weather variables are the largest determinant of variation in the severity of FAW and not necessarily farmer characteristics. The F-test results comparing two models, one with weather variables and the other with weather variables and farmer characteristics, show no significant difference between the two models.

In Table 2, I present the balance table from the 2015/16 agricultural season (baseline season) between groups and test for the difference in means using the normalized differences similar to the approach in the study done by Friedman et al. (2016). This is for the baseline year, which is the 2015/16 agricultural season prior to FAW infestations. Table 2 shows that the FAW produced treatment and control groups balanced along most characteristics. However, I find differences in rainfall between the two groups. I find that farming households with FAW infestations received relatively less rainfall, with an average of 931.29 mm, compared to households with no FAW 960.51

[16] I use 2012, which is the first year of available data, as the baseline for plotting differences.

[17] The high standard errors are due to extracting and plotting differences in deforestation at the district level, compounded by the satellite data's lack of calibration for non-tropical forests and its inherent inaccuracies.

mm. The difference is not economically relevant; however, I still control for it in my models.

6. Results

6.1. First stage results - Effects on Maize Production

In this section, I use a difference-in-differences model with fixed effects to assess the impact of FAWs on crop yields. As noted in the methods, I instrument for reported FAW infestation rates using camp-level averages in an instrumental variables framework to address potential measurement error (see subsection A.2 for details on the instrument). Our findings indicate a negative and significant effect of FAWs on agricultural productivity (see Table A.3 in the appendix). This implies that FAWs cause agricultural production shocks, which increase the likelihood of farmers participating in charcoal production (Mulenga et al., 2017).

6.2. Main results

For this paper, the CRE model is my preferred model. [18] I employ the CRE model because I are concerned that the population would suffer from incidental parameter problems if a fixed-effects model was used. In this study, I focus on the average partial effects, which represent the change in participation likelihood resulting from a change in the intensity while controlling for the covariates at their means. The estimates from Column 3 of Table 3 indicate that the intensity of FAW increases the likelihood of participation in charcoal production by 3.49 percentage points. Even though this study is different from the study by Mulenga et al. (2017), which broadly estimates the relationship between agricultural productivity and charcoal production, the marginal effects are very similar (3.7 percentage points).

A possible explanation for why the results are consistent with Mulenga et al. (2017) is that FAW damage has a direct negative effect on maize yields. The losses in yields could be interpreted as the differences in productivity and/or production due to the availability of income and other inputs possibly influencing the size of the yield losses, which is also dependent on the intensity of FAW in the previous agricultural season since and all that can be translated as agricultural productivity and/or production.

[18] The results presented are from the IV estimation unless otherwise specified.

Therefore, households that were affected by FAW in the previous season may have lower maize yields compared to those that did not get affected by FAW. Lower yields lead households to be financially constrained to buy more productive inputs such as certified seeds. Thus, since FAW affects the decision to participate in charcoal production through agricultural productivity/or production, it makes sense that my results are consistent with the findings by Mulenga et al. (2017).[19]

In terms of land, results show that cultivated land has a significant negative influence on the household's participation in charcoal production. Following the predictions of my model in Equation 3, labor and land are complements, and more land leads to a higher allocation of labor by the households towards the agricultural sector, which reduces the likelihood of households participating in charcoal production. This land (arable) is defined as the portion of land under the direct control of the household in accordance with the stipulated norms of the customary tenure system (Hichaambwa and Jayne, 2012). Although Zambia may seem to have plenty of uncultivated land, access to land for the rural poor is still a problem. In Zambia, the land is controlled under the customary land tenure system where the traditional leaders own the rights to the land, and thus, the production of charcoal is constrained by land availability (Munshifwa and Botswana, 2003).

I then further explore the effects of FAW on the quantity of charcoal produced using a random effects Tobit regression model. It is important to note that the number of observations is lower compared to Table 3 as some households while saying they produced charcoal, did not specify a quantity. The results are shown in Table 4. In column 2, I present the effect of the FAW intensity on the quantity of charcoal produced, and in column 3, I control for covariates as specified in Equation 6. Both sets of regressions control for district and year-fixed effects. The results indicate that as the intensity of FAW increases, households' charcoal production increases by 1343 kilograms (kgs). According to a study by Malimbwi and Zahabu (2008), a tree of 32 cm diameter at breast height (dbh) on average produces only 80 kgs of charcoal, which is sold for approximately K90 at current prices (4 United States dollars). A back-of-the-envelope calculation estimates that farmers are likely to cut down approximately 16 trees when the intensity of FAW intensity increases. The results indicate that a significant quantity of trees is cut down for charcoal production by a single

[19] In this paper, I run the treatment variable as a continuous variable and not as a categorical variable. As a robustness check, I show that FAW severity increases almost the same across all the intensity categories (See Table A.5 in the appendix).

household affected by FAW.[20]

6.3. Intensity of the FAW on Charcoal Production

Based on the model, the higher the share of the agricultural output lost to the FAW I should also expect a larger increase in charcoal production. In Table A.5, I see that consistent with the predictions that households that had a higher intensity of FAW infestation see a larger increase in the production of charcoal. Low, moderate, and high levels of infestation increase the probability of charcoal production by 4.8 percent, 8.5 percent, and 12.3 percent relative to households that did not experience an FAW infestation. I can argue that changes in FAW intensity levels can be largely interpreted as having a uniform percentage increase in charcoal production. Thus, I can state that a unit increase in FAW intensity corresponds to the same percentage increase in charcoal production.

6.4. Farmer heterogeneous effects

I further explore the effect of baseline farmer characteristics on charcoal production and the effects of those characteristics when farmers are affected by FAW. The results from Table 5 indicate that farmers with access to credit are less likely to participate in charcoal production. In terms of land for cultivation, I find that farmers with larger land are less likely to participate in charcoal production when affected by FAW. This is because as the household increases (clearing) the cultivated land, they allocate more labor to agriculture. Since labor and land are complements, increasing land increases labor in the agricultural sector, which in turn increases agriculture production and thus reduces charcoal production. This is consistent with my theoretical model.

With regard to land, matching the predictions of my model, I find that increases in land stock reduce the likelihood that a household will produce charcoal. I define land as household assets used in agricultural production, such as axes, machetes, hoes, etc., that can be used for both agriculture and charcoal production. In the presence of FAW infestation, the marginal productivity of land in agriculture decreases. As such, the households reduce the labor used in the agricultural sector, thus increasing the likelihood of households participating in charcoal production. This could be because, during FAW invasions, farmers divert some of their land to buy insecticides against FAW,

[20] See Figure A.6 in the appendix to see the number of trees from just a single medium-sized kiln.

which is consistent with the theory. Further, the results indicate that farmers who reported having land are less likely to participate in charcoal production. I then evaluate the potential effects of distance on the likelihood of charcoal production.

I find that distance to the nearby trees that can be used for charcoal reduces the likelihood of households engaging in charcoal production, which is also consistent with my model. My results also follow the study by (Malimbwi et al., 2000), which found that the distance to the suitable trees that can be used for charcoal has increased over time due to the depletion of the trees for charcoal production. However, in the presence of FAW invasions, the distance has an insignificant effect on reducing the likelihood of farmers participating in charcoal production. This could be attributed to the low marginal productivity of labor for agriculture during FAW invasions, and thus, farmers will still find charcoal production productive regardless of the distance and thus less likely to not produce charcoal. This is in line with the analysis of the theory where I show that as the number of trees reduces (distance to trees increases), given that labor and trees are complements of the charcoal production, then there will be an increased supply of labor in agriculture and less in charcoal production and hence the reduction of labor for charcoal production.

Lastly, the results indicate that the assets index does not significantly reduce the likelihood of participation in charcoal production. [Have to add here how assets are measured] Capital plays a significant role because in most cultures, the asset index is used as a sign of prestige and can not be used for liquidity even in times of crop failure. Even if it can be used as liquidity and would reduce the effects of FAW, it is rarely used compared to capital.

6.5. Coping strategies when affected by FAW

I analyze how farmers cope with having been affected by FAW in the previous agricultural season. The results from Table 6 indicate that farmers affected by FAW reduce the amount of land allocated to maize. The results are expected as FAW prefers to attack maize or any crop in the grass family, such as sorghum. In order to hedge against FAW infestation, the farmers reduced the maize share in the presence of the pest. As farmers reduce their maize share (the portion of the field dedicated to maize production), they increase the number of other crops they are planting, thus increasing crop diversification. Crop diversification involves the cultivation of a variety of crops in a mixed cropping method (Mofya-Mukuka and Hichaambwa, 2018). However, in this paper, crop diversification involves the shift from producing more staple crops to producing non-staple crops. I observe this effect in Column 3, where households affected by FAW in the previous agricultural season are 2.2 percent more likely to have reported crop diversification.

In column 2, I find that farmers who reported having higher FAW intensities are 23.3 percent more likely to spray insecticides than households that reported lower FAW severity. The results indicate that spraying is the most used and effective and most used coping strategy, which is also consistent with the findings by Kumela et al. (2019) (see the appendix for detailed information). The results in column 4 also indicate that farmers migrate to areas that may not have been affected by FAW. The estimate indicates that farmers who were previously affected by FAW are 3 percent more likely to migrate from their original household. A possible explanation is that farmers are worried about the recurrence of FAW and, as a result, seek to live in an area not affected by FAW. Another possible mechanism is that instead of migrating, the households seek off-farm work. The result in column 5 indicates that farmers affected by FAW are 2.3 percent more likely to engage in off-farm work. Given that FAW might affect the households' income, members of it would then look for other job possibilities to compensate for the loss of income.

6.6. Effect of coping strategies on charcoal production

The reduced form results from Table 7 show that not all the coping strategies that farmers employ when attacked by FAW reduce the likelihood of participating in charcoal production. My robust Hausman test indicated the presence of time-invariant unobserved heterogeneity correlated with the explanatory variables. This is important as it shows that the random-effects estimator would be inconsistent (Cameron and Trivedi, 2005). Further, the Kleibergen-Paap underidentification test results show that the instruments are significantly correlated with the endogenous explanatory variables. The weak instrument test for all the coping strategies indicates that the F-statistics from the first regression were all greater than 10. The Wald test indicates that the maximum amount that the instruments might be biased from weak instruments is below 5 percent for all the coping strategies except crop diversification. With all the F-statistics greater than 10, I can conclude that the instruments are statistically strong (see Table A.6 in the appendix section for the first-stage regression results). All my instruments appear to be relevant when tested across various diagnostic tests.

The results suggest that camps, where out-migration is practiced, are linked to a smaller increase in charcoal production as a response to FAW infestations. A study by Yang et al. (2016) finds that the migration or local off-farm employment has no negative effect on grain (maize) technical efficiency of grain production and, as such, does not affect household food security. Thus, during crop failure, the household opportunity cost of agricultural production reduces, and with possible off-farm wages increases, and bearing in mind that the technical efficiency is not negatively affected by this, it becomes relatively easy for households to migrate for off-farm employment and thus, less likely to produce charcoal.

Regarding the increased maize share, I use the inverse of the maize share to ease the interpretation of my results. I find that decreasing the maize share during FAW invasions increases the likelihood of farmers participating in charcoal production, given that maize is the most preferred crop by FAW. Farmers then shift their production to other crops, such as beans, sweet potatoes, and pumpkins, which are typically less affected by FAW invasions.

Crop diversification improves household food security, as households increase their consumption of diverse foods during income shocks caused by cash crop (maize) failure. When households diversify into high-value crops such as soybeans, their income is less significantly affected by the failure of maize, reducing the likelihood of charcoal production.

My estimates challenge the findings of Mzyece (2020), which suggest that crop diversification from staple to non-staple crops leads to reduced agricultural productivity and profitability due to the loss of efficiency benefits from economies of scale. I argue that crop diversification can be profitable and mitigate income shocks if it includes high-value crops.

My result indicates that as households reduce their maize production (maize share), they are less likely to participate in charcoal production or forest degradation. I argue that this depends on the presence or absence of FAW. In the absence of FAW, increasing agricultural production (maize) is likely to cause a reduction in charcoal production and forest degradation since farmers will have enough of the cash crop/staple food. This result contradicts a number of studies that find that increasing agricultural production leads to an increase in forest degradation (Abman and Carney, 2020; Chibwana et al., 2013; Doggart et al., 2020). I argue that the effect of agricultural production/productivity on forest degradation can either be negative or positive, depending on the shock. Studies that find a positive relationship use positive shocks in their analysis as opposed to my study, which uses a negative agricultural shock (FAW infestation).

To provide context for the above results, in Table 8, I examine the reduced form results to explain the effects of farmers' coping strategies on the quantities of charcoal produced. This analysis allows us to deduce the extent to which these coping mechanisms reduce charcoal production. The results indicate that nearly all coping strategies employed by farmers in response to FAW attacks lead to a reduction in charcoal production, ranging from 15 to 80 kg during an invasion. Among these strategies, crop diversification and spraying have the most significant impact in reducing the quantities of charcoal produced.

6.7. Effects of charcoal on the deforestation rate

In this section, I examine the effects of charcoal production on deforestation. I define deforestation rate as the annual loss of forest cover in a country (Hansen et al., 2013). More specifically, I adopt the definition from Bare et al. (2015), which describes the deforestation rate as the total area of 30m^2 plots where forest cover has decreased to approximately 20-50 percent below a specified threshold. [21]

The results in Table 9 indicate that a 50 kg increase in charcoal production would result in a 5.62 percent increase in deforestation rates.[22],[23] This aligns with the findings of Veen et al. (2022), who identified a positive relationship between charcoal production and deforestation, noting that charcoal production accounts for 7% of tropical deforestation and forest degradation. However, these studies do not clearly outline the mechanism that drives households to produce charcoal, which subsequently contributes to deforestation.

The income generated from selling this charcoal would be equivalent to the income from just 100 kg of maize. Thus, hundreds of trees may be required to sustain a family during a crop production shock, such as one caused by FAW infestation.

One might argue that deforestation results from households expanding cultivated land following a shock in the previous season. However, as shown in Table A.4, households experiencing a

[21] **Note**: The threshold referenced is used in Hansen.

[22] This might seem high, but it is important to note that a tree with a radius of 32 cm, when fully cut and used for charcoal production, produces only 80 kg of charcoal (Malimbwi and Zahabu, 2008). Given that farmers typically cut smaller trees, several trees may be required just to produce one bag of charcoal.

[23] In Figure A.6 in the appendix, the author stands behind a large pile of freshly cut trees prepared for charcoal production, likely to yield 400 kg of charcoal.

production shock actually reduce cultivated land. This aligns with my model: during a pest shock, the marginal product of labor is higher for charcoal than for agriculture, leading households to shift labor to charcoal production, thus making charcoal the primary driver of deforestation.

6.8. The impact of proximity to forests on charcoal production decisions

To understand the private social costs associated with charcoal production, I analyze the effects of the distance from the homestead to the forest to determine whether proximity to the forest influences households' decisions to produce charcoal. Additionally, I assess whether distance remains a significant factor in charcoal production and deforestation during FAW infestations. The results in columns 2-3 in Table 10 indicate that as the distance to the forest increases, deforestation rates and the likelihood of producing charcoal decrease. This finding aligns with my theoretical model (see Section 3), where I posit that households situated in proximity to forests, with greater access to trees, face a labor allocation trade-off. Given that labor and tree resources are complementary inputs in charcoal production, increased access to trees induces a reallocation of labor away from the agricultural sector and towards charcoal production, reducing labor supply to agriculture. Additionally, during FAW infestations, the impact of distance to the forest on deforestation rates and the likelihood of producing charcoal is comparatively smaller. This suggests that the distance to the forest during FAW invasions does not significantly constrain charcoal production or contribute to deforestation. The marginal product of labor in the agricultural sector diminishes due to anticipated crop failure, aligning with my model's assumption that it equates to the marginal product in charcoal production. Consequently, farmers may no longer perceive distance as a substantial cost, rendering it a less critical factor in their decision-making regarding charcoal production.

6.9. Does awareness of forest stock influence charcoal production decisions?

One of the most significant yet underexplored questions in the natural resource exploitation literature is how awareness of changes in forest stock affects the behavior of those involved in deforestation. In this study, I asked farmers whether they believe the forest stock has increased, remained constant, or decreased over the past 10 years. [24] I then assessed how their perceptions influenced their behavior towards charcoal production. Specifically, I evaluate whether they incorporate social

[24] The analysis focuses on the initial baseline characteristics.

costs into their production decisions.

In column 4 Table 10, I show how the perception of forest stock affects the decision to produce charcoal, both with and without FAW invasion. My results indicate that households are more likely to produce charcoal when they perceive an increase in forest stock compared to when they believe the stock has remained the same or decreased. However, these differences are minimal and statistically insignificant.

In all scenarios, regardless of their perception of forest stock, households are more likely to produce charcoal when they experience FAW invasion. Farmers who perceive an increase in forest stock may be more inclined to produce charcoal, possibly because they have forests nearby, and natural predators may have controlled the FAW, as suggested by Clarkson et al. (2022). Interestingly, my results show that households perceiving a constant forest stock are also more likely to produce charcoal. This could be because, in the absence of changes in stock and natural predators, they treat the situation as a control scenario.

My findings suggest that the perception of forest stock, serving as a proxy for social costs, has little impact on the decision to produce charcoal, particularly during FAW invasions. This supports my model, which assumes that households with access to trees either perceive social costs as negligible or do not consider them when forest stock is stable or increasing. Since labor and trees are complementary in charcoal production, this perception encourages a shift in labor from agriculture to charcoal production, thereby increasing charcoal output.

6.10. Does land ownership reduce the likelihood of charcoal production?

In most Sub-Saharan African countries, such as Zambia, the majority of land (60%) is customary land overseen by traditional leaders. This land, often owned or protected by small-scale farmers, is typically regarded as relatively low in value compared to titled land or state land (Honig and Mulenga, 2015).

Figure A.7 shows that the majority of land (58%) is under traditional authority, consistent with Honig and Mulenga (2015).[25] Despite some restrictions, because traditional land, where most smallholder farmers operate, is considered low value, I expect these restrictions to have a minimal effect on the likelihood of charcoal production.

[25] The analysis concentrates on the baseline characteristics.

In column 5 of Table 10 shows that households whose land is protected by traditional authority or state ownership are 1.84% less likely to produce charcoal compared to households that own their land. In the event of FAW infestation, households under traditional land ownership reduce the likelihood of charcoal production by 1.77%, a statistically significant but small increase. This indicates that traditional authorities are enforcing land protection even during production shocks caused by disasters such as FAW.

In Zambia, some traditional leaders are strict about charcoal production, ensuring that it does not occur in their districts, which may explain the low estimates.

7. Robustness checks

I analyze the effects of FAW on the likelihood of charcoal production using a linear probit model (LPM), the effect of insecticide spraying on FAW, and camp average FAW infestations as robustness checks. Column 2 of Table A.7 presents the LPM estimates with household and year-fixed effects while controlling for several household characteristics. The estimates from the LPM are very similar to the estimates from the CRE model in Table 3. One might be concerned that households that may have sprayed are less likely to participate in charcoal production than those who did not, and that can potentially bias the results. In column 3, I specify the CRE model similar to equation 3. In addition to controlling for household characteristics and household and year FE effects, I control for household spraying and its interaction with FAW. The results remain consistent even with controlling for spraying.

In column 4, I control for measurement error in farmer self-reports using the average prevalence of the FAW at the camp level as both a measure of threat in and of itself and as an instrument for self-reporting as specified in equation 8 using the CRE framework. The results from the weak instrument test indicate that the F-statistics from the first regression was 34.43, which is greater than 10. The Wald test indicates that the maximum amount that the instruments might be biased from weak instruments is 4 percent. Given that this maximum amount of bias is relatively low, I can reject the null hypothesis of weak instruments. With such high F-statistics, the choice of instrument is statistically strong, as it is in line with the literature. The results are consistent with the self-reported results in column 2. Further, I regress the treatment (FAW intensity variable) as a categorical variable (dummies). The results in Table 10 in the appendix section are consistent with the main results where I regress the treatment as a continuous variable.

The primary criticism of the two-way fixed effects estimator is that it calculates a weighted average of all possible 2x2 differences-in-differences estimates, where the weights are determined by group sizes and treatment variances (Borusyak et al., 2024; Goodman-Bacon et al., 2019). Essentially, it represents the weighted average of all potential average treatment effects on the treated (ATT), assuming variance-weighted common trends (VWCT) and time-invariant treatment effects. Recent research by Goodman-Bacon et al. (2019), Callaway and Sant'Anna (2021), and De Chaisemartin and d'Haultfoeuille (2020) indicates that the two-way fixed effects estimator can be biased in the presence of time-varying treatment effects, particularly in differential time designs. The strength of these recent work is that their estimators, which shut down the 2×2 difference in-differences comparisons between newly-treated and already-treated units, are designed to be consistent even in the presence of heterogeneous treatment effects across time and treated units. Table A.8 shows that the robust estimators' estimates are similar to my TWFE estimates. This is consistent with Wooldridge (2021), who note that the flexible TWFE approach provides all the necessary tools for analyzing staggered designs. Additionally, the flexible TWFE can be particularly useful when there is suspicion that the common trends assumption may be violated.

One of the concerns of this study is that there is reverse causality in the relationship between FAW and charcoal for nearby farms. To address the concern, I examine how the distance to forests affects the intensity and spread of FAWs .[26] When fields are nearer to households, birds and other predators feed on FAWs. The results in Table 11 show that for each 1 km increase in distance to the forest, FAW intensity increases by 4.42 percent. This finding aligns with a study by Clarkson et al. (2022), which demonstrates that closer proximity to forests reduces FAW intensity and spread due to natural predation. Although these results indicate that the distance to forests reduces FAW intensity, it remains unclear whether this reduction due to natural predation is sufficient to influence households' decisions regarding participation in charcoal production and deforestation. It is important to note that the positive relationship suggests my results may underestimate the true association between charcoal and FAW. In the absence of this relationship, the actual effect would likely be more pronounced.

[26] I use the distance at baseline and thus the analysis focuses on the baseline characteristics

8. Conclusion

In recent years, increasing rates of deforestation have become a major concern in Sub-Saharan Africa. Charcoal production is an important cause of deforestation. Charcoal production has been widely seen as an income safety net to cushion households against negative income shocks during crop failure. In this paper, I explicitly compare the effect of adopting charcoal production as a coping strategy when alternative strategies are available. I further quantify the effect of the invasion of FAW on charcoal production, deforestation, and the likelihood of farmers' participation in charcoal production. I find that FAW in the village increases the probability of producing charcoal by 3.49 percentage points, from 22 percent to 25 percent. I also find that as the intensity of FAW increases, farmers increase their production of charcoal by 1,343 kgs on average which translates to 16 around 16 felled trees, which is a huge piece of deforested land.[27]

My results also indicate that spraying chemical insecticides is the most widely used coping strategy. I find that reducing the maize share in a farmers' field and migration significantly reduces the likelihood of farmers participating in charcoal production. Crop diversification, which involves reducing the share of maize cultivation, decreases the likelihood of farmers participating in charcoal production. This shift occurs as farmers transition to crops less susceptible to FAW invasions, enhancing food security by increasing the production of other crops. If farmers diversify into more valuable cash crops such as soybeans, their income improves, reducing the need for them to engage in charcoal production.

My results shed new light on the impact of a new agricultural pest (FAW) on natural resources (forest) and the mechanisms that lead to natural resource degradation. In a resource-constrained economy like Zambia, it is imperative that these mechanisms be fully understood so the government can focus on effective mechanisms that reduce farmers' likelihood of contributing to natural resource degradation.

From a policy-making perspective, the results show that if the objective of the policymakers is to reduce natural resource degradation (deforestation), then the policymakers must focus on interventions that decrease the maize share and maize production in general when households are affected by FAW. The policy should be aimed at crop diversification to produce substitutes for

[27] see Figure A.6 in the appendix of deforested land that uses half the size of normal trees required for charcoal.

staple crops such as cassava which as a substitute of maize and most important crop diversification should be towards high-value crops such as soybeans. Policymakers could also help the farmers by making chemical insecticides more available and affordable and promoting access to off-farm employment opportunities.

One implication of my findings is that cash transfers provided during production shocks can reduce the likelihood of charcoal production and deforestation. Relatively small cash transfers help cushion the income shocks caused by production disruptions, thereby protecting the environment.

It is crucial to address the urgency of combating FAW and the cyclical, reinforcing relationship between crop pests and deforestation. Climate change expands the range and appetite of crop pests like FAW, which heightens the likelihood of increased charcoal production. As forests are depleted for charcoal, the distance to remaining forests grows, reducing natural predation by birds and other predators, which may in turn escalate FAW intensity. Moreover, charcoal production contributes to climate change through GHG emissions, further exacerbating the intensity of crop pests.

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Figures

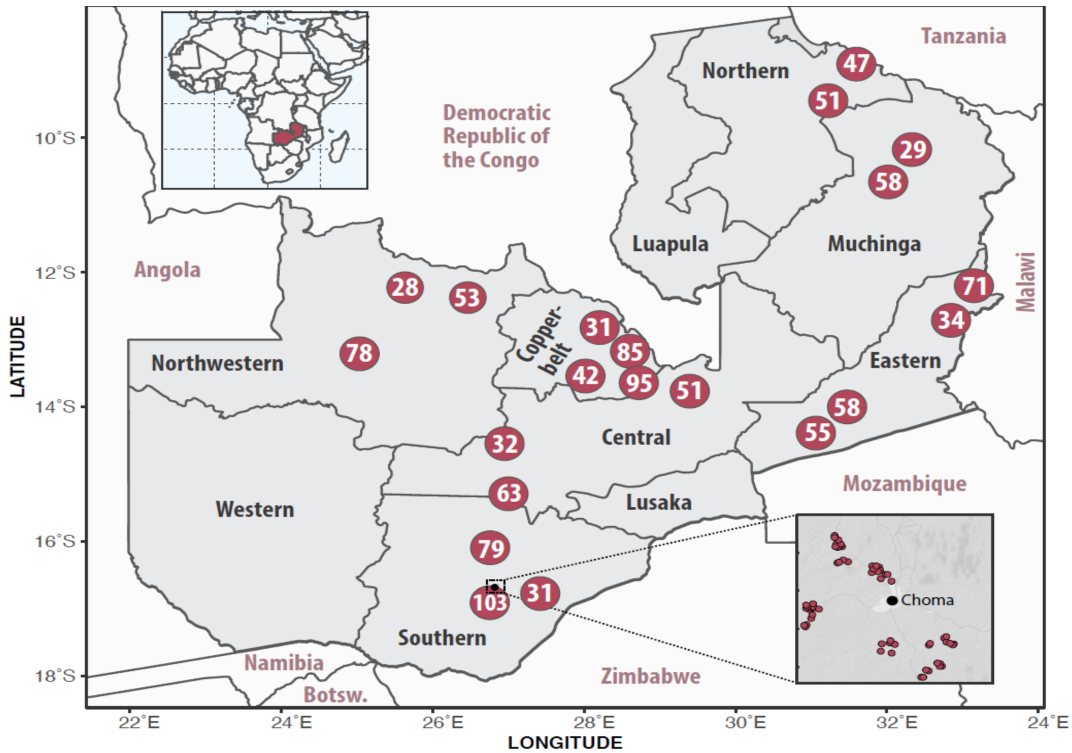

Figure 1: The shaded regions area are the districts that were randomly selected for the study. Source: Author's work from the HICPS data

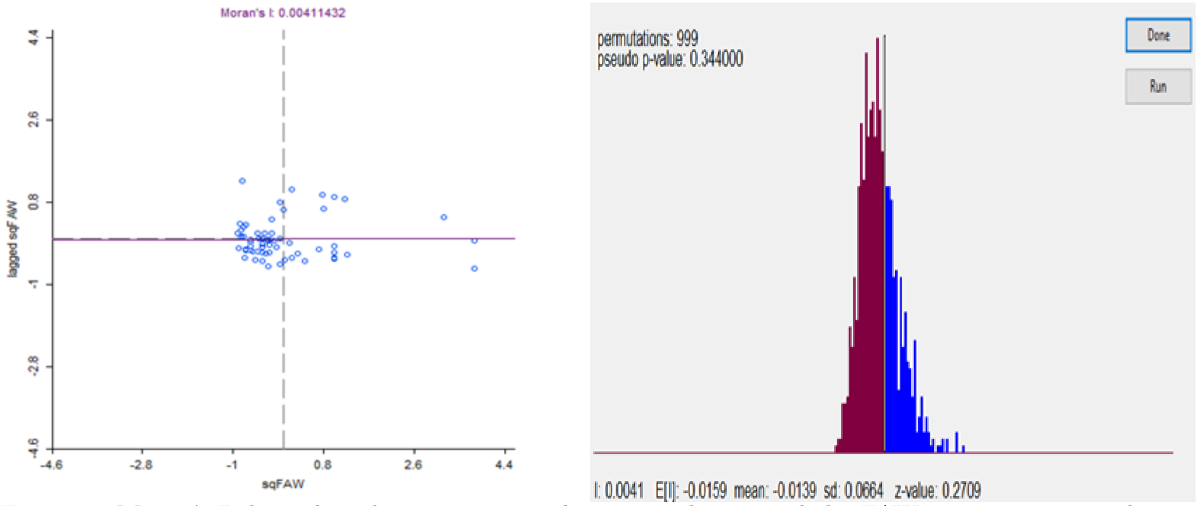

Figure 2: Moran's I show that there is no spatial autocorrelation and the FAW invasion was random

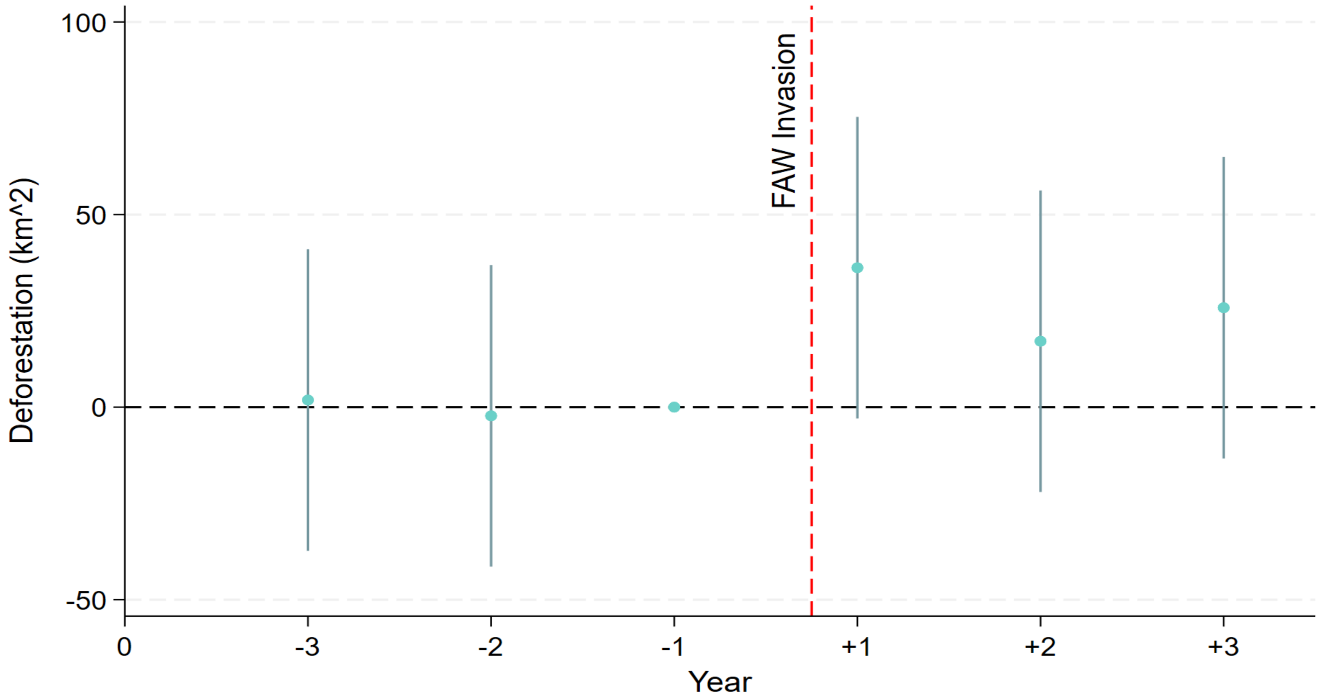

Figure 3: Estimates of the effects of FAW on deforestation using leads and lags in an event study model.

Tables

Table 1: Effects of temperature on FAW

	(1)	(2)
VARIABLES	FAW intensity	FAW intensity
Temperature	-0.3086*	-0.3195*
	(0.1864)	(0.1877)
Square of temperature	0.00415	0.00434*
	(0.00267)	(0.00269)
Rainfall	-0.00229*	-0.00258**
	(0.00089)	(0.00091)
Square rainfall	1.06e-06**	1.14e-06**
	(3.63e-07)	(3.68e-07)
Land cultivated (ha)		-0.00116
		(0.00275)
Education		-0.0114
		(0.0108)
Household size		0.0075
		(0.00461)
Year FE	Y	Y
District FE	Y	Y
R-squared	**0.364**	**0.366**
Observations	2,478	2,478

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

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

	Means (SD)		Normalized differences
	(1)	(2)	(3)
	No FAW	FAW	No FAW vs with FAW
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)	(54.43)	
Distance to the forest (km)	7.172	9.842	0.021
	(5.931)	(7.423)	
N	**425**	**495**	

Robust standard errors in parentheses

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

Table 3: Effects of FAW on charcoal production using the CRE model

	(1)	(2)
VARIABLES	Coefficient	Average Partial effects
Lag FAW	0.0891*	0.0349***
	(0.1366)	(0.00508)
Land cultivated (ha)	-0.1026**	-0.0017**
	(0.0346)	(0.00074)
Education	-0.00832	-0.00427
	(0.03354)	(0.00305)
Age of household head	0.1212***	0.0122
	(0.03354)	(0.01276)
Household size	-0.01894	-0.00125
	(0.0130)	(0.0013)
Weather controls	Y	Y
Observations	2,478	2,478

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

Note: Controlled for weather variables in the form of rainfall, temperature and their squared terms (weather controls)

Table 4: Effects of FAW on Quantity of Charcoal Produced

	(1)	(2)
VARIABLES	QChar (kg)	QChar (kg)
Lag FAW	1965.639	1343.62*
	(2003.717)	(345.28)
Controls	N	Y
Year FE	Y	Y
HHFE FE	Y	Y
Observations	1,634	1,572

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

Note: Controlled for weather variables (rainfall, temperature, and their squared terms) and household characteristics.

Table 5: Farmer heterogeneous effects

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Charc (=1 if y)	Charc (=1 if y)	Charc (=1 if y)	Charc (=1 if y)	Charc (=1 if y)
Lag FAW	0.0159**	0.01408*	0.01395**	0.01145	0.0141**
	(0.00789)	(0.00797)	(0.00611)	(0.00834)	(0.00789)
Access to credit (1= Yes)	-0.0198**				
	(0.00919)				
Access to credit × FAW	-0.00606				
	(0.00519)				
Land cultivated (ha)		0.00020			
		(0.00032)			
Land cultivated × FAW		-0.000034			
		(0.00062)			
Capital			-0.01201***		
			(0.00304)		
Capital × FAW			0.01395**		
			(0.00249)		
Distance to trees				-0.0413***	
				(0.0176)	
Distance to trees × FAW				-0.0137	
				(0.0165)	
Asset Index					-0.000753
					(0.00516)
Asset_Index × FAW					-9.49e-07
					(6.45e-07)
Weather controls	Y	Y	Y	Y	Y
Observations	2,478	2,478	2,345	2,478	2,478

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

Note: Controlled for weather variables in the form of rainfall, temperature, and their squared terms (weather controls).

Table 6: FAW on coping strategies employed by farmers

VARIABLES	(1) Maize share	(2) Spraying (=1 if yes)	(3) Crop diversification (=1 if yes)	(4) Migration (=1 if yes)	(5) Off-farm work (=1 if yes)
Lag FAW	-0.0153*	0.233***	0.0226**	0.0301***	0.0233*
	(0.00643)	(0.0441)	(0.00856)	(0.00708)	(0.0125)
HH controls	Y	Y	Y	Y	Y
Weather controls	Y	Y	Y	Y	Y
Observations	2,468	2,473	2,478	2,478	2,173

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

Note: Controlled for weather variables in the form of rainfall, temperature and their squared terms (weather controls)

Table 7: Coping strategies on Charcoal production

VARIABLES	(1) Charc
Inv_ Maize share	-0.0105
	(0.0332)
Inv_ Maize share × FAW	-0.0121
	(0.0124)
Crop diversification	-0.0241
	(0.0221)
Crop diversification × FAW	-0.0108
	(0.0103)
Migration	-0.123*
	(0.0585)
Migration × FAW	-0.0283
	(0.0321)
Off-farm work	-0.0103
	(0.0231)
Off-farm work × FAW	0.0370***
	(0.0141)
Spray	-0.00541
	(0.0147)
Spray × FAW	-0.0281***
	(0.00909)
Weather controls	Y
Observations	2,327

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

Note: Controlled for weather variables in the form of rainfall, temperature and their squared terms (weather controls)

Table 8: Coping strategies on quantities of charcoal production

VARIABLES	(1) Quantities of Charcoal (kg)
Inv_ Maize share	-492.4**
	(213.6)
Inv_ Maize share × FAW	-59.49
	(94.96)
Crop diversification	-26.80
	(171.6)
Crop diversification × FAW	-79.89*
	(57.74)
Migration	-47.24
	(159.3)
Migration × FAW	-21.69
	(98.01)
Off-farm work	-45.08
	(107.7)
Off-farm work × FAW	54.74
	(39.51)
Spray	-44.79
	(49.52)
Spray × FAW	-47.716**
	(9.015)
Weather controls	Y
Observations	1,527

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

Note: Controlled for weather variables in the form of rainfall, temperature and their squared terms (weather controls)

Table 9: Effects of Charcoal on deforestation

	(1)
VARIABLES	Deforestation rate (5 km)
Charcoal production (50 kg)	0.0562***
	(0.0197)
Weather controls	Y
District	Y
Year	Y
Observations	2,980

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

Note: Controlled for weather variables in rainfall, temperature, and their squared terms.

Table 10: Effects of distance to forests, perceptions of the forests, ownership on charcoal production and deforestation

	(1)	(2)	(3)	(4)
VARIABLES	Deforestation rates	Charc (=1 if y)	Charc (=1 if y)	Charc (=1 if y)
FAW	0.056**	0.0336	0.00986	0.0532
	(0.0113)	(0.0282)	(0.00671)	(0.0497)
Distance to the forest (km)	-0.0156*	-0.0413***		
	(0.0113)	(0.0176)		
Distance to the forest × FAW	-0.0109**	-0.0137		
	(0.00553)	(0.0165)		
Increased forest stock			0.0315	
			(0.0321)	
Increased forest stock × FAW			0.0425	
			(0.0281)	
Constant forest stock			0.0213	
			(0.0318)	
Constant forest stock × FAW			0.0812***	
			(0.0288)	
Decreased forest stock			0.0175	
			(0.0277)	
Decreased forest stock × FAW			0.0263	
			(0.0249)	
Ownership (1 = Yes)				-0.0184*
				(0.0500)
Ownership × FAW				-0.0177
				(0.0590)
Weather controls	Y	Y	Y	Y
District FE	Y	N	Y	Y
Observations	768	785	965	

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

Note: Controlled for weather variables in the form of rainfall, temperature, and their squared terms (weather controls).

Table 11: Effects of Distance to the forests and FAW Intensity

VARIABLES	(1) Log FAW Intensity
Distance to the forest (km)	0.0442
	(0.0321)
Weather controls	Y
District FE	Y
Observations	768

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

* Note: Controlled for weather variables in the form of rainfall, temperature, and their squared terms.

A. Appendix

A.1. FAW control practices

Farmers in Zambia use various methods to mitigate FAW infestations, with 61 percent of the farmers reporting chemical spray being their main method of control, which is slightly less than the 62 percent reported by Davis et al. (2018) for the previous agricultural season (see Figure 8 in the appendix). My findings are consistent with the finding by Kumela et al. (2019) done in Kenya and Ethiopia but in contrast to a study by Abate et al. (2000) in the Sahel region of Africa that found that smallholder farmers do not mainly use insecticides to control for FAW but rather use cultural methods. The higher use of pesticides could be due to the fact that following the sudden invasion of FAW, the Zambian government supplied farmers with free insecticides. According to my study, the second most popular methods was a cultural (traditional) method which involves the hand-picking egg masses with 31 percent of the farmers reporting having used as method of control. This is consistent with findings by Davis et al. (2018). Studies have shown that farmers perceive the use of chemical pesticide to control FAW as ineffective in controlling the pest (Kumela et al., 2019). My analysis equally shows that the majority of the farmers (86 percent) reported that the use of chemical pesticide was ineffective (see Figure 9 in the appendix). One concern is whether the insecticides are being applied appropriately. Spraying by farmers is usually done during the day when FAW are inactive as they are nocturnal for this reason some farmers may regard as ineffective even when it is just their wrong spraying timing (Kumela et al., 2019). According to Goergen et al. (2016) the insecticides are only effective on younger larva and late spraying may not be ineffective. Figure 10 (in the appendix) shows the reason why some farmers don't use insecticides on their crops. Most (59 percent) reported that they couldn't afford the insecticides. Even though the cost of insecticides in Zambia is usually subsidized, a farmer is expected to spend an average a farmer spent USD 6.5/ha on pesticide treatments alone i.e without subsidy (Davis et al., 2018). This is already too high for an average Zambian farmer to afford. A further 23 percent of the farmers reported that they did not spray because they had no access to the insecticides.

Table A.1: Effects of Charcoal on deforestation

	(1)
VARIABLES	Deforestation rate
Charc (=1 if yes)	0.397***
	(0.078)
Year FE	Y
District FE	Y
Weather controls	Y
Observations	2,158

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

Note: Controlled for weather variables in the form of rainfall, temperature, and their squared terms (weather controls)

Table A.2: Effects of FAW on Charcoal as a categorical variable (Robustness check)

	(1)
VARIABLES	Charc (=1 if yes)
Lag_FAW	0.0327***
	(0.00536)
Lead_FAW (current FAW)	-0.00634
	(0.00495)
Land cultivated (ha)	0.000049
	(0.00074)
Education	-0.00649*
	(0.00309)
Household size (Labor)	-0.00182
	(0.00132)
Weather controls	Y
Observations	2,158

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

Note: Controlled for weather variables in the form of rainfall, temperature, and their squared terms (weather controls)

Table A.3: Effects of FAWs on Maize yields

VARIABLES	(1) lyield	(2) lyield	(3) lyield
	OLS	ITT	IV
FAW	-0.055*	-0.116*	-0.398***
	(0.019)	(0.045)	(0.156)
Weather Controls	Y	Y	Y
HH Controls	Y	Y	Y
HH FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	2,742	2,537	2,537

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

Table A.4: Effects of FAWs on cultivated land

	(1)
VARIABLES	lcultivated land
Lag_FAW	-0.04297
	(0.2063)
Weather controls	Y
HHFE	Yes
Year	Yes
Observations	2,158

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

Note: Controlled for weather variables in the form of rainfall, temperature, and their squared terms (weather controls)

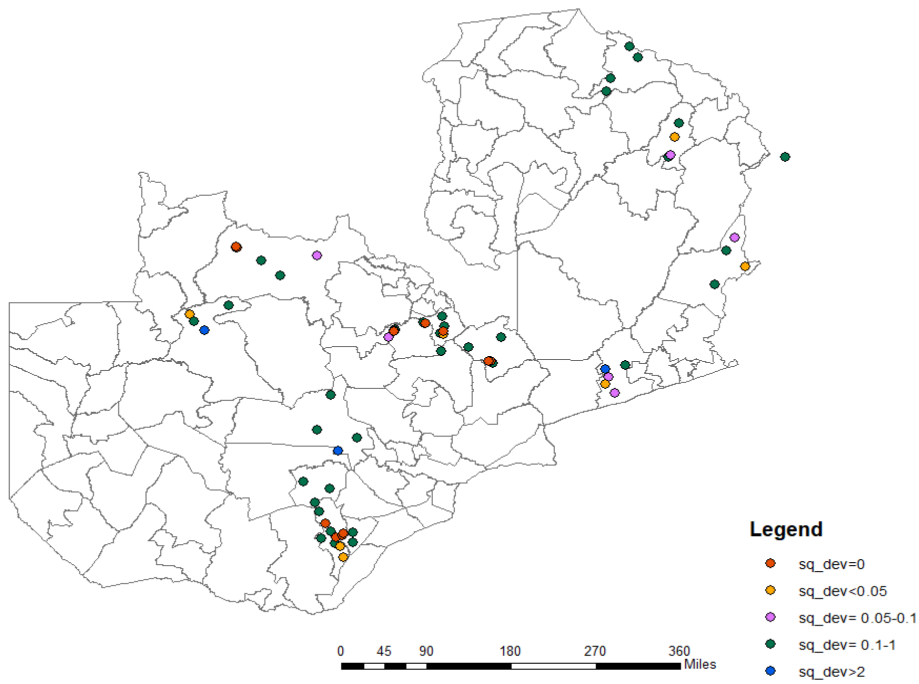

Figure A.1: Distribution of the deviations in farming households and average camp responses in FAW reporting.

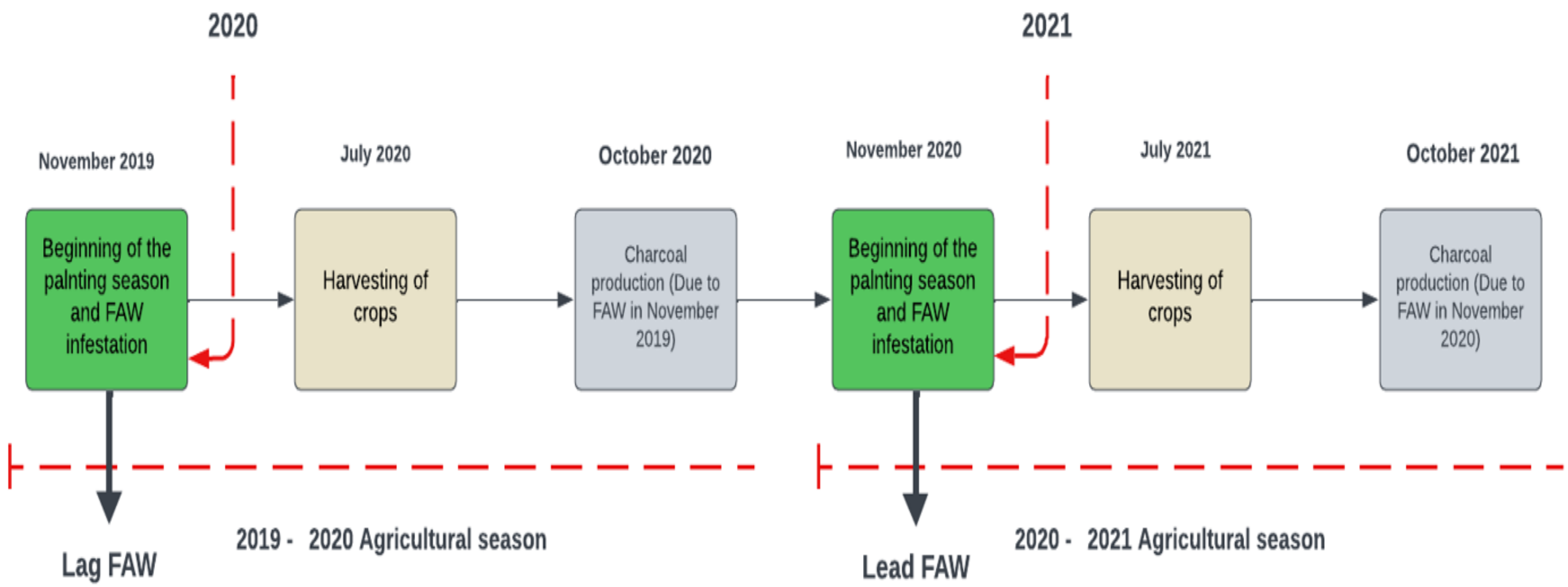

Figure A.2: Agricultural seasons and FAW leads and lags

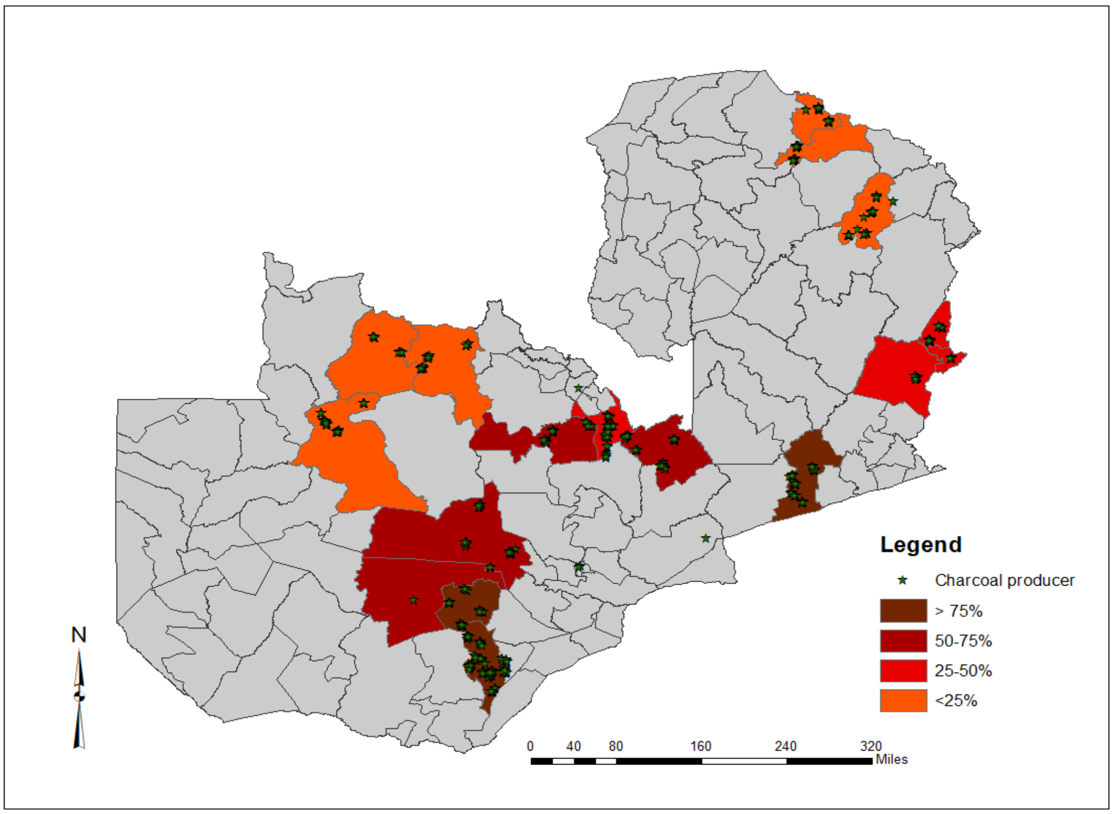

Figure A.3: FAW infestations and charcoal production.

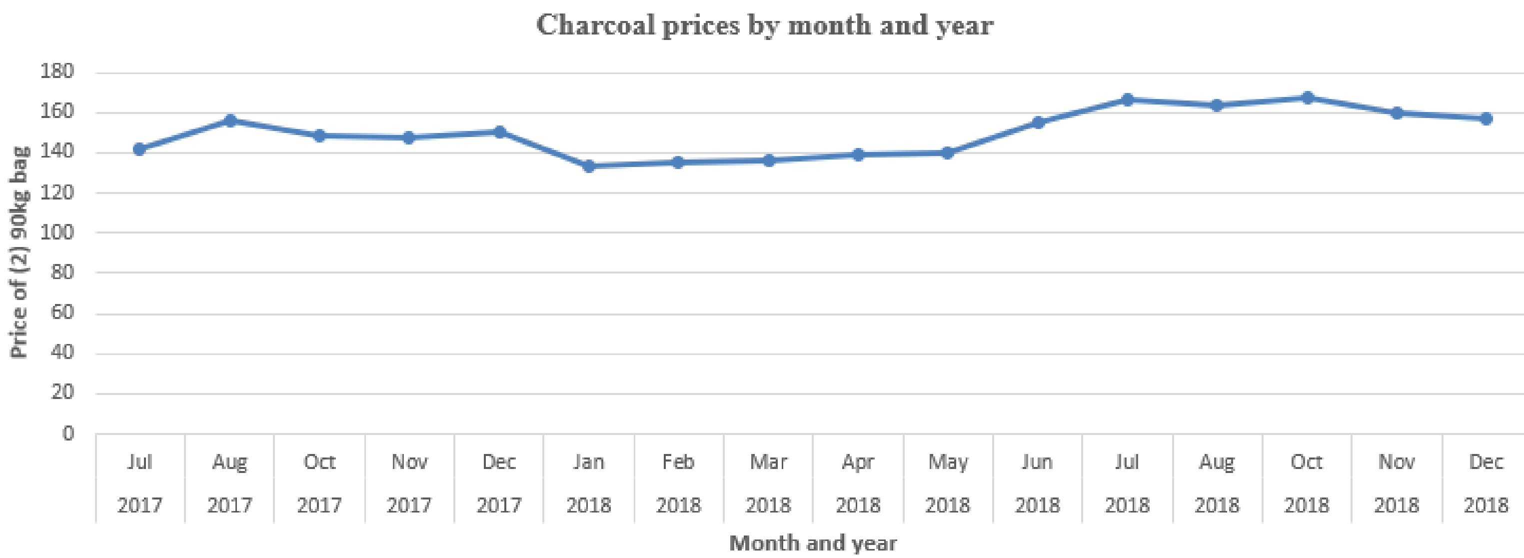

Figure A.4: Charcoal prices across time.

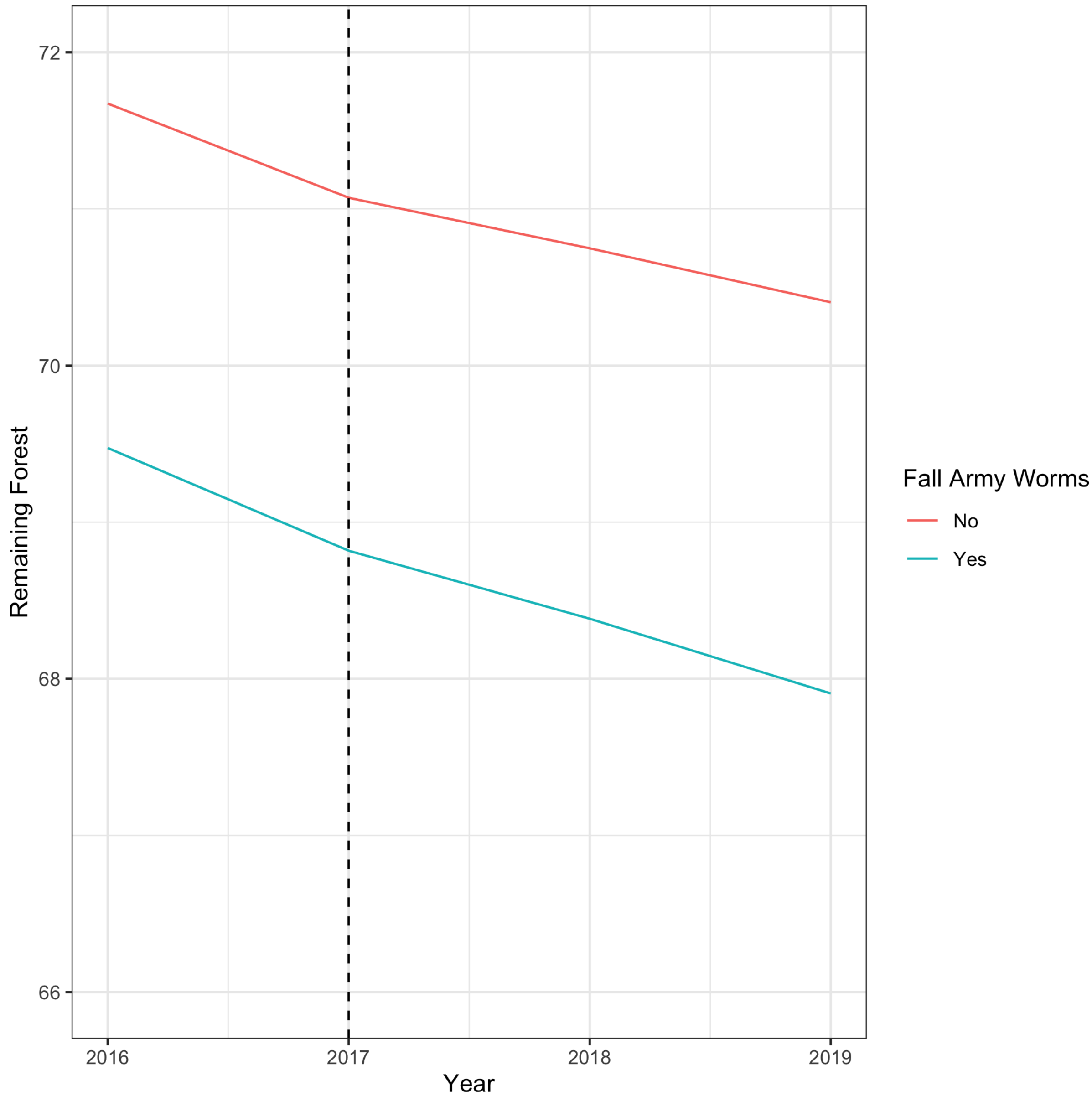

Figure A.5: Acess to forests in the baseline.

Figure A.6: The medium-sized charcoal kiln is constructed using small to medium-sized trees. The trees are cut from the stem, and together with the larger branches, are stacked to create a kiln where charcoal is made. As seen in the picture, the author is standing in an area that is completely cleared of trees for charcoal production.

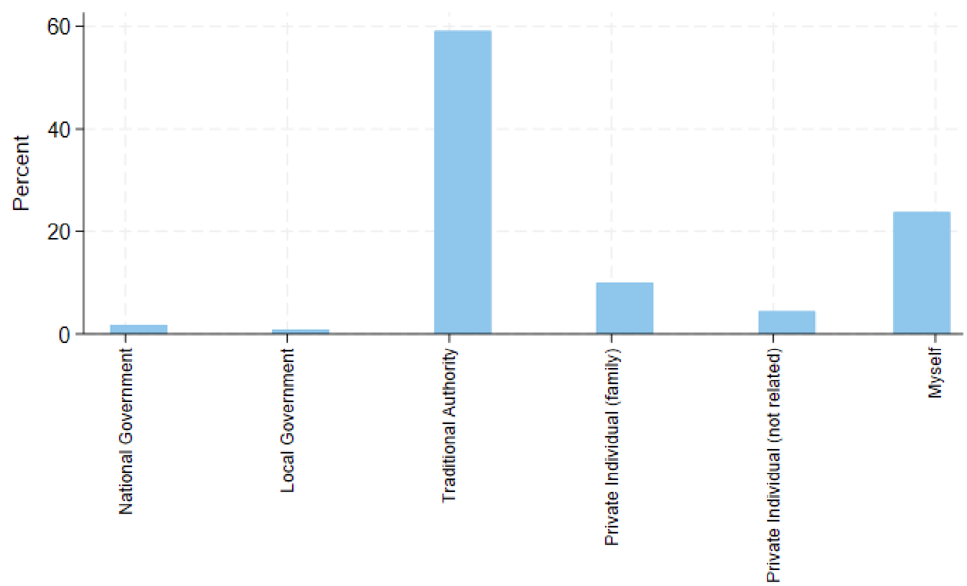

Figure A.7: Authority protecting the forest

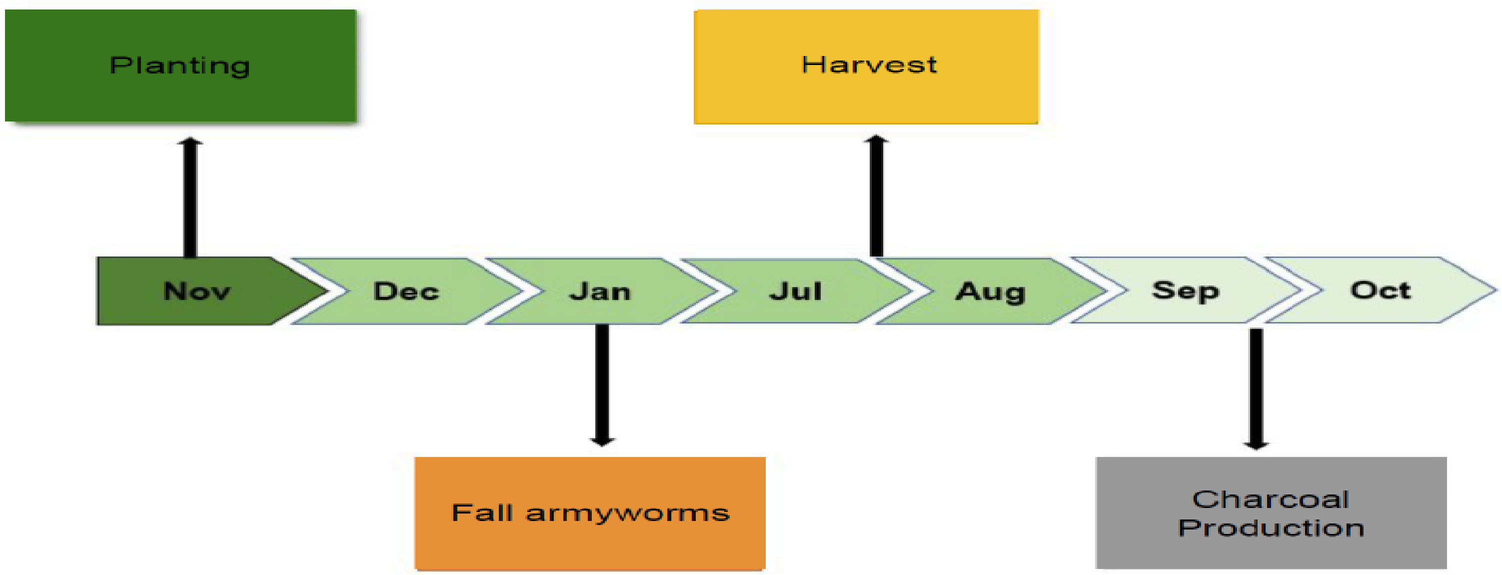

Figure A.8: Charcoal production and FAW timing.

Table A.5: Effects of FAW on Charcoal as a categorical variable (Robustness check)

	(1)
VARIABLES	Charc (=1 if yes)
1. Lag_Low intensity	0.0480***
	(0.0116)
2. Lag_Moderate intensity	0.0855***
	(0.0134)
3. Lag_High intensity	0.123***
	(0.0124)
Land cultivated (ha)	0.000372
	(0.000754)
Education	-0.00593**
	(0.00287)
Household size (Labor)	-0.00173
	(0.00127)
Weather controls	Y
Observations	2,325

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

Note: Controlled for weather variables in the form of rainfall, temperature, and their squared terms (weather controls)

Table A.6: First stage of coping strategies on charcoal production diagnostics results

VARIABLES	Maize share	Spraying	Crop diversification	Migration	Off-farm work
F-test	17.41	294.26	88.97	12.43	14.54
	(0.00310)	(0.0213)	(0.00397)	(0.00325)	(0.0125)
Robust Hausman test (χ^2)	57.45	43.65	34.43	33.54	28.76
	(0.016)	(0.0711)	(0.0134)	(0.0145)	(0.0123)

Table A.7: Robustness checks on the effect of FAW on charcoal production

	Effects of FAW		
VARIABLES	(1)	(2)	(3)
Lag FAW	0.0322***	0.0395***	
	(0.00534)	(0.00529)	
Ave campFAW			0.0378**
			(0.0117)
Spray		-0.01286*	
		(0.00842)	
Spray×LagFAW		-0.00149	
		(0.00151)	
Land cultivated (ha)	-0.00012	-0.00016	-0.00008
	(0.00071)	(0.00074)	(0.00074)
Education	-0.00637	-0.00386	-0.00662**
	(0.00309)	(0.00306)	(0.00308)
Household size (Labor)	-0.00196	-0.00115	-0.00182
	(0.00132)	(0.0013)	(0.00141)
Weather controls	Y	Y	Y
HH FE	Y		
Year FE	Y		
Observations	2,478	2,478	2,478

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

Note: Controlled for weather variables in the form of rainfall, temperature, and their squared terms (weather controls)

Table A.8: Alternative Difference-in-Differences Estimators - Robustness Check

	Point Estimate	Standard Error
Borusyak-Jaravel-Spiess	0.034*	0.012
Callaway-Sant'Anna	0.038**	0.043
DeChaisemartin-D'Haultfeuille	0.052*	0.041

Note: All these models do not include controls

Table A.9: First stage of Coping strategies on Charcoal production

	(1)
VARIABLES	Charc (=1 if yes)
Maize share	-0.06755**
	(0.02459)
Maize share * FAW	-0.00168
	(0.01283)
Crop diversification	-0.02171
	(0.02006)
Crop diversification * FAW	0.03211
	(0.00788)
Migration	0.00890
	(0.01967)
Migration * FAW	-0.00213
	(0.01407)
Off farm work	0.00583
	0.01139)
Off farm work * FAW	0.01311
	(0.00926)
Spray	-0.00739
	(0.00821)
Spray * FAW	-0.00179
	(0.00147)
Weather controls	Y
Observations	2,327

Standard errors in parentheses

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

Note: Controlled for weather variables in the form of rainfall, temperature, and their squared terms (weather controls)

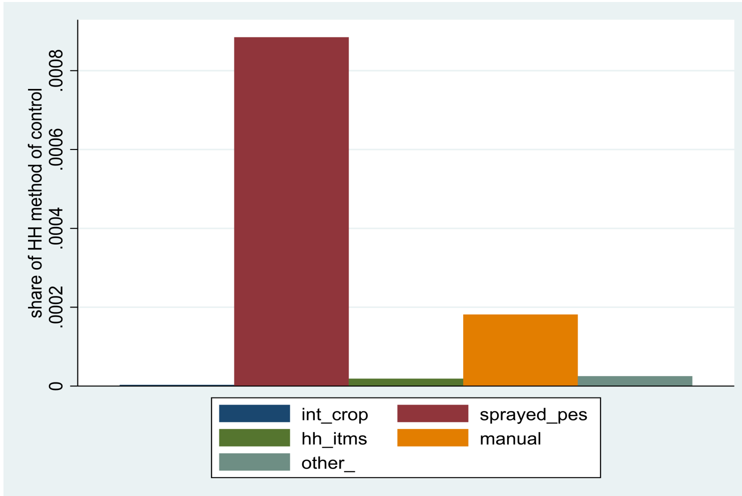

Figure A.9: Methods of Control of FAW.

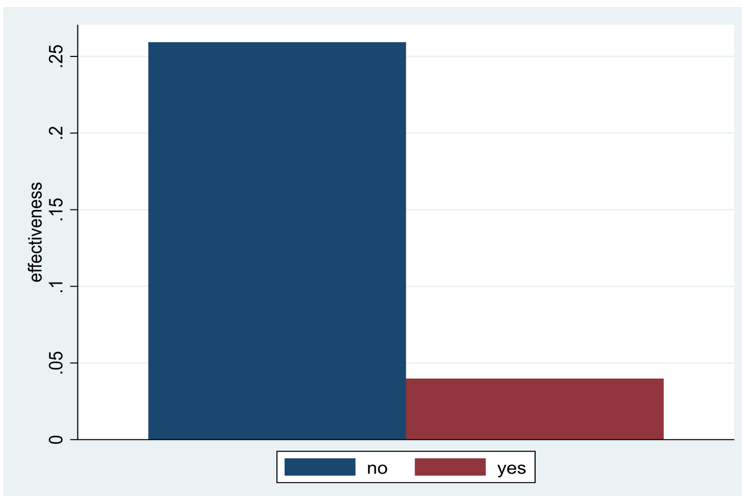

Figure A.10: Effectiveness of the insecticide.

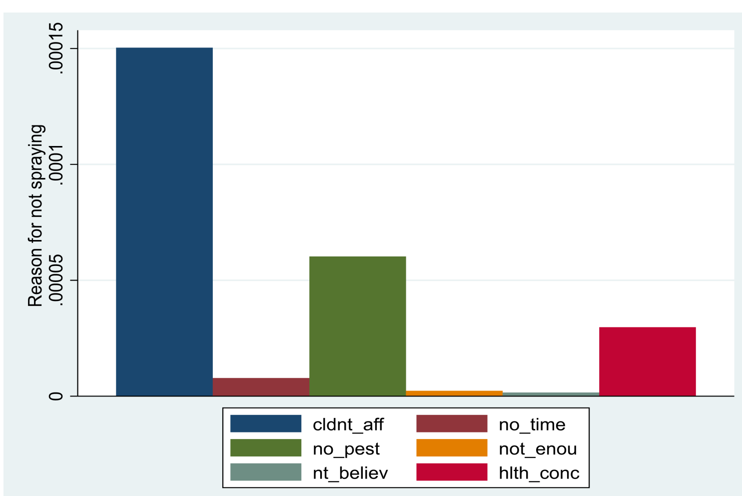

Figure A.11: Reason for not spraying.

A.2. Addressing Misreporting and Spatial Correlation

The instrument used in this study for all the equations above is the camp-level average of FAW intensity responses, excluding the observed household. I specify the instrument as follows:

$$CA_{ic} = \left[\sum_{i=1}^{n} FAW_{it}\right] / (n-1) \tag{14}$$

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 minus one.

The sum of the camp-level average response (IV) is an exogenous variable and highly correlated with household-level reported infestations through spatial spillover. The household's infestation intensities depend on the FAW intensities of neighboring farms within the camp. If the infestations in the camp are high, it is likely to affect the observed household's infestation intensities. However, my IV is uncorrelated with maize yields and other unobserved variables. The average camp-level infestations only determine maize yields through the spillovers to the households in the camp and do not directly affect the intensity of maize yields for the households in the camp. Thus, the IV meets the exclusion restriction, making it a valid instrument.

B. Charcoal Prices and Fall Armyworm: Assessing Spillover Effects on Economic Outcomes

Table A.10: Effects of FAW on Charcoal Prices (as percentage change)

	(1)	(2)
VARIABLES	Charcoal Price (%)	Charcoal Price (%)
Lag FAW	0.0126	0.0126
	(0.0556)	(0.0621)
Controls	N	Y
Year FE	Y	Y
District FE	Y	Y
Observations	1,634	1,572

* Note: Controlled for weather variables (rainfall, temperature, and their squared terms).
Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1