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Gravity With Lasso: Global Cereal Trade With Factors of Conflicts, COVID-19, Currency, China, Climate Change and Income ('6C')

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ABSTRACT

Global and open trade fosters peace, economic prosperity and food security worldwide, but it faces growing instability due to multidimensional factors. A range of new developments threaten the resilience of trade networks, with direct implications for food security. These include escalating conflicts along cereal trade routes, supply-chain disruptions such as COVID-19, high food inflation affecting exchange terms, China's increasing dominance in global trade, fluctuating yields due to climate change and rising food demand in high-growth countries. Appropriate policy responses are difficult to implement and typical short-term responses such as export bans, quotas or higher import tariffs tend to transfer vulnerabilities to other countries and to amplify global market volatility rather than to stabilise it. To address these challenges, policymakers need to first evaluate if and when to respond to these disruptions, and hence need to assess the relative importance of these threats. This paper first identifies six major influences on the world's economy that have the potential to disrupt trade flows: Conflicts, COVID-19, Currency, China, Climate change and inCome (the 6Cs). Second, it seeks to identify which of these factors are most relevant to cereal trade, using a gravity model of trade combined with the machine learning LASSO and Random Forest techniques. Results show that high income growth, China's weight and climate change are more consistently associated with trade fluctuations than abrupt events like COVID-19 or conflicts. Trade participation is more vulnerable to abrupt events than trade intensities, while instability from exporter countries matters more than from importer countries. Results differ by region, with Africa and Asia being more subject to global risk. These insights guide policymakers in assessing the importance of disruptions on trade fluctuations and prioritising responses that enhance trade resilience and food security globally.

JEL Classification: Q17, Q54, F14, F51, E31

1 | Introduction

Global trade patterns face a multitude of challenges that reflect international vulnerabilities in commodity trade. After a prolonged period of trade openness which translated in growing reliance on imports, changes in major players and rising trade complexity (Ji et al. 2024), the recent surge in geo-political tensions, push-backs against globalisation and destabilising shocks, such as climate change or currency movements, present major susceptibilities for global trade. Trade in agricultural commodities is particularly vulnerable to emerging shocks and crises, such as climate change, for example, as it directly affects the quality and quantity of agricultural production (Jones and Olken 2010). Yet, trade of food items is crucial to ensure global food security through the redistribution of food from surplus to deficient locations (Hasegawa et al. 2018; Huang et al. 2011).

Although the literature establishes and analyses multiple sources of shocks on trade in food commodities, the joint analysis of major, contemporary shocks happening simultaneously or in fast succession is missing. The convergence and interconnections of these crises demand strategic policy solutions, but short-term, misguided policy responses to trade shocks can exacerbate global instability (Abbott and Borot de Battisti 2011). Currently, specific threats are analysed individually without assessing their contextual importance. Since their frequency and complexity have increased, policy makers are confronted with an increased need to prioritise specific challenges and identify those challenges that most strongly affect food security. Understanding the relative importance of individual shocks in relation to others can help guide policy attention and prioritise measures. Fast, effective and responsive policy measures are relevant to maintain stable food trade and avoid growing food insecurity.

The objective of this study is to identify the relative importance of multiple contemporary shocks and disruptions on trade flows. Therefore, this paper conceptualises the '6C' as the major factors influencing current international trade dynamics, which are according to the literature Conflicts, COVID-19, Currency, China, Climate change and inCome. Sudden disruptions, such as armed conflicts (e.g., Ukraine) and the COVID-19 pandemic, originate outside the trade system but propagate through global supply chains affecting production and distribution, and presenting direct barriers for trade. COVID-19 induced supply-chain blockages and labour shortages (Amador et al. 2023; Erokhin and Gao 2020; Swinnen and McDermott 2020), while conflicts cause physical destruction of trade routes and insecurity which results in impossibility to trade and increased costs (Lin et al. 2023). Fear of insufficient food supply due to such events routinely leads import-dependent countries to impose short-term trade restrictions, which are shown to worsen global volatility (Falkendal et al. 2021). COVID-19 and conflicts are often analysed in tandem or trio with the role of climate change (Bloem and Salemi 2021; Lara-Arévalo et al. 2023; Paudel et al. 2023; Urak et al. 2024), as the literature highlights the interactive effect of these crises where one crisis adds to, reinforces or prolongs another one. Climate change affects trade not only through moderation of quantities and quality of agricultural output (Funk and Brown 2009), but also through the consolidation of export markets due to more unfavourable agricultural conditions, resulting in a few central players that control future commodity markets (Porfirio et al. 2018). This collection of events commonly translates into increases in food prices (Al-Rousan et al. 2024; Lin et al. 2023) and contributes to the less abrupt, but not less disruptive, problem of high food inflation originating in high energy prices. Food inflation leads to economic and social instability and is a source of concern for food security in food-importing countries (Giordani et al. 2016; Peersman 2022), but also transfers vulnerabilities across countries through trade. Urak et al. (2024) suggested the effects of the pandemic and the Russia–Ukraine war have been amplified by exchange rate fluctuations. These interlinkages present an added difficulty for policy makers to identify and address root causes of volatility.

Furthermore, these challenges pose both short-term and long-term threats to the production and distribution of food. For example, climate change materialises both in the short (e.g., through the growing frequency of extreme weather events) and in the long run (e.g., shifts in growing seasons). Additionally, longer developing factors also come into play as important determinants of current and future trade trends, namely China and income growth. With China's accession to the WTO in 2001, the country' role in global trade largely expanded. To date, China is the world's largest importer of agricultural commodities (Statista 2025). This results in substantial leverage towards its trading partners and consequent shifts in trade patterns. In addition to this long-developing trend, the renewal of the trade war between China and the United States underlines the potential for high short-term volatility in the exchanges with China. Further, sustained economic growth in China and other emerging economies, such as Nigeria, South Africa or India, translated in higher income levels for large shares of the population. Dietary shifts accompany higher living standards, changing the demand for traded commodity goods towards more diversified diets (World Bank 2025), although high-growth countries still remain vulnerable to shocks. Therefore, we question the role and relative importance of these factors, as clarity regarding which factor among these 6C exerts major influence on trade is much needed.

Common to all 6Cs is the global dimension of these trade disruptions, yet their effect is expected to differ across world regions and commodities. The study focuses on wheat, rice and maize, the crops most largely traded and most relevant for food security. An additional regional analysis is conducted for Asian and African countries, which are most exposed to problems of food insecurity and most vulnerable to shock propagation (Burkholz and Schweitzer 2019).

Methodologically, we follow previous literature and use structural gravity models, where shocks are conceptualised within the gravity theory as modifying either the economic size or the economic distance between trade partners. To establish relative importance among the 6C factors, we identify which of them is most strongly associated with fluctuations in trade flows by using a data-driven feature selection approach. The dynamic interplay between these factors and varying scales make it difficult to isolate the most influential drivers of trade changes using traditional regression or causal approaches. In contrast, we focus on predictions of the trade flows which allows us to identify important factors. The Least Absolute Shrinkage and Selection Operator (LASSO) (Tibshirani 1996) offers several advantages in identifying the key determinants of trade disruptions. LASSO simplifies models by retaining only the most significant drivers, making it easier to interpret the dominant forces shaping trade flows. It is applied to both a Heckman sample-selection approach and a Poisson pseudo-maximum likelihood approach. We enrich results with a feature selection guided by a Random Forest (RF) (Breiman 2001), whose approach of splitting the feature space complements the LASSO results. Results are robust for certain factors and diverge for others. A contribution of this study is to show the different, yet complementary, outcomes of various feature selection methods: LASSO detects factors whose small changes matter for trade (COVID, Conflicts), while RF detects the presence of turning points that matter for trade outputs (in rain and food inflation). This methodological approach allows for considering multiple shocks and their relative importance within the same model and eliminates the need to test many different model specifications or combinations of shocks.

The paper centres on monthly, quarterly and annual exports of rice, wheat and maize in volumes, between 2012 and 2022, taken from COMTRADE, and their implication for global food security. In the following, Section 2 offers an analysis of how each 6C is related to trade. Section 3 proposes a conceptual framework to reconcile all factors under one model and describes the methodology and data used to analyse it. Section 4 reports results, which are discussed in the global context in Section 5. Section 6 concludes.

2 | Literature Review

Maintaining resilient trade systems is paramount to ensuring the functioning of local and global food systems and food security in many regions of the world. However, many, often-interlinked challenges threaten the continuous and smooth flow of commodities. The following subsections attempt to disentangle the effect of each major threat on cereal trade and food security.

2.1 | Conflicts

Conflicts and wars interrupt supply chains and impede efficient trade partnerships, though the effects vary by conflict type and location. Intrastate conflicts generally have a larger negative impact than interstate conflicts, while conflicts in exporting countries are more detrimental than those in importing countries (Marano et al. 2013). Civil wars have been found to decrease bilateral trade by one-third and affect not only the countries involved but also intervening third parties (Bayer and Rupert 2004), negatively influencing trade flows in neighbouring nations (Marano et al. 2013). However, some studies suggest that war may only impact trade in the short run, with trade relationships remaining unaffected in the post-war period (Barbieri and Levy 1999). Most recently, the war in Ukraine has triggered fears of food insecurity for countries that rely on wheat imports from Ukraine and Russia, especially in the Near East and Sub-Saharan Africa. Ukraine's grain exports were severely impacted, falling 78.2% below expected levels between February and July 2022 (Ahn et al. 2023). Overall, the conflict's effects cascade through the global trade network, with lower-middle-income countries in North Africa, Southeast Asia and West Asia particularly vulnerable to supply shocks (Liu et al. 2023).

2.2 | COVID-19

The measures implemented to slow the spread of the COVID-19 pandemic, such as lockdowns and restrictions, have not only triggered a widespread economic recession but have also imposed significant constraints on international trade (Barbero et al. 2021; Swinnen and McDermott 2020). These impacts have unfolded through multiple pathways, including disruptions to global supply chains, shifts in trade policies and reduced consumer demand. First, the pandemic disrupted food supply chains through labour shortages in fields and processing facilities, interruptions in logistics and refrigeration chains, and increased transportation cost (Giordano and Ortiz de Mendívil 2020). These issues particularly affected labour-intensive sectors and perishable, high-value commodities. Second, fearing shortage of domestic food supply, as well as rising food prices, some countries applied an export tax, export quota or export ban to their food products (Mamun and Laborde 2024). In July 2020, 21 countries had announced or introduced (temporary) export restrictions covering almost 4% of the caloric value of globally traded food, which were lifted soon after (Laborde et al. 2020). Trade restrictions imposed by Russia and Vietnam in particular, among the major exporters of wheat and rice respectively, created fears for food security (Erokhin and Gao 2020). Overall, export of wheat declined by 17% in July 2020 and 27% in June 2021, while a decline of 10%–13% is seen during the COVID-19 period for rice, attributed more to supply chain disruption than export restrictions (Mamun and Laborde 2024).

2.3 | Currency

The many recent episodes of high food price inflation and fluctuations (2007–2008, 2011 and since mid-2020) interact with international trade through multiple pathways. First, domestic food inflation and macroeconomic outcomes are closely intertwined, for example, through adverse effects on the macroeconomic performance that require adjustments in monetary policy (Zhu and Yu 2025). There is evidence that money is not neutral in the long run, as food prices and output respond to monetary expansion, with effects on imports and exports (Meyer and Yu 2011; Yu 2014). Second, countries respond to large international food price shocks by imposing trade measures to isolate domestic markets from international price spikes (Peersman 2022). Restrictions or bans on exports as well as lower tariffs on imports are frequently used to provide short-term protection to domestic markets, though with undesirable outcomes (Abbott and Borot de Battisti 2011; Giordani et al. 2016; Porteous 2017). In the 2008 food price crisis, surges in food prices prompted rice export restrictions from Vietnam, Cambodia and Egypt, and precautionary rice purchases by the Philippines, which in turn further contributed to the increase in rice prices (Headey and Fan 2008). In practice, currency fluctuations affect the terms of trade, potentially making imports more expensive compared to exports. The magnitude of these effects differs between exporters and importers, with exporters deviating from usual trade cooperation when prices are high, and importers when prices are low (Gouel 2016). Besides, changes in the currency level modify the exchange rate between trade partners with negative albeit small effects on trade (Auboin and Ruta 2013; Bénassy-Quéré et al. 2021; Rose 1999). Before the global financial crisis, a positive link existed between real exchange rates and export volumes, but this connection largely disappeared after the crisis (Kang and Dagli 2018). Consequently, currency or food inflation shapes trade dynamics via macroeconomic outcomes, terms of trade and exchange rate.

2.4 | China

China's accession to the World Trade Organization in 2001 was followed by a large increase in China's share of global trade (Handley and Limão 2017), with multifold consequences. Dependency on Chinese' imports grew intensely. For example, the US trade deficit with China reached 47.7% of the total US trade deficit in 2018 (Kwan 2020). Fearing for US economic prosperity, their global influence and domination (Handley and Limão 2017), the US engaged in a trade war and imposed additional tariffs of 25% on 1300 products imported from China, who replicated by imposing tariffs of 25% on a number of US products, including soybeans and other agricultural products (Bown et al. 2021; Kwan 2020). Additional tariffs and retaliation continued until a deal in 2020, but new rounds of tariffs have been recently announced. According to Jiang et al. (2023), Chinese total exports to the United States declined by 8.91% on average from January 2017 to May 2019, mainly due to a decrease in quantity rather than a change in prices. Further, China responded by reallocating its exports to other countries (Fajgelbaum et al. 2024; Jiang et al. 2023), thereby not only affecting China's aggregate exports but also the trade balance of third-party countries. More recently, China's proactive role in global trade networks materialised with the Belt and Road Initiative, where partner countries can expect an increase of their exports (Dumor, Li, et al. 2021) due to improvements in infrastructure and trade facilitation (Ramasamy and Yeung 2019). This increases the possibilities of shifting trade flows and positions within trade networks. Overall, this evidence supports the claim that China has a major influence on world trade flows, including on the trade of staple foods.

2.5 | Climate

Climate change and global warming affect crop yield and alter countries' comparative advantages, thus reshaping food trade patterns (Bozzola et al. 2023; Dellink et al. 2017; Yu et al. 2020). Differences in climate between trading partners increase bilateral exports (Bozzola et al. 2023), while the effects of changes in climate vary across countries (Reilly et al. 1994). Higher temperatures and rainfall levels tend to benefit countries' export values, with one extra degree Celsius boosting export values by 11.91% and a 5 mm increase in rainfall levels boosting export values by 8.73%. In general, regions with low temperatures might be able to improve their export capacity due to higher yields, while the reverse is the case for regions with high temperatures (Bozzola et al. 2023). In poorer nations, however, temperature increases can substantially reduce export growth in the agricultural sector (Jones and Olken 2010). For example, in China, exports are more affected by climate shocks than imports, with poorer, warmer and non-coastal cities experiencing greater impacts (Li et al. 2015). Under a high CO_2 emissions scenario, the agricultural trade network is predicted to become more centralised, with a few countries dominating markets, potentially creating a more unstable system less able to reduce food insecurity (Porfirio et al. 2018). In detail, Porfirio et al. (2018) predict a sharp decline in the US share of global agricultural exports, compensated by increases in China's share by 2050–2059, attributed to changes in the countries' respective agricultural productivities due to climate change. Climate change is also relevant to trade infrastructure. Rising temperatures and precipitation levels might lead to destroyed road structures which would require higher levels of maintenance. Extreme weather events might also lead to the disruption of electronic transport infrastructure and involve higher maintenance and insurance costs (Dellink et al. 2017).

2.6 | InCome

A large body of literature examines the positive relationship between income growth and global trade (Feyrer 2019; Freund and Bolaky 2008; Gogebakan 2025), with estimated elasticities from 0.15 to 0.48, and higher for countries that are characterised by higher levels of income, education, lower business and labour market regulations (Herzer 2013). In middle- and low-income countries, rising incomes are a key driver of participation in global trade. In particular, the economic growth experienced in the BRICS countries (Brazil, Russia, India, China and South Africa) translates into the reallocation of the labour force away from agriculture towards non-agricultural sectors, and thus, stronger demand for imported food resources (FAO 2024) and higher integration into global agricultural trade (Beckman et al. 2017). This is important as several of the high-growth countries are major crop exporters (Russia, Brazil) (Ren et al. 2020). On the other hand, BRICS countries are experiencing a shift towards more diversified and 'westernised' diets, with increased consumption of animal products and processed foods, especially from the urban population (Hawkes et al. 2017). Population growth and rising per capita demand are key drivers of changes in global food systems, as seen for example in their role in GHG emissions increase (Li et al. 2023). Income growth is thus a powerful, yet ambiguous, driver of change for crop trade.

3 | Theoretical Framework, Methods and Data

Section 2 has shown how individual shocks or disruptions of the global economy interact with trade. To bring these various factors together, we position the 6Cs into trade theory and link them to either economic size or costs of trade between trade partners within the structural gravity model. To further guide the analysis, Figure 1 shows the interface between the 6C factors and the main components of the trade system (production, supply chain and demand).

As discussed in Section 2, conflicts primarily disrupt trading infrastructure and, to a lesser extent, impair production capacities. COVID-19 mainly disrupted the supply chain, with infrastructures operating at reduced capacity due to lockdowns and social distancing measures. Currency problems affect all parts of the trade system but are most disruptive to the smooth exchange of goods along the supply chain because of increased transaction costs. China's position as the world's leading food importer primarily influences global demand, while its investment in infrastructure shapes the supply chain component. Climate change has its most significant repercussions on productivity, though extreme weather events can also damage critical infrastructure along the supply chain. Finally, income growth translates

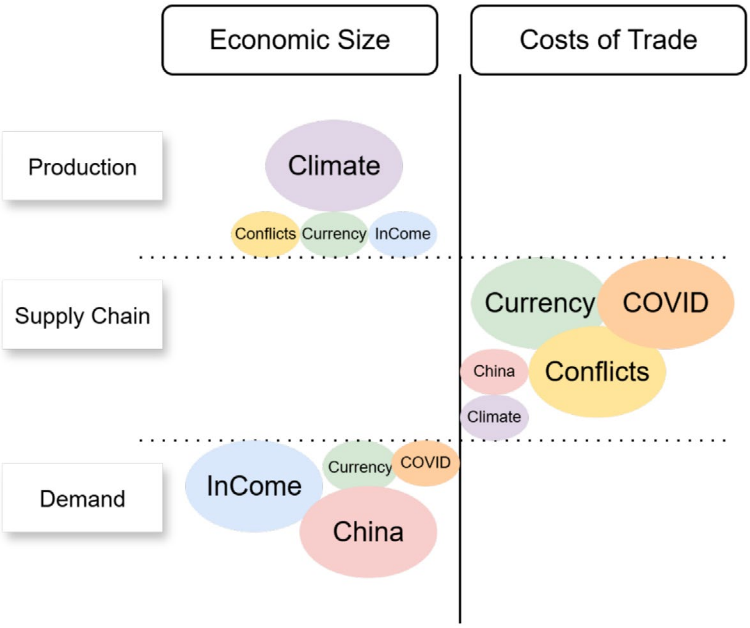


FIGURE 1 | Interface between 6Cs and main components of the trade system. Larger bubbles indicate main expected effects; smaller bubbles indicate where secondary effects are expected. Own representation. [Colour figure can be viewed at https://onlinelibrary.wiley.com/].

mostly into shifts in dietary patterns affecting demand, while only minor effects can be expected on the production capacities of the countries concerned.

3.1 | Trade Model

Following Dumor, Yao, et al. (2021), we start from the theoretical version of the gravity model (Anderson and van Wincoop 2003), which can be decomposed into two terms, namely the economic size of each partner, indicating that larger countries export and import more, and the bilateral trade costs, which reflect the ease of trading between two countries (Westerlund and Wilhelmsson 2011; Yotov et al. 2016). The base model can be written as:

$$T_{ijt} = \beta_0 + \beta_1 Economic\_Size_{it} + \beta_2 Economic\_Size_{jt} + \beta_3 Trade\_costs_{ijt} + e_{ijt} \quad (1)$$

where T_{ijt} is exports from country i and j at time t. In practice *Economic_Size* is estimated using GDP and population size of each country. Bilateral trade costs are difficult to observe practically and are commonly proxied by bilateral distance and a set of country-pair factors Com_{ijk} in (2), including contiguity, common language, common colonial past; e_{ijt} is noise. In addition, the role of multilateral resistance term in the trade costs can be specified using exporter fixed effects, accounting for all sources of unobserved heterogeneity that are constant for a given exporter across all importers (Anderson and van Wincoop 2003).[1]

To situate the 6Cs within a gravity theory, we evaluate their role on both economic size (which drives the scale of trade) and trade costs (which determine the frictions in trade) using information from Section 2. We find that inCome, China and Climate's main effects relate to the magnitude of production and demands and thus act as shifters of the economic size. COVID, Currency and Conflicts mainly increase difficulties in trade and thus act as shifters of trade costs. In our specification, the variable of interest *Economic_Size*, typically represented by the GDP (reflecting inCome) and population, is extended with China, and Climate, while *Trade_costs*, typically represented by distance and joint factors, is extended with COVID, Currency and Conflicts. They vary with time and country and can be included for both the importer i and the exporter j.

There is a risk of endogeneity due to the possible reverse causality between trade flows and some of the Cs, in particular COVID, China and Currency. Baier and Bergstrand (2007) identify three alternatives to address endogeneity with panel data, which overcome the difficulty of implementing good instrumental-variable approaches in trade models. The preferred approach is to include fixed effects to capture unobservable time-invariant country characteristics that could influence both the variable of interest and the outcome. This approach has been widely approved (Cavallo and Frankel 2008; Yotov et al. 2016) and implemented to avoid bias caused by potential endogeneity in trade analysis (Barbero et al. 2021; Liu et al. 2022; Ridley et al. 2023). Therefore time-invariant exporter fixed effects are used to absorb potential country-specific correlations to the 6C. The base model is also adjusted to control for months, in order to limit seasonal influences on the results, and is estimated in its log-linear form.[2] Modifying (1) with the additional C variables provides the following model to estimate trade flows:

$$\begin{aligned} \ln(T_{ijt}) = {} & \beta_0 + \beta_1 \ln(POP_{it}) + \beta_2 \ln(POP_{jt}) + \beta_3 \ln(GDP_{it}) \\ & + \beta_4 \ln(GDP_{jt}) + \beta_5 China_{it} + \beta_6 China_{jt} + \beta_7 Climate_{it} \\ & + \beta_8 Climate_{jt} + \beta_9 \ln(Dist_{ij}) + \beta_{10} Covid_{it} + \beta_{11} Covid_{jt} \\ & + \beta_{12} Currency_{it} + \beta_{13} Currency_{jt} + \beta_{14} Conflict_{it} + \beta_{15} Conflict_{jt} \\ & + \sum_{k=16}^{18} \beta_k Com_{ijk} + \beta_{19} IMR_{ijt} + F_i + F_m + e_{ijt} \end{aligned} \quad (2)$$

where F_i, F_m are fixed effects for exporter and month respectively. *IMR* is explained underneath.

Trade does not occur on all possible bilateral relationships. Lack of demand or supply compatibility, high fixed costs of trade preventing market entry, as well as political or economic barriers explain that not all countries exchange goods at every period. In addition, missing data also result in zero trade flows between some countries at some times. To model selection into trade, and avoid bias due to non-random zero trade flows, we adopt the Heckman's two-step selection model (Heckman 1979; Linders and de Groot 2006), which is well suited to gravity models of trade (Linders and de Groot 2006). Therefore, the probability of trade occurring between two countries at a given period is estimated with a probit model based on trade determinants:

$$H^*_{ijt} = Z_{ijt} + u_{ijt} \tag{3}$$

where H^*_{ijt} is a latent variable indicating the propensity to trade with $H^*_{ijt} > 0$ if $H_{ijt} = 1$ (the country-pair (i, j) trades), and $H^*_{ijt} \leq 0$ otherwise. Z_{ijt} contains trade determinants (e.g., GDP, distance, common language). $u_{ijt} \sim N(0,\ 1)$ is a normally distributed error term.

The probability of trade is modelled using GDP and population of all potential exporters and importers, whether they are landlocked, and a set of pair-specific characteristics. To fulfil the exclusion restriction, landlockedness and sharing a common ethnic language are not included in the model of trade flows (2) but are expected to affect trade participation. We further expand the set of trade determinants to the 6Cs, to model their potential role on the decision to engage in trade between two countries. The variables of interest *inCome* is already represented by the GDPs. Variables that represent the potential influence of *China, Currency, COVID, Conflict* and *Climate* are added as additional determinants. Therefore, trade participation is estimated by:

$$\begin{aligned} H^*_{ijt} = {} & \gamma_0 + \gamma_1 \ln\left(POP_{it}\right) + \gamma_2 \ln\left(POP_{jt}\right) + \gamma_3 \ln\left(GDP_{it}\right) \\ & + \gamma_4 \ln\left(GDP_{jt}\right) + \gamma_5 China_{it} + \gamma_6 China_{jt} + \gamma_7 Climate_{it} \\ & + \gamma_8 Climate_{jt} + \gamma_9 \ln\left(Dist_{ij}\right) + \gamma_{10} Covid_{it} + \gamma_{11} Covid_{jt} \\ & + \gamma_{12} Currency_{it} + \gamma_{13} Currency_{jt} + \gamma_{14} Conflict_{it} \\ & + \gamma_{15} Conflict_{jt} + \gamma_{16} Lock_i + \gamma_{17} Lock_j \\ & + \sum_{m=18}^{21} \gamma_m Com_{ijm} + u_{ijt} \end{aligned} \tag{4}$$

With *Lock* a binary measure of land landlockedness for country *i* and *j*. Country-pair factors Com_{ijm} now include contiguity, common language (official), common ethnic language and common colonial past. Using this equation, we compute the Inverse Mills Ratio (IMR), IMR_{ijt}, which is introduced in the gravity model (2) as an additional regressor that corrects for selection bias. The gravity model (2) explains only the intensity of flows based on the positive trade sample.

The PPML (Poisson Pseudo-Maximum Likelihood) approach is a popular alternative to deal with zero trade flows that does not require a separate first stage to model trade participation, and presents certain advantages in the estimation of trade flows (Larch et al. 2025; Santos Silva and Tenreyro 2006). A data-driven feature selection can be applied to the set of trade determinants in the PPML. Results for trade intensities using the PPML approach are included to verify robustness. However, modelling trade participation separately enables to observe whether shocks associated with trade participation and trading intensity differ. A further alternative is found in Egger and Larch's (2011) two-part PPML, but it remains marginally adopted in the literature.

3.2 | Feature Selection

To assess the importance of the six main vectors of global change on trade occurrence and trade quantity, they are included as explanatory factors of the bilateral flows in the gravity model. In a regression model, small (close to zero) but important effects could be shown as insignificant and be therefore dismissed, for example if standard errors are large due to small dataset, while in large datasets, small standard errors lead to many statistically significant variables. To identify variables that matter for the fluctuation of the output, machine learning's LASSO (Tibshirani 1996) offers a feature selection technique that shrinks the least relevant explanatory variables to zero, in effect removing them from the model. LASSO finds the set of coefficients that minimises the residual sum of squares (RSS) and an additional penalty, made of the absolute values of the coefficients weighted by a shrinking coefficient ≥ 0:

$$\min\left(RSS + \lambda \sum |\beta|\right)$$

In effect, the method shrinks all coefficients, bringing those with lowest explanatory power to zero. The shrinking coefficient is found by cross-validation to minimise the variance of the results. In order to single out which 6C are associated with occurrence of trade of cereals, the LASSO is first applied to the set of trade determinants in the estimation of model (4) for all possible pairs of importer and exporter at all possible time periods. Second, it is applied to the set of positive trade observations, for the identification of the most important 6C on trade flows. We apply the adaptive LASSO (Zou 2006) to the OLS model (2). This version of LASSO allows different penalties for each coefficient and typically generates more accurate predictions but is more computationally demanding and therefore only applied to the 2nd stage. Overall, in presence of a high number of predictors where many of them are expected to have little influence, this technique is well adapted to operate a feature selection (Ölkers et al. 2024). Although the LASSO is frequently used for feature importance detection (Höschle et al. 2023; Maruejols et al. 2022; Wang et al. 2022), its application to trade is so far very limited.[3,4]

Random Forest is another approach of machine learning which can be used to identify important variables in a prediction task (Speiser et al. 2019). However, its approach differs from LASSO. While LASSO works in a regression framework, the Random Forest adopts a non-linear approach that splits the feature space to make predictions. A limitation is that the 2nd stage does not integrate the trade participation (the IMR resulting from stage 1) linearly, but treats it as an additional potential predictor of trade intensities. Nevertheless, it provides supporting information about determinants of international trade. An advantage of Random Forest over LASSO lies in the ranking of variables by their importance. On the other hand, the standard Random Forest (Breiman 2001) lacks the clear cut-off offered by LASSO, which can be overcome by setting an arbitrary cut-off. Alternatives exist to find optimal feature sets with random forests (Speiser et al. 2019), notably from Jiang et al. (2004) that rely on a backward elimination, but this approach is computationally demanding for the high-dimensional dataset considered in this study. We implement the standard Random Forest with the same set of predictors as the LASSO. From a statistical perspective, the two model specifications differ as one is linear and the other non-linear. However, from a machine learning perspective, both are tools that aim to find the best set of predictors: LASSO by applying a penalty on coefficients and Random Forest by finding splits in predictors. According to the 'No Free Lunch Theorem' (Wolpert 1992), no method is inherently better at performing this task.

3.3 | Data

The analysis is conducted using worldwide exports of wheat, rice and maize in weight, obtained from the COMTRADE database for the period from 2012 to 2022. The analysis covers multiple temporalities (month, quarter, year) to allow exploring various short- to long-term disruptions in the dynamics of trade. Longer frequency data enable capturing longer response times between a shock and its translation into changes in trade flow, while monthly data questions whether trade responds within a very short timeline. Descriptive statistics (Table A1) show that bilateral exchanges are on average larger for rice, followed by maize and wheat. We observe the most variation (measured by the coefficient of variation) in annual data, followed by quarterly and monthly data. Variations at the quarterly level reflect seasonal effects that do not appear in monthly data, while variation at the annual level reflects long-term trends in crop markets. Over the period considered, average trade of all cereals increased yearly, except for 2015, 2016 and 2022. There are wide annual fluctuations in average global trade flows for wheat and rice, whereas the trade of maize follows a smooth and linear positive trend, with the exception of the year 2015 (Figure A1).

Traditional trade determinants (GDP, population, time-invariant country characteristics and country-pair characteristics) are taken from the World Bank and CEPII Gravity Dataset.[5] Data for the other 5C come from a variety of sources. Conflict is represented by the aggregated number of conflicts over the period and comes from the Armed Conflict Location & Event data project (ACLED).[6] Confirmed COVID-19 cases and related deaths come from the Johns Hopkins University, and their values are averaged into an index after being scaled. To represent China's growing role on the world economy and potential import or export dependency, we use each country's share of exports and imports to/from China (all goods, COMTRADE database) and average them into a 'China' dependency index. Climate change is captured by precipitation and surface temperature from NASA Earth Observation, where rain accumulation (since accumulated precipitations is mostly relevant for crop growth) over the period is considered, and average temperatures are taken. The role of currency fluctuation on trade is proxied by a food price indicator for each relevant temporality, obtained from the World Bank Cross Country Database of Inflation (Ha et al. 2023).

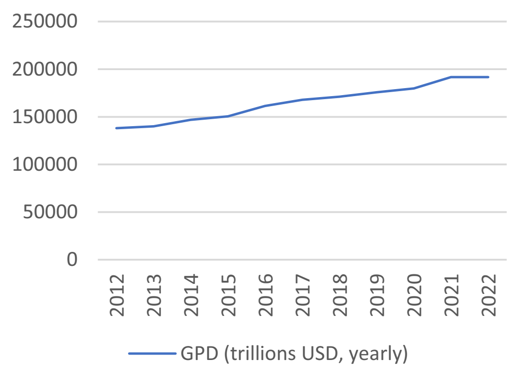
Figure 2 provides summary statistics of the 6C variables and their yearly fluctuations since 2012. We observe a mix of short-term abrupt events (Covid, Conflicts and Currency) mixed with longer-developing trends (China, GDP) and highly volatile factors (rain). Overall, these variables display a fluctuating pattern at global level; however, for example for climate, it is mostly local and punctual events, not visible at this level of aggregation, that matters.

4 | Results and Policy Implications

4.1 | Selection Into Trade

We first identify the key determinants of participation in trade by applying feature selection to the scaled 6Cs and the usual controls of the probit model (Equation 4). Table A2 reports the monthly model with traditional controls only (model 1), with all 'Cs' variables (model 2) and with only the variables selected by LASSO (model 3). The AIC criteria are consistently lower in model 2 than in model 1, indicating that the additional 6C variables are relevant to the trade of cereal and contribute to a better model fit. Second, the selection within these features (model 3) leads to a gain in interpretability and model parsimony, but without a loss in model fit, as AIC values are similar for model 2 and model 3. The LASSO selection is thus effective at removing variables with no explanatory power.

In the following, Table 1 reports the variable selection obtained using LASSO across all the temporalities considered and the selection obtained with a standard Random Forest (Breiman 2001) (retaining the 12 most important variables as a cut-off), to procure robustness across methodological variations. The results show that about the same number of variables is selected across all temporalities (by LASSO), but more variables are selected for rice and maize than for wheat, suggesting that wheat trade is influenced by fewer factors and shocks than the other cereals. Possibly, established routes of wheat trade vary less with global trends, compared to routes of rice and maize that open and close more in relation to the 6Cs. Further, we find that shocks among the exporter countries matter more often for global trade than shocks in importing countries, possibly denoting stronger responses of trade routes to supply-side characteristics than demand-side characteristics. As the two methodologies select slightly different sets of variables, we consider the joint set of selected variables the most robust one. This group includes the traditional gravity determinants (bilateral distance and populations), which are selected by both methodologies, for all crops and temporalities. The group also includes GDP of both trade partners, though not always selected by LASSO. Apart from this, we note the prominence of the factors China and Climate (temperature), across all crops and temporalities, selected by both methodologies in most cases. In contrast, Climate (rain) is almost always selected by Random Forest, but ignored by LASSO in wheat and maize. Since Random Forests function by finding optimal cut-offs to split the features, this suggests that trade participation may respond more strongly once precipitation crosses



Variables	Mean	Std. Dev.	Unit
Export to China	0.078	0.012	%
Import from China	0.13	0.018	%
COVID-19 deaths	246	474	Count
COVID-19 cases	23724	47594	Count
Food CPI	9428	21861	Indicator
Conflicts	61	46	Count
Temperature	26	0.2	°C
Rain	1146	13	mml
GDP per country	165014	19250	Trillion USD

FIGURE 2 | Trends and summary statistics for the six factors of trade change: global averages during 2012–2022; monthly data unless otherwise indicated. *Source:* Own projection based on data sources described in Section 3.3. [Colour figure can be viewed at https://onlinelibrary.wiley.com/].

certain thresholds, while gradual, linear changes may have less impact. This is different for rice, where rain is considered relevant to trade participation by both methods. The climate variables (temperature and rain) on both the importer's and the exporter's sides matter, pointing to the disruptive role of climate change in both suppliers' and consumers' decisions to trade. Among the remaining Cs, we note that food inflation is mostly selected by the Random Forest but often ignored by the LASSO, though it matters for all crops and both partners. This indicates that gradual changes in inflation rates are unlikely to translate into changes in trade participation, while crossing certain thresholds of inflation does. Inversely, conflicts are selected by LASSO only, indicating that linear changes in violent events are directly associated with the ability to trade. This is

TABLE 1 | Feature selection for participation in trade (stage I).

		Monthly		Quarterly		Annually	
Wheat							
Controls	Distance	•	►	•	►	•	►
	Population of exporter	•	►	•	►	•	►
	Population of importer	•	►	•	►	•	►
Exprorter's Cs	China	•	►	•	►	•	►
	COVID	•		•		•	
	Food inflation		►	•	►		
	Conflicts	•					
	Temperature	•	►	•	►	•	►
	Rain		►			•	►
	GDP		►	•	►	•	►
Importer's Cs	China	•		•	►	•	►
	COVID			•			
	Food inflation		►	•	►		
	Conflicts	•		•		•	►
	Temperature		►		►		►
	Rain		►		►		►
	GDP		►		►		►
Rice							
Controls	Distance	•	►	•	►	•	►
	Population of exporter	•	►	•	►	•	►
	Population of importer	•	►	•	►	•	►
Exprorter's Cs	China	•	►	•	►	•	►
	COVID	•		•		•	
	Food inflation		►		►	•	
	Conflicts	•		•		•	
	Temperature	•	►	•		•	►
	Rain	•		•	►	•	►
	GDP	•	►		►	•	►
Importer's Cs	China	•	►	•	►		►
	COVID	•		•		•	
	Food inflation		►		►	•	►
	Conflicts	•		•		•	
	Temperature	•	►	•	►	•	►
	Rain		►	•	►	•	►
	GDP		►		►		►
Maize							
Controls	Distance	•	►	•	►	•	►
	Population of exporter	•	►	•	►	•	►
	Population of importer	•	►	•	►	•	►

(Continues)

TABLE 1 | (Continued)

		Monthly		Quarterly		Annually	
Exprorter's Cs	China	•	►	•	►	•	►
	COVID	•		•		•	
	Food inflation	•	►	•	►		
	Conflicts	•		•			
	Temperature	•	►		►	•	►
	Rain	•	►				►
	GDP	•	►	•	►	•	►
Importer's Cs	China	•		•	►	•	►
	COVID			•		•	
	Food inflation		►		►	•	
	Conflicts	•		•		•	►
	Temperature	•	►		►	•	►
	Rain		►		►	•	►
	GDP		►		►		►

Note: Controls included in the model (not reported): landlocked (exporter and importer), contiguity, common official language, common ethnic language, common colonial past. '•' indicates the variable was selected by the LASSO; '►' indicates the variable was among the top 12 most important variables ranked by the Random Forest. Numerical results available in Table A3.

true for all crops and for conflicts in both partners, with some exceptions. Similarly, COVID incidence is also considered relevant to the ability to trade for all crops only by LASSO, pointing to the role of small changes in COVID incidence.

In summary, among the global trends identified as potentially disrupting participation in global value chains, all of the 6Cs are in some models linked to trade participation outcomes. GDP levels, integration with China and temperatures appear the most relevant to maintain or prevent trade, followed by certain precipitation thresholds. Small changes in conflicts and COVID are also able to open or close trade routes, but less consistently than the other factors; while only reaching certain levels of inflation appears to change trade participation. Trading in wheat, especially yearly, appears the most robust to international changes.

4.2 | Factors of Trade Intensity

In the second stage, the adaptive LASSO model is applied to all determinants of traded amounts in the gravity model (Equation 2), and the resulting feature selections are shown in Table 2 for all temporalities. Two further specifications are reported: feature selection with a Random Forest (retaining the 12 most important variables), and LASSO applied to the PPML approach.

First, the GDP is confirmed as a common determinant of trade, and the foundation of the gravity model, as it is selected for almost all crops, temporalities, partners and feature selection methods. Dependency on China is also selected in almost all models (LASSO or RF), partners (exporter or importer), crops and temporalities. Similarly, temperature is selected in almost all models by either LASSO or RF, though less often for maize. As another determinant of climate change and yield, precipitation is much less associated with changes in trade flows, except for yearly changes. Whether the exporter and importer rain matters varies across crops. Here again, the selection of precipitation by RF but not LASSO points to the existence of thresholds in precipitation (e.g., floods or droughts) that trigger changes in trade flows, rather than more gradual changes in rain levels. COVID and food inflation are selected mostly in monthly and quarterly models, for all crops and both partners, but seem irrelevant to explain yearly fluctuations of crop exchanges. COVID is mostly selected by LASSO, while food inflation is selected by RF. Food inflation of the importer matters mostly for the monthly fluctuations whereas the exporter's inflation matters for both monthly and quarterly trade. Conflicts do not show a uniform pattern: conflicts in importer countries matter for quarterly wheat trade, countries in exporters matter for annual trade of rice, while both affect monthly maize trade. Therefore, the variable's sporadic inclusion in trade models likely reflects the local and heterogeneous nature of conflicts and their contextual influence on trade, rather than long-term structural influence.

In summary, inCome, dependency on China and climate, in particular temperature, are most able to predict fluctuations in traded amounts. Regarding rain, it is mostly precipitation anomalies that last in time that matter for global trade. Second, currency (food price index), COVID and conflicts matter for short-term fluctuations in trade flows, reflecting the dynamism of the global trade system to respond to abrupt shocks. However, they do not contribute to modelling long-term developments in trade.

Unlike the decision to engage in trade, there is no marked distinction across crops regarding the association of the 6C with

TABLE 2 | Feature selection for size of trade flow (stage II).

		Monthly			Quarterly			Annually		
Wheat										
Controls	Distance		►	■		►	■	•	►	■
	Population (exporter)	•	►			►			►	■
	Population (importer)	•	►	■	•	►	■	•	►	■
Exprorter's Cs	China	•	►	■	•	►	■	•		■
	COVID	•			•					
	Food inflation		►			►				
	Conflicts									
	Temperature		►	■		►			►	
	Rain								►	
	GDP	•	►	■		►			►	
Importer's Cs	China	•	►	■	•	►	■	•	►	■
	COVID	•		■	•					
	Food inflation		►							
	Conflicts					►				
	Temperature		►	■	•	►	■		►	■
	Rain			■					►	
	GDP		►	■	•	►	■	•	►	■
Rice										
Controls	Distance	•	►	■	•	►	■	•	►	■
	Population (exporter)		►	■		►	■	•	►	■
	Population (importer)	•	►	■	•	►	■	•	►	■
Exprorter's Cs	China	•	►	■	•	►	■	•	►	■
	COVID	•		■	•		■			
	Food inflation		►							
	Conflicts								►	
	Temperature	•	►		•	►			►	
	Rain								►	
	GDP		►			►	■	•	►	■
Importer's Cs	China	•	►	■	•	►	■	•	►	■
	COVID				•	►	■			
	Food inflation		►							■
	Conflicts									
	Temperature	•		■		►	■		►	■
	Rain									
	GDP		►	■	•	►	■	•	►	■
Maize										
Controls	Distance	•	►	■	•	►	■	•	►	■
	Population (exporter)		►			►	■		►	■
	Population (importer)	•	►	■	•	►	■	•	►	■

(Continues)

TABLE 2 | (Continued)

		Monthly			Quarterly			Annually		
Exprorter's Cs	China	•		■	•		■	•	►	■
	COVID	•		■	•		■			
	Food inflation		►			►				
	Conflicts		►							
	Temperature			■					►	
	Rain									
	GDP	•	►	■		►			►	
Importer's Cs	China	•	►	■	•	►	■	•	►	■
	COVID	•		■	•	►	■			
	Food inflation		►							
	Conflicts		►	■						
	Temperature	•	►	■	•			•	►	
	Rain								►	
	GDP	•	►		•	►	■	•	►	■

Note: Controls included in the model (not reported): contiguity, common official language, common colonial past, IMR from stage I (calculated following Henningsen and Toomet 2011), time fixed effects, exporter fixed effects. '•' indicates the variable was selected by the LASSO; '►' indicates the variable was among the top 12 most important variables ranked by the Random Forest; '■' indicates the variable was selected by the LASSO applied to the PPML approach (no IMR in that case). Numerical results available in Table A4.

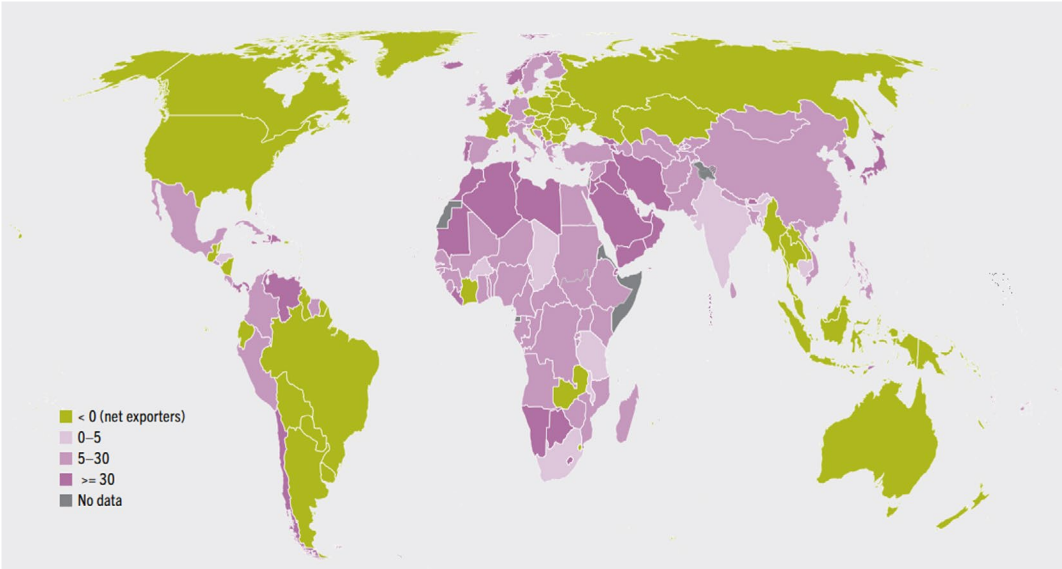
the magnitude of trade. The imbalance between the importance of exporter and importer characteristics also disappears, as both appear to be equally relevant to trade magnitude. It is noteworthy that the main features selected for trade magnitude (inCome, China, Climate) were also the most important for participation in trade. The secondary factors (Conflicts, COVID, Currency) are also common to both trade participation and intensities, but with differentiated roles across the intensive and extensive margins of trade. Events such as conflicts and COVID are mostly relevant for the trade participation of exporters (the extensive margin), while they are tied to trade amounts (intensive margin) only in the short- to mid-term. Notably, these variables are often selected by one methodology but not the other, reflecting the sensibility of the data to the approach used and their more fragile association with changes in trade patterns.

4.3 | Regional Analysis for Food Security

Trade is a crucial element of maintaining global and regional food security (Baldos and Hertel 2015; Dithmer and Abdulai 2017; D'Odorico et al. 2014; Smith and Glauber 2020). However, vulnerabilities can appear at the regional level (Abay et al. 2023; Kornher and Kalkuhl 2019). We refine the analysis to trade flows at the destination of Asia and Africa, hosts to large shares of the world's food insecure population and highly dependent on imports for their national food supply (see Figure 3 reproduced from FAO). Results for exports from Asia and Africa, which affect food security through their role in income generation, are available Table A6.

Overall, results (Table 3) show that dependency on China and economic growth are still omnipresent determinants of trade, while temperature and rain are not as omnipresent, but still shape trade. Food inflation appears somewhat more relevant than at the global level. Consistent with literature (Bahmani-Oskooee and Arize 2020; Mesagan et al. 2022; Sugiharti et al. 2020), changes in exchange rates and high inflation certainly affect Asia and Africa's ability to import and export. In this context, the African and Asian regions are clearly well integrated into the world economy and affected by global financial fluctuations. Moreover, it is possible that the other 6C tensions compound in stronger food inflation in Asia and Africa than globally due to weaker safety nets and limited policy capacity to cushion shocks (Agyei et al. 2021; Iliyasu et al. 2023). Next, conflicts also appear to have a more relevant role in trade for these regions than globally. Between 2020 and 2024, Africa and Asia had the highest number of conflicts (Raleigh and Kishi 2025). Imports in Africa are all tied to changes in conflicts, both in origin and destination countries, while imports to Asia are vulnerable to conflicts in Asia (for rice and maize), and conflicts in origin countries (maize). Finally, COVID-19 had mostly a supply-side effect, triggered by sudden bottle necks in global transportation routes and distribution, but did not affect demand strongly.

Table 3 further reports specific crop-region patterns of exposure to global volatility. Similar to the global analysis, wheat trade is the most robust to the diverse sources of disruptions, especially domestic. The relative unresponsiveness of wheat and maize demand from Africa may be related to the insufficiency of local production, as global wheat production is dominated by China, the EU, India and Russia (USDA 2025), together with high demand. Wheat and maize are the most consumed cereals in Africa (Erenstein et al. 2022; Silva et al. 2023) but production is primarily aimed at domestic markets and for self-consumption of smallholders. Import dependency for wheat in Africa is increasing over time, with about 20%–55% of consumption being imported, depending on the



NOTES: Countries coloured in green are net exporters of terrestrially produced food measured in energy content (kcal). Countries coloured in magenta are net importers. The darker the magenta, the higher the share of imports in domestic supply.
Refer to the disclaimer on the copyright page for the names and boundaries used in this map. Dotted line represents approximately the Line of Control in Jammu and Kashmir agreed upon by India and Pakistan. The final status of Jammu and Kashmir has not yet been agreed upon by the parties. Final boundary between the Republic of Sudan and the Republic of South Sudan has not yet been determined.

FIGURE 3 | Share of net food imports in total domestic supply (in kcal), 2020, percent. Reproduced from FAO (2024) The state of agricultural commodity markets 2024. With data from FAO (2024). FAOSTAT: supply utilization accounts. [accessed on 15 February 2024]. https://www.Fao.Org/Faostat/En/#Data/Scl. Licence: Cc-By-4.0. [Colour figure can be viewed at https://onlinelibrary.wiley.com/].

TABLE 3 | Features selected for monthly imports of wheat, rice and maize by Africa and Asia from the world (stage II).

		To Africa			To Asia		
	Imports	**Wheat**	**Rice**	**Maize**	**Wheat**	**Rice**	**Maize**
Controls	Distance	• ►	• ►	• ►	• ►	• ►	• ►
	Population of exporter	►	►	►	►	• ►	►
	Population of importer	• ►	►	• ►	►	• ►	►
Exprorter's Cs	China	• ►	• ►	• ►	•	• ►	• ►
	COVID			•		•	•
	Food inflation	►		►	►		►
	Conflicts	►	►	►			►
	Temperature	►	►	• ►	►		►
	Rain						
	GDP	►	►	• ►	►	►	• ►
Importer's Cs	China	•	• ►	• ►	• ►	• ►	• ►
	COVID						
	Food inflation	►	►	►	►	• ►	•
	Conflicts	►	►	•		• ►	►
	Temperature		►	•		• ►	•
	Rain					►	
	GDP	►	• ►	•	• ►	• ►	• ►

Note: Controls included in the model (not reported): contiguity, common official language, common colonial past, IMR from stage I, monthly fixed effects, exporter fixed effects. '•' indicates the variable was selected by the LASSO; '►' indicates the variable was among the top 12 most important variables ranked by the Random Forest. Numerical results available in Table A5.

specific country (Silva et al. 2023). The low production explains that domestic disruptions in the production or supply chain (COVID, temperature, rain) in Africa have little influence over their import pattern, while the primary role of wheat and maize for nutrition explains that demand-side disruptions (inflation, GDP) do matter. As for the global case, exporter-led volatility matters for crop imports and is consistent with concerns due to import dependency and self-sufficiency (Chen and Villoria 2022). Imports of rice also matter for Africa, as 40% of rice consumed on the African continent is imported (Yuan et al. 2024), but they are more responsive to the domestic 6Cs than wheat and maize, possibly because rice is mostly consumed in urban areas (Wopereis et al. 2013).

Rice, as a key component in Asian diets, exhibits a specific pattern. Asia's imports are responsive to all domestic disruptions (except COVID), unlike imports of wheat and maize, while they do not respond to exporters' trends in 6C. The top 10 producing countries of rice are located in Asia (USDA 2025), indicating strong leverage on global rice trade patterns which could explain trade responsiveness to domestic but not to exporter trends. Besides, overseas imports of rice grow over time, combined with a growth of domestic production as well, so that a decline in rice import dependency is observed in recent years (Tondel et al. 2020). An important difference in rice quality between domestic and international production exists, which limits the exportability of domestic production (Soullier et al. 2020; Tondel et al. 2020). Furthermore, Asian rice is the only trade that responds to rain variations. In comparison to wheat and maize, rice requires more water and is dependent on freshwater sources (Bouman et al. 2007). This makes rice production and trade more prone to precipitation shocks.

In summary, while the main determinants of trade remain consistent with the global level, Africa and Asia are more vulnerable to external shocks, particularly changes in inflation and conflicts. By contrast, the impact of COVID-19 was less pronounced. Results from the export-side (Table A6) further show that Africa and Asia are strongly dependent on importer conditions for their exports, which suggests they are more sensitive to global shocks in these regions. Divergences from global patterns may be attributed to differences in production structures and pre-existing import dependencies, often concentrated on specific regions or a limited number of exporters. For instance, North Africa relies heavily on European wheat imports, whereas Southern Africa depends more on American and Asian exporters for a wider range of crops (Erenstein et al. 2022). Similarly, Asia is particularly exposed to shocks originating in the USA (Erenstein et al. 2022). By contrast, regions with higher self-sufficiency or stronger domestic production capacity may be better able to counterbalance trade shocks, thereby reducing trade dependencies.

5 | Discussion

5.1 | Economic Size: Most Consistent Trade Determinants

The main trade determinants identified for both trade participation and trade intensity, and all temporalities, are consistently inCome (GDP), China and climate (temperature), which all relate to the economic size in gravity theory. In gravity theory, InCome (GDP) of the importer captures the income effect and preferences in an expenditure function, while the exporter's GDP reflects its export capacity or the supply available (de Benedictis and Taglioni 2011), both crucial determinants of trade. Despite other shocks and disruptions, the high growth of emerging economies and accompanying food demand in the last 15 years remain the key driving forces behind fluctuations in trade. These countries share an opening-up process which facilitates trade (Wu and Pan 2021) and also links to a reduction of trade costs. Next, China's role in international foods alters the global demand (Ali et al. 2017). This presents opportunities for food exporters, especially those along the Belt and Road Initiative that China actively pursues (Zhang et al. 2022), and therefore shifts global food supply towards Chinese consumers. The results highlight that the fluctuations in a country's trade with China (either imports or exports) are consistently among the main factors behind that country's changes in bilateral trade. Therefore, the combination of China's demand and its trade-facilitating infrastructure policies, which touches both foundations of gravity's theory (economic size and trade costs), is crucial to understanding dynamics in global trade. Finally, geographic differences in climate are a primary driver of food flows. Anthropogenic climate change, through shifts in long-term trends and abrupt weather events, can directly translate into production fluctuations that affect trade flows and prices (Villoria 2025). However, a flexible and well-functioning international trade can also partially compensate for lower supply emanating from affected regions (Huang et al. 2011). Huang et al. (2011), Villoria (2025) and others argue that reducing trade frictions (e.g., borders, trade tariffs or import restrictions) lowers the cost of trade, which could compensate for the climate-induced changes in economic size, leading to a more resilient trade system. Importantly, our results showed that temperature changes help explain movements in crop trade since 2012 as consistently as changes in GDP and China's economy. Both gradual and stepwise shifts in temperatures are related to changes in trade participation and trade intensity. Temperature changes in importer countries also matter, indicating that climate-induced productivity changes also affect the demand for international crops. All in all, our results highlight that trade determinants associated with economic size have a more direct role in trade, but that policies accompanying these changes also modify trade costs.

5.2 | Trade Costs: Supply Shocks Matter for Changes in Trade Participation

Factors that directly shock ease of trade and associated trade costs (COVID, Conflicts and Currency) have a less consistent role on trade. These are arguably more volatile in the short term than the more predictable economic size factors (inCome, China and Climate). This could explain why they tie to the intensive margin of trade in the short term (monthly) only, while the association often disappears in the long term (annually). On the extensive margin, participation in trade is more often determined by exporter shocks, whereas importer volatility is less relevant. Demand may be more inelastic to global change, possibly because crop purchases are crucial for food security and thus prioritised by importing policy makers. The predominance of exporter-led instability is consistent with importers' common (but criticised) response to increase protectionism in the face of global food crises (Evenett et al. 2022; Smith and Glauber 2020), as was seen in the responses to COVID-19 and high food inflation episodes. On the other hand, stabilising export sectors and the supply of crops to the international market might be a lower political priority for exporters than other economic or political domestic goals. This points towards a role for policies targeted towards exporting countries and the supply chain, to ensure trade stability and food security in importing countries.

5.3 | Policies Prioritisation: Short-Term Response or Long-Term Adaptation?

The threats to trade developed at different speeds and induced different policy responses. Based on the conceptual framework, shocks and crises can be attributed to specific components of the food trade system, helping prioritise policy response.

Conflicts, COVID and currency fluctuations are abrupt events that triggered intense fears of food insecurity. Often, responses to shocks further increase volatility in world markets or exacerbate food insecurity (Brander et al. 2023; Naylor and Falcon 2010). Instead, domestic measures that soften the shock, for example in the form of safety nets, direct cash transfers and support to farmers, are recommended (Abbott and Borot de Battisti 2011). We find that exporter shocks indeed impede trade through trade participation. However, we find no general long-lasting association with trade volumes. The literature confirms that initial fears of food shortages due to COVID were largely unfounded due to well-supplied global markets and healthy stocks (Glauber et al. 2020). Trade and supply chain disruptions were primarily short-term, affecting the extensive margin of trade during periods of high policy stringency and reduced mobility (Engemann and Jafari 2022). Staple foods proved more resilient than other agri-food products, with inter-regional trade in Asia, Africa and Latin America showing greater resilience than intra-regional trade (Engemann and Jafari 2022). Similarly, after initial fears of rising food insecurity due to the war in Ukraine, agreements were put in place rapidly to allow trade to take place conducting international negotiations (Ukraine-Russia Black Sea Grain Initiative of 2022), while in the medium-term networks adapted to the new situation and trade was often re-rooted, but with no change visible at the global level. For policy makers, this shows that preparedness can mitigate adverse consequences of abrupt crises and sustain trade participation. Overcoming the initial shock through fast response policies that stabilise supply chains and food production should be prioritised while food trade tends to normalise in the long run. Measures that stabilise disruption in production and supply chains, through for example increasing the stock-to-use ratio, are suggested.

As opposed to the short-term factors, China's growing role in the world economy, climate change and food demand patterns in high-growth countries develop over a longer term, with implications for structural changes in competitive advantages and terms of trade, affecting both extensive and intensive margins of trade. These developments affect both the demand and supply of food. Policies should target resilience measures that adapt local food systems to long-term changes in global food trade, for example in the form of preferential or free-trade agreement negotiations, or investment in trade infrastructure (China's Road and Belt Initiative). The omnipresent role of temperature in crop trade is consistent with the colossal amount of research demonstrating the effects of climate change on agriculture (Campbell et al. 2016; Fanzo et al. 2018; Godde et al. 2021). To ready the trade system for climate change, policies can first target both global climate mitigation as well as local climate adaptation measures, and thus aim to contain the changes in regional productivities. Second, policies adapting the trade infrastructure to the new trade routes emanating from the changes in production capacities can lower economic distance by facilitating trade, and help compensate for the changes. Increasing the resilience of exporting countries to these shocks therefore requires policies that strengthen production against climate risks and more generally buffer supply chain disruptions.

6 | Conclusion

Trade of food is crucial to ensure food security and economic prosperity of farmers globally, but it is subject to manifold crises. This article evaluates the resilience of the food trade system to today's crises and factors of destabilisation. We identify six major factors that have a growing influence on the world's economy and the potential to disrupt trade flows: Conflicts, COVID-19, Currency, China, Climate change and inCome (the 6Cs). The disruptive potential of each of these factors has been largely documented and analysed. However, no research so far has established the relative importance of these factors on the food trade system, and identified which present the most important threat. Using data on bilateral wheat, rice and maize trade flows for the period 2012–2022, we examine the influence of these factors jointly in the gravity model of trade and apply a data-driven feature selection with LASSO and Random Forest to identify which of the current potential disruptions are relevant to trade participation and trade magnitude. The main contribution of this article lies in analysing all factors in conjunction rather than individually, to help prioritise responses.

Despite some heterogeneity in the results, consistent patterns emerge. Fluctuations in inCome, China and climate are most consistently associated with variations at both the extensive and intensive margins of trade. In addition, conflicts, COVID and currency are also linked to the ability of countries to engage in trade, therefore affecting trade routes, but not the trade amounts in the long run. Among them, exporter-side shocks are more prominent, highlighting the need to prioritise stabilisation of production and supply, while demand-side risks appear less disrupting. The results provide detailed evidence that not all shocks result in the same amounts of disturbances in the trade system and the need to discretise policy response according to shocks.

The results are a stark reminder that, as geo-political and geo-economic tensions are growing globally, they pose an important risk to the trade of main crops and food security. However, these tensions divert the attention of policy makers and voters away from the global climate crisis, as seen by the slowing of progress towards ambitious climate-protection policies. This study shows on the contrary that climate change is also, unambiguously, a main driver of the trade of main food products and that its impact on the food system must stay at the focus of attention.

The current global instability, with US-imposed tariffs on a high number of trade partners presents an additional layer of trade disruptions. Within the framework of the paper, built for data from 2012 to 2022, tariffs enter as an added trade cost factor, and would thus affect trade participation while trade intensity would normalise in the long run. These changes may however trigger a new era of trade relationships, demanding new frameworks of analysis as new shocks arise.

Our analysis is subject to several limitations. First, the results are specific to the selected period and therefore should not be interpreted as having external validity beyond the years under study. Second, the aggregation of results at regional and global scales conceals substantial heterogeneity at finer spatial or sectoral levels. Third, our approach is correlational. While the annual specification provides some scope for shocks to be reflected in trade flows, the monthly specification may not fully capture shorter-term dynamics. A promising avenue for further research is therefore to conduct causal analyses to assess the robustness of our findings. Finally, the trade flow measures employed here reflect realised trade after policy responses may already have been enacted in reaction to shocks. As such, we cannot fully separate the pure association between shocks and trade outcomes from the effect of policy interventions. What we capture is the response to shocks conditional on the policies in place. A causal framework could help disentangle these effects.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available in COMTRADE at https://comtradeplus.un.org/. These data were derived from the following resources available in the public domain: Trade flows, https://comtradeplus.un.org/.

Endnotes

[1] In our practical implementation, we deviate from the theoretical specification that requires using inward multilateral resistance due to computational reasons.

[2] The traditional gravity determinants (GDP, distance, populations) are taken in their log form, following common practice. The variable 'China' is a share between 0 and 1, and the variable 'COVID' is a standardised index, so no further transformation is applied to them. Inflation, number of conflicts, temperature and rain are taken in their level, reflecting their smaller ranges. Binary variables (contiguity, colonial ties, common official language, common ethnic language) are kept as 0/1.

[3] The coefficients obtained by the feature selection are biased towards zero due to the shrinking mechanism. To provide the unbiased results shown in Appendix, the post-LASSO approach is used, keeping only the variables selected by LASSO in (4) and (2).

[4] LASSO may remove factors highly correlated with others. However, correlation among the 6C is verified to be not problematic and the focus of this approach is on prediction, as identifying pathways between the individual 6C, their interactions and trade flows would be plagued by complexity.

[5] https://www.cepii.fr/cepii/en/bdd_modele/bdd_modele.asp.

[6] Count of all event types: battles, explosions, protests, riots, strategic developments and violence against civilians. *Source:* https://acleddata.com/curated-data-files/.

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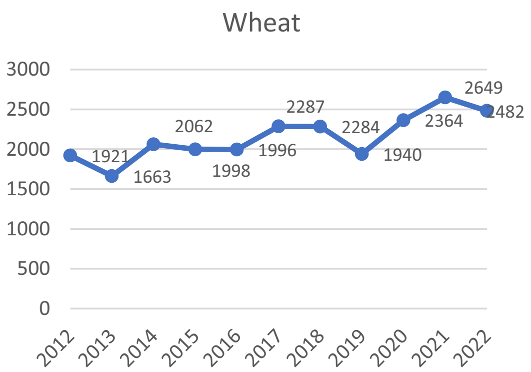
Appendix

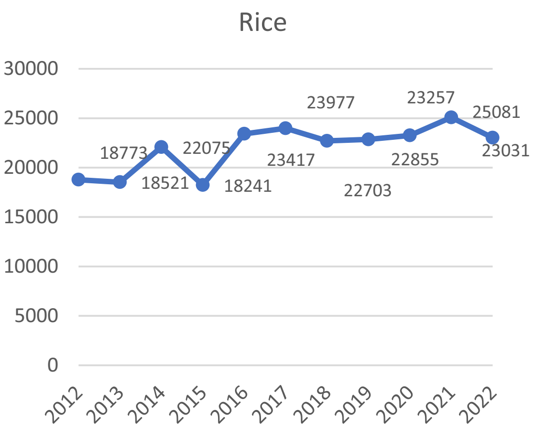
TABLE A1 | Summary statistics for bilateral trade in kg, period 2012–2022, World.

		N	Mean	SD	CV	Min	Max
Wheat	Monthly	76,652	23,288,115	68,882,369	2.96	0.035	4.54E+09
	Quarterly	38,064	46,896,821	1.49E+08	3.19	0.035	7.13E+09
	Annually	15,346	1.16E+08	4.16E+08	3.57	0.04	9.58E+09
Rice	Monthly	181,842	2,257,404	10,642,564	4.71	0.02	4.51E+08
	Quarterly	82,535	4,973,536	25,438,637	5.11	0.02	8.97E+08
	Annually	29,129	14,092,170	79,286,587	5.63	0.065	2.46E+09
Maize	Monthly	110,097	14,032,127	76,543,021	5.45	0.01	3.41E+09
	Quarterly	53,483	28,885,723	1.8E+08	6.23	0.01	8.71E+09
	Annually	20,901	73,914,890	5.18E+08	7.01	0.034	1.88E+10

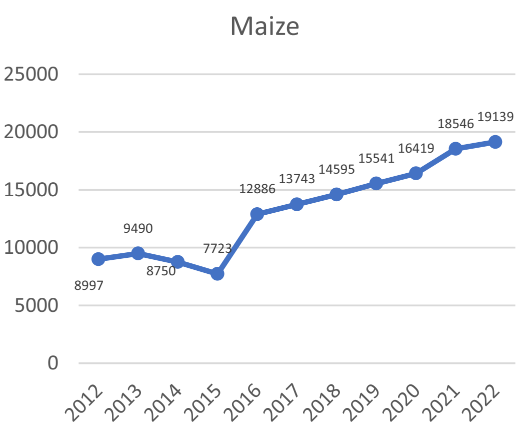
Abbreviations: CV, coefficient of variation; SD, standard deviation.
Source: Own compilation based on COMTRADE database.



Top 10 Exporters (Wheat)	*Top 10 Importers (Wheat)*
Russia	Egypt
Canada	Indonesia
Australia	Algeria
USA	Italy
France	Brazil
Ukraine	Türkiye
Argentina	Netherlands
Germany	Spain
Romania	Bangladesh
Bulgaria	Philippines



Top 10 Exporters (Rice)	*Top 10 Importers (Rice)*
India	China
Thailand	Benin
Pakistan	Côte d'Ivoire
Vietnam	Senegal
United States	Saudi Arabia
Myanmar	Iran
China	Philippines
Brazil	Iraq
Italy	United Arab Emirates
Paraguay	Bangladesh



Top 10 Exporters (Maize)	*Top 10 Importers (Maize)*
USA	Japan
Brazil	Mexico
Argentina	Korea
Ukraine	Vietnam
Romania	China
France	Egypt
Russia	Spain
Paraguay	Iran
India	Netherland
Serbia	Algeria

FIGURE A1 | Trade flows of wheat, rice and maize, in 1000's kg, aggregated at global and annual averages (left); major exporters and importers during 2012–2022 (right). *Source:* Own projection with COMTRADE data. [Colour figure can be viewed at https://onlinelibrary.wiley.com/].

TABLE A2 | Probit models for selection into trade (monthly).

		Wheat			Rice			Maize		
		(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Exporter's Cs	China		−6.049***	−5.834***		−0.780***	−0.777***		−1.516***	−1.515***
			(0.115)	(0.107)		(0.052)	(0.051)		(0.069)	(0.069)
	COVID-19		0.025***	0.026***		0.028***	0.028***		0.028***	0.029***
			(0.003)	(0.003)		(0.002)	(0.002)		(0.002)	(0.002)
	Food CPI		0.000***			0.000			0.000**	0.000**
			(0.000)			(0.000)			(0.000)	(0.000)
	GPD	−0.055***	0.017***		−0.022***	−0.017***	−0.017***	−0.062***	−0.027***	−0.027***
		(0.001)	(0.003)		(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
	Number of conflicts		0.000***	0.000***		0.000***	0.000***		0.000***	0.000***
			(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
	Temperature		0.007***	0.005***		−0.019***	−0.019***		−0.004***	−0.004***
			(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
	Rain		−0.000***			−0.000***	−0.000***		−0.000***	−0.000***
			(0.000)			(0.000)	(0.000)		(0.000)	(0.000)
Importer's Cs	China		−0.902***	−0.791***		−0.614***	−0.642***		−1.180***	−1.183***
			(0.069)	(0.064)		(0.047)	(0.044)		(0.063)	(0.059)
	COVID-19		0.015***			0.012***	0.012***		0.006	
			(0.004)			(0.003)	(0.003)		(0.004)	
	Food CPI		−0.000**			0.000+			0.000	
			(0.000)			(0.000)			(0.000)	
	GPD	−0.011***	0.005*		−0.016***	−0.003+		−0.011***	−0.000	
		(0.001)	(0.002)		(0.001)	(0.002)		(0.001)	(0.002)	
	Number of conflicts		−0.000***	−0.000***		−0.000***	−0.000***		−0.000***	−0.000***
			(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
	Temperature		−0.003***			0.004***	0.004***		−0.003***	−0.003***
			(0.000)			(0.000)	(0.000)		(0.000)	(0.000)
	Rain		0.000***			−0.000**			−0.000	
			(0.000)			(0.000)			(0.000)	

(Continues)

TABLE A2 | (Continued)

		Wheat			Rice			Maize		
		(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Controls	(Intercept)	−3.426***	−4.437***	−4.119***	−4.487***	−4.294***	−4.350***	−4.012***	−3.644***	−3.659***
		(0.026)	(0.081)	(0.066)	(0.020)	(0.062)	(0.058)	(0.024)	(0.072)	(0.067)
	Landlocked exporter (yes = 1)	−0.206***	0.079***		−0.503***	−0.392***	−0.391***	−0.192***	0.085***	0.085***
		(0.005)	(0.013)		(0.004)	(0.012)	(0.012)	(0.005)	(0.012)	(0.012)
	Landlocked importer (yes = 1)	−0.255***	−0.244***	−0.211***	−0.380***	−0.290***	−0.294***	−0.301***	−0.313***	−0.314***
		(0.005)	(0.013)	(0.013)	(0.004)	(0.010)	(0.010)	(0.004)	(0.012)	(0.012)
	Contiguity	0.504***	0.905***	0.895***	0.429***	0.859***	0.855***	0.654***	1.047***	1.048***
		(0.007)	(0.018)	(0.018)	(0.006)	(0.017)	(0.017)	(0.006)	(0.017)	(0.017)
	Common language (official)	−0.107***	0.300***		−0.077***	0.168***	0.099***	−0.131***	0.008	
		(0.008)	(0.033)		(0.006)	(0.025)	(0.011)	(0.007)	(0.027)	
	Common language (ethnic)	0.063***	−0.281***		0.128***	−0.073**		0.228***	0.086***	0.092***
		(0.008)	(0.032)		(0.006)	(0.024)		(0.007)	(0.025)	(0.012)
	Colonial tie	0.665***	0.371***	0.362***	0.733***	0.674***	0.671***	0.533***	0.389***	0.389***
		(0.008)	(0.026)	(0.025)	(0.007)	(0.021)	(0.021)	(0.008)	(0.024)	(0.024)
	Population of exporter	0.274***	0.174***	0.187***	0.346***	0.332***	0.332***	0.337***	0.255***	0.255***
		(0.001)	(0.004)	(0.003)	(0.001)	(0.003)	(0.003)	(0.001)	(0.004)	(0.004)
	Population of importer	0.123***	0.112***	0.114***	0.093***	0.057***	0.054***	0.113***	0.093***	0.092***
		(0.001)	(0.004)	(0.003)	(0.001)	(0.003)	(0.002)	(0.001)	(0.004)	(0.003)
AIC		1,347,028.0	90,928.8	91,280.0	2,236,854.6	157,643.8	157,660.4	1,603,090.6	113,543.5	113,538.3

Note: (1) Probit with usual controls, (2) Probit with usual controls and all 'Cs' variables, (3) Probit with LASSO applied to usual controls and all 'Cs' variables. No data indicates that the coefficient was shrunk to zero in the LASSO model.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Standard errors in parentheses.

TABLE A3 | Post-LASSO selection into trade (monthly, quarterly, annually).

		Monthly			Quarterly			Annual		
		Wheat	**Rice**	**Maize**	**Wheat**	**Rice**	**Maize**	**Wheat**	**Rice**	**Maize**
Controls	(Intercept)	−4.119***	−4.350***	−3.659***	−3.554***	−4.346***	−4.058***	−2.944***	−3.973***	−3.638***
	Landlocked exporter (yes = 1)		−0.391***	0.085***	−0.065***	−0.450***	−0.037**	−0.079***	−0.483***	−0.089***
	Landlocked importer (yes = 1)	−0.211***	−0.294***	−0.314***	−0.254***	−0.369***	−0.335***	−0.272***	−0.414***	−0.342***
	Contiguity	0.895***	0.855***	1.048***	0.621***	0.636***	0.785***	0.558***	0.718***	0.851***
	Common language (official)		0.099***		0.115***	0.164***			0.186***	
	Common language (ethnic)			0.092***	0.078***		0.218***	0.134***	0.017	0.235***
	Colonial tie	0.362***	0.671***	0.389***	0.309***	0.743***	0.395***	0.443***	0.919***	0.488***
	Distance	−0.273***	−0.282***	−0.309***	−0.338***	−0.321***	−0.363***	−0.359***	−0.327***	−0.371***
	Population of exporter	0.187***	0.332***	0.255***	0.228***	0.329***	0.304***	0.240***	0.345***	0.345***
	Population of importer	0.114***	0.054***	0.092***	0.105***	0.058***	0.099***	0.118***	0.078***	0.115***
Exprorter's Cs	China	−5.834***	−0.777***	−1.515***	−2.167***	−0.987***	−0.903***	−2.263***	−0.762***	−0.710***
	COVID	0.026***	0.028***	0.029***	0.039***	0.033***	0.049***	0.000***	0.000***	0.000***
	Food inflation			0.000**	0.000***		0.000***		−0.009***	
	Conflicts	0.000***	0.000***	0.000***		0.000***	0.000***		0.000***	
	Temperature	0.005***	−0.019***	−0.004***	0.005***	−0.015***		0.005***	−0.024***	−0.006***
	Rain		−0.000***	−0.000***		−0.000***		−0.000+	−0.000***	
	GDP		−0.017***	−0.027***	−0.024***		−0.035***	−0.041***	−0.011**	−0.065***
Importer's Cs	China	−0.791***	−0.642***	−1.183***	−0.586***	−0.292***	−0.618***	−0.685***		−0.464***
	COVID		0.012***		0.028***	0.034***	0.027***		0.000***	0.000***
	Food inflation				−0.000**				−0.004***	−0.002***
	Conflicts	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***
	Temperature		0.004***	−0.003***		0.004***			0.002**	0.002+
	Rain					−0.000***			−0.000***	−0.000***
	GDP									
AIC		91,280	157,660.4	113,538.3	93,595.9	147,237.5	110,479.5	36,262.4	48,973.5	41,366.8
BIC		91,420.2	157,865.3	113,743.2	93,794.1	147,435.7	110,656.9	36,409.5	49,194.2	41,541.5
Log.Lik.		−45,627.01	−78,811.203	−56,750.141	−46,778.944	−73,599.754	−55,222.76	−18,115,199	−24,462,736	−20,664,379
F		1628.114	2244.278	1556.664	1040.24	1944.339	1627.878	457,969	513,657	533,008
RMSE		0.18	0.26	0.21	0.23	0.3	0.25	0.27	0.32	0.29

Note: LASSO applied to usual controls and all ‘Cs’ variables. No data indicates that the coefficient was shrunk to zero in the LASSO model.
$*p<0.1$, $**p<0.05$, $***p<0.01$.

TABLE A4 | Post-LASSO trade intensity (monthly, quarterly, annually).

		Monthly			Quarterly			Annual		
		Wheat	**Rice**	**Maize**	**Wheat**	**Rice**	**Maize**	**Wheat**	**Rice**	**Maize**
Controls	(Intercept)	10.901+	22.932***	63.921***	10.688***	19.093***	16.121***	7.463***	47.510*	17.472***
	Contiguity	−0.722***	−0.229*	−1.742***	−0.246	0.282***	−0.724***	0.236	0.448***	
	Common language (official)	−0.113	−0.460***	−0.228*		−0.201***	−0.363***	0.287+	−0.09	−0.061
	Colonial tie	0.670***	−0.862***	−1.448***	−0.474***	−0.950***	−1.846***	−0.600*	−0.747***	−0.778***
	IMR[a]	−3.492***	−1.590***	−3.540***	−3.820***	−1.738***	−4.050***	−2.216***	−1.767***	−2.096***
	Distance		−1.239***	−0.448***		−1.141***	−0.464***	−0.748***	−1.280***	−1.372***
	Population of exporter	1.210***							−4.825**	
	Population of importer	0.445***	0.171***	0.296***	0.333***	0.223***	0.106***	0.377***	0.267***	0.269***
Exprorter's Cs	China	8.733***	−3.406***	−13.575***	−0.634	−3.235***	−11.562***	3.129	−5.025**	−3.93
	COVID	−0.279***	−0.066***	−0.236***	−0.118***	−0.060***	−0.173***			
	Food inflation									
	Conflicts									
	Temperature		0.012***			0.023***				
	Rain									
	GDP	−0.600***		−1.558***					1.853***	
Importer's Cs	China	0.766	−0.489**	2.422***	−1.227*	0.059	0.117	−2.621**	−1.288***	−0.959+
	COVID	0.081*		0.092*	−0.119***	0.020*	−0.074***			
	Food inflation									
	Conflicts									
	Temperature		0.019***	−0.006*	−0.012***		−0.016***			−0.020***
	Rain									
	GDP			0.047**	0.087***	−0.031***	0.137***	0.121***	−0.064***	0.121***
Num.Obs.		13,507	31,058	18,807	15,462	32,716	20,910	6693	12,028	8882
R^2		0.502	0.544	0.411	0.482	0.528	0.424	0.484	0.53	0.466
R^2 Adj.		0.498	0.543	0.408	0.479	0.527	0.421	0.476	0.526	0.46
AIC		70,886.3	144,597.2	100,076.1	83,249.2	156,960.8	111,945	36,998.2	60,094.3	47,745.6
BIC		71,539.8	145,439.9	100,868.1	84,013.8	157,842.3	112,771.6	37,754	60,937.4	48,518.6
Log.Lik.		−35,356.169	−72,197.614	−49,937.051	−41,524.584	−78,375.398	−55,868.519	−18,388.123	−29,933.171	−23,763.793
RMSE		3.32	2.47	3.44	3.55	2.66	3.5	3.78	2.91	3.51

Note: LASSO applied to usual controls and all 'Cs' variables. Models include time and exporter fixed effects. No data indicates that the coefficient was shrunk to zero in the LASSO model.
[a]Selection into trade, calculated following Henningsen and Toomet (2011).
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

TABLE A5 | Post-LASSO trade intensity (monthly) for exports to Africa and Asia.

		To Africa			To Asia		
		Wheat	**Rice**	**Maize**	**Wheat**	**Rice**	**Maize**
Controls	(Intercept)	33.729***	21.066***	69.508***	19.672***	−2.440	99.955***
	Contiguity	3.165***	3.542***	3.362***	−0.306	−1.967***	−2.366***
	Common language (official)		−1.986***	−1.284***	−1.355***	−1.451***	0.105
	Distance	−2.442***	−0.634***	−1.898***	−0.625***	−0.689***	−0.226
	Population of exporter					1.123***	
	Population of importer	0.351***		1.559***		0.262***	
	IMR[a]	−0.854+	−2.797***	0.346	−0.465	−3.021***	−2.025***
Exprorter's Cs	China	6.136*	−0.550	−5.081	−3.919	3.045*	−16.181***
	COVID			−0.012		0.021	−0.180***
	Food inflation						
	Conflicts						
	Temperature			−0.043*			
	Rain						
	GDP			−1.973***			−2.999***
Importer's Cs	China	3.160*	4.271***	−11.652***	−6.330***	1.562***	0.310
	COVID			−0.504		0.294***	
	Food inflation					−0.019***	0.006***
	Conflicts						
	Temperature			−0.062***		0.057***	0.028***
	Rain						
	GDP		0.081**	−0.195**	0.220***	−0.140***	0.189***
AIC		1306	3088	1417	3420	5307	5161
BIC		0.749	0.654	0.639	0.613	0.476	0.430
Log.Lik.		0.740	0.648	0.622	0.605	0.471	0.421
F		5689.5	14,265.1	7117.4	16,414.5	24,818.4	27,286.4
RMSE		5927.5	14,615.1	7459.1	16,825.7	25,127.5	27,797.2
Log.Lik.		−2798.750	−7074.529	−3493.719	−8140.238	−12,362.189	−13,565.184
RMSE		45,810	14,277	31,079	22,313	17,930	12,844

Note: LASSO applied to usual controls and all 'Cs' variables. Models include time and exporter fixed effects. No data indicates that the coefficient was shrunk to zero in the LASSO model.
[a]Selection into trade, calculated following Henningsen and Toomet (2011).
*$p<0.1$, **$p<0.05$, ***$p<0.01$.

TABLE A6 | Features selected for monthly exports of wheat, rice and maize by Africa and Asia to the world (stage II).

		From Africa			From Asia		
	Exports	**Wheat**	**Rice**	**Maize**	**Wheat**	**Rice**	**Maize**
Controls	Distance	• ►	•	• ►	• ►	• ►	• ►
	Population of exporter	►	►	►	• ►	•	►
	Population of importer	►	• ►	►	• ►	• ►	• ►
Exporter's Cs	China	•	• ►	•	•	•	• ►
	COVID			•		•	•
	Food inflation	►	►	►	•	►	• ►
	Conflicts		►				
	Temperature						
	Rain						
	GDP	►	►	►	• ►	►	• ►
Importer's Cs	China	• ►	• ►	• ►	• ►	• ►	• ►
	COVID						
	Food inflation		►	►	►	►	►
	Conflicts			•	• ►	►	• ►
	Temperature	►	►	• ►	• ►	• ►	• ►
	Rain				►	►	
	GDP	►	• ►	• ►	►	►	• ►

Note: Controls included in the model (not reported): contiguity, common official language, common colonial past, IMR from stage I, monthly fixed effects, exporter fixed effects. '•' indicates the variable was selected by the LASSO; '►' indicates the variable was among the top 12 most important variables ranked by the Random Forest.