Trade, Storage, and Climate Extremes: Theory and Evidence from Sub-Saharan Africa

Charlotte Janssens (Hasselt University and KU Leuven) *†‡

February 17, 2026

Climate extremes increasingly threaten food security in developing countries. This paper develops a dynamic stochastic model integrating consumption smoothing, storage, and trade to examine how agricultural markets buffer climate-induced food shortages. The theoretical framework provides new insights on the role of household market transaction costs, borrowing constraints, and spatiotemporal climate patterns. Building on the theory, the paper conducts a large-scale empirical analysis of food insecurity, climate extremes, and travel times at quarterly and subnational level across 12 Sub-Saharan African countries. The empirical results show that local dry conditions exacerbate food insecurity more severely in regions with longer travel times to cities, while country-level dry conditions have stronger effects in regions farther from ports. Countries' import capacity and stocks buffer the food insecurity impact of country-level climate extremes. Some empirical results diverge from the theoretical predictions, pointing to the need for further research on the functioning of market-based consumption smoothing.

*Center for Environmental Sciences, Hasselt University, Hasselt, Belgium; Department of Earth and Environmental Sciences, KU Leuven, Leuven, Belgium; Contact: charlotte.janssens@uhasselt.be

†I am very grateful to Miet Maertens, Christophe Gouel, David Atkin, Dave Donaldson, and John Sturm for the guidance, support, and helpful comments during the course of this project; to seminar participants at the BAAE 2022 PhD Symposium, BEED 2023, CSAE 2023 annual conference, MIT, IIASA, AgroParisTech, and KU Leuven for insightful discussions; and to the three anonymous reviewers for the numerous constructive comments that have improved the paper. Part of the research was executed while visiting the Economics Department at MIT in 2022 and the INRAE-AgroParisTech joint research unit Paris-Saclay Applied Economics in 2023. This work has been supported by funding from Research Foundation Flanders (FWO, grants 1SC1419N, V414821N, 12ATF24N-7028, and V471723N)

‡Manuscript accepted for publication at Journal of Development Economics (https://doi.org/10.1016/j.jdeveco.2026.103761), subject to CC BY-NC-ND end user license.

1 Introduction

Extreme weather or climate events can cause drastic harvest failures and severe food insecurity, particularly in low-income countries that heavily rely on rainfed agriculture. Starting in 2020, an unprecedented extreme, widespread, and multi-season drought in the Horn of Africa contributed to over 22 million people facing acute food insecurity [FEWSNET et al., 2023]. Agricultural markets may buffer such impacts. Under extreme climate events the supply and price of food will vary over space and time, which in turn creates opportunities for trade (spatial arbitrage) and storage (temporal arbitrage). Evidence about the effectiveness of agricultural markets in smoothing food consumption in the face of climate variability remains scarce. This research gap is particularly pertinent given that the Intergovernmental Panel on Climate Change (IPCC) expects a widespread increase in the frequency and intensity of extreme events under future global warming[1] [Seneviratne et al., 2021].

Sub-Saharan Africa is characterized by rainfed agriculture and highly variable climatic conditions. Years of adequate rainfall and bumper harvests alternate with years of droughts, floods, and harvest failures. Figure 1 compares the occurrence of exceptionally dry conditions with cereal production, imports, and stock levels for three countries in Sub-Saharan Africa. Kenya faced widespread dry conditions in 2009 and 2011, while Ethiopia and Zambia faced dry conditions in 2015 and 2016. In Ethiopia and Kenya, the dry years coincided with elevated imports of cereals from international markets. In Zambia, the drought years coincided with a depletion of cereal stocks that had been built up during the previous agricultural season [Chapoto et al., 2015]. While previous studies estimate the impact of climate shocks on trade flows [Jones and Olken, 2010, Felbermayr and Gröschl, 2013, Dall'Erba et al., 2021] and provide descriptive assessments of the rationale of cereal stocks [The World Bank, 2021, Wright, 2011], this study analyzes whether agricultural market mechanisms buffer the food insecurity impacts of climate extremes.

We focus on developing countries in Sub-Saharan Africa, where climate extremes strongly affect food production [Bezner Kerr et al., 2022], market failures are widespread [Dillon and Barrett, 2017], and trade and storage costs are high [Atkin and Donaldson, 2015, Porteous, 2019]. We first

[1]The IPCC defines an extreme weather event as an event that is rare at a specific location and time. When extreme weather lasts for some time (e.g., a drought that lasts for one or multiple seasons), it can be classified as an extreme climate event, in particular when the overall conditions themselves are extreme [IPCC, 2018]. This study investigates climatic conditions that are unusually dry or wet over the time frame of at least 3 months during the agricultural growing season. We bundle these conditions under the term "climate extremes".

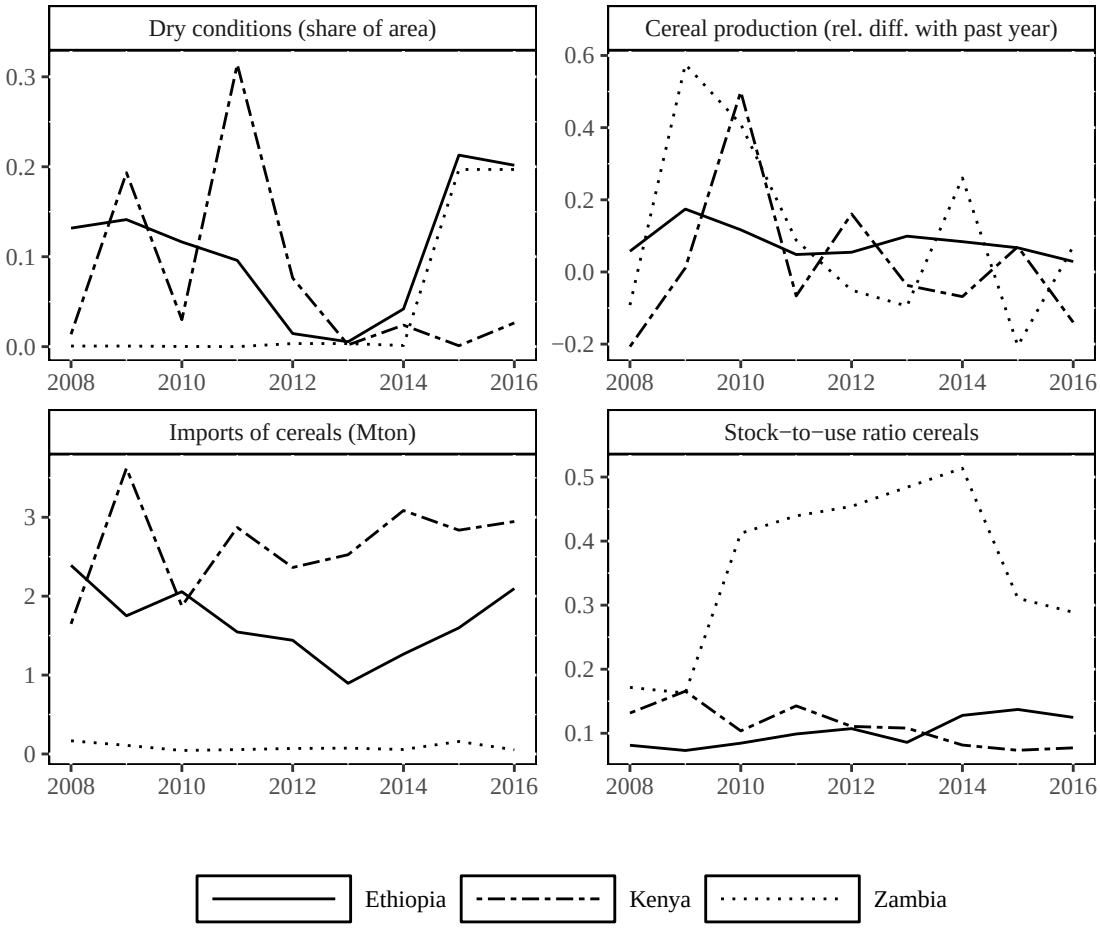


Figure 1: Dry climatic conditions, cereal imports, and cereal stocks for three countries in Sub-Saharan Africa. Share of country area under dry conditions in the most recent growing season based on the SPEI index (SPEI $\leq$ -1.5) from Peng et al. [2020]. Cereal production volumes from FAOSTAT. International cereal import volume from CEPII BACI [Gaulier and Zignago, 2010], aggregating primary and secondary products to primary equivalent. Stock-to-use ratio is the marketing year ending stock of cereals divided by marketing year domestic consumption of cereals from the USDA PSD database.

present a novel theoretical framework to introduce the mechanisms of market-based food consumption smoothing. We develop a stylized dynamic stochastic small open economy model that combines household-level consumption smoothing with market-level storage and trade. Agricultural production is stochastic due to uncertain climatic conditions. The economy consists of two locations, a subnational region and the rest of the country (which represents an aggregate of all other regions). The representative household in each location produces, consumes, and saves, while traders in each location respond to climate variability by trading goods domestically or with the world market, or by managing food stocks. We investigate the implication of transaction costs and borrowing constraints, two market failures commonly faced by households in developing countries [Stephens and Barrett, 2011, Janvry et al., 1991]. Storage facilitates household consumption smoothing via inter-temporal exchanges in assets within a location. Trade facilitates household consumption smoothing via intra-temporal exchanges in goods between locations and inter-temporal exchanges in assets between locations. Based on a set of model experiments, we derive four qualitative predictions: (1) when households face market transaction costs, food consumption is more responsive to local climate shocks and less responsive to national climate shocks; (2) when a region is isolated from the world market, food consumption is more responsive to local and national climate shocks; (3) storage and trade partly substitute one another in smoothing food consumption in the face of climate shocks; and (4) when climate shocks are temporally correlated, smoothing via storage is reduced to a larger extent than smoothing via trade.

Guided by the theoretical insights, the second part of the paper investigates the prevalence of food insecurity in 12 countries in Sub-Saharan Africa over the period 2009–2016. In specific, we analyze whether the food insecurity impacts of climate extremes are larger in regions where households have limited market access and whether the impacts are smaller in countries with import or stock capacity. We exploit exogenous variation in climatic conditions using panel data at the sub-annual (3 to 4-monthly time interval) and subnational level (second administrative units). The analysis controls for time-invariant unobserved regional characteristics, general time trends, and time-varying variables that are potentially correlated with food insecurity and market access. The empirical evidence provides mixed support for the theoretical predictions. Consistent with the theory, local dry conditions affect food insecurity to a larger extent in areas with longer travel times to the closest city, a proxy for households' market transaction costs. Country-level dry extremes affect food insecurity to a larger extent in areas with longer travel times to ports, a proxy for regions'

international market access. Countries' asset reserves and cereal stocks both buffer food insecurity impacts of country-level climate extremes. However, in contrast with the theoretical predictions, the empirical findings suggest that trade and storage are partly complementary, instead of partly substitutable, in buffering the impact of climate extremes. In addition, evidence on the role of temporal correlation of climate shocks remains inconclusive.

This paper contributes to the literature on climate change adaptation through trade. Adaptation through trade can be understood as the gains from trade due to climate-driven differences – across locations and commodities – in the *average* agricultural productivity [Costinot et al., 2016, Gouel and Laborde, 2021, Janssens et al., 2020, Stevanović et al., 2016, Porteous, 2024] or, as is done also in this paper, in the *variability* of agricultural productivity [Allen and Atkin, 2022, Dingel and Meng, 2025, Burgess and Donaldson, 2017, Dorosh et al., 2009, 2016, Gouel et al., 2016, Gouel and Jean, 2015, Haggblade et al., 2017, Porteous, 2019, Reimer and Li, 2009]. Research on trade and adaptation has expanded in terms of model complexity since the first studies in the 1990s [Randhir and Hertel, 2000, Reilly and Hohmann, 1993, Rosenzweig and Parry, 1994], but important gaps remain in terms of the spatiotemporal scales that are covered (Table S1).

The most critical research gap relates to the temporal scale. Very few studies consider the uncertainty of next season's crop yields, thereby leaving out forward-looking dynamics and inter-temporal trade (i.e., storage). Studies that do incorporate this reveal important interactions between storage and trade. The rational expectations storage and trade model by Williams and Wright [1991] pioneered this literature. Williams and Wright [1991] study trade and storage flows in the presence of weather variation in a partial equilibrium setting and show that the interaction between trade and storage depends on the correlation between the weather of trade partners. Coleman [2009] relaxes the assumption of instantaneous trade in the model of Williams and Wright [1991]. By doing so, he demonstrates that the joined management of weekly trade flows and stock levels explains temporary localized price spikes in 19th century Chicago and New York corn markets. Gouel and Jean [2015] use the rational expectations trade and storage model to investigate optimal trade and storage policies for price stabilization in a small open developing country. In such a setting, when domestic prices are linked to world market prices, storage policy on its own does not stabilize domestic prices in the event of price spikes, but rather needs accompanying trade policies. Porteous [2019] develops a large-scale model of monthly grain trade and storage that covers 230 markets across Sub-Saharan Africa, but that assumes deterministic crop yields. He finds that when storage is not considered,

the timing of trade is not correctly modelled and trade costs and welfare effects are underestimated. Regarding the spatial scale, most studies focus on either international or domestic trade, while there are important interactions. International prices affect regions within a country for example differently depending on domestic trade barriers [Atkin and Donaldson, 2015, Sotelo, 2020]. This paper develops a stylized model that considers uncertainty of future crop yields, that incorporates storage, and that includes domestic and international trade.

This paper relates also to the literature on consumption smoothing. The consumption-saving model of Deaton [1991] has been widely used to study consumption smoothing by risk averse households with uncertain agricultural incomes in developing countries. Smoothing mechanisms include formal credit and insurance markets [Janzen and Carter, 2019, Basu and Wong, 2015], informal insurance [Kazianga and Udry, 2006], livestock asset holdings [Kazianga and Udry, 2006, Carter and Lybbert, 2012], and on-farm grain stocks [Kazianga and Udry, 2006, Tesfaye and Gebremariam, 2020, Waldman et al., 2020]. While the model of storage and trade and the model of consumption smoothing are recognized as structurally related [Gouel et al., 2016, Yang, 2006], the explicit connection between consumption smoothing, storage, and trade is understudied. In the trade literature, Yang [2006] and Felbermayr and Gröschl [2013] link international trade to consumption smoothing by risk averse households in the context of country-level natural disasters. In the storage literature, stockholding is mostly linked to profit maximization by storage firms that are risk neutral [Williams and Wright, 1991, Larson et al., 2014, Gouel and Jean, 2015] or risk averse [Lence and Hayes, 1998, Netz, 1995], and not to consumption smoothing by risk averse households. An exception is the study of Arseneau and Leduc [2013], which combines the rational expectations storage model with household consumption (but leaves out trade).

This paper is the first to connect the rational expectations storage and trade model with the consumption-saving household model. While the closest related study by Park [2006] develops a model of inter-temporal household grain management, it treats the prices observed by households as determined in a separate, independent market model. Other studies that integrate consumption decisions directly into market models of trade, storage, and volatility do not incorporate inter-temporal consumer preferences [Gouel and Jean, 2015, Allen and Atkin, 2022]. Our approach demonstrates that inter-temporal consumption preferences create a fundamental rationale for inter-temporal exchanges of assets within and between regions through storage and trade mechanisms. By bridging these two largely disconnected strands of literature, this paper creates new avenues for future theo-

retical developments.

Building on this theoretical foundation, our key empirical contribution is to expand the limited evidence on how markets buffer climate-driven food shortages in developing countries. Historical evidence from Burgess and Donaldson [2010, 2017] shows that railroad infrastructure development in colonial India significantly reduced the impact of rainfall shortages on famines after districts gained access to trade. Similarly, in Ethiopia, while natural disasters have increased in frequency since 1960, deaths per disaster have declined [Rashid et al., 2018]—a reduction attributed to comprehensive policies including market liberalization, effective food reserve management, and infrastructure investments enabling private grain trade between deficit and surplus areas during crises. This paper provides new, detailed subnational evidence on how agricultural markets buffer the food insecurity impacts of climate extremes across 12 countries in Sub-Saharan Africa.

The paper proceeds as follows. Section 2 introduces a stylized model of consumption smoothing, storage, and trade, discussing the main model mechanisms and deriving four theoretical predictions based on model experiments. Guided by these theoretical insights, Section 3 empirically investigates whether markets have buffered the food insecurity impacts of past climate extremes in Sub-Saharan Africa. Section 4 summarizes the findings, discusses possible explanations for the differences between theoretical predictions and empirical results, and concludes.

2 Theoretical framework

2.1 A stylized model

In this section, we develop a stylized dynamic small open economy model to investigate the effect of storage and trade on consumption smoothing in the context of stochastic agricultural production. To reflect our empirical context, we assume that the economy consists of two locations: the "region", which represents a typical subnational administrative unit within a country (for example, a district), and the "rest of the country", which is the aggregate of all the other regions within the country. The model features farm households that produce, consume, and save, and traders that engage in intra- and inter-temporal price arbitrage.

Model Setup

Environment. We consider a small open economy that consists of a region, REG, and the rest of the country, ROC. Each location features an agricultural sector and an outside sector, indexed by $d \in \{ag, o\}$, producing food and an outside good, respectively. In each location there are two representative agents, the household who produces, consumes, and saves, and the trader who stores and trades. We assume that agents have a finite time horizon of three periods, $t \in [t_0, t_1, t_2]$. Goods and financial assets can be exchanged both within the domestic economy and with the world market W taking a fixed world market price and interest rate as given[2]. Locations are indexed by $(m, n) \in \{REG, ROC, W\}$.

Household. The representative household produces food and the outside good. Agricultural production is risky due to variable climatic conditions. We represent agricultural production as a stochastic endowment process, $H_{m,ag,t} = (1 + \nu_{mt})\overline{H}_{m,ag,t}$, with ν_{mt} a random variable reflecting positive or negative climate shocks and $\overline{H}_{m,ag,t}$ agricultural production under normal climatic conditions. The outside good production is assumed a constant endowment, $H_{m,o,t} = \overline{H}_{m,o,t}$. The household is risk averse and has intertemporal preferences over consumption[3]

$$U_m = \mathrm{E}\left[\sum_{t=t_0}^{t_2} \beta^t \ln(Q_{mt})\right], \tag{1}$$

with $\beta = 1/(1+\delta)$ the discount factor and $\delta > 0$ the rate of time preference parameter. Consumption Q_{mt} is a constant elasticity of substitution (CES) composite of food and the outside good

$$Q_{mt} = (\alpha C_{m,ag,t}^{(\sigma-1)/\sigma} + C_{m,o,t}^{(\sigma-1)/\sigma})^{\sigma/(\sigma-1)}, \tag{2}$$

where C_{mdt} is the quantity of household consumption of good d, α is the preference parameter, and $0 < \sigma < 1$ is the elasticity of substitution.

Transaction costs to agricultural market participation are widespread among households in rural areas of developing countries [Stephens and Barrett, 2011, Key et al., 2000]. Such transaction costs can consist, among others, of transport costs to and from the market, costs related to risk and

[2]The assumption of a fixed world market price limits the scope of the analysis to the impact of domestic supply uncertainty on the behavior of households and traders.

[3]The intertemporal utility function $U_m = \sum_{t=0}^{t_f}[\beta^t \ln(C_{mt})]$ is a specific case of the constant relative risk aversion utility function $U_m = \sum_{t=0}^{t_f}[\beta^t C_{mt}^{1-\eta}(1-\eta^{-1})]$ with the rate of risk aversion, η, equal to 1.

uncertainty, and search and information costs [Janvry et al., 1991]. We assume that when buying or selling food, the household faces an ad valorem transaction cost $\tau_m^{HH} > 0$ paid in terms of the outside good. The transaction cost implies that selling one unit of food to the market earns less than the market price, $P_{m,ag,t} - \tau_m^{HH} P_{m,o,t}$, while purchasing one unit of food from the market costs more than the market price, $P_{m,ag,t} + \tau_m^{HH} P_{m,o,t}$, where $P_{m,d,t}$ is the prevailing market price of good d in market m at time t. The household food balance is

$$C_{m,ag,t} = H_{m,ag,t} - qs_{mt} + qp_{mt}, \tag{3}$$

with qs_{mt} the quantity of food sold on the market and qp_{mt} the quantity of food purchased on the market.

In order to smooth consumption over time, the household can save and borrow subject to an intertemporal budget constraint

$$\begin{aligned} X_{mt} =& P_{m,o,t}(H_{m,o,t} - C_{m,o,t} - \tau_m^{HH}(qs_{mt} + qp_{mt})) \\ &+ P_{m,ag,t}(H_{m,ag,t} - C_{m,ag,t}) + \Phi_{mt} + (1+r)X_{m,t-1}, \end{aligned} \tag{4}$$

where X_{mt} are financial assets of the household, i.e. its "cash on hand", at the end of period t, r is the fixed interest rate, and Φ_{mt} the instantaneous storage profits accruing to the household (see discussion below). When credit markets are efficient, the household faces no constraint to saving and borrowing and X_{mt} is a free variable. However, as with market transaction costs, financial market failures are widespread in developing countries [Stephens and Barrett, 2011, Janzen and Carter, 2019, Carter and Lybbert, 2012]. In the case of imperfect credit markets, the household faces a borrowing ceiling $b > 0$ such that $X_{mt} > -b$, or a strict borrowing constraint such that X_{mt} is constrained to be non-negative ($X_{mt} > 0$).

Trader. The trader is risk neutral and operates in a competitive environment. The trader engages in price arbitrage across markets (within a single time period) subject to trade costs and price arbitrage across time periods (within a single market) subject to storage costs. The trader can buy one unit of food in market m at price $P_{m,ag,t}$, transport it at ad valorem trade cost $\tau_{mn} > 1$, and sell it at price $P_{n,ag,t}$ in market n. In addition, the trader can buy one unit of food in time period t at price $P_{m,ag,t}$, store it at the ad valorem storage cost $k_m > 1$, and sell it in the next period

$t+1$ at price $P_{m,ag,t+1}$[4]. The instantaneous profits from trade are

$$\Pi_{mt} = \sum_n (P_{n,ag,t} - \tau_{mn} P_{m,ag,t}) T_{mnt} + \sum_n (P_{m,ag,t} - \tau_{nm} P_{n,ag,t}) T_{nmt}, \tag{5}$$

with T_{mnt} the quantity traded from origin market m to destination market n and T_{nmt} the quantity traded from origin market n to destination market m. The instantaneous profits from storage are

$$\Phi_{mt} = P_{m,ag,t} S_{m,t-1} - P_{m,ag,t} k_m S_{mt}, \tag{6}$$

with $S_{mt} \geq 0$ the non-negative quantity stored in market m at time period t. The outside good is assumed to be freely traded but not storable and its price is normalized to one. In our small open economy setup, the trader takes the world price as given.

Discussion. The uncertainty in agricultural production caused by variable climatic conditions creates an incentive for households to save and for traders to store. Our model focuses on inter-annual storage, and we assume that storage decisions are made by traders rather than households. This assumption aligns with empirical evidence from Sub-Saharan Africa, which indicates that household storage, if it occurs, is typically limited to intra-annual storage during the first months after harvest and does not extend to inter-annual storage across different harvest cycles [Kaminski and Christiaensen, 2014, Stephens and Barrett, 2011, Tesfaye and Gebremariam, 2020, Waldman et al., 2020][5]. For instance, in Zambia 94.2% of the storage capacity is documented to be held by public and private actors versus 5.8% of on-farm storage capacity [The World Bank, 2021]. The instantaneous profits or losses from storage are part of the income of the representative household (equation 4).

Model Equilibrium

Utility maximization. The household maximises its utility in equation (1) by choosing in each period t how much to consume and how much to save or borrow subject to the intertemporal budget constraint in equation (4). The solution of the intertemporal optimization problem can be derived with Pontryagin's Maximum Principle. The solution satisfies the condition of optimal intra-temporal

[4] In the literature storage and trade costs have been modelled both as ad valorem costs or as additive costs, see Porteous [2019] for a discussion.

[5] Looking at household survey data from Malawi, Uganda and Tanzania, Kaminski and Christiaensen [2014] find that farmers sell between 84% and 91% of the marketed maize within three months after harvest. Our assumption differs from Park [2006] who allows for storage across cropping seasons at the household level.

household consumption allocation (derivation in Appendix section S5.1)

$$\begin{aligned}\alpha\left(\frac{C_{m,ag,t}}{C_{m,o,t}}\right)^{\frac{1}{\sigma}} &= \frac{P_{m,o,t}}{P_{m,ag,t}-\tau_m^{HH}P_{m,o,t}} \text{ if } qs_{mt}>0 \text{ and } qp_{mt}=0,\\ \alpha\left(\frac{C_{m,ag,t}}{C_{m,o,t}}\right)^{\frac{1}{\sigma}} &= \frac{P_{m,o,t}}{P_{m,ag,t}+\tau_m^{HH}P_{m,o,t}} \text{ if } qs_{mt}=0 \text{ and } qp_{mt}>0,\end{aligned} \tag{7}$$

or

$$\alpha\left(\frac{C_{m,ag,t}}{C_{m,o,t}}\right)^{\frac{1}{\sigma}} = \frac{P_{m,o,t}}{P'_{m,ag,t}}, \tag{8}$$

with $P'_{m,ag,t}$ the household shadow price of food determined by equating internal household demand and supply. The transaction cost creates a price band around the prevailing market price, $[P_{m,ag,t}-\tau_m^{HH}P_{m,o,t}, P_{m,ag,t}+\tau_m^{HH}P_{m,o,t}]$ [Janvry et al., 1991, Stephens and Barrett, 2011]. When the shadow price equals $P_{m,ag,t}-\tau_m^{HH}P_{m,o,t}$, the household will be a net seller of food ($qs_{mt}>0$ and $qp_{mt}=0$). When the shadow price equals $P_{m,ag,t}+\tau_m^{HH}P_{m,o,t}$, the household will be a net buyer of food ($qp_{mt}>0$ and $qs_{mt}=0$). When the shadow price falls within the price band, the household is autarkic in food ($qs_{mt}=qp_{mt}=0$). A shadow price above the market price but below the market price plus transaction cost means that the household will not buy food while it would in an unconstrained world. A shadow price below the market price but above the market price minus transaction cost means that the household will not sell food while it would in an unconstrained world.

The solution also satisfies the Euler equations determining inter-temporal household consumption allocation (derivation in Appendix section S5.1)

$$Q_{mt}^{\frac{\sigma-1}{\sigma}}C_{m,ag,t}^{\frac{1}{\sigma}}P'_{m,ag,t} = \frac{1}{(1+r)\beta}\,\mathrm{E}_t\left[Q_{m,t+t}^{\frac{\sigma-1}{\sigma}}C_{m,ag,t+1}^{\frac{1}{\sigma}}P'_{m,ag,t+1}\right], \tag{9}$$

$$Q_{mt}^{\frac{\sigma-1}{\sigma}}C_{m,o,t}^{\frac{1}{\sigma}}P_{m,o,t} = \frac{1}{(1+r)\beta}\,\mathrm{E}_t\left[Q_{m,t+t}^{\frac{\sigma-1}{\sigma}}C_{m,o,t+1}^{\frac{1}{\sigma}}P_{m,o,t+1}\right]. \tag{10}$$

In an optimal allocation, the marginal utility of consuming one unit of food (outside good) today equals the discounted expected marginal utility of consuming one unit of food (outside good) in the next period. In the case of imperfect credit markets, the Euler condition will only hold when the borrowing constraint is not binding. When the borrowing constraint binds, the marginal utility of current consumption will be higher than the discounted expected marginal utility of consumption in the next period. In that case the household will spend all its assets X_{mt} in the current period.

Lastly, accumulation of household debt is prevented by the transversality condition

$$\mathrm{E}_t\left[\frac{X_{m,t_2}}{(1+r)^2}\right]=0 \tag{11}$$

Profit maximization. Traders decide in each period t how much of the available supply in region m to store (S_{mt}), to export to other markets (exports T_{mnt}), or to import from other markets (imports T_{nmt}) in order to maximize inter-temporal profits

$$\begin{aligned}\max_{S_{mt},T_{mnt},T_{nmt}} \mathrm{E}_t\Bigg[\sum_{s=t}^{t_2}\Xi_{m,s-1,s}*(P_{m,ag,s}S_{m,s-1}-P_{m,ag,s}k_mS_{ms}\\ +\sum_n(P_{n,ag,s}-\tau_{mn}P_{m,ag,s})T_{mns}+\sum_n(P_{m,ag,s}-\tau_{nm}P_{n,ag,s})T_{nms})\Bigg],\end{aligned} \tag{12}$$

subject to the non-negativity constraint for storage $S_{mt}\geq 0$. $\Xi_{m,t,t+1}$ is the stochastic discount factor, which reflects the willingness of an investor (in this case the household investing in storage) to substitute consumption at time t for consumption at time $t+1$ [Cochrane, 2005]. The stochastic discount factor is determined by the household optimal consumption-saving decision [Arseneau and Leduc, 2013] and equals $\Xi_{m,t,t+1}=\beta(Q_{mt}^{(\sigma-1)/\sigma}C_{m,o,t}^{1/\sigma}P_{m,o,t})(Q_{m,t+1}^{(\sigma-1)/\sigma}C_{m,o,t+1}^{1/\sigma}P_{m,o,t+1})^{-1}$. Profit maximization leads to the following temporal and spatial no-arbitrage conditions

$$\begin{aligned}P_{m,ag,t}k_m &\geq \mathrm{E}_t[\Xi_{m,t,t+1}P_{m,ag,t+1}] \text{ with equality if } S_{mt}>0,\\ P_{m,ag,t}\tau_{mn} &\geq P_{n,ag,t} \text{ with equality if } T_{mnt}>0,\\ P_{n,ag,t}\tau_{nm} &\geq P_{m,ag,t} \text{ with equality if } T_{nmt}>0.\end{aligned} \tag{13}$$

The temporal no-arbitrage condition implies that the trader has an incentive to store as long as the price of food in the current period plus the storage cost is below the discounted price expected in the next period; at equilibrium the current price plus storage cost will equal the discounted expected future price. When the price in the current period is above the discounted expected future price by more than the storage cost, stock levels are zero. The spatial no-arbitrage condition implies that the trader has an incentive to export food to another market if the price plus trade cost is lower than the price in the destination market. In equilibrium, the price difference between the two markets will equal the trade cost.

Market clearing. Market clearing requires that in each market m food consumption equals

agricultural production plus carry-in stock and imports minus carry-out stock and exports

$$C_{m,ag,t} = H_{m,ag,t} + S_{m,t-1} - k_m S_{mt} - \sum_n (\tau_{mn} T_{mnt} - T_{nmt}). \tag{14}$$

For the outside good, consumption equals production minus net trade ($NT_{mt} > 0$ for net exports and $NT_{mt} < 0$ for net imports) and the quantity required to cover the market transaction costs

$$C_{m,o,t} = H_{m,o,t} - NT_{mt} - \tau_m^{HH}(qs_{mt} + qp_{mt}). \tag{15}$$

Equilibrium. The economy is in equilibrium when the representative household in locations REG and ROC maximizes intertemporal utility, the representative trader in each location maximizes intertemporal profits, and markets clear. Formally, the competitive dynamic equilibrium is defined as the set of prices P_{mdt} and the set of consumption C_{mdt}, market exchange qs_{mt} and qp_{mt}, storage S_{mt}, and trade T_{mnt} quantities that satisfy the optimality conditions 7, 10, and 13; the household good balance 3; the market clearing condition 14; the intertemporal budget constraint 4; and the transversality condition 11 for each location m and time period t.

Discussion. Our model builds on the framework of two canonical dynamic stochastic models, the consumption-saving model [Deaton, 1991] and the rational expectations storage and trade model [Williams and Wright, 1991]. To clarify the link, we can map our model variables to the standard framework of state, choice, and shock variables used in these models. Our model consists of four agents, the household and trader in location REG and the household and trader in location ROC, that each solve an intertemporal optimization problem. We have two exogenous random variables that follow a stochastic process, climate shocks $\nu_{REG,t}$ and $\nu_{ROC,t}$, and 4 state variables, market availability in REG and ROC ($A_{REG,t}$, $A_{ROC,t}$) and cash on hand in REG and ROC ($X_{REG,t}$, $X_{ROC,t}$). Availability A_{mt} is the amount of food available on the market at the start of period t, defined as the sum of production and carry-in stock

$$A_{mt} = H_{m,ag,t} + S_{m,ag,t-1} = (1 + \nu_{mt})\overline{H}_{m,ag,t} + S_{m,ag,t-1}. \tag{16}$$

We have 18 choice variables in our model: prices ($P_{REG,ag,t}$, $P_{ROC,ag,t}$), consumption ($C_{REG,ag,t}$, $C_{ROC,ag,t}$, $C_{REG,o,t}$, $C_{ROC,o,t}$), market exchanges ($qs_{REG,ag,t}$, $qs_{ROC,ag,t}$, $qp_{REG,ag,t}$, $qp_{ROC,ag,t}$), storage ($S_{REG,ag,t}$, $S_{ROC,ag,t}$), and trade ($T_{REG,ROC,ag,t}$, $T_{ROC,REG,ag,t}$, $T_{REG,W,ag,t}$, $C_{W,REG,ag,t}$,

$T_{ROC,W,ag,t}$, $T_{W,ROC,ag,t}$). The state variables depend on past choice variables, past state variables, and contemporaneous shocks according to a transition equation, which corresponds to equation 16 for availability and equation 4 for cash on hand. The choice variables are determined by the state variables and by future expectations according to equilibrium conditions 3, 7, 10, 11, 13, and 14.

2.2 Model mechanisms

Because the model encompasses future expectations, it is not possible to derive closed-form solutions for the choice variables in function of the state variables and model parameters. This is a well-known challenge of stochastic storage and trade models and explains the need for numerical approximation [Gouel, 2013]. Here, we specify a deterministic equivalent of the stochastic problem by substituting the expectations operators with deterministic sums using sparse grid integration [Heiss and Winschel, 2008]. The deterministic equivalent model is then solved as a mixed complementary problem in GAMS. Practically, we simulate the solution for a many-period time frame by solving a moving series of three-period problems. For a certain period t, traders are given initial stock $S_{m,t-1}$ and households are given initial assets $X_{m,t-1}$. We then solve the trader and household decisions for the three-period time horizon, record the endogenous variables only for the first period, update the state variables S_{mt} and X_{mt}, and then move to the next period $t+1$, repeating the same exercise with the updated stock and asset levels. This approach is an approximation of the solution of a more general infinite time horizon problem. The benefit is that it allows to solve the stochastic problem for four state variables, while the main limitation is that it reduces some of the incentive for saving and storage (see Appendix section S5.2).

To illustrate the model mechanisms and intuition, we start by quantifying the model for a small open economy with no transaction costs. The values of the exogenous variables and parameters are presented in Table 1. The values are chosen such that under the non-stochastic equilibrium, the two domestic markets are self-sufficient. To reflect the asymmetry between the locations, production in the rest of the country is assumed three times larger than in the region. Based on Comin et al. [2021] we set the elasticity of substitution σ between the agricultural good and the outside good equal to 0.5. Following standard life-cycle literature, we assume the rate of time preference equals the interest rate with $\delta = r = 0.05$ [Deaton, 1991]. The values of the storage and trade costs are chosen based on Gouel and Jean [2015]. The climate shock ν_{mt} follows a normal distribution with mean 0 and variance 0.025 and is independent between the two locations.

Table 1: Model parameterization under base case.

Exogenous variable	Economic interpretation	Value
$\overline{H}_{REG,o,t}$	Outside good production	10
$\overline{H}_{REG,ag,t}$	Agricultural good production	10
$\overline{H}_{ROC,o,t}$	Outside good production	30
$\overline{H}_{ROC,ag,t}$	Agricultural good production	30
$P_{m,o,t}$	Price of outside good (numeraire)	1
$P_{W,ag,t}$	World price of food	$P_{W,ag,t0} = 1$ $P_{W,ag,t1} = 1.1025$ $P_{W,ag,t2} = 1.2155$
Parameter	**Economic interpretation**	**Value**
α	Expenditure share	1
σ	Elasticity of substitution	0.5
δ	Rate of time preference	0.05
r	Interest rate	0.05
τ_m^{HH}	Transaction cost	0
k_m	Storage cost	1.06
τ_{mn}	Intra-national trade cost	1.1
	International trade cost	1.2
ν_{mt}	Probability distribution of climate shock	$N(0, 0.025)$

Without borrowing constraints. Figure 2 presents a simulation of 30 years for our base case parameterization with no borrowing constraints. We explore the impact of the climate shock in each location (plot a) on the state variables in each location (plot b) and on the consumption and marketing decisions of the household and trader in the region (plot c). We investigate the consumption smoothing mechanisms from the perspective of the region, but a similar analysis can be done from the perspective of the rest of the country.

At the beginning of each period, the regional trader observes the availability of food in the region and country market. The availability consists of production (which is subject to the exogenous climate shock) and stocks carried over from the previous period. The regional household observes its cash on hand, which is determined the net sales (or net purchases) of food and of the outside good in the previous period, the storage profit (or losses) obtained in the previous period, and any savings (or debts) carried over from the earlier periods.

When the region faces a negative climate shock, agricultural production will be below average. The household will be a net buyer of food in order to smooth consumption. To pay for market purchases, the household can tap into its savings, borrow, or sell the outside good. The trader will compensate the reduction in local food supply by depleting regional stocks or by importing from

the country or world market. For example, in period 4 the region experiences a negative climate shock of -29%, resulting in a proportional drop in availability of food on the market (in this period there are no stocks carried over from the previous period). The trader imports food from the country market, which experiences a positive shock in this period. To pay for imports, the household reduces expenditure on the outside good (exports of the outside good increase in period 4) and borrows (cash on hand in subsequent period 5 drop below zero). In periods 17 and 18, both the region and the country face a negative climate shock. In this case, the trader imports food from the world market instead of the country market.

When the region faces a positive climate shock, agricultural production will be above average. The household will be a net seller of food to smooth consumption. The income from market sales can be saved or spent on the outside good. The trader will absorb the increased food supply on the region market by building up stocks or by exporting food to the country or world market. For example, in period 15 the region experiences a positive climate shock of +30%, increasing the availability on the region market. The trader exports food to the country market, which experiences a negative climate shock, while the household saves and increases expenditure on the outside good. In period 20, both the region and the country experience a positive shock. In this case, the trader builds up stocks and exports food to the world market.

The simulation indicates two channels of trade-based consumption smoothing: the intra-temporal exchange of goods (trading food for the outside good) and the inter-temporal exchange of assets between locations (running temporary trade deficits or surpluses). The latter channel is constrained by the transversality condition (equation 11) which implies that there are no trade deficits or surpluses in the final period. Storage-based consumption smoothing in the other hand occurs via the inter-temporal transfer of assets within a location. In a period of stock accumulation, the household invests in storage (i.e., receives negative instantaneous storage profits), while in a period of stock utilization, the household receives the return of its investment (i.e., receives positive instantaneous storage profits).

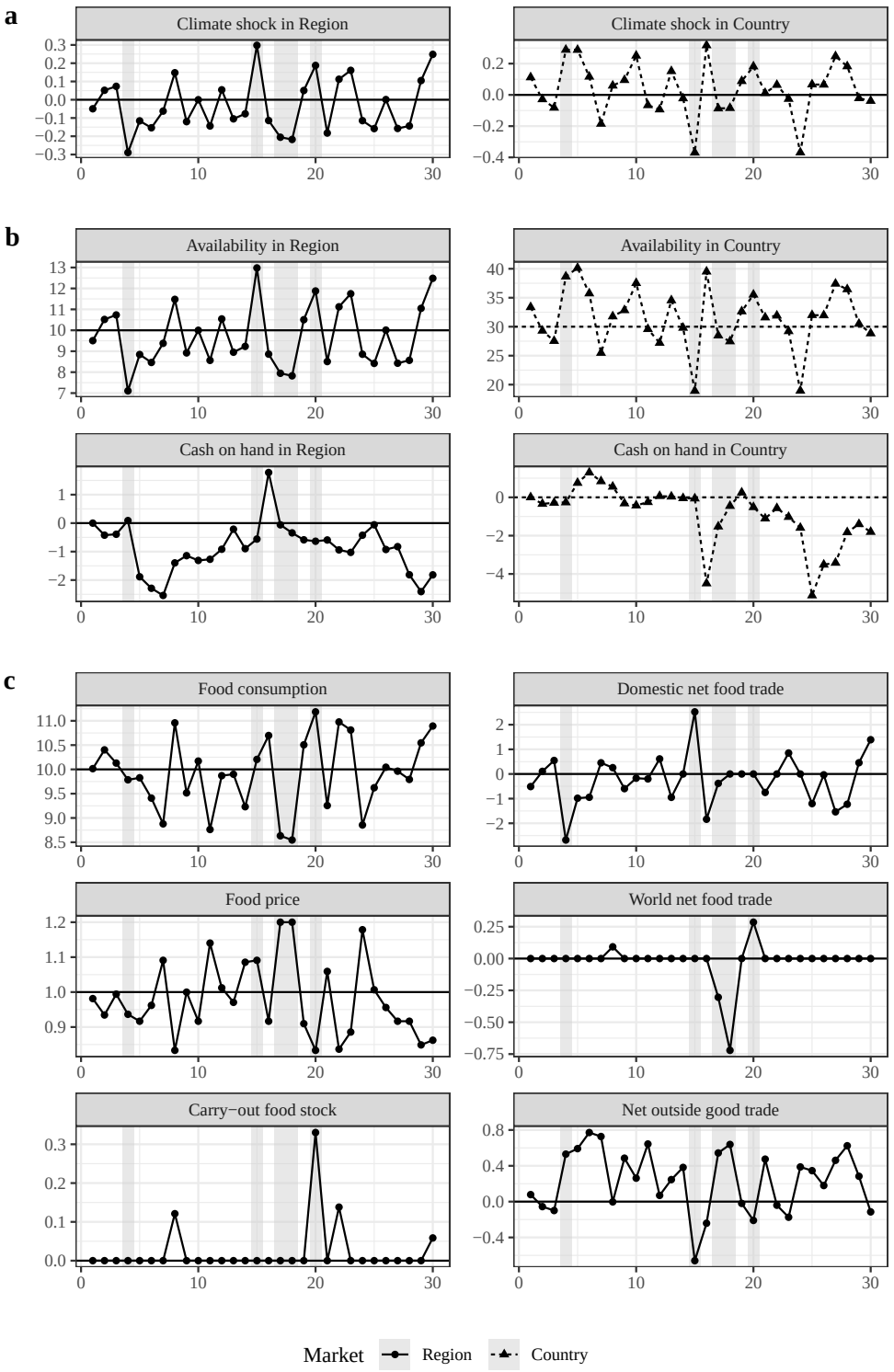


Figure 2: Results of the base case simulation (model parameterization in Table 1) without borrowing constraints. (a) Shock variable ν_{mt} in each location, (b) state variables A_{mt} and $X_{m,t-1}$ at the beginning of the period in each location, and (c) choice variables $C_{m,ag,t}$, $P_{m,ag,t}$, S_{mt}, T_{mnt}, and NT_{mt} in the region.

With borrowing constraints. When households face strict borrowing constraints, cash on hand is restricted to be non-negative (Figure S6 in Appendix). Compared to Figure 2, food trade flows in Figure S6 are reduced, while outside good trade flows and food stocks increase in magnitude. In the case of borrowing constraints, it is not possible to run temporary trade deficits. Imports of food can no longer be financed by borrowing, but only by exports of the outside good in the same period (intra-temporal exchange of goods) or by a trade surplus that has been built up in previous periods. Storage works as a priori investment and does not require households to borrow. Borrowing constraints thus affect food storage and food trade differently.

Discussion. It is useful to contrast the mechanism in this model with the price as insurance mechanism in the canonical model of Newbery and Stiglitz [1984]. In autarky, prices drop whenever production is high and rise whenever production is low. These price variations can provide perfect income insurance for farmers. Newbery and Stiglitz [1984] show that this mechanism explains why, in the presence of uncertainty and under specific assumptions, free trade can be pareto inferior to no trade. One of their key assumptions is that farmers and consumers are separate agents. Farmers have a variable income, depending on output and price fluctuations of the agricultural good, and maximize the expected utility of their profits. Consumers have a constant income derived from the outside good and maximize their utility from consuming the risky agricultural good. In our model, the farm household is both producer and consumer of the risky good. This assumption is in line with microeconomic theory and evidence indicating that farm households in developing countries cannot be viewed as independent profit-maximizing producers and utility-maximizing consumers [Janvry et al., 1991, LaFave et al., 2025, Le, 2010, Lofgren and Robinson, 1999]. Another key difference is that our model is dynamic compared to the static model of Newbery and Stiglitz [1984]. In our model, the farm household has a variable income that depends on output and price fluctuations, and, unlike in Newbery and Stiglitz [1984], it maximises the expected utility of its inter-temporal consumption. The relevant mechanism is thus not price as insurance for income stabilization, but saving and borrowing as insurance for consumption stabilization. In a good harvest year, the household is a net seller and saves part of its income. In a bad harvest year, the household is a net buyer and borrows or consumes its savings. When trade and storage costs are high, the local food price is low in good harvest years and high in bad harvest years. This means that there is little income to save in the good years and buying food is expensive in the bad years. When storage and trade costs are low, the food price will not drop as much in good harvest years and will not spike as much in bad harvest

years. There will be more income to save in the good years and buying food becomes less expensive in the bad years. By buffering food prices and enhancing saving and borrowing, storage and trade facilitate consumption smoothing.

2.3 Model predictions

The base case simulation has illustrated two market-based channels of household consumption smoothing: storage (via inter-temporal exchanges within a location) and trade (via intra- and inter-temporal exchanges between locations). To guide the subsequent empirical analysis, we now use our theoretical model to investigate under which conditions markets buffer the food insecurity impacts of climate extremes. We do so by exploring the sensitivity of food consumption to climate shocks under different model parameterizations. We perform two model experiments that run scenarios with varying transaction costs, temporal correlation in climate shocks, and storage and trade costs (Table 2). Following Park [2006] we set the transaction cost equal to 0.08 to represent food market failures for farm households. We define empirically-relevant levels of world market trade costs and storage costs based on trade and storage cost estimates for grain markets in Sub-Saharan Africa by Porteous [2019] (see Appendix S5.5). Climate shocks are either uncorrelated or temporally correlated in each location.

Table 2: Parameterization under two model experiments.

Experiment	Scenario		
1	Transaction cost	Low	$\tau_{\text{REG}}^{HH} = 0$
		High	$\tau_{\text{REG}}^{HH} = 0.08$
	World trade cost	Low	$\tau_{REG,W} = \tau_{W,REG} = 1.075$
		High	$\tau_{REG,W} = \tau_{W,REG} = 1.65$
	Storage cost	Low	$k_m = 1.05$
		High	$k_m = 1.45$
	Climate shock	Uncorrelated	$\nu_{\text{REG},t} \sim N(0, 0.025)$ and $\nu_{\text{ROC},t} \sim N(0, 0.025)$
2	Transaction cost	Low	$\tau_{\text{REG}}^{HH} = 0$
	World trade cost	Low to High	$\tau_{mW}, \tau_{Wm} \in \{1.075, 1.139, ..., 1.65\}$
	Storage cost	Low to High	$k_m \in \{1.05, 1.094, ..., 1.45\}$
	Climate shock	Uncorrelated	$\nu_{\text{REG},t} \sim N(0, 0.025)$ and $\nu_{\text{ROC},t} \sim N(0, 0.025)$
		Temporally correlated	$\forall s \in \{t, t+2, t+4, ...\}$: $\nu_{ms} \sim N(0, 0.025)$ and $\nu_{m,s+1} = \nu_{ms}$

Notes: Other parameter values as in Table 1. Households are assumed to face no borrowing constraints. Model experiment 1 consists of eight scenarios (2 transaction cost levels × 2 world trade cost levels × 2 storage cost levels × 1 climate shock implementation) with for each scenario a simulation of 400 periods. Model experiment 2 consists of 200 scenarios (1 transaction cost level × 10 world trade cost levels × 10 storage cost levels × 2 climate shock implementations) with for each scenario a simulation of 100 periods.

Based on the model experiments we derive the following four predictions:

1. When households face market transaction costs, food consumption is more responsive to local climate shocks and less responsive to national climate shocks;

2. When a region is isolated from the world market, food consumption is more responsive to local and national climate shocks;

3. Storage and trade partly substitute one another in smoothing food consumption in the face of climate shocks.

4. Temporal correlation in climate shocks reduces smoothing via storage to a larger extent than it reduces smoothing via trade.

Model experiment 1. We begin by exploring simulations of uncorrelated climate shocks under varying levels of households' market transaction costs, trade costs with the world market, and storage costs (Experiment 1 in Table 2). Figure 3 plots the relationship between food consumption in the region and climate shocks, providing three insights. First, food consumption is high during periods of

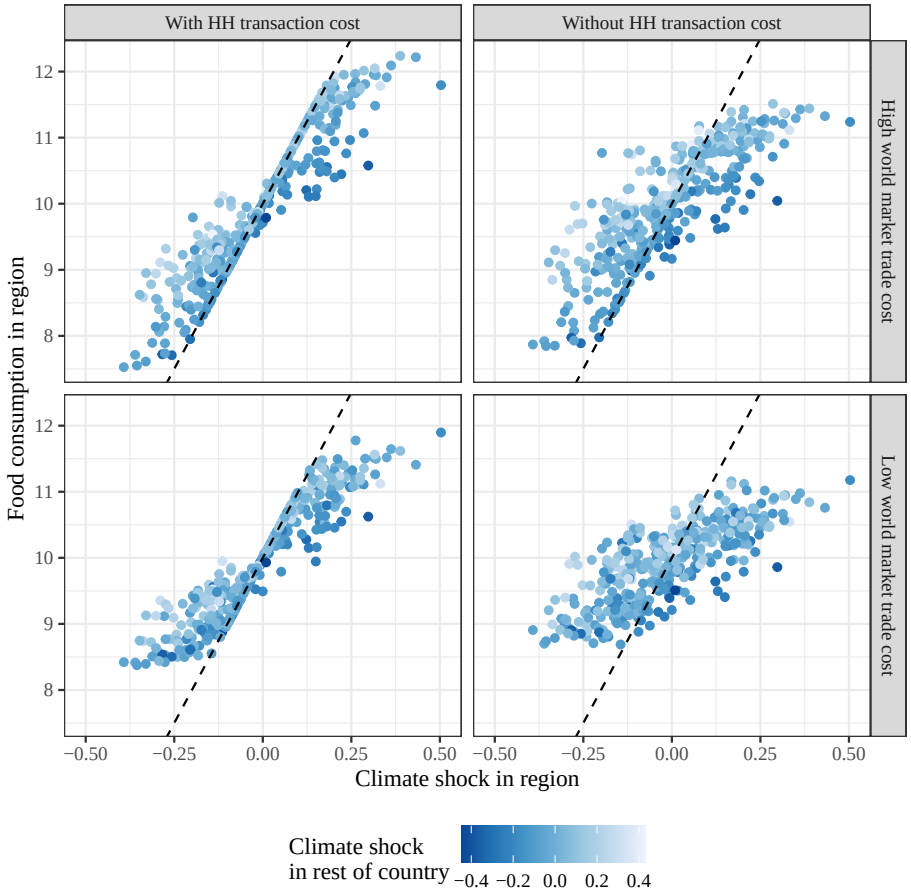


Figure 3: The sensitivity of food consumption in the region to climate shocks, with and without household's market transaction costs and under low and high levels of world market trade cost. The model is implemented with no borrowing constraints, low storage cost, and uncorrelated climate shocks. Each dot corresponds to one of the 400 simulated time steps. The striped line indicates where food consumption in the region would perfectly equal agricultural production in the region.

positive regional climate shocks and low during periods of negative regional climate shocks. Second, transaction costs and trade costs increase the sensitivity of food consumption to regional climate shocks. Third, food consumption in the region is also influenced by climate shocks in the rest of the country.

To derive qualitative predictions, we statistically estimate the relationship between the endogenous model variable (food consumption $C_{REG,ag}$) and the exogenous model parameters (climate

shocks ν_{REG} and ν_{ROC}, transaction costs τ^{HH}_{REG}, and trade costs $\tau_{REG,W}$) using OLS:

$$\begin{aligned} C_{REG,ag,t,scen} =& \gamma_1 \nu_{REG,t} * \tau^{HH}_{REG,scen} + \gamma_2 \nu_{ROC,t} * \tau^{HH}_{REG,scen} \\ &+ \gamma_3 \nu_{REG,t} * \tau_{REG,W,scen} + \gamma_4 \nu_{ROC,t} * \tau_{REG,W,scen} + \epsilon_{t,scen}. \end{aligned}$$

Table 3 presents the results of the linear regression of food consumption on climate shocks and transaction and trade costs. The results confirm the patterns of Figure 3. Transaction costs and world market trade costs make food consumption more sensitive to local climate shocks. World market trade costs make food consumption also more sensitive to climate shocks in the rest of the country. Transaction costs, on the other hand, reduce the sensivity of food consumption to climate shocks in the rest of the country. These results underscore predictions 1 and 2.

The results are consistent under high levels of the storage cost (column (2) compared to column (1) in Table 3). The sensitivity of food consumption to world market trade costs increases when storage costs are high. This observation suggests an interaction between storage and trade, which we further investigate in model experiment 2.

Table 3: Linear regression of food consumption in the region (experiment 1).

	Low storage cost (1)	High storage cost (2)
Climate shock region	2.882***	3.368***
	(0.082)	(0.072)
Climate shock country	1.291***	1.680***
	(0.092)	(0.081)
Climate shock region × τ HH high	2.075***	1.694***
	(0.095)	(0.083)
Climate shock country × τ HH high	−0.427***	−0.626***
	(0.106)	(0.093)
Climate shock region × τ W high	1.402***	1.988***
	(0.095)	(0.083)
Climate shock country × τ W high	0.758***	0.939***
	(0.106)	(0.093)
Observations	1,600	1,600
R^2	0.999	0.999
Note:		*p<0.1; **p<0.05; ***p<0.01

Model experiment 2. Model experiment 2 is designed to explore the interaction between trade and storage in smoothing food consumption and the implication of temporally correlated climate shocks (see Table 2). We analyze the smoothing ratio of food consumption, which quantifies the variability of consumption relative to the variability of production. It is defined as $1 - \frac{\text{CVconsumption}}{\text{CVproduction}}$, where CV represents the coefficient of variation. A value of 1 indicates perfect smoothing, meaning that food consumption remains constant over time regardless of the variability in food production. Conversely, a value of 0 indicates no smoothing, meaning that food consumption is as volatile as food production. Figure 4 plots the smoothing ratio of food consumption under varying storage cost and world market trade cost levels. The smoothing ratio increases as storage or trade costs decrease. If trade and storage would be perfect complements, we would observe L-shaped contour lines, while if they would be perfect substitutes, we would observe parallel downward sloping diagonal lines. The contour lines are curved, which indicates that trade and storage are imperfect substitutes in smoothing food consumption. Imperfect substitutes means that a unit reduction in trade costs has a larger benefit at high than at low storage cost levels. Similarly, the additional benefit of reducing storage costs is smaller at low trade cost levels than at high trade cost levels. At very low trade costs, the contour lines are horizontal indicating that this is an area where the benefits of reducing storage costs are particularly small.

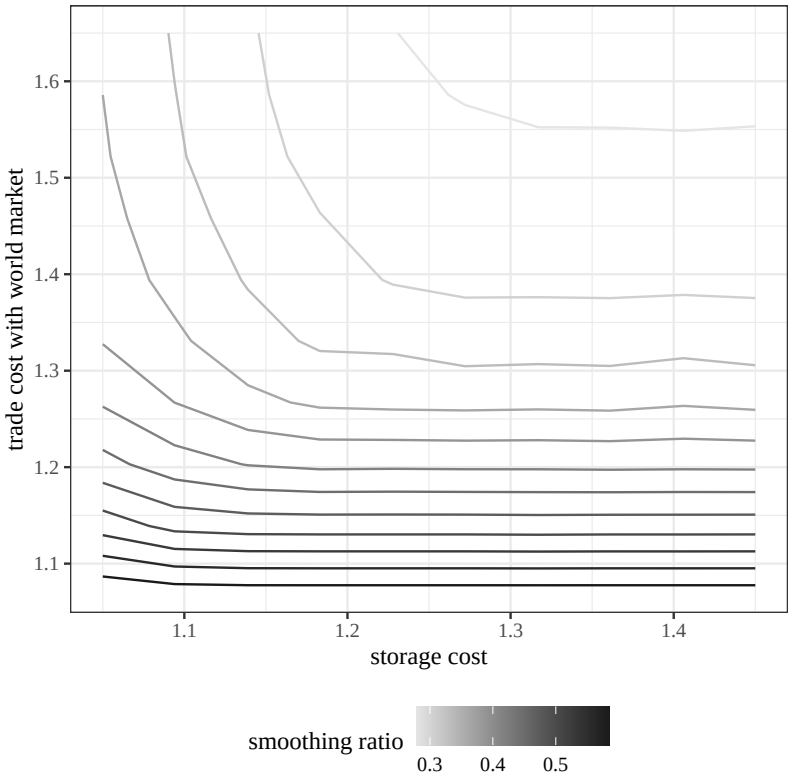


Figure 4: Food consumption smoothing ratio in the region for different combinations of storage costs and trade costs with the world market and uncorrelated climate shocks. For each storage and trade cost combination the smoothing ratio is calculated based on a simulation of 100 time periods. Results for temporally correlated climate shocks are shown in Figure S7 in Appendix.

To derive qualitative predictions, we again statistically estimate the relationship between an endogenous model outcome (the smoothing ratio of food consumption) and exogenous model parameters. In particular, we estimate the following linear regression models using OLS on the simulated output of model experiment 2:

$$SR_{scen}^{REG,REG} = \gamma_0 + \gamma_1 k_{m,scen} + \gamma_2 \tau_{mW,scen} + \gamma_3 k_{m,scen} * \tau_{mW,scen} + \epsilon_{scen},$$
$$SR_{scen}^{REG,ROC} = \gamma_0 + \gamma_1 k_{m,scen} + \gamma_2 \tau_{mW,scen} + \gamma_3 k_{m,scen} * \tau_{mW,scen} + \epsilon_{scen},$$

with $SR_{scen}^{REG,REG} = 1 - \frac{\text{CV}_{C_{REG}}}{\text{CV}_{H_{REG}}}$ the smoothing ratio of regional food consumption with respect to regional food production and $SR_{scen}^{REG,ROC} = 1 - \frac{\text{CV}_{C_{REG}}}{\text{CV}_{H_{ROC}}}$ the smoothing ratio of regional food consumption with respect to food production in the rest of the country.

The results in Table 4 show the impact of a unit change in storage cost, world market trade cost, and their interaction on smoothing ratios under temporally uncorrelated (columns (1) and (3)) and temporally correlated (columns (2) and (4)) climate shocks. Looking first at the uncorrelated shocks, we observe that food consumption smoothing improves with lower storage and trade costs, indicating that storage and trade both buffer the impact of climate shocks. The negative interaction effect confirms the observation from Figure 4 that trade and storage can partly, but not fully, substitute for one another. When climate shocks are temporally correlated, the coefficient of storage costs diminishes by factor 2.5 to 2.8 (column (2) compared to (1) and column (4) compared to (3)). The coefficient of world trade cost is less affected by temporal correlation. Storage becomes less effective at smoothing consumption when shocks persist across multiple periods, as food stocks may become saturated during recurring positive shocks or depleted during recurring negative shocks. In contrast, recurring climate shocks do not affect the availability of imports from foreign markets or the capacity of foreign markets to absorb domestic surpluses. These results underscore predictions 3 and 4, which, along with predictions 1 and 2, guides our empirical analysis.

Lastly, we noted in section 2.2 that borrowing constraints affect storage and trade differently. Table S2 in the Appendix presents the impact of storage and trade costs on the smoothing ratio of food consumption under different assumptions of borrowing constraints. When households face a strict borrowing constraint, the impact of trade costs on consumption smoothing reduces, while this is not the case for storage costs.

Table 4: Linear regression of smoothing ratio of food consumption in the region (experiment 2).

	SR w.r.t. production REG		SR w.r.t. production ROC	
	uncorr.	corr.	uncorr.	corr.
	(1)	(2)	(3)	(4)
Storage cost	-0.133^{***}	-0.047^{*}	-0.145^{***}	-0.059^{*}
	(0.036)	(0.026)	(0.039)	(0.033)
Trade cost world market	-0.457^{***}	-0.368^{***}	-0.501^{***}	-0.460^{***}
	(0.025)	(0.018)	(0.027)	(0.023)
Storage x Trade cost	-0.339^{*}	-0.139	-0.371^{*}	-0.173
	(0.196)	(0.144)	(0.214)	(0.181)
Constant	0.372^{***}	0.371^{***}	0.313^{***}	0.214^{***}
	(0.005)	(0.003)	(0.005)	(0.004)
Observations	100	100	100	100
R^2	0.786	0.807	0.786	0.807
Note:				*p<0.1; **p<0.05; ***p<0.01

3 Empirical evidence

3.1 Data sources and summary statistics

The empirical analysis uses economic, climatic, and agro-ecological data from various sources. Data on food insecurity, climate extremes, and travel times is composed at sub-annual temporal (3-month or 4-month interval) and subnational spatial (second administrative unit[6]) resolution, supplemented with annual country-level economic indicators. The composed panel dataset is fully balanced and covers 12 African countries (Burkina Faso, Chad, Ethiopia, Kenya, Mali, Mauritania, Mozambique, Malawi, Niger, Nigeria, Somalia and Zambia), 1,379 second administrative units, and 29 time periods from 2009 to 2016. To investigate the impact of dry climate extremes in specific, we define a subsample of Arid, Semi-Arid and Sub-Humid areas that consists of 1074 administrative units. To study the impact of import capacity and stocks, the sample is limited to 913 administrative units due to data availability. Table 5 presents the summary statistics of the main variables of interest.

Food insecurity.—We use information on food insecurity from the Famine Early Warning Systems Network (FEWS NET) food security assessment which is recorded at 3-month or 4-month intervals [FEWSNET, 2018]. FEWS NET classifies current and future expected food insecurity using the IPC 2.0 Acute Food Insecurity scale since March 2011 (prior to that a similar scale, i.e., the FEWS NET Food Insecurity Severity Scale, was used). We use the classification of current food insecurity, which is based on observed food security conditions (e.g., food prices, wage levels, labor demand), household level outcomes (food consumption, livelihood change), and nutrition and mortality data. Food insecurity is measured with a 5-point scale (1: no acute food insecurity, 2: moderately food insecure, 3: highly food insecure, 4: extremely food insecure, 5: famine) and recorded for livelihood zones, a spatial unit of which the boundaries vary over time. Backer and Billing [2021] process this data to a standardized uniform spatial resolution of 0.5° x 0.5° grid-cells. We aggregate the gridded data from Backer and Billing [2021] to second administrative units by taking the maximum value of the food insecurity scale within each unit. We then convert the 5-point food insecurity scale to a dummy variable (0, "food secure", if score = 1 and 1, "food insecure", if score > 1)[7], resulting in a

[6]Second administrative units are defined based on the Global Administrative Areas database (GADM) version 3.6. Although the size of the administrative units differs across countries, it ensures a more equal spread in terms of population size compared to a uniform grid. For the countries in our sample, the coefficient of variation of population size in 2010 is 3.41 when using 30 arc-minute grids as spatial unit (mean = 116,399 people, sd = 396,882 people) and 1.47 when using second administrative unit as spatial unit (mean = 223,675 people, sd = 328,141 people).

[7]We do not use the 5-point scale directly as the prevalence of the highest food insecurity scores $3, 4, 5$ in the sample is too low to allow for the identification of heterogeneous effects.

prevalence of food insecurity of 30% in our sample (Table 5).

Climate extremes.— We measure climate extremes using the Standardized Precipitation - Evapotranspiration Index (SPEI) pan-African dataset from Peng et al. [2020] available at high spatial resolution (5 x 5 km) in monthly intervals. The SPEI index indicates whether climatic conditions are moderately, severely, or extremely wet or dry for a certain time period [Beguería et al., 2014]. We use the 3–month, 12–month, and 24-month SPEI indeces, which reflect for each month the accumulated water balance of that month and the preceding 2, 11, or 23 months, respectively. We combine the 3–month SPEI index with data on the timing of agricultural growing seasons to determine, for each administrative unit and time period, the 3–month SPEI value of the previous growing season (see Appendix S5.3). The 12– and 24–month SPEI indeces reflect persistent dry or wet conditions over a prolonged period of 12 to 24 months. For all indeces, we calculate the share of area of each administrative unit affected by severely wet ($2 > SPEI \geq 1.5$), extremely wet ($SPEI \geq 2$), severely dry ($-2 < SPEI \leq -1.5$) or extremely dry ($SPEI \leq -2$) conditions as well as the share of the area in the rest of the country that is affected by climate extremes. We use the climate extremes indicator based on the 3–month SPEI value in the previous growing season as our default to take into account that the timing of climatic conditions matters for agricultural production (this indicator is shown in Table 5).

Travel times.—We use data on travel times to cities and ports in the year 2015 from Nelson et al. [2019] as a proxy for transaction and trade costs. We use travel times to the closest city of 100,000 - 200,000 inhabitants as a proxy for households' market transaction costs and travel times to the closest large port as a proxy for regions' trade costs to the world market. We aggregate the travel times from the grid-cell (approximately 1 x 1 km) to the second administrative level, using the grid-cell area as weight. The average travel time to the closest city in our sample is 198 minutes and the average travel time to port is 884 minutes (Table 5).

Agricultural employment.—We use country-level information from ILOSTAT on the share of agricultural employment in total employment in rural and urban areas. We multiply this with the share of people living in rural versus urban areas in each second administrative unit to obtain an estimate of the share of agricultural employment in total employment at subnational level. Rural and urban areas are differentiated based on the population density data from GPW UN WPP-Adjusted Population Density v4.11 using a cutoff of 300 people per km2 for urban areas[8].

[8]The cutoff of 300 people per km2 is based on the Degree of Urbanization method from the UN Statistical

Conflict intensity.—We use information on the occurrence of lethal conflicts from the UCDP Georeferenced Event Dataset (GED) Global version 21.1 [Pettersson et al., 2021, Sundberg and Melander, 2013], which records violent events at village level with daily resolution. We sum the number of causalities within each month-year for each second administrative level. An indicator of conflict intensity is then created based on the number of casualties: 0 (no deaths), 1 (minor conflict: 25–999 deaths), and 2 (war: $\leq$1000 deaths). The indicator is aggregated to the first administrative level and summed over the past 12 months to account for temporal and spatial spillovers [Harari and Ferrara, 2018].

Agro-Ecological Zone (AEZ).—Information on agro-ecological characteristics is taken from the Agro-Ecological Zones for Africa South of the Sahara database from IFPRI [HarvestChoice, 2015]. We use the 5-class classification scheme, which identifies Humid, Sub-Humid, Semi-Arid, Arid, Tropical Highlands and Sub-Tropical zones. We aggregate the data from grid-cell (approximately 10 x 10km) to second administrative unit by calculating the share of area covered by each AEZ class and allocating to each administrative unit the class with the largest coverage.

Reserves.—We use data on countries' reserves from the World Bank as a measure of national import capacity [The World Bank, 2025], which is available for Ethiopia, Kenya, Malazi, Mozambique, Nigeria, and Zambia. These are external assets that countries use among others for meeting balance of payment needs. The reserves are expressed in months of imports of goods and services they could pay for. In our sample, the average reserve level is 4.68 months (Table 5).

Stocks.—We use data on countries' stock levels of cereals (maize, rice, barley, millet, sorghum, and wheat) from the Production, Supply and Distribution (PSD) database of USDA [USDA, 2022]. The database covers public and private stock-holding. We compile the stock-to-use ratio (SUR) for cereals as the ratio of the ending stock summed over over the trend of domestic consumption in each marketing year. In our sample, the average stock-to-use ratio is 9% and the 90th percentile is 14% (Table 5).

Commission.

Table 5: Summary statistics of the three samples.

	All AEZs	Selected AEZs	Selected AEZs II
Administative unit-level variables			
Food insecurity (1 = yes, 0 = no)	0.30 (0.46)	0.29 (0.46)	0.28 (0.45)
	[0.00 - 1.00]	[0.00 - 1.00]	[0.00 - 1.00]
Share of administrative unit area under dry conditions	0.06 (0.20)	0.06 (0.21)	0.06 (0.22)
	[0.00 - 0.07]	[0.00 - 0.06]	[0.00 - 0.09]
Share of country area under dry conditions	0.06 (0.09)	0.06 (0.09)	0.06 (0.09)
	[0.00 - 0.17]	[0.00 - 0.15]	[0.00 - 0.31]
Share of administrative unit area under wet conditions	0.05 (0.18)	0.04 (0.16)	0.03 (0.14)
	[0.00 - 0.07]	[0.00 - 0.01]	[0.00 - 0.00]
Share of country area under wet conditions	0.05 (0.07)	0.04 (0.06)	0.04 (0.05)
	[0.00 - 0.11]	[0.00 - 0.07]	[0.00 - 0.07]
Travel time to city (100k-200k inhabitants) (minutes)	198.25 (397.63)	186.12 (282.84)	143.48 (202.09)
	[24.95 - 421.99]	[25.14 - 434.80]	[23.70 - 356.28]
Travel time to large port (minutes)	883.87 (583.39)	825.55 (599.14)	733.13 (535.11)
	[248.87 - 1702.59]	[219.84 - 1747.07]	[187.13 - 1597.68]
Country-level variables			
Cereals stock-to-use ratio in previous year	0.09 (0.08)	0.08 (0.07)	0.08 (0.08)
	[0.02 - 0.14]	[0.02 - 0.11]	[0.02 - 0.11]
Reserves to imports ratio in previous year (months)			4.68 (1.55)
			[3.20 - 7.88]
Number of observations	39991	31146	26477
Number of administrative units	1379	1074	913
Number of time periods	29	29	29

Summary statistics: mean (sd) [10th percentile - 90th percentile]. The samples cover 12 countries in Sub-Saharan Africa and 8 years (2009 - 2016). The AEZ zones in the selected sample are Arid, Semi-Arid and Sub-Humid areas.

3.2 Estimation strategy

Panel methods are widely used to examine the impact of climatic conditions on economic outcomes given their strong identification properties [Dell et al., 2014]. Here, we exploit exogenous variation in the occurrence of climate extremes over time within each administrative unit. Before we test the theoretical predictions, we investigate the empirical relationships between climate extremes and food insecurity using the following fixed effects linear probability model estimated with OLS (empirical model 1, EM1)

$$\begin{aligned} FI_{imy} =& \beta_1 D_{imy}^{\text{adm2}} * AEZ_i + \beta_2 D_{imy}^{\text{country}} * Arid_c + \beta_3 D_{cmy}^{\text{nb countries}} \\ & \beta_4 W_{imy}^{\text{adm2}} * AEZ_i + \beta_5 W_{imy}^{\text{country}} * Arid_c + \beta_6 W_{cmy}^{\text{nb countries}} \\ & + \mu_i + \mu_{my} + \epsilon_{imy}, \end{aligned} \tag{EM1}$$

with FI_{imy} a dummy variable indicating whether the second administrative unit i in country c was identified as food insecure by FEWS NET in month m of year y (1 = yes, 0 = no). A food insecure status in the data corresponds to a drop in food consumption, or a low level of food consumption smoothing, in our theoretical model. The variable D_{imy}^{adm2} indicates the share of the area within the second administrative unit that experienced severely (-2 < SPEI < -1.5) or extremely (SPEI < -2) dry conditions in the previous agricultural growing season. The variable W_{imy}^{adm2} indicates the share of the area within the second administrative unit that experienced severely (2 > SPEI > 1.5) or extremely (SPEI > 2) wet conditions in the previous growing season. The variables D_{imy}^{country} and W_{imy}^{country} indicate the share of the country area (excluding administrative unit i) that was affected by severe or extreme dry and wet conditions in the previous growing season. $D_{cmy}^{\text{nb countries}}$ and $W_{cmy}^{\text{nb countries}}$ indicate the share of the neighboring countries' area affected by severe or extreme dry and wet conditions in the last 12 months. We investigate the heterogeneity in the impact of climate extremes across baseline climatic and agricultural conditions with variable AEZ_i, the agro-ecological zone of unit i (arid, semi-arid, humid, sub-humid, tropical highlands). $Arid_c$ is a dummy variable with value 1 if the majority of country c's area is located in arid or semi-arid zones (i.e., Burkina Faso, Djibouti, Mali, Mauritania, Niger, and Chad). Administrative unit (μ_i) and time (μ_{my}) fixed effects control for time invariant administrative unit-specific characteristics and general time trends that influence food insecurity.

To test the theoretical predictions 1 and 2, we assess whether dry climate extremes affect food

insecurity differently depending on the level of households' market access and regions' international market access. We estimate the following model using OLS (empirical model 2, EM2)

$$\begin{aligned} FI_{imy} =& \beta_1 D_{imy}^{\text{adm2}} + \beta_2 D_{imy}^{\text{country}} \\ &+ (\beta_3 D_{imy}^{\text{adm2}} + \beta_4 D_{imy}^{\text{country}}) * T_i^{\text{city}} + (\beta_5 D_{imy}^{\text{adm2}} + \beta_6 D_{imy}^{\text{country}}) * T_i^{\text{port}} \\ &+ \beta_7 W_{imy}^{\text{adm2}} + \beta_8 W_{imy}^{\text{country}} + \mu_i + \mu_{my} + \epsilon_{imy}, \end{aligned} \tag{EM2}$$

with T_i^{city} the logarithm of the average travel time to the closest large city and T_i^{port} the logarithm of the average travel time to the closest large port. The former is a proxy for the transaction costs faced by households in market purchases or sales (corresponding to parameter τ_m^{HH} in the theoretical framework), while the latter is a proxy for a region's access to overseas international markets (corresponding to parameter τ_{mW} in the theoretical framework). The travel times are centered at the country mean to measure market access relative to other regions within a country. The variables D_{imy}^{adm2} and D_{imy}^{country} correspond to a negative realisation of the climate shock variables $\nu_{REG,t}$ and $\nu_{ROC,t}$ in the theoretical model. From prediction 1 we expect that β_3 is positive and significant and that β_4 is negative and significant. That is, in regions with longer travel times to city households experience a larger impact from local dry extremes and a smaller impact from country-level dry extremes. From prediction 2 we expect that β_5 and β_6 are both positive and significant. That is, in regions with longer travel times to port households experience a larger food insecurity impact from both local and country-level dry extremes.

As robustness check, we test for confounding factors that may influence the interaction between climate extremes and market access. A first potential source of bias is that climate extremes may lead to higher conflict intensity [Harari and Ferrara, 2018] and conflicts may have a larger impact on food insecurity in areas with low market access (e.g., conflict-related food aid not reaching remote areas). To assess whether the coefficients β_3–β_6 are driven by this mechanism, we add interaction terms between conflict intensity (defined at month-year and first administrative unit level) and our market access variables T_i^{city} and T_i^{port}. A second potential source of bias is that market access may be correlated with the availability of non-agricultural employment opportunities. As labor reallocation is an important coping mechanism to local weather shocks in rural areas [Branco and Féres, 2020], this may confound our estimation. We therefore control for the interaction between the share of agricultural employment (defined at year and second administrative unit level) and our

climate extreme variable D_{imy}^{adm2}. We use the annual lag of agricultural employment to mitigate over-controlling problems [Dell et al., 2014]. We further test sensitivity to the definition of our variables of interest by using alternative city and port size thresholds and by using the SPEI value in the past 12 months as climate extremes indicator.

To investigate prediction 3 on the substitutability of trade and storage, we test whether the food insecurity impacts of dry climate extremes are buffered by reserves and stocks and whether there is any interaction using the following specification (empirical model 3, EM3)

$$\begin{aligned} FI_{imy} =& \beta_1 D_{imy}^{\text{adm2}} + \beta_2 D_{imy}^{\text{country}} \\ &+ (\beta_3 + \beta_4 D_{imy}^{\text{adm2}} + \beta_5 D_{imy}^{\text{country}}) * R_{c,y-1} + (\beta_6 + \beta_7 D_{imy}^{\text{adm2}} + \beta_8 D_{imy}^{\text{country}}) * S_{c,y-1} \\ &+ (\beta_9 + \beta_{10} D_{imy}^{\text{adm2}} + \beta_{11} D_{imy}^{\text{country}}) * R_{c,y-1} * S_{c,y-1} \\ &+ \beta_{12} W_{imy}^{\text{adm2}} + \beta_{13} W_{imy}^{\text{country}} + \mu_i + \mu_{my} + \epsilon_{imy}, \end{aligned} \tag{EM3}$$

with $R_{c,y-1}$ the logarithm of a country's reserves (expressed in months of imports) in the previous year and $S_{c,y-1}$ the logarithm of a country's stock-to-use ratio of cereals in the previous year. From prediction 3, we expect that trade and storage both buffer the food security impacts of climate shocks. According to our theoretical framework, consumption smoothing via trade is constrained by household assets carried over from the previous period ($X_{m,t-1}$) and consumption smoothing via storage is constrained by stocks carried over from the previous period ($S_{m,t-1}$). We therefore hypothesize that the impact of local and national climate extremes on food insecurity is buffered when a country holds reserve assets or cereal stocks, implying that β_4, β_5, β_7, and β_8 are negative. Furthermore, prediction 3 suggests that trade and storage are partly substitutable in buffering climate shocks—meaning that the two mechanisms can partly replace each other—so the interaction effects (β_{10} and β_{11}) are expected to be positive. A negative value for β_{10} and β_{11} would suggest a positive synergy or partial complementarity between trade and storage, implying that the mechanisms work better together. A value of β_{10} and β_{11} not significantly different from zero would indicate that trade and storage are perfect substitutes and work independently in buffering the effect of climate extremes.

Finally, to investigate prediction 4 on temporally correlated shocks, we check whether reserves and stocks can buffer multi-year dry climate extremes using the following specification (empirical

model 4, EM4)

$$
\begin{aligned}
FI_{imy} =& \beta_1 mD^{\text{adm2}}_{imy} + \beta_2 mD^{\text{country}}_{imy} \\
&+ (\beta_3 + \beta_4 mD^{\text{adm2}}_{imy} + \beta_5 mD^{\text{country}}_{imy}) * R_{c,y-2} + (\beta_6 + \beta_7 mD^{\text{adm2}}_{imy} + \beta_8 mD^{\text{country}}_{imy}) * S_{c,y-2} \\
&+ (\beta_9 + \beta_{10} mD^{\text{adm2}}_{imy} + \beta_{11} mD^{\text{country}}_{imy}) * R_{c,y-2} * S_{c,y-2} \\
&+ \beta_{12} W^{\text{adm2}}_{imy} + \beta_{13} W^{\text{country}}_{imy} + \mu_i + \mu_{my} + \epsilon_{imy},
\end{aligned}
\tag{EM4}
$$

with mD^{adm2}_{imy} the share of the area within the administrative unit that experienced severely or extremely dry conditions in the past 2 years. We use the climate extremes indicators now based on the SPEI value of the last 24 months instead of the SPEI value in the previous growing season to investigate the impact of long-term droughts. $R_{c,y-2}$ and $S_{c,y-2}$ are the lagged variables of $R_{c,y-1}$ and $S_{c,y-1}$, respectively, and measure the availability of reserves and stocks at the beginning of the 2-year dry period. For the coefficients β_4 and β_5, and β_7 and β_8, a negative value indicates a buffering role of trade and storage, respectively. From prediction 4, we expect that the buffering role of storage under multi-year dry extremes is smaller than under short-term dry extremes. We compare the coefficients between model EM3 and model EM4 using bootstrap difference test with 1000 replications.

All empirical models are estimated using OLS with standard errors robust to spatial and temporal correlation, applying the Conley method [Conley, 1999]. This approach accounts for potential dependence among observations that are close to one another in space and time. Based on statistical tests of spatial corelation in our climate extreme indicator (section S5.4 in Appendix), we apply a bandwidth of 400 km for the spatial weighting matrix and a 3 period lag to account for temporal correlation. Results that apply bandwidths up to 1400 km and that correct for temporal correlation up to 7 period lags are provided in the Appendix.

3.3 Results

Climate extremes and food insecurity.—The results from the estimation of model EM1 are presented in Table 6. We find that climatic conditions in the most recent agricultural growing season have a significant effect on the likelihood of a region to experience food insecurity. In arid, semi-arid, and sub-humid areas, dry conditions increase the risk of food insecurity. For humid and tropical highland areas the opposite effect is observed with dry conditions reducing food insecurity. In humid areas, wet conditions significantly increase food insecurity. Similar patterns are observed at the country level. Country-wide dry conditions increase food insecurity to a much larger extent in arid countries than in non-arid countries. For example, for a 10 percentage points increase in the country area affected by severe or extreme dry conditions, the likelihood of a region to be food insecure increases with 21.5 percentage points in arid countries, while there is no significant impact in non-arid countries. Severe or extreme wet conditions reduce food insecurity in arid countries, while they increase food insecurity in non-arid countries. Extreme climatic conditions in neighbouring countries do not significantly influence regions' food security. The results are robust when being more conservative about spatial and temporal correlation in the data (Tables S3 and S4).

Table 6: The effect of climate extremes on food insecurity across Agro-Ecological Zones (EM1)

Dependent Variable	Food Insecurity (yes = 1, no = 0)
Dry adm2	-0.206***
	(0.064)
AEZ Arid × Dry adm2	0.295***
	(0.086)
AEZ Humid × Dry adm2	0.110
	(0.077)
AEZ Semi-Arid × Dry adm2	0.469***
	(0.086)
AEZ Sub-Humid × Dry adm2	0.264***
	(0.071)
Wet adm2	-0.045
	(0.032)
AEZ Arid × Wet adm2	-0.117
	(0.088)
AEZ Humid × Wet adm2	0.158*
	(0.094)
AEZ Semi-Arid × Wet adm2	-0.006
	(0.053)
AEZ Sub-Humid × Wet adm2	0.087
	(0.071)
Dry country	0.118
	(0.100)
Arid country x Dry country	2.147***
	(0.534)
Wet country	0.604***
	(0.164)
Arid country x Wet country	-0.870***
	(0.191)
Dry neighboring countries	0.202
	(0.221)
Wet neighboring countries	0.290
	(0.195)
Second administrative unit FE	Yes
Year-month FE	Yes
Number of observations	39991
R-squared	0.269

Notes: Standard errors in parentheses corrected for spatial correlation with bandwidth of 400km and corrected for temporal correlation with 3 period lag. Tropical Highlands is the base AEZ category. Asterisks denote significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Travel times, climate extremes, and food insecurity.—We next investigate whether the impact of climate extremes on food insecurity varies with households' and regions' market access, proxied by travel times to the closest large city and port, respectively. The results of the estimation of model EM2 are presented in Table 7. Given the importance of agro-ecological characteristics in determining the sign of the impact of climate extremes (Table 6), we focus on arid, semi-arid, and sub-humid zones and dry conditions to study climate extremes that increase food insecurity.

Based on prediction 1, we expect that local climate extremes affect food insecurity of a region more when households face high market transaction costs. We find indeed that local dry conditions in arid, semi-arid, and sub-humid zones have a larger impact on food insecurity in regions with a longer travel time to the closest city (column (2)). The estimated effect slightly reduces in magnitude and the significance level drops from 5% to 10% when controlling for travel time to port (column (3)). Based on column (3), a 10 percentage points increase in an administrative unit's area affected by dry conditions increases the likelihood of food insecurity on average with 1.86 percentage points. This is the effect for a region with average travel times in the sample. When travel time to city is at the 90th percentile, the effect increases to 2.42 percentage points, while if it is at the 10th percentile, the effect reduces to 1.28 percentage points[9]. This means that in regions where households face high market transaction costs, a 10 percentage points increase in the area affected by drought increases the likelihood of food insecurity with 8 percent above the sample mean (average prevalence of food insecurity in the sub-sample is 29 percent, see Table 5).

From prediction 1, we further expect a smaller impact of country-level climate extremes when households' market access is low, that is, a negative interaction effect between country-wide dry conditions and travel time to city. We observe a significant positive interaction effect between country-wide dry conditions and travel time to city in column (2), but this effect drops in magnitude and significance once we control for travel time to the closest large port (column (3)). There is thus no evidence that the impact of country-level climate extremes depends on the level of households' market access in the data.

Based on prediction 2, we expect that local and country-level adverse climate extremes hit a region harder when it is less connected to overseas international markets. Our estimation indicates

[9]Travel time to city is measured in logarithm and centered at the country mean to measure market access relative to other regions within a country. This implies that the magnitude of the percentiles differs by country. For example, for Kenya the mean travel time to city in our sample is 251 minutes, the 90th percentile is 573 minutes, and the 10th percentile is 106 minutes. For Nigeria, the mean travel time to city in our sample is 51 minutes, the 90th percentile is 115 minutes, and the 10th percentile is 21 minutes.

that country-level dry conditions have an impact on food insecurity particularly in regions with long travel times to port, a proxy for international market access (column (3)). Based on column (3), we estimate that a 10 percentage points increase in the country area affected by dry conditions leads to a 3.6 percentage points increase in food insecurity when travel time to port is at the 90th percentile[10]. This means that in regions disconnected from overseas markets, a 10 percentage points increase in the country area affected by drought increases the likelihood of food insecurity with 12 percent above the sample mean of 29 percent (Table 5). We find no evidence of a significant interaction effect between local dry conditions and travel time to port.

The Appendix provides additional results to verify the robustness of our findings. Tables S5 and S6 demonstrate that our two main effects, the interaction between local dry conditions and travel time to city and the interaction between country-level dry conditions and travel time to port, are robust when controlling for larger bandwidths of spatial correlation or for longer periods of temporal correlation. Table S7 shows that the estimated effects are robust to controlling for potential confounding factors (conflicts and agricultural employment). Tables S8 and S9 verify the robustness to uncertainty in the definition of the key variables of interest. The two interaction effects are robust in terms of sign and significance when we use an indicator for climate extremes based on the SPEI value in the past 12 months instead of the SPEI value in the previous growing season (Table S8). In addition, with the 12–month SPEI index, the interaction effect between local dry conditions and travel time to port is significant (at 10% significance level for 400km bandwidth). When applying different city and port sizes (Table S9), the interaction between local dry climate extremes and travel time to city remains present for smaller city population cut-off (50–100k inhabitants), but not for a larger population cut-off (200–500k inhabitants). The interaction between country-wide dry extreme and travel time to port is robust to using medium port sizes.

In summary, our results confirm part of prediction 1: when households face market transaction costs, food consumption is more responsive to local climate shocks (10% significance level); and part of prediction 2: when a region is isolated from the world market, food consumption is more responsive to national climate shocks (1% significance level).

[10]Similar as for travel time to city, travel time to port is measured in logarithm and centered at the country mean such that the interpretation differs by country. For example, for Kenya the mean travel time to port in our sample is 1232 minutes and the 90th percentile is 2150 minutes. For Nigeria, the mean travel time to port in our sample is 377 minutes and the 90th percentile is 658 minutes.

Table 7: The effect of climate extremes and market access on food insecurity (EM2)

	(1)	(2)	(3)
Dry adm2	0.120***	0.128***	0.186***
	(0.038)	(0.036)	(0.037)
Dry country	0.120	0.118	0.041
	(0.105)	(0.103)	(0.103)
Dry adm2 x Travel time to city		0.081**	0.068*
		(0.034)	(0.036)
Dry country x Travel time to city		0.204**	0.048
		(0.080)	(0.069)
Dry adm2 x Travel time to port			-0.033
			(0.074)
Dry country x Travel time to port			0.643***
			(0.197)
Second administrative unit FE	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes
Admin2 and country wet	Yes	Yes	Yes
Number of observations	31146	31146	31146
R-squared	0.269	0.272	0.276

Standard errors in parentheses corrected for spatial correlation with bandwidth of 400km and corrected for temporal correlation with 3 period lag. Sample of Arid, Semi-Arid and Sub-Humid areas. Asterisks denote significance: *** p < 0.01, ** p < 0.05, * p < 0.1.

Reserves, stocks, climate extremes, and food insecurity.—Next, we test prediction 3 on the buffering effect of international trade and storage and their substitutability in Table 8, focusing again on dry conditions in arid, semi-arid, and sub-humid areas.

The models in columns (2) to (4) investigate whether reserves and stocks buffer climate-related food insecurity. Based on the model in column (4), we estimate that a 10 percentage points increase in the region area affected by dry conditions increases the likelihood of food insecurity with 1.21 percentage points. A 10 percentage points increase in the country area affected by dry conditions increases the likelihood of food insecurity with 4.98 percentage points. These are the effects at average reserve and stock levels. If reserves are instead at the 90th percentile, which corresponds to a level of reserves covering almost 8 months of imports (Table 5), the effect of country-wide dry conditions on food insecurity is fully compensated. The positive main effect of reserves indicates that regions in countries with higher reserves generally experience higher food insecurity. For a stock-to-use ratio at the 90th percentile, which corresponds to a stock-to-use ratio of 11 percent (Table 5), the effect of country-wide dry conditions on food insecurity reduces to 1.59 percentage points and the effect of local dry conditions on food insecurity reduces to 0.3 percentage points. The results indicate that the availability of reserves reduces the impact of country-wide dry conditions,

while the availability of stocks reduces the impact of both local and country-wide dry conditions.

We next investigate whether reserves and stocks partly substitute one another in buffering climate shocks. The changes in the magnitude of the coefficients across columns suggests an interaction between reserves and stocks. In column (5), we observe that the interaction effect between reserves and stocks has a negative, though not statistically significant, value. When we do not consider any spatial correlation in the calculation of standard errors, or a lower bandwidth of 200km, the interaction effect is significantly negative (columns (1) and (2) in Table S10). These observations are in contrast with the positive interaction effect we hypothesized based on prediction 3. A negative interaction effect suggests that, instead of being partly substitutable, there is a positive synergy between reserves and stocks in buffering the food insecurity impacts of climate extremes. A possible explanation why the theoretical model in this study does not predict the possibility of a positive synergy between trade and storage is that the model reflects an annual time dimension. In contrast, by looking at a weekly time interval, Coleman [2009] identifies a positive synergy between storage and trade driven by the fact that trade does not occur instantaneously but takes a certain amount of time to arrive at the destination location[11].

The strength of the results varies depending on the spatial correlation considered in the standard errors. In our baseline specification that controls for spatial correlation up to a 400km bandwidth (column (5) in Table 8), the hypotheses for EM3 are confirmed for two of the six coefficients (β_7 and β_8) at a 5% significance level. When we do not consider any spatial correlation, the hypothesis is confirmed for three coefficients (β_5, β_7 and β_8) at 1% significance level (column (1) in Table S10). When we consider the largest bandwith of 1400km, two of the six β's (β_7 and β_8) remain significant at 10% significance level (column (6) in Table S10). Varying the temporal correlation cutoff between 0 and 7 periods does not affect the results (Table S11).

[11] In some countries, the recommended level of public grain stocks is the level that allows to bridge the waiting time for the arrival of imports. For example, in Ethiopia the recommended level of grain stocks is 407 kt to satisfy 4 months of cereal consumption [Rashid et al., 2018], while in Zambia the recommended level is 300 - 400 kt to satisfy 3 months maize consumption [The World Bank, 2021].

Table 8: The effect of climate extremes, stocks, and import capacity on food insecurity (EM3)

	(1)	(2)	(3)	(4)	(5)
Dry adm2	0.117***	0.113***	0.123***	0.121***	0.118***
	(0.039)	(0.036)	(0.034)	(0.033)	(0.034)
Dry country	0.279**	0.224**	0.483***	0.498***	0.630***
	(0.115)	(0.107)	(0.147)	(0.141)	(0.192)
Reserves (y-1)		0.281***		0.297***	0.318***
		(0.049)		(0.047)	(0.047)
Dry adm2 x Reserves (y-1)		0.221*		0.141	0.104
		(0.126)		(0.111)	(0.115)
Dry country x Reserves (y-1)		-1.065***		-1.072***	-0.734
		(0.413)		(0.405)	(0.528)
SUR (y-1)			-0.067**	-0.035	-0.063*
			(0.031)	(0.029)	(0.037)
Dry adm2 x SUR (y-1)			-0.206***	-0.178**	-0.183***
			(0.068)	(0.071)	(0.070)
Dry country x SUR (y-1)			-0.324	-0.651***	-1.265**
			(0.203)	(0.202)	(0.530)
Reserves (y-1) x SUR (y-1)					-0.027
					(0.077)
Dry adm2 x Reserves (y-1) x SUR (y-1)					-0.094
					(0.151)
Dry country x Reserves (y-1) x SUR (y-1)					-1.912
					(1.417)
Second administrative unit FE	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes
Admin2 and country wet	Yes	Yes	Yes	Yes	Yes
Number of observations	26477	26477	26477	26477	26477
R-squared	0.306	0.324	0.313	0.331	0.332

Standard errors in parentheses corrected for spatial correlation with bandwidth of 400km and corrected for temporal correlation with 3 period lag. Sample of Arid, Semi-Arid and Sub-Humid areas. Asterisks denote significance: *** p < 0.01, ** p < 0.05, * p < 0.1.

Lastly, we explore what happens when severe or extreme dry conditions persist for two consecutive years. The estimation of model EM4 (column (5) in Table 9) indicates that reserves buffer long-term local and country-wide droughts (negative β_4 and β_5) and stocks buffer long-term country-wide droughts (negative β_8). According to prediction 4, we expect the buffering effects of storage to be smaller for long-term than for short-term droughts. Comparing the results in Table 9 with those for short-term droughts (column (5) in Table 8) shows that the buffering effect of stocks is smaller for local long-term droughts but larger for country-wide long-term droughts. As these results are inconclusive, we cannot confirm prediction 4. Furthermore, similar to the estimation of model EM3, we observe a significant negative interaction effect between reserves and stocks for long-term country-wide droughts, suggesting a positive synergy between the two mechanisms.

Table 9: The effect of multi-year climate extremes, stocks and import capacity on food insecurity (EM4)

	(1)	(2)	(3)	(4)	(5)
Dry adm2 (24 months)	0.095***	0.078**	0.115***	0.111***	0.102***
	(0.036)	(0.035)	(0.040)	(0.035)	(0.033)
Dry country (24 months)	0.173	0.029	0.124	0.057	0.364**
	(0.112)	(0.105)	(0.154)	(0.138)	(0.178)
Reserves (y-2)		-0.084*		-0.095**	-0.051
		(0.047)		(0.046)	(0.050)
Dry adm2 (24m) x Reserves (y-2)		-0.382**		-0.418***	-0.492***
		(0.151)		(0.155)	(0.159)
Dry country (24m) x Reserves (y-2)		-2.555***		-3.298***	-2.405***
		(0.568)		(0.587)	(0.666)
SUR (y-2)			0.052	0.058*	-0.003
			(0.035)	(0.033)	(0.040)
Dry adm2 (24m) x SUR (y-2)			-0.071	-0.121**	-0.073
			(0.060)	(0.060)	(0.070)
Dry country (24m) x SUR (y-2)			-0.255	-0.805***	-1.912***
			(0.272)	(0.277)	(0.465)
Reserves (y-2) x SUR (y-2)					-0.177***
					(0.068)
Dry adm2 (24m) x Reserves (y-2) x SUR (y-2)					0.243
					(0.176)
Dry country (24m) x Reserves (y-2) x SUR (y-2)					-3.710***
					(1.206)
Second administrative unit FE	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes
Admin2 and country wet	Yes	Yes	Yes	Yes	Yes
Number of observations	26477	26477	26477	26477	26477
R-squared	0.303	0.316	0.305	0.32	0.322

Standard errors in parentheses corrected for spatial correlation with bandwidth of 400km and corrected for temporal correlation with 3 period lag. Sample of Arid, Semi-Arid and Sub-Humid areas. Asterisks denote significance: *** p < 0.01, ** p < 0.05, * p < 0.1.

4 Discussion and conclusion

This paper investigates consumption-smoothing via trade and storage in the context of climate extremes in a developing country. We develop a theoretical model that features stochastic agricultural production, risk averse farm households with inter-temporal consumption preferences, and risk neutral traders. The empirical analysis provides mixed support for the theoretical predictions. In line with theory, we find that local dry conditions have larger impacts on food insecurity in regions with longer travel times to cities (prediction 1), and that country-level dry conditions affect food insecurity more severely in regions with poor access to international markets via ports (prediction 2). Additionally, both asset reserves and cereal stocks buffer the food insecurity impacts of climate extremes (prediction 3). Contrary to theoretical expectations, however, we find no interaction between country-wide dry extremes and travel times to city or between local dry extremes and travel times to port (predictions 1 and 2). Furthermore, the evidence suggest that the buffering effect of reserves and stocks is enhanced when both are available, indicating a partial complementarity between trade and storage instead of the expected substitutability (prediction 3). Lastly, the empirical evidence regarding temporally correlated shocks (prediction 4) is inconclusive, with the buffering effect of stocks being smaller for local long-term droughts but larger for country-wide long-term droughts compared to short-term droughts.

There are different possible explanations for the mixed empirical support. On the one hand, the empirical sample may not provide sufficient spatiotemporal variation to identify all the effects, particularly given that climate extremes are by definition rare and some variables vary only at the country level (asset reserves and cereal stocks). It is therefore important to expand the analysis to more countries and years, while maintaining subnational and subannual data dimensions and accounting for spatial correlation in climate shocks. Further, it would be useful to explore spatial variation in access to storage, such as the location of storage facilities. The stock data from USDA [2022], besides facing challenges of accuracy [Wright, 2011], does not provide any information about the subnational distribution of stocks and storage facilities. Yet, descriptive evidence from Zambia suggests that this influences the effectiveness of food distribution in the face of emergencies [The World Bank, 2021]. Similar to our findings on travel times to port, we could expect that travel times to storage facilities influence the food insecurity impacts of climate extremes.

On the other hand, some of the simplifying assumptions in the theoretical model may have led to

incomplete predictions, explaining the unexpected and inconclusive results. First, the discrepancy between the theory and empirical findings regarding the reserves-stocks interaction may reflect the annual time dimension of the theoretical model versus the more complex temporal dynamics of real-world trade and storage decisions. In reality, imports take several weeks or months to arrive and stocks may serve to bridge waiting periods for imports, which could explain why trade and storage are complementary (rather than substitutable) in buffering negative impact of climate extremes. Second, the theoretical model may underestimate the buffering via storage relative to trade because it does not take into account geopolitical events that limit access to food imports and/or export revenue [Wright and Cafiero, 2011].

This study opens several promising avenues for future theoretical, empirical, and simulation research. First, the model assumed an inelastic supply response, thereby ignoring the reallocation of households' productive inputs and resources in response to climate shocks. Decisions for most agricultural inputs are taken before the harvest is realized and the output price is known. When farmers are price-takers with rational expectations and without alternative income generating activities, theory predicts that storage and production decisions strengthen each other in absorbing weather shocks [Williams and Wright, 1991]. In Sub-Saharan Africa, the supply response of farm households to shocks does, however, not behave as predicted for rational price-takers and depends on labor availability, the level of risk and risk aversion, market integration, and land availability [Girard et al., 2021]. Switching to alternative income generating activities, such as reallocating labor to the non-agricultural sector [Branco and Féres, 2020] or to migration-related jobs [Josephson and Shively, 2021], is furthermore an important coping strategy. This means that it is a priori unclear how supply decisions would interact with market-based consumption smoothing. In addition, improved access to agricultural inputs via the imports of fertilizers, pesticides, and machinery is shown to increase agricultural productivity [Farrokhi and Pellegrina, 2023]. If higher input adoption implies also a lower production variability, international trade in agricultural inputs could serve as an additional mechanism for market-based consumption smoothing. Second, future research can study heterogeneity according to households' and countries' income level. In the face of weather shocks, poor households are found to engage in asset smoothing rather than consumption smoothing [Carter and Lybbert, 2012, Janzen and Carter, 2019]. Market-based consumption smoothing may therefore not work for the poorest households. Low- and middle-income countries have limited access to foreign capital [Barnichon, 2009], which would, according to our theoretical model, particularly

affect the effectiveness of trade in buffering climate shocks. Third, it is relevant to compare the impact of the volatility of world market prices (see e.g., Gouel and Jean [2015]) with the impact of domestic productivity shocks on countries' storage and trade decisions. Lastly, future advances in machine learning may enable the development and calibration of multi-regional models of consumption smoothing, trade, and storage, facilitating quantitative policy analysis similar to that conducted in the spatial economics literature [Redding and Rossi-Hansberg, 2017].

Coping with extreme climatic conditions will be a huge and inevitable challenge for policy makers, particularly in developing countries. Market-based coping mechanisms can be facilitated by improving households' access to markets and expanding trade and storage infrastructure, tailored to a country's specific context. A country that already has storage facilities in place can further invest in reducing the costs and increasing the effectiveness, for example by stimulating private sector involvement and improving within-country distribution of the storage facilities [The World Bank, 2021]. A country that already has diverse export activities or growing export potential can further invest in the performance of its export sectors, thereby building up the necessary foreign exchange to cover years with heightened food import needs [WTO, 2019]. At the same time, the empirical findings suggest that trade and storage may complement one another, so that it is best to establish capacity for both. Future research should further explore the mechanisms behind this complementarity.

5 Appendix

S5.1 Derivation of the household problem

The household problem is an intertemporal optimization problem with one state variable, assets X_{mt}, and three control variables, market purchases of food qp_{mt}, market sales of food qs_{mt}, and consumption of the outside good $C_{m,o,t}$. The solution of the optimization can be derived with Pontryagin's Maximum Principle. The present value Hamiltonian L_{mt} is

$$\begin{aligned} L_{mt} =& \beta^t \ln\left((\alpha C_{m,ag,t}^{\frac{\sigma-1}{\sigma}} + C_{m,o,t}^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}}\right) \\ &+ \eta_{mt}\left[P_{m,o,t}(H_{m,o,t} - C_{m,o,t} - \tau_m^{HH}(qs_{mt} + qp_{mt}))\right. \\ &\left.+ P_{m,ag,t}(H_{m,ag,t} - C_{m,ag,t}) + \Phi_{mt} + (1+r)X_{mt}\right], \end{aligned} \tag{1}$$

with η_{mt} the co-state variable. According to the maximum principle, the optimal solution satisfies the conditions

a. $\frac{\partial L_{mt}}{\partial qs_{mt}} = 0$
$\Rightarrow \beta^t \frac{1}{(\alpha C_{m,ag,t}^{\frac{\sigma-1}{\sigma}} + C_{m,o,t}^{\frac{\sigma-1}{\sigma}})} \alpha C_{m,ag,t}^{\frac{-1}{\sigma}} = \eta_{mt}(P_{m,ag,t} - \tau_m^{HH} P_{m,o,t}) \text{ if } qs_{mt} > 0 \text{ and } qp_{mt} = 0,$

b. $\frac{\partial L_{mt}}{\partial qp_{mt}} = 0$
$\Rightarrow \beta^t \frac{1}{(\alpha C_{m,ag,t}^{\frac{\sigma-1}{\sigma}} + C_{m,o,t}^{\frac{\sigma-1}{\sigma}})} \alpha C_{m,ag,t}^{\frac{-1}{\sigma}} = \eta_{mt}(P_{m,ag,t} + \tau_m^{HH} P_{m,o,t}) \text{ if } qp_{mt} > 0 \text{ and } qs_{mt} = 0,$

c. $\frac{\partial L_{mt}}{\partial C_{m,o,t}} = 0 \Rightarrow \beta^t \frac{1}{(\alpha C_{m,ag,t}^{\frac{\sigma-1}{\sigma}} + C_{m,o,t}^{\frac{\sigma-1}{\sigma}})} C_{m,o,t}^{\frac{-1}{\sigma}} = \eta_{mt} P_{m,o,t},$

d. $\eta_{mt} = \frac{\partial L_{m,t+1}}{\partial X_{m,t+1}} \Rightarrow \eta_{mt} = (1+r)\,\mathrm{E}_t[\eta_{m,t+1}].$

Combining these conditions gives optimal intra-temporal household consumption allocation

$$\begin{aligned} \alpha\left(\frac{C_{m,ag,t}}{C_{m,o,t}}\right)^{\frac{1}{\sigma}} &= \frac{P_{m,o,t}}{P_{m,ag,t} - \tau_m^{HH} P_{m,o,t}} \text{ if } qs_{mt} > 0 \text{ and } qp_{mt} = 0, \\ \alpha\left(\frac{C_{m,ag,t}}{C_{m,o,t}}\right)^{\frac{1}{\sigma}} &= \frac{P_{m,o,t}}{P_{m,ag,t} + \tau_m^{HH} P_{m,o,t}} \text{ if } qs_{mt} = 0 \text{ and } qp_{mt} > 0, \end{aligned} \tag{2}$$

or

$$\alpha\left(\frac{C_{m,ag,t}}{C_{m,o,t}}\right)^{\frac{1}{\sigma}} = \frac{P_{m,o,t}}{P'_{m,ag,t}}, \tag{3}$$

with $P'_{m,ag,t}$ the household shadow price of the agricultural good, $P_{m,ag,t} - \tau_m^{HH} P_{m,o,t} \leq P'_{m,ag,t} \leq P_{m,ag,t} + \tau_m^{HH} P_{m,o,t}$. The optimality conditions also lead to the Euler equations determining household intertemporal consumption allocation

$$\begin{aligned} &(\alpha C_{m,ag,t}^{\frac{\sigma-1}{\sigma}} + C_{m,o,t}^{\frac{\sigma-1}{\sigma}}) C_{m,ag,t}^{\frac{1}{\sigma}} P'_{m,ag,t} \\ =&\frac{1}{(1+r)\beta} \mathrm{E}_t \left[(\alpha C_{m,ag,t+1}^{\frac{\sigma-1}{\sigma}} + C_{m,o,t+1}^{\frac{\sigma-1}{\sigma}}) C_{m,ag,t+1}^{\frac{1}{\sigma}} P'_{m,ag,t+1} \right], \end{aligned} \tag{4}$$

$$\begin{aligned} &(\alpha C_{m,ag,t}^{\frac{\sigma-1}{\sigma}} + C_{m,o,t}^{\frac{\sigma-1}{\sigma}}) C_{m,o,t}^{\frac{1}{\sigma}} P_{m,o,t} \\ =&\frac{1}{(1+r)\beta} \mathrm{E}_t \left[(\alpha C_{m,ag,t+1}^{\frac{\sigma-1}{\sigma}} + C_{m,o,t+1}^{\frac{\sigma-1}{\sigma}}) C_{m,o,t+1}^{\frac{1}{\sigma}} P_{m,o,t+1} \right], \end{aligned} \tag{5}$$

with $\Xi_{m,t,t+1} = \beta \left((\alpha C_{m,ag,t}^{(\sigma-1)/\sigma} + C_{m,o,t}^{(\sigma-1)/\sigma}) C_{m,o,t}^{1/\sigma} P_{m,o,t} \right) \left((\alpha C_{m,ag,t+1}^{(\sigma-1)/\sigma} + C_{m,o,t+1}^{(\sigma-1)/\sigma}) C_{m,o,t+1}^{1/\sigma} P_{m,o,t+1} \right)^{-1}$ the stochastic discount factor.

S5.2 Model quantification

The challenge with solving a stochastic storage model with rational expectations is deriving consistency between the equilibrium storage values and price expectations [Gouel, 2013]. The equilibrium values of storage depend on future price expectations, but the price in the next period in turn depends on that period's storage value, which in turn depends on future price expectations, etc. In a trade and storage model, additional complexity is generated by the fact that the trade and storage behavior of one market influences the price expectations of agents in other markets. As the complexity of the numerical problem grows exponentially with the number of state variables, the dimensionality that can be solved is so far often constrained to two state variables. One strategy to solve for more dimensions is to have agents assume no uncertainty in future agricultural production (e.g., Porteous [2019]). The impact of uncertainty on agents' behavior is, however, key to our analysis. We therefore adopt an alternative strategy to solve the model for four state variables by using a moving series of three-period problems. This approach is an approximation of a more general infinite time horizon problem. The main limitation is that it underestimates the amount of saving and storage. The incentive for saving/storage is not only to alleviate potential income/production shortfalls in the next period, but also to have sufficient savings/supplies available to alleviate potential income/production shortfalls in more distant future periods. For example, Williams and Wright [1991] illustrate the difference in storage volume between approximating the storage model as a series of two-period models and solving it with stochastic dynamic programming (Figure 3.3 (p. 66) and Table 3.1 (p. 71)).

The model is specified as a mixed complementary problem in GAMS. We quantify a deterministic equivalent of the stochastic problem by substituting the expectations operators with deterministic sums using sparse grid integration [Heiss and Winschel, 2008]. With accuracy level equal to 3 and using a nested integral, the procedure leads to 33 nodes for the simulation of shocks that are uncorrelated between the two locations. When the climate shock is assumed to be perfectly correlated between the two locations, the procedure leads to 9 nodes. To illustrate, Figure S1 shows the nodes and weights for the case of such a spatially correlated shock $\nu_{mt}(s)$ with three states s: $\nu_{mt}(s_1) = -0.387$, $\nu_{mt}(s_2) = 0$, and $\nu_{mt}(s_3) = 0.387$.

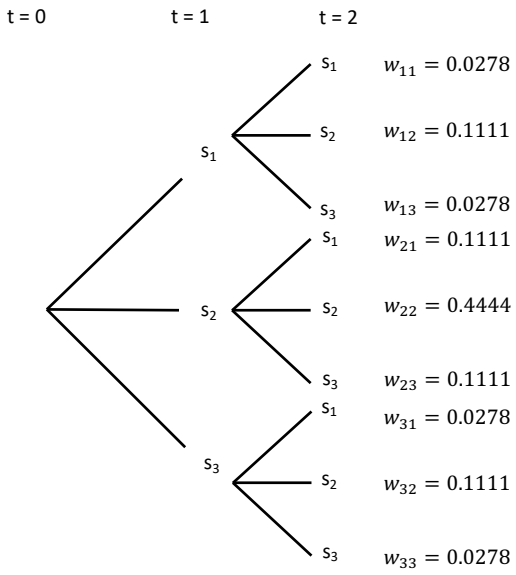


Figure S1: Nodes and weights for sparse grid integration of the expectation of a spatially correlated climate shock.

S5.3 Climate extremes in previous growing season

To measure climate extremes, we use the Standardized Precipitation Evapotranspiration Index (SPEI) [Beguería et al., 2014]. The SPEI index indicates whether climatic conditions are moderately, severely, or extremely wet or dry for a certain time period, and has been calculated for Africa by Peng et al. [2020]. We use the 3–month and 12–month SPEI indeces, which reflect for each month the accumulated water balance of that month and the preceding 2 or 11 months, respectively. The water balance is the difference between precipitation and potential evapotranspiration. We combine the 3–month SPEI index with data on the timing of agricultural growing seasons from FEWS NET to determine, for each administrative unit and time period, the 3–month SPEI value of the previous growing season.

The seasonal calendars from FEWS NET provide information on the pattern of agricultural production in a country during a typical year. To illustrate, Figure S2 shows the seasonal calendar for Kenya. The calendar is differentiated between three large regions in Kenya: Western Rift Valley areas, Southeastern and Coastal areas, and Northern and Eastern Pastoral areas. The agricultural planting and growing seasons overlap with the rainy seasons and are indicated in blue in Figure S2.

The Western Rift Valley areas have a single agricultural growing season, while the other two areas have two agricultural growing seasons.

Food availability from local agricultural production is determined by climatic conditions during the most recent agricultural growing season. For each administrative unit and each time period in our sample we determine the most recent month of the previous agricultural growing season. The 3–month SPEI value of that month then indicates the climatic conditions in the previous agricultural growing season for that specific administrative unit and time period. For example, in the Southeastern and Coastal areas of Kenya, the agricultural growing seasons run from March to May and from October to December. The climate extreme indicator for July 2009 will be based on the 3-month SPEI value in May 2009, which indicates whether conditions were exceptionally dry or wet in March, April, and May 2009. The climate extreme indicator for January 2010 will be based on the 3-month SPEI value in December 2009, which indicates whether conditions were exceptionally dry or wet in October, November, and December 2009.

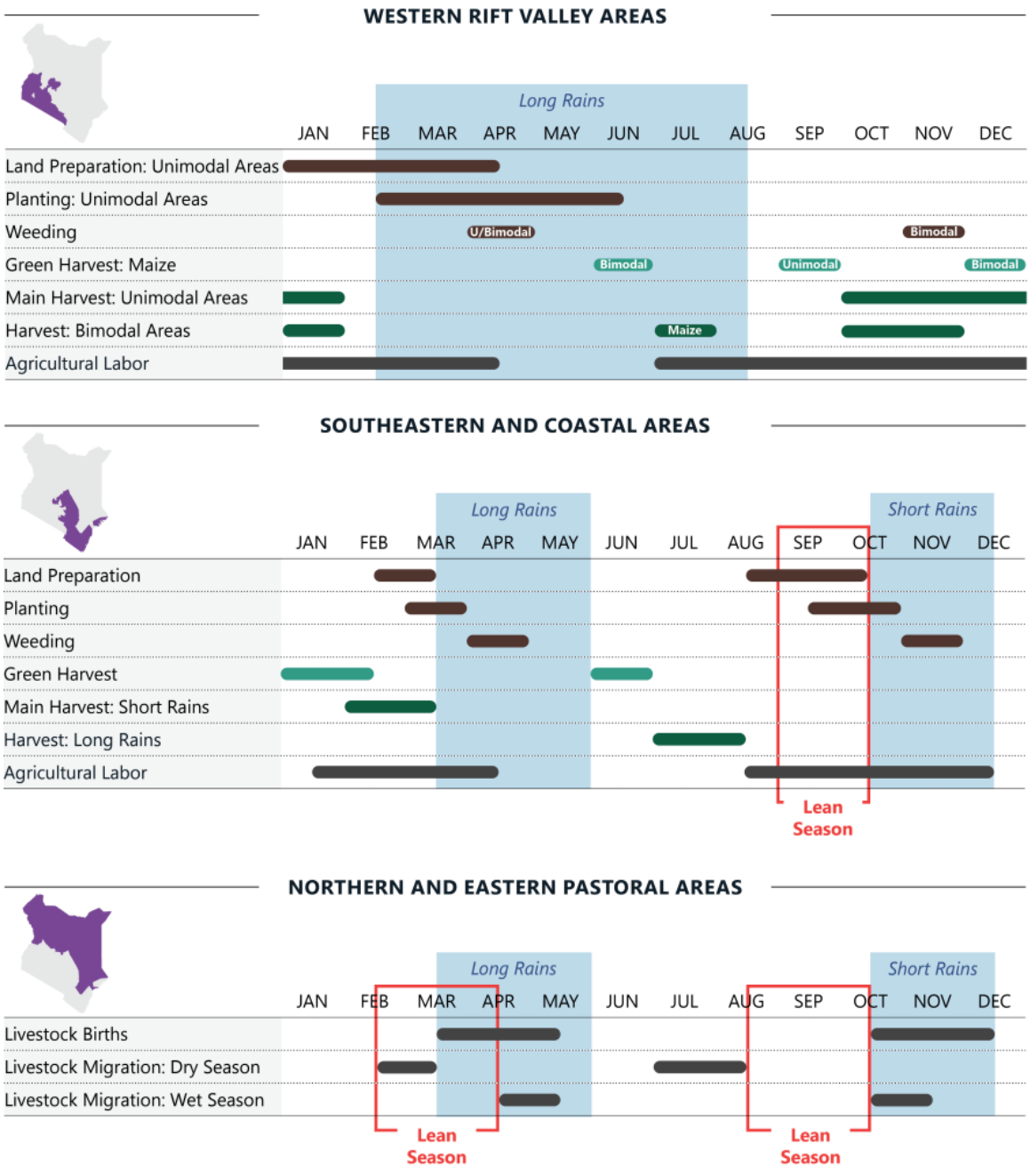


Figure S2: Seasonal calendar for Kenya. Source: FEWS NET.

S5.4 Spatial correlation of climate shocks

To investigate spatial correlation of climate shocks in our sample, we calculate the Local Moran's I statistic of the variable D_{imy}^{adm2}, which indicates the share of the area within the second administrative unit that experienced severely (-2 < SPEI < -1.5) or extremely (SPEI < -2) dry conditions in the previous agricultural growing season. The Local Moran's I statistic is a measure of local spatial autocorrelation and indicates whether the value of a variable at one location is similar or dissimilar to values of that variable at neighboring locations. A Moran's I value close to zero indicates that the variable is randomly distributed in space. Figures S3 and S4 show the Moran's I values in each period at the level of second administrative units in the 12 sample countries. The plots indicate the magnitude of the local Moran's I statistic at the spatial resolution of second administrative units. A blue color indicates that a spatial unit is negative correlated with its neighboring units, white indicates zero correlation with neigboring units, and red indicates positive correlation with neigboring units. If the correlation is significant at 5% level, this is indicated by a black colored border around the spatial unit.

The size of the clusters of units with significant positive autocorrelation can give an indication of the appropriate bandwidth to use in the estimation of Conley standard errors of the empirical models. Figure S5 gives the distribution of the diameters of the correlation clusters in each period. Across all time periods, the average diameter is 355 km and the median is 332 km. This analysis motivates our choice of a 400 km bandwidth in the main estimations of the empirical models and a range of 0 km – 1400 km bandwidth in the robustness checks.

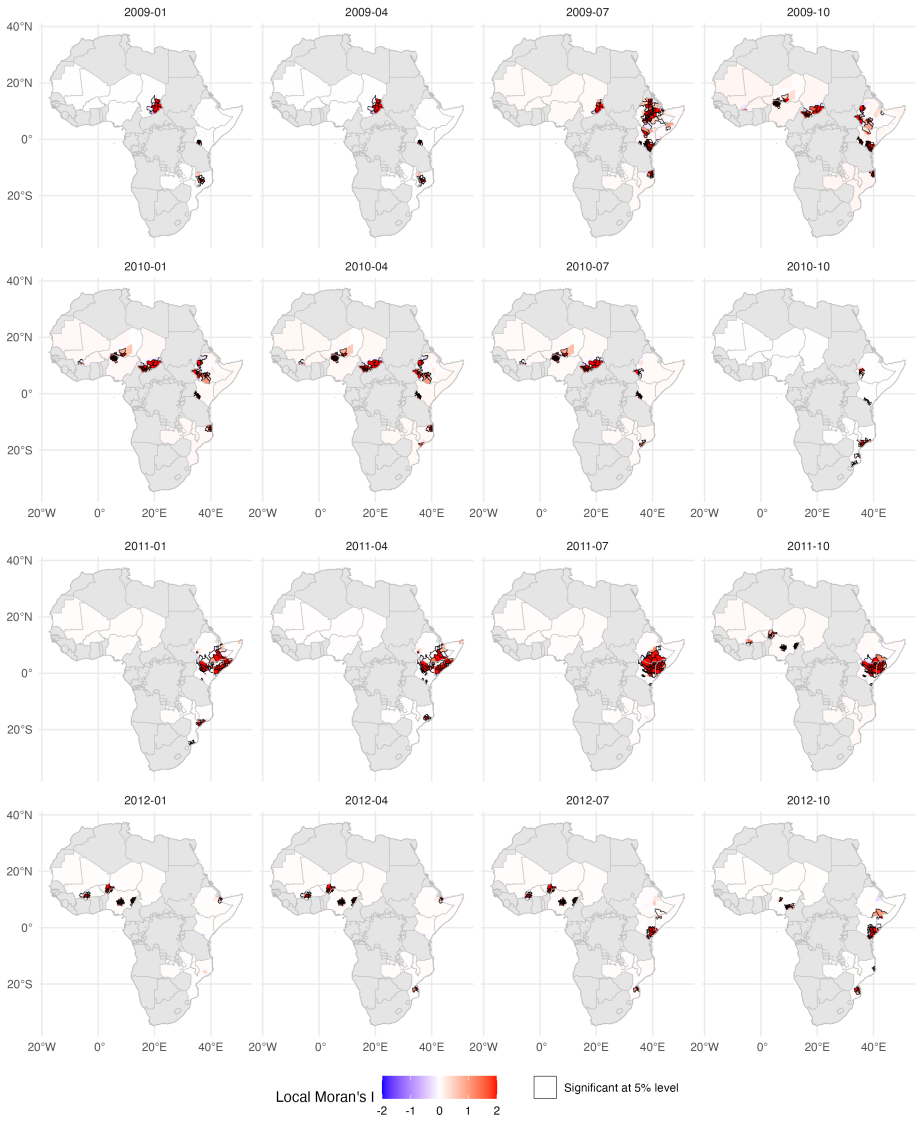


Figure S3: Local Moran's I statistic for drought experience based on 3-month SPEI values of the previous agricultural growing season (2009–2012).

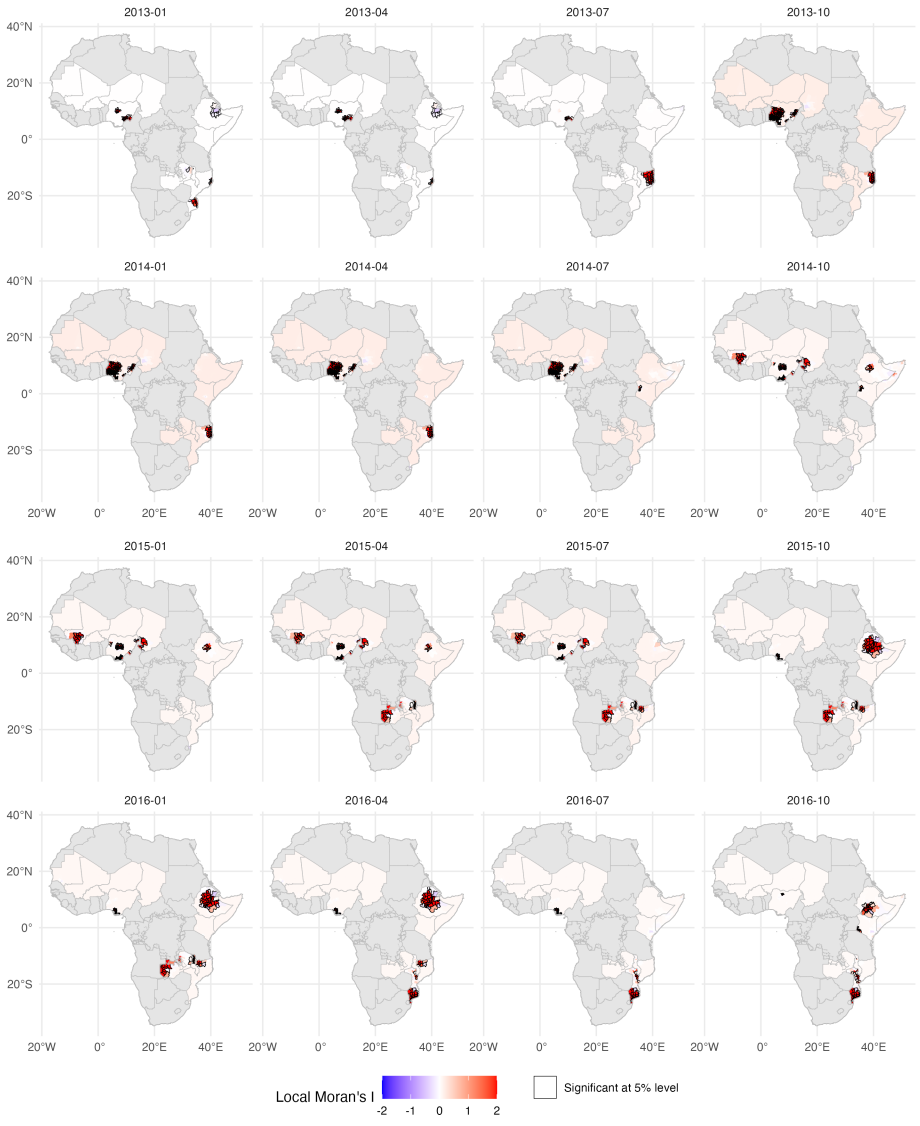


Figure S4: Local Moran's I statistic for drought experience based on 3-month SPEI values of the previous agricultural growing season (2013–2016).



Figure S5: Size of clusters with significant positive local Moran's I index for the SPEI growing season variable in each time period (5% significance level). Across all time periods, the smallest diameter is 19.5 km, the largest diameter is 1357 km, the average diameter is 355 km, and the median is 332 km. Dashed lines are indicated at 200km and 1000km to compare with bandwidths in regression analysis.

S5.5 Parameterization of model experiment 2

Porteous [2019] estimates per unit trade costs of grains from subnational hub markets to port cities in Sub-Saharan Africa (Table A11 in Porteous [2019]). We combine this with market level price data from FEWS NET and FAO GIEWS for the countries in our sample to calculate an estimate of the ad valorem trade cost to port. Based on this, we define the empirically-relevant range of ad valorem trade costs to world market for our model experiment to be 1.075 to 1.65. Porteous [2019] also estimates per unit monthly storage costs of grains by macro-region in Sub-Saharan Africa, ranging from 5 USD/ton in the Sahel region to 21.8 USD/ton in the Central region (Table 3 in Porteous [2019]). We combine this with the average price of six grains (maize, rice, sorghum, millet, wheat, and teff) by country in our sample to estimate annual ad valorem storage costs. Based on this, we define the empirically-relevant range of ad valorem storage costs for our model experiment to be 1.05 to 1.45.

S5.6 Supplementary Tables

Table S1: Spatiotemporal scales of structural models on trade, agriculture, and climate. The spatial scale is arranged according to the number of distinct endogenous trading markets in the model and according to the resolution and extent of the markets modelled. The temporal scale is arranged according to the inclusion of time and whether agricultural yields are considered deterministic or uncertain.

	Temporal scale			
Spatial scale (resolution — extent)	static (deterministic)	static (uncertain)	dynamic (deterministic)	dynamic (uncertain)
One market (national — single country)	Dorosh et al. [2009] Dorosh et al. [2016] Haggblade et al. [2017]			
Multiple markets (subnational — single country)	Burgess and Donaldson [2017] Sotelo [2020]	Allen and Atkin [2022]		Coleman [2009] *This paper*
(national — two countries)				Williams and Wright [1991] Gouel and Jean [2015] Gouel et al. [2016]
(national — multiple countries)	Reilly and Hohmann [1993] Rosenzweig and Parry [1994] Randhir and Hertel [2000] Reimer and Li [2009] Costinot et al. [2016] Gouel and Laborde [2021] Dingel and Meng [2025]		Stevanović et al. [2016] Janssens et al. [2020]	
(subnational — multiple countries)			Porteous [2019, 2024]	

Table S2: Linear regression of smoothing ratio of food consumption in the region (experiment 2 without and with borrowing constraint).

	SR w.r.t. production REG		SR w.r.t. production ROC	
	X free	$X > 0$	X free	$X > 0$
	(1)	(2)	(3)	(4)
Storage cost	-0.133^{***}	-0.148^{***}	-0.145^{***}	-0.162^{***}
	(0.036)	(0.021)	(0.039)	(0.023)
Trade cost world market	-0.457^{***}	-0.293^{***}	-0.501^{***}	-0.321^{***}
	(0.025)	(0.015)	(0.027)	(0.016)
Storage x Trade cost	-0.339^{*}	-0.368^{***}	-0.371^{*}	-0.403^{***}
	(0.196)	(0.116)	(0.214)	(0.127)
Constant	0.372^{***}	0.342^{***}	0.313^{***}	0.280^{***}
	(0.005)	(0.003)	(0.005)	(0.003)
Observations	100	100	100	100
R^2	0.786	0.824	0.786	0.824
Note:				*p<0.1; **p<0.05; ***p<0.01

Table S3: The effect of climate extremes on food insecurity across Agro-Ecological Zones, without and with spatial correlation robust inference

	(1)	(2) 200 km	(3) 400 km	(4) 600 km	(5) 1000 km	(6) 1400 km
Dry adm2	-0.206***	-0.206***	-0.206***	-0.206***	-0.206***	-0.206***
	(0.030)	(0.053)	(0.064)	(0.068)	(0.071)	(0.071)
AEZ Arid × Dry adm2	0.295***	0.295***	0.295***	0.295***	0.295***	0.295***
	(0.052)	(0.073)	(0.086)	(0.092)	(0.098)	(0.098)
AEZ Humid × Dry adm2	0.110***	0.110	0.110	0.110	0.110	0.110
	(0.033)	(0.067)	(0.077)	(0.080)	(0.083)	(0.083)
AEZ Semi-Arid × Dry adm2	0.469***	0.469***	0.469***	0.469***	0.469***	0.469***
	(0.044)	(0.073)	(0.086)	(0.090)	(0.094)	(0.096)
AEZ Sub-Humid × Dry adm2	0.264***	0.264***	0.264***	0.264***	0.264***	0.264***
	(0.035)	(0.061)	(0.071)	(0.075)	(0.076)	(0.075)
Wet adm2	-0.045***	-0.045	-0.045	-0.045	-0.045	-0.045
	(0.016)	(0.030)	(0.032)	(0.032)	(0.032)	(0.033)
AEZ Arid × Wet adm2	-0.117*	-0.117	-0.117	-0.117	-0.117	-0.117
	(0.062)	(0.079)	(0.088)	(0.092)	(0.095)	(0.096)
AEZ Humid × Wet adm2	0.158***	0.158*	0.158*	0.158*	0.158*	0.158*
	(0.031)	(0.089)	(0.094)	(0.093)	(0.092)	(0.092)
AEZ Semi-Arid × Wet adm2	-0.006	-0.006	-0.006	-0.006	-0.006	-0.006
	(0.029)	(0.047)	(0.053)	(0.055)	(0.057)	(0.058)
AEZ Sub-Humid × Wet adm2	0.087***	0.087	0.087	0.087	0.087	0.087
	(0.031)	(0.066)	(0.071)	(0.069)	(0.068)	(0.067)
Dry country	0.118***	0.118*	0.118	0.118	0.118	0.118
	(0.030)	(0.070)	(0.100)	(0.117)	(0.134)	(0.141)
Arid country x Dry country	2.147***	2.147***	2.147***	2.147***	2.147***	2.147***
	(0.253)	(0.393)	(0.534)	(0.628)	(0.746)	(0.824)
Wet country	0.604***	0.604***	0.604***	0.604***	0.604***	0.604***
	(0.044)	(0.115)	(0.164)	(0.190)	(0.210)	(0.217)
Arid country x Wet country	-0.870***	-0.870***	-0.870***	-0.870***	-0.870***	-0.870***
	(0.091)	(0.138)	(0.191)	(0.220)	(0.244)	(0.257)
Dry neighboring countries	0.202**	0.202	0.202	0.202	0.202	0.202
	(0.081)	(0.166)	(0.221)	(0.256)	(0.303)	(0.332)
Wet neighboring countries	0.290***	0.290**	0.290	0.290	0.290	0.290
	(0.073)	(0.141)	(0.195)	(0.230)	(0.273)	(0.298)

Notes: N = 39991. R-squared = 0.269. Second administrative unit and year-month fixed effects included. Column 1 includes robust standard errors clustered at the second administrative unit level in parentheses. Columns 2 – 6 include Conley standard errors corrected for spatial correlation with different bandwidths and for temporal correlation with 3 period lag. Tropical Highlands is the base AEZ category. Asterisks denote significance: *** p < 0.01, ** p < 0.05, * p < 0.1.

Table S4: The effect of climate extremes on food insecurity across Agro-Ecological Zones, without and with temporal correlation robust inference

	(1)	(2) 3-period lag	(3) 5-period lag	(4) 7-period lag
Dry adm2	-0.206***	-0.206***	-0.206***	-0.206***
	(0.062)	(0.064)	(0.064)	(0.064)
AEZ Arid × Dry adm2	0.295***	0.295***	0.295***	0.295***
	(0.082)	(0.086)	(0.087)	(0.088)
AEZ Humid × Dry adm2	0.110	0.110	0.110	0.110
	(0.075)	(0.077)	(0.077)	(0.077)
AEZ Semi-Arid × Dry adm2	0.469***	0.469***	0.469***	0.469***
	(0.083)	(0.086)	(0.087)	(0.087)
AEZ Sub-Humid × Dry adm2	0.264***	0.264***	0.264***	0.264***
	(0.069)	(0.071)	(0.072)	(0.072)
Wet adm2	-0.045	-0.045	-0.045	-0.045
	(0.031)	(0.032)	(0.032)	(0.032)
AEZ Arid × Wet adm2	-0.117	-0.117	-0.117	-0.117
	(0.082)	(0.088)	(0.088)	(0.087)
AEZ Humid × Wet adm2	0.158*	0.158*	0.158*	0.158*
	(0.094)	(0.094)	(0.093)	(0.093)
AEZ Semi-Arid × Wet adm2	-0.006	-0.006	-0.006	-0.006
	(0.052)	(0.053)	(0.054)	(0.054)
AEZ Sub-Humid × Wet adm2	0.087	0.087	0.087	0.087
	(0.070)	(0.071)	(0.071)	(0.071)
Dry country	0.118	0.118	0.118	0.118
	(0.099)	(0.100)	(0.100)	(0.100)
Arid country x Dry country	2.147***	2.147***	2.147***	2.147***
	(0.520)	(0.534)	(0.533)	(0.531)
Wet country	0.604***	0.604***	0.604***	0.604***
	(0.163)	(0.164)	(0.164)	(0.164)
Arid country x Wet country	-0.870***	-0.870***	-0.870***	-0.870***
	(0.187)	(0.191)	(0.192)	(0.193)
Dry neighboring countries	0.202	0.202	0.202	0.202
	(0.217)	(0.221)	(0.221)	(0.221)
Wet neighboring countries	0.290	0.290	0.290	0.290
	(0.192)	(0.195)	(0.196)	(0.196)

Notes: N = 39991. R-squared = 0.269. Second administrative unit and year-month fixed effects included. Column 1 includes robust standard errors clustered at the second administrative unit level in parentheses. Columns 2 – 4 include Conley standard errors corrected for spatial correlation with 400km bandwidth and for different temporal lags. Tropical Highlands is the base AEZ category. Asterisks denote significance: *** p < 0.01, ** p < 0.05, * p < 0.1.

Table S5: The effect of climate extremes and market access on food insecurity, without and with spatial correlation robust inference

	(1)	(2) 200 km	(3) 400 km	(4) 600 km	(5) 1000 km	(6) 1400 km
Dry adm2	0.186***	0.186***	0.186***	0.186***	0.186***	0.186***
	(0.018)	(0.031)	(0.037)	(0.040)	(0.042)	(0.044)
Dry country	0.041	0.041	0.041	0.041	0.041	0.041
	(0.044)	(0.076)	(0.103)	(0.122)	(0.143)	(0.155)
Dry adm2 x Travel time to city	0.068***	0.068**	0.068*	0.068*	0.068*	0.068*
	(0.024)	(0.033)	(0.036)	(0.036)	(0.036)	(0.035)
Dry country x Travel time to city	0.048	0.048	0.048	0.048	0.048	0.048
	(0.044)	(0.064)	(0.069)	(0.070)	(0.069)	(0.068)
Dry adm2 x Travel time to port	-0.033	-0.033	-0.033	-0.033	-0.033	-0.033
	(0.038)	(0.064)	(0.074)	(0.076)	(0.080)	(0.083)
Dry country x Travel time to port	0.643***	0.643***	0.643***	0.643***	0.643***	0.643***
	(0.099)	(0.157)	(0.197)	(0.211)	(0.219)	(0.219)

Notes: N = 31146. R-squared = 0.276. Second administrative unit and year-month fixed effects included. Admin2 and country wet climate extremes included. Column 1 includes robust standard errors clustered at the second administrative unit level in parentheses. Columns 2 – 6 include Conley standard errors corrected for spatial correlation with different bandwidths and for temporal correlation with 3 period lag. Sample of Arid, Semi-Arid and Sub-Humid areas. Asterisks denote significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table S6: The effect of climate extremes and market access on food insecurity, without and with temporal correlation robust inference

	(1)	(2) 3-period lag	(3) 5-period lag	(4) 7-period lag
Dry adm2	0.186***	0.186***	0.186***	0.186***
	(0.036)	(0.037)	(0.037)	(0.037)
Dry country	0.041	0.041	0.041	0.041
	(0.100)	(0.103)	(0.104)	(0.105)
Dry adm2 x Travel time to city	0.068**	0.068*	0.068*	0.068*
	(0.033)	(0.036)	(0.036)	(0.036)
Dry country x Travel time to city	0.048	0.048	0.048	0.048
	(0.063)	(0.069)	(0.071)	(0.072)
Dry adm2 x Travel time to port	-0.033	-0.033	-0.033	-0.033
	(0.070)	(0.074)	(0.075)	(0.075)
Dry country x Travel time to port	0.643***	0.643***	0.643***	0.643***
	(0.189)	(0.197)	(0.199)	(0.200)

Notes: N = 31146. R-squared = 0.276. Second administrative unit and year-month fixed effects included. Admin2 and country wet climate extremes included. Column 1 includes robust standard errors clustered at the second administrative unit level in parentheses. Columns 2 – 4 include Conley standard errors corrected for spatial correlation with 400km bandwidth and for different temporal lags. Sample of Arid, Semi-Arid and Sub-Humid areas. Asterisks denote significance: *** p < 0.01, ** p < 0.05, * p < 0.1.

Table S7: The effect of climate extremes and market access on food insecurity (EM2), with additional controls

	(1)	(2)	(3)	(4)	(5)
Dry adm2	0.120***	0.128***	0.186***	0.184***	0.186***
	(0.038)	(0.036)	(0.037)	(0.037)	(0.038)
Dry country	0.120	0.118	0.041	0.021	0.026
	(0.105)	(0.103)	(0.103)	(0.103)	(0.103)
Dry adm2 x Travel time to city		0.081**	0.068*	0.073**	0.061*
		(0.034)	(0.036)	(0.035)	(0.035)
Dry country x Travel time to city		0.204**	0.048	0.026	0.017
		(0.080)	(0.069)	(0.067)	(0.066)
Dry adm2 x Travel time to port			-0.033	-0.039	-0.073
			(0.074)	(0.074)	(0.084)
Dry country x Travel time to port			0.643***	0.649***	0.597***
			(0.197)	(0.194)	(0.188)
Conflict intensity (adm1)				0.146***	0.029
				(0.035)	(0.043)
Conflict x Travel time to city					0.046
					(0.031)
Conflict x Travel time to port					0.260**
					(0.114)
Share agricultural employment (y-1)				-0.277**	-0.253**
				(0.123)	(0.123)
Share ag. empl. (y-1) x Dry adm2					0.238**
					(0.110)
Second administrative unit FE	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes
Admin2 and country wet	Yes	Yes	Yes	Yes	Yes
Number of observations	31146	31146	31146	31146	31146
R-squared	0.269	0.272	0.276	0.284	0.287

Standard errors in parentheses corrected for spatial correlation with bandwidth of 400km and corrected for temporal correlation with 3 period lag. Sample of Arid, Semi-Arid and Sub-Humid areas. Asterisks denote significance: *** p < 0.01, ** p < 0.05, * p < 0.1.

Table S8: The effect of 12-month climate extremes and market access on food insecurity, without and with spatial correlation robust inference

Label	(1)	(2) 200 km	(3) 400 km	(4) 600 km	(5) 1000 km	(6) 1400 km
Dry adm2	0.157***	0.157***	0.157***	0.157***	0.157***	0.157***
	(0.016)	(0.028)	(0.034)	(0.036)	(0.037)	(0.038)
Dry country	0.158***	0.158***	0.158*	0.158*	0.158	0.158
	(0.034)	(0.060)	(0.082)	(0.096)	(0.111)	(0.120)
Dry adm2 x Travel time to city	0.087***	0.087**	0.087**	0.087**	0.087**	0.087**
	(0.025)	(0.034)	(0.038)	(0.039)	(0.039)	(0.039)
Dry country x Travel time to city	0.047	0.047	0.047	0.047	0.047	0.047
	(0.042)	(0.053)	(0.059)	(0.062)	(0.063)	(0.062)
Dry adm2 x Travel time to port	0.120***	0.120**	0.120*	0.120*	0.120*	0.120*
	(0.035)	(0.056)	(0.062)	(0.062)	(0.062)	(0.063)
Dry country x Travel time to port	0.261***	0.261**	0.261**	0.261*	0.261*	0.261*
	(0.056)	(0.102)	(0.132)	(0.142)	(0.144)	(0.141)

Notes: N = 31146. Column 1 includes robust standard errors clustered at the second administrative unit level in parentheses. Columns 2 – 6 include Conley standard errors corrected for spatial correlation with different bandwidths and for temporal correlation with 3 period lag. Arid, Semi-Arid and Sub-Humid areas. Asterisks denote significance: *** p < 0.01, ** p < 0.05, * p < 0.1.

Table S9: The effect of climate extremes and market access (varying city and port definition) on food insecurity

	(1) default	(2) city 50k - 100k	(3) city 200k - 500k	(4) medium port
Dry adm2	0.186***	0.185***	0.188***	0.162***
	(0.037)	(0.037)	(0.037)	(0.035)
Dry country	0.041	0.043	0.042	0.088
	(0.103)	(0.104)	(0.103)	(0.104)
Dry adm2 x Travel time to city	0.068*			0.062*
	(0.036)			(0.035)
Dry country x Travel time to city	0.048			0.119
	(0.069)			(0.074)
Dry adm2 x Travel time to city		0.066**		
		(0.033)		
Dry country x Travel time to city		0.018		
		(0.072)		
Dry adm2 x Travel time to city			0.046	
			(0.030)	
Dry country x Travel time to city			-0.035	
			(0.068)	
Dry adm2 x Travel time to port	-0.033	-0.027	-0.034	
	(0.074)	(0.074)	(0.081)	
Dry country x Travel time to port	0.643***	0.651***	0.692***	
	(0.197)	(0.199)	(0.209)	
Dry adm2 x Travel time to port				0.023
				(0.060)
Dry country x Travel time to port				0.328**
				(0.161)
Second administrative unit FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
Admin2 and country wet	Yes	Yes	Yes	Yes
Number of observations	31146	31146	31146	31146
R-squared	0.276	0.276	0.276	0.274

Standard errors in parentheses corrected for spatial correlation with bandwidth of 400km and corrected for temporal correlation with 3 period lag. Sample of Arid, Semi-Arid and Sub-Humid areas. Asterisks denote significance: *** p < 0.01, ** p < 0.05, * p < 0.1.

Table S10: The effect of climate extremes, stocks, and import capacity on food insecurity, without and with spatial correlation robust inference

	(1)	(2) 200 km	(3) 400 km	(4) 600 km	(5) 1000 km	(6) 1400 km
Dry adm2	0.118***	0.118***	0.118***	0.118***	0.118***	0.118***
	(0.016)	(0.029)	(0.034)	(0.035)	(0.034)	(0.033)
Dry country	0.630***	0.630***	0.630***	0.630***	0.630***	0.630**
	(0.061)	(0.139)	(0.192)	(0.220)	(0.244)	(0.256)
Reserves (y-1)	0.318***	0.318***	0.318***	0.318***	0.318***	0.318***
	(0.019)	(0.034)	(0.047)	(0.054)	(0.061)	(0.064)
Dry adm2 x Reserves (y-1)	0.104	0.104	0.104	0.104	0.104	0.104
	(0.067)	(0.097)	(0.115)	(0.121)	(0.124)	(0.123)
Dry country x Reserves (y-1)	-0.734***	-0.734*	-0.734	-0.734	-0.734	-0.734
	(0.215)	(0.387)	(0.528)	(0.603)	(0.671)	(0.703)
SUR (y-1)	-0.063***	-0.063**	-0.063*	-0.063	-0.063	-0.063
	(0.013)	(0.027)	(0.037)	(0.042)	(0.045)	(0.047)
Dry adm2 x SUR (y-1)	-0.183***	-0.183***	-0.183***	-0.183**	-0.183**	-0.183**
	(0.040)	(0.058)	(0.070)	(0.074)	(0.076)	(0.076)
Dry country x SUR (y-1)	-1.265***	-1.265***	-1.265**	-1.265**	-1.265*	-1.265*
	(0.170)	(0.383)	(0.530)	(0.600)	(0.653)	(0.685)
Reserves (y-1) x SUR (y-1)	-0.027	-0.027	-0.027	-0.027	-0.027	-0.027
	(0.024)	(0.057)	(0.077)	(0.084)	(0.087)	(0.088)
Dry adm2 x Reserves (y-1) x SUR (y-1)	-0.094	-0.094	-0.094	-0.094	-0.094	-0.094
	(0.080)	(0.126)	(0.151)	(0.157)	(0.159)	(0.158)
Dry country x Reserves (y-1) x SUR (y-1)	-1.912***	-1.912*	-1.912	-1.912	-1.912	-1.912
	(0.354)	(1.015)	(1.417)	(1.610)	(1.754)	(1.839)

Notes: N = 26477. R-squared = 0.332. Second administrative unit and year-month fixed effects included. Admin2 and country wet climate extremes included. Column 1 includes robust standard errors clustered at the second administrative unit level in parentheses. Columns 2 – 6 include Conley standard errors corrected for spatial correlation with different bandwidths and for temporal correlation with 3 period lag. Sample of Arid, Semi-Arid and Sub-Humid areas. Asterisks denote significance: *** p < 0.01, ** p < 0.05, * p < 0.1.

Table S11: The effect of climate extremes, stocks, and import capacity on food insecurity, without and with temporal correlation robust inference

	(1)	(2) 3-period lag	(3) 5-period lag	(4) 7-period lag
Dry adm2	0.118***	0.118***	0.118***	0.118***
	(0.033)	(0.034)	(0.035)	(0.035)
Dry country	0.630***	0.630***	0.630***	0.630***
	(0.189)	(0.192)	(0.193)	(0.193)
Reserves (y-1)	0.318***	0.318***	0.318***	0.318***
	(0.045)	(0.047)	(0.047)	(0.047)
Dry adm2 x Reserves (y-1)	0.104	0.104	0.104	0.104
	(0.111)	(0.115)	(0.116)	(0.117)
Dry country x Reserves (y-1)	-0.734	-0.734	-0.734	-0.734
	(0.519)	(0.528)	(0.530)	(0.530)
SUR (y-1)	-0.063*	-0.063*	-0.063*	-0.063*
	(0.036)	(0.037)	(0.037)	(0.037)
Dry adm2 x SUR (y-1)	-0.183***	-0.183***	-0.183***	-0.183***
	(0.067)	(0.070)	(0.070)	(0.071)
Dry country x SUR (y-1)	-1.265**	-1.265**	-1.265**	-1.265**
	(0.527)	(0.530)	(0.530)	(0.530)
Reserves (y-1) x SUR (y-1)	-0.027	-0.027	-0.027	-0.027
	(0.076)	(0.077)	(0.077)	(0.077)
Dry adm2 x Reserves (y-1) x SUR (y-1)	-0.094	-0.094	-0.094	-0.094
	(0.146)	(0.151)	(0.152)	(0.152)
Dry country x Reserves (y-1) x SUR (y-1)	-1.912	-1.912	-1.912	-1.912
	(1.420)	(1.417)	(1.413)	(1.412)

Notes: N = 31146. R-squared = 0.308. Second administrative unit and year-month fixed effects included. Admin2 and country wet climate extremes included. Column 1 includes robust standard errors clustered at the second administrative unit level in parentheses. Columns 2 – 4 include Conley standard errors corrected for spatial correlation with 400km bandwidth and for different temporal lags. Sample of Arid, Semi-Arid and Sub-Humid areas. Asterisks denote significance: *** p < 0.01, ** p < 0.05, * p < 0.1.

Table S12: The effect of multi-year climate extremes, stocks, and import capacity on food insecurity, without and with spatial correlation robust inference

	(1)	(2) 200 km	(3) 400 km	(4) 600 km	(5) 1000 km	(6) 1400 km
Dry adm2 (24 months)	0.102***	0.102***	0.102***	0.102***	0.102***	0.102***
	(0.017)	(0.029)	(0.033)	(0.034)	(0.034)	(0.035)
Dry country (24 months)	0.364***	0.364***	0.364**	0.364*	0.364	0.364
	(0.060)	(0.126)	(0.178)	(0.207)	(0.232)	(0.245)
Reserves (y-2)	-0.051**	-0.051	-0.051	-0.051	-0.051	-0.051
	(0.021)	(0.036)	(0.050)	(0.057)	(0.063)	(0.066)
Dry adm2 (24m) x Reserves (y-2)	-0.492***	-0.492***	-0.492***	-0.492***	-0.492***	-0.492***
	(0.077)	(0.141)	(0.159)	(0.166)	(0.169)	(0.167)
Dry country (24m) x Reserves (y-2)	-2.405***	-2.405***	-2.405***	-2.405***	-2.405***	-2.405**
	(0.315)	(0.480)	(0.666)	(0.778)	(0.893)	(0.953)
SUR (y-2)	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003
	(0.018)	(0.029)	(0.040)	(0.047)	(0.054)	(0.058)
Dry adm2 (24m) x SUR (y-2)	-0.073**	-0.073	-0.073	-0.073	-0.073	-0.073
	(0.036)	(0.063)	(0.070)	(0.072)	(0.074)	(0.074)
Dry country (24m) x SUR (y-2)	-1.912***	-1.912***	-1.912***	-1.912***	-1.912***	-1.912***
	(0.159)	(0.325)	(0.465)	(0.547)	(0.631)	(0.670)
Reserves (y-2) x SUR (y-2)	-0.177***	-0.177***	-0.177***	-0.177**	-0.177*	-0.177*
	(0.024)	(0.048)	(0.068)	(0.081)	(0.095)	(0.103)
Dry adm2 (24m) x Reserves (y-2) x SUR (y-2)	0.243***	0.243	0.243	0.243	0.243	0.243
	(0.083)	(0.161)	(0.176)	(0.186)	(0.195)	(0.198)
Dry country (24m) x Reserves (y-2) x SUR (y-2)	-3.710***	-3.710***	-3.710***	-3.710***	-3.710**	-3.710**
	(0.462)	(0.847)	(1.206)	(1.417)	(1.646)	(1.767)

Notes: N = 26477. R-squared = 0.322. Second administrative unit and year-month fixed effects included. Admin2 and country wet climate extremes included. Column 1 includes robust standard errors clustered at the second administrative unit level in parentheses. Columns 2 – 6 include Conley standard errors corrected for spatial correlation with different bandwidths and for temporal correlation with 3 period lag. Sample of Arid, Semi-Arid and Sub-Humid areas. Asterisks denote significance: *** p < 0.01, ** p < 0.05, * p < 0.1.

Table S13: The effect of multi-year climate extremes, stocks, and import capacity on food insecurity, without and with temporal correlation robust inference

	(1)	(2) 3-period lag	(3) 5-period lag	(4) 7-period lag
Dry adm2 (24 months)	0.102***	0.102***	0.102***	0.102***
	(0.033)	(0.033)	(0.033)	(0.033)
Dry country (24 months)	0.364**	0.364**	0.364**	0.364**
	(0.175)	(0.178)	(0.179)	(0.179)
Reserves (y-2)	-0.051	-0.051	-0.051	-0.051
	(0.049)	(0.050)	(0.050)	(0.050)
Dry adm2 (24m) x Reserves (y-2)	-0.492***	-0.492***	-0.492***	-0.492***
	(0.158)	(0.159)	(0.159)	(0.159)
Dry country (24m) x Reserves (y-2)	-2.405***	-2.405***	-2.405***	-2.405***
	(0.651)	(0.666)	(0.666)	(0.665)
SUR (y-2)	-0.003	-0.003	-0.003	-0.003
	(0.039)	(0.040)	(0.040)	(0.040)
Dry adm2 (24m) x SUR (y-2)	-0.073	-0.073	-0.073	-0.073
	(0.070)	(0.070)	(0.070)	(0.070)
Dry country (24m) x SUR (y-2)	-1.912***	-1.912***	-1.912***	-1.912***
	(0.459)	(0.465)	(0.466)	(0.466)
Reserves (y-2) x SUR (y-2)	-0.177***	-0.177***	-0.177***	-0.177***
	(0.067)	(0.068)	(0.068)	(0.068)
Dry adm2 (24m) x Reserves (y-2) x SUR (y-2)	0.243	0.243	0.243	0.243
	(0.182)	(0.176)	(0.176)	(0.175)
Dry country (24m) x Reserves (y-2) x SUR (y-2)	-3.710***	-3.710***	-3.710***	-3.710***
	(1.188)	(1.206)	(1.207)	(1.207)

Notes: N = 26477. R-squared = 0.322. Second administrative unit and year-month fixed effects included. Admin2 and country wet climate extremes included. Column 1 includes robust standard errors clustered at the second administrative unit level in parentheses. Columns 2 – 4 include Conley standard errors corrected for spatial correlation with 400km bandwidth and for different temporal lags. Sample of Arid, Semi-Arid and Sub-Humid areas. Asterisks denote significance: *** p < 0.01, ** p < 0.05, * p < 0.1.

S5.7 Supplementary Figures

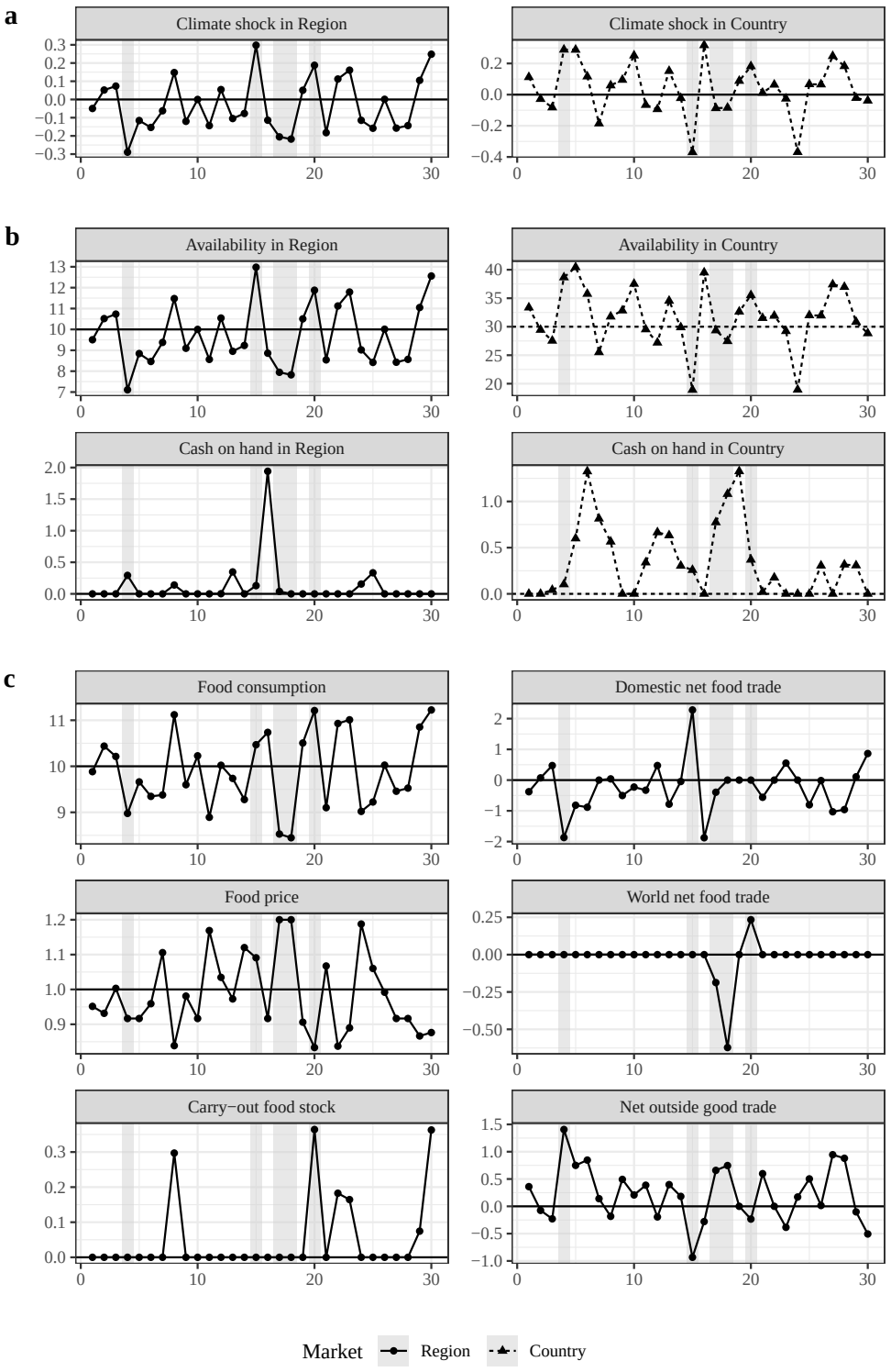


Figure S6: Results of the base case simulation (parameterization of Table 1) with borrowing constraints. (a) Shock variable ν_{mt} in each market, (b) state variables A_{mt} and X_{mt} at the beginning of the period in each market, and (c) choice variables $C_{m,ag,t}$, T_{mnt}, $P_{m,ag,t}$, S_{mt} and NT_{mt} in the region market.

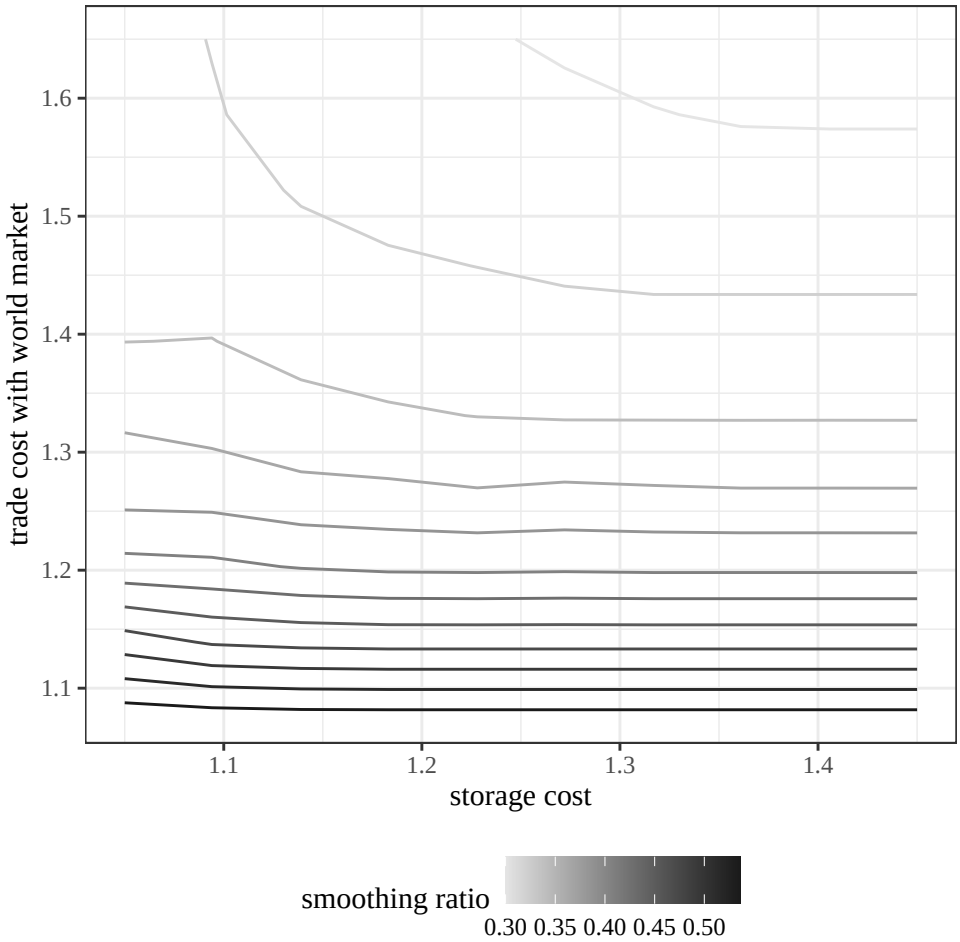


Figure S7: Food consumption smoothing ratio in the region market for different combinations of storage costs and trade costs with the world market and temporally corelated climate shocks. For each storage and trade cost combination the smoothing ratio is calculated based on a simulation of 100 time periods.

References

Treb Allen and David Atkin. Volatility and the Gains From Trade. *Econometrica*, 90(5):2053–2092, 2022. ISSN 0012-9682. doi: 10.3982/ecta14411.

David M Arseneau and Sylvain Leduc. Commodity Price Movements in a General Equilibrium Model of Storage. Technical report, 2013. URL https://about.jstor.org/terms. Publication Title: Source: IMF Economic Review Volume: 61 Issue: 1.

David Atkin and Dave Donaldson. Who's Getting Globalized? The Size and Implications of Intranational Trade Costs. Technical report, National Bureau of Economic Research, 2015.

David Backer and Trey Billing. Visualizing trends in food security across Africa, 2009–2020: Data and animations at a grid-cell level. *Data in Brief*, 36, 2021. ISSN 23523409. doi: 10.1016/j.dib.2021.106999. Publisher: Elsevier Inc.

Regis Barnichon. The Optimal Level of Reserves for Low-Income Countries: Self-Insurance against External Shocks. *IMF Staff Papers*, 56(4):852–875, November 2009. ISSN 1020-7635, 1564-5150. doi: 10.1057/imfsp.2009.15.

Karna Basu and Maisy Wong. Evaluating seasonal food storage and credit programs in east Indonesia. *Journal of Development Economics*, 115, 2015. doi: 10.1016/j.jdeveco.2015.02.001.

Santiago Beguería, Sergio M. Vicente-Serrano, Fergus Reig, and Borja Latorre. Standardized precipitation evapotranspiration index (SPEI) revisited: parameter fitting, evapotranspiration models, tools, datasets and drought monitoring. *International Journal of Climatology*, 34(10):3001–3023, 2014. ISSN 1097-0088. doi: 10.1002/joc.3887.

R. Bezner Kerr, T. Hasegawa, R. Lasco, I. Bhatt, D. Deryng, A. Farrell, H. Gurney-Smith, H. Ju, S. Lluch-Cota, F. Meza, G. Nelson, H. Neufeldt, and P. Thornton. Food, Fibre and Other Ecosystem Products. In *Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [H.-O. Pörtner, D.C. Roberts, M. Tignor, E.S. Poloczanska, K. Mintenbeck, A. Alegr*, pages 713–906. 2022. ISBN 978-1-00-932584-4. doi: 10.1017/9781009325844.007.714.

Danyelle Branco and José Féres. Weather Shocks and Labor Allocation: Evidence from Rural

Brazil. *American Journal of Agricultural Economics*, 103(4):1359–1377, 2020. ISSN 14678276. doi: 10.1111/ajae.12171.

Robin Burgess and Dave Donaldson. Can openness mitigate the effects of weather shocks? Evidence from India's famine era. *American Economic Review*, 100(2):449–453, 2010. ISSN 00028282. doi: 10.1257/aer.100.2.449.

Robin Burgess and Dave Donaldson. Railroads and the Demise of Famine in Colonial India. 2017.

Michael R. Carter and Travis J. Lybbert. Consumption versus asset smoothing: Testing the implications of poverty trap theory in Burkina Faso. *Journal of Development Economics*, 99(2):255–264, 2012. ISSN 03043878. doi: 10.1016/j.jdeveco.2012.02.003. Publisher: Elsevier B.V.

Antony Chapoto, Brian Chisanga, Auckland Kuteya, and Stephen Kabwe. Bumper Harvests a Curse or a Blessing for Zambia: Lessons from the 2014/15 Maize Marketing Season. Technical report, Indaba Agricultural Policy Research Institute (IAPRI), 2015. URL http://www.iapri.org.zm. Issue: 93.

John H. Cochrane. *Asset pricing*. Princeton University Press, Princeton, N.J, rev. ed edition, 2005. ISBN 978-0-691-12137-6. OCLC: ocm55518499.

Andrew Coleman. Storage, slow transport, and the law of one price: Theory with evidence from nineteenth-century U.S. corn markets. *Review of Economics and Statistics*, 91(2):332–350, 2009. ISSN 00346535. doi: 10.1162/rest.91.2.332.

Diego Comin, Danial Lashkari, and Martí Mestieri. Structural Change With Long-Run Income and Price Effects. *Econometrica*, 89(1):311–374, 2021. ISSN 0012-9682. doi: 10.3982/ECTA16317.

T.G. Conley. GMM estimation with cross sectional dependence. *Journal of Econometrics*, 92(1): 1–45, September 1999. ISSN 03044076. doi: 10.1016/S0304-4076(98)00084-0.

Arnaud Costinot, Dave Donaldson, and Cory Smith. Evolving Comparative Advantage and the Impact of Climate Change in Agricultural Markets: Evidence from 1.7 Million Fields around the World. *Journal of Political Economy*, 124(1):205–248, 2016. ISSN 0022-3808. doi: 10.1086/684719. ISBN: 0022-3808/2016/12401-0006$10.00.

Sandy Dall'Erba, Zhangliang Chen, and Noé J. Nava. U.S. Interstate Trade Will Mitigate the Negative Impact of Climate Change on Crop Profit. *American Journal of Agricultural Economics*, 00(00):1–22, 2021. ISSN 14678276. doi: 10.1111/ajae.12204.

Angus Deaton. Saving and Liquidity Constraints. *Econometrica*, 59(5):1221–1248, 1991.

Melissa Dell, Benjamin F. Jones, and Benjamin A. Olken. What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature*, 52(3):740–798, 2014. ISSN 00220515. doi: 10.1257/jel.52.3.740.

Brian Dillon and Christopher B. Barrett. Agricultural factor markets in Sub-Saharan Africa: An updated view with formal tests for market failure. *Food Policy*, 67:64–77, 2017. ISSN 03069192. doi: 10.1016/j.foodpol.2016.09.015.

Jonathan I Dingel and Kyle C Meng. Spatial Correlation, Trade, and Inequality: Evidence from the Global Climate. 2025.

Paul A. Dorosh, Simon Dradri, and Steven Haggblade. Regional trade, government policy and food security: Recent evidence from Zambia. *Food Policy*, 34(4):350–366, 2009. ISSN 03069192. doi: 10.1016/j.foodpol.2009.02.001. Publisher: Elsevier Ltd ISBN: 0030-7270.

Paul A. Dorosh, Shahidur Rashid, and Joanna van Asselt. Enhancing food security in South Sudan: the role of markets and regional trade. *Agricultural Economics (United Kingdom)*, 47(6):697–707, 2016. ISSN 15740862. doi: 10.1111/agec.12266.

Farid Farrokhi and Heitor S. Pellegrina. Trade, Technology, and Agricultural Productivity. *Journal of Political Economy*, 131(9), 2023. doi: https://doi.org/10.1086/724319.

Gabriel Felbermayr and Jasmin Gröschl. Natural disasters and the effect of trade on income: A new panel IV approach. *European Economic Review*, 58:18–30, 2013. ISSN 00142921. doi: 10.1016/j.euroecorev.2012.11.008.

FEWSNET. Scenario Development for Food Security Early Warning: Guidance document number 1. Technical report, USAID, 2018. URL www.fews.net.

FEWSNET, BRE, FAO, IOM, MERCY CORPS, OCHA, SWALIM, WHO, Climate Hazards Center, Columbia Climate School, IPC, UKAID, UNHCR, Unicef, WHH, WFP, and WMO. Sustained

"no regrets" humanitarian efforts urgently needed in response to drought in the Horn of Africa. Technical report, 2023.

Guillaume Gaulier and Soledad Zignago. BACI: International trade database at the product-level (the 1994-2007 version). *CEPII Working Papers*, pages 1–35, 2010. ISSN 1556-5068. doi: http://dx.doi.org/10.2139/ssrn.1994500. ISBN: 2010-23.

Julia Girard, Philippe Delacote, and Antoine Leblois. Agricultural households' adaptation to weather shocks in Sub-Saharan Africa: Implications for land-use change and deforestation. *Environment and Development Economics*, 26(5-6):538–560, 2021. ISSN 14694395. doi: 10.1017/S1355770X2000056X.

Christophe Gouel. Comparing Numerical Methods for Solving the Competitive Storage Model. *Computational Economics*, 41(2):267–295, 2013. ISSN 15729974. doi: 10.1007/s10614-012-9318-y.

Christophe Gouel and Sébastien Jean. Optimal Food Price Stabilization in a Small Open Developing Country. *The World Bank Economic Review*, 29(1):72–101, 2015. doi: 10.1093/wber/lht018.

Christophe Gouel and David Laborde. The crucial role of domestic and international market-mediated adaptation to climate change. *Journal of Environmental Economics and Management*, 106:102408, 2021. ISSN 10960449. doi: 10.1016/j.jeem.2020.102408. Publisher: Elsevier Inc.

Christophe Gouel, Madhur Gautam, and Will J Martin. Managing food price volatility in a large open country: the case of wheat in India. *Oxford Economic Papers*, 68(February):811–835, 2016. doi: 10.1093/oep/gpv089.

Steven Haggblade, Nathalie M. Me-Nsope, and John M. Staatz. Food security implications of staple food substitution in Sahelian West Africa. *Food Policy*, 71:27–38, 2017. ISSN 03069192. doi: 10.1016/j.foodpol.2017.06.003. Publisher: Elsevier Ltd.

Mariaflavia Harari and Eliana La Ferrara. Conflict, climate, and cells: a disaggregated analysis. *Review of Economic Studies*, 100(October):594–608, 2018. doi: 10.1162/rest.

HarvestChoice. Agro-Ecological Zones for Africa South of the Sahara. Technical report, International Food Policy Research Institute (IFPRI), 2015.

Florian Heiss and Viktor Winschel. Likelihood approximation by numerical integration on sparse grids. *Journal of Econometrics*, 144(1):62–80, 2008. ISSN 03044076. doi: 10.1016/j.jeconom.2007.12.004.

IPCC. Annex I: Glossary [Matthews, J.B.R. (ed.)]. In *Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change,*. [Masson-Delmotte, V., P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, P.R. Shukla, A. Pirani, W. Moufouma-Okia, C. Péan, R. Pidcock, S. Connors, J.B.R. Matthews, Y. Chen, X. Zhou, M.I. Gomis, E. Lonnoy, T. Maycock, M. Tignor, and T. Waterfield (eds.)]. In, 2018.

Charlotte Janssens, Petr Havlík, Tamás Krisztin, Justin Baker, Stefan Frank, Tomoko Hasegawa, David Leclère, Sara Ohrel, Shaun Ragnauth, Erwin Schmid, Hugo Valin, Nicole Van Lipzig, and Miet Maertens. Global hunger and climate change adaptation through international trade. *Nature Climate Change*, 10:829–835, 2020. doi: 10.1038/s41558-020-0847-4. ISBN: 4155802008474.

Alain de Janvry, Marcel Fafchamps, and Elisabeth Sadoulet. Peasant Household Behaviour with Missing Markets: Some Paradoxes. *The Economic Journal*, 101(409):1400–1417, 1991. ISSN 2046-2069.

Sarah A. Janzen and Michael R. Carter. After the Drought: The Impact of Microinsurance on Consumption Smoothing and Asset Protection. *American Journal of Agricultural Economics*, 101 (3):651–671, 2019. ISSN 14678276. doi: 10.1093/ajae/aay061.

Benjamin F. Jones and Benjamin A. Olken. Climate shocks and exports. *American Economic Review*, 100(2):454–459, 2010. ISSN 00028282. doi: 10.1257/aer.100.2.454.

Anna Josephson and Gerald E. Shively. Unanticipated events, perceptions, and household labor allocation in Zimbabwe. *World Development*, 141:105377, 2021. ISSN 18735991. doi: 10.1016/j.worlddev.2020.105377. Publisher: Elsevier Ltd.

Jonathan Kaminski and Luc Christiaensen. Post-harvest loss in sub-Saharan Africa-what do farmers say? *Global Food Security*, 3(3-4):149–158, 2014. ISSN 22119124. doi: 10.1016/j.gfs.2014.10.002. Publisher: Elsevier.

Harounan Kazianga and Christopher Udry. Consumption smoothing? Livestock, insurance and drought in rural Burkina Faso. *Journal of Development Economics*, 79(2):413–446, 2006. ISSN 03043878. doi: 10.1016/j.jdeveco.2006.01.011.

Nigel Key, Elisabeth Sadoulet, and Alain De de Janvry. Transactions costs and agricultural household supply response. *American Journal of Agricultural Economics*, 82(2):245–259, 2000. ISSN 00029092. doi: 10.1111/0002-9092.00022.

Daniel LaFave, Evan Peet, and Duncan Thomas. Farm profits, prices and household behavior. *Journal of Development Economics*, 174:103423, May 2025. ISSN 0304-3878. doi: 10.1016/j.jdeveco.2024.103423.

Donald F. Larson, Julian Lampietti, Christophe Gouel, Carlo Cafiero, and John Roberts. Food security and storage in the Middle East and North Africa. *World Bank Economic Review*, 28(1): 48–73, 2014. ISSN 02586770. doi: 10.1093/wber/lht015.

Kien T. Le. Separation Hypothesis Tests in the Agricultural Household Model. *American Journal of Agricultural Economics*, 92(5):1420–1431, 2010. ISSN 1467-8276. doi: 10.1093/ajae/aaq070.

Sergio H. Lence and Dermot J. Hayes. The Forward-Looking Competitive Firm under Uncertainty. *American Journal of Agricultural Economics*, 80(2):303–312, May 1998. ISSN 0002-9092. doi: 10.2307/1244503. Publisher: Wiley.

Hans Lofgren and Sherman Robinson. Nonseparable Farm Household Decisions in a Computable General Equilibrium Model. *American Journal of Agricultural Economics*, 1999. doi: 10.2307/1244031.

Andy Nelson, Daniel J. Weiss, Jacob van Etten, Andrea Cattaneo, Theresa S. McMenomy, and Jawoo Koo. A suite of global accessibility indicators. *Scientific Data*, 6(1):1–9, 2019. ISSN 20524463. doi: 10.1038/s41597-019-0265-5. Publisher: Springer US.

Janet S. Netz. The Effect of Futures Markets and Corners on Storage and Spot Price Variability. *American Journal of Agricultural Economics*, 77(1):182–193, February 1995. ISSN 0002-9092. doi: 10.2307/1243900. Publisher: Wiley.

David M. G. Newbery and Joseph E. Stiglitz. Pareto Inferior Trade. *The Review of Economic Studies*, 51(1):1–12, 1984. ISBN: 2013206534.

Albert Park. Risk and Household Grain Management in Developing Countries. *The Economic Journal*, 116(514):1088–1115, 2006.

Jian Peng, Simon Dadson, Feyera Hirpa, Ellen Dyer, Thomas Lees, Diego G. Miralles, Sergio M. Vicente-Serrano, and Chris Funk. A pan-African high-resolution drought index dataset. *Earth System Science Data*, 12(1):753–769, 2020. ISSN 18663516. doi: 10.5194/essd-12-753-2020.

Therése Pettersson, Garoun Engström, Margareta Sollenberg, Shawn Davies, Nanar Hawach, Magnus Öberg, Amber Deniw, and Stina Högbladh. Organized violence 1989 – 2020 , with a special emphasis on Syria. *Journal of Peace Research*, 58(4):809–825, 2021. doi: 10.1177/00223433211026126.

Obie Porteous. High trade costs and their consequences: An estimated dynamic model of african agricultural storage and trade. *American Economic Journal: Applied Economics*, 11(4):327–366, 2019. ISSN 19457790. doi: 10.1257/app.20170442.

Obie Porteous. Agricultural Trade and Adaptation to Climate Change in Sub-Saharan Africa, 2024.

T. Randhir and T. Hertel. Trade Liberalization as a Vehicle for Adapting to Global Warming. *Agricultural and Resource Economics Review*, 29(2):159–172, 2000. ISSN 1068-2805. doi: 10.1017/s1068280500005293.

Shahidur Rashid, Paul Dorosh, and Dawit Alemu. Grain markets, disaster management, and public stocks: Lessons from Ethiopia. *Global Food Security*, 19(September):31–39, 2018. ISSN 22119124. doi: 10.1016/j.gfs.2018.09.002. Publisher: Elsevier B.V.

Stephen J. Redding and Esteban Rossi-Hansberg. Quantitative spatial economics. *Annual Review of Economics*, 9:21–58, 2017. ISSN 19411391. doi: 10.1146/annurev-economics-063016-103713.

By John Reilly and Neil Hohmann. Climate Change and Agriculture: The Role of International Trade. *The American Economic Review*, 83(2):306–312, 1993.

Jeffrey J. Reimer and Man Li. Yield variability and agricultural trade. *Agricultural and Resource Economics Review*, 38(2):258–270, 2009. ISSN 10682805. doi: 10.1017/S1068280500003245.

Cynthia Rosenzweig and Martin L. Parry. Potential Impacts of Climate Change on World Food Supply. *Nature*, pages 87–116, 1994. doi: 10.1201/9781315136967-5.

S.I. Seneviratne, X. Zhang, M. Adnan, W. Badi, C. Dereczynski, A. Di Luca, S. Ghosh, I. Iskandar, J. Kossin, S. Lewis, F. Otto, I. Pinto, M. Satoh, S.M. Vicente-Serrano, M. Wehner, and B. Zhou. *Weather and Climate Extreme Events in a Changing Climate.* 2021. ISBN 978-1-00-915789-6. doi: 10.1017/9781009157896.013. Publication Title: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change.

Sebastian Sotelo. Domestic trade frictions and agriculture. *Journal of Political Economy*, 128(7): 2690–2738, 2020. ISSN 1537534X. doi: 10.1086/706859.

Emma C. Stephens and Christopher B. Barrett. Incomplete Credit Markets and Commodity Marketing Behaviour. *Journal of Agricultural Economics*, 62(1):1–24, 2011. ISSN 0021857X. doi: 10.1111/j.1477-9552.2010.00274.x.

Miodrag Stevanović, Alexander Popp, Hermann Lotze-Campen, Jan Philipp Dietrich, Christoph Müller, Markus Bonsch, Christoph Schmitz, Benjamin Bodirsky, Florian Humpenöder, and Isabelle Weindl. The impact of high-end climate change on agricultural welfare. *Science Advances*, (August):1–10, 2016.

Ralph Sundberg and Erik Melander. Introducing the UCDP Georeferenced Event Dataset. *Journal of Peace Research*, 50(4):523–532, 2013. ISSN 00223433. doi: 10.1177/0022343313484347.

Wondimagegn Tesfaye and Gebrelibanos Gebremariam. Consumption smoothing and price enhancement motives for grain storage: empirical perspectives from rural Ethiopia. *Agricultural and Food Economics*, 8(1), 2020. ISSN 21937532. doi: 10.1186/s40100-020-00169-x. Publisher: Agricultural and Food Economics.

The World Bank. The Role of Strategic Grain Reserves in Enhancing Food Security in Zambia and Zimbabwe. Technical report, Washington D.C., 2021.

The World Bank. Metadata Glossary | DataBank, 2025. URL https://databank.worldbank.org/metadataglossary/international-debt-statistics/series/FI.RES.TOTL.MO.

USDA. Production, supply, and distribution, 2022. URL https://apps.fas.usda.gov/psdonline/app/index.html#/app/downloads.

Kurt B Waldman, Stacey Giroux, Jordan P Blekking, Kathy Baylis, and Tom P Evans. Smallholder food storage dynamics and resilience. *Food Security*, 12:7–20, 2020. doi: https://doi.org/10.1007/s12571-019-00983-2. Publisher: Food Security ISBN: 1257101900.

Jeffrey C. Williams and Brian D. Wright. *Storage and Commodity Markets*. Cambridge University Press, Cambridge, 1991.

Brian Wright and Carlo Cafiero. Grain reserves and food security in the Middle East and North Africa. *Food Security*, 3(S1):61–76, 2011. ISSN 1876-4517. doi: 10.1007/s12571-010-0094-z.

Brian D. Wright. The economics of grain price volatility. *Applied Economic Perspectives and Policy*, 33(1):32–58, 2011. ISSN 20405790. doi: 10.1093/aepp/ppq033.

WTO. Natural Disasters and Trade: Study I. *Third Symposium on Natural Disasters and Trade*, pages 1–234, 2019.

Dean Yang. Coping With Disaster: The Impact of Hurricanes on International Financial Flows, 1970-2002. Technical report, 2006. Publication Title: NBER Working Paper Series Volume: 5 Issue: 1 ISBN: 9781538630426.