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Micro insights on the pathways to agricultural transformation: Comparative evidence from Southeast Asia and Sub-Saharan Africa

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Abstract

Most studies of agricultural transformation document the impact of agricultural income growth on macroeconomic indicators of development. Much less is known about the micro-scale changes within the farming sector that signal a transformation precipitated by agricultural income growth. This study provides a comparative analysis of the patterns of micro-level changes that occur among small-holder farmers in Uganda and Malawi in Sub-Saharan Africa (SSA), and Thailand and Vietnam in Southeast Asia (SEA). Our analysis provides several important insights on agricultural transformation in these two regions. First, agricultural income in all examined countries is vulnerable to changes in precipitation and temperature, an effect that is nonlinear and asymmetric. SSA countries are more vulnerable to these weather changes. Second, exogenous increases in agricultural income in previous years improve non-farm income and trigger a change in labor allocation within the rural sector in SEA. However, this is the opposite in SSA where the increase in agricultural income reduces non-farm income, indicating a substitution effect between farm and non-farm sectors. These findings reveal clear agricultural transformation driven by agricultural income in SEA but no similar evidence in SSA.

KEYWORDS

agricultural transformation, small-holder farmers, Southeast Asia, Sub-Saharan Africa

Résumé

La plupart des études sur la transformation agricole documentent l'impact de la croissance des revenus agricoles sur les indicateurs macroéconomiques de développement. On en sait beaucoup moins sur les changements à petite échelle au sein du secteur agricole qui signalent une transformation précipitée par la croissance des revenus agricoles. Cette étude fournit une analyse comparative des modéles de micro-changements qui se produisent chez les petits exploitants agricoles en Ouganda et au Malawi en Afrique subsaharienne (ASS), et en Thaïlande et au Vietnam en Asie du Sud-Est (SEA). Notre analyse fournit plusieurs informations importantes sur la transformation agricole dans ces deux régions. Premiérement, le revenu agricole dans tous les pays examinés est vulnérable aux variations des précipitations et de la température, un effet non linéaire et asymétrique. Les pays d'ASS sont plus vulnérables à ces changements climatiques. Deuxiémement, les augmentations exogénes du revenu agricole au cours des années précédentes améliorent le revenu non agricole et déclenchent un changement dans la répartition de la main-d'œuvre au sein du secteur rural en SEA. Cependant, c'est l'inverse en ASS où027;augmentation des revenus agricoles réduit les revenus non agricoles, indiquant un effet de substitution entre les secteurs agricole et non agricole. Ces résultats révélent une transformation agricole claire induite par le revenu agricole en SEA, mais aucune preuve similaire en ASS.

1 INTRODUCTION

Agricultural transformation is inevitable during economic growth in developing economies. This process can be considered as adjustments of economic entities in the agricultural sector in response to various driving forces (Odening & Grethe, 2012; Nguyen et al., 2021), both within and outside the sector. Within the sector, increases in farming ability facilitate the transfer of farmland from less to more efficient land users, and consequently enhance farm income (Gollin et al., 2002; Üngör, 2013). Outside the sector, economic growth induced non-farm employment opportunities allow the reallocation of labor from farm to non-farm sectors with higher labor returns (Hansen & Prescott, 2002) and consequently increase household income. These processes also facilitate mechanization in agriculture (Binswanger, 1986; Liu et al., 2020). Moreover, economic growth leads to changes in consumption patterns that demand more livestock products (Byerlee et al., 2009; Sharma et al., 2018), which pave the way for livestock development in the agricultural sector (Do et al., 2022).

Agricultural transformation can be observed at both macro and micro levels. However, macroeconomic research has dominated the agricultural transformation literature (e.g., Lewis, 1954; Johnston & Mellor, 1961; Hayami & Ruttan, 1971; Gollin et al., 2002; Diao et al., 2017). These studies focus on the effects of modern agricultural input usage and/or technology adoption on traditional macroeconomic indicators such as a declining labor share or gross domestic product (GDP) share of the agriculture sector (e.g., Bustos et al., 2016; Barrett et al., 2017; McArthur & McCord, 2017; Diao et al., 2018). There is a notable absence of empirical micro-economic research that explains the transformation process underlying these macro-economic changes at the farm level in general, and at the small-holder farm level in the developing world in particular. According to the Food and Agriculture Organization (FAO, 2019), among the 570 million farms worldwide 475 million are small-holders. The majority of these small-holder farms are in Asia and Sub-Saharan Africa (SSA), and they provide about 70% of food to the population in these two regions. Raising the income of small-holder farms in these regions is seen as vital to providing a market for domestically produced manufactures and services (Baumol, 1967; Jayne et al., 2016). Even when labor is believed to be in surplus in the rural sector, agricultural productivity growth is considered essential to prevent rising food prices and nominal wage costs from undermining industrial development (Lele & Mellor, 1981). The successful transfer of labor from farm to non-farm sectors requires investment in rural areas (Byerlee et al., 2009; Adamopoulos & Restuccia, 2014; Chowdhury, 2016). Therefore, an increase in agricultural income is expected to contribute to a higher level of investment in agriculture and promote agricultural transformation.

However, empirical evidence on agricultural transformation at the small-holder farm level is insufficient and incomplete, focusing mainly on farmland market operation (Chamberlin & Ricker-Gilbert, 2016). In addition, there are only a few comparative analyses between regions and countries in the developing world (Nguyen et al., 2017; Liu et al., 2020; Amare et al., 2021). Identifying micro-economic patterns that contribute to agricultural transformation will enable policymakers to enact strategies that accelerate that process; and undertaking comparative analyses between regions and countries offers a functioning instrument to enhance our understanding of agricultural transformation as this permits an examination of trends unfolding at various stages of the transformation process. This examination allows less developed economies to learn from the experience of more developed ones. One of the challenges in this regard is the lack of comprehensive and comparable data at the small-holder farm level in different regions and countries at different stages of the transformation process.

In this context, two key questions about agricultural transformation that still require to be examined are: (i) What are the micro-scale changes in agriculture that signal a transformation? And (ii) how are agricultural transformation patterns different between or among regions of the developing world? This article addresses these pivotal questions by examining how endogenous changes in agricultural income affect labor use and farm production at the small-holder farm level in Southeast Asia (SEA) and SSA as these two regions are in different stages of economic development. We identify early trends in cultivation and livelihood patterns that accompany the onset of agricultural transformation, comparing those that occur in the low-income countries of Uganda and Malawi in SSA with those in the middle-income economies of Vietnam and Thailand in SEA. We use micro-level household panel data from the Living Standards Measurement Study—Integrated Survey on Agriculture (LSMS-ISA) from Uganda (years 2010, 2011, 2012) and Malawi (years 2010, 2013, 2016) and from the Thailand Vietnam Socio Economic Panel (TVSEP) from Thailand and Vietnam (years 2007, 2008, 2010, 2013, 2016) to estimate a fixed-effects instrumental variable (IV) regression with changes in precipitation and temperature as instruments for agricultural income. Changes in precipitation and temperature are represented by deviation of log precipitation from long-term average, deviation of log growing degree days from long-term average growing degree days, and deviation of log harmful degree days from long-term average harmful degree days. We then estimate the impact of agricultural income from the previous year on agricultural transformation represented by non-farm income share in household income, livestock income share in agricultural income, and agricultural machinery expenses.

Our analysis results in several key findings. First, agricultural income is vulnerable to changes in precipitation and temperature. The effects of these variables are nonlinear and asymmetric, although SSA countries are more vulnerable to these weather changes. Second, an increase in agricultural income in previous years improves non-farm income in Thailand and Vietnam in SEA but reduces non-farm income in Uganda and Malawi in SSA. These indicate a complementarity effect between farm and non-farm development in SEA and a substitution effect between farm and non-farm development in SSA. Third, rural small-holders in these two regions are diversifying into livestock farming, which indicate a sign of agricultural transformation. Last, however, while an increase in agricultural income leads to a higher level of farm mechanization in SEA, this has not been observed in SSA. These findings reveal clear agricultural transformation driven by agricultural income in SEA, but less clear evidence in SSA.

Our study contributes to the agricultural transformation literature in several important ways. It is one of the first efforts to identify and compare micro-scale agricultural changes and patterns in several countries in these two regions. Methodologically, we control for non-uniform panel data trends (from different years) econometrically by interacting the instrumented lagged agricultural income variable with agricultural transformation variables to account for differences in the gap between the years of panel data collected for each country. This enables us to identify comparable annualized effects and the consecutive-year effect of agricultural income growth on our agricultural transformation variables of interest. We also consider the possible nonlinear effects of changes in precipitation and temperature. To the best of our knowledge, our work is the first effort to include nonlinear effects of changes in precipitation and temperature in agricultural transformation literature, although it has been described in agricultural sciences (see, e.g., Schlenker & Roberts, 2006, 2009; Kawasaki & Uchida, 2016; Lesk et al., 2016 Amare et al., 2018). This approach differs markedly from earlier regression-based approaches that typically use average weather outcomes which might give biased estimates of nonlinear and asymmetric effects of changes in precipitation and temperature.

The reminder of this article is organized as follows. Section 2 briefly explains the theoretical background of micro-scale agricultural transformation and identifies the indicators that characterize the beginning of the transformation. Section 3 provides some background information and data sources. Section 4 defines variables and describes the data used for the analysis, including rainfall, temperature, and household survey data. Section 5 presents the empirical estimation strategy, which include a two-step strategy. Section 6 discusses the findings. Section 7 concludes.

2 | MICRO-SCALE AGRICULTURAL TRANSFORMATION

2.1 | Weather variation and agricultural income

Suppose a farm household owns a certain farmland area, which, together with family labor, represents the major productive assets. The family labor can be allocated to agriculture (including crop and/or livestock production) and non-farm employment (including non-farm self-employment and/or off-farm wage-employment). Total household income includes agricultural income, non-farm income, and non-labor income. Agricultural income includes crop income and livestock income. Livestock income is equal to livestock revenue minus variable costs of livestock production. Similarly, crop income is the difference between crop revenue minus variable costs of crop production.

Agricultural income depends on changes in local weather conditions, affecting agricultural yield. This implies that agricultural income is endogenous because agricultural production is stochastic, driven partly by weather variables such as precipitation and temperature that affect yields exogenously during the growing reason (Jagnani et al., 2021). Recent evidence shows that the effects of changes in precipitation and temperature on agricultural production are nonlinear (Schlenker & Roberts, 2006; Deschenes & Greenstone, 2007). Favorable weather conditions during crop growing season might bring windfall agricultural income to the farm household, but extreme weather events might lead to a complete loss.

Livestock development can be a sign of agricultural transformation. It can be driven by an increase in consumers' purchasing power which leads to a higher return of livestock than that of crop production. Family labor can then be gradually allocated to livestock production. Depending on the scales of production, livestock production can be complementary or competitive with crop production. Similarly, family farm labor can also be reallocated to non-farm employment for higher returns (Nguyen et al., 2022). It should be noted that, in reality, it is not easy for the farm household to move from farm to non-farm sectors due to various reasons, including highly imperfect markets for both labor and non-labor factors. In addition, the mix of farm inputs can also change due to changes in farm labor and household income, that is, less farm labor and a higher level of farm mechanization. Hence, the household faces multiple livelihood choices, defined by the productive assets they own (e.g., land, livestock, machinery) and the activities in which they employ those assets (e.g., crop and livestock production or non-farm employment).

A farm household might be able to save some portion of windfall agricultural income in the form of productive assets, which can induce a shift in activity patterns and capital stocks. The question then arises: what does the household do in response to changes in agricultural income? Are they investing in livestock development and farm mechanization or are they spending for non-farm employment? These are empirical questions to which the answers provide important insights into agricultural transformation at the micro level.

2.2 | Indicators of micro-scale agricultural transformation

It is essential to explicitly define what constitutes agricultural transformation. In this subsection, we identify the following three indicators that signal agricultural transformation at the farm level, namely livestock income share in agricultural income, agricultural machinery expense, and non-farm income share in household income.

2.2.1 | Livestock income share in agricultural income

From a producer's perspective, livestock production is a popular livelihood activity and provides an important source of income for rural households in developing countries (Delgado et al., 2001; Ellis & Freeman, 2004; Carter & Barrett, 2006; Herrero et al., 2013). In addition, in many societies, livestock is considered an indicator of social importance within the community (Do et al., 2019a). It provides draft power for farming and transport (McMichael et al., 2017) and income for meeting an urgent need for cash through the sale of live animals and livestock products, such as eggs or milk. Moreover, livestock waste is used as manure to improve soil fertility, thus contributing to greater crop production for food and cash, or as fuel for cooking and heating. Livestock also offers an alternative source of capital that the poor can accumulate as a "savings account" to hedge against income fluctuations (Kazianga & Udry, 2006; Marenya & Barrett, 2007). Keeping livestock is then considered an alternative form of insurance, providing the household with assets that can be sold in times of shocks (Mogues, 2011; Hoddinott, 2006). From a consumer's perspective in a developing country context, an increase in income leads to a higher demand for livestock products (Sharma et al., 2018) and facilitates agricultural transformation from crop to more livestock production. Hence, we include changes in livestock income share in agricultural income as a potential sign of agricultural transformation.

2.2.2 | Agricultural machinery expense

Mechanization plays a defining role in transforming agriculture. According to Binswanger (1986), agricultural mechanization meets the growing requirement for power and timelines of operation as agricultural systems become more intensive. As population increases, so do pressures for intensification of agriculture, which is always associated with greater requirements for labor or power or both (Hayami & Ruttan, 1971; Huang & Ding, 2016; Sheahan & Barrett, 2017). Given a relatively higher labor-to-land ratio in developing countries, mechanization can play a significant role in enhancing agricultural intensification (Diao et al., 2017; Elbers et al., 2017; Wang et al., 2016). Thus, we include the expenses for agricultural machinery as a variable of mechanization in our analysis. This amount includes expenses incurred from usage of owned as well as rented machines. Farm expenditures on mechanization reflect a response to shifting input prices, especially increasing real wages relative to the real cost of capital. Thus, it signals agricultural transformation. Therefore, we consider changes in agricultural machinery expense as another indicator of agricultural transformation.

2.2.3 | Non-farm income share in household income

We follow Barrett et al. (2001) to define non-farm income as the income derived from non-farm self-employment and off-farm wage-employment of households' laborers. Despite being labor intensive, initiating non-farm self-employment of rural households requires relatively little capital and provides an important source of income (Reardon et al., 2003), while economic growth is expected to push or pull labor from agriculture to other sectors of the economy, thereby enhancing off-farm wage-employment opportunities for rural laborers, including temporary employment in rural service sectors (Do et al., 2019b). There is also evidence that the importance of non-farm employment has been increasing over the last few decades (de Janvry & Sadoulet, 2001; Do et al., 2022). At a micro-scale, this translates into an increasing number of household members involved in non-farm activities. The increase in non-farm income share is thus central to agricultural transformation (Barrett et al., 2017; Diao et al., 2017).

In sum, we therefore examine the effects of an endogenous change in agricultural income on agricultural transformation at the small-holder farm level represented by livestock income share in agricultural income, agricultural machinery expenses, and non-farm income share in total household income. The key point is to take into account that agricultural income is endogenous and stochastic on changes in precipitation and temperature.

3 | BACKGROUND AND DATA SOURCES

3.1 | Background

Uganda and Malawi rely heavily on the agriculture sector. Farming is the major source of income for 69% of Ugandan households, while 80% of the Malawian population are small-holder farmers (Gollin et al., 2017). Labor productivity (expressed as annual output per worker) in agriculture is relatively low compared to other sectors of the economy in SSA (Gollin et al., 2013; McCullough, 2017). As agricultural productivity increases, the labor force in agriculture tends to decline in Africa. Maize is the major food crop cultivated in both countries, supplemented by other crops including banana, cassava, plantain, and sweet potatoes.

Agriculture in SEA has witnessed rapid growth. Although the share of agriculture in GDP has consistently declined in both Thailand and Vietnam, the sector still employs 35% and 42% of the total labor force, respectively (ILO (International Labor Organization), 2017). Thailand and Vietnam are also net agricultural export countries and major rice producers (Pingali, 1997; Nguyen et al., 2017). Rice exports have helped many small-holder farmers out of poverty traps in Thailand (Flaherty et al., 1999) and Vietnam (Nguyen et al., 2021). The other major crops grown include rubber and sugarcane in Thailand, and sugarcane, cassava, maize, and sweet potatoes in Vietnam.

3.2 | Data sources

We use two data sources for our analysis. The first source is household panel survey data while the second one is rainfall and temperature data, as these two weather variables are critical in agriculture, especially in developing countries. In addition, the availability of household panel survey data with multiple waves is vital to the study of structural change happening at a micro-scale.

In SSA, we use high-quality panel datasets from the LSMS-ISA (see https://www.worldbank.org/en/programs/lsms/initiatives/lsms-ISA) from Uganda (for three waves: 2009–2010, 2010–2011, and 2011–2012) and from Malawi (for three waves: 2010–2011, 2013, and 2016–2017). The LSMS-ISA datasets are publicly available online for a number of African countries. The panel sample was selected through stratified random sampling methods for Uganda and Malawi and there is significant uniformity in the survey instruments used for both countries. The LSMS-ISA datasets are nationally representative and include detailed information on household characteristics, assets, agricultural production, non-farm income and other sources of income, allocation of family labor, hiring of labor, and access to services such as fertilizers and agricultural extension. The agriculture module, among others, contains information on agricultural and livestock production, farm technology, use of modern inputs, and productivity of crops and livestock. We only use data from agricultural households and only those that consistently appear in all the sampled waves (a balanced panel) so as to detect change in cultivation patterns. Hence, we have 1372 and 1256 households from each panel wave in Uganda and Malawi, respectively.

In SEA, we use data from the TVSEP survey designed to assess vulnerability to poverty in Asia (see www.tvsep.de). The data are from five survey waves (2007, 2008, 2010, 2013, and 2016) of household- and village-level surveys. The data were primarily collected from rural areas of three provinces in northeast Thailand and three provinces in central Vietnam (see, Klasen & Waibel, 2015). These datasets have detailed information on demographic characteristics, household shocks, assets, agricultural production, allocation of family labor, hiring of labor, access to services, consumption expenditures, and non-farm activities (Hartwig & Nguyen, 2023). They also have extensive information on agricultural and livestock production, farm technology, use of modern inputs, and productivity of crops and livestock. As in SSA, we only use data from households engaged in agriculture and that consistently appear in all the survey waves for this analysis. Hence, we have 1480 and 1576 households from each wave from Thailand and Vietnam, respectively.

For both LSMS-ISA and TVSEP datasets, data on income generating activities are recorded for the last 12 months (1 year) and thus allow to calculate annual household income, including agricultural income (from crop and livestock production), non-farm income (from non-farm self-employment and off-farm wage-employment), and other income. Crop and livestock income during the last 12-month period is equal to total revenue minus total variable cost. For livestock, total revenue includes the value of products such as eggs or meat that are sold or consumed by the household during the survey year, and the value of livestock at the end of the survey year. Total cost contains expenditures for food, veterinary treatment, and hired labor, the value of livestock at the beginning of the survey year, the value of livestock that the household purchased or received during the survey year, and allowance for depreciation and loan repayments. Since livestock income is calculated for each survey year while livestock can live more than 1 year, the values of livestock at the beginning of the survey year (which is from the end of the last year) and at the end of the survey year (which is for the next year) should be accounted for by identifying the difference between these two values. Thus, when calculating annual livestock income, the annual revenue of livestock includes the value of livestock at the end of the survey year and the value of products such as eggs or meat that are sold or consumed by the household during the survey year. Meanwhile, the annual cost of livestock also includes the value of livestock at the beginning of the survey year (similar to the cost of seedlings and seeds in crop production). This method of calculating annual income of livestock is used in the literature, for example, Do et al. (2019a). To facilitate the comparisons among countries and over years, income and agricultural machinery expenses are measured in purchasing power parity ($US PPP).

The second data source is for rainfall and temperature data. The LSMS-ISA dataset includes georeferenced information related to households and plots that allow us to merge these panel data with satellite-based spatial data on precipitation and temperature. Long-term precipitation data are from the daily Africa Rainfall Climatology Version 2 (ARC2) of the National Oceanic and Atmospheric Administration's Climate Prediction Center (NOAA-CPC) (Novella & Thiaw, 2013). It includes monthly rainfall in millimeters from 1980–2016 of spatial resolution of $0.05° \times 0.05°$ (~ 5 km $\times$ 5 km) (Funk et al., 2015). We extract temperature data from NASA MERRA-2 (Modern-Era Retrospective analysis for Research and Application). We develop monthly mean, maximum, and minimum temperatures in degrees Celsius over the 1980–2016 period of spatial resolution of $0.5° \times 0.625°$ ($\sim$55 km $\times$ 69 km) (GMAO, 2015). While the TVSEP datasets include georeferenced information at the village level that allow us to link any number of satellite-based precipitation and temperature datasets to the surveyed villages.

4 | DEFINITION OF WEATHER VARIABLES AND DESCRIPTIVE RESULTS

4.1 | Definition of weather variables

We follow the literature to calculate rainfall and temperature variables in a specific year by focusing on the main crop growing seasons (Maccini & Yang, 2009; Björkman-Nyqvist, 2013; Rocha & Soares, 2015; Barrett & Santos, 2014). The monsoon season typically extends from early May to late November for Thailand (crop cycle mainly for rice), from January to September for Vietnam (crop cycle mainly for rice), from early March to late October for Malawi (crop cycle mainly for maize), and from January to July for Uganda (crop cycle mainly for maize). We create a measure of rainfall anomalies during the monsoon season by first calculating the average total rainfall across the monsoon months for each country and georeferenced household for the 1980–2016 period. We construct the change in rainfall variable as a deviation of a given year's rainfall during the growing season from the historical averages (over the 1980–2016 period). The change in monsoon rainfall variable is defined as deviation of log rainfall from long-term average using: $\Delta R_{it} = ln\,(R_{it}) - ln\,(\,R_i)$, where R_{it} indicates the precipitation during the growing season at the location of household i for year t; R_i is the historical average rainfall (over the 1980–2016 period) during the growing season at the location of household i. The rainfall deviation implies a percentage deviation from mean rainfall (e.g., a value of 0.05 means rainfall was approximately 5% higher than normal).

Similarly for temperature, we follow agronomic literature, which suggests nonlinear transformations of temperature known as growing degree days (GDD) and harmful degree days (HDD). They find that nonlinear transformations strongly predict crop production when using reduced form functions of temperature (Jagnani et al., 2021; Aragón et al., 2021). We calculate GDD for each month in the 1980–2016 period by subtracting the standard base temperature of 10°C for maize and rice up to an upper threshold of 32°C from the mean temperature for each month of crop calendars (Jagnani et al., 2021). We then subtract the average season GDD for the 1980–2016 period for each crop cycle from the GDD for each of the data waves for all four countries. Thereby, we derive the GDD deviation for each wave during the respective crop cycles for each survey household as $\Delta GDD_{it} = ln\,(GDD_{it}) - ln\,(\,\underline{GDD}_i)$. In addition, as maize and rice decline physiologically due to heat stress above 32°C (Lobell et al., 2011; Schlenker & Roberts, 2009), we define degree days above 32°C (GDD > 32) as HDD to capture days with heat stress. In essence, HDDs are anomalies relative to mean of HDD over the period. We then calculate the HDD deviation for each survey household as $\Delta HDD_{it} = ln\,(HDD_{it}) - ln\,(\,\underline{HDD}_i)$. Finally, we use ΔR_{it}, ΔGDD_{it} and ΔHDD_{it} to estimate the impact of weather change on agricultural income (Deryng et al., 2014; Lobell et al., 2013; Lobell et al., 2011).

4.2 | Descriptive results

Table 1 presents the descriptive statistics of the main variables used in the analysis. There are wide variations among countries in the key structural change variables, namely share of non-farm income in household income, share of livestock income in agricultural income, and machinery expenses per cultivated land area. These variations reflect economies in different stages of structural transformation.

With respect to household characteristics, on average, SEA farmers are older and more educated with a smaller household size. They also have more access to non-farm income sources and own comparatively more livestock than SSA farmers. The share of non-farm income in household income is about 40% in Thailand and Vietnam, whereas it is only 20% in Malawi and around 28% in Uganda. Likewise, agricultural income per capita is highest in Thailand and lowest in Malawi. The possible explanation for higher non-farm income share and agricultural income per capita in Thailand and Vietnam as compared to Uganda and Malawi is that both Thailand and Vietnam are middle-income countries that have managed to achieve uninterrupted growth in per capita GDP over the last 30 years (Diao et al., 2018) whereas Uganda and Malawi are low-income countries with fluctuating income growth during the last several years.

In Vietnam around 34% of agricultural income comes from livestock whereas it is around 22% in Thailand. In fact, the study site includes the poorest provinces in Thailand. In addition, due to limited farmland per household in Vietnam (as indicated in Table 1, the average farm size is smallest in Vietnam), livestock has been developed in Vietnam (Do et al.,

TABLE 1 Descriptive statistics of household survey data (pooled over years)

	Southeast Asia (SEA)		Sub-Saharan Africa (SSA)	
	Thailand	***Vietnam***	***Uganda***	***Malawi***
Dependent variables				
Share of non-farm income in HH income (%)	42 (40)	39 (37)	28 (37)	20 (17)
Share of livestock income in agricultural income (%)	22 (33)	34 (34)	5 (19)	14 (31)
Agricultural machinery expenses/ha (PPP $US)	143.37 (179.38)	163.14 (436.96)	1.40 (6.89)	0.18 (0.33)
Variable of interest				
Agricultural income/capita (PPP $US)	908.01(1123.96)	679.34 (989.57)	294.97 (408.79)	159.58 (613.12)
Instruments				
Deviation of log precipitation from long-term average (ΔR)	−0.04 (0.12)	−0.03 (0.22)	−0.03 (0.22)	−0.02 (0.12)
Deviation of log GDD from long-term average (ΔGDD)	0.02 (0.03)	0.06 (0.03)	0.04 (0.02)	0.04 (0.03)
Deviation of log HDD from long-term average (ΔHDD)	0.01 (0.10)	0.02 (0.17)	0.01 (0.12)	0.03 (0.16)
Control variables				
Age of HH head (in years)	56.98 (12.58)	50.58 (12.89)	47.64 (14.68)	44.70 (16.49)
Gender of HH head (male = 1)	0.75 (0.43)	0.85 (0.35)	0.73 (0.44)	0.76 (0.46)
Have a demographic shock (yes = 1)	0.34 (0.47)	0.44 (0.50)	0.59(0.44)	0.67(0.47)
Education of HH head (in years)	4.82 (2.55)	6.74 (3.85)	2.20 (3.96)	2.57 (4.27)
HH size	4.13 (1.69)	4.25 (1.71)	6.71 (3.10)	5.27 (2.32)
Land area (in ha)	3.05 (2.71)	1.10 (1.35)	1.06 (1.21)	1.21 (2.48)
Have non-farm employment (yes = 1)	0.64 (0.47)	0.68 (0.47)	0.49 (0.47)	0.28 (0.45)
Have livestock (yes = 1)	0.55 (0.50)	0.65 (0.47)	0.39 (0.49)	0.25 (0.43)
Observations	7400	7880	4116	3768

Note: Non-farm includes non-farm self-employment and off-farm wage-employment. Standard deviations are in parentheses.
Abbreviations: HH, household; PPP, purchasing power parity.
Source: Authors' calculations based on LSMS-ISA Uganda 2010, 2011, and 2012; LSMS-ISA Malawi 2010, 2013, and 2016; TVSEP Thailand and Vietnam 2007, 2008, 2010, 2013, and 2016.

2019a). Livestock production seems to be at the early stages of development in the SSA countries; farmers in Malawi earn 14% of income from livestock, and in Uganda, only 5%.

The average farm size is well below 5 ha in all these countries, which qualifies surveyed farm households as smallholder farmers. Except for Thailand where the average farm size is about 3 ha, in the other countries the average farm size is only about 1 ha. Because Thailand is an upper-middle-income country, its average farm size could have witnessed slight growth over the last decade compared to Vietnam, a lower-middle-income country. Also, Thailand and Vietnam incur higher agricultural machinery expenses per hectare. In Uganda and Malawi, as in most African countries, agricultural mechanization (including purchasing or hiring machines and operating, maintenance, and repair costs) is at a nascent stage. Historically, cropland in these countries has been cultivated manually. The low level of agricultural mechanization is explained by both demand and supply constraints. The demand for agricultural mechanization is likely to develop once labor becomes sufficiently costly relative to capital and purchased inputs (Diao et al., 2017).

With regard to changes in the weather variables, we find that all sampled regions across all four countries received 2% to 4% less precipitation than normal during the survey years. This is consistent with previous studies (e.g., Hoerling et al., 2006). We also find that GDD and HDD have increased across all the sampled countries; GDD and HDD were approximately 1% to 6% and 1% to 3% above normal over the surveyed period, respectively.

Tables 2 and 3 presents the trends in agricultural transformation indicators for Thailand and Vietnam (Table 2), and for Uganda and Malawi (Table 3). Between 2007 and 2016, the share of non-farm income decreased by almost 13% in Thailand and increased by almost 16% in Vietnam. The results also show that the share of livestock income increased in both countries, by 56% in Thailand and 117% in Vietnam. This is consistent with previous studies (e.g., Reardon & Timmer, 2014) that Asian farmers invested heavily in livestock in order to meet a growing local demand for meat. Thailand and

TABLE 2 Trends in agricultural transformation indicators for Thailand and Vietnam

	2007	2008	2010	2013	2016	Δ (2007–2016) (%)
Thailand						
Share of non-farm income in HH income (%)	47	37	45	42	41	−12.77**
Share of livestock income in agricultural income (%)	16	25	23	21	25	56.25***
Agricultural machinery expenses/ha (PPP $US)	119.26	132.42	101.97	154.09	209.10	75.33***
Vietnam						
Share of non-farm income in HH income (%)	37	27	41	44	43	16.22**
Share of livestock income in agricultural income (%)	18	33	38	40	39	116.67***
Agricultural machinery expenses/ha (PPP $US)	156.64	131.75	142.51	151.40	233.41	49.01***

Note: Non-farm includes non-farm self-employment and off-farm wage-employment.
Abbreviations: HH, household; PPP, purchasing power parity.
*, **and *** denote significance at 10%, 5%, and 1%, respectively.
Source: Authors' calculations based on TVSEP Thailand and Vietnam 2007, 2008, 2010, 2013, and 2016.

TABLE 3 Trends in agricultural transformation indicators for Uganda and Malawi

Uganda	2010	2011	2012	Δ (2010–2012) (%)
Share of non-farm income in HH income (%)	30	25	29	−3.19
Share of livestock income in agricultural income (%)	8	3	3	−62.26**
Agricultural machinery expenses/ha (PPP $US)	1.34	1.46	1.68	25.19***
Malawi	2010	2013	2016	Δ (2010–2016) (%)
Share of non-farm income in HH income (%)	17	23	21	25.75**
Share of livestock income in agricultural income (%)	11	12	19	76.25***
Agricultural machinery expenses/ha (PPP $US)	0.16	0.18	0.20	25.11***

Note: Non-farm includes non-farm self-employment and off-farm wage-employment.
Abbreviations: HH, household; PPP, purchasing power parity.
*, **and *** denote significance at 10%, 5%, and 1%, respectively.
Source: Authors' calculations based on TVSEP Thailand and Vietnam 2007, 2008, 2010, 2013, and 2016.

Vietnam both experienced rising agricultural machinery expenses per hectare, up by almost 75% in Thailand and 49% in Vietnam between 2007 and 2016.

Meanwhile, between 2010 and 2012, the share of non-farm income declined in Uganda by 3%, while it increased by almost 16% in Malawi between 2010 and 2016. Between 2010 and 2012, the share of livestock income in agricultural income decreased by 62% in Uganda, while in Malawi it increased by 76% between 2010 and 2016. The results show a substantial growth in the share of agricultural machinery expenses per hectare (around 25%) between 2010 and 2012 in Uganda, and between 2010 and 2016 in Malawi. A possible explanation for this growth in both countries is the very low initial levels of agricultural machinery expenses.

5 | EMPIRICAL STRATEGY

We follow a two-step empirical approach to examine household-level variations in the agricultural transformation indicators. In the first step, we specify an agricultural income model in which agricultural income is instrumented with variation in weather variables, namely precipitation and temperature. In the second step, we identify the causal effect of agricultural income growth on agricultural transformation indicators. As our data are panel, we undertake econometric regressions for panel data.

5.1 | Agricultural income model

We follow the previous literature (e.g., Maccini & Yang, 2009; Björkman-Nyqvist, 2013) and use variations in precipitation and temperature as instrumental variables for agricultural income. We advance this strand of literature by considering possible nonlinear and asymmetric effects of these weather variables. Therefore, we specify a fixed-effects household agricultural income regression as:

$$ln(Y_{it}) = \gamma_0 + \alpha \Delta R_{it} + \beta \Delta R_{it}^2 + \gamma \Delta GDD_{it} + \rho \Delta HDD_{it} + \theta_1' X_{it} + \theta_2 T_t + \mu_i + \nu_{it} \quad (1)$$

where Y_{it} is the agricultural income per capita of small-holder farm household i in year t; ΔR_{it} refers to deviation of log precipitation from long-term average of small-holder farm household i in year t; ΔR_{it}^2 is square of deviation of log precipitation from long-term average of small-holder farm household i in year t, which denotes the nonlinearity of precipitation; ΔGDD_{it} is deviation of log growing degree days from long-term average of small-holder farm household i in year t during the crop growing reason; ΔHDD_{it} denotes deviation of log harmful degree days from long-term average during the crop growing reason of small-holder farm household i in year t; X_{it} is a vector of control variables and includes household and farm characteristics of small-holder farm household i in year t; T_t represents year dummies to indicate the year in which the households were surveyed, which may capture aggregate shifts in agricultural income or correlated shifts in our explanatory variables. The individual fixed effects are captured by μ_i and υ_{it} is a random error term for which the strict exogeneity condition is assumed to hold and is independently and identically normally distributed with zero mean and constant variance.

In this agricultural income equation, the nonlinear effect of precipitation is captured by square of ΔR_{it} whereas the effect of anomalies in temperature for heat stress is captured by ΔHDD_{it}. We expect α, β, and ρ to be negative but γ to be positive. Regarding X_{it}, we include gender, age, and education level of household head, household size, farmland area, whether the household experienced a demographics shock, and whether the household has livestock production and non-farm employment. As households living in the same enumeration area (EA) in SSA and village in SEA are likely to experience similar observable and unobservable shocks and services, we cluster standard errors at EA level for Malawi and Uganda and at village level for Vietnam and Thailand. In addition, since our data of agricultural income are all positive and the distribution of agricultural income is skewed, we use the natural logarithm (ln) of the real value agricultural income per capita (in \$US PPP).

5.2 | Micro-scale structural change model

Agricultural income could be endogenous elements of the structural transformation indicator equations. To account for this type of endogeneity, we use a fixed-effects IV model that links agricultural income from the previous year (lagged agricultural income) with structural transformation indicators in the current year. We follow the previous literature (e.g., Lobell et al., 2013; Jagnani et al., 2021) and use ΔR_{it}, ΔGDD_{it} and ΔHDD_{it} as IVs for agricultural income.

We need two identifying assumptions to validate the instruments and hence conduct causal inferences on the impact of agricultural income growth on structural transformation indicators. First, we need these instruments to be relevant. Weather variability constitutes a good proxy to predict agricultural income in these countries, as much of its agricultural production activities are rainfed. Second, the instruments should be exogenous, and hence uncorrelated with the error terms in the structural transformation indicators. A potential concern about the exogeneity of a weather instrument is that the weather variability of the locality may be correlated with the village's economic activities, such as non-farm employment (e.g., self-employment), local prices, and access to services. Thus, this variable may directly affect the outcome variables. To circumvent this problem, we include a dummy variable to indicate if the household participated in non-farm employment or not (yes = 1). This variable is part of the vector of control variables X_{it} in Equation (1). In addition, instead of using current year agricultural income change, we use agricultural income change from previous year to help ensure that income growth affects subsequent changes in structural transformation indicators.

As we have different time gaps between the panel waves for each country (unequally spaced panel data) (see Millimet & McDonough, 2017), it is not possible to uniformly compare the exogenous effect of the previous year's agricultural income on the consecutive next year without standardizing the interval changes in production patterns. Therefore, we create a survey interval dummy variable (lag_gap) to capture the difference in lags between each panel wave for each country and interact this dummy variable with the instrumented lagged agricultural income. As the panel waves are not from successive time periods for Thailand, Vietnam, and Malawi, the lagged instrumented agricultural income does not necessarily pertain to the immediate previous year. For Thailand and Vietnam, it is interacted with the lag_gap_1 dummy variable to indicate a 1-year gap, and with the lag_gap_2 or lag_gap_3 dummy variable to indicate a 2- or 3-year time gap, respectively. We interact with the lag_gap_3 dummy for Malawi as it has a 3-year uniform gap between the panel waves in our sample. However, to decipher the successive year impact, we take the cube root of the estimated coefficient. For the Uganda panel, waves are consecutive annual surveys, with a uniform gap of 1 year, so we interact with the lag_gap_1 dummy variable to indicate a 1-year gap. Specifically, we estimate a fixed-effects IV (FE-IV) model for structural transformation (Equation 2) using lagged estimated value of agricultural income ($\widehat{y_{it-1}}$) and interact it with the respective survey lag gap indicator variable for each country and wave after the first as follows.

$$SC_{it} = \alpha_0 + \alpha_1 \widehat{y_{it-1}} * lag\_gap_1 + \alpha_2 \widehat{y_{it-1}} * lag\_gap_2 + \alpha_3 \widehat{y_{it-1}} * lag\_gap_3 + \alpha_4 X_{it} + \varepsilon_i + \eta_{it} \tag{2}$$

where α_1 is identified by the instrumented exogenous values of the lagged agricultural income, which was estimated from Equation (1); SC indicates the different micro-scale indicators of agricultural transformation described in Section 2.2, namely share of non-farm income in household income, share of livestock income in agricultural income, and agricultural machinery expenses per hectare. The individual fixed effects are captured by ε_i and η_{it} is a random error term for which the strict exogeneity condition is assumed to hold and is independently and identically normally distributed with zero mean and constant variance.

Since some of our SC indicators have zero value, we take the inverse hyperbolic sine (IHS) transformation to keep zero values. Similar to Equation (1), the standard errors in Equation (2) are also clustered at EA level for Malawi and Uganda and at village level for Vietnam and Thailand.

6 | RESULTS AND DISCUSSION

6.1 | Agricultural income regression (first step)

Table 4 presents the results of agricultural income regression (Equation 1) in which we consider the ln as the transformation for the agricultural income per capita as the dependent variable. We first report unconditional regressions of agricultural income on deviations of precipitation, GDD, HDD and a time dummy capturing the wave of the sample for Thailand, Vietnam, Uganda, and Malawi, respectively (columns 1, 3, 5, 7). We then extend this specification by controlling for household-level characteristics (columns 2, 4, 6, 8). Results presented in Table 4 lead to several important findings.

First, comparing unconditional and conditional estimates in Table 4 provides insights on the potential mechanisms through which weather variability could affect agricultural income. For instance, the estimates on the effect of weather variables reduce when we control for household characteristics, suggesting, as expected, that part of the link between weather variables and agricultural income mediated through these channels.

Second, weather variables are a driving force of agricultural income, and their effects are nonlinear. The nonlinear patterns observed in the data are consistent with an emerging literature (e.g., Lobell et al., 2013; Jagnani et al., 2021) showing that nonlinear transformations have been shown to strongly predict crop production. For example, the coefficients of the weather changes are statically significant in the most of specifications for all countries. Precipitation change decreases

TABLE 4 First stage estimation for agricultural income (fixed-effects)

	Southeast Asia (SEA)				Sub-Saharan Africa (SSA)			
Dependent Variable: Agricultural income per capita (ln)								
	Thailand		***Vietnam***		***Uganda***		***Malawi***	
Instruments	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔR_{it}	−0.212***	−0.172**	−0.105***	−0.032*	−0.351***	−0.341***	−0.266***	−0.249***
	(0.040)	(0.061)	(0.022)	(0.017)	(0.003)	(0.003)	(0.041)	(0.041)
ΔR^2_{it}	−0.103***	−0.021	−0.004	−0.013*	−0.000***	−0.000***	0.547	−0.246
	(0.039)	(0.034)	(0.008)	(0.007)	(0.000)	(0.000)	(1.280)	(1.108)
ΔGDD_{it}	19.726***	22.228***	17.267***	12.188***	0.007	0.006	7.564***	7.509***
	(2.714)	(2.380)	(1.700)	(1.478)	(0.011)	(0.017)	(2.396)	(2.696)
ΔHDD_{it}	−0.394	−0.561	−0.245***	−0.217***	−0.821**	−0.748***	−0.641***	−0.515**
	(0.944)	(0.777)	(0.062)	(0.039)	(0.197)	(0.229)	(0.196)	(0.229)
Control variables								
Gender (male = 1)		0.041		0.214*		0.164**		0.316***
		(0.148)		(0.122)		(0.072)		(0.091)
Age (years)		0.041		−0.022		1.509		7.764***
		(0.048)		(0.031)		(1.939)		(2.822)
Age square		−0.331		0.171		−0.219		−1.050***
		(0.331)		(0.201)		(0.261)		(0.377)
Education (years)		−0.023		0.010		0.005		0.028***
		(0.030)		(0.014)		(0.010)		(0.010)
HH size		−0.218***		−0.205***		−0.087***		−0.107***
		(0.036)		(0.028)		(0.018)		(0.018)
Have a demographic shock		−0.253**		−0.131*		0.032		−0.011
(yes = 1)		(0.127)		(0.079)		(0.059)		(0.064)
Farm size (ha) (log)		0.595***		0.600***		0.409***		0.143***
		(0.033)		(0.044)		(0.063)		(0.015)
Have non-farm employment		−0.051		−0.109		0.037		−0.144
		(0.113)		(0.087)		(0.088)		(0.092)
Livestock production (yes = 1)		4.232***		3.212***		1.183***		2.181***
		0.041		0.214*		(0.141)		(0.108)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.062	0.272	0.113	0.276	0.262	0.331	0.101	0.256
Observations	7400		7880		4116		3768	

Note: Non-farm includes non-farm self-employment and off-farm wage-employment. Robust standard errors clustered at EA level for Malawi and Uganda and at village level for Vietnam and Thailand are in parentheses.

Abbreviations: HH, household; PPP, purchasing power parity.

*, **and *** denote significance at 10%, 5%, and 1%, respectively.

Source: Authors' calculations based on TVSEP Thailand and Vietnam 2007, 2008, 2010, 2013, and 2016.

agricultural income. A 15% (or one standard deviation) increase in precipitation leads to a reduction of 2.68% and 0.48% in agricultural income in Thailand and Vietnam, respectively. Similarly, a 15% (or one standard deviation) increase in precipitation leads to a decrease of 5.12 and 3.74 percent in agricultural income in Uganda and Malawi, respectively. In addition, a 15% increase in HDD leads to a reduction of 3.26%, 11.22% and 7.65% in agricultural income in Vietnam, Uganda, and Malawi, respectively. This is consistent with literature that has found higher temperatures reduce crop yields through heat stress (Schlenker & Roberts, 2009; Lobell et al., 2011). The insignificant effect of this variable for Thailand is probably due to an improved irrigation system in this country to help farmers overcome the negative effects of heat stresses (Nguyen et al., 2017). Thus, the instruments are relevant (i.e., good predictors of our outcome variables). Overall, these findings underpin

TABLE 5 Agricultural transformation regression on non-farm income share in household income

	Southeast Asia (SEA)		Sub-Saharan Africa (SSA)	
	Thailand	*Vietnam*	*Uganda*	*Malawi*
Dependent variable	Share of non-farm income in household income (IHS)			
Instrumented lagged agricultural income (interaction)				
* lag_gap_1	0.011	0.029***	−0.025**	−0.042***
	(0.009)	(0.010)	(0.011)	(0.010)
* lag_gap_2	0.019***	0.038***		
	(0.004)	(0.010)		
* lag_gap_3	0.024***	0.029***		−0.007**
	(0.005)	(0.009)		(0.003)
Control variables	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes
IV	Yes	Yes	Yes	Yes
Observations	5920	6304	2744	2512
Overall R^2	0.171	0.189	0.078	0.121
Over identification test of all instruments (Hansen J statistics): $\chi2$	5.11	4.33	4.23	4.21
Under identification test of all instruments (Kleibergen-Paap rk LM statistic)	25.45***	16.31***	22.12**	16.32**
Weak-instrument-robust inference (Stock–Wright LM S statistic)	22.01***	12.92**	42.48***	51.13***
F-test of excluded instruments	16.46***	13.89***	61.13***	61.13***
Endogeneity test	3.35	8.70	59.79***	61.09***

Note: Non-farm includes non-farm self-employment and off-farm wage-employment. Robust standard errors clustered at EA level for Malawi and Uganda and at village level for Vietnam and Thailand are in parentheses. Malawi l lag_gap_1 is cube root values.
Abbreviations: IHS, inverse hyperbolic sine transformation; IV, instrumental variables.
*, **and *** denote significance at 10%, 5%, and 1%, respectively.

the fact that agricultural income in Vietnam, Uganda and Malawi is vulnerable to weather changes when compared to Thailand, which can have implications for patterns of structural change. Interestingly, even though the nonlinear effects of precipitation and temperature are well-known in crop sciences, our finding indicates that the effects are also observed in agricultural transformation literature.

With regard to household characteristics, we find that male farmers are likely to earn more income than their female counterparts in Vietnam, Uganda and Malawi. Older farmers earn more agricultural income in Malawi but with decreasing returns. In this country, education level of household head is also positively associated with agricultural income. Having a larger household size significantly reduces agricultural income in all countries in our sample, perhaps due to reduced access to family labor and costs incurred in hiring agricultural labor. Suffering demographic shocks reduces agricultural income of farmers in Thailand and Vietnam. This is consistent with the findings of recent studies in SEA that shocks reduce both farm income and household income (see, Nguyen et al., 2020). A larger farm size and livestock ownership significantly and positively impacts agricultural income for all countries in our study sample, indicating possible economies of scale and the complementarity between livestock and crop production.

6.2 | Agricultural transformation (second step)

Tables 5, 6, and 7 present the estimation results on our key agricultural transformation indicators (Equation 2). The outcome variables in these tables are IHS transformations. We note that IHS transformation of small values require further adjustments to be interpreted as elasticities (Bellemare & Wichman, 2020). We examine the effect of exogenous changes in agricultural income in the previous year on these different indicators of agricultural transformation in the next year. We

TABLE 6 Agricultural transformation regression on livestock income share in agricultural income

	Southeast Asia		Sub-Saharan Africa	
	Thailand	***Vietnam***	***Uganda***	***Malawi***
Dependent variable	Share of livestock income in agricultural income (IHS)			
Instrumented lagged agricultural income (interaction)				
* lag_gap_1	0.028**	0.041***	0.012**	0.088***
	(0.012)	(0.009)	(0.004)	(0.013)
* lag_gap_2	0.015	0.040***		
	(0.011)	(0.011)		
* lag_gap_3	0.027**	0.044***		0.033***
	(0.012)	(0.011)		(0.008)
Control variables	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes
IV	Yes	Yes	Yes	Yes
Observations	5920	6304	2744	2512
Overall R^2	0.360	0.172	0.240	0.214
Over identification test of all instruments (Hansen J statistics): $\chi 2$	4.33	3.44	5.22	3.34
Under identification test of all instruments (Kleibergen-Paap rk LM statistic)	34.45***	23.24***	23.32**	14.21**
Weak-instrument-robust inference (Stock–Wright LM S statistic)	22.01***	12.92**	42.48***	51.13***
F-test of excluded instruments	43.61***	21.35***	35.487***	78.23***
Endogeneity test	6.57***	3.08**	59.87***	64.84***

Note: Robust standard errors clustered at EA level for Malawi and Uganda and at village level for Vietnam and Thailand are in parentheses. Malawi lag_gap_1 is cube root values.

Abbreviations: IHS, inverse hyperbolic sine transformation; IV, instrumental variables.

*, **and *** denote significance at 10%, 5%, and 1%, respectively.

check the validity of instruments using two major misspecification tests: the weak identification test and the overidentification tests (the results are reported in the last five rows of Tables 5–7). The Sargan-Hansen test is used for overidentifying and under identification restrictions; it fails to reject the joint null hypothesis that our instruments are valid. We also apply the Hansen specification test for the endogeneity of agricultural income and reject the null hypothesis that agricultural income can be treated as exogenous. In addition, we compute robust standard errors to correct for potential heteroskedasticity. The Kleibergen-Paap Wald F tests on the joint validity of using these weather variables indicate that the instruments are relevant.

Table 5 presents the results of non-farm income share in household income regression. Exogenous increases in agricultural income in the previous year have a positive and significant effect on non-farm income share in subsequent years in Thailand and Vietnam, and a negative effect on non-farm income share in Uganda and Malawi. The results indicate that intersectoral linkages are pronounced in Thailand and Vietnam, which could be because these two countries managed to achieve uninterrupted growth for more than three decades (Diao et al., 2018). There is a negative relationship between initial agricultural income change and non-farm income, suggesting agricultural income is not driving non-farm income growth in Uganda and Malawi. This could be because agricultural productivity growth hasn't yet become pronounced in these two economies, particularly in the absence of better functioning markets and services to improve access to information, finance, and technologies. The results clearly demonstrate that increases in agricultural income promote labor allocation from farm to non-farm sectors in SEA. However, that is not the case in SSA. This is consistent with previous literature. For example, Barrett et al. (2017) argues that for Africa, accelerating productivity and initiating structural change in the agriculture sector and the rural non-farm economy are required for economic growth.

Within agricultural production, the results of livestock income share in agricultural income regression presented in Table 6 show that exogenous increases in agricultural income in the previous year encourage investment in livestock in

TABLE 7 Agricultural transformation regression on agricultural machinery expenses

	Southeast Asia		Sub-Saharan Africa	
	Thailand	***Vietnam***	***Uganda***	***Malawi***
Dependent variable	Agricultural machinery expenses /ha (IHS)			
Instrumented lagged agricultural income (interaction)				
* lag_gap_1	0.378**	0.294**	0.044	−0.091
	(0.121)	(0.116)	(0.071)	(0.127)
* lag_gap_2	0.284**	0.311**		
	(0.123)	(0.132)		
* lag_gap_3	0.317***	0.337***		0.080**
	(0.154)	(0.091)		(0.039)
Control variables	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes
IV	Yes	Yes	Yes	Yes
Observations	5708	6169	2744	2512
Overall R^2	0.251	0.111	0.057	0.121
Under identification test of all instruments (Hansen J statistics): $\chi2$	35.48***	78.23***	17.05***	2.953*
F-test of excluded instruments	16.46***	13.89***	61.13***	61.13***
Endogeneity test	3.348	8.700	59.787***	61.089***

Note: Robust standard errors clustered at EA level for Malawi and Uganda and at village level for Vietnam and Thailand are in parentheses. Malawi lag_gap_1 is cube root values.

Abbreviations: IHS, inverse hyperbolic sine transformation; IV, instrumental variables.

*, **and *** denote significance at 10%, 5%, and 1%, respectively.

the next year in all countries. The evidence from this table shows that increases in agricultural income promote livestock development in these two regions. This is in line with previous literature that shows that economic growth leads to higher demand for livestock products (Delgado et al., 2001) because it shifts diets away from staple food crops like rice, wheat, and maize to livestock, fruits, and vegetables (Dercon, 1998; Reardon et al., 2003; Pingali, 2015). To cater to these changing dietary patterns, small-holders start venturing into livestock agriculture to meet growing local demand.

Table 7 presents the estimation results of agricultural machinery expenses. The consistent pattern we find is that most countries invest in mechanization from exogenous agricultural income increases in the previous year, although the magnitude varies across countries. Thailand and Vietnam invest significantly; a 1% increase in agricultural income in the previous year results in a significant 0.4% and 2% increase in agricultural machinery expenses in the next year, respectively. The coefficients continue to be positive for lag_gaps_3 (3-year time lags), implying that SEA farmers continue to invest in mechanization over the years, especially the Vietnamese farmers, suggesting farm mechanization expansion is likely driven by rising labor costs and farmers' better access to finance as farm productivity rises. For Malawi, it takes 3 years for the exogenous increase in agricultural income to significantly increase agricultural machinery expenses.

Overall, these findings reflect the fact that although labor is shifting from farm to non-farm sectors, changes in production portfolios are not uniform across countries. Thai and Vietnamese farmers tend to significantly diversify into non-farm and livestock farming and invest in farm mechanization. Malawian and Ugandan farmers seem to have just begun diversification into livestock farming as well as farm mechanization, although not at a significant pace for farm mechanization. In addition, in Uganda and Malawi, agricultural income in previous years has a reduce earnings from non-farm employment in the next year, which indicates a substitution between farm and non-farm income effect. These results imply that structural change at the micro-scale need not follow uniform labor use and production patterns across countries. The core study reveals clear structural change driven by agricultural income in Thailand and Vietnam, but no similar evidence in Malawi and Uganda.

7 CONCLUSIONS

In this article, we examine how agricultural income leads to agricultural transformation at the small-holder farm level and compare the patterns of agricultural transformation between SEA and SSA. We use multiple waves of farm household panel data from Thailand and Vietnam in SEA and Uganda and Malawi in SSA. We employ a fixed effects IV regression in which agricultural income is instrumented with changes in precipitation and temperature during crop growing reasons. We then use the lagged estimated agricultural income from previous year as one of the explanatory variables to examine agricultural transformation represented by non-farm income share in household income, livestock income share in agricultural income, and agricultural machinery expense. Our analysis results in several important findings.

First, agricultural income is vulnerable to changes in precipitation and temperature during the crop growing season and the effect is nonlinear and asymmetric in all countries, although SSA countries are more vulnerable to these weather changes. Second, an increase in agricultural income in previous year does lead to a general increase in earnings from non-farm employment in subsequent years in Thailand and Vietnam, suggesting intersectoral linkages are pronounced in these two economies. This perhaps indicates that structural transformation in these countries has been driven not only by rapid expansion of non-farm sectors but also by agricultural productivity growth. However, for Uganda and Malawi, agricultural income in previous years reduces earnings from non-farm employment in subsequent years, indicating a substitution effect between farm and non-farm sectors. This requires policies that stimulate synergies and reduce trade-offs in support of agricultural transformation in Africa. Third, an increase in agricultural income promotes livestock development in these two regions. This is in line with previous literature that shows that economic growth leads to higher demand for livestock products because it shifts diets away from staple food crops like rice, wheat, and maize to livestock products. To cater to these changing dietary patterns, small-holders start venturing into livestock production to meet growing local demand. Last, an increase in agricultural income led to higher investment in farm mechanization in Thailand and Vietnam. This indicates farm mechanization expansion is likely driven by rising labor costs and farmers' better access to finance as farm productivity grows.

In conclusion, understanding the underlying micro-scale transformation processes in agriculture can help policymakers identify subsectors in agriculture that require more support during the process of structural change and economic growth. The patterns of agricultural transformation are different between the two study regions. Our study reveals clear agricultural transformation driven by agricultural income in Thailand and Vietnam of SEA, but no similar evidence in Malawi and Uganda of SSA. Either agricultural income is not yet driving the structural change in Uganda and Malawi, or it hasn't yet become pronounced in these two countries. Targeted policies may be required to stimulate positive synergies between agriculture income and agricultural transformation. Framing policies that support and encourage investment in farm mechanization, input supply systems (e.g., seed, fertilizer, and extension), and better functioning labor markets in Uganda and Malawi might help to accelerate the transformation process in these countries.

Some issues remain for further research. First, we did not address the implication of the change in both temperature and precipitation at the same time. Second, while our study focuses on "within" agricultural transformation represented by growth in agricultural income, it is obvious that agricultural transformation, even at the micro level, might be triggered by macro changes.

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