Climate Change and Gendered Structural Transformation in Africa

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Abstract

We examine whether and how climate change affects structural transformation in Africa. We also examine potential gendered impacts as well as heterogeneities across different population groups. Combining census data covering 12 African countries and four decades (1974–2014) with gridded temperature and precipitation data, we document that a 1°C increase in decadal temperature increases employment in agriculture by about 6 percentage points while triggering a comparable decline in the share of employment in nonagricultural sectors. We also document heterogeneities in the impact of climate change and show that climate change leads to a gendered delay in structural transformation, with women and less-educated individuals more affected by the delay induced by climate change. These findings suggest that climate change can aggravate existing inequities in societies. We provide empirical evidence on potential mechanisms, including impacts through agricultural productivity and labor force participation. Medium-term increases in temperature reduce agricultural productivity while increasing demand for farm labor and hence labor force participation.

Key words: Climate, structural transformation, agriculture, gender, Africa.

JEL Codes: O13, O14, Q15, Q54.

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1 Introduction

Climate change continues to shape global economies, triggering immense socioeconomic and welfare implications (Solomon et al., 2009; Carleton and Hsiang, 2016). This is particularly the case in the agriculture sector, where weather events have been shown to significantly reduce yields of most crops (Lobell et al., 2011; Wollburg et al., 2024b).[1] Relatedly, recent projections and estimates show that climate change reduces total factor productivity by approximately 21 percent, especially in warmer regions in sub-Saharan Africa (Ortiz-Bobea et al., 2021). Indeed, these countries are witnessing a slowdown in agricultural productivity because of climate change and deterioration in soil health (Wollburg et al., 2024a,b). Thus, climate change is reinforcing the threat to food security, especially in countries where demand for food is growing because of urbanization and population growth. Among the most affected are the poor who live in developing countries in the tropics, where the impacts of climate change are more intense (Aragón et al., 2021). Because of these climate-induced yield reductions, climate change could induce change in labor demand and supply across sectors (Jessoe et al., 2018; Huang et al., 2020; Dasgupta et al., 2021; Feriga et al., 2025), which can ultimately affect the allocation of labor between agriculture and nonagricultural sectors (e.g., manufacturing and services) (Colmer, 2021; Liu et al., 2023; Feriga et al., 2025).

Developing countries exhibiting large productivity gaps between agriculture and nonagricultural sectors are expected to benefit (in aggregate productivity and welfare) from reallocation of labor from agriculture to nonagricultural sectors, a process defined as structural transformation (McMillan et al., 2014; Duarte and Restuccia, 2010; Gollin et al., 2014; Restuccia and Rogerson, 2017; Gollin and Kaboski, 2023; Barrett et al., 2023). Thus, understanding whether climate change catalyzes or inhibits structural transformation is crucial to inform climate adaptation and mitigation measures. Similarly, uncovering the differential impact of climate change across sectors and population groups is important to design

[1] For example, on average, climate shocks realized from 2008 to 2019 in Africa affected 35 percent of plots and reduced national crop production by 29 percent (Wollburg et al., 2024b).

policy instruments that can counteract these adverse impacts on vulnerable sectors and populations. For instance, extreme heat has been shown to reduce hours worked in industries with high exposure to heat, while other studies show a shift from outdoor to indoor leisure activities (Graff Zivin and Neidell, 2014; Neidell et al., 2021; Kuruc et al., 2025). Despite these insights, important knowledge gaps persist, especially in relation to potential differential responses and impacts on labor reallocation and structural transformation (Emerick, 2018; Hertel and de Lima, 2020; Barrett et al., 2023; Liu et al., 2023; Kuruc et al., 2025). Such knowledge gaps are particularly evident in Africa, where the brunt of climate change is projected to be highest (Burke et al., 2009; Schlenker and Lobell, 2010). Rigorous studies uncovering differential impacts of climate change on vulnerable populations, including women, youth, and less-educated individuals, are missing. Moreover, evidence on the impact and mechanisms through which climate change can affect social and income inequality remains scant (Islam and Winkel, 2017; Dennig et al., 2015; Palagi et al., 2022; Feriga et al., 2025; Smiley et al., 2022). These knowledge gaps persist mainly because of lack of detailed longitudinal data that would enable researchers to measure medium- and long-term impacts of climate variations.

In this paper, we investigate whether and how climate change inhibits or induces the transformation of typical agrarian economies in Africa. Structural transformation is an important phenomenon shaping the economies of many developing countries, as it generates efficiency and productivity gains by reallocating labor from the less productive to the more productive sectors of an economy (Herrendorf et al., 2014; Herrendorf and Schoellman, 2018; Gollin and Kaboski, 2023; Barrett et al., 2023).[2] We examine how medium-term change in temperature and precipitation affects employment shares in agriculture, manufacturing, and the service sectors. In doing so, we also investigate heterogeneities across gender, age, and educational attainment (Caselli and Coleman II, 2001; Bezu and Holden, 2014; Sumberg et al., 2017; Herrendorf and Schoellman, 2018; Metelerkamp et al., 2019; Rossi, 2020; Porzio

[2]This is an important transition because it can facilitate economic growth and poverty reduction (Rodrik, 2010; Herrendorf et al., 2014; McMillan and Headey, 2014; Herrendorf and Schoellman, 2018).

et al., 2022; Cheung, 2023). To explore potential mechanisms, we examine the impact of medium-term changes in temperature on agricultural productivity, labor force participation, and rural–urban migration. Beyond examining the impact of temperatures on employment shares in agriculture and nonagricultural sectors, we also evaluate impacts on labor force participation of men and women.

To address the above questions, we rely on unique census data from 30 national censuses covering 12 African countries between 1974 and 2014, collated by the Integrated Public Use Microdata Series (IPUMS) (Ruggles et al., 2024). These data enable us to study medium- and long-term changes in the reallocation of labor across the three broad sectors of economies: agriculture, manufacturing, and services. We merge these data with well-gridded earth observation precipitation and temperature data from the Terrestrial Air Temperature and Precipitation Gridded monthly time series (Willmott and Matsuura, 2001). Using these data, we observe monthly temperature and precipitation over a long period (1900–2017), with precision ($0.5° \times 0.5°$). We also use the Normalized Difference Vegetation Index (NDVI) dataset from the National Oceanic and Atmospheric Administration (NOAA), which enables us to capture vegetation cover of each district in our database from 1981 to 2014. Combining these datasets enables us to study medium- and long-term responses to climate change, which are likely to differ from short-term responses and adaptation strategies (Deschênes and Greenstone, 2011; Burke and Emerick, 2016; Colmer, 2021; Liu et al., 2023).

Exploiting plausibly exogenous temporal variations in (average) decadal temperature, we note several findings. First, we find that a medium-term (decadal) increase in temperature inhibits structural transformation by increasing the share of labor in agriculture and reducing the corresponding shares in manufacturing and service sectors. A 1°C increase in decadal temperature increases employment in agriculture by about 6 percentage points. We also document heterogeneities in the impact of climate change. We show that climate change leads to a gendered delay in structural transformation, with the delay triggered by climate change being more pronounced among women. A 1°C increase in decadal temperature increases the share of women's employment in agriculture by about 9 percentage points while delaying the transition to the service sector by about 7 percentage points, whereas the corresponding effects for men remain about half. Similarly, less-educated individuals are more likely to face additional constraints (because of climate change) to reallocate labor into nonagricultural sectors compared with educated individuals. These findings offer important insights on the vulnerability of women and less-educated individuals to climate change (Sitko et al., 2024). Furthermore, they suggest that climate change can trigger gendered structural transformation in Africa and may aggravate existing inequalities in societies.

We also explore potential mechanisms through which climate change may delay structural transformation. We show that climate change leads to a reduction in agricultural yield, which ultimately affects demand for nonagricultural goods and services and the ensuing demand for labor in nonagricultural sectors (Herrendorf et al., 2014). This is consistent with previous evidence showing that an increase in temperature is associated with a reduction in agricultural yield (Schlenker and Roberts, 2009; Schlenker and Lobell, 2010; Knox et al., 2012; Liu et al., 2023; Cui and Zhong, 2024), and an increase in the use of pesticides (Jagnani et al., 2021; Mayorga et al., 2025). Our results remain robust across a wide range of robustness checks. Moreover, our results are not driven by any specific country or a small share of the sample. Our results remain consistent even when excluding the warmest or coldest districts or when randomly dropping 20 percent of the districts from the sample.

To our knowledge, our study provides fresh evidence showing the effects of climate change on the much-needed structural transformation in Africa. The article most closely related to our study is Liu et al. (2023), which examines how slow-onset climate change affects structural transformation in India. Using a unique panel dataset covering six decades of district-level data, Liu et al. (2023) show that rising temperatures inhibit structural transformation. Their results suggest that higher temperature leads to a decline in agricultural productivity, which reduces demand for manufactured goods and services and in turn, lowers demand for labor in these sectors. Our results align with this study's findings, highlighting the broader relevance of climate change as a factor shaping labor market dynamics and structural transformation.

Our second and probably more unique contribution is uncovering whether climate change aggravates existing inequalities by inhibiting or facilitating labor reallocation among different population groups, for which empirical evidence remains scant. We demonstrate that in the presence of climate change women are more likely to face a larger delay in their reallocation of labor from agriculture to nonagricultural sectors, implying that climate change can trigger gendered structural transformation. We also show that less-educated households are less likely to engage in nonagricultural activities in areas experiencing climate change (Caselli and Coleman II, 2001; Herrendorf and Schoellman, 2018; Rossi, 2020; Porzio et al., 2022; Cheung, 2023). As agricultural productivity declines, limited nonagricultural job opportunities push the most vulnerable groups (women and less-educated individuals) further into agricultural employment (Tennhardt et al., 2024). Our findings contribute to an evolving literature on the impact of climate change in amplifying underlying socioeconomic inequalities in developing countries (Diffenbaugh and Burke, 2019; Pignède, 2025). Due to cultural norms and limited access to resources, women typically have fewer off-farm employment options than men, making them more likely to engage in agricultural employment even under low yields and profitability (Van den Broeck and Kilic, 2019; Van den Broeck et al., 2023; Sitko et al., 2024; Dinkelman and Ngai, 2022). Given that Africa is expected to be disproportionately affected by climate change, understanding its heterogeneous impacts on employment and sectoral transitions is critical for informing climate adaptation and mitigation policies.

Our final contribution comes through our effort to identify new mechanisms through which climate change can delay structural transformation, including an increase in labor force participation, and a reduction in agricultural productivity. Our evidence suggests that a medium-term increase in temperature reduces agricultural productivity—a finding that has been established in the literature (Schlenker and Roberts, 2009; Schlenker and Lobell, 2010; Knox et al., 2012; Liu et al., 2023). This reduction in agricultural productivity could reduce the demand for nontradable goods and services, and ultimately demand for labor in nonagricultural sectors.[3] Finally, we find that climate change and hence a medium-term increase in temperature leads to an increase in women's participation in the labor force.

The remainder of the paper is structured as follows. Section 2 delves into the data sources used for the analyses, including census and climate data. Section 3 presents our empirical strategy while Section 4 discusses the main results. Section 5 provides evidence on potential mechanisms and explanations while Section 6 reports a battery of robustness checks and sensitivity analyses. Section 7 concludes the paper.

2 Data and Descriptive Statistics

We rely on four main data sources. First, we use the IPUMS database, the world's largest archive of publicly available census data, and extract data for 12 African countries, which cover 30 national censuses conducted between 1974 and 2014 (Ruggles et al., 2024). This database offers a rich and extensive record of national censuses, which are organized in waves. We merge these census data with well-gridded earth observation precipitation and temperature data from the Terrestrial Air Temperature and Precipitation Gridded monthly time series (Willmott and Matsuura, 2001). We also merge these census data with NOAA's NDVI dataset so that we can estimate the vegetation cover of each district in our database from 1981 to 2014. Finally, we rely on FAOSTAT for extracting national level fertilizer and pesticide use data. Below we describe each of these datasets.

2.1 Census Data

We analyze data from 30 national censuses conducted in 12 African countries between 1974 and 2014. The dataset was constructed by collecting all available censuses in sub-Saharan

[3] Recent evidence shows that positive rainfall shocks increase agricultural productivity, which increases the share of labor in the nonagricultural sectors because of increased demand for nontradables (Emerick, 2018).

Africa from the IPUMS database (Ruggles et al., 2024). To refine the sample, we apply specific inclusion criteria, excluding surveys that (1) lacked information on labor force participation and employment sector or (2) were not spatially harmonized.[4] Additionally, we retained only countries with at least two censuses meeting these criteria. Table A1 and Figure A1 in the Appendix present the list of countries included, along with the census periods.

Each survey provides a nationally representative subsample, typically covering 10 percent of the total population. These records include information on age, gender, urban or rural residence, education, and employment sector. Using these data, we construct various district-level indicators,[5] including the total population in the district, share of urban residents, share of males, and share of individuals 15 to 64 years old. The main outcome variables for this study are employment shares across three sectors: agriculture, manufacturing, and services.[6] We also construct indicators to capture the percentage of men, women, children, and adults employed in each sector within each district.

2.2 Climate Data

To complement the demographic data from the censuses, we incorporate climate data from gridded datasets developed by Willmott and Matsuura (2001). These datasets provide long-term observations (1900–2017) of average monthly temperature[7] and precipitation[8] at a spatial resolution of $0.5° \times 0.5°$ (approximately 55 km $\times$ 55 km at the equator). The gridded estimates are primarily derived from observation station records, which are largely compiled from publicly available datasets. However, a major limitation of ground station data is their

[4] Spatial harmonization, performed by IPUMS, ensures consistent geographic units across survey years, either at the first administrative level (provinces) or the second administrative level (districts).

[5] For Botswana, Lesotho, and Liberia, we construct province-level indicators. For simplicity, these administrative units are referred to as districts throughout the text.

[6] Agriculture includes "agriculture, fishing, and forestry" (ISIC code 010); manufacturing includes "mining and extraction" (020), "manufacturing" (030), "electricity, gas, water, and waste management" (040), and "construction" (050); services include "wholesale and retail trade" (060), "hotels and restaurants" (070), "transportation, storage, and communications" (080), and other service-related categories (codes 090–130).

[7] Terrestrial Air Temperature: 1900–2017 Gridded Monthly Time Series (Version 5.01).

[8] Terrestrial Precipitation: 1900–2017 Gridded Monthly Time Series (Version 5.01).

incomplete spatial coverage, particularly in low-income regions and sparsely populated areas. To address this issue, Willmott and Matsuura (2001) employ an extrapolation algorithm to interpolate data between ground stations, generating a high-resolution database with extensive temporal coverage. The availability of panel data covering a long period makes this dataset a widely used tool in economic research. In particular, Willmott and Matsuura (2001) is the most frequently used source for measuring average climate conditions in economic studies (Dell et al., 2014). The advantage of these climate data over comparable datasets stems from their higher resolution.

Temperature is reported as the average monthly air temperature in degrees Celsius, while precipitation is reported as the total monthly precipitation in millimeters. For each district, we estimate average monthly temperature and precipitation by weighting the values from overlapping grid cells according to their area of overlap. We then compute annual and decadal averages. The temperature and precipitation variables correspond to the average values for the 10 years preceding the census year.

2.3 Agricultural Data

Finally, we aim to measure agricultural production across all districts in our sample. However, to the best of our knowledge, no single dataset comprehensively captures agricultural production at the district level across all the countries included in our study. Consequently, we rely on satellite imagery to capture some indicator of agricultural production and potential. Specifically, we use NOAA's NDVI to estimate the vegetation cover of each district in our database from 1981 to 2014. The NDVI value for each year corresponds to the annual average of the monthly NDVI values. The NDVI is calculated on the basis of the difference in reflectance between near-infrared (NIR) and red (RED) light, as expressed in Equation (1):

$$\text{NDVI} = \frac{(\text{NIR} - \text{RED})}{(\text{NIR} + \text{RED})} \tag{1}$$

Because healthy vegetation reflects a higher proportion of NIR light while absorbing more RED light, NDVI values are particularly useful for measuring vegetation cover. NDVI is not a perfect measure of agricultural productivity because it also reflects forested areas. Nonetheless, measuring vegetation is instructive, as it highlights potential challenges for agriculture. The NDVI average represents the mean NDVI value within each district. Similarly, the NDVI sum denotes the total sum of all NDVI values within the district. NDVI values are commonly used for monitoring crop growth and biomass as well as for predicting agricultural yield (Burke and Lobell, 2017; Asher and Novosad, 2020; Shammi and Meng, 2021; Nakalembe et al., 2021).[9]

2.4 Descriptive Statistics

Table 1 summarizes the main variables included in the study. The average decadal temperature across African districts and across all rounds is 24.63°C, with significant variation ranging from 11.76°C (a district in Lesotho) to 30.35°C (Mali). This suggests significant climate variations across the continent. Average rainfall also exhibits substantial heterogeneity, with values ranging from 0.34 mm to 28.22 mm and a mean of 8.3 mm. The NDVI, which underscores the diversity of vegetation coverage, has an average district value of 0.23—which is above the threshold for vegetated areas. Urban or desert districts tend to have low NDVI values, while districts with dense vegetation reach values close to 0.4, indicating significant vegetable cover.

Regarding our main outcome variables of interest, Table 1 shows an employment share in agriculture of about 69 percent (the percentage of individuals reporting agricultural employment), reinforcing that agriculture remains a major source of livelihood and employment in Africa. Manufacturing accounts for only 9 percent of employment, while services make up 22 percent. Substantial regional variation is evident, with some districts almost entirely reliant on agriculture, while in others, agriculture constitutes as little as 7 percent of employment.

[9] For example, Asher and Novosad (2020) use NDVI as an indicator of agricultural production for studying the impact of roads on agricultural income and productivity.

In terms of the other district characteristics, the average labor force participation rate is about 69 percent. These rates are comparable with those reported by the International Labor Organization (ILOSTAT, 2025).[10] Finally, Table 1 shows a self-employment rate of 25 percent.

We also present the summary statistics of the other variables that we control for in our estimations, finding that they are largely in line with some established statistics and stylized facts. For instance, about 77 percent of individuals in our sample have less than a primary education, while 23 percent attained a primary education. The share of the population residing in urban areas is about 24 percent, and the share of men is 49 percent.

Table 1: Summary Statistics.

Variables	**N**	**Mean**	**Median**	**SD**
Panel A: Climate outcomes				
Average monthly Temperature	1927	24.625	25.098	2.985
Average monthly Precipitation	1927	8.301	8.430	2.733
Average NDVI	1850	0.229	0.229	0.052
Panel B: Sectors outcomes				
Share of labor in Agriculture	1927	0.692	0.781	0.260
Share of labor in Manufacturing	1927	0.085	0.055	0.082
Share of labor in Services	1927	0.223	0.155	0.197
Share of labor in Non-Agriculture	1927	0.308	0.219	0.260
Panel C: District characteristics				
Labor Force Participation rate	1901	0.686	0.706	0.126
Employment rate	1901	0.647	0.667	0.146
Share of Self-Employed	1622	0.250	0.244	0.117
Share of Males	1927	0.487	0.488	0.017
Share of working-age Population (15-64 years)	1927	0.510	0.504	0.047
Share with Less than Primary Education	1927	0.773	0.826	0.180
Share of Population in Urban Area	1613	0.241	0.156	0.284
Log of Total Population	1927	11.631	11.621	0.974

Notes: This table presents the main summary statistics of districts for which we have complete data on sectoral engagement of labor. The census variables are weighted using person weights.

Figure 1 shows the climate data for the countries and districts covered in our study.

[10]This represents the share of working-age population participating or actively seeking to participate in economic activities. The share of working-age population stands at 51 percent.

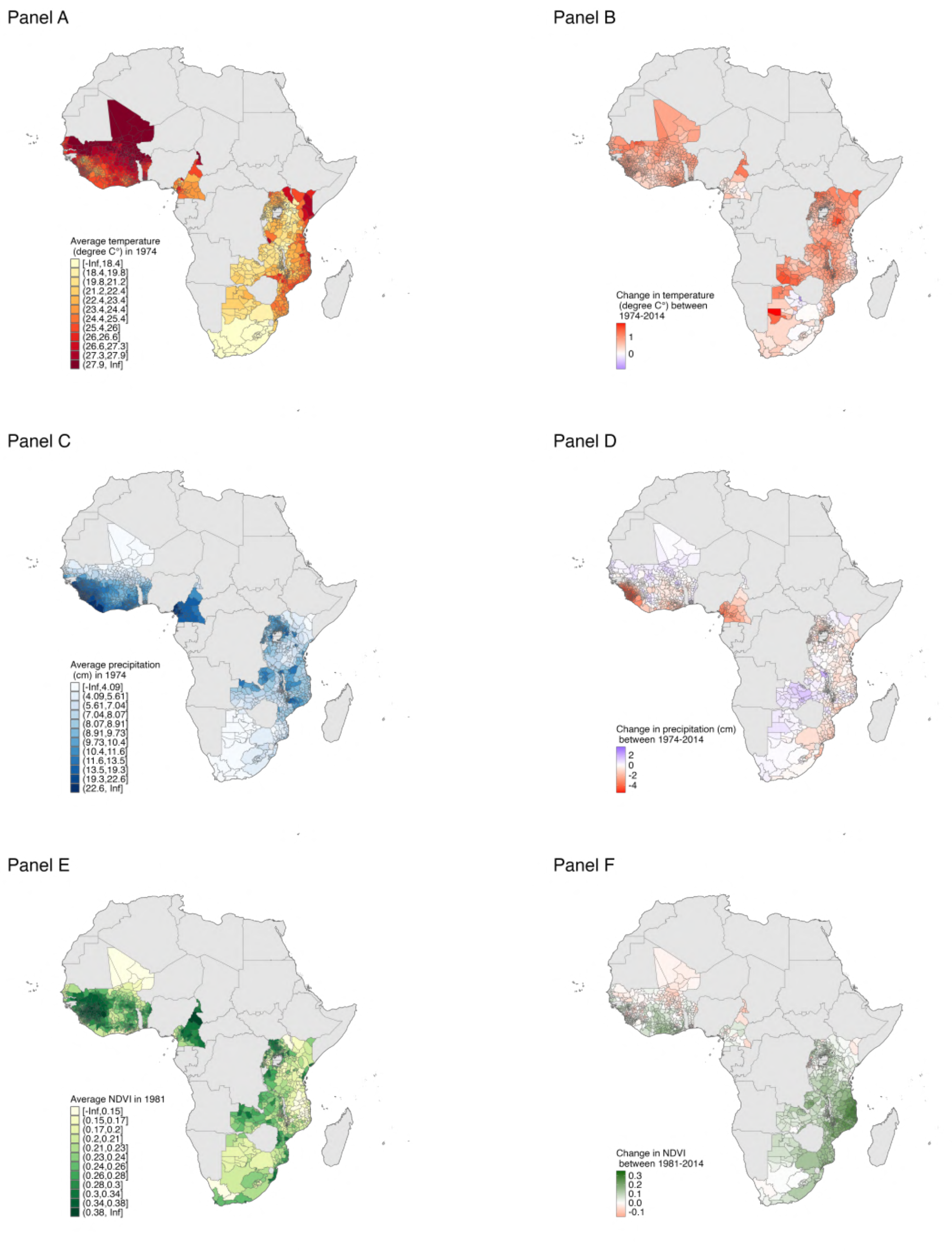

Figure 1: Climate Maps

Note: The figures on the left display the average temperature (Panel A), precipitation (Panel C), and vegetation (Panel E) for each district in 2014. The figures on the right depict changes in temperature (Panel B), precipitation (Panel D), and vegetation (Panel F) between 1974 and 2014.

The maps on the left show the average climate conditions of the decade preceding 2014,[11] revealing substantial heterogeneity between regions. The maps on the right show changes in temperature and precipitation between 1974 and 2014. Rising temperatures are observed in most districts, with many experiencing an increase of approximately 1°C between the decades preceding 1974 and 2014. Rainfall patterns show a general decline, although increases are also observed in historically arid regions such as the Sahel and southern Africa.

Figure A2 offers an alternative view of our climate data. In Panel A, we plot the annual mean temperature for each country in the main sample, while Panel B then shows the corresponding ten-year (decadal) averages. Both panels reveal a clear, global upward trend in temperature over time. Panels C and D apply the same approach to precipitation. No consistent trend is evident.

As shown in Figure A3, our census data reveal the hallmark patterns of structural transformation in Africa. In Panel A, we plot the average share of agricultural employment for each country in the main sample; Panel B shows the share of employment in manufacturing; and Panel C illustrates the share in services. These data confirm well-known facts about structural transformation in Africa: a decline in agricultural employment, a rise in services employment, and stagnation, or even a reduction, in the manufacturing sector.

3 Empirical Strategy

To estimate the effect of medium-term change in temperature and precipitation on structural transformation, we exploit temporal variations in average decadal temperature and precipitation, and hence estimate the following two-way fixed-effects specification:

$$Y_{cdt} = \gamma_0 T_{cdt} + \gamma_1 P_{cdt} + \gamma_3 X_{cdt} + \gamma_d + \gamma_{ct} + \varepsilon_{cdt} \tag{2}$$

where Y_{dct} represents the share of employment in agriculture, manufacturing, and services

[11] The NDVI maps (Panels E and F) show the value for the corresponding year, not the decade.

in country c, district d, and time t. T_{cdt} denotes the average decadal monthly temperature in degrees Celsius for district d during the decade preceding year t. P_{dct} refers to the average precipitation in millimeters per month for district d during the decade preceding year t. X_{dct} captures a set of control variables that account for key time-varying characteristics of district d in year t. We estimate Equation 2 with and without the inclusion of these control variables. γ_d stands for district fixed effects, which captures all time-invariant differences across districts, including fixed attributes such as topographic features and culture and norms shaping engagement in various sectors of economies. γ_{ct} captures country-by-year fixed effects absorbing any shocks or aggregate trends that are common to all districts within the same country in a given year, and thus controlling for country-specific temporal dynamics in sectoral engagement.

Our main parameters of interest are γ_0 and γ_1, which capture the impact of decadal change in temperature and precipitation on allocation of labor across various sectors of economies. Causal interpretation of these effects on structural transformation rests on the assumption that following the inclusion of district and year fixed effects, within-district decadal variations in mean temperature and precipitation can be random. This is a plausible and widely used assumption in the climate change literature (Colmer, 2021; Liu et al., 2023; Dell et al., 2014). If climate change and hence increase in temperature delays structural transformation in Africa as it has in India (Liu et al., 2023), we expect positive (negative) and a statistically significant value of γ_0 for the share of labor in agriculture (nonagricultural) sector. The impact of medium-term change in precipitation may trigger slightly different effects, although previous studies show that changes in temperature are more important than changes in precipitation (Colmer, 2021; Liu et al., 2023; Emerick, 2018).[12] As we follow districts across time, this can generate serial correlation in unobserved factors across districts. Thus, we cluster standard errors at the district level to account for serial correlation in unobservable factors over time within districts. Additionally, we provide results with

[12]For example, Emerick (2018) shows that favorable rainfall increases agricultural productivity and hence local demand and ultimately demand for nonagricultural goods and services.

standard errors clustered at a higher level to assess the robustness of our findings.

Although we have limited countries and districts with more than two rounds of census data, we also probe the robustness of our medium-term impacts using Equation 2 by estimating a first-difference equation focusing on the first and last censuses for each district. Such specification allows us to detect long-term impacts. This is sometimes referred to as the long differences approach (Burke and Emerick, 2016; Liu et al., 2023):

$$\Delta Y_{cd} = \beta_0 \Delta T_{cd} + \beta_1 \Delta P_{cd} + \beta_3 \Delta X_{cd} + \epsilon_{dc} \tag{3}$$

The difference between Equation 2 and 3 lies in the fact that ΔY_{cd} corresponds to the difference between the oldest and the most recent period in our census. Similarly, ΔT_{cd} and ΔP_{cd} are measures of the differences between temperatures and precipitation in these two periods. For example, ΔY_{cd} represents the change in the share of agricultural employment in Benin between 1979 and 2013. The estimate corresponding to this methodology therefore only includes observations from the earliest and most recent censuses. Comparing γ_0 and β_0 can offer important insights on potential differences between medium- and long-term responses to climate change, although we do not expect much difference in our sample simply because of the composition of our data.

We also implement the empirical specifications in Equation 2 for exploring potential mechanisms through which climate change and hence medium-term change in temperature can affect allocation of labor across sectors. Previous studies have identified several mechanisms through which rising temperature can affect structural transformation. First, an increase in medium-term temperature can reduce labor productivity, sometimes with varying degrees across agriculture and nonagricultural sectors (Schlenker and Roberts, 2009; Hsiang, 2010; Dell et al., 2012; Schlenker and Lobell, 2010; Knox et al., 2012; Liu et al., 2023). If an increase in temperature triggers a disproportionally higher impact on agricultural labor productivity, and labor can be reallocated without friction, individuals may respond by shifting to nonagricultural sectors, with the reverse effect anticipated if heat-induced labor productivity loss is higher in nonagricultural sectors.

Second, an increase in temperature can reduce agricultural yield and hence farm income, which can ultimately trigger two contrasting effects. On the one hand, lower agricultural incomes reduce the attractiveness of the farming sector, as lower wages incentivize workers to seek employment in nonagricultural sectors. This shift can decrease the supply of agricultural labor. On the other hand, as Liu et al. (2023) suggest, declining farm incomes and thus reduced purchasing power within farming communities can dampen local demand for goods and services, ultimately lowering labor demand in manufacturing and service sectors. This weak demand can force individuals to accept lower-paying agricultural jobs. In this scenario, the additional employment in the agriculture sector is likely to come from workers with limited alternatives in the labor market, such as women and less-educated individuals.

Third, climate change and hence an increase in medium-term temperature can also delay structural transformation by altering the cost of mobility and reallocation of labor across sectors. The reduction in farm income or labor productivity described above can shape the opportunity cost of reallocation of labor across sectors. Finally, the reduction in agricultural yield and farm income may affect labor force participation rates as well as rural–urban migration patterns.

Identifying and testing the above mechanisms require detailed data on labor productivity, labor force participation, wages, agricultural yield, and input use practices, some of which are not widely available for the period we are interested in for this study. While the census data we use offer information on labor force participation and related demographic trends, we lack detailed data on wages and agricultural yield. Thus, as a proxy for agricultural yield, we assemble historical NDVI data from NOAA. The NDVI data are widely used inputs for monitoring crop growth and biomass as well as for predicting agricultural yield (Burke and Lobell, 2017; Shammi and Meng, 2021; Nakalembe et al., 2021).

4 Results and Discussion

4.1 Main results

Table 2 presents the effect of climate change, measured through decadal change in temperature and precipitation, on labor allocation across various economic sectors, based on the estimation of Equation (2). All estimations control for district and country-by-year fixed effects. Odd-numbered columns exclude the set of control variables described at the bottom of the table, while even-numbered columns include them.[13] Columns 1 and 2 show effects of climate change on the share of labor in the agriculture sector. Columns 3 and 4 present the corresponding results for the share of labor in the manufacturing sector, while columns 5 and 6 show effects on the share of labor engaged in the services sector.

Table 2: Effect of climate on employment sectors

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature	0.064***	0.063***	-0.025***	-0.025***	-0.039***	-0.038***
	(0.014)	(0.012)	(0.008)	(0.007)	(0.012)	(0.011)
Precipitation	-0.029***	-0.016***	0.006**	0.003	0.023***	0.013***
	(0.006)	(0.006)	(0.003)	(0.003)	(0.005)	(0.005)
Num.Obs.	1927	1927	1927	1927	1927	1927
Num.Districts	819	819	819	819	819	819
CountryYear FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes

Notes: The dependent variables correspond to the share of individuals employed in agriculture, manufacturing, and services sectors. All regressions include district and country-by-year fixed effects. The included controls are the total population, the share of male, the share of individuals between 15 and 64 years old and the share of individuals with less than primary education. Standard errors clustered at the district level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The coefficient in column 1 of Table 2 indicates that decadal increase in temperature increases the share of labor in the agriculture sector. Specifically, a 1°C rise in decadal temperature increases the share of agricultural employment by about 6 percentage points. Upon the addition of controls, this effect remains robust and stable. This finding suggests that

[13] Figure A4 provides a graphical overview of these results.

climate change encourages or pushes labor into agriculture. Interestingly, the results for the manufacturing and service sectors, presented in columns 3 to 5, are also significant, but negative. A 1°C rise in decadal temperature decreases the share of employment in manufacturing by 3 percentage points and in services by 4 percentage points. Intuitively, these contrasting effects suggest that temperature change is delaying structural transformation by limiting the reallocation of labor from agriculture to nonagricultural sectors. Conversely, medium-term increase in average decadal precipitation significantly reduces agriculture's share of employment, while increasing employment shares in manufacturing and services. Hence, higher precipitation could speed up the shift of labor from agriculture to non-agricultural sectors. Although higher precipitation may drive a reduction in labor demand (Gunathilaka et al., 2018), it could increase agricultural productivity which could stir structural transformation through the local demand effect (Emerick, 2018).

The temperature results are consistent with those of Liu et al. (2023), which reports similar effects in India, but they found no visible effect of medium-term change in precipitation. Liu et al. (2023) find that climate change and hence decadal increase in temperature leads to a significant increase in the share of labor in agriculture while reducing the share of labor in nonagricultural sectors. With regards to the precipitation results, our findings corroborate earlier findings from Emerick (2018) who show that increases in agricultural productivity, driven by favorable rainfall shock, accelerates labor reallocation from the agriculture to nonagricultural sectors. In the same vein, Colmer (2021) finds that a short-term increase in temperature reduces agricultural output and the demand for agricultural labor, leading to higher employment shares in nonagricultural sectors. All these studies provide unique evidence that agricultural productivity is an important aspect linking climate change and structural transformation.

We also estimate medium - to long-term impacts of climate change by using the first-difference equation described in Equation (3). This estimation uses the first and latest censuses for each district. As reported in Table A1 these differences between the earliest and

Table 3: Effect of climate on employment sectors - Long difference specification

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Temperature	0.074***	0.073***	-0.029**	-0.028**	-0.045**	-0.045***
	(0.023)	(0.020)	(0.012)	(0.011)	(0.019)	(0.016)
Δ Precipitation	-0.031***	-0.015*	0.007	0.004	0.024***	0.011*
	(0.009)	(0.008)	(0.004)	(0.004)	(0.007)	(0.006)
Num.Obs.	819	819	819	819	819	819
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes

Notes: The dependent variables correspond to the difference in the share of individuals employed in agriculture, manufacturing, and services sectors between the earliest and last census. All regressions include district and country-by-year fixed effects. The included controls are the difference in the total population, the share of male, the share of individuals between 15 and 64 years old and the share of individuals with less than primary education between the earliest and latest census. Standard errors clustered at the region level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

latest censuses, generating differences across one decade for many countries and up to three decades for some countries (e.g., Benin and Botswana). Thus, these changes in temperature and associated responses in labor allocations can be interpreted as medium- to long-term responses. These results, reported in Table 3, are consistent with the main results reported in Table 2. Despite the slight reduction in our sample because of exclusion of census rounds in the middle, the effects of medium- to long-term change in temperature and precipitation are very similar to those reported in Table 2.[14]

4.2 Heterogeneity Analyses

4.2.1 Climate change and gendered structural transformation

The effect of climate change on structural transformation could vary across gender and other underlying characteristics (Jessoe et al., 2018; Sitko et al., 2024; Dinkelman and Ngai, 2022). We hypothesize that climate change could disproportionately affect vulnerable groups such as women and youth, who have fewer job prospects (Afridi et al., 2022; Tennhardt et

[14] We also re-estimate the first-difference model using all available census waves, rather than limiting the analysis to the earliest and latest censuses. As shown in Table A2, the results are essentially unchanged, agricultural employment still rises significantly with temperature, and decreases with precipitation.

al., 2024). In Africa, women typically have fewer off-farm employment options than men (Van den Broeck and Kilic, 2019; Van den Broeck et al., 2023; Dinkelman and Ngai, 2022), making them more likely to engage in agricultural work. To test this hypothesis, we examine the heterogeneous effects of climate change on labor allocations across sectors, disaggregated by gender. Table 4 and Figure A5 show these disaggregated impacts.

Table 4: Impacts of climate change by gender

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Male						
Temperature	0.039***	0.038***	-0.023**	-0.023***	-0.016	-0.015
	(0.014)	(0.013)	(0.009)	(0.009)	(0.012)	(0.011)
Precipitation	-0.029***	-0.015***	0.009***	0.003	0.020***	0.012***
	(0.005)	(0.005)	(0.003)	(0.003)	(0.004)	(0.003)
Panel B: Female						
Temperature	0.087***	0.087***	-0.018**	-0.017**	-0.069***	-0.070***
	(0.019)	(0.017)	(0.008)	(0.008)	(0.017)	(0.015)
Precipitation	-0.045***	-0.028***	0.005	0.006	0.040***	0.022***
	(0.010)	(0.008)	(0.004)	(0.004)	(0.008)	(0.007)
Num.Obs.	1927	1927	1927	1927	1927	1927
Num.Districts	819	819	819	819	819	819
CountryYear FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
p-value {Male=Female}	0.039	0.022	0.697	0.591	0.009	0.003

Notes: This table shows the impact of climate change on the employment shares of men and women in agriculture, manufacturing, and services sectors. Panel A shows the estimates for men, while Panel B shows the estimates for women. All regressions include district and country-by-year fixed effects. The included controls are the total population, the share of male, the share of individuals between 15 and 64 years old and the share of individuals with less than primary education. Standard errors clustered at the district level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The estimates are similar to those in Table 2, except that the dependent variables now represent the share of men's and women's employment in agriculture, manufacturing, and services, instead of overall sectoral employment shares. The results reported in Table 4 show a significantly larger impact of change in temperature on women's agricultural employment compared to men's. A 1°C increase in temperature increases women's agricultural employment by 9 percentage points, compared with 4 percentage points for men. The difference between these effects is statistically significant, as indicated by the pairwise tests reported at the bottom of Table 4. Consistent with our main findings, the share of labor employed in manufacturing and services declined significantly. While a 1°C increase in temperature reduces women's labor in services by about 7 percentage points, the corresponding effect for men is much smaller (about 2 percentage points, which appears to be statistically insignificant). These findings validate our hypotheses: Women are more likely to bear the brunt of climate change and hence changes in medium-term temperature, likely because they have fewer job opportunities outside of the agriculture sector (Jessoe et al., 2018; Afridi et al., 2022; Tennhardt et al., 2024; Sitko et al., 2024).

This implies that climate change may trigger a gendered structural transformation by disproportionally inhibiting reallocation of women's labor from agriculture to nonagricultural sectors. This generates a unique pattern and evolution of structural transformation, compared to those observed in other developed countries such as the United States, where women are more likely to transition from agriculture to services, while men shift from agriculture to manufacturing (Ngai et al., 2024). Given the pervasive productivity gaps between agriculture and nonagricultural sectors in Africa (McMillan et al., 2014; Duarte and Restuccia, 2010; Gollin et al., 2014; Restuccia and Rogerson, 2017), climate change is likely to limit productivity and welfare gains associated with reallocation of labor from agriculture to nonagricultural sectors, especially for women. Ultimately, given that labor income in the agricultural sector is lower than corresponding returns from the nonagriculture sector, climate change is likely to perpetuate underlying inequalities among societies (Herrendorf and Schoellman, 2018; Rossi, 2020).

4.2.2 Heterogeneity by age and educational attainment

The gender-based disparity in structural transformation raises the question of whether other segments of the population also experience heterogeneous effects of climate change. Younger individuals and those with less education may be disproportionately affected by climate change and related shocks (Sitko et al., 2024; Tennhardt et al., 2024). This is particularly expected to be the case in Africa, which has the youngest population in the world. Every year, 12 million young people enter the labor market (African Development Bank, 2016), although African economies are not creating enough jobs to absorb the "youth bulge," leading to high rates of youth unemployment (Filmer and Fox, 2014; Sumberg et al., 2021; Abay et al., 2021). About a third of young people in Africa are unemployed, and another third are vulnerably employed (African Development Bank, 2016), especially the less educated (Herrendorf and Schoellman, 2018). These sources of vulnerability are more likely to delay transition of youth from school to labor markets as well as from agriculture to the more remunerative nonagricultural sectors. For example, while relatively earlier studies suggest that agriculture may not be attractive to African youth, and hence they may leave agriculture (Bezu and Holden, 2014; Sumberg et al., 2017), recent studies show that African youth work nearly as much in agriculture as their older cohorts (Metelerkamp et al., 2019; Abay et al., 2021). Young people appear to face more barriers to employment and transition to nonagricultural activities (Metelerkamp et al., 2019; Abay et al., 2021). Consequently, they seem to have fewer career options compared to older groups. Individuals with fewer job opportunities are more likely to accept lower-paying agricultural jobs in the presence of climate change and associated pressures (Herrendorf and Schoellman, 2018). To probe these hypotheses empirically, we estimate our main empirical specifications by disaggregating our outcome variables across youth and adults.

Table 5 and Figure A6 present the results of the main estimations, split by age. Following the African Union definition, we define youths as those between 15 to 34 years old and compare youth to adults (above age 34). A 1°C increase in temperature leads to 7 percentage points rise in the agricultural employment share of youth. For adults, the effect is slightly smaller, at 5 percentage points. The pairwise comparison and associated p values reported at the bottom of the table indicates that the differences between these estimates are not statistically significant. With regards to the other sectors, Table 5 shows that climate change leads to larger reduction in employment shares in manufacturing among the youths than

Table 5: Impacts of climate change by age

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Youth (15-34)						
Temperature	0.073***	0.073***	-0.032***	-0.032***	-0.041***	-0.041***
	(0.016)	(0.014)	(0.009)	(0.009)	(0.014)	(0.012)
Precipitation	-0.032***	-0.019***	0.007**	0.004	0.025***	0.016***
	(0.006)	(0.006)	(0.003)	(0.003)	(0.005)	(0.005)
Panel B: Adults (above 34)						
Temperature	0.050***	0.049***	-0.014*	-0.014*	-0.036***	-0.036***
	(0.014)	(0.012)	(0.009)	(0.008)	(0.012)	(0.011)
Precipitation	-0.025***	-0.013**	0.007***	0.004*	0.019***	0.009**
	(0.006)	(0.005)	(0.002)	(0.002)	(0.005)	(0.004)
Num.Obs.	1927	1927	1927	1927	1927	1927
Num.Districts	819	819	819	819	819	819
CountryYear FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
p-value {Youth=Adult}	0.271	0.182	0.157	0.125	0.778	0.736

Notes: This table shows the impact of climate change on the employment shares of youths and adults in agriculture, manufacturing, and services sectors. Panel A shows the estimates for youths, while Panel B shows the estimates for adults. All regressions include district and country-by-year fixed effects. The included controls are the total population, the share of male, the share of individuals between 15 and 64 years old and the share of individuals with less than primary education. Standard errors clustered at the district level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

adults (3.2 versus 1.4 percentage points) and the differences in the impacts of climate change across youths and adults are marginally significant. Table A3 shows that the results remain unchanged using an alternate definition of youth as ages 15 to 24 and adults as above age 24.

Likewise, lack of education and skills may hinder the shift from agricultural activities into manufacturing or services (Caselli and Coleman II, 2001; Rossi, 2020; Porzio et al., 2022; Cheung, 2023). Individuals with education beyond the primary level typically have more opportunities than those with lower levels of schooling. Climate change could perpetuate such differences in opportunities and generate further inequality among those with varying levels of education and skill sets (Sitko et al., 2024). Table 6 and Figure A7 compares the impact of decadal change in temperature on labor allocations across sectors for those individuals who have not completed primary education and those with higher levels of education. The results indicate that the effect of climate change is more pronounced among individuals with less than a primary education, with the difference being statistically significant. For example, for those with less than primary education, a 1°C increase in average decadal temperature leads to an 8 percentage points increase in the share of employment in agriculture, which is significantly larger than the 2.2 percentage points increase for those with primary and above education level.

Table 6: Impacts of climate change by education level

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Less than primary						
Temperature	0.077***	0.075***	-0.027***	-0.027***	-0.050***	-0.048***
	(0.015)	(0.015)	(0.009)	(0.009)	(0.015)	(0.015)
Precipitation	-0.020***	-0.016***	0.004	0.003	0.016***	0.013***
	(0.006)	(0.006)	(0.003)	(0.003)	(0.005)	(0.005)
Panel B: Primary and above						
Temperature	0.022	0.022	-0.006	-0.005	-0.016	-0.017
	(0.015)	(0.015)	(0.009)	(0.009)	(0.014)	(0.014)
Precipitation	-0.018**	-0.017**	0.005	0.004	0.013*	0.012*
	(0.008)	(0.008)	(0.005)	(0.005)	(0.007)	(0.007)
Num.Obs.	1927	1927	1927	1927	1927	1927
Num.Districts	819	819	819	819	819	819
CountryYear FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
p-value {Less=Above}	0.01	0.013	0.106	0.098	0.099	0.12

Notes: This table shows the impact of climate change on the employment shares in agriculture, manufacturing, and services sectors by educational status. Panel A shows the estimates for individuals with less than a primary education, while Panel B shows the estimates for individuals with primary and above education. All regressions include district and country-by-year fixed effects. The included controls are the total population, the share of male, and the share of individuals between 15 and 64 years old. Standard errors clustered at the district level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

To sum up, our findings shed new light on potential and varying repercussions of climate change on different segments of the population. These patterns may be more evident in Africa than in other regions. For example, Liu et al. (2023) show that the effects of climate change do not significantly vary by educational attainment in India. In Africa, however, individuals with less education may face unique barriers in their quest to transition from the less-remunerative farming sector to the more attractive nonfarming sector, partly because the latter is either capital- or skill-intensive (Caselli and Coleman II, 2001; Rossi, 2020; Porzio et al., 2022; Cheung, 2023). A higher level of education tends to provide access to a broader range of employment opportunities, often leading to a reduced commitment to farming. To summarize, the results in 6 highlight that the varying impact of climate change based on educational attainment is likely to deepen existing inequalities between individuals with varying levels of educational attainment and skill sets.

5 Possible Mechanisms and Explanations

Building on previous studies, we identify four mechanisms through which rising temperatures can affect structural transformation. First, as previous studies show, an increase in medium-term temperature can reduce labor productivity, and these effects can vary across the agriculture and nonagriculture sectors (Schlenker and Roberts, 2009; Hsiang, 2010; Dell et al., 2012; Schlenker and Lobell, 2010; Knox et al., 2012; Liu et al., 2023). Although detailed and disaggregated empirical evidence on impacts of climate change on labor productivity across various sectors remains missing, LoPalo (2023) show that an increase in temperature reduces labor productivity. Potential disproportional impacts of climate change on labor productivity across sectors can lead to reallocation of labor in ways that can either facilitate or delay structural transformation.

Second, previous studies show that an increase in temperature can reduce agricultural yield and hence farm income (Jones and Thornton, 2003; Lobell et al., 2008; Hertel et al., 2010; Hertel and de Lima, 2020). This can ultimately reduce the attractiveness of the agriculture sector. It can also dampen local demand for goods and services, and hence demand for labor in nonagricultural sectors. Which of these two forces dominate may depend on context, creating an avenue for empirical investigation. Given that most smallholder farmers in Africa engage in subsistence farming, reduction in agricultural yields may also trigger an increase in allocation of labor and non-labor inputs in farming to ensure food security.

Related to the above, climate change and hence an increase in medium-term temperature can also delay structural transformation by altering the cost of mobility and reallocation of labor across sectors. The reduction in farm income or reduction in labor productivity described above can shape the opportunity cost of reallocation of labor across sectors.

Third, climate change may also affect labor force participation rates as well as modality of participation in various economic sectors (Feriga et al., 2025). For example, a medium-term increase in temperature may reduce labor force participation, while income variability associated with climate change may discourage self-employment. Finally, climate change may also affect structural transformation by altering migration and urbanization patterns, especially rural–urban migration (Barrios et al., 2006; Henderson et al., 2017; Peri and Sasahara, 2019). The literature on this relationship remains mixed, with some studies reporting positive implications on rural–urban migration (Mueller et al., 2014; Nawrotzki et al., 2015; Barnett and Adger, 2018) while others report the opposite (Suckall et al., 2017; Henderson et al., 2017; Peri and Sasahara, 2019). Although we lack detailed labor productivity as well as cost of mobility data across various sectors, we test some of these mechanisms and offer suggestive insights.

5.1 Climate change and agricultural productivity

To understand how climate change may delay structural transformation by inhibiting reallocation of labor from agriculture to nonagricultural sectors, we examine the implication of climate change on agricultural productivity (yield) as a possible factor explaining this relationship. Table 7 presents the results from estimating Equation (2) with our proxy (measure) of agricultural yield: the average NDVI value and the sum of the NDVI values in each district. The NDVI data are widely used for monitoring crop growth and biomass as well as for predicting agricultural yield (Burke and Lobell, 2017; Shammi and Meng, 2021; Nakalembe et al., 2021). To capture nonlinearities in agricultural productivity response, we also include the square of monthly temperature and precipitation. The results in Table 7 show that rising medium-term temperature reduces agricultural productivity, as proxied by NDVI. The impacts are consistent across both measures of NDVI, the average or total sum of NDVI in a district.

Table 7: Climate change and vegetation

	NDVI sum					NDVI average				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Temperature	-0.429***		-0.446***	0.004	0.005	-0.451***		-0.472***	0.007	0.010
	(0.165)		(0.172)	(0.023)	(0.024)	(0.170)		(0.178)	(0.023)	(0.024)
Temperature (Squared)	0.009***		0.010***			0.010***		0.010***		
	(0.003)		(0.004)			(0.003)		(0.004)		
Precipitation		-0.018	-0.015		0.002		-0.013	-0.010		0.004
		(0.020)	(0.020)		(0.008)		(0.020)	(0.020)		(0.008)
Precipitation (Squared)		0.001	0.001				0.001	0.001		
		(0.001)	(0.001)				(0.001)	(0.001)		
Num.Obs.	3360	3360	3360	3360	3360	3360	3360	3360	3360	3360
Num.Districts	1404	1404	1404	1404	1404	1404	1404	1404	1404	1404
CountryYear FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the impact of climate change on agricultural productivity proxied using the NDVI sum and average. All regressions include year and district fixed effects. Standard errors clustered at the district level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The negative impact of climate change on agricultural yield is well established in the literature (Schlenker and Roberts, 2009; Schlenker and Lobell, 2010; Knox et al., 2012; Aragón et al., 2021; Liu et al., 2023; Wollburg et al., 2024b; Amare and Balana, 2023). This reduction in agricultural productivity could lead to a reduction in overall farm income, which in turn could dampen local demand for nonagricultural goods and services. This contraction in local demand will likely reduce demand for nonagricultural labor, which implies an increase in the share of labor allocated for the agriculture sector (Liu et al., 2023). Evidence shows that positive rainfall shocks increase agricultural productivity, thereby increasing the share of labor in the nonagricultural sectors, driven by an increase in the demand for nontradables (Emerick, 2018). Our insights here corroborate and align with the empirical insights from Liu et al. (2023).

5.2 Climate change and labor force participation

So far, our findings reveal that climate conditions have a significant effect on agricultural employment, with rising temperatures increasing agriculture's share of total employment. However, these results do not clarify whether higher temperatures lead to reallocation of jobs or rather increase labor force participation. To explore these dynamics, we collate employment data from IPUMS to gauge the broader influence of climate change on labor force participation. Using these data, we construct two binary measures of labor force participation: (1) the share of working-age population employed or actively seeking employment in economic activities, and (2) the share of working-age population working or engaged in economic activities.[15]

There are plausible mechanisms through which climate change could affect overall labor force participation. For example, the decline in agricultural yield under climate change may lead to a decrease in wages, which is prevalent in the agriculture sector (Herrendorf and Schoellman, 2018). As wages fall, individuals may lack the incentive to participate in labor markets. Similarly, climate change may affect health and hence impair productivity and participation in income-generating activities (McMichael et al., 2006; Woodward et al., 2014). That said, the impacts could also go the other way, depending on some contextual realities. For instance, individuals may still be willing to participate in the labor market under climate change as a means to mitigate both productivity and income losses and ascertain food security. Under these conditions, they may engage in the labor markets even while earning poor wages and working in difficult conditions. And for the most part, women who are the most vulnerable to climate change may increase their participation in labor markets in response to the adverse effects of climate change (Sitko et al., 2024). Table 8 presents estimates of the impact of climate change on labor force participation. Panel A shows impacts on overall labor force participation rates, while Panel B shows impacts on

[15] These variables offer broader coverage than the sector-specific variable engagement, thereby increasing our sample (see Table A5).

actual employment and engagement in economic activities, excluding individuals actively seeking employment. Columns 1 and 2 focus on the overall impact of climate change on employment, while Columns 3 through 10 show disaggregated results by age and gender, examining impacts among youth, adults, men, and women. Overall, we find no increase in both labor force participation and employment following higher temperatures.

Table 8: Impacts of climate change on labor force participation and employment

	All		Youth		Adults		Male		Female	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Labor Force Participation										
Temperature	0.006	0.006	0.002	0.002	0.008	0.008	-0.010	-0.010	0.045*	0.045*
	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)	(0.015)	(0.011)	(0.011)	(0.025)	(0.025)
Precipitation	-0.003	-0.003	-0.005	-0.005	-0.001	-0.001	-0.001	-0.001	-0.011	-0.011
	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.009)	(0.009)
Panel B: Employment Rate										
Temperature	0.002	0.002	-0.001	-0.001	0.003	0.003	-0.008	-0.008	0.033	0.033
	(0.013)	(0.013)	(0.014)	(0.014)	(0.013)	(0.013)	(0.009)	(0.009)	(0.024)	(0.024)
Precipitation	-0.003	-0.003	-0.005	-0.005	0.001	0.001	0.001	0.001	-0.012	-0.012
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.009)	(0.009)
Num.Obs.	3431	3431	3431	3431	3431	3431	3431	3431	3431	3431
Num.Districts	1403	1403	1403	1403	1403	1403	1403	1403	1403	1403
CountryYear FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: This table shows the impact of climate change on labor force participation and when disaggregated by age and gender. Panel A shows the impact on labor force participation, while Panel B shows the impact on employment. All regressions include year and district fixed effects. The included control is the total population. Standard errors clustered at the district level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In terms of the age and gender disaggregation, we further obtain some interesting insights that corroborate our previous heterogeneous findings on the impact of climate change on structural transformation. We find that the increase in labor force participation and employment is more prevalent among women. While the impact on the labor force participation of men appears to be very small and statistically insignificant, a 1°C increase in medium-term temperature increases women's labor force participation by 5 percentage points. These patterns suggest that women are more inclined to enter the labor force in response to climate change. This insight on female employment should be viewed in conjunction with our earlier finding of an expanding agricultural workforce. Taken together, the evidence indicates that climate change pushes more women into the labor market, and disproportionately into agriculture. These insights add to the scarce literature on the effects of climate change on labor force participation (Jessoe et al., 2018; Feriga et al., 2025).

5.3 Climate change and self-employment

Although empirical evidence on this topic remains missing (Feriga et al., 2025), theoretically climate change can affect and shape modalities of participation in labor markets, as we note above. After showing a positive impact of climate change on labor force participation, we are interested in understanding whether some of this constitutes self-employment. For example, income risks and earnings variability associated with climate change can increase the vulnerability of the self-employed (Feriga et al., 2025), which in turn can push them out of self-employment. Given that self-employment opportunities and spells vary across sectors, this can shape allocation of labor and hence facilitate or delay structural transformation. To test this empirically, we estimate Equation 2 by focusing on the share of self-employed individuals in each district. We also perform disaggregated estimations by age and gender, looking at the impacts on youths and adults, as well as males and females, respectively. The results reported in Table A6 broadly show negligible impacts of medium-term changes in temperature and precipitation on the probability of self-employment. We also do not find any impacts on the disaggregations by age and gender specifically for youth, adults, and women.

5.4 Climate change, migration, and urbanization

Climate change may also affect labor allocation and structural transformation by shaping rural–urban migration patterns (Barrios et al., 2006; Bohra-Mishra et al., 2014; Henderson et al., 2017; Peri and Sasahara, 2019). However, empirical evidence on the impact of climate change on rural–urban migration remains mixed (Piguet et al., 2011; Feriga et al., 2025; Peri and Sasahara, 2019). While some studies find that an increase in temperature and related weather shocks increases rural–urban migration (Barnett and Adger, 2018; Barrios et al., 2006; Mueller et al., 2014; Bohra-Mishra et al., 2014; Nawrotzki et al., 2015), other studies find the opposite or a heterogeneous effect of climate change (Kubik and Maurel, 2016; Suckall et al., 2017; Henderson et al., 2017; Cattaneo and Peri, 2016; Peri and Sasahara, 2019). Cattaneo and Peri (2016) and Peri and Sasahara (2019) offer more nuanced empirical evidence on the impact of global warming on rural–urban migration: Rising temperatures reduce rural–urban migration in poor countries while increasing it in middle-income countries. A theoretical model linking climate change with a reduction in agricultural yield and liquidity constraints to migration can explain this finding. Following this argument, the reduction in agricultural yield documented above may imply that rising temperature can inhibit rural–urban migration by introducing liquidity constraints to finance migration endeavors. To assess the impact of climate change on rural–urban migration and hence urbanization, we characterize temporal changes in share of urban population as a function of decadal average changes in temperature and precipitation. Table A7 reports these results, which broadly suggest negligible impacts.

6 Robustness and Sensitivity Checks

To probe the robustness of the main results, we present several robustness and sensitivity checks: (1) estimation of alternative econometric specifications, (2) application of different definitions and measurements of climate change, (3) alternative clustering and fixed effects, (4) further insights on nonlinear effects, (5) alternative aggregation of climate variables, (6) subsample analysis, and (7) rural versus urban districts.

6.1 Alternative measurements of climate change

The first robustness check is in relying on alternative measurements of climate change. So far, we have relied on temperature and precipitation changes throughout the year. However, it may be argued that this is not specific to the agricultural sector especially in terms of growing seasons. To address this concern, we relied on temperature and precipitation in the growing season. Table A8 lists the periods of the growing-season for each of the countries included in the study. Table A9 presents the results of the main estimation using the ten-year average of temperature and precipitation in the growing season. The results remain broadly unchanged pointing to the robustness of our main estimates.

6.2 Alternative proxies of climate change

Related to the first check, the second robustness check is in employing alternative measures of climate change. Here, we rely on the Standardized Precipitation-Evapotranspiration Index (SPEI) which is a drought-based indicator that measures deviations of the current climatic water balance (precipitation minus the potential evapotranspiration) from its long-term mean. It ranges between negative to positive values: while the negative values signal drier-than-normal conditions, the positive values denote wetter-than-normal conditions. We use this to estimate how they drive structural transformation. These results are presented in Table A10. Here, we see that a one-standard-deviation increase in SPEI (i.e. a wetter year) reduces the agricultural share of employment by 13–21 percentage points. These results reinforce our previous findings about the impacts of temperature and precipitation changes on employment shares in agriculture, manufacturing and the service sectors.

6.3 Alternative clustering and fixed effects

The third robustness check we conducted entails controlling for different fixed effects and using alternative clustering approaches. Table A11 presents the results using an alternate fixed effects: Instead of relying on $Country \times Year$ fixed effects, columns 1 and 2 present the results with the inclusion of $Year$ and $District$ fixed effects. Columns 3 to 6 present the main results using a different level of clustering: Instead of clustering standard errors at the district level, we cluster them at the region level in columns 3 and 4 and at the country level in columns 5 and 6.[16] The significance levels are not affected by the additional fixed effects and slightly by the difference in the level of clustering.

6.4 Further insights on nonlinear effects

Building on previous evidence on nonlinear effects of temperature and precipitation (Schlenker and Roberts, 2009; Burke and Emerick, 2016; Graff Zivin and Neidell, 2014; Bohra-Mishra et al., 2014; Liu et al., 2023), we also allow nonlinear effects across districts characterized by long-term hot and cold climates. We compute the average monthly long-term temperature for each district from 1900 to 2017 and then classify districts into a hot and less-hot climate using the median long-term temperature. We then allow the effect of medium-term change in temperature to vary across the two climatic zones. This entails estimating Equation 2 by allowing the slope to vary across the two climatic zones. These results are reported in Table A12. The results reported in Table A12 show that the impacts are slightly higher among hot regions.

6.5 Alternative aggregation of climate variables

So far, we have relied on decadal (10 years) changes in temperature and precipitation as our main measures of climate change. Under this robustness check, we probe the robustness of our results by using different aggregations of climate variables. Indeed, we show that our results are robust to alternate period of aggregation of the climate variables. Table A13 shows results by aggregating climate indicators over a number of alternative periods. Panel A presents the results using the measurement of climate variables in the last two years preceding the census. Panels B, C, and D present the results using the average of the previous four, six, and eight years, respectively. These results offer some important insights. The impacts increase when we increase the period of aggregation of climate variables, implying potential

[16] We are cognizant that given the limited number of countries and regions we have in our sample, clustering at country and region level can suffer from small cluster bias (Wooldridge, 2003; Cameron et al., 2008)

differences in the medium- and short-term responses to climate events (Colmer, 2021; Liu et al., 2023). This may be explained by the lack of adaptation in the short term (Deschênes and Greenstone, 2011; Liu et al., 2023; Burke and Emerick, 2016).

6.6 Subsample analysis

To test whether our results are driven by the presence or absence of specific countries in our sample, we estimate our main results by dropping one country at a time. These results are reported in Table A14. The coefficients remain consistent regardless of which country is dropped. Furthermore, we also randomly drop 20 percent of the districts included in our sample and estimate the main equations. We repeat this process 1,000 times and estimate the average coefficients and the number of times in which the p value is above 0.05. Table A15 confirms that our results are robust to this robustness check as well. To probe whether few districts witnessing high or low temperature are driving our results, we further estimate some additional regressions in this regard. Table A16 shows the main estimates by dropping the 10 percent warmest and coldest districts.[17] The coefficients remain broadly consistent.

6.7 Rural versus urban districts

Finally, as discussed in Section 5 the lack of opportunities in other sectors and associated constraints to reallocate labor from agriculture to nonagricultural sector may moderate the effect of climate change on structural transformation. Therefore, the greater number of opportunities in the manufacturing and service sectors in urban areas may still facilitate reallocation of labor even in the presence of climate change. Table A17 compares rural districts (more than 50 percent of individuals living in a rural area) with urban districts (more than 50 percent of individuals living in an urban area). Results indicate that, as expected by our mechanism, the effect is positive and significant for rural districts but not for urban ones.

[17]We classify warmest/coldest districts according to the temperature measured at the baseline period.

7 Conclusion

Despite the consensus that ending poverty in Africa requires structural transformation of rural economies (Barrett et al., 2017; McMillan and Headey, 2014; De Vries et al., 2015; Senbet and Simbanegavi, 2017; Dinkelman and Ngai, 2022), what explains the sluggish progress and transformation of rural economies in Africa remains an active area of inquiry. We investigate the impact of climate change on structural transformation in Africa with a special focus on potential differential impacts across gender and educational attainment. We also examine possible mechanisms and channels through which climate change can delay structural transformation. We rely on several datasets, including rich census data for several African countries from IPUMS, temperature and precipitation data from the Terrestrial Air Temperature and Precipitation Gridded monthly time series, and NOAA's NDVI dataset. We exploit the plausibly exogenous temporal variation in decadal temperature and precipitation and estimate two-way fixed-effects models.

We report three key findings. First, we show that climate change delays structural transformation in Africa. This is evident as we observe significant increases in employment shares in agriculture and the corresponding reduction in the manufacturing and service sectors. We find that a 1°C increase in decadal temperature increases employment in agriculture by about 6 percentage points. Second, we show that women are more affected by climate change, as they face larger delays and constraints to reallocate labor from agriculture to nonagricultural sectors. This is an important finding, suggesting that climate change leads to a delayed gendered structural transformation. This is also the case for less-educated individuals, underscoring the heightened vulnerabilities of those with lower educational attainment to the impacts of climate change. Finally, we show that agricultural productivity as well as an increase in demand for farm labor and hence labor force participation are some of the possible pathways explaining this delayed structural transformation. Climate change leads to reduced yields, which could reduce the demand of tradable goods used in the nonagricultural sectors. It could lead to lower purchasing power, which could dampen labor demand and compel individuals to accept lower-paying agricultural jobs as a fallback option. As we note above, women and less-educated individuals, who usually face greater insecurity in the labor market, are more likely to continue engaging in these low-paying agricultural jobs. We also find suggestive evidence that a medium-term increase in temperature may drive up labor force participation, especially among women.

These findings highlight important insights shaping the sluggish structural transformation process in Africa, which is currently a highly debated but under-researched topic. Many African countries are pushing for industrialization as a pathway to economic development and poverty reduction. We show that climate change is significantly delaying this process of structural transformation. In this regard, investing in various adaptation and mitigation efforts may offset these delays. Because adaptation has been shown to offer the trifecta wins of increasing agricultural productivity (Burke and Emerick, 2016) while also building farm system resilience, investing in various adaptation practices can facilitate structural transformation in Africa. The gendered differences in the impact of climate change imply that climate change could aggravate existing inequities among societies. Women and less-educated individuals are more vulnerable to climate change because they face greater constraints to reallocate labor from the less remunerative agriculture sector to the relatively better paying nonagricultural sectors. This implies that climate change increases the earning ratio between men and women as well as between educated and less-educated people. These findings extend evolving evidence showing that global warming could increase income inequality across countries (Diffenbaugh and Burke, 2019) by demonstrating that climate change can increase inequality even among societies within the same country. This implies that given the disproportional burden of climate change on vulnerable populations such as women and less-educated individuals, investments in effective adaptation and mitigation practices can ensure sustainable and equitable structural transformation.

We end with a discussion of study limitations that future research could address. Although the census data we utilized provide valuable insights into structural transformation, they also come with certain limitations; for instance, the number of censuses available for each country remains limited. We excluded some countries because they had only one census, making them difficult to use for our analysis. Second, the amount of information available in the survey limits our ability to identify and test additional mechanisms. For example, we lack information related to migration spells, including inter-district migration, which could be endogenous to change in temperature and precipitation. Finally, we lack information on adaptation practices and therefore are not able to infer about their role in facilitating structural transformation.

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Supplementary Information

Tables

Table A1: Database description

Country	Periods	Observations
Benin	1979, 1992, 2002, 2013	291
Botswana	1981, 1991, 2001, 2011	84
Côte D'Ivoire	1988, 1998	100
Ghana	2000, 2010	200
Liberia	1974, 2008	10
Malawi	1998, 2008	350
Mali	1987, 1998, 2009	141
Mozambique	1997, 2007	284
Senegal	1988, 2013	54
South Africa	2001, 2007	34
Tanzania	2002, 2012	214
Zambia	1990, 2000, 2010	165
Total		1927

Notes: This table presents the countries, periods and number of observations in the main sample.

Table A2: Difference specification - Consecutive census periods

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Temperature	0.111***	0.108***	-0.003	-0.004	-0.108***	-0.104***
	(0.020)	(0.020)	(0.010)	(0.010)	(0.021)	(0.020)
Δ Precipitation	-0.015**	-0.005	0.007**	0.003	0.008	0.002
	(0.007)	(0.006)	(0.003)	(0.003)	(0.006)	(0.005)
Num.Obs.	1108	1108	1108	1108	1108	1108
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes

Notes: The dependent variables correspond to the difference in the share of individuals employed in agriculture, manufacturing, and services sectors between two consecutive census periods. All regressions include district and country-by-year fixed effects. The included controls are the difference in the total population, the share of male, the share of individuals between 15 and 64 years old and the share of individuals with less than primary education between the earliest and latest census. Standard errors clustered at the region level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Impacts of climate change by age - Alternative definition

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Youth (15-24)						
Temperature	0.080***	0.080***	-0.029***	-0.029***	-0.051***	-0.051***
	(0.018)	(0.016)	(0.010)	(0.009)	(0.018)	(0.016)
Precipitation	-0.033***	-0.021***	0.009**	0.004	0.024***	0.017***
	(0.007)	(0.006)	(0.003)	(0.003)	(0.006)	(0.005)
Panel B: Adults (above 24)						
Temperature	0.059***	0.058***	-0.024***	-0.023***	-0.035***	-0.035***
	(0.014)	(0.012)	(0.008)	(0.007)	(0.011)	(0.011)
Precipitation	-0.027***	-0.015***	0.007***	0.004	0.021***	0.011**
	(0.006)	(0.005)	(0.003)	(0.003)	(0.005)	(0.005)
Num.Obs.	1927	1927	1927	1927	1927	1927
Num.Districts	819	819	819	819	819	819
CountryYear FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
p-value {Youth=Adult}	0.332	0.26	0.644	0.602	0.442	0.407

Notes: This table shows the impact of climate change on the employment shares of youths and adults in agriculture, manufacturing, and services sectors. Panel A shows the estimates for youths, while Panel B shows the estimates for adults. All regressions include district and country-by-year fixed effects. The included controls are the total population, the share of male, the share of individuals between 15 and 64 years old and the share of individuals with less than primary education. Standard errors clustered at the district level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Effect of climates on agricultural inputs and arable land.

	Fertilizers per hectare	Insecticide	Pesticide	Arable land (% of land)
	(1)	(2)	(3)	(4)
Temperature	-0.001***	0.543***	0.034***	0.001***
	(0.000)	(0.125)	(0.008)	(0.000)
Precipitation	0.002***	-1.587***	-0.098***	-0.003***
	(0.000)	(0.210)	(0.013)	(0.000)
Num.Obs.	1927	1491	1491	1927
Num.Districts	819	712	712	819
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes

Notes: This table shows the impact of climate change on inputs use and arable land. All regressions include district and country-by-year fixed effects. Standard errors clustered at the district level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Database description - Labor Force Participation

Country	**Periods**	**Observations**
Benin	1979, 1992, 2002, 2013	291
Botswana	1991, 2001, 2011	63
Burkina Faso	1996, 2006	90
Cameroon	1976, 1987, 2005	117
Côte D'Ivoire	1988, 1998	100
Ghana	2000, 2010	200
Guinea	1996, 2014	410
Kenya	1989, 1999, 2009	105
Lesotho	1996, 2006	20
Malawi	1998, 2008	350
Mali	1987, 1998, 2009	141
Mozambique	1997, 2007	284
Senegal	1988, 2002, 2013	81
Sierra Leone	2004, 2015	230
South Africa	2001, 2007, 2011	51
Tanzania	1988, 2002, 2012	329
Uganda	1991, 2002, 2014	404
Zambia	1990, 2000, 2010	165
Total		3431

Notes: This table presents the countries, periods and number of observations in the employment sample.

Table A6: Effect of climate on self-employment

	All		Youth		Adults		Male		Female	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Temperature	0.003	0.003	0.009	0.009	-0.014	-0.013	0.004	0.004	0.003	0.003
	(0.008)	(0.008)	(0.015)	(0.015)	(0.015)	(0.015)	(0.008)	(0.008)	(0.011)	(0.011)
Precipitation	-0.011***	-0.011***	-0.020***	-0.020***	-0.018***	-0.018***	-0.010***	-0.010***	-0.014***	-0.014***
	(0.003)	(0.003)	(0.006)	(0.006)	(0.005)	(0.005)	(0.002)	(0.002)	(0.004)	(0.004)
Num.Obs.	2805	2805	2805	2805	2805	2805	2805	2805	2805	2805
Num.Districts	1116	1116	1116	1116	1116	1116	1116	1116	1116	1116
CountryYear FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: This table shows the impact of climate change on self-employment and when disaggregated by age and gender. All regressions include district and country-by-year fixed effects. The included control is the total population. Standard errors clustered at the district level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Effect of climate on urbanization

	Share of population in urban area	
	(1)	(2)
Temperature	-0.009	-0.001
	(0.013)	(0.013)
Precipitation	-0.007	-0.004
	(0.005)	(0.004)
Num.Obs.	2887	2887
Num.Districts	1289	1289
CountryYear FE	Yes	Yes
District FE	Yes	Yes
Controls	No	Yes

Notes: This table shows the impact of climate change on the share of population living in urban area. All regressions include district and country-by-year fixed effects. The included controls are the total population, the share of male, the share of individuals between 15 and 64 years old and the share of individuals with less than primary education. Standard errors clustered at the district level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Growing season of each country

Country	Growing season
Benin	April – September
Botswana	November – June
Côte D'Ivoire	March – December
Ghana	March – December
Liberia	February – December
Malawi	November – July
Mali	June – November
Mozambique	November – July
Senegal	June – November
South Africa	December – July
Tanzania	November – June
Zambia	October – June

Notes: This table presents the starting and ending month of the growing season for each country of the main sample. The starting and ending month are estimated using the Anomaly Hotspots of Agricultural Production (ASAP) of the Joint Research Centre of the European Commission for food security crisis prevention and response planning anticipation.

Table A9: Effect of climate on employment sectors - Seasonal periods

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature	0.051***	0.060***	-0.025***	-0.026***	-0.026**	-0.034***
	(0.013)	(0.012)	(0.008)	(0.007)	(0.011)	(0.011)
Precipitation	-0.021***	-0.012***	0.004**	0.002	0.017***	0.010***
	(0.004)	(0.004)	(0.002)	(0.002)	(0.004)	(0.003)
Num.Obs.	1927	1927	1927	1927	1927	1927
Num.Districts	819	819	819	819	819	819
CountryYear FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes

Notes: The dependent variables correspond to the share of individuals employed in agriculture, manufacturing, and services sectors. The climate variables correspond to the ten-year average of the growing season for each country. All regressions include district and country-by-year fixed effects. The included controls are the total population, the share of male, the share of individuals between 15 and 64 years old and the share of individuals with less than primary education. Standard errors clustered at the district level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Effect of Standardised Precipitation-Evapotranspiration Index on employment sectors

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
SPEI	-0.208***	-0.133***	0.074***	0.061***	0.134***	0.072***
	(0.024)	(0.024)	(0.011)	(0.012)	(0.018)	(0.018)
Num.Obs.	1927	1927	1927	1927	1927	1927
Num.Districts	819	819	819	819	819	819
CountryYear FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes

Notes: The dependent variables correspond to the share of individuals employed in agriculture, manufacturing, and services sectors. All regressions include district and country-by-year fixed effects. The included controls are the total population, the share of male, the share of individuals between 15 and 64 years old and the share of individuals with less than primary education. Standard errors clustered at the district level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A11: Alternatives fixed effect and level of clustering

	Fixed effects		Cluster			
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature	0.055***	0.056***	0.064***	0.063***	0.064*	0.063***
	(0.014)	(0.012)	(0.020)	(0.017)	(0.029)	(0.020)
Precipitation	-0.022***	-0.010*	-0.029***	-0.016**	-0.029**	-0.016
	(0.006)	(0.005)	(0.008)	(0.007)	(0.012)	(0.010)
Num.Obs.	1927	1927	1927	1927	1927	1927
Num.Districts	819	819	819	819	819	819
Year FE	Yes	Yes	No	No	No	No
District FE	Yes	Yes	Yes	Yes	Yes	Yes
CountryYear FE	No	No	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes

Notes: The dependent variables correspond to the share of individuals employed in agriculture, manufacturing, and services sectors. All regressions include districts fixed effects. Regressions 1-2 include country fixed effects. Regressions 3-6 include CountryYear fixed effects. The included controls are the total population, the share of male, the share of individuals between 15 and 64 years old and the share of individuals with less than primary education. Standard errors, shown in parentheses, are clustered at district level in columns 1 and 2, at region level in columns 3 and 4, and at country level in columns 5 and 6. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A12: Heterogeneous effect by temperature

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature X Less Hot	0.041***	0.048***	-0.024***	-0.026***	-0.016	-0.023*
	(0.013)	(0.012)	(0.008)	(0.007)	(0.012)	(0.012)
Temperature X Hot	0.169***	0.128***	-0.038***	-0.029**	-0.130***	-0.099***
	(0.025)	(0.022)	(0.011)	(0.012)	(0.020)	(0.017)
Num.Obs.	1927	1927	1927	1927	1927	1927
Num.Districts	819	819	819	819	819	819
CountryYear FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes

Notes: The dependent variables correspond to the share of individuals employed in agriculture, manufacturing, services, as well as in the nonagricultural sectors. All regressions include district and country-by-year fixed effects. The included controls are the total population, the share of male, the share of individuals between 15 and 64 years old and the share of individuals with less than primary education. Standard errors clustered at the district level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A13: Alternative climatic periods

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Two-year average						
Temperature	0.030***	0.024**	-0.007	-0.005	-0.023***	-0.019**
	(0.011)	(0.010)	(0.006)	(0.006)	(0.009)	(0.008)
Precipitation	-0.011***	-0.004	0.003*	0.001	0.009***	0.003
	(0.003)	(0.003)	(0.001)	(0.001)	(0.003)	(0.002)
Panel B: Four-year average						
Temperature	0.027**	0.026***	-0.010	-0.009	-0.017*	-0.016**
	(0.011)	(0.010)	(0.007)	(0.007)	(0.009)	(0.008)
Precipitation	-0.023***	-0.018***	0.005***	0.004**	0.018***	0.014***
	(0.004)	(0.004)	(0.002)	(0.002)	(0.004)	(0.003)
Panel C: Six-year average						
Temperature	0.036***	0.034***	-0.015***	-0.015**	-0.021**	-0.020***
	(0.010)	(0.010)	(0.006)	(0.006)	(0.008)	(0.008)
Precipitation	-0.021***	-0.016***	0.007***	0.006**	0.014***	0.010**
	(0.005)	(0.005)	(0.002)	(0.002)	(0.004)	(0.004)
Panel D: Eight-year average						
Temperature	0.046***	0.045***	-0.020***	-0.019***	-0.026***	-0.026***
	(0.012)	(0.011)	(0.007)	(0.006)	(0.010)	(0.009)
Precipitation	-0.024***	-0.015***	0.008***	0.006**	0.016***	0.009**
	(0.005)	(0.005)	(0.003)	(0.003)	(0.005)	(0.004)
Controls	No	Yes	No	Yes	No	Yes

Notes: The dependent variables correspond to the share of individuals employed in agriculture, manufacturing, and services sectors. All regressions include district and country-by-year fixed effects. The included controls are the total population, the share of male, the share of individuals between 15 and 64 years old and the share of individuals with less than primary education. Standard errors clustered at the district level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A14: Excluding countries one by one

	Benin	Botswana	Ivoire	Ghana	Liberia	Malawi	Mali	Mozambique	Senegal	South Africa	Tanzania	Zambia
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Temperature	0.040***	0.077***	0.062***	0.058***	0.063***	0.055***	0.069***	0.071***	0.063***	0.065***	0.074***	0.070***
	(0.013)	(0.017)	(0.014)	(0.015)	(0.014)	(0.015)	(0.014)	(0.018)	(0.014)	(0.014)	(0.015)	(0.015)
Precipitation	-0.016***	-0.029***	-0.033***	-0.031***	-0.030***	-0.029***	-0.026***	-0.036***	-0.029***	-0.029***	-0.025***	-0.032***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
Num.Obs.	1636	1843	1827	1727	1917	1577	1786	1643	1873	1893	1713	1762
Num.Districts	746	798	769	719	814	644	772	677	792	802	712	764
CountryYear FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variables correspond to the share of individuals employed in agriculture, manufacturing, and services sectors. The dropped country is indicated at the top of each estimate. All regressions include district and country-by-year fixed effects. The included controls are the total population, the share of male, the share of individuals between 15 and 64 years old and the share of individuals with less than primary education. Standard errors clustered at the district level are shown in parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A15: Randomized drop of the sample

Estimate	**Coefficient**	**P-value**	**Observations**	**Significant**
Agriculture	0.0640655	0.0002417	1531.655	100.0
Agriculture (Controls)	0.0630307	0.0000555	1531.708	100.0
Industry	-0.0250841	0.0091867	1531.236	97.7
Industry (Controls)	-0.0247169	0.0067797	1531.919	98.7
Services	-0.0391123	0.0094459	1531.636	98.1
Services (Controls)	-0.0383268	0.0055089	1531.535	99.0

Notes: This Table presents the results of 1,000 estimations with random drop of 20% of the districts. Column 1 presents the average coefficients, Column 2, the average p-value, Columns 3, the average number of observations. Column 4, present the percentage of significant results at 0.95. All estimates include year, and districts fixed effects. Standard errors are clustered at the district level.

Table A16: Drop top/bottom 10%

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Drop warmest 10%						
Temperature	0.054***	0.053***	-0.022***	-0.021***	-0.032**	-0.032***
	(0.014)	(0.012)	(0.008)	(0.007)	(0.013)	(0.012)
Precipitation	-0.022***	-0.010*	0.004	0.000	0.018***	0.010**
	(0.006)	(0.006)	(0.003)	(0.003)	(0.005)	(0.005)
Num.Obs.	1732	1732	1732	1732	1732	1732
Num.Districts	746	746	746	746	746	746
Panel B: Drop coldest 10%						
Temperature	0.070***	0.067***	-0.028***	-0.027***	-0.041***	-0.039***
	(0.015)	(0.013)	(0.008)	(0.008)	(0.014)	(0.012)
Precipitation	-0.029***	-0.016***	0.005*	0.002	0.024***	0.014***
	(0.006)	(0.006)	(0.003)	(0.003)	(0.005)	(0.005)
Num.Obs.	1733	1733	1733	1733	1733	1733
Num.Districts	734	734	734	734	734	734
CountryYear FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
p-value {Warmest=Coldest}	0.46	0.452	0.575	0.564	0.634	0.675

Notes: This table shows the impact of climate change on the employment shares in agriculture, manufacturing, and services sectors. Panel A shows the estimates without the warmest 10% districts, while Panel B shows the estimates without the coldest 10% districts. All columns include year, and districts fixed effects. The included controls are the total population, the share of male, the share of individuals between 15 and 64 years old and the share of individuals with less than primary education. Standard errors clustered at the district level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A17: Rural/Urban

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Rural 50%						
Temperature	0.072***	0.053***	-0.027***	-0.021***	-0.045***	-0.032***
	(0.016)	(0.015)	(0.007)	(0.007)	(0.012)	(0.011)
Precipitation	-0.032***	-0.022***	0.004*	0.001	0.027***	0.021***
	(0.006)	(0.006)	(0.003)	(0.003)	(0.005)	(0.005)
Num.Obs.	1318	1318	1318	1318	1318	1318
Num.Districts	626	626	626	626	626	626
Panel B: Urban 50%						
Temperature	0.043	0.038	0.005	0.008	-0.048	-0.046
	(0.043)	(0.043)	(0.022)	(0.022)	(0.031)	(0.032)
Precipitation	-0.006	0.001	0.001	0.000	0.005	-0.001
	(0.014)	(0.015)	(0.008)	(0.008)	(0.011)	(0.012)
Num.Obs.	197	197	197	197	197	197
Num.Districts	95	95	95	95	95	95
CountryYear FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
p-value {Rural=Urban}	0.533	0.751	0.166	0.212	0.914	0.674

Notes: This table shows the impact of climate change on the employment shares in agriculture, manufacturing, and services sectors. Panel A shows the estimates for rural districts, while Panel B shows the estimates for urban districts. All columns include year, and districts fixed effects. The included controls are the total population, the share of male, the share of individuals between 15 and 64 years old and the share of individuals with less than primary education. Standard errors clustered at the district level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figures

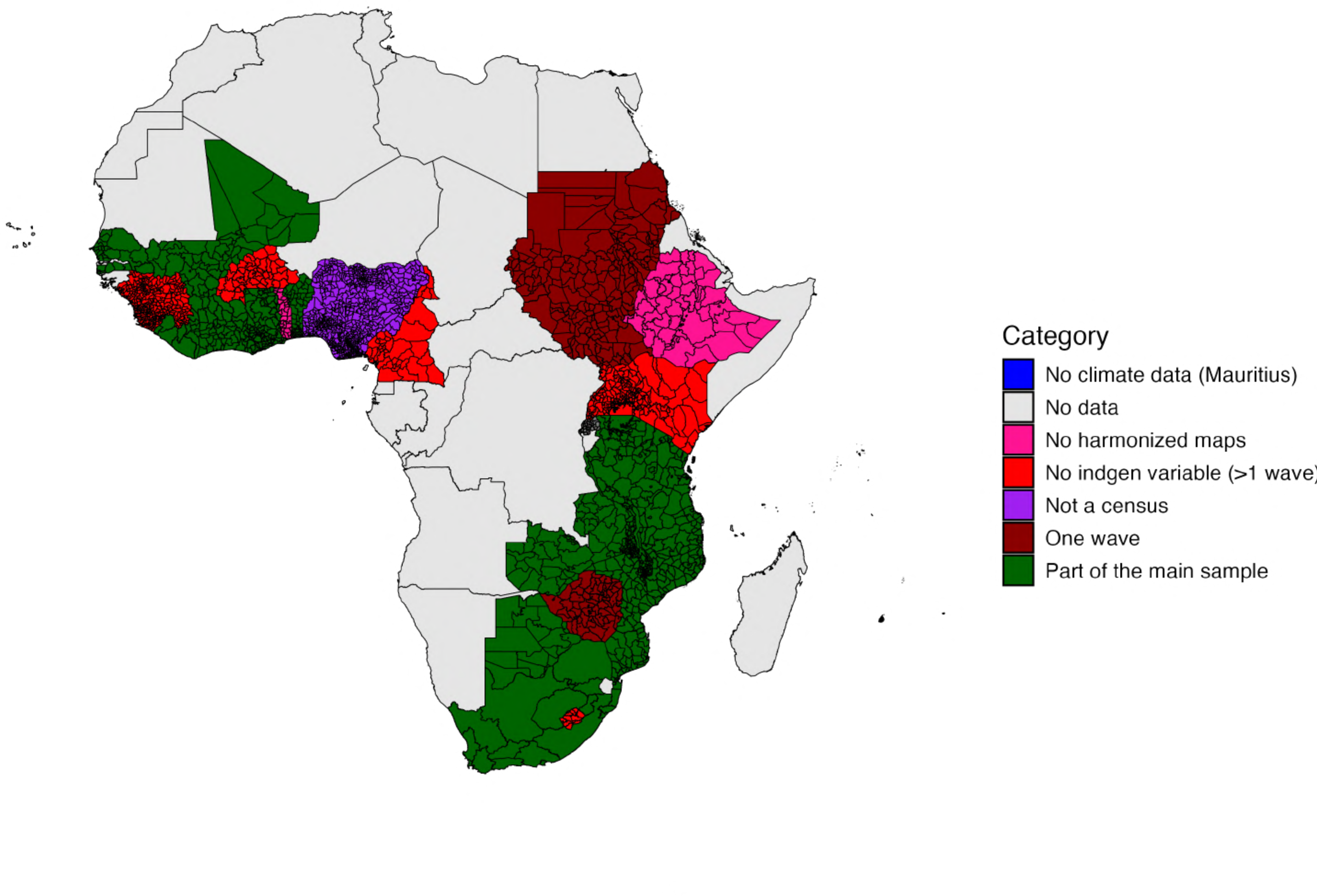

Figure A1: Database construction
Note: This map illustrates the inclusion/exclusion of IPUMS countries in the main sample.

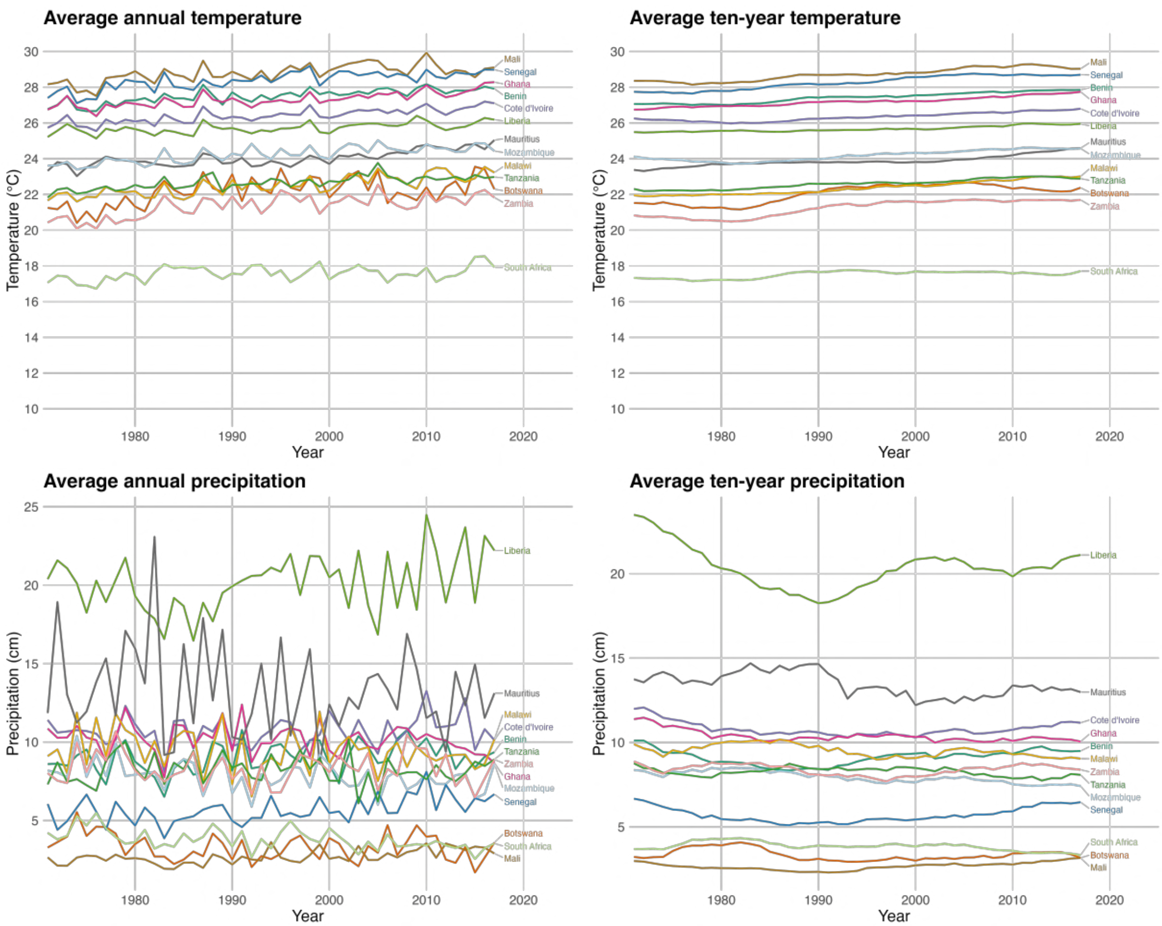

Figure A2: Visualization of countries' climate

Note: These figures provide a graphical representation of the temperature and precipitation of each country included in the main analysis.

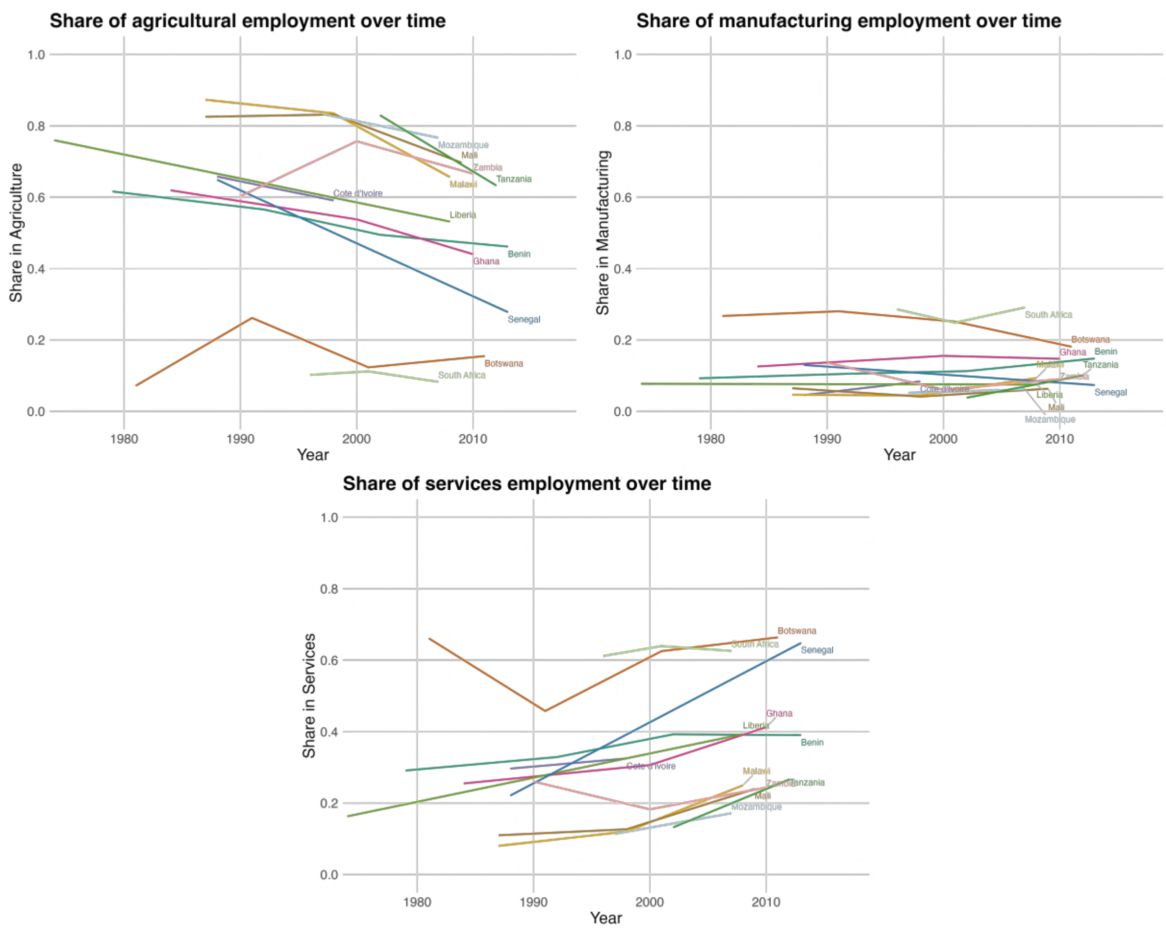

Figure A3: Visualization of countries' sectoral share

Note: These figures provide a graphical representation of each country's agricultural, manufacturing and services employment shares included in the main analysis.

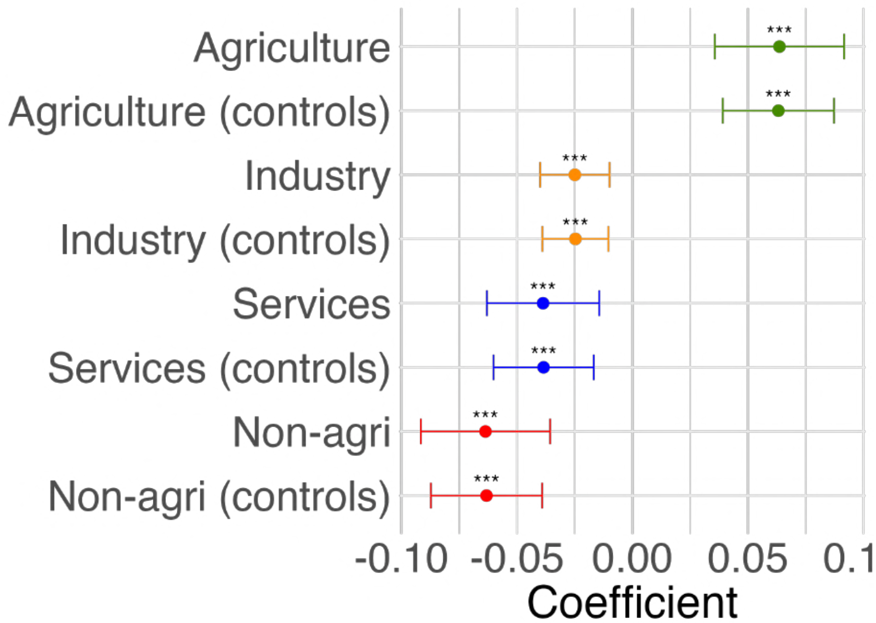

Figure A4: Visualization of Table 2 coefficients.
Note: This figure provides a graphical representation of the results presented in Table 2, with a 95 percent confidence interval.

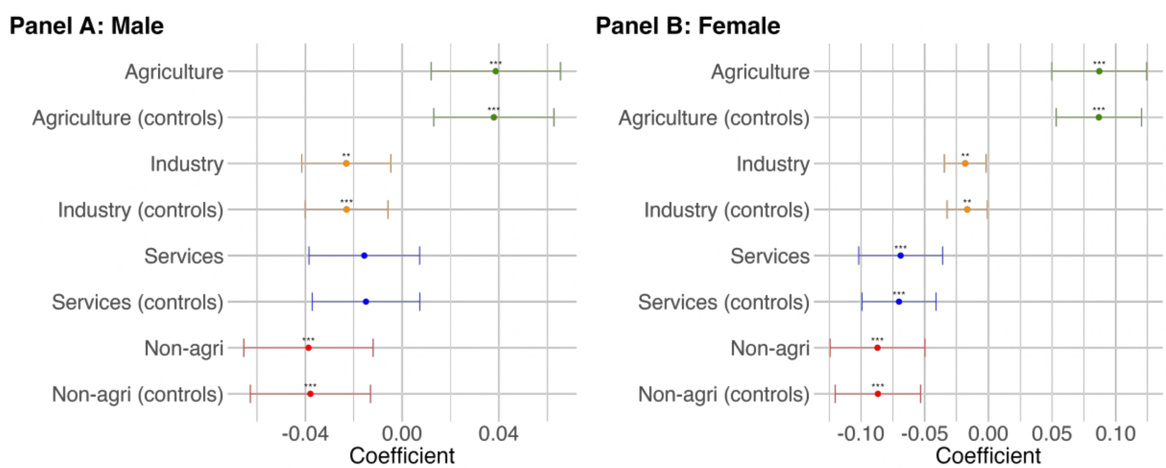

Figure A5: Visualization of Table 4 coefficients.
Note: This figure provides a graphical representation of the results presented in Table 4, with a 95 percent confidence interval.

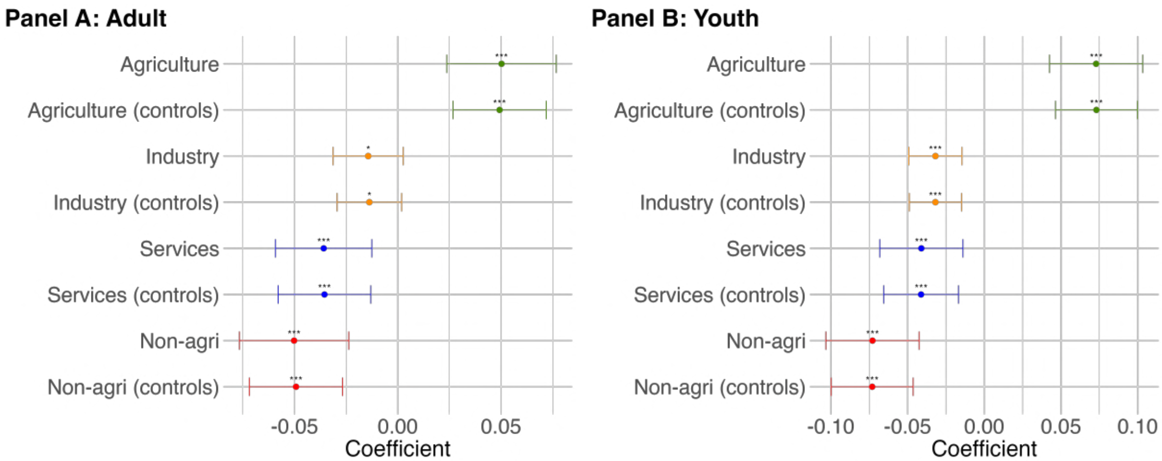

Figure A6: Visualization of Table 5 coefficients.
Note: This figure provides a graphical representation of the results presented in Table 5, with a 95 percent confidence interval.

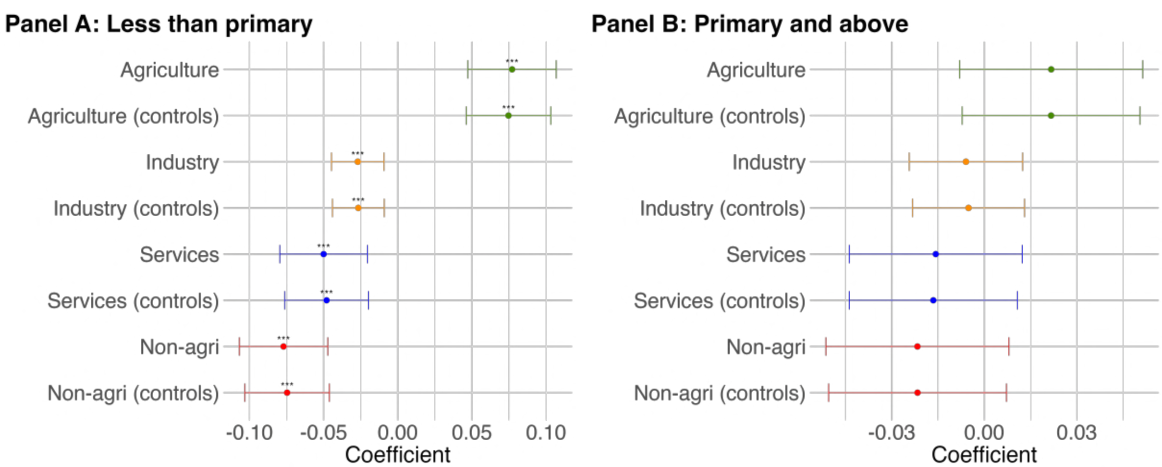

Figure A7: Visualization of Table 6 coefficients.
Note: This figure provides a graphical representation of the results presented in Table 6, with a 95 percent confidence interval.