Multiple-Season Farming and Resilience: Linking Agriculture, Food Security and Nutrition

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Abstract

The livelihoods of rural households in sub-Saharan Africa have been threatened by climate change and underperformance of the agricultural sector. To address this challenge, multiple-season farming has been suggested as a potential alternative to rain-fed cultivation in order to intensify agricultural production and improve farmers' well-being. This study employs a fixed effects-instrumental variable (FE-IV) model to estimate the impact of multiple-season farming on household food security and child nutrition. We find no significant impact on child nutrition; however, households that engage in multiple-season farming are significantly more food secure compared to those who solely rely on rainy season cultivation. This improvement is most pronounced among asset-rich and male-headed households. Multiple-season farmers also tend to cultivate a more diverse range of crops and are more likely to sell surpluses in markets, which enables them to access a more abundant and diverse food supply. Furthermore, we adopt a moment-based method to estimate household resilience, defined as the persistence of food security over time. However, we find that the current increase in food security from multiple-season farming does not necessarily translate into higher levels of resilience. Our study provides evidence of the potential of multiple-season farming to enhance agricultural productivity without expanding the area of cultivation. Future studies could focus on how the provision of inputs, irrigation, and market access may shape the decision to engage in multiple-season farming and the associated impact on households' welfare.

Résumé

Les moyens de subsistance des ménages ruraux en Afrique subsaharienne sont menacés par le changement climatique et les performances insuffisantes du secteur agricole. Pour relever ce défi, la culture sur plusieurs saisons a été suggérée comme une alternative potentielle à la culture pluviale afin d'intensifier la production agricole et d'améliorer le bien-être des agriculteurs. Cette étude utilise un modèle à effets fixes et variables instrumentales (FE-IV) pour estimer l'impact de la culture sur plusieurs saisons sur la sécurité alimentaire des ménages et la nutrition des enfants. Nous ne trouvons aucun impact significatif sur la nutrition des enfants ; cependant, les ménages qui pratiquent la culture sur plusieurs saisons sont significativement plus sûrs sur le plan alimentaire que ceux qui dépendent uniquement de la culture de la saison des pluies. Cette amélioration est plus prononcée chez les ménages aisés en termes d'actifs et dirigés par des hommes. Les agriculteurs pratiquant la culture sur plusieurs saisons ont également tendance à cultiver une gamme de cultures plus diversifiée et sont plus susceptibles de vendre les excédents sur les marchés, ce qui leur permet d'accéder à une offre alimentaire plus abondante et diversifiée. De plus, nous adoptons une méthode basée sur les moments pour estimer la résilience des ménages, définie comme la persistance de la sécurité alimentaire au fil du temps. Cependant, nous constatons que l'augmentation actuelle de la sécurité alimentaire grâce à la culture sur plusieurs saisons ne se traduit pas nécessairement par une plus grande sécurité alimentaire à long terme. Notre étude apporte des preuves du potentiel de la culture sur plusieurs saisons pour améliorer la productivité agricole sans étendre la superficie cultivée. Les futures études pourraient se concentrer sur la manière dont la fourniture d'intrants, l'irrigation et l'accès aux marchés peuvent influencer la décision de pratiquer la culture sur plusieurs saisons et l'impact associé sur le bien-être des ménages.

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Contribution of Authors

I, MingDa Li, am the primary author of this study. I took the lead in designing the study and can confidently claim that all the writing, figures, and analysis presented in this Master's thesis are the result of my original work. I conducted an extensive review of the literature and technical documents relevant to the survey design and implementation. Furthermore, I carefully selected appropriate samples and variables for analysis. I also took responsibility for cleaning and organizing the main dataset used for analysis, as well as building and testing various regression models and variable parametrization techniques using STATA.

Dr. Aurélie P. Harou, my co-author and research supervisor, played a significant role in the model design. She provided invaluable guidance during the literature review and data analysis stages and offered important feedback for each chapter of this thesis. Dr. Harou also reviewed various options and made the crucial decision regarding the appropriate model to use for estimating resilience. Additionally, she provided access to rainfall datasets and assisted in merging datasets, which further enriched the research.

Dr. Averi Chakrabarti, another co-author of this study, provided critical feedback on our research methodology, data processing techniques, and regression results. Her valuable contributions greatly facilitated our sample selection process and helped us avoid potential pitfalls in statistical analysis.

Together, the contributions of all authors significantly enhanced the quality and comprehensiveness of this study. Through our collaborative efforts, we were able to conduct thorough research, produce robust results, and address the research objectives effectively.

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Chapter 1: Introduction

1.1 Problem statement

Climate change is expected to increase temperatures and the frequency of extreme weather events. Rising temperatures and increasingly erratic rainfall patterns are expected to result in growing numbers of floods and droughts, thus leading to more frequent periods of acute food insecurity in several countries, especially sub-Saharan African (SSA) countries located along the equator (Aberman, Meerman and Benson 2018). In view of the crucial role of agriculture in supporting the welfare of smallholder farmers in SSA, it is imperative to introduce innovations in agronomic practices that can enhance agricultural productivity and ensure sustainable production of a diverse range of foodstuffs in the face of increasingly variable climate conditions.

Various studies have demonstrated different strategies for improving household food security, nutrition, and climate shock resilience, including agroecological practices such as intercropping and soil conservation (Santoso et al. 2021; Kansanga et al. 2021), crop diversification (Jones, Shrinivas, and Bezner-Kerr 2014; Chegere and Stage 2020), asset transfers (Phadera et al. 2019; Premand and Stoeffler 2020; Abay et al. 2022), investments in irrigation (Ringler et al. 2023; Kafle and Balasubramanya 2021; Mekonnen et al. 2022; Baye et al. 2021; Nhamo et al. 2016) and market access (Usman and Haile 2022; Chegere and Kauky 2022; Gupta, Sunder, and Pingali 2020), though with varying degrees of effectiveness.

Despite the extensive literature that explore various strategies to improve agricultural productivity and households' wellbeing in SSA, not much research has been done on the effect of overcoming the restriction of agricultural seasonality. Currently, agricultural production in much of sub-Saharan Africa (SSA) exhibits a clear pattern of seasonality, with farming predominantly taking place during the rainy seasons. Most agricultural production in sub-Saharan Africa is rain-fed, with only around 4% of arable land being irrigated (Burney, Nalor and Postel 2013). Farmers' reliance on rainfed agriculture has made crop production vulnerable to the increasingly erratic rainfall shocks (CIAT 2018). However, extending the farming period to cover more than one season has been deemed important giving mounting land pressures and high environmental costs of current agricultural practices (Jayne and Sanchez 2022). Waha et al. (2020) estimate that less than 10% of total crop area in SSA are cultivated for more than one season, which is considerably less than the share of 34% in East Asia and 29% in South Asia. Before promoting multiple season farming in SSA and associated technologies to enhance multiple-season farming, e.g., irrigation, further work is need to determine the effects of multiple-season farming on food security, nutrition, and resilience.

1.2 Study objectives

In this study, we investigate the effects of production intensification by expanding the farming period from just the rainy season to both rainy and dry seasons on household food security, resiliency[1] and child growth status. Additionally, we explore whether multiple-season farming leads to an increase in crop production diversity and the likelihood of selling outputs to markets. We use the World Bank Integrated Household Panel Survey (IHPS) data on Malawi spanning from 2010 to 2019. The panel structure of the IHPS data allows us to control for time-invariant heterogeneities through fixed effects. We use instrumental variable estimations to remove some of

[1] We define resilience in this study as the probability of staying above a subjectively defined threshold of food security over time

the bias associated with time-varying endogeneities in households' decision to farm multiple seasons. Moreover, we control for rainfall shocks by incorporating satellite data on household-specific rainfall deviation from the historical average during the rainy season planting months.

1.3 Summary of findings

We find that multiple season farming is positively associated with increased dietary diversity, consuming nutrient-rich foods more frequently, and adopting less severe coping mechanisms to manage food insecurity. Our instrumental variable (IV) analysis indicates that the magnitude of the IV coefficients is larger than that of the ordinary least squares (OLS) coefficients, which suggests a downward bias in the OLS estimates. We also find that multiple-season farming has a stronger impact on food security and wellbeing among households with greater asset wealth and male-headed households. Moreover, we observe that households that farm in multiple seasons exhibit greater crop production diversity and are more likely to sell their outputs to markets. Additionally, we conducted a robustness check to determine if multiple-season farmers differ inherently from those who only cultivate during the rainy season. We observed no statistically significant effect of multiple-season farming on food security measures when analyzing a separate group of similar households whose food security measures were recorded before both rainy and dry season harvests. This indicates that the impacts we discovered on our sample households are reliable and accurate.

We do not find a significant effect of multiple-season farming on child anthropometrics, and the IV estimation does not validate the impact of multiple-season farming on household resilience. In other words, the evidence of multiple-season farming on increasing households' long-term probability to remain food secure is less robust than the concurrent response in improving measures of food security. By comparing graphical evidence on different factors that determine households' status of resiliency, we further argue that changes in short-term agricultural practices, such as farming multiple-seasons or receiving input coupons are weaker determinants of long-term probability to be food secure compared to structural factors such as gender of household head and asset holdings.

1.4 Contribution to the literature

The impact of dry-season agriculture on household well-being in Malawi has received limited attention in the existing literature. Studies that investigate dry-season farming in Malawi have mainly focused on crop cultivation on seasonal wetland gardens (dimba), which rely on residual moisture from receded floods (Chinsinga and Kayuni 2011; Kambewa 2005; Msusa 2011; Nyirenda 2020; Kerr et al. 2019; Kansaga et al. 2021; Tchale 2009). While most of these studies report a positive impact of dimba farming on household food security, their analyses are either descriptive, based on cross-sectional data, or lack controls for endogeneity in dry season farming decisions. In contrast, our study examines both wetland and non-wetland farmers in both seasons (see Table A2 for the distribution) and employs rigorous research methods to control for heterogeneity through fixed-effects and instrumental variable estimations, thereby reducing the potential for omitted variable bias. Additionally, our study offers new insights into how multiple-season farming may influence the sustainability of food security over time by measuring resilience.

Our findings highlight the potential for multiple-season farming to increase food security and offer a new policy focal point that builds on the existing literature on agricultural inputs, markets, and irrigation (Walls et al. 2023; Cassim and Pemba 2021; Bonuedi, Kornher and Gerber 2022; Makate and Makate 2022; Chegere and Kauky 2022; Usman and Haile 2022; Ringler et al.

2023). Future research could therefore focus on increasing the provision of fertilizers, drought-tolerant seeds, mechanization, improving market access, and building irrigation infrastructure to enable dry-season farming and increase year-round crop production without expanding the area of cultivation.

Chapter 2: Literature Review

Our literature review is structured as follows: Firstly, we present an overview of existing literature that explores the relationship between agriculture and dietary diversity. The concept of dietary diversity serves as a fundamental aspect in our assessment of food security, as it significantly impacts the consumption of essential micro-nutrients. Subsequently, we broaden our focus to encompass child nutrition, by analyzing studies that investigate the interplay between agriculture, food security, and the nutritional well-being of children. Finally, we dedicate a section to examining scholarly works that aim to define resilience within the framework of applied economics. Additionally, we critically evaluate various approaches to quantifying resilience and their application in the realm of economic and developmental research.

2.1 Agriculture and dietary diversity

Agriculture and dietary diversity for households in developing countries are connected through multiple mutually influencing channels. For households whose primary source of income is farming, agriculture has the deterministic power over the affordability of nutritionally relevant food items (Headey and Masters 2021). Besides income, changes in agricultural practices, input accessibility, transportation and storage costs can influence food prices, thus affecting food consumption. Agricultural growth thus has important food and nutrition impact on localities characterized by high levels of food insecurity, where consumption of sufficient calories needs to be ensured through increasing staple crop production. Once caloric consumption has reached its standard, reforms need to be undertaken to stabilize food prices and make nutrient-rich food items more affordable and accessible for households to diversify away from staples (Headey and Masters 2021).

Furthermore, when foods are not perfectly tradable due to market failures, household production decisions will affect consumption patterns, a situation represented by an inseparable household model (de Janvry, Fafchamps and Sadoulet 1991; Dillon, McGee and Oseni 2015). Such inseparability between production and consumption can work through prices and income, making food security more vulnerable to input price fluctuations and climate shocks that impact yields, as farmers must substitute food items purchased from the market with home-produced foods. Lack of access to output markets also changes production orientation, forcing farmers to devote at least a portion of their resources to producing subsistence crops instead of growing cash crops that have higher income-generating potential when sold at the market (Headey et al. 2019; Headey and Masters 2021; Dillon, McGee and Oseni 2015). Therefore, an inseparable production mode posts limitations directly on food security by limiting food availability from market purchase and indirectly by constraining income generation and production specialization through agriculture.

Empirical studies of the relationship between agriculture and dietary diversity have thus focused mainly on household production mechanisms and market access. Jones, Shrinivas and Bezner-Kerr (2014) investigate the association between farm (crop) diversity and household dietary diversity in Malawi. They find that farm diversity is positively linked to households' dietary diversity and the consumption of specific types of micronutrient-rich foods such as legumes, fruits and vegetables. Their findings are suggestive of the complementarity between house production and market access in enhancing dietary diversity: on the one hand, household production of fruits, legumes and vegetables make a strong contribution to the diversity of household diets; on the other hand, households dedicating a larger share of land to cash crops have a greater dietary diversity overall, while households that focus on producing subsistence crops had less diverse diets. Echoing the findings of Jones, Shrinivas and Bezner-Kerr (2014), Gupta, Sunder and Pingali (2020) find that the cultivation of non-staple crops and livestock ownership are associated with higher dietary diversity in India. Furthermore, households' expenditure on pulses, dairy, vegetables and fruits is also linked to more diverse diets, suggesting the market complements the self-production of micronutrient-rich foods in ensuring their consumption. However, both studies rely on cross-sectional data, so the authors cannot conclude causality due to potential unobservable biases (Jones, Shrinivas and Bezner-Kerr 2014; Gupta, Sunder and Pingali 2020).

Dillon, McGee and Oseni (2015) use climate variables and the value of agricultural capital as instrumental variables to elicit bias-free variations in revenues from agriculture, which in turn they use to estimate the effect of agriculture revenue on dietary diversity in Nigerian farming households. In particular, the authors stress the importance of incorporating the inseparability between production decisions and food consumption for households facing food market imperfections: a concern that is resolved by including prices of agricultural inputs as control variables in estimating household consumption decisions. Their results reveal a positive but limited impact of agricultural revenue on dietary diversity. As the revenue from agriculture increases, households are more likely to consume tubers and vegetables. As the impact of agricultural revenue is small in magnitude, policy interventions need to increase the availability of other nutrient-rich food items in local markets to increase their consumption (Dillon, McGee and Oseni 2015).

Mondal et al. (2021) conduct stratified random sampling to control for sources of bias and establish a causal relationship between production, market access and dietary diversity. The authors interview semi-subsistence farmers in the State of Madhya Pradesh, India, and find that crop diversification through planting multiple crops in a year is insufficient to improve dietary diversity. Reliance on subsistence agriculture decreases food security while growing cash crops, and having access to market and non-farm income source lead to higher year-round food security. Surprisingly, even in a semi-subsistence system, producing food crops multiple times a year is insufficient to improve year-round dietary diversity and food security for smallholder farmers. However, while selling cash crops gives farmers more purchasing power, the diversity of foods available for purchase in markets also depends on local food production (Mondal et al. 2021). The authors thus argue that creating a local market structure where micronutrient-rich foods are locally grown and sold at local markets might help with increased availability and reduced prices of those foods.

Headey et al. (2019) used a longitudinal survey combining household, child and market information from rural Ethiopia to investigate the relationship between the rural food market and child dietary diversity. Their results suggest that when looked at individually, household production and market availability of non-staple foods are positively correlated with children's consumption of non-staple foods. But, the coefficient of the interaction term between the number of food groups produced by the household and market availability has a negative sign and is statistically significant, suggesting a substitutive relationship between house production and market purchase of non-staple foods. Their finding contradicts the findings of Jones, Shrinivas and Bezner-Kerr (2014), which point out that household production and market access are complementary. Notably, Headey et al. (2019) also find that children consume more dairy products if many neighbouring households produce them. Since dairy is highly perishable, its production by neighbouring households can be critical to increasing the local availability of dairy products at the market or providing households with direct access to them through non-market channels like gifts, barter and informal trade.

In addition, Hirvonen and Headey (2018) analyze potential driving forces behind the adoption of homestead gardens in rural Ethiopia, a practice promoted by the local government to increase the consumption of vegetables and fruits. They find that market access is the decisive factor in garden adoption in water-abundant areas. In contrast, access to water is the most important constraint to adoption in water-scarce regions. In other words, when gardening is made possible by having timely access to irrigation, the market outlet for fruits and vegetables becomes a critical condition that encourages production diversification. This, in turn, can increase dietary diversity since surpluses can be consumed directly and sold to the market to generate extra income to purchase food items.

In summary, the evidence on the relationship between agriculture and dietary diversity is complicated, with mixed results on the interplay between household production, market access and dietary diversity. Some studies further incorporate nutrition or growth indicators to develop further insights into the relationship between agriculture and food security.

2.2 Agriculture, food security and child nutrition

Household dietary diversity plays a critical role in improving child nutrition in developing nations. Gómez et al. (2013) describe three dimensions of malnutrition: *undernourishment*, namely the lack of basic needs of calories and proteins; *micronutrient deficiencies*; and *obesity and overweight*. While undernourishment has been largely tackled since the Green Revolution by the increase in productivity of staple crops to meet the basic needs of the malnourished, the lack of intake of micronutrient-rich foods such as pulses, vegetables and fruits and the overconsumption of staple crops exacerbate the latter two dimensions of malnutrition, making them the major food security issue that threaten the health of children in low- and middle-income countries.

Given the link between dietary diversity and nutrition, it is not surprising that research aimed at improving food security through agriculture aims to incorporate an analysis of nutrition outcomes. Agriculture can influence dietary diversity through different pathways like consumption of surpluses, food availability through markets, income, food prices, etc. Improving dietary diversity through these channels may have a considerable effect on child growth and nutrient intake (Gomez et al. 2013). Harou (2018), for instance, investigates whether receiving fertilizer vouchers in Malawi improves dietary diversity and child nutrition. The author applies fixed effects in panel data analysis and uses an instrumental variable to control the endogeneity in whether a farmer receives fertilizer vouchers. Her findings suggests that households who received vouchers consume cereals, nuts, vegetables, meats and fruits more frequently than non-recipients. Furthermore, children living in households that received vouchers exhibit higher weight-for-age z-score (WAZ) and weight-for-height z-score (WHZ). WAZ and WHZ are indicators of short-term nutrition status for children more responsive to acute changes in food security, and falling below -2 for each indicates wasting and undernutrition, respectively (Headey and Masters 2021; Gomez et al. 2013).

Harou (2018) thus proposes two mechanisms through which fertilizer voucher increases child nutrition. First, the application of fertilizer increases crop yields and generates more surpluses to be sold at the market to generate more income from crop sales, which in turn increases the budget for additional food purchases. Households may also consume their harvests directly, which saves their budget to purchase other types of food that contribute to dietary diversity for their children. Second, the increase in nutritious foods derived from sales and production may have benefitted the mothers who breastfed their children.

The production and sales channels through which agriculture affects dietary diversity and child nutrition are confirmed by a follow-up study of the same fertilizer voucher program in Malawi by Chakrabati et al. (2022). Positive and significant relationships are observed between receiving vouchers and the production and sales of maize crops, and correlations between receiving vouchers, increased dietary diversity and improved child nutrition persist even as the fertilizer subsidy program tapers down. Therefore, the authors conclude that the effect of fertilizer vouchers on child nutrition is likely to have operated through the crop production and income channels, as it allows households to apply more agricultural inputs to boost crop production and sales, which enables them to increase the consumption of micronutrient-rich foods that yield better short-term nutrition outcomes for their children.

Tesfaye (2021) uses a panel survey combined with historical weather data to explore the link between crop diversification and nutrition in the small farm sector in Ethiopia. The author take a step further from Jones, Shrinivas and Bezner-Kerr (2014) and Mondal et al. (2021) to incorporate child nutrition outcomes and consider the heterogenous effect of crop diversity on child growth through gender, market access and exposure to drought shocks. They apply an instrumental variable estimation to exploit the exogenous variation in crop diversification. The results suggest that crop diversity is positively associated with dietary diversity and diet quality (share of non-staples in diet). As for nutrition indicators, crop diversification is correlated with higher height-for-age z-scores (HAZ) but not with WHZ, meaning a diverse cropping profile reduces the chance of child stunting (long-term nutrition deficiency) but not child wasting. Furthermore, when the whole sample is disaggregated by gender and market access, crop diversity significantly reduces wasting for girls more than for boys, and it reduces stunting for households with limited market access (Tesfaye 2021). The impact of heterogeneous market access confirms the importance of household production in ensuring food security and child growth when nutrition needs cannot be met through the market purchase of food items (Gomez et al. 2013; de Janvry, Fafchamps and Sadoulet 1991; Dillon, McGee and Oseni 2015).

While the studies mentioned above acknowledge the connection between agriculture and nutrition, others find no significant correlation between agriculture and child growth outcomes. Like Tesfaye (2021), the study by Chegere and Stage (2020) investigates the link between crop production diversity, dietary diversity and child nutrition in rural Tanzania. They find that production diversity, income, female education and having a younger household head are positively linked to dietary diversity. While they also consider market access, the authors find no significant effect of higher market sales of crop surpluses on dietary diversity. A more salient relationship is observed between household production of cereal, animal protein, dairy and vegetables and within-household consumption. Sespite the correlation between production diversity and dietary diversity, no significant impact on child growth is observed, as increased production diversity displayed no effect on the possibility of child stunting and wasting (Chegere and Stage 2020).

Santoso et al. (2021) take a different approach by conducting a randomized controlled trial to disseminate knowledge about sustainable agriculture, nutrition, women's empowerment and participatory learning among farmers in Tanzania. Households that learned and applied agro-ecological practices display higher child dietary diversity but not better nutrition outcomes. The results of Santoso et al. (2021) and Chegere and Stage (2020) provide contradictory evidence against the notion that diverse diets necessarily result in better child growth outcomes.

Finally, Headey et al. (2018) provide evidence on how socioeconomic conditions determine food access, thus highlighting the need to control for household characteristics when investigating the effect of agriculture on dietary diversity and nutrition. While researching the effect of remoteness to urban centers (measured by travelling time) on child growth, the authors find that remoteness to an urban center does not affect child stunting and dietary diversity. Instead, the urban-rural differences in access to food markets and basic services contribute to differences in diets and nutrition. Furthermore, after controlling for socioeconomic status and infrastructural characteristics, the urban-rural difference becomes insignificant in determining child nutrition and dietary diversity. The authors conclude that wealth and socioeconomic status create demand for a more diverse food profile, and markets will emerge regardless of the distance to urban centers. Therefore, improved socioeconomic status may contribute to improved market access, diets, and nutrition.

2.3 Development resilience: definition, conceptual frameworks and measurement

There exists multiple definitions of resilience, most of which concern the ability to resist the adverse impact of shocks and maintain a certain standard of well-being, as measured by observable outcome indicators such as food security, wealth and nutrition (Béné et al. 2012; Barrett and Constas 2014; FAO 2016; d'Errico, Pietrelli and Romano 2016; Alfani et al. 2015; Quandt 2018). Various conceptualizations of resilience come with different underlying structures and components that explain the functioning of the resilience mechanism. In addition, some studies have also introduced frameworks to quantify resilience capacity.

Alinovi, Mane and Romano (2010) represent one of the earliest attempts to propose a methodology for measuring household resilience to food insecurity. In their model, resilience is considered a latent variable representing a household's capacity to mobilize available options to sustain food security when hit by shocks. The underlying resilience framework consists of four building blocks: income and food access, assets, access to public services, and social safety nets. Under each of these building blocks are individual variables of household and community characteristics that influence resilience through corresponding channels. Households showing high adaptability and stability (i.e. livelihood options don't vary by much over time) are considered resilient to shocks that threaten food security.

In a follow-up paper, Alinovi et al. (2010) test their resilience framework by measuring the household resilience capacity of various livelihood groups in Kenya. In this study, the resilience index is estimated using two-stage factor analysis: In the first stage, an index for each building block is estimated separately using an iterated principal factor over a set of observable variables. Then, in the second stage, another factor analysis is conducted on the components (estimated building blocks as factors) in the first stage. The resilience index is estimated in the end as a weighted sum of the factors generated, and the weights are the proportions of variance explained by each factor. The authors' analysis reveals considerable differences in determinants of resilience for each livelihood group. For instance, although large-holder farmers in their data have, on average, the highest overall resilience level, their access to basic services, such as water, electricity and education, is much lower than for salaried employees and entrepreneurs. On the other hand, pastoralists and small-holder farmers show an equal distribution across building blocks, but the average level of resilience is low. These between-group differences are relevant to policy implications as they inform the need for targeted policy interventions to increase certain specific components or reinforce the overall level of resilience.

Browne, Ortmann and Hendriks (2014) argue that asset ownership indicates a household's ability to cope with risk to food security, which motivates them to develop asset-based indices of resilience. They use three methods based on principal component analysis (PCA) and one simple additive index to separate households into five resilience quantiles, from the most resilient to the least resilient. To verify the consistency of resilience identification, the authors compare household categorization across indices. Their results suggest that their indices perform well in separating households with the greatest and the least level of resilience. However, ambiguity increases when more in-between quantiles are included, as certain households classified in the same quantile using one index are classified into different quintiles using another. The resilience measurement framework proposed in this study does not measure the absolute level of livelihood resilience. Rather, the score only serves to monitor resilience-building progress over time.

A slightly different conceptualization of household resilience is proposed by Alfani et al. (2015), in which resilience is defined as a household's ability to minimize deviations from a supposed permanent trajectory of consumption when hit by shocks. The authors are able to construct counterfactual welfare estimates using the Oaxaca-Blinder framework despite only having cross-sectional data. This framework enables the authors to divide households into three groups: chronically poor, not resilient and resilient. The findings of this paper suggest that resilient households tend to have smaller household sizes, fewer dependents, higher levels of education and more asset possession. Meanwhile, resilient households tend to have higher consumption and lower child malnutrition.

The resilience measurement frameworks proposed by the aforementioned studies have been criticized by Ansah, Gardebroek and Ihle (2019) for methodological flaws. Methods proposed by Alinovi, Mane and Romano (2010) and Browne, Ortmann and Hendriks (2014) consider resilience as the direct "cause" of food security instead of a factor that explains it. They measure resilience from a set of variables that relate to food security. For instance, Alinovi et al. (2010) directly measure food access as part of their resilience index's "income and food access" component. The resilience score is then used as an explanatory variable to estimate food security. Since resilience and food security are not separated, the result of these studies can lead to circular reasoning that resilience and food security depend on each other, leading to the bias of reverse causality. In addition, Ansah, Gardebroek and Ihle (2019) also criticize the method adopted by Alfani et al. (2015) for not providing a quantitative measure for resilience capacity. Resilience in this study is measured as the extent to which household consumption deviates from a supposed optimal path after a shock. However, whether the assumed optimal consumption path is indeed desirable is a question.

The resilience measurement framework proposed by Alinovi, Mane and Romano (2008) was later formalized into the Resilience Index Measurement and Analysis–I (RIMA-I) and applied to estimate household resilience capacity in studies conducted by the Food and Agricultural Organization (FAO). Having realized the problem of reverse causality in the underlying structure of RIMA-I, as explained in the last paragraph, the FAO introduced the upgraded RIMA-II framework in which food security is removed from the estimation procedure and is instead treated solely as a one-way outcome variable of resilience capacity.

The underlying structure of RIMA-II is comprised of four pillars: access to basic services, assets, social safety nets and adaptive capacity. Similar to RIMA-I, the first step of measuring resilience capacity is to use factor analysis to estimate the four pillars from observable indicators. In the second step, a Multiple Indicators Multiple Causes (MIMIC) model is estimated, in which a system of equations is constructed to specify the relationships between the estimated resilience pillars, the observable outcome indicators (e.g. food security indicators) and the unobservable resilience capacity (FAO 2016; d'Errico et al. 2018). After running the two steps, the model permits the estimation of a resilience capacity index (RCI), which provides a quantitative measure of resilience to inform policy analysis, target and rank households, or be included in empirical analyses as an explanatory variable. Several studies have used the estimated RCI to investigate the relationship between resilience capacity, climate shocks, policy intervention and household well-being indicators like food security (d'Errico, Pietrelli and Romano 2016; d'Errico et al. 2018; d'Errico et al. 2020), household expenditure (d'Errico et al. 2020) and child nutrition (d'Errico and Pietrelli 2017).

Béné et al. (2012) propose a three-dimensional framework to analyze resilience. In their conceptualization, resilience is considered an ability to deal with adverse changes and shocks. It can be represented by three capacities corresponding to responses to shocks at different intensities. Absorptive capacity is the ability to minimize shock exposure and speed up recovery when exposed to shocks at low intensities. When the absorptive capacity is exceeded, the household needs to use its adaptive capacity to engage in incremental changes based on changing conditions and adopt alternative livelihood strategies, such as adopting new framing techniques or acquiring new social networks. Finally, transformative capacity is required when the change required is so large that it overwhelms the adaptive capacity of the household. Changes result in alterations of the household or community's primary structure and function, e.g., when a household forgoes agriculture to avoid losses from harsh climate conditions. Since shocks at different intensities and scales may occur together, it is crucial that the three capacities need to be strengthened together. Resilience is then the result of all three capacities combined.

Two studies adopt the conceptualization of resilience in Béné et al. (2012) and attempt to measure resilience quantitatively. Béné, Riba and Wilson (2018) explore the effectiveness of the SUR1M project in building resilience to food insecurity due to climate change and weather shocks in Niger. The authors argue that the SUR1M project, if successfully implemented, should strengthen the three resilience capacities and lead the participants to adopt appropriate responses to shocks and stressors. Besides looking at responses to shocks, this paper also features a resilience index based on self-reported disaster recovery questionnaires. The findings suggest that treated households are 8%-39% less likely to resort to negative coping strategies, such as reducing food consumption and changing diet composition. Furthermore, treated households are also more likely to display positive coping behaviours and show higher capacity to cope with shocks as displayed in a self-assessed resilience index.

Smith and Frankenberger (2018) present another related study in which the three-dimensional framework of resilience conceptualization is applied in a difference-in-differences (DID) analysis of the 2014 flooding in northern Bangladesh. The paper's main objective is to determine whether households' resilience to the shock was boosted by their resilience capacities before the onset of flooding and which capacities matter the most in future shocks of this type. The authors construct their resilience capacity index (RCI) using factor analysis to reduce observables to the three capacities and then again use FA to estimate the resilience capacity. To investigate resilience's role as the mediating factor of the relationship between shock and food security, they include an interaction term between shock exposure and RCI. The study finds a significant and positive impact of resilience capacity alone and on the interaction term in reducing the negative impact of flooding on food security. Absorptive capacity is the most relevant factor to flooding, as shocks of this kind tend to exhibit rapid onset that prompt households to prioritize minimizing exposure and recovering in its immediate aftermath (Smith and Frankenberger 2018).

Quandt (2018) introduces an innovative approach for measuring and analyzing household livelihood resilience called the Household Livelihood Resilience Approach (HLRA). Resilience is conceived as consisting of five asset types: financial capital, human capital, social capital, physical capital and natural capital. Under each capital are independent variables chosen based on conceptual and empirical relevancy to each capital and their availability in the dataset. Values of each indicator are converted into numbers between 0 and 1. The composite index for each capital is the average value of individual variables contributing to that capital, and the overall index of resilience is the average of all five capitals. Quandt (2018) assigns equal weight to each indicator, but she also acknowledges the possibility of and the value in weighting indicators differently during analysis. The paper also provides empirical evidence of the method's application in resilience building through agroforestry. The author finds that planting trees results in the protection of farmers' physical capital (e.g. roads and other transportation infrastructures), which used to be vulnerable to natural disasters like flooding. Increased agroforestry also benefits natural and financial capitals through consolidation of soil and income diversification, which further increases resilience to covariate or idiosyncratic shocks.

Finally, Barrett and Constas (2014) define resilience as the long-lasting capacity for agents to avoid falling into the poverty trap when impacted by shocks and stressors. In their model, agents are expected to maximize expected well-being subject to resource constraints. While maximization is optimal for everyone, some may lead to an undesirable state of well-being due to idiosyncratic resource constraints that make non-poor outcomes infeasible. Development resilience thus entails being protected from downward shifts and enables upward shifts in well-being. Based on this theoretical foundation, Upton, Cissé and Barrett (2016) introduce a moment-based econometric approach to estimate resilience[2], and subsequent work by Cissé and Barrett (2018) further lay down the framework of non-parametric estimation of resilience as a conditional probability to avoid some undesirable states of well-being. Both the mean and variance of certain welfare functions of interest are estimated, and lags are included to account for the persistent impact of previous welfare levels on current-period welfare. This method relies on the availability of panel data for the inclusion of lags and a subjectively determined threshold level of welfare to separate the resilient households from the not resilient households. However, one could combine individual household estimates to generate aggregate development resilience measures for a population, which can in turn be broken down into various subgroups based on household characteristics and use the model's built-in path dynamics to project how resilience distribution will evolve for different groups given current and past status of well-being (Cissé and Barrett 2018). For instance, one can forecast how the proportion of resilient households will change for female-headed versus male-headed households in the presence of a drought shock in the near future.

Knippenberg, Jensen and Constas (2018) slightly modify Barret and Constas (2014)'s framework to quantify resilience. The authors collect panel data at the monthly frequency in Malawi to analyze resilience to the perceived persistence of shocks and predict future food insecurity. Food insecurity is measured by Coping Strategy Index (CSI), with a higher CSI indicating that the household has been compelled into more coping activities due to food insecurity. The authors use an auto-regressive linear probability model with one lag to estimate the probability of shock persistence and found an overall low resistance to drought. They then use the LASSO

[2] Upton, Cissé and Barrett (2016) cite the working paper version of the Cissé and Barrett (2018) paper to introduce their conceptualization and application of the resilience indicator, but they include no econometrical description of the process of estimation. Therefore, I cite Cissé and Barrett (2018) as the study that introduces the moments-based method of resilience quantification.

algorithm to identify the best predictors of future CSI. They find that geographic location, access to drinking water, house quality and whether they live in a floodplain are the most relevant factors in ensuring resistance to food insecurity.

To conclude this section, a heterogenous understanding of resilience exists in the literature. With different conceptual frameworks come a variety of methods for quantifying resilience. While some treat resilience as an indicator directly or indirectly causing changes in well-being (Browne, Ortmann and Hendriks 2014; Alinovi et al. 2010), others regard resilience as a capacity that enables more options for households to sustain their well-being in the face of shocks and stressors (FAO 2016; Béné et al. 2012; Quandt 2018; Smith and Frankenberger 2018). There is no universally agreed method for measuring resilience quantitatively (Alfani et al. 2015; Serfilippi and Ramnath 2018). But most recent studies tend to treat resilience as an intermediate outcome that influences the ultimate welfare outcomes and use data reduction techniques to reduce observable, context-specific dimensions into single variables (Smith and Frankenberger 2018; d'Errico et al. 2020; FAO 2016). In this paper, we align with subsequent studies building on Barrett and Constas (2014) by treating resilience as a direct outcome of household well-being. In addition, Serfilippi and Ramnath (2018) and Ansah, Gardebroek and Ihle (2019) provide a detailed review of the existing methods for conceptualizing and quantitatively evaluating resilience.

Chapter 3: Background of Research

3.1 Agriculture in Malawi

The agricultural sector plays a pivotal role in Malawi's economy by contributing 38% of its Gross Domestic Product (GDP) and providing livelihoods to almost 90% of the population (CIAT 2018; Bizikova et al. 2022). Smallholder farmers account for approximately 80% of the country's agricultural production, which is primarily oriented towards household consumption (CIAT 2018). The primary crop cultivated on nearly 75% of the smallholder farming land is maize, with other crops such as rice, cassava, legumes, and sweet potatoes also commonly grown (Bezner-Kerr et al. 2019; Kansaga et al. 2021). Notably, smallholder farmers only contribute 20% of agricultural exports, primarily in tobacco production.

Despite the critical role of agriculture in Malawi's economy, its productivity remains below potential. Various factors contribute to this underperformance, including poor market linkages, limited irrigation, low adoption of agricultural technologies such as chemical fertilizers and mechanization, pests and diseases, and climate vulnerability (CIAT 2018; Makate and Makate 2022). Moreover, post-harvest losses are significant due to limited storage technologies, transportation costs of produce and inputs are high due to poor infrastructure, agro-processing and value addition are hindered by the lack of investment in manufacturing facilities, and poor farmer organization reduces the opportunity for knowledge generation and dissemination among smallholder farmers (GoM 2021).

Programs and policies have been implemented to stimulate growth in the agricultural sector. Malawi has been a participant of the Comprehensive Africa Agriculture Development Programme (CAADP) since 2003, mandating its government to allocate at least 10% of its national budget towards promoting agricultural-led growth, poverty reduction, and food security (Matchaya, Nhlengethwa and Chilonda 2014). Malawi has consistently allocated more than 10% of its national budget to agriculture, and it has maintained an average sectoral GDP growth rate of around 6% since 2008, which has contributed to the realization of the goals of the CAADP (African Union, 2022; World Bank, 2021). Despite the steady growth in cereal (maize) productivity, the overall cereal productivity in Malawi is only half of the average productivity of OECD and Asian countries. Therefore, it is imperative to implement further policies that improve labour and land productivity, increase fertilizer consumption, and encourage investment in irrigation and industrialization to manufacture agriculture produce (Matchaya, Nhlengethwa and Chilonda 2014).

Another program that has garnered attention for enhancing agricultural productivity in Malawi is the Farm Input Subsidy Program (FISP), which has been replaced by the Affordable Inputs Programme (AIP) in 2020 (Chakrabarti et al. 2021). FISP aimed to improve food self-sufficiency and farm productivity by providing farmers with coupons and vouchers to purchase subsidised farm inputs, including fertilizers and seeds (Ajefu, Efobi and Beecroft 2021; Harou 2018). The AIP is an improved version of FISP, which aims to address FISP's weaknesses by implementing more efficient distribution and redemption of vouchers, improving the timing of fertilizer distributions, and better targeting households eligible for the subsidies (Walls et al., 2023).

There have been debates about the effectiveness of FISP in enhancing crop productivity, primarily maize, and promoting household well-being. On the positive side, FISP has led to increased fertilizer use and reportedly increased maize productivity from 1480 kg/ha in 2006 to 2100 kg/ha in 2013 (CIAT 2018). Chakrabarti et al. (2021) and Ricker-Gilbert and Jayne (2017) have identified a positive impact of FISP on maize production among recipient households. However, the latter found no cumulative effect of receiving input coupons from previous years on current maize production. In terms of household well-being, Harou (2018) and Chakrabarti et al.

(2021) find a positive impact of FISP on household dietary diversity through increasing the consumption of staples and micronutrient-rich foods. Ajefu, Efobi, and Beecroft (2021) confirm the positive effect of FISP on households' diet and further suggest that FISP beneficiary households exhibit smaller declines in food security when impacted by rainfall shocks.

While the above-mentioned studies find positive impacts of FISP, others have raised doubts about its efficacy. Lunduka, Ricker-Gilbert and Fisher (2013) estimate the benefit-cost ratio of providing subsidised fertilizers to farmers and find that it does not cover the cost to the government. Moreover, micro-level data suggests that the increase in overall maize production is smaller than officially claimed, and a significant proportion of subsidised fertilizers are resold by government officials at the commercial price, never reaching targeted recipients. Walls et al. (2022) contend that FISP overly emphasised increasing maize production, which led to a lower market price for maize and a decline in farmers' income and dietary diversity.

Despite the implementation of policies such as the Comprehensive Africa Agriculture Development Programme (CAADP) and FISP in promoting agricultural GDP growth and cereal crop productivity in Malawi, there is still a need for improvement in fertilizer consumption and productivity, and the ability of FISP to target vulnerable households and increase farmers' income and food security. With the replacement of FISP by the Affordable Inputs Programme (AIP) in 2020, it remains to be seen whether the new subsidy program will effectively provide cost-effective access to subsidised inputs to the most-needed households, leading to higher income, food security, and resilience to shocks in the agricultural sector. Therefore, the enhancement of agricultural productivity in Malawi remains a paramount issue.

3.2 Food security and nutrition

Malawi, with a population of over 19 million, has an overwhelmingly rural population, with 83% residing in rural areas. Poverty is a pressing concern in rural areas, with 77% of the rural population living below the international poverty line of USD $2.15/day as of 2019, and they almost rely solely on agriculture for their livelihoods (World Bank 2023). Food insecurity is a widespread issue in Malawi, especially in rural areas, where 52% of the population experienced severe food insecurity in 2018 (CIAT 2018). Despite a 3.1% increase in per capita GDP between 2005 and 2011, Malawi still faces a high prevalence of undernourishment, with 50.7% of the population not meeting the standard of sufficient calorie consumption (Aberman, Meerman and Benson 2018). The majority of the poor in Malawi are farmers who, despite producing enough calories annually, face food shortages during the hungry season and crop failures (Bizikova et al. 2022).

The dietary patterns of Malawians are primarily composed of cereals and starchy fruits, leading to high rates of micronutrient deficiencies and malnutrition (Bezner-Kerr et al. 2019; FAO et al. 2017). Food prices play a significant role in determining the consumption patterns of rural households. Aberman, Meerman, and Benson (2018) find that food consumption in Malawi depends heavily on food prices, with rural areas being particularly susceptible to inflation. A decrease in maize prices under FISP led to a 14% increase in maize consumption between 2004-2011, while the consumption of green leafy vegetables and pulses decreased sharply in rural areas during the same period due to a rise in their prices by approximately 400% and 100%, respectively. Aberman, Meerman, and Benson (2018) estimate that rural households in Malawi have limited access to micronutrients from their diets, primarily lacking Vitamin A (stored in vegetables) and iron (stored in pulses). Such findings are consistent with the high levels of undernourishment in

Malawi, with over 23% of the population experiencing undernourishment annually (CIAT 2018). Moreover, more than 40% of children under the age of 5 years are stunted, while 12% and 3% are underweight and wasted, respectively (FAO et al. 2017).

3.3 Influence of climate on agriculture and food security

Malawi experiences a two-season climate characterized a rainy and a dry season. The rainy season, which lasts from November to April, is the dominant season for crop production, while the dry season lasts from May to October (World Bank 2021). Rainfed agriculture accounts for over 90% of Malawi's agricultural production, with only 4% of the total cultivated area being irrigated (Makate and Makate 2022). The high dependence on rainfed agriculture coupled with limited irrigation infrastructure for smallholder farmers makes Malawi's agricultural sector vulnerable to climate change (GoM 2021).

Malawi's most common climate hazards include seasonal droughts, intense rainfall, and floods (CIAT 2018). Between 2015 and 2017, Malawi faced four successive climate-related shocks, including severe floods, erratic rains, prolonged dry periods, and one of the worst droughts in three decades (Bizikova et al. 2022). The most recent drought event experienced in 2015/16 was characterized by a delayed onset of the agricultural season, leading to severe crop failure, mainly in the Central and Southern regions (Makate and Makate 2022).

The impact of climate hazards on the agriculture sector has led to significant declines in output and concomitant price spikes for most food commodities. This vulnerability is compounded by limited alternative livelihood options and low governmental budgetary allocations for climate resilience and adaptation (CIAT 2018). Seasonal variation is observed in malnutrition rates, with high numbers of malnutrition occurring during the hot and drier seasons. The seasonal price variation is strongest for nutrient-dense foods that are difficult to store, and rural households face constrained supply in other periods (Bizikova et al. 2022). Since 2006, the average incidence of malnutrition has increased, and rates are expected to rise in the years to come due to climate change.

The government has implemented some measures to help address the high levels of malnutrition and increase farmers' adaptive capacity to climate change. These measures include diversifying crops, promoting winter cropping, fostering irrigation systems, promoting access to food in communities, including fish farming, the raising of small animals, and nutritional supplements for children and the sick, climate-smart agriculture, improved water and land-use practices, integrated soil fertility management and conservation and utilization of agrobiodiversity (Makate and Makate 2022). However, despite the government's investment into adaptive measures, Malawi is still challenged by climate variability due to unique characteristics like overreliance on maize as the staple crop, population growth, high poverty rates, malnutrition and widespread diseases (Makate and Makate 2022).

Chapter 4: Data

4.1 LSMS-ISA

This study draws on data from the Integrated Household Panel Survey (IHPS) conducted over four rounds, which is accessible through the Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) program, jointly implemented by the World Bank and the government of Malawi. The sample households were selected from 102 enumeration areas (EAs) during the 2010 survey round and were consistently monitored in 2010, 2013, 2016, and 2019. Furthermore, for individuals who split off from their baseline household, the new household they formed or joined since 2010 was also included in the sample.

The LSMS-ISA data comprises comprehensive information on agricultural activities, farm and household socioeconomic conditions, and georeferenced data, which allow for controlling climate conditions at the regional-household level. The sample households are representative of the Northern, Central, and Southern regions, and are stratified by urban and rural settlement.

To collect information on the two agricultural seasons in Malawi, the survey team attempted to visit the panel households twice for each round of the survey. The first visit was conducted during the post-planting period of the rainy season, in which all households completed the first half of the agricultural questionnaire, providing information related to the rainy season pre-harvest, such as land area, cultivation, and input use. The second visit was made approximately four months after the first visit, corresponding to the post-harvest period of the rainy season. During the second visit, farmers reported information on the rainy season harvest and post-harvest matters and complete information on the following dry season, including dry season planting, harvest, and/or expected harvest.

To collect consumption data from the Household Questionnaire evenly across the panel period, the survey team assigned half of the panel households to panel group A and the other half to group B at baseline. Any split-off households that joined the sample after the baseline round of the survey received the same group assignment as their baseline households. During the first visit, households in group A were administered the full household questionnaire, and households in group B were only administered the household roster. Group B received the full household questionnaire during the second visit, while group A received a household roster update.

Given the fieldwork organization described above, only households in group B had their data on food security, nutrition, and other household characteristics collected either concurrently with dry season harvest or after the completion of dry season harvest. To avoid reverse causality jeopardizing the analysis, this study restricts its sample to rural households assigned to group B, as it explores the impact of consecutive farming on household well-being. The total sample comprises 1125 households, of which 569 were consistently tracked from baseline (2010).

Figures A1-A4 plot target households' interview months against their timing of dry season harvests. Almost all rural households in group B who engaged in dry season farming have their full household questionnaires allocated simultaneously or after the initiation of dry season harvests, except for two households from 2019. This study hypothesizes that by the time food security and nutrition measures were recorded from our sample households, they would have had an expectation of dry season harvest for self-consumption or income from selling surpluses, generating changes in their food consumption patterns and short-term nutrition outcomes.

4.2 TAMSAT

The present study employs satellite-based rainfall data from the Tropical Applications of Meteorology using Satellite data and ground-based observations (TAMSAT) to accurately control for potential rainfall shocks. TAMSAT, established by the University of Reading in 1977, provides monthly rainfall estimates (RFE) for all of Africa at 4km resolution, and the archive spans 1983 to the present (Maidment et al. 2017; Tarnavsky et al. 2014; Maidment et al. 2014). Thus, it covers all four rounds of the Integrated Household Survey in Malawi. Datasets of monthly rainfall anomalies (RFA), which are deviations from local average rainfall levels from 1983-2012, are also available. The study incorporates both RFE and RFA into the main dataset to control for any potential influence of abnormal rainfall patterns on crop production and household well-being.

The LSMS-ISA panel contains georeferenced datasets of household latitude and longitude, which are calculated as the average of household GPS coordinates in each enumeration area (EA) plus a random off-set value (GoM 2020). By using these off-set GPS statistics and households' reported months of planting, the study generates accurate rainfall controls by matching household GPS coordinates with location-specific rainfall estimates provided by TAMSAT. The study chooses to control for monthly rainfall in the year and month in which a household plants its rainy season crops. This choice is based on the rationale that irregular rainfall patterns during the planting seasons can significantly decrease maize yields, which is the primary crop grown by smallholder farmers during the rainy seasons and has a dominant position in Malawian household diets (Tadross et al. 2009; Rashid and Rasul 2011). Monthly rainfall anomaly is included to account for possible rainfall shocks that may threaten the yield of maize and, thus, household food security and income from selling surplus crops.

Ajefu, Efobi and Beecroft (2021) construct their own index to measure deviations in rainfall from the long-run mean during months of planting. Their estimates suggest that negative rainfall shocks in the preceding year's planting season decrease household food and non-food consumptions. Therefore, the present study suspects that rainfall anomalies play a mediating role in determining a household's propensity to cultivate in the dry season (as rainfall shocks result in a disappointing harvest from the rainy season), as well as dietary diversity and nutrition directly by influencing food and non-food consumption.

Chapter 5: Methods

5.1 Determinants of Multiple-season Farming

We first want to examine the factors affecting multiple season farming. To do so, we estimate the following logistic regression:

$$M_{it} = \alpha + \theta_1 R_{it} + \eta X_{it} + \delta_d + \gamma_t + \epsilon_{it} \quad (1)$$

where the dependent variable M_{it} is binary, with the value of 1 indicating that the household *i* farms in multiple seasons in year *t*. The regression model controls for rainfall anomaly, R_{it}, during the household-specific month of planting in the rainy season (unit of measurement is millimetre). Moreover, X_{it} is a vector of time-variant household characteristics discussed further below. We also add district fixed effects, δ_d, and year fixed effects, γ_t, to control for location-specific unobservable factors and time-specific heterogeneities that are invariant across sample households. Robust standard errors ϵ_{it} are clustered at the enumeration area (EA) level.

5.2 The effects of multiple season farming on food security, resilience and nutrition

To examine the effect of multiple-season farming, M_{it}, on food security, resilience and nutrition we estimate the following ordinary least squares (OLS) model with fixed effects:

$$Y_{it} = \alpha + \beta_1 M_{it} + \beta_2 R_{it} + \mu X_{it} + v_i + \tau_t + \varepsilon_{it} \quad (2)$$

where the outcome variable, Y_{it}, is a food security measure, resilience index, farm production diversity or an indicator variable for farmers selling to markets of household *i* in year *t,* described in detail below. M_{it} and R_{it} are the same as described above in equation 1. Here we include a household fixed effect, v_i, and year fixed effect, τ_t. The idiosyncratic errors, ε_{it}, are again clustered at the EA level. In addition, we also conduct subgroup analyses by households' wealth and gender of household head to gain insight into the heterogeneous effects of farming in multiple seasons on food security, crop diversity and selling to markets. Our main parameter of interest is β_1 which represents the effect of farming in multiple seasons on our household and individual outcomes of interest.

To estimate the effect of multiple-season farming on child growth status, we estimate the following model,

$$Y_{itj} = \alpha + b_1 M_{it} + b_2 R_{it} + \varphi X_{it} + v_i + \tau_t + \omega_j + \varepsilon_{itj} \quad (3)$$

where Y_{itj} is the height-for-age z-score (HAZ), weight-for-age z-score (WAZ) or weight-for-height z-score (WHZ) of child *j* from household *i* in year *t*, described in more detail below. The other covariates in equation 3 are the same as in equation 2. Additionally, here we include a child-fixed effect ω_j to control for time-invariant characteristics of the child. Here the main parameter of interest is b_1.

5.3 Household food security outcomes

We measure household food security using the following three indexes:

- Household Dietary Diversity Score (HDDS): HDDS measures the quantity and quality of food access at the household level (Leroy et al. 2015; Chegere and Stage 2020; Gupta, Sunder and Pingali 2020). Food items are categorized into 10 food groups by the IHPS survey, and HDDS is a simple count of number of food groups consumed in the past seven days (GoM 2020). The 10 food groups and their respective contribution to household member's nutritional requirements are the following:

- Staple foods (cereals; roots and tubers)
- Micronutrient-rich foods (nuts and pulses; vegetables; fruits; meat, fish and animal products; dairy)
- Energy-rich foods (oil and fats; sugar; condiments)

HDDS ranges between 0 and 10 in our sample. The higher the HDDS, the more diverse the food consumption pattern is.

- Food Consumption Score (FCS): FCS is a composite score of household food security that takes into account dietary diversity, frequency of consumption and relative nutritional importance of different food groups (Leroy et al. 2015; Harou 2018; Jones, Shrinivas and Bezner-Kerr 2014). The frequency of consumption of different food groups are weighted based on their nutritional importance, and the sum of all weighted consumptions is the value of FCS. Food groups and their respective weights are listed as follows:
    - Staples (cereal, roots and tubers): (w = 2.0)
    - Legumes and pulses (w = 3.0)
    - Vegetables (w = 1.0)
    - Fruits (w = 1.0)
    - Meat, fish and animal products (w = 4.0)
    - Dairy (w = 4.0)
    - Sugar (w = 0.5)
    - Oil (w = 0.5)

A FCS of 35 is considered adequate (Leroy et al. 2015) -- households whose FCS fall below 35 are deemed to have poor food consumption.

- Coping Strategy Index (CSI): CSI assesses the frequency of occurrence of severe coping strategies by households when facing food insecurity (Leroy et al. 2015; Maxwell, Caldwell and Langworthy 2008; Knippenberg, Jensen and Constas 2018). The number of days in a week a household engaged in a coping strategy is multiplied by the corresponding weight of severity of that strategy. Summing the products of weight*frequency of occurrence gives the CSI of that household. A higher CSI indicates higher food insecurity and lower well-being (Knippenberg, Jensen and Constas 2018). The assignment of severity weights is context-dependent as frequencies and severities of coping strategies can vary across time and places (Leroy et al. 2015; Maxwell, Caldwell and Langworthy 2008). The coping strategies recorded by the IHPS and their respective weights of severity are listed as follows:
    - Consumption of less preferred foods (w = 1)
    - Limiting portion size of meals (w = 1)
    - Reducing number of meals per day (w = 1)
    - Restricting food consumption by adults (w = 2)
    - Being forced to borrow food from other households (w = 2)

In addition to food security measures, we use height-for age z-score (HAZ), weight-for-age z-score (WAZ) and weight-for-height z-score (WHZ) to measure child nutrition status. Z-scores compare the difference between the value of an individual and the median value of the reference population of the same age or height, divided by the standard deviation of the reference population (WHO 2006). While a low HAZ is regarded as a marker of chronic malnutrition, WAZ and WHZ indicate short-term nutritional status and are more responsive to acute changes in food security (Headey and Masters 2021; Gomez et al 2013). Specifically, z-scores are calculated using the following formula (WHO 2006):

$$Z - score = \frac{(measured\ value - median\ of\ reference\ population)}{(standard\ deviation\ of\ the\ reference\ population)} \quad (4)$$

In the baseline round (2010) of the Integrated Household Panel Survey (IHPS), anthropometric statistics were taken from children aged between 0 to 5. However, the panel structure of the IHPS data enables us to consistently track the same individual across survey rounds from the year his/her household joined the sample (GoM 2020). Therefore, the oldest children in our sample would be 18 years old in survey round 4 (2019), whose child anthropometrics were first recorded in 2010 when they were at the age of 5.

On the other hand, the reference statistics for calculating HAZ, WAZ and WHZ of individuals in our sample are derived from the World Health Organization growth reference data (WHO 2023). The World Health Organization (WHO) provides reference statistics of HAZ for children aged 0-19 years old, WAZ for children aged 0-10 years old, and WHZ for children aged 0-5 years old. Due to differences in the availability of reference statistics, our sample sizes vary across estimations on different growth indicators (see Tables 11-13 in the results section).

5.4 Household resilience outcomes

We also explore the effect of multiple-season farming on household resilience, defined as "… the capacity over time of a person, household or other aggregate unit to avoid poverty in the face of various stressors and the wake of myriad shocks. If and only if that capacity is and remains high over time, then the unit is resilient" by Barrett and Constas (2014). Their conceptualization of resilience concerns the household's probability to stay on the long-time path of well-being that can be measured by indicators such as income, expenditures, health or nutrition status. Cissé and Barrett (2018) lay down the framework for quantifying such probability by illustrating a moment-based approach to measure resilience, which has been adopted by several other studies to estimate household resilience using multidimensional indexes (Abay et al. 2022; Knippenberg, Jensen and Constas 2018; Phadera et al. 2019).

Following Cissé and Barrett (2018) and Abay et al. (2022), we first estimate the following model:

$$F_{it} = a_m + \sum_{\gamma=1}^{3} \hat{\beta}_{m\gamma} F_{i,t-1}^{\gamma} + R_{it} + \delta_m X'_{it} + \tau_t + \theta_d + u_{mit} \quad (5)$$

We use FCS as our indicator of household well-being for resilience estimation. Therefore, resilience in our case focuses on measuring the conditional probability a household will achieve a FCS above certain subjectively defined threshold of food security based on its FCS from the previous round and a series of household characteristics. The higher the estimated resilience, the more likely the household will remain food secure in the future. Where the current FCS F_{it} is regressed on a third-order polynomial of lagged FCS $F_{i,t-1}^{\gamma}$, rainfall anomaly R_{it} and a vector of household characteristics X'_{it}. The subscript m on coefficients denotes mean. Given that FCS is non-negative and has a slightly right-skewed distribution each year (Figure 1), we estimate equation 4 using generalized linear model (GLM) and assume a Poisson distribution of the dependent variable (Cissé and Barrett 2018). Since including household fixed effects will be computationally heavy in GLM using STATA, we decide to include year and district fixed effects in our resilience estimation instead. Since we do not control for household fixed effects and consecutive farming is not part of the estimation process, the vector of household characteristics X'_{it} contains more control variables at the household level. In addition, a_m is a constant term and u_{mit} is the standard error term.

Regressing current FCS on lagged FCS serves as investigating the persistence of food security overtime. A third order polynomial is the most parsimonious specification to accommodate possible nonlinear dynamics (Cissé and Barrett 2018). After running equation 4, we predict the conditional mean FCS $\hat{F}_{it}$ for household *i* in year *t* and the residuals $\hat{\sigma}_{it}$ from the estimation. We then square the residuals to obtain an estimate of the variance of household welfare σ_{it}^2 (Abay et al. 2022), which is used as the dependent variable in the following specification:

$$\sigma_{it}^2 = \alpha_v + \sum_{\gamma=1}^{3} \hat{\beta}_{v\gamma} F_{i,t-1}^{\gamma} + R_{it} + \delta_v X'_{it} + \tau_t + \theta_d + u_{vit} \quad (6)$$

All terms in equation 5 are the same as those defined in equation 4, where the subscript *v* here denotes variance. After running equation 5, we then predict conditional variance $\hat{\sigma}_{it}^2$ for each household.

After obtaining the estimated conditional mean $\hat{F}_{it}$ and conditional variance σ_{it}^2 of FCS for each household, we are able to estimate household resilience, $\hat{\rho}_{it}$, defined as the conditional probability that a household can achieve a minimum FCS above the normative threshold of 35 (Abay et al. 2022; Leroy et al. 2015) in year *t*. Following Cissé and Barrett (2018) and the distribution of FCS as shown in Figure 2, we assume a gamma distribution on our FCS probability density function and define the shape and scale parameters using $\hat{F}_{it}$, σ_{it}^2 and the FCS threshold *w* = 35. The household-year specific resilience $\hat{\rho}_{it}$ is then defined as the following:

$$\hat{\rho}_{it} = 1 - gammap(\frac{\sigma_{it}^2}{\hat{F}_{it}}, \frac{w*\sigma_{it}^2}{\hat{F}_{it}^2}) \qquad (7)$$

The two fraction terms inside the cumulative gamma distribution function *gammap()* are the shape and scale parameters, respectively. Therefore, $\hat{\rho}_{it}$ is the cumulative probability of household *i* achieving a FCS above 35 in year *t*, whose value ranges between 0 and 1. We can then regress the estimated resilience scores on the same regressors in equations 4 and 5 to observe how current resilience is affected by lagged FCS, rainfall anomaly and household characteristics:

$$\hat{\rho}_{it} = \alpha_r + \sum_{\gamma=1}^{3} \hat{\beta}_{r\gamma} F_{i,t-1}^{\gamma} + R_{it} + \delta_r X'_{it} + \tau_t + \theta_d + u_{rit} \qquad (8)$$

where subscript *r* denotes household resilience and the other variables are the same as those defined above for equations 4 and 5.

5.5 Crop type

Finally, to explore how multiple-season farming may affect production diversity and market access, we incorporate a count of crop types grown throughout the year and a dummy variable indicating whether a household has sold any agricultural produce to the market as outcome variables[3]. Different types of crop can be categorized into staple crops, cash crops and vegetables based on their nutritional content and purpose of cultivation, which allows us to investigate the relative changes in the cultivation of crops in each category as a result of multiple-season farming,

[3] Each household *i* is assigned a value based on the number of crop types they planted in year *t*, with a higher value indicating greater production diversity.

and the associated impact on household income and food consumption. Categorization of crops are based on the Basic Information Document of the Malawian IHPS (GoM 2020) as follows:

- o Staple crops: rice, maize, sweet potato, Irish potato, wheat, finger millet, sorghum, pearl millet.
- o Cash crops: cotton, sunflower, sugarcane, tobacco.
- o Vegetables: ground bean, peas, cabbage, tanaposi (a green leafy vegetable), nkhwani (a green leafy vegetable), okra, tomato, onion, paprika.
- o Legumes: groundnuts, beans, soyabean, pigeon pea.

5.6 Household characteristics

By including fixed effects in our regressions, we are able to control for time-invariant household characteristics, and we can control for certain time-varying variables:

- Household size: number of members in the household.
- Dependency ratio: the ratio between active working members aged 15-64 years old and the number of dependents aged 14 and below or 65 and above in the household. A low dependency ratio is desirable as it represents a higher proportion of working adults in the household to support the young and the elderly members.
- A dummy variable equals to 1 if the household has obtained any agricultural input coupons/vouchers in the year. Given the time frame of the IHPS data (2010 – 2019), households primarily received input coupons and vouchers from the Farm Input Subsidy Programme (FISP) in Malawi (Harou 2018; Ricker-Gilbert and Jayne 2017; Lunduka, Ricker-Gilbert and Fisher 2013). Receiving coupons and vouchers can affect households' usage of farm inputs and thus may determine crop productivity, farmers' income, food

consumption and nutrition (Gómez et al. 2013; Harou 2018; Chakrabarti et al. 2021; Ricker-Gilbert and Jayne 2017).

- Distances to the nearest road, population center of 20,000+ population and ADMARC outlet: We find considerable variations in the distances of households' location to infrastructures and facilities. Infrastructure like roads take less time and monetary costs to build, generating more variations in the distance variables per se and changing households' access to transportation, marketable goods and social services (Nakamura, Bundervoet and Nuru 2019; Headey et al. 2018). ADMARC stands for the Agricultural Development and Marketing Corporation. It is a parastatal corporation which acted as the sole buyer of smallholder farm produce up to the liberalization of agricultural markets in 1987 (Chinsinga and Kayuni 2011). Now, ADMARC competes with private traders in the procurement of crops from smallholder farmers, while its outlets are also responsible for crop storage, grading, financing, marketing, subsidizing agricultural inputs and selling reserve crops during food crises (Makuyana and Obhiambo 2014; Chirwa and Chinsinga 2015). In recent years, however, ADMARC has been withdrawing from remote rural areas of Malawi due to financial constraints (Makuyana and Obhiambo 2014; Chinsinga and Kayuni 2011), which is likely the cause of variations in household's distance to ADMARC outlets over the course of the IHPS.
- Asset index: we control for variations in household wealth status using an asset index. Using asset ownership to estimate household wealth is less likely to result in recall or measurement error; assets are also more indicative of long-term living standards than short-term income or expenditures (Moser and Felton 2009). We rely on Principle Component Analysis (PCA) to construct our asset index. PCA extracts common variations generated

by one variable on other variables (Moser and Felton 2009). For instance, if the ownership of one type of asset is highly indicative of the ownership of other assets, then it receives a positive coefficient; if owning one type of asset entails a lower likelihood of owning other assets, then it receives a negative coefficient. Coefficients of large magnitudes (positive or negative) are informative of the dynamics of variation in asset ownership that is the result of underlying household characteristics such as wealth, while coefficients near zero provide little information on household wealth.

We first run a LASSO regression to select from a larger pool of variables a subset of variables showing high levels of multicollinearity. We then use PCA to condense the information provided by the subset of variables into a single index. The pool of variables from which we selected the most relevant ones for index building are the following:

- Household assets: mortar and pestle, bed, table, chair, radio, fan, air conditioner, TV, bicycle, car, iron, electricity, refrigerator, lantern, clock.
- Housing characteristics: roof material, wall material, toilet facility, cooking fuel, lighting fuel, number of rooms, source of drinking water.
- Non-food expenditure: value of purchased food in the past seven days.
- Self-reported wealth: a categorical variable indicating whether the household is able to meet expenses and build savings.

- Additional covariates included for estimation of resilience (equations 5, 6 and 8): number of plots cultivated during the rainy season; gender of household head; whether the household has finished elementary school.

5.7 Instrumental variable estimations

Our OLS estimation of the impact of multiple-season farming on household food security, nutrition and resilience is likely subject to endogeneities due to time-varying unobservable characteristics of the household that might affect both households' decision to farm over multiple seasons and our outcomes of interest. The direction of this bias can be upward or downward. For instance, if the accumulation of farm experience overtime enables a household to farm in both rainy and dry seasons through more efficient allocation of inputs between the two seasons or by securing financial resources for hiring labors to help with dry season cultivation (Chinsinga and Kayuni 2011), then the bias will be upward as we would expect a higher likelihood to farm in multiple seasons and better well-being status from the more experienced households as a result of higher crop productivity. However, if the accumulation of farm experience overtime allows a household to produce enough crops in the rainy season to satisfy year-round food consumption, then we would see a negative correlation between farm experience and the likelihood to farm in multiple seasons. In this case, the direction of selection bias will be downward as less experienced farmers whose farm productivities are lower are also more likely to engage in multiple-season farming to compensate for their underproduction during the rainy season. Therefore, the OLS will underestimate the effect of multiple-season farming on households' food security, nutrition and resilience. The source of endogeneity in equations 2 and 3 comes from the fact that $Cov(M, \varepsilon) \neq 0$. In other words, the idiosyncratic error term is correlated with household's choice to farm in multiple seasons, since there exist unobservable characteristics (such as the accumulation of farm experience) that simultaneously affect households' multiple-season farming decisions and the outcomes of interest.

To overcome this remaining endogeneity and as a robustness check of our results, we estimate two stage least squares. Our first stage regression is as follows (individual fixed effect included for child nutrition outcomes):

$$M_{it} = \alpha + \rho_1 Z_{it} + \rho_2 X_{it} + v_i + \tau_t + u_{it} \quad (9)$$

We denote our instruments by the vector Z_{it}, and u_{it} is the first-stage error term. All the other coefficients are the same as in equations 2 and 3.

Reliable instruments need to satisfy two conditions (Newhouse and McClellan 1998): (1) they must generate sufficient amount of variation in the main predictor, i.e. $Cov(Z, M) \neq 0$ and (2) they must have no direct effect on the outcome variable other than through generating variations in M_{it}, i.e. $Cov(Z, \varepsilon) = 0$. Violating condition 1 will result in weak instruments, and violating condition 2 entails the correlation between the second-stage error term ε_{it} and $\widehat{M}_{it}$, and the IV coefficients will still be biased. The instrument we picked is the proportion of households nearby that engage in consecutive farming in the same year. The calculation of our instrument is as follows:

$$p_{it} = \frac{\# \; of \; CF \; households \; nearby}{total \; \# \; of \; households \; nearby} \quad (10)$$

The IHPS dataset contains geo-referenced variables on household locations. To preserve confidentiality, households in the same EA are assigned the same latitudes and longitudes plus a random 0-5 km offset value (GoM 2020). In other words, households located in close proximity share the same GPS coordinates. Therefore, we calculate the proportion of households that farmed consecutively across seasons out of all households that have the same latitude and longitude in that survey round.

Several studies have used the adoption decisions by neighbouring households to instrument for the endogenous decision of technology/program adoption by the household (Wossen et al. 2018; Ma and Abdulai 2016; Krishnan and Patnam 2014). The proportion of nearby multiple-season farmers is expected to be positively linked to the household's propensity to farm in multiple seasons. This could be due to, for example, year-specific regional variations of input prices and water availability during the dry season or possible spill-over effects due peer-support that encourage more households to engage in multiple-season farming (Krishnan and Patnam 2014).

Our first stage results (Table A1) suggest that the condition of instrument relevancy is satisfied. While the exclusion restriction cannot be tested, we see no apparent ways through which the proportion of nearby multiple-season farmers can directly influence household food security, nutrition and resilience. Therefore, we argue that the instrument satisfies condition 2, enabling the estimation of unbiased coefficients in our second stage regression:

$$Y_{it} = \alpha + \beta'_1 \widehat{M}_{it} + \mu X_{it} + v_i + \tau_t + \varepsilon_{it} \quad (11)$$

The estimated household propensity to farm in multiple seasons $\widehat{M}_{it}$ comes from the first-stage prediction. By construction, it has no correlation with the second-stage error term ε_{it}. The IV coefficient β'_1 thus provides an accurate estimation of the effect of multiple-season farming on households' well-being and is consistent and free of selection bias.

Chapter 6: Results

6.1 Descriptive Statistics

This section presents summary statistics of the sample households. Table 1 displays the number of households engaged in farming during both rainy and dry seasons in each district, the total number of households in each district, and the percentage of households that farmed in multiple seasons in each survey round. The summary statistics indicate that only a minority of households engaged in multiple-season farming in each district. However, some districts located in central and Southern Malawi, in particular Nkhotakota, Lilongwe, Michinji, Dedza, Ntcheu, Mangochi, Zomba, Thyolo, and Mulanje had a significant concentration of multiple-season farmers. Figure 1 shows the geographical location of these districts in Malawi. Farmers in these regions are exposed to persistent drought shocks, leading to severe crop failure (GoM 2016).

Table 2 provides a summary of the percentage of households in our sample cultivating staple crops, cash crops, vegetables and legumes during both rainy and dry seasons. Each column is represented by a binary indicator which takes the value of 1 if the household cultivates at least one type of crop that falls under the respective category. The majority of households in our sample plant staple crops during the rainy seasons, consistent with the agricultural structure in Malawi. Maize is predominantly grown as the primary staple crop by most smallholder farmers, and tobacco is widely cultivated as a major cash crop for export (CIAT, 2018). In addition to staple crops, a substantial proportion of households also grow legumes and cash crops during the rainy season. However, the percentage of households planting staple crops in the rainy season steadily decreased from 96.13% in 2010 to 85.20% in 2019, while the percentage of households cultivating vegetables during the rainy season increased over the same period.

During the rainy season, only a small fraction of households in our sample grow vegetables. However, the proportion consistently increased, with the percentage of households growing vegetables doubling from 12.54% in 2016 to 26.97% in 2019. The drought experienced in 2016 (Bizikova et al. 2022) adversely affected the production of water-demanding crops such as tobacco, resulting in a decline in the percentage of households cultivating cash crops during the rainy season from 16.53% in 2013 to 13.66% in 2016, and the percentage dropped even lower to 10.16% in 2019. The cultivation of legumes during the rainy season in 2016 appeared to have been hindered by the drought as the percentage increase in cultivation from 2010 to 2013 was almost reversed in 2016. However, the rainy season production of legumes among households quickly bounced back in 2019 as the percentage of legume-cultivating households raised from 47.59% in 2016 to 60.68% in 2019.

Conversely, a minimal proportion of households cultivate any crops during the dry season. The percentage of households growing staple crops in the dry season is the highest in 2013 (10.14%) and lowest in 2019 (5.95%). Only five households in our sample cultivate cash crops during the dry season, while the percentage of households growing vegetables is slightly lower than that of staple crops (4.22% - 11.53%). The percentage of households cultivating legumes in the dry season in each year is also negligibly small (0.18%-3.89%).

Finally, Table 3 provides descriptive statistics of all observations in the four survey rounds of the Integrated Household Panel Survey dataset, which is an unbalanced panel. The observations include baseline households that participated in all survey rounds from 2010 to 2019, as well as split-off households that joined the panel after 2010. Notably, the number of observations fluctuates across different variables in the table due to incomplete data records for some variables. The estimation of resilience relies on data from previous rounds, resulting in a lower number of observations for resilience, as observations from 2010 and households that joined in 2019 have no data for resilience estimates.

The first column of the table presents observations from households that consistently farmed in rainy seasons only, while the second column shows observations from households that switched between farming in the rainy season only and during both rainy and dry seasons. Column 3 contains observations from households that consistently farmed in both seasons. The last three columns provide t-test differences between each group of households: (1) – (2) is the mean of “rainy only” minus the mean of “switched between rainy and both seasons,” (1) – (3) is the difference in mean between “rainy only” and “both seasons only,” and (2) – (3) is the mean of “switched between rainy and both seasons” less the mean of “both seasons only.”

In our sample, the majority of households only farmed during the rainy season, while a significant portion switched between rainy and dry seasons. Consistently farming in both seasons is rare and was observed in only 73 households. However, these households tended to cultivate more plots during the rainy season than the “rainy only” and “switched” households. Additionally, “both seasons only” households were located closer to large population centers with 20,000+ population, and experienced a lower rainfall anomaly during rainy season planting months than the “rainy only” and “switched” households.

Comparing “rainy only” and “switched” households reveals that the former were located closer to an ADMARC outlet on average and had a lower dependency ratio, indicating fewer economically dependent members. However, “rainy only” households tended to be less well-off compared to households that switched in and out of multiple-season farming. They cultivated fewer plots in rainy seasons, had smaller household sizes, owned fewer assets, displayed a lower likelihood of obtaining input coupons, and experienced a higher rainfall anomaly. Furthermore, “rainy only” households were more food insecure, as evidenced by their higher average CSI and lower resilience than “switched” households. Adverse coping behaviors were also more frequent among “rainy only” households, making them less resilient than “switched” households on average.

6.2 Determinants of Multiple-Season Farming

Table 4 presents a logistic regression showing the determinants of multiple-season farming. The reported coefficients are odds ratios, which show the probabilities of multiple-season farming associated with a marginal increase in each covariate. Model 1, presented in column 1, only includes rainfall anomaly as an explanatory variable. Model 2, presented in column 2, adds household characteristics into the regression. Model 3, presented in column 3, further adds year and district fixed effects. Robust standard errors are clustered by enumeration area in Table 4 and those after.

The regression results show that the effect of rainfall anomaly on multiple-season farming is only statistically significant at the 10% level in model 2. An 1mm increase in rainfall anomaly during planting is associated with a 0.4% decrease in the probability of farming in multiple seasons. The distance to the nearest population center also has a negative effect on multiple-season farming. An increase by 1km in the distance to the nearest population center decreases the probability of multiple-season farming by 1.5%. Household size has a positive effect on multiple-season farming. Having an additional household member increases the probability to farm in both seasons by 7.6% in model 2 and by 8.9% in model 3. Obtaining input coupons has a strong positive effect on the probability of multiple-season farming. The probability increases by 25.8% in model 2 and by 38.3% in model 3. However, the effects of other covariates, such as household asset index, dependency ratio, and distance to the nearest road and ADMARC outlet, are not statistically significant in models 2 and 3. This implies that these variables have no deterministic power over a household's decision to farm in multiple seasons.

6.3 Food Security

In this subsection, we examine the effect of consecutive farming on households' food security measures. Table 5 presents the results of OLS regressions with household and year fixed effects, where measures of food security are regressed on households' decision to farm in multiple seasons.

The effect of multiple-season farming is positive and statistically significant at the 1% level for HDDS in columns 1 and 2. Households that farm in both rainy and dry seasons, on average, consume 0.366 more food groups in the simple model, and 0.372 more food groups in the full model, holding other factors constant. The effect of multiple-season farming is also positive on the FCS (columns 3 and 4), although the coefficients are only marginally significant at the 10% level. Households practicing multiple-season farming, on average, increase their FCS by around 1.75. The positive and statistically significant effects on HDDS and FCS suggest that multiple-season farming is associated with an increase in the diversity and frequency of adequate food consumption. No statistically significant effect is observed for the effect of multiple-season farming on CSI.

Regarding the other control variables, a higher rainfall anomaly during the month of planting in the rainy season only increases HDDS by 0.002 in column 2, and the coefficient is only significant at the 10% level. The household's distance to the nearest population center is negatively correlated with household food security measures, meaning living closer to population centers increases dietary diversity and decreases severe coping behaviours. Having a larger household size leads to a higher CSI. The effect of a higher asset index is consistently positive and significant at a 1% level for food security. An extra unit increase in the asset index contributes to 0.675 higher HDDS, 8.103 higher FCS, and 1.740 lower CSI. Additionally, the effect of obtaining input coupons is only positive and significant for HDDS in column 2.

Table 6 presents the results of IV regressions for HDDS, FCS, and CSI using the same set of household control variables as in the OLS regressions. The coefficients on multiple-season farming in the first row confirm the positive and significant impact of multiple-season farming on food security measures that is found in the OLS models. The only exception is column 3, where the effect of multiple-season farming on FCS has become insignificant in the reduced model. Moreover, the magnitudes of IV coefficients are substantially higher than the OLS coefficients. This suggests that the OLS estimates examining the effect multiple-season farming on food security are biased downward by the endogeneity in farmers' decision to cultivate multiple seasons.

Furthermore, the effect of control variables in Table 6 is largely consistent with those in Table 5. Smaller distance to the nearest population center and more asset holdings are both positively associated with higher HDDS and FCS and lower CSI, indicating that smaller distance to population centers and more household asset holding contribute to better food security for rural households in Malawi. Having an extra member in the household is linked to 0.308 higher CSI, pointing to an effect of the same magnitude as in the OLS. Obtaining input coupons is only significantly linked to higher HDDS in column 2, which is also consistent with the corresponding OLS estimate.

6.4 Heterogeneity Analyses on Food Security: Subgroup Analyses by Asset Holding and Gender of Household Head

Tables 7 and 8 report the results for the subset of households with an asset index score above and below the 50th percentile ("non-poor" HHs and "poor" HHs). Multiple-season farming appears to have a positive impact on HDDS in OLS regressions for both subgroups, with the magnitude of effect being larger for the "poor" households. The OLS coefficient of multiple-season farming on FCS is also statistically significant. When we apply IV estimation, however, multiple-season farming shows no significant impact on all three food security measures for the poor households. For the non-poor households, the positive effect on HDDS remains significant at the 5% level, and the magnitude of coefficient has increased from 0.310 to 1.365. The negative impact on CSI also becomes significant in column 6 of Table 7, suggesting that for wealthier households, farming in multiple seasons contributes to higher dietary diversity and less severe coping behaviours.

Comparing coefficients on control variables in Tables 7 and 8, the positive influence of asset holding on food security measures appears to be much more robust for the non-poor households: An increase in the asset index by one unit results in around 0.742 higher HDDS, 10.540 higher FCS and 2.004 lower CSI in OLS, and the estimated effects are consistent in IV regressions. For the poor households, we only observe a positive and significant impact on HDDS that is consistent in both OLS and IV regressions. In addition, obtaining input coupons decreases CSI for the non-poor households and increases the HDDS for the poor households.

We also present a subgroup analysis by the gender of the household head. The split of sample households by gender of the household head creates an uneven distribution of observations for Tables 9 and 10, as a majority of 947 households in our sample are headed by males, while only 324 households are led by females.

Table 9 shows the results from restricting our sample to male-headed households. The effect of multiple-season farming on HDDS is positive and statistically significant in both OLS (column 1) and IV (column 4), and the higher magnitude of coefficient in the IV indicates the presence of a downward selection bias in the OLS coefficient. The effects on FCS and CSI are significant only for IV (columns 5 and 6), indicating that households that farm in multiple seasons, on average, score 7.158 higher on FCS and 5.509 lower on CSI, both of which signify higher levels of food security. Table 10 presents the results of our study on female-headed households. The OLS coefficients on multiple-season farming is positive and significant for HDDS and FCS, but these effects do not persist in IV regressions. Overall, male-headed households that farmed in both rainy and dry seasons demonstrate a more robust increase in food security than female-headed households. The IV coefficients are also higher in magnitude for the male-headed households, pointing to the presence of negative selection bias among this subgroup.

The asset index appears to have a positive and robust influence on all three measures of food security for male- and female-headed households alike. For the male-headed households, no other household characteristic has an effect on food security that is significant in both OLS and IV. For the female-headed households, increase in household size and distance to the nearest population center are positively associated with CSI, meaning that both are linked to adopting more adverse strategies to cope with food insecurity. In addition, having obtained input coupons also increase HDDS for female-headed households.

6.5 Child Nutrition: HAZ, WAZ and WHZ

Table 11-13 presents the results of a regression analysis of the height-for-age z-score (HAZ), weight-for-age z-score (WAZ), and weight-for-height z-score (WHZ) on the decision of households to farm in multiple seasons, along with other household-level controls. Our analysis reveals no statistically significant effect of multiple-season farming on HAZ, WAZ, and WHZ in both OLS and IV estimations. Despite the positive impact of multiple-season farming on household food security, there have been no significant changes in the long-term (HAZ) and short-term (WAZ, WHZ) growth measures.

In Table 11, an increase of 1KM in household distance to the nearest road decreases HAZ by 0.069 in OLS (column 2) and 0.068 in IV (column 4), while an increase of 1KM in distance to the nearest population center decreases HAZ by 0.021 in OLS (column 2) and IV (column 4). No variable in our model exhibits a statistically significant impact on WAZ in Table 12. In Table 13, planting month rainfall anomaly positively influences child WHZ. However, we observe that a marginal increase in distance to the nearest population center increases WHZ by 0.013 (column 4) in IV estimation, which is puzzling since we expect that remoteness to urban centers will lead to worse health outcomes for children due to lower quality access to markets and basic infrastructures (Headey et al., 2018).

6.6 Household Resilience Estimates: the Probability of Sustaining Food Security

The results of our resilience estimation are presented in Table 14. In column 1, we regress households' current FCS on lagged FCS, rainfall anomaly and household characteristics. We observe no sign of persistence in food security, as the coefficient on lagged FCS is statistically insignificant.[4] Distance to the nearest road and ADMARC outlet are negatively associated with FCS. The household head being male, having finished at least elementary school, and having a higher household asset index increase current FCS. In column 2, we observe that higher planting month rainfall anomaly is associated with less variance in FCS, while the household head having finished at least elementary school and a higher asset index contribute to a greater variability in FCS.

Finally, the results of the resilience estimation are presented in column 3. The statistically significant coefficients on the third-order polynomial of lagged FCS (rows 1-3) suggest a non-linear relationship between lagged FCS and household resilience. Surprisingly, we find that lagged FCS has a coefficient of -0.032 on resilience, suggesting a negative inertia effect of past level food security on the current probability of staying above the satisfactory FCS threshold. This finding contradicts the positive inertia effect of past wellbeing on resilience as reported in previous studies (Cissé and Ikegami 2016; Cissé and Barrett 2018; Abay et al. 2022).

When comparing the results in Columns 1 and 3, we find that rainfall anomaly, distance to the nearest road and ADMARC outlet, and dependency ratio are negatively associated with both FCS and resilience. On the other hand, the household head being male, the head having finished elementary school, and a higher asset index positively determine FCS and resilience. While having no statistical significance in influencing FCS, the number of plots cultivated in the rainy season and household size are positively linked to resilience, while household obtained input coupons is negatively associated with resilience.

The following paragraphs present the results of the OLS and IV estimations investigating the effect of multiple-season farming on resilience. The variables included in the regression

[4] We also find that polynomials of lagged FCS with orders higher than three produce statistically insignificant coefficients.

specifications are identical to those used for investigating the effect on food security and child nutrition status. Coefficients are reported in Table 15.

The reduced OLS model (column 1) shows that multiple-season farming increases resilience by 0.012, while the full OLS model (column 2) indicates a smaller effect size of 0.007. These results suggest that multiple-season farming increases the likelihood of a household maintaining a FCS above 35 over time. However, such significant impact disappears when we apply IV estimations in columns 3 and 4, indicating that the positive impact of multiple-season farming on household resilience is less robust compared to the effect multiple-season farming has on food security measures.

Regarding other determinants of resilience, the coefficients associated with higher rainfall anomaly are consistently negative in all specifications, albeit with small magnitudes (-0.001). Similarly, the coefficients for household distance to the nearest road (-0.002) and population center (0.001), as well as household size (0.002) and dependency ratio (less than 0.001), are also small. The divergent signs on distances to road and population center may suggest different implications of transportation and access to social services on household resilience. In contrast, the asset index is found to be a robust determinant of resilience, with a marginal increase leading to more than 0.16 increase in resilience in both OLS and IV estimations. However, receiving input coupons is negatively associated with resilience, as indicated by a 0.013 decrease in OLS and IV.

6.7 Multiple-season Farming on Production Diversity and Selling to Markets

In this section, we investigate the potential pathways through which multiple-season farming improves food security. Specifically, we examine the relationship between farming in multiple seasons and farm production diversity, as well as the likelihood of selling agricultural harvests in the market. The sample was divided into various subgroups by asset index and by gender of household head, same as previous subgroup analyses on food security measures.

Our findings, as presented in Table 16, indicate that farming in multiple seasons is positively associated with crop production diversity for rural households. This relationship is statistically significant at the 1% level, and the magnitude of coefficients ranged from 1.088 to 1.282 across different subgroups, suggesting that households that farm in both rainy and dry seasons produce more than one extra type of crop on average compared to households that only farm in the rainy season, holding other factors constant. Furthermore, we find that higher asset levels are positively correlated with production diversity for the full sample and all subgroups. Having a larger household size and obtaining input coupons increases production diversity for full sample, poor households and male-headed households.

We display results from the IV estimations in Table 17. Compared to OLS coefficients in Table 16, the IV coefficients on multiple-season farming are higher in magnitude. Specifically, the IV coefficients on multiple-season farming range from 1.678 for not poor households to 2.595 for poor households. These results suggest that the presence of bias has attenuated the impact of multiple-season farming on farm production diversity for all of our sample households. Additionally, the coefficients on other covariates generally support the OLS estimates, except in a few cases where the IV coefficients have become insignificant. Asset index appears to have no significant effect in IV regression on poor households. We argue that marginal increases in asset index have little effect on increasing production diversity for financially disadvantaged households.

We disaggregate the crops count variable into staple crops, cash crops, vegetables and legumes to examine the effect of multiple-season farming on the cultivation of each. As few households grew any cash crops, we focus on the cultivation of staple crops, vegetables and legumes. Our results in Table 18 show a positive and statistically significant impact of multiple season farming on increasing the diversity of cultivation for staple crops, vegetables and legumes. The magnitude of coefficients and level of statistical significance are higher for staple crops and vegetable diversification in both OLS and IV models. Therefore, we argue that the observed increase in dietary diversity from previous tables was primarily a result of the induced diversity of staple crops and vegetable production among farmers who farmed in multiple seasons.

Finally, in Table 19, we present the results of a linear probability model that examines the effect of multiple-season farming on the likelihood of selling agricultural produce to markets. Subsequently, Table 20 displays the results of the IV estimation. The dependent variable is a binary variable that takes the value of 1 if the household has sold any agricultural produce to the market within a year. We provide results for the full sample in column 1. We disaggregate our sample by asset holding in columns 2 and 3, and by gender of household head in columns 4 and 5.

The OLS coefficients in Table 19 suggest that multiple-season farming increases the probability of selling agricultural produce to the market in all cases. However, when we compare the OLS and IV coefficients on multiple-season farming, statistical significance is only observed in IV (Table 20) for the full sample (column 1), poor households (column 2), and female-headed households (column 4). Distance to the nearest population center is negatively correlated with selling to the market for female-headed households, but positively correlated with male-headed households in both OLS and IV. Asset index increases the probability of selling to the market for the full sample, non-poor households, and male-headed households in OLS, but its effect on male-headed households becomes insignificant in IV. The positive effect of obtaining input coupons is robust and consistent in both OLS and IV estimations. Surprisingly, we do not find any significant effect of distance to the nearest ADMARC outlet on households' propensity to sell on markets.

Chapter 7: Discussion

7.1 Multiple-season Farming: Determinants of Adoption, and its Impacts on Measures of Well-being.

The results presented in Table 4 indicate that having a greater number of household members contributes to a higher availability of labor, while having access to input coupons facilitates the purchase of sufficient agricultural inputs to support farming during both the rainy and dry seasons. This finding is consistent with the work of Chinsinga and Kayuni (2011), who report that Malawian farmers who farm on seasonal wetlands during post-rainy season periods are required to invest in inputs and labor to compensate for the lack of rainfall and maintain soil fertility during the dry season. Thus, the positive association between household size and input coupons and the likelihood of farming in multiple seasons is consistent with empirical evidence.

In terms of the impact of multiple-season farming on food security, our analysis reveals that households that engage in farming during both the rainy and dry seasons have a more diverse and nutritious diet, as reflected by the positive OLS coefficients on multiple-season farming on Household Dietary Diversity Score (HDDS) and Food Consumption Score (FCS). Further IV estimations suggest that the positive impact of multiple-season farming on reducing Coping Strategies Index (CSI) is statistically significant, and the coefficients on HDDS and FCS become more pronounced. This provides robustness to the OLS estimates and supports the conclusion that multiple-season farming has a positive impact on household food security.

Negative biases in OLS coefficients are possible when multiple-season farming is inversely correlated with unobservable attributes of the households, such as learning potential or farm experience. When these factors are positively correlated with the outcome of interest, OLS estimates tend to underestimate the effect of the main predictor (Kabunga, Dubois, and Qaim 2012;

Uusitalo 1999; McArthur and McCord 2017). In the context of our analysis, a possible explanation for the downward bias in our OLS estimates is that farmers who lack experience or skills to obtain sufficient crop yields during the rainy season may choose to engage in dry-season farming. Consequently, multiple-season farming is often practiced by farmers who receive lower yields on average, resulting in a negative selection bias.

Our findings show that there is no significant impact of multiple-season farming on child anthropometrics. Specifically, there is no observable increase in HAZ, WAZ, or WHZ among children from households engaged in multiple-season farming. The lack of significant impact on HAZ is in line with our expectation, as HAZ is a measure of long-term nutrient deficiency that is less sensitive to short-term changes in farming patterns (Headey and Masters 2021). However, we anticipated that multiple-season farming would lead to changes in WAZ and WHZ, given that weight-based indicators tend to be more responsive to changes in dietary patterns brought about by multiple-season farming. Contrary to our expectations, we find that the induced improvement in dietary diversity among multiple-season farming households has not translated into better nutrition outcomes. This lack of synergy between improvements in food consumption patterns and nutrition status has also been observed in previous studies (Chegere and Stage 2020; Santoso et al. 2021). Improving nutrition outcomes requires addressing additional confounding factors, such as market quality, nutrient intake knowledge, and access to basic infrastructure (Chegere and Kauky 2022; Headey et al. 2018).

To estimate household resilience, we find a negative and significant correlation between households' lagged FCS and current FCS. This suggests that better food consumption patterns in the previous survey round are linked to worse resilience to becoming food insecure in the current survey round. This result contradicts the findings of previous studies (Abay et al. 2022; Cissé and

Barrett 2018), which find that households' recent welfare standing contributes to better household resilience. Moreover, we find that multiple-season farming increases household resilience in OLS, but such effect does not persist when we apply the IV estimation. Although multiple-season farming is associated with an increase in current FCS, as demonstrated by the results in Tables 5 and 6, such an increase does not necessarily predict a higher likelihood to remain food secure in the future, as our IV estimates fail to validate robustness of our OLS coefficients of multiple-season farming on resilience.

We also present graphical evidence to compare the deterministic power of various household characteristics over estimated resilience. In Figures 3-6, we disaggregate households into subgroups by multiple-season farming status, whether they obtained any input coupon, gender of household head and whether they have an asset index above or below the 50th percentile of the distribution, respectively in each figure. We have year on the x-axis of each figure, and on the y-axis we have the proportion of households that are not resilient in each subgroup[5]. We define non-resiliency as having an estimated resilience score below 0.7. In other words, households whose predicted probability of achieving a FCS over 35 are below 70% are deemed not resilient.

In Figure 3, when we disaggregate households by multiple-season farming status, we see only minimal difference between the proportion of households that are not resilient among multiple-season farmers and farmers who only farm in the rainy season. In Figure 4, households that obtained input coupons in 2013 and 2019 are slightly more resilient compared to households that did not obtain input coupons. However, we see no difference in the proportion of not-resilient households in each subgroup in 2016, which is the year when Malawi experienced a significant drought (Aberman, Meerman, and Benson 2018).

[5] See Figures A5-A8 in the appendix for details regarding the distribution of resilience in each subgroup.

However, difference in resilience among subgroups are highly discernible when households are disaggregated by structural variables. In Figure 5, male-headed households are consistently more resilient compared to female-headed households in every year. The same story goes when households are split by their asset holdings in Figure 6. Households with an asset index above 50th percentile of the distribution appear to be more resilient on average compared to those with an asset index below 50th percentile. Therefore, we argue that structural factors possess more deterministic power over households' long-term resilience compared to short-term changes in agricultural practices, such as multiple season farming and obtaining input coupons for the year.

Additionally, we find a surprising negative association between having obtained input coupons and resilience. Although having input coupons is associated with higher dietary diversity (HDDS), input coupon receivers are likely to exhibit lower resilience according to both OLS and IV estimations. One possible explanation for this result is that input voucher programs like the FISP are successful in targeting some vulnerable farmers but are flawed in consistent distribution over time due to issues such as capture of benefits by elites and intra-village sharing of coupons resulting from an egalitarian culture (Lunduka, Ricker-Gilbert and Fisher 2013; Holden and Lunduka 2013; Holden and Lunduka 2010). Therefore, the short-term increase in household food security among coupon receivers hardly predicts a sustainable improvement in resilience over the long run.

7.2 Heterogeneity Analysis

The impact of multiple-season farming on food security may vary at different levels of asset endowments, and gender differences can shape agricultural outcomes as well as decisions regarding food consumption (Makate and Makate 2022). Therefore, we disaggregate our sample by asset index and gender of the household head, and examine potential wealth and gender disparities.

Our findings indicate that multiple-season farming has a more robust impact on food security for households in the top 50% of the asset index distribution and households headed by males. In both OLS and IV estimations, multiple-season farming leads to an increase in dietary diversity for relatively wealthy households and male-headed households. Moreover, for non-poor and male-headed households, multiple-season farming is associated with less severe coping behaviors, as evidenced by the significant and negative coefficients on the coping strategy index (CSI) in their respective IV estimations. However, the positive influence of multiple-season farming on food security appears to be less consistent for the poor and female-headed households. Although the OLS estimations show improvements in household dietary diversity and food consumption scores (FCS), none of these effects remain statistically significant in the IV estimations. Therefore, we conclude that the benefits of multiple-season farming on food security are primarily realized by relatively wealthier and male-headed households. Asset-poor and female-headed households do not benefit as much, possibly due to their disadvantaged positions on receiving subsidies for procurement of agricultural inputs (Lunduka, Ricker-Gilbert and Fisher 2013) or low access to farm land and irrigation during the dry season (Nyirenda 2020; Makate and Makate 2020).

Furthermore, our results indicate that the positive association between the asset index and food security is much more pronounced for non-poor households compared to poor households. One possible explanation for this finding is that access to food markets is constrained by wealth, as measured by the asset index. According to Headey et al. (2018), increases in socioeconomic status and demand for more diverse foods lead to improved market access, enabling asset-rich households to diversify their diets through market purchases. In contrast, market access for poor households is limited by their lack of purchasing power, which explains why the increase in the asset index does not lead to significant improvements in dietary diversity.

7.3 Multiple-season Farming on Production Diversity and Selling to Markets

Our regression analyses in Tables 16 and 17 indicate that households that engage in multiple-season farming demonstrate higher crop diversity. This finding aligns with previous research, which has demonstrated that increased production diversity is associated with better dietary diversity (Jones, Shrinivas, & Bezner-Kerr, 2014; Chegere & Stage, 2020). It is likely that households practicing multiple-season farming achieve better food security outcomes by planting a more diverse range of crops for self-consumption. Notably, increased production diversity of vegetables and legumes has important implications for nutrient intake, as vegetables and legumes are a primary source of micronutrients such as Vitamin A and iron. On the other hand, in low-income rural areas, the supply of food items such as green leafy vegetables tends to be limited due to their perishability and low demand (Headey & Masters, 2021). Therefore, the increase in vegetable cultivation among multiple-season farmers is likely to satisfy their consumption demands, particularly in regions where the supply of vegetables from markets is absent.

Another important aspect of multiple-season farming is the increased likelihood of selling agricultural produce in markets. Farmers who cultivate crops in multiple seasons are more likely to harvest surplus compared to those who only farm in the rainy season. Thus, the greater probability of selling their produce in markets could be an indication of increased agricultural surplus and extra income from selling outputs. Chegere and Kauky (2022) have shown that a higher proportion of farm output sold significantly improves dietary diversity and nutritional status for low-income households, as they depend more on agriculture for their income. Our IV regression results suggest that poor and female-headed households demonstrate a higher probability of selling to markets when they practice multiple-season farming. We contend that multiple-season farming may provide agriculture-dependent households with a strategy to obtain agricultural surplus for commercial purposes. The additional income they earn from selling farm produce on markets can be used for food purchases or reinvestment into agriculture, resulting in improved food security outcomes.

7.4 Placebo test: Food Security, Crop Diversity and Selling to Market for Households in Group A

As aforementioned, we limit our analysis to rural households assigned to Group B in the IHPS sample because food security and nutrition outcomes were collected from these households several months after they had made the decision to farm multiple seasons (GoM 2020). On the other hand, data on food consumption patterns and coping strategies were collected from Group A before the dry season farming. As a result, we do not expect rural households in Group A to exhibit an increase in food security measures from multiple-season farming. As a placebo test, we run the same analysis as in Tables 5-6 and 16-20 and for Group A farmers only, shown in Tables 21 and 22. We find no effect on the HDDS, FCS, and CSI for Group A households in Table 21, except the marginally significant coefficient on CSI from the IV estimation. This validates our estimations from Group B and rules out the possibility of reverse causality, that is, households with superior food security outcomes are more likely to farm in multiple seasons.

Additionally, the positive and statistically significant coefficients in the first row of Table 22 confirm our hypothesis. Multiple-season farmers in Group A exhibit the same increase in crop diversity and propensity for selling to markets as those in Group B. Therefore, multiple-season farming improves household food security by increasing the diversity of crops cultivated and the likelihood of selling agricultural produce on output markets. Rural households in Malawi that farm in both rainy and dry seasons are likely to harvest a more diverse range of crops for food consumption or are more likely to sell their produce on the market to generate extra income for food purchases or farm investments.

7.5 Expansion of Plot Size Among Multiple-Season Farmers

An essential assumption underpinning our study is that multiple-season farming enables farmers to achieve increased outputs without expanding their cultivation area. However, if the adoption of multiple-season farming necessitates the conversion of uncultivated land or forests into crop fields, it may not serve as a welfare-enhancing strategy due to the escalating land pressure in the sub-Saharan region, as highlighted by Jayne and Sanchez (2022).

To investigate the validity of the production intensification assumption, we conducted regression analysis, regressing the total plot area on multiple-season farming, and present the results in Table 23. The OLS coefficients indicate that, on average, multiple-season farmers expand their cultivation area by 0.145 acres, and this effect is statistically significant at the 0.01 level. However, when employing IV estimation, the statistical significance of the coefficient disappears. The significant OLS coefficient raises concerns about whether multiple-season farming is genuinely compatible with the goal of production intensification.

One possible explanation for the expansion of cropping area among multiple-season farmers could be the portion of farmers with access to seasonal wetlands resulting from receded floods, as discussed in the introduction (Chinsinga and Kayuni 2011; Kambewa 2005). To investigate this hypothesis, we conduct additional OLS and IV regressions, excluding the group of multiple-season farmers who cultivate seasonal wetlands in columns 3 and 4, and then excluding the group of non-wetland farmers in columns 5 and 6.

Our results reveal that when wetland farmers are excluded from the analysis, there is no significant impact of multiple-season farming on plot size expansion. However, when we include wetland farmers, the coefficient on multiple-season farming becomes statistically significant at the 0.01 level in column 5. Multiple-season farmers who cultivate wetlands during the dry season have, on average, 0.2 acres more plots than farmers who do not engage in multiple-season farming. On the other hand, non-wetland farmers who farm in multiple seasons do not expand their plot size compared to farmers who only farm in the rainy season. Thus, the significant impact of multiple-season farming on plot size observed in column 1 of Table 23 could be driven by the group of farmers who temporarily expand their farming activity on seasonal wetlands during the dry season. If this is indeed the case, such expansion may not pose a problem, as wetland farming is temporary in nature, and the soil fertility of seasonal wetlands can be restored with the occurrence of the next flood (Kambewa 2005).

Chapter 8: Conclusion

8.1 Conclusion

In this study we have shown the potential of multiple-season farming in improving food security, child nutrition and resilience of rural households in Malawi. To address possible sources of omitted variable bias, we employ an instrumental variable with fixed effect model and utilize household-specific satellite data of rainfall anomaly to control for the effect of planting season rainfall. Our findings reveal that households practicing multiple-season farming tend to consume more diverse diets and frequently eat nutrient-dense foods. Moreover, they are less likely to adopt deleterious coping strategies to cope with hunger. Heterogeneity analyses indicate that asset-rich and male-headed households are the most likely to benefit from multiple-season farming in terms of food security Although our study did not find a significant impact on child nutrition, households practicing multiple- season farming produce a wider variety of staple crops and vegetables and are more likely to sell surplus outputs in markets. This enables them to acquire more diverse and nutritious foods. Additionally, our OLS results suggest multiple-season farming households display stronger resilience against chronic food insecurity, but our IV estimation fails to provide robustness in our OLS results. Short-term changes in agricultural practices exert less influence over long-term resilience compared to structural factors that determine households' fundamental ability to sustain their overall status of well-being.

8.2 Limitations and Future Research

Our study is limited by several factors. First, the lack of data on access to irrigation in the dry season for farmers who do not practice multiple-season farming means that we cannot differentiate the potential impact on households that do not have access to dry-season irrigation from those who have access but choose not to practice multiple-season farming. While our IV fixed effect model helps to avoid endogeneity issues, having data on dry-season irrigation for the entire sample could improve the accuracy of our estimates.

Furthermore, it is plausible that a greater number of multiple-season farmers in a village might have an impact on food availability by potentially increasing the food supply in local markets. This raises some concerns about the validity of the exclusion restriction associated with our instrumental variable. Notably, Heady et al. (2019) have observed a positive link between household and community production diversity and the consumption of perishable food items like dairy, fruits, and vegetables. If several households in the same village engage in vegetable cultivation during the dry season, it is possible that local markets would see an increase in the availability of fresh vegetables, thereby potentially improving vegetable consumption for neighboring households. This situation could potentially lead to the violation of the exclusion restriction, as farmers might experience greater dietary diversity through market purchases rather than solely from improved production diversity and higher agricultural income resulting from multi-season farming.

Additionally, our resilience estimates are subject to the commonly adopted FCS threshold of 35 (Leroy et al. 2015). Choosing a different threshold may result in different means and distributions, thus suggesting that our chosen method of resilience construction can be vulnerable to the subjectivity and local contexts in choosing the appropriate threshold of resilience classification (Upton, Constenla-Villoslada and Barrett 2022).

To extend the duration of agriculture, it is necessary to construct irrigation infrastructures and enhance market access. Several studies have demonstrated the significance of irrigation and market access in inducing crop diversification (Mondal et al. 2021; Hirvonen and Headey 2018).

Future research may examine whether increasing irrigation and market access can facilitate the adoption of multiple-season farming, particularly in remote regions lacking water bodies and market networks. Moreover, previous literature has provided evidence of the positive relationship between access to inputs, markets, irrigation, and improvements in household wellbeing (Harou 2018; Walls et al., 2023; Cassim and Pemba, 2021; Makate and Makate, 2022; Usman and Haile, 2022). Thus, future research can investigate whether the targeted provision of farm inputs, drought- tolerant seeds or high value-adding cash crops can enhance the income, food and nutrition outcomes among multiple-season farmers. This is particularly relevant if we seek to optimize returns in asset-poor and female-headed households, who appear to benefit less from extending their farming periods across rainy and dry seasons.

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Tables

TABLE 1: Number of households cultivate multiple season, by year and district

District	2010			2013			2016			2019		
	HHs farming multiple seasons	Total HHs	% HHs farming multiple seasons	HHs farming multiple seasons	Total HHs	% HHs farming multiple seasons	HHs farming multiple seasons	Total HHs	% HHs farming multiple seasons	HHs farming multiple seasons	Total HHs	% HHs farming multiple seasons
Chitipa	2	34	6	5	35	14	19	41	46	5	51	10
Karonga	0	18	1	29	3	4	0	30	0	2	54	4
Nkhatabay	0	33	0	3	36	8	1	44	2	6	63	10
Mzimba	3	36	8	1	48	2	1	42	2	7	99	7
MzuzuCity	2	64	3	4	67	6	8	103	8	2	88	2
Kasungu	0	34	0	3	47	6	3	58	5	0	86	0
Nkhotakota	7	32	22	12	42	29	1	44	2	7	67	10
Ntchisi	3	34	9	12	50	24	2	62	3	17	78	22
Dowa	1	62	2	23	84	27	18	103	17	11	149	7
Salima	2	17	12	2	25	8	4	38	11	4	49	8
Lilongwe	16	132	12	31	173	18	32	265	12	34	362	9
Mchinji	5	17	29	4	22	18	3	18	17	7	35	20
Dedza	11	85	13	40	102	39	17	132	13	30	190	16
Ntcheu	14	60	23	13	70	19	9	116	8	15	111	14
LilongweCity	1	172	1	0	233	0	7	317	2	4	323	1
Mangochi	23	113	20	31	139	22	20	141	14	12	205	6
Machinga	5	49	10	9	70	13	4	74	5	9	119	8
Zomba	4	65	6	14	84	17	7	91	8	26	137	19
Chiradzulu	4	32	12	8	40	20	10	51	20	14	55	25
Blantyre	4	28	14	4	40	10	0	35	0	9	85	11
Mwanza	4	28	14	2	30	7	12	41	29	13	37	35
Thyolo	3	61	5	22	79	28	24	101	24	18	111	16
Mulanje	4	68	6	14	78	18	16	96	17	41	134	31
Phalombe	1	31	3	3	41	7	0	56	0	3	55	5
Chikwawa	5	42	12	5	53	9	18	68	26	4	68	6
Nsanje	5	14	36	5	19	26	4	22	18	7	25	28
Balaka	9	46	20	10	57	18	12	78	15	22	101	22
Neno	0	0	0	0	5	0	0	0	0	1	9	11
ZombaCity	0	58	0	1	72	1	2	112	2	1	107	1
BlantyreCity	0	82	0	0	118	0	3	129	2	1	120	1

Table 2: Percentage of households cultivating different crop types, by year and seasons

	% Staple Crops (Rainy)	% Staple Crops (Dry)	% Cash Crops (Rainy)	% Cash Crops (Dry)	% Vegetables (Rainy)	% Vegetables (Dry)	% Legumes (Rainy)	% Legumes (Dry)	Total number of HHs
2010	96.13	8.26	17.40	0.53	7.73	4.22	46.40	0.18	569
2013	90.42	10.14	16.53	0.00	10.97	11.53	60.83	3.89	720
2016	88.69	9.41	13.66	0.00	12.54	6.49	47.59	2.13	893
2019	85.20	5.95	10.16	0.18	26.97	7.36	60.68	1.31	1142

Crop types are binary indicators = 1 if a household planted at least one type of crop in that category.
Categorization of crops: Staple crops: maize, rice, sweet potato, Irish potato, wheat, finger millet, sorghum, pearl millet; Cash crops: cotton, sunflower, sugarcane, tobacco; Vegetables: ground bean, peas, cabbage, tanaposi, nkhwani, okra, tomato, onion, paprika; Legumes: groundnuts, beans, soyabean, pigeonpea.

Table 3: Descriptive Statistics

	(1) always farmed in rainy seasons only		(2) switched between rainy and both seasons		(3) always farmed in both seasons		T-test Difference		
Variable	N	Mean/SE	N	Mean/SE	N	Mean/SE	(1)-(2)	(1)-(3)	(2)-(3)
Number of plots cultivated (rainy)	1968	1.570 (0.034)	1283	1.815 (0.047)	73	2.466 (0.187)	-0.245***	-0.896***	-0.650***
HH Distance in (KMs) to Nearest Population Center with +20,000	1966	30.414 (0.394)	1282	29.452 (0.445)	73	23.058 (1.507)	0.962	7.357***	6.395***
HH Distance in (KMs) to Nearest ADMARC Outlet	1966	8.277 (0.129)	1282	7.461 (0.151)	73	6.722 (0.747)	0.817***	1.556**	0.739
household size	1968	4.672 (0.051)	1283	5.221 (0.063)	73	5.110 (0.226)	-0.550***	-0.438	0.112
gender of household head (male=1)	1959	0.718 (0.010)	1276	0.741 (0.012)	73	0.795 (0.048)	-0.023	-0.076	-0.053
household head finished at least elementary school	1968	0.246 (0.010)	1283	0.231 (0.012)	73	0.151 (0.042)	0.015	0.095*	0.080
asset index	1967	-0.064 (0.007)	1283	-0.033 (0.009)	73	-0.033 (0.036)	-0.032***	-0.031	0.001
Dependency ratio	1838	106.726 (2.026)	1234	112.046 (2.396)	71	113.615 (9.235)	-5.321*	-6.889	-1.569
household obtained input coupons	1968	0.279 (0.010)	1283	0.379 (0.014)	73	0.342 (0.056)	-0.100***	-0.064	0.036
Rainfall Estimate	1822	138.098 (1.480)	1280	138.522 (1.811)	73	141.132 (8.229)	-0.424	-3.035	-2.610
Rainfall Anomaly	1822	-2.052 (0.680)	1280	-6.638 (0.779)	73	5.407 (3.154)	4.585***	-7.459**	-12.044***
Household Dietary Diversity Score (HDDS)	1968	7.382 (0.038)	1283	7.480 (0.046)	73	7.589 (0.191)	-0.099	-0.207	-0.109
Food consumption score (FCS)	1968	50.214 (0.403)	1283	50.737 (0.505)	73	51.404 (2.157)	-0.523	-1.190	-0.667
Coping Strategy Index (CSI)	1967	5.663 (0.162)	1282	4.872 (0.188)	73	4.890 (0.703)	0.791***	0.773	-0.018
resilience	1032	0.680 (0.004)	872	0.696 (0.004)	23	0.698 (0.021)	-0.016***	-0.018	-0.002

Notes: The value displayed for t-tests are the differences in the means across the groups. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table 4: Logistic regression with year and district fixed effects: Determinants of multiple-season farming.

	Multiple-season farming		
	(1)	(2)	(3)
Rainfall Anomaly	0.997	0.996*	0.998
	(0.002)	(0.002)	(0.002)
HH Distance in (KMs) to Nearest Road		0.992	1.015
		(0.012)	(0.018)
HH Distance in (KMs) to Nearest Population Center with +20,000		0.993	0.985**
		(0.009)	(0.007)
HH Distance in (KMs) to Nearest ADMARC Outlet		0.970	0.985
		(0.021)	(0.016)
household size		1.076***	1.089***
		(0.027)	(0.029)
asset index		1.050	1.096
		(0.196)	(0.157)
Dependency ratio		1.000	0.999
		(0.001)	(0.001)
household obtained input coupons		1.258*	1.383**
		(0.154)	(0.180)
Constant	0.176***	0.194***	0.495
	(0.026)	(0.081)	(0.260)
Year Control	NO	NO	YES
District Control	NO	NO	YES
N	3175	3005	2942

Standard errors in parentheses

Coefficients reported are odds ratios. Sample includes only rural HHs assigned to group B. Dependent variable is a binary indicator of whether a household has farmed during both rainy and dry seasons in a given year. Year and district controls included in column 3.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: OLS with year and household fixed effects: Multiple-season farming and food security (rural HHs in group B).

	(1) HDDS	(2) HDDS	(3) FCS	(4) FCS	(5) CSI	(6) CSI
Multiple-season farming	0.366***	0.372***	1.753*	1.733*	0.025	0.077
	(0.091)	(0.092)	(0.953)	(0.960)	(0.413)	(0.414)
Rainfall Anomaly	0.002	0.002*	0.015	0.024	-0.002	-0.002
	(0.001)	(0.001)	(0.019)	(0.018)	(0.007)	(0.007)
HH Distance in (KMs) to Nearest Road		0.012		0.069		-0.063
		(0.015)		(0.170)		(0.075)
HH Distance in (KMs) to Nearest Population Center with +20,000		-0.008*		-0.069*		0.028*
		(0.004)		(0.037)		(0.017)
HH Distance in (KMs) to Nearest ADMARC Outlet		0.005		0.121		-0.055
		(0.019)		(0.177)		(0.094)
Household size		-0.004		0.398		0.295**
		(0.023)		(0.258)		(0.131)
Asset index		0.675***		8.103***		-1.740***
		(0.119)		(1.720)		(0.579)
Dependency ratio		-0.000		-0.005		0.003
		(0.000)		(0.004)		(0.002)
Household obtained input coupons		0.190**		0.255		-0.542
		(0.086)		(0.812)		(0.501)
Constant	7.703***	7.803***	54.178***	54.337***	2.205***	0.859
	(0.087)	(0.341)	(0.908)	(2.695)	(0.319)	(1.499)
Year FE	YES	YES	YES	YES	YES	YES
HH FE	YES	YES	YES	YES	YES	YES
N	2795	2610	2795	2610	2792	2609

Sample includes only rural HHs assigned to group B. Dependent variables are Household Dietary Diversity Score (0-10) for columns 1-2, Food Consumption Score (0-126) for columns 3-4, and Coping Strategy Index for columns 5-6.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: IV regression with year and household fixed effects: Multiple-season farming and households' food security (rural HHs in group B only).

	(1) HDDS	(2) HDDS	(3) FCS	(4) FCS	(5) CSI	(6) CSI
Multiple-season farming	1.138*	1.241**	4.943	7.572*	-5.536**	-5.323**
	(0.598)	(0.558)	(4.509)	(4.082)	(2.582)	(2.453)
Rainfall Anomaly	0.002*	0.002*	0.016	0.025	-0.004	-0.003
	(0.001)	(0.001)	(0.018)	(0.017)	(0.006)	(0.006)
HH Distance in (KMs) to Nearest Road		0.010		0.058		-0.052
		(0.016)		(0.172)		(0.073)
HH Distance in (KMs) to Nearest Population Center with +20,000		-0.008**		-0.071*		0.029*
		(0.004)		(0.038)		(0.016)
HH Distance in (KMs) to Nearest ADMARC Outlet		0.011		0.159		-0.091
		(0.018)		(0.171)		(0.091)
household size		-0.006		0.383		0.308**
		(0.024)		(0.266)		(0.145)
asset index		0.666***		8.043***		-1.685***
		(0.127)		(1.776)		(0.503)
Dependency ratio		0.000		-0.004		0.002
		(0.000)		(0.005)		(0.002)
household obtained input coupons		0.184**		0.221		-0.510
		(0.091)		(0.826)		(0.491)
Year FE	YES	YES	YES	YES	YES	YES
HH FE	YES	YES	YES	YES	YES	YES
N	2795	2610	2795	2610	2792	2609

Standard errors in parentheses

Sample includes only rural HHs assigned to group B. Dependent variables are Household Dietary Diversity Score (0-10) for columns 1-2, Food Consumption Score (0-126) for columns 3-4 and Coping Strategy Index for columns 5-6. Excluded instrument: ratio of neighbouring households that farmed in multiple seasons.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: OLS and IV regressions with year and household fixed effects: Multiple-season farming and households' food security (non-poor HHs).

	(1) HDDS	(2) FCS	(3) CSI	(4) HDDS (IV)	(5) FCS (IV)	(6) CSI (IV)
Multiple-season farming	0.310**	0.912	-0.458	1.365**	8.823	-5.703**
	(0.123)	(1.440)	(0.512)	(0.657)	(5.950)	(2.690)
Rainfall Anomaly	0.002*	0.032	-0.005	0.003**	0.038*	-0.009
	(0.001)	(0.022)	(0.009)	(0.001)	(0.019)	(0.010)
HH Distance in (KMs) to Nearest Road	0.043***	0.067	-0.000	0.040**	0.040	0.017
	(0.016)	(0.125)	(0.126)	(0.015)	(0.123)	(0.123)
HH Distance in (KMs) to Nearest Population Center with +20,000	-0.014***	-0.039	0.056**	-0.015***	-0.047	0.061***
	(0.004)	(0.047)	(0.025)	(0.004)	(0.052)	(0.021)
HH Distance in (KMs) to Nearest ADMARC Outlet	0.030	0.447	-0.080	0.032	0.466*	-0.092
	(0.026)	(0.270)	(0.114)	(0.026)	(0.252)	(0.110)
household size	-0.011	0.680**	0.211	-0.013	0.668**	0.219
	(0.025)	(0.289)	(0.148)	(0.024)	(0.302)	(0.169)
asset index	0.742***	10.540***	-2.004***	0.748***	10.584***	-2.034***
	(0.148)	(2.244)	(0.702)	(0.159)	(2.281)	(0.701)
Dependency ratio	-0.001	-0.013**	0.004	-0.001	-0.013**	0.004
	(0.001)	(0.005)	(0.003)	(0.000)	(0.005)	(0.003)
household obtained input coupons	0.083	-1.024	-1.083*	0.098	-0.913	-1.156**
	(0.129)	(0.986)	(0.564)	(0.132)	(1.031)	(0.545)
Constant	7.822***	52.465***	0.209			
	(0.398)	(2.892)	(1.532)			
Year FE	YES	YES	YES	YES	YES	YES
HH FE	YES	YES	YES	YES	YES	YES
N	1344	1344	1344	1344	1344	1344

Standard errors in parentheses

Sample includes only rural HHs assigned to group B and have an asset index score above the 50th percentile. Dependent variables are Household Dietary Diversity Score (0-10) for columns 1 and 4, Food Consumption Score (0-126) for columns 2 and 5, and Coping Strategy Index for columns 3 and 6. Excluded instrument for IV estimations: ratio of neighbouring households that farmed in multiple seasons.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: OLS and IV regressions with year and household fixed effects: Multiple-season farming and households' food security (poor HHs).

	(1) HDDS	(2) FCS	(3) CSI	(4) HDDS (IV)	(5) FCS (IV)	(6) CSI (IV)
Multiple-season farming	0.447***	2.776**	0.575	1.228	6.500	-5.194
	(0.111)	(1.223)	(0.586)	(0.769)	(6.042)	(3.506)
Rainfall Anomaly	0.002	0.011	0.001	0.001	0.011	0.002
	(0.002)	(0.022)	(0.010)	(0.002)	(0.021)	(0.009)
HH Distance in (KMs) to	-0.012	0.068	-0.125	-0.012	0.066	-0.123
Nearest Road	(0.023)	(0.287)	(0.081)	(0.024)	(0.288)	(0.081)
HH Distance in (KMs) to	-0.002	-0.102*	-0.001	-0.001	-0.101*	-0.003
Nearest Population Center with +20,000	(0.007)	(0.055)	(0.028)	(0.007)	(0.055)	(0.025)
HH Distance in (KMs) to	-0.019	-0.118	-0.045	-0.011	-0.080	-0.106
Nearest ADMARC Outlet	(0.030)	(0.235)	(0.166)	(0.027)	(0.252)	(0.171)
household size	0.002	-0.044	0.419*	-0.002	-0.060	0.444*
	(0.043)	(0.423)	(0.226)	(0.045)	(0.423)	(0.227)
asset index	0.575**	4.356	-1.526*	0.541**	4.190	-1.269
	(0.235)	(2.709)	(0.879)	(0.254)	(2.798)	(0.785)
Dependency ratio	0.000	0.003	0.001	0.001	0.004	-0.001
	(0.001)	(0.007)	(0.002)	(0.001)	(0.007)	(0.003)
household obtained input	0.292***	1.403	-0.090	0.272***	1.311	0.053
coupons	(0.091)	(1.000)	(0.571)	(0.094)	(1.030)	(0.597)
Constant	7.684***	54.456***	1.734			
	(0.546)	(5.053)	(2.394)			
Year FE	YES	YES	YES	YES	YES	YES
HH FE	YES	YES	YES	YES	YES	YES
N	1266	1266	1265	1266	1266	1265

Standard errors in parentheses

Sample includes only rural HHs assigned to group B and have an asset index score below the 50th percentile. Dependent variables are Household Dietary Diversity Score (0-10) for columns 1 and 4, Food Consumption Score (0-126) for columns 2 and 5, and Coping Strategy Index for columns 3 and 6. Excluded instrument for IV estimations: ratio of neighbouring households that farmed in multiple seasons.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: OLS and IV regressions with year and household fixed effects: Multiple-season farming and households' food security (male headed HHs).

	(1) HDDS	(2) FCS	(3) CSI	(4) HDDS (IV)	(5) FCS (IV)	(6) CSI (IV)
Multiple-season farming	0.286***	1.021	0.302	1.525**	7.158*	-5.509**
	(0.092)	(1.036)	(0.345)	(0.605)	(4.043)	(2.646)
Rainfall Anomaly	0.001	0.024	-0.003	0.001	0.025	-0.004
	(0.001)	(0.019)	(0.006)	(0.001)	(0.018)	(0.007)
HH Distance in (KMs) to	0.016	0.115	-0.078	0.013	0.100	-0.064
Nearest Road	(0.020)	(0.162)	(0.096)	(0.021)	(0.161)	(0.093)
HH Distance in (KMs) to	-0.007	-0.078	0.026	-0.008	-0.082	0.030
Nearest Population Center with +20,000	(0.006)	(0.049)	(0.021)	(0.005)	(0.050)	(0.020)
HH Distance in (KMs) to	0.015	0.219	-0.101	0.023	0.259	-0.139
Nearest ADMARC Outlet	(0.021)	(0.197)	(0.103)	(0.021)	(0.194)	(0.107)
household size	-0.002	0.511*	0.097	-0.007	0.484	0.122
	(0.026)	(0.303)	(0.145)	(0.028)	(0.320)	(0.160)
asset index	0.649***	8.366***	-1.635**	0.629***	8.266***	-1.541**
	(0.122)	(1.745)	(0.721)	(0.146)	(1.818)	(0.626)
Dependency ratio	-0.001	-0.008	0.006**	-0.000	-0.007	0.005
	(0.001)	(0.006)	(0.003)	(0.001)	(0.006)	(0.004)
household obtained input	0.152	0.297	-0.600	0.178*	0.422	-0.719
coupons	(0.093)	(0.882)	(0.533)	(0.103)	(0.912)	(0.513)
Constant	7.795***	54.181***	1.971			
	(0.400)	(3.212)	(1.771)			
Year FE	YES	YES	YES	YES	YES	YES
HH FE	YES	YES	YES	YES	YES	YES
N	1902	1902	1901	1902	1902	1901

Standard errors in parentheses

Sample includes only rural HHs assigned to group B and headed by a male HH member. Dependent variables are Household Dietary Diversity Score (0-10) for columns 1 and 4, Food Consumption Score (0-126) for columns 2 and 5, and Coping Strategy Index for columns 3 and 6. Excluded instrument for IV estimations: ratio of neighbouring households that farmed in multiple seasons.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: OLS and IV regressions with year and household fixed effects: Multiple-season farming and households' food security (female headed HHs).

	(1) HDDS	(2) FCS	(3) CSI	(4) HDDS (IV)	(5) FCS (IV)	(6) CSI (IV)
Multiple-season farming	0.610***	3.719**	-0.483	0.284	8.479	-4.553
	(0.169)	(1.783)	(1.083)	(0.743)	(8.621)	(5.201)
Rainfall Anomaly	0.004*	0.025	0.001	0.004*	0.029	-0.002
	(0.002)	(0.032)	(0.011)	(0.002)	(0.032)	(0.008)
HH Distance in (KMs) to Nearest Road	-0.012	-0.178	0.028	-0.012	-0.187	0.036
	(0.024)	(0.299)	(0.059)	(0.024)	(0.315)	(0.063)
HH Distance in (KMs) to Nearest Population Center with +20,000	-0.009*	-0.043	0.033*	-0.009*	-0.039	0.030*
	(0.005)	(0.067)	(0.017)	(0.005)	(0.068)	(0.016)
HH Distance in (KMs) to Nearest ADMARC Outlet	-0.050	-0.396	0.258	-0.052	-0.369	0.234
	(0.038)	(0.621)	(0.165)	(0.037)	(0.631)	(0.162)
household size	-0.001	0.153	0.704***	-0.002	0.166	0.693***
	(0.045)	(0.428)	(0.231)	(0.045)	(0.420)	(0.243)
asset index	0.720***	6.460**	-1.658*	0.715***	6.533**	-1.720*
	(0.265)	(3.130)	(0.879)	(0.265)	(3.098)	(0.879)
Dependency ratio	0.001	0.001	-0.002	0.001	0.002	-0.003
	(0.001)	(0.007)	(0.003)	(0.001)	(0.007)	(0.004)
household obtained input coupons	0.246*	-0.286	-0.249	0.270**	-0.640	0.053
	(0.128)	(1.354)	(0.766)	(0.123)	(1.541)	(0.915)
Constant	8.180***	57.574***	-3.796*			
	(0.520)	(6.244)	(2.216)			
Year FE	YES	YES	YES	YES	YES	YES
HH FE	YES	YES	YES	YES	YES	YES
N	708	708	708	708	708	708

Standard errors in parentheses

Sample includes only rural HHs assigned to group B and headed by a female HH member. Dependent variables are Household Dietary Diversity Score (0-10) for columns 1 and 4, Food Consumption Score (0-126) for columns 2 and 5, and Coping Strategy Index for columns 3 and 6. Excluded instrument for IV estimations: ratio of neighbouring households that farmed in multiple seasons.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: OLS and IV regression with year, household and child fixed effects: Multiple-season farming and height-for-age z-score. (Rural HHs in Group B)

	(1) HAZ	(2) HAZ	(3) HAZ (IV)	(4) HAZ (IV)
Household practiced agriculture during both rainy and dry seasons	-0.252 (0.594)	-0.208 (0.569)	-0.889 (2.067)	-0.735 (1.823)
Rainfall Anomaly	-0.007 (0.005)	-0.007 (0.005)	-0.007 (0.005)	-0.006 (0.005)
HH Distance in (KMs) to Nearest Road		-0.069** (0.031)		-0.068** (0.031)
HH Distance in (KMs) to Nearest Population Center with +20,000		-0.021*** (0.008)		-0.021*** (0.007)
HH Distance in (KMs) to Nearest ADMARC Outlet		0.058 (0.078)		0.058 (0.075)
household size		-0.015 (0.068)		-0.010 (0.062)
asset index		0.242 (0.318)		0.233 (0.322)
Dependency ratio		0.001 (0.002)		0.001 (0.002)
household obtained input coupons		-0.227 (0.242)		-0.235 (0.258)
Constant	-0.762*** (0.176)	0.142 (0.658)		
Year FE	YES	YES	YES	YES
HH FE	YES	YES	YES	YES
Child FE	YES	YES	YES	YES
N	1908	1898	1908	1898

Standard errors in parentheses

Dependent variable: Height-for-age Z-score (HAZ). Results from OLS are displayed in column 1-2 and IV in column 3-4. Excluded instrument: ratio of neighbouring households that farmed in multiple seasons

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: OLS and IV regression with year, household and child fixed effects: Multiple-season farming and weight-for-age z-score (Rural HHs in Group B).

	(1) WAZ	(2) WAZ	(3) WAZ (IV)	(4) WAZ (IV)
Household practiced agriculture during both rainy and dry seasons	-2.180	-2.114	-9.399	-8.572
	(2.182)	(2.076)	(8.855)	(7.961)
Rainfall Anomaly	-0.013	-0.012	-0.012	-0.011
	(0.018)	(0.017)	(0.017)	(0.016)
HH Distance in (KMs) to Nearest Road		-0.081		-0.070
		(0.062)		(0.058)
HH Distance in (KMs) to Nearest Population Center with +20,000		-0.029		-0.022
		(0.029)		(0.024)
HH Distance in (KMs) to Nearest ADMARC Outlet		0.258		0.243
		(0.293)		(0.252)
household size		-0.147		-0.046
		(0.259)		(0.187)
asset index		0.738		0.603
		(0.585)		(0.881)
Dependency ratio		0.003		0.003
		(0.005)		(0.005)
household obtained input coupons		-0.272		-0.448
		(0.456)		(0.684)
Constant	0.721	0.705		
	(0.463)	(0.899)		
Year FE	YES	YES	YES	YES
HH FE	YES	YES	YES	YES
Child FE	YES	YES	YES	YES
N	1487	1484	1487	1484

Standard errors in parentheses

Dependent variable: Weight-for-age Z-score (WAZ). Results from OLS are displayed in column 1-2 and IV in column 3-4. Excluded instrument: ratio of neighbouring households that farmed in multiple seasons.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: OLS and IV regression with year, household and child fixed effects: Multiple-season farming and weight-for-height z-score (Rural HHs in Group B).

	(1) WHZ	(2) WHZ	(3) WHZ (IV)	(4) WHZ (IV)
Household practiced agriculture during both rainy and dry seasons	0.016	0.057	-1.098	-0.759
	(0.305)	(0.303)	(1.269)	(1.250)
Rainfall Anomaly	0.005*	0.005*	0.005	0.005*
	(0.003)	(0.003)	(0.003)	(0.003)
HH Distance in (KMs) to Nearest Road		0.016		0.019
		(0.025)		(0.028)
HH Distance in (KMs) to Nearest Population Center with +20,000		0.013		0.014*
		(0.008)		(0.008)
HH Distance in (KMs) to Nearest ADMARC Outlet		-0.028		-0.027
		(0.044)		(0.046)
household size		0.312		0.313
		(0.268)		(0.271)
asset index		0.643		0.620
		(0.643)		(0.624)
Dependency ratio		-0.003		-0.003
		(0.002)		(0.002)
household obtained input coupons		0.514		0.493
		(0.343)		(0.340)
Constant	0.386	-1.438		
	(0.450)	(0.990)		
Year FE	YES	YES	YES	YES
HH FE	YES	YES	YES	YES
Child FE	YES	YES	YES	YES
N	1153	1151	1153	1151

Standard errors in parentheses

Dependent variable: Weight-for-height Z-score (WHZ). Results from OLS are displayed in column 1-2 and IV in column 3-4. Excluded instrument: ratio of neighbouring households that farmed in multiple seasons.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Multiple-season farming and households: Estimation based on FCS (Rural HHs in Group B only).

	(1) FCS	(2) Variance of FCS	(3) Resilience
lag FCS	-0.004	-0.036	-0.032***
	(0.006)	(0.025)	(0.002)
lag FCS^2	0.000	0.001	0.001***
	(0.000)	(0.000)	(0.000)
lag FCS^3	-0.000*	-0.000	-0.000***
	(0.000)	(0.000)	(0.000)
Rainfall Anomaly	0.000	-0.005***	-0.002***
	(0.000)	(0.001)	(0.000)
HH Distance in (KMs) to Nearest Road	-0.004***	-0.002	-0.012***
	(0.001)	(0.009)	(0.000)
HH Distance in (KMs) to Nearest Population Center with +20,000	-0.001	0.003	0.000
	(0.001)	(0.004)	(0.000)
HH Distance in (KMs) to Nearest ADMARC Outlet	-0.004**	-0.003	-0.009***
	(0.002)	(0.009)	(0.001)
Number of plots cultivated in the rainy season	0.008	-0.014	0.009***
	(0.005)	(0.027)	(0.002)
household size	0.002	0.013	0.013***
	(0.004)	(0.018)	(0.001)
gender of household head	0.049***	0.057	0.143***
	(0.017)	(0.092)	(0.005)
household head finished at least elementary school	0.084***	0.338***	0.453***
	(0.022)	(0.121)	(0.007)
asset index	0.250***	0.476***	0.879***
	(0.027)	(0.165)	(0.010)
Dependency ratio	-0.000*	-0.000	-0.001***
	(0.000)	(0.001)	(0.000)
household obtained input coupons	-0.004	-0.067	-0.055***
	(0.019)	(0.099)	(0.005)
Constant	3.962***	5.239***	0.818***
	(0.128)	(0.545)	(0.045)
Year FE	YES	YES	YES
District FE	YES	YES	YES
N	1927	1927	1927

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: OLS and IV regression with year and household fixed effects: Multiple-season farming and households' resilience (Rural HHs in group B only).

	(1) Resilience	(2) Resilience	(3) Resilience (IV)	(4) Resilience (IV)
Multiple-season farming	0.012***	0.007**	0.035	0.022
	(0.004)	(0.003)	(0.029)	(0.022)
Rainfall Anomaly	-0.000***	-0.001***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
HH Distance in (KMs) to Nearest Road		-0.002***		-0.002***
		(0.000)		(0.000)
HH Distance in (KMs) to Nearest Population Center with +20,000		0.001**		0.001***
		(0.000)		(0.000)
HH Distance in (KMs) to Nearest ADMARC Outlet		-0.001		-0.001
		(0.001)		(0.001)
household size		0.002**		0.002**
		(0.001)		(0.001)
asset index		0.165***		0.164***
		(0.007)		(0.008)
Dependency ratio		-0.000***		-0.000***
		(0.000)		(0.000)
household obtained input coupons		-0.013***		-0.013***
		(0.005)		(0.005)
Constant	0.699***	0.725***		
	(0.003)	(0.012)		
Year FE	YES	YES	YES	YES
HH FE	YES	YES	YES	YES
N	1692	1692	1692	1692

Standard errors in parentheses

Urban HHs are dropped from the dataset. Excluded instrument: ratio of neighbouring households that farmed consecutively across seasons.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: OLS with household and year fixed effects: Multiple-season farming on the number of crops planted.

	Full Sample	Asset index		Gender of HH head	
	(1)	(2)	(3)	(4)	(5)
Dependent variable: Number of crops planted					
Multiple-season farming	1.143***	1.176***	1.103***	1.282***	1.088***
	(0.088)	(0.113)	(0.087)	(0.136)	(0.098)
Rainfall Anomaly	-0.001	-0.001	-0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
HH Distance in (KMs) to Nearest Road	0.016*	0.019	0.010	0.023	0.016**
	(0.008)	(0.015)	(0.010)	(0.016)	(0.008)
HH Distance in (KMs) to Nearest Population Center with +20,000	0.005	0.002	0.007*	0.002	0.006
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
HH Distance in (KMs) to Nearest ADMARC Outlet	0.007	-0.002	0.015	0.059**	-0.004
	(0.011)	(0.013)	(0.020)	(0.028)	(0.013)
household size	0.060***	0.100***	0.030	0.036	0.069***
	(0.020)	(0.023)	(0.028)	(0.028)	(0.025)
asset index	0.272***	0.307**	0.271**	0.404***	0.216**
	(0.076)	(0.133)	(0.122)	(0.125)	(0.091)
Dependency ratio	-0.000	-0.001	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
household obtained input coupons	0.149*	0.174*	0.111	0.151	0.148*
	(0.077)	(0.099)	(0.097)	(0.108)	(0.081)
Constant	1.140***	1.121***	1.202***	0.773**	1.135***
	(0.161)	(0.247)	(0.240)	(0.329)	(0.181)
Year FE	YES	YES	YES	YES	YES
HH FE	YES	YES	YES	YES	YES
N	2610	1266	1344	708	1902

Standard errors in parentheses

Sample includes only rural HHs assigned to group B. Dependent variable is a count of crop types that the household plants in a given year. Samples included for each of the columns are listed as follows: (1) All sample HHs (2) Poor HHs (3) Not poor HHs (4) Female headed HHs (5) Male headed HHs. Household and year fixed effects included.

* $p < 0.10$, **

Table 17: IV regression with household and year fixed effects: Multiple-season farming on the number of crops planted.

	Full Sample	Asset index		Gender of HH head	
	(1)	(2)	(3)	(4)	(5)
Dependent variable: Number of crops planted					
Multiple-season farming	2.043***	2.595***	1.678***	1.809**	2.118***
	(0.574)	(0.608)	(0.592)	(0.788)	(0.565)
Rainfall Anomaly	-0.000	-0.002	0.000	-0.000	-0.001
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
HH Distance in (KMs) to Nearest Road	0.014	0.018	0.008	0.022	0.014
	(0.009)	(0.015)	(0.010)	(0.017)	(0.008)
HH Distance in (KMs) to Nearest Population Center with +20,000	0.005	0.003	0.007*	0.003	0.006
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
HH Distance in (KMs) to Nearest ADMARC Outlet	0.012	0.012	0.016	0.062**	0.002
	(0.013)	(0.014)	(0.022)	(0.027)	(0.015)
household size	0.058***	0.094***	0.029	0.038	0.064***
	(0.020)	(0.025)	(0.027)	(0.029)	(0.023)
asset index	0.262***	0.244	0.274**	0.412***	0.199*
	(0.082)	(0.156)	(0.130)	(0.122)	(0.101)
Dependency ratio	-0.000	0.000	0.000	-0.000	0.000
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
household obtained input coupons	0.143*	0.139	0.119	0.112	0.169*
	(0.075)	(0.093)	(0.100)	(0.104)	(0.086)
Year FE	YES	YES	YES	YES	YES
HH FE	YES	YES	YES	YES	YES
N	2610	1266	1344	708	1902

Standard errors in parentheses

Sample includes only rural HHs assigned to group B. Dependent variable is a count of crop types that the household plant in a given year. Samples included for each of the columns are listed as follows: (1) All sample HHs (2) Poor HHs (3) Not poor HHs (4) Female headed HHs (5) Male headed HHs. Excluded instrument for IV estimations: ratio of neighbouring households that farmed in multiple seasons. Household and year fixed effects included.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18: OLS and IV regression with household and year fixed effects: Multiple-season farming on the number of crops planted, disaggregated by crop types.

	Staple Crops		Cash Crops		Vegetables		Legumes	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Multiple-season farming	0.301***	0.802**	0.032	0.202*	0.614***	0.577***	0.150***	0.435*
	(0.042)	(0.304)	(0.023)	(0.103)	(0.079)	(0.149)	(0.038)	(0.238)
Rainfall Anomaly	-0.000	0.000	0.001**	0.001***	-0.001*	-0.001*	-0.001	-0.001
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
HH Distance in (KMs) to Nearest Road	0.010**	0.009**	0.002	0.002	-0.002	-0.002	0.004	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)
HH Distance in (KMs) to Nearest Population Center with +20,000	-0.000	-0.000	-0.000	-0.000	0.002	0.002	0.003	0.003*
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
HH Distance in (KMs) to Nearest ADMARC Outlet	0.001	0.005	-0.003	-0.002	0.007	0.007	0.001	0.003
	(0.007)	(0.006)	(0.004)	(0.004)	(0.006)	(0.006)	(0.010)	(0.011)
household size	0.023***	0.022**	0.005	0.004	0.007	0.007	0.024**	0.023**
	(0.008)	(0.008)	(0.006)	(0.005)	(0.007)	(0.007)	(0.011)	(0.011)
asset index	0.048	0.042	0.065***	0.064***	0.102***	0.103***	0.061	0.058
	(0.040)	(0.046)	(0.021)	(0.023)	(0.038)	(0.038)	(0.061)	(0.060)
Dependency ratio	0.000	0.000	-0.000**	-0.000*	0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
household obtained input coupons	0.069*	0.066*	0.005	0.004	0.020	0.020	0.063*	0.062
	(0.038)	(0.037)	(0.019)	(0.018)	(0.028)	(0.028)	(0.036)	(0.037)
Constant	0.887***		0.212***		-0.105		0.182	
	(0.079)		(0.042)		(0.094)		(0.112)	
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
HH FE	YES	YES	YES	YES	YES	YES	YES	YES
N	2610	2610	2610	2610	2610	2610	2610	2610

Standard errors in parentheses

Sample includes only rural HHs assigned to group B. Dependent variables are counts of different crop types planted in a given year: Columns (1) and (2) are staple crops, columns (3) and (4) are cash crops, columns (5) and (6)are vegetables and columns (7) and (8) are legumes. Excluded instrument for IV estimations: ratio of neighbouring households that farmed in multiple seasons. Household and year fixed effects included.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 19: Linear probability model with household and year fixed effects: Multiple-season farming on the probability of selling to market.

	Full Sample	Asset index		Gender of HH head	
	(1)	(2)	(3)	(4)	(5)
Dependent variable: household sold any of its harvest to the market					
Multiple-season farming	0.146***	0.147**	0.137***	0.248***	0.105**
	(0.041)	(0.057)	(0.045)	(0.071)	(0.045)
Rainfall Anomaly	0.000	0.001*	-0.000	0.000	0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
HH Distance in (KMs) to Nearest Road	0.002	0.006	-0.002	-0.002	0.005
	(0.007)	(0.011)	(0.006)	(0.011)	(0.007)
HH Distance in (KMs) to Nearest Population Center with +20,000	-0.000	0.001	-0.001	-0.006***	0.003**
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
HH Distance in (KMs) to Nearest ADMARC Outlet	0.005	0.003	0.008	0.013	0.002
	(0.007)	(0.007)	(0.011)	(0.018)	(0.007)
household size	-0.003	0.003	-0.009	0.006	-0.009
	(0.006)	(0.010)	(0.011)	(0.015)	(0.009)
asset index	0.089**	0.083	0.094*	0.103	0.080*
	(0.036)	(0.060)	(0.054)	(0.074)	(0.043)
Dependency ratio	-0.000	-0.000*	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
household obtained input coupons	0.077***	0.086**	0.069**	0.104**	0.062*
	(0.027)	(0.033)	(0.032)	(0.051)	(0.033)
Constant	0.386***	0.331**	0.423***	0.423*	0.322***
	(0.084)	(0.124)	(0.094)	(0.221)	(0.096)
Year FE	YES	YES	YES	YES	YES
HH FE	YES	YES	YES	YES	YES
N	2610	1266	1344	708	1902

Standard errors in parentheses

Sample includes only rural HHs assigned to group B. Dependent variable is the probability of selling agricultural surplus to the market in a given year. Samples included for each of the columns are listed as follows: (1) All sample HHs (2) Poor HHs (3) Not poor HHs (4) Female headed HHs (5) Male headed HHs. Household and year fixed effects included.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 20: IV linear probability model with household and year fixed effects: Multiple-season farming on the probability of selling to market.

	Full Sample	Asset index		Gender of HH head	
	(1)	(2)	(3)	(4)	(5)
Dependent variable: household sold any of its harvest to the market					
Multiple-season farming	0.528^{*}	1.023^{***}	0.194	0.891^{***}	0.375
	(0.274)	(0.309)	(0.255)	(0.330)	(0.274)
Rainfall Anomaly	0.001	0.001	-0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
HH Distance in (KMs) to Nearest Road	0.001	0.005	-0.002	-0.004	0.004
	(0.008)	(0.011)	(0.006)	(0.013)	(0.007)
HH Distance in (KMs) to Nearest Population Center with +20,000	-0.000	0.001	-0.001	-0.005^{**}	0.003^{**}
	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)
HH Distance in (KMs) to Nearest ADMARC Outlet	0.008	0.012	0.008	0.017	0.004
	(0.008)	(0.008)	(0.011)	(0.021)	(0.007)
household size	-0.004	-0.001	-0.009	0.007	-0.010
	(0.006)	(0.012)	(0.011)	(0.015)	(0.008)
asset index	0.085^{**}	0.044	0.094^{*}	0.113	0.075
	(0.041)	(0.081)	(0.054)	(0.080)	(0.048)
Dependency ratio	-0.000	-0.000	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
household obtained input coupons	0.074^{***}	0.064^{*}	0.070^{**}	0.057	0.068^{**}
	(0.026)	(0.036)	(0.032)	(0.059)	(0.033)
Year FE	YES	YES	YES	YES	YES
HH FE	YES	YES	YES	YES	YES
N	2610	1266	1344	708	1902

Standard errors in parentheses

Sample includes only rural HHs assigned to group B. Dependent variable is the probability of selling agricultural surplus to the market in a given year. Samples included for each of the columns are listed as follows: (1) All sample HHs (2) Poor HHs (3) Not poor HHs (4) Female headed HHs (5) Male headed HHs. Excluded instrument for IV estimations: ratio of neighbouring households that farmed in multiple seasons. Household and year fixed effects included.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 21: Robustness check: Multiple-season farming on food security of rural households in Group A.

	HDDS		FCS		CSI	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Multiple-season farming	0.114	-0.497	1.680	2.481	-0.525	-6.495*
	(0.093)	(0.652)	(1.259)	(5.427)	(0.334)	(3.874)
Rainfall Anomaly	0.001	0.000	0.013	0.014	-0.005	-0.008
	(0.001)	(0.001)	(0.017)	(0.017)	(0.006)	(0.006)
HH Distance in (KMs) to Nearest Road	-0.011	-0.015	-0.062	-0.057	-0.083**	-0.118***
	(0.009)	(0.011)	(0.137)	(0.138)	(0.033)	(0.044)
HH Distance in (KMs) to Nearest Population Center with +20,000	0.004	0.004	-0.007	-0.007	-0.012	-0.015
	(0.003)	(0.003)	(0.066)	(0.067)	(0.016)	(0.019)
HH Distance in (KMs) to Nearest ADMARC Outlet	0.020	0.023	0.341	0.337	-0.121*	-0.091
	(0.025)	(0.026)	(0.263)	(0.269)	(0.071)	(0.085)
household size	0.004	0.010	-0.141	-0.149	0.337***	0.401***
	(0.022)	(0.024)	(0.245)	(0.241)	(0.109)	(0.106)
asset index	0.654***	0.670***	9.380***	9.359***	-1.691***	-1.532***
	(0.107)	(0.116)	(1.429)	(1.422)	(0.530)	(0.550)
Dependency ratio	-0.001**	-0.001***	-0.017***	-0.017***	0.004	0.004
	(0.000)	(0.000)	(0.006)	(0.006)	(0.004)	(0.004)
household obtained input coupons	0.127	0.133	-0.039	-0.047	-0.144	-0.089
	(0.083)	(0.085)	(0.821)	(0.808)	(0.377)	(0.381)
Constant	7.516***		52.595***		3.775***	
	(0.286)		(2.880)		(1.115)	
Year FE	YES	YES	YES	YES	YES	YES
HH FE	YES	YES	YES	YES	YES	YES
N	2729	2729	2729	2729	2728	2728

Standard errors in parentheses

Sample includes only rural HHs assigned to group A. Dependent variables are Household Dietary Diversity Score (0-10) for columns 1-2, Food Consumption Score (0-126) for columns 3-4, and Coping Strategy Index for columns 5-6. Excluded instrument for IV estimations: ratio of neighbouring households that farmed consecutively across seasons. Household and year fixed effects included.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 22: Robustness check: Multiple-season farming on crop diversity and probability of selling to markets

	Crop Diversity		Selling to Markets	
	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
Multiple-season farming	1.185***	2.180***	0.179***	0.333
	(0.084)	(0.661)	(0.043)	(0.209)
Rainfall Anomaly	-0.002**	-0.002	-0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.000)
HH Distance in (KMs) to Nearest Road	0.016	0.022*	0.003	0.004
	(0.011)	(0.011)	(0.003)	(0.003)
HH Distance in (KMs) to Nearest Population Center with +20,000	-0.005*	-0.004	-0.002**	-0.002**
	(0.003)	(0.003)	(0.001)	(0.001)
HH Distance in (KMs) to Nearest ADMARC Outlet	-0.022	-0.027	0.001	0.001
	(0.014)	(0.017)	(0.006)	(0.006)
household size	0.078***	0.067***	0.019***	0.017**
	(0.017)	(0.021)	(0.007)	(0.007)
asset index	0.192*	0.166	0.025	0.021
	(0.112)	(0.114)	(0.028)	(0.029)
Dependency ratio	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
household obtained input coupons	0.253***	0.243***	0.026	0.025
	(0.063)	(0.067)	(0.022)	(0.022)
Constant	1.543***		0.388***	
	(0.282)		(0.062)	
Year FE	YES	YES	YES	YES
HH FE	YES	YES	YES	YES
N	2729	2729	2729	2729

Standard errors in parentheses

Sample includes only rural HHs assigned to group A. Dependent variables are the count of crop types that the household plant in a given year (columns 1-2) and the probability of selling agricultural surplus to the market in a given year (columns 3-4). Excluded instrument for IV estimations: ratio of neighbouring households that farmed in multiple seasons. Household and year fixed effects included.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 23: OLS and IV Regressions: Multiple-season Farming on Household Plot Expansion.

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
Multiple-season farming	0.145***	0.337	0.038	0.238	0.200***	0.499
	(0.052)	(0.249)	(0.066)	(0.542)	(0.071)	(0.376)
Rainfall Anomaly	0.001	0.001	0.001*	0.001*	0.001*	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
HH Distance in (KMs) to	0.002	0.001	-0.003	-0.003	0.001	0.001
Nearest Road	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)
HH Distance in (KMs) to	0.001	0.001	0.001	0.001	0.001	0.001
Nearest Population Center with +20,000	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
HH Distance in (KMs) to	0.002	0.004	0.007	0.008	0.000	0.002
Nearest ADMARC Outlet	(0.013)	(0.013)	(0.015)	(0.015)	(0.013)	(0.012)
household size	0.105***	0.105***	0.113***	0.113***	0.098***	0.097***
	(0.017)	(0.017)	(0.018)	(0.018)	(0.017)	(0.017)
asset index	0.201**	0.198**	0.218**	0.221**	0.193**	0.189**
	(0.082)	(0.084)	(0.088)	(0.088)	(0.083)	(0.083)
Dependency ratio	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
household obtained input	0.070*	0.070*	0.066	0.065	0.080*	0.082*
coupons	(0.040)	(0.040)	(0.046)	(0.045)	(0.042)	(0.043)
Constant	1.180***		1.155***		1.226***	
	(0.149)		(0.167)		(0.155)	
Year FE	YES	YES	YES	YES	YES	YES
HH FE	YES	YES	YES	YES	YES	YES
Group dropped	None	None	Wetland	Wetland	Non-wetland	Non-wetland
N	2263	2263	1955	1955	2081	2081

*N*otes:Standard errors in parentheses. This table displays the OLS and IV results obtained by regressing total plot size on multiple-season farming and other household controls. Plots with areas below the 5th percentile and above the 95th percentile have been trimmed out to control for extreme values. Sample includes only rural HHs assigned to group B. Columns 1 and 2 display results on all sample HHs. Farmers who farm on seasonal wetlands during the dry season are dropped in columns 3 and 4, whereas farmers who do not farm on wetlands during the dry season are dropped in columns 5 and 6. Dependent variable is the total plot size cultivated by a household in a given year (in acres).Excluded instrument for IV estimations: ratio of neighbouring households that farmed in multiple seasons. Household and year fixed effects included.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figures

Figure 1. Map of Malawi

Source : Maduekwe and de Vries 2019

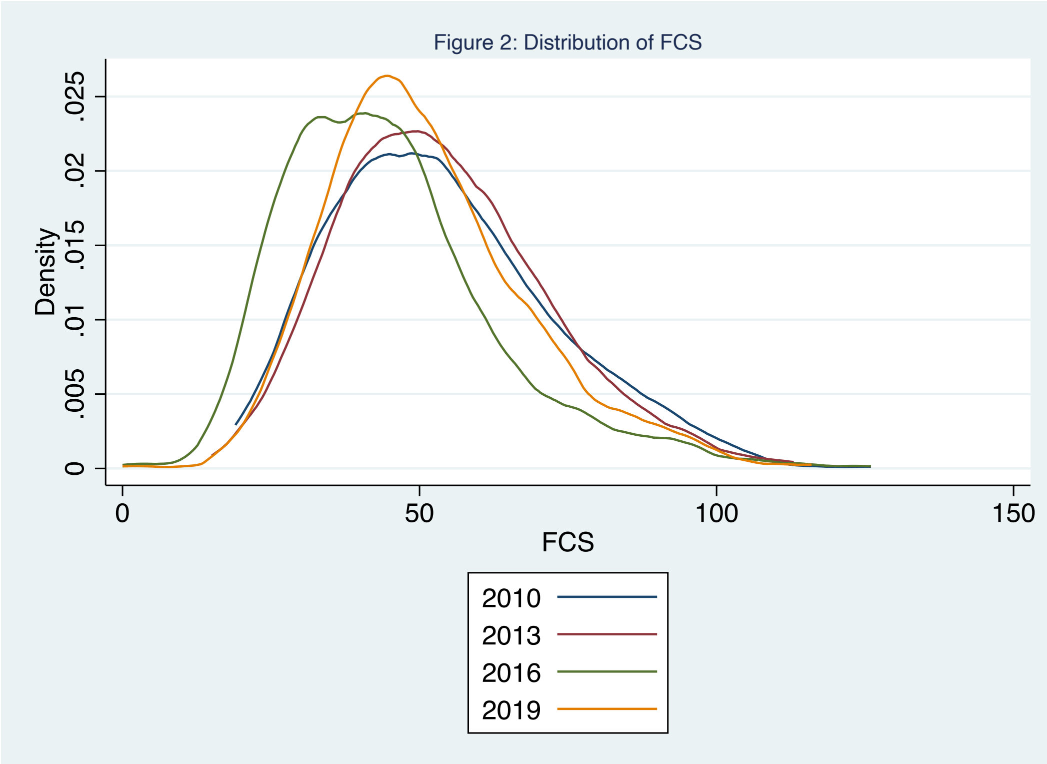


Figure 2: Distribution of FCS
Density
0
.005
.01
.015
.02
.025
0
50
100
150
FCS
2010
2013
2016
2019

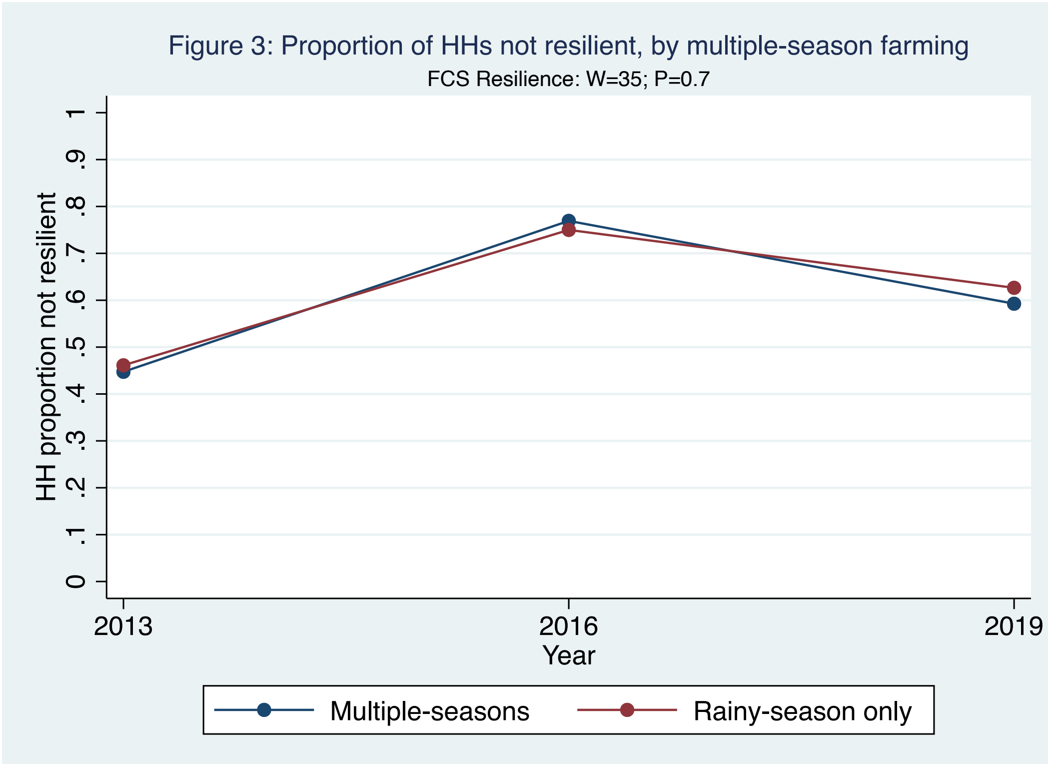


Figure 3: Proportion of HHs not resilient, by multiple-season farming
FCS Resilience: W=35; P=0.7
HH proportion not resilient
0
.1
.2
.3
.4
.5
.6
.7
.8
.9
1
2013
2016
2019
Year
Multiple-seasons
Rainy-season only

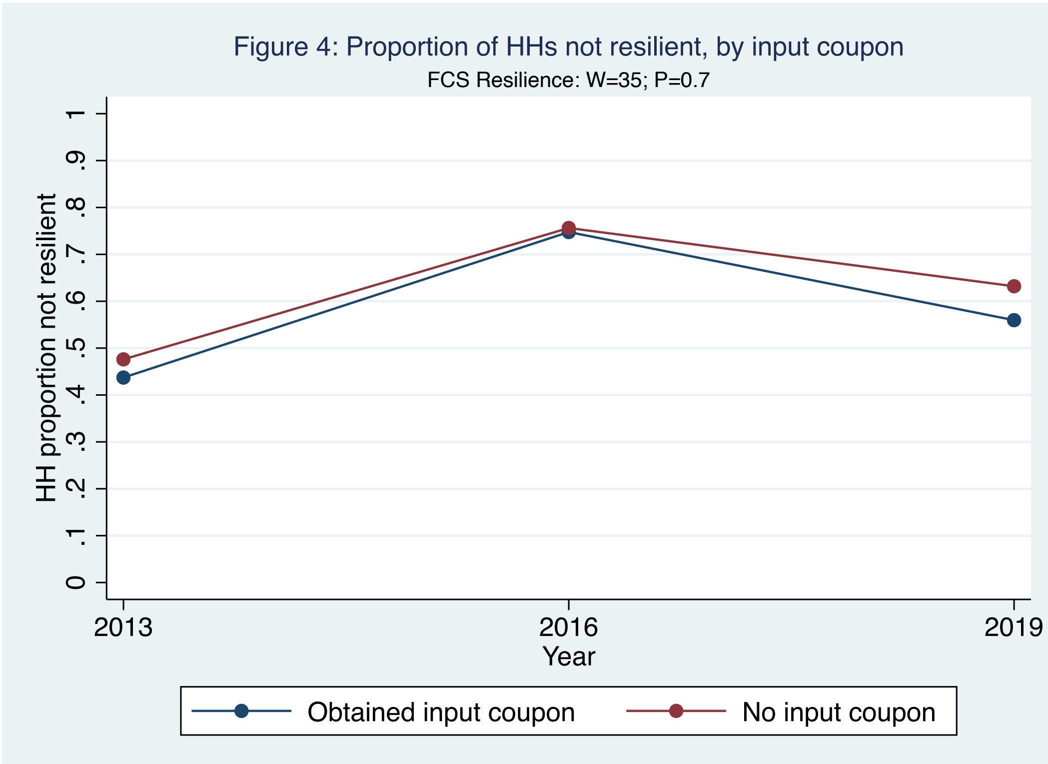


Figure 4: Proportion of HHs not resilient, by input coupon
FCS Resilience: W=35; P=0.7
HH proportion not resilient
0
.1
.2
.3
.4
.5
.6
.7
.8
.9
1
2013
2016
2019
Year
Obtained input coupon
No input coupon

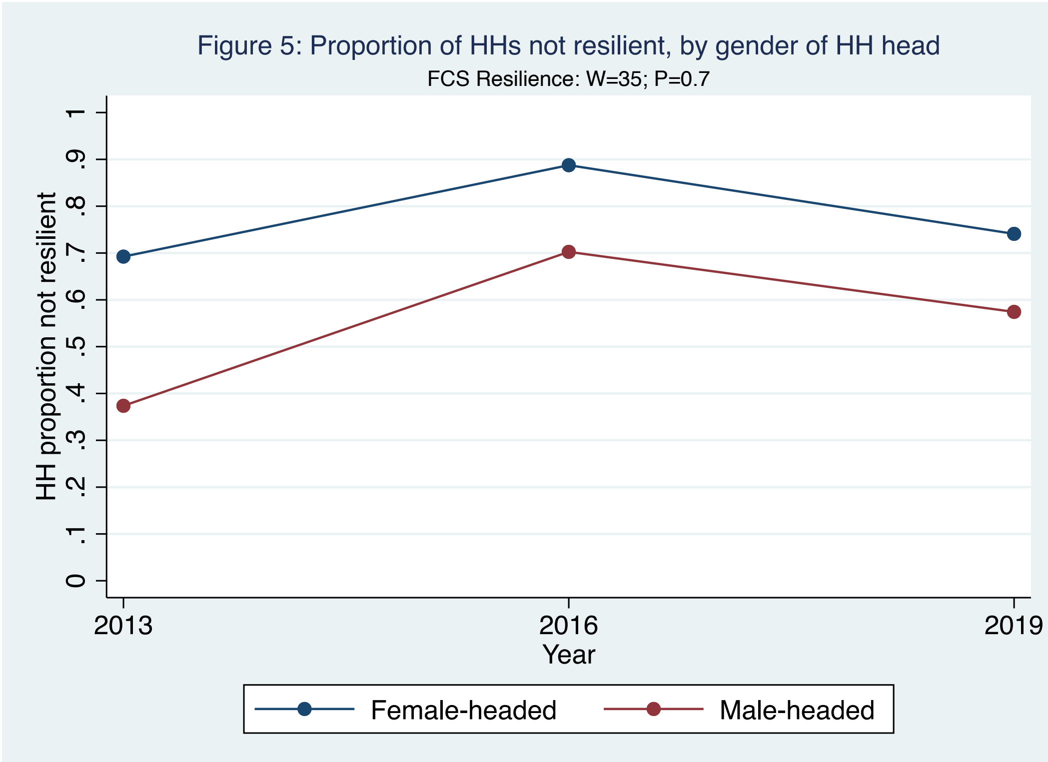


Figure 5: Proportion of HHs not resilient, by gender of HH head
FCS Resilience: W=35; P=0.7
HH proportion not resilient
0
.1
.2
.3
.4
.5
.6
.7
.8
.9
1
2013
2016
2019
Year
Female-headed
Male-headed

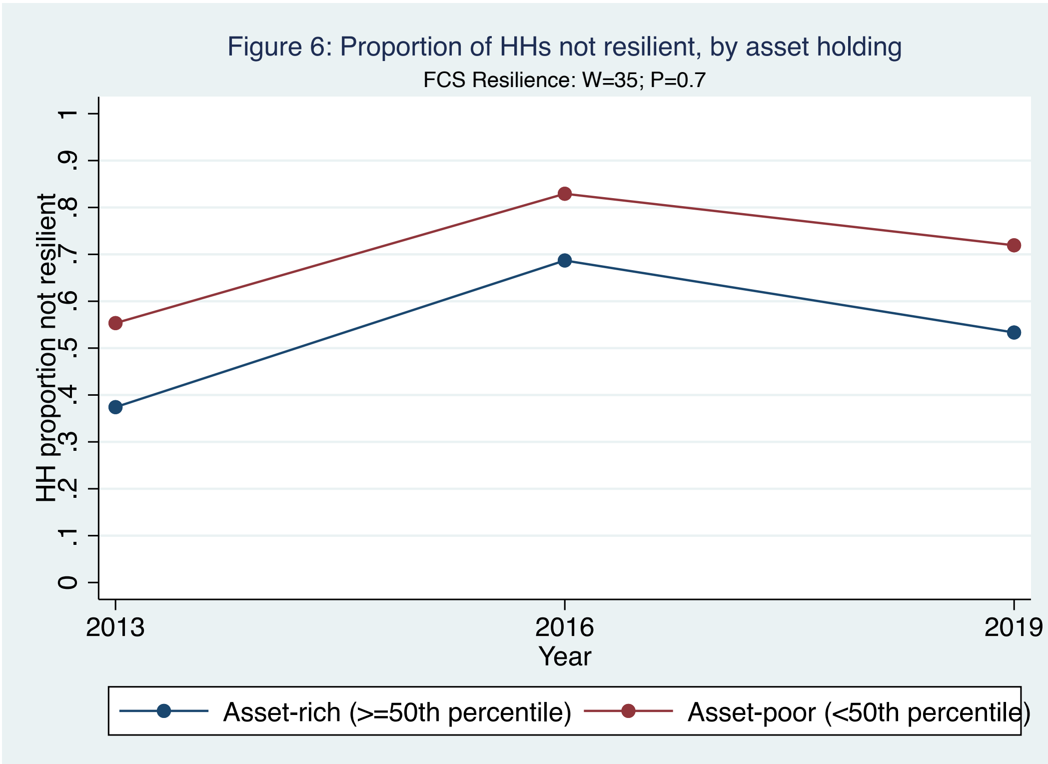


Figure 6: Proportion of HHs not resilient, by asset holding
FCS Resilience: W=35; P=0.7
HH proportion not resilient
0
.1
.2
.3
.4
.5
.6
.7
.8
.9
1
2013
2016
2019
Year
Asset-rich (>=50th percentile)
Asset-poor (<50th percentile)

Appendix

Table A1: IV First-stage regression: Rainfall anomaly and ratio of nearby HHS farming multiple seasons on multiple-season farming

	(1) Multiple-season farming
Local rate of adoption of multiple-season farming	0.655***
	(0.081)
Rainfall Anomaly	-0.000
	(0.000)
HH Distance in (KMs) to Nearest Road	0.001
	(0.002)
HH Distance in (KMs) to Nearest Population Center with +20,000	0.001
	(0.001)
HH Distance in (KMs) to Nearest ADMARC Outlet	-0.001
	(0.003)
household size	0.003
	(0.005)
asset index	0.017
	(0.031)
Dependency ratio	-0.000**
	(0.000)
household obtained input coupons	0.005
	(0.017)
Year FE	YES
HH FE	YES
N	2610

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Cultivation on wetland among Multiple-season farmers, by year.

	2010	2013	2016	2019
Number of dry-season farmers on wetland	39	112	96	79
Number of households farming both seasons	70	140	125	145
Percentage of wetland	56	80	77	54

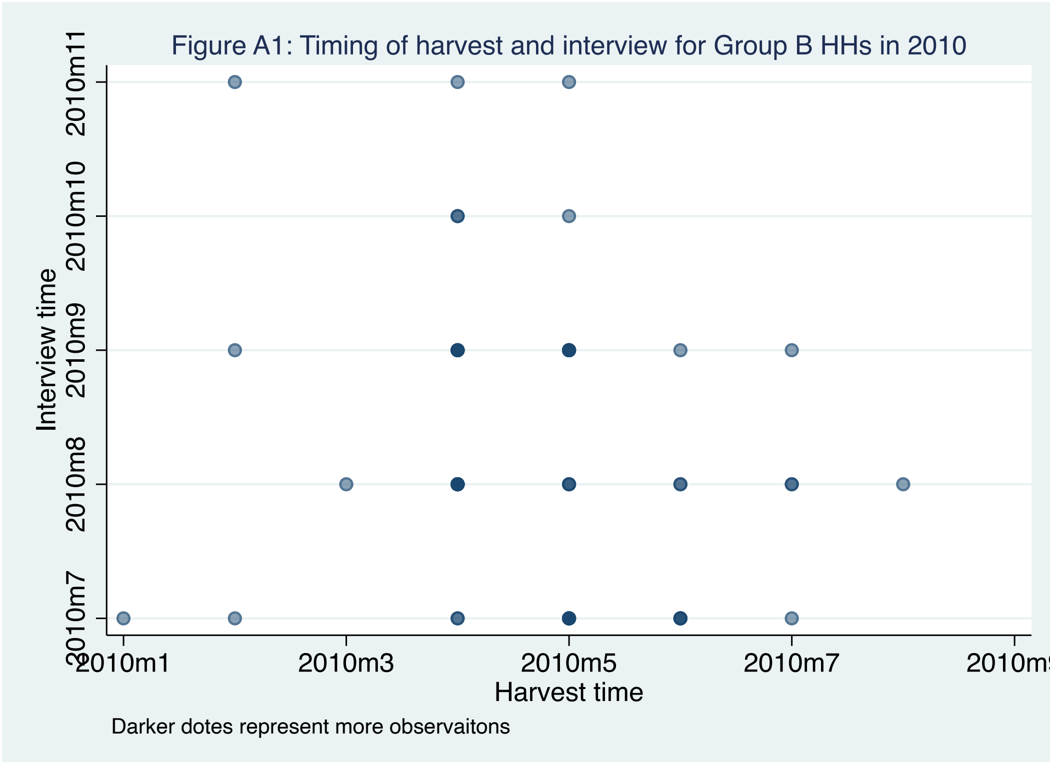


Figure A1: Timing of harvest and interview for Group B HHs in 2010
Interview time
2010m11
2010m10
2010m9
2010m8
2010m7
2010m1
2010m3
2010m5
2010m7
2010m9
Harvest time
Darker dotes represent more observaitons

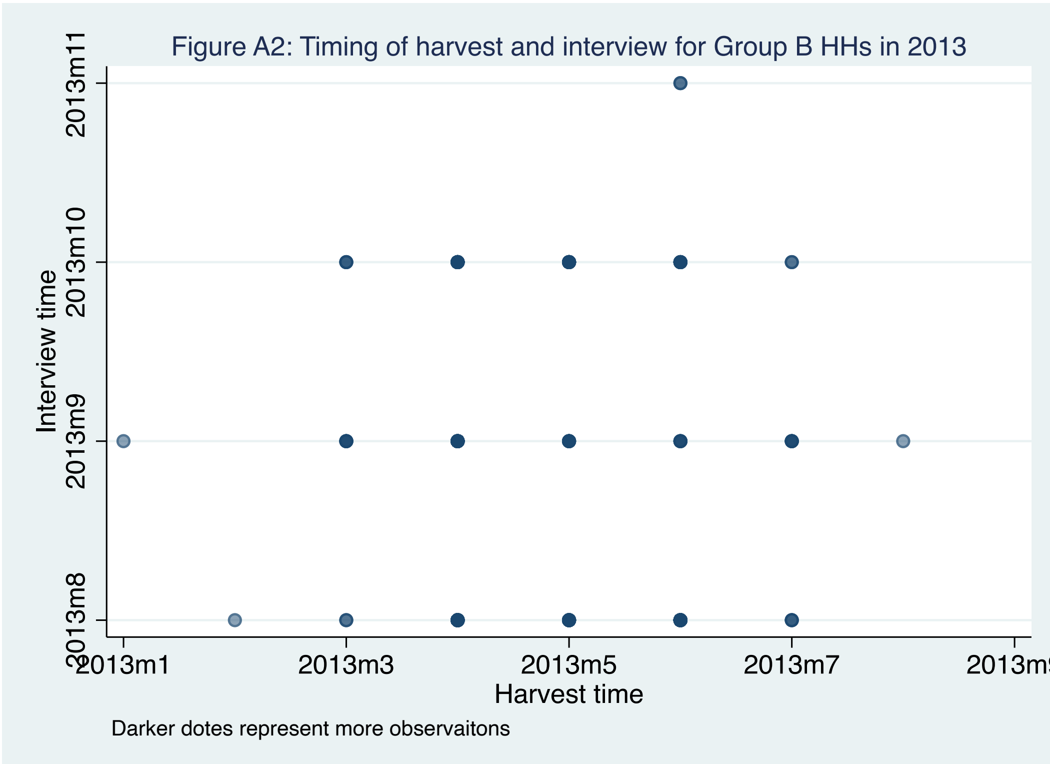


Figure A2: Timing of harvest and interview for Group B HHs in 2013
Interview time
2013m8
2013m9
2013m10
2013m11
2013m1
2013m3
2013m5
2013m7
2013m9
Harvest time
Darker dotes represent more observaitons

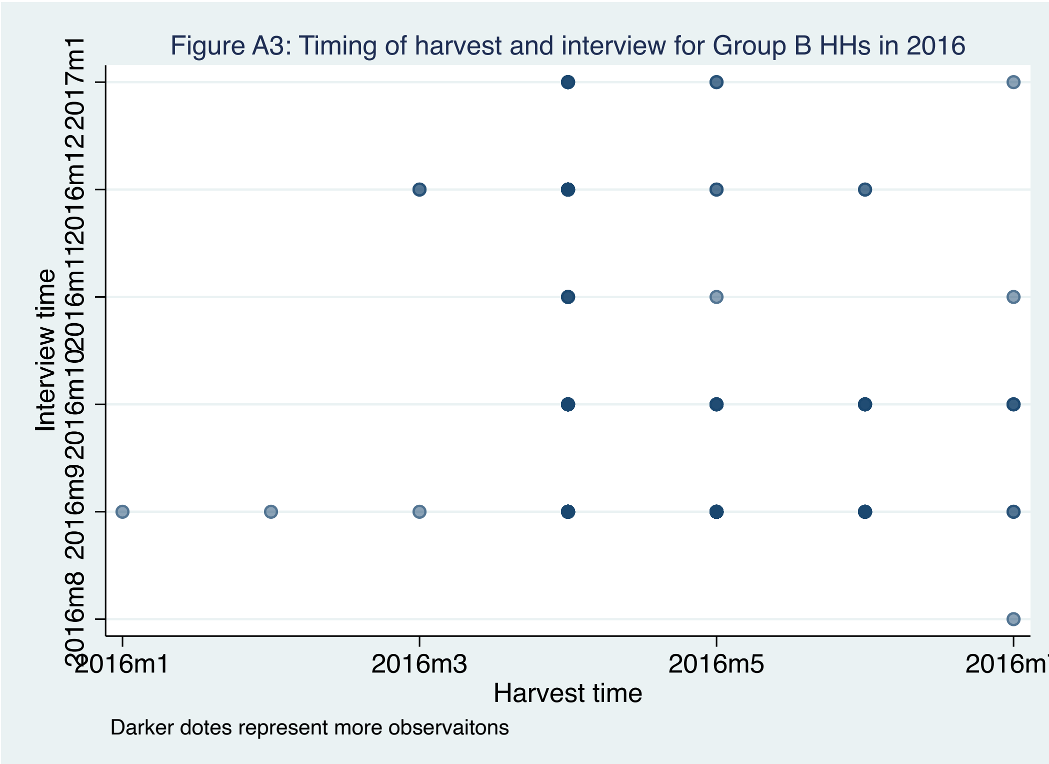
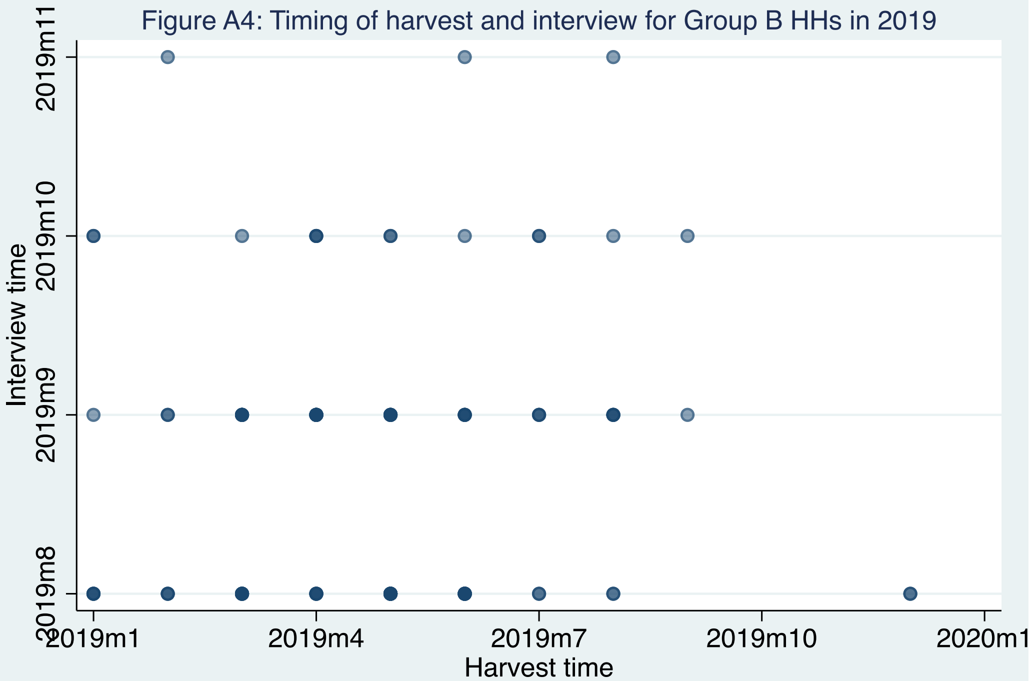


Figure A3: Timing of harvest and interview for Group B HHs in 2016
Interview time
2016m8
2016m9
2016m10
2016m11
2016m12
2017m1
2016m1
2016m3
2016m5
2016m7
Harvest time
Darker dotes represent more observaitons

Figure A4: Timing of harvest and interview for Group B HHs in 2019



Darker dotes represent more observaitons

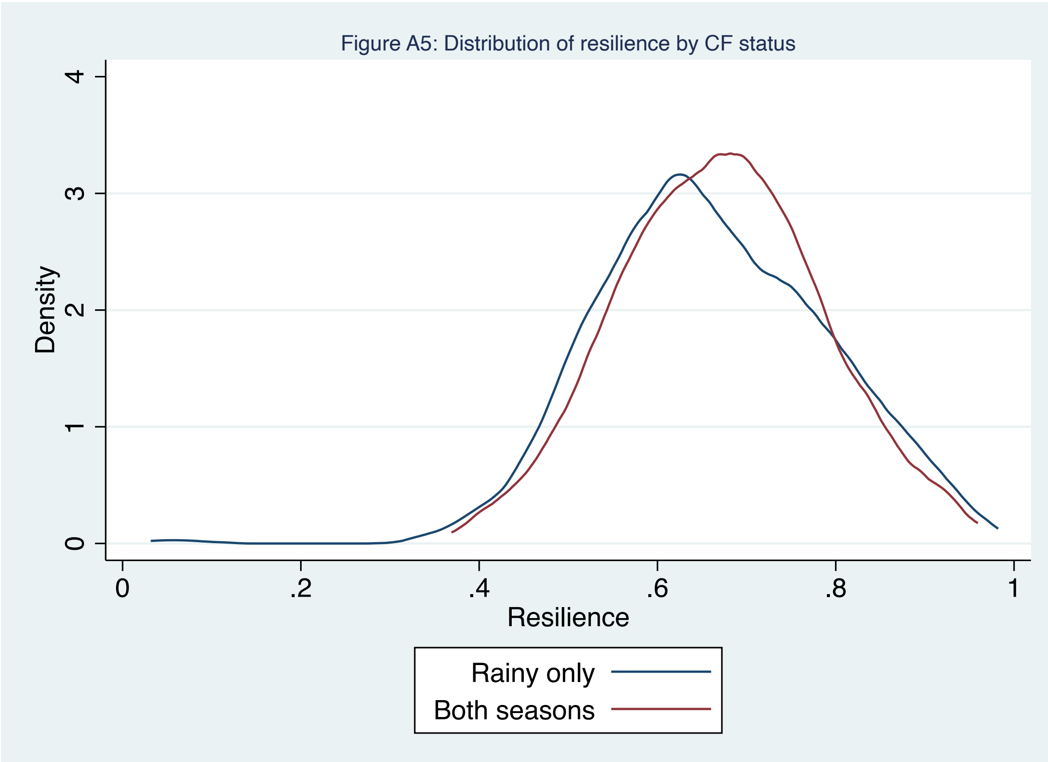


Figure A5: Distribution of resilience by CF status
Density
0
1
2
3
4
0
.2
.4
.6
.8
1
Resilience
Rainy only
Both seasons

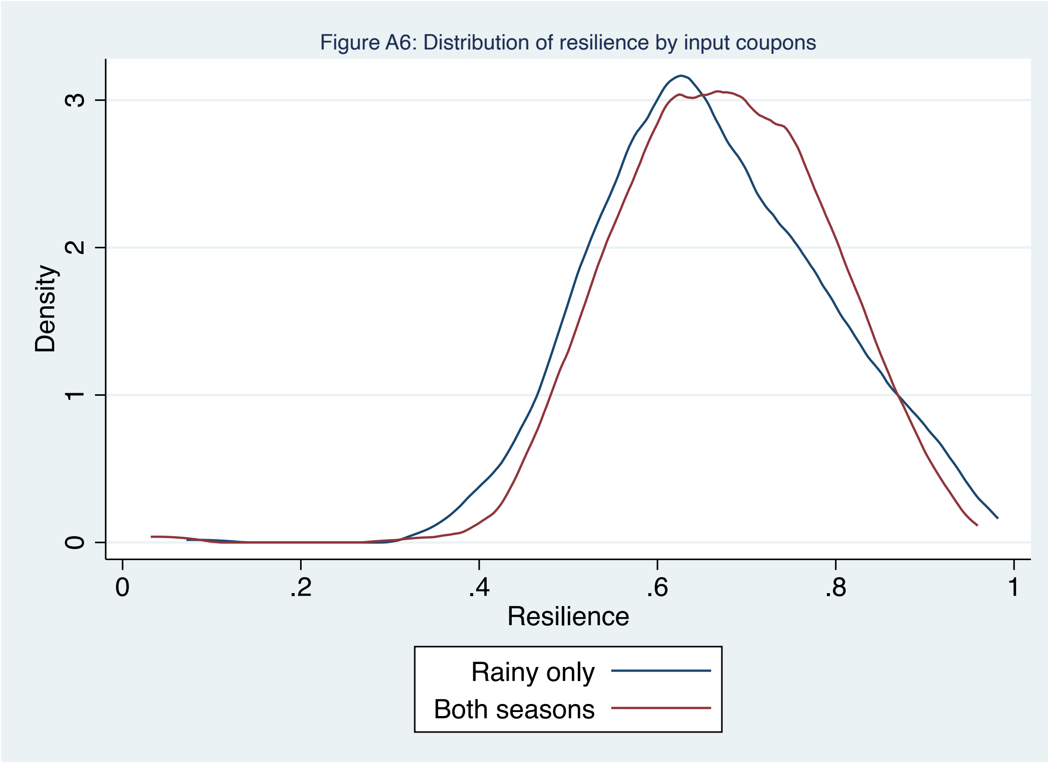


Figure A6: Distribution of resilience by input coupons
Density
0
1
2
3
0
.2
.4
.6
.8
1
Resilience
Rainy only
Both seasons

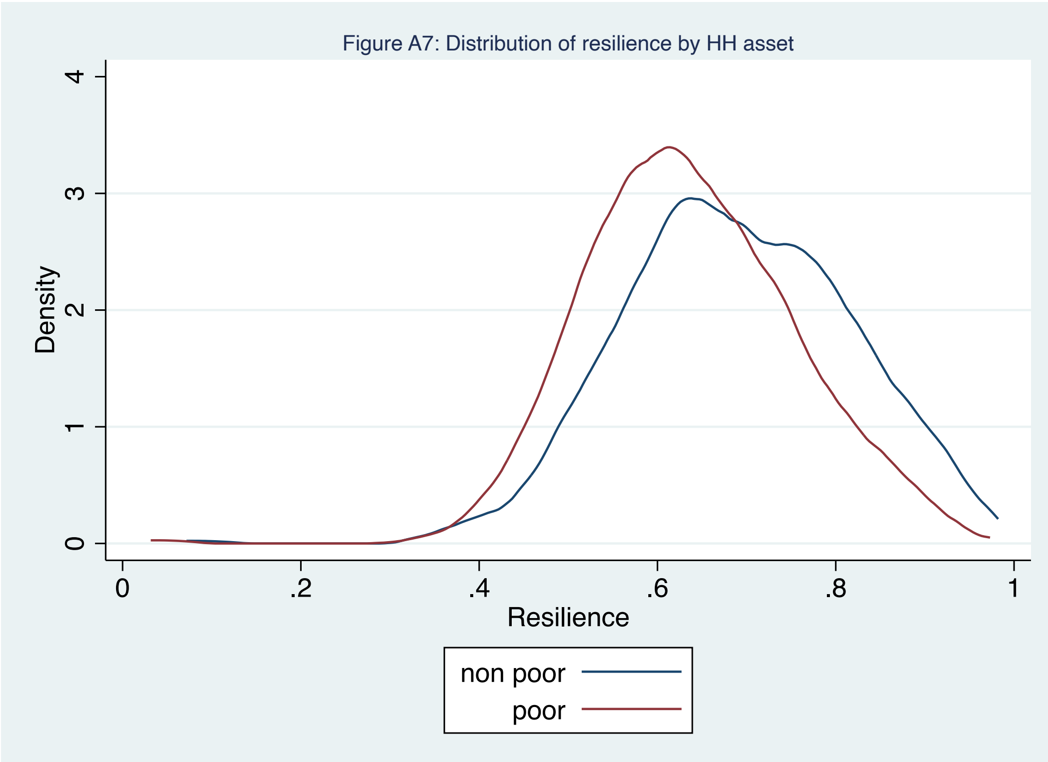


Figure A7: Distribution of resilience by HH asset
Density
0
1
2
3
4
0
.2
.4
.6
.8
1
Resilience
non poor
poor

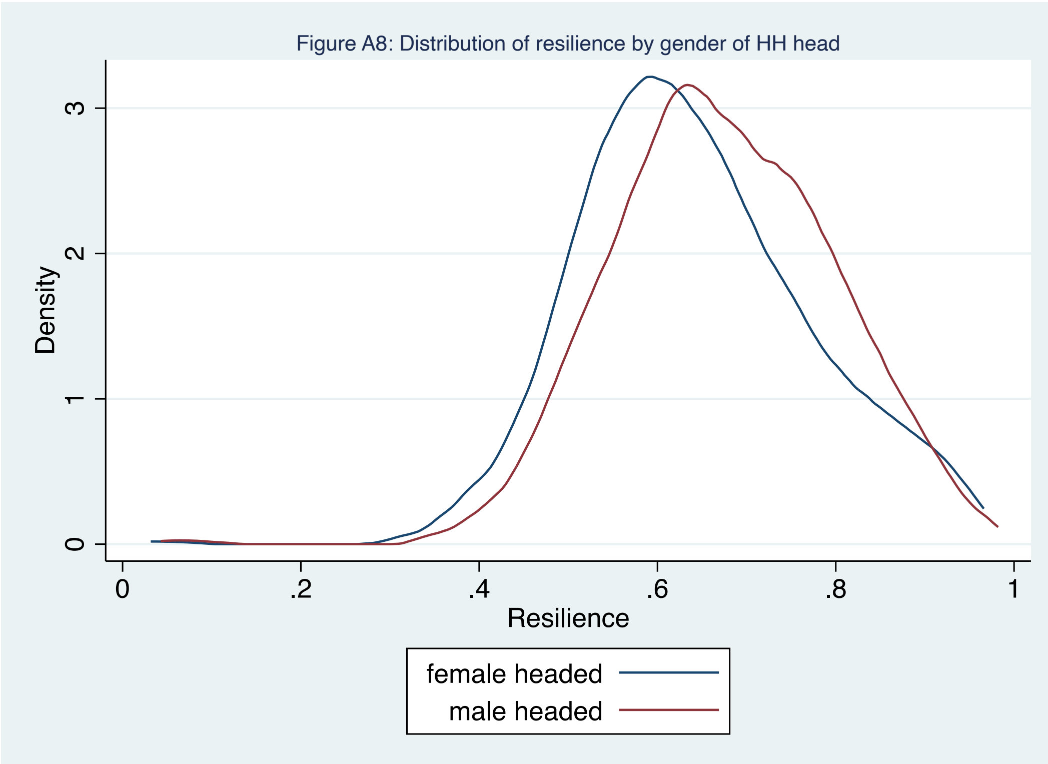


Figure A8: Distribution of resilience by gender of HH head
Density
0
1
2
3
0
.2
.4
.6
.8
1
Resilience
female headed
male headed