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Global food prices, local weather and migration in Sub-Saharan Africa*

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ABSTRACT

In this paper, we study the effect of exogenous global crop price changes on migration from agricultural and non-agricultural households in Sub-Saharan Africa. We show that, similar to the effect of positive local weather shocks, the effect of a locally-relevant global crop price increase on household out-migration depends on the initial household wealth. Higher international producer prices relax the budget constraint of poor agricultural households and facilitate migration. The order of magnitude of a standardized price effect is approx. one third of the standardized effect of a local weather shock. Unlike positive weather shocks, which mostly facilitate internal rural-urban migration, positive income shocks through rising producer prices only increase migration to neighboring African countries, likely due to the simultaneous decrease in real income in nearby urban areas. Finally, we show that while higher producer prices induce conflict, conflict does not play a role for the household decision to send a member as a labor migrant.

Keywords: labour migration, food prices, climate, Africa
JEL Codes: O15, O55, Q56, Q54

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1 Introduction

Variability in global food prices has increased significantly over the past two decades, with the annual standard deviation around the decade mean of the FAO food price index tripling in the 2000s compared to the 1990s and remaining high until today. This phenomenon became highly visible during the global food crisis of 2007/08, when international prices of most commodities, including staple grains, increased to an all time high [Minot, 2010, von Braun, 2008]. The crisis was importantly driven by a decrease in agricultural production in Australia, the United States, Russia, and Ukraine, resulting from adverse climatic shocks [Headey and Fan, 2008].[1] Overall, variability in global climate has been responsible for approximately 32 to 39% of global crop yield variation between 1979 and 2008, with significant effects on international food prices [Ray et al., 2015].

At the same time, climate-induced fluctuations in income have been shown to significantly impact the decision to move in developing countries, where a large share of households is dependent on agricultural production. In this context, the aggregate impact of short-term income shocks on the migration decision is determined through an interplay of two opposing forces: Households' ability to bear the up-front costs of migration on the one hand, and the opportunity costs of migration that increase with rising income levels on the other [Clemens, 2014, Cattaneo and Peri, 2016]. To study and disentangle this phenomenon, empirical studies typically exploit exogenous income variation induced by local weather conditions [Cattaneo and Peri, 2016, McKenzie and Rapoport, 2007, Hirvonen, 2016]. This focus on implications of geographically localized shocks extends to the climate migration literature, which is primarily concerned with the effect of climatic events on areas where biophysical impacts occur [Hoffmann et al., 2020, Sedova et al., 2021]. With the notable exception of Bazzi [2017], who analyzes migration implications of domestic rice price changes due to an import ban in Indonesia, the impact of global price fluctuations on migration in developing countries has thus far received almost no attention in the literature.

This paper therefore sets in with two main objectives. First, it provides a full picture of climatic effects on human migration in Sub-Saharan Africa during the decade of the global food price crisis, by i) studying the implications of exogenous global food price changes on the probability of households sending one of their members as a migrant, the pre-dominant type of migration in Sub-Saharan Africa, and ii) complementing the analysis by comparing the effects of global prices to those of local weather conditions. Second, it sheds light on heterogeneous

[1]The 2007/08 food price crisis was driven by a combination of various factors, including climate-related decrease in agricultural productivity, a lack of transparency in markets, rising costs of oil, biofuel demand, depreciation of the U.S. dollar and export restrictions on agricultural goods [Headey and Fan, 2008, von Braun, 2008].

effects of these climate-related factors on the migration decision along the household wealth distribution, arguing that both global crop prices and the quantity of agricultural produce importantly determine household incomes. Finally, the study also examines whether local conflict could have been a concurring mechanism at play, potentially explaining the price-migration association.[2]

Our focus is on Sub-Saharan Africa for two main reasons. First, the region is a net importer of food and agricultural commodities and a significant share of households are net consumers of staple crops [Minot, 2010, Berazneva and Lee, 2013]. Second, countries in Sub-Saharan Africa are characterized by low average incomes and agricultural products represent a high average share of household production and consumption compared to other regions [McGuirk and Burke, 2020]. Thus, changes in agricultural prices significantly affect real income of both crop producing and crop consuming households.[3]

For the analysis, we build a household panel dataset for Burkina Faso, Kenya, Nigeria, Uganda and Senegal by combining several data sources. We draw on the World Bank's African Migration and Remittances Surveys (AMRS) and use retrospectively reported data on internal and international migration at the household level to construct our dependent variable. We proxy local crop prices by constructing a producer price index (PPI) at the district-year level, our main variable of interest by following the methodology of McGuirk and Burke [2020]. The PPI combines high-resolution, time-invariant spatial data on crop-specific agricultural land cover from 2000 with annual international commodity price data over the subsequent years. We then complement these with daily temperature data and monthly precipitation averages using ERA5 weather reanalysis data to calculate local degree days and average precipitation during the growing season at the district level, following Schlenker et al. [2007]. Finally, to explore a possible mediating role of conflict, we draw on the Uppsala Conflict Data Program's geo-referenced conflict event dataset and the Armed Conflict Location and Event Data Project database.

We derive our main empirical specification from a simple theoretical framework where utility maximizing households are budget constrained. Our empirical analysis then incorporates household and year fixed effects such that our coefficients of interest capture the effect of global price and local weather deviations from their location specific long-term mean over time, thus allowing us to compare a given household under different global price and/or local

[2]Both global food price changes [Bellemare, 2015, McGuirk and Burke, 2020, De Winne and Peersman, 2019] and local weather [Abel et al., 2019, Hsiang et al., 2013] may cause political instability and violent conflict, which may in turn constitute a mediating factor of climate-related migration [Cattaneo et al., 2019].

[3]Strong evidence suggests that steadily rising global food prices over the past decades particularly affect the welfare of poor households that spend a large share of their income on food. [Valin et al., 2014, Hallegatte and Rozenberg, 2017, Ivanic et al., 2012].

weather regimes. Four reasons allow for a plausibly causal interpretation of the coefficients on global food prices in this particular setting: First, to isolate the effect of global crop prices from local weather conditions, we focus on the observation period from 2000 to 2008. This time span covers the global food price crisis 2007/08, when global food prices rose sharply for reasons entirely exogenous to agricultural activity in Sub-Sahara African [Berazneva and Lee, 2013, Demeke et al., 2009, Dorward, 2012]. Second, between 1989-2013, the entire continent of Africa accounted for only 5.9% of global cereal production, minimizing its effect on global prices [McGuirk and Burke, 2020]. Third, to ensure that out-migration and global food prices are not simultaneously determined by variation in third factors such as time-varying oil prices or global economic activity, we incorporate time fixed effects into our analyses. Finally, we show in all our analyses that the effect of global prices on our outcomes are not sensitive to conditioning estimates on the local quantity produced, proxied by local weather conditions.

Our findings complement the existing literature in a number of ways. First, by simultaneously analyzing implications of local and distant effects of climatic events, we depart from the existing climate migration research that has thus-far primarily focused on locally occurring climatic impacts as potential drivers of migration [Millock, 2015, Hoffmann et al., 2020, Sedova et al., 2021]. We show that an increase in locally-relevant global crop prices by one standard deviation increases household out-migration at 37% of the net effect of a comparable local weather shock. Global prices thus constitute an important driver of household out-migration, implying that the link between short-term variation in climate and labour migration from agricultural households has thus-far been underestimated. Second, we contribute to the recent efforts to better understand the contextual effects, i.e. when and how climate migration emerges [Cattaneo et al., 2019]. We show that implications of both global and local shocks for migration similarly depend on the initial household wealth, i.e. positive income shocks from higher international food prices and local weather help to relax the budget constraint of poor agricultural households and facilitate migration. Finally, we contribute to the literature on the link between climate, migration and conflict. It has been shown that, while climate-related migration can lead to conflict, climate-related conflict can also trigger migration [Ash and Obradovich, 2020, Abel et al., 2019, Missirian and Schlenker, 2017]. In this study, we add to this literature by considering the implications of conflict induced by global crop price fluctuations on household out-migration. We find that, while crop prices are indeed associated with conflict, conflict does not play a role for the household decision to send a member as a labor migrant.

The remainder of this paper proceeds as follows. The next section presents the theoretical framework. In section 3, we provide an overview of the data and discuss our constructed variables in detail. In section 4, we lay out our empirical strategy. Our findings are presented in section 5. In section 6, we extend the analysis to considering conflict as a potential driver of climate migration. The last section provides a discussion and concluding remarks.

2 Theoretical framework and research hypotheses

As discussed in the above, the picture that emerges from the literature on the relation between variation in global food prices and household out-migration in developing countries is mixed and context specific. The framework that guides our thinking on the interdependence of global crop prices, local growing conditions and the household migration decision closely follows Dustmann and Okatenko [2014] and incorporates insights from Bazzi [2017] and Marchal and Naiditch [2020]. We use this parsimonious framework to build the intuition that a) the effect of global food prices on household out-migration is a priori ambiguous on aggregate due to its differential effects along the household wealth distribution and b) can be expected to differ between agricultural and non-agricultural households.

2.1 General framework

In the simple framework we suggest in the following, households themselves are immobile and all decisions they make relate to sending one of their household members as a migrant. Similar to Dustmann and Okatenko [2014], we formalise this household decision as a comparison of utility flows in the current location compared to potential destinations. We use subscripts $l = h$ (home) and $l = d$ (destination) for all variables relating to location choices l of the potential migrant. The subscripts $y = a$ (agricultural household) and $y = n$ (non-agricultural households) describe the type of household y. The flow of utility in location l for household type y is then given by:

$$U_{hly} = INC_{hy}(p_{hy}, q_{hy}) + inc_{ly}(p_{ly}, q_{ly}) + \epsilon_{ly}, \tag{1}$$

where INC denotes the household real income generated by all non-migrant household members and inc denotes the real income generated by the potential migrant. ϵ_{ly} denotes a random variable capturing all non-income utility components. Both INC and inc are a function of the price of locally grown crops, p_l, and the local quantity produced, q_l. Both p_l and q_l are exogenously determined. For p_l, this is due to short-term fluctuations in world market prices. For q_l, it is due to unpredictable fluctuations in local growing conditions. In addition, we assume

$$corr(q_h, p_h) = 0. \tag{2}$$

Thus, we rule out feedback loops between the local quantity produced at home and the exogenously determined global prices, an assumption we will discuss further in section 4. The second term of $inc_{ly}(p_{ly}, q_{ly})$ is a simplification: The income generated by the potential migrant is a future (expected) income flow; however, since no information on the future is available, households maximise their utility based on contemporarily observed income flows in all destinations d, which they assume to be accurate measures of what the potential migrant would earn in the future.

Migration is costly and when households make the decision to send a migrant, households are budget constrained by their initial household wealth. Assuming that households face borrowing constraints we can write this budget constraint as:

$$W_x + INC_{hy}(p_{hy}, q_{hy}) + inc_{hy}(p_{hy}, q_{hy}) \geq C_d, \tag{3}$$

where C_d is the location specific migration cost and W_x is the initial, idiosyncratic wealth of household x. $INC_{hy}(p_{hy}, q_{hy})$ is the income generated by the core household and $inc_{hy}(p_{hy}, q_{hy})$ is the income earned by the migrant at home.[4] We therefore implicitly assume that the household decision to send a migrant is made after income is earned at home. Equation 3 thus describes the threshold above which we could potentially observe migration from a given household. Combing equation (1) and (3) allows us to write the probability of a household sending a migrant as:

$$Pr(migration) = Pr(U_{hdy} > U_{hhy}, W_x + INC_{hy}(p_{hy}, q_{hy}) + inc_{hy}(p_{hy}, q_{hy}) \geq C_d). \tag{4}$$

Thus, two potential reasons may lead us to observe changes in household out-migration rates when households experience exogenous shocks to their household income: First, for non-budget constrained households, i.e. when the following equation holds

$$W_x + INC_{hy}(p_{hy}, q_{hy}) + inc_{hy}(p_{hy}, q_{hy}) \geq C_d,$$

the opportunity costs of migration are altered in response to income shocks. A positive income shock increases U_h and renders staying home more attractive, while the reverse holds for a negative income shock. However, for households whose household budget lie marginally above C_d, a negative shock to $INC_{hy}(p_{hy}, q_{hy}) + inc_{hy}(p_{hy}, q_{hy})$ may push them below the budget constraint such that it becomes binding and out-migration rates decrease from these households.

[4] The assumption that borrowing constraints are a negative function of household wealth would lead to a qualitatively similar conclusion.

Second, for households that are initially budget constrained such that

$$W_x + INC_{hy}(p_{hy}, q_{hy}) + inc_{hy}(p_{hy}, q_{hy}) < C_l,$$

a positive income shock may increase migration if the shock to $INC_{hy}(p_{hy}, q_{hy})+inc_{hy}(p_{hy}, q_{hy})$ is sufficiently large and $U_d > U_h$ still holds. This is, household out-migration only increases if the increase to U_h is not too large to make staying the relatively most attractive option. For budget-constrained households, negative income shocks have no effect on the decision to send a migrant since they simply remain below C_l.

2.2 Agricultural and non-agricultural households

In this subsection, we turn more closely to the household income, given by

$$INC_{hy}(p_{hy}, q_{hy}) + inc_{hy}(p_{hy}, q_{hy}),$$

and its dependence on globally determined prices and the growing conditions of locally produced crops by type of household. For the remainder of this section, we assume that both $INC_{h,y}$ and $inc_{h,y}$ are differentiable in p_h and q_h. The sign of the first derivative then depends on the type of household, y. We expect changes in global food prices of locally grown crops p_h to have a strictly non-negative effect on the household income of agricultural households, a, which we define as net producers. All other crop prices equal, only subsistence farming households that consume all their produce do not experience a positive income shock to their household wealth. Thus, we assume the following derivatives:

$$\frac{\partial inc_{ha}}{\partial p_{ha}} \geq 0; \frac{\partial INC_{ha}}{\partial p_{ha}} \geq 0. \tag{5}$$

Similarly, a positive (negative) shock to local growing conditions that increases (decreases) the quantity produced, increases the income of agricultural households:

$$\frac{\partial inc_{ha}}{\partial q_{ha}} \geq 0; \frac{\partial INC_{ha}}{\partial q_{ha}} \geq 0. \tag{6}$$

Note that in some cases, households farming at subsistence levels may consume all additional produce such that the derivative in equation is not strictly larger than zero.

For non-agricultural households, which we define as consumers of agricultural goods, this relation is unambiguously non-positive. If locally consumed and produced crop varieties partly coincide, i.e. if local crop consumption patterns are partly correlated with locally produced crops, real income - and thus household wealth - declines for non-agricultural households. If the correlation between local consumption patterns and local production equals zero, we would observe no effect of global prices relevant for local production on the household budget of non-agricultural households. Thus, for non-agricultural households, we have

$$\frac{\partial inc_{hn}}{\partial p_{ha}} \leq 0; \frac{\partial INC_{hn}}{\partial p_{ha}} \leq 0. \tag{7}$$

We further expect non-agricultural households to be significantly less affected by changes in local growing conditions. With their household income not directly related to the local quantity produced and local consumer prices following the world market, we expect real income of non-agricultural households to remain unaffected by the quantity of crop harvested locally. Thus, we assume that

$$\frac{\partial inc_{hn}}{\partial q_{ha}} = 0; \frac{\partial INC_{hn}}{\partial q_{ha}} = 0. \tag{8}$$

In summary, we derive the following research hypotheses from the above simple framework: The aggregate observed effect of exogenously determined fluctuations in household income on household out-migration is a priori ambiguous. It depends on two factors. First, it depends on the initial wealth distribution of households through the interplay of three forces: the opportunity costs of migration, the household budget constraint and the migration costs. Second, the aggregate effect depends on the type of household, which determines the direction of the wealth shock induced by global prices and the quantity produced locally: Agricultural households can be expected to experience an income (and thus, wealth) increase when locally relevant global crop prices rise or local growing conditions improve, whereas non-agricultural households experience an income shock that is unambiguously non-positive for global prices or strictly zero for local growing conditions.

In the following, we describe in detail how we test the derived hypotheses empirically.

3 Data

To create our dataset, we draw on several data sources. The household data are presented in section 3.1. Data used to generate the producer prices are discussed in section 3.2. Our variables related to weather data are presented in section 3.3. In section 3.4, we introduce the conflict data.

3.1 Household data

To generate our main dependent variable and the various derivatives of it, we draw on the World Bank's African Migration and Remittances Surveys (AMRS).

Within AMRS, households were surveyed in five countries in Sub-Saharan Africa. In Kenya, Burkina Faso, Nigeria and Senegal interviews were conducted in late 2009, in Uganda in early 2010.[5] AMRS contains retrospective information on non-resident household members' years of out-migration as well as their destination choices and their reasons for moving. In sum, this information is available for approximately 2000 households in each country. We draw on these household-specific migration histories to generate the dependent variable. To minimize the errors related to the retrospection, we limit our sample to the ten years prior to the year of the interview to generate a nine-year household time series from 2000 to 2008.[6] We restrict our sample to households whose head is 25 years or older in 2000 to account for the fact that households with heads younger than 25 years old were unlikely to exist in 2000 [Gray and Wise, 2016]. We further include return migrants, defined as migrants who left the household in the past and returned at a later stage; however, these constitute less than 5 per cent of our migrant sample. Household members that left for the purpose of studying are not treated as migrants to account for the fact that migration for education reasons is guided by different dynamics than labor migration, which is the primary focus of our analysis. Our main dependent variable (M) is binary and takes on a value of one if the sum of households' (h) migrants (m) in a given year (t) increases compared to the preceding year and is equal to zero otherwise. More formally, we define

$$M_{ht} = \begin{cases} 1, & \text{if } m_{ht} > m_{ht-1} \\ 0, & \text{otherwise.} \end{cases}$$

To test our hypotheses as presented in section 2, we split our sample into households whose livelihoods do (throughout the text referred to as agricultural) and do not (throughout the text referred to as non-agricultural) depend on agricultural production. Households are considered to depend on agriculture if they own agricultural land or at least one of their members is full-time employed in agriculture. Non-agricultural households, on the contrary do not own land and none of their members works in agriculture. Districts are the finest geographical level that we are able to reliably identify our households at.

Table 1 presents the corresponding summary statistics where N indicates the number of

[5]We treat all countries in our sample as being interviewed in 2009 for consistency reasons.

[6]Using the AMRS data, Gray and Wise [2016] apply a similar approach to generate their migration variables for a six-year migration panel.

household-years. The table shows that almost 8% of agricultural and almost 7% of non-agricultural households experience out-migration in every given year. Most of household out-migration takes place internally to urban areas for both types of households. International migrants from agricultural households are likely to move to other African countries, while international migrants from non-agricultural households are likely to move to OECD countries.

Table 1: Summary statistics: Households' migration (by destination)

Variable	Mean	Std. Dev.	Min.	Max.	N
Agricultural households					
Overall	0.076	0.265	0	1	52101
Internal	0.058	0.235	0	1	52101
Internal: Rural	0.013	0.113	0	1	52101
Internal: Urban	0.046	0.209	0	1	52101
Africa	0.02	0.141	0	1	52101
OECD	0.008	0.091	0	1	52101
Non-agricultural households					
Overall	0.066	0.248	0	1	17307
Internal	0.046	0.209	0	1	17307
Internal: Rural	0.007	0.082	0	1	17307
Internal: Urban	0.04	0.195	0	1	17307
Africa	0.009	0.093	0	1	17307
OECD	0.019	0.135	0	1	17307

All variables were constructed at the household-year level using World Bank's African Migration and Remittances Surveys data. They are binary and take on a value of one if a household increased its number of out-migrants to a given destination compared to the year before, and zero otherwise.

To proxy household wealth in the cross-section, we construct a household wealth index similar to Dustmann and Okatenko [2014]. The index is based on the following seven survey questions:

- *Does the household own the house it lives in?* Yes/No.
- *Does the household have access to electricity?* Yes/No.
- *Does the household have access to piped water?* Yes/No.
- *Does the household own a television?* Yes/No.
- *Does the household own a computer?* Yes/No.
- *Does the household own a bank account that was not set up in response to a migrant leaving the household?* Yes/No.
- *Has the head of household attended a school?* Yes/No.

We conduct a principal component analysis on these variables and use the factor loadings of the first principle component as weights to construct an aggregate wealth index. The corresponding Kaiser-Meyer-Olkin measure of sampling adequacy indicates a value of 0.74, supporting the suitability of the approach [Dziuban and Shirkey, 1974]. The resulting wealth index is then normalized to lie between 0 and 1.

Since variables, which we use to construct the wealth index can only be observed in 2009, they can be endogenous to the previous migration decision. We therefore also approximate wealth by a wealth measure based only on variables with information for the year 2000, the first year in our household panel. The first variable we use to calculate the pre-migration wealth is the indicator on whether or not the household head received any kind of formal education, guided by the idea that the level of education of the household head is a good predictor of household wealth in African countries [Duflo, 2001, 2004, Maccini and Yang, 2009, Wantchekon et al., 2015]. We implicitly assume that the decision to receive formal education is finalised at the beginning of the observation period and does not change over time.[7] The second variable is based on the question whether the respective household - this is, anyone in the household - owns a bank account. The question is followed up by a second question on whether this bank account was opened in response to a previous member of household leaving the household, allowing us to correct the bank account indicator for reverse causality. We then combine these two survey questions to construct a parsimonious wealth measure exogenous to the household decision to send a migrant. This measure divides households into the following three categories: low wealth households (0) with no bank account and where the head has zero years of schooling, medium wealth households (1) with either a bank account or where the head has received some schooling and upper-wealth households (2) with both a bank account and where the head attended school. Table 2 presents the corresponding summary statistics.

3.2 Global prices

We follow McGuirk and Burke [2020] in the construction of a plausibly exogenous price index that allows us to analyse the causal effect of price changes on migration. Similar to the authors, we require price data that varies sufficiently over time, is not determined by local factors and that allows us to differentiate real income effects across households. We therefore generate district-specific price time series by combining exogenous *temporal* variation in global crop prices with local *spatial* variation in crop production at the beginning

[7] Since we limit our sample to households whose head is 25 years or older at the beginning of the observation period, the assumption of schooling being finalised is plausible.

Table 2: Summary statistics: Households' wealth indexes

Variable	Mean	Std. Dev.	Min.	Max.	N
Owns house	0.716	0.451	0	1	7712
Access to electricity	0.482	0.5	0	1	7712
Access to piped water or public well	0.718	0.45	0	1	7712
Attended school (head)	0.569	0.495	0	1	7712
Owns computer	0.116	0.32	0	1	7712
Owns television	0.471	0.499	0	1	7712
Bank account (pre-migration)	0.335	0.472	0	1	7712
Wealth index	0.406	0.297	0	1	7712
Wealth index pre-migration	0.903	0.813	0	2	7712

All wealth index variables were constructed at the household level using World Bank's African Migration and Remittances Surveys data. The variable *Wealth index* is a binary indicator constructed using household level information from 2009 as shown in the upper part of the table, with higher valuer indicating more wealth. *Wealth index pre-migration* uses information from 2000. It is a categorical variable dividing households into low (0), medium (1) and upper-wealth (2) categories.

of our observation period.

(Producer) Price Index (PPI): To generate the spatial variation in the PPI, we utilise the high-resolution crop-specific fraction of harvested area in year 2000 (i.e. the first year of our observation period) which contains information on harvested area and yield for 175 crops, initially compiled by Monfreda et al. [2008]. The authors create this land use dataset by combining national-, state- and county-level census statistics with a global dataset of croplands with a 5×5 minute grid cell resolution. Using these data, in Figures 8, 9, 10 and 11 in Appendix B, we provide illustrative examples of how production of different commodities differs by country. To generate the temporal variation in the PPI, we draw on annual global commodity prices from the IMF International Finance Statistics series and the World Bank Global Economic Monitor. Prices are indexed at 100 in year 2010. We then compute the annual district-specific PPI by combining the temporal variation of commodity prices and the spatial variation of crop-specific fraction of harvested area in 2000 in the following way:

$$PPI_{dt} = \sum_{i=1}^{n} (P_{it} \times F_{idc}), \tag{9}$$

whereby crops ($i ... n$) capture a set of 12 major traded crops for the five countries in our dataset that are simultaneously covered by the land use dataset and for which international prices exist, F_{idc} captures the district-specific crop share of land. For a full list of crops used to generate the international food prices, see Table 10 in Appendix B. To better capture the nature of unexpected shocks, we express the PPI as a percentage change from its district-specific long-run mean constructed for the pre-sample period 1990-1999. To summarize, the district-level variation of PPI comes from annual global crop price changes and a district-specific mix of locally produced crops. In addition, following McGuirk and Burke [2020], we also generate two disaggregated versions of the PPI for robustness checks: i) PPI (food), which captures price index for crops that constitute more than 1% of calorie consumption in the overall sample as suggested by food consumption data from the UN Food and Agriculture Organization (FAO), and ii) PPI (cash) which is the price index covering the remaining crops.

Figure 6 in Appendix B further captures how the PPI developed over time, suggesting a sharp spike during years of the food price crisis in 2007/08 in all countries. The spatial distribution of average PPI for the years of 2007/08 food price crisis in Figure 7 in Appendix B suggests that, likely due to the spatial correlation of soil-suitability in combination with spatially correlated climatic conditions that result in geographically correlated crop-production, our price index shows patterns of spatial correlation. We will attend to this phenomenon in more detail in section 5.3.

One of the key identifying assumption in all subsequent analyses - and in fact, of all empirical studies utilising local weather as a source of exogenous variation in local agricultural income - is the exogeneity of global crop prices to local production in Sub-Saharan Africa. If the quantity of agricultural goods produced locally was a predictor of global commodity prices, these prices would, to some extent, co-move with local production and attenuate shocks on quantities produced locally. A number of reasons should convince the reader that agricultural households in Sub-Saharan Africa are indeed price takers: First, to isolate the effect of global crop prices from local weather conditions, we focus on the observation period from 2000 to 2008. This time span covers the global food price crisis 2007/08, when global food prices rose sharply for reasons entirely exogenous to agricultural activity in Sub-Sahara African [Berazneva and Lee, 2013, Demeke et al., 2009, Dorward, 2012]. Second, between 1989-2013, the entire continent of Africa accounted for only 5.9% of global cereal production, minimizing its effect on global prices [McGuirk and Burke, 2020]. Finally, we show in all our analyses that the effect of global prices on our outcomes are not sensitive to conditioning estimates on the local quantity produced, proxied by local weather conditions.

3.3 Local weather

To generate a set of climate-related variables, we draw on ERA5 reanalysis data produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) [Copernicus Climate Change Service (C3S), 2017]. ERA5 is the fifth generation of ECMWF atmospheric reanalyses of the global climate. It is a high quality reanalysis dataset which relies on information from weather stations, satellites, and sondes. ERA5 provides data at a geographical resolution of 31km and has been regridded to a 0.25×0.25 degrees latitude-longitude grid. Currently, the weather data is available from January 1979 with a temporal resolution of up to one hour. We use the daily mean temperature as well as total monthly precipitation and aggregate these to the district level, using Google Earth Engine.

The existing literature shows that the effect of temperature on economic outcomes is highly non-linear [Burke et al., 2015, Carleton and Hsiang, 2016, Schlenker and Roberts, 2009, Kalkuhl and Wenz, 2020]. Growing degree days (GDD) is one common way to capture this non-linear relationship. One degree day counts the total amount of degrees above a lower threshold as long as the mean local temperature is below an upper threshold on a given day. If mean temperature (t) exceeds the upper threshold, degree days are counted as the difference between the upper bound and a lower bound. More formally, growing degree days D above a lower threshold l_1 and below an upper threshold l_2 are defined as:

$$D = \begin{cases} l_2 - l_1 & \text{if } t > l_2 \\ t - l_1 & \text{if } l_1 < t \leq l_2 \\ 0 & \text{if } t \leq l_1. \end{cases}$$

GDD then capture the total number of degree days over the crop-growing season, defined as the time period stretching from June to August (JJA) [Dell et al., 2014, Schlenker et al., 2007, Schlenker and Roberts, 2009].

Following the literature, we generate two GDD-related variables at the district-level: i) degree days between 10 and 30°C, and ii) degree days above 30°C. The intuition behind the choice of the bounds is that temperature between 10-30°C generally enhances yield, while temperatures above 30°C is considered yield-decreasing [Schlenker and Roberts, 2009, Schauberger et al., 2017]. We control for the average growing season precipitation, measured as the average of daily (total) precipitation during the growing season in meters height collected on each square meter. However, precipitation is not of the main interest in our analysis for several reasons. First, in the context of Sub-Saharan Africa, precipitation has been shown not to be an important predictor of migration [Missirian and Schlenker, 2017] and conflict [Burke et al., 2009]. Second, relative temperature changes under future climate change scenarios translate into much larger changes in yields than do precipitation changes in Sub-Saharan Africa [Schlenker and Lobell, 2010]. Third, even though weather data sets agree on long-run averages, particularly in the case of precipitation they do not necessarily agree on anomalies [Auffhammer et al., 2013]. Since deviations from the mean are the main source of identification in our setting, this could potentially be problematic. We nevertheless control for precipitation in all regression analyses for completeness. Table 3 presents the summary statistics of main local climatic variables of interest at the district-level.

Table 3: Summary statistics: Climate-related variables at the district-year level

Variable	Mean	Std. Dev.	Min.	Max.	Units
Growing Degree Days (10-30°C) (GDD1030)	13.993	2.844	4.889	17.722	Hundred
Growing Degree Days (>30°C) (GDD30)	0.299	0.492	0	3.1	Hundred
Precip. (JJA)	0.121	0.073	0.008	0.45	m
N		1260			

All weather variables were constructed at the district-year level using ERA5 reanalysis data and capture conditions during the growing season covering months June-August.

3.4 Conflict data

We follow state-of-the-art approaches in conflict analyses [McGuirk and Burke, 2020, De Winne and Peersman, 2019] and distinguish between i) small-scale *output* conflicts associated with appropriation of surplus, and ii) large-scale *factor* conflicts over the control of territory. We only focus on conflicts in the second half of each year (i.e. the period from July to December) to link all conflict events to the district-specific crop yield of each growing season from June to August. Mid-growing season, households will have plausibly assessed their potential agricultural income.

Output conflicts: To capture output conflict, we draw on the Armed Conflict Location and Event Data Project (ACLED) database [Raleigh et al., 2010]. ACLED provides temporally and geographically disaggregated data on dates, actors, locations, fatalities, and types of all reported political violence and protest events, collected from a range of media and agency sources. Since output conflict is likely to be transitory and disorganized, we further draw on information on riots, protests and violence against civilians [McGuirk and Burke, 2020, De Winne and Peersman, 2019]. We then construct a binary output conflict variable on the external margin of output conflict incident, covering our sampling period from 2000 to 2008.[8]

Factor conflicts: We further draw on geo-coded conflict-related fatality count data from the Uppsala Conflict Data Program (UCDP) [Sundberg and Melander, 2013, Pettersson and Öberg, 2020]. UCDP provides temporally and geographically disaggregated information on conflict events, which entail the use of armed force by an organized actor against another organized actor, or against civilians, resulting in at least one direct death. It covers all dyads

[8] The decision to code our conflict variables as binary (and thus only consider the external margin) is guided by the conflict literature [Bazzi and Blattman, 2014, Berman et al., 2017, Nunn and Qian, 2014, McGuirk and Burke, 2020] and reduces the potential measurement error stemming from the recording of the original conflict events [McGuirk and Burke, 2020]

that have crossed a threshold of 25 battle deaths per year. The data is gathered from local and national media, agencies, NGOs and international organizations. Since UCDP data capture relatively larger scale conflicts, the data is suitable to approximate conflicts associated with the control of territory, i.e. factor conflicts [McGuirk and Burke, 2020]. We aggregate the fatality counts to the district-year level for the period 2000-2008 to match the fatality counts with our other data sources. Similar to output conflict, our main variable of interest is binary and takes the value one if any conflict event took place in a given district-year between July to December, and zero otherwise.

The constructed conflict-related variables at the district level are summarized in Table 4 below.

Table 4: Summary statistics: Conflict occurrence at the district-year level

Variable	Mean	Std. Dev.	Min.	Max.
Output conflict (July - December)	0.2405	0.4275	0	1
Factor conflict (July - December)	0.0722	0.259	0	1
N		1260		

Output conflict was constructed using Armed Conflict Location and Event Data Project data and captures occurrence of smaller-scale conflicts at the district-year level. Factor conflict was constructed using Uppsala Conflict Data Program data and captures occurrence of large-scale conflicts at the district-year level.

4 Methodology

We first examine the effect of the exogenous variation in international food prices measured by the PPI on households' decision to send out a migrant, while controlling for local climatic variables. To do so, we estimate the following baseline equation:

$$Pr[M_{hdt} = 1 | x_{dt}, \phi_t, \alpha_h] = \beta_0 + \beta_1 PPI_{dt} + \beta_2 GDD_{dt;10:30} + \beta_3 GDD_{dt;30:\infty} + \beta_4 GP_{dt} + \alpha_h + \phi_t + \epsilon_{hdt}. \quad (10)$$

Thus, our binary indicator capturing a household-specific (h) increase in migration in a given year (t) relative to the preceding year (M_{hdt}) is regressed on yearly district-specific (d) food price index (PPI), district-specific number of growing degree days (GDD) between 10-30°C and above 30°C, district-specific average precipitation during the growing season and its squared term (summarized by GP) and year (ϕ_t) and household (α_h) fixed effects. By applying a two-way fixed effects approach, the identification comes via deviation of global prices from their historical district-specific mean over time. Thus, a given households' out-migration rate is compared under different price regimes. The year fixed effects ensure that out-migration and global food prices are not simultaneously determined by variation in third factors, such that the estimated effect can be interpreted causally. Figure 1 presents the yearly, district-specific variation in PPI from the district-specific mean from 2000 to 2008, which serves as the main source of identification of the response coefficient. We cluster standard errors at the level of the treatment, i.e. at the district-level.

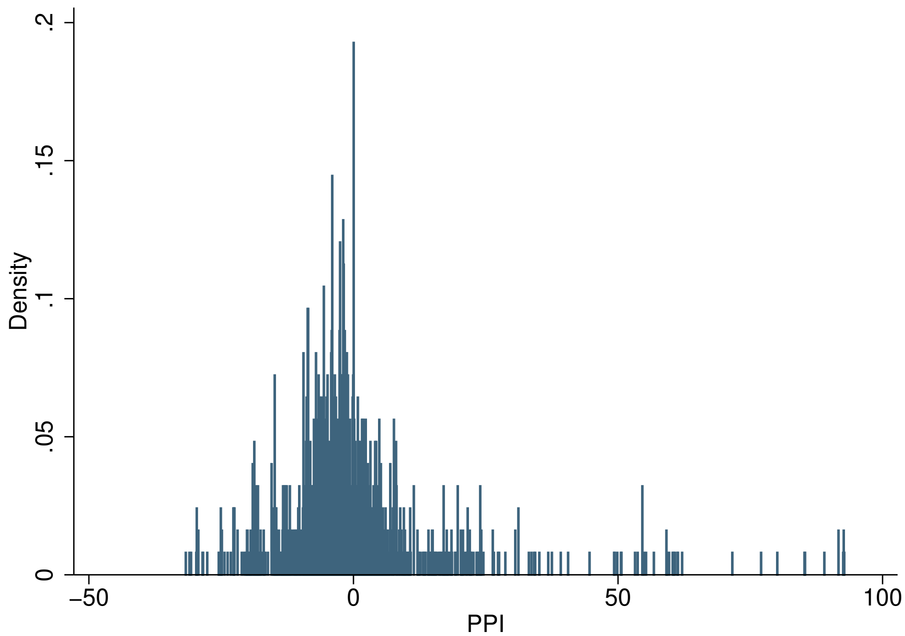

Figure 1: Within-district variation in PPI

In our next specification, we then study how international prices interact with households' wealth and affect households' migration decision in the following way:

$$Pr[M_{hdt} = 1|x_{dt}, \phi_t, \alpha_h] = \beta_0 + \beta_1 PPI_{dt} + \sigma PPI_{dt} \times Wealth_h + \beta_2 GDD_{dt;10:30} + \beta_3 GDD_{dt;30:\infty} + \beta_4 GP_{dt} + \alpha_h + \phi_t + \epsilon_{hdt}. \quad (11)$$

Thus, the coefficients on β_1 and σ combined capture the differential effect of locally-relevant global prices along the household wealth distribution. $Wealth_h$ enters the equation as either a continuous (post-migration wealth) or categorical (pre-migration wealth) variable as explained in the previous section.

We estimate equations 10 and 11 using both a reduced-form linear probability model (LPM) and a logistic (Logit) model. The LPM assumes a linear relation between the household decision to send a migrant and the changing local income conditions. While no additional modelling choices are required, this assumption is potentially strong in a setting when the majority of household-years contain zero values. Maximum likelihood based probability models such as the Logit allow for a more flexible, non-linear probability function more suitable for such a setting and recent advances in logistic models that incorporate large number of fixed effects also overcome the incidental parameter problem inherent to these models (see [Lancaster, 2000] for a detailed discussion).

However, maximum-likelihood based fixed effects Logit models also have their disadvantages in the setting at hand: First, since it is mathematically impossible for maximum-likelihood models to converge when there is no within-category variation, these models often fail to converge when high dimensional fixed effects are incorporated. For example, when including country-by-year fixed effects, the likelihood function fails to find a global maximum for all subsamples. Second, when reporting the marginal effects from the Logit models, additional assumptions on the values of the fixed effects -which are not estimated - are required.[9]

We therefore suggest an estimation strategy based on an LPM with a common time-trend and climatic controls to obtain our parameters of interest as our preferred specification. To ensure that the choice of the model does not drive our results, we also show obtained average marginal effects from the conditional fixed effects Logit specification following Kitazawa [2012] and Kemp et al. [2016]. We then also estimate a more conservative specification of our models that include country by year fixed effects (LPM) or country-specific linear time trends (Logit). We do not choose these specification as our preferred ones for two main reasons. First, because of within-country spatial correlations in our main variable of interest - which we will explore further in subsection 5.3 - the country-year trends could potentially absorb a significant share of the variation of interest. Second, the additional loss in degrees of freedom is critical compared to the additional precision our estimates gain in a setting where the essential household fixed effects absorb a high number of degrees of freedom. Nevertheless, we will present these estimates for robustness.

As outlined in the introduction, we further aim to examine conflict as a potential mechanism that could in part explain the relationship between producer prices and household out-migration. The analysis of the channeling effect of conflict in similar econometric settings is a widely discussed empirical challenge (see for example Berlemann and Steinhardt [2017]). Including conflict as a control variable in 10 could bias the coefficient on our main independent variables if conflict itself is an outcome of changes in locally-relevant food prices and local climatic conditions, a problem commonly referred to as an *over controlling* [Dell

[9]Some modellers in the migration literature choose to report the marginal effects by setting the fixed effects to zero (see for example [Bazzi, 2017]. However, this is an arbitrary choice.

et al., 2014] or a *bad control* problem [Angrist and Pischke, 2008].

We therefore structure our thinking on the global prices-conflict-migration nexus as follows. We start out by estimating the association of household out-migration and the different types of conflict in the following parsimonious regression framework:

$$Pr[M_{hdt} = 1 | x_{dt}, \phi_t, \alpha_h] = \theta_0 + \theta_1 Conflict_{dt} + \alpha_h + \phi_t + \epsilon_{hdt} \tag{12}$$

where the dependent variable is defined as the household out-migration from household h, residing in district d in year t as before. We distinguish between output and factor conflict, both of which enter equation 12 separately as $Conflict_{dt}$. The estimated coefficient on conflict, θ_1, should not be interpreted causally due to the potential problems of reverse causality and omitted variable bias. Nevertheless, these correlations can provide us with first valuable information as they reveal how household out-migration and conflict relate to one another. To more directly explore the link between locally-relevant global prices and conflict, we study the district-level association between the PPI and the different types of conflict in Appendix F.

5 Results

In this section, we present all outcomes from our regression analyses. Specifically, in section 5.1, we present results of the aggregate association between global food prices and migration. In section 5.2, we study the heterogeneity of these effects along the initial household wealth distribution. Finally, in section 5.3, we turn to destination choices in response to changes in locally-relevant global food prices. We present outcomes from both the LPM and the Logit model in all of our main analyses and for the more specific results, we only show our preferred specification as described in the previous section.[10]

5.1 Aggregate effect of global food prices

Tables 5 and 6 show the estimated effects of changes in global food prices (PPI) on the probability of migration for agricultural and non-agricultural households respectively. We will refer to model (5) as the result from our preferred specification.

[10]Note that output tables of the Logit regressions show the average semi-elasticity of $Pr[M_{hdt} = 1 | x_{dt}, \phi_t, \alpha_h]$ with respect to our variables of interest. The magnitude of these coefficients is therefore not directly comparable to the OLS estimates, which capture level-level (percentage point) changes.

For the **sub-sample of agricultural households**, both the LPM and the Logit show similar outcomes throughout different specifications. Our preferred specification (5) suggests that a one percentage point increase in locally-relevant global food prices over its district specific long-run mean increases the likelihood that households send out a migrant by 0.06 percentage points. Even in the most demanding model specifications (3 and 6), the effect remains highly visible and does not change in its order of magnitude. Importantly, comparing models (1) to (2) and (3) to (4), it becomes evident that the magnitude of the effect of producer prices on household out-migration remains unchanged when conditioned on local weather. These controls even add precision to the obtained estimates, albeit only marginally. This first finding provides reassurance that international food prices and local weather are not linked causally.[11]

The estimated coefficients on the local weather variables indicate that an increase of the number of degree days during the growing season above 30°C by 100 decreases the likelihood of households sending one of their members as a migrant in the same year by almost three percentage points (model 5). On the other hand, 100 additional growing degree days between 10 and 30°C significantly increase the likelihood of households sending out a migrant by 2 percentage points. A note of caution is warranted when interpreting these findings. While the sign of the estimates on our generated weather variables is stable throughout all specifications, the coefficients are not always significant at conventional statistical levels. A potential reason for this is the inherent collinearity of the two variables at their intersection points around the bounds defined in the previous section; however, the particular modelling of the variables is necessary to capture the non-linearity in increasing temperatures as discussed in 3.3.

For the **sub-sample of non-agricultural households**, we generally do not find any statistically significant effects of global food prices on household out-migration. However, the sign of the association is positive throughout specifications and turns significant at the five percent level in model (3); these outcomes could capture the pull effects of the agricultural sector, a potential explanation we will offer more detail on in section 5.3 and Appendix E. We do not find a significant impact of adverse local weather on non-agricultural households. This suggests that if local production conditions deteriorate, non-agricultural households are able to diversify their consumption via world markets, as implied by equation 8.

[11] To further test that PPI is exogenous and thus is not determined by local conditions we regressed it on local climatic variables. By using a fixed effects panel data regression, location and time effects absorb potential large-scale correlation of climatic events and related trends. The remaining variation identifies responses from deviations of local climatic conditions over time from the long-term, location-specific mean. The results suggest that local climate-related variations do not significantly predict variation in PPI. Since we use the same identification strategy in the main analysis, we can plausibly claim that the variation that identifies PPI responses is not defined by local conditions as potential sources of correlation are captured by fixed effects. The estimation results are available upon request.

Taken together, for households whose livelihoods depend on agricultural production, we find that higher international food prices facilitate migration, an indication that positive producer price shocks have a similar migration-inducing effect as positive weather shocks. Our explanation as proposed by the theory in section 2 is that positive income shocks, either via increases in the PPI or yield enhancing temperatures, push households above the previously binding budget constraint. Lower PPI or yield decreasing temperatures, on the contrary, reduce migration by imposing a stricter budget constraint [Cattaneo and Peri, 2016, Deaton, 1989, Bellemare et al., 2018, McGuirk and Burke, 2020]. Households in the agricultural context of Sub-Saharan Africa are typically characterized by low income levels [McGuirk and Burke, 2020]. Thus, the migration-inducing effect of the PPI appears to be larger than the rising opportunity costs of out-migration due to better income opportunities at home. We turn to these suggested interpretations of our aggregate findings in more detail in the next section.

To better understand the estimated associations, we further run the fully specified LPM model by distinguishing the PPI of cash and food crops (see Table 11, Appendix C). Finally, we also run the fully specified LPM models with common and state-specific trends, presented in Appendix C, to check our results for robustness with respect to alternating definitions of the growing season. In Tables 12 and 13 we present the outcomes for agricultural and non-agricultural households respectively. Even though none of these robustness checks seem to change our main results, we find that these results are mainly driven by price changes of food crops rather than cash crops, further suggesting that domestic consumption plays an important role in the setting of Sub-Saharan Africa. Moreover, the sensitivity tests confirm that households respond most strongly and consistently to the growing season conditions as defined in the main analysis.

Finally, to put the effect of locally-relevant prices into perspective, it is useful to compare changes in the PPI to the effect of local weather directly. To do so, consider a hypothetical scenario where both the PPI and the DD30 increase by one standard deviation over their long-run mean. A back-of-the-envelope calculation that considers the non-linear effect of local temperatures on household out-migration (i.e. that accurately factors in the corresponding changes in DD1030), then shows that the overall climatic effect on migration of both, global prices and local temperature is positive. More precisely, the standardized effect of a global price increase on household out-migration is around 37% of the standardized (and so comparable) net effect of a rise in local temperature. Overall, these findings therefore suggest that in the context of Sub-Saharan Africa, the magnitude of short-term climatic effects on migration have thus-far been underestimated.[12]

[12]These calculations are available upon request.

Table 5: Aggregate effect of PPI on the probability of migration: Agricultural households

	(1)	(2)	(3)	(4)	(5)	(6)
PPI	0.0051*	0.0052**	0.0106***	0.0006***	0.0006***	0.0004*
	(0.0026)	(0.0025)	(0.0025)	(0.0002)	(0.0002)	(0.0002)
DD1030		0.1800	0.0885		0.0219*	0.0203
		(0.1703)	(0.1493)		(0.0112)	(0.0135)
DD30		-0.3563	-0.2043		-0.0254*	-0.0448***
		(0.2322)	(0.2007)		(0.0148)	(0.0167)
N	23742	23742	23742	52101	52101	52101
R^2				0.012	0.013	0.017
Time trend	Year	Year	Country x Year	Year	Year	Country x Year
Model	Logit	Logit	Logit	LPM	LPM	LPM
Precip. controls	No	Yes	Yes	No	Yes	Yes

The dependent variable is binary and captures household-level out-migration incidence in a given year. The producer price index (*PPI*) is measured in percent and captures *PPI* change (%) compared to the long-run average (1990-1999). *DD1030* captures 100 degree days between 10 and 30°C and *DD30* above 30°C during the growing season (June-August). The migration variable is constructed using World Bank's African Migration and Remittances Surveys data. Weather variables are constructed using ERA5 data. PPI is constructed by combining crop-specific fraction of harvested area data by Monfreda et al. [2008] and annual global commodity prices from the IMF International Finance Statistics series and the World Bank Global Economic Monitor. The sample captures agricultural households only. Models 2-3 and 5-6 further control for growing season precipitation and their squared terms. Models 1-3 are estimated with fixed effects logit model and models 4-6 with LPM. Models 1-2 and 4-5 use a common and models 3 and 6 country-specific time trend. Model 5 corresponds to the preferred specification. Standard errors clustered at the district level are displayed in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

Table 6: Aggregate effect of PPI on the probability of migration: Non-agricultural households

	(1)	(2)	(3)	(4)	(5)	(6)
PPI	0.0039	0.0037	0.0077**	0.0004	0.0004	0.0003
	(0.0031)	(0.0031)	(0.0034)	(0.0003)	(0.0003)	(0.0004)
DD1030		0.2265	0.1836		0.0156*	0.0208*
		(0.1378)	(0.1380)		(0.0093)	(0.0113)
DD30		0.3363	0.5591		0.0205	0.0031
		(0.3793)	(0.3751)		(0.0214)	(0.0201)
N	7443	7443	7443	17307	17307	17307
R^2				0.016	0.016	0.023
Time trend	Year	Year	Country x Year	Year	Year	Country x Year
Model	Logit	Logit	Logit	LPM	LPM	LPM
Precip. controls	No	Yes	Yes	No	Yes	Yes

The dependent variable is binary and captures household-level out-migration incidence in a given year. The producer price index (*PPI*) is measured in percent and captures *PPI* change (%) compared to the long-run average (1990-1999). *DD1030* captures 100 degree days between 10 and 30°C and *DD30* above 30°C during the growing season (June-August). The migration variable is constructed using World Bank's African Migration and Remittances Surveys data. Weather variables are constructed using ERA5 data. PPI is constructed by combining crop-specific fraction of harvested area data by Monfreda et al. [2008] and annual global commodity prices from the IMF International Finance Statistics series and the World Bank Global Economic Monitor. The sample captures non-agricultural households only. Models 2-3 and 5-6 further control for growing season precipitation and their squared terms. Models 1-3 are estimated with fixed effects logit model and models 4-6 with LPM. Models 1-2 and 4-5 use a common and models 3 and 6 country-specific time trend. Model 5 corresponds to the preferred specification. Standard errors clustered at the district level are displayed in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

5.2 The role of household wealth

In this section, we explore the role of households wealth, one of the contextual factors that could determine the direct associations between PPI and migration. To explore this particular heterogeneity, we turn to the results of regression model 11, detailed in section 4. First, in Table 7 we interact the PPI with the continuous wealth index and present the results from a series of fully specified LPMs and Logit models with and without country-specific trends for agricultural (models 1-4) and non-agricultural (models 5-8) households. Second, because the continuous wealth index is based on values partially measured in 2009 and the wealth it captures could therefore be endogenous to the migration decision, in Appendix D in Tables 14 and 15, we interact the PPI with the exogenous categorical wealth index based on values from 2000 for agricultural and non-agricultural households respectively. Using this more exogenous measure without time variation also solves the over-controlling problem [Dell et al., 2014].

For the **sub-sample of agricultural households**, in Table 7 we find robust evidence across all specifications that wealthier households are less likely to send out migrants when the locally-relevant global prices increase. The marginal effects of PPI by wealth, i.e. the outcomes from the main specification (model 3), are depicted in Figure 2. The marginal effect is positive but decreases with increasing wealth. It remains statistically significant only for approximately the lower half of the wealth distribution. In Table 14 (in Appendix D), we draw on the exogenous measure of wealth to test the validity of these results. In five out of six specifications, we find further evidence that richer households are less likely to send out migrants when the PPI increases. In our preferred model 5, the interactions show that if PPI increases by one p.p., medium-wealth and upper-wealth households become 0.03 p.p. and 0.09 p.p. less likely to send out migrants respectively, compared to households with low levels of wealth. Figure 3 further presents these outcomes visually only for the lower and upper wealth categories (i.e. the medium wealth households are not included). It shows that a higher PPI increases the marginal probability of low-wealth and decreases the probability of upper-wealth households to send out migrants. When using this more exogenous wealth measure, the effect of the PPI is statistically significant from zero along the entire wealth distribution. The presented evidence underlines the interpretation of the direct effects of locally-relevant global prices on household out-migration, as suggested in the previous section. Implications of global price changes for migration differ depending on households' wealth. The findings strongly suggest that increases in household income induced by exogenous changes in relevant agricultural commodity prices push poor households above the previously binding budget constraint and facilitate their out-migration, exceeding contrary opportunity costs effect. The opportunity costs only start to play a more significant role for wealthier households, reducing their likelihood to send out migrant as income increases.

We do not find similar evidence for **sub-sample of non-agricultural households**. Both the baseline effect of the PPI and its interaction with household wealth show no statistically significant association with household out-migration, visible in both Table 7 and 15 (in Appendix D). We interpret this as evidence that PPI does not capture prices of locally consumed crops, but rather captures the conditions in the agricultural sector. Thus, the weak evidence of positive aggregate effects of the PPI on out-migration from non-agricultural, net-consuming households shown in 5.1 seem to rather capture pull effects. We will discuss these in more detail in the next section.

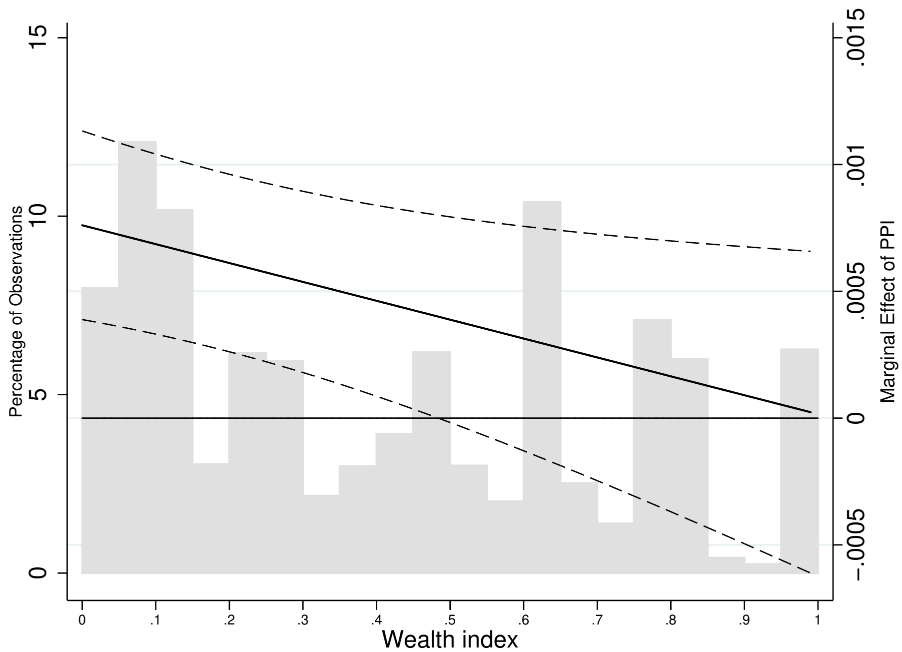

Figure 2: Partial effects of PPI by wealth according to model 3, Table 7 with 90% CIs

5.3 Destination choices

Throughout this paper, we have made the case for both global prices and local weather being a) exogenously determined and b) the two factors being uncorrelated. A third, albeit less crucial source of potential bias in our estimates is the spatial correlation in production pattern and local weather conditions. Due to the necessary arbitrariness in drawing district borders, neighbouring districts tend to grow similar crops and may therefore experience income shocks that are spatially correlated. Similarly, neighbouring regions may experience climatic and weather conditions that are not entirely dissimilar across districts. We illustrate the presence of spatial correlations in our setting in figures 7, 4 and 5 of appendices B and A.

Table 7: Heterogeneous effects of PPI by household wealth: Agricultural (models 1-4) and non-agricultural (models 5-8) households

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PPI	0.0069**	0.0128***	0.0008***	0.0006**	0.0033	0.0087	0.0005	0.0002
	(0.0027)	(0.0024)	(0.0002)	(0.0002)	(0.0081)	(0.0083)	(0.0007)	(0.0007)
PPI × Wealth	-0.0078*	-0.0106***	-0.0007*	-0.0005*	0.0007	-0.0018	-0.0002	0.0002
	(0.0043)	(0.0036)	(0.0004)	(0.0003)	(0.0115)	(0.0116)	(0.0010)	(0.0010)
DD30	-0.3819*	-0.2289	-0.0264*	-0.0435**	0.3334	0.5687	0.0209	0.0024
	(0.2270)	(0.1950)	(0.0146)	(0.0168)	(0.3802)	(0.3812)	(0.0214)	(0.0203)
DD1030	0.1958	0.1044	0.0228**	0.0203	0.2262	0.1845	0.0157*	0.0208*
	(0.1679)	(0.1461)	(0.0111)	(0.0135)	(0.1390)	(0.1391)	(0.0094)	(0.0113)
N	23742	23742	52101	52101	7443	7443	17307	17307
R^2			0.013	0.017			0.016	0.023
Time trend	Year	Country x Year	Year	Country x Year	Year	Country x Year	Year	Country x Year
Model	Logit	Logit	LPM	LPM	Logit	Logit	LPM	LPM
Precip. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Agri.	Agri.	Agri.	Agri.	Non-agri.	Non-agri.	Non-agri.	Non-agri.

The dependent variable is binary and captures household-level out-migration incidence in a given year. The producer price index (*PPI*) is measured in percent and captures *PPI* change (%) compared to the long-run average (1990-1999). *DD1030* captures 100 degree days between 10 and 30°C and *DD30* above 30°C during the growing season (June-August). The wealth index lies between 0 and 1, where higher values represent higher wealth. The migration and wealth variables are constructed using World Bank's African Migration and Remittances Surveys data. Weather variables are constructed using ERA5 data. PPI is constructed by combining crop-specific fraction of harvested area data by Monfreda et al. [2008] and annual global commodity prices from the IMF International Finance Statistics series and the World Bank Global Economic Monitor. Models 1-4 capture agricultural and models 5-8 non-agricultural households. All models further control for growing season precipitation and their squared terms. Models 1-2 and 5-6 are estimated using a Logit model and models 3-4 and 7-8 using LPM. Models 1, 3, 5 and 7 use a common and models 2, 4, 6 and 8 country-specific time trend. Standard errors clustered at the district level are displayed in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

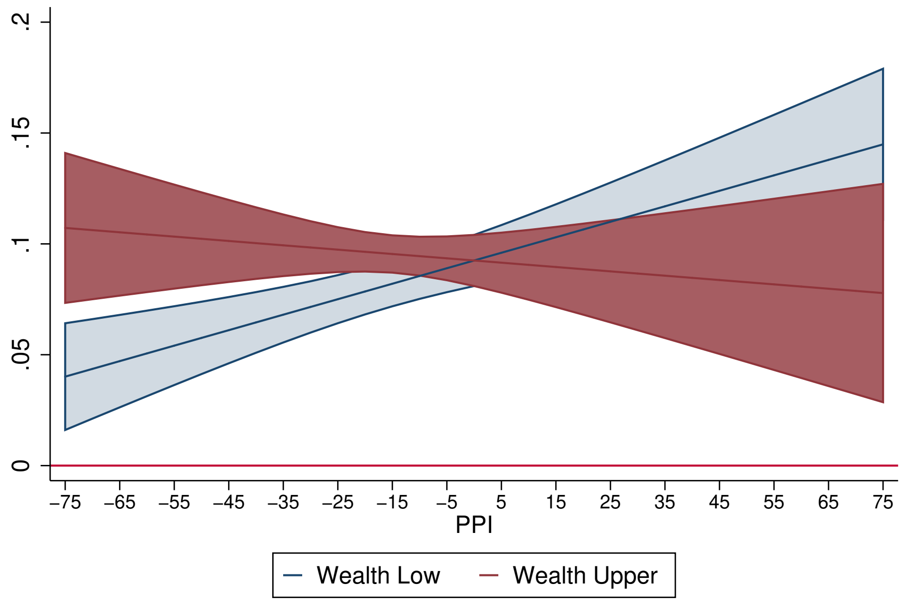

Figure 3: Partial effects of PPI on agricultural households by wealth according to model 5, Table 14 (Appendix D) with 90% CIs

The consequence of these spatial correlations follows immediately from our characterization of the household out-migration probability in equation 4: For example, spatial correlations in local production patterns mean that a positive income shock through a rise in locally-relevant global crop prices that increases the utility of the potential migrant staying home, U_{hhy}, simultaneously changes the households' expected utility flows in destination districts, U_{hdy}. Thus, the attractiveness of some nearby destinations may co-move when locally relevant global prices change. It follows that, due to spatial correlations, locally-relevant global prices can be expected to have less of an impact on internal rural migration, a type of migration that makes only for a very small share of total migration (see Table 1).

However, destination choices may not only be influenced by spatial correlations. Unless local production and local consumption of agricultural products are uncorrelated, the real income in urban areas will be negatively affected by increases in locally relevant global crop prices (see equation 7). For potential migrants in agricultural rural households, this means that with rising income at home, urban destinations in the same district (or nearby districts if spatial correlations are considered) may become less attractive whenever income at home rises through increases in producer prices. We note that the same reasoning does not hold for local weather shocks: Local weather conditions, which act on the locally produced quantity have no effect on the attractiveness of urban areas (see equation 8), where real income remains unaffected. In sum, these points lead us to conclude that the aggregate positive effect of

Table 8: The effect of PPI by destination choice: Agricultural households

	(1) Total	(2) Internal	(3) Internal: rural	(4) Internal: urban	(5) Other African	(6) OECD
PPI	0.0006***	-0.0001	-0.0000	-0.0001	0.0006***	-0.0000
	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0000)
DD1030	0.0219*	0.0233***	0.0006	0.0234***	0.0033	0.0031
	(0.0112)	(0.0081)	(0.0033)	(0.0079)	(0.0041)	(0.0048)
DD30	-0.0254*	-0.0257**	0.0002	-0.0261**	-0.0068	-0.0043*
	(0.0148)	(0.0118)	(0.0040)	(0.0100)	(0.0061)	(0.0026)
N	52101	52101	52101	52101	52101	52101
R^2	0.013	0.014	0.004	0.011	0.008	0.000
Time trend	Year	Year	Year	Year	Year	Year
Model	LPM	LPM	LPM	LPM	LPM	LPM

The dependent variables are binary and capture household-level out-migration incidence by destination in a given year. The producer price index (*PPI*) is measured in percent and captures *PPI* change (%) compared to the long-run average (1990-1999). *DD1030* captures 100 degree days between 10 and 30°C and *DD30* above 30°C during the growing season (June-August). The migration variable is constructed using World Bank's African Migration and Remittances Surveys data. Weather variables are constructed using ERA5 data. PPI is constructed by combining crop-specific fraction of harvested area data by Monfreda et al. [2008] and annual global commodity prices from the IMF International Finance Statistics series and the World Bank Global Economic Monitor. All models capture agricultural households, control for growing season precipitation and their squared terms and are estimated with LPM. Standard errors clustered at the district level are displayed in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

locally-relevant global prices on out-migration in agricultural households is unlikely to be driven by an increase in rural-urban migration.

We test these consideration within our baseline specification (10) for each of the destination choices we observe in the data.[13] Table 8 shows the results of these analyses derived from our preferred specification. For completeness, we present the results for non-agricultural households in Appendix E, Table 16. We also present robustness tests of specifications that include country-by-year fixed effects in the Appendix E in Tables 17 and 18 gor agriculutral and non-agricultural households, respectively. Including these more demanding fixed effects does not alter our results.

The results confirm that the aggregate effect of changes in locally-relevant prices on household out-migration among agricultural households is driven by migration to destinations in other African countries. On the contrary, changes in local weather mostly affects internal migration into urban areas within agricultural households. While our data does not allow us to precisely pin down the effect of spatial correlations, our results are highly suggestive of a simultaneous decline in real income in urban areas when locally-relevant prices rise. Thus,

[13] We consider each destination separately at a time and set all other destinations to zero in these analyses. An alternative econometric approach would be to condition estimates on locally-relevant global producer prices and weather conditions in nearby district, potentially weighing these by distance. However, due to the high spatial correlation of adjacent districts in our setting, the collinearity introduced by such an approach does not allow for reliable inference.

while the aggregate income effect of locally-relevant global prices and local weather is positive in our sample, the type of migration induced through the income channel differs: A rise in global prices increases migration into neighbouring African countries, while an improvement in local weather conditions increases internal rural-urban migration.

It should further be noted that the income fluctuations agricultural households experience from exogenous changes in global prices and local weather conditions are unlikely to be sufficient to cover the necessary investment cost of migration into OECD countries. These have been shown to be significantly higher than the costs of internal migration and migration into nearby African destinations [Marchal and Naiditch, 2020]. Our results indeed suggest that migration to these destinations are unaffected by fluctuations in both prices and weather.

6 The role of conflict

Here, we explore whether in addition to wealth, conflict is a concurring mechanism behind the PPI - migration association, revealed in section 5.1. Socio-political conditions importantly affect the relationship between climate-related events and human migration [Black et al., 2011, Cattaneo et al., 2019]. Ample evidence suggests a general link between local climatic pressure and conflict [Abel et al., 2019, Hsiang et al., 2013], which can spill over into migration and displacement [Missirian and Schlenker, 2017, Abel et al., 2019]. Fluctuations in global food prices specifically have been shown to affect political instability and violent conflicts [Bazzi and Blattman, 2014, Bellemare, 2015, McGuirk and Burke, 2020, De Winne and Peersman, 2019]. Therefore, while not making general claims about wider displacement, we study if these changes in international food prices can indirectly influence the specific type of labour migration at hand, household out-migration.

As detailed in section 4, analyzing the channeling effect of conflict in such settings is connected to numerous empirical challenges. We therefore first estimate equation 12 to study the general correlation between household out-migration and conflict in the setting of Sub-Saharan Africa. The results are shown in Table 9. Models 1-2 and 5-6 show the effects of output conflict on migration from agricultural and non-agricultural households, respectively. Models 3-4 and 7-8 then show the effects of factor conflict for agricultural and non-agricultural households, respectively. For agricultural households, we do not find any statistically significant association between output conflict and migration or between factor conflicts and migration. For non-agricultural households, we find weak evidence that household out-migration may be negatively correlated with factor conflicts. One explanation of this negative correlation could be that out-migration serves as an *escape valve* for local tensions [Bosetti et al., 2020]; however, we abstain from a strong interpretation of the result.

To complete our analyses, we also examine the general link between global commodity price changes and their effect on output and factor conflicts in Table 19 of Appendix F. Our results reveal that a rise in producer commodity prices decreases the likelihood of output conflicts (for a more in-depth discussion, see Appendix F). Thus, we find no evidence for a link between rising producer prices and conflict onset as a mechanism for migration in our particular setting. Taken together, the association between prices and conflict previous studies have documented does not seem to play a role for the household decision to send a member as a labor migrant, the predominant type of migration in Sub-Saharan Africa. If anything, household out-migration shows a negative correlation with conflict, possibly since migration decreases the local tensions and competition over resources, as documented by previous literature [Bosetti et al., 2020].

7 Concluding remarks

In this paper, we conduct household-level analyses on the relation between global prices, local weather and the household decision to send a migrant. We derive a series of new conclusions on climate-related migration. First, we study how international crop price changes, to a large extent induced by distant climatic shocks in agricultural production, affect migration in Sub-Saharan Africa. By acknowledging the importance of transmission of climatic shocks in an interconnected world, our study provides a new perspective on climate migration. Second, we provide new evidence on households' budget constraints that can affect households' ability using migration to optimally adapt to these global change dynamics. We find that higher food prices can help agricultural households to overcome their budget constraint and higher producer prices thus facilitate migration similar to positive income shocks from local weather. The aggregate positive effect of global prices on household out-migration is driven by the low average household wealth level in agricultural Sub-Saharan Africa. With household wealth rising over time, the opportunity cost channel is likely to take over, at least in partial equilibrium. Third, unlike positive weather shocks, which mostly facilitate internal rural-urban migration, positive income shocks through rising producer prices only increase migration to neighboring African countries, likely due to the simultaneous decrease in real income in nearby urban areas. This finding has important implications for projected migration dynamics in the poor regions of Sub-Saharan Africa: While we confirm that climate change scenarios rightly assume that local climatic conditions mostly drive internal migration, interconnected global shocks with repercussions for wider geographical areas may trigger migration into regions outside the home country. We further estimate that the magnitude

Table 9: Effect of conflict on migration

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Output conflict	0.0074	0.0076			-0.0002	-0.0009		
	(0.0054)	(0.0051)			(0.0052)	(0.0056)		
Factor conflict			-0.0167	-0.0118			-0.0169	-0.0160*
			(0.0127)	(0.0086)			(0.0118)	(0.0081)
N	52101	52101	52101	52101	17307	17307	17307	17307
R^2	0.012	0.016	0.012	0.016	0.016	0.023	0.016	0.023
Time trend	Year	Country x Year	Year	Country x Year	Year	Country x Year	Year	Country x Year
Model	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM
Precip. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Agri.	Agri.	Agri.	Agri.	Non.-agri.	Non.-agri.	Non.-agri.	Non.-agri.

The dependent variable is binary and captures household-level out-migration incidence in a given year. The *Output conflict* variable is binary and measures smaller scale conflict incidence. The *Factor conflict* variable is binary and measures smaller larger conflict incidence. The migration and wealth variables are constructed using World Bank's African Migration and Remittances Surveys data. *Output conflict* is constructed using ACLED data. *Factor conflict* is constructed using UCDP data. All models are estimated using LPM. Models 1-4 capture agricultural and models 5-8 non-agricultural households. Models 1, 3, 5 and 7 use a common and models 2, 4, 6 and 8 country-specific time trend. Standard errors clustered at the district level are displayed in parentheses.* $p<0.10$, ** $p<0.05$, *** $p<0.01$.

of the standardized global price effect on household out-migration is around one third of the standardized effect of local weather, implying that in the context of Sub-Saharan Africa the magnitude of climate-related impacts on migration has thus-far been underestimated. Finally, despite the significant effect global prices have on output conflict, we show that conflict does not play a role for the household decision to send a member as a labor migrant.

The implications of our results will become increasingly important in the future and have direct policy implications. For instance, the cereal demand in Sub-Saharan Africa is expected to triple by 2050 and the subcontinent is likely to depend on imports to a larger extent than it does today [De Winne and Peersman, 2019]. At the same time, episodes of rising food prices are expected more frequently as a result of the adverse climate change impacts on agricultural productivity [Lobell et al., 2011, Burke and Emerick, 2016]. On the one hand, higher food prices could help particularly poorer agricultural households cover migration-related costs. Migration is often used as an important livelihood strategy for these households and a rise in income could ease existing budget constraints. On the other hand, higher international prices are likely to impose adverse income effects on net-consumers. These opposing implications should be comprehensively considered by policy makers when designing policies to minimize welfare losses in a changing climate.

A few limitations apply and need to be discussed in this context. Based on our empirical results, we can derive only weak conclusions on the implications of rising producer prices for non-agricultural households, which mostly reside in urban areas. Data limitations do not allow the approximation of consumer prices relevant for local consumption at geographical levels similar to the district level analyses we conduct for producer prices. For instance, by combining annual variation on global crop prices with country variation of consumption fractions, McGuirk and Burke [2020] calculate international consumer prices at the country-year level. In our sample of five countries and nine years of observation, this approach would leave us with 45 data points, insufficient to capture meaningful effects. Future scientific efforts should therefore aim to improve the evidence base on migration implications of international price changes for non-agricultural households.

Considering migration of whole households rather than labor migration would be an additional promising avenue for future research on the global prices - conflict - migration nexus. By incorporating household wealth data that varies over time, one could then test the absolute importance of household wealth compared to the conflict mechanism. Such analysis would enable us to evaluate the overall welfare effects of international price variations in a changing climate.

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Appendices

A Local weather

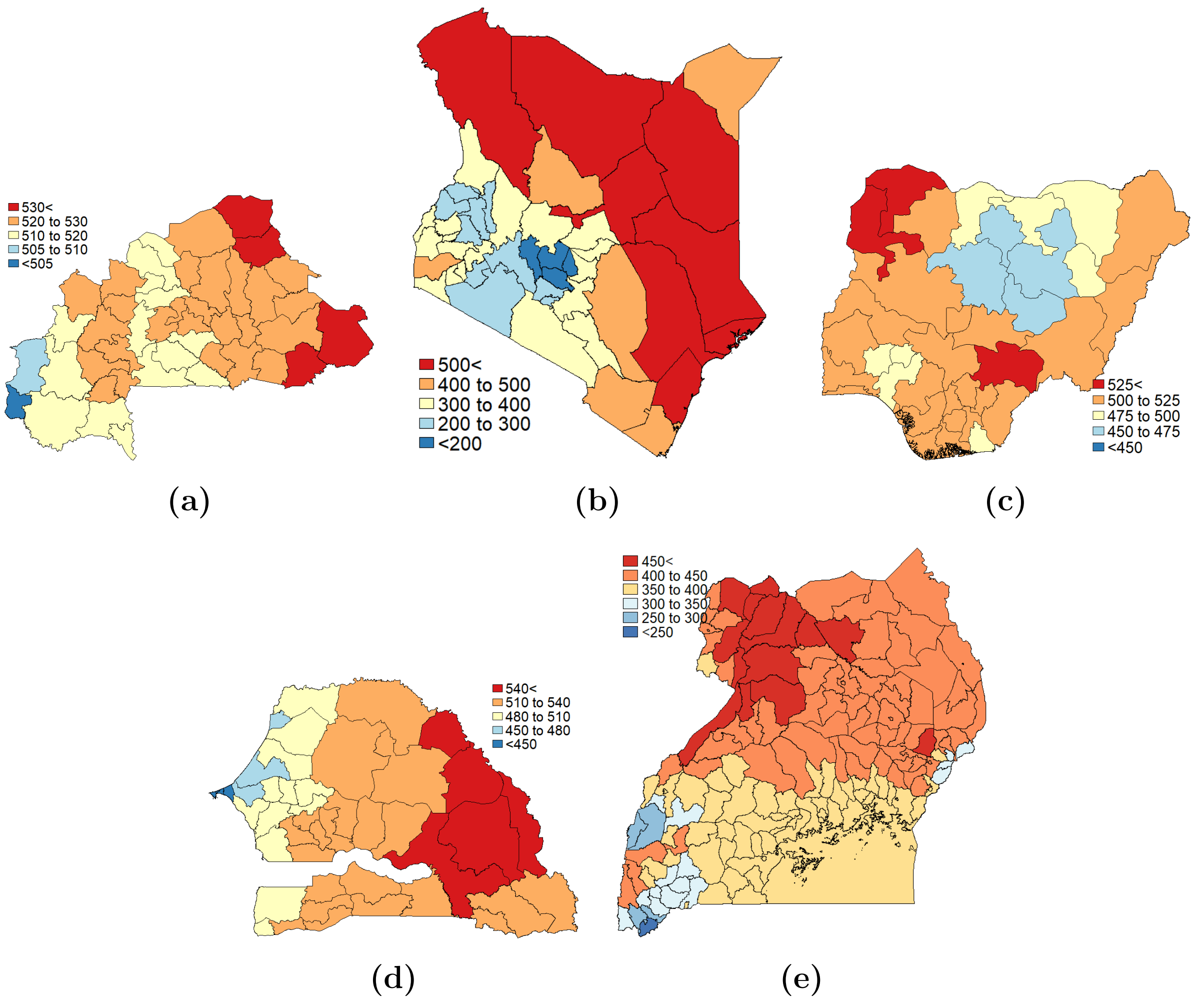

Figure 4: District-specific growing degree days (10-30°C): average for 2000-2008 (**(a)** Burkina Faso **(b)** Kenya **(c)** Nigeria **(d)** Senegal **(e)** Uganda)

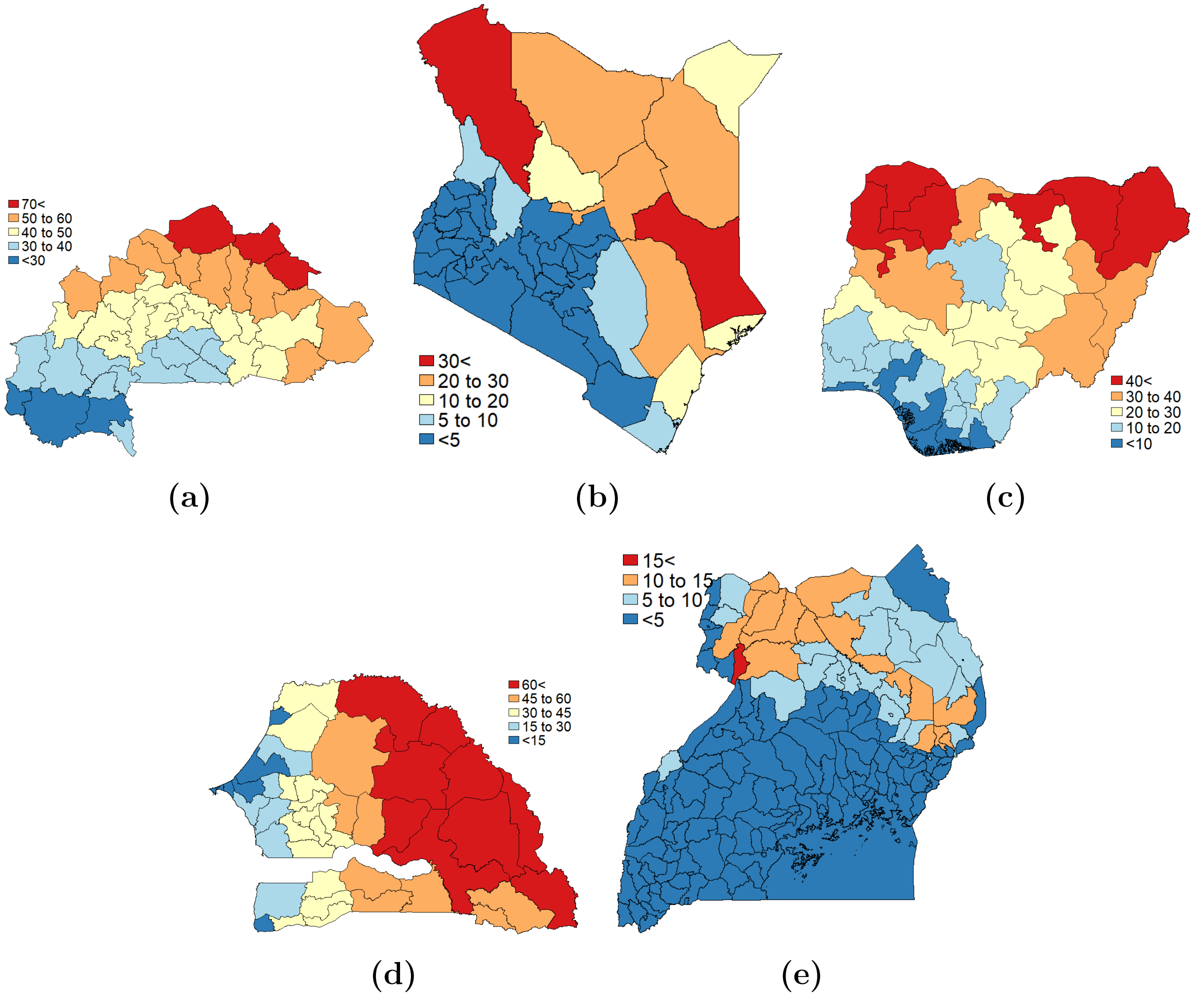

Figure 5: District-specific growing degree days (30°C): Average for 2000-2008 (**(a)** Burkina Faso **(b)** Kenya **(c)** Nigeria **(d)** Senegal **(e)** Uganda)

B International food price index

Table 10: Commodity price data to generate PPI

Crop	**Source**	**PPI**
Cereals		
Maize	IMF	Yes (food)
Rice	IMF	Yes (food)
Wheat	IMF	Yes (food)
Fruits and vegetables		
Soybean	IMF	Yes (cash)
Tomatoes	IMF	Yes (cash)
Vegetable oils		
Palm oil	IMF	Yes (food)
Sugar		
Raw equivalent	IMF	Yes (food)
Refined	IMF	Yes (food)
Beverages & others		
Cocoa	IMF	Yes (cash)
Coffee	IMF	Yes (cash)
Tea	IMF	Yes (cash)
Tobacco	World Bank	Yes (cash)

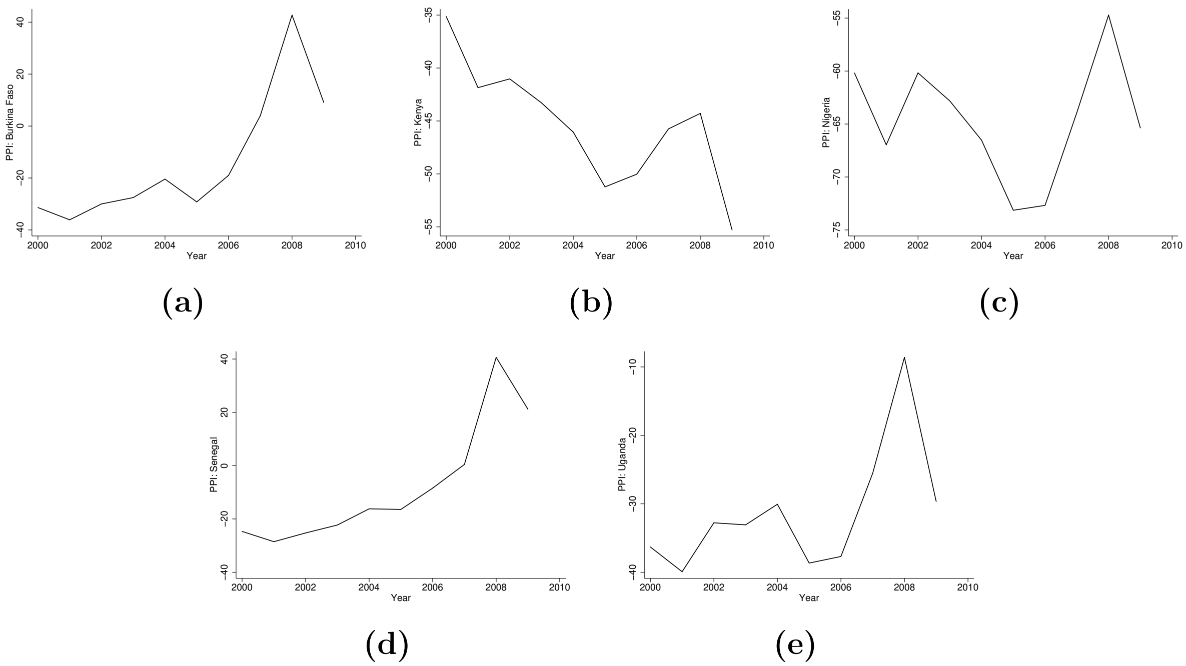

Figure 6: Country-specific PPI by year (**(a)** Burkina Faso **(b)** Kenya **(c)** Nigeria **(d)** Senegal **(e)** Uganda)

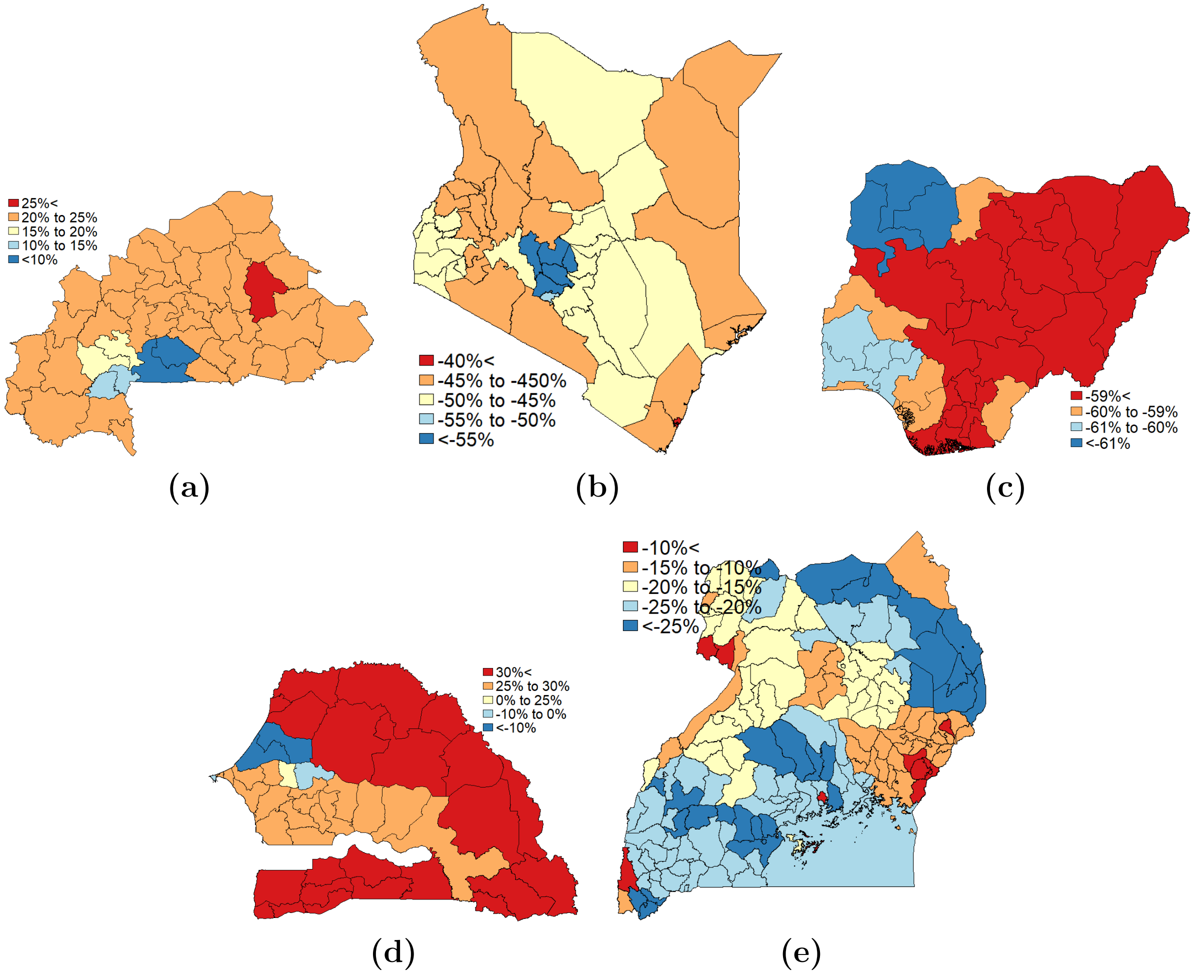

Figure 7: Average PPI (district-specific percentage change from the long-run average) during the 2007/08 food price crisis ((**a**) Burkina Faso (**b**) Kenya (**c**) Nigeria (**d**) Senegal (**e**) Uganda)

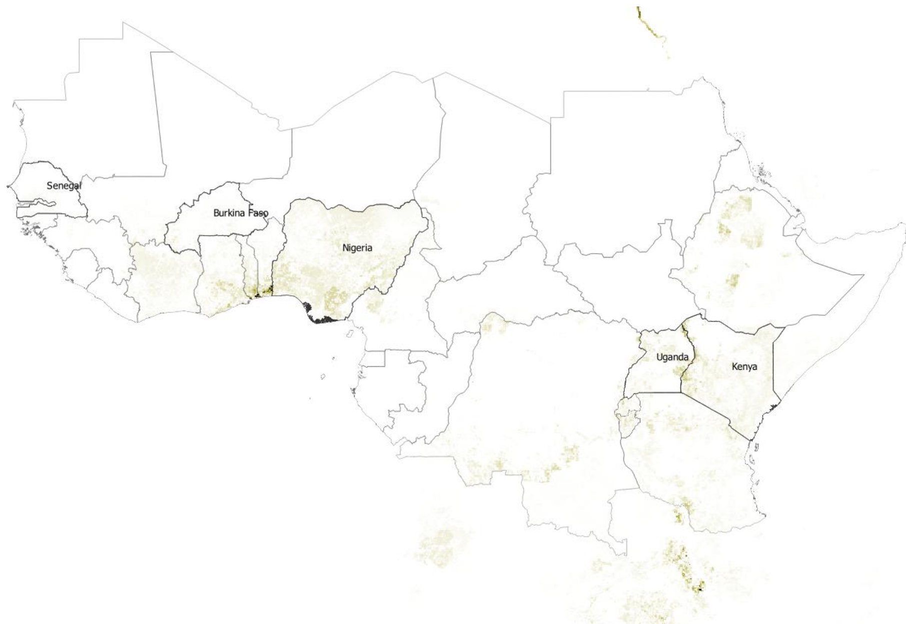

Figure 8: Fraction of harvested area of maize at the grid-cell level, darker color indicates higher fraction

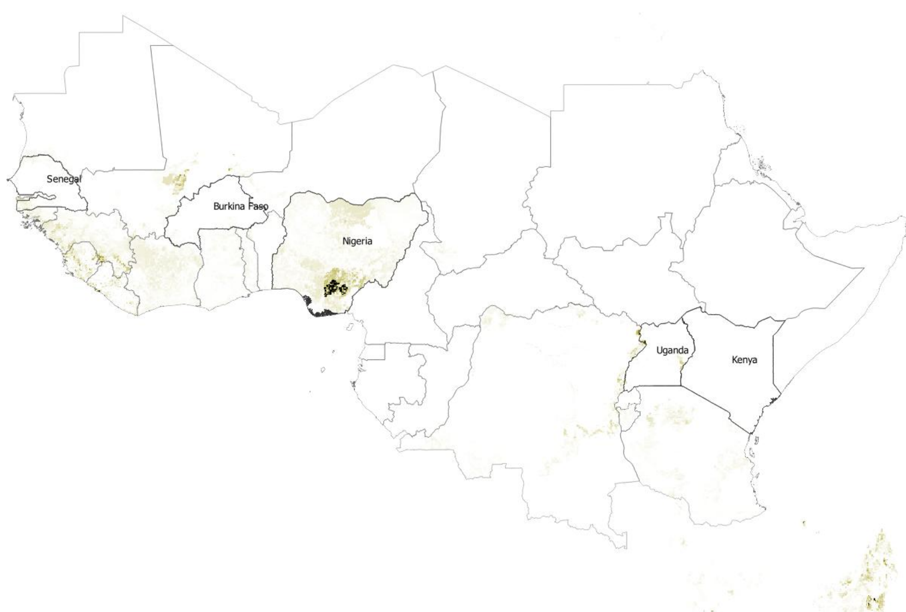

Figure 9: Fraction of harvested area of rice at the grid-cell level, darker color indicates higher fraction

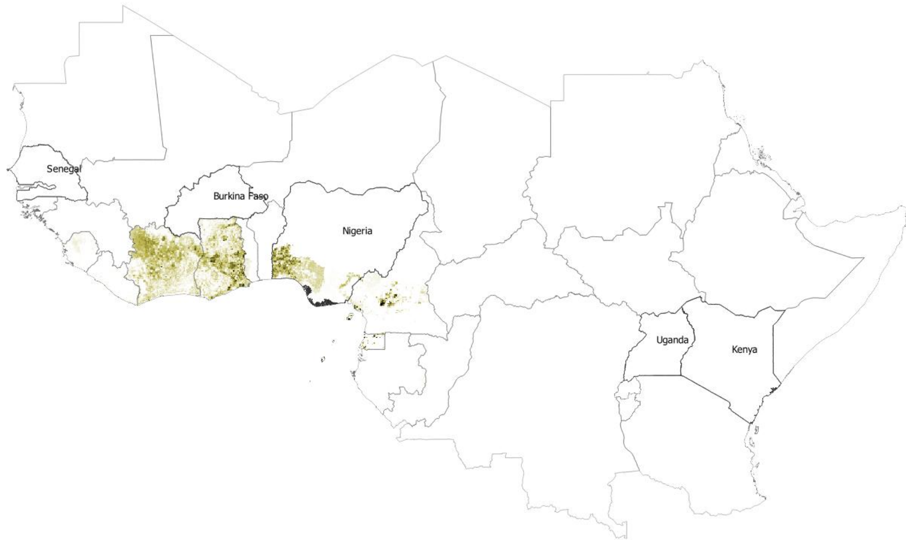

Figure 10: Fraction of harvested area of cocoa at the grid-cell level, darker color indicates higher fraction

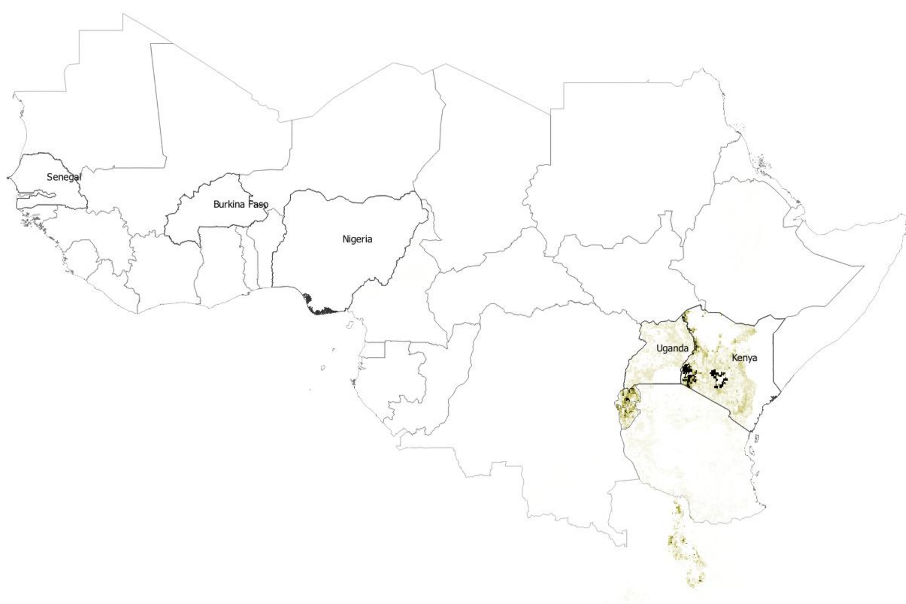

Figure 11: Fraction of harvested area of tea at the grid-cell level, darker color indicates higher fraction

C Sensitivity tests: Aggregate effects

As suggested in the main text, we further run the fully specified LPM model by distinguishing the PPI of cash and food crops. The outcomes are presented in Table 11. For the **sub-sample of agricultural households**, we find that the estimated effects in Table 5 are mainly driven by price changes of food crops. Thus, in our sample covering the food price crisis, commodities that were both locally produced and consumed were more prominently to help producing households relax their budget constraints than cash crops. For the **sub-sample of non-agricultural households**, we find weak evidence that an increase in PPI of food crops reduces the probability that households send out a migrant. PPI of food crops better captures prices of locally consumed goods, suggesting that higher food prices impose a stricter budgetary constraint on net consumers, reducing their ability to move.

We then turn to robustness checks on the alternative definition of the growing season. In Tables 12 and 13 we present the outcomes for agricultural and non-agricultural households respectively. First, in models 1-2 we extend the definition of the growing season by one month in each direction. Second, in models 3-4 we look at the effects of annual weather conditions. As for the agricultural households, in models 1-3 the effect of 10 to 30°C degree days remains positive, but is only significant in model 1. In model 4 the effect stays insignificant but swaps the sign. The effect of degree days above 30°C is insignificant throughout the specifications and except of model 3 it remains negative. As for the non-agricultural households, the effect of 10 to 30°C degree days remains positive but insignificant throughout the specifications. These outcomes suggest that even though the direction of the local weather effects remain mostly unchanged when using alternative growing season definitions, migration reacts significantly particularly to weather conditions during the growing season as defined in the main analysis (June-August) and suggested by broader literature. For non-agricultural households, we find new evidence that degree days above 30°C outside the growing season drive out-migration. Even though analysis of weather-related migration from non-agricultural and urban households is an existing gap in the literature [Sedova et al., 2021] this is beyond the scope of this paper and thus we abstract from the interpretation.

Table 11: Effect of PPI of cash and food crops on the probability of migration

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PPI (food)	0.0007***	0.0006**			0.0003	-0.0007*		
	(0.0002)	(0.0003)			(0.0003)	(0.0004)		
PPI (cash)			0.0001	0.0000			-0.0001	0.0007
			(0.0001)	(0.0003)			(0.0001)	(0.0007)
DD30	-0.0255*	-0.0460**	-0.0258	-0.0510***	0.0263	-0.0092	0.0358	-0.0039
	(0.0147)	(0.0178)	(0.0176)	(0.0193)	(0.0241)	(0.0265)	(0.0234)	(0.0265)
DD1030	0.0269**	0.0249*	0.0212*	0.0237*	0.0166	0.0247	0.0121	0.0258
	(0.0118)	(0.0142)	(0.0120)	(0.0141)	(0.0143)	(0.0159)	(0.0145)	(0.0159)
N	51075	51075	51075	51075	14427	14427	14427	14427
R^2	0.013	0.017	0.012	0.017	0.018	0.027	0.018	0.027
Time trend	Year	Country x Year	Year	Country x Year	Year	Country x Year	Year	Country x Year
Model	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM
Precip. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Agri.	Agri.	Agri.	Agri.	Non-agri.	Non-agri.	Non-agri.	Non-agri.

The dependent variable is binary and captures household-level out-migration incidence in a given year. The producer price indexes (*PPI (food)* and *PPI (cash)*) are measured in percent and capture *PPI* change (%) compared to the long-run average (1990-1999) for food and cash crops separately. *DD1030* captures 100 degree days between 10 and 30°C and *DD30* above 30°C during the growing season (June-August). The migration variable is constructed using World Bank's African Migration and Remittances Surveys data. Weather variables are constructed using ERA5 data. PPI is constructed by combining crop-specific fraction of harvested area data by Monfreda et al. [2008] and annual global commodity prices from the IMF International Finance Statistics series and the World Bank Global Economic Monitor. Models 1-4 capture agricultural and models 5-8 non-agricultural households. All models further control for growing season precipitation and their squared terms and are estimated with LPM. Models 1, 3, 5 and 7 use a common and models 2, 4, 6 and 8 country-specific time trend. Standard errors clustered at the district level are displayed in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

Table 12: Effects of PPI and local weather on the probability of migration of agricultural households: Alternative growing season definition

	(1)	(2)	(3)	(4)
PPI	0.0006***	0.0005**	0.0006***	0.0005*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
DD30 (May-Sep.)	-0.0103	-0.0213		
	(0.0121)	(0.0130)		
DD1030 (May-Sep.)	0.0154**	0.0127		
	(0.0076)	(0.0087)		
DD30 (Annual)			0.0037	-0.0131
			(0.0067)	(0.0082)
DD1030 (Annual)			0.0033	-0.0005
			(0.0036)	(0.0049)
N	52101	52101	52101	52101
R^2	0.013	0.017	0.012	0.017
Time trend	Year	Country x Year	Year	Country x Year
Model	LPM	LPM	LPM	LPM
Precip. controls	Yes	Yes	Yes	Yes
Sample	Agri.	Agri.	Agri.	Agri.

The dependent variable is binary and captures household-level out-migration incidence in a given year. The producer price index (*PPI*) is measured in percent and captures *PPI* change (%) compared to the long-run average (1990-1999). *DD1030 (May-Sep.)* and *DD1030 (Annual)* capture 100 degree days between 10 and 30°C and *DD30 (May-Sep.)* *DD30 (Annual)* above 30°C between May and September and annually. The migration variable is constructed using World Bank's African Migration and Remittances Surveys data. Weather variables are constructed using ERA5 data. PPI is constructed by combining crop-specific fraction of harvested area data by Monfreda et al. [2008] and annual global commodity prices from the IMF International Finance Statistics series and the World Bank Global Economic Monitor. The sample captures agricultural households only. All models further control for precipitation and their squared terms during the considered time frame. All models are estimated with LPM. Models 1 and 3 use a common and models 2 and 4 country-specific time trend. Standard errors clustered at the district level are displayed in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

Table 13: Effects of PPI and local weather on the probability of migration of non-agricultural households: Alternative growing season definition

	(1)	(2)	(3)	(4)
PPI	0.0003	0.0003	0.0004	0.0003
	(0.0003)	(0.0004)	(0.0003)	(0.0004)
DD30 (May-Sep.)	0.0443***	0.0361*		
	(0.0148)	(0.0206)		
DD1030 (May-Sep.)	0.0051	0.0078		
	(0.0051)	(0.0081)		
DD30 (Annual)			0.0233**	0.0082
			(0.0117)	(0.0157)
DD1030 (Annual)			0.0038	0.0010
			(0.0034)	(0.0046)
N	17307	17307	17307	17307
R^2	0.017	0.023	0.017	0.023
Time trend	Year	Country x Year	Year	Country x Year
Model	LPM	LPM	LPM	LPM
Precip. controls	Yes	Yes	Yes	Yes
Sample	Non-agri.	Non-agri.	Non-agri.	Non-agri.

The dependent variable is binary and captures household-level out-migration incidence in a given year. The producer price index (*PPI*) is measured in percent and captures *PPI* change (%) compared to the long-run average (1990-1999). *DD1030 (May-Sep.)* and *DD1030 (Annual)* capture 100 degree days between 10 and 30°C and *DD30 (May-Sep.)* *DD30 (Annual)* above 30°C between May and September and annually. The migration variable is constructed using World Bank's African Migration and Remittances Surveys data. Weather variables are constructed using ERA5 data. PPI is constructed by combining crop-specific fraction of harvested area data by Monfreda et al. [2008] and annual global commodity prices from the IMF International Finance Statistics series and the World Bank Global Economic Monitor. The sample captures non-agricultural households only. All models further control for precipitation and their squared terms during the considered time frame. All models are estimated with LPM. Models 1 and 3 use a common and models 2 and 4 country-specific time trend. Standard errors clustered at the district level are displayed in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

D Sensitivity tests: Household wealth

Table 14: Heterogeneous effects of PPI on migration by household wealth: Agricultural households

	(1)	(2)	(3)	(4)	(5)	(6)
PPI	0.0057**	0.0059**	0.0110***	0.0007***	0.0007***	0.0005**
	(0.0027)	(0.0025)	(0.0025)	(0.0002)	(0.0002)	(0.0002)
PPI × Medium-Wealth	-0.0026	-0.0026	-0.0025	-0.0003*	-0.0003*	-0.0001
	(0.0016)	(0.0016)	(0.0017)	(0.0002)	(0.0002)	(0.0002)
PPI × Upper-Wealth	-0.0089**	-0.0088**	-0.0079**	-0.0009**	-0.0009**	-0.0004
	(0.0044)	(0.0044)	(0.0040)	(0.0003)	(0.0003)	(0.0003)
DD30		-0.3586	-0.2100		-0.0254*	-0.0438***
		(0.2265)	(0.1974)		(0.0145)	(0.0167)
DD1030		0.1783	0.0934		0.0215*	0.0204
		(0.1701)	(0.1479)		(0.0111)	(0.0135)
N	23742	23742	23742	52101	52101	52101
R^2				0.013	0.013	0.017
Time trend	Year	Year	Country x Year	Year	Year	Country x Year
Model	Logit	Logit	Logit	LPM	LPM	LPM
Precip. controls	No	Yes	Yes	No	Yes	Yes
Sample	Agri.	Agri.	Agri.	Agri.	Agri.	Agri.

The dependent variable is binary and captures household-level out-migration incidence in a given year. The wealth variable is categorical and takes on values for the year 2000: low wealth (0), medium wealth (1) upper wealth (2). The producer price index (*PPI*) is measured in percent and captures *PPI* change (%) compared to the long-run average (1990-1999). *DD1030* captures 100 degree days between 10 and 30°C and *DD30* above 30°C during the growing season (June-August). The migration and wealth variables are constructed using World Bank's African Migration and Remittances Surveys data. Weather variables are constructed using ERA5 data. PPI is constructed by combining crop-specific fraction of harvested area data by Monfreda et al. [2008] and annual global commodity prices from the IMF International Finance Statistics series and the World Bank Global Economic Monitor. The sample captures agricultural households only. Models 2-3 and 5-6 further control for growing season precipitation and their squared terms. Models 1-3 are estimated with fixed effects logit model and models 4-6 with LPM. Models 1-2 and 4-5 use a common and models 3 and 6 country-specific time trend. Model 5 corresponds to the preferred specification. Standard errors clustered at the district level are displayed in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

Table 15: Heterogeneous effects of PPI on migration by household wealth: Non-agricultural households

	(1)	(2)	(3)	(4)	(5)	(6)
PPI	0.0061	0.0059	0.0102**	0.0007	0.0007	0.0006
	(0.0043)	(0.0044)	(0.0049)	(0.0005)	(0.0005)	(0.0005)
PPI × Medium-Wealth	-0.0037	-0.0038	-0.0049	-0.0005	-0.0005	-0.0004
	(0.0034)	(0.0035)	(0.0036)	(0.0004)	(0.0004)	(0.0004)
PPI × Upper-Wealth	-0.0053	-0.0053	-0.0051	-0.0007	-0.0007	-0.0005
	(0.0078)	(0.0079)	(0.0081)	(0.0007)	(0.0007)	(0.0007)
DD30		0.3779	0.6080		0.0220	0.0042
		(0.3685)	(0.3776)		(0.0208)	(0.0196)
DD1030		0.2256	0.1854		0.0157*	0.0205*
		(0.1381)	(0.1379)		(0.0094)	(0.0112)
N	7443	7443	7443	17307	17307	17307
R^2				0.016	0.017	0.023
Time trend	Year	Year	Country x Year	Year	Year	Country x Year
Model	Logit	Logit	Logit	LPM	LPM	LPM
Precip. controls	No	Yes	Yes	No	Yes	Yes
Sample	Non-agri.	Non-agri.	Non-agri.	Non-agri.	Non-agri.	Non-agri.

The dependent variable is binary and captures household-level out-migration incidence in a given year. The wealth variable is categorical and takes on values for the year 2000: low wealth (0), medium wealth (1) upper wealth (2). The producer price index (*PPI*) is measured in percent and captures *PPI* change (%) compared to the long-run average (1990-1999). *DD1030* captures 100 degree days between 10 and 30°C and *DD30* above 30°C during the growing season (June-August). The migration and wealth variables are constructed using World Bank's African Migration and Remittances Surveys data. Weather variables are constructed using ERA5 data. PPI is constructed by combining crop-specific fraction of harvested area data by Monfreda et al. [2008] and annual global commodity prices from the IMF International Finance Statistics series and the World Bank Global Economic Monitor. The sample captures non-agricultural households only. Models 2-3 and 5-6 further control for growing season precipitation and their squared terms. Models 1-3 are estimated with fixed effects logit model and models 4-6 with LPM. Models 1-2 and 4-5 use a common and models 3 and 6 country-specific time trend. Model 5 corresponds to the preferred specification. Standard errors clustered at the district level are displayed in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

E Sensitivity tests: Destination choices

Table 16: The effect of PPI by destination choice: Non-agricultural households

	(1) Total	(2) Internal	(3) Internal: rural	(4) Internal: urban	(5) Other African	(6) OECD
PPI	0.0004	0.0002	0.0000	0.0002	0.0000	0.0001
	(0.0003)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
DD1030	0.0156*	0.0165*	0.0059**	0.0106	0.0051	0.0050
	(0.0093)	(0.0094)	(0.0026)	(0.0095)	(0.0032)	(0.0071)
DD30	0.0205	-0.0186	-0.0082	-0.0106	0.0255**	0.0058
	(0.0214)	(0.0210)	(0.0073)	(0.0206)	(0.0103)	(0.0091)
N	17307	17307	17307	17307	17307	17307
R^2	0.016	0.023	0.006	0.018	0.003	0.002
Time trend	Year	Year	Year	Year	Year	Year
Model	LPM	LPM	LPM	LPM	LPM	LPM

The dependent variables are binary and capture household-level out-migration incidence by destination in a given year. The producer price index (*PPI*) is measured in percent and captures *PPI* change (%) compared to the long-run average (1990-1999). *DD1030* captures 100 degree days between 10 and 30°C and *DD30* above 30°C during the growing season (June-August). The migration variable is constructed using World Bank's African Migration and Remittances Surveys data. Weather variables are constructed using ERA5 data. PPI is constructed by combining crop-specific fraction of harvested area data by Monfreda et al. [2008] and annual global commodity prices from the IMF International Finance Statistics series and the World Bank Global Economic Monitor. All models capture non-agricultural households, control for growing season precipitation and their squared terms and are estimated with LPM. Standard errors clustered at the district level are displayed in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

Table 17: PPI and destination choices: Agricultural households

	(1) Total	(2) Internal	(3) Internal: rural	(4) Internal: urban	(5) Other African	(6) OECD
PPI	0.0004*	0.0001	0.0000	0.0000	0.0005***	-0.0000
	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
GDD1030	0.0198	0.0223**	0.0034	0.0189*	-0.0011	0.0038
	(0.0150)	(0.0102)	(0.0039)	(0.0102)	(0.0065)	(0.0060)
GDD30	-0.0473***	-0.0265**	0.0033	-0.0293***	-0.0166**	-0.0054
	(0.0167)	(0.0132)	(0.0062)	(0.0110)	(0.0070)	(0.0046)
N	54099	54099	54099	54099	54099	54099
R^2	0.017	0.018	0.005	0.014	0.009	0.002
Time trend	CountryXYear	CountryXYear	CountryXYear	CountryXYear	CountryXYear	CountryXYear
Model	LPM	LPM	LPM	LPM	LPM	LPM
Precip. controls	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variables are binary and capture household-level out-migration incidence by destination in a given year. The producer price index (*PPI*) is measured in percent and captures *PPI* change (%) compared to the long-run average (1990-1999). *DD1030* captures 100 degree days between 10 and 30°C and *DD30* above 30°C during the growing season (June-August). The migration variable is constructed using World Bank's African Migration and Remittances Surveys data. Weather variables are constructed using ERA5 data. PPI is constructed by combining crop-specific fraction of harvested area data by Monfreda et al. [2008] and annual global commodity prices from the IMF International Finance Statistics series and the World Bank Global Economic Monitor. All models capture agricultural households, control for growing season precipitation and their squared terms and are estimated with LPM employing country-specific trends. Standard errors clustered at the district level are displayed in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

Table 18: PPI and destination choices: Non-agricultural households

	(1) Total	(2) Internal	(3) Internal:rural	(4) Internal:urban	(5) Other African	(6) OECD
PPI	0.0003	0.0003	0.0001***	0.0002	-0.0001	0.0001
	(0.0004)	(0.0003)	(0.0000)	(0.0003)	(0.0001)	(0.0002)
GDD1030	0.0186	0.0169	0.0106**	0.0073	0.0074	-0.0041
	(0.0121)	(0.0125)	(0.0047)	(0.0124)	(0.0049)	(0.0102)
GDD30	0.0142	-0.0072	-0.0124*	0.0039	0.0233**	0.0018
	(0.0244)	(0.0228)	(0.0073)	(0.0242)	(0.0113)	(0.0104)
N	18342	18342	18342	18342	18342	18342
R^2	0.024	0.031	0.009	0.026	0.006	0.005
Time trend	CountryXYear	CountryXYear	CountryXYear	CountryXYear	CountryXYear	CountryXYear
Model	LPM	LPM	LPM	LPM	LPM	LPM
Precip. controls	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variables are binary and capture household-level out-migration incidence by destination in a given year. The producer price index (*PPI*) is measured in percent and captures *PPI* change (%) compared to the long-run average (1990-1999). *DD1030* captures 100 degree days between 10 and 30°C and *DD30* above 30°C during the growing season (June-August). The migration variable is constructed using World Bank's African Migration and Remittances Surveys data. Weather variables are constructed using ERA5 data. PPI is constructed by combining crop-specific fraction of harvested area data by Monfreda et al. [2008] and annual global commodity prices from the IMF International Finance Statistics series and the World Bank Global Economic Monitor. All models capture non-agricultural households, control for growing season precipitation and their squared terms and are estimated with LPM employing country-specific trends. Standard errors clustered at the district level are displayed in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

F Further tests on the link between producer prices and conflict

In this section, we present outcomes from a set of LPM regressions with and without state-specific trends, analyzing the association between PPI, local weather and the probability of conflict incidence. We conduct the analyses at the district level. In models 1-2 and 5-6 of Table 19, we study the direct effects on output and factor conflict likelihoods, respectively. In models 3-4 and 7-8 of Table 19 we then interact the PPI and local weather variables with a district-specific fraction of agricultural households, to study if the effect of international prices varies by districts' dependence on agricultural production.

From the theoretical perspective, the direct effect of higher food prices on conflict is a priori not clear. On the one hand, the predation (or rapacity) and deprivation theories imply that higher food prices can result in more violent events. The so-called predation effect suggests that higher prices increase the value of the appropriable surplus, leading to more conflicts [Besley and Persson, 2008, Dube and Vargas, 2013]. The deprivation effect indicates that among consumers, an increase in prices can induce perceptions of relative deprivation in comparison to others and thus lead to public unrests [Hendrix and Haggard, 2015]. On the other hand, the opportunity costs effect suggests that higher food prices reduce conflicts, by increasing the opportunity costs of insurrection for farmers as higher wages and revenues make it more attractive to work [Bazzi and Blattman, 2014, Dube and Vargas, 2013, De Winne and Peersman, 2019]. Moreover, higher commodity prices can increase state revenues and so the capacity of the state to reduce conflicts [Besley and Persson, 2008, De Winne and Peersman, 2019].

Our results reveal that a rise in producer commodity prices decreases the likelihood of output conflicts. This is in line with findings by Brückner and Ciccone [2010] or Berman and Couttenier [2015] and the opportunity cost theory [Bazzi and Blattman, 2014, Dube and Vargas, 2013]. These findings contrast the evidence by Bellemare [2015], Hendrix and Haggard [2015], Raleigh et al. [2015] or De Winne and Peersman [2019] in line with the predation (also called rapacity) and deprivation effects, both of which outline how higher food prices can increase violence. The magnitudes of the interaction terms between output conflict and agricultural dependence are very close to zero. We also do not find significant effect of producer prices on factor conflict.

The direct effect of yield decreasing temperatures (*DD30*) on the likelihood of factor conflict is negative and becomes significant only in models 3-4. When interacted with the agricultural dependence, the effect is positive suggesting that yield decreasing temperatures are more likely to increase the probability of output conflict in areas that are more dependent on agricultural production. This outcome is in line with the findings on PPI, namely that the opportunity costs of violence decrease with decreasing agricultural incomes [Koubi, 2019]. We do not find a significant effect of yield decreasing temperatures on factor conflict.

The effect of yield enhancing temperatures (*DD1030*) on output conflict likelihood is positive in models 1 and 3 but looses its significance in model 2 and additionally swaps the sign in model 4. When it comes to factor conflict, the effect of yield enhancing temperatures is positive throughout specifications but it only becomes significant in model 5. These generally positive associations are in line with the predation theory and seem to be relevant primarily for net-consumers (the interaction with agricultural dependence is insignificant), for whom the increase in agricultural surplus increases the rewards from engaging in conflict.

Table 19: Effect of PPI on conflict

	Output conflict				*Factor conflict*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PPI	-0.001233*	-0.000677	-0.002686*	-0.003222*	-0.000408	0.000377	0.000012	0.000603
	(0.000689)	(0.000967)	(0.001444)	(0.001782)	(0.000485)	(0.000638)	(0.000818)	(0.000926)
DD1030	0.131833***	0.005112	0.156017*	-0.079531	0.076543**	0.018637	0.077876	0.078093
	(0.049673)	(0.066760)	(0.087221)	(0.095586)	(0.038051)	(0.048522)	(0.091138)	(0.090370)
DD30	-0.092142	-0.106884	-1.235795***	-1.429446**	-0.112580	-0.102938	-0.354520	-0.398344
	(0.075057)	(0.143670)	(0.467423)	(0.591827)	(0.069739)	(0.088839)	(0.302292)	(0.259986)
PPI × Agricultural (%)			0.000021	0.000032*			-0.000005	-0.000003
			(0.000014)	(0.000017)			(0.000007)	(0.000007)
DD1030 × Agricultural (%)			-0.000295	0.001175			-0.000031	-0.000755
			(0.001240)	(0.001361)			(0.001167)	(0.001126)
DD30 × Agricultural (%)			0.012997***	0.014654**			0.002724	0.003311
			(0.004928)	(0.005820)			(0.003243)	(0.002746)
N	1260	1260	1260	1260	1260	1260	1260	1260
R^2	0.045	0.125	0.052	0.134	0.011	0.043	0.012	0.044
Time trend	Year	Country x Year	Year	Country x Year	Year	Country x Year	Year	Country x Year
Model	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM
Precip. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Conflicts	Jul.-Dec.	Jul.-Dec.	Jul.-Dec.	Jul.-Dec.	Jul.-Dec.	Jul.-Dec.	Jul.-Dec.	Jul.-Dec.

The dependent variable is binary and captures district-level conflict incidence in a given year. The *Output conflict* variable is binary and measures smaller scale conflict incidence. The *Factor conflict* variable is binary and measures larger conflict incidence. The producer price index (*PPI*) is measured in percent and captures *PPI* change (%) compared to the long-run average (1990-1999). *DD1030* captures 100 degree days between 10 and 30°C and *DD30* above 30°C during the growing season (June-August). *Output conflict* is constructed using ACLED data. *Factor conflict* is constructed using UCDP data. Weather variables are constructed using ERA5 data. PPI is constructed by combining crop-specific fraction of harvested area data by Monfreda et al. [2008] and annual global commodity prices from the IMF International Finance Statistics series and the World Bank Global Economic Monitor. All models are estimated using LPM. Models 1, 3, 5 and 7 use a common and models 2, 4, 6 and 8 country-specific time trend. Standard errors clustered at the district level are displayed in parentheses.* $p<0.10$, ** $p<0.05$, *** $p<0.01$.