DISSERTATION

THREE ESSAYS ON WEATHER SHOCKS, NUTRITION, AND FORESTS

Submitted by

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ABSTRACT

THREE ESSAYS ON WEATHER SHOCKS, NUTRITION, AND FORESTS

This dissertation has three essays that focus on three important and interrelated issues in many developing countries: weather shocks, forest access, and nutrition. Nutrition and climate change are among the top global challenges that need urgent attention. Climate-related extreme events such as droughts and floods are predicted to increase in both frequency and spatial coverage in the future. These weather shocks have detrimental effects on the livelihoods of the rural people who mainly depend on agriculture for their livelihood. How households behaviorally and strategically cope with these shocks to mitigate their impact is not well understood. I contribute to understanding by answering specific questions related to how households cope with shocks and the role of forests, how they adapt input use as a result of shocks and understanding how agriculture can contribute more to nutrition. By focusing on these issues, I provide much needed empirical evidence in developing countries on the impacts that weather shocks have on outcomes such as food security, income, and agricultural input use.

Malnutrition and food insecurity remain among the top global challenges. According to the Food and Agriculture Organization's Status of Food and Nutrition Security, there are more than 820 million undernourished people worldwide, representing about 10.8% of the global population. In Africa, undernourishment afflicts nearly 20% of the population, despite recent progress. Micronutrient deficiencies result from undiversified diets that contain fewer sources of minerals and vitamins. As extreme weather events increase in frequency across a large portion of Sub-Saharan Africa, malnutrition is likely to worsen among rural communities that directly depend on rain-fed agriculture for food. Natural resources (such as fisheries or forests) provide an economically important source of wild foods (e.g., fruits and insects) that facilitate dietary diversification. Despite

this, the role of wild natural resources in supporting human food security and nutrition remains poorly understood.

In the first essay (chapter 2) of this dissertation, I determine the role that forests play in protecting nutrition and food security in the event of a weather shock in Malawi, which has a high percentage of the rural population extracting non-timber forests products for food and nutrition. I use the Living Standards Measurement Survey (LSMS) and Global Climate data (for rainfall) to test the use of forests as natural insurance in the event of a weather shock and if access to forests buffers the negative impacts of weather shocks on nutrition and food security. Finally, I determine if having access to forests reduces reliance on other costly coping mechanisms such as reducing expenditure or selling off assets. To identify the impact of forest access on nutrition, I exploit exogenous variation in forest access and make use of household fixed effects to control for unobserved heterogeneity at the household and village level (level of forest access). I find that households allocate labor away from agriculture and into forests in the event of a weather shock and that access to forests offsets the negative impact of weather shocks on nutrition and food security, especially for dense forests. Policies that make agriculture more resilient to climate change can reduce the pressure on forests in the event of weather shocks while forest institutions must balance access for natural insurance with efforts to improve forest stocks by restricting use.

In the second essay (chapter 3), I determine the effect of previous weather shocks on input use in agriculture. I investigate if farmers are more likely to use fertilizer and improved seeds after a drought. Climate change will affect the agriculture sector more directly than any other sector because of the relationship between crop production and weather. Smallholder farmers who depend on agriculture will have to adapt to the changing climate. In the literature, there are two contrasting theories of how people adjust risky behavior in response to shocks. On the one hand, literature suggests that people become more risk averse after experiencing a shock. On the other hand, others argue that people become risk seeking in a bid to cover losses. I add to this literature in the context of smallholder farmers. Using panel data collected from more than 6000 maize growing smallholder farmers in Zambia in 2012 and 2015, results show that weather shocks lead to a reduced likelihood of using fertilizer and increased likelihood of using improved seed. To explore the mechanisms for this response, I estimate the impact of fertilizer and improved seeds on the riskiness of agricultural production and find that fertilizer is a relatively high return and high-risk input while improved seed is a low-risk, lower return input. I use this information to calculate the average Arrow-Pratt and downside risk aversion for household-years with and without a shock in the previous year. I find that, after a shock, households become more risk averse. Therefore, I attribute the observed differences in input use after weather shocks to changes in risk aversion. Heterogeneity tests show that access to credit can mitigate the negative impact of a shock on the likelihood of using fertilizer after a shock. This highlights the importance of credit and insurance markets in allowing smallholders to make risky investments as shocks increase in frequency.

In the third essay (chapter 4), I study agricultural households' post-harvest decision making and how it relates to nutrition. Specifically, I determine if selling agricultural output that would have contributed to household nutrition if consumed at home is detrimental to nutritional outcomes. Despite increasing agricultural productivity, its effect on nutrition has remained ambiguous, leading to the 'hungry farmer paradox.' This essay explores how production consumed in the household relative to the household's nutritional requirement affects food security, dietary diversity, and children's health. I derive a variable that describes nutrition not met from a household's own production—own-produced nutrition deficiency (OPND)—to test the effect on nutrition outcomes. This variable increases because of low production and because of food sales to the market when keeping some of that food in the home would have contributed to the household nutrition requirement. Data collected from 211 household in Mbala district of Northern Zambia was used for the analysis. I find that OPND, both as a result of underproduction relative to household nutrition requirement, and as a result of marketing output, is detrimental to nutrition. The increase in lean season prices relative to the harvest season prices reduces the quantity demanded of foods from the market, making it difficult to use the market to compensate for the nutrition shortfall from own production. Results also show that focusing on market participation only misses the differential impact of participation that does not improve nutrition outcomes for those who sell food crop output but are not self-sufficient from own production.

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Any errors in this dissertation are my own.

DEDICATION

To my brothers-

For their understanding and love

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CHAPTER 1: INTRODUCTION

According to the World Economic Forum[1], climate change and malnutrition are among the top 10 global challenges facing the world. Climate change's most noticeable effect is through extreme weather events such as storms, droughts, and floods. Sub-Saharan Africa is not spared from these extreme events. For example, Malawi had more than 40 extreme weather-related events between 1976 and 2011, resulting in GDP loss of more than 1.76% per year (Pauw et al., 2011). Zambia has not had *normal* rainfall at a national scale in more than 4 decades (Thurlow et al., 2012). There are always regions within the country that experience droughts as measured by the palmer drought index (Thurlow et al., 2012). Climate models predict that extreme events will become more frequent, cover wider spatial areas, and increase in intensity across Africa. These shocks have affected all aspects of life including health, agriculture, food, and employment. In particular, Africa's heavy reliance on rainfed agriculture and low adaptive capacity mean that it will likely experience some of the worst effects of weather shocks. Smallholder farmers will bear a large cost from the effects of climate change. Within this group, the effects on agricultural productivity and nutrition are likely to be particularly large.

In this introduction, I provide an overview of undernutrition problems, how weather shocks exacerbate them, and how agriculture has failed to significantly contribute to improving nutrition in developing countries. Then, I provide a brief over of the role that nutrition and improved technology play in economic development. Finally, I review the essays in this dissertation and how they improve our understanding of undernutrition and weather shocks. This understanding contributes to the overall objective of improving livelihoods and economic development outcomes.

[1] https://www.weforum.org/agenda/2016/01/what-are-the-10-biggest-global-challenges/

As of 2017, more than 800 million people worldwide were undernourished, representing about 11% of the global population. This number has increased since 2014 (Figure 1). This alludes to the fact that although hunger worldwide has gradually declined since 2000, in many places progress is too slow, and hunger remains severe. In 2017–2019, more than one in five people, representing about 230 million people—21.2 percent—in Sub-Saharan Africa did not get enough calories. This rate has also been rising gradually since 2014 (Grebmer et al., 2020). Malnutrition is estimated to contribute to more than one third of all child deaths globally and about 54% of all deaths in children in developing countries in 2001 (Bain et al., 2013).

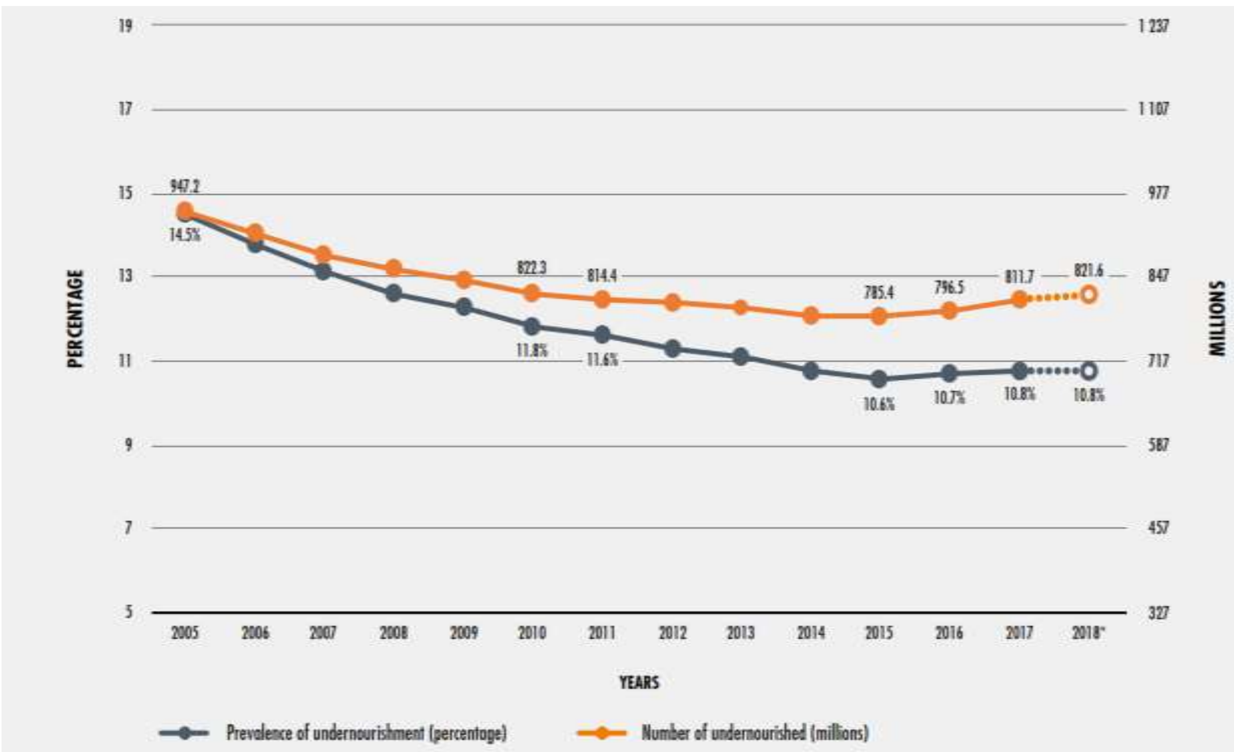

Figure 1: Prevalence of undernourishment in the world. *Source:* FAO et al. (2019)

Extreme weather events pose a significant threat to the nutrition and food security of rural households. There is almost a direct relationship between the level of child malnutrition and climate variables such rainfall. Grace et al. (2012) found that the level of stunting in Kenya was negatively correlated with the amount of rainfall received in each area—indicating that dryer conditions would result in greater incidence of child stunting. According to the FAO et al. (2020), droughts are one of the factors behind the recent increase in undernourished people in sub-Saharan Africa. This points to the role that weather shocks play in exacerbating problems of malnutrition. Further, weather shocks invoke behavioral responses from rural households that result in more conservative or more risky decisions, which in turn affect their livelihoods. How smallholder households respond to these shocks remains not clearly understood as most studies are done in developed countries.

Agricultural improvements, which are negatively affected by weather shocks, have not contributed significantly to improving the nutrition of smallholder farmers. In places like India, agriculture and income have grown over the past 3 decades but without accompanying reductions in malnutrition, resulting in what has been labelled the "Indian enigma" (Headey et al., 2012). The picture is not different for sub-Saharan Africa. For example, a cursory look at per capita agricultural production in Africa indicates that both cereals (sources of calories) and pulses (sources of proteins) have been on the rise since 2000 (Figure 2). However, undernourishment has only modestly changed and in fact worsened since 2014 (Figure 1). The failure of agriculture to positively contribute to nutrition is attributed to the emphasis on the use of agriculture for income generation. For decades, the policy emphasis has been on agricultural commercialization (growing for market) with little concern for its ability to nourish those who grow the crops. Agricultural commercialization was promoted hoping that agricultural income would allow households to purchase a variety of foods through the market and improve their nutrition (Carletto et al., 2017). Using agriculture to generate income to improve nutrition has not worked because, among other reasons, markets in developing countries are less-integrated, higher lean season prices, and because marketing is mostly done by men who are not in charge of food security in the household (Bacon et al., 2014).

Most stakeholders have recognized the failure of agriculture to improve nutrition through income and are looking for new ways to elevate agriculture's direct contribution to nutrition. As the International Food Policy Research Institute puts it, "After 75 years [since the UN conference on food and agriculture in 1943], agriculture and nutrition meet again"[2]. This is an indicator of the changing global priorities in the fight against hunger. These changing priorities have resulted in the "nutrition sensitive agriculture" movement in policy circles (Rosenberg et al., 2018). Nutrition-sensitive agriculture was reflected in the discussions leading up to the United Nations' 2030 Agenda for Sustainable Development (Ruel et al., 2018) and in the growing number of initiatives to support countries in integrating nutrition interventions into their agricultural investment plans, as illustrated by the Comprehensive Africa Agriculture Development Programme investment plans (Rampa & van Seters, 2013). There are, therefore, calls to understand in more detail how agriculture can contribute to nutrition.

For rural households, nutrition and income does not only come from agriculture, but also from harvesting wild foods from forests. Non-timber forest products (NTFPs) contribute as much as 40% to household income in countries such as the Democratic Republic of Congo (Vira et al., 2015), while in countries like Malawi, more than 82% of the rural population get part of their livelihood from forests (Fisher, 2004). Because forests are more resilient to weather shocks such as droughts and floods, they become an important source of income and food when such extreme weather is experienced (Pattanayak & Sills, 2001; Asprilla-Perea & Díaz-Puente, 2019). Even though forests are important for the food and nutrition of households (Galway et al., 2018), just how much they can buffer the negative effect of weather shocks on nutrition is not well explored in literature. Chapter 2 in this dissertation fills this gap in literature.

[2] http://www.ifpri.org/blog/after-75-years-agriculture-and-nutrition-meet-again

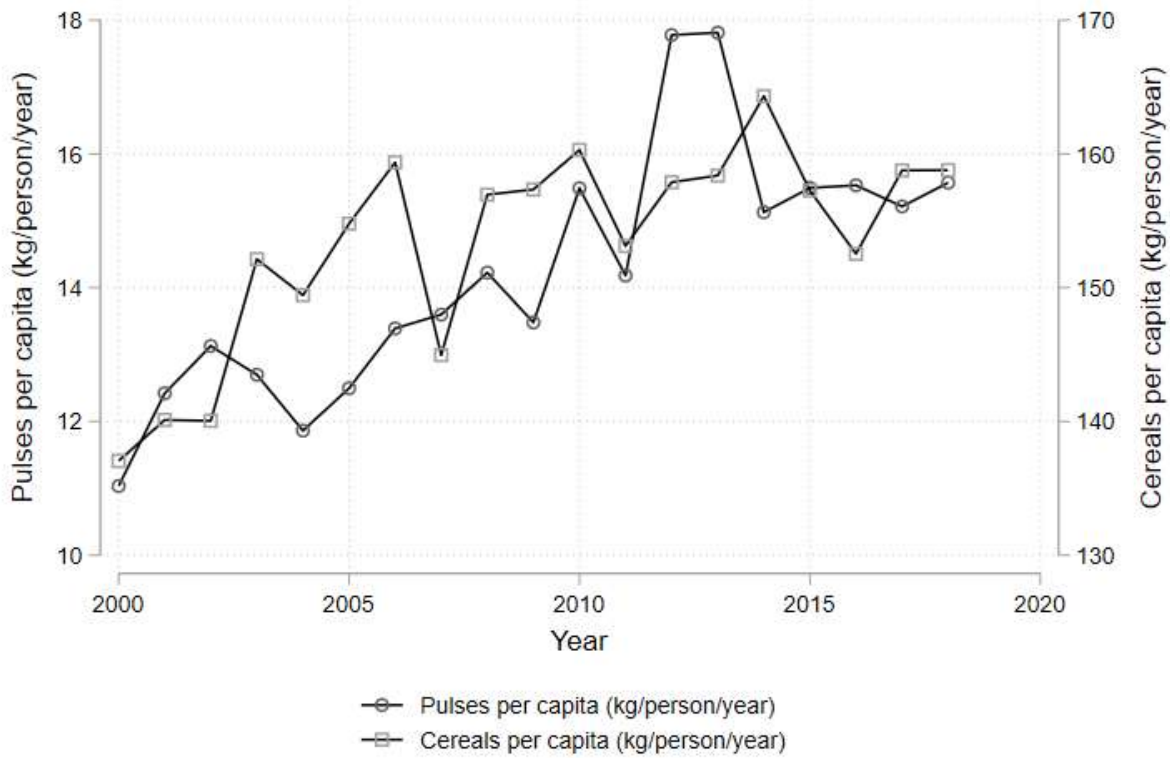

Figure 2: Agricultural production trends in Africa. *Source:* World Bank, several years.

Malnutrition is both a result and a contributing factor to the process of economic development of a nation (Hoddinott, 2016). A well-nourished individual is likely to be more productive and contribute to solving individual, communal, and societal challenges (Babu et al., 2017). Undernutrition early in a child's life affects adult-life outcomes such as education, income, and productivity (Muthuuri et al., 2019). The economic costs of undernutrition, in terms of lost national productivity and economic growth, are significant— ranging from 2 to 11% of GDP in each year (World Bank, 2015). Maintaining a healthy and well-nourished population is, therefore, an investment in the future of a country because it results in more productive human capital and contributes to economic growth. For Africa, which is lagging behind in terms of development, addressing factors that negatively affect economic development is important. Sustained economic growth in turn leads to improved human development outcomes. Successful policy requires an early focus on human development (such as undernutrition), not only because of its direct impact on human wellbeing but also because of its feedback effect on sustaining economic development (Suri et al., 2011).Adoption of new technologies is equally connected to economic development. Use of improved technologies leads to efficiency and an increase in total factor productivity (Foster & Rosenzweig, 2010). Among macro-economists, there is consensus that differences in technology adoption account for a significant share of the variation in total factor productivity, which in turn accounts for the major differences in per-capita GDP and the wages of workers with similar skills across countries (Comin & Hobijn, 2004). For developing countries to catch up with the developed countries, use of improved technologies and inputs is vital. And since agriculture is the main economic activity for the majority of the people in sub-Saharan Africa, use of improved technologies in agriculture will likely drive efficiency and economic growth. If use of improved inputs significantly contributes to lifting countries out of poverty, and Africa has low adoption of improved inputs, then understanding of the constraints on adoption and allocation of improved inputs is useful in understanding a major component of economic growth.

The three essays in this dissertation, therefore, contribute to the understanding of the constraints to development by focusing on malnutrition, and specifically how forests and agriculture can improve nutrition. By studying malnutrition and weather shocks, appropriate policy responses can be devised to protect nutrition and encourage the use of improved inputs in the face of climate change—resulting in economic development in the long-term.

In the first essay (chapter 2), I provide evidence of the ability of forests to protect nutrition outcomes in the face of adverse weather shocks and whether forest quality improves the nutrition protection role. I also determine if access to forests reduces reliance on costly shock coping mechanisms (reducing expenditure and selling assets). I use the Living Standards Measurement Survey (LSMS) and global climate data (for rainfall) to examine the main empirical questions. To identify the impact of forest access on nutrition outcomes, the study exploits exogenous variation in forest access and makes use of household fixed effects to control for any unobserved heterogeneity at the village (level of forest access) and household level. Results show that households allocate labor away from agriculture to forests in the event of a negative weather shock and that access to forests offsets the negative impact of weather shocks on nutrition and food security, especially for dense forests. Finally, I find that access to forests reduces reliance on costly coping mechanisms.

In the second essay (chapter 3), I explore how previous weather shocks affect the use of inputs with different risk-attributes. Specifically, I determine the effect of previous weather shocks (droughts) on fertilizer and improved seed use. The effect of weather shocks on risk attitudes is also estimated. Nationally representative Rural Agricultural Livelihoods Survey (RALS) panel data collected from more than 6000 maize growing households in Zambia in 2012 and 2015 are combined with TAMSAT rainfall data to link weather shocks to household decisions. The rainfall data are used to calculate weather anomalies and categorize them as weather shocks. Using structural equations, I account for the direct and indirect (income) effect of weather shocks on input use. Results indicate that previous weather shocks reduce the likelihood of using fertilizer and increase the likelihood of using improved seed. These observed input use decisions are attributed to changes in risk aversion after a weather shock. This has implications for the adoption of agricultural output-enhancing technologies in the face of climate change.

In the third essay, I study agricultural households' post-harvest decisions' effect on nutrition outcomes. Measuring production in nutrient terms, I construct a variable that indicates how much nutrition deficiency a household has from own production—own-produced nutrition deficiency

(OPND)—and determine its effect on nutrition outcomes. I also conduct heterogeneity tests between OPND from underproduction and from selling output beyond the household nutrition requirement. Data were collected from 211 households in Mbala district of Northern Zambia. Generally, results show that OPND is detrimental to nutrition, and increase in prices in the lean season reduces the quantity of market-bought foods demanded. This suggests that incentives to store more produce for home consumption could benefit nutrition.

Lastly, the dissertation concludes by highlighting the major findings from all three essays in chapter 5. Some of the weaknesses and future research directions are pointed out. Overall, even though I have provided marginal improvements to the understanding of the effectiveness of forests as natural insurance, how weather shocks affect input use, and explaining the hungry farmer paradox, there are still some gaps that future research could help fill.

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CHAPTER 2: NUTRITION PROTECTION WITH NATURAL INSURANCE: THE ROLE OF FORESTS

Summary

Malnutrition and food insecurity affect nearly one billion people worldwide. In developing countries, negative weather shocks exacerbate these challenges by diminishing agricultural productivity. In addition to agriculture, rural households in these countries often rely on forests for food. In this paper, I estimate the effect of forest access on nutrition and asset smoothing in rural Malawi. Our identification strategy exploits exogenous variation in forest access and weather shocks. I find that households that experience negative weather shocks shift labor from agriculture to forests, suggesting that forests provide a form of natural insurance. Households without forest access that are confronted with shocks experience drops in nutritional outcomes. In addition, I find evidence that better-quality forests offer improved nutrition protection. Furthermore, I determined that households with forest access are less likely to reduce expenditure and sell assets to cope with shocks. These results suggest a benefit to resource management institutions that consider the returns from alternative economic activities, particularly in regions without robust agricultural insurance markets.

1 Introduction

Malnutrition and food insecurity remain among the top global challenges. According to the Food and Agriculture Organization of the United Nations (2019), more than 820 million people are undernourished, representing about 11% of the global population. In Africa, undernourishment afflicts nearly 20% of the population despite recent progress (FAO, IFAD, UNICEF, WFP, & WHO, 2019). Other prevalent forms of malnutrition in Sub-Saharan Africa include micronutrient deficiencies and food insecurity (Gómez et al., 2013). Micronutrient deficiencies result from undiversified diets that contain few sources of minerals and vitamins (Bailey, West Jr., & Black, 2015). As extreme weather events increase in frequency across a large portion of Sub-Saharan Africa (Kendon et al., 2019), malnutrition is likely to worsen among the rural communities that directly depend on agriculture for food (Alderman, 2010).

In many developing countries, natural resources such as forests provide an economically important source of wild foods (e.g., fruits, vegetables, and insects) that facilitate dietary diversification (Baudron et al., 2019; Powell, Maundu, Kuhnlein, & Johns, 2013; Sunderland, Powell, Ickowitz, & Foli, 2013). Despite this, the role of wild food plants in supporting human food security and nutrition remains poorly understood (Jamnadass, McMullin, Iiyama, & Dawson, 2015; Sunderland et al., 2013). In the context of forests, evidence suggests that households increase forest use in the presence of adverse economic shocks (Fisher, Chaudhury, & McCusker, 2010; Pattanayak & Sills, 2001; Smith, Hudson, & Schreckenberg, 2017; Takasaki, Barham, & Coomes, 2004) and that income drops can be partially offset through forest use (Oviedo & Moroz, 2014). However, no evidence exists on the ability of forests to protect nutritional outcomes or on households' reliance on other costly coping mechanisms when experiencing adverse weather shocks.

Common property resources, unfortunately, are prone to overexploitation and may suffer from the tragedy of the commons (Hardin, 1968). Traditionally, economists have recommended privatization as a remedy for the tragedy of the commons which results as more households allocate labor to an open access resource until the value average product is zero (all rents are dissipated). By allocating use rights to the resource users, they (resource users) can maximize the total economic product from using the resource. This has been applied in resources like fisheries where individual transferable quotas have been allocated to the fishers (Wilen, 2013). In the forest literature, management approaches include government ownership such as protected areas and forest reserves, private ownership such as those owned by individual landlords and common property forests where communities have usufruct use rights but the state retains transfer and cessation rights (Barrow et al., 2016). However, approaches to rationalize forests have the potential to affect resource users negatively and result in unequal distribution of the benefits. Classic studies by (Samuelson, 1974) and (Weitzman, 1974) point out the potentially regressive distributional consequences of resource privatization. Recent empirical studies have demonstrated that privatization is not always Pareto improving (Okonkwo & Quaas, 2019; Quaas et al., 2019). This happens as the poor who mostly depend on common pool or open access resources are excluded at least in part. This limits their ability to use the forest to smooth consumption in the event of shocks that affect other sources of livelihoods such as agriculture. I provide empirical evidence that households can benefit from access to common forests in the event of a shock.

This paper explores how households in rural villages in Malawi use extraction of non-timber forest products (NTFPs) to mitigate the impact of adverse weather shocks on nutritional outcomes. I test if rural Malawian households increase their use of forests during extreme weather events. Then, I explore if households with access to common property forests experience smaller declines in nutritional outcomes such as dietary diversity, food security, and the number of meals for children per day. I extend the empirical analysis by conducting heterogeneity tests across forest quality (measured by forest density). Finally, I test if forest access reduces reliance on other costly coping mechanisms (e.g., asset sales or consumption reduction) in the event of a negative weather shock.

We find that households with access to forests increase the use of NTFPs during a negative weather event. Households with access to forests do not experience a drop in dietary diversity or food security while those without access experience significant declines in these nutritional outcomes. Therefore, access to forests offsets the negative effect of weather shocks on nutrition. I also find that forest access leads to smaller decreases in assets and allows households to maintain expenditure on market goods. In addition, the study shows that nutrition protection increases with the density of forests.

These results have important implications for forest management in developing countries. While unrestricted access to a natural resource can lead to degradation and a tragedy of the commons (Hardin, 1968; Manning, Taylor, & Wilen, 2018), access during shocks can allow vulnerable households to smooth food consumption and maintain adequate nutrition (López-Feldman, 2014; Morduch, 1995; Pattanayak & Sills, 2001). This suggests the need to balance exclusion and conservation goals with forest access to allow households to protect their well-being in the event of adverse shocks.

This analysis contributes to the resource and development economics literature by highlighting the importance of NTFPs for household nutrition in the event of weather and climate uncertainty. Many studies have established a correlation between shocks and the use of common-pool resources (CPRs) (Agarwal, 1990; López-Feldman, 2014; Pattanayak & Sills, 2001; Paumgarten & Shackleton, 2011). Despite this, the relationship between NTFP extraction and food and nutritional outcomes remains poorly described in the literature. Thus, the current study adds to the recent literature that builds a typology of household responses to shocks and the ways in which coping strategies can be improved (Janzen & Carter, 2018; Kazianga & Udry, 2006).

In the following section, I provide an overview of the current literature relating to resource management, natural insurance, and nutritional outcomes, and precisely state our hypotheses. In section 3, I describe the context in which I empirically examine the linkages between shocks and nutrition, and the data used. Section 4 describes our empirical strategy, while results are presented in section 5. Finally, section 6 concludes with a discussion of policy implications and avenues for future work.

2 Non-Timber Forest Products, Insurance, Shocks, and Nutrition

This section provides an overview of the literature on household shocks, coping strategies, and the connections between NTFPs as natural insurance and nutrition. A stylized theoretical model that corresponds to the research questions drawn from the literature is presented in Appendix 2.1: Theoretical Framework for Household Labor Allocation and Nutrition.

2.1 Weather Shocks and the Use of Natural Resources as Insurance

In developing countries, households frequently experience severe shocks that affect consumption, income, and asset accumulation. These shocks are broadly categorized as idiosyncratic (i.e., household-level shocks such as death, injury, or unemployment) or covariate shocks (i.e., community-level shocks such as natural disasters or epidemics) (Dercon, 2002). While not universally true, studies generally show that covariate shocks have a larger and more significant impact on households' consumption than idiosyncratic shocks (Günther & Harttgen, 2009).

Weather shocks, which are predicted to increase in Africa, are among the most common covariate shocks affecting rural households. Malawi, for example, has experienced 40 weather-related disasters between 1970 and 2006, and these have increased poverty and had negative effects on health, food security, and nutrition (Fisher et al., 2010; Nangoma, 2007). In this paper, I focus on covariate weather shocks and household reallocation of labor between natural resources (forests) and agriculture, in addition to the effects on food and nutrition security and the sale of assets as a coping mechanism.

Households allocate labor to common property resources as a way of smoothing consumption after a shock (Nkem et al., 2010; Takasaki et al., 2004; Wunder, Börner, Shively, & Wyman, 2014). CPRs often act as a resource of last resort in times of economic hardship (Agarwal, 1990; Baland & Francois, 2005). Those in most need (i.e., those with relatively poor outside-earning chances) allocate relatively higher effort to gathering resources from the commons and obtain a relatively high share of resource value (Baland & Francois, 2005). The poor, therefore, depend more on CPR extraction to cope with shocks. For example, Pattanayak & Sills (2001) develop a theoretical model of household dependence on forest collection in times of a shock and empirically show that the number of trips to the forest (as an indicator of use/dependence) increases in the event of a shock that affects agricultural production. McSweeney (2004) reveals that young household heads who have not acquired assets depend more on CPR extraction when there is a shock while those with assets liquidate them to cope. Liquidating private assets, a costly coping mechanism compared to extracting from CPRs, is used to buffer income. Fisher, Chaudhury, & McCusker (2010) found that, in Malawi, households headed by less-educated adults, households with less marketed crop surplus, and households located near the forest depend more on forests.

However, some studies show that households do not always allocate more labor to the collection of NTFPs in the event of a shock. Takasaki et al. (2004) found that households resort more to off-farm labor supply than on extraction of CPRs and that demand for in-kind payment in the form of food increased with shocks. Belayneh (2017) indicates that in Mozambique, a neighboring country of Malawi that has similar weather conditions, households depend more on salaried employment and "significantly pull away from fishery, forestry and fauna activities" (p. 4) in the event of a shock. Reduced local employment also occurs. For example, in Mexico, Jessoe et al. (2018) show that weather anomalies led to reduced local agricultural and non-agricultural employment. These studies, therefore, show that the literature on labor allocation and weather shocks still depicts mixed results and demonstrates that the effects are context-based—warranting our investigation into the case of Malawi. This literature provides us with background for our first empirical question: *What are the effects of weather shocks on labor allocation to agriculture and forests in Malawi?*

2.2 Nutritional Outcomes and Non-Timber Forest Products Collection

The impact of weather shocks on nutrition has received considerable attention in the literature. Negative (adverse) weather shocks affect nutrition because households cope by reducing consumption, reducing the number of meals, or resorting to less nutritious food. Ibrahim & Alex (2008) show that in Malawi, more than 80% of households respond by reducing the number of meals eaten. Falling agricultural incomes as a result of weather shocks also lead to decreased food consumption (Heltberg, Oviedo, & Talukdar, 2015). Grace et al. (2012) find that rainfall anomalies, and not temperature, are associated with malnutrition. The current study focuses on rainfall shocks but also extends the literature by investigating the role that access to forests plays in buffering the impact of shocks.

There are two main ways that the extraction of NTFPs can affect nutritional outcomes: through direct consumption and through income. In cases where markets for forest products are not well developed, the income channel is of less significance (Baudron et al., 2019; Manning & Taylor, 2015). While some researchers (Mujawamariya & Karimov, 2014; Mulenga, Richardson, Tembo, & Mapemba, 2014) have found that participation in the commons contributes significantly to household income, others (Delacote, 2009) have theorized that the returns to labor in the commons are lower than engaging in a private enterprise, hence placing those households that participate in a worse situation (poverty trap in the commons). Takasaki, Barham, & Coomes (2010) find that resorting to CPRs was not enough to protect income, while Rose (2001) finds that CPRs buffered income by only 10%. Our contribution is to focus on the food consumption channel in the event of a shock and determine if forest access can significantly contribute to nutrition and food security and offset the negative effects of weather shocks.

In Malawi, studies have attempted to estimate the role of forests in nutrition and food security. In a correlational study that used forest satellite images, Johnson et al. (2013) find that forest cover positively correlates with dietary diversity. However, the researchers do not estimate the correlation with food security, and the study is not causal. In an econometric study, Hall et al. (2019) finds that in Malawi, forest density is only associated with improved vitamin A intake and not with macro-nutrients or food security. In other countries, correlational studies find that regardless of the presence or absence of shocks, forest foraging by both rural and urban communities (Clark & Nicholas, 2013) helps to improve food security (Broegaard et al., 2017; Erskine et al., 2014). These results, although important, are firstly, not causal. With the poor more likely to depend on the use of NTFPs, it is difficult to interpret these correlational studies due to significant endogeneity. Secondly, the above-mentioned studies do not estimate if access to forests and the subsequent use of NTFPs is sufficient to offset the negative impact of shocks on food and nutrition security.

It thus remains unclear in the literature if the increased use of forests in the event of a shock is enough to protect nutrition. Our second research question, therefore, attempts to bridge this gap in the literature: *Does forest access protect nutrition in the event of a weather shock?* If it does, this would mean that households with forest access should experience smaller (or zero) declines in nutrition in the event of a weather shock. I focus on food and nutritional security because they are the most pressing concerns for rural households (Harris, Chisanga, Drimie, & Kennedy, 2019; Phalkey, Aranda-Jan, Marx, Höfle, & Sauerborn, 2015). The contribution I make is to estimate the causal effect of forest access on nutrition protection (defined as buffering the negative effects of weather shocks on nutrition).

2.3 Shock Coping Strategies

Here, I discuss the literature that has revealed the ways in which households respond to negative shocks, beyond the use of natural resources. In developing countries, social safety nets are less developed (Dercon, 2002), and this leaves the poor particularly vulnerable to weather shocks. Lack of potential markets, high rates of poverty, and other institutional factors mean that insurance programs that could protect the poor in times of shocks do not exist (Delacote, 2009; Janzen & Carter, 2018).

Households therefore employ multiple strategies to cope with risk. These strategies include both ex-post strategies such as the sale of assets, the use of kinship ties, consumption reduction, labor re-allocation, and ex-ante strategies such as the adoption of resilient technologies, migration, and livelihood diversification (Heltberg et al., 2015; Takasaki et al., 2004). Ex-post coping strategies are part of diversification born out of necessity and not choice (Ellis, 2008). Our focus is on ex-post coping strategies.

According to Fisher et al. (2010), common ex-post strategies adopted as ways of coping with climate shocks in Malawi (in order of proportion of households indicating use of the strategy) include off-farm labor supply, business start-up, extraction of forest products, assistance from family or government, and sale of livestock. Heltberg et al. (2015) summarizes the coping strategies from 16 developing countries by combining data from different surveys and finds that there is significant variation in terms of the most relied-upon strategy. For example, they find that in Nigeria, the most relied-upon strategy (indicated by the number of households reporting the strategy) is informal credit or assistance, while in Malawi, the most common strategy is looking for salaried work. In both countries, however, sale of assets is the second-most-used coping strategy (Heltberg et al., 2015). In Uganda, sale of assets is the most-reported coping strategy, and in Asian countries such as Afghanistan, Iraq, and Tajikistan, consumption reduction is the most-used strategy. However, these analyses do not consider forest or CPR extraction as a coping option.

According to Carter and Lybbert (2012), between consumption and asset smoothing, the strategy chosen depends on income, with the poor smoothing assets and the rich smoothing consumption. Selling assets to smooth consumption is considered a costly coping mechanism because it reduces future productive capacity, leading to poverty traps while reducing consumption, especially food consumption, has long-lasting health effects (Carter & Lybbert, 2012). Exploring income levels at which these coping strategies bifurcate is beyond the scope of this paper. Instead, I investigate if access to forests reduces reliance on reducing consumption and selling assets as coping mechanisms. Following Janzen & Carter (2018) who found that the availability of livestock insurance reduces reliance on costly coping mechanisms, our third research question is: *Does forest access reduce reliance on costly coping strategies?* To the best of our knowledge, there is no evidence on the substitutability or complementarity of forest access and other costly coping strategies. Our contribution is to causally determine the degree to which forest access reduces reliance on costly coping strategies. Results from such an analysis have implications for the conservation of forests and the policies implemented for the poor to escape poverty traps. I explore these empirical questions in the context of rural Malawi.

3 Context and Data

3.1 Context

To answer the empirical questions described in the previous section, I examine forest use in the southern African country of Malawi. Malawi is a good context for studying the role that forests play in food consumption protection because the rural population relies heavily on agriculture and forest products (Fisher, 2004). Achieving good nutrition, which is a direct result of food consumption, is a challenge across the country. For example, Malawi has one of the worst child-malnutrition rates in the world, with the fifth-highest stunting rate of 48% of children under the age of five years while wasting is estimated at 15% (V. Doctor & Nkhana-Salimu, 2017). Micronutrient deficiency is equally high, with vitamin A deficiency estimated at 60% for preschool-aged children and 47% for pregnant mothers (WHO, 2008). Zinc and iron deficiencies are also prevalent among children and pregnant women. The nutrition statistics are worse in rural areas and among the poor; stunting is 54% in the 20^{th} percentile of the poorest households and 31% in the top 20^{th} percentile of wealthiest households (NSO & ICF Macro, 2011).

In Malawi, about 80% of rural households depend on forests (Fisher et al., 2010). Forest cover is about 36%, of which 33% is categorized as primary cover—the most diverse form of forest (Munthali & Murayama, 2015). Despite the importance of NTFPs in nutrition and income generation, policymakers often underappreciate the role played by NTFPs, partly because quantitative measures of the impact on nutrition and health are not available. With the Malawi government committed to using forests for poverty alleviation (Government of Malawi, 2017), this study contributes towards understanding the role that forests can play in protecting nutrition. Malawi has two main seasons, cold-dry and hot-wet. The dry season is from April to November, while December to March is the wet (rainfall) season.

Figure 3: Annual Rainfall patterns in Malawi
Source: Department of Climate Change and Meteorological Services, Malawi

Figure 3 shows the rainfall distribution, with most parts of the country having annual rainfall between 800 mm and 1,000 mm per year. Daily average temperatures range from 14°C to 32°C. The country has experienced several climate shocks, including during the period considered by this study. For example, between 1970 and 2006, the country experienced 40 weather-related disasters, mostly droughts and floods, which led to a drop of 1.7% in GDP per year (Pauw, Thurlow, Bachu, & Van Seventer, 2011). This makes Malawi a good case study for understanding the impact of weather shocks on nutrition.

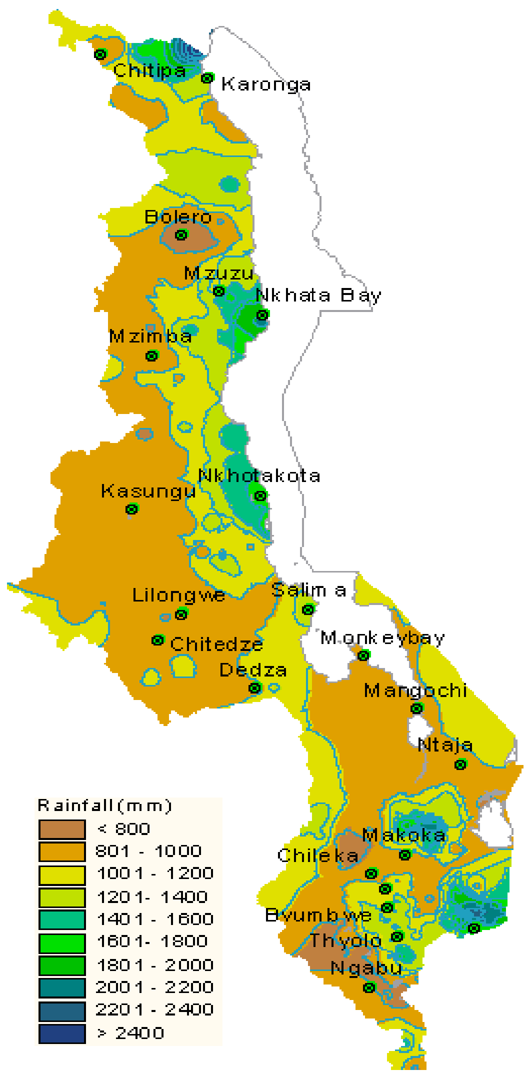

Figure 3: Annual Rainfall patterns in Malawi
Source: Department of Climate Change and Meteorological Services, Malawi

3.2 Data

We use Living Standards Measurement Survey (LSMS) data, which is a unique panel dataset that collects information on forest products used by households such as caterpillars and other insects, mushrooms, honey, wild fruits, and vegetables together with information on food security and dietary diversity. The LSMS is a global effort to measure and understand living standards in developing countries that is supported by the World Bank. In Malawi, the LSMS data were collected in 2010, 2013, and 2016 as part of a broader survey effort called the Integrated Households Long-Term Panel Survey (IHPS) (National Statstical Office Malawi, 2017). These data were combined with forest data to examine the role of forest quality.

While the IHPS contains information on self-reported weather shocks, I do not use this for two reasons. Firstly, self-reported weather shocks are not reliable and are not standardized across households. Secondly, poor households may over report shocks, leading to endogeneity. Instead, I employ rainfall data to construct an objective measure of weather shocks using the Standardized Precipitation Index (SPI). Before making the household data public, the World Bank and country statistical offices use the GPS coordinates that are part of the household survey data to link the household data to the world bioclimatic variables (www.worldclim.org) that are captured at a resolution of about 1 km^2. The variables are averaged at the enumeration area level to preserve confidentiality. Probabilities of occurrence for a given category are transformed into a standardized series with an average of 0 and a standard deviation of 1. It is an alternative to the more complicated and physically based Palmer Drought Severity Index (PDSI), which uses a water balance model. The SPI has been used to measure floods and droughts and is found to perform well at predicting these events (Beguería, Vicente-Serrano, Reig, & Latorre, 2014; Livada & Assimakopoulos, 2007; Wu, Svoboda, Hayes, Wilhite, & Wen, 2007). In addition, the SPI has the highest correlation with agricultural yields among the common indices (Vicente-Serrano et al., 2012). All values below –1.6 and above 1.6 were taken as weather shocks because this is when major crop/pasture losses occur.[3]

Table 1: Categorizing weather shocks using the Standardized Precipitation Index

SPI values	Description	Categorization used
SPI >= 2.0	exceptionally wet	Weather shock (=1)
1.60 <= SPI < 1.99	extremely wet	
1.30 <= SPI < 1.59	very wet	Normal (=0)
0.80 <= SPI < 1.29	moderately wet	
0.51 <= SPI < 0.79	abnormally wet	
-0.50 <= SPI <= 0.50	near normal	
-0.79 <= SPI < -0.51	abnormally dry	
-1.29 <= SPI < -0.80	moderately dry	
-1.59 <= SPI < -1.30	severely dry	
-1.99 <= SPI < -1.60	extremely dry	Weather shock (=1)
SPI <= -2.0	exceptionally dry	

Notes. Alternative categorizations were tried but this was the best categorization.

In Figure 4, the distribution of the SPI is shown as a continuous variable. From the figure, it can be seen that rainfall was 'more' normal in 2010, but above normal in 2013 and below normal in 2016. Malawi experienced flooding in the 2012/2013 season from December 2012 to January 2013, which affected 16,000 households.[4] In 2016, there were widespread droughts that affected not only Malawi but also most of Southern Africa. The El Niño-induced drought left more than 6.5 million people in need of humanitarian aid because agricultural production was below the national food demand.[5]

For the dependent variables on food consumption measures, I use dietary diversity, food insecurity, and the number of meals per day for children. Dietary diversity is measured using the household dietary diversity score (HDDS) obtained from a 1-week recall of the foods eaten by the

[3] https://droughtmonitor.unl.edu/About/AbouttheData/DroughtClassification.aspx
[4] https://reliefweb.int/disaster/fl-2012-000210-mwi
[5] https://www.csis.org/analysis/drought-ravaged-malawi-faces-largest-humanitarian-emergency-its-history

household (Figure 5). The HDDS is a significant predictor of children's nutritional status (Arimond & Ruel, 2004; Kennedy, Pedro, Seghieri, Nantel, & Brouwer, 2007). Therefore, when evaluating outcomes at the household level, it can be used as a proxy for children's nutritional status. The distribution of the HDDS is shown in Figure 5. Unlike a typical count data variable that has inflated zeros, dietary diversity has no zeros since zero would mean no food is eaten. In the current study, I had a mode of 9 food groups consumed out of 10 possible groups, a mean of 8 and a small variance of about 2.83.

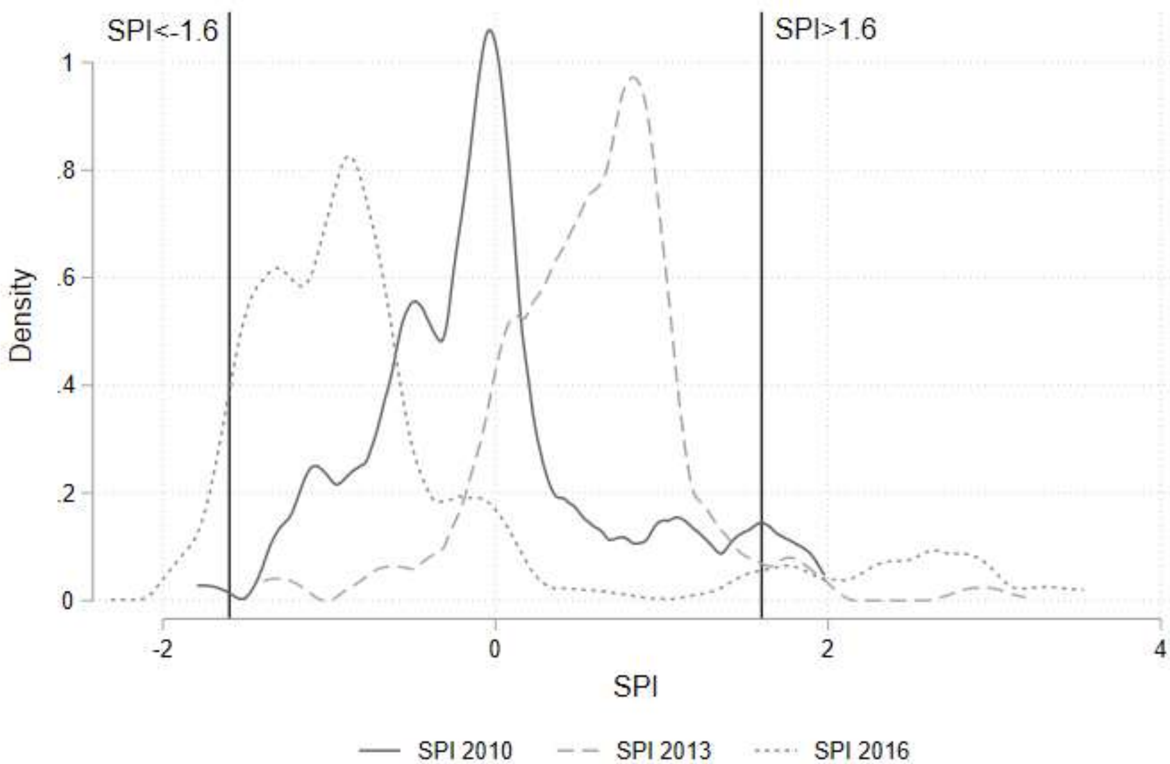

Figure 4: Standardized Precipitation Index distribution by year for Malawi. SPI <-1.6 or SPI>1.6 is categorized as a shock.

Food insecurity is defined as insufficient food for all members of a household over the previous 12 months. In times of food shortage or insecurity, parents' first efforts are to shield their children from the food shortage (Connell, Lofton, Yadrick, & Rehner, 2005; Harvey, 2016). I, therefore, also examine the number of meals eaten by children and define a variable equal to 1 if children ate at least three meals per day over 1 week (previous 7 days before the survey date) and zero if otherwise.

The final dataset used to understand the relationship between dietary diversity and forests contains data that give a measure of the size and quality of forests together with forest loss. This collection of data is on global forest cover and is accessible for Malawi at the village level (Hall et al., 2019; Hansen et al., 2013), which is equivalent to an enumeration area used for sampling purposes regarding the IHPS data. The forest data have time-varying variables on forest loss in hectares for different forest categories that are based on canopy cover (density). The data also indicate the sizes of forests at different canopy-cover percentages at the village level for 2010, although this is time invariant for the period under study.

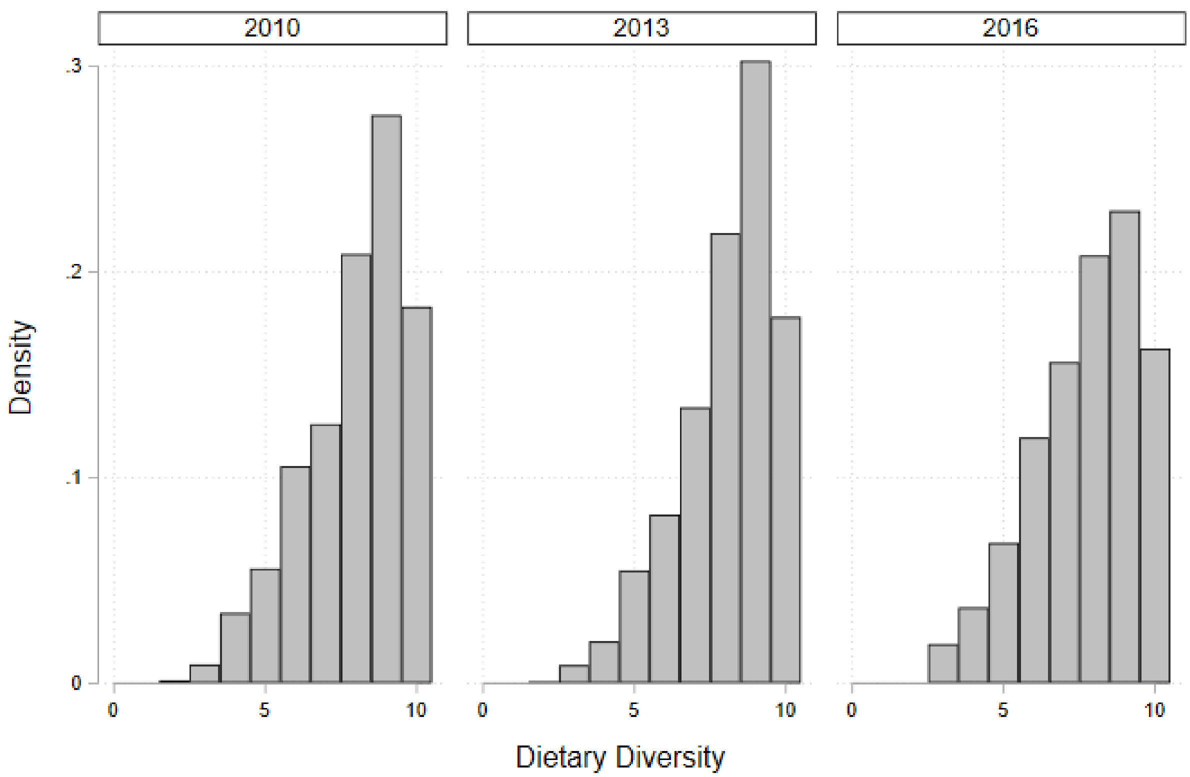

Figure 5: Distribution of household dietary diversity scores.
Note. The overall mean is 7.93, and the variance is 2.83.

Using the forest data, I follow Hall et al. (2019) and construct a new variable that reflects the proportion of the forest that is dense (75% canopy cover). Forest density is positively correlated with the availability of NTFPs (Hall et al., 2019; Johnson et al., 2013; Paletto & Tosi, 2009). Canopy cover (forest density) is a good measure of forest quality since it reflects density and is a measure of plant species richness, the forest ecosystem, and the wildlife habitat (Paletto & Tosi, 2009)—all essential indicators of NTFPs availability. The forest data are merged with the livelihood data using villages that are available in both datasets.

The key variables are summarized for each year in Table 2. The mean dietary diversity remained almost the same over the years with an approximate score of 8 out of a potential score of 10. However, the proportion of households experiencing food insecurity increased from about 36% in 2010 to about 54% in 2016; this is matched by the steady increase in the number of households that experienced weather shocks from 13% in 2010 to 14% in 2016. Furthermore, the number of households able to provide at least three meals per day for their children reduced from 84% in 2010 to 66% in 2016. Additionally, more forests are being lost with time. These variables indicate that overall, there are major differences from year to year in terms of the lives of rural households in Malawi, with conditions appearing to worsen qualitatively except for variables related to assets. For example, marginally, more households owned cattle in 2016 compared to 2010. The number of assets and expenditures increased in 2013 but reduced in 2016.

In the current study, labor allocated to agriculture is measured in hours per week, while labor allocated to CPRs is measured as the value of output from CPR collection. For this analysis, I assume that the value of output increases as the labor allocated to the CPR increases, accounting for price inflation from year to year (Delacote, 2009), meaning that CPR labor increases in CPR output value. For the labor variables that are used in the first hypothesis, I determine that households allocated about 19 hours per week to agriculture in 2013 (when rainfall was 'more normal'), and this reduced to about 11 hours in 2016. In terms of value of CPR output, a proxy for labor allocation to CPR since I assume it is increasing in labor, this was highest in 2016 and lowest in 2010.

Table 2: Summary of key variables used in the analysis

	2010		2013		2016	
Variable	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Dietary diversity (count)	7.978	1.680	8.078	1.610	7.761	1.735
Food insecurity (1 = Not enough food)	0.359	0.480	0.407	0.492	0.549	0.498
Number of meals for children (1=3 or more/day)	0.845	0.362	0.798	0.401	0.663	0.473
Number of durable assets owned	6.83	7.84	7.40	8.17	7.18	7.43
Real total expenditure (MK##)	8737	42860	11831	33334	11315	31628
Owns livestock (1 = Yes)	0.457	0.498	0.527	0.499	0.529	0.499
Labor to agriculture (hours per week)	16.936	28.637	19.192	32.163	11.418	19.477
Real value of CPR output ('000 MK)	0.440	0.564	0.767	0.742	1.337	1.481
Village labor to fuelwood (number of HHs per village)	8.942	7.680	7.319	7.127	8.656	7.833
Family size (number of members)	4.911	2.246	5.350	2.245	5.487	2.309
Family age (years)	22.691	12.110	23.764	12.251	25.951	12.889
Distance to main road (in kilometers)	7.604	9.347	7.716	9.462	7.740	9.506
Wild foods eaten (kg/week)	2.05	20.46	4.03	34.33	1.25	16.04
Weather shock (1 = Present)	0.127	0.333	0.130	0.336	0.140	0.347
Forest quality (75% tree cover forest/total forest)*1000)	.2258	.6016	.2239	.5981	.2261	.602

Notes. ## MK is Malawi Kwacha, the currency for Malawi. All variables measured in MK are in real terms with 2010 as the base year. In 2010 $1= MK150.5. HH = Household

4 Empirical Models

In this section, I describe the econometric models used to explore the use of common property forests as protection against declines in nutrition. Firstly, I identify the effect of weather shocks on the use of common property forests. Secondly, I determine if forest access mitigates drops in nutritional outcomes, and I examine the importance of forest quality in the nutrition-protection role of forests. Finally, I investigate if forest use decreases reliance on other coping strategies.

4.1 Weather Shocks and Use of Common Property Forests

In the current study, NTFPs are collected primarily for food and nutrition using family labor. Using Equation 1, I first examine if labor allocated to the collection of forest resources and to agriculture ($L_{ivt}{}^{j}$) responds to weather shocks.

$$L_{ivt}{}^{j} = \alpha_i + \alpha_v + \beta_1 S_{vt} + \beta_x \boldsymbol{X}_{ivt} + \gamma_t + \varepsilon_{ivt} \tag{1}$$

Where $L_{ivt}{}^{j}$ is labor allocated by household i belonging enumeration area v in period t to j= *agriculture, CPR (forests)*. α_i is a household fixed effect, S_{vt} is an indicator of whether enumeration area v experienced a weather shock in period t (=1 if SPI in village v and year t exceeds 1.6 in absolute value), $\boldsymbol{X}_{ivt}$ is a vector of household characteristics, γ_t is a year fixed effect, and ε_{ivt} is an idiosyncratic error term.

Differences in labor productivity from forest collection that are household-specific and do not change over time are captured by α_i. The identification of β_1 requires that, conditional on household and year fixed effects and household characteristics, a realization of the weather shock is exogenous to the household. If labor allocated to forests increases while labor to agriculture reduces in the presence of a weather shock, then this would be consistent with Hypothesis 1.

4.2 Weather Shocks, Forest Access, and Nutrition

Next, I explore if forest access can help buffer the effect of weather shocks on nutrition, measured as dietary diversity, food insecurity, and three or more meals per day for children. Equation 2 is used to answer the second empirical question regarding whether forest access protects nutrition in the event of a weather shock.

$$E\left[Y_{ivt}^{h}\right] = \alpha_i + \delta_1 S_{vt} + \delta_2 Acc_v * S_{ivt} + \delta_x \boldsymbol{X}_{ivt} + \gamma_t \tag{2}$$

Where Y_{ivt}^{h} is the outcome variable and $h = HDDS, FI_{ivt}, MC_{ivt}$ are household dietary diversity, food insecurity, and number of meals for children per day respectively.

The expectations operator is used to allow for nonlinear specifications. Forest access, Acc_v, was defined at the village level using the community-level questionnaire that asked communities if they have access to a communal forest resource. Because access at the community level does not change over time, it was absorbed by the household fixed effects. Since the households comprising the sample of the current study do not change villages, α_i is the household-level fixed effect that captures any unobserved household and village heterogeneity such as types of forests present and soil fertility. By adding the household-level fixed effects, I control for unobserved heterogeneity specific to each household that would otherwise compromise causal inference due to omitted variable bias (Correia, Correia, & Sergio, 2016; Gormley & Matsa, 2014). Other variables remain as defined previously.

When $h = HDDS$, Equation (2) is estimated using the fixed effects Poisson (FEP) model to consider the count nature of HDDS. In this case, Y_{ivt}^{HDDS} is the log of the dietary diversity count. The FEP model is the most robust model among nonlinear panel data models (Cameron & Trivedi, 2013; Wooldridge, 1999). Given that the mean of the HDDS is greater than the variance (Figure 5), our data is underdispersed and not overdispersed. However, as Wooldridge (1999) proves, the FEP estimator allows any type of variance-mean relationship as long as robust standard errors are used. Even with underdispersion, the FEP provides an unbiased estimate of the parameters of the mean (Cameron & Trivedi, 2013). The coefficients of the FEP are interpreted as the proportional change in the expected value of the dependent variable if the regressor changes by one unit.

When $h = FI_{ivt}; MC_{ivt}$, then (2) is estimated using a fixed effects linear probability model (LPM) with a linear error term. An alternative model would be a fixed effects logit (also called conditional logit), but the average marginal effects are not recoverable after a fixed effects logit (Greene, 2002; Wooldridge, 2010) model. With an LPM, the average marginal effects are easily recovered (Fernández-Val & Weidner, 2016). Because the goal is to be able to interpret the effects of access on food and nutritional outcomes in the event of a shock, recovering the average marginal effects is important. Heteroscedasticity, which is a problem in LPMs, is corrected by clustering the standard errors at the enumeration area level (Fernández-Val, 2009)—the level at which shocks are measured.

The parameter, δ_1, tests for the effect of a negative weather shock on food and nutritional outcomes for those without access to forests, while δ_2 tests the nutrition-protection role of having access to forests given a weather shock. The impact of the weather shock for those with access to forests is $\delta_1 + \delta_2$. Since δ_1 and δ_2 are expected to have opposite signs, I test if access to forests offset the negative effect of a weather shock by testing the null hypothesis that $\delta_1 + \delta_2 = 0$. Rejecting the null hypothesis means that one of the coefficients is larger in magnitude. If δ_1 is significantly larger in absolute magnitude, then it means access to forests does not fully protect against the negative effects of a weather shock. Failing to reject the null hypothesis means that I cannot reject that forest access fully offsets the impact of a shock.

To explore the heterogeneity of impact by forest quality, I include the interaction between forest access, weather shock, and a measure of forest quality. This augmented regression analysis is used to test the hypothesis that denser forests provide better nutrition protection.

4.3 Reliance on Costly Coping Mechanisms and Access to Forests

To test if access to forests reduces reliance on costly coping mechanisms (third empirical question), I estimate (2) but with the dependent variable equal to the total number (and value) of durable household assets owned, and the log of total expenditure as a proxy for consumption. The hypothesis is that in times of shocks, households sell their assets (or do not accumulate more), and the number of assets owned would decrease. They may also reduce expenditure (consumption in the economic sense) to cope with the shock. As before, I determine if access to forests offsets reliance on such costly coping mechanisms.

4.4 Identification and Estimation Issues

In this sub-section, I outline some of the challenges and threats to identification that arise with estimating the above empirical models and how I overcome them.

One potential threat relates to the estimation of equation (2). Specifically, household forest use may be endogenous to food and nutritional outcomes. Therefore, if forest use is included as an explanatory variable, there is potential endogeneity (in the sense of reverse causality or simultaneity) because people who use the forest more may have been poor before the shock. To avoid the potentially endogenous forest 'use' variable, I use exogenous 'access' instead, which is defined as a household living in a village that has a common property forest within the village. This approach of using access is common in literature(Sekhri, 2013; Swaminathan, Salcedo Du Bois, & Findeis, 2010).

We take advantage of data collected through community-level focus group discussions together with the household surveys in the IHPS. The community-level questions asked the community members and leaders if they had access to a community resource such as a forest where they were able to extract NTFPs. I use these responses to define forest access. Access to a forest in the community is exogenous and is not influenced by income, at least not in the medium term where depletion of a whole forest is not conceivable. In practice, the extraction of NTFPs, the focus of our analysis, does not often lead to forest depletion (Arnold & Pérez, 2001; Zulu, 2010), meaning access remains exogenous in relation to the type of use/access.

Household level fixed effects control for time-invariant village characteristics because households do not move out of the village. Hence, I control for any broad differences across villages. So, δ_2 is identified, conditioned on the household fixed effects to account for any household-level heterogeneity, year fixed effects for any changes in prices or other shocks common to all households, and exogenous variation in shocks at the household level with a further assumption that there is no self-selection into villages with and without access to forests. Because it may be argued that access does not equate to use, I conduct a robustness check using a control function approach (Appendix 2.2: A Control Function Approach) using the quantity of wild foods used for food. The robustness check confirms the main result.

Our assumption that households do not deliberately organize themselves into communities with or without forest access is reasonable in rural Malawi because the most common land tenure system is communal, and formal land markets are almost non-existent (Kaarhus, 2010; Place & Otsuka, 1997). Migration from one village to the other is rare. In her analysis of inter-rural migration, Peters (2001) notes that it is extremely difficult for people to move to another chiefdom and "beg"

(p. 158) for land. The land is inherited along matrilineal or patrilineal lines, and a person usually only leaves their family land after rupture of the family (Peters, 2001).

To estimate whether dense forests offer better protection, I need to make additional assumptions regarding the effect of dense forests on nutrition and food security. I contend that the impact of local communities allocating labor to the collection of wild food products has little impact on forest depletion (Gbetnkom, 2009; Sassen, Sheil, & Giller, 2015). Rather, the extraction of timber is responsible for forest depletion and hence forest density loss. Timber processing companies are rarely owned by locals and, therefore, local decisions do not significantly affect forest cover (Gbetnkom, 2009; Meilby et al., 2014). I explore alternative estimations of total labor at the community level (results not shown here) as a regressor on forest quality, and none of the models were significant. This provides suggestive evidence that forest density is not affected by the use of the forest for food collection—the focus of this study. Timber harvesting, which is mainly done by urban-based companies, is exogenous to local community decisions.

5 Results

In this section, I present our econometric results. I begin with results of labor allocation in response to shocks. Then, the nutrition-protection role of forest access, and the quality of forests are considered. Lastly, I determine if access to forests reduces reliance on costly coping mechanisms and offsets the negative impact of the shock.

5.1 Weather Shocks and Use of the Forest

Table 3 presents the results that answer the first empirical question. In columns (1) and (2), I estimate a model for labor allocation to agriculture and collection of NTFPs. Columns (3) and (4) focus only on labor allocated to forests by splitting the sample into households with access to forests (Column 3) and households without access to forests (Column 4) for the placebo test[6].

Table 3: Labor allocation to common-pool resources and agriculture as a response to weather shocks

	Overall		Access=1	Access=0
	(1)	(2)	(3)	(4)
VARIABLE	Labor to agric	Labor to forests	Labor to forests	Labor to forests
Weather shock	-7.97736**	0.40951***	0.53234***	0.41821
	(3.76423)	(0.15199)	(0.19916)	(0.34352)
Constant	-10.39168*	0.01832	0.50858	-0.11642
	(5.58243)	(0.19164)	(0.45726)	(0.27979)
Household controls	YES	YES	YES	YES
Household fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Observations	3,807	3,807	2,750	1,076
R-squared	0.06458	0.19944	0.22598	0.17970
Number of households	1,294	1,294	930	364

Robust standard errors in parentheses clustered at the enumeration area level

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

Model (1) is labor allocation to agriculture with hours allocated per week as the dependent variable. Models (2), (3), and (4) are labor allocation to CPR with hours allocated proxied by the log of the value of NTFPs collected. Household controls include age of household head and family size.

In the presence of a shock, there is an increase in labor allocated to the forests as the value of output increases. The hours of labor allocated to agriculture reduce by about 8 hours per week in the event of a weather shock. When the analysis is done by subsamples, I find that as predicted, those with forest access increase the labor allocated to forests as a response to a weather shock while those without forest access do not. The results generally confirm Hypothesis 1 that labor allocated to a common resource increases in response to a negative weather shock while labor allocated to agriculture decreases. This result is consistent with other studies (Fisher et al., 2010; Pattanayak &

[6] Even without explicitly stated access to common property forests within a village, households could still allocate labor to forests such as private forests, or forests in other villages.

Sills, 2001; Wunder, Börner et al., 2014) and suggests that households allocate labor to forest resources when returns from private activities fall because of adverse shocks.

5.2 Weather Shocks, Forest Access, and Nutrition

We now investigate if forest access offers enough food and nutrition protection to offset the negative impact of weather shocks. Forests when used for extraction of wild foods provide food that is rich in diversity and nutrients (Fentahun & Hager, 2009; Wunder, Angelsen et al., 2014), reflecting the diversity of forests (Bone, Parks, Hudson, Tsirinzeni, & Willcock, 2017; Johnson et al., 2013). I estimate the nutrition-protection role of forests for dietary diversity using the HDDS, food insecurity, and the number of meals for children per day.

Results in Table 4 (columns 1–3) indicate that if there is a weather shock, households' food and nutrition as measured by the HDDS, food security, and number of meals for children per day becomes worse. Having access to a forest smooths dietary diversity and food security. While weather shocks reduce the HDDS by about 6.6%, such shocks increase the probability of being food insecure by 21% and reduce the probability of children having 3 or more meals per day by about 19.6%. However, forest access offsets the negative effect of a weather shocks on HDDS by about 6.2%, on the probability of being food insecure by about 17%, and on the probability of children having 3 or more meals by 24%. When I compute the marginal impact of a weather shock on those with forest access, I find that the effect is not significantly different from zero for all three measures of food and nutrition. This means that forest access offsets the negative impact of shocks on dietary diversity, food insecurity, and meals for children. Forests mainly offer access to vitamins and micronutrients, with less access to macronutrients such as calories and proteins (except for certain seasonal insects) (Ambrose-Oji, 2003; Powell et al., 2013). While studies such as that of Hall et al. (2019) fail to find a significant relationship between forest use and dietary diversity, I demonstrate that in the event of a shock when significantly more labor is allocated to the forest, there is a significant relationship and that forests clearly protect food and nutrition security.

To determine if denser forests provide better protection against the negative impact of weather shocks, I estimate a model that includes an interaction between shocks, access to forests, and forest density, as described earlier. In Table 4, columns (4), (5) and (6) demonstrate the mediating role of forest quality on nutrition protection. The impact of shocks is still negative. I find that better-quality forests enhance the natural insurance role of forests by improving food and nutrition protection in the event of a shock. Generally, this means that dense forests (better quality) can offer better food and nutrition protection in the event of weather shocks and hence improve the natural insurance role of forests.

Further analysis of forest quality and nutrition protection is shown in Figure 6 for food security (a) and dietary diversity (b). The plot for the number of meals for children per day is omitted because the effect was positive at all levels and, therefore, does not demonstrate interesting results. For food security, the plot in Figure 6 shows that for forest density below approximately 0.4%, allocating labor to the forest in the event of a shock increases the probability of being food insecure. However, forest density above 0.7% helps to protect food security in the event of a weather shock. For dietary diversity, the plot of marginal effects at different levels of forest quality for those who experienced a shock and had access to forests show that forests where 75% of the canopy cover is lower than 0.3% do not offer any dietary diversity protection.

Table 4: Effect of forest access on dietary diversity and food consumption smoothing

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	HDDS	FI	MC	HDDS	FI	MC
Weather shock	-0.06575***	0.21311***	-0.19649***	-0.06587***	0.21381***	-0.19677***
	(0.01271)	(0.07218)	(0.07027)	(0.01271)	(0.07225)	(0.07029)
[Weather shock] x [Access]	0.07056***	-0.16894**	0.24692***	0.06735**	-0.15056*	0.23949***
	(0.02717)	(0.08405)	(0.07880)	(0.02759)	(0.08279)	(0.07918)
[Weather shock] x [Access] x [Forest quality]				0.05497*	-0.32519***	0.13143***
				(0.03247)	(0.04948)	(0.04516)
Constant		0.42216***	0.78597***		0.42078***	0.78653***
		(0.09010)	(0.07938)		(0.09047)	(0.07947)
Household and village controls	YES	YES	YES	YES	YES	YES
Household fixed effects	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES
Observations	3,804	3,807	3,807	3,804	3,807	3,807
R-squared		0.05282	0.06496		0.05359	0.06513
Number of households	1,294	1,294	1,294	1,294	1,294	1,294
Marginal impact of weather shock for those with forest access						
Estimate	0.00481	0.0442	0.0504			
p-value	0.833	0.249	0.147			

Standard errors clustered at the enumeration area level in parentheses. *** p<0.01, ** p<0.05, * p<0.1
HDDS = household dietary diversity score, FI= food insecurity, MC = number of meals for children. (1) and (4) have dietary diversity as the dependent variable and use an FEP model; (2), (3), (5) and (6) use an LPM as the dependent variable. In (2) is a binary variable = 1 if the household did not have enough food, and in (3), it is equal to 1 if the children had at least 3 meals a day. Household controls include family size (total labor endowment), family age, and number of households in the village allocating labor to the forest.

Dense forests improve dietary and food security consumption smoothing for households because of the diverse products that are found within them and the number of products that are collected (Baudron et al., 2019; Hall et al., 2019). It is also possible that dense forests improve the average product of labor in the resource. When quality is low, households spend more time collecting meagre amounts of products, resulting in low returns to labor (Delacote, 2009; Fisher, 2004) and making their food insecurity worse.

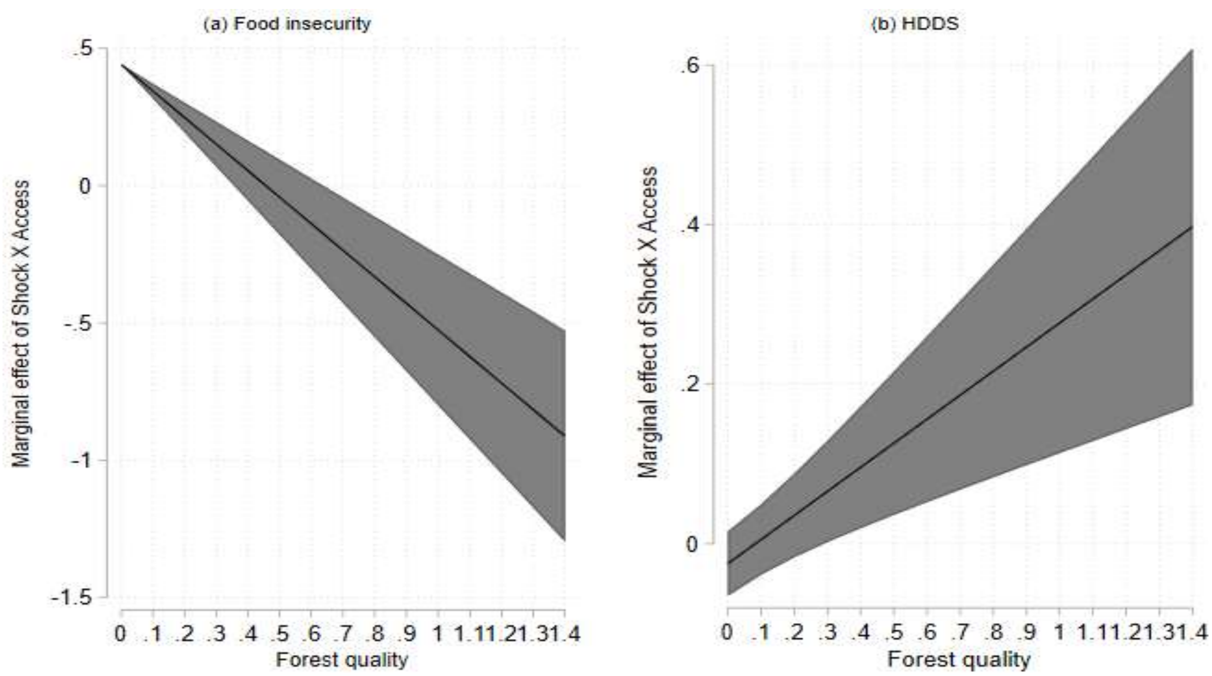

Figure 6: Nutrition-protection role of forests at different quality levels. The graphs show the conditional marginal effect of Shock x Access at different levels of forest quality on food insecurity (a), and dietary diversity (b). The gray area shows the 95% confidence intervals. Forest quality is measured as the proportion (percent) of the forest that has 75% canopy cover.

5.3 Access to Forests and Reliance on Costly Coping Mechanisms

In Table 5 I estimate if shocks lead to the sale of assets (or non-accumulation of assets) as a coping mechanism and if forest access can protect assets or encourage the accumulation of assets as suggested in the literature. Both the number of assets (a count) and the total value of the assets were included because the value of the assets could, for example, be influenced by the existence of a shock in the village if more households started to sell assets. This relates to the third empirical question. I find that in the event of a shock, the number of assets decreases by about 31%; however, forest access reduces this negative impact on assets by about 26%, meaning the reduction in assets for those with access to forests is only approximately 5%. However, access to forests did not significantly reduce the negative impact of the shock on the value of assets.

The results show that in the event of a shock, expenditure on market goods reduces by about 52% for those without forest access, while forest access reduces this negative impact to zero. This suggests that access to forests significantly reduces the drop in expenditure in the event of a shock. Overall, these results suggest that access to forests in the event of a shock appears to be a partial substitute for costly coping mechanisms, especially reduction in consumption (expenditure) and the sale or non-accumulation of assets. Paumgarten & Shackleton (2011) in South Africa found that the use of NTFPs was the fifth-most relied-upon strategy after invoking kinship ties, sale of assets, expenditure reduction, and reduction of both quantity and quality of foods. This means that access to forests has the potential for the poor to avoid the poverty traps in which they reduce consumption and sell assets to cope with shocks, thus reducing their future earning ability.

Table 5: Does access to forests reduce reliance on costly coping mechanisms?

VARIABLE	(1) Durable Asset Count	(2) Durable Asset Real Value	(3) Expenditure
Weather shock	-0.3122***	-0.37137**	-0.51784***
	(0.07192)	(0.16336)	(0.17570)
[Weather shock] x [Access]	0.26311***	0.35257	0.55083**
	(0.08612)	(0.21867)	(0.21411)
Constant		8.75050***	7.45115***
		(0.03375)	(0.25018)
Household and village controls	YES	YES	YES
Household fixed effects	YES	YES	YES
Year fixed effects	YES	YES	YES
Observations	3,759	3,516	3,807
R-squared		0.06847	0.08806
Number of households	1,275	1,280	1,294

Robust standard errors clustered at the enumeration area level in parentheses

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

The dependent variable for model (1) is the total durable assets owned and uses the FEP model. Durable assets are household items such as televisions, solar panels, bicycles, beds, and radios. Model (2) is the log of total expenditure (both food and non-food). Household controls include age of household head, and family size.

The number of observations changes by about 20 because some households have missing assets data and are therefore not included in the model.

6 Discussion and Conclusion

Using panel data from Malawi where natural resource dependence is high (Bone et al., 2017; Zulu, 2010), I fill a gap in the literature on the effect of forest access on nutrition when households experience adverse shock. First, I explore how labor allocated to agriculture and forest resources changes when there is a weather shock that negatively affects the productivity of agriculture. Thereafter, I determine if forest access protects food security, and dietary diversity and tested for heterogeneity across forest quality. Our identification strategy relies on the use of exogenous forest access and weather shocks, conditional on household and year fixed effects.

We found that in the event of a weather shock, rural households reduce the labor allocated to private (agricultural) enterprises and increase collection of NTFPs from forests. Weather shocks reduce the productivity of agriculture (Pauw et al., 2011), hence, households shift labor to the forest, which in most cases has products that are more resilient to weather shocks (Shackleton, 2014; Wunder, Angelsen et al., 2014). This shift in labor is only available for those who live in villages with access to a forest. Access to forests is, therefore, an important avenue for households to readjust labor to buffer the effects of weather shocks that reduce the productivity of agriculture.

We also found that forest access offsets the negative impact of weather shocks on nutrition—meaning access to forests allows households to smooth their nutrition and food consumption. In addition, it was determined that access to forests reduces reliance on costly coping mechanisms. Forests, therefore, could be brought into the typology of coping strategies that are sufficiently important to offer nutrition and food protection in the event of a weather shock, but only to complement other coping strategies, not to substitute. Since households sometimes save their income through assets, asset coping, although costly, may not always be considered as detrimental as reducing expenditure, particularly in relation to food (Deaton, 1991; Lee & Sawada, 2010).

Examining heterogeneous impacts shows that dense forests, defined as 75% canopy-cover forests, provide an improved level of protection on nutritional outcomes. An increase in the proportion of dense forests provides extra nutrition protection for households. On the other hand, low or poor forest quality does not provide nutrition protection. Results show that households that rely on poor quality forests could in effect reduce their food security because of the low returns on labor from such forests.

Households adopt many approaches to cope with shocks. I have shown that access to forests can offset the negative impact of shocks on dietary diversity and food security. Bu reducing the reliance on costly coping mechanisms, forests can also help break the shock-induced poverty traps. However, this does not mean that only forests are used for coping but rather that forests may comprise an important part of the coping strategies. According to Wunder, Börner, Shively, & Wyman (2014), the use of forests for coping is important for specialized households who live near forests but overall, may not be as important as previously thought for other households. As a coping mechanism, forest collections could complement other mechanisms such as sale of assets and reduced consumption. I have shown that forest access significantly reduces reliance on consumption and reliance on sale of assets. However, access to forests does not eliminate reliance on sale of assets. This could be because wealthy households tend to rely more on selling assets (Carter & Lybbert, 2012) and less on forests (Fisher et al., 2010) to smooth consumption .

Increased labor allocation to the forest in the event of a shock has the potential to degrade forests because more weather shocks that are wide in spatial coverage are predicted from climate change models. Degraded forests not only face the risk of being completely lost but they also have a reduced ability to be used as natural insurance for the households that depend on them. Therefore, protecting forests for times when they are most needed would allow poor households to benefit from higher quality.

Although some studies that focus on markets show that CPRs are not able to insure against income (Kalaba, Quinn, & Dougill, 2013; Rose, 2001), the current study demonstrates that CPR forests are able to offer nutrition and food security protection. These findings present interesting policy options for the management of CPRs. While open access may grant maximum accessibility, which is associated with the use of CPRs in the event of a shock, management options that can improve the biological state of the resource will result in better returns from use, offsetting the negative impacts of the shock for those with access. Management approaches that aim at balancing flexibility in access and strategic rules that ensure the resource stock or quality improve are more likely to succeed at allowing users to gain the maximum benefits from the resources while protecting both livelihoods and conserving the resources. However, benefits (rents) that may accrue from management may not be equally distributed. As Wilen (2013) demonstrates, rents realized from a rationalized resource must be sufficient to compensate those who may have reduced their labor and hence failed to benefit. Otherwise, management may hurt those who depend most on the resource, usually the poor and landless. Hybrid management approaches that do not involve privatization or centralization but emphasize common ownership are key in this case. For example, a hybrid institution that links agricultural productivity and access to the forest could improve forest quality while maintaining access for dependent households that experience negative shocks.

In addition, other safety nets such as weather index-based insurance programs, government social welfare programs, and relief efforts of developmental organizations could be improved in times of shocks to reduce the dependence on forests. These programs could also be effective in protecting assets that are important for agricultural productivity resilience. For example, in Kenya, Janzen & Carter (2018) found that a drought-induced livestock insurance program can reduce reliance on the sale of assets by 96%. Other programs that would also reduce dependency on forests and that could increase agricultural productivity and make it resilient in the event of a shock include improved varieties that are more drought-resistant, diversity of crops, and irrigation. Improved agricultural resilience would mean that even in the event of a shock, less labor would be shifted away from agriculture to forests because the value marginal product of labor in agriculture would not fall by as much. This reduced labor reallocation would allow forest stocks to improve over time, leading to a better natural insurance role when there are significantly greater shocks with which agriculture may not be able to cope.

While our study estimated the labor response to shocks, one weakness was the lack of actual labor data on CPR exploitation. Using the value of what is collected relies on labor productivity being constant. Future research that has actual labor data and data regarding a range of collected products could investigate in detail if some forests are better suited to one type of use (e.g., offer nutrition protection while others are better suited for timber).

With this understanding, future work could focus on the trade-offs between accessibility and institutions that can ensure the quality of the resource to improve the resource rents while guaranteeing sufficient access. Analyzing the use of the forest for the competing needs of different groups can help us determine an optimal design for the institutions that manage these resources. While the poor typically use the forests for collection of NTFPs, which does not result in forest loss, the rich usually allocate labor to more intensive activities such as charcoal burning and timber logging (Ainembabazi, Shively, & Angelsen, 2013), which degrade the forest. Timber activities affect the quality of the forest and hence its ability to provide ecosystem services associated with NTFPs, while the collection of NTFPs does not affect the use of the forest for timber. Understanding community-level thresholds and steady-state labor allocations that result in maximum benefits for both groups is vital.

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CHAPTER 3: ONCE BITTEN, TWICE SHY: DIRECT AND INDIRECT EFFECTS OF PREVIOUS WEATHER SHOCKS ON INPUT USE IN AGRICULTURE

Summary

Evidence suggests that negative shocks can either increase or decrease risk aversion. This study examines whether farmers are more likely to use a high-risk, high-return input (fertilizer) or a low-risk, low-return input (improved seed) after experiencing a drought. Panel data collected from more than 6000 smallholder households in 2012 and 2015 in Zambia were combined with objectively measured rainfall data. I use fixed effects structural equation modeling to disentangle the direct and indirect effects (through income) of shocks on input use. Results show that farmers who experience a drought are less likely to use fertilizer and more likely to use improved seeds, with 7% of the effect attributable to income effects. I provide evidence that the direct effect is driven by an increase in risk aversion. These results suggest that weather shocks affect the timing and type of technology adopted in the agricultural sector. This has important implications for climate change adaptation and food security in the developing world.

1 Introduction

Climate change models predict an increased frequency of extreme weather events such as droughts and floods ('weather shocks') across the globe. Estimates for sub-Saharan Africa suggest that negative weather shocks will reduce crop yields by 2-27% (Blanc, 2012; Connolly-Boutin & Smit, 2016) and push millions of households into poverty (Hallegatte et al., 2015). Weather shocks negatively affect nutrition, educational outcomes, health, food security, and agricultural production in rural households. Identifying the behavioral mechanisms through which weather shocks affect decision-making is key to designing appropriate policies that facilitate mitigating responses.

Standard economic models assume that risk attitudes are stable over time (Stigler, Becker, Stigler, & Becker, 1977). However, many recent studies suggest that individual risk attitudes and thus, risk-taking behavior, can be altered by adverse shocks such as financial crises (Malmendier & Nagel, 2011), trauma from conflict or violence (Moya, 2018), and natural disasters such as earthquakes (Hanaoka, Shigeoka, & Watanabe, 2018), hurricanes (Kahsay & Osberghaus, 2018), floods, and droughts (Page, Savage, & Torgler, 2014). Risk attitudes (and income) in turn affect the adoption and use of improved technologies (Asfawa, Di Battista, & Lipper, 2016; Dercon & Christiaensen, 2011; S. Holden & Westberg, 2016). While shocks affect risky decisions, it remains unclear if smallholder farmers respond by becoming more (Ariely et al., 2005; Dillenberger & Rozen, 2015) or less (Andrade & Iyer, 2009; Hanaoka et al., 2018) risk averse, and what this implies for the adoption of specific technologies. Improved agricultural technology use is critical for improving rural incomes and growing the economies of developing countries that rely mainly on agriculture (Foster & Rosenzweig, 2010; Khonje, Manda, Mkandawire, Tufa, & Alene, 2018). Therefore, any factors that affect technology adoption ultimately affect wellbeing and the development paths of entire countries.

In this paper, I examine how previous weather shocks affect the use of inorganic fertilizer and improved seeds the following year among smallholder farmers. Using panel data on 6000 households in rural Zambia, I first estimate the direct and indirect (income channel) effects of previous weather shocks and use them to obtain the total effect of shocks on the use of fertilizer and improved seeds. I then estimate the effect of shocks on risk attitudes and attribute the direct effect to changes in risk-aversion. To do this, I empirically determine if fertilizer and improved seeds are risk decreasing or risk increasing. I use fixed effects and a system of equations to provide causal evidence that shocks influence technology use through a risk aversion channel. Lastly, I explore impact heterogeneity across gender, wealth, and access to credit.

With effective insurance and financial markets, risk should not be a major source of concern. However, in developing countries, insurance for rural households is lacking and welfare programs are weak (Gao & Mills, 2018). Households affected by shocks may then make more conservative investment decisions, trading expected productivity gains for lower risk (Giné, Townsend, & Vickery, 2007). Understanding how past weather shocks affect input use through risk attitudes is the main objective of this study. Analyzing the effects of shocks on input use under weather risk is essential for several reasons. First, smallholder farmers cope with risk and shocks in ways that are not predicted by economic models of risk-taking and insurance (Fafchamps, 2003). Secondly, risk aversion, combined with the absence of insurance, is often mentioned as a contributing factor to poverty traps as poor households shy away from high-return technologies in fear of total loss (Dercon & Christiaensen, 2011). It also answers the question of whether experiencing a loss leads households to mitigate the impact of future shocks.

This study contributes to the literature in four ways. First, I we estimate the effect of weather shocks on input use causally and disentangle the total effect into the direct and indirect mechanisms. Estimating both the direct and indirect effect is important as previous shocks do not only alter risk attitudes, but also affect income. For example, Salazar-Espinoza et al. (2015) acknowledge that precious weather shocks affect income but they did not model the income channel. Policy recommendations resulting from each impact channel differ. Easing credit constraints after weather shocks could mitigate the income channel impact while providing accurate information and better safety nets would allow farmers to make potenially risky but high return investments (Karlan, Osei,

Osei-Akoto, & Udry, 2014). Secondly, instead of assuming the effect of inputs on the riskiness of output, I empirically show how output risk responds to the use of two inputs. By using two important and common inputs in crop production, I minimize output uncertainty from their effectiveness conditional on weather conditions. Third, because the effect of weather shocks varies across different contexts (Wood, Jina, Jain, Kristjanson, & DeFries, 2014), I also contribute by providing an estimate for Zambia. Finally, I show how shocks differentially affect households by wealth (measured by value of assets), access to credit, and gender.

Results show that households that experience weather shocks in the previous year are more risk-averse and more likely to avoid using a high-risk input (fertilizer) but more likely to use a less-risky input (improved seeds). I also find evidence that access to credit allows households to take on risky investments even after a negative weather shock. This implies that weather shocks affect both the timing and the type of improved technologies adopted in agriculture.

The rest of this paper is organized as follows. In section 2, I briefly review the literature related to risk attitudes, weather shocks, and decisions in agriculture. In section 3, I describe the context, empirical model, and identification strategy. Section 4 presents the data used for the anaysis. Results are presented in section 5 and section 6 concludes.

2 Weather Shocks and Input Use

In this section, I review the literature on shocks and how they affect risky decisions on input use and show the theoretical and empirical ambiguities that are unresolved. I also highlight literature on shocks and income to situate our study and its contribution.

Improved agricultural practices and technologies are important because they can make agriculture more resilient to climate change by improving productivity. They also reduce poverty, especially in sub-Saharan Africa where the productivity of major crops is low while poverty is high (Alene & Coulibaly, 2009; Khonje et al., 2018). However, some of the technologies may increase the variability of output and incomes, making agriculture riskier. Fertilizer and improved seeds are the two most important technologies for raising agricultural productivity (Kaliba et al., 2000; Nin-Pratt & McBride, 2014). However, their adoption remains low for most of Africa (Ariga, Mabaya, Waithaka, & Wanzala-Mlobela, 2019). Therefore, determining if and how shocks deter adoption of different inputs is crucial to understanding adoption incentives for rural smallholder households.

In Tanzania, Arslan et al. (2017), found that within-season rainfall variability decreases the chance of adopting both inorganic and organic fertilizers but increases the likelihood of using improved seeds. However, the observed decisions are reactionary as they use within-season weather variability. They also do not distinguish risk aversion and income effects. In a study in Kenya, Bozzola et al. (2018) found that climatic variables (long term weather anomalies) reduce the likelihood of farmers using hybrid seed, while within-season weather shocks are associated with farmers increasing the area seeded with hybrids. These conflicting results show that the impacts of weather shocks and climate differ and may vary across contexts.

Shocks affect the use of inputs mainly through risk attitudes (Brown, Daigneault, Tjernström, & Zou, 2018; Kahsay & Osberghaus, 2018; Salazar-Espinoza et al., 2015), income or liquidity (Bezabih & Sarr, 2012; Hansen et al., 2018), and to a lesser extent through changing expectations (Freudenreich & Kebede, 2019; Giné et al., 2007). The literature is conclusive on the impact of weather shocks on income—they negatively affect income, and hence tighten liquidity constraints. However, the risk-attitude channel is ambiguous. Here, I review the contradicting findings from the existing literature.

Farmers must make risky decisions before fully knowing how input use translates into output. Negative shocks can greatly reduce food production conditional on input use. Generally, farmers have been found to be sensitive to risk. They are concerned not only with the first moment (expected returns) but also with the second moment (variability of return) and how inputs affect these moments (Bozzola, 2014; de Brauw & Eozenou, 2014; Groom, Koundouri, Nauges, & Thomas, 2008). The risk of failure influences farmers' investment decisions. Recent studies have shown the importance of considering the probability of failure, and different inputs can have varying effects on downside risk (i.e., lower tail of the payoff distribution) (Just & Pope, 1979; Liverpool-Tasie, Omonona, Sanou, & Ogunleye, 2017).

Smallholder farmers are assumed to be risk-averse generally (de Brauw & Eozenou, 2014; Mulwa, Marenya, Rahut, & Kassie, 2017). This risk-aversion is said to be one of the main reasons why there is low adoption of risky technologies such as fertilizer (Baerenklau, 2005; Cullen, Anderson, Biscaye, & Reynolds, 2018; Fafchamps, 2009). However, empirical research has found mixed results, with some studies showing that smallholder farmers are in-fact risk-seeking (Henrich & McElreath, 2002). As Fafchamps (2003) argues, risking substantial portions of household wealth in agriculture contradicts the assumption that farmers are risk averse.

Decision-making theories generally assume that risk attitudes are stable over time (Baucells & Villasís, 2010; Weber & Milliman, 1997). However, risk attitudes may change with personal experiences. Emotions, which may be caused by exogenous factors or by the outcomes of past choices, play a significant role in the decision to bear risk (Dillenberger & Rozen, 2015). Specifically, previous events that may have resulted in a loss or a gain from a gamble (in this case, investing in agriculture) affect risk attitudes. This means individual risk attitudes depend on the history of losses and gains (Cohen, Etner, & Jeleva, 2008; Imas, 2016). In this paper, I focus on what would be termed losses or disappointments resulting from a previous weather shock.

Two conflicting strands of literature address history-dependent risk attitudes. Several studies have found that previous losses result in risk-seeking behavior, sometimes to cover those losses (Andrade & Iyer, 2009; Hanaoka et al., 2018), while other studies find that individuals become risk-averse after a loss (Ariely et al., 2005; Dillenberger & Rozen, 2015; Imas, 2016). Other empirical studies continue to show this contradiction in risk attitudes after a shock. Estimating the effect of the Great Japan Earthquake of 2011, Hanaoka et al. (2018) found that the earthquake led to more risk-seeking with effects lasting up to five years after. In Mozambique, Salazar-Espinoza et al. (2015b) found shifts in cropland decisions responding to previous weather shocks but not from the previous two years, suggesting that these responses are potentially short-term. Malmendier & Nagel (2011) found evidence that the generations that experienced major macroeconomic shocks in the US are more risk-averse, including those that experienced stock-market crashes. In Germany, Decker & Schmitz (2016) found that experiencing a health shock leads to higher risk-aversion. The drop in risk-taking behavior was not driven by reduced income. Andersen et al. (2019) used the 2007-2009 financial crisis for shareholders who lost through banks that defaulted and showed that only first-hand experience of a loss leads to increases in risk aversion. Most of these studies (except for Decker & Schmitz, 2016) do not account for the effect of shocks through income. If the effect of shocks through income is large, then the total effect could be wrongly attributed to the risk attitude channel.

Meanwhile, studies showing that negative shocks result in increased risk-seeking are also common. Kahsay & Osberghaus (2018) found that in Germany, household heads were more risk-seeking after a cyclone storm but that this only held if they suffered a direct loss from the storm. Floods resulted in more risk-seeking behavior, with homeowners who incurred losses in the flood being 50% more likely to prefer a risky gamble with a higher return than a sure amount (Page et al. 2014). Significant changes in risk and time preferences before and after exposure to a volcanic eruption were observed by Willinger et al. (2013).

These contradictory results in empirical studies are a result of different factors. For some studies, backed by theory, there is a real difference in how people respond to experiencing a shock. For some, differences arise because they are focusing on different aspects of shocks (for example, studies above looking at losses to assets such as homes like, Kahsay & Osberghaus (2018) and Page et al. (2014) show consistent results that households become risk-seeking). For others, these differences are because shocks affect households differently depending on the household's capacity to cope and the available resources (Wood et al., 2014), with households with higher resource endowments likely to become risk-seeking. It is also worth noting that the measure of risk attitudes is not the same across studies. While others ask for self-reported risk attitudes (Decker & Schmitz, 2016), others use revealed investment decisions to determine risk attiudes (Malmendier & Nagel, 2011; Andrade & Iyer, 2009). It is also possible that differences in identification strategies explains the differences in results as well as whether laboratory or real losses data is used (Page et al., 2014).

Existing evidence also suggests considerable heterogeneity in risk attitudes across factors such as landholdings, income (Rosenzweig & Binswanger, 1993), and access to credit (Bai, Xu, Qiu, & Liu, 2015). Farmers exhibit decreasing absolute risk aversion as well as increasing partial relative risk aversion preferences as their wealth increases. Gendered differences are also found, often showing that men are more risk-seeking compared to women (Charness & Gneezy, 2012; Hanaoka et al., 2018).

An overview of the literature highlights that the impact of shocks on risk aversion and risky behavior remains an open question. Impacts can also vary across shocks and contexts. Therefore, I empirically estimate the impact of shocks on technology use and risk aversion among smallholder farmers in Zambia. In addition, most of the cited studies are done in the developed world. I therefore contribute by measuring the effect of weather shocks among smallholder farmers. The poverty reduction effects of relaxing constraints on improved input use are great since more than 70% of the labor force in Zambia is engaged in smallholder farming (Mulungu & Ng'ombe, 2017).

3 Identification Strategy and Empirical Models

In this section, I first describe the seasonality of agriculture in Zambia, including the time at which shocks take place and when input use decisions are made. I then present the empirical models used to understand the effects of shocks on decisions and risk aversion.

3.1 Context and Shock Impact Pathways

In this section, I describe the context of Zambian smallholder agriculture within which this study is conducted. Specifically, I describe the agricultural season and timing of shocks, planting decisions, and earning of income. I also describe the two impact pathways through which previous shocks affect input use decisions.

The previous season's weather shocks affect input use the following season directly (through changing risk attitudes) and indirectly (through affecting income and hence the ability of the household to purchase inputs). Regardless of the risk attitudes, previous weather shocks may impact income negatively, resulting in additional liquidity constraints. I model decisions to use inputs in the current growing period t, which, in Zambia, is from November to February. Period $t-1$ is the previous growing season (November to February) that is followed by a marketing season between April and September, during which income is earned. Figure 7 shows the agricultural seasons timeline for

Zambia. Decisions to use inputs are made after the previous marketing season but before weather realizations for the following period (period *t*). For example, the final month to deposit an installment for the government-subsidized fertilizer and seed, which is the source of both inputs for about 75% of farmers, is between September and October[7].

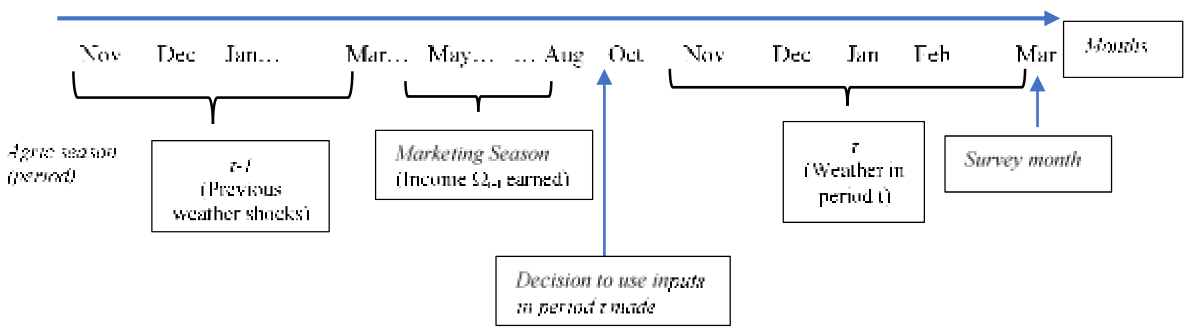

Figure 7: Periods, agricultural seasons and paths for weather shocks impacts.
Note: The RALS survey happens in March of period *t* and asks for income for the past 12 months, from April (start of marketing season after period *t-1*) the previous year to March the following year (just before period *t* marketing season begins).

Figure 7 illustrates the seasonality and sequence of decisions for input use. Previous agricultural income (Ω_{t-1}), which is earned in the marketing season, is affected by weather shocks in period *t-1*. This is the annual (April to March) agricultural income reported at the time of the survey in March of period *t*. So, while the survey captures production for period *t*, it does not capture income from period *t*'s production as the marketing season for period *t* begins in May, after the survey was conducted. Ω_{t-1} becomes part of total liquid wealth available at the start of growing season t (Figure 8). Total wealth outside of agricultural earnings is generally constant over a short period (Heltberg, Oviedo, & Talukdar, 2015); hence, I include household fixed effects in the empirical analysis. For most rural households, the levels of savings are negligible, and variation in liquid wealth is driven by variation in income earned in period *t-1* (Michael, Swetha, Michael, & K

[7] https://www.lusakatimes.com/2019/10/08/over-800000-farmers-adhere-to-fisp-guidelines/

Benjamin, 2019). Period *t-1* shocks affect income earned in the marketing season and consequentially input use in period *t.* Weather in period *t* does not, therefore, affect reported income that could be used in the purchase of inputs. This timeline allows us to causally identify the effect of (predetermined) income on input use because reported income (earned in the previous year) is not a function of input use in period *t*.

I test the validity of this assumption empirically in Table 6. If it holds, I expect no correlation between a shock (drought) in period *t* and reported income. As shown in Table 6, period *t* droughts are not significantly correlated with reported income, but *t-1* shocks are negatively correlated with income. This holds even when I allow for differential impacts in high and low rainfall regions. This supports the assumption that reported income is earned in period *t-1* and is thus predetermined as of the start of period t.

We also consider a direct effect of period *t-1* shocks on input use in period *t* driven by risk attitudes and hence risk-taking behavior and input choices (Dillenberger & Rozen, 2015). Figure 8 graphically shows these two impact pathways. I rely on the spatial and temporal variation and the exogeneity of objectively measured rainfall shocks to identify both the direct and indirect effects. Controlling for household time-invariant unobserved heterogeneity (e.g., weather distributions), shocks can be thought of as a random draw.

Table 6: Effects of negative weather shocks on household income

VARIABLES	(1)	(2)
Drought (t-1)	-0.16888***	-0.26034***
	(0.05043)	(0.05857)
Drought (t)	0.03318	0.01894
	(0.03609)	(0.05585)
Drought(t-1) x High rainfall region		0.26123***
		(0.08456)
Drought (t) x High rainfall region		0.08368
		(0.07774)
Constant	7.86374***	7.81507***
	(0.23977)	(0.23882)
Household controls	Yes	Yes
Household FE	Yes	Yes
Year FE	Yes	Yes
Observations	12,114	12,114
Households	6,057	6,057
R-squared	0.00623	0.00853

Robust standard errors in parentheses

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

Column (1) is a regression of household income on droughts, and household other controls, (2) includes an interaction of droughts and AER III. Household controls include the number of prime age adults (16-59 years), age of household head, and remittances.

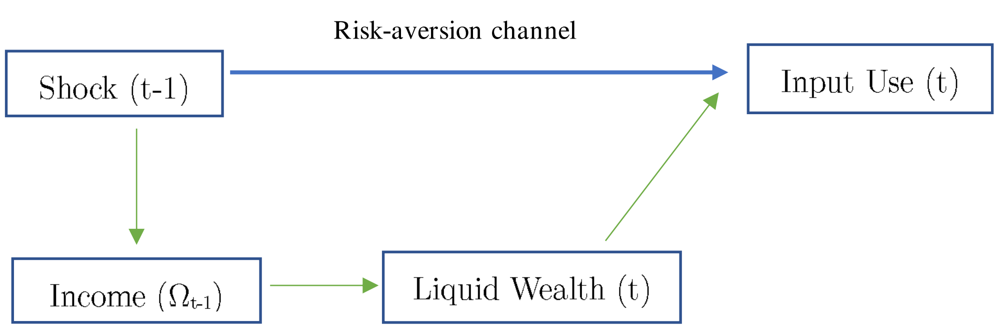

Figure 8: Impact pathways of *t-1* shocks on input use in period *t*

In the next section, I empirically model this relationship to separately estimate the magnitudes of both direct and direct effects of shocks on input use.

3.2 Empirical Approach

Our empirical approach consists of first estimating the effect of *t-1* shocks on input use using a model that simultaneously accounts for the direct and indirect effects. I then outline the analysis to explore the mechanisms for the observed input use responses. For this, I use an expected utility framework to derive estimable equations to test if shocks affect risk attitudes. This exercise consists of estimating the impact of input use on the moments of the agricultural output distribution. Then, I estimate the effect of shocks on risk attitudes by estimating average risk parameters for households in years that they do and do not experience shocks. Finally, I test for impact heterogeneity across access to credit, gender, and wealth.

Effect of shocks on input use

We first test if households that experienced a shock in the previous year are more or less likely to use either of two inputs. Empirically, I start with a household fixed effects model that tests for the effect of *t-1* shocks (W_{nt-1}) for household n, on the probability (and intensity) of using fertilizer or improved seed in period *t*[8]. Conditioning on income in $t-1$, Ω_{nt-1}, isolates the direct effect of W_{nt-1} on the probability of using fertilizer or improved seed. I estimate the parameters of

$$x_{nt}^{j} = \omega_n + \vartheta_1 W_{nt-1} + \vartheta_2 W_{nt} + \vartheta_3 \Omega_{nt-1} + \vartheta_z Z_{nt} + \vartheta_t T + \epsilon_{nt} \qquad (1)$$

where x_{nt}^{j}=0,1 is an indicator of whether household *n* used input *j* or not in period *t,* and ω_n is a household fixed effect. $W_{nt-1} = 0{,}1$ is a binary variable for whether the household experienced objectively defined weather shocks in period *t-1*, $W_{nt} = 0{,}1$ indicates if the household experienced a weather shock in period *t.* This is defined with a binary variable, though a continuous variable for

[8] The intensive margins are in the appendix. The main interpretations are based on the extensive margins for two reasons. Firstly, risk aversion is more related to the likelihood of choosing one lottery over a sure payment. As O'donoghue & Somerville (2018) state, "when an individual compares two lotteries where one has a higher expected value but also more risk, I assume that the person's choice will depend on the extent of risk aversion—for example, if risk aversion is small enough, the person will choose the lottery with higher expected value and more risk" (p.1). Further, Roosen & Hennessy (2003) showed that there is no significant correlation between the level of input (fertilizer application rate) use and level of risk aversion—suggesting that this has more to do with choices than intensity. Studying looking at risk-aversion in agriculture equally follow this approach by using binary defined measures of input adoption/use (Holden & Fisher, 2015; Holden & Westberg, 2016; Holden & Quiggin, 2017; Katengeza et al., 2019). Secondly, the discrete data on improved seed and fertilizer use is more reliable than the continuous measures. For example, the continuous measure for proportion of improved seed is fairly discrete with households allocating mostly all area, nothing, and few allocating a proportion in between.

weather anomalies produces similar results (Table A2 in appendices). Z_{nt} is a vector of household characteristics. T is a year fixed effect capturing year-to-year shocks common to all households. ϵ_{nt} is the random error term clustered at the household level. ϑ_1 is the parameter of interest that measures the direct effect of shocks on input use. I also control for weather realizations in period *t*, unlike previous studies (Bozzola & Di Falco, 2017; Salazar-Espinoza et al., 2015), because farmers can react to the weather within the same period (Arslan et al., 2017, 2015).

The total effect of weather shocks depends on the direct effect plus an indirect effect through impacts to household income. To facilitate calculation of the indirect effect, I also separately model the impact of a shock on income as

$$\Omega_{nt-1} = \omega_n + \gamma_1 W_{nt-1} + \gamma_2 W_{nt} + \gamma_z Z_{nt} + \gamma_t T + \epsilon_{nt} \tag{2}$$

The parameter of concern is γ_1. The indirect effect of a shock on input use is the product of θ_3 from equation 1 and γ_1 from equation 8. The total effect of the shock on input use is then given as $\vartheta_1 + (\vartheta_3 * \gamma_1)$.

We follow previous economic studies in estimating the indirect and direct effect (Han, Norton, & Powell, 2011; Xiang, Malik, & Nielsen, 2020; Zouabi & Peridy, 2015) by estimating equations (1) and (2) simultaneously. While earlier pioneering work on mediation (indirect) effects by Baron & Kenny (1986) had claimed that both ϑ_3 and γ_1 need to be significant for the indirect effect to be significant, this has since been disapproved. Zhao et al. (2010) showed that the direct effect need not be significant to establish an indirect effect. Bootstrapping standard errors in the calculation of the indirect effect provides more statistical power (Preacher & Hayes, 2004; Zhao et al., 2010), as the distribution of the indirect effect is highly skewed. There is also evidence that a two-step estimation is less efficient and produces larger standard errors when compared to a one-step approach (Iacobucci, Saldanha, & Deng, 2007). Therefore, the models are estimated here using a one-step approach.

Identification for the direct effect (ϑ_1) follows the standard assumptions in a fixed effects framework with exogenous regressors. Since the variable of concern is weather shocks (which are computed from objectively measured rainfall), it is exogenous to household decisions. Conditioned on household and year fixed effects to control for any unobserved time-invariant confounders, and other unobserved changes from one year to the other such as fertilizer subsidy levels, the direct effect of weather shocks is identified.

Because income reported at the survey month comes from the previous season's harvest and weather, and because *t-1* income does not depend on a shock in *t* (as shown in Table 6), the indirect effect is also identified. Specifically, in order to identify the indirect effect, the ignorability condition (treatment—income—should be exogenous to the outcome) must be met (de Luna & Johansson, 2006). Income does not generally meet the ignorability condition as it may be influenced by the same unobserved factors that affect input use. The solution, in most observational experiments, is to condition on all pretreatment covariates. We, therefore, condition on covariates and unobserved heterogeneity through household fixed effects—making the identification stronger than in studies using cross-sectional data. So, after controlling for all observable and time-invariant unobservable household characteristics, income (from the previous season) is ignorable. I also assume that risk averse individuals have not systematically migrated away from areas more prone to weather shocks (Fafchamps, 2009)—a valid assumption given the land tenure systems that do not allow for easy moving (Makondo & Thomas, 2019).

The literature suggests that the impact of shocks on risk aversion may drive the direct effect estimated here. To examine this hypothesis, I test if observed impacts are consistent with changes in household risk aversion parameters.

Explaining the direct channel

To examine the role of risk aversion in explaining the direct effect of shocks on input choices, I describe an expected utility maximization model in which producers choose input levels to maximize utility, which depends on the moments of the agricultural output distribution. Within this framework, I determine the risk properties of the two inputs and link any changes in their use to their risk attributes. Second, I determine the effect of shocks on risk parameters within the model. If shocks make farmers more risk averse, then I expect that households will make more conservative input decisions in years following shocks.

Input attributes and effects of weather shocks on risk attitudes

We now examine how experiencing a shock affects household risk aversion parameters. To do this, I first estimate how the use of fertilizer and improved seeds impacts the moments of the distribution of maize output. I focus on maize because it is the national staple grown by more than 80% of smallholder farmers, occupying more than 65% of the total cropped area, and because fertilizer and improved seed are used almost exclusively in maize production (Burke, Frossard, Kabwe, & Jayne, 2019; Burke, Jayne, & Black, 2017). Further, I use output instead of net value because I do not have input cost information. Also, evidence in the literature suggests that smallholder producers may maximize production instead of net value (Umar, 2014; Zellner, Kmenta, & Dreze, 1966). Next, following methods described in Antle (1987) and applied in Bozzola and Finger (2020) I use the estimated effect of inputs on the output distribution to infer risk aversion parameters. I apply this method separately for household-years that experience a shock and those that do not and compare resulting estimates of risk aversion.

We assume that maize output, $y_n(X; Z_n)$, depends on the use of inputs $X = \{x^f, x^s\}$, where x^f is the quantity of fertilizer and x^f is the quantity of improved seeds, and a vector of household characteristics, Z_n. As Bozzola & Smale (2020) note, agricultural returns are characterized by extreme loss events that make farmers averse to downside risk exposure, especially in areas with no or limited insurance coverage. It is likely that household expected utility depends on mean production, the risk (variance) of production, and the downside risk (skewness) of production. Given this, I assume that household expected utility can be approximated by the first three moments of the output distribution. I do not consider higher order moments because they do not generally improve the approximation of output as a random variable (Antle, 1987). Therefore, the household's objective function is to choose inputs X to maximize:

$$Max \;\; Eu_n(y_n) = \;\; U\big(\mu_{1\mathrm{n}}(X; Z_n), \mu_{2n}(X; Z_n), \mu_{3n}(X; Z_n)\big) \tag{3}$$

Where $\mu_{in}(X)$ is the i^{th} moment of the output distribution for household *n*. Specifically, the first moment of the output distribution, μ_{1n} is the expected output $(E(y_n)\,)$, the second moment, $\mu_{2n} = \Big(y_n(X) - E\big(y_n(X)\big)\Big)^2$, and the third moment, $\mu_{3n} = \Big(y_n(X) - E\big(y_n(X)\big)\Big)^3$. The first-order conditions of this problem for household *n* are:

$$\frac{\partial Eu_n}{\partial \, x_n^f} = \frac{\partial U}{\partial \mu_{1n}} \frac{\partial \mu_{1n}}{\partial x_n^f} + \frac{\partial U}{\partial \mu_{2n}} \frac{\partial \mu_{2n}}{\partial x_n^f} + \frac{\partial U}{\partial \mu_3} \frac{\partial \mu_{3n}}{\partial x_n^f} = 0 \tag{4}$$

$$\frac{\partial Eu_n}{\partial x_n^s} = \frac{\partial U}{\partial \mu_{1n}} \frac{\partial \mu_{1n}}{\partial x_n^s} + \frac{\partial U}{\partial \mu_{2n}} \frac{\partial \mu_{2n}}{\partial x_n^s} + \frac{\partial U}{\partial \mu_{3n}} \frac{\partial \mu_{3n}}{\partial x_n^s} = 0 \tag{5}$$

We divide (4) and (5) by the marginal contribution of the first moment to utility $\frac{\partial U}{\partial \mu_{1n}}$. Letting $\frac{\partial U}{\partial \mu_{2n}} / \frac{\partial U}{\partial \mu_{1n}} = \theta_{2n}$ and $\frac{\partial U}{\partial \mu_{3n}} / \frac{\partial U}{\partial \mu_{1n}} = \theta_{3n}$, I can rewrite (4) and (5) as:

$$\frac{\partial \mu_{1n}}{\partial x_n^f} = -\theta_{2n}^f \frac{\partial \mu_{2n}}{\partial x_n^f} - \theta_{3n}^f \frac{\partial \mu_{3n}}{\partial x_n^f} \tag{6}$$

$$\frac{\partial \mu_{1n}}{\partial x_n^s} = -\theta_{2n}^s \frac{\partial \mu_{2n}}{\partial x_n^s} - \theta_{3n}^s \frac{\partial \mu_{3n}}{\partial x_n^s} \tag{7}$$

We now relate the parameters (θ) of expressions (6) and (7) to the Arrow-Pratt (AP) and downside risk (DS) coefficients (Kimball, 1990; Pratt, 1964). For this, I assume that the expected utility function (LHS of 3) can be approximated by a 3rd-order Taylor series expansion around the expected output[9], μ_1 (dropping the household subscripts for conciseness; see Appendix 3.1: **Derivation of Equation 8 in Chapter 3** for the full derivation):

$$Eu(y) \approx u(\mu_1) + u''(\mu_1)\mu_2 \frac{1}{2!} + u'''(\mu_1)\mu_3 \frac{1}{3!} \tag{8}$$

The FOCs of this approximation are:

$$\frac{\partial Eu}{\partial \mu_1} \approx u'(\mu_1) + u''(\mu_1)\mu_2 \frac{1}{2!} + u'''(\mu_1)\mu_3 \frac{1}{3!} = u'(\mu_1) = 0 \tag{9.1}$$

$$\frac{\partial Eu}{\partial \mu_2} \approx u''(\mu_1) \frac{1}{2!} = 0 \tag{9.2}$$

$$\frac{\partial Eu}{\partial \mu_3} \approx u'''(\mu_1) \frac{1}{3!} = 0 \tag{9.3}$$

[9] The expansion to approximate expected utility can be done around zero or the mean (Levy & Markowitz, 1979). However, in tests with empirical distributions by Young & Trent (1969), the approximation using the mean performed markedly better than the approximation using zero.

The equality of (9.1) (i.e., $Eu'(\mu_1) = u'(\mu_1) = 0$), holds when the marginal utility function is linear, meaning that $u''' = 0$ (Koekebakker, Koekebakker, & Zakamouline, 2007). Otherwise $u''' \neq 0$ and the equality would not hold (Antle, 1987). Note that (9.2) implies that the second term in (9.1) $(u''(\mu_1)\mu_2 \frac{1}{2!})$ is also zero.

We know that $Eu(y) = U\big(\mu_{1n}(X;Z_n), \mu_{2n}(X;Z_n), \mu_{3n}(X;Z_n)\big) \approx u(\mu_1) + u''(\mu_1)\mu_2 \frac{1}{2!} + u'''(\mu_1)\mu_3 \frac{1}{3!}$. $\theta_2 = \frac{\partial U}{\partial \mu_2} / \frac{\partial U}{\partial \mu_1}$ from the FOCs of maximizing U. Therefore, using the FOCs of the function that approximates U (9.1-9.3), $\theta_2 \approx \frac{u''(\mu_1)}{u\prime} \frac{1}{2!}$. Similarly, $\theta_{3n} \approx \frac{u'''(\mu_1)}{u'} \frac{1}{3!}$.

Formally, AP and DS risk coefficients are defined as:

$$AP = -\frac{u''(\mu_1)}{u'} \tag{10}$$

$$DS = \frac{u'''(\mu_1)}{u'} \tag{11}$$

Therefore, $-2\theta_2 \approx AP$ and $6\theta_3 \approx DS$. To empirically estimate the AP and DS coefficients, I solve for θ_2 and θ_3 and plug into equation (12) and (13) to obtain (re-introducing household subscript, n):

$$\frac{\partial \mu_{1n}}{\partial x_n^f} = \frac{1}{2} AP_f \frac{\partial \mu_{2n}}{\partial x_n^f} - (\frac{1}{6} DS_f) \frac{\partial \mu_{3n}}{\partial x_n^f} + \xi_{nf} \tag{12}$$

$$\frac{\partial \mu_{1n}}{\partial x_n^s} = \frac{1}{2} AP_s \frac{\partial \mu_{2n}}{\partial x_n^s} - (\frac{1}{6} DS_s) \frac{\partial \mu_{3n}}{\partial x_n^s} + \xi_{ns} \tag{13}$$

Where ξ_{nf} and ξ_{ns} are econometric error terms representing possible random errors in the household maximization process. The marginal effects of inputs on the moments of output are estimated and included as data in (12) and (13). The dependent and input use variables are standardized so that marginal effects are comparable. Using a system of questions to estimate AP_j and DS_j in equations (12) and (13), I impose the constraints that $AP_f = AP_s = AP, DS_f = DS_s = DS$ (Groom et al., 2008; Simtowe, Mduma, Phiri, Thomas, & Zeller, 2006; Torkamani & Shajari, 2008). Even though each input could have a different effect on variance and downside risk, the AP and DS coefficients are related to the risk attitudes of decision-makers; hence they are constrained to be the same across fertilizer and seed use.

Estimation Strategy

To estimate the AP and DS risk aversion coefficients, I first estimate the derivatives of the moments of output with respect to the use of fertilizer and seeds. These estimated derivatives serve as the data used when estimating AP and DS. Therefore, I estimate the effect of each input (conditional on controls) on the three moments of the output distribution. Then, I use the estimates to calculate marginal effects and use them as variables to estimate AP and DS as parameters.

To test the effect of fertilizer and improved seed on expected output, the variance of output (Chen et al., 2004; Cabas et al., 2010; Sarker et al., 2019), and skewness (Bozzola & Smale, 2020; Wossen et al., 2017), I estimate 3 models (14-16) sequentially. The first model (14) determines the effect of the inputs on expected output. The model is empirically estimated by specifying a quadratic functional form following other studies (Chen et al., 2004; Koundouri & Nauges, 2005). By including level, squares, and an interaction of fertilizer and improved seed, I obtain household-specific marginal effects. Mean crop output for household *n* in year *t,* y_{nt} is presented as:

$$y_{nt} = \nu_0 + \nu_1 x_{nt}^f + \nu_2\left(x_{nt}^f\right)^2 + \nu_3 x_{nt}^s + \nu_4(x_{nt}^s)^2 + \nu_5\left(x_{nt}^s x_{nt}^f\right) + \nu_6 W_{nt} + \nu_z Z_{nt} + \alpha_i + T_t + \epsilon_{nt} \tag{14}$$

Since $E[\epsilon_{nt} = 0]$, predicted squared residuals (variance) from (14) are used to represent the second moment (μ_{2n}). This estimation (15), with ρ_j parameters, indicates whether an input is risk-increasing or risk-decreasing.

$$(\hat{\epsilon}_{nt})^2 = \rho_0 + \rho_1 x_{nt}^f + \rho_2\left(x_{nt}^f\right)^2 + \rho_3 x_{nt}^s + \rho_4(x_{nt}^s)^2 + \rho_5\left(x_{nt}^s x_{nt}^f\right) + \rho_6 W_{nt} + \rho_z Z_{nt} + \alpha_i + T_t + \varepsilon_{nt} \tag{15}$$

And finally, I estimate the effect of input use on downside risk by using the cubed residuals (skewness) from (14) to determine the effect of inputs on downside risk:

$$(\hat{\epsilon}_{nt})^3 = \varphi_0 + \varphi_1 x_{nt}^f + \varphi_2 \left(x_{nt}^f\right)^2 + \varphi_3 x_{nt}^s + \varphi_4 (x_{nt}^s)^2 + \varphi_5 \left(x_{nt}^s x_{nt}^f\right) + \varphi_6 W_{nt} + \varphi_z Z_{nt} + \alpha_i + T_t + e_{nt} \tag{16}$$

where y_{nt} is average maize crop output in kilograms, and x_{nt}^f is fertilizer use, x_{nt}^s is improved seed use, W_{nt} is weather shocks for period *t,* and Z_{nt} is a vector of household-level control variables. α_i and T_t are household and year fixed effects, respectively. ν_j, ρ_j, φ_j are the paramaters to be estimated in each equation, where *j* is inputs or variables in the regressions. Fertilizer use is measured as fertilizer application rate—kilograms of fertilizer per hectare of maize while seed use is measured as a proportion of maize area that is under improved seed to capture the intensity of use, similar to Bozzola et al. (2019) and Kim et al. (2019). Because binary endogenous variables do not provide consistent estimates (Wooldridge, 2010) under instrumental variables estimation, and to be able to estimate non-constant marginal effects (necessary for estimating risk parameters), I use only continuous measures of fertilizer and seed (intensity).

The variables of interest (fertilizer and improved seed use) are potentially endogenous due to omitted variable bias, unobserved heterogeneity. I therefore use fixed effects and instrumental variables to correct for omitted variables and unobserved sources of endogeneity. In the first stage, an instrumental variables fixed effects (IV-FE) approach was used to estimate (14). Rainfall in the previous year, distance to the nearest agro-dealer (shop selling agricultural inputs), access to extension services, distance to the nearest government fertilizer depot, and average maize prices at the district level were used as instruments. The economic criteria for the inclusion of these instruments are that I assume they are correlated with input use decisions but uncorrelated with the error term of the equation estimating the effects of input use on expected output (equation 14).

The next step is to include estimated marginal effects as the data to estimate AP and DS risk aversion coefficients using equations (12) and (13). Once the estimates, $\hat{\nu}_j, \hat{\rho}_j, \hat{\varphi}_j$, are obtained for the three moments of the distribution from estimating equations (14)-(16), I compute the marginal effect of fertilizer and improved seed on the moments of output to estimate (12) and (13). The marginal effects for fertilizer are recovered as $\frac{\partial \mu_{1n}}{\partial x_n^f} = \hat{v}_1 + 2\hat{v}_2 x_{nt}^f + \hat{v}_3 x_{nt}^s$, $\frac{\partial \mu_{2n}}{\partial x_n^f} = \hat{\rho}_1 + 2\hat{\rho}_2 x_{nt}^f + \hat{\rho}_3 x_{nt}^s$ and $\frac{\partial \mu_{3n}}{\partial x_n^f} = \hat{\varphi}_1 + 2\hat{\varphi}_2 x_{nt}^f + \hat{\varphi}_3 x_{nt}^s$. For improved seed, the marginal effects are given as; $\frac{\partial \mu_{1n}}{\partial x_n^s} = \hat{v}_4 + 2\hat{v}_5 x_{nt}^s + \hat{v}_3 x_{nt}^f$, $\frac{\partial \mu_{2n}}{\partial x_n^s} = \hat{\rho}_4 + 2\hat{\rho}_5 x_{nt}^s + \hat{\rho}_3 x_{nt}^f$ and $\frac{\partial \mu_{3n}}{\partial x_n^s} = \hat{\varphi}_4 + 2\hat{\varphi}_5 x_{nt}^s + \hat{\varphi}_3 x_{nt}^f$.

We use a system of equations to estimate (12) and (13) and obtain the AP and DS. The equations are estimated separately for a subsample that experienced weather shocks in the previous year, and those that did not, using household-years as the unit of analysis. The coefficients are then stored for each of the regressions and a t-test is used to test for equality of AP and DS parameters across the two sub-samples. I bootstrap the standard errors, resampling over households to obtain heteroscedasticity-robust standard errors in the estimation of (12) and (13) and the t-test.

Heterogeneous impacts

To test for the heterogeneity of impact of shocks on input use across gender, wealth (measured by asset values), and credit access, I estimate three different models similar to (1) and (2). For heterogeneity across gender, I include an interaction of gender and shock in the precious period. Gender on its own is not included in the regression because it is time-invariant. For access to credit and wealth, I split the samples into two subsamples and estimate the models separately. This is done because access to credit and wealth are potentially endogenous, and I would not want to include them in the model. In addition, there is little within variation in access to credit (Table 7).

4 Data and Data Sources

In this section I present the data used for the analysis and present summary statistics of the key variables used in the regressions

4.1 Data Sources

Two datasets are used in this study. Household data come from the Rural Agricultural Livelihoods Survey (RALS) collected in 2012 and 2015 in Zambia. The RALS data were collected by the Indaba Agricultural Policy Research Institute (IAPRI) in collaboration with the Central Statistical Office (CSO) and the Ministry of Agriculture (MAL) with support from Michigan State University. The RALS sampling is based on the 2010 Census of Housing and Population. It is nationally and provincially representative, with a sample size of more than 8,000 farming households. However, not all households are surveyed in both years. The balanced sample is about 7,000 households and only about 6,000 of these households grow maize. This reduces the sample size to 6,058 households. In both years, the GPS coordinates of the households are collected and used to match a household to the weather data. From the RALS dataset, I obtain all household level variables. Area planted to maize and the type of seed used are collected and used to define whether a household used improved seed and fertilizer. Fertilizer application rate is calculated as total quantity of basal dressing fertilizer used (in kgs) divided by the total maize hectarage and total quantity of top dressing fertilizer used divided by the maize hectarage. The two application rates are then averaged to get the average fertilizer application rates. Improved seed proportion is calculated as area planted to improved seed divided by the total maize hectarage.

Weather shocks are determined by using dekadal (10-day) spatial rainfall data from the Climate Hazards Group Infrared Precipitation with Station database (CHIRPS). The CHIRPS dataset, developed by the U.S. Geological Survey (USGS) and the Climate Hazards Group at the University of California, Santa Barbara, is a blended product combining dekadal rainfall estimates, created from satellite data and ground-based observations from weather stations. Quasi-global gridded datasets are available from 1981 to near-present at 0.05° spatial resolution (~5.3 km^2) and at pentadal, dekadal, and monthly temporal resolution (Funk et al., 2014). At this high resolution, these data were merged at the household level and not at the village level.

Like other studies (Amare, Jensen, Shiferaw, & Cissé, 2018; Birthal & Hazrana, 2019; Marchetta, Sahn, & Tiberti, 2019), this study defines rainfall anomalies (RA) as the standardized deviation of annual rainfall from its long-term mean to make it comparable over time and space. For each 5.3km^2 area, the annual rainfall for the previous season (R_{nt-1}) is subtracted from the long-term mean (35 years, 1981-2015) of annual rainfall (in mm/season) ($\bar{R}_n$) and divided by its long-term standard deviation as (R_n^{SD});

$$RA_{nt-1} = \frac{\bar{R}_n - R_{nt-1}}{R_n^{SD}} \tag{17}$$

where RA_{nt-1} is the rainfall anomaly for period *t-1* for household *n* (roughly representing 5.3km^2 area). The same was done for period *t* weather to get RA_{nt}. Negative shocks (droughts) are defined as;

$$\begin{aligned} W_{nt-1} &= 1 \; if \;\; RA_{nt-1} < -0.5 \\ &= 0 \qquad otherwise \end{aligned} \tag{18}$$

I concentrate on negative shocks because they impact agricultural livelihoods negatively compared to positive shocks in the arid and semi-arid regions (Gao & Mills, 2018) and very few households experienced floods in the data. For robustness, shocks were also defined using the Standardized Precipitation Evapotranspiration Index (SPEI) that includes temperature and accounts for potential evapotranspiration (PET) in defining shocks (Beguería, Vicente-Serrano, Reig, & Latorre, 2014; Shi & Tao, 2014). Generally, results are confirmed, even when using SPEI (see Table A3 in the appendix).

4.2 Descriptive Statistics

Table 7 summarizes the main variables used in the analyses. Average maize output for the whole sample are almost the same between the two years, at about 3.2 tonnes per household. Household income is also virtually unchanged between the two years. However, highlighting the importance of year fixed effects in econometric models, there are differences in fertilizer use, with about 64% of the surveyed households using fertilizer in 2012 compared to 71% in 2015. Meanwhile, more households used improved seed in 2012 (62%) compared to 2015 (47%). About 42% of the farmers experienced negative shocks in the 2013/14 season. Period *t* negative shocks were experienced by about 18% of the farmers in 2012 and 22% in 2015. Access to credit stood at about 19%.

Table 7: Descriptive statistics for the main variables

	2012			2015		
Variable	N	Mean	SD	N	Mean	SD
Maize output (kgs)	6058	3291.894	6006.117	6058	3261.59	5704.253
Log household income (real ZMW)	6058	7.802	1.771	6058	7.902	1.663
Fertilizer use (1=Yes)	6058	0.644	0.479	6058	0.710	0.4536
Improved seed use (1=Yes)	6058	0.620	0.485	6058	0.478	0.499
Fertilizer application rate	6058	99.284	110.283	6058	111.156	92.379
Improved seed proportion	6058	59.596	47.999	6058	66.141	46.028
Shock (t-1)	6058	.002	.0426	6058	0.421	0.4938
Shock (t)	6058	0.188	0.391	6058	0.223	0.416
Has access to credit (1=Yes)	6058	0.199	0.399	6057	0.187	0.390
Productive assets (count)	6058	1.108	2.763	6058	2.342	7.074
Remittances received (real ZMW)	6058	207.786	788.964	6058	258.688	925.006
Household head age (years)	6056	46.356	14.565	6058	49.134	14.499
Prime age adults (count)	6058	3.908	1.943	6058	1.930	1.385
Sex of household head	6058	0.177	0.381	6058	0.200	0.400
Distance to extension office (kms)	6058	18.781	25.398	6058	16.516	21.743

Notes: ZMW is Zambian Kwacha (currency), in 2012, $1=ZMW5.5. All monetary variables in real 2012 ZMW.

For the weather shock variables, the continuous anomalies before categorizing them are plotted in Figure 9 for period *t-1* rainfall anomalies. Generally, the figures show that in 2015 there were more negative anomalies than positive anomalies, while in 2012 there were fewer negative and positive anomalies. The rainfall distribution for 2012 period *t-1* was closer to the long-term average, except for wet regions in the eastern part of Zambia.

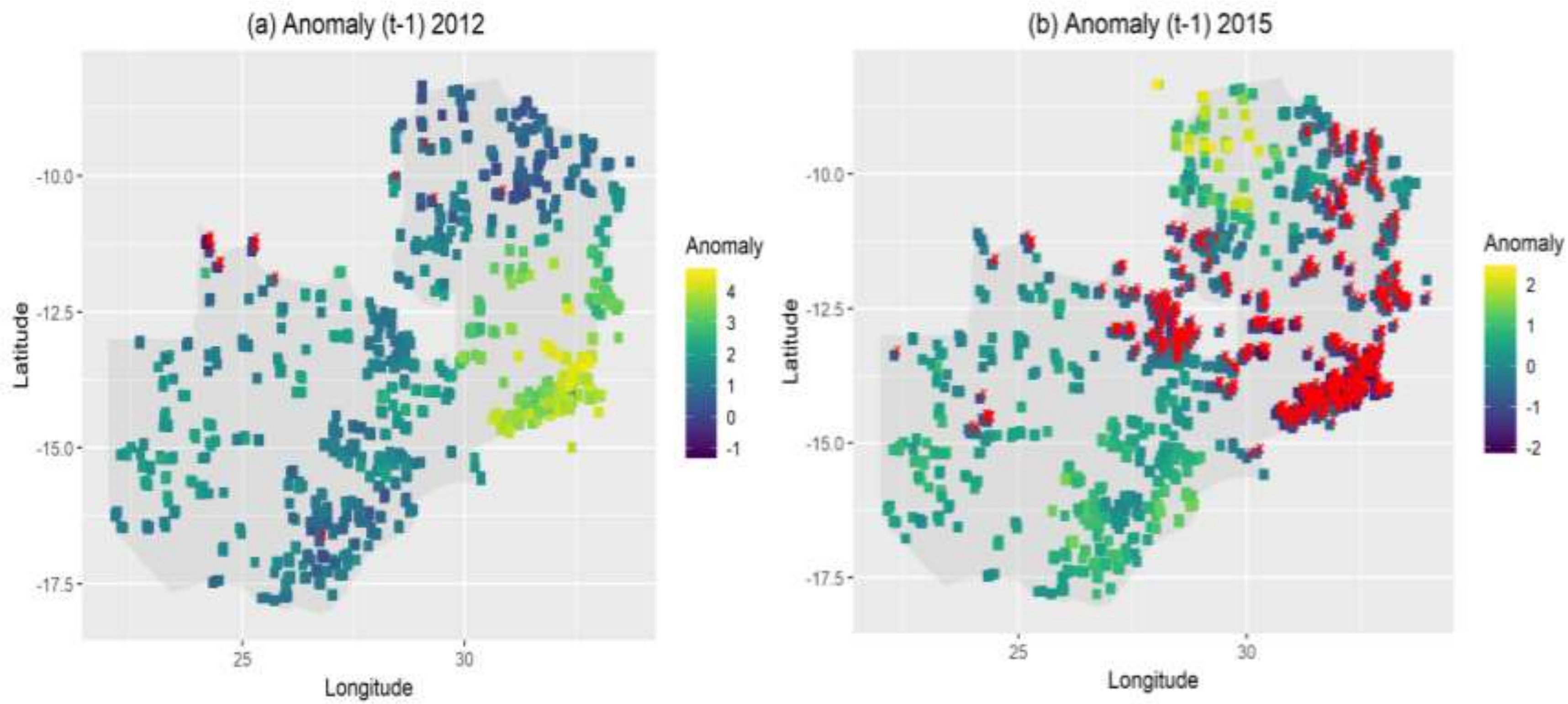

Figure 9: Standardized period *t-1* (2009/10 season for 2012, and 2012/13 season for 2015) anomalies for Zambia. The anomalies are graphed using a color scheme and superimposed on the map of Zambia in the background. Positive anomalies indicate too much rainfall compared to the long-term average, while negative anomalies indicate too little rainfall compared to the long-term average. A unit represents a standard deviation above or below the long-term mean. Points with red ‘x’ indicate areas where shocks were experienced, anomaly <-0.5

5 Results

In this section, I present results starting with the effect of weather shocks on input use. Then I present results determining the attributes of the two inputs are shown, followed by determining the effect of weather shocks on risk attitudes. Finally, I present results on expectations to provide evidence that the observed input use decisions are not driven by expectations.

5.1 Effect of Weather Shocks on Input Use

Table 8 presents the results of the main regressions estimating both the direct and indirect effects of previous negative weather shocks on input use[10]. The system of equations is estimated to derive the direct, indirect, and total effect of previous shocks. The previous season's drought reduces the likelihood of using fertilizer in the following season by about 3 percentage points, with about 7% (0.00230/0.0312) of the effect coming from the indirect income effect. This means that the effect is reinforced by the negative indirect income effect, leading to a higher decrease in the probability of using fertilizer than the direct channel only. Other significant factors in the fertilizer model include the number of prime age adults, average maize prices, and access to extension services, and distance to the nearest fertilizer depot. The number of prime age adults, and access to extension services increase the likelihood of using fertilizer while distance to the nearest fertilizer depot and higher maize prices reduce the likelihood of using fertilizer. Higher prices could mean higher risk, resulting in farmers investing less in a risky input to self-insure (Barrett, 1996). Risk-averse households will reduce input use if they anticipate price volatility (Barrett, Sherlund, & Adesina, 2007). It must be noted that at the time of making the decision to use inputs, farmers are not aware of the output price.

[10] I focus on improved seed and fertilizer use and not joint use to be able to differentiate the likelihood in use to input attributes. However, I estimate a similar model on the probability of using both fertilizer and improved seed. Results in Table A4 in the appendix show that previous weather shocks have no statistically and economically significant effect on the likelihood of using both fertilizer and improved seeds. I believe the direct effects cancel out.

It is also possible that an inverse relationship exists between shocks in period *t* and prices, such that good rainfall implies higher supply and consequentially lower prices.

Results further show that a previous drought directly increases the probability of using improved seeds by about 4.5 percentage points, but the negative effect of the drought on income reduces this likelihood to 4.2 percentage points. The indirect effect accounts for about 6.7% of the total effect. Higher income is positively correlated with higher likelihood of using improved seeds. Other variables significant in the improved seed model are number of prime age adults, average maize prices, and access to extension services, and distance to the nearest fertilizer depot with all having the same signs as in the fertilizer model. In addition, the improved seed model shows that period *t* droughts increase the likelihood of using improved seed. This could be a result of farmers reacting through the adoption of improved drought tolerant varieties compared to local varieties (Katengeza, Holden, & Lunduka, 2019).

Table 8: Direct and indirect effect of previous weather shocks on input use

	Fertilizer Use			Improved Seed Use		
	Direct	Indirect	Total	Direct	Indirect	Total
Drought (t-1)	-0.0289**	-0.00230***	-0.0312***	0.0450***	-0.00281**	0.0422***
	(0.015)	(0.009)	(0.009)	(0.005)	(0.011)	(0.008)
Log household income	0.0160***			0.0196***		
	(0.000)			(0.000)		
Drought (t)	-0.00877			0.0382***		
	(0.294)			(0.001)		
Prime age adults	0.0104***			0.0227***		
	(0.001)			(0.000)		
Age of HH head	-0.000714			-0.00162		
	(0.536)			(0.286)		
Maize prices (ZMW/kg)	-0.0755*			0.271***		
	(0.095)			(0.000)		
Distance to agro-dealer (kms)	0.000319			-0.000175		
	(0.150)			(0.533)		
Access to extension	0.0153*			0.0137		
	(0.080)			(0.244)		
Distance to fertilizer depot (kms)	-0.0005**			0.00056**		
	(0.012)			(0.032)		
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12112	12112	12112	12112	12112	12112
Households	6056	6056	6056	6056	6056	6056

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
ZMW is Zambian Kwacha currency.

We also determine the effect of weather shocks on the intensity of fertilizer and improved seed use (including zeros for those who do not use). Fertilizer use intensity is measured as fertilizer application rate (total quantity of fertilizer used divided by maize cropped area) and improved seed is measured as the proportion of maize area under improved seed. Effects on intensive margins are shown in Table A5 in the appendices section. Previous weather shocks lead to intensification of fertilizer use. The plausible explanation for this counter-intuitive result is that well-to-do households are the ones who mainly use fertilizer after a shock, and they use more per hectare (higher intensity) on average. This can be seen from the fact that the indirect effect is not significant, meaning previous shocks do not affect the income of those that continue to use fertilizer. It is also confirmed in Table 14, where I find that poor households are the ones least likely to use fertilizer after a weather shock.

The effect of previous weather shocks on intensity of improved seed use is consistent with the extensive margins. Previous weather shocks have positive effect on the proportion of maize area planted with improved seed. The proportion of area cultivated under improved seed increases because more households are likely to use improved seed as a result of weather shocks.

5.2 Explaining the Direct (Risk-Aversion) Effect Channel

To quantify how risk aversion changes in response to shocks, I first present how the use of fertilizer and improved seeds affects the mean, variance, and skewness of maize output. The results from an instrumental-variables fixed effects (IV-FE) model are shown in Table 9. First stage regression results with the excluded instruments are displayed in Table A6 in appendix. An increase in the area maize under improved seeds significantly increases maize output. As hypothesized, fertilizer significantly increases expected output relatively more than improved seed. I also show the marginal effect of fertilizer application and improved seed proportion at the 25th, 50th, 75th, and 90th percentile in Table 10. Overall, the marginal effects indicate that putting more area under improved seed increases output. Fertilizer seems to have decreasing marginal effects with no benefits at higher rates of application. When I use dummy variables for improved seed and fertilizer use such that coefficients are comparable, I find that improved seeds on their own do not increase output (Table A7 in the appendix). Fertilizer increases the variance of maize output, while improved seed reduces the variance of maize output. On skewness, I find that improved seeds have no significant effect while fertilizer significantly decreases the risk of a negative outcome (downside risk) with a positive coefficient. Therefore, I find that fertilizer is a high-return but risk-increasing input, while improved seed is a relatively low-return but risk-decreasing input. The positive and non-significant effect on output for improved seeds once fertilizer has been controlled for has also been reported by other studies (Jones, Dalton, & Smale, 2012; Liverpool-Tasie et al., 2017).

The next step is to determine if households that experienced weather shocks in the previous year are more risk averse as measured by the AP and DS risk aversion parameters. The same IV-FE approach was used to derive the necessary moments and marginal effects for the estimation. Results are shown in Table 11. Overall, both groups of farmers are risk-averse but those that experienced shocks in period *t-1* are more risk-averse compared to those that did not. I find similar results for downside risk aversion—indicating that those that experienced shocks are more averse to negative outcomes in output than those that did not.

Table 9: Effect of input use on mean, variance and skewness of output-IV-FE

	(1)	(2)	(3)
VARIABLES	Mean (Output)	Variance (Output)	Skewness (Output)
Improved seed proportion (ISP)	0.28991***	-1.41175***	-501.93604
	(0.03535)	(0.05139)	(310.36792)
(Improved seed proportion)^2	0.24532***	-2.03959***	234.38045***
	(0.05668)	(0.06650)	(75.57649)
Fertilizer application rate (kg/ha)	0.52252***	0.67968***	1,044.89723*
	(0.03471)	(0.07373)	(630.58100)
(Fertilizer application rate (kg/ha))^2	-0.01430***	0.00790	20.12138***
	(0.00127)	(0.00599)	(4.72494)
ISP x Fertilizer application rate	-0.02339	-0.70060***	-1,609.03879*
	(0.01591)	(0.08008)	(890.73939)
Number of prime age adults	0.03031***	-0.00433	-15.88354
	(0.01158)	(0.01210)	(16.06612)
Age of household head	0.01305**	0.00440	-15.78879
	(0.00535)	(0.00430)	(13.99229)
Log of period t rainfall (mm/annum)	-0.24851**	-0.47214***	19.44846
	(0.12147)	(0.10635)	(42.79628)
Constant	8.47045***	21.85280***	965.35562
	(0.87058)	(0.75336)	(787.30490)
Year FE	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Observations	12,110	12,110	12,110
R-squared	0.90953	0.16125	0.28198
Number of Households	6,058	6,058	6,058

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Instruments for improved seed, fertilizer, their squares and interaction in the mean output estimation include: Distance to agro-dealer (kms), distance to fertilizer deport (kms), access to extension services (0,1), average maize prices in the district, and rainfall (mm/annum) in period *t-1*. Improved seed proportion is measured as proportion of maize area planted under improved seeds.

Table 10: Marginal effect of improved seed proportion and improved fertilizer at different percentiles

	Percentile	Improved Seed	Fertilizer
Marginal effect at each percentile			
	25th	-0.543***	0.847***
		(0.113)	(0.0518)
	50th	-0.182***	0.434***
		(0.0532)	(0.0669)
	75th	0.178***	0.0208
		(0.0230)	(0.158)
	90th	0.539***	-0.392
		(0.0767)	(0.254)
Observations		12,110	12,110

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

This result is different from the only available study that estimates the effects of weather shocks on farmers' risk attitudes. Bozzola & Finger (2020) find that AP risk-aversion measure decreases after droughts, but they tested this over a longer period instead of immediately after the shocks, and their context (Italy) is different from smallholder farmers in Zambia. As Salazar-Espinoza et al. (2015) find in the context of smallholder farmers in Mozambique, these changes in risk attitudes are temporal.

Table 11: Arrow-Pratt (AP) absolute and Downside (DS) risk aversion by weather shocks

VARIABLES	Shock (t-1)	No Shock	Difference (t-test)
AP	0.97157***	0.88503***	0.08654***
	(0.01403)	(0.01052)	(0.01751)
DS	0.02539***	0.02330***	0.00209***
	(0.00036)	(0.00025)	(0.00044)
Improved seed constant	8.41960***	7.89702***	
	(0.05697)	(0.04028)	
Fertilizer constant	13.36696***	12.88187***	
	(0.10331)	(0.07990)	
Observations	2,563	9,553	12,116
Households	1,282	4,776	6,058

Bootstrap standard errors in parentheses. 300 replications were used.
*** p<0.01, ** p<0.05, * p<0.1

5.3 Is the Direct Effect Driven by Expectations?

Throughout the study, I have emphasized risk aversion as the main driver of the direct effect, supported by the input risk attributes and farmers' risk attitudes after a shock. However, it is possible that households' subjective expectations of the weather in period *t* are also affected by previous weather shocks and hence input use decisions. The subjective expectations attached to weather shocks are a result of experience and memory (Slegers, 2008). Households become better at predicting the events that they experience more frequently in a specific pattern (Giné et al., 2007; McKenzie, Gibson, & Stillman, 2013). If droughts are more likely to occur after a previous drought, this could explain our estimated behavioral response (i.e., reduced use of risky fertilizer and increased use of safer improved seeds). Therefore, I determine if a drought in period *t-1* is positively or negatively correlated with a drought in period *t* using the same CHIRPS rainfall data covering 34 years (1981 to 2014). Econometric results in Table 12 show that a drought in the previous period is negatively correlated with a drought in the following period.

Table 12: Correlation between drought in period *t-1* and period *t*

VARIABLES	Drought (t)	Drought (t)
Drought (t-1)	-0.04726***	-0.04263***
	(0.00184)	(0.00193)
Constant	0.33593***	0.25372***
	(0.00058)	(0.00489)
Year fixed effects	NO	YES
Observations	269,552	269,552
R-squared	0.00222	0.42941
Number of households	6,058	6,058

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

The graph in Figure 10 confirms the econometric results, indicating that in the past 34 years, a drought in the previous period was only followed by another drought once, in 1994 and 1995. Therefore, if farmers had this experience and acted rationally based on these data, the expectations channel should lead to more risk taking after a drought in period *t-1* since the chances of a weather shock are lowered. This behavior lowers the magnitude of estimated direct effects.

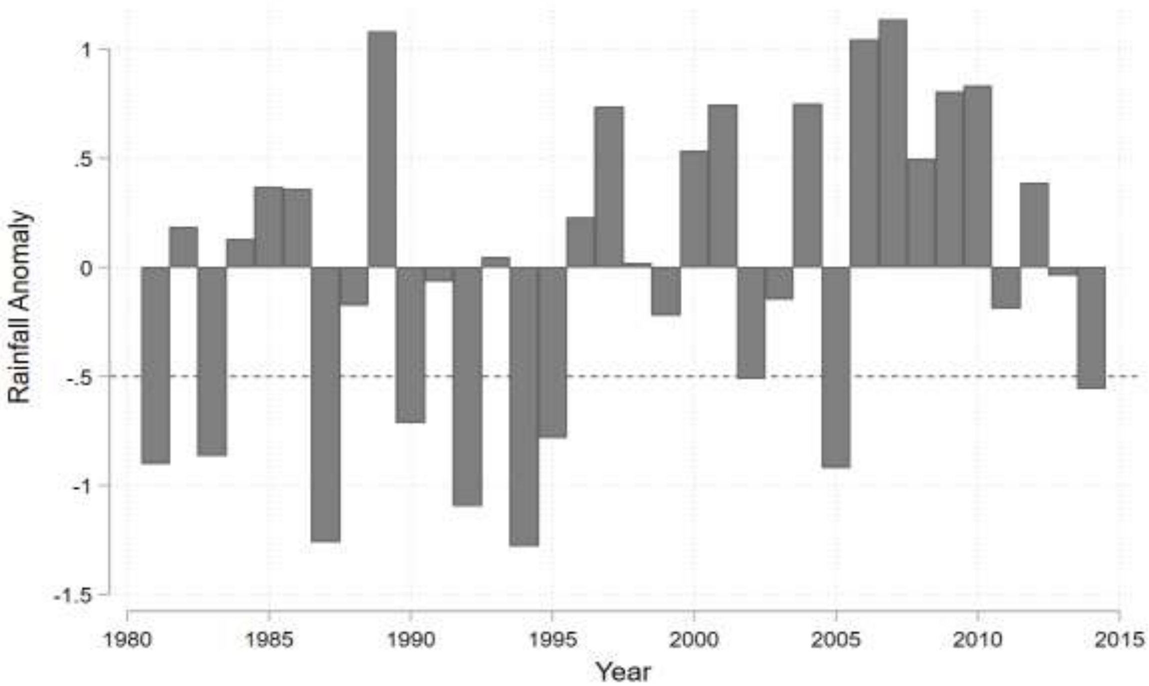

Figure 10: Standardized rainfall anomalies at the country level from 1981-2015. Positive values are above long-term average rainfall while negative values are below long-term average rainfall. The dotted horizontal line indicates a drought as defined in this study.

5.4 Heterogeneous Impacts

Finally, I test for heterogeneity of impact across: i) gender, ii) wealth, and iii) access to credit. Results for each of the regressions are shown in in Table 13, Table 14 and Table 15. For tests across gender of the household head (Table 13), I find no significant difference in the effect of previous weather shocks on input use between male and female-headed households.

Wealth was calculated using the value of assets. Because assets may be endogenous, the sample was split into those with asset value below (poor) and above the median (rich). Results are shown in Table 14. Those with below-median asset value (the poor) are less likely to use fertilizer as a result of a shock in the previous season, while previous shocks have no impact on the likelihood of using fertilizer for the rich. For improved seed, both the rich and poor are more likely to use it after a weather shock. If this observed input use behavior is a result of risk-aversion, then these results imply that the poor are more risk averse towards riskier inputs than the rich since they are less likely to use fertilizer but both are more likely to use a safe input. The poor are more risk averse because failure has catastrophic consequences on their livelihoods (Bchir, Willinger, Bchir, & Willinger, 2013) and since fertilizer increases downside risk, this could explain the observed results.

Table 13: Effect of the previous droughts on input use by gender of the household head

	Fertilizer Use			Improved Seed Use		
	Direct	Indirect	Total	Direct	Indirect	Total
Drought (t-1)	-0.0342***	-0.00181**	-0.0360***	0.0496***	-0.00219**	0.0474***
	(0.008)	(0.046)	(0.005)	(0.004)	(0.049)	(0.006)
Drought (t-1) x Female	0.0248	-0.00235	0.0224	-0.0216	-0.00285	-0.0245
	(0.228)	(0.112)	(0.278)	(0.428)	(0.116)	(0.372)
Household income	0.0161***			0.0195***		
	(0.000)			(0.000)		
Drought (t)	-0.00884			0.0382***		
	(0.290)			(0.001)		
Prime age adults	0.0103***			0.0228***		
	(0.001)			(0.000)		
Age of HH head	-0.000586			-0.00173		
	(0.614)			(0.255)		
Maize prices (ZMW/kg)	-0.0763*			0.272***		
	(0.092)			(0.000)		
Distance to agro-dealer (kms)	0.000324			-0.000178		
	(0.144)			(0.524)		
Access to extension	0.0153*			0.0137		
	(0.079)			(0.244)		
Distance to fertilizer depot (kms)	-0.000555**			0.000562**		
	(0.011)			(0.032)		
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	12112	12112	12112	12112	12112	12112
Households	6056	6056	6056	6056	6056	6056

Robust standard errors in parentheses. ZMW is Zambian Kwacha currency.
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Effects of previous droughts on input use by asset value

	Below Median Asset Value (Poor)						Above Median Asset Value (Rich)					
	Fertilizer Use			Improved Seed Use			Fertilizer Use			Improved Seed Use		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
Drought (t-1)	-0.0455**	-0.0024	-0.048**	0.0517**	-0.0027	0.049**	-0.0195	-0.002**	-0.0218	0.0391*	-0.003*	0.0363*
	(0.025)	(0.104)	(0.019)	(0.035)	(0.107)	(0.047)	(0.169)	(0.044)	(0.126)	(0.065)	(0.056)	(0.086)
Household income	0.0191***			0.023***			0.015***			0.018***		
	(0.000)			(0.000)			(0.000)			(0.002)		
Drought (t)	-0.0120			0.0399**			-0.00120			0.039***		
	(0.400)			(0.024)			(0.902)			(0.010)		
	(0.028)			(0.034)			(0.242)			(0.366)		
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	12112	12112	12112	12112	12112	12112	12112	12112	12112	12112	12112	12112
Households	6056	6056	6056	6056	6056	6056	6056	6056	6056	6056	6056	6056

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. ZMW is Zambian Kwacha currency. Household controls include number of prime-age adults, and age of household head.

Table 15: Effects of previous droughts on input use by access to credit

	No Access to Credit						Has Access to Credit					
	Fertilizer Use			Improved Seed Use			Fertilizer Use			Improved Seed Use		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
Drought (t-1)	-0.034***	-0.002**	-0.037***	0.0268	-0.003**	0.0237	-0.0288	-0.00324	-0.0320	0.101***	-0.003	0.098***
	(0.008)	(0.013)	(0.005)	(0.133)	(0.012)	(0.186)	(0.320)	(0.218)	(0.271)	(0.006)	(0.285)	(0.007)
Household income	0.0145***			0.019***			0.0224***			0.0211**		
	(0.000)			(0.000)			(0.002)			(0.047)		
Drought (t)	-0.00814			0.036***			-0.0299			0.0303		
	(0.375)			(0.005)			(0.161)			(0.256)		
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5352	5352	5352	5352	5352	5352	6712	6712	6712	6712	6712	6712
Households	2676	2676	2676	2676	2676	2676	3356	3356	3356	3356	3356	3356

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. ZMW is Zambian Kwacha currency. Household controls include number of prime-age adults, and age of household head.

Those without access to credit are less likely to use fertilizer as a result of shocks in the previous year, but a previous shock has no effect on the probability of using improved seeds. More importantly, previous weather shocks have no indirect effect on the probability of using fertilizer for those with access to credit. This result amplifies the role that credit and insurance markets play in allowing smallholders to make riskier investments (Cole, Giné, & Vickery, 2017; Karlan et al., 2014). Financial innovations can, therefore, mitigate production risk and allow households to engage in high-return and high-risk investments. Households tend to use credit as insurance by relying on it when there is a shock, hence reducing the effect of the shock through income (Berg & Schrader, 2012; Yilma et al., 2014).

6 Conclusion

In this study, I empirically describe the effect of previous weather shocks on the use of two common inputs—fertilizer and improved seed—among smallholder farmers. I account for both the direct (risk aversion) and the indirect (income) pathways—an important distinction for policy. Understanding previous weather shocks' effects on input use is important given that extreme weather events are predicted for much of Africa (Serdeczny et al., 2017), and improved input use in sub-Saharan Africa has remained stubbornly low. Insights from this study have policy-relevant implications as governments across Africa search for incentives to improve the productivity of agriculture to lift rural households out of poverty (Tittonell & Giller, 2013). Using panel data collected from over 6,000 smallholder farmers in Zambia in 2012 and 2015, I also determine the mechanisms that explain the input use decisions. The identification strategy relies on the exogeneity of weather shocks and the timeline of agricultural income and input use decisions.

Results show that after a negative weather shock (below long term average rainfall), farmers are less likely to use risky inputs and more likely to use less risky but low-return inputs. The indirect effect accounts for about 7% of the total effect of shocks on input use. While relatively low, this effect is missed or confounded in other studies that estimate only the direct effect of shocks on technology adoption, acreage, and other outcomes. The indirect income effect reinforces the direct effect of shocks on fertilizer use while it mitigates the direct effect on improved seeds. For both inputs, shocks reduce the ability of farmers to use improved inputs by imposing liquidity constraints.

Even though it is challenging to use observational data to attribute input use decisions to risk attitudes fully, the analysis carried out in this study makes it plausible to do so. First, I determine that fertilizer is a high-return and high-risk input, while improved seed is a relatively low-return and low-risk input. Other studies have shown similar evidence for fertilizer and improved seeds (Liverpool-Tasie et al., 2017; Paulson & Babcock, 2010). Second, I show that previous weather shocks are associated with higher absolute risk and downside risk aversion. Several recent studies argue against the stability of risk attitudes, and show that individuals' risk attitudes change after natural disasters like earthquakes (Hanaoka et al., 2018), cyclones (Brown et al., 2018) and droughts (Bozzola & Finger, 2020). I add to this literature by showing that those who experience weather shocks are more risk-averse on both measures of risk aversion. Combining the two results, I find that risk averse farmers (those who experience shocks) are less likely to use a risky input and more likely to use a less risky input—explaining the observed results. Heterogeneity tests show that farmers with access to credit or high wealth levels do not shy away from using fertilizer even after a drought—suggesting the importance of financial markets in encouraging risky investments.

Third, I have shown that if households update their expectations rationally using the past experience of weather shocks, I would have found different results. Given the negative correlation between droughts in period *t-1* and *t*, then the effects observed are conservative estimates as the expectations channel would be opposite.

The main results are robust to different definitions of shocks and estimation approaches. Even though the main model does not account for the correlation between fertilizer and improved seeds in adoption decisions, the use of fixed effects makes the identification strategy much stronger. One limitation of the study is the lack of a yearly panel that allows exploring long-term dynamics in input use decisions. Dynamic decisions may be necessary in understanding the inter-temporal tradeoffs that farmers make between risk avoidance and switching to different types of crop varieties and farming methods to offset the impact of weather shocks. I have also not explored all margins of response, such as households completely switching away from agriculture to other sectors including manufacturing and services, which has implications for structural change.

Despite these limitations, results demonstrate that as negative weather shocks increase in frequency, adoption of productivity-improving technologies may slow down, depending on the risk properties of the technologies. Technologies that are risk-increasing, even if they are high-return, like fertilizer, will be less likely to be adopted while risk-decreasing technologies may be used more. This could have negative implications for poverty and food security especially productivity increasing comes at the expense of higher risk. It may also increase rural-urban migration as people shift from agriculture to other off-farm activities. Therefore, policies aimed at improving agricultural productivity could increase the adoption of technologies by integrating innovations that relax liquidity constraints such as microfinance. Access to credit allows farmers to make more risky investments (Karlan et al., 2014) and improve productivity and incomes. Increasing incomes could also have a multiplier effect, as results show that wealthy farmers are not likely to shy away from using risky inputs after a drought. Income enhancing productivity gains could partly offset the effect of shocks on the use of risky inputs as results show that the income channel accounts for about 7% of the reduction in the likelihood of using fertilizer.

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CHAPTER 4: FARM PRODUCTION, MARKETING, AND NUTRITION OUTCOMES IN RURAL ZAMBIA

Summary

Despite increasing agricultural productivity, malnutrition has remained stubbornly high among food producers in many developing countries. I provide new insights to explain this "hungry farmer paradox." In this study, I focus on how own-produced nutrition deficiency (OPND), impacts household nutritional and health outcomes. I use a rich set of instruments to correct for both production and marketing endogeneity. Generally, OPND has a negative effect on nutrition. Results also show that crop production diversity is positively correlated with dietary diversity and children's health. I find that both underproduction (relative to nutritional requirements) and OPND as a result of selling more output negatively impact nutrition outcomes. Higher lean season food prices reduce the quantity demanded of market-bought foods and can diminish the possibilities for households to obtain adequate nutrition through food markets. Finally, I show that crop sales improve nutrition outcomes on average only if households retain sufficient production to meet basic nutrition needs. With imperfect food markets, designing incentives to store own-produced food has the potential to improve the nutrition outcomes of food-producing households.

1 Introduction

Malnutrition in Zambia remains a substantial public health problem. Nationally, 35% of children under age five are stunted (short for their age), 4% are wasted (thin for their height), 12% are underweight (thin for their age), and 5% are overweight (heavy for their height) (Zambia Demographic and Health Survey, 2019). Micro-nutrient deficiencies such as iron deficiency (which affects about 31% of pregnant and lactating women) and vitamin A deficiency (affecting about 52%

of all children of school age (UNICEF, 2009)) are also common. Northern province, a largely rural economy in Zambia, has one of the worst child malnutrition, with the highest stunting prevalence in the country, as Figure 11 shows.

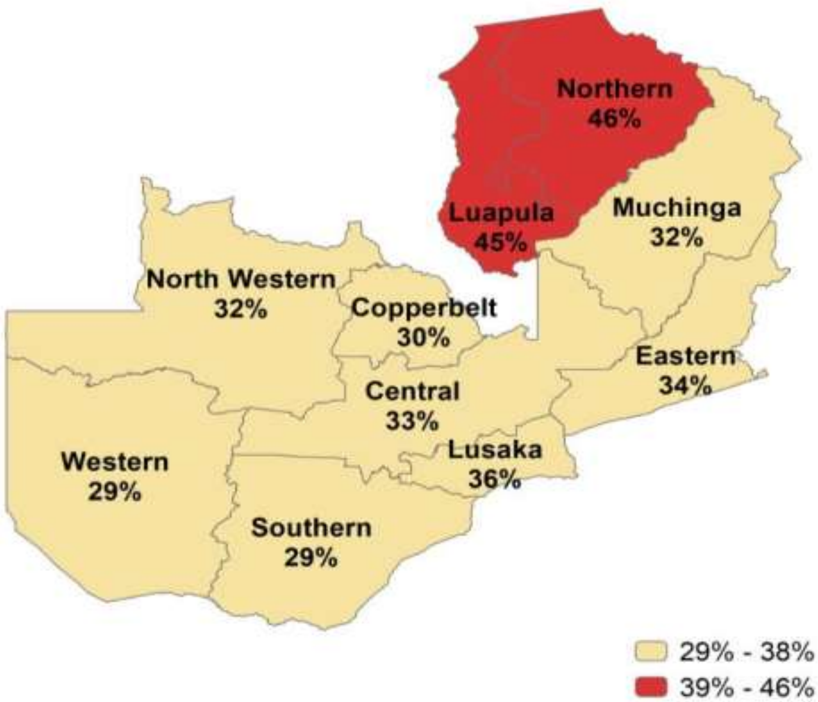

Figure 11: Stunting prevalence for children between 6-59 months by province in Zambia. Source: Zambia Demographic and Health Survey, 2018.

The majority of those affected by poor nutrition are smallholder farmers, who also produce about 80% of the country's food—resulting in the "hungry farmer paradox" (Bacon et al., 2014). The paradox that agricultural production and productivity have been increasing and raising incomes, but with limited nutritional benefits, has been shown in different countries (Fan & Pandya-Lorch, 2012). For example, Kadiyala et al. (2014) investigate what they call the "Indian enigma," where agricultural productivity and production grew rapidly in a context of economic growth between the 1990s and 2000s, but undernutrition remained the same. They conclude that there are still gaps in the literature to understanding agriculture-nutrition linkages. In some studies, both production (quantity) and agricultural income had no significant effect on nutrition (Kumar et al. 2015). Whyte & Kyaddondo (2006) find that in a major rice-producing area in Uganda, households experience food shortages because they sell everything and leave little for home consumption. Crop diversification similarly shows benefits to nutrition in some studies but not in others (Sibhatu & Qaim, 2018). One aspect that remains unexplored in the literature is the effect of selling output that would have improved a household's nutrition adequacy, and hence food security and dietary diversity, if consumed at home. In theory, specialization and increased productivity incentivized by market integration should increase household income and improve nutrition outcomes (Zanello, Shankar, & Poole, 2019). Yet, this approach relies on access to food markets that allow households to purchase nutrition with higher income. In practice, it remains unclear if dependence on markets for nutrition improves outcomes.

In this study, I examine the impact of selling production that, consumed at home, could have contributed to household nutrition on outcomes such as food security and child health. I begin by determining household food requirements relative to production that is kept in the household and use this to define "own-produced nutrition deficiency" (OPND). I then investigate associations between household OPND—whether from insufficient production or selling food that would have contributed to nutrition adequacy at the household level—and dietary diversity, food security, and children's health outcomes. This provides an important empirical test of the ability to use income from agricultural sales to purchase food that improves nutrition. For children's nutritional status, I use height for age z-score (HAZ).

The study is conducted in Mbala district in Northern Zambia, which has one of the worst child stunting rates despite high agricultural productivity (Central Statistical Agency, 2018). Our data, collected in the lean season (the period in which most households run out of own-produced food, from around December to February), allow us to observe production and marketing decisions from the previous season's production and associate them with food and nutritional security. I implement an instrumental variables strategy to account for the endogeneity of crop production diversity and marketing decisions using soil and weather variables, farm size, and prices as instruments. I also explicitly model seasonal price variation and how it affects the use of markets to buy food for home consumption. This has been noted as a gap in the literature (Dillon, McGee, & Oseni, 2015).

We find that, on average OPND is detrimental to children's height-for-age z-scores (HAZ), household dietary diversity, and household food security (collectively called nutrition outcomes). There is no difference in the effect of OPND between those who underproduce and those who have market-induced OPND. Results also demonstrate that crop selling improves nutrition only for households that are self-sufficient with respect to macro-nutrients from their production. Taken together, this analysis provides new insight into factors that lead to the hungry farmer paradox and explain the relationship between production, marketing, and nutrition outcomes better than traditional approaches that focus solely on market access.

In the literature, there is evidence that household post-harvest decisions imply a tradeoff between nutrition and marketing. For example, Estrada-Carmona et al. (2020) found that there are few (less than 8%) crop choice combinations that result in both improved income and nutrition. With well-functioning food markets, producer households can rely on markets to sell output and to purchase nutritious food (Ogutu, Gödecke, & Qaim, 2020; Zanello et al., 2019). While these studies are insightful, they do not directly model the effect of both production diversity and post-harvest decisions on nutrition, especially as they relate to nutrition adequacy. Only two recent studies include market access as explaining nutrition (Hirvonen & Hoddinott, 2017; Zanello et al., 2019). However, these two studies do not include the household's consumption and marketing trade-off. Our results suggest that it is not simply marketing that determines nutrition but rather marketing of output that would have contributed to household nutrition if consumed at home.

For decades, the policy emphasis has been on agriculture as an income generation activity with less concern for its other role—to provide food and nutrition. Recently, the priorities in the fight against hunger have changed. As the International Food Policy Research Institute puts it, "After 75 years [since the U.N. conference on food and agriculture in 1943 in Rome, Italy], agriculture and nutrition meet again"[11]. The commercialization (growing for market) of agriculture was promoted in the hope that through increased income, it would allow households to purchase a variety of foods to improve nutrition (Carletto, Corral, & Guelfi, 2017). This approach was based on earlier studies that found a positive link between agricultural income and nutrition. Market production generates income that empowers a household to purchase a variety of foods it does not produce (Timmer, 1997). Abdulai & Aubert (2004) argue that as income increases, households would diversify diets away from mainly cereals and tubers to meats, dairy, and fruits. Govereh & Jayne (2003) show that part of agricultural income can be invested back and used to improve food crop production, leaving more food for households over time.

However, the market channel, compared to own-produced nutrition, faces multiple challenges. For example, income from agriculture is lumpy and often received at one point in time. This implies market reliance. However, evidence suggests that food markets remain underdeveloped and do not provide households with abundant food options at affordable prices (Alene et al., 2008; Linderhof, Janssen, & Achterbosch, 2019). Poor market access and higher prices in the lean season worsen nutrition (Phalkey, Aranda-Jan, Marx, Höfle, & Sauerborn, 2015). After spending

[11] http://www.ifpri.org/blog/after-75-years-agriculture-and-nutrition-meet-again

agricultural income at harvest, households often have limited savings for the purchase of food later in the lean season (Sibhatu & Qaim, 2017). The second problem is that most marketing is handled by males, who are not in charge of food security in the household; hence, commercialization can disrupt decisions by women to ensure food security (Lenjiso, Smits, & Ruben, 2016).

The empirical literature on the effect of marketing on nutrition has shown mixed results. In Ghana, for example, Anderman et al. (2014) show that increased production of cash crops (coffee and cocoa) lowers food security because of food price inflation from seasonal price variation. Some argue that subsistence farming is the only way to ensure food security (Kostov & Lingard, 2004) because even in areas where food crops are promoted as cash crops, households are still food insecure (Kilimani, 2020). Carletto et al. (2017) use nationally representative data from three sub-Saharan African countries and find no effect of commercialization on nutrition. Among the reasons for this poor relationship is competition for land and increases in lean season prices, depending on the region where the study was done. Producers, however, benefit from high lean season prices if they sell in the lean season.

We add to this literature by focusing on own-produced nutrition deficiency. Specifically, this paper contributes to the literature by explicitly considering the nutritional requirements of all household members using nutrient reference intakes. Production and nutrition deficiency are defined relative to household nutritional requirements for 13 selected nutrients. By using nutritional content to measure deficiency, I provide a more holistic measure of nutrition outcomes compared to production quantity measures. I show the causal effect of OPND and marketing on nutrition outcomes (HAZ, dietary diversity, and food security) and contribute towards studies that identify exceptions to the conventional wisdom that “the impact of commercialization on nutrition outcomes is generally positive” (Carletto et al., 2017). I also contribute to the literature by estimating the marginal effect of marketing on nutrition outcomes, conditioned on own-produced nutritional sufficiency.

The rest of this paper proceeds as follows. In the following section 2, I outline the relationship between agriculture and nutrition that has been explored in the existing literature. In section 3, I precisely define own-produced nutrition deficiency and household nutritional requirements, while in section 3 the sampling methodology and data are presented. In section 5, the econometric approach is presented with results and conclusions in sections 6 and 8, respectively.

2 The relationship between agriculture and nutrition

A number of authors have investigated the relationship between agricultural production and nutrition (Carletto et al., 2017; Kumar et al., 2015; World Bank, Hawkes, & Ruel, 2007). This relationship is complex, but the two main mechanisms described in the literature include agricultural production as food and as a source of income. In this section, I provide an overview of the existing evidence related to these key pathways.

The first linkage between agricultural production and nutrition is through influencing the income of household producers. Most agricultural support policies focus on the income pathway (Pingali, Mittra, & Rahman, 2017). This approach assumes that higher incomes lead to better outcomes (Carletto et al., 2017). For this to be consistent with better nutrition outcomes, household must have access to reliable food markets, even when products are not in-season. In practice, while income growth precipitated by agricultural productivity is on the rise, its contribution to nutrition remains ambiguous (Kirk, Kilic, & Carletto, 2018; Smith & Haddad, 2015). The empirical studies on the agricultural income pathway mostly show a weak link to nutrition. Kumar et al. (2015), in a pre-post project evaluation study in Zambia, found no link between agricultural productivity and agricultural income and nutrition. Even when income is distinguished by whether it is earned by men or women, there is no significant relationship with nutrition (Kirk et al., 2018b). Poor access to markets could be playing a role in this link (Zanello et al., 2019). After income from agriculture has been earned, household consumption decisions may not be optimal for nutrition. Babu et al. (2017) argue that how households allocate their income among different needs such as food, water and sanitation, and non-food items such as clothing, paying for children's school fees, helps in understanding the behavior of the households toward their nutritional choices. However, it is difficult to justify intertemporal trade-offs between children's nutritional needs and non-food consumption as child-malnutrition problems continue into adulthood affecting their school performance and earnings as adults (Muthuuri, Seroney Some, & Chege, 2019).

Food prices impact the income pathway as households rely on the market to buy food. When food prices rise faster than incomes, the ability of households to buy food is reduced (Masters et al., 2018). For agricultural households, the effect of seasonal variation in prices also matters as they earn income during the marketing season (when prices are relatively low) and buy food during the lean season (when prices are relatively high). There is evidence that those with good access to food markets have better nutrition in the lean season compared to those without (Zanello et al., 2019).

Agricultural productivity can also provide an important source of food (Sibhatu & Qaim, 2017). For households to have own-produced nutrition adequacy, they must grow diversified crops and store enough for the whole year. When storage is a problem for most food crops, this approach is not feasible (Zanello et al., 2019). However, even when storage capacity is available, households often do not store enough to be self-sufficient throughout the year (Omotilewa, Ricker-Gilbert, Ainembabazi, & Shively, 2018). Self-sufficient households (i.e., those that do not have OPND) can still suffer from malnutrition even if they have adequate food, but do not have appropriate health care practices (Smith & Haddad, 2015). Own-produced nutrition adequacy also shields households from food price inflation and related costs in the lean season. As households make post-harvest decisions, they maximize some objective function unknown to the researcher. This may not always include optimizing nutrition. For example, some households may sacrifice current nutrition for future benefits. This strategy may not lead to socially desired outcomes because low nutrition can have lasting consequences (Tiwari, Jacoby, & Skoufias, 2017).

In summary, the income channel can improve nutrition but the evidence for this is mixed. Improvements through this channel rely on integrated markets that can provide affordable food year-round. Our contribution is to show that households that keep needed nutrition in the household do better than those that only have higher sales. Particularly in the absence of good food markets, the income channel improves nutrition only if households have achieved own-produced nutritional adequacy.

3 Defining Nutrition Deficiency

In this section, I describe how I define own-produced nutrition deficiency at the household level. Both food crop production and quantities kept for home consumption are measured in nutritional terms. I group the food crops in three groups, staples (s), pulses (p), and vegetables (v). Considering a specific food crop group, I assume that the production of i (in kilograms) in a household is y_i where i=*s,p,v*. From, y_i, households keeps for home consumption quantity q_i and sells quantity s_i such that $q_i + s_i = \overline{y}_i$, assuming amounts kept for seeds and gifts are negligible (Omotilewa et al., 2018; Ntakyo & van den Berg, 2019). For notation, $\sum_i q_i^* = f_h^*$, defines household total quantity kept home consumption, and $\sum_i \overline{y}_i = \overline{y}_h$ as the total household production.

Income earned from selling output is given as $p_{si}s_i$ with p_{si} being the output price for food crop i per kilogram. Assuming the household has some exogenous off-farm income, I_h, total household income is $p_i s_i + I_h$. Total food consumption at home is $\sum_i m_i + \sum_i q_i$, the sum of market-bought foods, m_i, and own-produced foods kept for home consumption, q_i. Market bought foods have a price $p_{bi} \geq p_{si}$. The buyer price is higher because food purchases are made in the lean season while selling is mostly done during the marketing season (Stephens & Barrett, 2011). Based on preferences for food and non-food items, the household chooses the optimal level of production to keep (q_i^*) and sell (s_i^*) and the quantity of market-bought foods (m_i^*).

We now define $\bar{n}_h^j$ as the household nutrient requirement for nutrient j=1,…,J[12]. To determine $\bar{n}_h^j$ at the household level, I calculate the household food requirements using the adult male equivalent for a reference male between 30-50 years of age (Coates, Rogers, Blau, Lauer, & Roba, 2017; Jayne & Argwings-Kodhek, 1997). The adult equivalent is a function of demographics (age and gender). Let p_h be the number of individuals in household h, while the household's demographic structure is described by the vector d_h. This vector provides the number of individuals in various demographic groups based on age and gender (Bermudez, Lividini, Smitz, & Fiedler, 2012). Using these definitions, the adult male equivalent size of household h may be expressed as $m_h = m(p_h, d_h)$. The household nutrition requirement for nutrient j and household h with a given number of adult male equivalents ($\bar{n}_h^j$) is the product of the reference minimum annual intake of j for an adult male equivalent (Appendix 4.2: Extra Tables

Table A8 in the appendix) and the number of adult male equivalents in the household.

[12] Nutritional requirement is defined over 13 nutrients: fat, carbohydrates, fiber, protein, vitamin A, vitamin C, vitamin B1, vitamin B2, vitamin B6, calcium, iron, and zinc. I focus on macro- and micro-nutrients and vitamins that are of concern in Zambia. See Table A1 in the appendix for additional detail on household nutrient requirements.

I group the food crops in our study area into three categories: staples, pulses, and vegetables, and obtain the average nutrient content for each group (see Table A8 in the appendix). To get the amount of nutrient j that household h keeps for home consumption, I sum the nutrients across the three food groups: $n_h^j = n_s^j q_s + n_p^j q_p + n_v^j q_v$, where q_s is the observed quantity of staples kept for home consumption, q_p is the observed quantity of pulses kept for home consumption, and $q_v$is the observed quantity of vegetables kept for home consumption. n_i^j is the amount of nutrient j per kilogram of food group i.

For each nutrient, j, I normalize the quantity kept for home consumption of nutrient j by the household nutrient requirement of j, $n_h^{nj} = \frac{n_h^j}{\bar{n}_h^j}$. The household nutrition requirement for each nutrient is also normalized such that $\bar{n}_h^{nj} = \frac{\bar{n}_h^j}{\bar{n}_h^j} = 1$. The nutrient-specific deficiency is then calculated as $b_h^{nj} = (1 - n_h^{nj})$ if $(1 - n_h^{nj})$>0, and 0 otherwise. This gives nutrient j deficiency as a proportion of the household requirement for the same nutrient. Own-produced nutrition (defined as nutrition since it is deficiency across all nutrients) deficiency (OPND) for the household is then given as:

$$b_h^n = \sum_{j=1}^{J} b_h^{nj} \equiv OPND_h. \tag{1}$$

The normalization by the household nutrition requirement makes it possible to compare across households of different sizes and demographic compositions. This aggregation of nutrition deficiency proportions across the J nutrients assumes that increases in any nutrients relative to requirements from any starting point have the same weights in contributing to household nutritional requirements. For example, a person with a 20% vitamin A shortfall relative to the nutrition requirement is just as worse off as a person with 20% protein shortfall. This is a simplification because the marginal benefits of each nutrient to total nutrition may not be constant and could interact in complex ways.[13] Nevertheless, this allows us to simultaneously consider multiple nutrients when calculating household nutrition variables. This represents a more holistic approach to measuring nutrition than, for example, focusing only on calories (Chiputwa & Qaim, 2016; Falkowski, Chankin, Diemont, & Pedian, 2019) or quantities consumed without taking into account the nutritional value (Mushaphi, Dannhauser, Walsh, Mbhenyane, & Van Rooyen, 2017).

To examine if household production is adequate to meet household nutrition requirements, I calculate a variable that considers the production of each nutrient j. $\bar{y}_h^j = n_s^j \bar{y}_s + n_p^j \bar{y}_p + n_v^j \bar{y}_v$, where $\bar{y}_i$ is the production of crop type i, with $i =$ staples, pulses, and vegetables as earlier defined. A household produces enough of nutrient j if $\bar{y}_h^j \geq \bar{n}_h^j$. At the household, I define a household as producing enough if $\bar{y}_h^j \geq \bar{n}_h^j \,\forall\, j$, that is, if a household produces enough of all nutrients[14]. For notation purposes, I define $\bar{y}_h$ as the sum of $\bar{y}_h^j$ across all nutrients. For a household that produces enough, $\bar{y}_h < \bar{n}_h$ and this holds for each nutrient. In this section I consider households with $\bar{y}_h < \bar{n}_h$ and further assume that this also holds for each individual nutrient.

OPND could occur under two circumstances. First, a household may produce less than its nutritional requirements ($\bar{y}_h < \bar{n}_h$). I call this case underproduction. Second, OPND could occur if a household sells agricultural production that could have contributed to household nutrition ($\bar{y}_h > \bar{n}_h$ and $\bar{y}_h^j \geq \bar{n}_h^j \;\forall\; j$ but $f_h^* < \bar{n}_h$). I refer to this as market-induced OPND.

[13] For example, considering the minimum nutrient consumed may inform the study of some outcomes. At the end of this paper, I discuss other ways to aggregate across nutrients.
[14] Household sales, s_h, and market-bought food, m_h, could be defined similarly as a proportion of nutrient requirements, considering only the amounts of each nutrient that are sold or bought. Note that income from sales, $p_s^j s_h^j$, should not be aggregated across nutrients and in practice the price per nutrient may differ by crop.

To illustrate the two types of OPND, consider the graphical presentation shown in Figure 12[15] for two households (1 and 2). Both households have the same level of $\bar{n}$ (so the subscript drops). Household 1 produces at $\bar{y}_1$ and only keeps f_1^* for household consumption. Therefore, its OPND is $b_1^n = \bar{n} - f_1^* > 0$. Household 1 sells $\bar{y}_1 - f_1^* > 0$. Of the total sales, b_1^n would have contributed to household nutrition but was sold. In this case, household 1 produced enough food to meet $\bar{n}$ but did not keep enough food crops to have nutritional adequacy from own production and therefore has market-induced OPND.

Household 2, however, does not produce enough to meet the household food requirements. Even if it kept all production ($\bar{y}_2$), it would not be enough to meet the household food requirements, $\bar{n}$. Household 2's OPND is equal to $b_2^n = \bar{n} - f_2^*$. Unlike household 1, household 2's OPND consists of nutrition that was sold to the market ($\bar{y}_2 - f_2^*$)—market induced OPND plus underproduction relative to nutrition needs ($\bar{n} - \bar{y}_2$). Most of the households that underproduce sell negligible amounts, hence in the empirical section, I categorize these as underproducing (ignoring the small market-induced component).

[15] The nutrition curve in Figure 12 shows constant returns above the required nutrition level. In practice, if f>>n, the marginal benefit of nutrients could turn negative. In the context of rural Zambia, this occurs very infrequently. For most households, the marginal benefit of additional nutrients remains positive

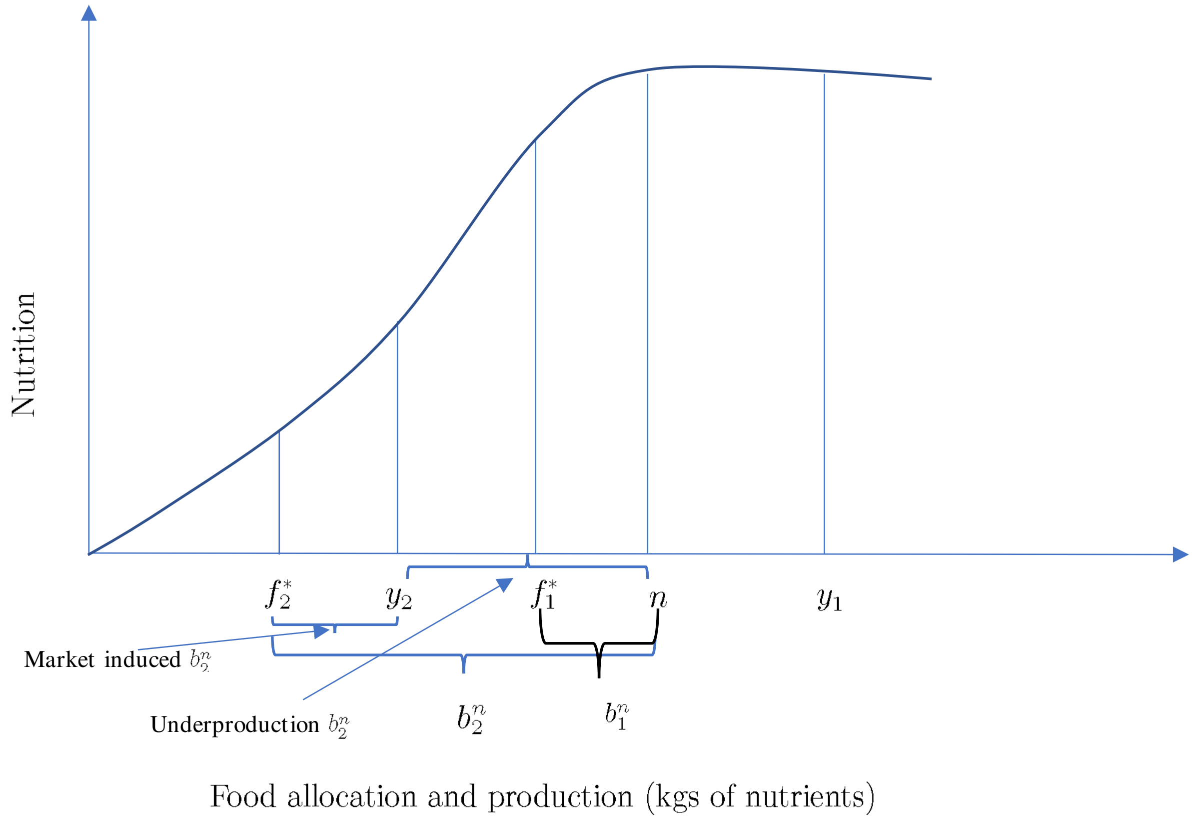

Figure 12: marketed nutrition, production and household requirement illustration

With perfectly functioning food and financial markets, households with OPND could meet the deficiency through market bought foods, at least for those who produce more than the household requirement. However, markets are imperfect (Hirvonen & Hoddinott, 2017), and agricultural income is lumpy, with seasonal price increases, and household preferences and needs may lead households to purchase non-food items with income earned. Therefore, the nutrition deficiency may not be easily compensated for by purchasing food. In this paper, I explore if households can use markets to make up for OPND. I infer this from nutrition outcomes and by testing if the monthly purchases of food during the lean season are correlated with OPND.

In this study, I explore the implications of $f_h^* < \bar{n}_h$ (i.e., $b_h^n > 0$) when $\bar{y}_h > \bar{n}_h$ (market-induced own-produced nutrition deficiency) (Kilimani, 2020; Zanello et al., 2019) and when $\bar{y}_h <$

$\bar{n}_h$ and $\bar{y}_h^j < \bar{n}_h^j \; \forall \; j$ (underproduction). Households that don't meet nutritional requirements through f_h^* have to depend on the market to meet their nutrition needs. Therefore, even when households do not meet the nutritional requirements from own-produced foods, it is possible that they could do so using market-bought foods. This would require particularly high productivity relative to nutritional needs since buying prices are higher than selling prices. I do not observe market-bought foods all-year round in our data, but instead concentrate on how own-produced food consumption compares to $\bar{n}_h$. If households use the market to meet nutrition needs, then market-induced own-produced nutrition deficiency would have no effect on nutrition outcomes (HAZ, dietary diversity, and food security).

Taken together, in our research context, I expect household nutrition outcomes to decrease with OPND. While food markets mean that this is not guaranteed, in rural settings in developing countries, underdeveloped food markets likely mean that deficiencies in own-produced nutrition (through inadequate production or sales) are unlikely to be made up through market purchases. In the empirical section of this paper, I test if OPND decreases nutrition outcomes and how the impact depends on market sales, food prices, and the sufficiency of food production. I determine if underproduction and market-induced OPND have different effects on nutrition outcomes and how seasonal price increases affect the nutrition outcomes of households with OPND.

4 Data and Descriptive Analysis

4.1 Data

In order to test the impact of OPND on household nutrition outcomes, household data on agricultural production and marketing, nutrition and anthropometric measures for children under five years were collected by the author and a team of research assistants from Northern Zambia. Mbala district in

Northern Zambia was purposively selected because it has the highest agricultural productivity in the Northern province but also one of the worst child malnutrition rates (ZSA, 2018; ZDHS, 2019). Therefore, a large benefit exists to understanding why the productivity-nutrition linkage is broken. A list of agricultural camps in the district was collected from the district agricultural office. From the list, five agricultural camps were randomly selected, and about 30 households were randomly sampled from the list of households in each of the five camps. A total of 211 households were interviewed between December 2019 and January 2020 (Colorado State University institutional review board number 00000202. See Appendix 4.1: Institutional Review Board Approval for the Study (Chapter 4) for the approval letter). GPS coordinates of the households were also collected.

The household survey provides data that is used in the calculation of OPND and other key variables. Households were asked about farm production for the previous season, how much they sold of each crop, and how much was kept for home consumption (q_i) was calculated from the difference of production (z_i) and sales. Crop production and marketing data were collected at household level. In addition to these variables, the survey also had a module on children's anthropometric measures. A total of 183 children between 6-59 months were surveyed from 141 households that had at least 1 child. The remaining households had no children between 6-59 months. Child-specific data include mother/guardian's literacy, level of education, age when child stopped breastfeeding, and weight for height, weight for age, and height for age. Child data is used in the estimation of the effect of OPND on HAZ.

Next, I use dekadal (10-day) spatial rainfall data from the Climate Hazards Group Infrared Precipitation with Station database (CHIRPS). The CHIRPS dataset, developed by the U.S. Geological Survey (USGS) and the Climate Hazards Group at the University of California, Santa Barbara, is a blended product combining dekadal rainfall estimates, created from satellite data and ground-based observations from weather stations. Quasi-global gridded datasets are available from 1981 to near-present at 0.05° spatial resolution (~5.3 km^2) (Funk et al., 2014). The soil data come from the Rural Agricultural Livelihoods national soil analysis that was done in 2015. The soils analysis data contain variables on soil organic matter, phosphorus per million parts, and cation exchange capacity (CEC)—all important indicators of soil quality. These data are merged with the household data using the GPS coordinates. Weather and soil data are used as instruments for OPND in the analysis. I define a binary variable equal to 1 if a household had more than 0.5 hectares of land per adult (roughly the land size required to grow enough food for an adult per year). As I show, OPND may be endogenous, hence, I instrument it with variables that are correlated with production but not child nutrition, dietary diversity, and food security except through influencing production.

The third piece of data is the nutrient content of common food crops in the study area. This information was obtained from the Zambia Food and Nutrition Commission (NFNC)'s Food Composition Tables (NFNC, 2007). Other sources included the NutriSurvey software with databases for food composition from Mozambique, Kenya, and other African countries. The crops/foods were entered in the *NutriSurvey* software (Ehardt, 2007) with the nutrition database loaded from African countries to determine the nutritional content of raw foods. The NutriSurvey database is commonly used, especially in developing countries where other food tables might not be available (Benefice, Luna-Monrroy, & Lopez-Rodriguez, 2010; Lowe et al., 2011). These data are used to derive n_s^j, n_p^j, and n_v^j—which are in turn used to calculate production ($\bar{y}_h^j$) and nutrition home allocation ($\bar{n}_h^{nj}$) from the quantities kept for home consumption. The OPND is then calculated given the home nutritional requirements.

A summary of all variables is presented in Table 16. The mean height for age z-score is about -1.8, just slightly above the threshold (-2) for moderate stunting. Seasonal prices on average increased by K7 in the lean season but some areas witnessed increases of up to K30. About 13% are female-headed households. The other key variable is OPND. On average, OPND is about 31% of household food requirements, but others have a deficiency as high as 89% of the household food requirement. Overall, only about 25% of the households were nutritionally self-sufficient (i.e., $b_h^n = 0$, they did not have OPND). About 63% of the households produced enough to meet the household nutritional requirements (as defined above), while about 53% sold output that could have contributed to nutrition—market-induced OPND. About 27% of the households are food insecure, and average household dietary diversity score is about 8 of 10.

At the time of the survey, I observe the effect of decisions made almost 9 months ago; hence, HAZ captures the effect of such long-term decisions better than weight for height (WHZ), or weight for age (WAZ) (Manda et al., 2016). Furthermore, WHZ and WAZ are not as worse as stunting (HAZ) in the sample, and with the small sample size in this study, regressions on these variables were not significant—something common in literature (see for example, Grace et al., 2012; Kumar et al., 2015). Therefore, only HAZ is summarized to measure child malnutrition. HAZ is defined at the child-level (i.e. if a household has more than one child, all of the children are included in the analysis, each with their own HAZ and other child-level variables as in Table 1).

Household dietary diversity, defined at the household level, is a 7-day food intake recall asking households for the types of foods they ate in the past 7 days before the survey. A total of 10 food groups were included and households were scored based on the foods eaten in 7 days. Food insecurity was defined as equal to 1 if a household experienced at least one month in the past one year in which they did not have enough food to meet the household's food needs, and 0 otherwise. Food security refers to the opposite of food insecurity (i.e., the household had enough food throughout the year).

Table 16: Descriptive statistics for the key variables used

Variable	Obs	Mean	Std. Dev.	Min	Max
Child-specific variables					
Height for Age Z-scores (HAZ)	183	-1.751	1.540	-4.933	4.356
Age (months) at complimentary feeding	183	6.239	2.426	0	26
Mother's years of schooling	183	5.951	2.694	0	12
Mother/Guardian literate (1=Yes)	183	0.467	0.500	0	1
Household-level variables					
Food insecurity (1=Yes)	210	0.271	0.446	0	1
Dietary diversity (10 food groups)	210	8.081	1.301	4	10
Seasonal price change (ZMK/kg)	211	6.953	6.867	0	30
Female head of households (1=Yes)	211	0.128	0.335	0	1
Received nutrition infor (1=Yes)*	211	0.249	0.433	0	1
Owns livestock	211	0.861	0.347	0	1
Herfindahl crop diversification index	211	0.029	0.169	0	1
OPND, b (% of household requirement)**	211	0.309	0.327	0	0.898
Production>HH req. (1=Yes) ($\bar{y}_h > \bar{n}_h$)	211	0.632	0.483	0	1
Self-sufficient, $f_h^* > \bar{n}_h$ (1=Yes)	211	0.368	0.483	0	1
Sold output and $f_h^* < \bar{n}_h$ (1=Yes)	211	0.533	0.500	0	1
Instruments					
Long term rainfall average (mm/year)	211	1060.296	67.493	775.457	1196.388
Organic matter (Soil organic carbon %)	211	1.253	0.258	0.25	1.96
Phosphorus (parts per million)	211	22.304	18.849	5	58
Staples price (ZMW/kg)	211	1.806	.529	0.742	3.121
Pulses price (ZMW/kg)	211	4.275	1.882	0.724	7.447
Vegetables price (ZMW/kg)	211	1.364	5.796	0	44.555
Land size (hectares)	211	3.117	3.324	0.3	27.25
Enough land (1=Yes)	211	0.495	0.501	0	1

Note: *households were asked if they received nutrition information from the ministry of agriculture extension system. **OPND=own-produced nutrition deficiency.

5 Econometric Approach

The econometric approach focuses on the relationship between household OPND and nutrition outcomes, including children's malnutrition (HAZ). While these are the key variables, I control for other things that could affect food security and children's health, including the education level of guardian/mother to the child, sex, whether the household received nutrition information from any organization, or whether the household keeps livestock.

5.1 Effect of OPND on nutrition and child health

A linear regression model (2) is estimated to understand the relationship between nutrition outcomes and OPND (b_h^n) while controlling for other variables. A negative coefficient suggests that a higher OPND is associated with lower nutrition outcomes.

$$A_{ch} = \alpha + \rho_1 b_h^n + \rho_2 \mathrm{D_h} + \gamma C_{ch} + \varphi_k \boldsymbol{H}_\mathrm{h} + \varepsilon \qquad (2)$$

where A_{ch} is the anthropometric measure for child c, belonging to household h, C_{ch} are the child-level characteristics such as mother/guardian's level of education, and age when complementary feeding was introduced while b_h^n is OPND. $\mathrm{D_h}$ is household-level variable that measures lack of crop diversification using the Herfindahl Crop Diversification index that captures both the variety of crops grown and shares of cropped area allocated to each crop (Jones, Shrinivas, & Bezner-Kerr, 2014; Murendo, Nhau, Mazvimavi, Khanye, & Gwara, 2018). The index ranges from 0 to 1 and a higher value (towards 1) indicates lower diversification. $\boldsymbol{H}_h$ is a vector of household characteristics that include household size, sex of household head, education level of household head, whether the household received nutrition information or not, ratio of adults to children (between 0-15 years), and whether the household owns livestock or not. The model includes a random error term. The parameter of interest is the coefficient on b_h^n. I also estimate similar models using household food security and dietary diversity as the dependent variables and dropping the subscript c and vector C_{ch} since these models are at household level.

Identification

The variable of interest in equation (2), b_h^n, depends on production and marketing decisions. There are two reasons why this parameter may be biased. Firstly, if there is classical measurement error of quantity sold (the key variable in calculating OPND), then the ρ_1 may be biased towards zero.

Secondly, nutrition outcomes (i.e. HAZ, dietary diversity, and food security) and OPND may be influenced by the same unobserved factors. Equally, crop diversification, D_h, may be endogenous for the same reason that it may be influenced by the same unobserved factors that affect the outcome variables. For example, households that have diversified production and attach more value to nutrition, hence, keep more for home consumption, may share a common trait of caring more (or less) about their children's health and nutrition. Alternatively, households that sell food crop output (and have OPND) may have some unobserved factors that pressure them to while simultaneously affecting child health. I correct for this potential endogeneity by using instrumental variables.

The literature on production, marketing and dietary diversity has handled the issue of endogeneity differently. Most studies include a rich set of controls to account for systematic differences in both production diversity, marketing, and nutrition. However, endogeneity may still be a problem despite the inclusion of a rich set of controls. In their review, Sibhatu & Qaim (2018) find that only two (Dillon et al., 2015; Hirvonen & Hoddinott, 2017a) out of more than 40 studies have directly addressed endogeneity while the rest ignored it. Another recent study that has addressed endogeneity by using an instrumental variables approach is Zanello et al. (2019). I follow Dillon et al. (2015) and address both production diversity and OPND endogeneity.

For OPND, I use village level crop prices during the marketing season and land size owned by the household. Output prices during the marketing season when most farmers are selling their produce are exogenous and not determined by any individual farmer or village. I use an average of staple, pulses, and vegetable prices per kilogram that each household receives as instruments. For land size, I argue its exogenous as there are no private land markets in Zambia, and households are restricted in terms of where they can live as land is owned by the state and inherited along family lines (Bigsten & Tengstam, 2011). Individual farmers have usufruct rights granted by local government authorities who provide privileged access to those who already live in that locality. However, the cropped area could be increased beyond owned farm size through land rental markets (Chamberlin & Ricker-Gilbert, 2016). For crop diversification, I use rainfall, organic matter in the soil (measured as soil organic carbon percent), and phosphorus parts per million in the soil. More productive soils can support many types of crops even for housholds who cannot afford inputs.

5.2 Heterogenous impacts: underproduction and seasonal price changes

To differentiate the effect of market-induced OPND and underproduction, I estimate a model (3) that includes an interaction between b_h^n and whether a household produced enough food or not. The rest of the variables are the same as in (2).

$$A_{ch} = \alpha + \beta_1 b_h^n + \beta_2 b_h^n * G_h + \beta_3 D_h + \gamma C_{ch} + \varphi_k \boldsymbol{H}_{\mathrm{h}} + \varepsilon \tag{3}$$

G_h is an indicator of whether the household produced enough food or not, i.e. $\bar{y}_h > \bar{n}_h$. The interaction ($b_h^n * G_h$) tests the effect of market-induced OPND. I instrument for b_h^n and the interaction $b_h^n * G_h$ using output prices and land size, similar to (2).

We also estimate a model that interacts OPND and seasonal price change to determine how OPND and seasonal price changes jointly affect nutrition outcomes. Similar to (3), I instrument for OPND and the interaction with average prices and seasonal price change. Households that have a high OPND are expected to rely more on the market and hence negatively affected by a higher price in the lean season relative to the marketing season.

5.3 OPND and Market-bought Foods

Own-produced nutrition deficiency does not guarantee poor nutrition. As I showed in the definition section of OPND, conceptually, households can potentially supplement in the deficiency with market bought foods. It is possible that market-induced OPND may improve nutrition as it allows households to buy foods that they do not produce. Here, I investigate if households with (market-induced?) OPND rely more on the market for food quantities or diversity. I also explore the role of seasonal price changes in influencing this outcome. Because the effect of price seasonality on food security is not well documented (Dillon et al. 2015). I add to the literature by explicitly modeling the effect of seasonal price increases on market dependence to supplement nutrition. I determine if households that have OPND buy more foods from the market, both in quantity and diversity, and the effect of seasonal price. Conceptually, households that market nutrition should rely on the market to supplement food and nutrition. Therefore, I estimate (4) to determine if this holds:

$$m_h = \alpha + \tau_1 b_h^n + \tau_2 SP_h + \tau_3 G_h * SP_h + \tau_k \boldsymbol{H}_h + \varepsilon \tag{4}$$

where m_h is market bought foods quantity or diversity, SP_h is the seasonal price increase in Kwacha terms. SP_h is derived as the difference in average prices between the harvest and lean seasons. It shows how much lean season prices have increased relative to harvest prices. All other variables are as defined earlier. Coefficients of interest are τ_1 to τ_3 which determine if market-bought foods are correlated with OPND, the effect of seasonal price increase for those who underproduce, and the effect of OPND for those with market-induced OPND. The model is estimated on both the quantity of market-bought foods and the diversity of market-bought foods. I expect that OPND is positively correlated with quantity and diversity of market-bought foods as households cover the shortfall from own-production. Similar to (2), I instrument for OPND and the interaction with production. As before, I instrument for OPND and the interaction of OPND and seasonal price increase for causal inference.

Seasonal price change (in equation 4) may equally be endogenous at the household level for two reasons. First, the time of the year the household buys most of the food from the market, and hence the price at which it buys, depends on OPND—which is potentially endogenous as previously stated. Secondly, the prices the household faces depend on the type of food it purchases. Therefore, I use the average of the village level seasonal price change that other household members faced excluding that particular household. Ogutu et al. (2020) used a similar strategy to instrument for commercialization in Kenya. Further, only prices for May (harvest period) and December (lean period) are used in calculating the seasonal price variation. This eliminates endogenous monthly prices faced by different households depending on their OPND. I average all food prices to remove endogeneity from purchasing different food types.

6 Results

We present the results of all three estimations, beginning with the main model that looks at OPND overall, and discuss the implications for efforts towards nutrition sensitive agriculture. The first subsection presents the main estimation results of the effect of OPND on food and nutrition outcomes, then I differentiate the impact by underproduction and market induced OPND, and by season price changes. Finally, as a test of the mechanism, I present results of the effect of OPND and seasonal price change on quantity and diversity of market bought foods.

6.1 OPND effect on Nutrition Outcomes

Results of the main regression estimating the effect of OPND on nutrition outcomes are shown Table 17. The all models are estimated using two-stage least squares. The effect of OPND on all three outcomes is negative. An increase in OPND by a unit reduces HAZ by 3.7 standardized scores (for comparison, an in increase in OPND by 1 standard deviation increases HAZ scores by 1.4), dietary diversity by about 3 points, and increases the likelihood of being food insecure by about 0.8. Most of the household controls are not significant except for nutrition information. Those who received nutrition information through the extension service have higher dietary diversity compared to those who did not. These results do not differentiate between OPND from underproduction and market participation. As descriptive statistics show in Table 16, more than 63% of the household produce enough to meet the household nutrition requirement, meaning that market-induced OPND is the main source of nutrition inadequacy from own production. The next section differentiates between underproduction and market-induced OPND and controls for crop diversification. It also includes results that test for the effect of seasonal price change on nutrition and food security.

Other significant variables are crop diversification index and provision of nutrition information. When crop diversity index increases, there are significant gains in children's nutrition and household dietary diversity score. Households that grow more crops are less likely to experience total crop loss in case of a climatic disaster (Di Falco & Chavas, 2009; Meldrum et al., 2018), shielding them from weather-related risk. These households are also able to capture higher agricultural income by selling some crops while retaining diversified food crops for home consumption. Households that received nutrition information through the extension system have better dietary diversity compared to those that did not—similar result to the main model. This points to the role that nutrition-centered extension systems can play in improving nutrition. Some studies have shown that providing nutrition information improves nutrition outcomes at the household level (Fitzsimons, Malde, Mesnard, & Vera-Hernández, 2016)—adding to the calls to make agriculture more nutrition-sensitive.

Table 17: Effect of OPND on nutrition outcomes-Instrumental Variables estimation

Variable	HAZ	Dietary Diversity	Food Insecurity
OPND	-3.65114***	-2.97224***	0.83605***
	(1.02319)	(0.82028)	(0.24476)
Lack of crop diversification	-5.32905**	-11.26752**	1.01375
	(2.23198)	(5.23167)	(1.33624)
Female HH head (1=Yes)	0.20741	-0.43962	0.17992
	(0.43946)	(0.44582)	(0.11674)
Age of HH head	-0.00052	0.00959	-0.00226
	(0.01198)	(0.00915)	(0.00255)
Education of HH head (years)	0.01129	-0.05527	0.01077
	(0.04429)	(0.04592)	(0.01315)
Received nutrition information(1=yes)	0.03994	0.94704***	-0.10894
	(0.27749)	(0.21981)	(0.08497)
Owns livestock (1=Yes)	0.54318	-0.00677	0.14922
	(0.34769)	(0.48036)	(0.10206)
Household size	-0.08697	-0.01945	0.02017
	(0.14222)	(0.11121)	(0.03000)
Children to adult ratio	-0.01394	-0.00734	0.00344
	(0.01465)	(0.00867)	(0.00211)
Child level controls			
Education level of mother/guardian to child	0.00536		
	(0.06401)		
Mother/guardian to child literate? (1=Yes)	0.20508		
	(0.30974)		
Age (months) when child started complimentary feeding	-0.05055		
	(0.04646)		
Constant	5.38814*	20.31575***	-1.39834
	(2.98923)	(5.58810)	(1.41447)
Observations	183	210	210

Bootstrapped standard errors in parentheses with 300 replications. OPND is instrumented for with output prices and land-size while crop diversification is instrumented for with soil carbon percent, phosphorus parts per million, and log of rainfall. First stage results for OPND are shown in Table B2 and crop diversification are shown in Table B1.
*** p<0.01, ** p<0.05, * p<0.1.

6.2 Heterogenous impacts

We estimate the effect of OPND on nutrition outcomes, differentiated by underproduction, and market induced OPND. OPND as a result of underproduction has an adverse effect on child nutrition, dietary diversity, and food security (Table 18). Results show that an increase in underproduction (OPND) by 1 unit reduces HAZ by about 4 standardized scores (an increase in OPND by 1 standard deviation reduces HAZ by 0.98) and dietary diversity by 2.8 points. No significant effect on food security is observed. From the interaction, there is no significant difference in the effect of OPND on nutrition outcomes due to underproduction and selling of output (market-induced OPND). Any form of OPND negatively affects HAZ and food security. This confirms what other studies have found. For example, Kilimani (2020) showed that crop sales in Uganda reduced the intake of major nutrients. While most studies estimate the effect of crop sales or commercialization (Hirvonen & Hoddinott, 2017; Snapp & Fisher, 2014) and find mixed results, I show that selling output beyond the home nutritional requirement is just as harmful to food and nutrition security as not producing enough food.

Table 18: Effect of OPND on nutrition outcomes by underproduction and market-induced

Variable	HAZ	Dietary Diversity	Food Insecurity
OPND	-4.42151**	-2.80972**	0.55640
	(1.93549)	(1.31423)	(0.36935)
OPND x G (Enough production, $\bar{y}_h > \bar{n}_h$)	-3.01467	-0.67497	-0.45216
	(2.36750)	(1.60158)	(0.47694)
Constant	5.35926	20.82425***	-0.93669
	(3.60159)	(4.37172)	(1.09163)
Household controls	Yes	Yes	Yes
Child level controls	Yes	No	No
Observations	183	210	210

Bootstrapped standard errors in parentheses with 300 replications.
OPND and OPND x G interaction are instrumented for with output prices and land-size and enough land (see Table B2 for first stage regression results).
*** p<0.01, ** p<0.05, * p<0.1

To determine the effect of seasonal price change on nutrition outcomes, and how seasonal price increases and OPND jointly affect nutrition, I estimate a model that includes an interaction between the two variables. Results are displayed in Table 19. No variable is significant in the model using HAZ. OPND is still negatively affecting dietary diversity and food security as in previous models. The interaction effect generally shows a negative effect but not statistically significant.

Table 19: Effect of OPND on nutrition outcomes by seasonal price change

Variable	HAZ	Dietary Diversity	Food Insecurity
OPND	-1.12494	-2.77424**	0.67581**
	(1.50390)	(1.08727)	(0.30002)
Seasonal price change	0.06985	0.01449	-0.00571
	(0.05470)	(0.04015)	(0.01424)
OPND x Seasonal price change	-0.15559	0.05398	0.01796
	(0.15010)	(0.12807)	(0.04389)
Constant	1.55076	16.79205***	-1.00644
	(3.35908)	(3.99094)	(1.02632)
Household controls	Yes	Yes	Yes
Child level controls	Yes	No	No
Observations	183	210	210

Bootstrapped standard errors in parentheses with 300 replications.
OPND is instrumented for with output prices and land-size, while OPND x seasonal price change is instrumented for with the interaction of output prices and seasonal price change (see Table B4 for first stage regression results).
*** $p<0.01$, ** $p<0.05$, * $p<0.1$. HAZ regressions include child-level variables

6.3 OPND and Market-bought Foods

We determine if an increase in OPND is correlated with buying more food from the market to cover the shortfall and the effect of seasonal price changes on the quantity and diversity of market bought foods. This analysis helps to explain the observed results that any form of OPND is detrimental to nutrition and is exacerbated by an increase in lean season prices.

Results in Table 20 show that OPND resulting mainly from underproduction and that resulting from marketing of output is not associated with an increase in the quantity of market bought foods. However, OPND is positively correlated with diversity of market-bought foods (column 3). This shows a tradeoff between dietary diversity and food security. Diversity of market bought foods is generally small, with the highest being 4 food groups compared to an average of 8 in the household dietary diversity scores. While an increase in OPND is associated with buying more diversified food from the market, the diversity of market bought foods is low to impact household dietary diversity.

As Kilimani (2020) showed, households that participate in market are able to buy foods from the market that are rich in micronutrients and vitamins but have a shortage of macro nutrients such as carbohydrates and proteins. In our dataset, majority of the households have market-induced OPND. Households that have higher OPND supplement their nutrition by buying foods that they do not produce, but the quantities are not enough to cover the shortfall. This relationship holds even when actual agricultural income earned from selling of crops is used (Table A9 in the appendix).

Seasonal price increase has a negative correlation with quantity of market bought foods. Low supply and high demand in the lean season push prices up, reducing the quantity bought by households. Selling at a low price at harvest and buying at a higher price is what has been termed “sell low, buy high” in the literature (Stephens & Barrett, 2011), a puzzle that contributes to undernutrition. This explains the negative correlation between seasonal price increase and food and nutrition security. Increase in prices in the lean season makes it difficult for households to use the market to supplement nutrition.

Table 20: Effect of OPND and seasonal price change on market bought foods

VARIABLES	(1) Quantity of market bought foods	(2)	(3) Diversity of market bought foods	(4)
OPND	0.41798	1.59789	0.60989**	0.39138
	(0.55888)	(1.12134)	(0.25798)	(0.50115)
OPND x G (Enough production, $\bar{y}_h > \bar{n}_h$)		1.98263		-0.38011
		(1.61194)		(0.76742)
Seasonal price change	-0.0399***	-0.03024**	-0.00212	-0.00348
	(0.01238)	(0.01414)	(0.00697)	(0.00743)
Female HH head (1=Yes)	-0.11469	-0.10125	-0.00115	-0.00865
	(0.30969)	(0.30684)	(0.14879)	(0.15129)
Age of HH head	-0.00205	-0.01012	0.01483	0.01574
	(0.03218)	(0.03200)	(0.01845)	(0.01877)
Education of HH head (years)	-0.00086	0.00240	-0.0083**	-0.00845**
	(0.00790)	(0.00806)	(0.00420)	(0.00424)
Received nutrition information(1=yes)	0.36339*	0.29982	0.11752	0.12298
	(0.21130)	(0.22745)	(0.10703)	(0.10893)
Owns livestock (1=Yes)	-0.27295	-0.44858	0.04219	0.07037
	(0.29179)	(0.34421)	(0.12719)	(0.13900)
Household size	-0.00410	-0.03394	-0.05135	-0.04236
	(0.07826)	(0.08477)	(0.06343)	(0.06267)
Children to adult ratio	0.00121	0.00311	-0.00659	-0.00659
	(0.00448)	(0.00461)	(0.00577)	(0.00565)
Constant	1.90691**	1.18740	0.98137	1.06655
	(0.78661)	(1.03166)	(0.74556)	(0.75495)
Observations	211	211	211	211

Robust standard errors in parentheses. Quantity bought models (columns 1 and 2) are estimated using two-stage least squares instrumental variables regression. Diversity of bought foods models (columns 3 and 4) used Poisson model with continuous endogenous covariates. OPND and OPND x G interaction same instruments as in Table B2 in appendix 4.3.
*** p<0.01, ** p<0.05, * p<0.1

7 Extension: Effect of Crop Sales on Nutrition Outcomes

To compare with what is traditionally done in literature, I estimate a regression model to determine the effect of crop selling on nutrition outcomes. The goal is to demonstrate that simply focusing on market access or participation does not adequately capture the household dynamics related to post-harvest decisions. Without considering if market participation is resulting in selling of production that would have been kept at home, these studies mask the differential impacts. Results are shown Table 21. Output prices, distance to output markets and whether the household has enough land or not are used as instruments for output sold and its interaction with self-sufficiency. Generally, I find that the effect of crop sales on nutrition outcomes is positive as is mostly reported in literature. Selling output (commercialization) has positive effects dietary diversity, and food security (columns 1-3). However, this masks the differentiated effect of commercialization on households that grow or keep less than the household requirement (columns 4-6). When the regressions include the interaction of quantity of output sold and whether the household did not keep enough for home consumption but sold some output, I find that crop selling only benefits households that leave enough for home consumption (Table 7, column 4 and column 5). Though not statistically significant, point estimates for marginal effect suggest that crop selling actually harms HAZ for the those who are not self-sufficient. On dietary diversity, the results corroborate with what I found on market induced OPND and diversity of market bought foods. I find that crop selling has positive effects on dietary diversity (effect for those who self-sufficient, 0.17010**) those that are self-sufficient. By participating in the output markets, income earned allows households to buy foods that they do not produce and hence have access to more diversified diets.

Table 21: Effect of crop selling on nutrition outcomes-Instrumental Variables estimation

Variable	(1) HAZ	(2) Dietary Diversity	(3) Food Insecurity	(4) HAZ	(5) Dietary Diversity	(6) Food Insecurity
Log of quantity sold	0.11909	0.17922**	-0.10366***	-0.20714	0.00244	-0.07187**
	(0.11474)	(0.07871)	(0.02754)	(0.13895)	(0.12782)	(0.03608)
Log of quantity sold x Self-sufficiency ($OPND = 0$)				0.29211***	0.16766**	-0.01892
				(0.08566)	(0.08337)	(0.02210)
Constant	-0.64855	12.56086**	0.92235	0.14755	12.5691***	0.67782
	(2.50305)	(5.10741)	(1.33180)	(2.62368)	(4.25687)	(1.02709)
Other household controls	Yes	Yes	Yes	Yes	Yes	Yes
Child-specific controls	Yes	No	No	Yes	No	No
Observations	183	210	210	183	210	210

Bootstrapped standard errors in parentheses with 300 replications. Log of quantity sold and its interaction with self-sufficiency is instrumented for with output prices interacted by whether the household has enough land, and distance to output markets. Log of quantity and its interaction with self-sufficiency are instrumented with the interaction of output prices x enough land, and distance to output markets (Table B3 in appendix 4.3).
*** p<0.01, ** p<0.05, * p<0.1.

8 Conclusion

Studies on crop diversification, market access, or commercialization and nutrition have continued to produce mixed results. While agricultural policies focus on using agriculture to generate income and for farmers to use this income to buy more diversified foods, this approach has produced unsatisfactory results in the last 40 years (Headey, Chiu, & Kadiyala, 2012), mainly in developing countries—leading to the hungry farmer paradox. This study focused on marketing and own-consumption decisions to understand the hungry farmer paradox. Specifically, I constructed a variable to measure nutrition deficiency from own production to determine the effects on height for age z-scores, dietary diversity, and food insecurity. Using primary data collected from one of the most productive but 'hungry' districts in Zambia, I found that households have OPND as a result of both underproduction and selling output and leaving less than what is required for household nutrition (determined by the number of adult male equivalents in the household). This could be a result of household pressures such as the need to meet other non-food expenditures.

Empirically, both underproduction and market induced OPND negatively affect HAZ, dietary diversity, and food security. This suggests that households that have OPND do not buy enough foods from the market to cover this deficiency. I test this and find that OPND is not significantly correlated with the quantity of market bought foods, and weakly correlated with the diversity of market-bought foods. Even though OPND is positively correlated with the diversity of market bought foods, the diversity of foods from the market is too small to have any significant effect on household dietary diversity or nutrition outcomes. Further, higher lean season prices reduce the quantity of market-bought foods significantly. This suggests that relying on markets for nutrition is a challenge when markets are less integrated and supply and demand are seasonal.

While I find that marketing food that would contribute to household nutrition can lead to worse household outcomes, this may not always be the case. This study offers some insights to explain the conditions when selling output is beneficial and shows why studies that simply consider selling output or commercialization find mixed results. Market participation to the point of selling produce that *should* have been kept for home consumption harms nutrition outcomes just as much as not producing enough food even though it may have positive effects on dietary diversity. However, selling output improves nutrition much stronger if a household sells the surplus *nutrition* and uses it to diversify diets. I show that once a household has achieved self-sufficiency from own production (at least for the selected major nutrients), selling a unit of the surplus has positive effects on nutrition outcomes as it allows the household to buy other nutrients not produced. With markets that are not well integrated in most of sub-Saharan Africa (Alene et al., 2008), and most farmers failing to exploit attractive inter-temporal arbitrage opportunities for storable commodities, lean season prices increase from scarcity and high search costs (Cardell & Michelson, 2020; Key, Sadoulet, & De de Janvry, 2000), impeding the reliance on markets on to supplement nutrition.

Our results have strengths that cannot be overlooked. Unlike most studies that ignore the issue of endogeneity, I use an instrumental variables approach to estimate the effect of both crop diversification and marketing. I believe the instruments used are plausible economically and statistically, allowing us to identify the effects more causally. I also control for several household and child characteristics to strengthen the identification of the effects. One limitation of the current study is the relatively small sample size and the focus on one area. While a small study area presents a chance to have a more nuanced understanding of the crop production and marketing interactions, it limits generalization to other areas that may be producing different crops both in terms of market value and nutritional value. However, even with small sample size, the insights from this study have implications for policy.

Though providing insightful results, this study has some weaknesses. First, I rely on instrumental variables for identification of the effect of OPND. Though theoretically sound, in practice it is hard to find good instruments. Therefore, some of the results reported here depend on the instruments used. Secondly, measuring both production and consumption in nutrition terms, although important, presents challenges on aggregation. Micrograms of vitamin A deficiency cannot be aggregated with grams of protein deficiency. The attempt made to normalize the production and deficiency by household helps to overcome, albeit not perfectly. Future studies could consider alternative ways of measuring aggregated nutrient deficiency than the simple summation used in this study.

Overall, our results suggest that selling food crop output that could improve nutrition in a poor food market environment could help explain the contradiction of high productivity and low nutrition (the hungry farmer paradox). While it is clear that income from selling crops is probably used in non-food consumption (Ntakyo & van den Berg, 2019) as other things than food also matter for the welfare of the household, there is a need to rethink agricultural commercialization. There is a benefit for policy to incentivize both higher productivity but also better in-home storage and production diversity so that households can retain more food in the home and meet nutritional requirements. A better approach is the promotion of household own food self-sufficiency and marketing—a mixture of both and not just a focus on marketing or crop sales. For example, cash crops could be promoted for marketing, while food crops are grown for home consumption. The income from cash crops can then be used to buy nutrition not produced by the household.

The provision of nutrition information is another aspect that can be integrated into the ministry of agriculture extension system. I found evidence that households that received nutrition information had better dietary diversity, indicating the value of information on choices that households make. Improvements in infrastructure that reduces transaction costs and incentivize storage for the lean season can lower the seasonal price increase and improve nutrition outcomes for households that are market dependent.

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CHAPTER 5: CONCLUSION

Rural livelihoods in developing countries are vulnerable to weather shocks because of their dependence on rainfed agriculture for food and income. With climate models predicting an increase in severity, spatial distribution, and frequency weather shocks such as droughts (Kendon et al., 2019), understanding how weather shocks affect livelihoods is an essential first step in designing policies to help rural households cope. These shocks affect outcomes such as dietary diversity, food security, and income negatively while invoking behavioral responses such as making an individual more risk-averse. Behavioral responses, in turn, affect investment decisions and the use of different agricultural inputs. Most studies have ignored the role that forests can play in mitigating the negative impact of shocks on nutrition, while those that focus on the effect on agricultural decisions do not control for the indirect (income) effect. This dissertation fills these gaps in literature by determining if forest access protects nutrition outcomes in the event of a weather shock as forests are more resilient to weather shocks. In the second essay, I estimate both the direct and indirect effects of weather shocks on input use and show that risk aversion drives the direct effect. In essay three, I provide an alternative explanation for the hungry farmer paradox by focusing on production and marketing of nutrients relative to household requirements.

The main findings from the first essay (chapter 2) are that weather shocks have a statistically and economically significant negative effect on rural households' nutrition outcomes, reducing dietary diversity and increasing the probability of being food insecure. Forest access, however, protects nutrition outcomes and completely offsets these negative effects of shocks. Forest access also reduces reliance on costly shock coping mechanisms such as selling assets and reducing expenditure. An increase in forest quality improves the nutrition protection role of forests.

In the second essay (chapter 3), I use data from Zambia to understand behavioral responses to shocks. I find that previous weather shocks make households more risk-averse and less likely to use risky inputs while more likely to use less risky inputs. Heterogeneity tests show the importance of credit markets in helping farmers make risky investments in the face of weather shocks. Finally, in the last essay, I make a contribution to explaining the hungry farmer paradox by showing that selling food crops and leaving less than the requirement for home consumption has the same effect on nutrition outcomes as not producing enough food to meet the household food needs. The study also provides an exception to the conventional wisdom that commercialization is beneficial to nutrition outcomes by empirically determining that it (selling output or commercialization) is only beneficial if the household is selling output conditional on having kept enough to meet the household nutrition requirement.

Overall, the first essay has marginally improved our understanding of the role that forests can play in protecting livelihoods in the event of a shock. While there are policy debates around whether common property resources are a form of natural capital or natural insurance, (Quaas et al., 2019), I have shown here that there is value in using CPRs as natural insurance. In the second essay, I have contributed to literature attempting to understand the role of weather shocks on risk aversion in agriculture (Bozzola & Finger, 2020) by studying smallholder farmers in a developing country where the welfare state is weak. Overall, the first essay shows that in such environments where there is lack of insurance and formal safety nets, forests can protect nutrition outcomes. At the same time (second essay), informal credit and income-improving interventions can reduce the negative effects of shocks on farmers' investment decisions. Forests and credit markets could form part of plans to facilitate adaptation to climate change and contribute towards economic development in the long run.

Like most research, there are weaknesses in this dissertation that future research could improve on. In the first essay, the study did not use actual hours allocated to the forest, forest types, and the range of products collected. Further, the study does not include forest institutions that are key in determining both quality and access. Future research could focus on determining the type of products and forests that protect welfare better in the event of shocks. For example, are some forests better suited for timber while others for NTFPs? What is the direct impact of weather shocks on forest products collected? Further, research on institutional design that can balance forest quality/insurance capacity with access for when its needed would be of value. These questions can help with forest management efforts. Overall, to understand household shock-coping mechanisms, there is a need for more holistic studies that can account for the whole range of responses from agriculture, use of forests, off-farm labor, and others. Compared to micro-analysis studies like the ones in this dissertation, such a study would give better understanding of how different resources affect the choice of coping mechanisms and the effectiveness of these mechanisms at protecting livelihoods.

While weather shocks have a direct impact on livelihood outcomes such as dietary diversity and food security, they also result in behavioral responses. The second essay shows that weather shocks affect risk attitudes, which explain the observed input use decisions. Even though we show this, the use of observational data to infer risk as done in the second essay still has challenges due to the fact that there could be other factors behind the observed investment (input use) decisions. Improvements in understanding the effect of shocks on risk attitudes, and risk attitudes on input use could be made by using data that explicitly elicits for risk attitudes.

There are still gaps in understanding how best the agriculture-nutrition link can be improved (Anderman et al., 2014). Even though we have shown one aspect that improves our understanding, the sample size and study area are too small to generate conclusive generalizations. Future studies could benefit from using large and more nationally representative data to disentangle regional differences and provide a more nuanced role of markets. Further, future work should delve into understanding the trade-offs households make between non-food consumption and nutrition, something that could help explain the decision-making processes.

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APPENDICES

Appendix: Chapter 2

Appendix 2.1: Theoretical Framework for Household Labor Allocation and Nutrition

In order to conceptualize the linkages between weather shocks, labor allocation, and nutrition, I develop a model of a subsistence agricultural household. I first consider a household with forest access and compare this household to one that lacks access. Assume a household with a labor endowment of $\bar{L}$ that can be allocated to a private food-producing activity (agriculture) or to forest resource collection for food. In the absence of a labor market, the amount of labor allocated to the private activity, L_P , plus labor allocated to resource collection, L_R, must equal the total household time endowment, $\bar{L}$.

Food production in the private activity is $f(L_p; \theta_j)$ where $j \in \{g, b\}$. θ_b represents a negative weather shock such as a drought or flood in the private activity while θ_g is good weather (bad and good states of the world respectively). Production is strictly concave, with $f_{L_p} > 0$, $f_{L_p L_p} < 0$. Bad weather reduces the marginal productivity of labor, or

$$f_{L_p}(L_p; \theta_g) > f_{L_p}(L_p; \theta_b) \tag{A1}$$

Food production in the resource sector is $g(L_R; s_R)$ where s_R represents the quality of the resource stock. The production function has properties $g_{L_R}(L_R; s_R) > 0$, $g_{s_R}(L_R; s_R) > 0$ and $g_{L_R L_R}(L_R; s_R) = 0$. Therefore, resource collection has constant returns to scale with respect to labor, conditional on the resource stock. Constant returns to labor mean that labor allocation is linearly related to output given forest quality and that the marginal product (MP) of labor is equal to the average product (AP). Forest quality is assumed exogenous in any given time period. I define the constant marginal product of resource collection that is dependent on the resource quality as $\kappa(S_R)$. In the good state of the world, all units of labor are more productive in the private activity than in the resource such that:

$$f_{L_p}(\bar{L}; \theta_g) > \kappa(\mathrm{S_R}). \tag{A2}$$

In the bad state of the world, there exists some $L_p^0 < \bar{L}$ such that

$$f_{L_p}(L^0\,;\theta_b) = \kappa(\mathrm{S_R}). \tag{A3}$$

Finally, the household has asset wealth equal to A in food consumption units and in a given period can sell a part of assets owned, φ (where $\varphi \leq$ A), after the realization of θ_j such that the utility of assets after sales (A_+) is[16] $V(A_+) = V(A - \varphi)$ with $V' > 0$ and $V'' < 0$.

The household also receives utility from total food consumption, $u(c_j)$ which comes from agricultural production, resource collection, and food bought from asset sales. The total quantity of food consumption is given as $c_j = f(L_p;\theta_j) + g(L_R;s_R) + \varphi$.

Assume that the household experiences a realization of θ_j and allocates labor between the private activity (agriculture) and resource collection, and chooses asset sales to maximize utility, which is a separable function of current food consumption and remaining asset value. Then, I have (1) as the objective function to be maximized:

$$\max_{L_p,L_R,\varphi,c} u(c_j) + V(A-\varphi) \tag{A4}$$

s.t.

$$L_p + L_R = \bar{L} \tag{A4.1}$$

$$c_j = f(L_p;\theta_j) + g(L_R;s_R) + \varphi \tag{A4.2}$$

$$\varphi, L_p, L_R, L_l, \geq 0 \;\;, \varphi \leq A \tag{A4.3}$$

Substituting c_j in the objective function, the Lagrangian is given as:

$$l = u\big(f(L_p;\theta_j) + g(L_R;s_R) + \varphi\big) + V(A-\varphi) - \lambda_1(L_p + L_R - \bar{L}) \tag{A5}$$

Assuming the household allocates some labor to agriculture and does not sell all assets ($\varphi < A$), the FOCs with respect to labor and the use of assets for consumption are:

$$\frac{\partial l}{\partial L_p} = u' f_{L_p}(L_p;\theta_j) - \lambda_1 = 0 \tag{A6.1}$$

$$\frac{\partial l}{\partial L_R} = u' g_{L_R}(L_R;s_R) - \lambda_1 \leq 0, (u' g_{LR}(L_R;S_R - \lambda_1)L_R = 0 \tag{A6.2}$$

$$\frac{\partial l}{\partial \varphi} = u' - V' \leq 0; (u' - V')\varphi = 0 \tag{A6.3}$$

[16] For simplicity, I assume that the assets do not earn any interest or depreciate within the period.

When $j = g$, then $u' f_{L_p}(\bar{L}; \theta_g) = \lambda_1 > u' g_{L_R}(L_R; s_R)$ and all labor is allocated to agriculture.[17] I know this because $f_{L_p}(\bar{L}; \theta_g) > \kappa(S_R)$. If $j = b$, and resource collection is used to cope, $f_{L_p}(L_p; \theta_b) = \kappa(\mathrm{S_R})$ which can be solved for the optimal amount of labor allocated to agriculture, $L_p^*(\theta_b)$. Using the household time constraint, $L_R^*(\theta_b) = \bar{L} - L_p^*(\theta_b)$. Since $\bar{L}$ is allocated to agriculture in the good state of the world, $L_R^*(\theta_b)$ is equal to the amount of labor moved from agriculture in response to the negative shock. Labor allocation in the good state of the world equates the marginal food production from labor across the two sectors, maximizing the quantity of food production.

Finally, I see that $u' \leq V'$. I assume that in the good state of the world, $u'\left(f\left(L_p^*(\theta_g); \theta_g\right) + g\left(L_R^*(\theta_g); s_R\right)\right) < V'(A)$. This implies that the household sells no assets in the good state. Also, in the bad state of the world, assume $u'\left(f\left(L_p^*(\theta_b); \theta_b\right) + g(L_R^*(\theta_b); s_R)\right) > \mathrm{V}'(\mathrm{A})$. Therefore, $u'\left(f\left(L_p^*(\theta_b); \theta_b\right) + g(L_R^*(\theta_b); s_R) + \varphi^*(\theta_b)\right) = V'(A - \varphi^*(\theta_b))$, where $\varphi^* > 0$ is the optimal quantity of assets to sell. For completeness, the optimal level of food consumption is $c_b^* = f\left(L_p^*(\theta_b); \theta_b\right) + g(L_R^*(\theta_b); s_R) + \varphi^*(\theta_b)$ when there is weather shock and $c_g^* = f\left(L_p^*(\theta_g); \theta_g\right) + g\left(L_R^*(\theta_g); s_R\right)$ if there is none.

We now consider a household that does not have access to the forest. In this case, all labor is allocated to agricultural production in both states of the world (i.e. with or without a weather shock). The maximization problem becomes:

$$\max_{\varphi} = u\left(f\left(\bar{L}; \theta_j\right) + \varphi\right) + V(A - \varphi) \tag{A7}$$

where the labor constraint and definition of food consumption have been substituted in. In this case, the optimal labor to agriculture is $L_p^{\#}(\theta_j) = \bar{L}$. Again, assuming not all assets are sold, the first-order condition becomes:

[17] In practice, I observe some labor in resource collection in the absence of a negative shock, though this labor is significantly less than labor allocated to agriculture (see Section 4.2 for more detail).

$$\frac{\partial L}{\partial \varphi} = u' - V' \leq 0, (u' - V')\varphi = 0 \quad \text{(A8.1)}$$

To examine asset sales, note that food production is the same as the household with resource access when $j = g$. $u'\left(f(\bar{L};\theta_g)\right) < V'(A)$, which again implies that the household sells no assets in the good state of the world. In the bad state, production is $f(\bar{L};\theta_b) < f\left(L_p^*(\theta_b);\theta_b\right) + g(L_R^*(\theta_b);s_R)$ since the right-hand side maximizes food production from $\bar{L}$ when $j = b$. If $u'\left(f\left(L_p^*(\theta_b);\theta_b\right) + g(L_R^*(\theta_b);s_R)\right) > V'(A)$, then $u'\left(f(\bar{L};\theta_b)\right) > V'(A)$, and the household sells some assets to cope with the bad state of the world. Further, for A6.3 and A8.1 to both hold and since $f\left(L_p^*(\theta_b);\theta_b\right) + g(L_R^*(\theta_b);S_R) > f(\bar{L};\theta_b)$, then, $\varphi^{\#}(\theta_b) > \varphi^*(\theta_b)$. In other words, a household with no resource access sells more assets than a household with resource access.

Finally, these results imply that $c_b^{\#} < c_b^*$. I know this because $u'(c_b^*) = V'(A - \varphi_b^*) < V'\left(A - \varphi_b^{\#}\right) = u'\left(c_b^{\#}\right)$. Strict concavity of u means that $u'(c_b^*) < u'\left(c_b^{\#}\right) \rightarrow c_b^* > c_b^{\#}$. This also allows us to conclude that c_b^* is increasing in $\kappa(S_R)$. This occurs because the marginal product of the same amount of labor is increasing in in $\kappa(S_R)$. This will lead to less asset sales to equate $u'(c_b^*) = V'(A - \varphi_b^*)$.

To summarize, this model produces four testable hypotheses. First, households with access to a forest should allocate labor to the forest in the event of a negative shock (research question 1 in the main text). Second, households with forest access experience smaller drops in food consumption (and thus nutritional outcomes) (research question 2 in the main text). This occurs because both households have the same level of consumption when $j = g$ but the household without forest access experiences a bigger drop in consumption when $j = b$. The first two hypotheses suggest that access to forests provides household with a form of natural insurance for food consumption. Third, better quality forest leads to smaller drops in consumption. Finally, forest access allows households to respond to shocks by selling fewer assets, suggesting that the forest could substitute for other costly coping mechanisms (Janzen & Carter 2018).

Appendix 2.2: A Control Function Approach to Test the Main Results

Two concerns might be advanced in the estimation of equation (1) and Table 4 that use communally defined access to a forest. First, there may be a concern that access does not equate to actual use.

Even though the community has a forest within their jurisdiction, it may not be all household members who use the forest to access food as use requires labor (time and effort) and in some cases knowledge (Pattanayak & Sills, 2001). Hence, some members may be constrained to use the forest as natural insurance even if they live in communities that have access to. Secondly, dependence, and hence protection, varies depending on how much one uses the forest. For example, the poor may extract more food products from the forests compared to those who are relatively well-to-do in the community. It is possible therefore that the natural insurance role is correlated more with the quantity extracted than just mere access. For these two reasons, I use an alternative identification strategy to test if our results are robust to a different identification. For this exercise, I sum all wild foods[18] that the household collected and consumed and obtain the total quantity consumed in kilograms. I choose quantity collected and consumed as it would be highly indicative of labor allocation to forests and forest dependence.

We use a control function approach (Terza, Basu, & Rathouz, 2008; Wooldridge, 2015) for the robustness check. Earlier authors such as (Barrow, Cain & Goldbeger, 1981) defined control functions as any variable that when added to a regression, renders an endogenous variable appropriately exogenous—similar to what is currently defined as a proxy variable. An example is IQ in a typical wage-education equation where conditioning on IQ controls for unobserved cognitive ability hence allowing for consistent estimation of the causal impact of education on wages. However, more recent definitions and applications differentiate a control function approach from a proxy variable approach. For example, Wooldridge (2010 & 2015) explains that a control function approach relies on instruments. That is, in the structural equation (the equation of interest), a variable that is suspected to be endogenous is included and renders the estimates inconsistent. So, in our case, I suspect that quantity of wild foods collected, which is an explanatory variable, is endogenous given the dependent variables of nutrition and food security. Therefore, I must find instruments for this endogenous variable. I use shocks (s_{vt}) and family size (h_{it}) as the two instruments for wild foods quantity collected. The control function approach is estimated using the Mundlak-Chamberlain device (Chamberlain, 1984; Mundlak, 1978). The MC device employs household-level averages of time-varying components of the model in order to control for unobserved time-constant

[18] Lists of wild foods that were collected in the survey include 1. "GATHERED WILD GREEN LEAVES", 2. "MUSHROOM", 3. "SMALL ANIMAL – RABBIT, MICE, ETC.", 4. "TERMITES, OTHER INSECTS (EG NGUMBI, CATERPILLAR", 5. "WILD FRUIT (MASAU, MALAMBE, ETC.)" and 6. "HONEY"

heterogeneity, under the assumption that such heterogeneity is correlated with the time average of the household characteristics and other exogenous variables (Chamberlin & Ricker-Gilbert, 2016; Wooldridge, 2007). We, therefore, assume a linear reduced form model for wild foods (WF_{ivt}) collected as;

$$WF_{ivt} = \psi + \tau_1 s_{vt} + \tau_2 h_{it} + \sigma_1 \bar{s}_v + \sigma_2 \bar{h}_i + v_{it} \tag{R1}$$

Where $\bar{s}_{vt}$and $\bar{h}_{it}$are the time averages for shocks and average household age respectively. Using the Chamberlain approach, I can allow unobserved heterogeneity to be correlated with WF and the instruments. Denoting the heterogeneity (m_{it}) as $m_{it} = \psi + \sigma_1 \bar{s}_v + \sigma_2 \bar{h}_i + \omega_i$ with ω_i being normally distributed errors with mean zero and variance of ${\sigma_\omega}^2$. However, time-varying omitted variables captured by v_{it} are assumed not to be correlated with any of the instruments, so that $Corr(v_{it}, s_{vt}) = 0$ and $Corr(v_{it}, h_{it}) = 0$. I also estimate (R1) with an interaction of WF and shock (s_{vt}) as the dependent variable. This corrects for any endogeneity in the interaction variable. So, the second stage equation, the equation of interest with nutrition (HDDS) and food security (FI and MC) measures as dependent variables is estimated as;

$$E(y_{it} | s_{vt}, h_{it}, v_{it}) = \phi(\beta y_{it} + \tau_{e1} s_{vt} + \tau_{e2} h_{it} + \sigma_{e1} \bar{s}_v + \sigma_{e2} \bar{h}_i + \theta_e v_{it}) \tag{R2}$$

Where $y_{it} = \{HDDS_{it}, FI_{it}, MC_{it}\}$. $v_{it}$is not directly observable, so it is estimated as the residuals from (R1). Test on the coefficient of v_{it}saves as a test of the null hypothesis that quantity of wild foods collected is exogenous (Wooldridge, 2010, 2015).

In Table A1 I show the results of the robustness check on nutrition, shocks and collection of wild foods from the forest. I use quantity of wild foods collected[19] Generally, the results are confirmed under alternative identification and estimation strategy. Weather shocks still negatively impact nutrition by reducing dietary diversity, increasing the chances of food insecurity, and reducing the probability of children having at least 3 meals per day. The impact of a 100kg increase in forest foods collection has the expected sign and significant for dietary diversity but not for food insecurity and

[19] The measure for the quantity of foods collected is quite grainy in terms of what households report and there may be challenges in how well households recall the quantities. The survey collected data in units that they usually collect these foods in, e.g. bucket, sack, tin, meda etc and then measure what these units are in kilograms. I used the conversion rates provided in the data to sum the collected foods into total kilograms of wild foods collected by the household.

number of meals for children. This indicated that that, even without a weather shock, increasing the amount of forest products consumed by 100kgs increased dietary diversity by about 2 percent. In the event of a shock, the impact of a 100kg increase in forest foods consumed has a much higher impact on nutrition. There is 6.6 percent increase in dietary diversity, and a 12.6 percent decrease in probability of being food insecure and about 14 percent increase in chances of children having at least 3 meals per day. However, even an increase of 100kg per week (which is higher than the average for all years) on forest foods consumed does not seem enough to completely offset the negative impact of the shocks.

Table A1: Robustness check on access and nutrition protection using a control function approach and quantity of forest foods consumed per week

VARIABLES	HDDS	FI	MC
Shock	-0.17863***	0.39881***	-0.35530***
	(0.06845)	(0.12570)	(0.11025)
Wild Foods (in kgs)	0.01761*	-0.00695	0.00086
	(0.00916)	(0.02007)	(0.01615)
[Shock] x [Wild Foods]	0.06599***	-0.12568***	0.13793***
	(0.02524)	(0.04691)	(0.04108)
Average household age	0.00014	-0.00334**	0.00362*
	(0.00117)	(0.00164)	(0.00202)
Literate (1=Yes)	-0.13343***	0.15064***	-0.15340***
	(0.01249)	(0.02130)	(0.02252)
Sex (1= Female)	-0.04263***	0.12923***	-0.03762**
	(0.01224)	(0.02452)	(0.01899)
Residuals (Wild foods)	0.00049***	-0.00032	0.00012
	(0.00008)	(0.00026)	(0.00023)
Residuals (Shock x Wild foods)	-0.06659***	0.12522***	-0.13767***
	(0.02525)	(0.04691)	(0.04111)
Constant	2.27894***	0.29249***	0.80277***
	(0.02249)	(0.04151)	(0.04116)
Year FE	YES	YES	YES
Household FE	YES	YES	YES
Time averages (shock, family age)	YES	YES	YES
Observations	3,746	3,746	3,746

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

The coefficients on the residuals from the first regression of wild foods collected on shocks and household age are all positive, indicating that labor allocation/quantity of foods collected is indeed endogenous as I reject the null that it is exogenous. On dietary diversity, the interpretation is that households with better dietary diversity allocate less labor to forests or that households allocate more labor when they expect dietary diversity to be worse based on some unobservable factors that are not included like expectations of harvest/rainfall. This interpretation holds for food insecurity and number of meals for children i.e. households with worse nutritional indicators collect more forest foods compared to those with better nutritional status. The key results that shocks affect nutrition, and that relying on NTFPs (wild foods in this case) buffers the effect of the shocks on nutrition and food security are confirmed.

Appendix: Chapter 3

Appendix 3.1: Derivation of Equation 8 in Chapter 3

Generally, a 3rd order Taylor series expansion of f(x) at a is;

$$\mathrm{f}(\boldsymbol{x}) = \boldsymbol{f}(\boldsymbol{a}) + \frac{\boldsymbol{f}'(\boldsymbol{a})}{\mathbf{1}!}(\boldsymbol{x}-\boldsymbol{a}) + \frac{\boldsymbol{f}''(\boldsymbol{a})}{\mathbf{2}!}(\boldsymbol{x}-\boldsymbol{a})^{\mathbf{2}} + \frac{\boldsymbol{f}'''(\boldsymbol{a})}{\mathbf{3}!}(\boldsymbol{x}-\boldsymbol{a})^{\mathbf{3}}$$

So, given a utility function, Eu(y), where *y* is random output and applying a 3rd order Taylor series expansion around the mean output, μ_1, it becomes;

$$Eu(y) = \int u(y)U(y)dy$$

$$u(y) = u(\mu_1) + u'(\mu_1)(y-\mu_1)\frac{1}{1!} + u''(\mu_1)(y-\mu_1)^2\frac{1}{2!} + u'''(\mu_1)E(y-\mu_1)^3\frac{1}{3!}$$

Applying the expectation on both sides;

$$Eu(y) \approx u(\mu_1) + u'(\mu_1)E(y-\mu_1)\frac{1}{1!} + u''(\mu_1)E(y-\mu_1)^2\frac{1}{2!} + u'''(\mu_1)E(y-\mu_1)^3\frac{1}{3!}$$

Taking the expectation of the difference, $E(y-\mu_1) = E[y] - E[\mu_1] = 0$, $\mu_1 - \mu_1 = 0$ hence the first order term drops out. And I know that $E\big(y-E(y)\big)^2 = \mu_2$ (variance) and $E\big(y-E(y)\big)^3 = \mu_3$ (skewness). Therefore,

$$Eu(y) \approx u(\mu_1) + u''(\mu_1)\mu_2\frac{1}{2!} + u'''(\mu_1)\mu_3\frac{1}{3!} = U(\mu_1, \mu_2, \mu_3)$$

Which is equation 8 in the main text.

Appendix 3.2: Robustness Check Tables

Table A2: Effect of previous weather shocks on input use: continuous measure of negative anomaly

	Fertilizer Use			Improved Seed Use		
	Direct	Indirect	Total	Direct	Indirect	Total
Negative anomaly (t-1)	-0.0198**	-0.0025***	-0.0223**	0.0318**	-0.0029***	0.0288**
	(0.049)	(0.001)	(0.026)	(0.017)	(0.002)	(0.030)
Log household income	0.0170***			0.0196***		
	(0.000)			(0.000)		
Negative anomaly (t)	-0.00336			0.0478***		
	(0.696)			(0.000)		
Prime age adults	0.0103***			0.0211***		
	(0.001)			(0.000)		
Age of HH head	-0.000374			-0.00244		
	(0.744)			(0.121)		
Maize prices (ZMW/kg)	-0.104**			0.275***		
	(0.020)			(0.000)		
Distance to agro-dealer (kms)	0.000318			-0.000254		
	(0.147)			(0.370)		
Access to extension	0.0171**			0.0125		
	(0.050)			(0.289)		
Distance to fertilizer depot (kms)	-0.00067***			0.00058**		
	(0.002)			(0.027)		
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12112	12112	12112	12112	12112	12112
Households	6056	6056	6056	6056	6056	6056

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
ZMW is Zambian Kwacha currency.

Table A3: Effect of previous weather shocks on input use using the Standardized Precipitation Evapotranspiration Index (SPEI)

	Fertilizer Application Rate			Improved Seed Proportion		
	Direct	Indirect	Total	Direct	Indirect	Total
Drought (t-1)	-0.0440***	-0.0039***	-0.048***	0.0454***	-0.0043***	0.041***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.005)
Log household income	0.0175***			0.0191***		
	(0.000)			(0.000)		
Drought (t)	0.0174			0.165***		
	(0.292)			(0.000)		
Prime age adults	0.00160			0.0297***		
	(0.544)			(0.000)		
Age of HH head	0.00132			-0.00353**		
	(0.263)			(0.015)		
Maize prices (ZMW/kg)	-0.261***			0.293***		
	(0.000)			(0.000)		
Distance to agro-dealer (kms)	0.000287			-0.0000469		
	(0.193)			(0.866)		
Access to extension	0.0227***			0.00781		
	(0.008)			(0.501)		
Distance to fertilizer depot (kms)	-0.00071***			0.000537**		
	(0.649)			(0.442)		
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12112	12112	12112	12112	12112	12112
Households	6056	6056	6056	6056	6056	6056

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
ZMW is Zambian Kwacha currency.

Table A4: Effect of previous weather shocks on fertilizer and improved seed use

	Fertilizer and Improved Seed Use		
	Direct	Indirect	Total
Drought (t-1)	0.00749	-0.00340***	0.00409
	(0.632)	(0.007)	(0.794)
Log household income	0.0238***		
	(0.000)		
Drought (t)	0.0431***		
	(0.000)		
Prime age adults	0.0212***		
	(0.000)		
Age of HH head	-0.00191		
	(0.198)		
Maize prices (ZMW/kg)	0.185***		
	(0.000)		
Distance to agro-dealer (kms)	-0.000124		
	(0.651)		
Access to extension	0.0159		
	(0.165)		
Distance to fertilizer depot (kms)	0.0000298		
	(0.908)		
Household FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	12112	12112	12112
Households	6056	6056	6056

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
ZMW is Zambian Kwacha currency.

Table A5: Direct and indirect effects of weather shocks on intensity of input use

	Fertilizer Application Rate			Improved Seed Proportion		
	Direct	Indirect	Total	Direct	Indirect	Total
Drought (t-1)	2.613**	-0.282***	2.331*	6.818**	-0.500**	6.317**
	(0.044)	(0.008)	(0.072)	(0.026)	(0.015)	(0.039)
Log household income	1.968***			3.496***		
	(0.000)			(0.000)		
Drought (t)	-2.637***			0.358		
	(0.004)			(0.878)		
Prime age adults	1.190***			0.429		
	(0.000)			(0.557)		
Age of HH head	-0.0386			-0.0848		
	(0.770)			(0.753)		
Maize prices (ZMW/kg)	6.831			-6.221		
	(0.231)			(0.511)		
Distance to agro-dealer (kms)	-0.0461**			0.0275		
	(0.048)			(0.627)		
Access to extension	2.026**			6.566***		
	(0.032)			(0.003)		
Distance to fertilizer depot (kms)	0.0500**			-0.0537		
	(0.033)			(0.276)		
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7142	7142	7142	6464	6464	6464
Households	3,570	3,570	3,570	3,232	3,232	3,232

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
ZMW is Zambian Kwacha currency.

Table A6: First stage regression results

VARIABLES	(1) Improved Seed Proportion	(2) Improved Seed Proportion Squared	(3) Fertilizer Application Rate	(4) Fertilizer Application Rate Squared	(5) Improved Seed Prop. X Fertilizer Application Rate
Distace to agrodealer (kms)	-0.00100**	0.00079***	0.00024	-0.00152	-0.00011
	(0.00050)	(0.00030)	(0.00056)	(0.00314)	(0.00055)
Distance to fertilizer depot (kms)	0.00119**	-0.00068**	-0.00045	-0.00134	-0.00005
	(0.00050)	(0.00029)	(0.00049)	(0.00242)	(0.00052)
Access to extension (1=Yes)	0.04584**	-0.03176***	0.06357***	0.11940	0.00637
	(0.02015)	(0.01207)	(0.02186)	(0.13914)	(0.02199)
Average district maize prices (ZMW/kg)	0.21389*	-0.16388**	-0.03955	0.53273	-0.33969***
	(0.12331)	(0.07120)	(0.09911)	(0.34743)	(0.13104)
Rainfall in period *t-1* (mm/annum)	-0.00013	0.00014***	-0.0003***	-0.00059*	0.00004
	(0.00008)	(0.00005)	(0.00008)	(0.00030)	(0.00008)
Constant	-1.49817**	2.33807***	0.21585	4.51035	1.52468**
	(0.58661)	(0.34000)	(0.62286)	(2.95019)	(0.62953)
Included instruments	Yes	Yes	Yes	Yes	Yes
R-squared	0.02458	0.02542	0.01645	0.00625	0.00303
F-statistic	18.46***	19.85***	13.98***	5.17***	2.31**
Observations	12,114	12,114	12,114	12,114	12,114
Households	6,058	6,058	6,058	6,058	6,058

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Instruments included in the second stage were: number of prime-age adults, age of household head, and rainfall in period *t*

Table A7: Effect of improved seed and fertilizer use on mean, variance, and skewness of output (binary defined input use)

VARIABLES	(1) Mean (Output)	(2) Variance (Output)	(3) Skewness (Output)
Improved Seed (1=Yes)	16.40302	-0.08189	1.11116
	(109.34144)	(0.08419)	(1.66700)
Fertilizer Use (1=Yes)	927.58675***	0.58074***	0.38301
	(112.55761)	(0.07165)	(1.28714)
Improved Seed & Fertilizer	415.05124***	0.15313	-0.12469
	(151.90393)	(0.10115)	(1.73053)
Number of prime age adults	40.91923	0.00272	-0.29343
	(49.39191)	(0.01838)	(0.22326)
Age of household age	-6.56486	-0.00877	0.03409
	(14.89852)	(0.00673)	(0.10423)
Log of period *t* rainfall (mm/annum)	-122.50042	-0.19342	-3.38995
	(340.62148)	(0.17301)	(2.30024)
Year FE	46.62920	-0.00224	-1.11281*
	(113.39770)	(0.04985)	(0.66530)
Constant	3,450.06418	16.25665***	20.66605
	(2,419.78342)	(1.21727)	(17.08184)
Household FE	Yes	Yes	Yes
Observations	12,110	12,110	12,110
R-squared	0.01085	0.01423	0.00151
Households	6,058	6,058	6,058

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

No instruments are used in this regression because the endogenous variables are binary. Identification uses household fixed effects assuming that the unobserved time-invariant factors are affect both yield and use of fertilizer and improved seed have been controlled for.

Appendix: Chapter 4

Appendix 4.1: Institutional Review Board Approval for the Study (Chapter 4)

Colorado State University
Knowledge to Go Places

eProtocol
Office of the Vice President for Research
321 General Services Building - Campus Delivery 2011 eprotocol
TEL: (970) 491-1553
FAX:

NOTICE OF APPROVAL FOR HUMAN RESEARCH

DATE:	June 20, 2019	
TO:	Manning, Dale	
	Chouinard, Hayley, Mulungu, Kelvin, Bruce, Kathy	
FROM:	Chance, Claire, CSU IRB 2	
PROTOCOL TITLE:	Optimizing Household Agricultural Production for Nutrition: Association between Farm Production Diversity, Marketing and Child Nutritional outcomes in Rural Zambia	
FUNDING SOURCE:	NONE	
PROTOCOL NUMBER:	19-8869H	
APPROVAL PERIOD:	Approval Date: June 18, 2019	Expiration Date: June 17, 2022

The CSU Institutional Review Board (IRB) for the protection of human subjects has reviewed the protocol entitled: Optimizing Household Agricultural Production for Nutrition: Association between Farm Production Diversity, Marketing and Child Nutritional outcomes in Rural Zambia. The project has been approved for the procedures and subjects described in the protocol.
Full Board Review: This protocol must be reviewed for renewal at least annually for as long as the research remains active. Should the protocol not be renewed before expiration, all activities must cease until the protocol has been re-reviewed.
Expedited Review: This protocol is approved for a duration of three years, unless otherwise notified. You remain obligated to submit amendments, deviations, unanticipated problems per policy.
Exempt Review: This protocol is approved for a duration of five years. You remain obligated to submit amendments, deviations, unanticipated problems per policy.

Important Reminder: If you will consent your participants with a signed consent document, it is your responsibility to use the consent form that has been finalized and uploaded into the consent section of eProtocol by the IRB coordinators. Failure to use the finalized consent form available to you in eProtocol is a reportable protocol violation.

If approval did not accompany a proposal when it was submitted to a sponsor, it is the PI's responsibility to provide the sponsor with the approval notice.

This approval is issued under Colorado State University's Federal Wide Assurance 00000647 with the Office for Human Research Protections (OHRP). If you have any questions regarding your obligations under CSU's Assurance, please do not hesitate to contact us.

Please direct any questions about the IRB's actions on this project to:

IRB Office - (970) 491-1553; RICRO_IRB@mail.Colostate.edu
Evelyn Swiss, Senior IRB Coordinator - (970) 491-1381; Evelyn.Swiss@Colostate.edu
Tammy Felton-Noyle, IRB Biomedical Coordinator - (970) 491-1655; Tammy.Felton-Noyle@Colostate.edu

Chance, Claire

Initial review has been completed on 6/18/2019. Protocol has been approved to recruit participants with the approved

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recruitment and consent procedures. Review was conducted under expedited review categories 4 and 7. Continuing review is not required in accordance with .109(f)(1)(i) expedited; [.109(f)(1)(ii). The study was assessed as being in accordance with 45 CFR 46.111.

Approved documents include:

- respondent_sheet_and_consent.final.v.6.18.2019
- Questionnaire_Optimizing_HH_Ag_Prod_Nestle

NOTE: When available, please submit an amendment via eProtocol to include the updated Ethics Approval from University of Zambia that reflects the collaboration with CSU researcher, Mulungu

Approval Period:	June 18, 2019 through June 17, 2022
Review Type:	EXPEDITED
IRB Number:	00000202

Appendix 4.2: Extra Tables

Table A8: Nutritional content of common food crops in Mbala

Nutrient	Protein	Fat	Carbohydr	Vit. A	Vit. B1	Vit. B2	Vit. B6	Fol. acid	Vit. C	Calcium	Iron	Zinc
Units	g	g	G	µg	mg	mg	mg	µg	mg	mg	mg	mg
Maize	85.4	38	646.6	1850	3.6	2	4	260	0	150	15	25
Cassava	11	3	319	60	1.3	0.2	2.9	150	300	190	8	3
Sorghum	103	30	737	70	3	1	1.9	140	0	250	41	16
Millet	66	13	762	50	2.7	1.4	2.3	100	0	2750	27	12
Sweet potatoes	21	1	229	0	1	0.3	2.3	160	120	80	8	5
Staples	**57.28**	**17**	**538.72**	**406**	**2.32**	**0.98**	**2.68**	**162**	**84**	**684**	**19.8**	**12.2**
Beans	87	5	228	0	1.6	0.6	1.2	1300	10	280	29	11
Groundnuts	258	492	161	0	2.5	1.1	2.6	1260	0	920	46	33
Soybean	317	164	284	410	6.7	4.1	1.5	2840	440	3710	64	23
Pulses	**220.67**	**220**	**224.33**	**136.67**	**3.6**	**1.93**	**1.767**	**1800**	**150**	**1636.67**	**46.33**	**22.33**
Kale	19	4	56	7400	0.5	0.7	1.4	130	410	720	9	2
Tomato	10.6	2.3	29	940	0.5	0.3	0.9	240	152.3	60	5.3	2
Onion	12.6	2.5	38.6	10	0.2	0.1	0.9	100	41.1	330	4.2	1.9
Impwa	8	2	66	60	0.8	0.2	0.9	140	10	60	4	2
Okra	18.7	2.1	45.1	140	1.3	0.6	1.9	460	163	770	2.8	4.3
Cabbage	18	0.9	54.1	440	0.5	0.2	1.5	460	170	300	3.8	2.3
Bean leaves	23.8	2.4	31.9	560	0.6	0.9	2	240	121.9	630	7.8	3.5
Cassava leaves	37	2	73	5190	0.9	1.9	5.4	1040	330	2110	31	4
Pumpkin leaves	11	2	44	5500	0.5	0.7	1.8	1180	270	1370	8	1
Vegetables	**17.63**	**2.24**	**48.63**	**2248.9**	**0.64**	**0.62**	**1.86**	**443.33**	**185.4**	**705.56**	**8.43**	**2.56**
Minimum daily requirement per adult	60.1	69.1	290.7	1000	1.2	1.4	1.5	400	100	1000	10	10

Table A9: Agricultural income, market bought foods and seasonal price change

VARIABLES	(3) Quantity	(4) Diversity
Log of agric income	-0.04472	-0.04384
	(0.10358)	(0.04275)
Log of agric income x G (Enough production, $\bar{y} > n$)	0.02217	0.00250
	(0.09654)	(0.04169)
Seasonal price change (ZMK/kg)	-0.02035**	-0.00187
	(0.00950)	(0.00517)
Female HH head	-0.27400	-0.01920
	(0.33025)	(0.16545)
Age of HH head	0.00157	0.01849
	(0.03364)	(0.01835)
Education of HH head (years)	-0.00236	-0.00932**
	(0.00931)	(0.00429)
Received nutrition information(1=yes)	0.43450*	0.10220
	(0.22823)	(0.11045)
Owns livestock (1=Yes)	-0.09551	0.20239
	(0.30218)	(0.13602)
Household size	0.03962	-0.01523
	(0.08434)	(0.05664)
Children to adult ratio	0.00235	-0.00642
	(0.00462)	(0.00509)
Constant	1.96982**	1.28526*
	(0.92059)	(0.67003)
Observations	204	204
R-squared	0.03634	

Robust standard errors in parentheses. OPND, OPND x (=1 if $\bar{y} > n$), Log of agric income, Log of agric income x (=1 if $\bar{y} > n$) are intrumented for with prices, distance to markets, and land (Table B3 in appendix B).
*** p<0.01, ** p<0.05, * p<0.1

Appendix 4.3: Chapter 3 First Stage Results (Excluded Instruments)

Table B1: First stage results for crop diversification

Variable	Crop diversification (Dependent variable)
Log of rainfall in the season	-0.56018***
	(0.17563)
Phosphorus parts per million	-0.00174***
	(0.00059)
Organic carbon (%)	-0.09551***
	(0.03306)
Land size (hectares)	0.00787
	(0.00915)
Constant	5.02353***
	(1.25404)
Observations	210
R-squared	0.05382
F-statistic	3.3**

Table B2: First stage regression results for OPND and OPND x enough production

Variable	OPND	OPND x Enough production
Average price of staples (ZMW/kg)	-0.05486***	0.00429
	(0.01271)	(0.01150)
Average price of pulses (ZMW/kg)	-0.02126***	0.01744***
	(0.00502)	(0.00457)
Land size (hectares)	-0.01676***	
	(0.00591)	
Land per adult>0.5 ha (1=Yes) (enough land)		0.13756***
		(0.03377)
Constant	0.55031***	0.01109
	(0.03713)	(0.03241)
Observation	210	210
R-squared	0.22343	0.17852
F-statistic	11.03***	5.64***

Table B3: First stage results for log of quantity sold, and log of quantity sold x self-sufficiency

	Log quantity sold	Log quantity sold x self sufficiency
Average staple price x enough land	0.25009**	0.76270***
	(0.11698)	(0.25495)
Average pulse price x enough land	0.17176***	0.08763
	(0.05452)	(0.11350)
Log of distance to pulse market	-0.09180	-0.03275
	(0.07321)	(0.11249)
Log of distance to staple market	-0.39301**	0.14997
	(0.16558)	(0.22842)
Constant	6.40658***	2.23140***
	(0.24712)	(0.40055)
Observations	210	210
R-squared	0.21030	0.17755
F-statistic	10.81***	8.76***

Table B4: First stage results for OPND x seasonal price change

Variable	OPND x Seasonal price change
Average staple price	0.10488
	(0.17761)
Average pulse price	-0.05128
	(0.07392)
Average staple price x Seasonal price change	-0.06354*
	(0.03544)
Average pulse price x Seasonal price change	-0.00499
	(0.01634)
Enough land	-1.63065***
	(0.42268)
Constant	0.88124
	(0.57935)
N	210
R-squared	0.42989
F-statistic	25.51***