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

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Global warming is associated with increasingly widespread and frequent climate extremes. This paper develops a dynamic stochastic multi-region model of consumption smoothing, storage, and trade to investigate the buffering effect of agricultural markets in the context of climate extremes. The theory provides new insights on the impact of household market transaction costs, borrowing constraints and the spatiotemporal pattern of climate shocks. A large-scale empirical analysis of market access, climate extremes, and food insecurity at quarterly subnational level in Sub-Saharan Africa supports the theoretical predictions. Regions with shorter travel times to cities and ports experience a smaller detrimental impact on food insecurity from severe and extreme dry conditions. Trade and storage appear partly substitutes in buffering the food insecurity impacts of country-wide and multi-year climate extremes.

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1 Introduction

Climate change alters the distribution of temperature and precipitation and thereby critically affects agricultural production. Particularly extreme weather or climate events[1] such as droughts or floods can cause drastic harvest failures and severe food insecurity. Starting in 2020, an unprecedented extreme, widespread, and multi-season drought in the Horn of Africa contributed to over 22 million people in the region facing acute food insecurity[2]. Agricultural markets may buffer such impacts. Climate extremes create spatiotemporal variation in food supply and food prices that may create 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 however 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 global warming (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. This variation is reflected in countries' trade and storage patterns. Figure 1 compares the occurrence of exceptionally dry conditions with cereal imports and stock levels for three countries in Sub-Saharan Africa. Ethiopia faced widespread dry conditions in 2011, 2015 and 2016, Kenya in 2009 and 2011, and Zambia in 2015. In Ethiopia and Kenya, the dry years coincided with elevated imports of cereals from international markets. In Zambia, the drought year coincided with a depletion of cereal stocks that had been build up during a bumper maize harvest in the previous agricultural season (Chapoto et al. 2015). These observations raise the question whether such market responses are effective in reducing the food insecurity impacts of extreme climate events.

The objective of this paper is to investigate, theoretically and empirically, under which conditions trade and storage buffer the food insecurity impacts of climate extremes. In the first part of the paper, we develop a dynamic stochastic small open economy model that combines consumption smoothing with storage and trade. The economy consists of multiple regions, each facing climate-driven variability in agricultural production. The representative household in each region is both

[1]The Intergovernmental Panel on Climate Change 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., 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 focuses on weather conditions that are unusually dry or wet over the time frame of at least 12 months, bundled under the term "climate extremes".

[2]The drought in the Horn of Africa started with poor rainfall during the October-December 2020 season and persisted with poor rains in all four subsequent seasons (FEWS NET, February 16, 2023).

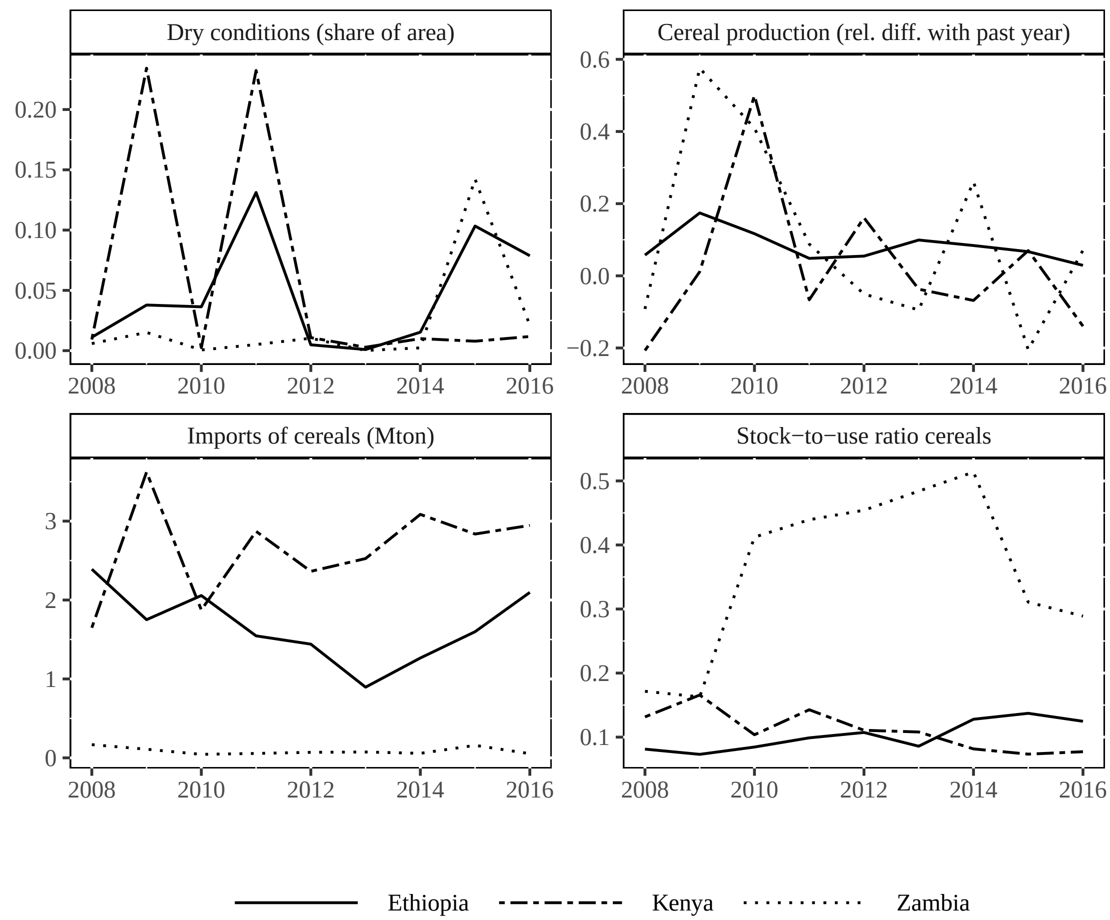

Figure 1: Dry climatic conditions, cereal imports, and stocks for three countries in Sub-Saharan Africa. Share of country area under dry conditions based on the 12 month SPEI index (SPEI $\leq$ -1.5) from Peng et al. 2020. Cereal production volumes from FAOSTAT. International cereal import volume from 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.

consumer and producer of food and may face market transaction costs and borrowing constraints. Traders in each region respond to climate variability by engaging in spatial and temporal arbitrage. Using numerical model simulations, two market-based channels of household consumption smoothing are assessed: storage (via inter-temporal exchanges within a region) and trade (via intra- and inter-temporal exchanges between regions). Households' transaction costs limit both smoothing channels, while borrowing constraints primarily affect smoothing through trade. The simulations lead to three qualitative predictions: (1) for households that are isolated from markets, food consumption is more responsive to local climate extremes; (2) for regions that are isolated from the world market, food consumption is more responsive to local and national climate extremes; and (3) storage and trade partly substitute one another in smoothing food consumption but the degree of substitutability reduces when climate shocks are temporally correlated.

The theoretical model predicts under which economic and climatic conditions market-based food consumption smoothing is likely to occur and under which conditions it is not. In the second part of the paper we quantitatively investigate these predictions by studying the prevalence of food insecurity, which corresponds to a failure of food consumption smoothing. Empirical evidence from 12 African countries for 2009–2016 confirms that the spatiotemporal pattern of climate extremes and the degree of market access both affect food insecurity. The analysis exploits exogenous variation in climatic conditions using panel data at the sub-annual (3 to 4-monthly time interval) and subnational level (second administrative units). Consistent with the theoretical predictions, areas where households face higher market transaction costs, approximated by longer travel times to the closest large city, experience a larger negative food insecurity impact from extreme dry conditions. Dry extremes also affect food insecurity to a larger extent in areas with longer travel times to ports (a proxy for trade costs to the world market). International cereal imports and cereal stocks both buffer food insecurity impacts of country-wide climate extremes. Lastly, the findings confirm that trade and storage are partly substitutes, partly complements in buffering climate-driven variability. The analysis controls for time-invariant unobserved regional characteristics, for general time trends, and for time-varying variables that are potentially correlated with food insecurity and market access.

This paper contributes to the body of literature linking trade, agriculture, and climate, and in specific 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 in the average agricultural productivity across locations and commodities (Costinot et al. 2016; Gouel and Laborde 2021;

Janssens et al. 2020; Stevanović et al. 2016), or as the gains from trade due to climate-driven differences in the variability of agricultural productivity across locations and commodities (Allen and Atkin 2022; Burgess and Donaldson 2017; Dingel et al. 2023; Dorosh, Dradri, et al. 2009; Dorosh, Rashid, et al. 2016; Gouel, Gautam, 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 economic and climatic modelling 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 of the structural frameworks adopted (Table S3).

On the spatial level, studies have primarily, with the exception of Porteous 2019, focused on international trade or intra-national trade. Yet, changes in international prices affect regions within a country differently depending on the level of domestic trade barriers (Atkin and Donaldson 2015; Sotelo 2020). The most critical research gap relates, however, to the temporal scale. Very few studies incorporate forward-looking dynamics, future yield uncertainty, or inter-temporal trade (i.e., storage). 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 deterministic model of monthly grain trade and storage for 230 markets across Sub-Saharan Africa, focusing on intra-annual dynamics between harvest periods. He finds that when storage is not considered, trade costs and welfare effects are underestimated as the timing of trade is in that case not correctly considered.

This paper relates also to the macro- and micro-economic literature on consumption smoothing. At the macro level, Yang 2006 and Felbermayr and Gröschl 2013 study the role of international trade in consumption smoothing in the context of a risk averse representative household and idiosyncratic country-level natural disasters. In the macro-economic storage literature, stockholding is mostly linked to profit maximization by storage firms that are risk neutral (Gouel and Jean 2015; Larson et al. 2014; Williams and Wright 1991) 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 that combines the rational expectations storage model with household consumption smoothing. At the micro level, 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 (Basu and Wong 2015; Janzen and Carter 2019), informal insurance (Kazianga and Udry 2006), livestock asset holdings (Carter and Lybbert 2012; Kazianga and Udry 2006), and on-farm grain stocks (Kazianga and Udry 2006; Tesfaye and Gebremariam 2020; Waldman et al. 2020). While these macro- and micro-models are recognized as structurally related (Gouel, Gautam, et al. 2016; Yang 2006), the explicit connection between consumption smoothing, storage, and trade has not been studied.

The contribution of this paper is to link the rational expectations storage and trade model with a consumption-saving household model for a small open economy with subnational regions. The closest related study is Park 2006, who develops a model of inter-temporal household grain management decisions in which the prices observed by the household are determined in a separate independent market model. Other studies on trade, storage, and volatility do integrate consumption decisions directly into the market model, but do not consider inter-temporal consumption preferences (Allen and Atkin 2022; Gouel and Jean 2015), thereby overlooking the possibility of inter-temporal exchanges within and between regions. By taking into account inter-temporal consumption preferences, this paper formally demonstrates consumption smoothing as a source of gains from (intra- and inter-temporal) trade in the context of variability in local production.

Besides the structural contribution, this paper also adds to the limited empirical evidence on markets and climate-driven food shortages and price spikes in developing countries. Burgess and Donaldson 2010, 2017 investigate the expansion of railroad infrastructure in the colonial times in India and find that the impact of rainfall shortages on famines significantly reduced after districts open up to trade. In Ethiopia, natural disasters have been increasing in frequency since 1960 and, while they have been affecting more people, the number of deaths per disaster is reducing (Rashid et al. 2018). The reduced impact is attributed to a set of comprehensive policies, including market liberalization, an effective food reserve agency, and infrastructure investments that enable private grain trade between deficit and surplus areas in times of crisis. Besides domestic markets, also international markets have been shown to reduce price volatility. Using data from 1700 up to 2008, Jacks et al. 2011 find that world market integration is associated with lower commodity price volatility. Chen and Villoria 2019 analyze maize markets of 27 net importing countries between 2000 and 2015 and conclude that international maize imports on average reduce monthly domestic price variability. At the micro-level, food price stabilization is found to be welfare enhancing, but with negative distributional impacts across households (Bellemare et al. 2013). This paper provides new evidence on the impact of market access, trade, and storage in buffering the impact of climate extremes on food insecurity in Sub-Saharan Africa.

The paper proceeds as follows. Section 2 introduces the model of consumption smoothing, storage, and trade. Numerical simulations lead to three qualitative theoretical predictions that are taken to the data. Section 3 documents the data sources, the estimation strategy, and the empirical results. Section 4 discusses the findings in relation to the literature and section 5 concludes.

2 Theoretical framework

2.1 The model

In this section we develop a dynamic small open economy model of consumption smoothing, storage, and trade in the context of stochastic agricultural production. The model features farm households that consume and save, and traders that engage in intra- and inter-temporal price arbitrage. The model focuses on households' and traders' marketing behavior in the face of climate shocks, and simplifies the supply side by assuming a perfectly inelastic production.

Environment. We consider a small open economy with M subnational regions indexed m, n and a discrete infinite time horizon $t \in [0, +\inf]$. Each region has an agricultural sector and an outside sector (composite of services and manufacturing) producing an agricultural good (food) and an outside good (indexed by $d \in \{ag, o\}$, respectively). The outside good production is assumed a constant endowment, while agricultural production is represented as a stochastic endowment process to reflect the impact of variability in climatic conditions. In each region there are two representative agents, risk averse households and risk neutral traders. Food can be stored and traded subject to household-level transaction costs and market-level storage and trade costs. The outside good is assumed freely traded but not storable and its price is normalized to one. The uncertainty in future agricultural production caused by variable climatic conditions creates an incentive for households to save and for traders to store[3]. Goods and financial assets can be exchanged both within the economy and with the rest of the world W taking a fixed world price and interest rate as given[4].

Household problem. The representative household in region m has a utility function defined over consumption in each time period t[5]

$$U_m = \mathrm{E}_0 \left[\sum_{t=0}^{\infty} \beta^t \ln(Q_{mt}) \right], \tag{1}$$

with $\beta = 1/(1+\delta)$ the discount factor and $\delta > 0$ the rate of time preference parameter. Q_{mt} is a constant elasticity of substitution (CES) composite of food and the outside good: $Q_{mt} = (\alpha C_{m,ag,t}^{(\sigma-1)/\sigma} + C_{m,o,t}^{(\sigma-1)/\sigma})^{\sigma/(\sigma-1)}$ with α the preference parameter. The household maximises utility by choosing in each period t how much to consume and how much to save or borrow subject to the budget constraint

$$\begin{aligned} X_{m,t+1} = & P_{m,o,t}(H_{m,o,t} - C_{m,o,t} - \tau_m^{HH}(qs_{mt} + qp_{mt})) \\ & + P_{m,ag,t}(H_{m,ag,t} - C_{m,ag,t}) + \Phi_{mt} + (1+r)X_{mt}, \end{aligned} \tag{2}$$

and the household food balance

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

where C_{mdt} is the household consumption of good d; H_{mdt} is the endowment of good d; qs_{mt} is the quantity of food sold on the market; qp_{mt} is the quantity of food purchased on the market; P_{mdt} is the market price of good d; $\tau_m^{HH} > 0$ is the transaction cost incurred by the household in market exchanges of food; $\Phi_{mt} = P_{m,ag,t}S_{m,t-1} - P_{m,ag,t}kS_{mt}$ are the instantaneous storage profits accruing to the household with S_{mt} the storage of food from period t to period $t+1$ subject to the ad valorem

[3]We assume that storage is only done by traders and not by households, in contrast to Park 2006 who allows for household level storage across cropping seasons. Empirical evidence from Sub-Saharan Africa indicates that household storage, if it occurs, is limited to intra-annual storage between harvest cycles (Kaminski and Christiaensen 2014; Stephens and Barrett 2011; Tesfaye and Gebremariam 2020; Waldman et al. 2020). Looking at household survey data from Malawi, Uganda and Tanzania, Kaminski and Christiaensen 2014 for example find that farmers sell between 84% and 91% of the marketed maize within three months after harvest. In Zambia, on-farm storage represents only 5.8% of total storage capacity and the largest share is owned by the government (50%), followed by private traders (32.7%) and millers (11.7%) (The World Bank 2021).

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

[5]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.

storage cost $k_m > 1$; X_{mt} are financial assets of the household at the start of period t[6]; and r is the fixed interest rate. The endowment of the outside good $H_{m,o,t}$ is constant while agricultural production $H_{m,ag,t}$ is a random variable with distribution $N(\mu, \sigma^2)$. The household can either be a net seller, a net buyer, or autarkic in each good. For market exchanges of food households face a transaction cost τ_m^{HH} that is paid in terms of the outside good. Selling a quantity of food qs_{mt} to the market earns $P_{m,ag,t} - \tau_m^{HH} P_{m,o,t}$, while purchasing a quantity of food qp_{mt} from the market costs $P_{m,ag,t} + \tau_m^{HH} P_{m,o,t}$.

The solution of the intertemporal optimization problem can be derived with Pontryagin's Maximum Principle (see Appendix). The optimal solution satisfies the conditions of optimal intra-temporal household consumption allocation

$$\begin{aligned} \alpha \left(\frac{C_{m,ag,t}}{C_{m,o,t}} \right)^{\frac{1}{\sigma}} &= \frac{P_{m,o,t}}{P_{m,ag,t} - \tau_m^{HH} P_{m,o,t}} \text{ if } qs_{mt} > 0 \text{ and } qp_{mt} = 0, \\ \alpha \left(\frac{C_{m,ag,t}}{C_{m,o,t}} \right)^{\frac{1}{\sigma}} &= \frac{P_{m,o,t}}{P_{m,ag,t} + \tau_m^{HH} P_{m,o,t}} \text{ if } qs_{mt} = 0 \text{ and } qp_{mt} > 0, \end{aligned} \tag{4}$$

or

$$\alpha \left(\frac{C_{m,ag,t}}{C_{m,o,t}} \right)^{\frac{1}{\sigma}} = \frac{P_{m,o,t}}{P'_{m,ag,t}}, \tag{5}$$

with $P'_{m,ag,t}$ the household shadow price of food, $P_{m,ag,t} - \tau_m^{HH} P_{m,o,t} \leq P'_{m,ag,t} \leq P_{m,ag,t} + \tau_m^{HH} P_{m,o,t}$, and the Euler equations determining optimal inter-temporal household consumption allocation

$$Q_{mt}^{\frac{\sigma-1}{\sigma}} C_{m,ag,t}^{\frac{1}{\sigma}} P'_{m,ag,t} = \frac{1}{(1+r)\beta} \mathrm{E}_t \left[Q_{m,t+t}^{\frac{\sigma-1}{\sigma}} C_{m,ag,t+1}^{\frac{1}{\sigma}} P'_{m,ag,t+1} \right], \tag{6}$$

$$Q_{mt}^{\frac{\sigma-1}{\sigma}} C_{m,o,t}^{\frac{1}{\sigma}} P_{m,o,t} = \frac{1}{(1+r)\beta} \mathrm{E}_t \left[Q_{m,t+t}^{\frac{\sigma-1}{\sigma}} C_{m,o,t+1}^{\frac{1}{\sigma}} P_{m,o,t+1} \right]. \tag{7}$$

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. We define $\Xi_{m,t,t+1} = \beta(Q_{mt}^{(\sigma-1)/\sigma} C_{m,o,t}^{1/\sigma} P_{m,o,t})(Q_{m,t+t}^{(\sigma-1)/\sigma} C_{m,o,t+1}^{1/\sigma} P_{m,o,t+1})^{-1}$ as the stochastic discount factor.

[6]We allow households to both borrow and save, with $X_{mt} < 0$ in case of borrowing. In the simulations we test the implications of a strict borrowing constraint in which case X_{mt} is constrained to be strictly positive.

Accumulation of debt is prevented by the transversality condition

$$\lim_{j\to\infty} \mathrm{E}_t \left[\frac{X_{m,t+j}}{(1+r)^j}\right] = 0. \tag{8}$$

Trade and storage firms. Traders operate in a competitive environment and 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

$$\begin{aligned}\max_{S_{mt},T_{mnt},T_{nmt}} \mathrm{E}_t \Bigg[\sum_{t=s}^{\infty} \Xi_{m,t,t+1} * (&P_{m,ag,t}S_{m,t-1} - P_{m,ag,t}kS_{mt} \\ &+\sum_n (P_{n,ag,t} - \tau_{mn}P_{m,ag,t})T_{mnt} + \sum_n (P_{m,ag,t} - \tau_{nm}P_{n,ag,t})T_{nmt})\Bigg],\end{aligned} \tag{9}$$

subject to the non-negativity constraint for storage

$$S_{mt} \geq 0, \tag{10}$$

with $k_m > 1$ the ad valorem storage cost, $\tau_{mn} > 1$ the ad valorem trade costs for trading food from origin market m to destination market n[7], and $\Xi_{m,t,t+1}$ the stochastic discount factor determined in equilibrium by the household optimal consumption-saving decision. The optimization leads to the following temporal and spatial no-arbitrage conditions

$$\begin{aligned}
&P_{m,ag,t}k_m \geq \mathrm{E}_t[\Xi_{m,t,t+1}P_{m,ag,t+1}] \text{ with equality if } S_{mt} > 0,\\
&P_{m,ag,t}\tau_{mn} \geq P_{n,ag,t} \text{ with equality if } T_{mnt} > 0,\\
&P_{n,ag,t}\tau_{nm} \geq P_{m,ag,t} \text{ with equality if } T_{nmt} > 0.
\end{aligned} \tag{11}$$

Market clearing. In each region m market clearing requires that food consumption equals agricultural production plus carry-in stock and imports minus carry-out stock and exports. For the outside good, consumption equals local production minus net trade (NT_{mt} with $NT_{mt} > 0$ for net exports and $NT_{mt} < 0$ for net imports) and the quantity required to cover the transaction costs

$$C_{m,ag,t} = H_{m,ag,t} + S_{mt-1} - kS_{mt} - \sum_n (\tau_{mn}T_{mnt} - T_{nmt}), \tag{12}$$

[7]The standard approach in agricultural storage and trade models is to work with additive storage and trade costs (e.g., Porteous 2019). Here we use ad valorem costs to simplify the numerical simulations.

$$C_{m,o,t} = H_{m,o,t} - NT_{mt} - \tau_m^{HH}(qs_{mt} + qp_{mt}). \tag{13}$$

Equilibrium. A competitive equilibrium is defined as the set of prices P_{mdt}, and consumption C_{mdt}, storage S_{mt}, and trade T_{mnt} quantities that satisfy optimality conditions 4, 7, and 11; the household good balance 3; the market clearing conditions 12 and 13; the transition equation 2; and the transversality condition 8.

2.2 Qualitative model predictions

A well-known feature of stochastic trade and storage models with rational expectations is the inability to derive a closed-form solution and thus the need for numerical approximation (Gouel 2013). The complexity of the numerical problem grows exponentially with the number of markets considered. The dimensionality of the models is therefore in practice often constrained to two markets and one commodity. One strategy to solve for more dimensions is to have agents assume no uncertainty in future agricultural production (e.g., Porteous 2019). Another strategy is to use a finite-period approximation. Here, we convert the infinite-horizon problem into a moving series of three-period problems. The finite-period approximation reduces some of the incentive for saving and storage (see Appendix), but allows to solve the model for multiple markets whilst still considering the impact of uncertainty on agents' behavior. We can thus study the impact of local market access relative to other regions' market access as well as the impact of both local shocks and shocks in other markets.

The default parameter values used for the model quantification are presented in Table 1. The simulations are run for a hypothetical country consisting of four regions (A, B, C, and D) that can trade with one another and with the world market. The four regions are identical except for household market transaction costs τ_m^{HH} and trade costs to the world market τ_{mW}. Agricultural production varies according to a normal distribution with mean 10 and variance 2.5. Regions are self-sufficient when agricultural production is at the mean. We run counterfactual simulations that vary in terms of the spatial and temporal correlation of agricultural production shocks and the level of storage and trade costs.

We start by illustrating the market-based consumption smoothing mechanisms using a simulation of idiosyncratic agricultural production shocks shown in Figure 2[8]. Agricultural production is in each region and in each time period an independent random draw from the distribution. When a region

[8] We focus the discussion in this section on food consumption smoothing rather than welfare in order to create a link with the empirical analysis on food insecurity (which corresponds to a failure of food consumption smoothing).

Table 1: Model parameterization.

Parameter	Economic interpretation	Value
σ	elasticity of substitution	0.5
α	expenditure share	0.5
δ	rate of time preference	0.05
β	discount factor	0.95
r	interest rate	0.05
τ_m^{HH}	household transaction cost	$m \in \{A, C\} : 1.05$
		$m \in \{B, D\} : 1.01$
k_m	storage cost	$m \in \{A, B, C, D\} : 1.05$
τ_{mn}	intra-national trade cost	$m, n \notin W : \tau_{mn} = 1.2$
	international trade cost	$m \in \{A, B\} : \tau_{mW} = 1.4$
		$m \in \{C, D\} : \tau_{mW} = 1.2$
$H_{m,ag,t}$	agricultural production	$N(10, 2.5)$
$H_{m,o,t}$	outside good production	10
$P_{m,o,t}$	price of outside good (numeraire)	1
$P_{W,ag,t}$	world price of food	$P_{W,ag,t0} = 1$
		$P_{W,ag,t1} = 1.05$
		$P_{W,ag,t2} = 1.1025$

experiences a negative shock, traders can compensate the reduction in local supply by depleting stocks, importing from other regions with more favorable climatic conditions, or importing from the world market. In order to pay for market purchases of food, households may reduce expenditure on the outside good, sell assets, or borrow. In period 4 in Figure 2 region B experiences a negative production shock of -29% and imports food from regions that experience positive production shocks (A and D). To pay for imports, the household in region B borrows (net asset position drops below zero) and reduces expenditure on the outside good (exports of the outside good increase). When a region experiences a positive shock, traders can absorb the increased local supply by building up stocks, exporting food to other regions, or exporting to the world market. The household can save the additional income from market sales or spend it on the outside good. In period 15, region B experiences a positive production shock of +30%, which leads to the build up local stocks and exports to regions A and C. The household in region B invests in storage, saves (net asset position rises above zero), and increases expenditure on the outside good (imports of the outside good increase).

The example illustrates that trade-based consumption smoothing occurs via two channels: the intra-temporal exchange of goods and the inter-temporal exchange of assets between regions. The latter is constrained by the expectation that there will be no trade deficits or surpluses in the final period (i.e., the household's net asset position is expected to be zero in the final period). In contrast

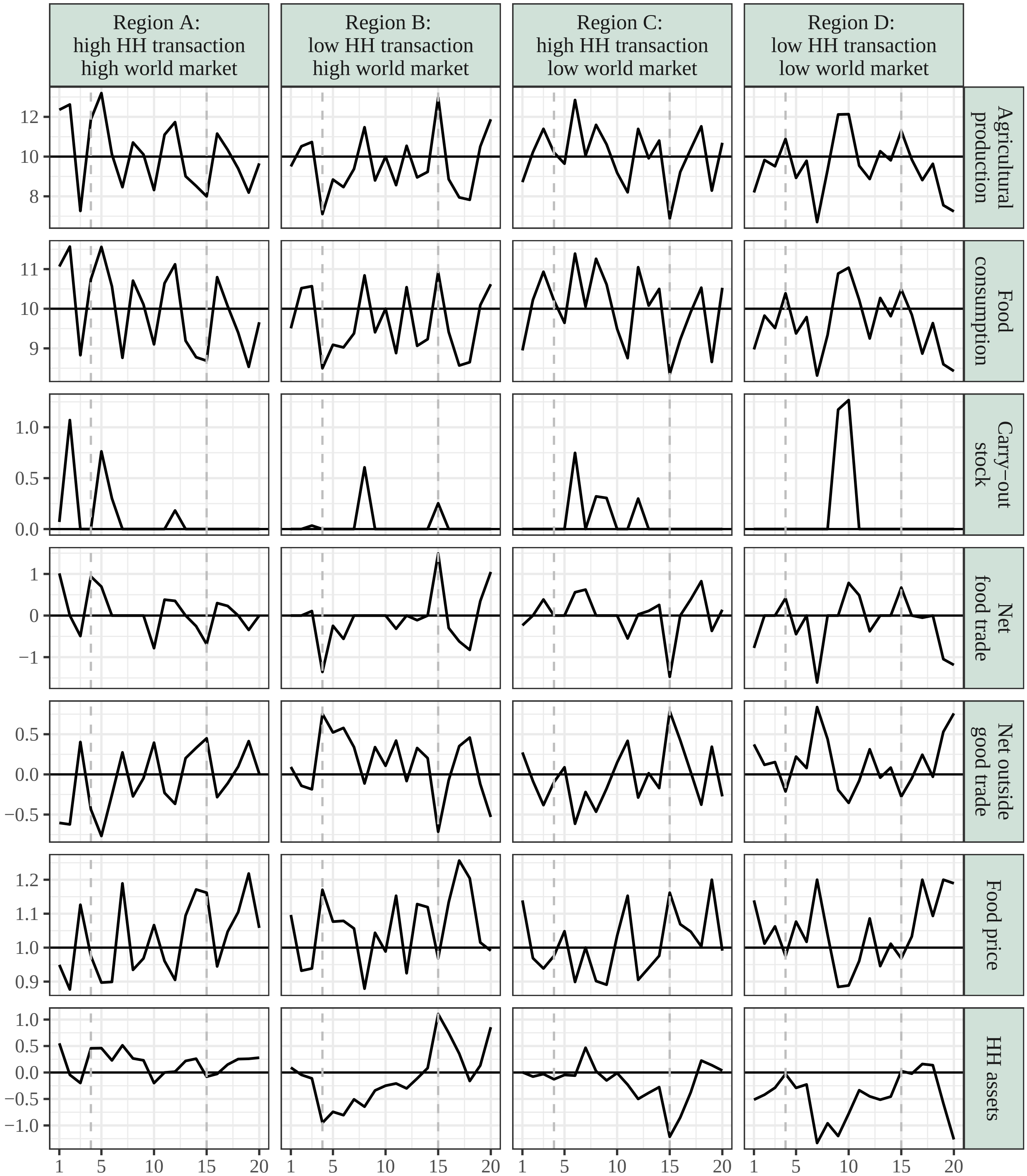

Figure 2: Simulation results under idiosyncratic agricultural production shock for 20 time periods. Results with borrowing constraint in Figure S2 in Appendix.

with the trade-based channel, storage-based consumption smoothing occurs via the inter-temporal transfer of assets between agents (the household and the storage firm) within a region. In a period with build up of stock, the household invests in storage, while in a period of stock utilization, the household receives the return of its investment.

Impact of market access. Table 2 presents the estimated responsiveness of food consumption to agricultural production under different parameterizations of the model. In the case of idiosyncratic shocks (columns 1–2), agricultural production is for each region and in each period a random draw. Shocks can be smoothed through domestic trade with other regions, storage, or trade with the world market. In the case of covariate shocks (columns 3–4), agricultural production is still a random draw in each period, but is the same for all four regions. Under the covariate shock, market-based smoothing is therefore limited to storage and trade with the world market. Comparing the results between the individual regions, which face different transaction costs (A and C high, B and D low) and trade costs with the world market (A and B high, C and D low), provides insights on the impact of market access. First, the responsiveness of food consumption to local production is significantly larger when household market transaction costs are high (column 1: the coefficient on production H is larger for regions A and C than for regions B and D). This remains the case when all regions are facing the same shock (column 3). Second, food consumption is also affected by shocks occurring in other regions and the magnitude of the effect depends on access to world markets. The impact of production shocks in other regions is significantly lower when both household transaction costs and trade costs to the world market are low (column 1: the coefficient on $Hother$ is larger for regions A, B and C than for region D). A region well connected to international markets will be less sensitive to shocks occuring in other regions within the country. Third, the impact of a higher level of storage costs (columns 2 and 4) is larger under covariate shocks than under idiosyncratic shocks (the difference in coefficient H from column 3 to 4 is larger than from column 1 to 2). Storage becomes a more important mechanism for consumption smoothing when shocks are correlated across regions as one of the alternative smoothing mechanisms, domestic trade, becomes unavailable. In addition, the impact of trade costs to the world market becomes larger under high storage cost levels (column 4: larger difference between regions A and B on the one hand, and regions C and D on the other hand). These results suggest an interaction between storage and trade that we explore next.

The interaction of storage and trade. We investigate the interaction between storage and international trade based on simulations of covariate production shocks (thus leaving out domestic

Table 2: Linear regression of food consumption to agricultural production (H)

	Dependent variable:			
	Food consumption			
	idiosyncratic (1)	idiosyncratic (k = 0.25) (2)	covariate (3)	covariate (k = 0.25) (4)
Region A	1.278***	−0.007	2.434***	0.638***
	(0.425)	(0.363)	(0.293)	(0.163)
Region B	2.855***	1.257***	3.531***	1.164***
	(0.425)	(0.363)	(0.293)	(0.163)
Region C	1.802***	0.561	3.182***	2.204***
	(0.425)	(0.363)	(0.293)	(0.163)
Region D	3.743***	2.172***	4.388***	2.933***
	(0.425)	(0.363)	(0.293)	(0.163)
H	0.663***	0.706***	0.755***	0.938***
	(0.018)	(0.015)	(0.029)	(0.016)
H x Region B	−0.087***	−0.069***	−0.112***	−0.054**
	(0.025)	(0.021)	(0.041)	(0.023)
H x Region C	−0.023	−0.019	−0.072*	−0.159***
	(0.025)	(0.021)	(0.041)	(0.023)
H x Region D	−0.141***	−0.125***	−0.194***	−0.234***
	(0.025)	(0.021)	(0.041)	(0.023)
H other	0.207***	0.294***		
	(0.035)	(0.030)		
H other x Region B	−0.077	−0.064		
	(0.050)	(0.042)		
H other x Region C	−0.029	−0.038		
	(0.050)	(0.042)		
H other x Region D	−0.113**	−0.099**		
	(0.050)	(0.042)		
Observations	320	320	320	320
R^2	1.000	1.000	0.998	0.999

Note: *p<0.1; **p<0.05; ***p<0.01
Region A is the base category. Standard errors in parentheses.
Based on a simulation of 80 periods for each parameterization.

trade). We run simulations at different storage and trade cost levels assuming that all regions face the same storage and trade cost levels[9]. Figure 3 plots the smoothing ratio of food consumption, which takes a value between 0 and 1 with 0 indicating zero smoothing and 1 perfect smoothing. The smoothing ratio increases as storage or trade cost levels reduce. The gain from reducing storage costs is large at high trade cost levels but small at low trade cost levels. Similarly, the gain from reducing trade costs is large at high storage cost levels but small at low storage cost levels. This implies that storage and trade can partly substitute one another in smoothing food consumption. Storage and trade are however not perfect substitutes and also partly complement one another. The smoothing ratio achieved by the combination of low levels of both costs is larger than that achieved by any of the two separately.

Table 3 estimates the unit change in the smoothing ratio for a unit change in storage cost, trade cost, or both. The degree of substitutability between storage and trade corresponds to the interaction effect between the storage and trade cost. The negative interaction effect indicates that the additional effect of reducing trade costs is smaller at low storage cost levels than at high storage cost levels. When agricultural production shocks are temporally correlated, the magnitude of the interaction effect reduces (column 2). In the event of temporally correlated climate shocks, trade and storage are thus less substitutable. Storage becomes less effective at smoothing consumption when shocks persist for multiple time periods as stocks will become saturated in the case of recurring positive shocks and run out in the case of recurring negative shocks. International trade is not as much affected because recurring domestic shocks do not affect the availability of imports from foreign markets or the capacity of foreign markets to absorb the domestic surplus. When households face strict borrowing constraints, international trade becomes less effective at smoothing shocks (column 3). Part of the flexibility of trade lies in the possibility to buffer domestic shortages by running temporary trade deficits. Under strict borrowing constraints, trade deficits are not possible and imports of food can only be financed by exports of the outside good in the same period or by a trade surplus that was build up in previous periods. Storage is less affected by borrowing constraints as it works as an a priori investment and therefore does not require households to borrow. The interaction effect reduces in magnitude (column 3 vs. column 1), which indicates that storage and trade are less substitutable in the face of borrowing constraints. The difference is, however, less pronounced

[9]The heterogeneity between the four regions is reduced in order to unambiguously identify the implication of different levels of trade and storage costs. The four regions remain different in terms of household transaction costs.

than in the case of temporal correlation in climate shocks (column 2 vs. column 1).

Table 3: Linear regression of smoothing ratio to storage and trade costs with the world market

	Dependent variable:		
	Smoothing ratio		
	default	temp. correlated	borrowing constraint
	(1)	(2)	(3)
storage cost	-0.695^{***}	-0.506^{***}	-0.662^{***}
	(0.059)	(0.048)	(0.048)
trade cost	-0.841^{***}	-0.879^{***}	-0.743^{***}
	(0.059)	(0.048)	(0.048)
storage x trade cost	-2.188^{***}	-1.343^{***}	-2.070^{***}
	(0.514)	(0.415)	(0.416)
Constant	0.282^{***}	0.253^{***}	0.273^{***}
	(0.007)	(0.005)	(0.005)
Observations	64	64	64
R^2	0.857	0.886	0.885

Note: *p<0.1; **p<0.05; ***p<0.01
Run for 64 different combinations of trade and storage costs
For each combination, the smoothing ratio is calculated based
on a simulation of 50 time periods. For temporal correlation,
each shock persists for two periods (i.e., 100 periods).

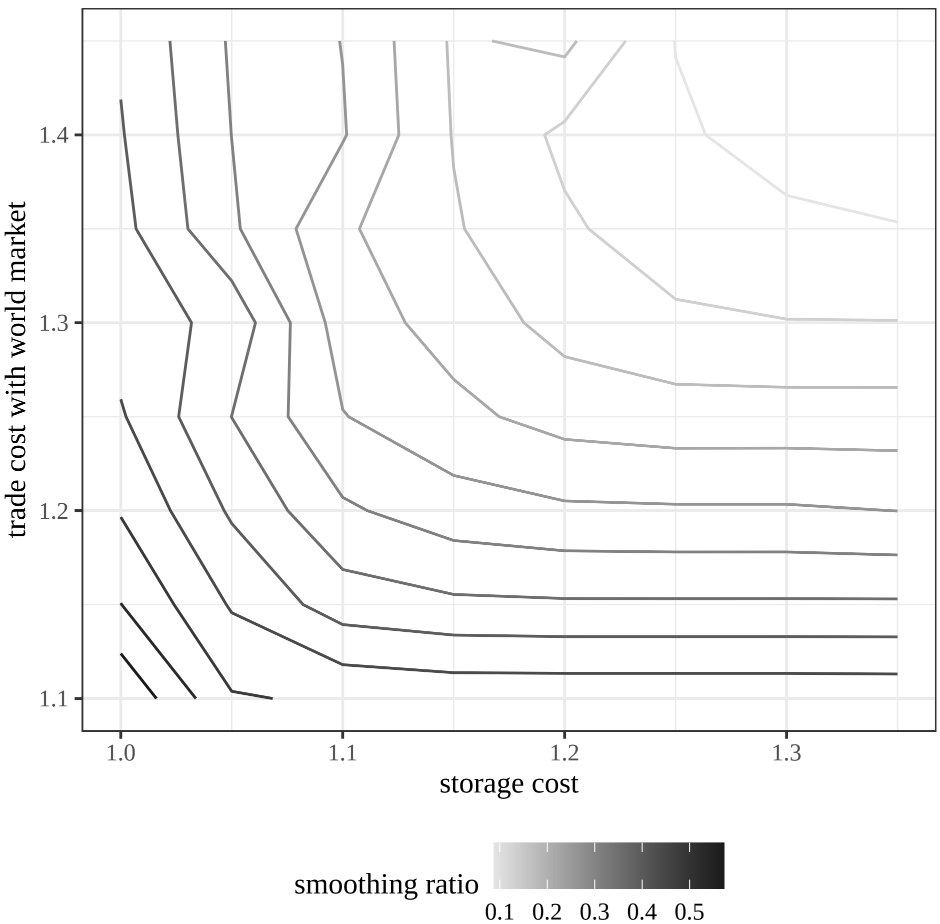

Figure 3: Food consumption smoothing ratio (smoothing ratio = $1 - CV_{\text{consumption}}/CV_{\text{production}}$) under covariate agricultural production shocks for different combinations of storage costs and trade costs with the world market. For each storage and trade cost combination the smoothing ratio is calculated based on a simulation of 50 time periods. Results for temporal correlation in climate shocks and borrowing constraints in Figure S3 in Appendix.

Based on the results in Tables 2 and 3, we derive three predictions that we take to the data:

- Prediction 1 (household transaction cost, τ^{HH}): When households are isolated from the market, food consumption is more responsive to local climate extremes.
- Prediction 2 (trade cost, τ_{mW}): When a region is isolated from the world market, food consumption is more responsive to local and national climate extremes.
- Prediction 3 (storage versus trade): Storage and trade partly substitute one another in smoothing food consumption. The degree of substitutability reduces when climate shocks are temporally correlated.

In the following section we empirically investigate predictions 1, 2, and 3 using data on food insecurity, climate extremes, and market access in Sub-Saharan Africa.

3 Empirical evidence

3.1 Data sources and summary statistics

We combine economic, climatic, and agro-ecological data from multiple sources for our empirical analysis. 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[10]) 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), 1,400 second administrative units, and 29 time periods from 2009 to 2016. Table 4 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

[10] Second administrative units are defined based on the GADM version 3.6 database. Although the size of the administrative units differs across countries, it ensures a more equal spread in terms of population size compared a uniform grid. For the countries in our sample, the coefficient of variation of population size in 2010 is 4.43 when using 30 arc-minute grids as spatial unit (mean = 194,842 people, sd = 862,537 people) and 2.06 when using second administrative unit as spatial unit (mean = 171,787 people, sd = 354,250 people).

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 at the spatial unit of livelihood zones, of which the boundaries vary over time. To facilitate multi-year analysis, Backer and Billing 2021 process the FEWS NET food security data to a standardized uniform spatial resolution of 0.5° x 0.5° grid-cells. We aggregate the grid-cell 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 scale to a dummy variable (0, "food secure", if FEWS NET score = 1 and 1, "food insecure", if FEWS NET score > 1)[11], resulting in a prevalence of food insecurity of 29.7% in our sample (Table 4).

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. We use the 12 month SPEI index which reflects for each month the accumulated water balance of that month and the preceding 11 months[12]. For each administrative unit, we calculate the share of area 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.

Trade flows.—We compile country level trade flows of the main cereals (i.e., the sum of maize, wheat, rice, barley, sorghum, and millet trade) from CEPII's BACI data base (Gaulier and Zignago 2010). We focus on the volume of cereal imports from outside Africa[13] and calculate a trade response

[11] 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. We test the robustness of the findings to alternative specifications of the dependent variable: food insecure = 0 when FEWS NET score $\in 1$ and food insecure = 1 when FEWS NET score $\in 3, 4, 5$ (observations with score 2 are dropped); or food insecure = 0 when FEWS NET score = 1 and food insecure = 1 when FEWS NET score = 2 (observations with score $\in 3, 4, 5$ are dropped) (Tables S7 and S6).

[12] The water balance is the difference between precipitation and potential evapotranspiration. The 12 month SPEI index reflects persistent dry or wet conditions over a prolonged period of 12 months and does not capture short-term extreme conditions, which may or may not affect food production depending on the agricultural growing season of the location. Taking account of the seasonal cropping calendars of every location and crop lies beyond the scope of this study. We use the 12 month SPEI index such that climatic conditions in the previous growing season are captured for all administrative units, irrespective of the precise timing of the location's growing season. As a result we may be underestimating the impact of climate extremes on food insecurity.

[13] We focus on extra-African rather than intra-African trade as there is substantial informal cross-border trade in

indicator as the difference between a certain year's cereal imports and cereal imports from the previous year, relative to previous year's imports.

Trade costs.—There is no comprehensive dataset on transaction and trade costs available at subnational level for the sample. We therefore use data on travel times to cities and ports in the year 2015 from Nelson et al. 2019 as a proxy for market transaction costs and trade costs to the world market respectively. We use travel time to the closest city of 100,000 - 200,000 inhabitants and to the closest large port and aggregate these from the grid-cell (approx. 1 x 1 km) to the second administrative level using the grid-cell area as weight.

Stocks.—We use data on national stock levels of cereals (maize, rice, barley, millet, sorghum, and wheat) from the Production, Supply and Distribution (PSD) database of USDA. 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 all cereals over domestic consumption summed over all cereals in each marketing year.

GDP per capita & population.—Data on GDP per capita is taken from Un Statistics Division, measured in 2015 USD. Information on population density (number of people per km2) is taken from GPW UN WPP-Adjusted Population Density, v4.11. We aggregate the data from 30 min (approx. 55 x 55 km) to the second administrative level using grid-cell area as weight. The data is available in 5 year intervals (2005, 2010, 2015, 2020). Population density for the years in between is linearly interpolated.

Agricultural employment.—We use information from ILOSTAT on the share of agricultural employment in total employment in urban areas and rural areas at the country level. 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 second administrative unit. Rural and urban areas are differentiated based on the population density data using a cutoff of 300 people per km2 for urban areas[14].

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). Violent events are recorded at village level with georeferenced coordinates and daily resolution. We take the sum of the number of causalities within each month-year and each

Africa (Mitaritonna 2016) such that estimates of intra-African trade using the official statistics are likely biased.

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

second administrative level. We then create an indicator of conflict intensity based on the number of causalities (0: no deaths, 1: minor conflict (25 - 999 deaths), 2: war ($\geq$1000 deaths)).

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 (approx. 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[15].

Table 4: Summary statistics: 12 countries in Sub-Saharan Africa, 2009 - 2016

	Full sample		Selected AEZs	
	mean	sd	mean	sd
Food insecurity (yes = 1, no = 0)	0.297	0.457	0.296	0.457
Share adm2 area dry	0.053	0.197	0.053	0.199
Share country area dry	0.051	0.095	0.050	0.093
Share adm2 area wet	0.068	0.216	0.056	0.195
Share country area wet	0.056	0.076	0.054	0.073
Travel time to city of 100k-200k in 2015 (minutes)	235.781	546.292	215.123	400.785
Travel time to large port in 2015 (minutes)	909.793	652.792	860.842	688.477
Cereals stock-to-use ratio (y-1)	0.087	0.082	0.077	0.073
International cereal imports (rel. diff. with y-1)	0.048	0.333	0.041	0.290
Observations	40600		31552	

Selected AEZs 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 over time in the occurrence of climate extremes within each administrative unit. The following fixed effects linear probability model is estimated to explore the link between climate extremes and food

[15] With this method only two administrative units in our sample are identified as sub-tropical (Bir Moghrein in Mauritania and Tibesti in Chad). We reclassify these units as arid zone, which is the zone with the second largest coverage in those administrative units, to create a balanced set of different AEZ groups.

insecurity[16] (empirical model 1, EM1)

$$\begin{aligned} FS_{imy} = & \beta_1 CE^{\text{adm2}}_{imy} + \beta_2 CE^{\text{country}}_{imy} + \beta_3 CE^{\text{nb countries}}_{cmy} \\ & + \beta_4 CE^{\text{adm2}}_{imy} * AEZ_i + \beta_5 CE^{\text{country}}_{imy} * AEZ_c + \gamma_1 C^1_{imy} + \gamma_2 C^2_{cy} \\ & + \mu_i + \mu_{my} + \epsilon_{imy}, \end{aligned} \tag{14}$$

with FS_{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). The variable CE^{adm2}_{imy} (Climate Extreme) indicates the share of the area within the second administrative unit that experienced severely wet or dry (2 > SPEI > 1.5 or -2 < SPEI < -1.5) or extremely wet or dry (SPEI > 2 or SPEI < -2) conditions in the last 12 months. To limit the number of variables, we pool extreme and severe conditions, but differentiate between wet and dry conditions[17]. The variable $CE^{\text{country}}_{imy}$ indicates the share of the country area (excluding administrative unit i) that was affected by severe or extreme conditions in the last 12 months, while $CE^{\text{nb countries}}_{cmy}$ indicates the share of the neighboring countries' area affected by severe or extreme conditions in the last 12 months. We investigate the heterogeneity in the impact of climate extremes in terms of the baseline climatic and agricultural conditions. AEZ_i represents the agro-ecological zone of unit i (Arid, Semi-Arid, Humid, Sub-Humid, Tropical Highlands). AEZ_c is a dummy indicator 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 global time trends that influence food insecurity. Time-varying variables that influence food insecurity are included to control for residual variation. At the administrative level (C^1_{imy}) we include population density (iy), share of agricultural employment in total employment (iy), and conflict intensity (imy), while at the country level GDP per capita is added as a control variable (C^2_{cy}). Conflict intensity is aggregated to the first administrative level and indicates the occurrence of violent conflict in the last 12 months in order to account for temporal and spatial spillovers (Harari and Ferrara 2018). These variables have been shown to determine country-level food security (Dithmer and Abdulai 2017), but may be endogenous

[16] An alternative approach to the fixed effects linear probability model would be to estimate a fixed effects logit model. However, such a model would drop all observations that are never or always food insecure. This would ignore cases where climate extremes do not lead to food insecurity, possibly due to access to domestic or international markets.

[17] Results that disentangle severe versus extreme conditions are reported in Table S4 in Appendix.

to weather and climate variation (Barrios et al. 2010; Branco and Féres 2020; Harari and Ferrara 2018) and may create an "over-controlling" problem (Dell et al. 2014). For agricultural employment and GDP per capita, we therefore use the annual lag of the variable. For conflict intensity, we keep the current value in order to control for potential interactions between conflicts and climate extremes (Maystadt and Ecker 2014), and between conflicts and market access (e.g., conflict-related food aid not reaching remote areas), which could bias our estimated interaction between climate extremes and market access. The models are estimated using OLS with standard errors clustered at the second administrative unit level.

To test the theoretical predictions 1 and 2, we assess whether climate extremes affect food insecurity differently depending on the level of local and international market access. We estimate the following model using OLS (EM2)

$$\begin{aligned} FS_{imy} =& \beta_1 CE^{\text{adm2}}_{imy} + \beta_2 CE^{\text{country}}_{imy} + \beta_3 CE^{\text{adm2}}_{imy} * CE^{\text{country}}_{imy} + \beta_4 CE^{\text{nb countries}}_{cmy} \\ &+ (\beta_5 CE^{\text{adm2}}_{imy} + \beta_6 CE^{\text{country}}_{imy} + \beta_7 CE^{\text{adm2}}_{imy} * CE^{\text{country}}_{imy}) * TT^{\text{city}}_i \\ &+ (\beta_8 CE^{\text{adm2}}_{imy} + \beta_9 CE^{\text{country}}_{imy} + \beta_{10} CE^{\text{adm2}}_{imy} * CE^{\text{country}}_{imy}) * TT^{\text{port}}_i \\ &+ \gamma_1 C^1_{imy} + \gamma_2 C^2_{cy} + \mu_i + \mu_{my} + \epsilon_{imy}, \end{aligned} \tag{15}$$

with TT^{city}_i the average travel time to the closest large city (100k-200k inhabitants[18]) and TT^{port}_i 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^{HH}_m in the theoretical model), while the latter is a proxy for a region's access to overseas international markets (corresponding to parameter τ_{mW} in the theoretical model). The travel times are centered at the country mean such that we measure market access relative to other regions within a country. From prediction 1 we expect that β_5 is positive and significant, while from prediction 2 we expect that β_8 and β_9 are both positive and significant.

To investigate prediction 3 on the substitutability of storage and trade, we test whether storage and trade both buffer the food insecurity impacts of country-wide climate extremes, and whether

[18]Results with an alternative city size threshold of 50k-100k or 200k-500k inhabitants are shown in Table S5 in the Appendix.

there is any interaction between the two using the following specification (EM3)

$$\begin{aligned} FS_{imy} =& \beta_1 CE^{\text{adm2}}_{imy} + \beta_2 CE^{\text{country}}_{imy} + \beta_3 CE^{\text{adm2}}_{imy} * CE^{\text{country}}_{imy} + \beta_4 CE^{\text{nb countries}}_{cmy} \\ & + (\beta_5 + \beta_6 CE^{\text{adm2}}_{imy} + \beta_7 CE^{\text{country}}_{imy} + \beta_8 CE^{\text{adm2}}_{imy} * CE^{\text{country}}_{imy}) * I^{\text{trade}}_{cy} \\ & + (\beta_9 + \beta_{10} CE^{\text{adm2}}_{imy} + \beta_{11} CE^{\text{country}}_{imy} + \beta_{12} CE^{\text{adm2}}_{imy} * CE^{\text{country}}_{imy}) * I^{\text{storage}}_{c,y-1} \\ & + (\beta_{13} + \beta_{14} CE^{\text{adm2}}_{imy} + \beta_{15} CE^{\text{country}}_{imy} + \beta_{16} CE^{\text{adm2}}_{imy} * CE^{\text{country}}_{imy}) * I^{\text{trade}}_{cy} * I^{\text{storage}}_{c,y-1} \\ & + \gamma_1 C^1_{imy} + \gamma_2 C^2_{cy} + \mu_i + \mu_{my} + \epsilon_{imy}, \end{aligned} \tag{16}$$

with I^{trade}_{cy} a measure of international cereal import response, measured as the relative difference in imports with respect to the preceding year, and $I^{\text{storage}}_{c,y-1}$ the previous year's stock-to-use-ratio of cereals. We expect that β_6, β_7, β_8, β_{10}, β_{11}, and β_{12} are negative, that is, the impact of local and national climate extremes on food insecurity is buffered when a country increases international imports or when stocks are available. We are further interested in the interaction effects between climate extremes, trade, and storage (β_{14}, β_{15}, and β_{16}). When these β's are not significantly different from zero, it indicates that trade and storage perfectly complement one another in buffering the impact of climate extremes. When the β's are significantly positive, it indicates that trade and storage partly substitute one another. Lastly, negative β's would suggests a positive synergy between trade and storage[19].

Lastly, we check whether storage and trade can buffer multi-year climate extremes using the following specification (EM4)

$$\begin{aligned} FS_{imy} =& \beta_1 CE^{\text{adm2}}_{imy} + \beta_2 CE^{\text{country}}_{imy} + \beta_3 CE^{\text{nb countries}}_{cmy} \\ & + \beta_4 CE^{\text{adm2}}_{im,y-1} + \beta_5 CE^{\text{adm2}}_{imy} * CE^{\text{adm2}}_{im,y-1} \\ & + (\beta_6 + \beta_7 CE^{\text{adm2}}_{imy} + \beta_8 CE^{\text{adm2}}_{im,y-1} + \beta_9 CE^{\text{adm2}}_{imy} * CE^{\text{adm2}}_{im,y-1}) * I^{\text{trade}}_{c,y-1} \\ & + (\beta_{10} + \beta_{11} CE^{\text{adm2}}_{imy} + \beta_{12} CE^{\text{adm2}}_{im,y-1} + \beta_{13} CE^{\text{adm2}}_{imy} * CE^{\text{adm2}}_{im,y-1}) * I^{\text{storage}}_{c,y-2} \\ & + (\beta_{14} + \beta_{15} CE^{\text{adm2}}_{imy} + \beta_{16} CE^{\text{adm2}}_{im,y-1} + \beta_{17} CE^{\text{adm2}}_{imy} * CE^{\text{adm2}}_{im,y-1}) * I^{\text{trade}}_{c,y-1} * I^{\text{storage}}_{c,y-2} \\ & + \gamma_1 C^1_{imy} + \gamma_2 C^2_{cy} + \mu_i + \mu_{my} + \epsilon_{imy}, \end{aligned} \tag{17}$$

[19] Our inter-annual model does not predict a positive synergy between trade and storage. In contrast, by looking at a weekly time interval, Coleman 2009 identifies a positive interaction 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. 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 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).

with $CE^{\text{adm2}}_{im,y-1}$ the share of the area within the administrative unit that experienced severely or extremely dry or wet conditions not in the last 12 months, but in the 12 months preceding those. Similarly, $I^{\text{trade}}_{c,y-1}$ and $I^{\text{storage}}_{c,y-2}$ are the lagged variables of I^{trade}_{cy} and $I^{\text{storage}}_{c,y-1}$, respectively. For the coefficients β_7 to β_9 and β_{11} to β_{13} a negative value indicates a buffering role of storage and international trade, respectively. Similar as in the previous empirical model, the interaction effects (β_{15}, β_{16}, and β_{17}) indicate to which extent trade and storage act as substitutes or complements in buffering the impact of multi-year climate extremes.

3.3 Results

Climate extremes and food insecurity.—The results from the estimation of model EM1 are presented in Table 5. We find significant differences in the impact of climate extremes on food insecurity across agro-ecological zones. In arid areas, dry conditions increase the risk of food insecurity, while wet conditions reduce food insecurity. For humid areas the opposite pattern is observed: dry conditions reduce food insecurity and wet conditions increase food insecurity. Semi-arid areas are negatively affected by severe or extreme dry conditions, while sub-humid areas are negatively affected by severe or extreme wet conditions. These patterns are mimicked at the country level. Country-wide dry conditions increase food insecurity to a larger extent in arid countries than in non-arid countries. For a 10 percentage points increase in the country area affected by severe or extreme dry conditions, the likelihood to be food insecure increases with 9.6 percentage points in arid versus 2.1 percentage points in non-arid countries. Severe or extreme wet conditions reduce food insecurity in arid countries, while they increase food insecurity in non-arid countries. Violent conflicts and population growth are correlated with a higher likelihood of a region to be food insecure, while the opposite holds for economic growth and agricultural employment. These effects are in line with the cross-country food security analysis of Dithmer and Abdulai 2017.

Travel times, climate extremes, and food insecurity.—We next investigate whether the impact of climate extremes varies with the average travel time to the closest large city in a region. The results of the estimation of model EM2 are presented in Table 6. Given the importance of agro-ecological characteristics in determining the sign of impacts, we focus on dry conditions and take a sub-sample of arid, semi-arid and sub-humid zones (i.e., the areas where dry conditions increase food insecurity as was shown in Table 5). Based on prediction 1, we expect that these adverse climate extremes affect the population of a region more when market access is low. We find indeed that local dry

Table 5: The effect of climate extremes on food insecurity across Agro-Ecological Zones

	Food Insecurity (yes = 1, no = 0)		
	b		se
CE adm2 dry	0.006		(0.04)
AEZ Arid × CE adm2 dry	0.138	**	(0.05)
AEZ Humid × CE adm2 dry	-0.108	**	(0.04)
AEZ Semi-Arid × CE adm2 dry	0.265	***	(0.05)
AEZ Sub-Humid × CE adm2 dry	0.058		(0.04)
CE adm2 wet	-0.069	***	(0.02)
AEZ Arid × CE adm2 wet	-0.197	**	(0.06)
AEZ Humid × CE adm2 wet	0.064	**	(0.02)
AEZ Semi-Arid × CE adm2 wet	-0.017		(0.02)
AEZ Sub-Humid × CE adm2 wet	0.153	***	(0.02)
CE country dry	0.209	***	(0.03)
Arid country × CE country dry	0.747	***	(0.14)
CE country wet	0.141	**	(0.04)
Arid country × CE country wet	-0.812	***	(0.08)
CE neighboring countries dry	-0.415	***	(0.08)
CE neighboring countries wet	0.417	***	(0.08)
Conflict intensity (adm1)	0.123	***	(0.01)
Log population density	0.354	*	(0.14)
Log GDP pc (country, y-1)	-0.415	***	(0.12)
Share agricultural employment (y-1)	-0.333	***	(0.09)
Second administrative unit FE	Yes		
Year-month FE	Yes		
N	40600		
R-squared	0.274		

Standard errors in parentheses are clustered at panelid. Tropical Highlands is the base AEZ category.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

conditions in arid, semi-arid, and sub-humid zones have a larger impact on food insecurity in regions with a longer travel time to city (column (1)). The estimated effect reduces but remains significant when additionally controlling for travel time to port (column (2)). Column (3) shows that the estimated effect is robust to controlling for factors that may be correlated with local market access (conflicts and agricultural employment). Based on the preferred specification in column (3), a 10 percentage points increase in an administrative unit's area affected by dry conditions is estimated to increase the likelihood of food insecurity on average with 1.56 percentage points. This is the effect for a region with average travel times to city. When the travel time to city is at the 90th percentile, the effect increases to 2.42 percentage points, while at the 10th percentile the effect is only 0.66 percentage points.

Based on prediction 2, we expect that local and national adverse climate extremes hit a region harder when it is less connected to overseas international markets. We indeed find that local dry conditions in arid, semi-arid, and sub-humid zones have a larger impact on food insecurity in areas with longer travel times to the closest large port, a proxy for international market access (column (2)). Column (3) shows that also this effect is robust to controlling for factors that are potentially correlated with market access. Based on column (3) we estimate that the effect of a 10 percentage points increase in local dry conditions is a 2.69 percentage points increase in food insecurity for a travel time to port at the 90th percentile. At the 10th percentile, the effect is only 0.25 percentage points. In regions that are less connected to overseas international markets, food insecurity is also more sensitive to dry climate extremes in the rest of the country (column (2)). Also this effect remains robust when controlling for potential confounding factors (column (3)).

Table 6: The effect of climate extremes and market access on food insecurity (Arid, Semi-Arid and Sub-Humid areas)

	(1) b		(1) se	(2) b		(2) se	(3) b		(3) se
CE adm2 dry	0.161	***	(0.02)	0.149	***	(0.02)	0.156	***	(0.02)
CE country dry	0.248	***	(0.03)	0.222	***	(0.03)	0.152	***	(0.03)
CE adm2 dry × CE country dry	-0.238	**	(0.09)	-0.070		(0.10)	0.271	**	(0.10)
CE adm2 dry × Log tc	0.151	***	(0.03)	0.099	**	(0.03)	0.102	**	(0.03)
CE country dry × Log tc	0.105	*	(0.04)	0.040		(0.04)	-0.025		(0.04)
CE adm2 dry × CE country dry × Log tc	-0.173		(0.14)	-0.070		(0.14)	-0.131		(0.14)
CE adm2 dry × Log tp				0.242	***	(0.05)	0.198	**	(0.06)
CE country dry × Log tp				0.252	***	(0.05)	0.129	*	(0.05)
CE adm2 dry × CE country dry × Log tp				-0.677	**	(0.22)	-0.040		(0.22)
Control variables	Yes			Yes			Yes		
Admin2 and country wet CE	Yes			Yes			Yes		
Neighboring countries' CE	Yes			Yes			Yes		
Second administrative unit FE	Yes			Yes			Yes		
Year-month FE	Yes			Yes			Yes		
Additional controls	No			No			Yes		
N	31552			31552			31552		
R-squared	0.285			0.287			0.296		

Standard errors in parentheses are clustered at panelid. The variables tc (Log travel time to city) and tp (Log travel time to port) are centered at country mean. The default control variables are conflict intensity, GDP pc, population density, and agricultural employment. Additional controls are conflict intensity x travel times, conflict intensity x climate extremes, agricultural employment x climate extremes.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Trade, storage, climate extremes, and food insecurity.—Lastly, we explore the substitutability and complementarity of international trade and storage for country-wide and multi-year climate extremes in Tables 7 and 8. We again focus on dry conditions in arid, semi-arid, and sub-humid areas. Table 7 shows the results of model EM3 that estimates the impact of international cereal imports (column (1)), storage (column (2)) and their interaction (column (3)) on the food insecurity impacts from country-wide climate extremes. In column (3) we estimate that a 10 percentage points increase in the country area affected by dry conditions increases the likelihood of food insecurity with 3.39 percentage points. For an increase in cereals imports to the 90th percentile (+18% points increase in cereal imports compared to previous year), the effect of dry conditions on food insecurity reduces to 2.38 percentage points. For an increase in stock-to-use ratio to the 90th percentile (+ 3% in previous year's stock to use ratio), the effect of dry conditions on food insecurity reduces to 0.35 percentage points. Both imports and storage have a buffering impact, and the significant positive interaction in column (3) suggests that they partly substitute one another. The food insecurity reduction achieved by the combination of storage and trade is larger than any of the two separately. At the same time, there is some degree of substitutability as, when a country increases cereal imports, the additional impact of previous year's stocks on food insecurity is smaller. Similarly, when a country has cereal stocks available from last year, the additional impact of cereal imports on buffering food insecurity is smaller. Lastly, we explore what happens when severe or extreme dry conditions persist for multiple years. Imagine a year with dry conditions that are buffered by an increase in cereals imports or the availability of cereal stocks. The estimation in Table 8 investigates whether the buffering effects of imports or stocks persists when a drought occurs also in the subsequent year. The estimated interaction effects in column (3) provide three insights. First, the buffering effect of cereal imports persists also when dry conditions occur two years in a row. Second, the buffering effect of stocks reduces when dry conditions occur two years in a row. Third, the positive interaction effect between stocks and imports is smaller in magnitude than in Table 7. These results suggest that in the case of multi-year droughts, there is less smoothing via storage, and trade and storage are less substitutable. As stocks can become depleted, imports may present an important buffer against extreme conditions that persist for multiple years.

Table 7: The effect of climate extremes, storage and international cereal imports on food insecurity (Arid, Semi-Arid and Sub-Humid areas)

	(1)			(2)			(3)		
	b		se	b		se	b		se
CE adm2 dry	0.159	***	(0.02)	0.186	***	(0.02)	0.143	***	(0.02)
CE country dry	0.284	***	(0.04)	0.255	***	(0.03)	0.339	***	(0.04)
CE adm2 dry × CE country dry	-0.268	**	(0.09)	-0.356	***	(0.09)	-0.206	*	(0.10)
Cereal imports	0.003		(0.01)				-0.048	***	(0.01)
CE adm2 dry × Cereal imports	-0.064		(0.06)				-0.276	**	(0.09)
CE country dry × Cereal imports	-0.326	***	(0.08)				-0.567	***	(0.10)
CE adm2 dry × CE country dry × Cereal imports	-0.195		(0.25)				0.627		(0.33)
SUR (y-1)				0.204		(0.12)	-0.390	**	(0.15)
CE adm2 dry × SUR (y-1)				0.003		(0.51)	-2.813	***	(0.64)
CE country dry × SUR (y-1)				-1.177	**	(0.44)	-9.821	***	(1.29)
CE adm2 dry × CE country dry × SUR (y-1)				-14.699	***	(2.42)	-7.570	*	(3.02)
Cereal imports × SUR (y-1)							0.193	**	(0.07)
CE adm2 dry × Cereal imports × SUR (y-1)							-2.126		(1.12)
CE country dry × Cereal imports × SUR (y-1)							7.345	***	(0.88)
CE adm2 dry × CE country dry × Cereal imports × SUR (y-1)							35.062	**	(10.96)
Control variables	Yes			Yes			Yes		
Admin2 and country wet CE	Yes			Yes			Yes		
Neighboring countries' CE	Yes			Yes			Yes		
Second administrative unit FE	Yes			Yes			Yes		
Year-month FE	Yes			Yes			Yes		
N	31552			31552			31552		
R-squared	0.285			0.287			0.292		

Standard errors in parentheses are clustered at panelid. Control variables are conflict intensity, GDP pc, population density, and agricultural employment.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: The effect of multi-year climate extremes, storage and international cereal imports on food insecurity (Arid, Semi-Arid and Sub-Humid areas)

	(1)			(2)			(3)		
	b		se	b		se	b		se
CE country dry	0.189	***	(0.05)	0.246	***	(0.05)	0.167	***	(0.05)
CE country dry (y-1)	-0.021		(0.05)	-0.072		(0.04)	-0.032		(0.05)
CE country dry × CE country dry (y-1)	0.485		(0.72)	0.978		(0.72)	0.867		(0.70)
CE adm2 dry	0.131	***	(0.02)	0.117	***	(0.02)	0.138	***	(0.02)
CE adm2 dry (y-1)	0.018		(0.01)	0.020		(0.01)	0.026	*	(0.01)
CE adm2 dry × CE adm2 dry (y-1)	0.152	**	(0.06)	0.043		(0.07)	0.094		(0.05)
Cereal imports (y-1)	-0.055	***	(0.01)				-0.095	***	(0.01)
CE adm2 dry × Cereal imports (y-1)	0.051		(0.04)				0.025		(0.04)
CE adm2 dry (y-1) × Cereal imports (y-1)	-0.080	**	(0.03)				-0.122	***	(0.03)
CE adm2 dry × CE adm2 dry (y-1) × Cereal imports (y-1)	-1.338	***	(0.34)				-2.161	***	(0.28)
SUR (y-2)				1.049	***	(0.10)	0.968	***	(0.11)
CE adm2 dry × SUR (y-2)				-1.062	***	(0.22)	-0.907	***	(0.27)
CE adm2 dry (y-1) × SUR (y-2)				-0.947	***	(0.26)	-1.100	*	(0.48)
CE adm2 dry × CE adm2 dry (y-1) × SUR (y-2)				3.318	**	(1.05)	7.206	***	(2.02)
Cereal imports (y-1) × SUR (y-2)							0.266	***	(0.05)
CE adm2 dry × Cereal imports (y-1) × SUR (y-2)							-0.127		(0.23)
CE adm2 dry (y-1) × Cereal imports (y-1) × SUR (y-2)							0.406		(0.24)
CE adm2 dry × CE adm2 dry (y-1) × Cereal imports (y-1) × SUR (y-2)							3.150	**	(1.05)
Control variables	Yes			Yes			Yes		
Admin2 and country wet CE	Yes			Yes			Yes		
Neighboring countries' CE	Yes			Yes			Yes		
Second administrative unit FE	Yes			Yes			Yes		
Year-month FE	Yes			Yes			Yes		
N	31552			31552			31552		
R-squared	0.286			0.291			0.296		

Standard errors in parentheses are clustered at panelid. Control variables are conflict intensity, GDP pc, population density, and agricultural employment.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.4 Robustness tests

As a first robustness test, we investigate the responsiveness of local food prices to local climatic conditions (see Appendix Section S6.3). Using data on subnational monthly cereal prices from 11 countries for the period 2010–2016, we find that dry climatic conditions increase local food prices in arid and semi-arid areas (Table S1). This effect is significantly larger for regions that face above average travel times to cities of a size larger than 200,000 inhabitants (Table S2 columns (4) and (5)). The effect is not significant for travel times to smaller cities of less than 200,000 inhabitants (Table S2 columns (2) and (3)).

Next, we test the robustness of the findings on local market access, climate extremes, and food insecurity to the definition of the key variables of interest. The interaction effect between local climate extremes and travel time to city is driven by moderate food insecurity (Table S7). The interaction is mostly driven by severe local dry conditions (Table S4). The interaction is overall robust to altenative cutoffs of a city. It remains present for smaller cities (50–100k inhabitants), but reduces in significance and magnitude for larger cities (200–500k inhabitants) when combined with the travel time to port indicator (Table S5).

Lastly, we test the robustness of the findings on international market access, climate extremes, and food insecurity. The estimated interaction effect between travel time to port and local climate extremes is driven by moderate food insecurity (Table S7). When we distinguish between severe and extreme local dry conditions, the interaction with travel time to port is shown to be driven by the latter (Table S4). The estimated interaction effect between travel time to port and country level climate extremes is present for both moderate and high levels of food insecurity (Tables S7 and S6) and driven by severe dry conditions (Table S4).

4 Discussion

This paper investigates under which conditions agricultural markets can buffer the food insecurity impacts of climate extremes. For a region that is isolated from outside markets, food prices drop when local production is high and rise when local production fails. While the price response smooths households' nominal incomes, food consumption remains as variable as local production. When connected to outside markets, nominal incomes become more responsive to local production, but food consumption becomes less responsive to local production. Under a beneficial climate shock, markets direct the surplus local supply to exports and the build-up of stocks. This buffers the drop in local prices, thereby raising agricultural income and allowing for asset accumulation. Under a detrimental climate shock, markets compensate the deficit in local supply through imports and the utilization of stocks. This buffers the increase in local prices, thereby making food purchases less expensive. Households can borrow or use the assets accumulated during the good harvest years for food purchases. We derive these findings from a dynamic stochastic model that integrates household-level consumption smoothing with market-based storage and trade. Numerical simulations reveal the importance of households' transaction costs and regions' trade costs to the international market in buffering local and national climate shocks. The relative contribution of storage and trade is determined by the spatiotemporal pattern of climate shocks. We find empirical support for the theoretical predictions using subnational and sub-annual data from 2009 to 2016 for 12 countries in Sub-Saharan Africa, a region where climate extremes pose severe food security risks. In areas where households face relatively larger market transaction costs, approximated by longer travel times to the closest large city, dry climatic conditions have a larger detrimental impact on food insecurity. Severe and extreme dry conditions have also a larger detrimental impact on food insecurity in areas with longer travel times to ports. International cereal imports and storage buffer the food insecurity impacts of climate extremes and are partly substitutes, partly complements for one another.

The study complements previous work on the linkages between trade costs, prices, and agricultural production shocks in India (Allen and Atkin 2022; Burgess and Donaldson 2017). Infrastructure development – through expansion of railroads from 1861 to 1930 in Burgess and Donaldson 2017 and expansion of highway network from 1970 to 2009 in Allen and Atkin 2022 – is linked with a reduction in the responsiveness of local prices to local yield shocks and an increase in the responsiveness of nominal agricultural incomes to local yield shocks. The net effect on real incomes is theoretically ambigous (Burgess and Donaldson 2010). Empirical results in terms of real incomes indeed differ, with Allen and Atkin 2022 finding an increase in the responsiveness of real incomes to local yield shocks with increased market access, while Burgess and Donaldson 2017 a decrease. Here, we demonstrate that the ambiguity on real incomes does not necessarily hold for consumption as consumption can be decoupled from real income via inter-temporal transfers. By considering savings and asset accumulation, the theoretical model predicts a lower responsiveness of food consumption to local climate shocks under increased market access. The prediction in confirmed by the empirical analysis and is in line also with Burgess and Donaldson 2010, who find a smaller impact of rainfall shocks on famines in India due to improved railroad infrastructure.

This study did not explore all possible climatic and economic conditions that could influence market-based consumption smoothing. First, we did not consider reallocation of households' productive inputs and resources in response to climate shocks. Decisions for most agricultural inputs (e.g., acreage, crop varieties, planting dates) are taken before the harvest is realized and the output price is known. The agricultural supply response exhibits thus a one period lag: when a climate shock affects the current harvest, farmers adjust the production planned for the next harvesting period. When farmers are price-takers with rational expectations and without alternative income generating activities, theory predicts that storage and planned production move in opposite directions (Williams and Wright 1991). Empirical studies are, however, inconclusive about the supply response of farm households in Sub-Saharan Africa to climate and weather shocks, finding that it depends on labor availability, the level of risk and risk aversion, market integration, and land availability (Girard et al. 2021). Switching income generating activities is furthermore an important coping strategy, with rainfall shortages reallocating labor to the non-agricultural sector (Branco and Féres 2020) or to migration-related jobs (Josephson and Shively 2021). Further research could expand the theoretical model with elastic labor and land supply and investigate how the buffering effect of markets varies across livelihood strategies. Second, we did not investigate how the buffering effect of markets varies with households' income level. Market participation increases asset ownership, livestock holding, and income mostly for rich households (Ojong et al. 2022). In the face of weather shocks, poor households are more vulnerable (Letta et al. 2018) and engage in asset smoothing rather than consumption smoothing (Carter and Lybbert 2012; Janzen and Carter 2019). Future empirical research, building on rich household-level data, is needed to investigate how to achieve equal gains from market-based adaptation policies. Third, we focused on the impact of local and national climate extremes and abstracted from climate extremes and other shocks elsewhere that may affect price volatility on the world market. The theoretical model could be extended to include a stochastic world market by building on Gouel and Jean 2015. Empirically, combining household survey data with historical price data (Amolegbe et al. 2021) or with local trade liberalization measures (Baylis et al. 2019; Topalova 2010) are promising approaches to investigate distributional aspects of world market shocks on local food insecurity.

5 Conclusion

Global warming is associated with changes in the frequency, intensity, duration, timing, and the spatial extent of temperature and precipitation extremes (Seneviratne et al. 2021). Coping with these extreme conditions will be a huge and inevitable challenge for policy makers, especially in developing countries. This paper provides new theoretical and empirical insights on the importance of facilitating market-based coping mechanisms. First, the findings show that investments in access to markets and credit markets are necessary to ensure that macro-level mechanisms (trade and storage) are effective at buffering local food insecurity. This can be achieved by expanding local transport infrastructure, investing in port facilities, and improving access to banks. Second, the findings show that storage and trade are partly substitutes in buffering the food insecurity impacts of climate extremes. This implies that coping strategies can, to some extent, be tailored to countries' own context, including countries' borrowing constraints and infrastructure. 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 a diverse export activity or a growing export potential can further invest in the performance of its export sectors, thereby building up the necessary foreign exchange to cover years with enhanced food import needs (WTO 2019). At the same time, it appears important to establish some capacity for both market mechanisms given their complementarity in buffering climate extremes with different spatiotemporal patterns, including multi-year and widespread events.

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6 Appendix

S6.1 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 is

$$\begin{aligned} H_{mt} =& \beta^t \ln\left((\alpha C_{m,ag,t}^{\frac{\sigma-1}{\sigma}} + C_{m,o,t}^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}} \right) \\ & + \eta_{mt} \left[P_{m,o,t}(H_{\{}m,o,t\} - C_{m,o,t} - \tau_m^{HH}(qs_{mt} + qp_{mt})) \right. \\ & \left. + P_{m,ag,t}(H_{\{}m,ag,t\} - C_{m,ag,t}) + \Phi_{mt} + (1+r)X_{mt} \right], \end{aligned} \tag{18}$$

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

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

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

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

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

Combining these conditions gives optimal intra-temporal household consumption allocation

$$\begin{aligned} \alpha \left(\frac{C_{m,ag,t}}{C_{m,o,t}} \right)^{\frac{1}{\sigma}} &= \frac{P_{m,o,t}}{P_{m,ag,t} - \tau_m^{HH} P_{m,o,t}} \text{ if } qs_{mt} > 0 \text{ and } qp_{mt} = 0, \\ \alpha \left(\frac{C_{m,ag,t}}{C_{m,o,t}} \right)^{\frac{1}{\sigma}} &= \frac{P_{m,o,t}}{P_{m,ag,t} + \tau_m^{HH} P_{m,o,t}} \text{ if } qs_{mt} = 0 \text{ and } qp_{mt} > 0, \end{aligned} \tag{19}$$

or

$$\alpha \left(\frac{C_{m,ag,t}}{C_{m,o,t}} \right)^{\frac{1}{\sigma}} = \frac{P_{m,o,t}}{P'_{m,ag,t}}, \tag{20}$$

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

$$\begin{aligned}&(\alpha C_{m,ag,t}^{\frac{\sigma-1}{\sigma}} + C_{m,o,t}^{\frac{\sigma-1}{\sigma}}) C_{m,ag,t}^{\frac{1}{\sigma}} P'_{m,ag,t} \\ =&\frac{1}{(1+r)\beta} \, \mathrm{E}_t \left[(\alpha C_{m,ag,t+1}^{\frac{\sigma-1}{\sigma}} + C_{m,o,t+1}^{\frac{\sigma-1}{\sigma}}) C_{m,ag,t+1}^{\frac{1}{\sigma}} P'_{m,ag,t+1} \right],\end{aligned} \tag{21}$$

$$\begin{aligned}&(\alpha C_{m,ag,t}^{\frac{\sigma-1}{\sigma}} + C_{m,o,t}^{\frac{\sigma-1}{\sigma}}) C_{m,o,t}^{\frac{1}{\sigma}} P_{m,o,t} \\ =&\frac{1}{(1+r)\beta} \, \mathrm{E}_t \left[(\alpha C_{m,ag,t+1}^{\frac{\sigma-1}{\sigma}} + C_{m,o,t+1}^{\frac{\sigma-1}{\sigma}}) C_{m,o,t+1}^{\frac{1}{\sigma}} P_{m,o,t+1} \right],\end{aligned} \tag{22}$$

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.

S6.2 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 highlighted by Porteous 2019, applications of rational expectations trade and storage models are therefore generally limited to two markets. Here we use a finite-period approximation to solve the model for four markets[20]. In particular, the infinite-horizon problem is converted into a moving series of three-period problems. A limitation of this approach is that it underestimates storage as the incentive for storage is not only to alleviate potential production shortfalls in the next period, but also to have sufficient supplies available to alleviate potential production shortfalls in more distant future periods. The difference in storage volume between a series of two-period models and stochastic dynamic programming is illustrated in Williams and Wright 1991 Figure 3.3 (p. 66) and Table 3.1 (p. 71). The model is specified as a Mixed Complementary Problem (MCP) 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 9 nodes for the covariate shock simulations and 129 nodes for the idiosyncratic shock simulations. Figure S1 shows the nodes and weights for a covariate shock $H_{m,ag,t}(s)$ with states s $\in \{s_1 = -6.13, s_2 = 0, s_3 = 6.13\}$.

The equations for the model solution of the finite period problem are the same as the ones of the infinite period problem developed in the main text except for the transversality condition. For a problem with a finite number of T periods, the transversality condition is:

$$\mathrm{E}_t \left[\frac{X_{m,T}}{(1+r)^T} \right] = 0 \tag{23}$$

[20]The method allows us to solve the rational expectations model for 8 state variables (agricultural good availability and household assets in each of the four markets).

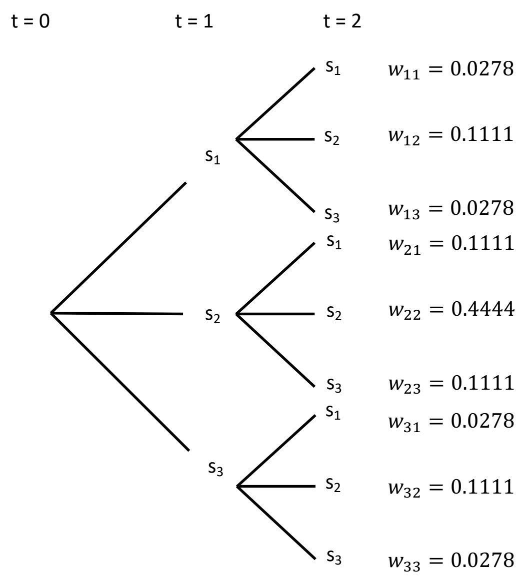

Figure S1: Nodes and weights for sparse grid integration of the expectation of a covariate production shock.

S6.3 Food price analysis

For the food price regressions, data is available for 11 countries (Burkina Faso, Chad, Ethiopia, Kenya, Mali, Mauritania, Mozambique, Niger, Nigeria, Somalia, and Sudan), 97 second administrative units and 84 time periods from 2010 to 2016[21].

Data on cereal prices is obtained from the FEWS NET Staple Food prices and FAO GIEWS domestic food prices databases. We select local prices of storable cereal crops (maize, rice, millet, sorghum, teff, and wheat) and their derived products (maize meal, wheat flour, ...)[22]. Prices are recorded monthly at the market level. When more than one market is recorded for one administrative unit, we take a simple average. Prices are corrected for inflation (using January 2010 as base year) and converted into US Dollars using the local inflation and exchange rates from IMF.

[21] We select only those areas with at least 1 observation per quarter of the year between 2010 and 2016. The dataset obtained is balanced at 4-month time interval, such that the same seasonal variation as in the food insecurity regression is covered.

[22] There is not sufficient data available on imported food products in order to study the relationship between import food prices and travel time to port.

We estimate the following two log-linear models

$$\begin{aligned} Log(P_{i\omega my}) =& \beta_1 CE^{\text{adm2}}_{imy} + \beta_2 CE^{\text{country}}_{imy} + \beta_3 CE^{\text{nb countries}}_{cmy} \\ &+ \beta_4 CE^{\text{adm2}}_{imy} * AEZ_i + \beta_5 CE^{\text{country}}_{imy} * AEZ_c \\ &+ \mu_i + \mu_\omega + \mu_{my} + \epsilon_{i\omega my}, \end{aligned} \tag{24}$$

$$\begin{aligned} Log(P_{i\omega my}) =& \beta_1 CE^{\text{adm2}}_{imy} + \beta_2 CE^{\text{country}}_{imy} + \beta_3 CE^{\text{nb countries}}_{cmy} \\ &+ \beta_4 CE^{\text{adm2}}_{imy} * TT^{\text{city}}_{i} \\ &+ \mu_i + \mu_\omega + \mu_{my} + \epsilon_{i\omega my}, \end{aligned} \tag{25}$$

with $P_{i\omega my}$ the local price of cereal product ω in administrative unit i in month m of year y. The independent variables are the same as in the food security analysis in the main text. Product fixed effects (μ_ω) are included to control for time invariant product-specific characteristics that influence food prices. Administrative unit (μ_i) and time (μ_{my}) fixed effects are included to control for time invariant administrative unit-specific characteristics and global temporal trends that influence food prices. The results are presented in Tables S1 and S2.

Table S1: The effect of climate extremes on local cereal prices across Agro-Ecological Zones.

	(1)			(2)			(3)		
	b		se	b		se	b		se
CE adm2 dry	-0.034	*	(0.02)	-0.028		(0.02)	-0.000		(0.02)
AEZ Arid × CE adm2 dry	0.384	***	(0.04)	0.211	***	(0.05)	0.175	***	(0.05)
AEZ Semi-Arid × CE adm2 dry	0.259	***	(0.04)	0.173	***	(0.04)	0.142	***	(0.04)
AEZ Sub-Humid × CE adm2 dry	0.152		(0.09)	0.152		(0.09)	0.138		(0.08)
CE adm2 wet	-0.038		(0.02)	-0.073	***	(0.02)	-0.066	***	(0.02)
AEZ Arid × CE adm2 wet	-0.127	***	(0.03)	-0.026		(0.03)	-0.024		(0.03)
AEZ Semi-Arid × CE adm2 wet	0.016		(0.02)	0.090	***	(0.02)	0.080	***	(0.02)
AEZ Sub-Humid × CE adm2 wet	0.133	***	(0.03)	0.189	***	(0.03)	0.181	***	(0.03)
CE country dry				0.123		(0.20)	-0.005		(0.21)
Arid country				0.322	***	(0.05)	0.325	***	(0.05)
Arid country × CE country dry				0.183		(0.20)	0.068		(0.21)
CE country wet				0.810	***	(0.13)	0.866	***	(0.13)
Arid country × CE country wet				-1.289	***	(0.13)	-1.239	***	(0.13)
CE neighboring countries dry							0.631	***	(0.08)
CE neighboring countries wet							-0.274	**	(0.08)
N	17099			17099			17099		
R-squared	0.799			0.805			0.806		

Second administrative unit (Adm2), Product, and Year-Month fixed effects included. Robust standard errors are reported. No occurrence of climate extremes in Humid AEZ in the sample. AEZ Tropical Highlands is the base category.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table S2: The effect of climate extremes and market access on local cereal prices in Arid, Semi-Arid and Sub-Humid Zones.

	(1)			(2)			(3)			(4)			(5)		
	b		se	b		se	b		se	b		se	b		se
CE adm2 dry	0.147	***	(0.03)	0.133	***	(0.03)	0.131	***	(0.03)	0.165	***	(0.03)	0.199	***	(0.03)
CE country dry	0.224	***	(0.05)	0.224	***	(0.05)	0.227	***	(0.05)	0.209	***	(0.05)	0.180	***	(0.05)
Share adm2 area wet	-0.002		(0.01)	-0.002		(0.01)	-0.001		(0.01)	-0.002		(0.01)	-0.002		(0.01)
CE country wet	-0.359	***	(0.04)	-0.358	***	(0.04)	-0.358	***	(0.04)	-0.361	***	(0.04)	-0.359	***	(0.04)
CE neighboring countries dry	0.404	***	(0.10)	0.406	***	(0.10)	0.399	***	(0.10)	0.406	***	(0.10)	0.367	***	(0.10)
CE neighboring countries wet	-0.269	**	(0.10)	-0.270	**	(0.10)	-0.272	**	(0.10)	-0.254	**	(0.10)	-0.278	**	(0.09)
Log tc 50-100k				0.171	***	(0.02)									
CE adm2 dry × Log tc 50-100k				-0.030		(0.04)									
Log tc 100-200k							0.210	***	(0.02)						
CE adm2 dry × Log tc 100-200k							-0.043		(0.04)						
Log tc 200-500k										0.259	***	(0.02)			
CE adm2 dry × Log tc 200-500k										0.142	*	(0.06)			
Log tc > 500k													0.209	***	(0.02)
CE adm2 dry × Log tc > 500k													0.338	***	(0.04)
N	14629			14629			14629			14629			14629		
R-squared	0.782			0.782			0.782			0.783			0.785		

Second administrative unit (Adm2), Product, and Year-Month fixed effects included. Robust standard errors are reported.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

S6.4 Supplementary Tables

Table S3: 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 the consideration of uncertainty in agricultural yields.

	Temporal scale			
Spatial scale (resolution — extent)	static (deterministic)	static (uncertain)	dynamic (deterministic)	dynamic (uncertain)
One market				
(national — single country)	Dorosh, Dradri, et al. 2009 Dorosh, Rashid, et al. 2016 Haggblade et al. 2017			
Two markets				
(national — two countries)				Williams and Wright 1991 Gouel and Jean 2015 Gouel, Gautam, et al. 2016
(subnational — single country)				Coleman 2009
Multiple markets				
(subnational — single country)	Burgess and Donaldson 2017 Sotelo 2020	Allen and Atkin 2022		*This paper*
(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 et al. 2023		Stevanović et al. 2016 Janssens et al. 2020	
(subnational — multiple countries)			Porteous 2019	

Table S4: The effect of climate extremes (severe versus extreme dry conditions) and market access on food insecurity (Arid, Semi-Arid and Sub-Humid areas)

	Food Insecurity (yes = 1, no = 0)		
	b		se
CE adm2 severe dry	-0.094		(0.07)
CE country severe dry	-0.713	***	(0.15)
CE adm2 severe dry × CE country severe dry	3.973	***	(0.59)
CE adm2 extreme dry	0.169	***	(0.02)
CE country extreme dry	0.511	***	(0.07)
CE adm2 extreme dry × CE country extreme dry	0.255		(0.17)
CE adm2 severe dry × Log tp	-0.564	**	(0.22)
CE country severe dry × Log tp	1.129	***	(0.20)
CE adm2 severe dry × CE country severe dry × Log tp	8.578	***	(1.92)
CE adm2 extreme dry × Log tp	0.358	***	(0.06)
CE country extreme dry × Log tp	-0.268	**	(0.10)
CE adm2 extreme dry × CE country extreme dry × Log tp	-0.942	*	(0.41)
CE adm2 severe dry × Log tc	0.483	***	(0.13)
CE country severe dry × Log tc	-0.100		(0.16)
CE adm2 severe dry × CE country severe dry × Log tc	-4.089	***	(1.15)
CE adm2 extreme dry × Log tc	0.044		(0.04)
CE country extreme dry × Log tc	-0.001		(0.08)
CE adm2 extreme dry × CE country extreme dry × Log tc	-0.086		(0.27)
N	31552		
R-sqr	0.299		

Admin2 and Year-Month fixed effects included. Standard errors clustered at panelid. The variables tc (Log travel time to city) and tp (Log travel time to port) are centered at country mean. The same control variables as in the main regression are included.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table S5: The effect of climate extremes and market access (varying city definition) on food insecurity

	(1) city 100k-200k		(2) city 50-100k		(3) city 50-100k		(4) city 200-500k		(5) city 200-500k	
	b	se	b	se	b	se	b	se	b	se
CE adm2 dry	0.156***	(0.02)	0.155***	(0.02)	0.151***	(0.02)	0.151***	(0.02)	0.148***	(0.02)
CE country dry	0.152***	(0.03)	0.150***	(0.03)	0.154***	(0.03)	0.153***	(0.03)	0.156***	(0.03)
CE adm2 dry × CE country dry	0.271**	(0.10)	0.092	(0.09)	0.301**	(0.10)	0.104	(0.09)	0.298**	(0.10)
CE adm2 dry × Log tp	0.198**	(0.06)			0.204***	(0.06)			0.238***	(0.06)
CE country dry × Log tp	0.129*	(0.05)			0.131*	(0.05)			0.144*	(0.06)
CE adm2 dry × CE country dry × Log tp	-0.040	(0.22)			0.044	(0.22)			-0.065	(0.23)
CE adm2 dry × Log tc	0.102**	(0.03)								
CE country dry × Log tc	-0.025	(0.04)								
CE adm2 dry × CE country dry × Log tc	-0.131	(0.14)								
CE adm2 dry × Log tc			0.129***	(0.03)	0.085**	(0.03)				
CE country dry × Log tc			0.006	(0.04)	-0.027	(0.04)				
CE adm2 dry × CE country dry × Log tc			-0.281*	(0.14)	-0.250	(0.14)				
CE adm2 dry × Log tc							0.082**	(0.03)	0.030	(0.03)
CE country dry × Log tc							-0.011	(0.04)	-0.049	(0.04)
CE adm2 dry × CE country dry × Log tc							-0.162	(0.10)	-0.072	(0.11)
Control variables	Yes		Yes		Yes		Yes		Yes	
Admin2 and country wet CE	Yes		Yes		Yes		Yes		Yes	
Neighboring countries' CE	Yes		Yes		Yes		Yes		Yes	
Second administrative unit FE	Yes		Yes		Yes		Yes		Yes	
Year-month FE	Yes		Yes		Yes		Yes		Yes	
Additional controls	31552		31552		31552		31552		31552	
N	0.296		0.293		0.295		0.292		0.296	

Standard errors in parentheses are clustered at panelid. The variables tc (Log travel time to city, of 100 – 100k inhabitants, 50 – 100k inhabitants, or 200 – 500k inhabitants) and tp (Log travel time to port) are centered at country mean. The same control variables as the main regression are included.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table S6: The effect of climate extremes and market access on alternative definition of food insecurity.

	FS high (1 = yes, 0 = no)		
	b		se
CE adm2 dry	0.098	***	(0.02)
CE country dry	0.222	***	(0.02)
CE adm2 dry × CE country dry	-0.116		(0.08)
CE adm2 dry × Log tp	-0.094		(0.06)
CE country dry × Log tp	0.105	**	(0.03)
CE adm2 dry × CE country dry × Log tp	-0.081		(0.20)
CE adm2 dry × Log tc	0.032		(0.03)
CE country dry × Log tc	0.081	***	(0.02)
CE adm2 dry × CE country dry × Log tc	-0.185		(0.12)
Control variables	Yes		
Admin2 and country wet CE	Yes		
Neighboring countries' CE	Yes		
Second administrative unit FE	Yes		
Year-month FE	Yes		
N	24275		
R-squared	0.166		

Standard errors in parentheses are clustered at panelid. The variables tc (Log travel time to city) and tp (Log travel time to port) are centered at country mean. The default control variables are conflict intensity, GDP pc, population density, and agricultural employment. Additional controls are conflict intensity x travel times, conflict intensity x climate extremes, agricultural employment x climate extremes.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table S7: The effect of climate extremes and market access on alternative definition of food insecurity.

	FS low (1 = yes, 0 = no)		
	b		se
CE adm2 dry	0.122	***	(0.02)
CE country dry	0.066	*	(0.03)
CE adm2 dry × CE country dry	0.394	***	(0.10)
CE adm2 dry × Log tp	0.291	***	(0.05)
CE country dry × Log tp	0.095	*	(0.05)
CE adm2 dry × CE country dry × Log tp	0.127		(0.19)
CE adm2 dry × Log tc	0.094	**	(0.03)
CE country dry × Log tc	-0.051		(0.04)
CE adm2 dry × CE country dry × Log tc	-0.106		(0.14)
Control variables	Yes		
Admin2 and country wet CE	Yes		
Neighboring countries' CE	Yes		
Second administrative unit FE	Yes		
Year-month FE	Yes		
N	29478		
R-squared	0.317		

Standard errors in parentheses are clustered at panelid. The variables tc (Log travel time to city) and tp (Log travel time to port) are centered at country mean. The default control variables are conflict intensity, GDP pc, population density, and agricultural employment. Additional controls are conflict intensity x travel times, conflict intensity x climate extremes, agricultural employment x climate extremes.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

S6.5 Supplementary Figures

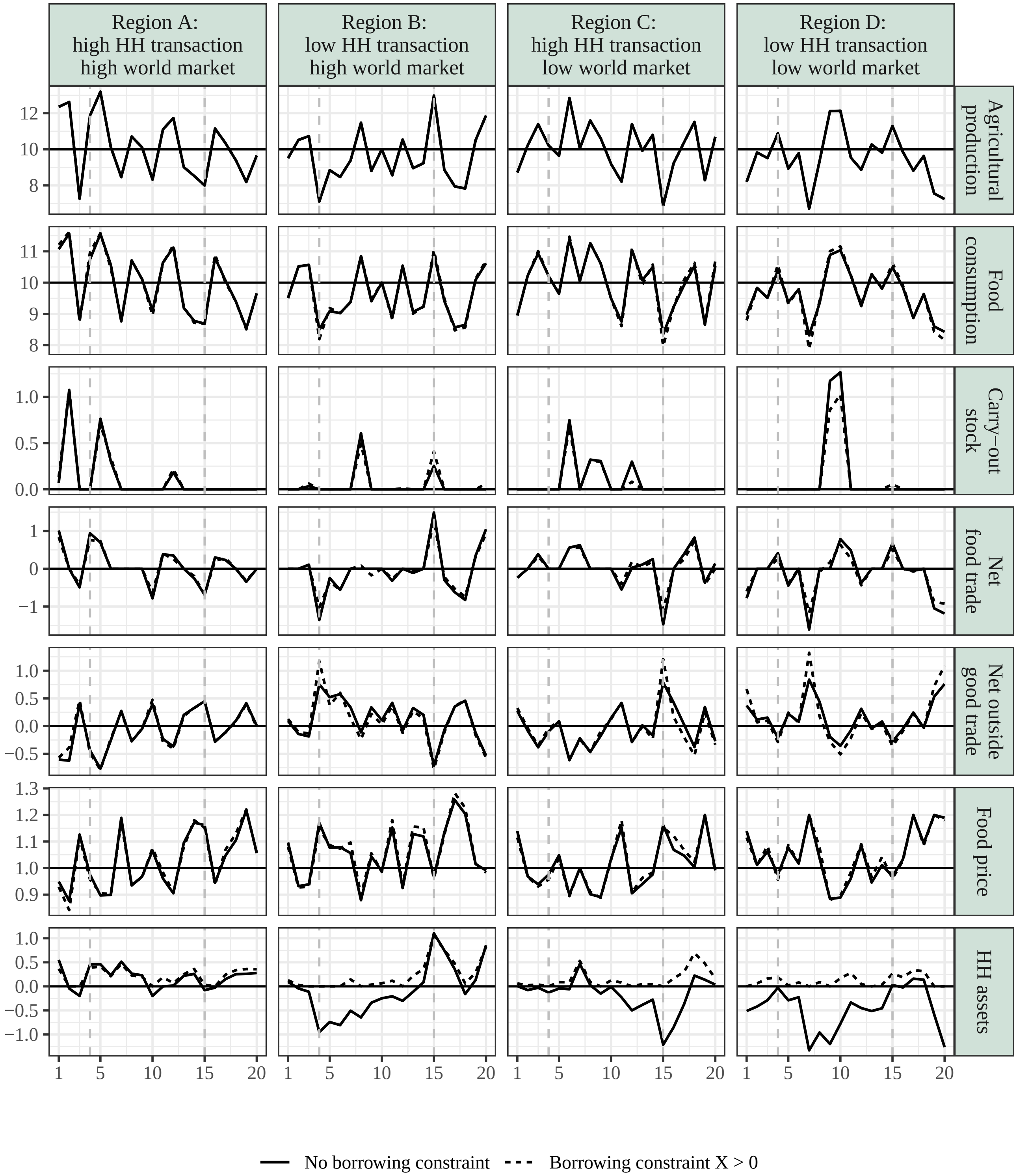

Figure S2: Simulation results under idiosyncratic agricultural production shock for 20 time periods with and withut borrowing constraints.

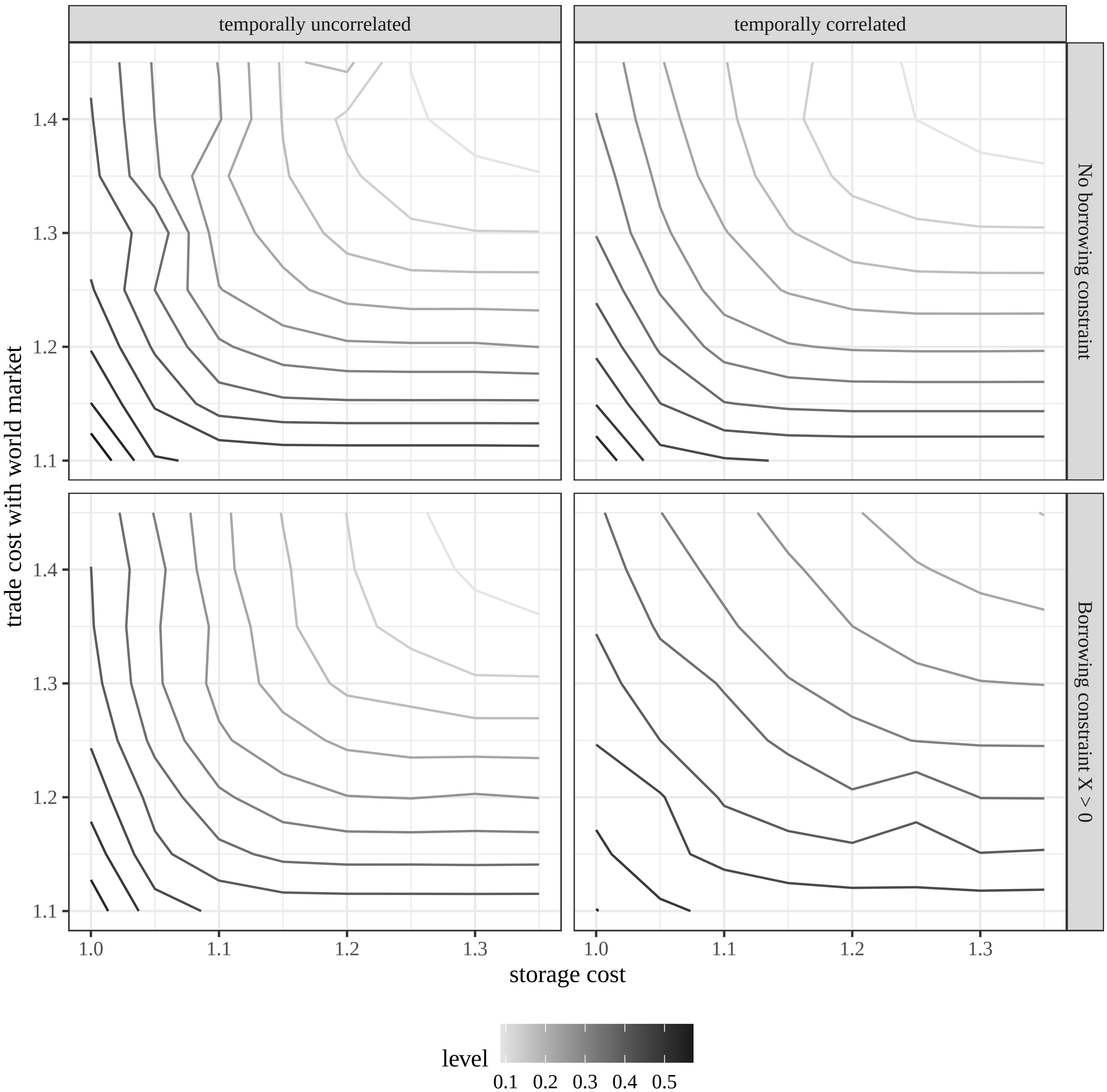

Figure S3: Food consumption smoothing ratio (smoothing ratio $= 1 - CV_{\text{consumption}}/CV_{\text{production}}$) under covariate agricultural production shocks for different values of storage costs and trade costs with the world market. The smoothing ratio is calculated based on a simulation of 50 time periods for the default set-up and for borrowing constraints. For temporal correlation, the simulation is done for 100 periods where each shock persists for two periods.