Climate Shocks and Conflicts Related to GMO Approval

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Abstract

Among the threats to agricultural production and food security, this study focuses on climate shocks and social disputes over genetically modified organisms (GMOs). Although GMO cultivation is considered an effective strategy to mitigate the adverse effect of climate shocks on agricultural production, regulation of GMOs remains a controversial topic worldwide. This study investigates the countervailing effects of protectionist policies on the relationship between climate shocks and GMO approvals. We develop a structural model that accounts for equilibrium consumption and production at the country level; the model predicts that climate shocks decrease GMO approval events in countries with comparative disadvantages in producing GMO crops (relative to other countries). In the empirical analysis, we use the local projection method to trace the cumulative effects of climate shocks. The results show that an increase in climate shocks significantly decreases GMO approvals in the next 2 years. The cumulative adverse effect is significant for up to 6 years post-shock. The moderating effect confirms that the negative impact on GMO approvals may be more prominent among countries with comparative disadvantages in producing GMOs. Our study implies that global conflicts around GMO approval may be augmented by increasingly frequent climate shocks, which is likely to raise food security concerns.

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1. Introduction

Climate shocks raise agricultural prices and expose people to hunger risks. A strand of the literature suggests a causal link between climate shocks and crop yield. For example, without adaptation, climate change lowers wheat yields in North America by 1.0–10.0% per degree of warming (Zhang et al. 2022). To mitigate the adverse effects of weather, genetically modified organism (GMO) technology, which has been expanding since 1996, facilitates the development of climate-resilient cultivars; it has become an important mechanism for adapting to climate shocks (Janssens et al. 2020; Nelson et al. 2014; Taranto et al. 2018; Zhang et al. 2022). In 2019, the global commercial cultivation of GMO crops reached 190.4 million hectares across 29 countries, boosting the livelihoods of 17 million biotech farmers and their families (James 2019; Stein and Rodríguez-Cerezo 2010a). Although GMO crops are considered a mitigation strategy for climate shocks, this study has an inverse conclusion, that is, countries with less comparative advantage in crop production are more inclined to use restrictive GMO adaptive policies as a measure to counter the comparative advantage of countries in GMO crop production.

Indeed, the disputes about GMO technology are becoming more severe and affecting more product fields (Faria et al. 2014). European countries adopt more restrictive GMO regulations, whereas the United States has a more permissive attitude. Acting as first movers, Europe and the United States create historical benchmarks for follower countries seeking to develop legislation relating to the cultivation and commercialization of GMO crops. Nonetheless, GMO crops and related legislation remain a controversial topic. GMO disputes pose a dilemma to follower countries, who are obliged to seek guidance on servicing trading partners with diverse GMO policies (Smith and Katovich 2017). In addition, GMO disputes disrupt global supply chains (Mitchell 2007; Stein and Rodríguez-Cerezo 2010b; Vermij 2006; Wang and Johnston 2007). Therefore, double exposure to both rapidly increasing climate shocks and volatile social disputes over GMOs threaten to worsen the global food deficit (Brown et al. 2017).

To date, the literature has rarely examined the link between GMO policies and climate shocks. Although GMO technologies mitigate yield shocks, they are rarely approved by countries in response to disaster damage. Related literature shows that the acceptance of GMOs reflects the interests of various groups (i.e., decision-makers, traders, and producers), health concerns, and intellectual patent protections; clashes between these interest groups result in global controversies over GMO commercialization (Fulton and Giannakas 2004; Gruère et al. 2009; Lusk et al. 2006; Rosa et al. 2020; Smith et al. 2018; Swinnen and Vandemoortele 2011; Vigani and Olper 2015). This study investigates the extent to which countries adopt GMO technology against the background of global GMO disputes and increasingly frequent climate shocks.

This paper contributes to the GMO dispute literature. A strand of this literature finds that countries use restrictive GMO regulation as a protectionist measure to counterbalance their comparative disadvantages in GMO production and trigger synchronization of GMO regulations with their importing countries (Curtis et al. 2008; Gruère et al. 2009; Janssens et al. 2020; Rosa et al. 2020; Vigani and Olper 2013). Conte et al. (2021) propose that climate shocks diminish a country's comparative advantage internationally; the affected country adapts to the shocks by switching to other sectors and counterbalancing its comparative disadvantages. However, although there is extensive research on global GMO adoption, few studies connect climate shocks and GMO disputes. Accordingly, we posit that climate shocks affect GMO adoption through their detrimental impact on the comparative advantages of GMO technology development.

This study first develops a structural model that accounts for equilibrium consumption and production at the country level. On the consumption side, using a constant elasticity-of-substitution (CES) utility function, we model each country's consumption of domestic and foreign varieties with different levels of GMO content. On the supply side, overall production is calculated in the context of climatic conditions, accounting for determinants of labor, capital, and technology affected by GMO adoption. At market clearance, we derive equilibrium domestic consumption and net exports to all trading partners. The theoretical model suggests that a country's GMO approvals depend on its comparative advantage in trade, which is impacted by extreme climate shocks. We predict increasing (decreasing) climate shocks correspond with declining (inclining) GMO approvals that confer comparative disadvantages (advantages) in exporting GMO crops internationally.

Secondly, we empirically test whether countries adopt new GMO technologies in response to climate shocks. GMO approval data is collected from the International Service for the Acquisition of Agri-biotech Applications (ISAAA) at the country and industry levels. Climate shock data are obtained from the International Disaster Database (EM-DAT), which provides the number of drought, heat wave, cold wave, and flood events from 2000 to 2018. Using the local projection method, we conjecture that countries experiencing exogenous climate shocks decrease GMO approvals; new GMO approvals decrease more significantly in countries with stronger comparative disadvantages in exporting such commodities. We also focus on regulation relating to different uses of GMOs. Specifically, regulatory stringency may differ according to whether it refers to GMO cultivation and commercialization vs. GMO use in food and feed. Approval of regulation relating to domestic cultivation might relate to domestic consumption and exporting, whereas regulatory approval relating to use for food and feed but not cultivation might be used for importing (Faria and Wieck 2014; Kalaitzandonakes 2011). We find that one year after a climate shock occurs, countries with comparative advantages in GMO-related commodities are more likely to show new GMO approvals relating to food and feed use, whereas countries with comparative disadvantages are more stringent in GMO events even 3 years after severe winter, extreme temperature, or storms occur. Our results imply that if a country's comparative advantage in trade is more vulnerable to exogenous disasters, it is more likely to decrease GMO adoption as a protectionist policy in global markets. The finding that protectionist trade policy has a countervailing effect on the relationship between climate shocks and GMO approvals has the potential to inform related policymaking.

2. Model

2.1 Consumption

Following Do et al. (2015), we consider a CES utility function over GMO and non-GMO sectors. Consumers in country j maximize

$$U_j = C_j^0 + (C_j^s)^\tau (C_j^{-s})^{1-\tau} \tag{1}$$

where C_j^s aggregates domestic GMO commodity demand and C_j^{-s} denotes non-GMO commodity demand. We assume consumption relating to GMO ($l = s$) and non-GMO ($l = -s$) sectors is substitutable. The consumption quantity of sector l (i.e., $l \in s, -s$) is subject to a budget constraint

$$s.t. \sum_l p_j^l C_j^l = I_j \tag{2}$$

where I_j is the nominal consumption income of country j. We assume p_j^l denotes the factory-gate price of sector l in country j's market. The utility maximization problem solves that

$$C_j^s = \tau \frac{I_j}{p_j^s}; C_j^{-s} = (1-\tau)\frac{I_j}{p_j^{-s}}. \tag{3}$$

2.2 Production and climate shocks

On the supply side, country i's profit function is shown as

$$\pi_i^l = p_i^l n_i^l A_i^l {K_i^l}^{\alpha} {L_i^l}^{1-\alpha} - r_i K_i^l - w_i L_i^l \tag{4}$$

where A_i^l denotes total factor productivity (TFP) in sector l, and $n_i^l(\omega_i)$ denotes the quantitative exercise of productivity affected by climate shocks ω_i, such that $\frac{\partial n_i^l A_i^l}{\partial w_i} < 0$. We assume that country i's endowment of capital can move between GMO and non-GMO sectors such that the market clearing condition for labor is $\overline{K_i^s} + \overline{K_i^{-s}} = 1$ and relative capital between GMO and non-GMO sectors is $\theta_i = K_i^s / K_i^{-s}$; accordingly, $K_i^s = \frac{\theta_i}{1+\theta_i}$. We also assume that country i's labor in both sectors is $\overline{L_i^s} = \overline{L_i^{-s}} = 1$. Following Do et al. (2015), we normalize

$$(p_i^s)^{\eta}(p_i^{-s})^{1-\eta} = 1. \tag{5}$$

The first order condition of π_i^l with respect to K_i^l yields that $\frac{r_i}{p_i^l} = n_j^l A_i^l \alpha (\frac{L_i^l}{K_i^l})^{1-\alpha}$, where p_i^l is the aggregate price of sector l in country i. The relative prices of two sectors is $\frac{p_i^s}{p_i^{-s}} =$

$\frac{n_j^{-s} A_i^{-s} \alpha (\frac{L_i^{-s}}{K_i^{-s}})^{1-\alpha}}{n_j^s A_i^s \alpha (\frac{L_i^s}{K_i^s})^{1-\alpha}} = \frac{n_j^{-s}}{n_j^s} \frac{A_i^{-s}}{A_i^s} (\theta_i)^{1-\alpha}$. Given $(p_i^s)^{\eta}(p_i^{-s})^{1-\eta} = 1$, prices are equal to

$$\begin{cases} p_i^s = (\frac{n_i^{-s}}{n_i^s}\frac{A_i^{-s}}{A_i^s})^{1-\eta}(\theta_i)^{(1-\alpha)(1-\eta)} \\ p_i^{-s} = \left(\frac{n_i^{-s}}{n_i^s}\frac{A_i^{-s}}{A_i^s}\right)^{-\eta}(\theta_i)^{-(1-\alpha)\eta} \end{cases} \quad (6)$$

which yields the return to capital

$$r_i = n_i^s A_i^s \alpha (\frac{1+\theta_i}{\theta_i})^{1-\alpha} (\frac{n_i^{-s}}{n_i^s}\frac{A_i^{-s}}{A_i^s})^{1-\eta}(\theta_i)^{(1-\alpha)(1-\eta)}. \quad (7)$$

Similarly, the first order condition of π_i^l with respect to L_i^l yields $\frac{w_i}{p_i^l} = n_i^l A_i^l (1-\alpha)(\frac{K_i^l}{L_i^l})^{\alpha}$. The relative prices of two sectors is $\frac{p_i^s}{p_i^{-s}} = \frac{n_i^{-s}A_i^{-s}(\frac{K_i^{-s}}{L_i^{-s}})^{\alpha}}{n_i^s A_i^s (\frac{K_i^s}{L_i^s})^{\alpha}} = \frac{n_i^{-s}A_i^{-s}}{n_i^s A_i^s}(\frac{1}{\theta_i})^{\alpha}$. Labor wage is

$$w_i = n_i^s A_i^s (1-\alpha)\left(\frac{\theta_i}{1+\theta_i}\right)^{\alpha}\left(\frac{n_i^{-s}A_i^{-s}}{n_i^s A_i^s}\right)^{1-\eta}\left(\frac{1}{\theta_i}\right)^{\alpha(1-\eta)}. \quad (8)$$

2.3 Market clearance

For market clearance, the total expenditure of sector l in both countries is equal to the total income derived from labor wages and capital returns in both countries. Thus, market clearance also implies that

$$\sum_i [p_i^S A_i^S {K_i^S}^{\alpha} {L_i^S}^{1-\alpha}] = \tau[\sum_i (r_i K_i^s + w_i)]. \quad (9)$$

We define country i's technological or Ricardian comparative advantage in non-GMO commodities as $\gamma_i = \frac{n_i^{-s}A_i^{-s}/n_i^s A_i^s}{n_j^{-s}A_j^{-s}/n_j^s A_j^s}$. Considering a two-country model, based on Eqs. (6), (7), and (8), the market clearing condition can be rewritten as

$$\frac{n_i^s A_i^s}{n_j^s A_j^s}(\gamma_i)^{1-\eta}(\theta_i)^{(1-\alpha)(1-\eta)}(\frac{\theta_i}{1+\theta_i})^{\alpha} + (\theta_j)^{(1-\alpha)(1-\eta)}(\frac{\theta_j}{1+\theta_j})^{\alpha} =$$

$$\tau_i[\left(\alpha\left(\frac{1+\theta_i}{\theta_i}\right)^{-\alpha}\frac{n_i^s A_i^s}{n_j^s A_j^s}(\gamma_i)^{1-\eta}(\theta_i)^{(1-\alpha)(1-\eta)} + (1-\alpha)\left(\frac{\theta_i}{1+\theta_i}\right)^{\alpha}\frac{n_i^s A_i^s}{n_j^s A_j^s}(\gamma_i)^{1-\eta}\left(\frac{1}{\theta_i}\right)^{\alpha(1-\eta)}\right] +$$

$$\tau_j[(\alpha\left(\frac{1+\theta_j}{\theta_j}\right)^{-\alpha}(\theta_j)^{(1-\alpha)(1-\eta)} + (1-\alpha)\left(\frac{\theta_j}{1+\theta_j}\right)^{\alpha}\left(\frac{1}{\theta_j}\right)^{\alpha(1-\eta)}] \quad (10)$$

Proposition 1: Holding the productivity of other countries constant (i.e., $n_j^{-s}A_j^{-s}$ and $n_j^s A_j^s$ are unchanged), if the productivity of non-GMO commodities is more vulnerable to climate shocks ($\frac{\partial n_i^{-s}A_i^{-s}}{\partial w_i} < \frac{\partial n_i^s A_i^s}{\partial w_i} < 0$), country i's comparative advantage in producing non-GMO commodities is negatively affected by climate shocks, $\frac{\partial \gamma_i}{\partial w_i} < 0$. In addition, decreasing comparative advantage in the non-GMO sector increases country i's GMO-intensive capital and reduces capital in the non-GMO sector, i.e., $\frac{\partial K_i^s}{\partial \gamma_i} < 0$.

Proof of Proposition 1. We simulate the relationship between the comparative advantage of country i in the non-GMO sector γ_i and the allocation of GMO-intensive capital $K_i^s = \frac{\theta_i}{1+\theta_i}$ by defining the exogenous model parameters as pre-determined values $\{\alpha = \eta = 0.5, \tau_i = \tau_j = 0.4, \theta_j = 10\}$. Normalizing the relative TFP in GMO sector $\frac{n_i^s A_i^s}{n_j^s A_j^s} = 1$, we depict the relationship between γ_i and K_i^s in Figure 1. We find that if country i's comparative advantage in the non-GMO sector is significantly damaged by climate shocks, it will increase the allocation of GMO-intensive capital and decrease capital allocation in the non-GMO sector. In Figure 2, we also depict the excessive output value of GMO commodities with varying γ_i and K_i^s. We find that given a constant comparative advantage in the non-GMO sector, increasing the country's capital allocation in the GMO sector yields excessive production of GMO commodities. Furthermore, since increasing comparative advantage in GMOs results from greater adoption of GMO technology, such countries are more prone to producing GMO commodities. The intuitive explanation is that a country with low comparative advantages in the non-GMO sector is more likely to adopt GMO technologies to remain competitive in the global market and mitigate the countervailing effects of climate shocks. This conclusion is consistent with previous literature showing that countries adapt to shocks by switching to other sectors (Conte et al. 2021).

3. Data

Climatic disaster data is collected from The International Disaster Database (EM-DAT). For a disaster to be entered into the database at least one of the following criteria must be fulfilled: ten or more people reported killed, one hundred or more people reported affected, declaration of a state of emergency, or call for international assistance (Brás et al. 2019). The dataset has been widely used in previous studies on natural disasters (Borensztein et al. 2017; El Hadri et al. 2019; Khurana et al. 2022; Permani and Xu 2022). Disaster types include geophysical, meteorological, hydrological, climatological, biological, and extra-terrestrial. In this study, we consider climate shocks, i.e., droughts, heat waves, cold waves, severe winter conditions, extreme temperatures, and storms. In addition, we create a weighted disaster number, using the inverse of the standard deviation of a disaster type within a country's overall years as a precision weight, teasing out the impacts by which one single disaster component may dominate the movement of the disaster number.

Since GMO and non-GMO crops cannot be distinguished in the dataset, we consider industries that have the largest shares of GMO content, i.e., cotton, maize, soybeans, and rapeseed. GMO approval data is collected from the ISAAA, which contains all GMO events at the commodity and country levels for each year. In addition, GMO events are differentiated by their intended application purpose (for feed and food vs. for cultivation). Note that, for the same new GMO event, countries may have different approval timings for commercial use as feed and food or for cultivation, which results in multiple counts in different years. We handle this by using the first time that an event is approved for any commercial use.

Based on Anderson and van Wincoop (2003, 2004) and Bergstrand and Egger (2013), we calculate the revealed comparative advantage (RCA) index by collecting data from the United Nations (UN) Comtrade, which consists of the value of bilateral exports at the commodity and country levels in current (rather than constant) dollars. We define products according to the SITC Revision 3 aggregates: soybeans (2222), maize (044), cotton seeds (2223), and rape or colza seeds (22261).

The control variables include agricultural share, arable land per capita, GMO area, infrastructure conditions, an international agreement indicator, infrastructure conditions, a developing country dummy, and an EU country dummy. Data on agricultural share and arable land per capita are collected from World Bank Open Data. Annual biotech acreage in million hectares is obtained from James (2019). The infrastructure score is generated by the Notre Dame Global Adaptation Index (ND-GAIN), which measures indicators such as projected change in hydropower generation capacity, dependence on imported energy, electricity access, and disaster preparedness. The international agreement indicator, collected from Vigani et al. (2010, 2012), measures whether a country subscribes to the two GMO-specific international agreements, i.e., Codex Alimentarius and the Cartagena Protocol on Biosafety. The UPOV indicator measured by

Campi and Nuvolari (2015) measures country adherence to revisions of the International Convention for the Protection of New Varieties of Plants (UPOV). Table 1 reports the descriptive statistics for all estimated variables.

4. Empirical Results

Before considering the countervailing effects of protectionist policies on the link between climate shocks and GMO approvals, we need to identify the adverse yield effects from climate shocks; this is fundamental for the following analysis. The assumption is tested based on the following linear estimation model:

$$yield_{ijt} = \sum_{s=0,\dots,3} \varphi_s \, event_{i(t-s)} + \gamma\sigma_{it} + \delta_{ij} + \theta_t + \varepsilon_{it} \tag{11}$$

$yield_{ijt}$ indicates country i's production in hectogram per hectare (Hg/Ha) of crop j in year t, which is measured in logarithm form. $Event_i$ denotes the number of climate shocks in country i and includes up to s year lags. We use both yearly disaster numbers and weighted disaster numbers, following Felbermayr and Gröschl (2014). σ_{it} is a vector of controls relating to the country's characteristics in the production of GMO crops (i.e., agricultural share, arable land, UPOV agreement indicator, an international agreement indicator, infrastructure conditions, a developing country dummy, and an EU country dummy), which are exogenous variables. δ_{ij} and θ_t denote country-commodity and time fixed effects, controlling for unobserved country and commodity-specific characteristics and time trends.

Table 2 reports the OLS estimates of the impact of climate shocks on crop yields. Columns (1) and (2) report the impact of all climate shocks on crop yields without and with controls, respectively. We find that by controlling the exogenous variables, climate shocks have a contemporaneous negative impact on crop yields. Columns (1) and (2) use yearly disaster numbers, and column (3) uses weighted disaster numbers. The results are consistent with existing studies finding that climate shocks decrease crop yield (Janssens et al. 2020; Nelson et al. 2014; Taranto et al. 2018; Zhang et al. 2022). In column (3), after teasing out one single disaster component which dominates the movement of the disaster number, we find that climate shocks occurring in the current year and one year before are negatively associated with crop yield. Columns (4)-(9) differentiate natural disaster types. A cold wave in the previous year decreases crop yield, and heat waves, droughts, and extreme temperatures occurring within the previous two years also have adverse effects on crop yield, when country-commodity and time-fixed effects are controlled.

4.1 Baseline: Average impacts of climate shocks on GMO approvals

Following Acevedo et al. (2020), Jordà and Taylor (2013), and Wilson (2021), we now use the local projection method to estimate the long-term impacts of climate shocks on GMO policy adoption events. This method is favored because it estimates the coefficients of vector autoregressions and thus accounts for the impulse response of new GMO adoption events. That is, the dynamic multiplier of GMO adoptions with respect to a change in climate shocks can be estimated, keeping all other variables constant. Olea et al. (2021) propose that lag-augmented local projections handle issues of highly persistent data and a wide range of response horizons, making them more robust than standard autoregressive inference.

We use direct linear regressions of future GMO approvals on current covariates, i.e., climate shocks. The derived impulse response is estimated as the following model:

$$\Delta_h Ap_{ij,t+h} = \beta_1^h \Delta S_{i,t} + \sum_r \beta_2^r \Delta_r S_{i,t-r} + \beta_3^h (\Delta Ap_{ij,t-1}) + \beta_4^h \sigma_{i,t} + \delta_{ij}^h + \theta_t^h + \varepsilon_{i,t}^h \quad (12)$$

where $\Delta S_{i,t}$ denotes the changes (or "shocks") to country i's GMO approvals between year $t-1$ and year t, which is our main variable of interest. The dependent variable is $\Delta_h Ap_{ij,t+h} = Ap_{ij,t+h} - Ap_{ij,t-1}$ which denotes the cumulative change in the number of GMO approvals between horizons $t-1$ and $t+h$. Horizon h is the estimation time period, ranging from horizon 0 to horizon 6, which therefore captures the contemporaneous and cumulative effects up to 6 years after the shock. $\Delta_r S_{i,t-r}$ controls the change of climate shock on r lags (i.e., between horizons $t-r$ and $t-r-1$). Based on the Akaike information criterion, we first use a univariate autoregression to select the optimal r lags and then select the optimal horizon h by projecting h period ahead on r lags. $\Delta Ap_{ij,t-1}$ measures the change in approval of new GMO events in $t-1$, which controls for one lag of the change of the dependent variable. $\sigma_{i,t}$ controls for other potential covariates, i.e., agricultural share, arable land per capita, infrastructure condition, the international agreement indicator, the developing country dummy, and the EU member dummy. For example, a lagged infrastructure index ahead of the shock is used to control for countries' heterogeneous adaptative capacity to shocks; countries with less agile physical infrastructure and lower human capital, TFP, and R&D are less likely to use GMO technology as an adaptive measure (Chen et al., 2021; Okolo and Wen, 2022).

The country-commodity fixed effect δ_{ij}^h absorbs all unobservable variables that vary across countries and commodities. For example, if the country primarily produces corn, and a flood damages rice crops, this may have little impact on the country's corn production. Costinot et al. (2014) show that rice yields are unchanged in the southern island, whereas wheat yields are more vulnerable; the situation is reversed in the northern island. The errors are clustered at the country level, which allows for arbitrary correlation across commodities within country years or across years within countries.

Short-term and cumulative effects on GMO approval

To show the short- and long-term effects of climate shocks on GMO approvals, we list both the contemporaneous and cumulative effects of climate shocks up to six lags in Table 3, conditioned on their lags of change and macroeconomic variables. The first column shows the estimated contemporaneous effects of one additional climate shock (i.e., at horizon 0). Columns (2)-(7) report the cumulative effects in the following years. The first row in Panel A shows that the cumulative adverse effect on GMO adoption due to climate shocks is significant for up to 4 years after the shock. For the robustness check, using the weighted disaster number as an alternative measure, we find that approval for new GMO events is decreasing in the immediate year of shocks. [1]

Panel B disaggregates disaster types, i.e., cold waves, severe winter conditions, heat waves, droughts, and storms, controlling for the country-commodity fixed effect. We find the impact of heat waves on GMO approvals is negligible, yet all other shocks affect GMO approvals in subsequent years. The contemporaneous effect and cumulative effect at the maximum horizon, 6 years after the shock, are most severe for severe winter condition shocks. The marginal effect of severe winter conditions is twice as large as the effect of drought and cold wave shocks. Figure 3 depicts the cumulative changes in GMO approvals for years 1–6 following climate shocks according to disaster types. Overall, we find that GMO approvals are affected differently by different disaster types.

[1] The poisson estimates of the impact of climate shocks on GMO approvals are summarized in Appendix Table A1.

For the robustness check, we control for time trends to account for global changes resulting from specific historical events, such as the 2008 Great Recession, and report the results in Panel C. Across all specifications, we find the impacts of severe winter conditions are still more long-lasting than the impacts of other climate risks.

4.2 Moderating effect

We now investigate the mechanisms behind the inverse relationship between climate shocks and GMO approvals. Existing literature empirically proposes that developing countries are more vulnerable to natural disasters because they experience higher physical exposure, rely heavily on agriculture, and have a lower adaptive capacity (Klomp 2016; Klomp and Hoogezand 2018). In this paper, our theoretical model suggests that countries with strong comparative advantages in developing GMO technologies behave rather permissively with regard to GMO crops; contrastingly, countries with comparative disadvantages in GMO technologies are more restrictive to protect domestic markets. This section extends this analysis by empirically revealing the moderating effect of comparative advantage in GMO technology.

Comparative advantage in a particular commodity is measured by RCA,[2] which compares a country's share of exports in a particular product to its share of exports in all products. A value greater than zero indicates that the country has a comparative advantage in that product. In contrast, a value smaller than zero indicates that the country is comparatively disadvantage in the

[2] RCA is calculated as $RCA_{ijt} = \log\frac{E_{ij}}{E_{it}} - \log\frac{E_{-i,j}}{E_{-i,t}}$. E_{ij} denotes the exports of country i in industry j. E_{it} is country i's total exports. $E_{-i,j}$ indicates all other countries' exports in industry j, and $E_{-i,t}$ denotes the other countries' total exports.

world. We divide our sample into comparatively advantaged and comparatively disadvantaged groups in terms of zero as a reference point.

Controlling the country-commodity fixed effect, we conjecture that compared with comparatively advantaged countries, approval for new GMO events among countries affected by climate shocks will more significantly decrease when they have stronger comparative disadvantages in producing GMO-related commodities (shown at the bottom of Table 4). From Panel A.1 in Table 4, using weighted climate shocks, we find that for comparatively advantaged countries, climate shocks decrease GMO approvals in the immediate year and 2 years after the shock. Contrastingly, for comparatively disadvantaged countries, climate shocks cumulatively reduce GMO approvals up to 2 years after the shock (Panel A.2 in Table 4). For comparatively advantaged countries, an increase in storm shocks even increases GMO approvals in the following year, whereas increases in cold waves or servere winter conditions adversely impact GMO approvals for 2 years after the shock (Panel B.1 in Table 4). For comparatively disadvantaged countries, the cumulative effects of cold waves, severe winter conditions, heat wave, and storms reduce GMO approvals up to the following 6, 6, 1, and 5 years, respectively (Panel B.2 in Table 4). In summary, climate shocks rarely affect GMO approvals among countries with comparative advantages, whereas GMO approvals are more restricted in countries without such comparative advantages. This relationship may primarily be because countries with comparative disadvantages in GMO-intensive commodities would use GMO disputes as a protection measure in the aftermath of a climate shock; more vulnerable countries would have stronger protectionist GMO policies (Klomp and Hoogezand 2018).

4.3 Robustness checks: GMO regulation purpose

As mentioned above, the stringency of GMO regulation differs in terms of GMO commercialization purposes, i.e., for cultivation vs. for food and feed. Approval relating to cultivation within a country's territory is likely to relate to domestic consumption and exporting purposes, whereas approval for commercial food and feed but not for cultivation is likely to relate to importing (Faria and Wieck 2014; Kalaitzandonakes 2011). As a robustness check, we substitute the dependent variable with GMO approval events for food and feed only and for cultivation only. Identifying GMO approval purposes helps us differentiate trade attitudes in two circumstances, i.e., domestic production and international imports.

Table 5 reports the local projection estimation of the cumulative impact of climate shocks moderated by countries' comparative advantage. Using weighted total shocks, Panel A.1 in Table 5 implies that 3 year after a climate shock occurs, countries with comparative advantages in GMO-related commodities are more likely to approve new GMO events relating to food and feed use, whereas countries with comparative disadvantages are more stringent in GMO events approved for food or feed up to 6 years after a shock. Overall, we find that the relationship between climate shocks and GMO approval events is more volatile when approvals relate to feed or food use compared to approval relating to cultivation. If a country's comparative advantage in the global market is low, its protectionist policy in trade plays a countervailing effect on the relationship between climate shocks and GMO approvals. This can potentially inform policymaking that exogeneous climate shocks trigger disputes around GMOs and increasing the threats to food security.

5. Conclusion

This study investigates the impact of climate shocks on GMO approval events. We find GMO approvals are negatively associated with climate shocks both theoretically and empirically. Incorporating countries' agricultural production in both GMO and non-GMO sectors, we first derive the GMO adoption decision at equilibrium based on the country-level CES utility function and production function. The theoretical model shows that national comparative advantage in producing non-GMO commodities is negatively affected by climate shocks; decreasing comparative advantage in the non-GMO sector increases the allocation of GMO-intensive capital and reduces capital in the non-GMO sector.

In the empirical analysis, we employ the local projection method to trace the cumulative effects of climate shocks. The results show the cumulative adverse effect of an increase in climate shocks is significantly negative for up to 6 years after the shock. Specifically, severe winter conditions have stronger adverse effects on GMO approvals in subsequent years. To investigate which mechanisms are responsible for the inverse relationship between climate shocks and GMO approvals, we generate an RCA measure and separate our sample into comparatively advantaged and disadvantaged groups. We find the impact of climate shocks on GMO disputes is more long-lasting for comparatively disadvantaged countries. Compared with countries with strong comparative advantages in GMO production, countries with comparative disadvantages are less likely to approve GMO regulations.

In addition, countries with comparative disadvantages in GMOs have more stringent attitudes towards GMO approvals related to food and feed purposes rather than cultivation purposes. The intuitive explanation is that a comparatively disadvantaged country is sensitive to climate shocks and thus decreases GMO approvals as a protectionist policy in international trade.

Our study implies that climate shocks (particularly severe winter conditions) may worsen global conflicts around GMO approval, potentially raising GMO disputes and food security concerns.

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Tables and Figures

Table 1. Descriptive statistics for all variables

	Obs	Mean	SD	Min	Max
Climate shocks	5168	1.61	2.95	0	23
Agricultural share	4892	7.41	8.84	0.03	57.14
Arable land (per capita)	5168	0.27	0.25	0	1.42
GMO area (million hectares)	5168	1.91	8.53	0	75
UPOV dummy	5168	0.69	0.46	0.00	1.00
Infrastructure	4608	0.35	0.1	0.14	0.64
International agreements	3420	0.9	0.2	0.5	1
Developing country dummy	5168	0.53	0.5	0	1
EU dummy	5168	0.4	0.49	0	1
Yield	3425	31900.95	25353.43	0	137419
RCA	3833	-3.01	3.86	-17.87	6.61
Cold wave	5168	0.12	0.37	0	3
Severe winter	5168	0.03	0.17	0	2
Heatwave	5168	0.09	0.29	0	3
Drought	5168	0.11	0.34	0	3
Extreme temperature	5168	0.23	0.51	0	3
Storm	5168	1.04	2.49	0	19

Table 2. OLS estimates for the impact of climate shocks on crop yield (hg/ha)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Total	Total	Total, weighted	Cold wave	Severe winter	Heatwave	Drought	Storm
Current year	-161.278	-269.326***	-263.316***	-355.995***	-354.769	865.356	-2504.655***	-116.538
	(288.527)	(99.992)	(83.821)	(74.960)	(391.369)	(551.233)	(613.695)	(79.373)
One-year lag	12.798	-36.781	50.200	-65.983	-47.410	-558.534	-904.715**	111.893
	(358.661)	(81.177)	(69.545)	(68.203)	(362.955)	(530.618)	(451.076)	(82.726)
Constant	32440.955***	28264.866***	-2074.685	1219.266	1182.753	-2643.682	-2659.179	-6326.611
	(2145.785)	(9459.174)	(9425.042)	(9499.931)	(8943.516)	(9324.046)	(9290.088)	(17195.616)
N	3247	3046	3046	3046	3046	3046	3046	3046
R2	0.000	0.938	0.939	0.940	0.939	0.939	0.940	0.939
Controls	N	Y	Y	Y	Y	Y	Y	Y
Time FE	N	N	Y	Y	Y	Y	Y	Y
Country-Commodity FE	N	Y	Y	Y	Y	Y	Y	Y

Note. Standard errors are in parentheses. FE = fixed effect. Controls include arable land (per capita), lagged agricultural share, UPOV dummy, lagged infrastructure index, international agreements on GMOs, a dummy for developing countries, a dummy for countries in the EU.

Table 3. Local projections of the cumulative change in GMO approvals relative to climate shocks (up to 6 years post-shock)

	Horizon 0	Horizon 1	Horizon 2	Horizon 3	Horizon 4	Horizon 5	Horizon 6	
Panel A:								
Total	-0.025	0.008	-0.026	0.040	-0.088**	-0.042	-0.068	
	(0.028)	(0.027)	(0.022)	(0.028)	(0.029)	(0.034)	(0.035)	Country-Commodity FE
Total_weighted	-0.064**	0.026	-0.087***	0.005	-0.020	0.022	-0.033	
	(0.019)	(0.024)	(0.026)	(0.030)	(0.037)	(0.034)	(0.029)	
Panel B:								
Cold wave	-0.058	0.046	-0.458***	0.201	0.025	0.018	-0.372**	
	(0.092)	(0.115)	(0.093)	(0.118)	(0.114)	(0.151)	(0.135)	
Severe Winter	-0.443**	-0.313	-0.294	-0.007	-0.434	0.069	-0.629**	
	(0.165)	(0.185)	(0.151)	(0.158)	(0.243)	(0.226)	(0.210)	
Heat Wave	-0.208	-0.081	0.164	-0.074	0.095	0.072	0.201	Country-Commodity FE
	(0.115)	(0.120)	(0.165)	(0.117)	(0.197)	(0.160)	(0.236)	
Drought	-0.050	0.167	-0.154	0.115	-0.088	0.002	-0.332*	
	(0.097)	(0.100)	(0.091)	(0.125)	(0.120)	(0.154)	(0.149)	
Storm	-0.005	-0.012	0.040	0.030	-0.099*	-0.093*	-0.050	
	(0.038)	(0.033)	(0.032)	(0.034)	(0.041)	(0.037)	(0.046)	

Panel C:								
Cold wave	-0.124	-0.057	-0.514***	0.197	0.021	0.095	-0.151	
	(0.100)	(0.111)	(0.115)	(0.118)	(0.099)	(0.160)	(0.164)	
Severe Winter	-0.307	-0.041	-0.209	0.206	-0.159	0.372	-0.576**	
	(0.179)	(0.188)	(0.142)	(0.153)	(0.231)	(0.192)	(0.197)	
Heat Wave	-0.167	-0.120	0.160	-0.089	0.051	-0.079	-0.043	Country-Commodity FE and Time Trends
	(0.120)	(0.125)	(0.178)	(0.122)	(0.189)	(0.205)	(0.246)	
Drought	-0.013	0.223	-0.106	0.243	0.041	0.242	-0.081	
	(0.106)	(0.118)	(0.099)	(0.138)	(0.115)	(0.141)	(0.182)	
Storm	0.004	-0.011	0.046	0.060	-0.044	-0.011	-0.043	
	(0.043)	(0.036)	(0.043)	(0.035)	(0.063)	(0.046)	(0.053)	
N	3328	3072	2816	2560	2304	2048	1792	

Note. Standard errors are in parentheses. FE = fixed effect. Controls include arable land (per capita), lagged agricultural share, UPOV dummy, lagged infrastructure index, international agreements on GMOs, a dummy for developing countries, a dummy for countries in the EU.

Table 4. Impact of climate shocks on GMO approvals: Moderating effect of comparative advantage in GMO production

	Comparatively advantaged countries						
	Horizon 0	Horizon 1	Horizon 2	Horizon 3	Horizon 4	Horizon 5	Horizon 6
Panel A.1							
Total	0.031	0.132**	0.001	0.028	-0.015	-0.058	-0.042
	(0.039)	(0.044)	(0.044)	(0.049)	(0.052)	(0.053)	(0.055)
R-squared	0.279	0.386	0.147	0.166	0.336	0.163	0.185
Total_weighted	-0.062*	0.023	-0.078*	-0.008	-0.031	0.067	0.064
	(0.024)	(0.035)	(0.035)	(0.037)	(0.037)	(0.045)	(0.042)
R-squared	0.282	0.383	0.156	0.174	0.339	0.162	0.184
Panel B.1							
Cold wave	-0.324**	0.254	-0.300*	0.186	0.098	0.130	0.023
	(0.119)	(0.205)	(0.150)	(0.152)	(0.155)	(0.221)	(0.206)
Severe Winter	-0.515**	-0.448	-0.795***	-0.394	-0.171	0.065	-0.357
	(0.177)	(0.332)	(0.225)	(0.254)	(0.485)	(0.333)	(0.343)
Heat Wave	0.304	-0.037	0.214	0.342	-0.163	0.463	0.772
	(0.213)	(0.215)	(0.265)	(0.273)	(0.296)	(0.252)	(0.437)
Drought	-0.028	0.051	-0.289	-0.045	-0.113	-0.020	-0.280
	(0.116)	(0.188)	(0.180)	(0.224)	(0.163)	(0.212)	(0.243)
Storm	0.046	0.147*	0.056	0.007	0.005	-0.050	-0.089
	(0.049)	(0.061)	(0.071)	(0.066)	(0.062)	(0.064)	(0.078)
R-squared	0.293	0.395	0.167	0.195	0.337	0.181	0.215
N	1374	1276	1179	1077	978	881	777
	Comparatively disadvantaged countries						
	Horizon 0	Horizon 1	Horizon 2	Horizon 3	Horizon 4	Horizon 5	Horizon 6
Panel A.2							
Total	-0.055	-0.039	-0.035	0.043	-0.130**	-0.031	-0.102
	(0.041)	(0.033)	(0.025)	(0.036)	(0.041)	(0.047)	(0.055)
	0.308	0.449	0.245	0.197	0.359	0.147	0.109
Total_weighted	-0.066*	0.028	-0.094*	0.012	-0.048	-0.008	-0.091*
	(0.029)	(0.035)	(0.037)	(0.045)	(0.048)	(0.052)	(0.043)
	0.307	0.448	0.243	0.201	0.361	0.162	0.127
Panel B.2							
Cold wave	0.059	-0.064	-0.537***	0.212	-0.102	-0.177	-0.509*
	(0.132)	(0.150)	(0.126)	(0.173)	(0.150)	(0.221)	(0.206)

Severe Winter	-0.426*	-0.353	-0.362	-0.321	-0.965*	0.600*	-0.978**
	(0.210)	(0.248)	(0.259)	(0.278)	(0.450)	(0.301)	(0.332)
Heat Wave	-0.436**	-0.153	0.071	-0.238	0.114	-0.086	-0.316
	(0.156)	(0.145)	(0.192)	(0.146)	(0.289)	(0.190)	(0.328)
Drought	0.020	0.290	-0.145	0.117	0.165	0.156	-0.208
	(0.186)	(0.152)	(0.150)	(0.215)	(0.248)	(0.258)	(0.279)
Storm	-0.035	-0.092*	0.021	0.032	-0.176**	-0.158**	-0.043
	(0.060)	(0.045)	(0.032)	(0.047)	(0.067)	(0.060)	(0.087)
	0.320	0.472	0.268	0.217	0.387	0.192	0.154
	1954	1796	1637	1483	1326	1167	1015

Note. Standard errors are in parentheses. All estimations use country-commodity fixed effect.

Table 5. Impact of climate shocks on GMO approvals according to commercialization purpose and comparative advantage in GMO

	Only food or feed													
	Comparatively advantaged							Comparatively disadvantaged						
	Horizon 0	Horizon 1	Horizon 2	Horizon 3	Horizon 4	Horizon 5	Horizon 6	Horizon 0	Horizon 1	Horizon 2	Horizon 3	Horizon 4	Horizon 5	Horizon 6
Panel A.1														
Total	0.018	0.114***	0.036	0.065	0.008	-0.009	0.008	-0.025	-0.011	0.007	0.022	-0.132*	-0.068	-0.077
	(0.033)	(0.032)	(0.036)	(0.038)	(0.046)	(0.048)	(0.042)	(0.048)	(0.057)	(0.076)	(0.055)	(0.051)	(0.062)	(0.060)
R-squared	0.182	0.338	0.107	0.136	0.286	0.082	0.140	0.251	0.379	0.184	0.158	0.298	0.113	0.079
Total_weighted	-0.051*	0.031	-0.060*	0.055*	-0.003	0.058	0.025	-0.088**	0.028	-0.093*	0.042	-0.054	-0.014	-0.105*
	(0.021)	(0.030)	(0.028)	(0.025)	(0.030)	(0.037)	(0.042)	(0.029)	(0.033)	(0.036)	(0.049)	(0.049)	(0.058)	(0.047)
R-squared	0.186	0.335	0.114	0.142	0.287	0.086	0.146	0.255	0.375	0.183	0.162	0.297	0.126	0.089
Panel B.1														
Cold wave	-0.271*	0.273	-0.299*	0.213	0.122	0.074	-0.076	0.014	-0.016	-0.565***	0.256	0.115	-0.117	-0.488*
	(0.107)	(0.209)	(0.132)	(0.130)	(0.147)	(0.201)	(0.182)	(0.144)	(0.154)	(0.141)	(0.179)	(0.151)	(0.224)	(0.211)
Severe Winter	-0.330	-0.259	-0.416*	-0.116	-0.128	-0.003	-0.348	-0.625**	-0.056	-0.405	-0.085	-1.412**	0.554	-1.158*
	(0.170)	(0.317)	(0.175)	(0.229)	(0.449)	(0.194)	(0.278)	(0.232)	(0.431)	(0.268)	(0.345)	(0.515)	(0.383)	(0.485)
Heat Wave	0.171	0.166	0.128	0.601**	0.473*	0.345*	0.860*	-0.475**	-0.315	0.150	-0.270	0.251	-0.225	-0.577
	(0.145)	(0.164)	(0.158)	(0.224)	(0.223)	(0.170)	(0.413)	(0.181)	(0.222)	(0.237)	(0.225)	(0.325)	(0.212)	(0.325)
Drought	-0.050	0.041	-0.217	-0.118	-0.015	0.070	0.109	-0.055	0.355	-0.325	-0.047	-0.219	0.239	0.123
	(0.087)	(0.135)	(0.136)	(0.155)	(0.140)	(0.161)	(0.125)	(0.202)	(0.198)	(0.177)	(0.215)	(0.297)	(0.290)	(0.441)
Storm	0.031	0.099*	0.083	0.042	-0.028	-0.010	-0.059	0.032	-0.063	0.077	0.001	-0.129	-0.196**	-0.048

	(0.041)	(0.045)	(0.061)	(0.047)	(0.046)	(0.063)	(0.060)	(0.075)	(0.075)	(0.086)	(0.068)	(0.081)	(0.073)	(0.081)
R-squared	0.203	0.352	0.146	0.170	0.297	0.099	0.185	0.273	0.403	0.211	0.176	0.328	0.159	0.117
N	1374	1276	1179	1077	978	881	777	1954	1796	1637	1483	1326	1167	1015

	Only cultivation													
	Comparatively advantaged							Comparatively disadvantaged						
	Horizon 0	Horizon 1	Horizon 2	Horizon 3	Horizon 4	Horizon 5	Horizon 6	Horizon 0	Horizon 1	Horizon 2	Horizon 3	Horizon 4	Horizon 5	Horizon 6
Panel A.2														
Total	0.002	0.006	-0.004	0.000	-0.001	-0.002	-0.005	-0.000	-0.002	-0.005	-0.004	-0.001	-0.010	-0.002
	(0.007)	(0.014)	(0.013)	(0.011)	(0.012)	(0.013)	(0.012)	(0.003)	(0.003)	(0.005)	(0.003)	(0.004)	(0.010)	(0.005)
R-squared	0.003	0.006	0.009	0.009	0.034	0.066	0.097	-0.001	0.001	-0.001	0.000	-0.004	0.007	-0.001
Total_weighted	-0.015	0.002	0.002	-0.015*	-0.006	0.016	-0.004	0.004	-0.003	-0.003	-0.004	0.003	0.007	0.000
	(0.011)	(0.010)	(0.006)	(0.007)	(0.004)	(0.010)	(0.008)	(0.003)	(0.004)	(0.004)	(0.006)	(0.003)	(0.006)	(0.002)
R-squared	0.013	0.013	0.011	0.016	0.037	0.071	0.098	-0.000	0.003	0.002	0.001	-0.002	0.007	-0.003
Panel B.2														
Cold wave	-0.033	-0.030*	-0.008	-0.019	0.008	-0.010	-0.067*	-0.014	-0.022	-0.026	-0.019	-0.025	-0.008	0.013
	(0.019)	(0.015)	(0.019)	(0.017)	(0.031)	(0.019)	(0.033)	(0.023)	(0.024)	(0.025)	(0.021)	(0.027)	(0.015)	(0.011)
Severe Winter	0.060	-0.011	0.019	0.031	0.055	0.170	0.031	0.168	0.065	0.045	0.049	0.086	0.082	0.010
	(0.062)	(0.039)	(0.045)	(0.054)	(0.044)	(0.108)	(0.052)	(0.125)	(0.038)	(0.042)	(0.043)	(0.076)	(0.073)	(0.031)
Heat Wave	0.008	-0.023	-0.042	-0.023	-0.056	0.015	0.045	0.007	0.004	0.013	-0.002	0.013	0.014	0.002
	(0.013)	(0.021)	(0.027)	(0.022)	(0.041)	(0.033)	(0.030)	(0.007)	(0.005)	(0.007)	(0.009)	(0.010)	(0.013)	(0.013)
Drought	0.011	0.030	0.035	0.001	-0.035	-0.027	-0.033	0.033	0.018	-0.002	-0.000	0.035	0.007	-0.038
	(0.035)	(0.031)	(0.036)	(0.029)	(0.028)	(0.051)	(0.051)	(0.021)	(0.019)	(0.027)	(0.019)	(0.042)	(0.033)	(0.024)
Storm	0.004	0.007	-0.010	0.003	0.011	0.001	0.004	-0.006	-0.004	-0.004	-0.005	-0.006	-0.016	0.001
	(0.010)	(0.020)	(0.011)	(0.009)	(0.012)	(0.015)	(0.015)	(0.005)	(0.003)	(0.005)	(0.004)	(0.006)	(0.019)	(0.006)

R-squared	-0.007	-0.007	0.000	-0.003	0.023	0.067	0.090	0.003	-0.003	-0.002	-0.001	-0.005	0.001	-0.012
N	1374	1276	1179	1077	978	881	777	1954	1796	1637	1483	1326	1167	1015

Note. Standard errors are in parentheses. All estimations use country-commodity fixed effect. For simplicity, we only refer to cumulative change in GMO approvals in horizons 0, 5, and 6.

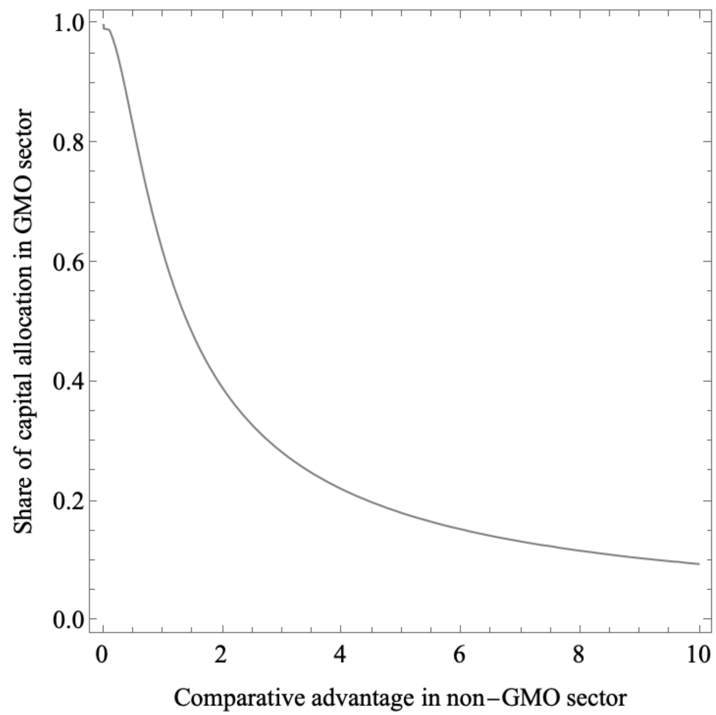

Figure 1. The impact of comparative advantage in the non-GMO sector on GMO adoption

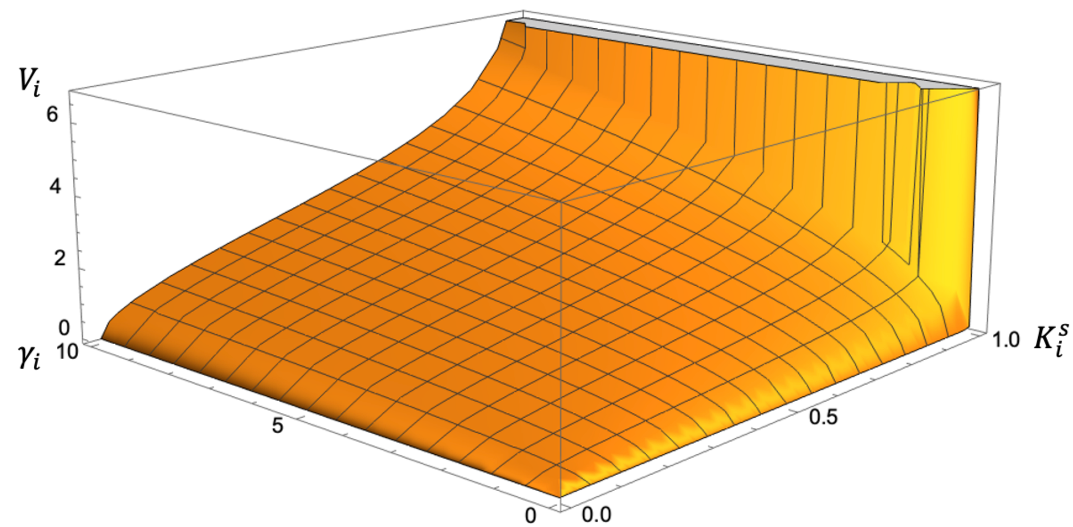

Figure 2. Comparative advantage in the non-GMO sector and the excessive output value of the GMO sector

Note. The vertical axis V_i in Figure 2 denotes the excessive production of GMO commodities ($\sum_i [p_i^S A_i^S {K_i^S}^{\alpha} {L_i^S}^{1-\alpha}] - \tau[\sum_i (r_i K_i^s + w_i)]$).

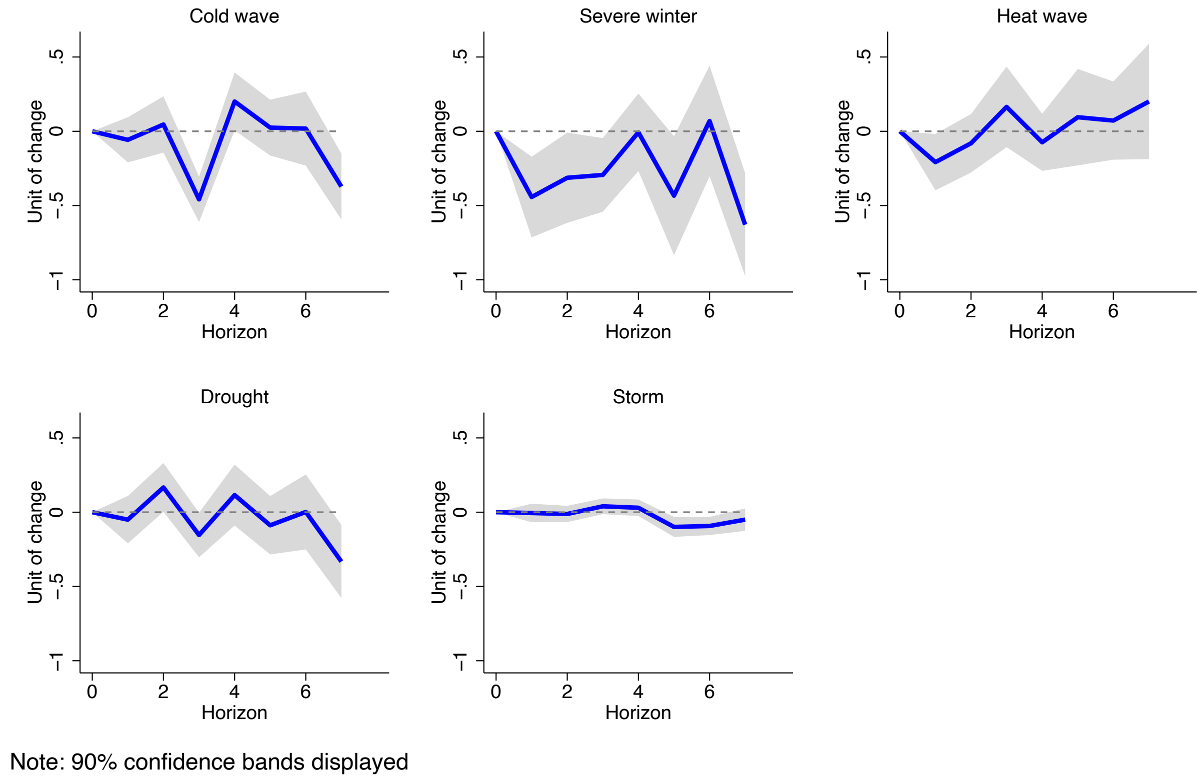

Figure 3. Cumulative change of GMO approvals from 1–6 years after climate shocks 6 according to disaster types

Appendix

Table A1. Poisson estimates: Impact of climate shocks on GMO approvals

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Total	Total	Cold wave	Severe winter	Heatwave	Drought	Storm
Climate shocks (current year)	0.005	0.011	-0.010	-0.011	-0.229	-0.255**	0.028
	(0.021)	(0.020)	(0.026)	(0.091)	(0.213)	(0.118)	(0.029)
Climate shocks (1-year lag)	0.003	0.013	-0.001	0.109	-0.705***	-0.114	-0.009
	(0.021)	(0.021)	(0.021)	(0.091)	(0.148)	(0.125)	(0.028)
Climate shocks (2-year lag)	-0.016	-0.004	-0.029	-0.302***	-0.151	-0.069	0.008
	(0.018)	(0.018)	(0.019)	(0.087)	(0.150)	(0.124)	(0.027)
Climate shocks (3-year lag)	0.059***	0.054**	0.030	0.317***	-0.413***	-0.327***	0.034
	(0.022)	(0.021)	(0.020)	(0.088)	(0.152)	(0.111)	(0.027)
Climate shocks (4-year lag)	-0.049***	-0.059***	-0.089***	0.138	-0.292*	0.051	-0.102***
	(0.017)	(0.017)	(0.021)	(0.087)	(0.150)	(0.118)	(0.027)
Climate shocks (5-year lag)	0.032*	0.025	-0.001	0.163*	0.175	-0.101	-0.024
	(0.019)	(0.019)	(0.023)	(0.086)	(0.153)	(0.117)	(0.028)
Climate shocks (6-year lag)	-0.021	-0.021	-0.054**	-0.138*	0.106	0.049	-0.026
	(0.019)	(0.019)	(0.024)	(0.082)	(0.157)	(0.114)	(0.030)
Agricultural share (1-year lag)		-0.018***	-0.024*	-0.023	-0.018	-0.025	-0.026
		(0.006)	(0.014)	(0.020)	(0.020)	(0.020)	(0.020)
Infrastructure (1-year lag)		-1.036	0.807	1.280	1.960	1.095	1.231
		(0.655)	(1.900)	(2.626)	(2.634)	(2.629)	(2.635)
International agreements		0.356**	-2.917***	-1.047	-1.588	1.079	-2.117**
		(0.160)	(0.675)	(1.357)	(1.362)	(1.014)	(0.983)
Developing		-0.250	-0.831	-0.708	-0.912	-0.189	-0.110
		(0.200)	(0.619)	(0.692)	(0.693)	(0.709)	(0.842)
EU dummy		0.524**	0.390	0.498	0.337	-0.536	1.046
		(0.204)	(0.606)	(0.693)	(0.693)	(0.755)	(0.824)

Constant	0.970***	1.169***	3.803***	1.194*	1.485**	0.764	2.223
	(0.077)	(0.282)	(1.393)	(0.676)	(0.677)	(0.928)	(1.778)
R-squared	0.0027	0.0726	0.3579	0.3058	0.3016	0.3009	0.3023
N	3536	3328	3328	3328	3328	3328	3328
Country-Commodity FE	N	N	Y	Y	Y	Y	Y