Hoping or Coping? Livelihood Diversification and Household Resilience to the COVID-19 Pandemic[1]

by

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A Thesis Submitted to the Faculty of the

Department of Agricultural and Resource Economics

In Partial Fulfillment of the Requirements
For the Degree of

Master of Science

In the Graduate College

The University of Arizona

2 0 2 2

[1]The pre-analysis plan for this study was filed at https://osf.io/nu593.

THE UNIVERSITY OF ARIZONA
GRADUATE COLLEGE

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Final approval and acceptance of this thesis is contingent upon the candidate's submission of the final copies of the thesis to the Graduate College.

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Acknowledgments

I would like to thank Drs. Anna Josephson and Jeffrey Michler for their support, advice, and patience. I thank them for the many opportunities they have afforded me and hours they have spent answering my questions.

I would also like to thank Talip Kilic and Corrie Hannah for their advice and technical assistance.

Lastly, I thank my amazing partner, friends, and family for making these last two years so wonderful.

Land Acknowledgement

I respectfully acknowledge the University of Arizona is on the land and territories of Indigenous peoples. Today, Arizona is home to 22 federally recognized tribes, with Tucson being home to the O'odham and the Yaqui.

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Abstract

In this paper, we examine the impact of livelihood diversification on household welfare outcomes in Sub-Saharan Africa amid the COVID-19 pandemic. We use panel survey data in Ethiopia, Malawi, Nigeria, and Uganda to investigate livelihood diversification as a coping strategy to mitigate the socioeconomic repercussions of COVID-19. We explore heterogeneous income strategies and welfare outcomes for sub-populations such as urban and rural households as well as female- and male-headed households. Findings from our dynamic panel models and ANCOVA specifications do not support the hypothesis that livelihood diversification boosts household resilience to major events like the pandemic. But, in some cases, our results suggest that the opposite is true: household income *specialization* is associated with more favorable welfare outcomes. When observing heterogeneous impacts, we find some evidence that income diversification may be an effective strategy to enhance resilience for female-headed households. However, our results are not statistically significant nor consistently found across all specifications. We hope these findings encourage researchers to investigate alternative methods to enhancing resilience to calamitous shocks, such as those experienced during the COVID-19 pandemic.

Introduction

The COVID-19 pandemic has brought to the fore many of the hardships faced by poor households and individuals. These challenges are exacerbated as impoverished households attempt to cope with the reverberating impacts of the pandemic. Smallholder farmers across Sub-Saharan Africa (SSA) may be particularly vulnerable to these socioeconomic shocks due to their high exposure to contemporaneous shocks and limited resource availability. While farmers cannot control their risk of exposure, they can employ *ex ante* and *ex post* coping strategies to mitigate risks and enhance resilience. One such strategy is diversification of household livelihood sources away from solely subsistence farming. For farming households across SSA, among whom formal insurance against realized risks is not common, these strategies often involve reallocation of resources, monies, and labor within the family or household.

A rich body of literature evaluates livelihood diversification as a coping strategy to improve resilience to shocks, particularly those related to climate and civil unrest. These studies generally coalesce around the conclusion that income diversification improves household welfare outcomes (Arslan et al., 2018; Dagunga et al., 2020; Welderufael, 2014). However, there is limited empirical evidence on the efficacy of diversification coping strategies to mitigate negative impacts under extreme conditions, such as the public health threat and subsequent government restriction during the COVID-19 pandemic. We seek to fill this gap, investigating livelihood diversification as a coping strategy for dealing with the pandemic in Ethiopia, Malawi, Nigeria, and Uganda. We also investigate the heterogeneous reallocation strategies and outcomes for various population subgroups such as urban and rural households as well as female- and male-headed households.

To better understand how households use livelihood diversification to cope with shocks and stressors, we investigate three research questions:

1. How has household income composition/diversification changed since the pandemic?

2. How does household income composition/diversification impact household-level welfare outcomes amid the pandemic?

3. How do changes in income composition/diversification and subsequent effects on household-level livelihood outcomes vary across different population subgroups?

To answer these questions, we use face-to-face survey data collected in Ethiopia, Malawi, Nigeria, and Uganda prior to the COVID-19 pandemic as a baseline for the study. To form a panel, we append post-outbreak phone surveys in the four countries. Both data sets are made available by the World Bank. Questionnaires included in these two data sets allow us to observe household activities and choices over time. These questionnaires include information about household characteristics, income-generating activities, food insecurity, and education. We use data on household income sources to generate six indices measuring income diversification, which serve as our key variables of interest in our empirical specifications.

Prior to the release of the phone survey data, we pre-specified our analysis and posted a pre-analysis plan (PAP) publicly on OSF. In the PAP, we outline the data, variables, empirical specifications, and hypotheses used in this analysis. In the registry, we explain how we generate each of our six livelihood diversification indices and which variables we use to measure welfare outcomes. We outline each of our research questions and the empirical strategies we use to address them. Pre-specifying these components of the research before conducting any analysis mitigates the opportunity to cherry-pick, HARK, or p-hack results.

To address our first research question, we observe trends in income composition and livelihood diversification over time. We hypothesize that household income composition changed following the onset of the pandemic. In some Malawi and Uganda, the percent of household receiving remittances and wage income declined between 2019 and early 2020 following the onset of COVID-19. Other countries and income sources do not exhibit observable changes over time. Overall, these findings do not point to a substantial or systematic change in household income strategies since the onset of the pandemic.

In response to our second research question, we use our rich data sources to employ dynamic panel models and difference-in-difference estimation, accounting for unobserved heterogeneity. To assess household welfare outcomes, we use household food insecurity and child educational engagement as dependent variables. We hypothesize that income diversification is associated with better household welfare outcomes (Arslan et al., 2018; Dagunga et al., 2020; Welderufael, 2014). Ultimately, our findings do not generally support this hypothesis. In fact, in Ethiopia, evidence suggests that livelihood diversification may be associated with worse welfare outcomes. We do not find sufficient evidence to reject the null hypothesis for any empirical specification.

Last, we include interaction terms in our ANCOVA specifications to observe heterogeneous effects for population subgroups. We hypothesize that the relationship between livelihood diversification and household welfare varies based on household characteristics such as sector and head-of-household gender. While we find some evidence to suggest that income diversification may be more effective for female-headed households, these results are not consistent across all models and are not statistically significant. We do not observe a different relationship between livelihood diversification and household welfare outcomes for urban and rural populations.

Ultimately, our findings do not support our hypotheses. We do not find evidence that (1) income composition changed since the onset of the pandemic, (2) income-diverse households are better equipped to cope with the socioeconomic ramifications of the COVID-19 pandemic, or (3) livelihood diversification impacts vary for different population subgroups. These result suggest that alternative means of augmenting resilience may be more effective than livelihood diversification in the face of a socioeconomic disaster such as the COVID-19 pandemic. More research is required to better understand which household strategies or characteristics are associated with higher resilience capacity in SSA.

Literature Review

We conduct our literature review using a structured search method. This systematic review covers 1,200 Boolean searches in three search engines to find relevant research articles. We ultimately find 88 relevant articles, many of which are discussed in this section. For more details about the structured search methodology used to conduct this literature review consult Appendix A.

Despite the recency of the COVID-19 outbreak, there is a substantial body of literature summarizing the socioeconomic ramifications of the pandemic on households in low-income countries. Stoop et al. (2021) examine a sample in the eastern portion of the Democratic Republic of the Congo to compare the impacts of COVID-19 to those suffered during the Ebola outbreak. They find the coronavirus to be more damaging to household finances due to its high transmissability coupled with global economic interconnectedness, despite the relatively low number of cases in the area. Kansiime et al. (2021) also evaluate the impact of the COVID-19 pandemic on income, but extend the analysis to include how changes in income impact food security. Their results indicate that income-poor and wage-dependent households in Kenya and Uganda were particularly vulnerable to income shocks, which led to poorer nutrition outcomes. Research suggests that COVID-19 also reduced food security, employment, and education in Ethiopia (Habtewold, 2021). Similarly, Mahmud and Riley (2021) found that households in Uganda responded to a 60 percent decrease in income after the COVID-19 outbreak by reducing food purchases by 50 percent, dipping into savings, and increasing labor supply to household farm activities. In Nigeria, Balana et al. (2020) find that households reacted in a similar manner, with 88 percent of households losing approximately 50 percent of their income as a result of the pandemic. Subsequently, about 66 percent of respondents reported they reduced food consumption to cope with these loses. Furbush et al. (2021) find that about 80 to 90 percent of households in Ethiopia, Malawi, Nigeria, and Uganda were concerned about the financial ramifications of the pandemic, an even higher percentage than those concerned about themselves or their families falling ill with the virus.

Households in low-income countries may suffer from contemporaneous shocks and persistent risk exposure, which increases their vulnerability to poverty and food insecurity. To understand the dynamics of compounding risks, Tranchant et al. (2020) employ a two-stage least squares regression model to study the effects of conflict, drought, and illness in India. They find that illness and drought only impacted child nutrition in areas already stressed by political violence. Josephson and Shively (2021) study the effect of rainfall shocks and the unexpected death of a household member in the context of hyperinflation in Zimbabwe. Households in the country responded to these compounding shocks and stressors by reallocating household labor to different activities. The authors further conclude that different types of income shocks led to disparate responses and coping strategies. Similarly, in the Philippines, one shock increased the chances of another: experience of natural disasters was associated with increased family violence, parental stress, and physical abuse (Edwards et al., 2021).

The directionality of the relationship between shocks and livelihood diversification is debated in the literature. Do households diversify their incomes to bolster resilience to future shocks and uncertainty (an *ex ante* coping behavior), or decide to diversify only after a shock exposes their vulnerability (an *ex post* coping behavior)? Arslan et al. (2018) suggest that households diversify their livelihoods in preparation for future shocks, finding that households in areas in Zambia with highly variable rainfall perceived income, crop, and livestock diversification as *ex ante* risk management strategies. Findings further indicate that all three types of diversification increased per capita income while reducing the probability of falling into poverty. Similarly, Welderufael (2014) find diversification of livelihoods raised consumption and helped ensure food security among household in Ethiopia. Alternatively, Mulwa and Visser (2020) find that past experience of shocks was a key determinant of farm diversification and Cely-Santos and Hernández-Manrique (2021) find that livelihood diversification was a strategy to cope with resource scarcity. Asfaw et al. (2019) also find evidence that livelihood diversification is used as an *ex post* coping strategy, finding that exposure to extreme rainfall was associated with increased livelihood diversification in Malawi, Niger, and Zambia.

Certain household characteristics may dictate households' adaptive capacity and ability to reallocate household resources to cope with the realization of shocks. Farming families in Ethiopia, Kenya, Tanzania, Malawi, and Mozambique whose household head was female, married, or elderly opted to change farming methods and decrease consumption in the face of climate-related shocks but were less likely to seek alternate livelihood options (Rahut et al., 2021). In Bangladesh, social and human capital, exposure to information, asset holdings, safety nets, access to markets and services, women's empowerment, and psycho-social capabilities enhanced adaptive capacity to flooding events (Smith and Frankenberger, 2018). Education and participation in household enterprises enhanced resilience capacity in Uganda, while female-headed households remained least resilient (d'Errico and Di Giuseppe, 2018). Exposure to conflict was found to reduce adaptive capacity among households in Gaza (Brück et al., 2019). In somewhat contrast to these findings, Tran (2015) find that physical asset holdings, rather than household characteristics, determined shock recovery in Vietnamese households.

For those households able to adapt, livelihood allocation affects household and individual resilience and welfare outcomes. Many studies conclude that livelihood diversification reduces poverty and enhances resilience in SSA (Dagunga et al., 2020; Welderufael, 2014; Arslan et al., 2018; Mulwa and Visser, 2020). Often, food security measures serve as a proxy for household well-being. Numerous studies illustrate the negative impacts of climate events or economic shocks on household food security (Ebhuoma and Simatele, 2017; Gupta et al., 2021; Harttgen et al., 2016; Oskorouchi and Sousa-Poza, 2021; Wossen et al., 2018). However, determining the portion of these negative impacts associated with income loss or offset by income diversification is more nuanced. Picchioni et al. (2021) survey recent literature on COVID-19 and conclude that the major effects of the pandemic on nutritional outcomes in low- and middle-income countries stem from its impact on employment, income generating activities, and purchasing power. Similarly, George et al. (2020) determine that income loss is also a key mechanism through which conflict is associated with food insecurity in Nigeria.

Child educational engagement is another indicator of household welfare that may be impacted by livelihoods. Di Maio and Nandi (2013) report that job loss in occupied Palestinian Territories increased school dropout probability by nine percentage points. Likewise, unemployment shocks in Brazil significantly increased the probability that children dropped out or failed to advance in school (Duryea et al., 2007). Grimm (2011) seeks to quantify the income elasticity of school enrollment in Burkina Faso, finding that a 10 percent decline in income decreased enrollment by 2.5 percentage points.

Often, welfare effects are heterogeneous across genders, income classes, and employment types. Farm households in coastal Bangladesh that experienced a cyclone shock subsequently invested less in men's education than women's (Mottaleb et al., 2015). Conversely, conflict in Tajikistan resulted in decreased schooling of girls but had no effect on boys' education (Shemyakina, 2011). Josephson et al. (2021) and Hirvonen et al. (2020) find that impoverished households were disproportionately harmed by COVID-19 in terms of dietary diversity and food insecurity. Ahmed et al. (2021) explore heterogeneous effects of livelihood diversification across employment types. They find that households in rural Bangladesh that depended on casual labor were the most impacted by the COVID-19 pandemic while households with regular jobs were affected least.

Some evidence supports an alternative hypothesis that livelihood diversification in itself does not influence household resilience and welfare outcomes, but rather engagement in certain economic activities. For example, Gautam and Andersen (2016) use data from Nepal to determine that welfare outcomes were not related to income diversification per se, but rather to involvement in high-return sectors such as trade or salaried work. Kesar et al. (2021) also find that salaried workers in India were least likely to lose their jobs during the COVID-19 pandemic. Similarly, Bezu et al. (2012) find that higher shares of non-farm income were associated with higher consumption expenditures in Ethiopia. The receipt of remittances, regardless of other household labor allocation schemes, may also ameliorate welfare outcomes and strengthen household resilience (Fisher et al., 2017; Akim et al., 2021; Mora-Rivera and van Gameren, 2021; Murakami, 2021).

This paper builds upon this body of existing literature to extend our understanding the role of livelihood diversification in bolstering household resilience to severe socioeconomic shocks. We expand existing literature on food security and educational outcomes amid shocks to cover the COVID-19 context. Our empirical strategy utilizes multiple indices to measure income diversification. We take advantage of novel high-frequency panel data to analyze our research questions. Ultimately, we exploit this rich longitudinal data to go farther than much of the existing literature to establish a causal link between livelihood diversification and welfare outcomes.

Data

To examine the relationship between livelihood diversification and welfare outcomes, we use panel data from high frequency phone surveys (HFPS) in Ethiopia, Malawi, Nigeria, and Uganda. In each country, interviewers conduct these phone interviews, following up with households for a period of 12 months following the outbreak of COVID-19. The following agencies implement the monthly surveys with support from the World Bank Living Standards Measurement Study (LSMS): Laterite Ethiopia, the Malawi National Statistical Office, the Nigeria Bureau of Statistics, and the Uganda Bureau of Statistics. The surveys result in anonymized, unit-record data and basic information documents, interviewer manuals, and questionnaires associated with each monthly survey. All HFPS data rounds are publicly available through the World Bank Microdata Library.

HFPS are not nationally representative because participation requires that each household have (1) at least one member who owned a phone, (2) cell network coverage, and (3) access to electricity. These requirements may lead to selection bias in the survey sample. Additionally, the surveys may suffer from non-response bias if targeted households were not willing or able to participate. In most cases, non-response was not a result of refusal to participate but rather due to non-working phone numbers or prospective respondents not answering calls (Josephson et al., 2021). To address these challenges, we use survey weights provided in the HFPS data which include selection bias corrections and post-stratification adjustments. With the inclusion of these weights, we ensure that sample populations are representative at the national, regional, and urban/rural levels. For a detailed description of the weight calculations used in this study, see Josephson et al. (2021).

The sample for these post-COVID-19 outbreak surveys is drawn from households that had been interviewed during the most recent (2019) round of the national longitudinal household survey implemented by the respective national statistical office, with assistance from the World Bank LSMS. These pre-Covid-19 Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA) data are representative at the national, regional, and urban/rural levels and serve as a baseline for post-COVID-19 analysis. The pre-COVID-19 surveys and data are also made publicly available through the World Bank LSMS.

The integration of data from the post-outbreak HFPS and pre-COVID-19 LSMS-ISA surveys allows us to capture the variation in the effects of the pandemic across a diverse set of SSA countries and over time. Importantly, the combined data afford us the opportunity to examine the effects of COVID-19 while considering a baseline, collected before the onset of the pandemic. The surveys feature cross-country comparable questionnaires on a range of topics including participation in income-generating activities, food security, and child educational engagement. In total, over 9,000 households are included in this analysis. With baseline LSMS-ISA data in all four countries and 10 rounds of HFPS data in Ethiopia, 11 in Malawi and Nigeria, and five in Uganda, our research draws from a total of over 81,000 observations. The mean number of households in each round of data is 2,784 in Ethiopia, 1,611 in Malawi, 1,943 in Nigeria, and 2,164 in Uganda.

3.1 Variable Specification and Summary Statistics

3.1.1 COVID-19 Shock

Our analysis focuses on COVID-19 as the primary covariate shock experienced by households. The spread of the virus impacts household finances indirectly, largely through the closure of businesses and schools and interruption of supply chain activities. Governments in the four countries imposed various restrictions to movement, business interactions, and on educational institutions throughout the course of the pandemic. While these restrictions sought to slow the spread of the virus and protect citizens from infection, they disrupted normal activities and household income generation.

Survey reports accompanying each round of HFPS data provide details about government restrictions related to the pandemic that were in place during each data round (World Bank, 2022). We describe some of the important restrictions, relevant for this work, here. First, following the global outbreak, Ethiopia closed schools and suspended public gatherings on 16 March 2020. On 8 April 2020, the country declared a state of emergency which included closing non-essential business and limiting international and domestic travel. Restrictions in Ethiopia were, by and large, implemented at the national-level. Conversely, Nigeria's response primarily occurred at the state-level. Most Nigerian states closed schools and suspended large gatherings by 24 March 2020 and closed all non-essential businesses and suspended inter-state travel by early April 2020. Restrictions in Uganda were similar in nature to Nigeria, though nationally implemented. By the end of March 2020, Uganda closed schools, limited large gatherings, closed international borders, closed all non-essential businesses, and suspended public and private transport. Similarly, the President of Malawi declared a state of disaster on 20 March 2020, which included closing schools and limiting the size of public gatherings. A few weeks later on 14 April 2020, Malawi also issued a stay-at-home order. However, the order faced legal challenges, which culminated in the High Court barring the regulation and preventing a stay-at-home order in the country.

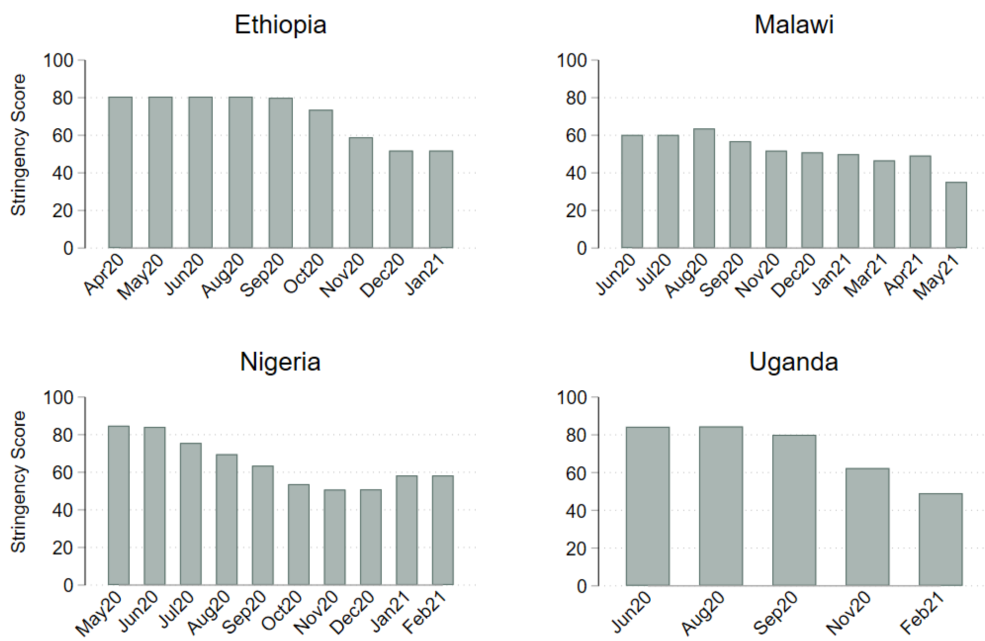
Since the initial wave of lockdowns and closures in early 2020, some restrictions were lifted while others were imposed. By late 2020, movement restrictions in Ethiopia eased and schools began to reopen. In Malawi, restrictions increased in early August when the government introduced new safety measures including mask requirements and limits on public gatherings, hospitality, and recreation. By September 2020, schools began reopening for some classes in Malawi before fully reopening the following month. Schools in Malawi closed again in January 2021 following a surge in COVID-19 cases but reopened again in late February of the same year. In Nigeria, lockdown restrictions eased in June 2020 and by August 2020 some states began to reopen schools. In December 2020, some restrictions, such as limits on large gatherings, were reimposed following a rise in COVID-19 cases. These reinstated restrictions remained through February 2021. In Uganda, lockdown measures eased by September 2020 and by March 2021 schools began gradually reopening for some grades.

To account for the variation in COVID-19-related restrictions over time, we use *Our World in Data*'s COVID-19 Government Stringency Index in some of our empirical specifications (Ritchie et al., 2020). The index considers nine metrics to calculate daily scores for each country: school closures; workplace closures; cancellation of public events; restrictions on public gatherings; closures of public transport; stay-at-home requirements; public information campaigns; restrictions on internal movements; and international travel controls. The stringency index is calculated as the mean score of the nine metrics, each taking a value between 0 and 100. A higher score indicates a stricter regulatory regime. To match these daily data to each round of HFPS data, we take the average daily score during each survey period. Figure 3.1 displays the average government stringency index in each country over time.

3.1.2 Livelihood Diversification Indices

The primary independent variables of interest in for our analysis consist of a series of indices measuring income diversification. Following methodology from Michler and Josephson (2017), we generate these indices using survey variables provided in the pre- and post-COVID-19 outbreak LSMS data. We use two measures to evaluate household income diversification: a simple fraction and a Herfindahl-Hirschman Index (HHI). HHI scores are negatively related to diversification; they are larger for less diversified households and smaller for more specialized households. For consistency, we adjust the fraction indices to maintain this negative relationship. As a result, both indices can be thought of as specialization indices that are inversely related to

Figure 3.1: COVID-19 Government Restriction Stringency Score Over Time



Note: The figure presents government stringency scores for each of the four countries over time. The scores are provided by *Our World in Data* and measure the severity of COVID-19-related government restrictions on a daily basis, with higher scores indicating stricter regulatory regimes (Ritchie et al., 2020). We average these daily scores to match with our monthly HFPS data. In general, government restrictions were harshest in early 2020 and relaxed in the fall of 2020. In some cases, new restrictions were imposed in early 2021 as cases surged.

diversification.

The simple fraction indices are calculated using the count of the income sources each household is engaged in (i) and the total number of income-generating opportunities in their area (n). The fraction is subtracted from one such that a higher score is associated with less income-generating activities while a lower score indicates a more diversified income portfolio.

$$1 - \frac{i}{n} \tag{3.1.1}$$

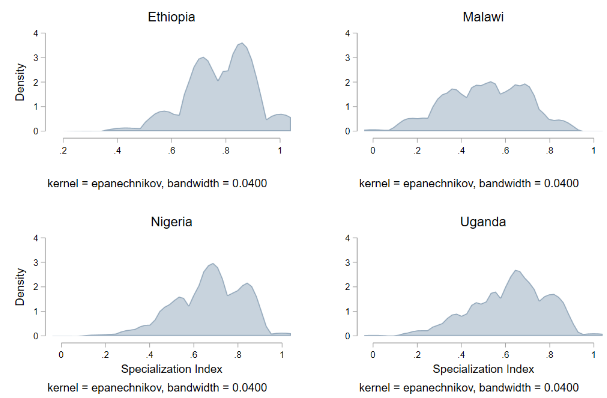
Alternatively, the HHI considers the portion of a household's income generated from each income source. For simplicity and to avoid negative incomes, in calculating this index we include all revenues generated by households and do not net out costs of production. The HHI is calculated using the following formula:

$$\sum_{j=1}^{i} p_j^2, \tag{3.1.2}$$

where, as before, i represents each household's total number of income sources. Each p_j represents the percentage (as a decimal) of the household's income generated from income source j. A highly specialized household with only one income source would receive the highest possible score of 1 (1^2). Alternatively, a household with two income sources each accounting for 50 percent of household's total income would receive a score of .5 ($.5^2 + .5^2$). In this context, as with the fraction measure, higher scores indicate more income specialization and less diversification.

The survey questionnaires includes questions about a variety of household income sources such as farm, family business, pension, remittances, wages from employment, money from governments and NGOs, and others. We make some adjustments to accommodate the fact that some of these income source variables are not consistently available for every country and round of data. Further, the pre-COVID-19 surveys provide richer data than the phone surveys, including additional income sources and the amount of household income generated from each income source. To provide the most detailed analysis possible with available data, we generate six income source as outlined in Table 3.1:

Table 3.1: Livelihood Diversification Indices Summary

Index ID	Index Type	Standardized Across Countries	Time Period	Description	Pre-COVID-19 Kernel Density Graph
1	Fraction	Yes	Pre- and Post-COVID-19	To generate this uniform index, we collapse multiple income sources into seven broad income-generation categories: farm; wage; pension; remittances; non-farm business; income from properties, investments and savings; and other. The “other” income category varies across countries and rounds but generally includes asset sales, income from NGOs, and government assistance.	

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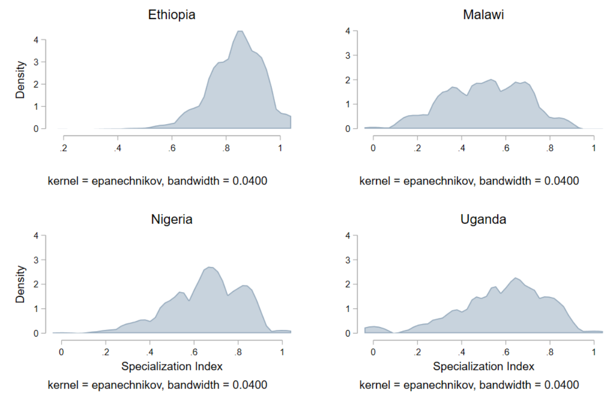
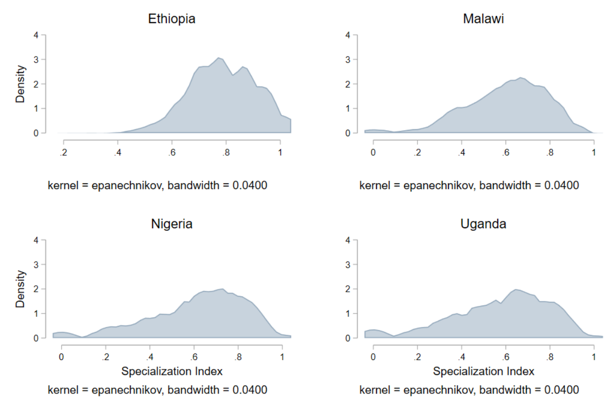
Index ID	Index Type	Standardized Across Countries	Time Period	Description	Pre-COVID-19 Kernel Density Graph
2	Fraction	No	Pre- and Post-COVID-19	To generate this fraction index, we again collapse variables into broader categories, but these categories vary across countries, allowing for more specified income groups and thus more income categories than the uniform index. As a result, this index allow us to observe income sources at the most granular level available over multiple waves for each country individually. This fraction index considers 10 income source categories in Ethiopia, 7 in Malawi and Nigeria, and 8 in Uganda.	
3	Fraction	Yes	Pre-COVID-19	This fraction index focuses on the pre-COVID-19 period. As such, this index uses the most detailed level of data available in the LSMS-ISA surveys while maintaining uniformity across countries. This index includes 12 income categories available across all four countries: remittances; in-kind assistance from friends and family; investments and savings; income from properties; pension; non-farm business; crop sales and consumption; livestock sales; livestock products sales and consumption; wages; government and NGO assistance; and other.	

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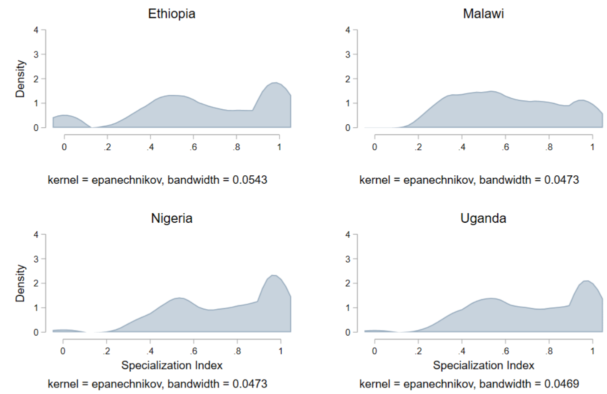
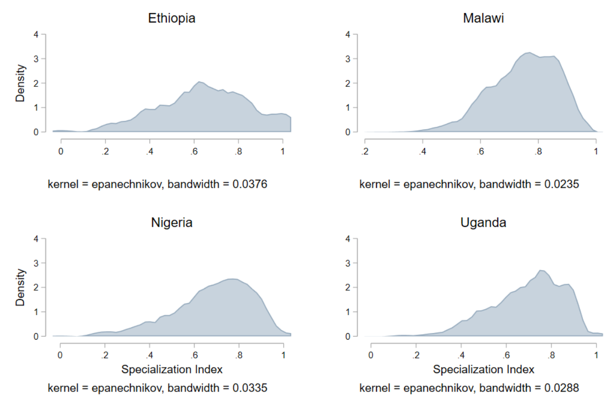
Index ID	Index Type	Standardized Across Countries	Time Period	Description	Pre-COVID-19 Kernel Density Graph
4	HHI	Yes	Pre-COVID-19	Given the level of detail provided in the pre-COVID survey data, we are able to generate an HHI to capture household income diversity more precisely. For this index, we use the same 12 income categories used in Index 3 but consider the amount earned from each source.	
5	Fraction	No	Pre-COVID-19	This measure is similar to the standardized pre-COVID-19 fraction index (Index 3). However, this index is unique to each country, allowing for country-specific variations in income source engagement. We generate this index using 19 income sources in Ethiopia, 21 in Malawi, 15 in Nigeria, and 13 in Uganda.	

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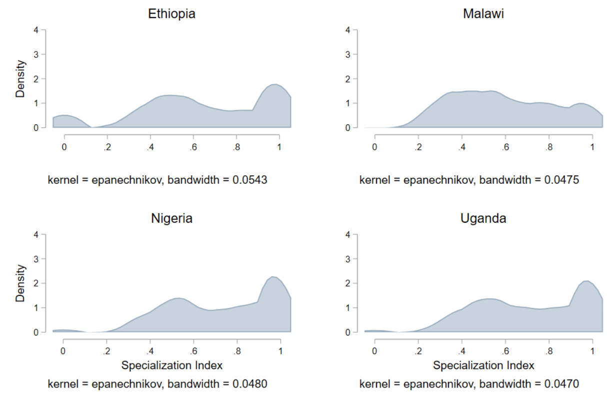
Index ID	Index Type	Standardized Across Countries	Time Period	Description	Pre-COVID-19 Kernel Density Graph
6	HHI	No	Pre-COVID-19	This measure is identical to Index 5 but uses an HHI instead of a fraction to evaluate the distribution of income from each source.	

Note: The table summarizes the six livelihood diversification indices used in our analysis. The indices are either a simple fraction indicating engagement in various income-generating activities or an HHI that considers the amount of income earned from each source. LSMS-ISA data in the pre-COVID-19 period provide richer evidence of household income sources than the HFPS data. Indices 3-6 take advantage of this detail and thus only measure income diversification in the pre-COVID-19 period. In some cases, we allow the income sources considered in the index to vary across countries. In other cases, we consider a standard set of income sources for all countries. Higher index values indicate more household specialization (less income diversification).

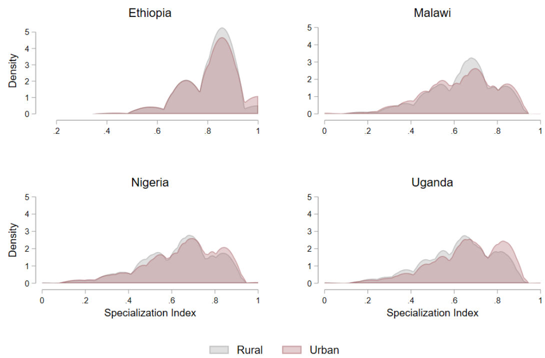
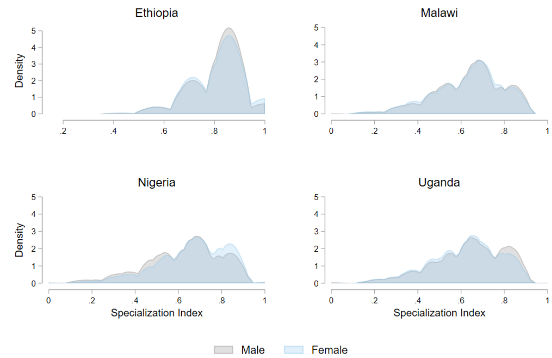
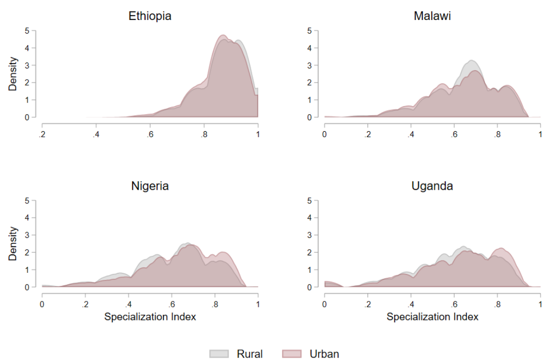
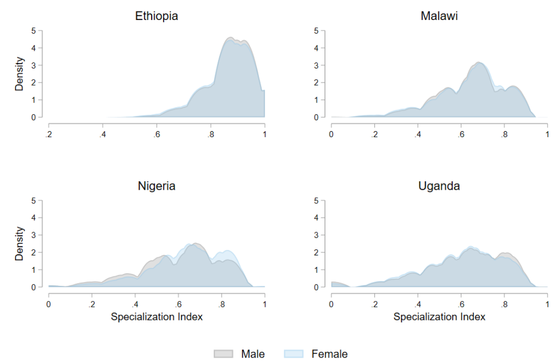
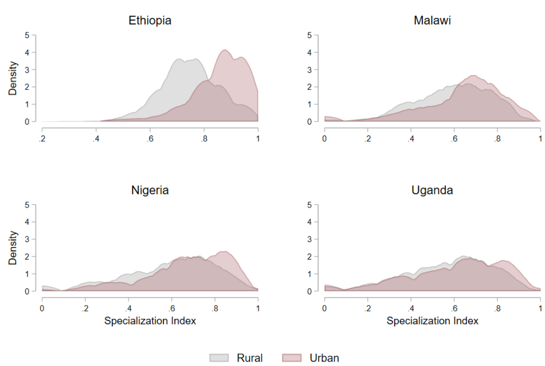
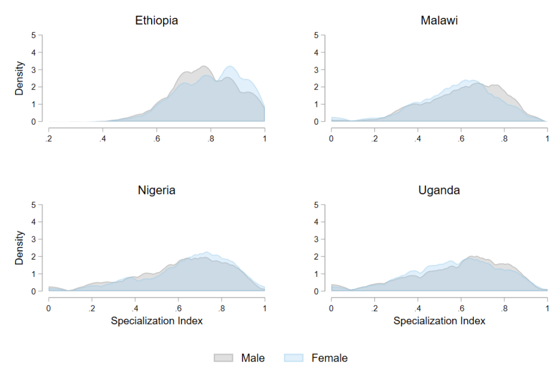
We generate the fraction indices (Indices 1, 2, 3, and 5) based on geographic area to capture livelihood specialization relative to regional diversification opportunities. For example, if government and NGO assistance is only offered to rural households, households residing in urban areas would not have the option to receive this income source. Thus these types of assistance are not considered as a possible source of income and the denominator in the index calculation for urban households is reduced accordingly. To automate this process, we count the total number of income sources households participate in for all geographic areas available in the data (e.g., region, zone, district, postal code, ward). We then determine the smallest geographic area with at least 10 available observations. The count of income sources households are engaged in in that smallest geographic area with sufficient observations then serves as the denominator (n) in the index calculation for households residing in that area.

Each of the six indices has unique advantages and limitations. The fraction indices (Indices 1, 2, 3, and 5) consider engagement in income-generating activities. These measures include binary responses and thus are not subject to potential measurement error. Further, the dichotomous nature of these variables allows for comparison in income-generating activities over time with the inclusion of the HFPS rounds. However, fraction indices do not consider the amount of income earned from each source. As such, these indices are a less nuanced representation of household income diversity than HHI measures. For example, suppose Household A was engaged in casual employment for one week in 2019. During that week, the household earned five percent of their total annual income and the remaining 95 percent was generated through farm work. Suppose their neighbor, Household B, was also engaged in casual labor and farm work but generated equal incomes from these two sources (a 50 percent split). In our data, Households A and B would receive the same fraction score, even though Household A is much more dependent on a single income source than Household B.

Alternatively, HHI indices (Indices 4 and 6) consider the portion of total income generated from each source and thus provide a more detailed measure of income diversity. However, these estimates are swayed by outlier values. Income calculations often involve multiplication of different variables (e.g., $wage\ earnings = hourly\ income * hours\ worked\ per\ week * weeks\ worked\ per\ month * months\ worked\ per\ year$), aggregation across income sub-categories (e.g., $income\ from\ livestock\ products = income\ from\ milk\ sales + value\ of\ household\ milk\ consumption + income\ from\ meat\ sales + value\ of\ household\ meat\ consumption...$), and other data manipulations. As a result, an error in any one of these intermediate variables can lead to erroneous estimations. Further, when considering crop and livestock product income, prices are not available for household consumption. To remedy this limitation, we assume the value of a consumed product is equal to the median sale price for that product in the household's geographic area. To account for large outliers, for each income category we winsorize outliers greater than two standard deviations from the median and impute their values. Despite this adjustment, the data are still vulnerable to potential error and subjective assumptions that affect their accuracy, which may lead to inaccuracy and/or bias in our estimated values. Because HHI scores are calculated based on a percentage, a measurement inaccuracy in one income source distorts the overall score.

Within fraction and HHI categories, the income sources considered in each index differ. Indices 1, 3, and 4 include a standard set of income categories for all countries to allow for more direct comparisons across nations. The other indices consider different income sources across countries to provide the most granular level of income generation data available within each country. Ultimately, the inclusion of these six indices provides a robust measure of household diversification. While each individual index has strengths and limitations, the inclusion of all six throughout our analysis provides a vigorous assessment of household income diversification.

Table 3.2: Pre-COVID-19 Indices Density by Urban/Rural and Head-of-Household Gender

ID	Urban/Rural	Male-Headed/Female-Headed
1		
2		
3		

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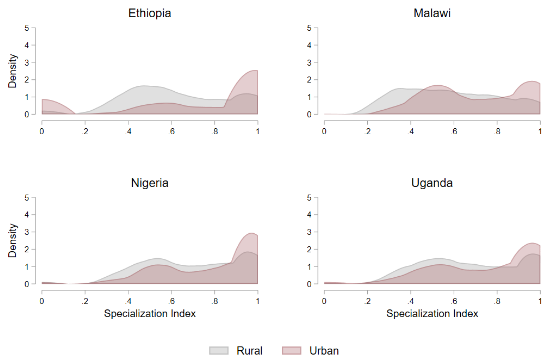
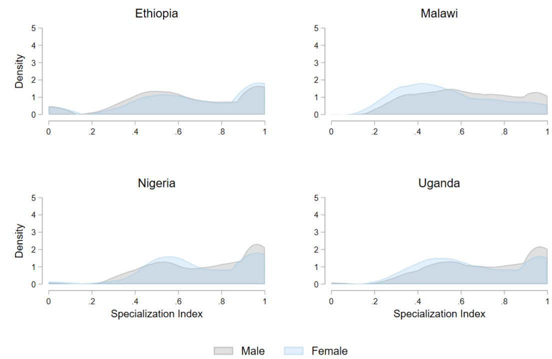
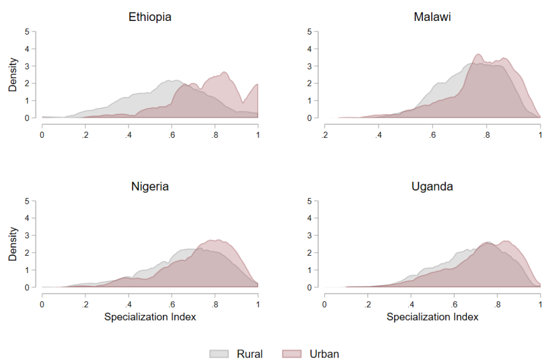
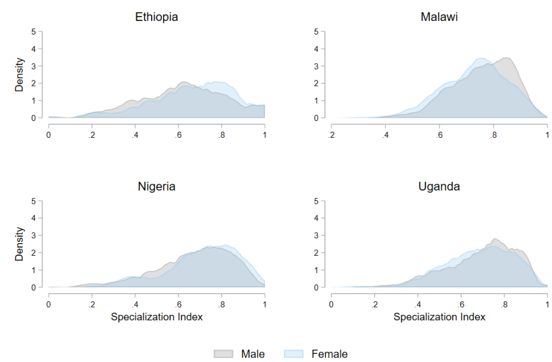
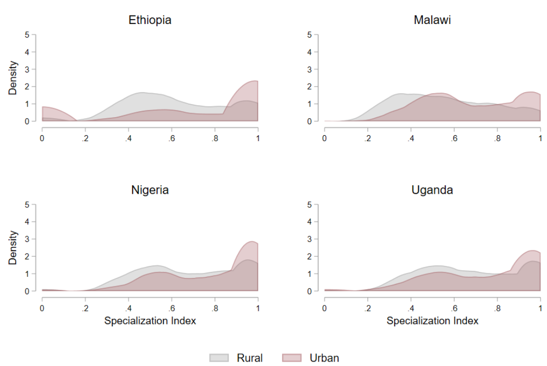
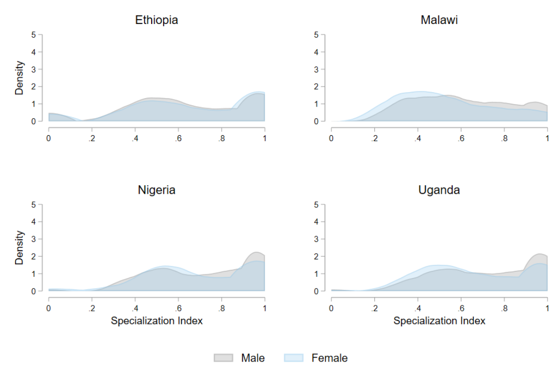
ID	Urban/Rural	Male-Headed/Female-Headed
4		
5		
6		

Note: The table displays kernel density graphs for the pre-COVID-19 round for each of the six livelihood diversification indices. The first column of graphs shows densities for urban versus rural populations while the second column of graphs separates the data by male- versus female-headed households. Urban households tend to be more specialized than rural households, a result that is particularly evident in Ethiopia. However, questionnaires in Ethiopia did not inquire about agricultural engagement in urban areas and thus likely underestimate livelihood diversification in urban homes. There are not notable differences in income diversification by head-of-household gender. Higher index values indicate more household specialization (less income diversification).

Table 3.2 illustrates heterogeneous distributions of the six indices comparing urban and rural as well as male- and female-headed households. For the purposes of this comparison, we only include the pre-COVID-19 data, even when post-outbreak rounds are available for that index. Differences are muted in Indices 1 and 2 and for male- versus female- headed households. However, in Indices 3-6, urban households tend to be more specialized than rural. This shift may be due to the more granular level of data used in Indices 3-6. For example, households that plant crops, sell livestock, and sell livestock products report three distinct income sources in the later indices, but only one (farming income) in Indices 1 and 2. Thus, rural households tend to have lower specialization indices when farming activities are disaggregated. In Ethiopia, agricultural questionnaires were not given to urban households in the pre-COVID-19 round. As a result, the LSMS-ISA data do not capture urban agricultural engagement and may underestimate livelihood diversification in urban areas. This discrepancy likely explains the relatively large difference between income diversification scores in urban versus rural areas in Ethiopia.

Tables 3.3 and 3.4 show the percent of households engaged in and the amount of income earned from each livelihood source. The tables display the income sources used in Indices 5 and 6, representing the most granular level of detail available in each country. Other indices incorporate these income sources but aggregate them for consistency across rounds and countries. We employ simple regressions with standard errors clustered at the smallest geographic area available in each country (generally comparable to a postal code in the USA). These regressions explore the statistical significance of differences in income engagement and earnings for male- and female-headed households (Table 3.3) as well as urban and rural households (Table 3.4). As anticipated, rural households are more engaged in farming and livestock activities while urban households participate in wage work and non-farm enterprises at higher rates. Of those engaged in non-farm enterprises and wage work, urban households earn more income than rural households in all countries. Rental income is also more common and profitable in urban areas than rural. In terms of gender, female-headed households receive remittances and transfers at a higher rate than male-headed households. Male-headed households are more likely to have members engaged in wage work and non-farm enterprises in all countries except Ethiopia, though these differences are not consistently significant for all countries. In all instances with statistically significant gender differences, male-headed households earn more than female-headed ones. The only exception to this is for assistance income and remittances or transfers.

Non-farm enterprises and wages account for a relatively large portion of household earnings and engagement. A common non-farm enterprise in Ethiopia, Malawi, and

Nigeria in 2019 is offering services from home or a household-owned shop, such as a car wash, metal worker, mechanic, carpenter, tailor, barber, etc. Of households that generate income from non-farm enterprises, 46, 23, and 28 percent of households in Ethiopia, Malawi, and Nigeria, respectively, engage in the service industry. Another common non-farm enterprise in 2019 is trading businesses with 16, 31, and 35 percent engagement in Ethiopia, Malawi, and Nigeria. In Uganda, LSMS questionnaires ask about participation in trade and service work combined. About 68 percent of respondents who generate income from non-farm enterprises report engagement in these industries in 2019. An industry breakdown of engagement in wage work is available in Ethiopia and Nigeria. In Ethiopia, public administration and defense account for 16 percent of wage work in 2019, while trade and education account for about 13 and 12 percent, respectively. In Nigeria, education is the most common source of wage income with 25 percent engagement, followed by public administration (18 percent) and personal services (10 percent).

Table 3.3: 2019 Engagement in and Earnings from Income Sources by Head-of-Household Gender

	Percent Engaged			**Mean Income (USD)**		
	Male	Female	Difference	Male	Female	Difference
			Panel A: Ethiopia			
Crop Income	0.576	0.353	0.223***	304	155	149***
Livestock Sales	0.359	0.187	0.172***	256	206	50
Livestock Product Income	0.556	0.280	0.276***	546	457	89
Wages	0.210	0.228	-0.018	1609	1153	456
Casual Employment Wages	0.084	0.099	-0.015	193	138	55*
Temporary Employment Wages	0.071	0.139	-0.068***	90	104	-13
Non-Farm Enterprises	0.213	0.259	-0.046**	1431	858	573***
In-Kind Transfers/Gifts	0.022	0.029	-0.007	56	58	-2
Cash Transfers/Gifts	0.057	0.230	-0.173***	375	248	127**
Food Transfers/Gifts	0.035	0.088	-0.053***	49	76	-28
In-kind Transfers from Govt and NGOs	0.006	0.016	-0.010**	45	31	15
Cash Transfers from Govt and NGOs	0.023	0.059	-0.036***	59	71	-12
Free Food	0.047	0.058	-0.011	31	48	-16**
Pension	0.009	0.025	-0.016**	350	196	154***
Rental Income	0.073	0.122	-0.050*	358	298	60
Asset Sales	0.103	0.036	0.067***	254	331	-77
Savings, Interest, Investment	0.002	0.003	-0.001	216	22	193
Other	0.008	0.007	0.000	409	174	235
Observations	2251	996		2251	996	
			Panel B: Malawi			
Crop Income	0.757	0.823	-0.066*	151	88	63***
Tree Crop Sales	0.053	0.084	-0.031	25	32	-7
Livestock Sales	0.265	0.258	0.007	58	50	8
Livestock Product Income	0.320	0.247	0.073*	43	39	4
Wages	0.311	0.139	0.172***	1704	1138	566
Casual Employment Wages	0.580	0.678	-0.098**	338	263	75
Non-Farm Enterprises	0.469	0.362	0.108**	2115	1183	933**
Cash Transfers/Gifts	0.212	0.387	-0.175***	55	85	-30*
Food Transfers/Gifts	0.230	0.374	-0.143***	13	13	-0
In-Kind Transfers/Gifts	0.096	0.156	-0.060*	35	22	13
Cash from Children	0.169	0.264	-0.095***	70	59	10
In-Kind Transfers from children	0.104	0.197	-0.093***	49	40	9
Free Food	0.153	0.253	-0.100***	20	20	-0
Cash Transfers from Govt and NGOs	0.038	0.128	-0.091***	57	56	1
Cash or Inputs for Work	0.016	0.026	-0.010	52	61	-9
MASAF Public Works Program	0.042	0.048	-0.006	36	25	11*
Pension	0.014	0.002	0.011***	1393	825	567**
Rental Income	0.086	0.067	0.019	357	208	150**
Asset Sales	0.084	0.055	0.029	88	82	7
Savings, Interest, Investment	0.069	0.065	0.005	61	74	-13
Other	0.044	0.041	0.003	54	14	40*
Observations	1343	383		1343	383	

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	Percent Engaged			Mean Income (USD)		
	Male	Female	Difference	Male	Female	Difference
Panel C: Nigeria						
Crop Income	0.679	0.492	0.187***	439	173	266***
Tree Crop Sales	0.059	0.085	-0.026	270	121	148
Livestock Sales	0.230	0.157	0.073**	179	74	105***
Livestock Product Income	0.215	0.066	0.149***	97	35	62***
Wages	0.281	0.171	0.110***	1614	1480	135
Non-Farm Enterprises	0.631	0.591	0.040	3092	2152	940**
Domestic Remittances	0.231	0.419	-0.188***	117	91	27
Foreign Remittances	0.023	0.084	-0.061***	310	216	95
In-Kind Remittances	0.102	0.226	-0.124***	56	29	27***
Cash, Food, or In-kind Assistance	0.044	0.032	0.012	60	17	43***
Pension	0.035	0.012	0.023***	673	903	-230
Rental Income (Non-Ag)	0.041	0.083	-0.042*	360	320	40
Rental Income (Ag)	0.039	0.039	-0.000	48	32	16
Savings, Interest, Investment	0.023	0.010	0.013*	296	90	206
Other	0.010	0.013	-0.003	665	425	240
Observations	1578	372		1578	372	
Panel D: Uganda						
Crop Income	0.705	0.655	0.050	455	287	168***
Livestock Sales	0.218	0.168	0.051**	318	195	123***
Livestock Product Income	0.106	0.087	0.019	362	266	96
Wages	0.458	0.403	0.055*	2401	2255	145
Non-Farm Enterprises	0.488	0.377	0.111***	4494	3089	1405**
Domestic Remittances	0.231	0.483	-0.252***	118	171	-53***
Domestic In-Kind Transfers	0.168	0.379	-0.210***	75	107	-31**
Foreign Remittances	0.016	0.037	-0.021*	454	458	-4
Foreign In-Kind Transfers	0.004	0.016	-0.013*	101	120	-19
SAGE assistance	0.011	0.013	-0.002	180	206	-26
Pension	0.003	0.002	0.002	1040	1981	-941
Rental Income	0.112	0.109	0.003	518	554	-37
Interest and Investments	0.023	0.013	0.010	54	51	3
Other	0.023	0.014	0.008	388	523	-135
Observations	1494	731		1494	731	

Note: The table displays the percent of households engaged in (columns 1 and 2) and the mean income earned from (columns 4 and 5) each income category used to generate Indices 5 and 6. We present average values by head-of-household-gender. We use LSMS-ISA data to generate the table, which covers the pre-COVID-19 period. In the data, income is reported in the local currency. To allow for cross-country comparisons, we convert income values to US dollars using 2019 exchange rates found at https://exchangerates.org. We calculate statistical significance of male- versus female-headed household differences using simple regressions with standard errors clustered at the region level (*** p<0.001, ** p<0.01, * p<0.05).

Table 3.4: 2019 Engagement in and Earnings from Income Sources by Urban/Rural

	Percent Engaged			**Mean Income (USD)**		
	Rural	Urban	Difference	Rural	Urban	Difference
			Panel A: Ethiopia			
Crop Income	0.780	0.000	0.780***	279	.	.
Livestock Sales	0.474	0.000	0.474***	249	.	.
Livestock Product Income	0.730	0.000	0.730***	533	.	.
Wages	0.107	0.433	-0.326***	721	1853	-1132***
Casual Employment Wages	0.078	0.108	-0.030	98	294	-195***
Temporary Employment Wages	0.112	0.036	0.076***	88	142	-54**
Non-Farm Enterprises	0.173	0.328	-0.154***	596	1996	-1400***
In-Kind Transfers/Gifts	0.019	0.034	-0.015	28	90	-62***
Cash Transfers/Gifts	0.078	0.141	-0.064***	180	441	-261***
Food Transfers/Gifts	0.039	0.065	-0.026	38	89	-52***
In-kind Transfers from Govt and NGOs	0.008	0.010	-0.002	38	40	-1
Cash Transfers from Govt and NGOs	0.035	0.027	0.008	58	81	-23
Free Food	0.060	0.029	0.031*	31	55	-24*
Pension	0.001	0.038	-0.038***	327	277	50
Rental Income	0.073	0.108	-0.035**	205	518	-313***
Asset Sales	0.121	0.017	0.103***	257	320	-63
Savings, Interest, Investment	0.000	0.006	-0.006**	.	145	.
Other	0.006	0.010	-0.004	382	321	62
Observations	977	2270		977	2270	
			Panel B: Malawi			
Crop Income	0.867	0.386	0.481***	135	88	47**
Tree Crop Sales	0.070	0.029	0.041*	24	66	-42*
Livestock Sales	0.302	0.095	0.206***	56	54	2
Livestock Product Income	0.332	0.151	0.181***	43	26	17
Wages	0.203	0.512	-0.309***	1034	2617	-1584***
Casual Employment Wages	0.660	0.387	0.273***	299	423	-123**
Non-Farm Enterprises	0.399	0.603	-0.204***	1437	3209	-1772***
Cash Transfers/Gifts	0.260	0.277	-0.017	55	123	-68***
Food Transfers/Gifts	0.275	0.260	0.015	12	18	-5**
In-Kind Transfers/Gifts	0.118	0.094	0.024	29	38	-9
Cash from Children	0.215	0.121	0.094***	59	122	-63***
In-Kind Transfers from children	0.141	0.091	0.050*	45	47	-2
Free Food	0.214	0.046	0.168***	20	17	4
Cash Transfers from Govt and NGOs	0.076	0.016	0.060***	55	98	-43***
Cash or Inputs for Work	0.022	0.004	0.018**	57	15	42***
MASAF Public Works Program	0.044	0.042	0.001	31	37	-6
Pension	0.007	0.025	-0.018*	1352	1358	-6
Rental Income	0.060	0.168	-0.108***	173	548	-375***
Asset Sales	0.086	0.033	0.052	82	144	-62***
Savings, Interest, Investment	0.072	0.052	0.019	55	121	-66*
Other	0.035	0.078	-0.044*	27	74	-47
Observations	1092	634		1092	634	

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	Percent Engaged			Mean Income (USD)		
	Rural	Urban	Difference	Rural	Urban	Difference
Panel C: Nigeria						
Crop Income	0.799	0.306	0.494***	433	220	213***
Tree Crop Sales	0.067	0.056	0.011	251	186	65
Livestock Sales	0.274	0.091	0.183***	173	113	60**
Livestock Product Income	0.239	0.075	0.164***	98	54	45**
Wages	0.224	0.339	-0.115***	1583	1619	-36
Non-Farm Enterprises	0.583	0.712	-0.128***	2690	3348	-658*
Domestic Remittances	0.253	0.294	-0.040	94	139	-45***
Foreign Remittances	0.023	0.059	-0.036***	246	286	-40
In-Kind Remittances	0.125	0.124	0.002	44	54	-10
Cash, Food, or In-kind Assistance	0.037	0.052	-0.015	58	48	10
Pension	0.018	0.057	-0.040***	792	620	172
Rental Income (Non-Ag)	0.041	0.065	-0.024	236	501	-266**
Rental Income (Ag)	0.049	0.018	0.031**	45	44	0
Savings, Interest, Investment	0.019	0.024	-0.004	131	537	-406
Other	0.014	0.004	0.010	557	1036	-479
Observations	1195	755		1195	755	
Panel D: Uganda						
Crop Income	0.852	0.332	0.520***	400	413	-12
Livestock Sales	0.251	0.095	0.156***	258	435	-177*
Livestock Product Income	0.114	0.069	0.045***	296	471	-175
Wages	0.376	0.579	-0.203***	2093	2729	-636**
Non-Farm Enterprises	0.411	0.539	-0.128***	2964	6000	-3035***
Domestic Remittances	0.315	0.313	0.002	112	215	-103***
Domestic In-Kind Transfers	0.242	0.229	0.013	68	145	-77***
Foreign Remittances	0.015	0.039	-0.023**	240	642	-402***
Foreign In-Kind Transfers	0.007	0.009	-0.002	90	157	-67**
SAGE assistance	0.015	0.004	0.011***	185	220	-35
Pension	0.002	0.003	-0.001	858	1686	-828*
Rental Income	0.074	0.191	-0.117***	346	683	-337***
Interest and Investments	0.021	0.015	0.006	47	70	-22
Other	0.011	0.040	-0.029***	457	399	58
Observations	1642	583		1642	583	

Note: The table displays the percent of households engaged in (columns 1 and 2) and the mean income earned from (columns 4 and 5) each income category used to generate Indices 5 and 6. We present average values by urban/rural population. We use LSMS-ISA data to generate the table, which covers the pre-COVID-19 period. In the data, income is reported in the local currency. To allow for cross-country comparisons, we convert income values to US dollars using 2019 exchange rates found at https://exchangerates.org. We calculate statistical significance of urban/rural differences using simple regressions with standard errors clustered at the region level (*** p<0.001, ** p<0.01, * p<0.05). Urban households in Ethiopia were not asked about agricultural engagement in the 2019 LSMS survey.

3.1.3 Outcome Variables

Food Insecurity

We use the Food Insecurity Experience Scale (FIES) as an indicator of household well-being and the primary outcome variable. The FIES is an experience-based metric of food insecurity severity, which relies on people's direct responses to questions about their experiences with access to adequate food. This metric makes it possible to compare prevalence rates of food insecurity across national and sub-national populations.

Following the FIES standard survey model, respondents in LSMS-ISA and HFPS data answer eight questions aimed to capture whether the respondent or other adult households members:

1. were worried they would not have enough to eat,
2. were unable to eat healthy and nutritious food,
3. ate only a few kinds of food,
4. had to skip a meal,
5. ate less than they thought they should,
6. ran out of food,
7. were hungry but did not eat, or
8. went without eating for a whole day.

We count the number of affirmative answers to these eight questions to categorize households into mild, moderate, and severe food insecurity. Households which answered affirmatively to at least one FIES question are classified as experiencing mild food insecurity; households which answered yes to four or more questions are moderately food insecure; severely food insecure households responded affirmatively to all eight questions.

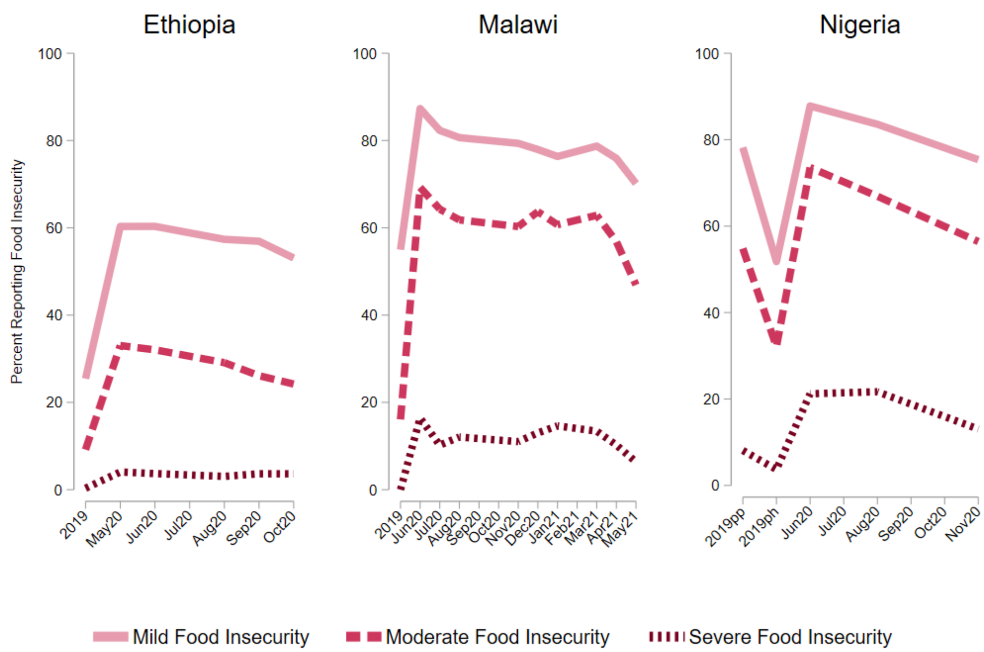
FIES scores using these integer values are limited by several factors. First, some HFPS rounds do not include food insecurity modules, so there are gaps in the data. Second, there are inconsistencies in the reference period for food insecurity questions in the LSMS-ISA and HFPS data. In the LSMS-ISA pre-COVID-19 data, the reference period varies across countries, with Ethiopia and Malawi inquiring about the last seven days and Nigeria asking about the past 30 days. FIES data are not available in the pre-pandemic data in Uganda. Alternatively, in monthly HFPS data the reference period is 30 days. Last, not all eight questions are included in every country's LSMS-ISA survey. Ultimately, only surveys in Nigeria 1) ask all eight FIES questions, 2) phrase the questions in a similar way in the pre- and post-outbreak periods, and 3) have the same recall period for the pre- and post-outbreak periods. To address the second issue, we incorporate a standardized measure of the raw FIES score developed by Bloem and Farris (2021). This measure counts the number of affirmative answers to FIES questions in the LSMS-ISA data by country and uses survey weights to standardize the variable such that its mean is zero and weighted standard deviation is one. Following a similar process, the HFPS data are standardized by country across all data rounds to account for seasonality in the post-outbreak surveys. As such, the FIES index allows for comparison between LSMS-ISA and HFPS data in each country.

FIES data are available in the pre- and post-COVID-19 outbreak periods in Ethiopia, Malawi, and Nigeria. In Nigeria, the LSMS surveys ask respondents food security questions in both the post-planting (labeled "pp" in Figure 3.2) and post-harvest (labeled "ph") surveys. As seen in Figure 3.2, food insecurity in the three countries increased substantially between 2019 and the summer of 2020, following the onset of the COVID-19 pandemic. Recovery in food security throughout the subsequent year was slow in all three countries, with about 80 percent of households experiencing mild food insecurity in almost every month following the outbreak in Malawi and Nigeria and about 60 percent in Ethiopia. Prior to the onset of the pandemic, mild food insecurity affected less than 30 percent of households in Ethiopia and about 60 percent in Malawi and the post-harvest period in Nigeria. Similarly, moderate food insecurity spiked after the COVID-19 outbreak and slowly recovered in subsequent months. Severe food insecurity increased in Malawi and Nigeria in June 2020 and rose slightly in Ethiopia after the initial outbreak period.

Child Educational Engagement

We include child educational engagement as a second measure of household well-being and resilience to socioeconomic shocks. This dichotomous variable indicates whether or not any children in the household are engaged in educational activities during the reference time period. When schools are open, this variable includes school attendance or educational engagement from home. When schools are closed due to COVID-19-related restrictions, this indicator includes communication with teachers, engagement in educational television or radio programs, reading educational materials at home, studying with family members, and other forms of at-home learning. As seen in Figure 3.3, in 2019, prior to the onset of the pandemic, about 90 percent or

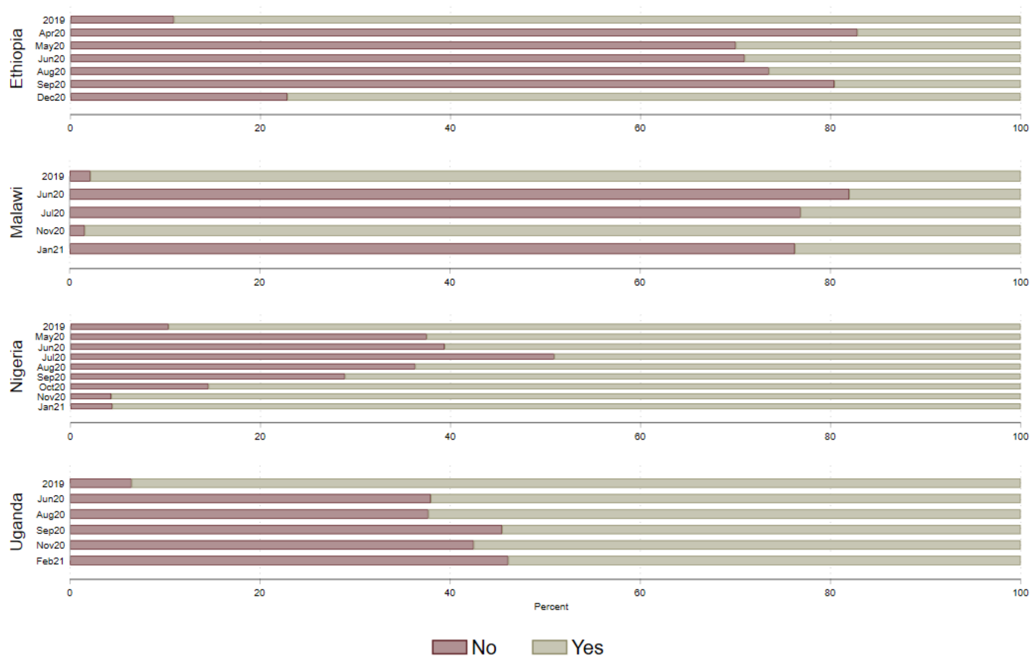
Figure 3.2: Food Insecurity Measures Over Time



Note: The figure shows the mean portion of households experiencing mild, moderate, and severe food insecurity in each round of available data. Food insecurity information is not available in Uganda in the pre-COVID-19 period.

more of households with school-aged children were sending children to school in all four countries. Substantially fewer children in all four countries were participating in educational activities following the initial COVID-19 outbreak in early 2020. This result is particularly pronounced in Malawi and Ethiopia, where over 80 percent of children were not engaged in learning activities immediately following the initial outbreak. In Nigeria and Ethiopia, school participation rebounded after school reopened in October 2020. After schools reopened in Malawi in October 2020, about 96 percent of households were sending children to school. However, when schools closed again in January 2021 to prevent the spread of COVID-19, educational engagement fell to just over 20 percent.

Figure 3.3: Child Educational Engagement Over Time



Note: The figure shows the mean portion of households in which children are engaged in educational activities for each round of available data. Educational engagement includes attending school or participating in learning activities from home. Prior to the onset of the COVID-19 pandemic, educational engagement was near universal in the four countries. Following COVID-19-related restrictions and school closures, a much smaller portion of children were participating in educational endeavors.

Method

4.1 Research Question 1: Income Composition Over Time

To evaluate trends in household income composition over time, we use summary statistics and graphical analysis. Responses in the post-outbreak questionnaires disallow analysis of earnings over time. However, we can observe changes in income-generating engagement in the pre- and post-outbreak periods. Further, we observe livelihood diversification indices over time to assess changes in household-level resource allocation. We also evaluate heterogeneous trends in income composition for urban and rural as well as male- and female-headed households.

4.2 Research Question 2: Livelihood Diversification and Welfare Outcomes

To study how changes in household income diversification impact livelihood outcomes, we use both the pre-COVID-19 LSMS-ISA data and COVID-19 HFPS data to estimate panel data models. We estimate effects using two primary approaches: (1) dynamic panel data estimators, in which the outcome of interest for a particular HFPS round is explained by the diversity index from the previous round and (2) difference-in-difference-type estimators in which we regress the outcome of interest for a particular HFPS round on the pre-COVID-19 diversity index. For each specification, we run regressions for each country separately.

Our dynamic panel data model with lagged variables takes the following functional form:

$$y_{it} = \alpha + \beta_1 y_{it-1} + \beta_2 (y_{it-1} * div_{it-1}) + \beta_3 div_{it-1} + \delta_t + r_j * t_t + u_i + \epsilon_{it} \tag{4.2.1}$$

Here, y_{it} is the outcome variable (food insecurity or child educational engagement) for household i at time t. y_{it-1} is the lagged value of the outcome and div_{it-1} is the lagged value of the diversity index. We lag these values to account for the time it takes for the independent variables to actually impact the dependent variable. In this case, livelihood diversification does not immediately effect household welfare. Rather, diversification may improve household resilience to shocks, thus improving welfare outcomes following the COVID-19 pandemic. Including the lagged outcome variable y_{it-1} in our specifications ensures that the variation we observe in our dependent variable is due to livelihood diversification rather than household-level characteristics or differences. As such, we are able to more precisely attribute the variation the dependent variable to our variable of interest. In this specification, β_2 is our variable of interest, measuring how lagged income diversification impacts a household's welfare outcomes, dependent on that household's welfare status in the prior round of data.

Through a series of indicator variables, we account for regional and time differences in COVID-19 policies and mitigation strategies. We include time (round) indicators δ_t to capture variation in COVID-19 cases and COVID-19-related policies occurring nation-wide. This control also captures other large-scale temporal events such as the presidential election and subsequent civil unrest in Uganda in early 2021. Region indicators r_j are interacted with a time trend t_t to control for idiosyncratic shocks such as regional differences in COVID-19 mitigation strategies over the evolution of the pandemic and other covariate shocks such as drought or conflict. Last, u_i is a household fixed effect to control for time-invariant, unobservable household heterogeneity, and ϵ_{it} is an idiosyncratic error term. Robust standard errors clustered by household control for within-household correlation over time. Together, these controls ensure that our variable of interest is not influenced by confounding factors and isolate the relationship the between livelihood diversification and household well-being.

To credibly claim these specification represent causal impacts, we must also demonstrate that livelihood diversification indices are not correlated with the error term. Endogeneity arises when there is (1) simultaneity or reverse causality between the independent and dependent variables, (2) omitted variable bias, or (3) measurement error. In regards to the first issue, it is possible that households with better welfare outcomes have more resources enabling them to diversify their livelihoods. In this case, a simultaneity problem arises as the dependent and independent variables are co-determined. To account for simultaneity, we use lagged independent variables to ensure temporal precedence of livelihood diversification relative to observed household welfare outcomes, thus isolating the relationship between past diversification and subsequent outcomes. Our rich panel data with a pre-COVID-19 baseline help us avoid omitted variable bias. By including household fixed effects, we account for observable and unobservable time-invariant household characteristics that might influence the dependent variable. As a result, we greatly reduce the probability of omitting crucial variables. We address potential measurement error by including six distinct measures of livelihood diversification, including fraction indices generated from dichotomous variables. While we cannot account for all possible causes of endogeneity, our series of controls and livelihood diversification measures reduce the likelihood of correlation between dependent and independent variables and enable us to credibly claim to identify causal relationships.

To enrich the above dynamic panel data model, we add interaction effects to account for the socioeconomic impacts associated with COVID-19 government restrictions:

$$\begin{aligned} y_{it} = \alpha + \beta_1 y_{it-1} + \beta_2 div_{it-1} + \beta_3 str_t + \beta_4(y_{it-1} * div_{it-1}) + \beta_5(y_{it-1} * str_t) \\ + \beta_6(div_{it-1} * str_t) + \beta_7(y_{it-1} * div_{it-1} * str_t) + \delta_t + r_j * t_t + u_i + \epsilon_{it} \end{aligned} \tag{4.2.2}$$

Here str_t is the government stringency score at time t. The triple interaction term (β_7) indicates the combined impact of lagged welfare, lagged income diversity, and government stringency. As with the original dynamic panel model, this specification includes household fixed effects to account for unobserved heterogeneity between households and clustered standard errors by household to account for within-household correlation across time.

As an alternative to the lagged dynamic panel data models, we also use an ANCOVA estimator to generate difference-in-difference estimates.[1] Here we explicitly control for pre-pandemic welfare:

$$y_{it} = \alpha + \beta_1 div_{it=0} + \beta_2 y_{it=0} + \delta_t + r_j * t_t + u_i + \epsilon_{it} \tag{4.2.3}$$

In this equation, $div_{it=0}$ and $y_{it=0}$ are the diversity index and outcome variables in the pre-COVID-19 LSMS-ISA data. All other terms are as previously defined. As compared to a difference-in-difference model, including the pre-COVID-19 outcome variable $y_{it=0}$ more precisely attributes the variation the dependent variable to our variable of interest. In this model, we evaluate the impact of pre-shock income diversification on post-shock welfare. In this context, β_1 is the variable of interest, which is the relationship between pre-COVID-19 income diversification and household well-being during the COVID-19 pandemic. By observing the impacts of pre-COVID-19 diversification on post-outbreak welfare outcomes, we avoid simultaneity issues and potential reverse causality. Because we compare within-household variation over time, the difference-in-difference-type estimation controls for unobserved heterogeneity between households, reducing the risk of omitted variable bias. Standard errors are robust and clustered at the household level to account for within-household correlation over time.

[1] We also estimate simple difference-in-difference models in which we include an indicator for the start of the lockdown. We prefer the ANCOVA specifications to the difference-in-difference models because coefficients are more precisely estimated. However, we present difference-in-difference results in Appendix B.

4.3 Research Question 3: Heterogeneous Effects of Livelihood Diversification

Our last research question examines the heterogeneous effects of livelihood diversification for different population subgroups. Specifically, we assess differences for male- and female-headed households as well as urban and rural households. To analyze our third research question, we use the above ANCOVA specifications but include an indicator variable for head-of-household gender or household sector. We also interact these indicator variables with livelihood diversification to understand the differential impacts for these two subgroups.

$$y_{it} = \alpha + \beta_1 div_{it=0} + \beta_2 div_{it=0} * sub_i + \beta_3 sub_i + \beta_4 y_{it=0} + \delta_t + r_j * t_t + u_i + \epsilon_{it} \quad (4.3.1)$$

Here, sub_i is an indicator variable for population subgroups based on head-of-household gender or household sector for household i. All other terms are as previously defined. The interaction term, β_2, represents the differential impact of pre-COVID-19 livelihood diversification on household welfare outcomes for these population subgroups. For this specification we again use robust standard errors clustered at the household level to account for within-household correlation over time.

Results

5.1 Research Question 1: Income Composition Over Time

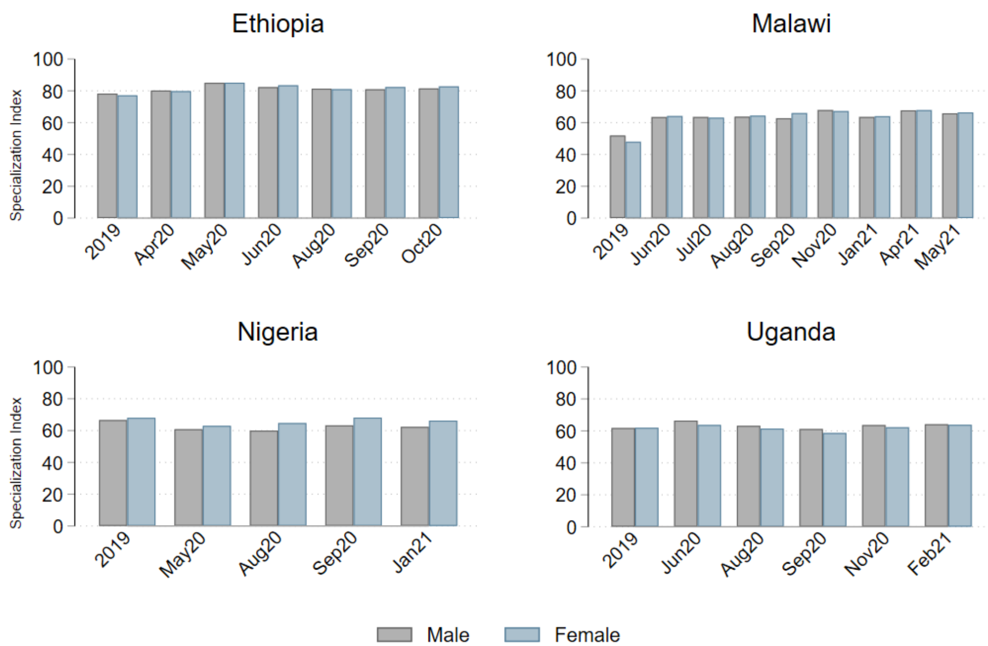
In investigate to our first research question, we use summary statistics and graphical analysis to evaluate if household income composition changed after the onset of the pandemic. For Index 1, where cross-sectional and cross-country comparisons are available, Figures 5.1 and 5.2 display household specialization by sector and head-of-household gender over time. Household specialization indices are generally not discernibly or consistently different for male- and female-headed households (see Figure 5.1). As seen in Figure 5.2, urban households tend to be more specialized than rural households in 2019, a result that is statistically significant at the 95 percent level for all four countries. This result holds across HFPS rounds in Uganda, but is not consistent in other countries over time. In general, Figures 5.1 and 5.2 do not show a substantial change in income diversification strategies between 2019 and 2020. This observation suggests that households either did not use livelihood diversification as a *ex post* coping strategy after the onset of the pandemic, or their attempts to diversify were offset by job losses during the socioeconomic crisis in 2020.

Figure 5.3 illustrates how engagement in income-generating sources changed over time. For consistency across countries, the income sources displayed in the graph are those used in Index 1, the standardized pre- and post-COVID-19 outbreak fraction index. In Ethiopia, Malawi, and Uganda, the percent of household receiving income from wage work fell in the first round of post-outbreak data. Remittances also fell substantially in Malawi and Uganda during that time. In all four countries, farm engagement increased slightly in the first round of data in 2020, though some of that change may be due to seasonality. There was a small uptick in the portion of households receiving assistance in Nigeria and Uganda, though the overall percentage remained low in all countries. Ultimately, we do not observe systematic trends of substantial changes in household income composition since the onset of the pandemic.

5.2 Research Question 2: Livelihood Diversification and Welfare Outcomes

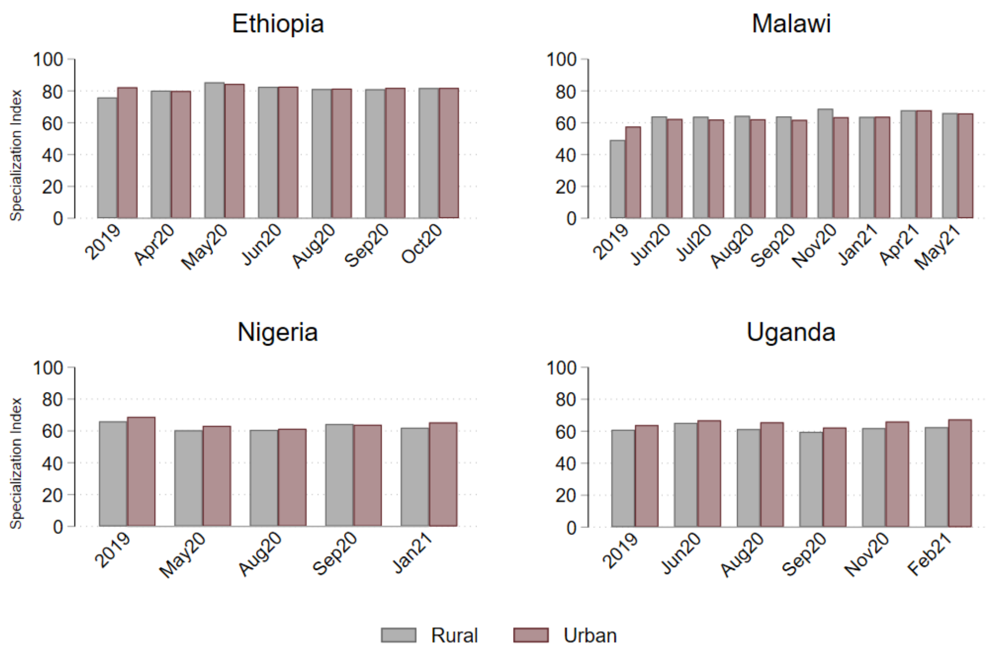
Next, in this section, we present empirical evidence in response to our second research question. Specifically, we present country-level results for our three empirical

Figure 5.1: Index 1 Over Time for Male- and Female-Headed Households



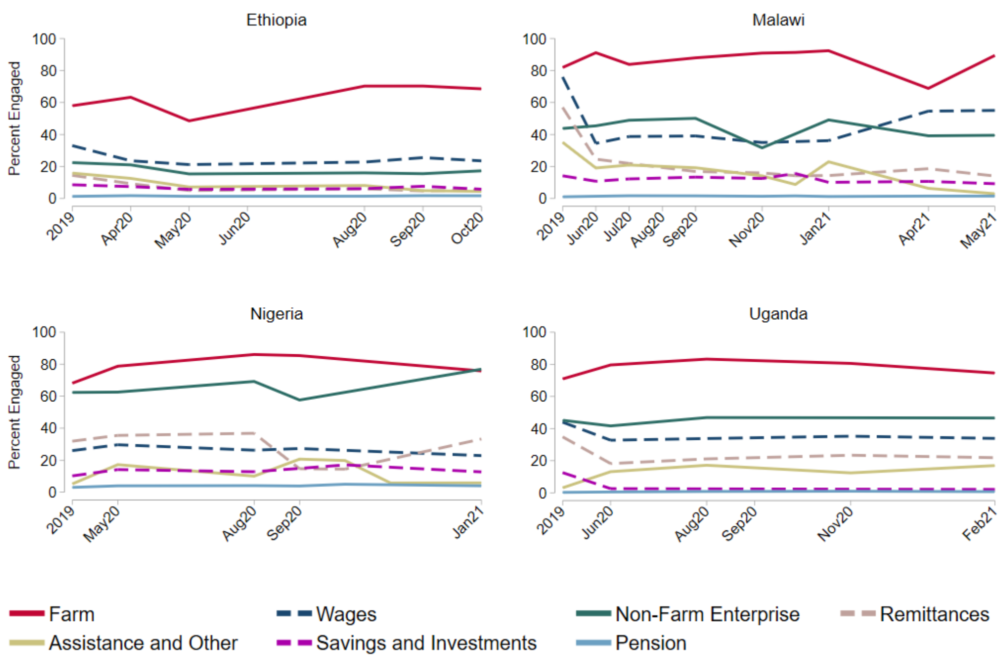
Note: The figure shows Index 1 over rounds of available data. The graphs display mean values for male- and female-headed households. Higher average values indicate more household specialization (less income diversification).

Figure 5.2: Index 1 Over Time for Urban and Rural Households



Note: The figure shows Index 1 over rounds of available data. The graphs display mean values for urban and rural populations. Higher average values indicate more household specialization (less income diversification).

Figure 5.3: Index 1 Income Sources Over Time



Note: The figure shows each of the seven income sources used to generate Index 1. In the figure, we observe the percent of households engaged in each income source over rounds of data.

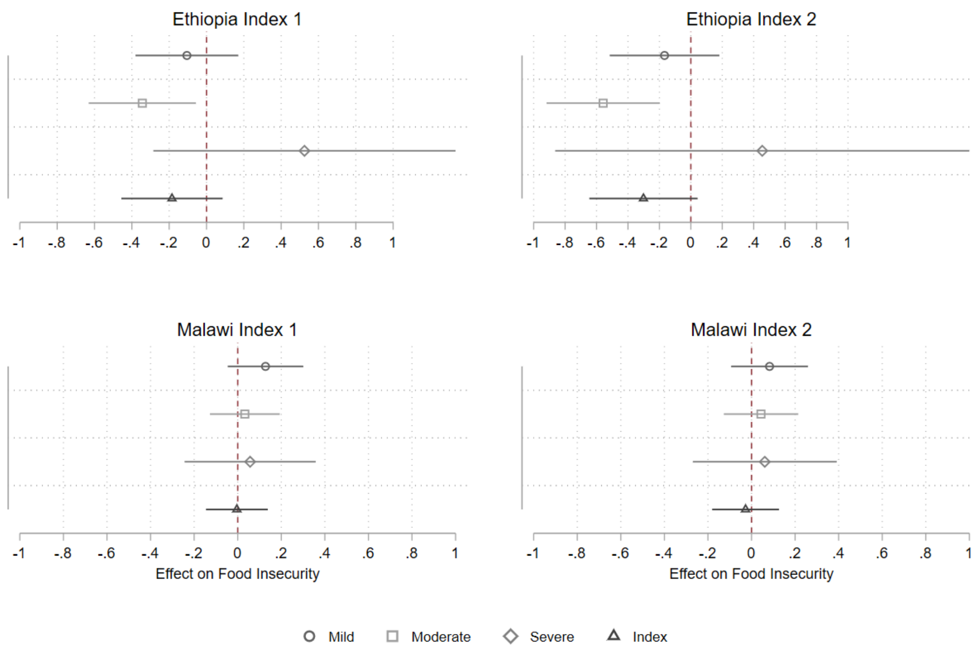
specifications examining the impact of livelihood diversification on household welfare outcomes. When possible, we include all four countries of interest in our regression analysis. However, limited availability of food insecurity and income index data in Nigeria and Uganda prevented the use of those countries in the dynamic panel specifications with food insecurity as the dependent variable. Uganda is also excluded from ANCOVA specifications observing impacts on food insecurity because no baseline food insecurity data are available. For all coefficient plots, we consider a 95 percent threshold for statistical significance.

Dynamic panel specifications use a balanced panel of households with sufficient available data over time. Figure 5.4 displays regressions results for the dynamic panel model with four food insecurity levels as dependent variables. These specifications use Indices 1 and 2 where consistent specialization information is available in both baseline LSMS-ISA data and HFPS rounds in the COVID-19 period. In Ethiopia, negative coefficients for mild, moderate, and indexed food insecurity indicate that income specialization is associated with less food insecurity. However, this result is only statistically significant for moderate food insecurity regressions. The large standard error for severe food insecurity is likely because less than three percent of households in Ethiopia report this level of insecurity. In Malawi, coefficients are generally slightly positive but are not statistically different from zero in any regression.

We include all four countries in our dynamic panel models with education as the outcome variable of interest. As shown in Table 5.1, coefficients in these regressions are neither statistically significant nor consistent across countries and indices in almost all cases. The exception to this finding is Ethiopia, where the coefficient on the interaction term is both larger and more statistically significant than the other three countries. In Ethiopia, household income strategies that were more specialized in the prior time period are associated with an increase in child educational engagement of approximately 46 percent. Consistent with food security regressions, this finding suggests that specialized households in Ethiopia are better off, a result contrary to our hypothesis. In other countries, our results do not substantiate any relationship between household livelihood diversification and welfare.

Figure 5.5 shows coefficient estimates for the dynamic panel with government stringency score interactions. The outcome variable in this specification is food insecurity. As compared to Figure 5.4, coefficient estimates in this specification are more precisely estimated. In Ethiopia, the triple interaction term coefficients are consistently negative, indicating that higher income specialization is associated with lower food insecurity. While this finding again suggests that specialized households experience better welfare outcomes, the impacts are small and not consistently sta-

Figure 5.4: Dynamic Panel Regressions [Dependent Variable: Food Insecurity]



Note: The figure plots regression results from our dynamic panel empirical specification with region and round controls and standard errors clustered at the household level (see Equation 4.2.1). We display coefficients for the interaction of lagged food insecurity and lagged income diversity indices (Indices 1 and 2) for Ethiopia and Malawi. Horizontal lines represent 95 percent confidence intervals.

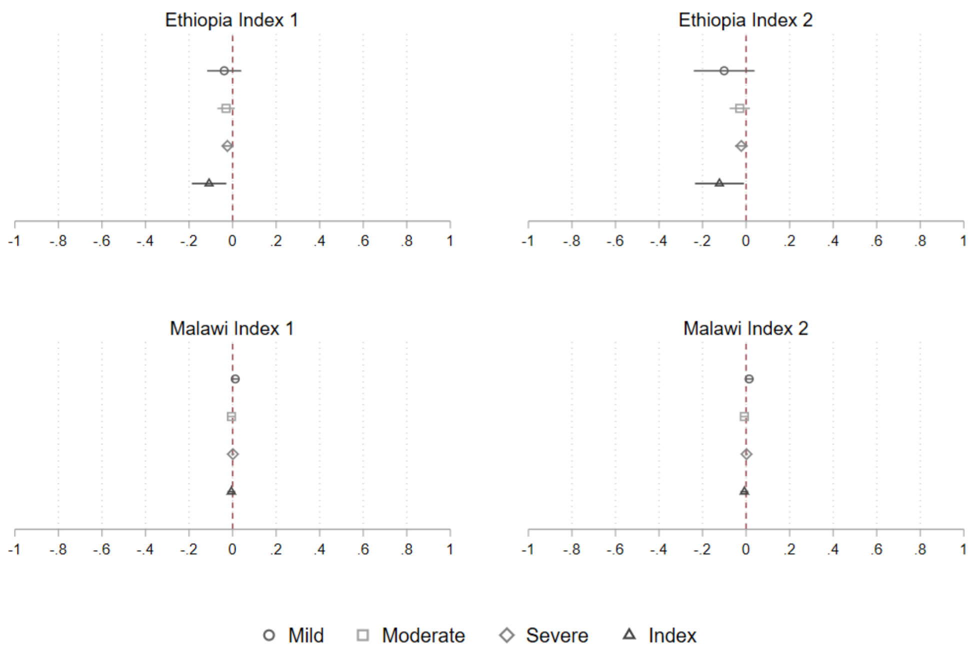
Table 5.1: Dynamic Panel Regressions [Dependent Variable: Child Educational Engagement]

	Ethiopia	Malawi	Nigeria	Uganda
	Index 1			
Lagged Education=1	-0.449***	-0.206**	0.045	-0.145
	(0.129)	(0.070)	(0.087)	(0.074)
Lagged Index 1	-0.304*	-0.003	0.117	0.029
	(0.136)	(0.089)	(0.127)	(0.102)
Lagged Education=1 × Lagged Index 1	0.458**	-0.072	-0.060	0.013
	(0.166)	(0.107)	(0.129)	(0.109)
	Index 2			
Lagged Education=1	-0.487**	-0.200**	0.094	-0.143*
	(0.185)	(0.071)	(0.090)	(0.061)
Lagged Index 2	-0.345*	-0.040	0.103	0.059
	(0.158)	(0.090)	(0.140)	(0.088)
Lagged Education=1 × Lagged Index 2	0.465*	-0.083	-0.036	0.010
	(0.218)	(0.105)	(0.140)	(0.091)
Observations	5,392	3,752	4,100	7,210

Note: The table displays regression results from our dynamic panel empirical specification with region and round controls and standard errors clustered at the household level (see Equation 4.2.1). Columns represent our four countries of interest and we display results for Indices 1 and 2. Cells report coefficients and standard errors are reported in parentheses (*** p<0.001, ** p<0.01, * p<0.05).

tistically significant. In Malawi, coefficient estimates are not statistically different from zero.

Figure 5.5: Dynamic Panel Regressions with Government Stringency Score Interactions [Dependent Variable: Food Insecurity]



Note: The figure plots regression results from our dynamic panel empirical specification with government stringency score interactions. For these regressions, we include region and round controls and standard errors clustered at the household level (see Equation 4.2.2). We display coefficients for the triple interaction term of lagged food insecurity, lagged income diversity indices (Indices 1 and 2), and government stringency score for Ethiopia and Malawi. Horizontal lines represent 95 percent confidence intervals.

The dynamic model with government stringency index interactions does not show significant results in any country when considering educational engagement as the dependent variable (see Table 5.2). Like the food insecurity regressions, coefficients in this specification are small and not significantly different from zero. Unlike the other regressions, this specification with stringency scores does not evidence a relationship between livelihood diversification and welfare outcomes in Ethiopia.

Table 5.2: Dynamic Panel Regressions with Government Stringency Score Interactions [Dependent Variable: Child Educational Engagement]

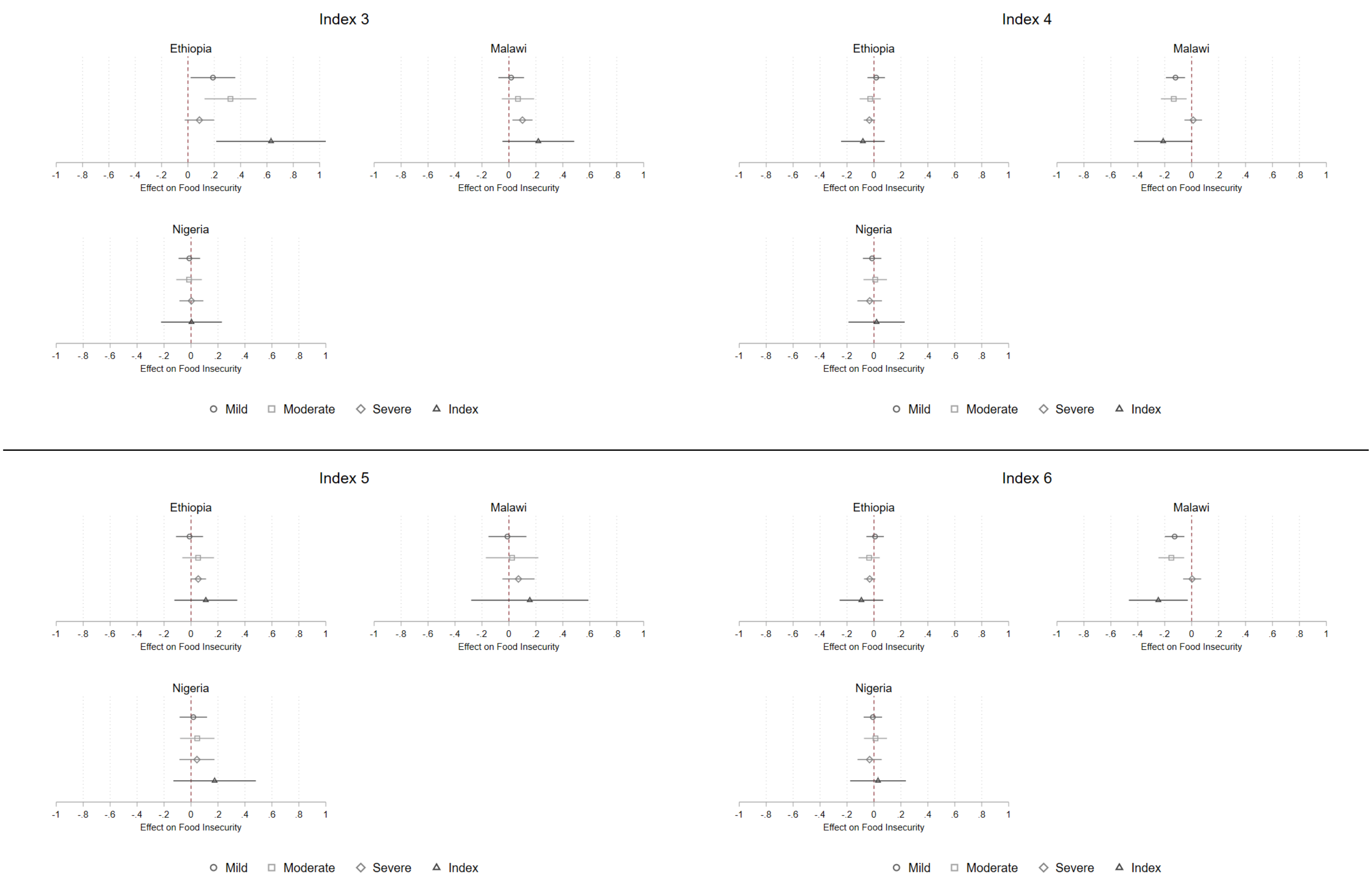
	Ethiopia	Malawi	Nigeria	Uganda
	Index 1			
COVID-19 Stringency Index	-0.034**	-0.019	-0.022**	-0.002
	(0.012)	(0.017)	(0.008)	(0.004)
Lagged Education=1	-0.945	-2.113*	-0.962	-0.245
	(1.385)	(0.847)	(0.495)	(0.319)
Lagged Education=1 × COVID-19 Stringency Index	0.008	0.034*	0.014*	0.001
	(0.018)	(0.015)	(0.007)	(0.004)
Lagged Index 1	-1.629*	1.860*	-0.721	-0.510
	(0.826)	(0.895)	(0.734)	(0.358)
COVID-19 Stringency Index × Lagged Index 1	0.018	-0.033*	0.012	0.008
	(0.011)	(0.016)	(0.010)	(0.005)
Lagged Education=1 × Lagged Index 1	-0.259	-0.395	1.400	0.380
	(1.748)	(1.221)	(0.762)	(0.480)
Lagged Education=1 × COVID-19 Stringency Index × Lagged Index 1	0.008	0.006	-0.021	-0.005
	(0.023)	(0.022)	(0.011)	(0.007)
	Index 2			
COVID-19 Stringency Index	-0.036**	-0.022	-0.012	0.003
	(0.014)	(0.016)	(0.008)	(0.003)
Lagged Education=1	-1.442	-2.062*	-0.215	0.082
	(2.022)	(0.829)	(0.551)	(0.283)
Lagged Education=1 × COVID-19 Stringency Index	0.013	0.033*	0.004	-0.003
	(0.026)	(0.015)	(0.007)	(0.004)
Lagged Index 2	-1.807*	1.591*	-1.667	0.022
	(0.889)	(0.800)	(0.929)	(0.339)
COVID-19 Stringency Index × Lagged Index 2	0.019	-0.029*	0.022	0.000
	(0.012)	(0.015)	(0.012)	(0.005)
Lagged Education=1 × Lagged Index 2	0.332	-0.473	2.492**	-0.132
	(2.290)	(1.168)	(0.928)	(0.431)
Lagged Education=1 × COVID-19 Stringency Index × Lagged Index 2	0.001	0.008	-0.033**	0.002
	(0.029)	(0.021)	(0.012)	(0.006)
Observations	5,392	3,752	4,100	7,210

Note: The table displays regression results from our dynamic panel empirical specification with stringency score interactions (see Equation 4.2.2). For these regressions, we include region and round controls and standard errors are clustered at the household level. Columns represent the four countries of interest and we display results for Indices 1 and 2. Cells report coefficients and standard errors are reported in parentheses (*** p<0.001, ** p<0.01, * p<0.05).

Table 5.3 displays ANCOVA regression results with food insecurity as the dependent variable.[1] For these specifications, we use both fraction (Indices 3 and 5) and HHI indices (Indices 4 and 6) in the pre-COVID-19 period. We elect to use Indices 3-6 for ANCOVA specifications because they focus on the pre-pandemic period and provide the most detailed information available for that time period. Coefficients for regressions with Indices 3 and 5 generally indicate a positive relationship between income specialization and food insecurity, though this finding is not maintained in Nigeria using Index 3. In the other specifications, this positive relationship suggests that more specialized households tend to be more food insecure, a result in opposition to the general findings from the dynamic panel models in Ethiopia. However, once again the coefficients remain insignificant in most cases. When considering the amount of income generated from each source in the HHI specifications (Indices 4 and 6), results flip. Here, livelihood specialization tends to be negatively related to food insecurity in Ethiopia and Malawi, suggesting that more specialized households are less food insecure. Yet, these results are also generally not significantly different from a null result. In Nigeria, the coefficients are not notably different from the null result for HHI specifications.

[1] As a robustness check, simple difference-in-difference regression results are included in Appendix B.

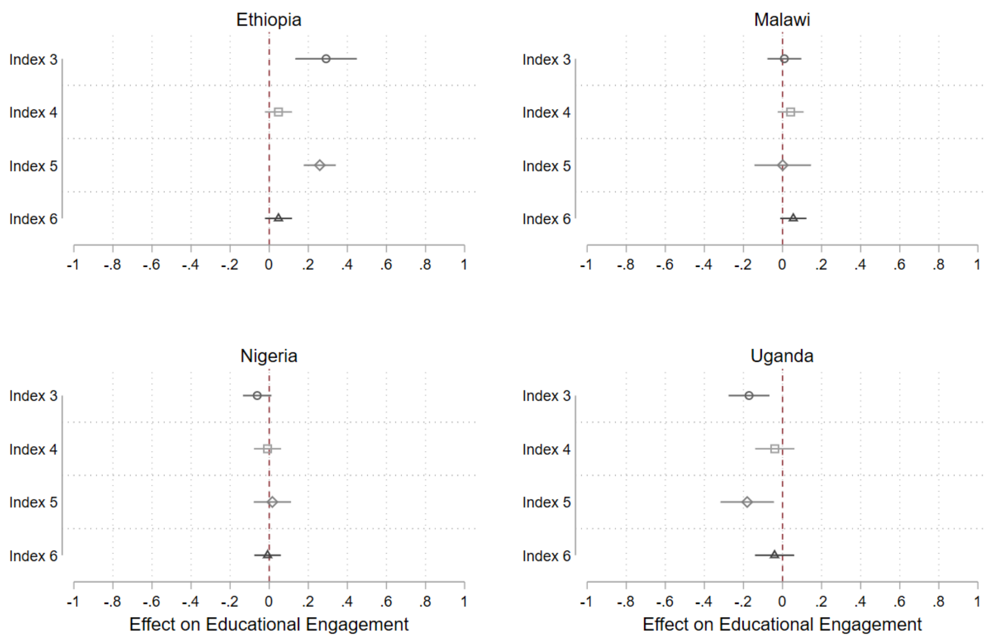
Table 5.3: ANCOVA Regressions [Dependent Variable: Food Insecurity]



Note: The figure plots ANCOVA regression results with region and round controls and standard errors clustered at the household level (see Equation 4.3.1). We display coefficients for lagged income diversity indices (Indices 3-6) for Ethiopia, Malawi, and Nigeria. Horizontal lines represent 95 percent confidence intervals.

Results are inconclusive for the ANCOVA specification observing impacts on education. As seen in Figure 5.6, no clear pattern emerges across countries or indices suggesting a consistent relationship between livelihood specialization and child educational engagement. In Ethiopia, particularly for fraction indices (Indices 3 and 5), specializations seem to have a positive impact on educational engagement. However, in Uganda the opposite appears to be true. HHI indices (Indices 4 and 6) do not have a discernible or significant impact on educational engagement in any of the four countries.

Figure 5.6: ANCOVA Regressions [Dependent Variable: Child Educational Engagement]



Note: The figure plots ANCOVA regression results with region and round controls and standard errors clustered at the household level (see Equation 4.3.1). We display coefficients for lagged income diversity indices (Indices 3-6). Horizontal lines represent 95 percent confidence intervals.

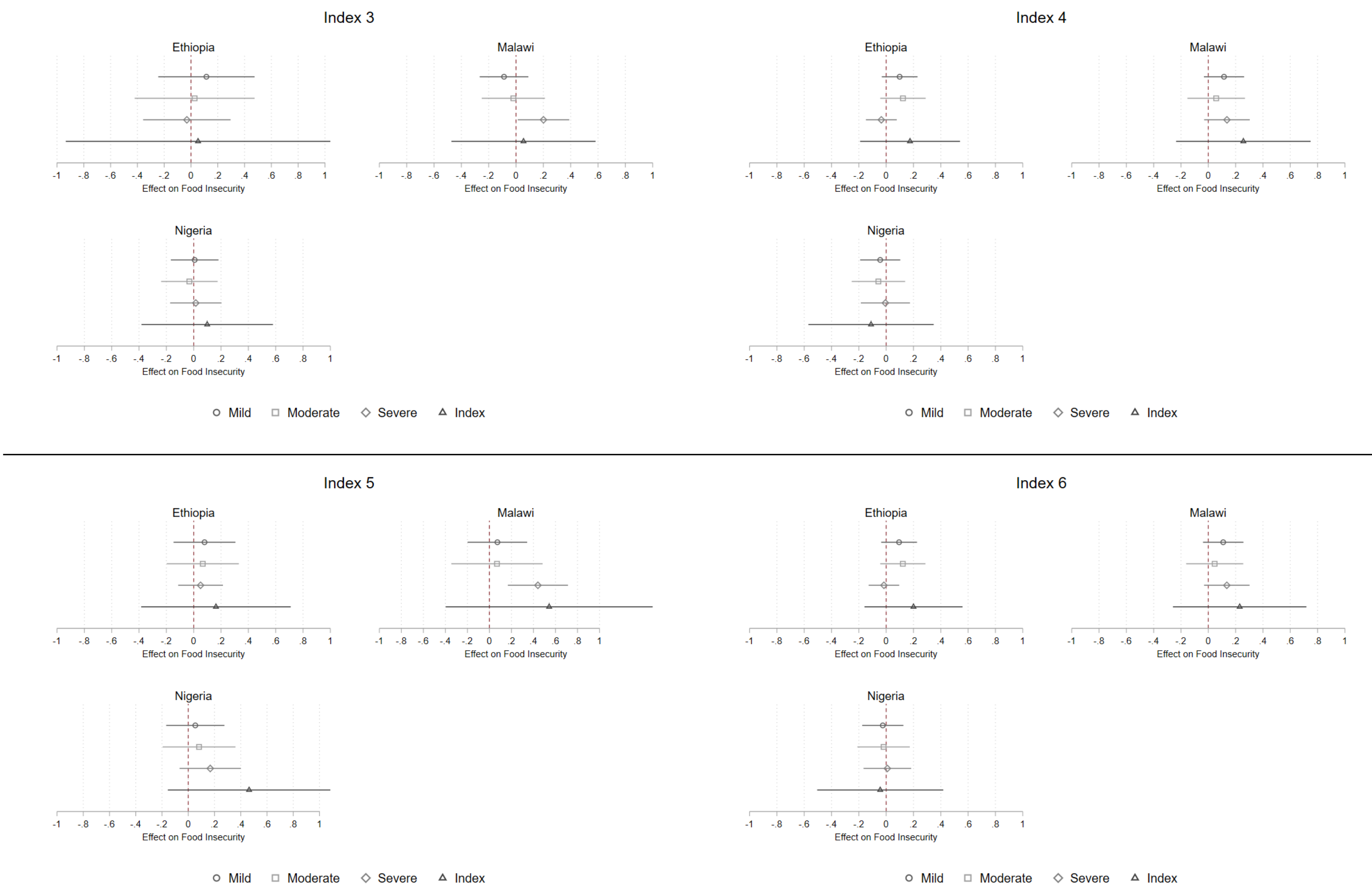
5.3 Research Question 3: Heterogeneous Effects of Livelihood Diversification

Finally, in this section, we explore our final research question: if income diversification has disparate impacts on different country subgroups in the context of the COVID-19 pandemic. Specifically, we investigate heterogeneous impacts for male- and female-headed households as well as urban and rural households. To detect these potentially disparate effects, we include binary interactions term in our ANCOVA specifications indicating head-of-household gender and household sector.

5.3.1 Head-of-Household Gender

Table 5.4 displays coefficient estimates for the ANCOVA specification with a head-of-household gender interaction. In this context, male-headed households are the comparison group. Compared to male-headed households, female-headed households tend to have positive coefficients for Index 5, indicating that households headed by women may experience increased food insecurity when household incomes are more specialized. While these coefficients are consistently positive across the three countries for Index 5 the result is never statistically significant. Further, this finding is not maintained when considering Index 3, the other fraction index. However, positive result found in Index 6 generally also holds in Ethiopia and Malawi for Indices 4 and 6, which use the HHI to measure income specialization. In Ethiopia, this finding for female-headed households represents a shift in sign as compared to the pooled regression results in Table 5.3. The positive result for female-headed households supports our hypothesis that income specialization increases food insecurity, or inversely, income diversification is associated with decreased food insecurity. As such, diversifying income sources may be beneficial for female-headed homes. However, this finding is not evident in Nigeria where HHI coefficients are not notably different from zero. Further, the credibility of our findings is once again hindered by statistical insignificance.

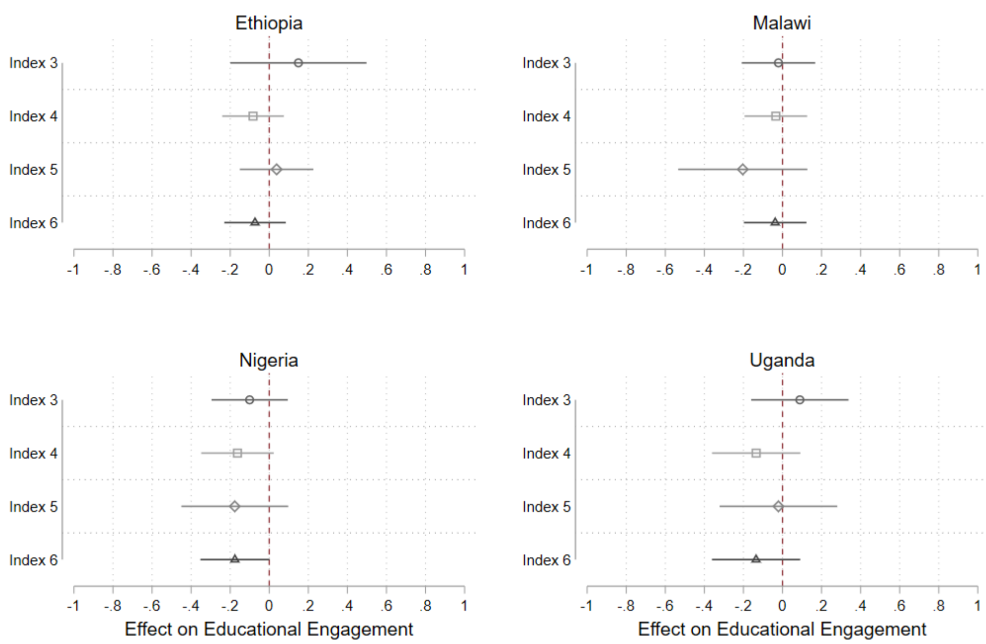
Table 5.4: ANCOVA Regressions by Head-of-Household Gender [Dependent Variable: Food Insecurity]



Note: The figure plots ANCOVA regression results with region and round controls and standard errors clustered at the household level (see Equation 4.3.1). We display coefficients for the interaction of lagged income diversity indices (Indices 3-6) and a head-of-household gender indicator. Male-headed households serve as the comparison group. Horizontal lines represent 95 percent confidence intervals.

Similarly, our evidence suggests that income-specialized female-headed households experience worse child educational outcomes than male-headed households. Figure 5.7 displays ANCOVA coefficient results for the interaction of income specialization indices and head-of-household gender with child educational engagement as the dependent variable. The coefficients tend to be negative, though not statistically significant, in most cases. This negative result suggests that compared to male-headed households, specialized female-headed households experience a greater educational disadvantage than male-headed households. Inversely, this finding again indicates that diversification of household income may have pronounced benefits for female-headed households.

Figure 5.7: ANCOVA Regressions by Head-of-Household Gender [Dependent Variable: Child Educational Engagement]



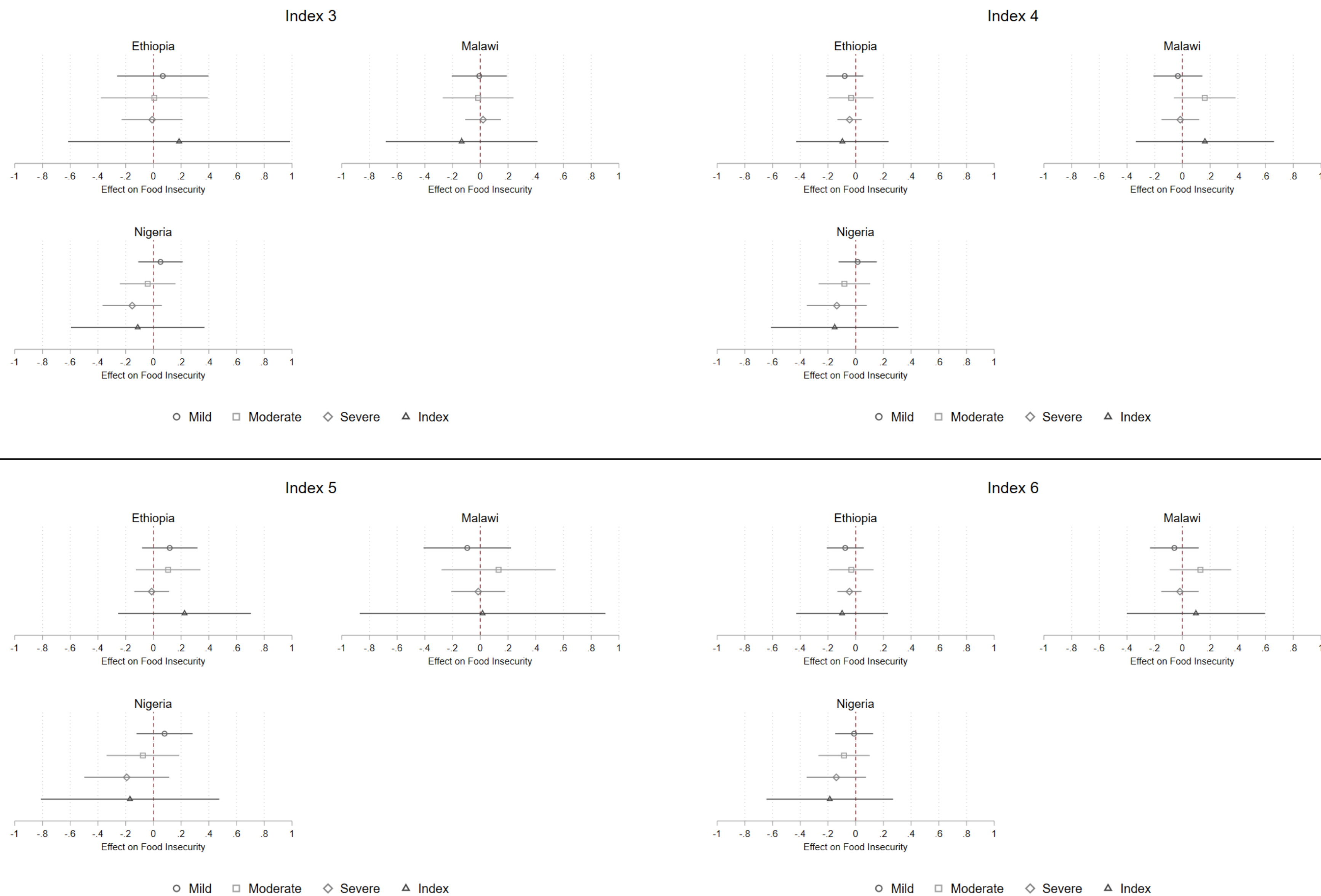
Note: The figure plots ANCOVA regression results with region and round controls and standard errors clustered at the household level (see Equation 4.3.1). We display coefficients for the interaction of lagged income diversity indices (Indices 3-6) and a head-of household gender indicator. Male-headed households serve as the comparison group. Horizontal lines represent 95 percent confidence intervals.

5.3.2 Sector

We also test for heterogeneous impacts across rural and urban populations. These specifications do not point to a consistent relationship and do not indicate heterogeneous effects by sector. For these specifications, rural households serve as the comparison group. As seen in Table 5.5, coefficients for the interaction term do not evidence a differential impact of livelihood diversification on food security for urban versus rural populations. Coefficient estimates are never statistically significant and do not follow a discernible trend across countries or income index specification.

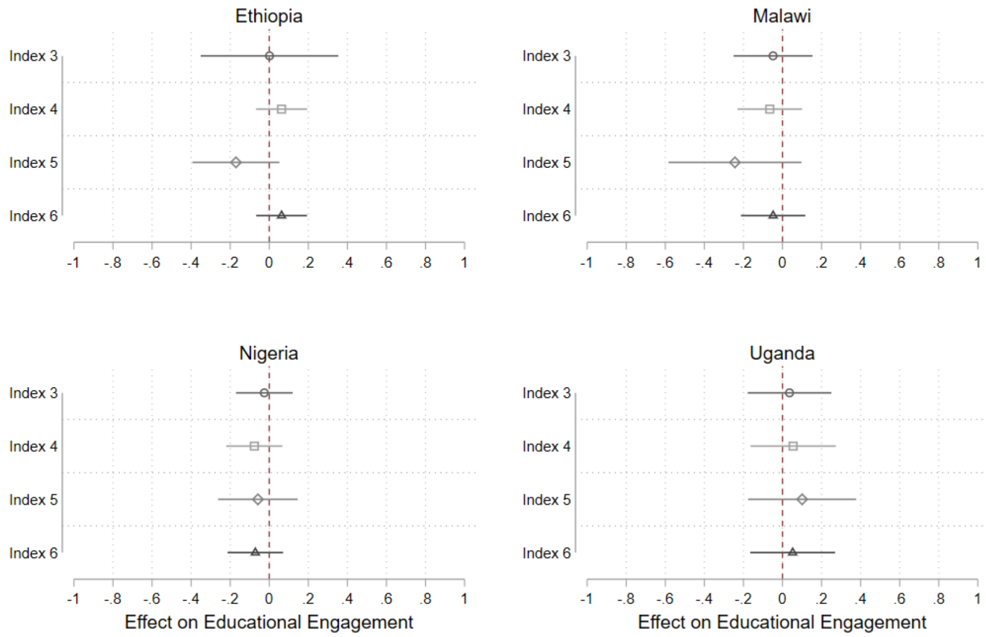
Further, regression results displayed in Figure 5.8 do not signify a heterogeneous impact of livelihood specialization on educational engagement for rural versus urban populations. For these specifications, coefficients for urban households are slightly positive in Uganda, slightly negative in Malawi and Nigeria, and inconclusive in Ethiopia. No relationships are statistically significant.

Table 5.5: ANCOVA Regressions by Urban/Rural [Dependent Variable: Food Insecurity]



Note: The figure plots ANCOVA regression results with region and round controls and standard errors clustered at the household level (see Equation 4.3.1). We display coefficients for the interaction of lagged income diversity indices (Indices 3-6) and an urban/rural indicator. Rural households serve as the comparison group. Horizontal lines represent 95 percent confidence intervals.

Figure 5.8: ANCOVA Regressions by Urban/Rural [Dependent Variable: Child Educational Engagement]



Note: The figure plots ANCOVA regression results with region and round controls and standard errors clustered at the household level (see Equation 4.3.1). We display coefficients for the interaction of lagged income diversity indices (Indices 3-6) and an urban/rural indicator. Rural households serve as the comparison group. Horizontal lines represent 95 percent confidence intervals.

Conclusions

The COVID-19 pandemic exposed and exacerbated the many challenges households in SSA face. For many of these households, subsistence farming serves as a primary income source. Prior literature suggests that income diversification into other industries bolsters household resilience to shocks. However, the literature focuses on climate and conflict shocks and does not capture major global disasters like the COVID-19 pandemic. This research fills that gap in the literature, exploring three questions related to household income composition and welfare outcomes in this new context. We take advantage of rich survey data to assess trends in income composition strategies over time and understand the relationship between livelihood diversification and welfare outcomes. Importantly, our data include a pre-outbreak baseline, allowing us to observe households over time and to identify causal relationships.

First, we inquire how household income composition has changed since the onset of the pandemic. Our hypothesis asserts that household income strategies change between 2019 and early 2020. However, when considering this first question, we do not observe substantial changes in household income composition since the onset of the pandemic in early 2020. While we are not able to compare incomes over time, we can examine how engagement in various income-generating activities changed since the outbreak. Participation in wage work and receipt of remittances were most impacted by the pandemic, particularly in Malawi and Uganda. However, these changes did not translate into substantially different income diversification scores. Prior to the pandemic, urban households tended to be more specialized than rural. After the onset of COVID-19, the two sectors did not exhibit significant differences. Overall, household livelihood diversification scores are not indicative of a meaningful of systematic change in household resource allocation strategies.

Next, we examine our second research question which seeks to understand how household income composition impacts livelihood outcomes. Our pooled regressions do not provide evidence to support our hypothesis that livelihood diversification betters welfare outcomes amid the pandemic. In Ethiopia, we find some evidence to the contrary: livelihood *specialization* is associated with more favorable welfare outcomes. In other countries, findings from the pooled regressions do not point to a significant relationship between livelihood diversification and welfare outcomes during the COVID-19 pandemic. Coefficients in these models are rarely statistically significant and either coalesce around zero or do not exhibit a consistent sign across our various specifications.

Last, we inquire if income composition might have disparate effects on different population subgroups. We hypothesize that the impact of livelihood diversification on welfare outcomes varies based on household characteristics. Specifications that include heterogeneous impacts by head-of-household gender provide some evidence in support of our hypothesis for female-headed households. Most specifications that include a head-of-household gender indicator suggest that diversification of household income may be beneficial for female-headed households. Compared to their male counterparts, female-headed households with specialized incomes may experience worse outcomes both in terms of food insecurity and child educational engagement. Inversely, this finding suggests that household livelihood diversification may improve welfare outcomes and help female-headed households cope with the effects of the COVID-19 pandemic. While the coefficients on these interaction terms are often statistically insignificant at the 95 percent level, the consistency of the sign on the coefficients across specifications evinces a relationship. It is worth nothing, though, these impacts are not consistent for all specifications and the magnitude of the impact is unknown. We find no evidence to suggest differential effects for urban compared with rural households.

We hope these results prompt constructive discussions to facilitate recovery and enhance resilience to disasters in SSA. Previous literature promotes diversification of household income as a pathway to mitigate vulnerability to shocks. Income diversification remains a sound coping mechanism for many moderate shocks, in particular those related to climate and weather. However, while we find some evidence that this conclusion may hold for female-headed households, our study suggests, by and large, that for disasters on the scale of the COVID-19 pandemic, a different adaptation strategy may be appropriate. While our hypotheses are ultimately not supported, our results are somewhat unsurprising. The extreme socioeconomic impacts of the pandemic may necessitate alternative adaptation strategies or may be too disastrous and omnipresent to prepare for. Fear of COVID-19 and government restrictions to stop the spread of the virus may have stripped resource-rich households of their comparative advantages and equalized vulnerability of income-diverse and income-specialized households. Or perhaps moving away from subsistence farming left households unable to access sufficient food during time of crisis, leaving income-diverse households worse off. In the end, we do not find evidence that income diverse households were better equipped to cope with the socioeconomic impacts of the COVID-19 pandemic.

More research is required to better understand which household characteristics or income strategies are associated with more resilience to shocks such as the COVID-19 pandemic. Perhaps a starting place for this continued research lies in the exploration of the alternative hypothesis discussed in the literature: that the presence of non-farm income or the receipt of remittances influences welfare outcomes more than diversification itself. Or perhaps social safety nets could provide some stability to households, as was the case in many high-income countries. Maybe the inclusion of contemporaneous climate, conflict, and other shocks would provide a more nuanced picture of the household livelihood landscape. We hope our timely contribution to the COVID-19 literature encourages researchers to further explore this topic and provide meaningful recommendations to those seeking to strengthen household resilience and better prepare for disasters in the future.

Appendix

A Structured Search

To conduct our structured search literature review, we closely follow the methodology from Dizon et al. (2021), which breaks down the process into three phases: (1) search (database and targeted), (2) screening, and (3) coding.

I Search

In the first phase, we employ three categories of search terms: Category A includes our intervening factors of interest, focused on labor; Category B includes our outcomes of interest; and Category C includes shocks (See Figure A.1). Terms from the three categories are joined by "AND" in the Boolean searches. The combination of search terms from each category results in 400 Boolean searches. Each of the 400 combinations was searched in the following three databases: EconLit, Science Direct, and IDEAS/RePEc, resulting in 1,200 total searches. For these searches, we employ a stopping rule when ten consecutive studies from the list of results are deemed irrelevant.

II Screening

The screening stage considers titles, subjects, and publication outlets from a returned search, and applies inclusion and exclusion criteria to quickly determine the relevance of the study. Screening a each articles takes roughly one to two minutes.

We use the following inclusion and exclusion criteria to screen search results:

- **Relevant interventions and outcomes**: confirm that at least one of the relevant interventions and one of the relevant outcomes are measured
- **Language**: include only studies written in English
- **Publication date**: include studies from January 1, 2001 to August 1, 2021
- **Unit of analysis**: include all studies, even those which look at regional or national time series

Category	Search terms
Category A: Intervention	
Labor	---
Diversification	livelihood diversification; livelihood diversity income diversity household labor allocation
Income Types	household income remittances pension wages
Category B: Outcome	
Food Security	food security; food insecurity
Education	school enrollment child education
Poverty	poverty alleviation
Category C: Shocks	
Type	COVID-19 epidemic; pandemic economic shock; recession weather shock; climate shock income shock violent conflict; civil unrest

Figure A.1: Search Terms

- **Peer reviewed**: include papers with some peer review, including papers submitted to conferences

Generally, qualitative research are restricted to include research reports with empirical studies that include a description of the sampling strategy, data collection procedures, and the type of data-analysis considered.

Included studies should contain the methodology chosen and the methods or research techniques opted for while descriptive papers, editorials, or opinion papers are excluded.

When screening papers, we consider two stages of questions: 1) screening (questions 1 and 2) and 2) details (questions 3 through 10):

1. Was there a clear statement of the aims of the research?

2. Is a qualitative methodology appropriate?

3. Was the research design appropriate to address the aims of the research?

4. Was the recruitment strategy appropriate to the aims of the research?

5. Were the data collected in a way that addressed the research issue?

6. Has the relationship between researcher and participants been adequately considered?

7. Have ethical issues been taken into consideration?

8. Was the data analysis sufficiently rigorous?

9. Is there a clear statement of findings?

10. How valuable is the research?

Figure A.2 shows the results of the screening process. The 1,200 search terms produced 10,334 results of which 951 were deemed relevant (including duplicate articles). After accounting for duplicates, the screening process produced 331 unique articles.

Database	Search Results	Relevant Results	Unique Articles	Level 2 Relevance	Level 1 Relevance
EconLit	169[a]	107[a]	51	13	6
ScienceDirect	10,066[a]	803[a]	273	49	20
IDEAS	99[a]	41[a]	17	7	0
Total	**10,334**[a,b]	**951**[a,b]	**331**[*]	**65**[*]	**23**[*]

a. Includes duplicated articles across searches
b. Includes duplicated articles across databases
* Value excludes articles duplicated across databases and thus does not reflect the sum of the above rows

Figure A.2: Search Results

III Coding

The 331 articles from the screening process were further reviewed to hone in on the most pertinent works. This process can be described in three steps:

Step 1 Review & Sort: a closer look at all 331 screened studies to ensure that the work does meet the above criteria. During this step, we spent about five minutes per paper to read the study's abstract and sort it into one of three levels of relevance. Level 1 includes the most relevant papers, which incorporate some measure of livelihood diversity and attempt to measure its impact on well-being. Level 2 papers pertain to similar topics but do not attempt to establish a relationship between livelihood diversification and welfare outcomes directly. Level 3 is composed of all remaining papers from the screening process. As seen in Figure A.2, 65 papers were sorted into Level 2 and 23 into Level 1, leaving 243 in Level 3 (not shown).

Step 2 Code: each Level 1 and Level 2 study is fully coded, by registering the following details

- Country, district / province, author, year
- Data source(s) and collection procedures
- Livelihood diversification measure
- Shock(s) considered
- Econometric model specification
- Relevant control variables
- Key results

Step 3 Quality Rating: each Level 1 and Level 2 paper is further assessed to assign it one of three possible ratings - AAA, AA, or A. The ratings are primarily based on internal validity or the quality of evaluation design. For example, AAA includes causal studies, or studies which rely on regression discontinuity, difference-in-difference, instrumental variables, or matching; AA includes studies which consider some weak counterfactual (such as pre-post studies or a self-selected comparison group); and A studies are observational work that focuses on trends and correlations. The rating can further consider the presence and quality of robustness checks. Of the 87 reviewed articles, 40 received a A quality rating and 47 received AA. No papers received a AAA rating.

The results from select papers found in this structured search are presented in Section 2.

B Difference-in-Difference Specifications

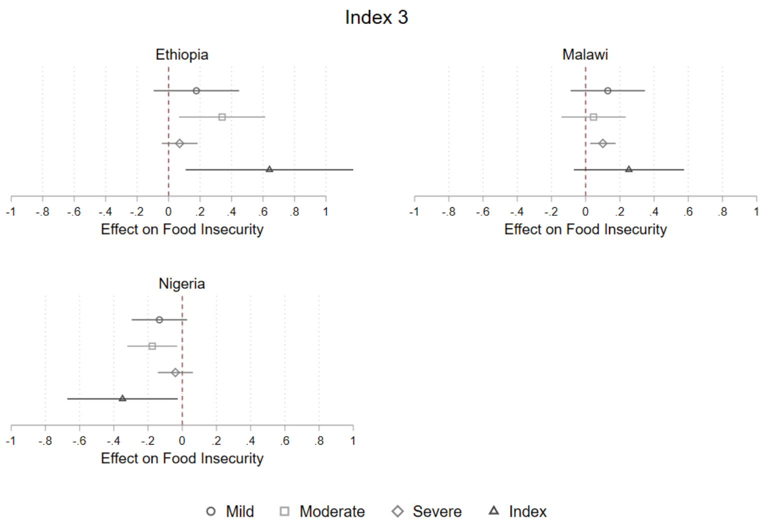
In addition to ANCOVA specifications, we estimate a simple difference-in-difference model in which we include an indicator for the start of COVID-19-related restrictions in SSA. This specification takes on the following functional form:

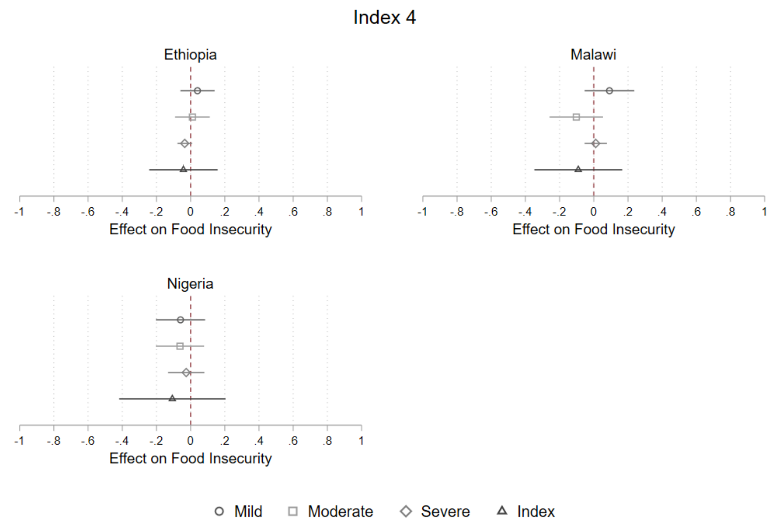
$$y_{it} = \alpha + \beta_1 div_{it=0} + \beta_2 div_{it=0} * covid_t + \beta_3 covid_t + \delta_t + c_j * t_t + u_i + \epsilon_{it}. \tag{B.1}$$

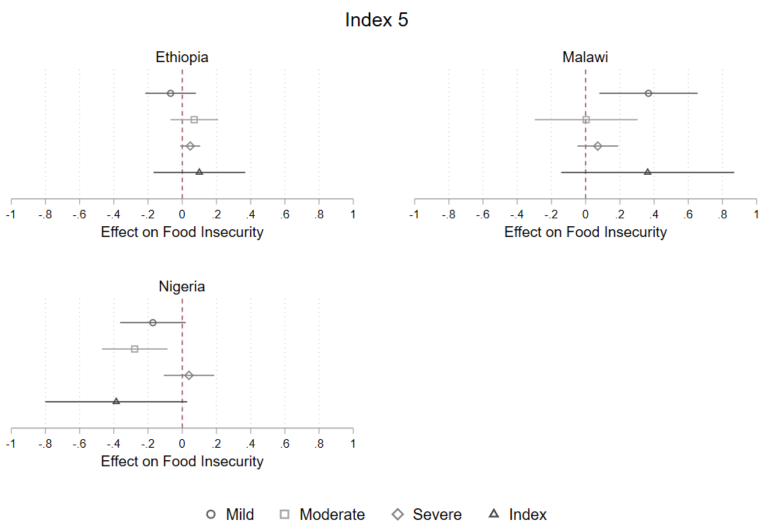
Here $div_{it=0}$ is the diversity index in the pre-pandemic period and $covid_t$ is an indicator for before and after the start of the pandemic. The variable of interest in this specification is β_2, the difference-in-difference effect of income diversity post-pandemic.

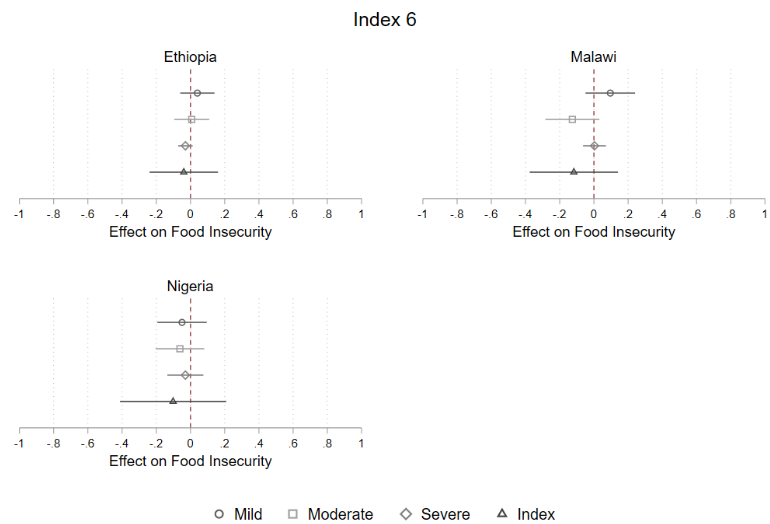
As seen in Table A.1 and Figure A.3, results from these specifications are generally consistent with their ANCOVA counterparts (Table 5.3 and Figure 5.6) but with less precise measures of standard errors. A similar pattern emerges for results by head-of-household gender (Table A.2 as compared to Table 5.4 and Figure A.4 as compared to Figure 5.7) and sector of household (Table A.3 as compared to Table 5.5 and Figure A.5 as compared to Figure 5.8).

Table A.1: Difference-in-Difference Regressions [Dependent Variable: Food Insecurity]



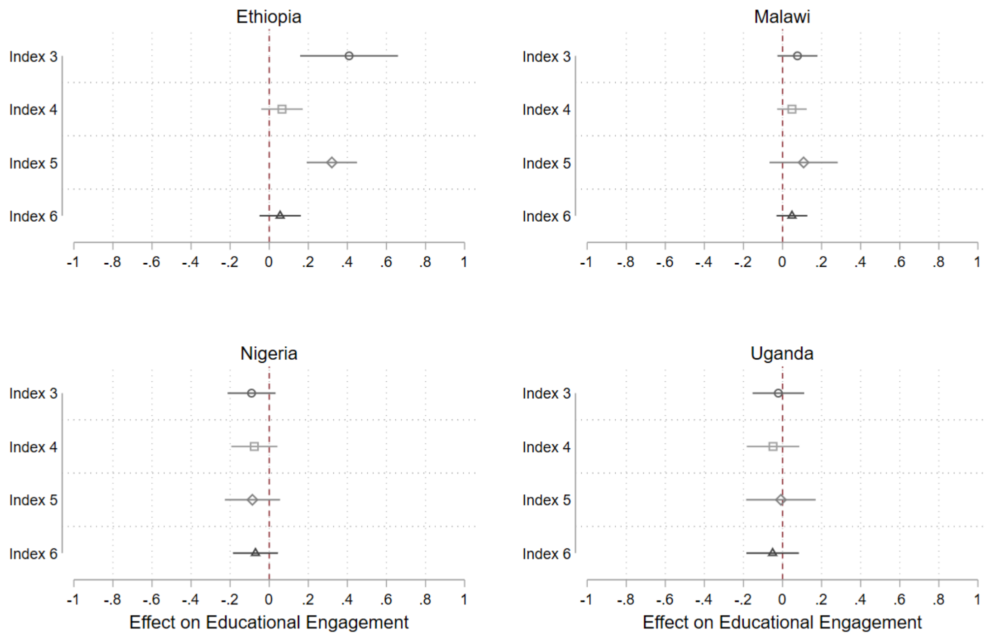






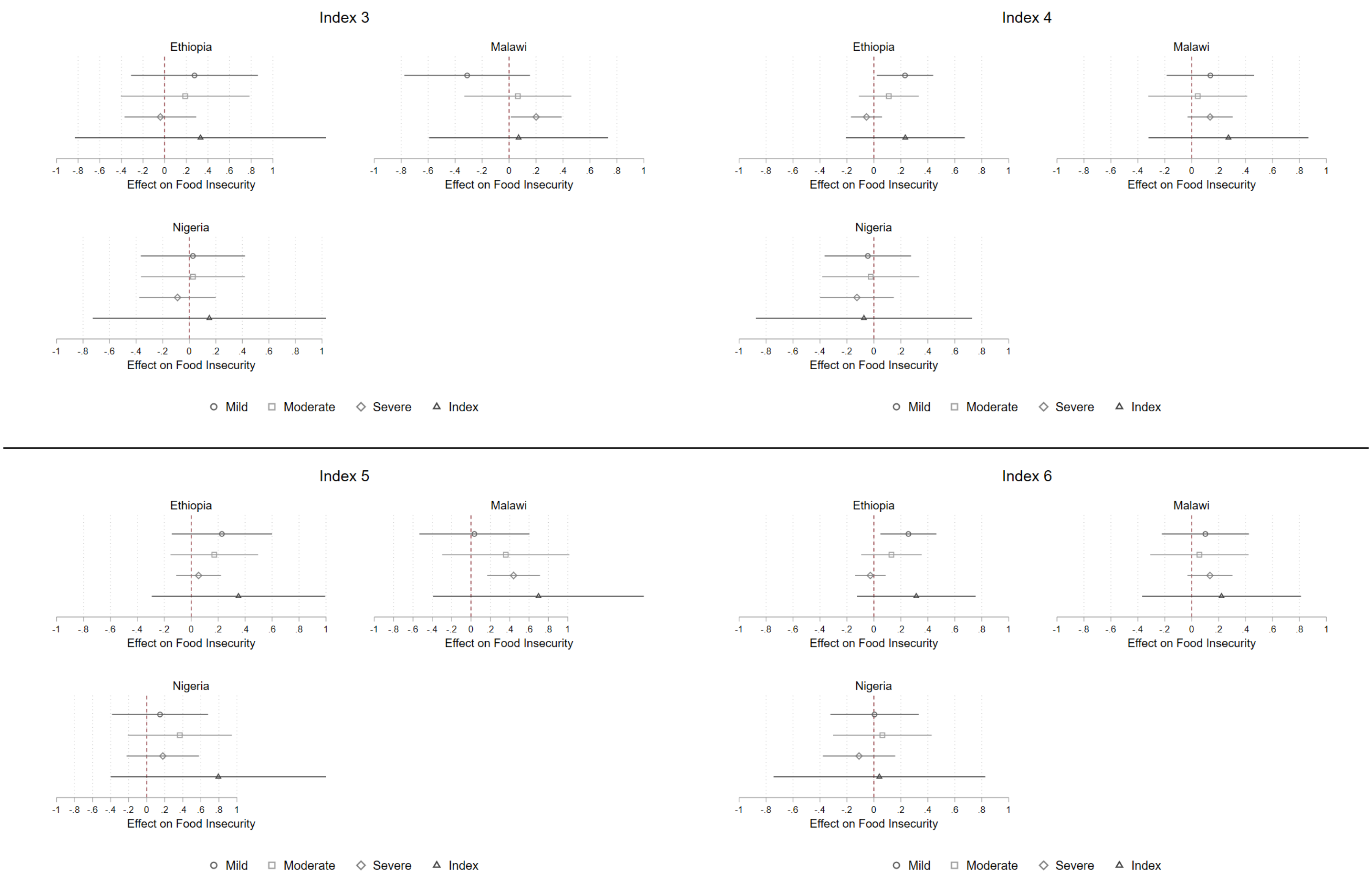
Note: The figure plots difference-in-difference regression results with region and round controls and standard errors clustered at the household level (see Equation B.1). We display coefficients for the interaction of lagged income diversity indices (Indices 3-6) and a COVID-19 indicator for Ethiopia, Malawi, and Nigeria. Horizontal lines represent 95 percent confidence intervals.

Figure A.3: Difference-in-Difference Regressions [Dependent Variable: Child Educational Engagement]



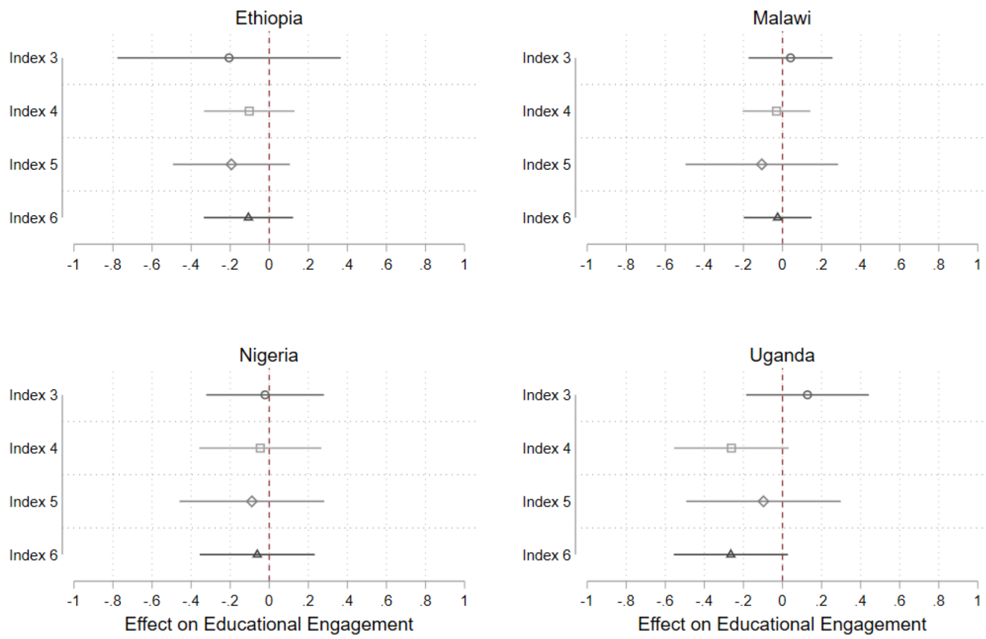
Note: The figure plots difference-in-difference regression results with region and round controls and standard errors clustered at the household level (see Equation B.1). We display coefficients for the interaction of lagged income diversity indices (Indices 3-6) and a COVID-19 indicator. Horizontal lines represent 95 percent confidence intervals.

Table A.2: Difference-in-Difference Regressions by Head-of-Household Gender [Dependent Variable: Food Insecurity]



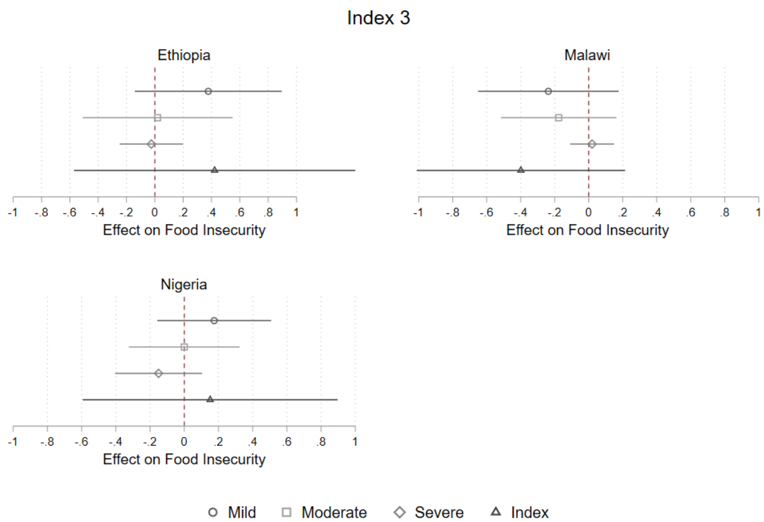
Note: The figure plots difference-in-difference regression results with region and round controls and standard errors clustered at the household level (see Equation B.1). We display coefficients for the triple interaction of lagged income diversity indices (Indices 3-6), a COVID-19 indicator, and a head-of-household gender indicator. Male-headed households serve as the comparison group. Horizontal lines represent 95 percent confidence intervals.

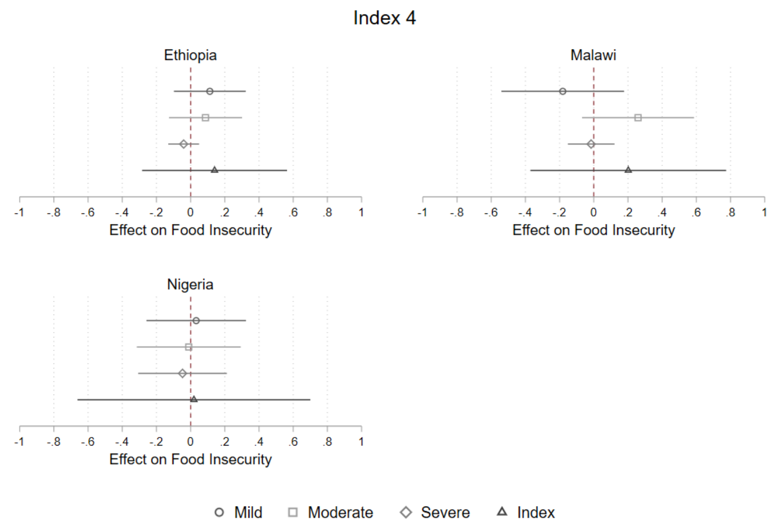
Figure A.4: Difference-in-Difference Regressions by Head-of-Household Gender: [Dependent Variable Child Educational Engagement]

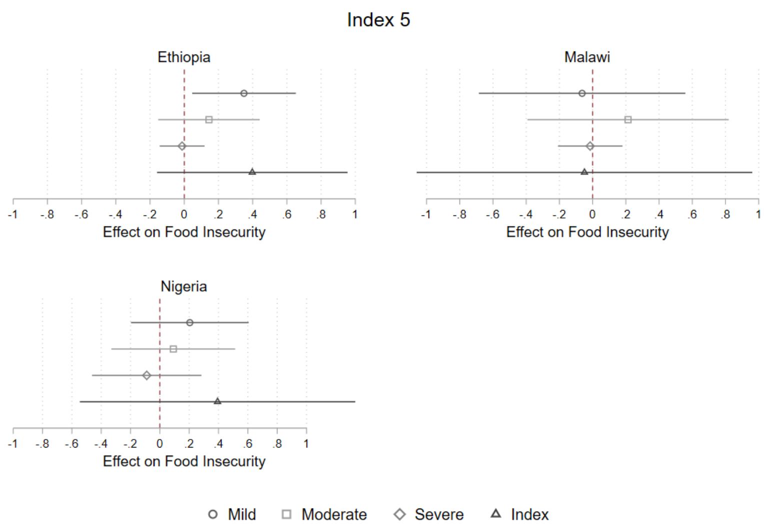


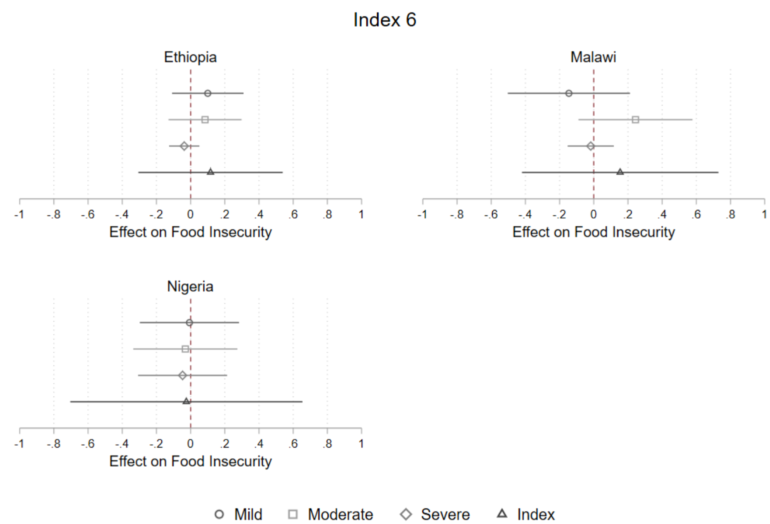
Note: The figure plots difference-in-difference regression results with region and round controls and standard errors clustered at the household level (see Equation B.1). We display coefficients for the triple interaction of lagged income diversity indices (Indices 3-6), a COVID-19 indicator, and a head-of household gender indicator. Male-headed households serve as the comparison group. Horizontal lines represent 95 percent confidence intervals.

Table A.3: Difference-in-Difference Regressions by Urban/Rural [Dependent Variable: Food Insecurity]



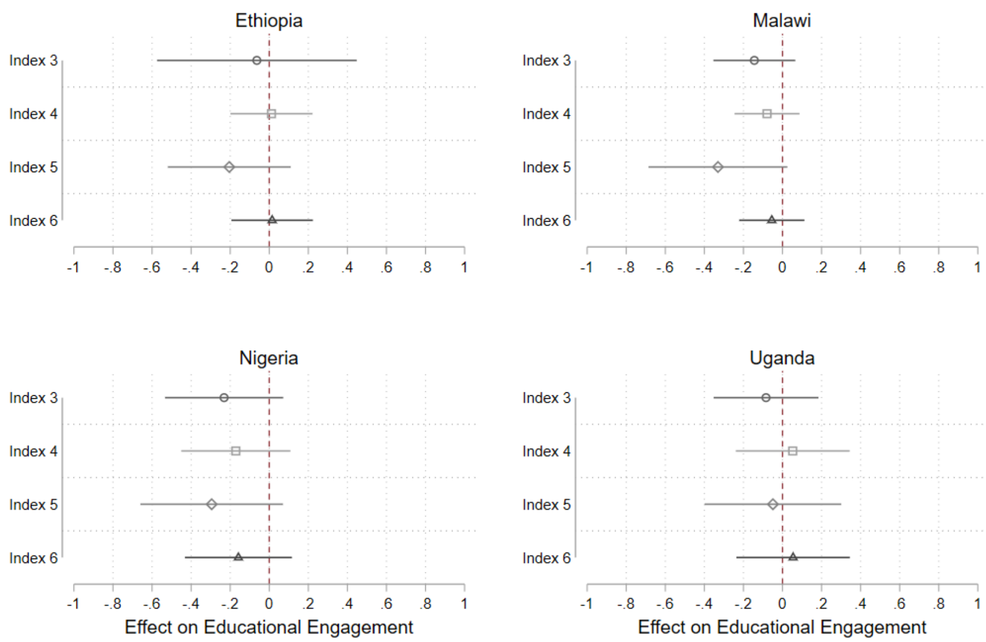






Note: The figure plots difference-in-difference regression results with region and round controls and standard errors clustered at the household level (see Equation B.1). We display coefficients for the triple interaction of lagged income diversity indices (Indices 3-6), a COVID-19 indicator, and an urban/rural indicator. Rural households serve as the comparison group. Horizontal lines represent 95 percent confidence intervals.

Figure A.5: Difference-in-Difference Regressions by Urban/Rural [Dependent Variable: Child Educational Engagement]



Note: The figure plots difference-in-difference regression results with region and round controls and standard errors clustered at the household level (see Equation B.1). We display coefficients for the triple interaction of lagged income diversity indices (Indices 3-6), a COVID-19 indicator, and an urban/rural indicator. Male-headed households serve as the comparison group. Horizontal lines represent 95 percent confidence intervals.

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