Crop Shocks: Farmer Responses to Past Pest and Disease Losses in Malawi

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April 27, 2020

Abstract

Pests and diseases are an important cause of crop losses globally, but their impacts on smallholder farm livelihoods have not received as much attention as the impacts of weather and price fluctuations, potentially due to limited data on pest and disease prevalence at a fine spatial and temporal level. I address this gap using panel data from farm households in Malawi who report causes of preharvest losses including pests and diseases. Applying household fixed effects and controlling for planting decisions which may affect vulnerability, I find that households that experienced preharvest losses from pests or diseases apply 25% more non-harvest labor inputs per acre and purchase 65% more seed per acre in the following season relative to households that did not. Other input and livelihood decisions are largely not affected. Impacts of a prior season pest/disease shock on current season inputs are not driven by tighter resource constraints following an adverse effect of the shock on the value of crop production in that season. Instead, households may be updating beliefs about the probability of experiencing a pest/disease shock. Households purchase more seed only in the season immediately following a pest/disease shock. This does not seem to be due to constraints on saving seed but may rather reflect a desire to acquire more tolerant/resistant seed varieties. Labor input decisions seem to reflect recency or availability bias, with impacts driven by more recent pest/disease shock realizations.

1. Introduction

Farmers deal with a wide variety of sources of preharvest losses, both abiotic (lack or excess of water, extreme temperatures, high or low irradiance, poor nutrient supply) and biotic. Sources of biotic losses include weeds, animal pests, and plant pathogens and viruses. Oerke (2006) reports estimates of losses due to biotic factors for six major crops globally, and finds that total global potential crop production losses from these sources varied from 50% for wheat to over 80% for

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cotton, and that actual losses ranged from 26% for soybeans to 40% for potatoes, with wheat, rice, maize, and cotton losses falling somewhere in between. Several studies report that vulnerability to such losses may grow with climate change as the range of certain pests and diseases expands (Dhanush et al. (2015), Garrett et al. (2013), Lamichhane et al. (2015)). As a recent example, in 2016 Fall Army Worm spread from the Americas to Sub-Saharan Africa and resulted in farmers losing up to 100% of their crop in many areas across the continent in the season the pest arrived. While a broad literature analyzes how farm households attempt to prevent, respond to, and cope with biotic and abiotic shocks during a given growing season, few studies consider the longer term impacts of such shocks. Those that do have largely focused on long-term effects on consumption (see for e.g., Dercon et al. (2005)). The literature on long-term impacts on livelihood decisions largely focuses on abiotic shocks. Ji and Cobourn (2018) report that farmers in Idaho overreact to more recent fluctuations in weather and water reliability when making acreage and crop allocation decisions. Soumaila and Dillon (2019) find that households that face more weather and output price variation in Malawi reduce fertilizer application and adoption of improved seed.

As far as I am aware no paper considers whether pest and disease ("PD") shocks affect farm household livelihood and decisions in subsequent years. This is an important question as such shocks may be more idiosyncratic than weather shocks, for example only affecting households growing certain crops, and may alter the impacts on farm output of weather realizations if these favor the proliferation of pests and diseases. Responses to PD shocks may also have externalities, as crop protection/pest deterrence measures may also help protect neighboring fields while spraying pesticides may have adverse health and environmental consequences. This paper addresses this gap by asking whether farm households in Malawi that report losing a portion of their planted area to damages from pests or diseases in a given season make different farm input decisions in subsequent seasons. Pests and diseases are the second most cited production risk in Malawi after weather (Giertz et al. (2015)), though data on prevalence of particular pests and diseases and on estimated losses from pests or diseases are limited. Indeed, the lack of data on pest and disease presence at a fine geographic and temporal level is a major constraint on analysis, in contrast to more readily available data on weather and prices. I attempt to overcome this limitation using seasonal reports of crop losses by cause from the Malawi Integrated Household Panel Survey (IHPS), and leverage the panel nature of the data to address concerns over selection into reporting of such losses.

Using household fixed effects and controlling for basic household characteristics, geography, and planting decisions in the prior rainy season that may affect vulnerability, I present the first estimates of farm production decisions responses to past crop PD shock realizations. My results are identified by variation within households of prior season PD shock experiences. A prior season PD shock increases non-harvest labor by 21 days per acre, an increase of over 25% relative to mean labor application, and are large compared to the effects of prior season preharvest losses due to drought or irregular rains, the most common shocks reported in the data. There is no effect on use of pesticide or herbicide; few households in the sample of largely smallholders ever use these inputs suggesting possible access and resource constraints. Prior season PD shocks also have no effect on most other household livelihood decisions. Increases in non-harvest labor intensity are driven by increases in household labor, the input with which households may have most ability to re-optimize following a shock realization. Farm labor increases are not accompanied by decreases in household participation in other forms of employment, suggesting the increase mainly reduces slack in household labor employment. I find no effects on crop area allocation or on other inputs which I have data, with the exception of a large increase on the value of seed purchases per acre. Seed purchases per acre increase by over 65% relative to the mean after a season with a PD shock but do not increase following other types of preharvest losses, suggesting the effect is not due to inability to save output as seed stock following a shock. Households with a prior season PD shock are more likely to travel far from their village to purchase seed, which suggests they may be seeking varieties more tolerant of or resistant to PD shocks.

The results indicate that PD shocks do not significantly reduce the value of crop production after controlling for household characteristics and planting decisions, which may explain why farm households do not change many of their production decisions the next season. Other prior season crop shocks, particularly drought and irregular rains, appear to affect a larger portion of farm area planted and have more severe impacts on output value, though estimates of output value may suffer from measurement error from estimation of prices for unsold crops. However, prior season PD shocks do negatively impact measures of household food security. The fact that farm households increase their labor allocations in seasons following a season with a PD shock suggests that farmers may perceive a change in PD risk and see a benefit from re-optimizing their production decisions.

Along these lines, I explore two main mechanisms by which prior season pest or disease shocks may be affecting household decisions in the next growing season. First, if separation between farm and household decisions does not hold farmers may face a tighter resource constraint for their input decisions in the season after a preharvest shock. Results are broadly unchanged after controlling for the value of prior season agricultural production, and its interaction with prior season PD shocks is generally not significant, which suggests that this is not the main mechanism. Second, if farm households update their beliefs about the probability of a pest or disease shock each season, they might change their decisions in response to a shock depending on how they are updating beliefs. Testing this mechanism is difficult with so few years of data, but I consider a few possible models of household belief updating. Results for labor decisions are consistent with farmers placing greater weight on more recent shock realizations when forming expectations, while seed purchases appear to be heavily influenced by the most recent shock realization only.

This paper contributes to the literature on farm household responses to agricultural shocks in low-income countries. While several studies of the impacts of pest or disease shocks (Dercon and Krishnan (2000), Dimova et al. (2015), Lazzaroni and Wagner (2016), Porter (2012), Teklewold et al. (2013), Tibesigwa et al. (2016), Wagstaff and Lindelow (2010)) or weather and price shocks (Hoddinott (2006), Ito and Kurosaki (2006), Kochar (1999), Nikoloski et al. (2018)) analyze impacts on household consumption or coping mechanisms, this paper is the first to ask whether and how pest or disease shocks affect farm household decisions in subsequent seasons. Anderson et al. (2018) find that households in Malawi that experience lean season hunger harvest their first crop earlier, but do not test whether seasonal hunger is affected by prior season production shocks. Di Falco and De Giorgi (2019), Ji and Cobourn (2018), and Soumaila and Dillon (2019) consider the long-term impacts of weather and price fluctuations. I extend the analysis beyond weather and price, for which external data are generally available at a relatively fine spatial and temporal scale, to pest and disease shocks where such data are not readily available leading to reliance on farmer reports.

My findings also contribute to a broader literature on learning and belief updating following shocks. Kelly et al. (2005) present a model of firm learning about changes in the distribution of a shock, and estimate adjustment costs to climate change for farmers. Davis (2004) considers how households may update their perceived cancer risk, and measures effects on housing values. Gallagher (2014) analyzes take-up of flood insurance in years following a flood in individuals' own and nearby communities, and finds that patterns are most consistent with Bayesian learning that allows for forgetting or incomplete information about past floods. Ji and Cobourn (2018) find that farmer decision-making in Idaho is inconsistent with strict Bayesian updating and reflects other cognitive heuristics. My results on the possible belief updating channel for impacts of prior season pest and disease shocks on farm household decisions extend the literature on learning mechanisms to a new type of fluctuations which is of great importance to farm livelihoods in Sub-Saharan Africa but whose long-term effects are not well studied.

2. Theory

I assume farm households are risk averse and use inputs X to produce output where there the production technology can be represented by a well-behaved production function $G(.)$[1]. The farmer receives output price p and pays input prices r. I assume farmers take these prices as given[2]. The farmer faces production risk from a variety of factors represented by a random vector W which enters into the production function. The shock probabilities are distributed according to some function $\psi(\omega, \rho)$ known to the farmer, where ω is the mean realization and ρ is the variance. Timing is such that farmers choose inputs X_t (which may include productive and defensive actions) prior to the realization W_t of random shocks, and then realize farm output. Suppose farm production decisions for a farm household are separable from their consumption decisions. The farmer solves

$$\max_{X_t} E_t[U(\pi_t)] = \max_{X_t} \int_{W_t} U[p_t G(X_t, W_t) - r_t X_t]\psi(\omega, \rho) dW_t \quad (1)$$

where $U(.)$ is the von Neumann-Morgenstern utility function and π_t is agricultural profit. Then farmer optimization gives ex ante demand for inputs as a function of prices and the shock distribution parameters, $X_t^* = X(\omega, \rho, p_t, r_t)$. In this model, farmers know the distribution of shocks and

[1]For simplicity I ignore considerations around the choice of crop or crop combinations, though these could be represented by crop-specific production functions. Alternatively, $G(.)$ could include additively separable crop-specific production functions normalized such that all crop ouput has the same value. $G(.)$ can similarly incorporate normalized functions for livestock and non-farm household enterprise production and casual wage labor. I abstract from these possibilities and mainly consider aggregate crop output.

[2]This is a reasonable assumption given the small size of farm households in the Malawi IHPS study, where mean landholdings are 2.8 acres - about the size of 1.5 soccer pitches. I ignore uncertainty around prices in this simple model, to focus on uncertainty around biotic shocks.

its parameters which do not vary over time, so optimal input decisions each period are not affected by shock realizations in prior periods.

Two primary mechanisms could explain an effect of a prior season shock realization on farm household production decisions. First, if separation of the household's production and consumption problems fails and households pay for both their own consumption and agricultural inputs from the value of their agricultural output, an adverse shock realization reducing household farm profit one season will tighten the resource constraint the household faces in choosing inputs the next season. The majority of households in my sample are smallholder farmers that consume a large portion of their crop production, and depend on sales of output to finance next season inputs. Credit markets are limited in this context, meaning households are also limited in their ability to borrow to finance production[3]. In addition, agricultural insurance was generally unavailable to farm households during the period studied, meaning that they bore all risk from crop production shocks. Though households may receive support through informal community insurance networks, it is reasonable to think of them paying for inputs from the value of their production. A FAO (2018) report on smallholders in Malawi estimates that these households spend on average 45% of the value of their crop production on inputs, and that only 6% have access to credit.

I present a simple two period model with no borrowing or farm insurance to explain this mechanism. The household problem is:

$$\max_{C_1,C_2} U(C_1) + \beta U(C_2) \text{ s.t. } q_t C_t \leq E_t[p_t G(X_t, W_t) - r_t X_t + S_t] \text{ and } r_t X_t \leq S_t \quad \forall t \tag{2}$$

C_t is a composite consumption good with price q_t. I suppress the conditions giving the change of prices q_t, p_t, r_t over time but assume these are not time-varying and are known to the household. S_t represents household savings from the prior period, with S_1 given and $S_2 = \pi_1 - C_1$. In this model, the household chooses the sequence of input decisions $\{X_t\}$ and consumption $\{C_t\}$ at the start of period 1 to maximize present utility of the stream of consumption given expectations about exogenous shocks W_t, and may revise its period 1 consumption decision after the shock realization

[3]The mean number of loans taken in the past 12 months by households in the panel sample is 0.19 and the mean total amount borrowed is 3048 MK (worth around USD 8 at the time). 81% of households did not borrow on credit from someone outside the household or from an institution in the past 12 months.

W_1. At the start of period 2 the household can reoptimize its production decisions given how the realization of W_1 and the choice of C_1 affect its resource constraint. Finally, the household consumes all of its profit at the end of period 2. An adverse shock realization in period 1 would lead to a smaller than expected π_1, and given the choice of C_1 (which may be subject to some minimal level of survival consumption), the household may be more tightly constrained in optimizing its period 2 input decisions. In this way, a prior season pest or disease shock could be expected to affect subsequent household production decisions, through its effect on prior season agricultural profit.

An alternative mechanism by which prior season shock realizations could affect production decisions is if households are updating their beliefs about the parameters of the shock distribution over time, rather than assuming the household treats the parameters as constants. In this scenario, a farm household that experienced a pest or disease shock the prior season may update its beliefs and consider itself more likely to experience such a shock in the current season, and adjust its production decisions accordingly. Suppose the farmer believes $W_t \sim S(\{W_s\}_{s=0}^{t-1})$, where $S(.)$ is a particular distribution and the farmer's subjective estimate of the distribution parameters at time t is based on the history of shock realizations $\{W_s\}_{s=0}^{t-1}$. Initial beliefs are based on the empirical distribution of shocks at time 0 at some level of aggregation. In season t the farmer's problem is

$$\max_{X_t} E_t[U(\pi_t)] = \max_{X_t} \int_{W_t} U[p_t G(X_t, W_t) - r_t X_t] S(\{W_s\}_{s=0}^{t-1}) dW_t \tag{3}$$

As the farmer's beliefs about the distribution is a function of prior shock realizations, the farmer's optimal production decisions may be affected by prior season shocks, since demand for inputs becomes $X_t = X(\{W_s\}_{s=0}^{t-1}, p_t, r_t)$. The farmer may update beliefs in a variety of ways including Bayesian updating, but may also be subject to forgetting, recency bias, or other learning heuristics.

3. Data

I use data from the 2010-11 and 2013 waves of the Malawi Integrated Household Panel Survey (IHPS) collected by the Malawi National Statistics Office (NSO) as part of the World Bank's Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA). Each survey wave observation includes questions on the current and prior rainy season[4]. For the prior season,

[4]The rainy agricultural season in Malawi refers to the period between November and May for the majority of the country, though there is some spatial variation in the start and end dates of the rains and timing of production may

households give information about planting decisions and harvest outcomes by crop, but are not asked about inputs. Current season modules include more detailed questions about inputs and farm outcomes. Thus within a given observation, I can test the impact of the prior planting season outcomes on current season decisions. I refer to the 2008-09 and 2011-12 seasons as *prior* rainy seasons and the 2009-10 and 2012-13 seasons as *current* rainy seasons in the first and second survey wave, respectively. I do not have data on the 2010-11 season.

A major challenge with analyzing the effects of pest and disease shocks on farm households is the lack of exogenous data on pest and disease prevalence at a fine geographic and temporal level. Although recent efforts are being made to track the spread of certain pests in low-income countries, such as Fall Army Worm across Sub-Saharan Africa, these data are too recent to match to existing panel survey data from households in the affected areas. For the purpose of this analysis, I consider self-reported preharvest crop shocks. For each crop on each plot, respondents are asked whether the area harvested was less than the area planted, and if yes, to list the top two reasons for this area loss (the data do not include questions on the extent of the preharvest losses caused by the shock). I consider a household as having experienced a preharvest pest or disease (henceforth "PD") shock if they report losing some of their area planted on any plot due to damage from insects or diseases[5]. This should be a conservative measure of preharvest PD shocks, as only losses severe enough to lead to complete loss of a portion of the plot are counted, as opposed to losses spread evenly across a plot. Further, respondents are only allowed to list two reasons for preharvest losses for a given crop. The most common reasons given are drought and effects of irregular rains or flooding; a combination of multiple factors leading to preharvest losses may lead to underreporting of PD shocks. This measure is thus likely to capture only particularly severe preharvest PD losses. Households reporting a PD shock are therefore likely those that experience greater prevalence of

also vary somewhat by crop. Some households in Malawi also have a second "dry season" agricultural production cycle each year, though the crops grown in this period often differ from those in the rainy season (NSO (2014)). My analysis focuses on rainy season, production when nearly all farm household grow crops.

[5] As far as I am aware there were no major insect or crop disease outbreaks in the years included in the study, so the shocks do not represent some broad aggregate spread of a new pest, as is the case for example with the later arrival of the Fall Army Worm. Therefore the shocks are likely more localized and due to circulation and proliferation of pests largely already present in parts of Malawi. The PD shocks that households experience may be due to the arrival of a new pest to their area, a bad draw from the distribution of prevalence of an existing pest, or a change in production decisions that left them more vulnerable to pests. Without data on the prevalence of pests or disease it is not possible to disentangle the reasons for household PD shock reports.

pests or diseases or those that were least able to prevent or mitigate damages. The latter possibility suggests the need to attend to possible selection of households in reporting PD shocks.

Table 1 presents summary statistics on shocks to crop output reported by households in the prior and current rainy seasons. I restrict my analysis to the panel of households that cultivate crops and are observed in both waves. This omits non-farm households, Wave 1 households not surveyed in Wave 2, and households of individuals that split off from Wave 1 households and are surveyed separately in Wave 2. I refer to this as the panel sample, and separately report statistics for the full panel sample and for Wave 2 panel households as later analyses focus on this subsample.

Table 1: Household reports of preharvest and postharvest losses, by season

	Full Panel Mean	SD	Wave 2 Mean	SD	Wave 1 = Wave 2 t-test p-value
Prior Season					
Any preharvest loss	0.418	0.493	0.480	0.500	0.000***
Pests/Diseases	0.039	0.193	0.038	0.192	0.933
Drought	0.120	0.325	0.158	0.365	0.000***
Irregular rains/Flooding	0.137	0.343	0.158	0.365	0.000***
Lack of labor	0.044	0.204	0.051	0.221	0.017*
Other cause of preharvest loss	0.182	0.386	0.207	0.405	0.000***
Any EA pest/disease loss	0.353	0.478	0.349	0.477	0.611
Any postharvest loss	0.158	0.365	0.128	0.335	0.000***
Current Season					
Any preharvest loss	0.598	0.490	0.618	0.486	0.012*
Pests/Diseases	0.060	0.238	0.081	0.273	0.000***
Drought	0.198	0.398	0.115	0.320	0.000***
Irregular rains/Flooding	0.276	0.447	0.318	0.466	0.000***
Lack of labor	0.042	0.200	0.054	0.226	0.000***
Other cause of preharvest loss	0.228	0.419	0.294	0.456	0.000***
Any EA pest/disease loss	0.465	0.499	0.583	0.493	0.000***
Any postharvest loss	0.092	0.289	0.099	0.298	0.179
Observations	3814		1907		

Preharvest loss variables are dummies for whether a household reported losing part of its planted area for any crop on any plot due to damage from a particular cause, with exception of "Any EA pest/disease loss" which is a dummy for whether any household in the EA reported preharvest pest/disease losses. Postharvest loss variables are dummies for any postharvest crop loss in a particular season.
Wave 1 statistics are not shown, but the last column presents p-values of t-tests of the equality across waves.
*p<.10, **p<.05, ***p<.01

Reports of preharvest losses are higher in the current than in the prior season. For pest/disease preharvest losses in particular, 3.9% of households report a prior season shock compared to 6% in the current season. This may suggest variation in the intensity of these stressors across seasons or respondent recall issues. Wave 2 households are significantly more likely to report having experienced preharvest losses for nearly all causes, for both the prior and current season. This suggests households faced greater stress from these biotic and abiotic factors in 2012-13 compared to 2009-10. PD shocks are not concentrated in any particular part of Malawi. On average in a given season between a third and half of households are in an Enumeration Area (roughly corresponding to villages and typically including around 20 sampled households) where at least one household reports a PD shock, and around 3/4 of districts have at least one household reporting a PD shock.

Shock reports appear to align with observed variation in weather realizations measured at the EA level[6]. In particular, deviations in rainfall relative to the 10 year average have a significant positive impact on the likelihood that a household reports PD and rains shocks, and a negative impact on drought shocks. This is consistent with prevalence of many types of pests and diseases typically being higher when there is early rainfall to create conditions for their growth.

It is likely that certain preharvest shocks are spatially correlated. I explore spatial correlations in shock reports by regressing household reports of a given preharvest shock on the share of households in the district/EA reporting that type of preharvest shock, excluding the household itself (and dropping EAs with fewer than 6 households in the panel sample)[7]. In general, the probability that a household reports a PD, drought, or rainfall shock is significantly increasing in the share of households in the EA or district that report experiencing that same shock. The relationship is stronger for drought and rainfall than for PD shocks, and weaker at the district level. By way of comparison, for theft shocks the coefficients are very close to 0. I control for spatial correlation in my empirical specification by clustering standard errors at the district level.

Table 2 presents summary statistics for the full panel sample (with each household appearing twice) and for the subset of households reporting a prior season PD shock in a given wave. The top 1% of continuous variables are winsorized, and values in Malawian Kwacha (MK) are all expressed in 2013 values to account for inflation[8]. Households in the sample are typically male-headed with around 5.5 household members and just over 2 plots, on which they plant over 2.5 acres of crops, usually planting 2 crops (not distinguishing among varieties within crops)[9]. Most households grow at

[6]Results available upon request. Further extension of this research could incorporate daily temperature and rainfall data, which may be more precise than the aggregate and quarterly data included with the data.

[7]Results available upon request

[8]For reference, in 2013 1 USD was worth around 330 MK at international exchange rates.

[9]Households are asked about 27 crop categories, and I count the number of crops using these categories, though I aggregate categories when reporting area planted.

Table 2: Household summary statistics, by household report of prior season pest/disease shock

	Full Panel			PD Shock			PD Shock = No PD
	Mean	SD	Med.	Mean	SD	Med.	t-test p-value
Household characteristics							
Age of household head	45.475	16.206	42.0	43.646	15.616	40.0	0.163
Education of household head (years)	5.166	4.101	5.0	5.714	3.839	6.0	0.098*
Male household head	0.761	0.427	1.0	0.755	0.431	1.0	0.873
Number of household members	5.307	2.344	5.0	5.469	2.255	5.0	0.392
Number of plots	2.206	1.152	2.0	2.592	1.374	2.0	0.000***
Geographic characteristics							
Distance to nearest road (km)	9.449	9.562	6.1	8.626	8.515	6.0	0.287
Avg 12-month total rainfall (mm)	849.315	91.109	822.0	849.933	94.508	833.0	0.933
Elevation (m)	909.084	329.499	930.0	877.689	391.163	800.0	0.239
Nutrient availability constraint[a]	1.689	1.268	1.0	1.660	1.372	1.0	0.776
Soil workability constraint[a]	1.896	1.315	1.0	2.061	1.444	2.0	0.121
Prior season crop variables							
Area planted (acres)	2.504	7.238	2.0	2.658	1.728	2.2	0.792
Count of crops planted	2.189	1.122	2.0	2.735	1.240	2.0	0.000***
Maize acres planted	0.913	6.606	0.5	0.706	0.854	0.5	0.698
Hybrid maize acres planted	0.580	1.263	0.0	0.603	0.700	0.5	0.818
Rice acres planted	0.142	0.956	0.0	0.125	0.370	0.0	0.824
Other grains acres planted	0.267	1.036	0.0	0.272	0.450	0.0	0.950
Tobacco acres planted	0.053	0.495	0.0	0.046	0.207	0.0	0.857
Groundnut acres planted	0.107	0.404	0.0	0.168	0.761	0.0	0.059*
Beans acres planted	0.172	0.662	0.0	0.174	0.496	0.0	0.972
Pigeon pea acres planted	0.034	0.221	0.0	0.041	0.187	0.0	0.657
Potato acres planted	0.090	0.414	0.0	0.142	0.492	0.0	0.118
Cotton acres planted	0.067	0.515	0.0	0.248	0.643	0.0	0.000***
Other crops acres planted	0.079	0.455	0.0	0.131	0.401	0.0	0.153
Any preharvest non-pest/disease crop loss	0.357	0.479	0.0	0.558	0.498	1.0	0.000***
Any postharvest crop loss	0.158	0.365	0.0	0.408	0.493	0.0	0.000***
Total value of crop production (MK 1000s)	91.948	171.342	40.9	101.683	168.752	44.2	0.482
Current season crop variables							
Any pesticide or herbicide use	0.057	0.231	0.0	0.143	0.351	0.0	0.000***
Non-harvest labor days per acre	81.675	81.036	58.1	96.124	101.660	65.6	0.027**
Harvest labor days per acre	20.872	22.984	13.0	24.500	26.800	14.3	0.051*
Seed purchases per acre (MK 1000s)	0.752	1.548	0.0	1.114	1.905	0.1	0.004***
Fertilizer/chemical input purchases per acre (MK 1000s)	5.248	10.408	0.0	6.255	11.579	0.2	0.231
Total input and labor purchases (MK 1000s)	14.143	27.495	2.7	16.416	28.575	6.0	0.307
Total value of crop production (MK 1000s)	152.602	455.522	44.3	152.450	500.254	47.1	0.997
Observations	3814			147			

Summary statistics for households that did not report a pest/disease shock the prior rainy season are not shown, but the last column presents p-values of t-tests of the equality across groups. [a] 1=no/slight, 2=moderate, 3=severe. *p<.10, **p<.05, ***p<.01

least some maize, with no other crop grown by more than half of households. Few households use any pesticide/herbicide, and most households do not report any purchases of seed or fertilizer/chemical inputs[10]. Paying for casual labor accounts for most of the median household's total input and labor purchases. I do not impute costs for inputs the household does not purchase, such as saved seed, household labor, or land. I calculate the value of crop production by valuing all crops sold by the household at the value for which they were sold, and then back out prices to value unsold crops as follows. If the household sold the crop, all unsold quantity of that crop is valued at the household sales price. For crops the household did not sell, I use the median price at the lowest level of geography (EA, district, region, or country) for which I observe at least 5 households selling the crop. Crops with fewer than 5 sales observations nationally are not valued.

Most variables are not significantly different across households that do and do not report experiencing a prior season PD shock. Households reporting a prior season PD shock have about 0.4 more plots, cultivated about 0.5 more crops in the prior season, allocated more area to groundnuts and cotton, and are more likely to report a postharvest crop loss. They are also more likely to report other prior season preharvest shocks, suggesting that certain shocks may be more likely to occur with a PD shock. Motivating our analysis, these households are more likely to use any pesticide or herbicide in the current season and also report more labor use and seed purchases per acre cultivated, but have nearly identical mean value of current season crop production.

4. Empirical Strategy

My empirical approach applies household fixed effects to compare production decisions by the same households in seasons when they did and did not experience a prior season shock. Taken together with controls for time-varying household characteristics, prior season planting decisions, and season fixed effects, this should allow me to causally identify the effect of the shock. This approach is used in other studies (Dercon and Krishnan (2000), Porter (2012), Tibesigwa et al. (2016)), though all of these consider effects of shocks on consumption within the same year, as opposed to the effects of a prior year shock. Household fixed effects regressions take the form

$$Y_{idt} = \alpha + \lambda PDShock_{idt} + H_{idt}\beta_1 + F_{idt}\beta_2 + \tau_t + \mu_i + \epsilon_{idt} \tag{4}$$

Y_{idt} are current season household production and livelihood decisions for household i in district d

[10]Most small farmers in Malawi rely on saved seed and informal local seed exchange networks (Nordhagen and Pascual (2013)).

in survey wave t[11]. $PDShock_{idt}$ is a dummy for whether the household experienced a preharvest PD crop loss shock in the season prior to the rainy season in wave t[12]. Since Table 2 suggests households may experience multiple shocks simultaneously, in F_{idt} I include controls for all other categories of prior season shocks to ensure the coefficient on PD shocks does not reflect impacts of other co-occurring shocks. μ_i is a household fixed effect, τ_t is a wave fixed effect, and ϵ_{idt} is an error term. For all specifications, I cluster standard errors at the district level. Based on equation (1), if farm households separate their production and consumption decisions and are not updating their beliefs, I showed that farmer production decisions should depend only on current season prices and the parameters of the shock distribution. We would therefore expect $\lambda = 0$. The combination of household and wave fixed effects will capture effects of differences in prices faced by the household in the production decisions, as well as fixed beliefs about the distribution of crop shocks.

Certain farmers may be more susceptible to particular shocks based on their location or choice of crops. In addition, farmers taking some preventive or damage control measures are less likely to be report a crop loss shock for a given level of PD prevalence. Relying on farmer reports of shocks rather than outside data means that I may only observe shocks among a selected sample of farmers. While the household fixed effects will capture time invariant factors that may make households more vulnerable to a PD shock, I also include a series of control variables that may affect the likelihood that households report such a shock to account for this possibility. H_{idt} is a vector of household characteristics that can be considered fixed before the realization of the prior season shock, including age, education, and sex of the household head, household size, number of plots and geographic variables[13]. These household and geographic variables do not vary much over time so are largely absorbed by the household fixed effects. Results do not vary much when they are excluded, but I include them to capture any possible effect of variation in these measures on vulnerability to PD shocks. F_{idt} is a vector of prior season farm variables including other shocks and

[11]The majority of the variables in this specification are reported at the household level, so I conduct my analyses at that level. However, preharvest loss data and some production decisions data are collected at the crop level or below. Future research may consider an analysis of the effects of shocks at the plot or crop level.

[12]Ideally I would instrument for shock reports, but I lack objective data on exogenous PD shock correlates that satisfy the exclusion restriction. The lack of data on pest prevalence in particular is a significant limitation to this analysis.

[13]Household geographic variables include distance to a paved road, annual mean rainfall, elevation, nutrient availability, and soil workability.

production decisions made before the realization of the shocks, notably the count of crops cultivated and area planted to specific crop categories[14]. The data do not include information on prior season inputs. As noted, I also control for other prior season preharvest and postharvest shocks, to isolate the effect of PD shocks in particular.

The household control variables may have some effect on production decisions through their effects on the production function, but I include them because they may also capture factors which affect households' vulnerability to preharvest losses. Households with very young or uneducated household heads may have less experience on how to prevent crop losses, while households with female household heads may lack the resources, and households with old household heads or few members may lack the household labor needed to prevent or mitigate losses. Households with more plots may lack the ability to adequately monitor all of them. Prior season planting decisions may also affect households' vulnerability if particular crops are more prone to PD losses or if more planted area increases the difficulty of protecting the full area from pests/diseases. The wave fixed affects may also capture differences in vulnerability over time. I argue that the combination of household and wave fixed effects together with pre-shock planting controls and household and geographic controls address concerns about selection into which households report experiencing a pest/disease shock, so that estimated prior season PD shock impacts λ can be interpreted causally.

Most other studies that use self-reports to measure household shocks do not have panel data so use a selection on observables specification with location and time fixed effects (Dercon et al. (2005), Lazzaroni and Wagner (2016), Nguyen et al. (2020), Porter (2012), Teklewold et al. (2013), Tibesigwa et al. (2016), Wagstaff and Lindelow (2010)). I present only results using regressions with household fixed effects as I argue that these are superior to a selection on observables regression approach when panel data are available, but the basic results on the impact of a prior season pest/disease shock on next season crop production decisions are similar[15].

Among current season agricultural production decisions, I look first at pesticide and herbicide use because of its direct connection with prevention or mitigation of pest/disease shocks. I also focus on labor as this is a primary input that all households in the sample apply for farming, and

[14] I categorize crops as maize, hybrid maize, tobacco, groundnut, rice, beans, pigeon pea, potato, other grains, cotton, and all other crops based on the frequency in which these crops are reported in the sample

[15] Results available upon request.

because many of the recommended practices for dealing with crop pests and disease in Malawi, such as ploughing, intercropping, weeding, mulching, field monitoring, and removing pests by hand, involve increased labor inputs(MOA (2017)). I distinguish between harvest and non-harvest labor, as activities related to pest/disease prevention or control should primarily affect non-harvest labor. These variables are measured in days per acre planted and are summed across labor sources. In addition, I analyze impacts on seed purchases, since most households farm using saved seed and preharvest losses may reduce their ability to use save seed, or push them to purchase different varieties. Beyond these primary outcomes, I evaluate effects on fertilizer use, input purchases, number of crops planted, and crop diversity as measured by the Herfindahl index[16].

In addition, I consider effects on household livelihood decisions beyond crop production in the current season, as a change in resource constraints or beliefs about the shock distribution may lead farm households to reoptimize decisions across all household livelihood activities. I look at household area planted in acres, whether any household member engages in *ganyu* labor (short-term rural labor, largely agricultural and often informal), in wage labor, or in a non-farm enterprise, household livestock holdings (measured in tropical livestock units), sales of livestock and livestock products, the count of current household loans, and remittances and other transfers received by the household. I later analyze impacts of prior season PD shocks on measures of household welfare, looking at crop production value in the prior and current season and at total annual consumption per capita and measures of household food security in the 12 month period beginning after the prior rainy season harvest and ending after the current rainy season harvest.

5. Results

Table 3 presents the results of regressions of the impacts of prior season crop shocks[17] on current season livelihood decisions, following Equation (4). I include all shock types in each regression to control for the possibility that households might experience multiple shocks together and isolate

[16]The Herfindahl index is calculated as the sum of squared shares of area planted across all crops. A larger Herfindahl index indicates lower crop diversity by planted acres.

[17]I also analyze effects of current season shocks. There are generally no significant effects of any type of current season shock on current season agricultural decisions. This may be because households making the majority of input decisions prior to experiencing any shocks and have limited ability to respond to an unexpectedly bad shock realization. It may also be because some households change their production decisions in response to PD prevalence and are able to avoid a crop loss shock and so do not report one. There are also largely no significant effects of current season shocks on other household livelihood decisions. Results are available upon request.

the effects of each shock, though I only show coefficients for non-pest/disease shocks in Panel A.

Panel A shows impacts of different prior season crop loss shocks on current season production decisions. I find no effect of a prior season PD shock on pesticide/herbicide use, consistent with very few households using these chemicals in the sample, and with this not being a margin on which households are able to vary their production decisions. 84% of panel households that use pesticide/herbicide in the sample use it in both the 2010 and 2013 rainy seasons. A 2017 Malawi Ministry of Agriculture Pest Management Plan indicates that herbicides, pesticides, and other chemicals are mainly used on cash crops such as tobacco, tea, sugarcane, coffee, and cotton, and that some maize farmers use insecticides (MOA (2017)). While the panel household sample in the Malawi IHPS survey includes one large-scale tobacco farmer cultivating over 300 acres, the largest cotton producer cultivates 4.5 acres and the largest sugarcane producer cultivates less than 1 acre, while coffee and tea are not asked about specifically but grouped under "other" crops, suggesting their production is not common in the sample. Thus the sample of primarily smallholder farmers in this survey likely does not include the farmers most likely to use pesticides/herbicides in Malawi, at the time of the survey, even if some maize farmers do use insecticides.

Non-harvest labor increases by 20.8 days per acre cultivated, which represents a greater than 25% increase in labor application compared to the overall mean. This effect is driven by increases in household labor, which is consistent with this being the main crop input (besides plot area) that households can control and vary across seasons. In particular, land preparation labor increases by 12.5 days/acre (29%, suggesting more ploughing, intercropping, or other PD prevention techniques) and weeding, fertilizing, and pre-harvest labor increases by 5.5 days/acre (16%, suggesting more pest monitoring and control activities). I observe no significant impact on hired labor per acre, consistent with households that experience a shock perhaps having less savings with which to hire labor. The coefficient on harvest labor is positive by not significant, consistent with expectations that activities related to dealing with PD prevalence would primarily be non-harvest. However, I do find that household harvest labor increases significantly, by 4.6 days/acre (23%). There might be a mechanical effect on harvest labor if household labor allocated to crop production becomes somewhat fixed, so additional non-harvest labor would carry over into harvest activities. There could also be a mechanical impact on harvest labor if the increased non-harvest labor following a

Table 3: Effects of prior season agricultural shocks on current season agricultural and livelihood decisions

Panel A: Agricultural Decisions	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Any pesticide or herbicide use	Non-harvest labor days per acre	Harvest labor days per acre	Any organic fertilizer	Any inorganic fertilizer	Seed purchases per acre (MK 1000s)	Total input and labor purchases (MK 1000s)	Count of crops planted	Herfindahl index of crop diversity
Pests/Diseases	0.001	20.827**	3.509	0.035	0.018	0.488***	1.440	-0.097	0.014
	(0.041)	(8.949)	(2.314)	(0.045)	(0.040)	(0.127)	(1.145)	(0.118)	(0.028)
Drought	0.009	8.296	-1.441	0.018	-0.018	-0.200**	-0.884	-0.028	0.004
	(0.016)	(7.742)	(1.625)	(0.026)	(0.023)	(0.088)	(0.691)	(0.101)	(0.018)
Irregular rains/ Flooding	-0.014	-3.615	-2.663*	0.017	-0.017	-0.208***	-1.436**	0.041	-0.015
	(0.015)	(6.423)	(1.446)	(0.024)	(0.023)	(0.073)	(0.656)	(0.061)	(0.016)
Lack of Labor	-0.043*	-23.738**	-2.915*	-0.034	-0.038	-0.013	-1.692***	-0.052	0.009
	(0.021)	(9.140)	(1.676)	(0.040)	(0.044)	(0.144)	(0.581)	(0.123)	(0.021)
Other	-0.017	6.557	0.264	-0.020	-0.007	0.029	-0.573	0.090	-0.032**
	(0.013)	(4.584)	(1.410)	(0.023)	(0.019)	(0.090)	(0.634)	(0.083)	(0.014)
Any postharvest crop loss	0.007	4.652	1.742	0.023	0.014	-0.035	0.946	0.056	-0.005
	(0.013)	(5.973)	(1.335)	(0.024)	(0.018)	(0.088)	(0.617)	(0.090)	(0.019)
Mean of Dependent Variable	0.057	81.675	20.872	0.202	0.808	0.752	7.283	2.654	0.552
Panel B: Livelihood Decisions and Outcomes	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Area planted (acres)	Any wage labor	Any ganyu labor	Any non-farm enterprise	Tropical Livestock Units	Livestock sales (MK)	Livestock product sales (MK)	Count of current loans	Log remittances (MK)
Pests/Diseases	-1.853	0.063*	0.040	0.005	-0.012	-2264.299	-95.522	0.047	-0.022
	(2.095)	(0.033)	(0.050)	(0.042)	(0.045)	(1741.585)	(166.899)	(0.059)	(0.478)
Mean of Dependent Variable	2.708	0.174	0.441	0.232	0.448	5092.916	260.622	0.187	3.730
Observations	3814	3814	3814	3814	3814	3814	3814	3814	3814

District-clustered standard errors in parentheses. The main independent variables reported are dummy variables for whether the household reported not harvesting a portion of its area cultivated on any plot due to damage from a specified source (preharvest losses), in the previous rainy season, and a dummy for any postharvest losses.

All regressions include household and wave fixed effects, household and geographic controls, and controls for previous rainy season planting decisions. Regressions in Panel B also include other types of prior season shocks as in Panel A but the coefficients are not shown.

*p<.10, **p<.05, ***p<.01

prior season PD shock results in a larger or more time-consuming current season harvest (e.g., if crops are intercropped and take longer to harvest). The increases in household labor throughout the season may reflect reallocation from other activities, or decreased slack in labor allocations if household members are not fully employed during the growing season and are therefore able to increase farm labor without quitting other livelihood activities.

Although drought is the most common source of prior season preharvest losses, along with irregular rains, drought shocks do not appear to have any effect on farm decisions the next season except seed purchases. Losses due to irregular rains of flooding result in reductions in harvest labor, seed purchases, and total input and labor purchases. The combination of reduced labor inputs and reduced input and labor spending caused by prior season labor shocks may indicate that households suffering such losses choose to scale down their agricultural production the following season. Though these households do not appear to reduce their area planted, they might plant less densely or use less labor-intensive production techniques. Prior season postharvest losses and preharvest losses other than the four main sources of losses[18] do not appear to have any significant effect on household agricultural decisions the following year.

Negative point estimates on seed and total input and labor purchases for all shocks besides PD are consistent with the proposed income mechanism, as crop loss shocks reduce crop production value and thus may reduce household income available for next season input purchases. The main exception is the large positive impact of prior season PD shocks on seed purchases per acre the following season. The effect on seed purchases is not driven by outliers, as median seed purchases are also higher among households with a prior season PD shock. Nordhagen and Pascual (2013) note that farmers in Malawi typically purchase seed when the vigor of their stock decreases over time, when they want to grow new varieties, or when they lack their own saved seed. In light of the otherwise negative point estimates, the positive impact of PD shocks is unlikely to be explained by reduced ability to save seed, since other shocks would presumably also reduce output from which to save seed in the same way. This suggests that farmers may be more likely to respond to a PD shock than other shocks by seeking out seed with greater vigor or new seed varieties. The Malawi Integrated Pest Management Plan (MOA (2017)) indicates that purchasing certified seed

[18] Other causes of preharvest losses are animals, theft, fire, and "other".

and planting pest-tolerant varieties are recommended practices for a variety of pests (insects, weeds, diseases) and crops. Similar responses would also seem appropriate in response to drought or rainfall shocks, unless farmers are already planting varieties they believe well-adapted to expected weather regardless of particular realizations. PD shocks may be sufficiently outside the norm for farmers that they respond by changing the varieties they plant.

In further regressions[19] I find negative associations between a PD shock and households' decisions to store prior season production or save output as seed, but these effects are not significant, and households with a PD shock are not significantly less likely to use leftover seed during the current season. This indicates that inability to save output as seed stock does not drive the result. Unfortunately, I do not have data on what varieties households purchase or why they purchase seed. Households with a PD shock are slightly more likely to acquire seed from any given source except local or mobile markets, but the differences are not significant, so the effect is not driven by increased purchases from formal sources. However, households with a PD shock are significantly more likely (by 11% compared to a mean of 18%) to source their seed from the district/urban center or outside the district as opposed to within/near the village or the nearest town. This may drive the higher seed purchase costs which includes spending on transportation. It may be that households travel farther following a PD shock to seek out new seed with characteristics not available in local seed networks. Therefore it seems most likely that increased seed purchases following a PD shock reflect efforts to obtain seed that is more tolerant or resistant to PD stressors.

No prior season shock has a significant effect on fertilizer use decisions[20] or decisions around crop diversity[21]. This indicates that if households are changing production decisions in response to updated beliefs about the probability of a shock, optimal fertilizer use and crop diversity are not affected. No impact on fertilizer use may suggest that farmers do not see those inputs as related to shock risk. No effect on count of crops planted or diversity of area planted may suggest farmers face constraints (e.g., experience, seed availability) in varying their choice of crops, though again I do not capture whether farmers may be changing varieties of a given crop.

[19] Results available upon request.

[20] Information on application rates are collected in the survey but can only be converted into standard units for a small proportion of households.

[21] Crop count and crop diversity does not consider possible diversification of varieties within crop types.

Panel B of Table 3 reports estimated effects of prior season shocks on other household livelihood decisions and outcomes. Coefficients for shocks other than PD are not shown. Overall the evidence suggests that prior season shocks to crop production do not have much effect on broader household livelihood decisions in the current season. Only 6 of 45 coefficients are statistically significant at at least a 10% confidence level, barely more than would occur by chance[22]. A prior season PD shock increases the likelihood of any household wage labor by 6.3pp (a 36% increase relative to the mean), but does not affect household area planted, participation in *ganyu* labor or non-farm enterprise, livestock production, loans, or remittance receipts. Overall, the results indicate that households respond to pest/disease shocks in the prior season by changing some of their agricultural production decisions in the current season, but not other livelihood decisions. The fact that household participation in wage labor, *ganyu* labor, or non-farm enterprise does not change following a PD shock while household farm labor increases suggests there must be some slack in household labor employment such that increased farm labor does not crowd out other labor. I further test this and find no significant impacts of a prior season PD shock on engagement, hours, or earnings/profits for these other outlets for household labor. In general, the effect of labor hours per acre on other household labor activities is negative but the coefficient is typically very small and is only significant for wage labor participation and *ganyu* labor earnings[23].

Robustness[24]*:* A possible concern is that weather realizations may confound the impacts of PD shocks. My primary specification controls only for average annual rainfall. I find that PD shocks are more likely when there is more rainfall than average, but it is possible that the increased rainfall might otherwise leads to improved farm outcomes. The results on the impacts of various types of shocks in Table 3 are robust to including extended weather controls in addition to average annual rainfall: deviations in rainfall, timing of the start of the wettest quarter, change in greening, and timing of the start of onset of greening. This suggests that weather realizations are not an omitted variable biasing the estimated impacts of PD shocks.

[22]Drought shocks increase the likelihood of any ganyu labor by 7.0pp and of any non-farm enterprise by 6.1pp. Lack of labor shocks increases log remittances received by 3.5 percent. "Other" preharvest loss shocks increase the likelihood of ganyu labor by 4.0pp and decrease livestock holdings by 0.06 tropical livestock units (about half a goat or sheep). Postharvest losses reduce the likelihood of any wage labor by 5.1pp.

[23]Results available upon request.

[24]Results of these robustness checks are available upon request.

My primary specification assumes that the effects of a pest or disease shock do not vary based on co-occurrence of other shocks. I find that the results for PD shocks are nearly unchanged when not controlling for other kinds of prior season shocks, despite the fact that 82 of 147 HHs that experience a prior season PD shock also report some other preharvest shock. As a second robustness check, I also test whether the impacts of a PD shock differ depending on whether a household also experiences another prior season shock by fully interacting PD shocks with each other type of prior season shock. The estimated impacts of a PD shock on labor per acre are slightly larger when interacting PD shocks and drought, rains, and postharvest crop loss shocks, but the differences are minor and the significance does not change. The impacts of a PD shock on seed purchases per acre are larger when interacting with drought and postharvest loss shocks and smaller when interacting with rains shocks, though again differences are minor and the impact of a PD shock is always highly significant. The only significant interactions are that households with both a PD and a drought or postharvest loss shock purchase significantly less seed per acre[25], and households with a both a PD and an "other" preharvest loss shock apply more harvest labor per acre. Overall, these tests suggests including prior season shocks separately in the regressions is not inappropriate.

6. Discussion

I next consider possible mechanisms that might explain these results. As described in Section 2, we should see no effects of prior season shocks on current season production decisions for a farm household that separates its production and consumption decisions and optimizes its production decisions based on a known and unchanging distribution for shock realizations. However, I find that a prior season PD shock causes households to change their crop labor and seed purchase decisions, suggesting some aspect of this model does not hold.

The first mechanism I consider is an effect of preharvest shocks on value of crop production, and thus on resources available for consumption and next season production. The fact that prior season PD shocks have an impact on labor primarily through changes in household labor which doesn't need to be paid would be consistent with this interpretation, as would the generally negative (but mainly insignificant) point estimates for effects of other shocks on input spending, though the increase in

[25]This could be taken as indicating that income constraints on next season input purchases are more likely to bind when the household experiences multiple shocks reducing its value of output, though if that were the case we might expect more of the interaction effects to be significant for the input purchase outcomes.

seed purchases following a PD shock do not fit this interpretation. To test for this mechanism, I add the interaction between the prior season PD shock dummy and the value of prior season crop production to Equation (4):

$$Y_{idt} = \alpha + \lambda PDShock_{idt} + \psi PValue_{idt} + \phi PDShock * PValue + H_{idt}\beta_1 + F_{idt}\beta_2 + \tau_t + \mu_i + \epsilon_{idt}$$

ψ gives the effect of prior season value of crop production when there is no PD shock, and ϕ indicates the change in the effect of the shock as the value of crop production increases. If the mechanism for the impact of the shock on current season production decisions is its impact on the household resource constraint, we should see a negative value for ϕ, meaning the impact of the shock decreases as the value of production increases, as a higher prior season value of production should mitigate the adverse effects of the shock on the household resource constraint the next season.

I first analyze the impacts of preharvest losses on the value of crop production in the same prior season. Column (1) of Table 4 shows that the point estimate for the effect of preharvest pest/disease crop losses on the total value of crop production in total in the prior season is negative, but I cannot reject the null of no effect when controlling for household fixed effects, household and geographic characteristics, and prior season planting decisions. I obtain the same result using value of production per acre, and when considering shocks and value of production in the current season. In contrast, preharvest shocks due to irregular rains, lack of labor, and "other" causes significantly decrease value of production[26]. This suggests PD shocks may be less severe than other shocks, and could explain the difference in impacts between PD and other prior season shocks on current season input purchases. While the data do not include information on the severity of preharvest crop losses, I find that PD shocks typically affect a smaller proportion of the total area planted by the household in a given wave than other types of shocks. This would be consistent with pests or

[26]The significance varies somewhat when considering shocks and value of production in prior vs. current season. The lack of precision may be due to measurement error in value of crop production. For most households, I impute the value of crops they did not sell themselves using median sales prices for the crop at the lowest level of geographic aggregation with at least 5 observations of sales for that crop. This process may lead to measurement error if households that do not experience shocks are storing more of their output to consume or sell later at a higher price, while I impute the value of those crops using prices that include sales by households that experienced a shock and may be induced to sell their production when prices are low. Indeed, I do observe that households experiencing prior season shocks are less likely to store crops and more likely to sell crops, and households experiencing current season shocks make their first sales of crops sooner, when prices are likely lower in the period soon after harvests.

diseases that affect only particular crops and plots whereas droughts, rains, or lack or labor shocks would apply across crops, and further indicates that PD shocks may have less of an effect of the value of crop production, especially after conditioning on area planted to different crops.

Table 4: Effects of Prior Season Pest/Disease Losses and Value of Crop Production

	(1) Prior Season Value of production (MK 1000s)	(2) Current Season Any pesticide or herbicide use	(3) Non-harvest labor days per acre	(4) Harvest labor days per acre	(5) Seed purchases per acre (MK)	(6) Total input and labor purchases (MK 1000s)
Pest/disease shock	-4.160	0.046	22.151**	2.142	0.535**	2.435
	(17.554)	(0.042)	(10.546)	(2.349)	(0.196)	(1.524)
Value of crop prod. (MK 1000s)		-0.000	-0.028***	-0.005*	0.000	0.001
		(0.000)	(0.008)	(0.003)	(0.000)	(0.001)
Pest/disease shock* Value of crop prod.		-0.000**	-0.014	0.013	-0.000	-0.010
		(0.000)	(0.030)	(0.014)	(0.001)	(0.010)
Mean of dep. var.	91.948	0.057	81.675	20.872	0.752	7.283
Observations	3814	3814	3814	3814	3814	3814

District-clustered standard errors in parentheses. The main independent variables reported are a dummy variable for whether the household reported not harvesting a portion of its area cultivated on any plot due to damage from pests or diseases, the value of crop production in 1000s of MK, and the interaction of these terms, for the prior rainy season. Outcome variables are reported for the current rainy season, except for the the prior season value of production. Value of production refers only to crop production. All regressions include household and wave fixed effects, as well as household and geographic controls and controls for previous rainy season planting decisions and other prior season shocks.
*p<.10, **p<.05, ***p<.01

The lack of an impact of PD shocks on value of crop production in the prior season indicates that impacts on resource constraints are unlikely to be the main mechanism explaining the effects of prior season PD shocks on current season production decisions, but columns (2)-(6) of Table 4 report results from the model with the interaction of prior season PD shocks and production value[27]. The impacts of prior season PD shocks on non-harvest labor and seed purchases remain significant and are similar to those in Table 3. Value of prior season crop production has a small negative impact on labor days per acre and a small positive impact on total input and labor purchases, perhaps indicating substitution of labor for other inputs among households with higher value of production. The insignificant effect of prior season production value on current season purchased inputs suggests that loosening resource constraints does not significantly alter short-term input purchase decisions, which might be the case if households typically make similar inputs purchases across seasons in the absence of production shocks. There may also be measurement error in the value of crop production

[27]Results are similar when using the value of crop production per acre.

introduced by the imputation of unsold crop value using observed sales prices of nearby households.

The coefficient on the interaction term is of greatest interest for testing this mechanism. As predicted, it is negative, except for the impact on harvest labor, but the impact is only statistically significant for pesticide use where it is not economically significant. These results suggest that a change in the resource constraints is not the main mechanism by which prior season PD shocks affect current season decision, though this mechanism might explain the impacts of other prior season shocks which more severely affect prior season crop production value. The lack of consistency in the effects of PD as opposed to other prior season shocks on current season decisions is further evidence that another mechanism must be involved. If changing the resource constraint was the main mechanism, I would expect to see similar effects of all types of preharvest shocks since they all reduce the value of crop production, but Table 3 indicates that other shocks generally decrease labor application and input purchases, in contrast with the impact of pest/disease shocks.

Table 5: Welfare impacts of prior season pest/disease shocks

	Impact	Mean of Dep. Variable	Observations
Worried about running out of food in past 12 months	0.113***	0.680	1907
	(0.041)		
HH ran out of food in past 12 months	0.126**	0.632	1907
	(0.048)		
HH members skipped meals in past 12 months	0.032	0.519	1907
	(0.065)		
HH members ate less than should in past 12 months	0.153***	0.644	1907
	(0.044)		
HH members went hungry for a day in past 12 months	0.050	0.494	1907
	(0.063)		
Annual consumption per capita (MK 1000s)	-1.964	133.671	3814
	(7.344)		

The reported impacts are coefficients and district-clustered SEs for on a dummy for whether household reported not harvesting a portion of its area cultivated on any plot due to damage from pests or diseases in the prior season. Outcome variables are reported for the current rainy season. The specific food security questions are only asked in Wave 2, so these regressions include only district fixed effects. Regressions on next season crop production value and household consumption include household and wave fixed effects. All regressions include household and geographic controls and controls for previous rainy season planting decisions and other prior season shocks.
*p<.10, **p<.05, ***p<.01

The other mechanism I consider, which would support different effects for different shocks, is that households are updating their beliefs about the distribution of shocks. Although I do not find that preharvest PD shocks significantly reduce household crop production value after controlling for household characteristics and planting decisions, Table 5 shows that PD shocks have significant negative impacts on some measures of household food security[28]. The point estimate for the effect on next year annual consumption per capita is also negative, though economically small and not significant. These negative welfare impacts may motivate households to update their beliefs about the probability of shocks and make production decisions accordingly.

To explore this mechanism, as explained in Section (2) I assume that farm households optimize current production decisions based on expectations about shocks that are a function of prior shock realizations. I run the following regression specification for Wave 2 panel households:

$$Y_{id} = \alpha + \lambda S(PDShock09_{id}, PDShock10_{id}, PDShock12_{id}) + H_{id}\beta_1 + F_{id}\beta_2 + \delta_d + \epsilon_{id}$$

$S(.)$ represents the function determining how households use past PD shock realizations to update their beliefs. For Wave 2 households making production decisions in 2013, the past shock realizations I observe are for the 2009, 2010, and 2012 rainy seasons. I include household and geographic controls H_{id} and prior season controls F_{id} as in my previous specifications. As I only include Wave 2 households, I can no longer include household or time fixed effects, but do include district fixed effects to capture the impacts of differences in prices on household decisions.

I consider three approaches to modeling the form of $S(.)$. I first follow Ji and Cobourn (2018), who model how farmers react to fluctuations in weather and water availability, in representing expectations in the current season by a weighted sum of prior shock realizations. I therefore include the shock realizations in 2009, 2010, and 2012 linearly in the model. This does not specify any particular form of updating, other than to consider that past shock realizations contribute to current beliefs and therefore may affect decisions. This approach also provides some insight as to how past realizations might be incorporated into different models of belief updating. Results are presented in in Panel A of Table 6 for four main crop production decisions in the 2013 rainy season. They are consistent with earlier results showing that experiencing a PD shock in the season immediately before (2012 in this case) significantly affects production decisions, even after controlling for ear-

[28]These significant impacts may indicate that value of crop production is measured with noise, which attenuates the true significant negative impact of PD shocks, since we would expect the impact of PD shocks on food insecurity to go through its effect on value of crop production. Results are similar when controlling for prior season value of crop production and its interaction with PD shocks. Value of production is significantly negatively associated with food insecurity measures, as would be expected. The PD shock impacts fall slightly in magnitude and they become slightly less significant, but the interaction terms with value of production are not significant.

lier shock realizations. Estimated effect sizes for 2012 pest/disease shocks are larger than those estimated in Table 3 using observations in both waves, and the impact of harvest labor becomes marginally significant. Earlier PD shock experiences do not significantly impact decisions in 2013, with the exception that a 2009 shock significantly decreases seed purchases per acre in 2013.

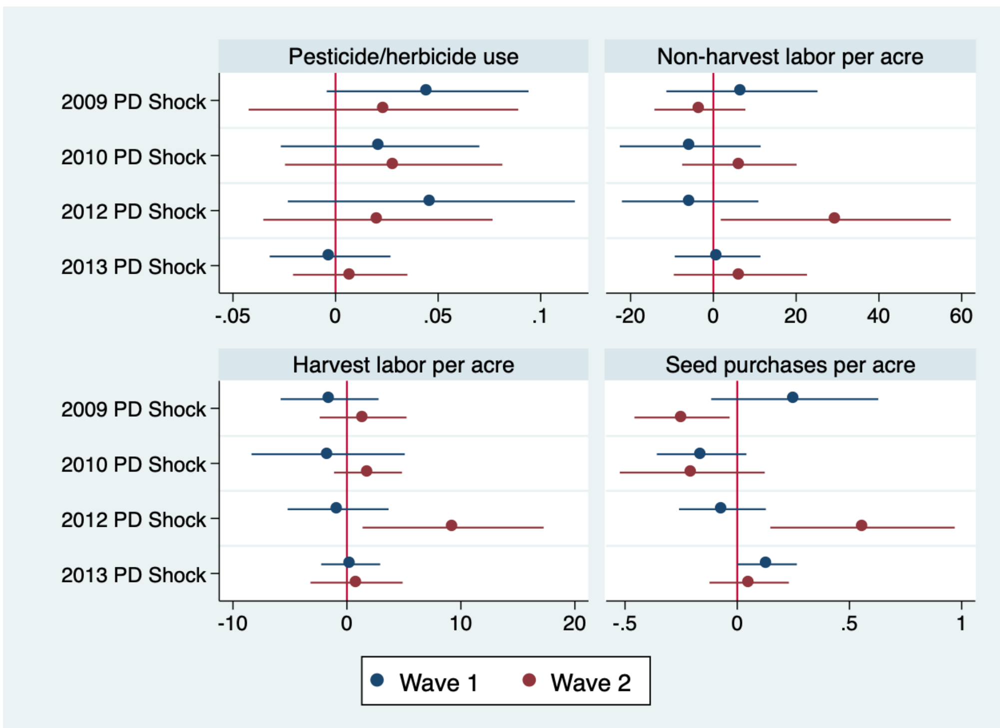
Table 6: Effects of beliefs of pest or disease shock probability on agricultural production decisions

	(1) Any pesticide or herbicide use	(2) Non-harvest labor days per acre	(3) Harvest labor days per acre	(4) Seed purchases per acre (MK)
Panel A				
2009 PD shock	0.023	-3.416	1.400	-0.247*
	(0.039)	(6.377)	(2.221)	(0.124)
2010 PD shock	0.028	6.268	1.848	-0.201
	(0.031)	(8.095)	(1.760)	(0.190)
2012 PD shock	0.022	30.942*	9.491*	0.569**
	(0.033)	(17.043)	(4.874)	(0.249)
R squared	0.264	0.181	0.156	0.181
Root MSE	0.226	81.858	20.959	1.538
p-value: $\beta_{12} > \beta_{10}$	0.558	0.102	0.079	0.009
p-value: $\beta_{10} > \beta_{09}$	0.443	0.189	0.432	0.429
p-value: $\beta_{12} > \beta_{09}$	0.51	0.032	0.061	0.002
Panel B				
Perceived 2013 PD shock	0.073	28.554	11.385*	0.059
probability - Beta Bayesian	(0.075)	(17.333)	(5.921)	(0.343)
R squared	0.261	0.161	0.143	0.151
Root MSE	0.226	82.706	21.081	1.563
Panel C				
Perceived 2013 PD shock	0.063*	21.373	0.766	0.321
probability - DeGroot	(0.036)	(25.032)	(5.437)	(0.316)
R squared	0.270	0.159	0.140	0.132
Root MSE	0.226	81.689	20.989	1.438
Observations	1907	1907	1907	1907

District-clustered standard errors in parentheses. All outcome variables are for the 2013 rainy season. Independent variables in Panel A are dummy variables for whether the household reported not harvesting a portion its area cultivated on any plot due to damage from pests or diseases in a particular rainy season. The independent variable in Panel B is the estimated household belief about the probability of experiencing preharvest pest/disease losses, constructed based on shock experiences in prior rainy seasons. Note that data are not available on shock realizations in 2011. All regressions include district fixed effects and are restricted to Wave 2 households (surveyed in 2013) to allow for an analysis of responses to preharvest losses in the long-term. All regressions include household and geographic controls as well as controls for 2012 rainy season planting decisions other 2012 crop shocks.
*p<.10, **p<.05, ***p<.01

My ability to determine whether there is any particular trend in the coefficients of shock realizations is limited by the small number of years and observations, but these results could be consistent with recency bias by farm households, basing beliefs only on the most recent shock realization. The results on labor and seeds would also be consistent with an availability heuristic, where households put decreasing weight on shock realizations further back in time. The coefficients on the 2012 shock are significantly larger than the coefficients on the 2010 and 2009 shocks, and for labor the confidence level increases for the more distant shock. The negative coefficients on seed purchases per acre for 2009 and 2010 PD shocks are consistent with the evidence that households greatly increase their purchases of seed the season following a PD shock. A possible explanation is that having recently renewed their seed stock these households choose to purchase less seed in 2013, unless they also experienced a PD shock in 2012. Results on pesticide/herbicide use are again consistent with this not being a margin on which most households in the sample respond to PD shocks.

Figure 1: Effect of yearly PD shocks on current season production decisions, by wave



Coefficients and 90% confidence intervals are from regressions of current season agricultural decisions on PD shock realizations in different years. All regressions include district fixed effects and are restricted to a single wave of households to allow for an analysis of responses in a particular season - 2010 for Wave 1 and 2013 for Wave 2. All regressions include household and geographic controls as well as controls for prior rainy season planting decisions and non-PD shocks. Standard errors are clustered at the district level.

The coefficients from a similar regression that also includes the effects of a same season PD shock in 2013 are plotted in Figure 1. For comparison, I also include the coefficients for effects of PD shocks in different season on farm production decisions in 2010 by limiting the sample to Wave 1 households instead of Wave 2. These clearly illustrate that only PD shocks in the season immediately before significantly affect production decisions in the current season. The only evidence suggestive of persistent effects is the negative impact of a 2009 PD shock on seed purchases per acre in 2013. I consistently see no effect of shocks on production decisions in the same season, indicating households may not be able to change input choices in response to current shocks so the main impact of PD shocks may be through changing beliefs about the likelihood of a later PD shock[29]. The lack of any significant effect of 2012 or 2013 shocks on 2010 production decisions lends support to the argument that the PD shocks I observe are exogenous conditional on household and wave fixed effects, household and geographic controls, and prior season crop area allocations.

My second approach to modeling belief updating follows Gallagher (2014), who models how homeowners react to floods in their community, in modeling beliefs about the probability of a shock as following a $Beta \sim (\alpha, \beta)$ distribution[30]. The farmer's initial beliefs (α_0, β_0) are based on the empirical distribution of shocks at time 0. In season t the farmer has observed realized shocks $\{W_s\}_{s=0}^{t-1}$ and updates her prior to yield the posterior beliefs (α_t, β_t). I largely following Gallagher (2014) in considering how the farmer may set her priors and update her beliefs. I set initial household beliefs based on PD shocks in 2009, matching the first two moments of the Beta distribution to the first two moments of the empirical distribution at the national or district level. Results are not sensitive to this choice, so in what follows I only present results where priors are based on the district-level distributions. I then model the updating of household perceived probability p of a shock as $E[p|\omega_T, t] = \frac{\omega_T+\alpha}{T+\alpha+\beta}$ where $T = \sum_{s=1}^{t-1} \delta^{t-1-s}$ is a discounted sum of yearly observations and $\omega_T = \sum_{s=1}^{t-1} W_s \delta^{t-1-s}$ is a discounted sum of the household's shock realizations. Updating with $\delta = 1$ is equivalent to full information Bayesian updating, while $\delta < 1$ puts smaller weight on older realizations, either because households forget, because there is a cost to recalling those realizations, or because there is some bias towards more recent realizations. In what follows I report only results based on full information Bayesian updating, as the small number of years used in the updating limits my ability to identify differences in discounting of past observations[31].

[29]Again, for labor it may also reflect the fact that some portion of households experiencing PD stressors may successfully prevent crop area losses by increasing their labor inputs, meaning I likely observe households with high labor caused by PD prevalence that do not report a PD shock.

[30]The Beta distribution is the conjugate prior probability distribution to the Bernoulli, binomial, negative binomial and geometric distributions and is commonly used in models of Bayesian inference. This distribution is appropriate when characterizing beliefs over the probability of a shock.

[31]Results from analyses with different discounting are available upon request. For all production decisions, the regression MSE is nearly identical across specifications, meaning no model provides meaningfully different explanatory power for differences in farmer decisions. This may be because the sample does not include many households which

Panel B of Table 6 presents results from estimating Beta Bayesian updating of beliefs with full information (no discounting of past shock experiences) where the prior is based on the distribution of PD shocks in a household's district in 2009. The mean estimated perceived probability of a PD shock in 2013 among Wave 2 households is 3.87%. This is remarkably close to the proportion of Wave 2 households that had a PD shock in 2012, 3.83%. The estimated perceived probability is 37.09% among households that experienced a PD shock in 2012. The estimated impacts on pesticide/herbicide use and labor are similar to those of 2012 PD shocks in Panel A, though the effect on non-harvest labor is no longer significant at the 90% confidence level[32]. This may reflect the fact that very few households experience a PD shock in more than one season: just 4.8% of Wave 2 households experiencing any PD shock in this time frame experience more than 1. Thus, some of the households that have higher perceived 2013 pest/disease shock probability will be households that experienced a shock only in 2009, for which the point estimate on 2013 non-harvest labor in Panel A is negative. This would also explain why the coefficient on seed purchases is no longer significant in Panel B and is an order of magnitude smaller compared to the effect of a 2012 shock. In this Bayesian updating model with full information, households in the same district that experienced shocks only in 2009 or in 2010 will have the same perceived probability of a pest/disease shock in 2013 as households in that district that experienced a shock only in 2012. But the previous results suggest that the purchase of seeds increases only in the season immediately after a pest/disease shock. This means that some households perceiving a higher probability of a shock in 2013 will have already purchased the seed they desired in the season following the one in which they experienced the pest/disease shock, and therefore will not need to increase seed purchases in 2013. This intuition is supported by results running the same regression excluding households that experienced pest or disease shocks in 2009 or 2010. For this sub-sample, households that believe the probability of a 2013 pest/disease shock is 1 increase their seed purchase per acre by 2,524 MK relative to households that believe the probability is 0 ($p = .051$)[33].

experience different possible combinations of shock realizations. Just 10.4% of Wave 2 panel households experience any pest or disease shock in 2009, 2010, or 2012, and 4.8% of these households experience more than one. As a result, relative beliefs in 2013 may not vary as much, regardless of the updating process.

[32]The coefficients in Panel B can be interpreted as follows: A household that perceives the probability of a 2013 pest/disease shock is 1 uses 11.385 more days of harvest labor per acre than a household that perceives this probability is 0.

[33]Results available upon request.

A third approach to modeling belief updating considers the possibility that households update their beliefs based not just on their own PD shock experiences but on learning about PD shocks of others in their EA. I first replicate the analyses in Table 3 for the four main current season production decisions, but fully interacting household prior PD shocks with either the count of share of households reporting a PD shock in the EA. I find similar results for the impacts of a household prior season PD shock[34]. The impacts on harvest labor and seed purchases per acre remain significant and are somewhat larger in magnitude. The coefficient on pesticide use becomes negative and the coefficient on harvest labor per acre is smaller, but these remain insignificant. The interaction term is positive and significant for pesticide use but is not significant for the other outcomes. No coefficient on EA shocks is significant, which indicates that households do not appear to change next season behavior based on others' shocks if they are not shocked themselves.

Nevertheless, in Table 6 Panel C I analyze the impacts of beliefs based on a simple DeGroot learning framework, largely following Chandrasekhar et al. (2020). The household believes a current season PD shock will occur only if at least 1/4 of the EA households (including the household itself) experienced a PD shock the prior season, unless exactly 1/4 of households experienced a PD shock in which case the household's belief is based on its own prior season experience[35]. I run the same specification as for the belief updating using the individual Beta Bayesian model. The coefficients for DeGroot beliefs updated based on EA PD experiences on pesticide use and nonharvest labor are similar to those for Beta Bayesian beliefs updated based on individual PD experiences, though the former is now marginally significant. The coefficient on harvest labor is an order of magnitude smaller and no longer significant, and the coefficient on seed purchases is larger but also not significant. It does not appear that this model of DeGroot belief updating explains the results any better than the proposed model of Bayesian belief updating.

All three models have very similar explanatory power in terms of the R^2 and Root MSE. I do not explore further possible models of belief updating as the small number of years of PD shock

[34] Results available upon request.

[35] I use 1/4 rather than 1/2 as in Chandrasekhar et al. (2020) as no EA had more than 40% of households report a PD shock in any given year, and I take 25% of households reporting a PD shock as strong evidence that a larger share likely experienced PD stressors, even if their damages were not severe enough to lead to crop loss shocks. I restrict the sample to EAs with at least 6 panel households (this is necessary because I drop HHs that did not cultivate crops and were not observed in both waves).

realizations and the lack of variation in the trends of PD shock experiences among households (very few experience shocks in multiple years making it difficult to identify effects of different patterns of shock realization) mean that variations in the model are unlikely to result is significantly better explanatory power. That said, the results in Table 6 taken together indicate that if households are changing production decisions due to updated beliefs following past PD shock experiences, this updating is strongly biased toward PD shock realizations in only the season immediately prior.

Another possible mechanism that I consider is that prior season PD shocks might also affect current season production decisions if they increase vulnerability of a repeated PD shock[36]. In general, I find that prior season PD shocks have no effect on later season P shocks, with the exception of a strong and significant relationship that reporting a PD shock in 2012 is significantly associated with increasing the likelihood of reporting another in 2013. Thus although I argue that experiencing a prior season PD shock is exogenous after controlling for household and geographic characteristics and prior season planting decisions, there does appear to be some serial correlation in PD shocks. I test whether this could help explain the effect on current season planting decisions of a prior season PD shock by running my main specification for the 4 main current season production decisions of interest but also including current season PD shocks as an independent variable. The impacts of the prior season PD shock are nearly identical to those in Table 3, and the impacts of the current season shock are of small magnitude and not significant. This suggests that impacts on current season PD shock vulnerability do not explain the results.

However, when I include the interaction between prior and current season shocks in this specification, the results change. The impacts of the current season shock remain small and insignificant. For seed purchases the magnitude and significance of the prior season shock impact are largely unchanged. The impact of the prior season shock on non-harvest labor is no longer significant and the magnitude falls by about one third. The same is true for harvest labor, though this was already insignificant. In both cases there is a large magnitude for the interaction term, which is marginally significant for harvest labor. Thus, impacts of prior season PD shocks on labor may be concentrated among households that experience another PD shock. Since the current season shock doesn't have an independent effect on current season labor, this suggests households may have learned after

[36]Results available upon request.

their prior season PD shock that additional labor can help reduce PD losses. Households becoming informed about how to deal with PD shocks if they re-occur in the current season could therefore be another possible mechanism for impacts of prior season PD shocks. Unfortunately these efforts do not appear sufficient as these households are still reporting losing some area to PD damages. The positive significant impact of the interaction on harvest labor compared to the negative effect of a current shock does suggest that losses may be mitigated among households with a prior shock, to the extent more harvest labor indicates a larger harvest. However, these results should be treated with great caution as the likelihood of reporting a current season PD shock is endogenous to current season production choices. These results are therefore merely illustrative of correlations that could suggest another mechanism to explain the results in Table 3.

7. Conclusion

Pests and diseases are an important cause of crop losses globally, but their impacts on smallholder farm livelihoods have not received as much attention as the impacts of weather and price fluctuations, potentially due to limited data on pest and disease prevalence at a fine spatial and temporal level. I address this gap using panel data on causes of preharvest losses including pests and diseases for farm households in Malawi. Applying household fixed effects and controlling for planting decisions which may affect vulnerability, households that experience preharvest losses from pests or diseases increase non-harvest labor per acre by over 25% and seed purchases per acre by over 65% in the following season, relative to the mean. There is no effect on chemical inputs, as the sample does not include larger cultivators of cash crops that are the main users of pesticides/herbicides in Malawi. Households do not vary the use of fertilizers or planting decisions (at the crop level) after a prior season PD shock, which may indicate that they do not consider these inputs to reduce PD risk. Other livelihood decisions are also mainly not affected, suggesting increased farm labor primarily reduces slack in household labor employment rather than substituting other labor.

Impacts of a prior season PD shock on labor and seed do not appear to be driven by an effect of the shock on the value of crop production. Prior season crop value is not significantly affected by PD shocks after controlling for planting decisions, though this may in part be due to measurement error in estimating crop values. Instead, households may be updating beliefs about the probability of experiencing preharvest PD losses and modifying input decisions to reduce risk, with any updating strongly biased towards PD shock realizations in the most recent season. Updating would appear to be motivated by concerns about food insecurity following a shock. Households purchase more seed only in the season immediately following a PD shock. This does not seem to be due to constraints on saving seed but may rather reflect a desire to acquire more tolerant/resistant seed varieties. Labor input decisions seem to reflect recency or availability bias, with impacts driven by more recent PD shock realizations, consistent with results from Ji and Cobourn (2018) on farmer reactions to weather and water availability fluctuations in Idaho. Determining the model of belief updating that best explains the results is challenging due to the small number of years and limited variation in patterns of PD shocks across households, and is an area for future work with a longer time series.

Further research is also needed to explore whether the impacts prior season pest/disease shocks on production decisions are welfare-enhancing for farm households, and whether market constraints such as the availability of credit or chemical inputs may limit farmers' ability to optimally respond to changes in the probability of a shock.

Another avenue for additional research is considering the possibility of externalities and spillovers. Evidence on the correlation of reports of preharvest crop shocks suggests there is less spatial correlation for the PD shocks reported in my sample than for drought or rainfall shocks, so there may be less scope for spatial spillovers and general equilibrium effects. As an initial exploration of this possibility, using my main FE specification I find no significant effect of mean household labor or pesticide use at the EA level on the likelihood that a household experiences a PD shock in a given season. In general such an analysis is interesting but complicated in my data where the unobserved prevalence of pests and diseases affects both dependent and independent variables, so results should be interpreted with great caution.

A primary weakness of this analysis is the lack of data on prevalence of insects and diseases over space and time. Data is improving for new and more recent pests, but historical data are extremely limited. As far as I am aware such data are not available for Malawi or most other low-income contexts other than to indicate which pests are present at the country level and what crops they affect, which may include information on what year those pests were first observed. Lacking data on pest prevalence and instead observing only when pest prevalence results in a negative shock greatly limits the analyses I can conduct, but I present these analyses as a foundation for future work, ideally with data on observed pest or disease prevalence rather than household-reported shocks.

References

Anderson, C. L., T. Reynolds, J. D. Merfeld, and P. Biscaye (2018): "Relating seasonal hunger and prevention and coping strategies: A panel analysis of Malawian farm households," *The Journal of Development Studies*, 54, 1737–1755.

Chandrasekhar, A. G., H. Larreguy, and J. P. Xandri (2020): "Testing models of social learning on networks: Evidence from two experiments," *Econometrica*, 88, 1–32.

Davis, L. W. (2004): "The effect of health risk on housing values: Evidence from a cancer cluster," *American Economic Review*, 94, 1693–1704.

Dercon, S., J. Hoddinott, T. Woldehanna, et al. (2005): "Shocks and consumption in 15 Ethiopian villages, 1999-2004," *Journal of African economies*, 14, 559.

Dercon, S. and P. Krishnan (2000): "Vulnerability, seasonality and poverty in Ethiopia," *The Journal of Development Studies*, 36, 25–53.

Dhanush, D., B. K. Bett, R. B. Boone, D. Grace, J. Kinyangi, J. F. Lindahl, C. V. Mohan, J. Ramírez Villegas, T. P. Robinson, T. S. Rosenstock, et al. (2015): *Impact of climate change on African agriculture: focus on pests and diseases*, CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS).

Di Falco, S. and G. De Giorgi (2019): *Farmers to Entrepreneurs*, Selected Paper prepared for presentation at the 2019 AAEA Annual Meeting, Atlanta, GA, July 21 – July 23.

Dimova, R., S. Gangopadhyay, K. Michaelowa, and A. Weber (2015): "Off-farm labor supply and correlated shocks: New theoretical insights and evidence from Malawi," *Economic Development and Cultural Change*, 63, 361–391.

FAO (2018): *Malawi Small Family Farms Country Factsheet*, Food and Agriculture Organization of the United Nations.

Gallagher, J. (2014): "Learning about an infrequent event: evidence from flood insurance take-up in the United States," *American Economic Journal: Applied Economics*, 206–233.

Garrett, K. A., A. Dobson, J. Kroschel, B. Natarajan, S. Orlandini, H. E. Tonnang, and C. Valdivia (2013): "The effects of climate variability and the color of weather time series on agricultural diseases and pests, and on decisions for their management," *Agricultural and Forest Meteorology*, 170, 216–227.

Giertz, Å., J. Caballero, M. Dileva, D. Galperin, and T. Johnson (2015): "Managing agricultural risk for growth and food security in Malawi," *Agriculture Global Practice Note-October 2015; World Bank Group.*

Hoddinott, J. (2006): "Shocks and their consequences across and within households in rural Zimbabwe," *The Journal of Development Studies*, 42, 301–321.

Ito, T. and T. Kurosaki (2006): *Weather risk and the off-farm labor supply of agricultural households in India*, Contributed paper prepared for presentation at the International Association of Agricultural Economists Conference, Gold Coast, Australia, August 1218, 2006.

Ji, X. and K. M. Cobourn (2018): "Weather Fluctuation, Expectation Formation, and the Short-run Behavioral Responses to Climate Change," *Working Paper*.

Kelly, D. L., C. D. Kolstad, and G. T. Mitchell (2005): "Adjustment costs from environmental change," *Journal of Environmental Economics and Management*, 50, 468–495.

Kochar, A. (1999): "Smoothing consumption by smoothing income: hours-of-work responses to idiosyncratic agricultural shocks in rural India," *Review of Economics and Statistics*, 81, 50–61.

Lamichhane, J. R., M. Barzman, K. Booij, P. Boonekamp, N. Desneux, L. Huber, P. Kudsk, S. R. Langrell, A. Ratnadass, P. Ricci, et al. (2015): "Robust cropping systems to tackle pests under climate change. A review," *Agronomy for Sustainable Development*, 35, 443–459.

Lazzaroni, S. and N. Wagner (2016): "Misfortunes never come singly: structural change, multiple shocks and child malnutrition in rural Senegal," *Economics & Human Biology*, 23, 246–262.

MOA (2017): *Pest Management Plan: Agricultural Sector Wide Approach Support Project II (ASWAp-SP II)*, Republic of Malawi Ministry of Agriculture, Irrigation and Water Development.

Nguyen, T.-T., T. T. Nguyen, and U. Grote (2020): "Multiple shocks and households' choice of coping strategies in rural Cambodia," *Ecological Economics*, 167, 106442.

Nikoloski, Z., L. Christiaensen, and R. Hill (2018): "Coping with shocks: The realities of African life," *Agriculture in Africa: Telling myths from facts*, 123–134.

Nordhagen, S. and U. Pascual (2013): "The impact of climate shocks on seed purchase decisions in Malawi: implications for climate change adaptation," *World Development*, 43, 238–251.

NSO (2014): *Basic Information Document: Integrated Household Panel Survey (IHPS) 2013*, Republic of Malawi National Statistics Office.

Oerke, E.-C. (2006): "Crop losses to pests," *The Journal of Agricultural Science*, 144, 31–43.

Porter, C. (2012): "Shocks, consumption and income diversification in rural Ethiopia," *Journal of Development Studies*, 48, 1209–1222.

Soumaila, G. and B. Dillon (2019): *Weather risk, price risk, and agricultural technology adoption*, Working Paper.

Teklewold, H., M. Kassie, B. Shiferaw, and G. Köhlin (2013): "Cropping system diversification, conservation tillage and modern seed adoption in Ethiopia: Impacts on household income, agrochemical use and demand for labor," *Ecological Economics*, 93, 85–93.

Tibesigwa, B., M. Visser, M. Collinson, and W. Twine (2016): "Investigating the sensitivity of household food security to agriculture-related shocks and the implication of social and natural capital," *Sustainability Science*, 11, 193–214.

Wagstaff, A. and M. Lindelow (2010): *Are health shocks different? Evidence from a multi-shock survey in Laos*, The World Bank.