Changing rural labor markets and welfare in Malawi

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Abstract

Labor is a critical asset for rural populations in sub-Saharan Africa yet underemployment is common with important welfare implications. This study analyzes shifts in working hours allocated to income-generating activities among Malawian rural residents from 2010 to 2019. Using temporally and nationally representative data we estimate weekly hours spent each month on household agriculture, non-farm household enterprises, casual labor, and wage employment for both years. We document small reductions in seasonality and an increase in mean working hours from 17.4 to 18.4 hours per week. We observe substantial changes in hour allocations across activities: weekly hours spent on household farm work have dropped by 1.6 hours while hours worked in casual labor and household non-farm enterprises increase by 2.6 and 0.7 hours respectively. Concurrently, though average consumption has increased by 22%, poverty rates remain high and food insecurity has increased by 43% as households rely more on purchased food making them vulnerable to fluctuating market prices. We document an increasingly strong correlation between casual labor and food insecurity, a worrisome trend given casual labor's growing economic importance. Through an Oaxaca-Blinder decomposition, we show that the shift towards casual labor is experienced relatively more by men, the young, the less educated, those with small land holdings, and those residing near big cities. As Malawi navigates the complex transition from a subsistence-based to a market-oriented economy, targeted policies and interventions will be critical to prevent further entrenchment of poverty among vulnerable segments of its population.

Keywords: Rural labor markets, Casual labor, Seasonality, Sub-Saharan Africa, Malawi.

1 Introduction

Labor is a critical asset for the rural population of sub-Saharan Africa (SSA). Though fundamental to the welfare of households, and political and economic stability, we lack good empirical characterizations of how labor in income generating activities is evolving. Rapid urbanization and increased reliance on labor and food markets are transforming work throughout the region, but we have limited insights into how these changes are affecting the working patterns of rural households and their well-being. This is in large part due to data limitations, which are particularly pronounced in contexts where seasonality can cause large fluctuations in labor patterns from one month to the next and where levels of labor informality are high.

This paper leverages the geographic and seasonal structure of Malawi's Integrated Household Survey (IHS) to provide a representative description, with spatial representation down to the district level and temporal resolution down to the month level, for rural Malawi in 2010 and 2019. Using these data, we map hours worked across four distinct income generating activities and examine how work changed between 2010 and 2019. To our knowledge, this is the first study to examine long-term shifts in rural labor patterns with such granularity across an entire low-income country. We further explore the welfare changes associated with these shifts in labor and identify which groups are experiencing them. Overall we find that Malawi is undergoing a fraught transition from an economy based on subsistence-farming to a market-based economy, wherein the rural population increasingly relies on markets to sell their labor and purchase food.

Our analysis consists of three parts. First, we document the changes in the labor hours reported by rural Malawians. We use reported hours worked in income generating activities over the past 7 days from 35,819 rural working-age individuals to build representative month-by-month labor calendars for 2010 and 2019. The short recall period gives us confidence that the reports are accurate (Arthi et al., 2018; Gaddis et al., 2021), while the temporal representativeness of the sample allows us to calculate monthly averages. In an average week in 2010 rural working age Malawians reported working 17.4 income generating hours, well below what might be considered a full work schedule. During the busy planting and weeding months of December and January, we count 24.6 income generating hours per week, while during the less busy post-harvest months of July and August, that figure drops to 12.6 hours per week. In 2019 working-age rural residents work 8.3% more income generating hours per year, a statistically significant shift compared to 9 years earlier. The largest shift occurs during the low season, with weekly income generating hours going up by 17.1% (an increase of 2.2 hours), while hours in the busy season increase by 5.9% (a 1.5 hour per week increase). These patterns are driven by shifts in the composition of income generating activities. Hours worked are reported separately for four different income sources: working on the household farm, in a household non-farm enterprise, as a casual laborer or in wage labor. Disaggregating the increase in hours worked by rural Malawians between 2010 and 2019, we see a remarkable 14.6% reduction in hours spent on the household farm, from an average of 10.98 to 9.38 weekly hours. This decline is compensated by time spent running small businesses and in casual labor. Hours spent on household non-farm enterprises rise from 1.9 weekly hours to 2.6 - a 36.8% increase, mostly driven by increased work during the post-harvest season. Finally, casual labor experiences the most dramatic shift. The share of people engaging in such work in an average week jumped from 15% in 2010 to 32% in 2019 and the mean number of hours spent on this activity increased from 2 to 4.6 hours per week - a dramatic 130% increase. The increase in casual labor is statistically significant in both high and low seasons, but much more pronounced during the busiest months of the agricultural cycle.[1]

Second, we link the shifts in labor calendars across the 9-year period to changes in welfare. While poverty incidence remains stubbornly high at 57%, the depth of poverty is slightly lower in 2019, and mean consumption per capita increased by 22% over this period. Interestingly, despite increasing consumption, the proportion of households reporting food insecurity in the last 12 months increased from 51% to 73%, with a fourfold rise in respondents reporting high market food prices as the primary cause. Closer examination shows an increased reliance on markets to access food. The proportion of maize, Malawi's key staple crop, consumed in the past week from home production dropped from 63% to 47%. Furthermore, food insecurity and poverty are increasingly correlated with casual labor, a worrisome trend considering the growth in this informal labor arrangement between 2010 and 2019.

Finally, we investigate which groups experience these labor shifts using an Oaxaca-Blinder decomposition. We decompose the changes in mean hours worked into a portion explained by compositional changes in the population between 2010 and 2019 and a portion attributable to structural changes in the relationship between population characteristics and hours worked. We find that the shift from household farm work to casual labor is disproportionately occurring among

[1] Hours spent in wage labor dropped by 0.6 weekly hours, a 25% decrease - but few rural Malawians report wage labor.

men, youth, and those lacking a primary education. The increase in hours spent running family businesses is smaller for young people and those who never completed primary education. Land scarcity contributes to the shift from household farm work to casual labor and business, both compositionally (because land holdings are shrinking) and structurally (because smallholders are increasingly engaged in these activities). Proximity to a major city is associated with an increase in hours worked in both household business activities and household farming, as well as in casual labor mostly during the peak agricultural season. In the aggregate, structural changes are much more important than compositional ones.

Our article builds on and contributes to several literatures. First, the literature on underemployment in rural labor markets in SSA is relatively underdeveloped despite it being a key characteristic of these labor markets (Fox, Senbet, & Simbanegavi, 2016; Golub & Hayat, 2014; ILO, 2020; ILO, 2024; Yeboah & Jayne, 2018). Seasonal swings in rural labor demand and supply cause excess supply in some seasons and shortages in others, negatively impacting both producers and workers (Breza, Kaur, & Shamdasani, 2021; Chirwa, Dorward, & Vigneri, 2013; Fink, Jack, & Masiye, 2020; Wodon & Beegle, 2006). Those same fluctuations also make it challenging to measure labor accurately (Arthi et al., 2018; Gaddis et al., 2021), a problem compounded by high levels of labor informality (Meagher, 2016; Mueller & Chan, 2015; Lagakos & Shu, 2023; Oya, 2013; Rizzo, Kilama, & Wuyts, 2015). Unemployment and underemployment present significant challenges for both individuals and governments in Sub-Saharan Africa. They imply substantial losses in foregone earnings in environments where the marginal utility of additional income is particularly high (Chirwa et al., 2013; de Janvry, Duquennois, & Sadoulet, 2022; McCullough, 2017; Wodon & Beegle, 2006). Moreover, they pose a serious threat to political stability, as public frustration, particularly among the youth, mounts in response to the persistent inability of economic structures to generate employment opportunities for a rapidly expanding workforce (Azeng & Yogo, 2013). Using household data from several African countries, McCullough (2017) shows that underemployment, rather than low labor productivity per hour worked, explains the productivity gap between agriculture and non-agriculture sectors. With respect to Malawi, de Janvry et al. (2022), use the same 2010 data we use to show that seasonality in own-farm work accounts for two thirds of Malawi's rural underemployment. Our analysis builds on their findings to examine how these patterns are evolving over time.

Next, we observe a substantial increase in the market engagement of rural Malawians. Rural residents increasingly participate in, and rely on, both labor and food markets, with significant implications for rural economies. The traditional view of rural Africa as populated by smallholder subsistence farmers, primarily consuming food they produce themselves, is increasingly outdated. The majority of food consumed in developing countries is now purchased from local markets which have become essential to guaranteeing food security (Dzanku, Liverpool-Tasie, & Reardon, 2024). While increased participation in food markets generally has positive effects on, for instance, household dietary diversity and food security, such markets can expose households to new types of volatility and do not always protect households from seasonal fluctuations (Bonuedi, Kornher, & Gerber, 2021; Matita et al., 2021). Abay & Hirvonen (2017) note that while proximity to markets improves children's nutritional outcomes, it does not insulate them from seasonal fluctuations. Food markets can experience substantial seasonal price fluctuations (Gilbert, Christiaensen, & Kaminski, 2017). Poor households are especially vulnerable to this variability as they allocate a large share of their budgets to food (Dzanku et al., 2024; Harttgen, Klasen, & Rischke, 2016; Minot, 2014). This vulnerability to price fluctuations stems from several factors, including market failures such as liquidity constraints that prevent households from smoothing consumption across seasons (Burke, Bergquist, & Miguel, 2019; Fink et al., 2020; Stephens & Barrett, 2011), technological limitations in food storage (Omotilewa, Ricker-Gilbert, Ainembabazi, & Shively, 2018), and discretionary government interventions that can exacerbate volatility and intensify the effects of seasonality (Benson, 2021; Cornia, Deotti, & Sassi, 2016; Duchoslav, Nyondo, Comstock, & Benson, 2022; Gilbert et al., 2017; Minot, 2014).

Rural residents are also increasingly leveraging markets for income generation, through self-employment in household enterprises and/or by selling their labor on the labor market, rather than using their labor on their own farms (Benson & De Weerdt, 2023). A large literature has examined how rural populations in developing countries are increasingly engaging in small, low-capital, household enterprises (Beegle & Bundervoet, 2019; Dabalen, De La Fuente, Goyal, Karamba, & Tanaka, 2017; Fox & Sohnesen, 2012; Nagler & Naude, 2017). On the one hand, the growth of these enterprises may signal strengthening rural economies, where rising incomes drive demand for locally produced goods and services (Haggblade, Hazell, & Reardon, 2009; Haggblade, Hazell, & Reardon, 2010; Reardon, Stamoulis, & Pingali, 2007; Christiaensen & Maertens, 2022). However, the literature also underscores that many of these businesses are born out of necessity rather than opportunity, as households attempt to cope with economic pressures. These enterprises often engage in activities with low entry barriers and do not operate year-round (Barrett, Reardon, & Webb, 2001; Barrett, Bezuneh, & Aboud, 2001; Beegle & Bundervoet, 2019; Benson & De Weerdt, 2023; Dabalen et al., 2017; Ellis, 1998; Fox & Sohnesen, 2012; Nagler & Naudé, 2017). With regards to wage work, formal wage employment is rare. Labor market opportunities available to rural laborers are mostly low paying and informal, involving low-skill short-term and seasonal tasks, either on other people's farms—such as preparing fields, weeding, or harvesting—or in non-agricultural sectors like loading trucks or construction work. Such casual labor is often the most accessible form of employment, requiring no land or capital. Because of this, though casual labor provides an important source of income, it is often associated with vulnerability, poverty, and food insecurity (Benson & De Weerdt, 2023; Bezner Kerr, 2005; Bryceson, 2006; Caruso & Cardona-Sosa, 2022; Davis et al., 2020; Jayne, Yeboah, & Henry, 2017; Mueller & Chan, 2015; Oya, 2013; Whiteside, 2000). While the opportunities these developing labor markets are providing to rural Malawians are potentially critical to maintaining and improving living standards, they can also expose them to new sources of economic fluctuations and vulnerability.

Finally, an expanding literature is documenting how growing cities impact their rural hinterlands. Urban growth changes the relative prices of production factors and outputs, often raising land prices while lowering prices for other agricultural inputs, such as seed, fertilizer or irrigation equipment (Abay, Chamberlin, & Berhane, 2021; Hazell, Haggblade, & Reardon, 2024; Tione & Holden, 2020). At the same time, increased demand from urban areas can increase prices for farm produce, benefiting those who sell, but hurting those who buy. We find that urban proximity increases hours worked, in line with Abay, Asnake, Ayalew, Chamberlin & Sumberg (2021)'s finding that more accessible areas offer a larger set of labor opportunities. This is especially true for casual labor in the planting and weeding season. These patterns are consistent with a literature documenting the rise of urban-based absentee farmers that rely on local labor (Anseeuw, Jayne, Kachule, & Kotsopoulos, 2016; Jayne, Chamberlin, & Headey, 2014; Jayne, Chapoto, et al., 2014; Jayne et al., 2019; Jayne, Wineman, Chamberlin, Muyanga, & Yeboah, 2022; Ricker-Gilbert, Jayne, & Chamberlin, 2021; Sitko & Jayne, 2014; Tione & Holden, 2020). Though underemployment is reduced, such procyclical labor demand in low wage casual labor can create a vicious cycle of poverty and food insecurity (Bezner Kerr, 2005; Bryceson, 2006; Whiteside, 2000). In contrast to other contexts, we do not find that this increase in labor demand comes at the expense of work on the family farm in our aggregate data.

The outline of the paper is as follows. Section 2 introduces the context of Malawi and the data. Section 3 explains the methodology used to calculate the labor estimates and describes stylized facts on labor patterns and their changes over a 9-years period. Section 4 reports the association between labor and welfare indicators in rural Malawi. Section 5 introduces the Oaxaca-Blinder decomposition methodology, and presents how the changes in mean hours worked between 2010 and 2019 can be decomposed. Section 6 concludes with a policy discussion.

2 Context and data

2.1 Rural Malawi

The focus of our study is Malawi, one of the poorest countries in SSA with an economy that has been centered around low-productivity smallholder agriculture. Maize is the main staple crop and production for home consumption has historically guided farming decisions (Benson, 2021). Smallholder production is primarily rainfed during a single cropping season.[2]

Between 2010 and 2019, our period of analysis, Malawi's population density increased from 157 to 201 people per square kilometer, one of the highest in Africa (United Nations, 2024). Figure A.1 shows that a large share of this growing number of rural households own less than 0.5 ha of land, which is too little to earn enough from traditional farming to cover basic needs (Benson & De Weerdt, 2023). The expected doubling of the population within the next three decades makes providing employment opportunities to this rapidly expanding work force a pressing policy challenge (Caruso & Cardona-Sosa, 2022; IFPRI, 2022a). Though still quite rural, Malawi is also rapidly urbanizing, offering expanded opportunities for off-farm work in both rural and urban areas (De Weerdt, Pienaar, Hami, & Durand, 2023; Van Cappellen & De Weerdt, 2024).[3]

[2]The rainfed agricultural season starts in October with land preparations. Planting takes place in November and December. Weeding happens in January and February, and the harvest goes from March/April to May/July. Planting and weeding are the most labor intensive activities and, hence, when labor demand is the highest (Kamanga, 2002). Right after the harvest labor demand is at its lowest. Most farmers sell their produce soon after harvest (Chiwaula et al., 2024; Dillon, 2021), bringing cash to the rural economy and boosting the activities of the small rural off-farm enterprises. Households often finish consuming the food they harvested by December or January, when the lean season starts, with many households experiencing food insecurity until the start of the harvest period. It is also during this period that food prices increase (Chiwaula et al., 2024).

[3]Malawi is one of the least urbanized countries in Africa with 84% of the population classified as rural in 2018 (National Statistical Office, 2019). Yet it is also one of the most rapidly urbanizing African countries, going from just one urban agglomeration with a population of 24,483 in 1950 to 77 urban areas in 2015 with 4,835,999 residents (OECD/SWAC, 2020).

2.2 The Third and Fifth rounds of the Integrated Household Survey (IHS)

We use the cross-sectional data from the Third and Fifth rounds of the Integrated Household Survey (IHS), collected between March 2010 and March 2011 and between April 2019 and April 2020, respectively (National Statistical Office, 2020). We refer to these as the 2010 and 2019 survey rounds as the bulk of the observations fall in these years.[4] We focus on rural residents aged 15 to 64 years old who are not attending school. These rural working-age individuals account for 18,618 and 17,201 observations in IHS3 and IHS5, respectively (see Appendix Table A.2 for more information on the sample composition). A unique design feature of the IHS in Malawi is that it is both spatially and temporally representative. Each survey round was implemented over a period of 13 months so as to be representative in each month.[5] We supplement the IHS data with the Africapolis dataset to measure rural enumeration areas (EAs)' proximity to urban agglomerations of differing population sizes[6]. We adjust all values using survey weights to maintain the sample's representativeness. Table 1 provides summary statistics for our main variables.

Our main labor variables come from the household questionnaire's time and labor module. All individuals over the age of five report the hours they spent in the last seven days on activities which we classify into four categories:[7] own-farm (agricultural, livestock, and fishing activities), business (running and helping in household businesses[8]), casual labor,[9] and wage labor.[10] Using

[4]We do not use the 2016/17 IHS4, as that year experienced a particularly bad harvest. Labor allocations in the 2016/17 survey may be more reflective of this shock than of long run trends.

[5]Section A.1 gives a more in depth presentation of the data. Appendix Tables A.3 and A.4 assess the survey's temporal balance.

[6]Africapolis, produced by OECD Sahel and West Africa Club, identifies urban agglomerations in Africa. Urban agglomerations are built-up spatial units with more than 10,000 inhabitants (OECD/SWAC, 2020). In Malawi, Africapolis has identified 77 urban agglomerations detailed in Table A.5 in the Appendix. Using these, we calculate the minimum distance to urban agglomerations by population size: tiny (10,000 to 30,000 inhabitants), small (30,000 to 100,000 inhabitants), medium (100,000 to 300,000 inhabitants) and large (over 300,000 inhabitants). We define a rural area as proximate to an urban agglomeration if it is within 20 kilometers.

[7]Time spent in unpaid apprenticeships is also reported. We drop this category as few respondents engage in it.

[8]Household enterprises cover a wide variety of activities such as preparing and selling small batches of roasted peanuts and doughnuts, brewing and selling local beer, selling roast meat or samosas, retailing second-hand clothes, running small grocery stores, weaving baskets and mats, pottery making, tailoring, producing and selling charcoal and bricks, bicycle repair, running local bicycle and motorbike taxi services, agricultural processing, sale and trade, and so forth.

[9]The question asks individuals whether in the past 7 days they have engaged in "casual, part-time or ganyu labour". The enumerator manual explains that "ganyu labour is short-term labor hired on a daily or other short-term basis." Most commonly, casual work involves weeding or ridging fields for other smallholders or on agricultural estates. However, casual labor can also be used for non-agricultural tasks, such as construction and gardening (National Statistical Office, n.d.). A large portion of this work does not require specialized skills or equipment, but rather the capacity to perform basic manual labor. Van Cappellen & Oliveres-Mallol (2024) provide a descriptive overview of casual *ganyu* labor in Malawi.

[10]Wage employment is not common in rural areas, but there are rural residents employed as agricultural estate managers or tenant farmers, agricultural extension agents, rural-based government or parastatal employees, staff at local grain mills and so forth. There are also cooks, cleaners, caregivers, guards and gardeners employed in full-time wage employment by private households.

the date of the interview, we know the week and the month in which these activities took place (referred to as the "reference week", and the "reference month"). By exploiting the temporal representativeness of the survey, we can thus characterize labor calendars and investigate how labor allocations change across months in the survey year. We restrict our analysis to working-age individuals aged between 15 and 64 and to income generating activities. As in previous work (de Janvry et al. (2022), McCullough (2017) and Hamory, Kleemans, Li, & Miguel (2021)), we focus on income generating activities and do not include time spent on the production of home services such as domestic chores, fetching water, and firewood collection.[11] As such, our measure is strictly a measure of income generating work, not of leisure. This allows us to focus on the welfare consequences of changes in income generating opportunities, but is not meant to negate the long hours that households spend on the production of home goods.

Using the weekly (as opposed to annual) reported labor data allows us to study the seasonality of labor hours and labor engagement throughout the year. Moreover, the seven-day recall period reduces recall error, giving more reliable estimates of annual hours worked and reducing what could otherwise be serious coefficient biases (De Weerdt, Gibson, & Beegle, 2020). These also avoid the problems associated with end-of-season 12 months recall data when labor schedules are highly irregular (Arthi, Beegle, De Weerdt, & Palacios-López, 2018; Gaddis, Oseni, Palacios-Lopez, & Pieters, 2021).[12]

3 Working more, and shifting from own-farm to off-farm work

This section first introduces how we quantify monthly and annual hours worked. We then show that the share of people reporting work in any of the four activities during the reference week increased from 79% to 82% between 2010 and 2019, and that average annual hours worked increased from 910 to 986 hours. Unemployment and underemployment declined though underemployment is still pronounced at only 18.4 hours worked per week. We also document a decline in the seasonality of the labor calendar. Underlying these trends is a reduction in work on household farms and an increase in work off of the household farm.

[11] Time spent on domestic chores is not reported in the 2010 and 2019 data which only asks respondents about time spent yesterday on collecting firewood and water. Time spent on peripheral production related activities such as commuting is also not reported making it impossible to clearly categorize time use beyond that spent in income generating activities.

[12] The 7-day labor module in Malawi's IHS is used in Abay, Asnake et al. (2021) and Wodon & Beegle (2006). The 12 month recall is analyzed by Van Cappellen & De Weerdt (2024) and compared to estimates using the 7-day labor module in de Janvry et al. (2022).

Table 1: Mean values of key variables in rural areas for 2010 and 2019, and the change over time.

	(1) 2010	(2) 2019	(3) Difference
Panel A: All rural households			
Total (rainy and dry season) hectares of land owned	0.900	0.575	-0.326
Share reporting...			
Food insecurity in the last week	0.327	0.648	0.321***
Food insecurity in the last 12 months	0.512	0.731	0.219***
Expensive food as main cause of food insecurity in the last 12 months	0.033	0.128	0.096***
Share of weekly maize consumption...			
Purchased	0.259	0.442	0.183***
Own-produced	0.631	0.466	-0.165***
Gifted	0.044	0.069	0.025***
Not consumed	0.066	0.022	-0.043***
N, all rural households	10037	9342	
Panel B: All rural individuals			
Consumption per capita	152283	185431	33148***
Poverty headcount	0.57	0.57	-0.00
Ultra-poverty headcount	0.29	0.24	-0.06***
N, all rural individuals	46046	41652	
Panel C: All rural working-age individuals			
Reported in the last week...			
Total hours	17.380	18.442	1.063**
Hours in own-farm	10.978	9.377	-1.600***
Hours in household enterprise	1.892	2.572	0.680***
Hours in casual labor	1.989	4.607	2.618***
Hours in wage employment	2.521	1.886	-0.635***
Total engagement	0.791	0.809	0.019*
Eng. in own-farm	0.666	0.605	-0.061***
Eng. in household enterprise	0.099	0.121	0.022***
Eng. in casual labor	0.148	0.312	0.163***
Eng. in wage employment	0.071	0.059	-0.011**
Population characteristics			
Male	0.464	0.450	-0.014***
Young (15 to 24 years old)	0.264	0.279	0.015**
No primary education	0.811	0.773	-0.038***
Household owns < 1 hectare of land	0.775	0.819	0.043***
Small urban agglomeration within 20 kms	0.430	0.416	-0.014
Medium urban agglomeration within 20 kms	0.129	0.143	0.014
Big urban agglomeration within 20 kms	0.173	0.162	-0.011
N, all rural working-age individuals	18618	17201	

Note: The table shows the mean values of key variables in rural areas in 2010 (column 1), in 2019 (column 2) and the mean difference between the two years (in column 3). Panel A reports the means for all rural households, Panel B for all rural individuals and Panel C for rural working-age individuals (aged between 15 and 64 reporting not attending school). The categorization of urban agglomerations into small, medium and big is found in Table A.5. The final row of each panel reports the sample size for each subsample. Due to missing georeferenced data for 9 EAs in 2019 because of confidentiality reasons, the sample of rural-working age individuals in 2019 for the variables capturing the distance of the EA from the urban agglomerations is 17,057 (rather than 17,201). Tests for statistical significance of the difference between 2010 and 2019 being different from 0 are reported for column 3 with $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. Values are adjusted using survey weights.

3.1 Estimating seasonal labor calendars

To construct rural Malawi's 2010 and 2019 labor calendars, we borrow the approach introduced by de Janvry et al. (2022). Total weekly hours worked per individual each month is estimated as

$$H_i = \sum_{m=1}^{14} \beta_{1m} Month_i + \sum_{m=1}^{14} \beta_{2m} Month_i * 2019_i + \varepsilon_i \tag{1}$$

where H_i is hours worked in labor activities (total, own-farm, business, casual labor, and wage employment) by individual i during their reference week in month m; $Month_i$ are dummy variables set to one if the reference week of individual i falls in that month;[13] and 2019_i is an indicator variable set to one for individuals in 2019 (IHS5), and 0 for those in 2010 (IHS3). All estimates use survey weights. The parameters of interest, $\widehat{\beta}_m^{wave}$, can be calculated as $\widehat{\beta}_m^{2010} = \widehat{\beta}_{1m}$ and $\widehat{\beta}_m^{2019} = \widehat{\beta}_{1m} + \widehat{\beta}_{2m}$. These capture the average weekly hours worked per individual in month m in 2010 and 2019, respectively. We also examine labor engagement using an indicator for having worked in the past week as a dependent variable. Parameters then give the share of individuals engaging weekly in an activity for each month m in both 2010 and 2019.

Total yearly individual labor hours, $\widehat{YH}^{wave}$, is calculated by multiplying the $\widehat{\beta}_m^{wave}$ parameters estimated in equation (1) by the number of weeks in the associated month and summing across months,[14]

$$\widehat{YH}^{wave} = \sum_{m=1}^{12} \widehat{\beta}_m^{wave} * \#\text{weeks in } m. \tag{2}$$

With the same approach, we also estimate the annual mean share of individuals who were active in the past week by using the labor engagement indicator as the dependent variable.

To characterize the seasonality of labor calendars, we calculate the difference between average weekly hours worked in the high season (defined as December and January) and the low season (defined as July and August).[15] We estimate the average hours worked per week in the high season and the low season by taking the mean of the corresponding months' estimated $\widehat{\beta}_m^{wave}$ parameters.

[13] Each IHS round covers a 13-months period. IHS3 was conducted from March 2010 to March 2011, and IHS5 was conducted from April 2010 to April 2019. For our analysis, subscript m can take values from 1 to 14. Value 1 corresponds to March 2010, value 2 to both April 2010 and April 2019, value 3 for both May 2010 and May 2019, and so on. Finally, value 14 corresponds to April 2019.

[14] For IHS3, we have two observations for March, one in 2010 and one in 2011. For IHS5, we have two observations for April, one in 2019 and the other one in 2020. Figures report them separately. In calculations of annual totals, we pool all March observations for IHS3 and all April observations for IHS5.

[15] As shown in Figure 1, the high season is in December and January, which is the most labor intensive period on the farm, when planting and weeding take place. The low season is in July and August, after the harvest when there is little agricultural farm work (Kamanga, 2002).

Labor seasonality is interpreted as declining when the gap between the mean hours worked per week in the low season and the high season shrinks.

3.2 Increasing labor hours and a shift towards off-farm activities

Table 2 shows that between 2010 and 2019, annual hours worked in income generating activities increased from 910 to 986 per rural working-age individual (going from 17.5 to 18.9 hours per week, as reported in Table 1).[16] Though increasing, this remains far removed from all benchmark measures of full time employment.[17] Labor engagement in the past week also went up from 79% to 82% over the same period. Together we interpret this as a decline in labor underemployment and unemployment.

When we disaggregate the hours worked into the four activities – own-farm, household business, casual labor and wage labor – some intriguing labor patterns and changes become observable. First, we observe that during this 9-year period both the share of individuals reporting any work on the household farm during the reference week, and the average yearly hours spent in own-farm work have declined (the share decreased from 67% to 62%, and average yearly hours dropped from 577 to 504 hours). At the same time, individuals' engagement and annual hours worked in other activities increased. Hours and engagement in household businesses increased and an even sharper increase is observed for casual labor. The increase in the share of individuals engaging in a household enterprise is modest (going from 10% to 12%, representing a 20% increase) while the increase in average hours worked per year in the family business has grown proportionally more (from 98 to 134 hours, representing a 36.3% increase). More strikingly, between 2010 and 2019 there has been a substantial increase in the probability respondents report that they worked in casual labor in the week prior to their survey (going from 15% to 32%) and in the annual hours worked in casual labor (going from 103 hours to 249 hours). Engagement in wage labor in these rural areas was low to begin with and has declined further between 2010 and 2019.

Figure 1 clearly depicts the seasonal nature of labor in rural Malawi, showing its connection to the agricultural calendar. Labor hours are highest in December and January when labor intensive agriculture activities (planting and weeding) take place; in July and August hours are low as the

[16] These estimates, calculated as $\widehat{YH}/52.14$ are consistent with the mean of weekly hours reported in Table 1 though there are minor divergences due to the difference in estimation approach.

[17] There is no objective measure of what a full working schedule looks like. 220 work days at 8 hours per day gives 1,760 annual work hours, or 33.8 hours per week. Individuals in our data who only report wage employment work 42.37 and 37.68 hours per week in 2010 and 2019, respectively. de Janvry et al. (2022) use a benchmark of 28.05 hours a week based on the mean rural work hours reported for Malawi's 2010 peak agricultural season.

Table 2: Estimated hours worked and labor engagement of rural individuals in 2010 and 2019.

Panel A: Rural areas - Labor supplied ***(hours worked)***

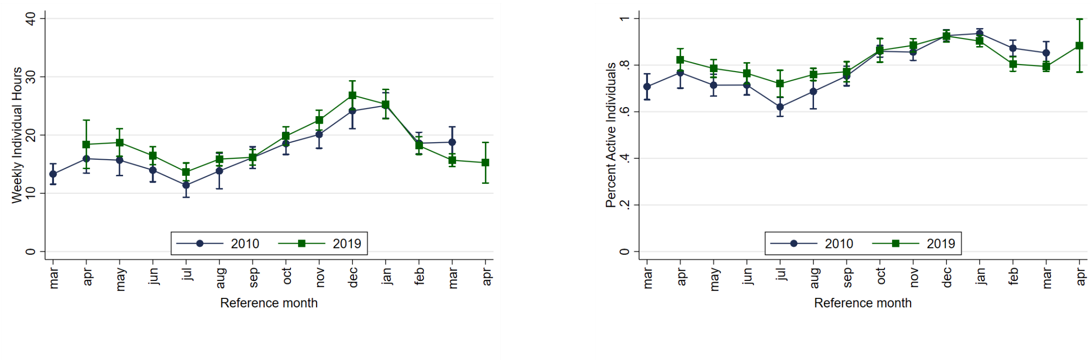
		Total hrs/yr	High season hrs/wk	Low season hrs/wk	Diff. high and low season
Total	2010	910.11	24.61	12.61	11.99
	2019	985.76	26.07	14.77	11.30
	2019-2010	75.65***	1.46	2.16**	-0.69
Own-farm	2010	577.01	17.87	6.69	11.18
	2019	504.35	15.76	5.84	9.93
	2019-2010	-72.66***	-2.11*	-0.85	-1.25
Business	2010	98.26	1.97	1.66	0.31
	2019	133.95	2.02	2.92	-0.91
	2019-2010	35.69***	0.05	1.26***	-1.22**
Casual labor	2010	103.49	1.99	2.09	-0.10
	2019	248.62	6.13	4.37	1.77
	2019-2010	145.13***	4.14***	2.28***	1.87***
Wage labor	2010	131.35	2.78	2.17	0.61
	2019	98.83	2.16	1.64	0.51
	2019-2010	-32.52**	-0.62	-0.53	-0.10

Panel B: Rural areas - Labor engagement ***(indicator set to 1 if any labor hours are reported)***

		Mean % active	High season % active	Low season % active	Diff. high and low season
Total	2010	0.79	0.93	0.65	0.28
	2019	0.82	0.91	0.74	0.17
	2019-2010	0.03***	-0.02	0.09***	-0.11***
Own-farm	2010	0.67	0.86	0.49	0.37
	2019	0.62	0.78	0.48	0.31
	2019-2010	-0.05***	-0.08***	-0.01	-0.06
Business	2010	0.10	0.09	0.10	-0.01
	2019	0.12	0.10	0.14	-0.04
	2019-2010	0.02***	0.01	0.04**	-0.03
Casual labor	2010	0.15	0.18	0.13	0.04
	2019	0.32	0.40	0.28	0.12
	2019-2010	0.17***	0.22***	0.15***	0.08**
Wage labor	2010	0.07	0.07	0.07	0.01
	2019	0.06	0.07	0.05	0.01
	2019-2010	-0.01*	0.00	-0.02	0.00

Note: This table reports estimated hours worked (Panel A) and labor engagement (Panel B) for rural working-age individuals in total and in each income generating activity for 2010 and 2019. The difference between these years is also reported. Column 1 reports the yearly estimate, columns 2 and 3 the weekly average per season, and column four reports the difference in weekly hours in the high and low season. 'High season' is December and January, 'low season' is July and August. The sample consists of rural working age individuals who are not in school, covering 18,618 individuals in 2010 and 17,201 in 2019. Differences between 2010 and 2019 are tested for statistical significance with $^{*}p < 0.1$, $^{**}p < 0.05$ and $^{***}p < 0.01$. Values are adjusted using survey weights.

Figure 1: Total weekly hours worked and labor engagement for rural working-age individuals by month in 2010 and 2019.



(a) Total hours worked

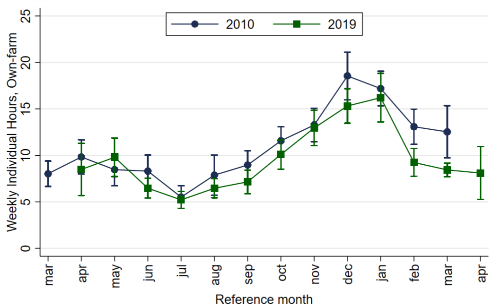
(b) Labor engagement

Note: Panel a reports estimated total weekly hours worked by rural working-age individuals by month in 2010 and 2019. Panel b reports the probability that rural working-age individuals report engaging in any work activity in the past week by month. Coefficients are reported with 95% confidence intervals. Values are adjusted using survey weights.

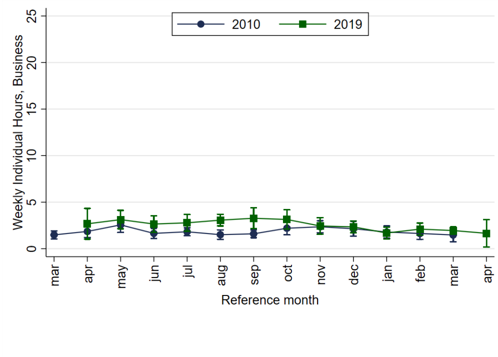
harvest period is over and the next agricultural season has not yet started. Figure 2 shows the same plot for each of the four activities. During the high season people work about twice as many hours as in the low season (Table 2 , Panel A). This is primarily driven by fluctuations in own-farm work. However, between 2010 and 2019, we observe a drop in own-farm hours worked during the high season, accompanied by a rise in hours spent in casual labor during the high season. This suggests a transition away from own-farm work towards working as hired agricultural labor on other farms. In section 5 we will show that both trends are experienced by the same demographic groups: men, youth, individuals lacking primary education as well as individuals owning little land.

In contrast, hours spent in household enterprises has increased since 2010, particularly in the low season, suggesting an increasingly countercyclical pattern. Figure 3 unpacks this trend further. Panel (a) highlights the large increase in the total number of household enterprises in Malawi. However, it also shows that enterprises in 2019 are increasingly seasonal, operating only some months of the year. Enterprises operating year-round grow in absolute terms, but their share of the total drops from 55% in 2010 to 27% in 2019 (see Figure A.2 for data on shares). Panel (b) shows an increasingly pronounced seasonal pattern. In 2019 the largest share of enterprises operate from May to October. This post-harvest period is when farmers sell their crops, generating cash to spend in the local economy and creating demand for local goods and services. During this period rural households may also have more cash to use as capital to start operating small businesses.

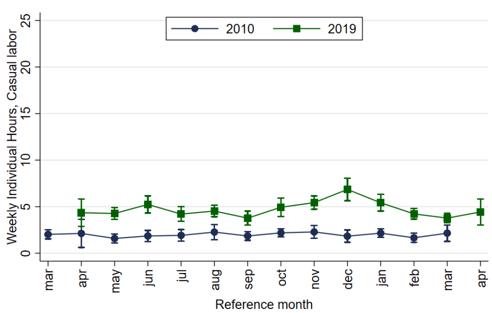
Figure 2: Total weekly hours worked and labor engagement for rural working-age individuals by activity and month in 2010 and 2019.



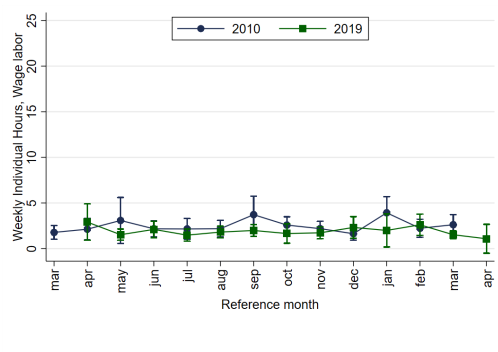
(a) Hours worked in own-farm



(b) Hours worked in household businesses



(c) Hours worked in casual labor

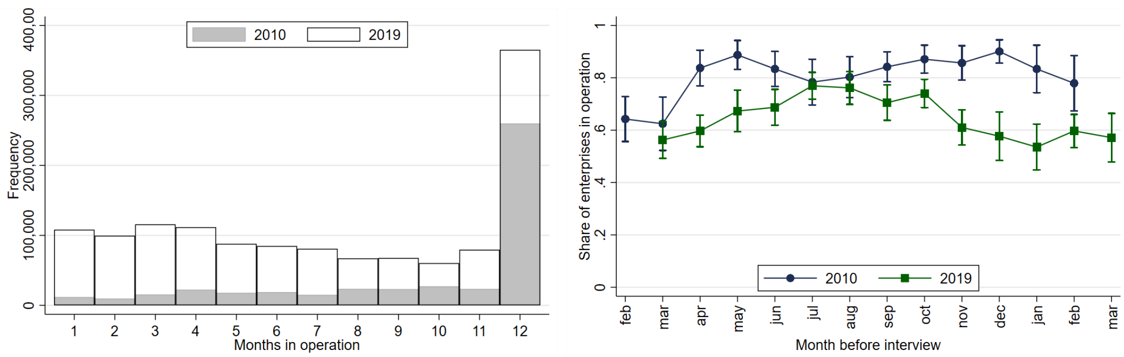


(d) Hours worked in wage labor

Note: This figure reports the estimated total weekly hours worked by rural working-age individuals by month in 2010 and 2019 for four different income generating activities: own-farm (panel a), non-farm household business (panel b), casual labor (panel c) and wage labor (panel d). Coefficients are reported with 95% confidence intervals. Values are adjusted using survey weights.

Some enterprises might also involve the processing or trade of agricultural output and are therefore inherently linked to the agricultural production cycle. Although most household enterprises do not operate year-round, their countercyclical timing makes their labor demand complementary to the labor needs of agricultural activities.

Figure 3: Non-farm household enterprises in rural areas.



(a) Number of months operated last year (b) Share of enterprises operating in each month

Note: The figures report data for 1,872 rural non-farm household enterprises in 2010 and 3,711 in 2019. Panel a reports the number of non-farm household enterprises reported by rural households by the number of months that the enterprise was in operation during the 12-month period preceding the interview month. Panel b reports the share of non-farm household enterprises in operation by month. Values are adjusted using survey weights.

Overall, as documented in Table 2 panel A, total hours have increased in both the high and low seasons leading to a small but statistically insignificant decrease in seasonality. Although total hours worked per week remain higher in the high season (24.6 hours in 2010 and 26 hours in 2019) than in the low season (12.6 and 14.8 in 2010 and 2019, respectively), the increase in hours worked over the 9-year period is only statistically significant in the low season - increasing on average by 2.16 hours per week. Thus, the gap between these two differentiated seasons has been reduced. These same broad patterns also hold for labor engagement (appendix Figure A.3).

4 Both consumption and food insecurity rise with growing reliance on casual labor and food markets

The previous section shows that between 2010 and 2019 there has been a decline in underemployment with people working more hours in both the high and low seasons, accompanied by a shift from own-farm to off-farm activities. In this section we examine whether there has been an accompanying increase in welfare. We note that although consumption levels increase and the depth of poverty is reduced, food insecurity levels are rising. Casual labor is increasingly correlated with poverty and food insecurity, a concerning pattern given the sharp increase in casual labor between 2010 and 2019.

Poverty has stagnated but is less severe, with increased consumption. Table 1 shows that between 2010 and 2019, the incidence of poverty in rural Malawi has stagnated at 57%,[18] Estimates of the absolute number of rural poor have increased by 1.8 million, from 6.95 to 8.73 million (Caruso & Cardona-Sosa, 2022). Nonetheless, the incidence of extreme poverty has slightly declined – from 29% in 2010 to 24% in 2019.[19] Appendix Table A.6 shows that the depth of poverty in rural areas has declined as the poor become less poor. Consumption is also increasing as captured in Tables 1 and A.7. Between 2010 and 2019, the mean consumption per capita increased by 22% while the median increased by 30%.[20] Much of this increase is coming from increased working hours. Indeed, household consumption per household hour worked, a proxy for productivity (McCullough, 2017), exhibits an increase of 4.4% at the mean and 13% at the median over this period (Table A.7).

Food insecurity and reliance on market purchased food increased. Despite these improvements in consumption per capita, the share of rural households reporting food insecurity in the last 12 months increased substantially – from 51% in 2010 to 73% in 2019 (see Table 1 and Table A.8). This increase is not concentrated in specific months but rather observed throughout the year (as illustrated in Figure 4). When asked about the main cause of food insecurity, there is a pronounced increase in the share of households reporting that "*food in the market was very expensive*" - going from only 3.3% of all rural households in 2010 to 12.8% in 2019 (Tables 1 and A.8).[21] Indeed, since 2010 rural households increasingly purchase their food in markets, consuming less self-produced food. We illustrate this using maize which accounts for two thirds of caloric intake and close to

[18] The incidence of poverty is calculated using the national poverty line established by the Government of Malawi. If, instead, the incidence of poverty is calculated using the international poverty line equivalent to US$ 1.90 per person per day at purchasing power parity (PPP) in 2011 prices, this value goes up to 68.5%, making Malawi the 6th poorest country in Africa (IFPRI, 2022b).

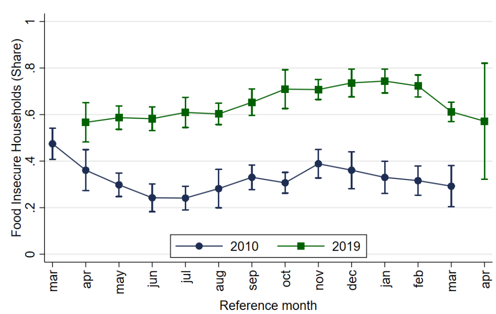
[19] The NSO calculates the cost of basic needs to determine both a poverty line and a line for ultra-poverty. Ultra-poverty is the 'food poverty line' which is set to the cost of meeting the basic nutritional needs of 2215 calories per person per day. The poverty line accounts for the additional cost of other basic needs. In April 2019 values, the national poverty line was MK 131,380 and MK 165,879 per person annually in 2010 and 2019, respectively. The national ultra-poverty line was MK 81,510 and MK 101,293 per person per year in 2010 and 2019, respectively (Caruso & Cardona-Sosa, 2022; IFPRI, 2022b; National Statistical Office, 2021).

[20] These values are reported for all rural individuals. Similarly, mean consumption at the rural household level increased by 17% while the median increased by 27% (shown in Table A.7).

[21] Conditional on being food insecure, these shares are 6.4% and 17.6% in 2010 and 2019, respectively.

half of the country's consumer price index (IFPRI, 2020). While in 2010 25% of the annual maize consumption was market purchased, in 2019 this increased to 46% (Table A.9).[22] In value terms the trend is even starker. In 2019 rural households spent 135% more on purchased maize than in 2010. The increased reliance on purchased maize is observed in both the high and low season (Figure A.4). The increase in food insecurity despite simultaneous reductions in extreme poverty and overall higher levels of consumption could be explained by households being increasingly exposed to unreliable and volatile markets (Benson, 2021; Chiwaula et al., 2024).

Figure 4: Reported food insecurity by rural households by month in 2010 and 2019.



Note: This figure shows the share of rural households reporting food insecurity in the past 7 days by month in 2010 and 2019. Coefficients are reported with 95% confidence intervals. Values are adjusted using survey weights.

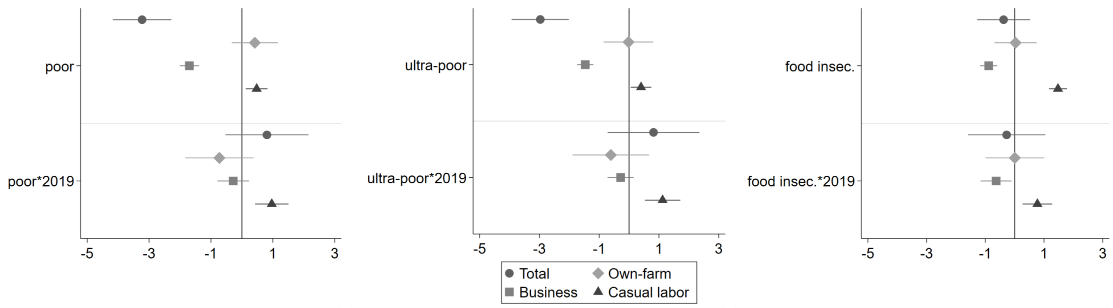
Casual labor's correlation with poverty and food insecurity has increased. We estimate several versions of the following model:

$$H_i = \beta_0 + \beta_1 Welfare_i + \beta_2 2019_i + \beta_3 Welfare_i * 2019_i + \varepsilon_i \quad (3)$$

where H_i are reported weekly work hours in total and by labor activity (own-farm, household enterprise, and casual labor), and $Welfare_i$ is one of three welfare indicators (poverty, ultra-poverty, and food insecurity). 2019_i is an indicator variable set to one for individuals surveyed in 2019. Figure 5 reports our estimates of β_1, capturing how total hours worked, own-farm hours, casual labor hours, and hours in household enterprises correlate with being poor, ultra-poor, and food insecure. Estimates of β_3 are also reported, and show how these correlations are changing between 2010 and

[22]These estimates, calculated using the approach detailed in section 3.1 are consistent with the means reported in Table 1 though there are minor divergences due to the difference in estimation approach.

Figure 5: Correlations between welfare indicators and hours worked in total and by activity for rural individuals in 2010 and 2019.



(a) Poverty (b) Ultra-poverty (c) Food insecurity

Note: This figure reports the β_1 and β_3 coefficients from equation 3. Coefficients are reported with 95% confidence intervals. Values are adjusted using survey weights.

2019.[23] In general, people who work more hours and who work more in household enterprises are less likely to be poor and ultra-poor, a correlation that changes little between 2010 and 2019. In contrast, hours in casual labor is predictive of poverty, ultra-poverty and food insecurity, a relationship that grew significantly stronger between 2010 and 2019. This suggests that the growing number of casual laborers are not experiencing welfare growth as Malawi's labor market undergoes this process of transformation.

5 Which groups experience these changes in labor and why?

Having documented the changes in labor patterns between 2010 and 2019 and examined associated changes in welfare, we now examine which groups of working-age individuals are most likely to experience these changing labor patterns. Aggregate changes in hours worked could reflect changes in the characteristics of the working-age population – which we refer to as "compositional changes". Alternatively, they could be due to a change in the relationship between population characteristics and hours worked – which we refer as "structural changes".[24] We perform an Oaxaca-Blinder decomposition (Blinder, 1973; Oaxaca, 1973) to distinguish between these two channels. We find that structural changes are more important than compositional changes. Men, youth and individuals lacking primary education are disproportionately driving the structural shift away from own-farm

[23] The complete regression results are detailed in Table A.10.

[24] For example, if young workers tend to work more casual labor, the aggregate increase in casual labor hours could be due to more young workers in 2019 (a compositional change), or due to young workers working more hours in casual labor in 2019 compared to 2010 (a structural change).

towards off-farm activities. Land scarcity is also an important factor, both compositionally and structurally: people are working less on their own-farms because farms are getting smaller, but also because they are working fewer hours on these small farms. Proximity to large urban centers is associated with more employment in 2019, as hours worked in own-farm, business and casual labor have grown faster in the urban periphery, although the latter mostly during the labor intensive period of the agricultural calendar.

5.1 The Oaxaca-Blinder decomposition method

Using the Oaxaca-Blinder decomposition method, we decompose the difference in mean weekly hours worked between 2010 and 2019 (overall and by labor activity) into two components. The first component, which we call the "compositional effect", is the portion of the difference in hours worked between 2010 and 2019 explained by how the composition of the working-age population's characteristics changed over this period. The second component, the "structural effect", is the portion of the difference in hours worked explained by a change in the relationship between population characteristics and hours worked over this period. The structural effect can in turn be divided into two subcomponents: the "attributable structural effect" which is the portion attributable to a change in the relationship between hours worked and observable population characteristics, and the "unexplained structural effect" which is the portion of the structural effect that is not attributable to either of the two previous components.[25]

Formally, the Oaxaca-Blinder decomposition can be implemented as follows. The weekly hours worked H of individual i interviewed in wave w are modeled as:

$$H_i^w = \beta_0^w + \sum_{k=1}^{K} X_{ki}^w \beta_k^w + \varepsilon_i^w \tag{4}$$

where β_0 is the constant; X_k is a vector of k observable individual characteristics; β_k is the vector of k associated coefficients; and ε is the error term. It is assumed that $E(\varepsilon^{2010}) = E(\varepsilon^{2019}) = 0$.

The change over time in expected hours worked, $\Delta E(H)$, is then given by

[25] The discrimination literature studying wage differentials between men and women generally refers to these decomposition components as the"endowment" or "explained" effect for the first component, and the "structural", "coefficients" or "unexplained" effect for the second component (Jann, 2008; Kilic, Palacios-López, & Goldstein, 2015; Van den Broeck, Kilic, & Pieters, 2023). We opt to use terms more appropriate to the context of this paper.

$$\Delta E(H) = E(H^{2019}) - E(H^{2010}) \tag{5}$$

$$= (\hat{\beta}_0^{2019} - \hat{\beta}_0^{2010}) + \sum_{k=1}^{K} [E(X_k^{2019})\hat{\beta}_k^{2019} - E(X_k^{2010})\hat{\beta}_k^{2010}]. \tag{6}$$

The Oaxaca-Blinder decomposition then decomposes this difference into the compositional and the structural components by use of a counterfactual. The counterfactual mean is calculated for 2019 as $\sum_{k=1}^{K} E(X_k^{2019})\hat{\beta}_k^{2010}$. This estimates the hours the 2019 population would have worked if its vector of average characteristics, $E(X_k^{2019})$, predicted hours worked in the same way it would have in 2010 (Bourguignon, Ferreira, & Leite, 2008; Fortin, Lemieux & Firpo, 2011). This term is added and subtracted from equation 6 to obtain

$$\Delta E(H) = \underbrace{\sum_{k=1}^{K} [E(X_k^{2019}) - E(X_k^{2010})]\hat{\beta}_k^{2010}}_{\text{Component 1: Compositional effect}} + \underbrace{\overbrace{\sum_{k=1}^{K} [E(X_k^{2019})(\hat{\beta}_k^{2019} - \hat{\beta}_k^{2010})]}^{\text{Attributable}} + \overbrace{(\hat{\beta}_0^{2019} - \hat{\beta}_0^{2010})}^{\text{Unexplained}}}_{\text{Component 2: Structural effect}}. \tag{7}$$

Equation 7 formally captures the decomposition of the difference in mean weekly hours worked between 2010 and 2019 into the components discussed above. The compositional effect is the portion of the change in hours worked explained by the change in observable population characteristics between 2010 and 2019, if these characteristics predicted hours worked in the same way as in 2010. In other words, the compositional effect is how hours would have changed if the only change was level differences in the population's characteristics between the two surveys. The remainder is attributed to structural effects. These can be interpreted as the change in predicted working hours had there been no changes in population characteristics over this period. Within the structural effect, the attributable structural effect is the change in hours worked between 2010 and 2019 attributable to a change in how observable population characteristics relate to working hours (i.e. the difference in the $\hat{\beta}_k$ coefficients). Finally, the unexplained structural effect is the portion that is not accounted for by the other components and that cannot be attributed to the observable variables in the decomposition. Formally, the latter corresponds to the difference in the intercepts of the regressions estimated separately for 2010 and 2019. Note that decomposition methods like the Oaxaca-Blinder decomposition are based on a partial equilibrium approach as they do not account for general equilibrium effects.[26] Thus, the results need to be interpreted a purely descriptive and claims of causality are not possible (Fortin et al., 2011).

In practice, the decomposition is estimated as follows. First, we select observable explanatory variables that characterize Malawi's working-age population. These include demographic variables, such as gender, age and education, as well as a variable capturing owned land, and community variables capturing the proximity to urban agglomerations of different sizes. We avoid including variables that could be impacted by short-run adaptive behaviors to labor market circumstances. All these variables are coded as dummy variables to allow for interpretation relative to changes experienced by our omitted category: adult women (aged between 25 to 64 years old), with at least a primary education, owning more than on hectare of land, and residing more than 20 kilometers away from an urban agglomeration.[27] Mean values for each population characteristic in 2010 and 2019, $E(X_k^{2010})$ and $E(X_k^{2019})$, are reported in table 1. Next, we estimate equation 4 for 2010 and 2019 separately to obtain the vectors of $\hat{\beta}^{2010}$ and $\hat{\beta}^{2019}$ coefficients. These are reported for each outcome variable in appendix Table A.12. Finally, we plug the mean values, $E(X_k^{2010})$ and $E(X_k^{2019})$, and the estimated $\hat{\beta}^{2010}$ and $\hat{\beta}^{2019}$ coefficients into equation 7 to calculate the decomposition components.[28] We can also calculate the contribution of each specific population characteristic to the overall change in working hours between 2010 and 2019.

5.2 Where are changes in working hours coming from?

Table 3 decomposes the mean change in weekly hours worked overall and by activity. Panel A reports the mean change in the outcome variable between 2010 and 2019. Panel B presents the aggregate decomposition, showing the total contribution of the compositional effects and structural effects. Panel C presents the detailed decomposition, reporting the contribution of each population characteristic to the different components of the decomposition. In all panels, a positive sign

[26] In other words, it is assumed that compositional changes do not affect the relationship between the explanatory characteristics and hours worked, and that changes in this relationship do not impact the explanatory characteristics (O'Donnell, van Doorslaer, Wagstaff, & Lindelow, 2008).

[27] In the decomposition methods literature, precise results in the detailed decomposition of the structural effects depend on the choice of the omitted group when (some of) the explanatory variables are categorical variables (see Jann (2008) for a detailed discussion). Accordingly, when we interpret the detailed decomposition of the structural effect, we interpret them in relation to the omitted group captured by the intercepts. In our multivariate decomposition, the omitted group is adult women with at least primary education owning more than 1 hectare of land and residing far from an urban agglomeration. For ease of interpretation and to check the sensitivity of our results, we perform the Oaxaca-Blinder decomposition separately for each explanatory variable (Appendix Table A.15). We find that the results are qualitatively the same to the multivariate decomposition results. Note that aggregate decomposition results in Panel B and the compositional effects in Panel C.1 are not affected by this choice.

[28] We use the `oaxaca` command in Stata (Jann, 2008).

Table 3: Oaxaca-Blinder decomposition of the changes in mean hours worked per week between 2010 and 2019, overall and by activity.

	Total hrs (1)	Own-farm hrs (2)	Business hrs (3)	Casual hrs (4)	Wage hrs (5)
Panel A: Mean differential					
Difference	1.059**	-1.609***	0.683***	2.625***	-0.640***
	(0.494)	(0.413)	(0.154)	(0.150)	(0.228)
Panel B: Aggregate decomposition					
Compositional effect	0.018	-0.171*	0.021	-0.008	0.175*
	(0.157)	(0.102)	(0.031)	(0.024)	(0.092)
Structural effect	1.041**	-1.438***	0.662***	2.633***	-0.815***
	(0.493)	(0.408)	(0.154)	(0.150)	(0.227)
Attributable structural effect	-1.826*	-3.421***	-0.076	1.917***	-0.246
	(1.072)	(0.817)	(0.370)	(0.361)	(0.533)
Unexplained structural effect	2.867**	1.983**	0.738*	0.716**	-0.569
	(1.205)	(0.972)	(0.398)	(0.339)	(0.492)
Panel C: Detailed decomposition					
Panel C.1: Compositional effect					
Male	-0.082***	-0.006*	-0.012***	-0.020***	-0.044***
	(0.025)	(0.003)	(0.004)	(0.006)	(0.014)
Young	-0.075**	-0.030**	-0.014**	-0.004*	-0.027**
	(0.031)	(0.013)	(0.006)	(0.002)	(0.012)
No primary education	0.062**	-0.077***	0.018**	-0.037***	0.158***
	(0.025)	(0.025)	(0.009)	(0.011)	(0.044)
HH owns less than 1ha	0.027	-0.103***	0.008	0.044***	0.079***
	(0.023)	(0.035)	(0.009)	(0.014)	(0.026)
Close to small urb aggl	-0.020	0.003	0.001	-0.003	-0.021
	(0.049)	(0.010)	(0.003)	(0.007)	(0.050)
Close to medium urb aggl	0.053	0.006	0.015	0.006	0.027
	(0.086)	(0.014)	(0.024)	(0.010)	(0.044)
Close to big urb aggl	0.052	0.037	0.006	0.006	0.004
	(0.125)	(0.087)	(0.015)	(0.015)	(0.010)
Panel C.2: Attributable structural effect					
Male	0.142	-0.249*	0.146	0.662***	-0.417***
	(0.221)	(0.134)	(0.097)	(0.100)	(0.157)
Young	-0.323**	-0.309***	-0.274***	0.135**	0.125
	(0.144)	(0.103)	(0.064)	(0.063)	(0.077)
No primary education	-0.225	-0.847**	-0.833***	0.444**	1.011***
	(0.566)	(0.403)	(0.255)	(0.187)	(0.370)
HH owns less than 1ha	-1.319*	-2.165***	0.665***	0.657***	-0.476*
	(0.763)	(0.680)	(0.233)	(0.244)	(0.260)
Close to small urb aggl	-0.906**	-0.343	0.103	-0.143	-0.524***
	(0.396)	(0.331)	(0.125)	(0.122)	(0.198)
Close to medium urb aggl	-0.150	0.024	-0.074	0.033	-0.133
	(0.202)	(0.171)	(0.081)	(0.076)	(0.110)
Close to big urb aggl	0.955***	0.469**	0.190**	0.129*	0.168*
	(0.248)	(0.200)	(0.085)	(0.078)	(0.091)
Panel C.3: Unexplained structural effect					
Constant	2.867**	1.983**	0.738*	0.716**	-0.569
	(1.205)	(0.972)	(0.398)	(0.339)	(0.492)

Note: This table reports the Oaxaca-Blinder decomposition of the changes in hours worked between 2010 and 2019, overall and by activity. The differences in mean weekly hours worked between 2010 and 2019 differ slightly from the values reported in table 1 due to our omission here of 9 EAs that do not have georeferenced data. The mean values in 2019 omitting these EAs are: 18.439 total hours worked per week, 9.368 hours worked in own-farm, 2.575 hours worked in business, 4.614 hours worked in casual labor, and 1.881 hours worked in wage employment. Our sample consists of 18,618 rural working-age individuals in 2010 and 17,057 in 2019. Standard errors are reported in parentheses. Significant coefficients are indicated with $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. Values are adjusted using survey weights.

indicates that the component increased weekly hours worked between 2010 and 2019, whereas a negative sign indicates that the component decreased weekly work hours. Finally, to explore seasonal variation in these changes in labor hours, similar decompositions are done for work hours in the high and low seasons (Appendix Tables A.13 and A.14).

Structural rather than compositional changes are driving the observed changes in work hours. Malawi's population in 2019 differs somewhat from its 2010 population. As reported in Table 1, we know that it is slightly younger, more female, with higher primary education completion levels, and higher shares of households owning less than 1ha of land. The aggregate decomposition reported in Table 3, Panel B, shows that structural effects, rather than these observed compositional changes, account for most of the changes in hours worked. Table 3, Panel B, column 1 shows that structural effects accounts for 1.041 hours of the increase in total hours worked, almost the entire increase. If there were no structural changes, the sum of all the compositional effects stemming from observed compositional changes in the rural population between 2010 and 2019 would only predict a 0.018 increase in average hours worked per week. This is true across the different labor activities. Column 2 reports the aggregate decomposition of hours worked in own-farm. The compositional effect accounts for only the 10.63% (0.171/1.609) of the reduction in hours worked, while the structural effect accounts for the remaining 89.37%. Column 3 and 4 present the equivalent results for the increases in average weekly hours worked in non-farm household enterprises and casual labor, respectively. It is again structural effects that account for almost the entirety of both increases observed between 2010 and 2019. Column 5 presents the decomposition results for the decrease in hours worked in wage employment. The compositional effect accounts for an increase in hours worked, partially mitigating the decrease attributed to the structural effect.

Panel C1 of Table 3 reports the disaggregated compositional effect to examine which compositional changes are associated with changes in hours worked. None of the compositional changes play a substantial role in changing work hours. Work hours are slightly reduced due to the population being less male (-0.082 weekly hours) and younger (-0.075 weekly hours) in 2019 as compared to 2010, though this is counteracted by an increase in primary education over this period (+0.062 weekly hours). We also see that shrinking farm sizes account for a small reduction in own-farm hours (-0.103 weekly hours) and an increase in casual labor hours (+0.044 weekly hours). The magnitude of all these compositional effects is small relative to that of structural effects.

We turn now to discussing the substantial structural shifts that are changing how population characteristics predict work hours in Malawi between 2010 and 2019. It should be noted that in addition to the structural changes described below, the large and statistically significant coefficients in panel C.3 that capture unexplained structural effects signal changes in the relationship between demographics, human and physical capital, and urban proximity with hours worked also explain an increase in hours worked, overall and in each activity (except wage employment) for our omitted category: adult women who own more than 1 hectare and do not reside close to an urban agglomeration.

A structural shift in how demographics predict hours worked. Examining columns 2 and 4 of Table 3, Panel C.2, we see that the general trend of a shift away from work on the household farm towards work in casual labor is more pronounced for men than it is for women. It is also more pronounced for younger workers, between the ages of 15 and 24, as compared to those who are older than 24. These younger workers also do not experience as large of an increase in business hours. Specifically, men experience a 0.249 hour greater decline in weekly hours spent on own-farm work and a 0.662 hour larger increase in weekly hours worked on casual labor compared to women. Similarly, young workers face a 0.309 hour greater decline in hours worked on the household farm relative to adults, alongside a 0.135 hour greater increase in weekly hours spent in casual labor. Compared to adults, the change in weekly hours worked in a household enterprise undergone by young workers is 0.274 hours smaller.

A structural shift in how human capital predicts hours worked. Compared to those who completed their primary education, the population of respondents who did not complete their primary education experienced larger drops in own-farm hours and larger increases in casual labor hours (seen in Panel C.2, columns 2 and 4). The increase in hours worked in household businesses is disproportionally driven by those who have completed primary education (seen in Panel C.2, column 3). This stresses the increasing importance of education to engage in countercyclical income generating activities. Note that the patterns associated with youth are quite similar to those experienced by workers who did not complete their primary schooling. This suggests that the labor changes we observe for young workers may be due to their lack of work experience, another form of human capital.

A structural shift in how physical capital predicts hours worked. Turning to physical capital, we note a particularly strong association between owning less than 1 ha of land and fewer hours worked on the family farm. The change in hours worked per week in own-farm is on average 2.165 additional hours lower for individuals owning less than 1 hectare of land as compared to those with more than 1 hectare (panel C.2, column 2). Owning less than 1 hectare is associated with both a larger increase in casual labor hours and in hours worked in business - of 0.66 and 0.67 hours more for casual labor and business, respectively (panel C.2, columns 4 and 3). This comes in addition to the (much smaller) contribution of the compositional shift (due to the larger share of households with small landholdings in 2010 compared to 2019) in the same direction. Overall, structural rather than compositional changes in land ownership account for the shift from own farm to business and casual labor.

A structural shift in how urban proximity predicts hours worked. The changing relationship between residing in proximity to a big city and hours worked in total is an important contributor to the increase in mean total hours worked (panel C.2, column 1). Living in these connected rural areas is associated with an increase in average hours worked in own-farm (column 2) and in business (column 3) relative to other rural areas. Column 4 suggests a smaller change in the association with hours in casual labor (only significant at the 10% level) when hours are summed across the whole year, though this hides an important seasonal component. Living close to a city of over 300,000 inhabitants does contribute to larger increases in casual labor during the high season (as shown in Table A.13, panel C.2, column 2 and 4), but not during the low season (Table A.14). Who could be creating this growing demand for rural labor close to these cities? One possibility is urban-based individuals who have invested in nearby farms. Several authors have documented the rising presence of emergent medium- and large-scale farmers. These are often urban residents whose main income comes from non-farm activities, such as regular wage or civil service employment, who rely on hired labor to cultivate their farm (Anseeuw et al., 2016; Jayne, Chamberlin, et al., 2014; Jayne, Chapoto, et al., 2014; Jayne et al., 2019; Jayne et al., 2022; Ricker-Gilbert et al., 2021; Sitko & Jayne, 2014; Tione & Holden, 2020).

To summarize, we find that the observed changes in labor hours are primarily attributable to structural changes in the economy rather than changes in the composition of the working-age population between 2010 and 2019. Compositionally, we see that having a younger and more female pool of working-age individuals predicts a small but statistically significant decline in hours worked, while increases in education predict more work hours. Additionally, the trend of shrinking farm sizes predicts a decline in own-farm hours and an increase in casual labor hours. However, the potential predicted impacts of these compositional changes are second order to the structural shifts in how demographics, human and physical capital and location predict hours worked. The increase in hours worked is more pronounced among adults, larger land owners, and those close to large urban centers. The shift away from own-farm work to casual labor is experienced relatively more by men, the young, the less educated and those with smaller land holdings. The increase in business hours is more pronounced for adults, those with primary education, those who own less land and those living near larger cities. Finally, proximity to a big city contributes to increasing hours worked in business and own-farm as well as in casual labor though the latter mostly during the most labor intensive period in the agricultural calendar.

6 Policy Discussion

Rural labor markets in Malawi are undergoing rapid change. Using nationally and temporally representative data from 2010 and 2019, we build rural individuals' labor calendars for these years. We document an increase in working hours and a shift away from working on household farms towards work in household businesses and, especially, towards casual labor. These trends have coincided with increased consumption, but also increased reports of food insecurity and increased reliance on markets to purchase food. Whereas in 2010 25% of maize consumed was purchased on the market, by 2019 this rose to 46%. Over this nine-year period, we observe substantial structural changes in the labor market. These have reshaped how an individual's endowments, characteristics, and location, predict the time they spend working on their own farms, in household enterprises, in casual labor, and in wage employment. As Malawi navigates a complex transition from an economy based on household farms to one increasingly driven by markets for production factors and consumption goods, what policy interventions might support rural populations through this transition?

First, the increase we observe in food insecurity is extremely concerning, highlighting the essential need to reduce food price volatility and establish robust safety nets to protect vulnerable populations. Because of poorly functioning factor and food markets, for many rural families the household farm acts as a safety net to increase food security and reduce market dependence (Madsen, 2022; Poulton, Kydd, Wiggins, & Dorward, 2006). Yet, it is a weakening and risk prone safety net (Dzanku, 2019; Orr, Mwale, & Saiti, 2001). Shrinking farm sizes and declining soil fertility no longer guarantee self-sufficiency, and crop failures associated with increased climactic risk make it unreliable. Despite this, for many households, agriculture will remain a key fallback strategy. Policy-makers must consider this while also internalizing that rural households are net purchasers of food. Many government policies still assume — or even promote — a subsistence economy. For example, Malawi has implemented a substantial fertilizer subsidy program for the past 20 years, costing 1.7% of the country's GDP in 2020/21 (Benson, De Weerdt, Duchoslav, & Masanjala, 2024). This program provides a subsidized package of fertilizer and seeds that caters to small-scale maize production, primarily aimed at ensuring recipient households can produce enough for their own needs. Meanwhile, market interventions such as export bans, minimum farmgate prices, and parastatal maize purchases and sales increase prices and price volatility. These adversely affect the growing number of people who purchase their food, especially the poor for whom food expenses constitute a large share of household expenditures (Benson, 2021; Jayne, Mather, & Mghenyi, 2010; Jayne, Zulu, & Nijhoff, 2006; Minot, 2014; Poulton et al., 2006). The increased reliance on markets we document heightens the urgency of ensuring stable food markets for those who now depend on them for food. Investing in infrastructure and public goods, improving access to markets, promoting regional and international trade, as well as promoting rural financial markets to ensure access to farming inputs for small-scale farmers and to enhance traders' capacity to acquire surplus production have been proposed as measures to address market price volatility and mitigate seasonal food insecurity (Bonuedi et al., 2022), conditional on having good and effective governance (Jayne et al., 2006; Jayne et al., 2010; Minot, 2014; Poulton et al., 2006).

Supporting the growth of off-farm enterprises is another promising avenue for policy interventions. Although the growth in hours worked in these small businesses is not as substantial as that in casual labor, this dynamic sector is worthy of investment, and increases hours worked in the low season when underemployment is particularly severe. Currently, household enterprises are often seasonal small businesses in low value added activities that rely on family labor. Developing a thriving ecosystem of rural household enterprises could generate employment opportunities in rural areas and help diversify the incomes of rural households, creating more stable incomes and improving food security (Dzanku, 2019; Dzanku et al., 2024). Developing this sector will require both sustained rural economic growth to ensure reliable demand for goods and services, as well as fostering an environment that supports emerging and successful enterprises. Particularly promising are policies designed to improve access to the factors of production needed by these small business such as grants programs or the promotion of microfinance to ease the entry barriers to more lucrative activities or to help existing businesses grow, investments in infrastructure to improve access to markets and increase the demand for the goods and services produced by these rural household enterprises (Beegle & Bundervoet, 2019), and training programs especially for subsistence-level enterprises (McKenzie et al., 2023). Furthermore, the association between work in household businesses and schooling points to the continued need to invest in rural education to develop entrepreneurial potential and ensure the supply of workers these small businesses may need.

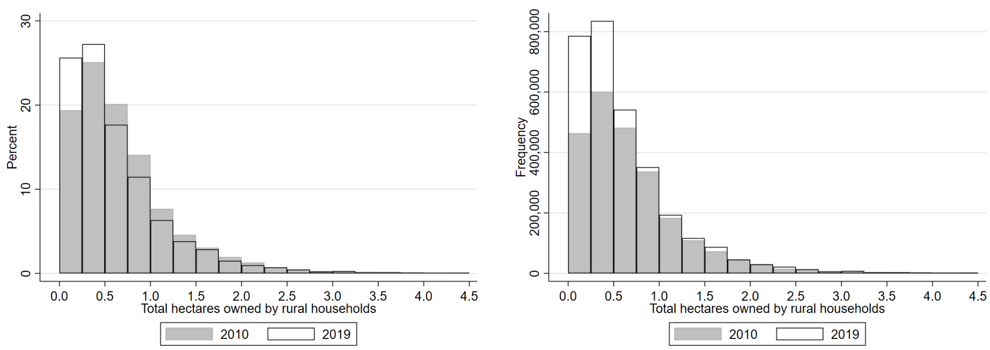
The rapid growth of casual labor and the increase in casual labor hours during the high season suggest some of this casual labor is in agriculture, possibly due to the growth of larger farms and farms managed by non-residents. Where larger farmers have a presence in rural communities, they can play key roles by creating demand for casual labor, initiating outgrower schemes, incubating businesses, and purchasing local goods and services — thereby supporting local economies. Such local spill-over effects will be larger when these farmers reside and spend their own income in rural areas, compared to when they reside elsewhere. Unfortunately data on larger farmers are mostly lacking in population-based household survey data. Specific data collection exercises and additional research will be needed to understand how these large farms are evolving and which policies would ensure they contribute optimally to the country's development. Similarly, though increasingly important, our understanding of casual labor remains limited as we do not know how this labor is being used, nor in what sectors, due to data limitations. Improving the information available about this type of labor would help inform policy.

The unique patterns of change in urban adjacent rural communities highlight the potential to leverage urbanization and urban spillovers. Our data indicate positive trends in household enterprises near major cities, where hours spent in casual labor also rise during peak seasons, likely driven by labor demand from larger urban-based farmers. While concerns exist about potential competition with labor on family farms, our data show that urban proximity can actually increase hours worked on the farm overall, likely due to rising food demand in urban areas. Policymakers should prioritize strengthening urban-rural linkages to enable rural areas to benefit from rising urban demand for food and labor, and invest in value chains that use urban centers to connect rural areas with international input and output markets. Our findings suggest that, currently, only Malawi's primary cities drive positive labor market connections, highlighting a need for investment in secondary cities to more evenly distribute urbanization's benefits.

As Malawi navigates a transition from an economy based on subsistence farming to one increasingly driven by markets, policy makers should adopt a multipronged approach. Attention should be given to fostering the growth of high-return off-farm opportunities, while also supporting household farms that continue to be central to the economy and act as an important safety-net for the rural population. Critically, emphasis should be placed on guaranteeing that the factor and food markets the population increasingly relies on function well and are accessible so that these markets may generate opportunities for vulnerable populations without exposing them to undue risks.

A Appendix

Figure A.1: Total hectares owned by rural households in the rainy and dry season by year, share and count.



(a) Share

(b) Count

Note: These figures illustrate the share and count of rural households by total hectares of land owned in 2010 and 2019. The histograms are constructed using land size measured with GPS and, when not available, using self-reported land size. Total hectares owned includes land owned in both the rainy and dry season. The sample is restricted to rural households that completed the agricultural questionnaire (10,140 households in 2010 and 8,936 households in 2019), thus excluding rural households that do not engage in any type of agricultural activities. For visualization purposes, the histogram are truncated to show the data up to 4.5 hectares. Values are adjusted using survey weights.

Table A.1: Total average and median hectares owned and/or cultivated by rural households by year.

	Mean			Median		
	2010	2019	Difference	2010	2019	Difference
All	1.04	0.71	-0.33	0.61	0.52	-0.09
Cultivated	1.02	0.68	-0.34	0.60	0.51	-0.09
Owned	0.97	0.65	-0.33	0.56	0.47	-0.09

Note: This table reports the mean and median hectares owned and cultivated (all), cultivated or owned by rural households that complete the agricultural questionnaire in the corresponding year 2010 and 2019. To measure land size we use land size measured with GPS and, when not available, using self-reported land size. Land size reported in this table includes land owned and/or cultivated both in the rainy and dry season. Tests for statistical significance of the difference between averages in 2010 and 2019 being different from 0 are reported in column 3 with $*p < 0.1$, $**p < 0.05$ and $***p < 0.01$. Values are adjusted using survey weights.

A.1 Data

We use two rounds of the Integrated Household Survey (IHS) for Malawi. The IHS is implemented by the Government of Malawi's National Statistical Office (NSO) with the assistance of the World Bank Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) initiative.

We use the cross-sectional data from the Third (IHS3) and Fifth (IHS5) rounds. IHS3 was conducted between March 2010 and March 2011, and was administered in 768 enumerations areas (EAs) across the country covering 12,266 households. IHS5 was conducted between April 2019 and April 2020, and was administered in 717 EAs covering 11,434 households. Table A.2 shows the sample composition for both IHS3 and IHS5, overall and by place of residence (urban or rural). It shows the number of EAs where the survey was administered, as well as the number of households and working age individuals interviewed[29]. The table also reports the weighted number of households and working-age individuals, calculated using the survey weights.

The IHS of Malawi is both spatially and temporally representative. The IHS uses a stratified two-stage sample design. The first sampling stage selects EAs from the 2008 (2018) Malawi Population and Housing Census for IHS3 (IHS5). The stratification of EAs is done by district to ensure statistical representativeness at the district level and provides implicit stratification by rural/urban location. In a second stage, a sample of households is drawn from a list previously constructed for each sampled EA. To ensure the temporal representativeness, a multiple of 12 EAs is sampled in each district, with a minimum of 24 in each. Subsamples of EAs for each quarter of the data collection are selected from the full sample systematically with equal probability. Within each quarter, EAs are randomly allocated to each month. The sample is thus district-level spatially representative and monthly-temporally representative (National Statistical Office, 2012, 2020). Note that IHS3 has a panel subcomponent, consisting of 204 EAs, which is part of the Integrated Household Panel Survey (IHPS). For this reason, sample households are allocated to three type of surveys: the cross-section survey, the Panel A survey, and the Panel B survey. The panel households (both in Panel A and Panel B) are visited twice during the survey year in order to collect information on the two agricultural seasons in the country. For both Panel A and B, the first visit took place in the post-planting period (between March and June) and the second visit took place about three months later in the post-harvest period. Panel A and Panel B differ in the moment when they were

[29]We define working-age individuals as the individuals aged between 15 and 64 years old who report not attending school.

administered the household questionnaire, which includes the time use and labor module that is at the core of this study. For the purpose of our study, it is important to determine the month when the household completed the time use module: Panel A received the household questionnaire in full in the first visit, while Panel B was administered the household questionnaire in the second visit (except the household roster which was administered in the first visit). The IHS5 was implemented separately from the IHPS so that there is only one survey type and sampled households were only visited once (de Janvry et al., 2022; National Statistical Office, 2012).

Table A.3 shows the percentage of EAs and households interviewed by quarter and month for IHS3 and IHS5.[30] The EAs are reasonably well distributed across quarters and months for both IHS3 and IHS5, despite observing some imbalances. Covid-19 disrupted the data collection, which explains the few observations in April 2020.[31] The data collection is also reasonably well distributed across the survey year in terms of weighted rural households, our group of interest.

Table A.4 examines whether time invariant variables - at the EA and household level - are balanced for rural households across quarters and months. As the selected variables are time invariant, we would expect to observe no significant differences in their mean value throughout the survey year. The first column shows the variable's mean and the standard error. The remaining columns report the p-values of tests for joint significance for quarters (column 2) and months (column 3). F-tests are reported for continues variables and Chi-squared tests are reported for dummy variables. EA characteristics such as distances of the EAs to urban agglomerations of different sizes are balanced across quarters and months. Time invariant household characteristics are also balanced. However, in IHS3 there is an imbalance in reporting that the household operated a household enterprise in the past 12 months. de Janvry et al. (2022) hypothesize that it could be explained by the reporting suffering from recall bias as there is seasonality in the operation of household enterprises.

The IHS data is complemented with the Africapolis data (Version 1) to establish the distance of the rural EAs from urban agglomerations. Africapolis is a unique data base on cities and urbanization in Africa produced by the OECD Sahel and West Africa Club. This data provides a comparable data set covering the evolution of the urban network in 54 African countries from

[30]Households within the same EA can be interviewed in different months. To determine the month at the EA level, we assign EAs to the month closest to the mean interview date of households within the EA (as in de Janvry et al., 2022).

[31]Due to Covid-19, data was not collected from 854 households which represents 7% of the original sampled households.

1950 to 2020. Africapolis identifies urban agglomerations as those spatial units characterized by being continuously built-up areas that contain no unbuilt spaces greater than 200 meters and have more than 10,000 inhabitants (OECD/SWAC, 2020). Africapolis also provides estimates of the population in each urban agglomeration as well as a GIS file of the 2015 urban agglomerations. For Malawi, Africapolis identified 77 urban agglomerations in 2015. Combining the Africapolis GIS file with the IHS GPS coordinates data, we calculate the distance from each EA to each of the 77 urban agglomerations. We categorize the urban agglomerations in Malawi in four groups according to their population size. Table A.5 enumerates the four different categories – tiny, small, medium and big – and lists the urban agglomerations that fall within each category.

Table A.2: Sample composition by survey wave.

	IHS3			IHS5		
	All	Rural	Urban	All	Rural	Urban
EAs	768	628	140	717	586	131
Households	12,266	10,037	2,229	11,434	9,342	2,092
Individuals	23,181	18,618	4,563	21,386	17,201	4,185
Weighted HHs	3,070,958	2,592,855	478,103	4,122,702	3,452,625	670,078
Weighted indiv.	5,801,458	4,817,208	984,250	7,657,096	6,302,652	1,354,444

Note: The first panel reports the unweighted count of enumeration areas, households and individuals by survey wave. The second panel reports the weighted data (using the survey weights) for number of households and individuals. 'Individuals' refers to working-age individuals aged between 15 and 64 years old that report not attending school. The data is reported for the overall sample (columns 1 and 4), for rural areas only (columns 2 and 5) and for urban areas only (columns 3 and 6).

Table A.3: Distribution of labor surveys throughout the year by survey wave.

Interview period	Percent of EAs	Percent of households	Weighted % of households	Weighted % of rural households	Weighted % of urban households
Panel A: IHS3 (2010/11)					
Panel A.1: By quarter					
Mar-Jun 2010	25.00	25.04	26.95	27.75	22.59
Jul-Sep 2010	24.61	24.50	24.96	22.25	39.63
Oct-Dec 2010	26.43	26.46	26.31	27.32	20.89
Jan-Mar 2011	23.96	24.00	21.78	22.68	16.88
Panel A.2: By month					
Mar. 2010	6.77	6.82	7.79	8.10	6.10
Apr. 2010	5.21	5.10	4.99	4.70	6.56
May 2010	7.42	7.51	8.56	8.57	8.50
Jun. 2010	5.60	5.76	5.82	6.63	1.43
Jul. 2010	9.51	9.31	10.55	9.53	16.10
Aug. 2010	6.25	6.24	6.31	5.35	11.52
Sep. 2010	8.85	8.85	8.00	7.26	12.01
Oct. 2010	10.16	10.02	9.95	10.35	7.74
Nov. 2010	11.07	11.26	10.74	11.38	7.23
Dec. 2010	5.21	5.23	5.65	5.65	5.64
Jan. 2011	10.03	9.95	9.16	9.47	7.50
Feb. 2011	9.51	9.51	8.73	9.17	6.32
Mar. 2011	4.43	4.44	3.75	3.82	3.34
Panel B: IHS5 (2019/20)					
Panel B.1: By quarter					
Apr-Jun 2019	20.78	20.84	20.17	20.56	18.16
Jul-Sep 2019	27.48	27.52	26.71	26.81	26.17
Oct-Dec 2019	22.45	22.52	21.15	21.40	19.87
Jan-Apr 2020	29.29	29.11	31.97	31.23	35.80
Panel B.2: By month					
Apr. 2019	3.35	3.38	3.22	3.19	3.39
May 2019	9.90	9.75	9.89	10.29	7.82
Jun. 2019	7.53	7.85	7.38	7.42	7.19
Jul. 2019	7.39	7.17	6.58	6.21	8.51
Aug. 2019	11.58	11.64	10.89	11.41	8.24
Sep. 2019	8.51	8.70	9.03	9.07	8.80
Oct. 2019	5.16	5.01	4.34	4.63	2.81
Nov. 2019	9.76	9.62	10.16	10.84	6.66
Dec. 2019	7.53	7.55	6.38	5.54	10.72
Jan. 2020	8.65	8.84	7.80	6.23	15.89
Feb. 2020	8.23	8.14	9.34	9.31	9.48
Mar. 2020	12.27	12.03	14.61	15.45	10.28
Apr. 2020	0.14	0.30	0.37	0.40	0.22

Note: Following de Janvry et al. (2022), this table details the distribution of survey administration throughout the year by survey quarters and months for the IHS3 (Panel A) and the IHS5 (Panel B). The first column shows the percent of survey enumeration areas with reference weeks for the time-use module in the indicated time period. The second columns shows the percent of households with reference weeks for the time-use module in the indicated time period. The third column replicates the previous column using survey weights. The fourth and fifth columns report the percent of weighted households for rural areas and urban areas separately. Panels A.1 and B.1 display the distribution over the survey quarters for the IHS3 and IHS5, respectively, while panels A.2 and B.2 display the distribution over the survey months for each survey wave. Values are adjusted using survey weights.

Table A.4: Balance of survey timing of key variables in rural areas by survey wave.

	Mean (1)	Quarters (2)	Months (3)
Panel A: IHS3 (2010/11)			
Panel A.1: Enumeration areas			
Distance (kms) to tiny urban aggl.	26.27	[0.62]	[0.57]
	(0.99)		
Distance (kms) to small urban aggl.	24.67	[0.77]	[0.61]
	(0.80)		
Distance (kms) to medium urban aggl.	110.39	[0.56]	[0.79]
	(3.92)		
Distance (kms) to big urban aggl.	86.77	[0.82]	[0.57]
	(3.77)		
Panel A.2: Households			
Reported in the agriculture questionnaire	0.93	<0.34>	<0.39>
	(0.01)		
Total hectares owned	0.90	[0.80]	[0.35]
	(0.23)		
Household reports operating an enterprise in the past 12 months	0.17	<0.36>	<0.03>
	(0.01)		
Panel B: IHS5 (2019/20)			
Panel B.1: Enumeration areas			
Distance (kms) to tiny urban aggl.	25.58	[0.82]	[0.31]
	(0.95)		
Distance (kms) to small urban aggl.	25.57	[0.96]	[0.21]
	(0.87)		
Distance (kms) to medium urban aggl.	112.57	[0.70]	[0.69]
	(4.15)		
Distance (kms) to big urban aggl.	86.34	[0.93]	[0.53]
	(4.02)		
Panel B.2: Households			
Reported in the agriculture questionnaire	0.89	<0.30>	<0.42>
	(0.01)		
Total hectares owned	0.57	[0.51]	[0.41]
	(0.02)		
Household reports operating an enterprise in the past 12 months	0.34	<0.75>	<0.16>
	(0.01)		

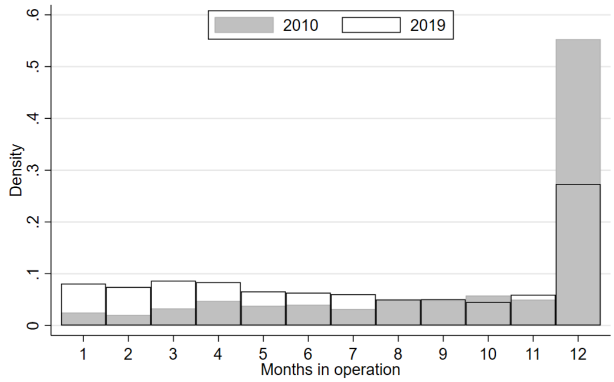
Note: The table examines the balance of mean values for key time-invariant variables across survey quarters and months. Panel A reports the data for IHS3 and Panel B for IHS5. The sample for the first subpanel within each panel are rural enumeration areas and for the second subpanel rural households. Column 1 reports the variable's mean value and the standard errors of the mean are reported below in parenthesis. Column 2 and 3 test for the joint significance of the survey weighted regression coefficients for survey quarters and months, respectively. Values in square brackets report the p-values of the F-statistic. When the dependent variable is a binary variable, the values in triangular brackets report the p-values of the survey weighted chi-squared test. The variable 'Reported in the agriculture questionnaire' indicates if the household was administered the agricultural questionnaire, which is restricted to households that report either owning or cultivating land in the last completed rainy and dry seasons, producing cassava, tea, coffee or any other fruits, and/or owning livestock in the last 12 months. Values are adjusted using survey weights.

Table A.5: Categories of urban agglomerations in Malawi based on Africapolis population statistics in 2015.

Category	Population (based on Africapolis 2015)	N	Names
Tiny urban aggl.	10,000-30,000	45	Bereu UA, Bunda UA, Bweteka, Chipoka UA, Dowa, Dwangwa UA, Dzaleka UA, Dzoole UA, Ekwendeni UA, Jombo UA, Kadozo UA, Kamange UA, Kasankha UA, Lirangwe UA, Lukwa UA, Madisi, Maganaa UA, Makanjila UA, Makoko UA, Malindi/Mizingo UA, Malomo UA, Miseu Folo UA, Mitundu UA, Mkanda UA, Mponda UA, Mposa UA, Mwanza, MWI3081388, Nayuchi UA, Nchalo UA, Ndamera UA, Neno, Ngabu, Ngabu UA, Nkhata Bay, Nkhoma UA, Nkotakata UA, Nkwazi UA, Nsangwe UA, Ntchisi, Rhumpi, Senga UA, Thornwood UA, Thyolo, Timbiri
Small urban aggl.	30,000-100,000	27	Balaka, Bangula UA, Bvumbwe UA, Chikwawa, Chintheche UA, Chitipa, Dedza, Karonga, Kasungu, Liwonde, Luchenza, Lumbadzi, Mangochi, Mchinji, Mponela, Mulanje, Mzimba, Nkanda/Chikumbu UA, Nkhotakota, Nkopola UA, Nsanje, Ntcheu, Phalombe, Phodgoma UA, Salima, South of Mabuka UA, Uliwa UA
Medium urban aggl.	100,000-300,000	3	Mpana/Likoswe UA, Mzuzu, Zomba
Big urban aggl.	$> 300,000$	2	Blantyre, Lilongwe

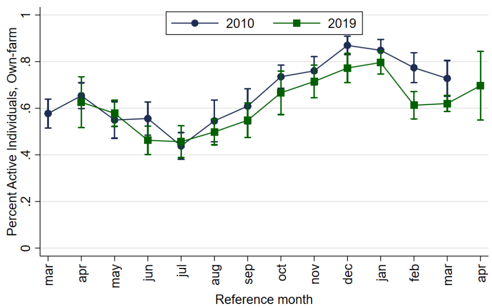
Note: This table classifies the 77 urban agglomerations in Malawi into four categories based on the population size in 2015. The list of the urban agglomerations and the population number is derived from the Africapolis data set.

Figure A.2: Non-farm household enterprises in rural areas by number of months in operation and year, share.

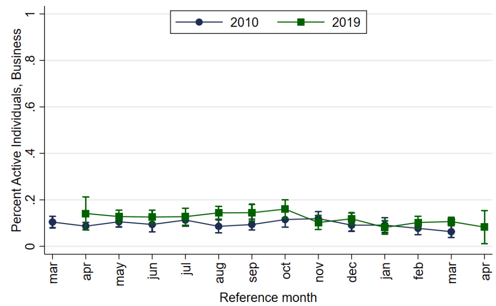


Note: This figure reports the share of non-farm household enterprises reported by rural households by the number of months that the enterprise was in operation during the 12-month period preceding the interview month. Sample consists of 1,872 rural non-farm household enterprises in 2010 and 3,711 in 2019. Values are adjusted using survey weights.

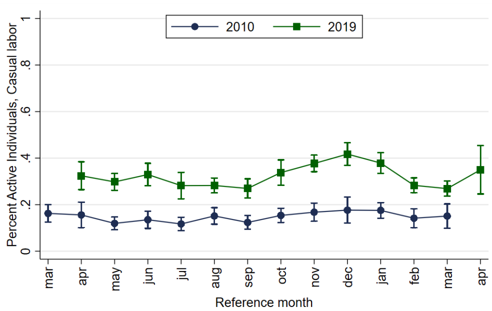
Figure A.3: Labor engagement in the past week per rural working-age individual by month and activity in 2010 and 2019.



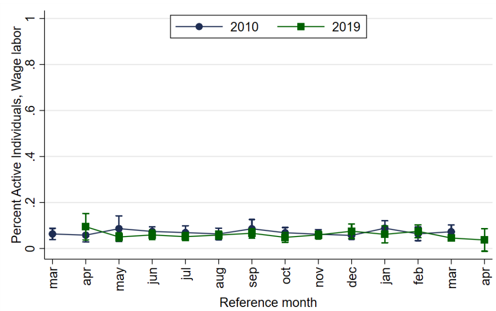
(a) Labor engagement in own-farm



(b) Labor engagement in household businesses



(c) Labor engagement in casual labor



(d) Labor engagement in wage labor

Note: This figure reports the probability that any rural working age individual reports engaging in own-farm (panel a), non-farm household business (panel b), casual labor (panel c) and wage labor (panel d) in the past week by reference month. Coefficients are reported with 95% confidence intervals. Values are adjusted using survey weights.

Table A.6: Poverty and ultra-poverty in rural areas in 2010 and 2019.

		2010 (1)	2019 (2)	Diff. (3)
Headcount ratio	Poor	0.57	0.57	-0.00
	Ultra-poor	0.29	0.24	-0.06***
Poverty gap	Poor	21.82	19.28	-2.53***
	Ultra-poor	8.33	5.63	-2.70***
Poverty severity	Poor	10.87	8.74	-2.12***
	Ultra-poor	3.38	1.99	-1.39***

Note: This table reports three poverty measures (the headcount ratio, poverty gap and poverty severity) for both the poverty line and the ultra-poverty line. These measures are reported for all rural individuals. Column 1 reports the measures for 2010, column 2 for 2019, and column 3 reports the difference between the two years. Tests for statistical significance of the difference between 2010 and 2019 are reported in column 3 with $*p < 0.1$, $**p < 0.05$ and $***p < 0.01$. Values are adjusted using survey weights.

Table A.7: Total household consumption in rural areas in 2010 and 2019.

		2010 (1)	2019 (2)	2019/2010 (3)
Per capita	Mean	152,283	185,431	1.22***
	Median	116,251	151,157	1.3
Per household	Mean	700,387	821,991	1.17***
	Median	539,976	685,063	1.27
Per household hour worked	Mean	340	355	1.04
	Median	262	296	1.13

Note: The first panel displays mean and median annual consumption per capita for all rural individuals in 2010 (column 1) and 2019 (column 2) in Malawian Kwacha, and the ratio between these two values (column 3). The second panel displays mean and median household consumption. The third panel takes the values from the second panel and divides them by our estimate of the mean annual hours worked by households in 2010 and 2019, 2059 and 2315 hours respectively. Values are total real annual consumption (spatially and temporally adjusted) in April 2019 prices. Tests for statistical significance of the ratio between 2010 and 2019 being different from 1 are reported for the mean values in the first and second panels in column 3 with $*p < 0.1$, $**p < 0.05$ and $***p < 0.01$. Values are adjusted using survey weights.

Table A.8: Main causes of reported food insecurity by rural households in the last 12 months, in 2010 and 2019.

Main cause	2010 (1)	2019 (2)	Difference (3)
Reporting food insecurity in the last 12 months	0.512	0.731	0.219***
Inadequate HH stocks due to drought/poor rains	0.167	0.168	0.001
Inadequate HH food stocks due to crop pest damage	0.008	0.016	0.008***
Inadequate HH food stocks due to small land size	0.055	0.074	0.019***
Inadequate HH food stocks due to lack of farm inputs	0.219	0.247	0.028**
Food in the market was very expensive	0.033	0.128	0.095***
Unable to reach the market due to high transportation costs	0.001	0.002	0.001*
No food in the market	0.001	0.012	0.011***
Floods/water logging	0.004	0.036	0.032***
Other	0.024	0.048	0.024***

Note: This table captures the share of rural households that report experiencing food insecurity in the last 12 months and the main cause of food insecurity reported by these households, for both 2010 (column 1) and 2019 (column 2). The difference between the two years is reported in column 3. Tests for statistical significance of the difference between 2010 and 2019 are reported in column 3 with $^{*}p < 0.1$, $^{**}p < 0.05$ and $^{***}p < 0.01$. Values are adjusted using survey weights.

A.2 Maize consumption by rural households overall and by source of consumption in 2010 and 2019.

Household maize consumption is divided into three sources: purchased, own-produced, and gifted, with some households reporting no maize consumption. We use data from the IHS household questionnaire Module G to determine the average kilograms of maize consumed by rural households overall and by source, the proportion of maize consumption attributable to each source, and the expenditure on purchased maize. Maize consumption includes maize (normal flour), maize (fine flour), maize (bran flour), maize grain, and green maize. As maize consumption - quantities and prices - is reported by households for the past 7 days, we can exploit the temporal representativeness of our data to estimate yearly maize consumption per capita and construct a maize consumption calendar, overall and by source. We use equations 1 and 2, the same approach we use to construct labor calendars. Prices and quantities are winsorized for each year at the 5th and 95th percentile, removing exceptionally low or high levels.[32] We use these values to calculate kilograms per capita consumed on average by rural households, and average money spent per capita on purchased maize by these same households. The shares of maize consumption at the household level are computed using the per capita consumption values.

Table A.9 reports estimates of rural households' maize consumption per capita overall and by source (in kilograms and proportions) as well as money spent per capita on purchased maize, in 2010 and 2019. Figure A.4 illustrates the average weekly kilograms of maize consumed per capita by month (overall and by source), and the average money spent weekly on purchased maize.

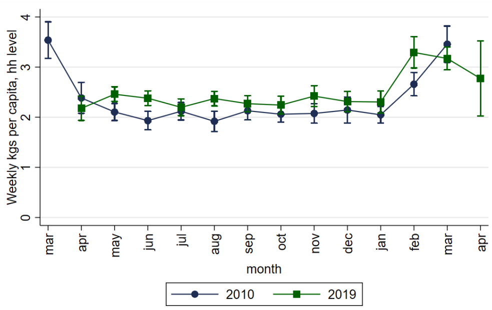
[32] This follows the procedure used by the Malawi National Statistical Office (NSO) who relies on winsorized prices and quantities at the 5th and 95th percentile to construct the consumption aggregates (NSO, 2021).

Table A.9: Maize consumption by source at the rural household level in 2010 and 2019.

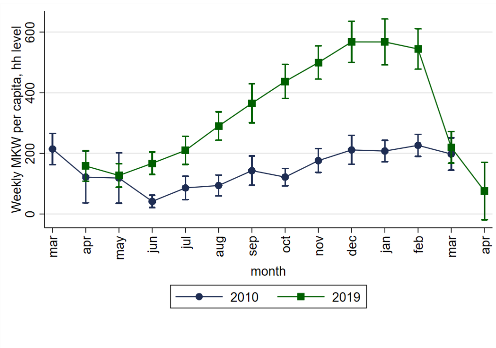
		Total per year	High season per week	Low season per week	Diff. high and low season
Panel A: Kgs of maize consumed per capita by source					
Total, kgs per capita	2010	117.55	2.10	2.02	0.08
	2019	130.11	2.31	2.29	0.02
	2019-2010	12.56**	0.21*	0.27***	-0.06
Purchased, kgs per capita	2010	29.70	0.87	0.34	0.53
	2019	57.04	1.59	0.92	0.67
	2019-2010	27.34***	0.72***	0.58***	0.14
Produced, kgs per capita	2010	81.48	1.09	1.55	-0.46
	2019	62.41	0.51	1.20	-0.69
	2019-2010	-19.07***	-0.58***	-0.35***	-0.23
Gifted, kgs per capita	2010	6.47	0.13	0.12	0.02
	2019	9.60	0.19	0.15	0.03
	2019-2010	3.13***	0.06*	0.03	0.01
Panel B: Share of maize consumed per capita by source					
No maize consump., share	2010	0.07	0.07	0.07	0.01
	2019	0.02	0.02	0.03	-0.02
	2019-2010	-0.05***	-0.05***	-0.04**	-0.03
Purchased, share	2010	0.25	0.42	0.16	0.26
	2019	0.46	0.71	0.41	0.31
	2019-2010	0.21***	0.29***	0.25***	0.05
Produced, share	2010	0.64	0.45	0.73	-0.28
	2019	0.45	0.20	0.51	-0.31
	2019-2010	-0.19***	-0.25***	-0.22***	-0.03
Gifted, share	2010	0.04	0.05	0.04	0.01
	2019	0.07	0.07	0.05	0.02
	2019-2010	0.03***	0.02**	0.01	0.01
Panel C: Expenditures on purchased maize					
Purchased, MKW per capita	2010	7603.95	209.50	90.04	119.46
	2019	17890.39	567.48	249.99	317.49
	2019-2010	10286.44***	357.98***	159.95***	198.03

Note: MKW values are adjusted to April 2019 prices. Column 1 reports the yearly estimate, columns 2 and 3 the weekly average per season, and column 4 reports the difference in weekly values for the high and low season. 'High season' is December and January, 'low season' is July and August. The sample consists of rural households, covering 9,342 households in 2010 and 10,037 in 2019. Differences between 2010 and 2019 are tested for statistical significance with $^{*}p < 0.1$, $^{**}p < 0.05$ and $^{***}p < 0.01$. Values are adjusted using survey weights.

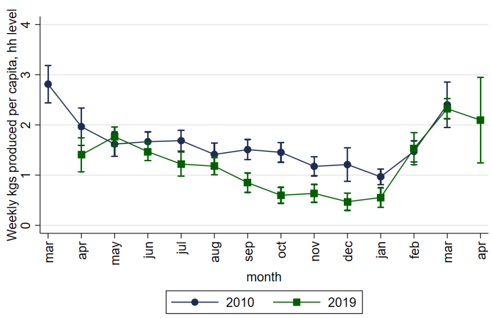
Figure A.4: Maize consumed per capita by rural households by month in 2010 and 2019.



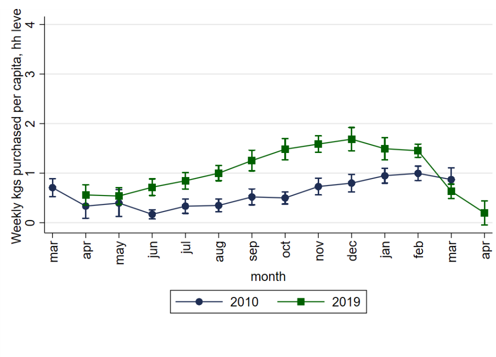
(a) Total, kgs per capita



(b) Purchased, MKW per capita



(c) Own-produced, kgs per capita



(d) Purchased, kgs per capita

Note: This figure reports the estimated weekly per capita maize consumption at the rural household level by month for 2010 and 2019. Panel a reports the mean kilograms of total maize consumed weekly per capita by month. Panel b reports the mean weekly expenditure (in MKW adjusted to April 2019 prices) per capita in purchased maize by month. Panel c reports the mean kilograms of own-produced maize consumed weekly per capita by month. Panel d reports the mean kilograms purchased maize consumed weekly per capita by month. Coefficients are reported with 95% confidence intervals. Values are adjusted using survey weights.

Table A.10: OLS regression results estimating the relationship between hours worked (total and by activity) and welfare indicators for 2010 and 2019.

	Total	Own-farm	Business	Casual	Wage
	(1)	(2)	(3)	(4)	(5)
Panel A: Poverty					
poor	-3.225***	0.419	-1.697***	0.478***	-2.424***
	(0.48)	(0.38)	(0.16)	(0.18)	(0.32)
2019	0.640	-1.224**	0.824***	2.118***	-1.077***
	(0.61)	(0.51)	(0.25)	(0.20)	(0.39)
poor*2019	0.809	-0.726	-0.280	0.966***	0.849**
	(0.68)	(0.56)	(0.26)	(0.28)	(0.38)
constant	19.053***	10.760***	2.772***	1.741***	3.780***
	(0.45)	(0.37)	(0.15)	(0.13)	(0.34)
Panel B: Ultra-poverty					
ultra-poor	-2.971***	-0.018	-1.466***	0.401**	-1.889***
	(0.49)	(0.42)	(0.14)	(0.18)	(0.24)
2019	0.752	-1.474***	0.670***	2.403***	-0.847***
	(0.52)	(0.44)	(0.19)	(0.16)	(0.29)
ultra-poor*2019	0.819	-0.610	-0.283	1.122***	0.589**
	(0.78)	(0.65)	(0.22)	(0.30)	(0.30)
constant	18.139***	10.982***	2.266***	1.887***	3.004***
	(0.39)	(0.33)	(0.12)	(0.10)	(0.24)
Panel C: Food insecurity					
food insecure	-0.377	0.031	-0.885***	1.476***	-0.999***
	(0.46)	(0.37)	(0.15)	(0.16)	(0.21)
2019	1.361**	-1.614***	1.375***	1.638***	-0.038
	(0.62)	(0.48)	(0.26)	(0.19)	(0.32)
food insecure*2019	-0.273	0.006	-0.631**	0.775***	-0.423
	(0.67)	(0.51)	(0.27)	(0.26)	(0.29)
constant	17.500***	10.968***	2.174***	1.518***	2.840***
	(0.43)	(0.35)	(0.12)	(0.09)	(0.23)

Note: This table shows the OLS regression coefficients estimating the relationship between hours worked (total and by activity) and three welfare indicators: poverty, ultra-poverty, and food insecurity. Coefficients are indicated with significance levels with $*p < 0.1$, $**p < 0.05$ and $***p < 0.01$. Standard errors are reported in parentheses. Values are adjusted using survey weights.

Table A.11: Mean values in the high and low seasons in 2010 and 2019.

	2010 (1)	2019 (2)	Difference (3)
Panel A: High season			
Outcome variables			
Reported in the last week...			
Total hours	24.724	26.026	1.302
Hours in own-farm	17.693	15.785	-1.908*
Hours in household enterprise	1.922	1.998	0.076
Hours in casual labor	2.034	6.094	4.060***
Hours in wage employment	3.074	2.149	-0.925
Predictor variables			
Male	0.461	0.448	-0.013
Young (15 to 24 years old)	0.253	0.283	0.030*
No primary education	0.800	0.778	-0.022
Household owns $<$ 1 hectare of land	0.800	0.792	-0.007
Small urban agglomeration within 20 kms	0.408	0.463	0.054
Medium urban agglomeration within 20 kms	0.115	0.145	0.030
Big urban agglomeration within 20 kms	0.135	0.192	0.057
N	2768	2464	
Panel B: Low season			
Outcome variables			
Total hours	12.282	15.081	2.798***
Hours in own-farm	6.367	6.012	-0.355
Hours in household enterprise	1.704	2.965	1.260***
Hours in casual labor	2.043	4.412	2.369***
Hours in wage employment	2.167	1.691	-0.476
Predictor variables			
Male	0.461	0.448	-0.013
Young (15 to 24 years old)	0.253	0.283	0.030*
No primary education	0.800	0.778	-0.022
Household owns $<$ 1 hectare of land	0.800	0.792	-0.007
Small urban agglomeration within 20 kms	0.408	0.463	0.054
Medium urban agglomeration within 20 kms	0.115	0.145	0.030
Big urban agglomeration within 20 kms	0.135	0.192	0.057
N	2660	3298	

Note: This table reports the mean values for 2010 and 2019 of reported hours worked and the predictor variables included in the Oaxaca-Blinder decomposition in the high (Panel A) and low season (Panel B). 'High season' is December and January, 'low season' is July and August. Differences between the years are reported in column 3 with statistical significance indicated for $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Values are adjusted using survey weights.

Table A.12: OLS regression results used in the Oaxaca-Blinder decomposition, overall and by season.

	Total		Own-farm		Business		Casual		Wage	
	2010	2019	2010	2019	2010	2019	2010	2019	2010	2019
Panel A: All										
male	5.96***	6.28***	0.41**	-0.15	0.87***	1.20***	1.46***	2.93***	3.23***	2.30***
	(0.33)	(0.36)	(0.18)	(0.24)	(0.14)	(0.16)	(0.12)	(0.18)	(0.28)	(0.20)
young	-4.95***	-6.11***	-1.99***	-3.09***	-0.91***	-1.89***	-0.25**	0.23	-1.80***	-1.35***
	(0.33)	(0.39)	(0.23)	(0.29)	(0.15)	(0.18)	(0.11)	(0.20)	(0.21)	(0.17)
no primary	-1.66***	-1.95***	2.07***	0.97***	-0.48**	-1.56***	0.98***	1.56***	-4.22***	-2.92***
	(0.51)	(0.52)	(0.38)	(0.36)	(0.21)	(0.26)	(0.13)	(0.20)	(0.39)	(0.27)
owns < 1 ha	0.63	-0.98	-2.38***	-5.03***	0.18	0.99***	1.01***	1.81***	1.82***	1.24***
	(0.50)	(0.78)	(0.42)	(0.71)	(0.21)	(0.19)	(0.15)	(0.26)	(0.26)	(0.19)
by small cty.	1.45**	-0.73	-0.18	-1.01*	-0.06	0.19	0.21	-0.14	1.48***	0.22
	(0.70)	(0.63)	(0.60)	(0.53)	(0.18)	(0.24)	(0.19)	(0.23)	(0.40)	(0.25)
by med. cty.	3.74***	2.69**	0.40	0.57	1.04***	0.52	0.42	0.65	1.88***	0.95**
	(0.92)	(1.06)	(0.76)	(0.92)	(0.27)	(0.49)	(0.31)	(0.43)	(0.65)	(0.39)
by big cty.	-4.67***	1.23	-3.27***	-0.37	-0.55**	0.62	-0.54**	0.25	-0.31	0.72**
	(0.81)	(1.12)	(0.67)	(0.99)	(0.23)	(0.46)	(0.24)	(0.41)	(0.43)	(0.34)
constant	16.48***	19.35***	12.08***	14.06***	1.97***	2.71***	-0.25	0.47	2.68***	2.11***
	(0.82)	(0.88)	(0.64)	(0.73)	(0.28)	(0.29)	(0.18)	(0.29)	(0.40)	(0.28)
N	18618	17057	18618	17057	18618	17057	18618	17057	18618	17057
Panel B: High season										
male	5.60***	6.98***	-0.60	-0.40	0.98**	1.45***	1.08***	3.26***	4.14***	2.67***
	(0.95)	(0.82)	(0.51)	(0.46)	(0.44)	(0.34)	(0.26)	(0.46)	(0.76)	(0.70)
young	-4.40***	-7.24***	-2.18***	-3.17***	-0.56	-1.81***	0.08	0.09	-1.73***	-2.35***
	(0.85)	(1.25)	(0.63)	(0.79)	(0.42)	(0.32)	(0.26)	(0.62)	(0.60)	(0.79)
no primary	-1.08	0.39	3.00***	1.74	-0.92*	-0.62	1.01***	1.87***	-4.18***	-2.61***
	(0.98)	(1.32)	(0.80)	(1.08)	(0.55)	(0.51)	(0.31)	(0.54)	(0.85)	(0.88)
owns < 1 ha	1.64	-2.38	-2.41**	-5.54***	0.69	0.92**	0.77**	0.79	2.59***	1.44**
	(1.19)	(1.56)	(0.92)	(1.17)	(0.46)	(0.44)	(0.37)	(1.04)	(0.73)	(0.71)
by small cty.	2.39	-1.93	-1.67	-2.67*	-0.10	0.38	0.54	0.04	3.63***	0.32
	(1.79)	(1.58)	(1.52)	(1.43)	(0.55)	(0.46)	(0.39)	(0.60)	(1.21)	(1.08)
by med. cty.	2.99	-0.38	0.03	-5.23**	0.49	0.64	0.86*	2.67*	1.61*	1.53
	(2.52)	(3.25)	(1.73)	(2.00)	(0.57)	(0.61)	(0.48)	(1.43)	(0.92)	(1.07)
by big cty.	-8.17***	5.59**	-6.39***	3.63**	0.27	-0.00	-0.88	2.70**	-1.17	-0.73
	(2.68)	(2.68)	(1.80)	(1.81)	(0.61)	(0.62)	(0.57)	(1.06)	(0.93)	(0.81)
constant	22.59***	26.42***	19.59***	21.19***	1.74***	1.34**	-0.11	1.60*	1.37	2.28**
	(1.71)	(1.67)	(1.23)	(1.37)	(0.66)	(0.63)	(0.42)	(0.94)	(1.01)	(1.06)
N	2768	2464	2768	2464	2768	2464	2768	2464	2768	2464
Panel C: Low season										
male	6.29***	8.13***	0.68*	0.62	0.83**	1.99***	1.75***	3.28***	3.03***	2.24***
	(0.87)	(0.76)	(0.38)	(0.42)	(0.34)	(0.39)	(0.41)	(0.53)	(0.65)	(0.45)
young	-4.55***	-5.12***	-2.06***	-2.86***	-0.83***	-2.05***	-0.41	0.66	-1.25***	-0.88**
	(0.80)	(0.85)	(0.49)	(0.43)	(0.31)	(0.43)	(0.34)	(0.51)	(0.42)	(0.40)
no primary	0.50	-1.34	1.15	0.71	0.52	-1.41**	1.26***	1.60***	-2.42***	-2.24***
	(1.20)	(0.97)	(0.75)	(0.57)	(0.33)	(0.59)	(0.37)	(0.55)	(0.84)	(0.47)
owns < 1 ha	1.55	0.20	-0.73	-3.24***	-0.04	1.35***	1.22***	1.71**	1.10**	0.38
	(1.03)	(1.30)	(0.73)	(0.88)	(0.44)	(0.50)	(0.31)	(0.69)	(0.51)	(0.37)
by small cty.	2.42	-0.65	1.07	-0.68	0.31	0.02	-0.51	-0.32	1.55*	0.32
	(1.72)	(1.01)	(1.19)	(0.69)	(0.34)	(0.55)	(0.48)	(0.47)	(0.83)	(0.50)
by med. cty.	5.31**	1.57	0.61	1.46	1.32**	-0.77	0.47	0.68	2.90**	0.20
	(2.39)	(1.63)	(1.20)	(1.19)	(0.54)	(0.56)	(0.92)	(0.82)	(1.43)	(0.72)
by big cty.	-2.55	-0.08	-1.88	-0.44	-0.36	-0.08	-0.46	-1.59**	0.15	2.04**
	(1.78)	(1.53)	(1.22)	(1.08)	(0.41)	(0.84)	(0.53)	(0.71)	(0.63)	(1.02)
constant	8.06***	13.83***	6.14***	8.82***	0.97**	2.73***	-0.39	0.39	1.35	1.90***
	(1.61)	(1.50)	(1.20)	(0.94)	(0.42)	(0.66)	(0.51)	(0.75)	(0.84)	(0.62)
N	2660	3298	2660	3298	2660	3298	2660	3298	2660	3298

Note: This table reports the OLS regression coefficients estimating the relationship between between hours worked (in total and by activity) and the explanatory variables in 2010 and 2019, overall (panel A), in the high season (Panel B), and in the low season (Panel C). 'High season' is December and January, 'low season' is July and August. Standard errors are reported in parentheses. Statistically significant values are indicated with $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Values are adjusted using survey weights.

Table A.13: Oaxaca-Blinder decomposition of the changes in mean hours worked per week between 2010 and 2019 in the high season, overall and by activity.

	Total hrs (1)	Own-farm hrs (2)	Business hrs (3)	Casual hrs (4)	Wage hrs (5)
Panel A: Mean differential					
Difference	1.302	-1.908*	0.076	4.060***	-0.925
	(1.282)	(1.093)	(0.350)	(0.426)	(0.788)
Panel B: Aggregate decomposition					
Compositional effect	-0.437	-0.560	0.011	-0.034	0.146
	(0.654)	(0.484)	(0.077)	(0.105)	(0.372)
Structural effect	1.739	-1.348	0.065	4.094***	-1.071
	(1.454)	(1.160)	(0.330)	(0.433)	(0.792)
Attributable structural effect	-2.083	-2.949	0.462	2.382**	-1.977
	(2.521)	(1.905)	(0.916)	(1.015)	(1.823)
Unexplained structural effect	3.822	1.602	-0.397	1.712*	0.906
	(2.385)	(1.835)	(0.911)	(1.023)	(1.465)
Panel C: Detailed decomposition					
Panel C.1: Compositional effect					
Male	-0.072	0.008	-0.013	-0.014	-0.053
	(0.069)	(0.010)	(0.013)	(0.014)	(0.052)
Young	-0.133*	-0.066*	-0.017	0.002	-0.052
	(0.073)	(0.039)	(0.015)	(0.008)	(0.032)
No primary education	0.024	-0.066	0.020	-0.022	0.092
	(0.035)	(0.078)	(0.026)	(0.027)	(0.108)
HH owns less than 1ha	-0.012	0.018	-0.005	-0.006	-0.019
	(0.053)	(0.077)	(0.022)	(0.025)	(0.083)
Close to small urb aggl	0.130	-0.091	-0.005	0.029	0.197
	(0.227)	(0.166)	(0.031)	(0.051)	(0.318)
Close to medium urb aggl	0.090	0.001	0.015	0.026	0.049
	(0.181)	(0.052)	(0.032)	(0.050)	(0.093)
Close to big urb aggl	-0.464	-0.363	0.016	-0.050	-0.067
	(0.571)	(0.443)	(0.039)	(0.067)	(0.095)
Panel C.2: Attributable structural effect					
Male	0.616	0.090	0.212	0.974***	-0.659
	(0.560)	(0.307)	(0.248)	(0.235)	(0.462)
Young	-0.806*	-0.278	-0.355**	0.003	-0.176
	(0.430)	(0.286)	(0.149)	(0.189)	(0.281)
No primary education	1.145	-0.979	0.233	0.669	1.222
	(1.275)	(1.044)	(0.584)	(0.485)	(0.952)
HH owns less than 1ha	-3.191**	-2.481**	0.180	0.016	-0.907
	(1.553)	(1.178)	(0.504)	(0.873)	(0.805)
Close to small urb aggl	-1.999*	-0.461	0.223	-0.230	-1.531**
	(1.136)	(0.965)	(0.331)	(0.333)	(0.775)
Close to medium urb aggl	-0.488	-0.762*	0.022	0.263	-0.011
	(0.611)	(0.444)	(0.121)	(0.231)	(0.204)
Close to big urb aggl	2.640**	1.923***	-0.053	0.686**	0.084
	(1.040)	(0.730)	(0.166)	(0.300)	(0.237)
Panel C.3: Unexplained structural effect					
Constant	3.822	1.602	-0.397	1.712*	0.906
	(2.385)	(1.835)	(0.911)	(1.023)	(1.465)

Note: This table reports the Oaxaca-Blinder decomposition of the changes in hours worked in the high season between 2010 and 2019, overall and by activity. 'High season' is December and January. Sample consists of 2,768 rural working-age individuals in 2010 and 2,464 in 2019. Standard errors are reported in parentheses. Significant coefficients are indicated with $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Values are adjusted using survey weights.

Table A.14: Oaxaca-Blinder decomposition of the changes in mean hours worked per week between 2010 and 2019 in the low season, overall and by activity.

	Total hrs (1)	Own-farm hrs (2)	Business hrs (3)	Casual hrs (4)	Wage hrs (5)
Panel A: Mean differential					
Difference	2.798***	-0.355	1.260***	2.369***	-0.476
	(1.001)	(0.690)	(0.308)	(0.350)	(0.461)
Panel B: Aggregate decomposition					
Compositional effect	0.393	0.067	0.033	-0.018	0.311
	(0.381)	(0.188)	(0.082)	(0.076)	(0.238)
Structural effect	2.405**	-0.423	1.228***	2.387***	-0.787
	(1.002)	(0.700)	(0.312)	(0.346)	(0.501)
Attributable structural effect	-3.364	-3.105**	-0.530	1.611*	-1.340
	(2.175)	(1.326)	(0.780)	(0.949)	(1.181)
Unexplained structural effect	5.769***	2.682*	1.758**	0.776	0.553
	(2.198)	(1.521)	(0.780)	(0.905)	(1.040)
Panel C: Detailed decomposition					
Panel C.1: Compositional effect					
Male	-0.061	-0.007	-0.008	-0.017	-0.029
	(0.070)	(0.008)	(0.010)	(0.020)	(0.034)
Young	-0.007	-0.003	-0.001	-0.001	-0.002
	(0.065)	(0.030)	(0.012)	(0.006)	(0.018)
No primary education	-0.027	-0.061	-0.028	-0.067*	0.129*
	(0.065)	(0.050)	(0.022)	(0.039)	(0.078)
HH owns less than 1ha	0.076	-0.036	-0.002	0.060*	0.054
	(0.066)	(0.041)	(0.021)	(0.036)	(0.039)
Close to small urb aggl	0.139	0.061	0.018	-0.029	0.089
	(0.220)	(0.111)	(0.032)	(0.050)	(0.135)
Close to medium urb aggl	0.143	0.016	0.035	0.013	0.078
	(0.268)	(0.044)	(0.066)	(0.034)	(0.148)
Close to big urb aggl	0.130	0.096	0.019	0.023	-0.008
	(0.185)	(0.134)	(0.031)	(0.039)	(0.033)
Panel C.2: Attributable structural effect					
Male	0.827	-0.027	0.518**	0.689**	-0.354
	(0.517)	(0.253)	(0.231)	(0.298)	(0.355)
Young	-0.161	-0.224	-0.343**	0.302*	0.104
	(0.328)	(0.183)	(0.150)	(0.174)	(0.162)
No primary education	-1.419	-0.332	-1.489***	0.259	0.142
	(1.185)	(0.719)	(0.522)	(0.512)	(0.738)
HH owns less than 1ha	-1.112	-2.059**	1.143**	0.402	-0.597
	(1.361)	(0.940)	(0.548)	(0.625)	(0.520)
Close to small urb aggl	-1.347	-0.768	-0.127	0.086	-0.539
	(0.887)	(0.609)	(0.283)	(0.294)	(0.431)
Close to medium urb aggl	-0.487	0.110	-0.272**	0.027	-0.353
	(0.398)	(0.222)	(0.125)	(0.160)	(0.229)
Close to big urb aggl	0.336	0.195	0.039	-0.154	0.255
	(0.331)	(0.227)	(0.127)	(0.128)	(0.178)
Panel C.3: Unexplained structural effect					
Constant	5.769***	2.682*	1.758**	0.776	0.553
	(2.198)	(1.521)	(0.780)	(0.905)	(1.040)

Note: This table reports the Oaxaca-Blinder decomposition of the changes in hours worked in the low season between 2010 and 2019, overall and by activity. 'Low season' is July and August. Sample consists of 2,660 rural working-age individuals in 2010 and 3,298 in 2019. Standard errors are reported in parentheses. Significant coefficients are indicated with $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Values are adjusted using survey weights.

Table A.15: Oaxaca-Blinder decomposition of the changes in mean hours worked conducted for each explanatory variable separately.

	Male	Young	No primary education	Owns less than 1ha	Near small urb.aggl.	Near med. urb.aggl.	Near big urb.aggl.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Total hours							
Compositional effect	-0.087***	-0.081**	0.111***	0.013	-0.020	0.031	0.039
	(0.027)	(0.034)	(0.036)	(0.023)	(0.050)	(0.051)	(0.094)
Structural effect	1.146**	1.140**	0.948*	1.046**	1.079**	1.028**	1.020**
	(0.500)	(0.493)	(0.496)	(0.498)	(0.500)	(0.490)	(0.500)
Attributable	0.039	-0.232	-0.175	-1.394*	-0.957**	0.139	0.856***
	(0.227)	(0.148)	(0.578)	(0.743)	(0.411)	(0.193)	(0.256)
Unexplained	1.108**	1.372**	1.123	2.440***	2.036***	0.889*	0.164
	(0.509)	(0.546)	(0.767)	(0.923)	(0.690)	(0.533)	(0.523)
Panel B: Own-farm hours							
Compositional effect	-0.004	-0.032**	-0.075***	-0.117***	0.003	-0.018	0.038
	(0.003)	(0.014)	(0.025)	(0.039)	(0.012)	(0.030)	(0.090)
Structural effect	-1.605***	-1.578***	-1.534***	-1.493***	-1.612***	-1.592***	-1.647***
	(0.419)	(0.418)	(0.418)	(0.413)	(0.419)	(0.418)	(0.416)
Attributable	-0.211	-0.340***	-0.976**	-2.094***	-0.399	0.196	0.430**
	(0.136)	(0.106)	(0.410)	(0.658)	(0.341)	(0.173)	(0.195)
Unexplained	-1.394***	-1.238***	-0.558	0.601	-1.213**	-1.788***	-2.077***
	(0.446)	(0.457)	(0.574)	(0.827)	(0.587)	(0.451)	(0.447)
Panel C: Business hours							
Compositional effect	-0.013***	-0.015**	0.026**	0.007	0.001	0.013	0.002
	(0.004)	(0.006)	(0.010)	(0.009)	(0.003)	(0.021)	(0.007)
Structural effect	0.696***	0.698***	0.657***	0.676***	0.682***	0.670***	0.681***
	(0.158)	(0.157)	(0.156)	(0.157)	(0.158)	(0.157)	(0.158)
Attributable	0.165*	-0.250***	-0.841***	0.579**	0.112	-0.001	0.173**
	(0.097)	(0.064)	(0.255)	(0.233)	(0.131)	(0.075)	(0.080)
Unexplained	0.531***	0.948***	1.498***	0.097	0.570***	0.671***	0.508***
	(0.147)	(0.195)	(0.337)	(0.246)	(0.218)	(0.163)	(0.165)
Panel D: Casual hours							
Compositional effect	-0.018***	-0.005*	-0.025***	0.042***	-0.003	0.004	0.004
	(0.006)	(0.003)	(0.008)	(0.014)	(0.008)	(0.008)	(0.010)
Structural effect	2.644***	2.630***	2.651***	2.584***	2.628***	2.621***	2.621***
	(0.151)	(0.151)	(0.149)	(0.152)	(0.151)	(0.151)	(0.151)
Attributable	0.634***	0.182***	0.358*	0.725***	-0.122	0.055	0.144*
	(0.098)	(0.064)	(0.183)	(0.246)	(0.124)	(0.074)	(0.079)
Unexplained	2.009***	2.448***	2.293***	1.858***	2.751***	2.567***	2.477***
	(0.147)	(0.160)	(0.220)	(0.265)	(0.209)	(0.156)	(0.157)
Panel E: Wage hours							
Compositional effect	-0.052***	-0.030**	0.186***	0.081***	-0.021	0.032	-0.005
	(0.016)	(0.013)	(0.052)	(0.026)	(0.052)	(0.052)	(0.014)
Structural effect	-0.588**	-0.611***	-0.826***	-0.721***	-0.619***	-0.672***	-0.635***
	(0.235)	(0.235)	(0.236)	(0.242)	(0.235)	(0.237)	(0.238)
Attributable	-0.549***	0.176**	1.284***	-0.604**	-0.547**	-0.111	0.109
	(0.170)	(0.080)	(0.406)	(0.271)	(0.216)	(0.126)	(0.114)
Unexplained	-0.039	-0.786***	-2.110***	-0.117	-0.072	-0.561**	-0.744***
	(0.119)	(0.293)	(0.579)	(0.185)	(0.227)	(0.238)	(0.254)

Note: This table reports the Oaxaca-Blinder aggregate decomposition of the changes in weekly hours worked, in total and by activity, conducted for each explanatory variable separately. The column title indicates the explanatory variable examined. The first panel decomposes the changes in mean total weekly hours worked. The subsequent panels decompose the change in mean weekly hours worked by activity. Standard errors are reported in parentheses. Significant coefficients are indicated with $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Values are adjusted using survey weights.

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