OECD publishing

MITIGATING THE IMPACT OF EXTREME WEATHER EVENTS ON AGRICULTURAL MARKETS THROUGH TRADE

OECD FOOD, AGRICULTURE AND FISHERIES

PAPER

June 2023 **n°198**

OECD
BETTER POLICIES FOR BETTER LIVES

Mitigating the Impact of Extreme Weather Events on Agricultural Markets Through Trade

Marcel Adenäuer and Clara Frezal (OECD),
Thomas Chatzopoulos (FAO consultant)

Extreme weather events can disrupt agricultural markets, but agricultural trade can help address subsequent food security concerns. Using the Aglink-Cosimo model, this stochastic scenario analysis sheds light on the complex relationships between trade and food security in an environment where extreme weather events create uncertainty. The analysis suggests that trade integration makes countries less vulnerable to negative yield shocks by mitigating the risk of extreme food prices and by stabilising food availability. Although no model can capture the complex process and consequences of opening this sector to trade, it is clear that trade integration needs to be part of a wider coherent policy package to improve food security.

Key words: Climate change, Trade integration, Food security, Resilience, Partial equilibrium modelling

JEL codes: Q17, Q18, Q56, Q54, C54

Acknowledgments

This report benefited from the reviews of colleagues from the OECD Trade and Agriculture Directorate, as well as colleagues from the European Comission’s Joint Research Centre in Seville. It also benefited from all the work done in the C2ESAM project at the European Commission.

The authors are grateful to the delegates of the OECD Joint Working Party on Agriculture and the Trade for their comments. They would also like to extend their thanks to Michèle Patterson and Caitlin Boros of the OECD Trade and Agriculture Directorate for their substantial editorial work on the report and for helping to co-ordinate the publication process.

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Key messages

- Extreme weather events are expected to increase in frequency and intensity over the coming decades, worsening disruptions to agricultural markets and trade. An open and resilient trading system can mitigate the impact of these disruptions on food security.
- This scenario analysis bridges a gap in the literature by including the effects of the increased frequency and intensity of extreme weather events in an analysis that assesses the interaction between market variability and trade integration.
- The scenario results suggest that trade integration reduces the upward pressure on agricultural prices from extremely low domestic yields.
- Despite concerns countries may have about exposure to price volatility from international markets, in most cases trade integration is also found to reduce upward pressure on domestic prices from extreme yield reductions in key exporters.
- The risk of high domestic food prices decreases with greater trade integration, suggesting that open trade can help stabilise food expenditures.
- Trade integration also moderates the extent to which extreme weather events reduce food availability, indicating that trade integration can help stabilise food supply in the case of extreme yield reductions.
- The scenario results highlight the potential for trade to mitigate the negative effects of extreme weather events on food prices and food availability. However, the process and consequences of opening to trade are more complex than can be captured by the model. Trade liberalisation thus needs to be part of a wider coherent policy package to enhance food security.
- The results of this study are subject to limitations. First, the representation of climate change impacts remains partial as long-term changes in temperature and precipitation patterns are not explicitly modelled in Aglink-Cosimo. Second, the model scenarios consider a stylised representation of yield reductions arising from extreme weather events as well as changes in countries' trade policies. Further research could be conducted to assess the impact of a unilateral change in trade policies on domestic agricultural markets in the context of extreme weather events.

Introduction

Extreme weather events can disrupt agricultural markets and trade, but agricultural trade can, in turn, help address food security concerns in the wake of these events (OECD, 2017[1]; OECD, 2017[2]). However, existing market access barriers and support to producers affect the global trade environment and influence food supply and food security outcomes. What does this mean for the potential of trade to mitigate the negative impacts of extreme weather events on food security?

This report explores this question using the stochastic framework of the Aglink-Cosimo model under different trade specifications. The Aglink-Cosimo model has already been used in the context of extreme weather events (Chatzopoulos et al., 2020[3]; Chatzopoulos et al., 2021[4]; EC, 2022[5]; EC, 2017[6]), but these applications did not explicitly focus on the potential for trade integration to mitigate the impact of negative yield shocks. This analysis also complements recent OECD work simulating the impact of agriculture policy reforms on climate adaptation in agriculture, which looked at long term climate scenarios using the GLOBIOM model (Guerrero et al., 2022[7]).

In an increasingly connected world, trade affects each of the four dimensions of food security: food availability, access, utilisation, and stability. Theoretically, trade integration is expected to reduce domestic price volatility and stabilize food consumption, but simultaneous yield shocks occurring in several countries could offset this effect. This report sheds light on the complex relationships between trade and the different dimensions of food security in an environment where extreme weather events create uncertainty. The analysis suggests that trade integration makes countries less vulnerable to the consequences of negative yield shocks by mitigating the risk of extreme food prices and stabilizing food availability.

The report is organised as follows. Section 1 reviews existing studies applying extreme weather event modelling in agriculture and exploring the shock-mitigation potential of trade. Section 2 describes the methodology to explore the impact of extreme events on agricultural markets, using the stochastic framework of Aglink-Cosimo. Section 3 presents the assumptions behind the different trade scenarios. Section 4 summarises the key results of the analysis and Section 5 discusses the implications of the main findings.

1. Literature review

1.1. What are extreme weather events and why do they matter for agriculture?

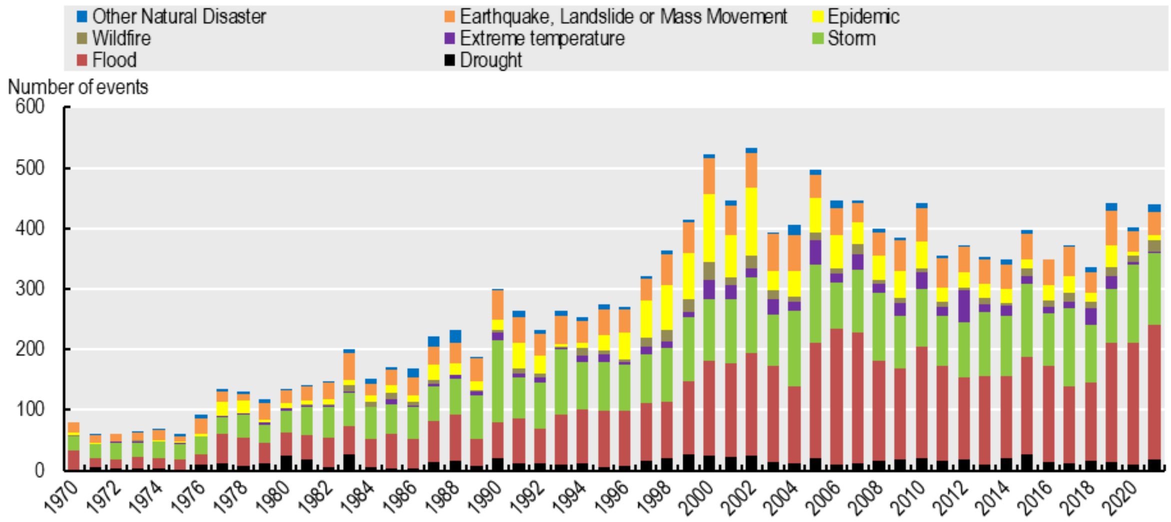
Extreme weather events can be defined in various ways (Sillmann et al., 2017[8]; National Academies of Sciences, 2016[9]; Stephenson, 2008[10]). They generally refer to rare and short-lived events, lasting from hours up to several months, with devastating potential (e.g., heat waves, drought, flood, storms). Definitions of "rare" vary, but an extreme weather event would typically be below the 10th percentile or above the 90th percentile of the observed probability density function, with respect to climate variables such as temperature and precipitation (IPCC, 2007[11]).

Climate change is increasing the frequency, intensity, and spatial extent of extreme weather events. Between 1971-1980 and 2011-2020, climate-related disasters increased from 92 events per year to 372 events per year, on average. The number of droughts has doubled; severe storms have more than tripled; and floods and heat waves have become much more prevalent (Figure 1.1). Without near-term actions that limit global temperature increases to close to 1.5°C, the frequency, intensity, and spatial extent of extreme weather events is expected to continue increasing (IPCC, 2021[12]; IPCC, 2012[13]).

Agriculture is particularly vulnerable to climate change due to its dependency on weather and natural conditions that are being reshaped by long-term climate change. The agricultural sector is already experiencing negative impacts from higher temperatures, increased variability of rainfall, spread of invasive pests, and the greater intensity and frequency of extreme events (OECD, 2022[14]). Extreme weather events can increase productivity losses beyond those from changes in mean climatic conditions by directly damaging crops at specific development stages or by making the timing of field applications more difficult, thus reducing the efficiency of agricultural inputs (Tubiello, Soussana and Howden, 2007[15]).

The Intergovernmental Panel on Climate Change (IPCC) 6th assessment report states with high confidence that changes in the frequency and severity of extreme weather events will have more serious consequences for food production and food insecurity than changes in mean climatic conditions alone (IPCC, 2021[12]). Therefore, both changes in mean climate and changes in the frequency and severity of extreme events should be considered when assessing climate change impacts on agriculture.

Figure 1.1. Frequency of natural disasters, 1970-2021



Note: Data include all natural disasters meeting at least one of the following criteria: 10 or more people dead; 100 or more people affected; a declaration of a state of emergency; a call for international assistance.
Source: EM-DAT, CRED / UCLouvain, Brussels, Belgium – www.emdat.be.

1.2. How have climate change impacts on agriculture been modelled?

Research has looked at climate change impacts on agriculture over the past four decades, producing hundreds of modelling studies (Hasegawa et al., 2022[16]). To date, most of the climate change literature has focused on the impacts associated with mean climatic changes only. However, the literature on extreme weather events is expanding and includes several modelling studies.

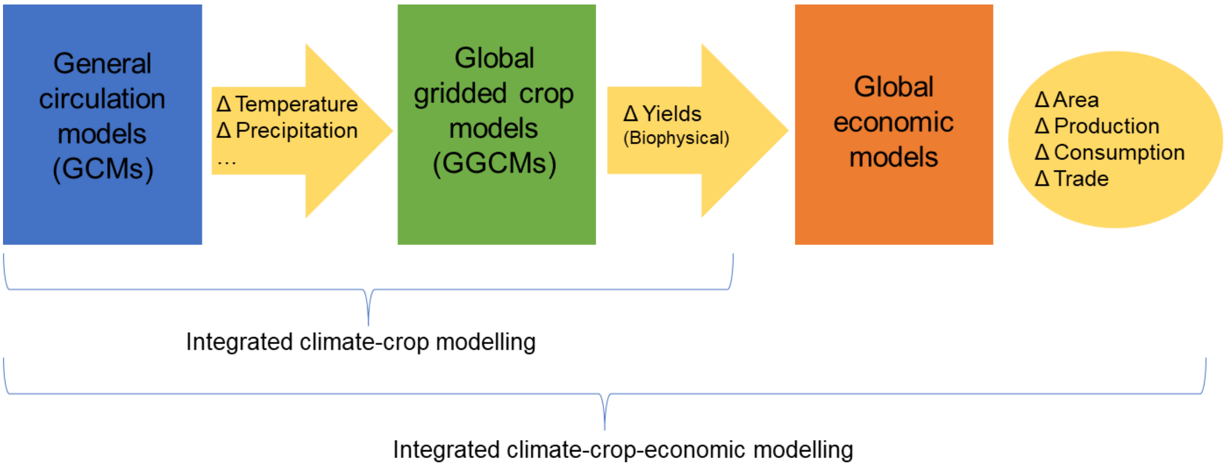
1.2.1. Studies based on changes in mean climatic conditions

Simulation studies using integrated climate-crop modelling (Figure 1.2) suggest that gradual changes in mean values for temperature and precipitation will have widespread impacts on yields in the next decades, but with important differences among crops and countries (Rosenzweig et al., 2013[17]; Challinor et al., 2014[18]; Jägermeyr et al., 2021[19]). Northern countries that currently experience cold temperatures and short growing seasons may benefit from higher yields for some crops, while tropical countries may see reduced yields because of very high temperatures. These differential changes in crop productivity will lead to changes in the comparative advantages of production between countries (Rosenzweig et al., 2013[17]).

Integrated climate-crop-economic assessments (Figure 1.2) have been used to explore the responses of key economic variables to yield shocks from climate change. Overall, these studies find a net negative productivity shock, globally and for most regions, which lowers production, increases prices, reduces consumption and stimulates a global reallocation of production and consumption, facilitated by international trade.[1] While the direction of the impacts of climate change on agriculture is similar between studies, the magnitude varies significantly due to differences in models, scenarios, and data (Nelson et al., 2013[20]) (Wiebe et al., 2015[21]). Important efforts have been made to identify and understand differences in model projections through systematic model comparisons, including via the Agricultural Model Intercomparison and Improvement Project (AgMIP) (Nelson et al., 2013[20]; Nelson et al., 2014[22]; von Lampe et al., 2014[23]; Jägermeyr et al., 2021[19]).

[1] By running scenarios with multiple climate, crop and economic models, (Nelson et al., 2014[22]) found global average yield reductions of 11% and price increases of 20% from climate change relative to the baseline for major crops in 2050. This study is based on a high warming scenario (RCP8.5) without consideration of potentially beneficial CO_2 fertilisation effects on crop yields.

Figure 1.2. The impact modelling chain



Source: Adapted from Nelson et al. (2013[20]).

1.2.2. Studies considering the additional impact of extreme weather events

As discussed, studies assessing the impacts of climate change on agriculture have primarily focused on the effects of mean climatic changes, leaving the role of extreme weather events relatively under researched (Chatzopoulos et al., 2020[3]). Yet, there are some modelling studies that consider both the impacts of extreme events and of changes in mean climatic conditions on agriculture. These are described in more detail below.

Simulation studies using integrated climate-crop modelling (Figure 1.2) tend to investigate a specific aspect of climate extremes – such as heavy precipitation (Li et al., 2019[24]) or extreme heat - within climate change scenarios (Tubiello, Soussana and Howden, 2007[15]). Most studies have focused on the consequences of higher temperature on the frequency and intensity of heat stress during critical crop development stages, both at the regional (Moriondo, Giannakopoulos and Bindi, 2011[25]; Hawkins et al., 2013[26]; Feng et al., 2019[27]) and global levels (Deryng et al., 2014[28]; Teixeira et al., 2013[29]). Overall, the inclusion of extreme heat stress (i.e. days exceeding critical temperature thresholds) leads to lower projected outcomes for yields than when only considering mean climatic changes (Deryng et al., 2014[28]; Moriondo, Giannakopoulos and Bindi, 2011[25]; Feng et al., 2019[27]). Deryng et al. (2014[28]), for instance, found that extreme heat stress could double global losses in maize yields, and reduce projected gains in spring wheat yields by half, and in soybean yields by a quarter by 2080 (relative to the 1980s).[2]

In addition, some studies have looked at the impact of yield shocks from extreme weather events on agriculture using economic modelling. These global simulation studies use different methods. Some rely on a ‘’supply-shock approach’’, which consists of replicating historical yield shocks in future projections. Willenbockel (2012[30]), for instance, uses a general equilibrium model to explore the impact on food prices of hypothetical extreme events taking place in 2030 in different regions. The size of the assumed yield shock is based on historical deviation from the trend in bad harvests over past three decades. The author found that extreme weather events negatively impact on agricultural production and lead to higher world export prices compared to the baseline that only includes change in mean temperature and precipitation.

Using a similar method as Willenbockel (2012[30]), OECD (2017[1]) looked at the impacts of droughts occurring in water hotspot regions (i.e. southwest United States, northeast People’s Republic of China (hereafter “China”) and northwest India) on global agricultural markets, with and without mean climatic changes. They use a partial equilibrium model (i.e. IMPACT) and consider exogenous yield shocks, basing the duration and magnitude of these shocks on evidence from past drought events. The authors found that domestic yields and production reduction from a drought have negative global market implications but that the magnitude of these impacts depend on the affected region. Moreover, the global impact of a drought

[2] These results are based on RCP 8.5 and take into account CO_2 fertilisation effects.

occurring in key regions is exacerbated when gradual changes in mean temperature and precipitation are also considered.[3]

The OECD-FAO Aglink-Cosimo model (Box 2.1) has recently been used for extreme event modelling both at the regional (EC, 2022[5]; EC, 2017[6]) and global levels (Chatzopoulos et al., 2020[3]; Chatzopoulos et al., 2021[4]).[4] Chatzopoulos et al. (2020[3]) incorporated an indicator of compound heat and water stress into this partial equilibrium model, which attributes yield deviations from the baseline trend to climatic stress throughout the period 1980–2010. The authors then used two methods to simulate a shock from an extreme weather event. First, they performed deterministic simulations of single-case events based on the historical maximum and minimum values of the yield stress indicator (Chatzopoulos et al., 2020[3]). Second, partial-stochastic simulations of concurrent and recurrent events were performed (Chatzopoulos et al., 2021[4]), using an approach that shares similarities with the one presented in this report (Section 2). Overall, the authors found that extreme weather events can alter crop availability and significantly distort expected market equilibria. The negative production shock from an extreme event translates into production shortfall, increase in agricultural prices and reduced consumption. Moreover, domestic supply reductions generally dictate lower export demand and higher import demand resulting in a decline in net-trade.

Finally, some studies use integrated climate-crop-economic assessments (Figure 1.2) to explore the potential impact of extreme weather events on agriculture. To our knowledge, Hasegawa et al (2021[31]) is the only global study looking at the impact of extreme events on future food insecurity under different climate scenarios.[5] This study considers the inter-annual variability and frequency of extreme events projected to occur by the middle of the century. The authors found that an additional 11% to 36% of people might face hunger by 2050 when extreme climate variability is considered compared to when only considering change in mean climatic conditions.[6]

1.3. Can international trade help cushion the negative impacts of climate change on agriculture?

This question has been addressed since the early 1990s with partial equilibrium (Reilly, Hohmann and Kane, 1994[32]) and general equilibrium models (Randhir and Hertel, 2000[33]; Rosenzweig and Parry, 1994[34]), but mainly under changes in mean climatic conditions.

Overall, most studies report that trade restrictions exacerbate the negative impact of changes in mean climate on welfare, agricultural prices, and food security, whereas trade liberalisation can alleviate it.

Costinot, Donaldson and Smith (2016[35]) and Gouel and Laborde (2018[36]), for instance, fed Global Agro-Ecological Zones (GAEZ) data into a general equilibrium model of trade to look at the impact of climate change on GDP/welfare if trade adjustments are permitted versus if they are prevented by forcing bilateral import/export shares to stay constant. Costinot, Donaldson and Smith (2016[35]) found that international trade plays a minor role in adapting to climate change compared to the reallocation of domestic production. Gouel and Laborde (2018[36]) extended the model developed by Costinot, Donaldson and Smith (2016[35])

[3] The authors used regional climate change projections (RCP 8.5 IPSL S1 and Hadley S1).

[4] The European Commission's Agricultural Outlook features scenario analyses with the Aglink-Cosimo model, exploring the potential effects of concurrent (i.e. happening once, at the same time, over a large area) and recurrent (i.e. happening repeatedly over time in the same area) extreme weather events on EU agricultural markets (EC, 2022[5]; EC, 2017[6]).

[5] The method used in this study captures different aspects of extreme cases, most of which are biophysical anomalies that exert biophysical stress during growing seasons.

[6] An additional 11% to 36% of people might face hunger by 2050 when extreme climate variability is considered, under representative concentration pathway (RCP) 2.6 with CO2 fertilisation effects and RCP 8.5 without CO2 fertilisation effects, respectively. The CO_2 fertilisation effect refers to the increase in plants photosynthesis as CO_2 concentration rise. CO_2 fertilisation can partially offset the negative effects of higher temperatures and lower precipitations on crop yields. It is especially important for crops such as rice, oilseeds, and wheat that use the C3 photosynthetic pathway (Nelson et al., 2014[22]).

but made different assumptions, including regarding supply and demand elasticities.[7] The authors found that international trade is a key adaptive mechanism in the face of climate change; welfare losses from climate change increasing by 76% when trade adjustments are prevented. Stevanovic et al. (2016[37]) also found that global welfare losses from climate change increase substantially in a scenario assuming the same level of trade protection as in 1995, compared to a hypothetical scenario allowing for free agricultural trade worldwide.

Wiebe et al. (2015[21]) examine the impact of climate change on agricultural prices in 2050, with liberalised and restricted trade, using three global circulation models (GCM) and five global economic models (both general and partial equilibrium models). They found that agricultural price increases due to climate change are greater and more widespread when trade is restricted across regions, compared to when all tariffs and export subsidies on agricultural and food products are removed.

More recently, two studies used a partial equilibrium model of agriculture (i.e. the GLOBIOM model) to analyse the impact of a change in trade policies on climate change adaptation (Guerrero et al., 2022[7]; Janssens et al., 2020[38]). The OECD study by Guerrero et al. (2022[7]) looked at the removal of a set of trade barriers (including tariffs) and coupled payments to commodities. The authors found that policy reform reduces the extent to which climate change increases agricultural prices and undernourishment by enabling production shifts to regions with a comparative advantage and by facilitating trade flows into regions negatively affected by climate change. Janssens et al (2020[38]) also found lower increase in undernourishment from climate change when considering a reduction in tariffs and institutional and infrastructural barriers from the current level of trade integration.

To our knowledge, only a few global studies have looked at impacts of a change in trade policy in the context of extreme weather events. Reimer and Li (2009[39]) examine the impact on welfare of increased crop yields variability associated with extreme weather events, using a Ricardian trade model. The authors found that welfare losses, which are mainly attributed to increases in crop prices, are significantly larger when global trade volume is fixed at baseline level compared to when it remains flexible.

Willenbockel (2012[30]) considers a yield shock from an extreme event in North America and assumes that developing countries with significant baseline export of maize and wheat impose a temporary export tax to protect consumers from increases in domestic prices. The author found that export restrictions lead to further increases in export prices thus accentuating the global price impact from an extreme event.

1.4. Bridging the gaps in the literature

This analysis fills a gap in the literature by factoring increased frequency and intensity of extreme weather events into the shock on future crop yields (Section 2). To date, most global simulation studies using economic modelling, including the four using Aglink-Cosimo (Chatzopoulos et al., 2020[3]; Chatzopoulos et al., 2021[4]; EC, 2022[5]; EC, 2017[6]), assume the same frequency and strength of extreme weather events as in past decades. Only a couple of studies consider increased frequency of extreme weather events in the future (Hasegawa et al., 2022[16]; Reimer and Li, 2009[39]).

Furthermore, although the Aglink-Cosimo model has already been used in the context of extreme weather events, the potential for trade integration to mitigate the impact of these shocks on food prices and availability remains relatively unexplored. As noted above, only a couple of studies have looked at the impact on prices of a change in trade policy in the context of extreme weather events (Willenbockel, 2012[30]; Reimer and Li, 2009[39]).

The proposed approach also has some limitations. First, climate change is not explicitly modelled in Aglink-Cosimo. The baseline assumes lower yield growth in the future than over the last decades due to climate change and other factors (e.g. narrowing yield gaps). However, these impacts are built into trends provided by countries, which can be based on expert judgment, rather than on climate models. Therefore, a counterfactual scenario considering only changes in mean climatic conditions cannot be constructed.

[7] In Gouel and Laborde (2018[36]), elasticities are taken from the literature, which consistently finds that food demand and supply are inelastic, while Costinot, Donaldson and Smith (2016[35]) estimate these elasticities in cross-section.

Second, in this analysis an extreme weather event is defined as an "extremely low yield"; more specifically a historical yield deviation from the trend that is in the lowest 5th percentile of the probability density function (Section 2). However, in reality, low yields can be due to other factors than extreme weather events, including pests or economic shocks. No attempt is made in this analysis to empirically attribute yield variability to climate stressors, as done through the integration of a climate-stress index by Chatzopoulos et al. (2020[3]; 2021[4]).

2. Methodology

This scenario analysis is based on the baseline of the *OECD-FAO Agricultural Outlook 2022-2031* (OECD/FAO, 2022[40]) and the corresponding Aglink-Cosimo release. Aglink-Cosimo is a comprehensive partial equilibrium model for global agriculture, which underlies the baseline projections of the *OECD-FAO Agricultural Outlook*. Detailed information on the model is provided in Box 2.1.

The *OECD-FAO Agricultural Outlook* presents 10-year projections for global agricultural markets, with the latest publication covering the period 2022 to 2031 (OECD/FAO, 2022[40]). In recent years, internal projections have been produced until 2040. The present analysis makes use of this extended baseline.

The partial stochastic analysis that is usually performed on the *Outlook* projections highlights how alternative scenarios diverge from the baseline by treating a number of variables stochastically. These variables usually target the main sources of uncertainty for agricultural markets, such as country-specific macroeconomic variables, the crude oil price (as a proxy for input costs), and country- and product-specific yields. In this scenario analysis, only crop yields are treated as uncertain within this partial stochastic framework to focus on the potential impact of extreme weather events on agricultural markets.

The approach applied to determine the stochastic draws of these variables in the *Outlook* publication is based on a simple process, which captures the historical variance of each single variable and generates 500 sets of combinations of the stochastic variables. This method generates future variations of the variables from their past variability, which implies that extreme weather events would occur with the same intensity and frequency as they did over the past 25 years. However, research suggests that one consequence of climate change is increasing frequency and intensity of extreme weather events in the future (Section 1.1) (IPCC, 2021[12]). Therefore, this methodology has been adjusted to factor increased frequency and intensity of extreme weather events into the shocks on future crop yields. Specifically, the following changes have been made to the original methodology:

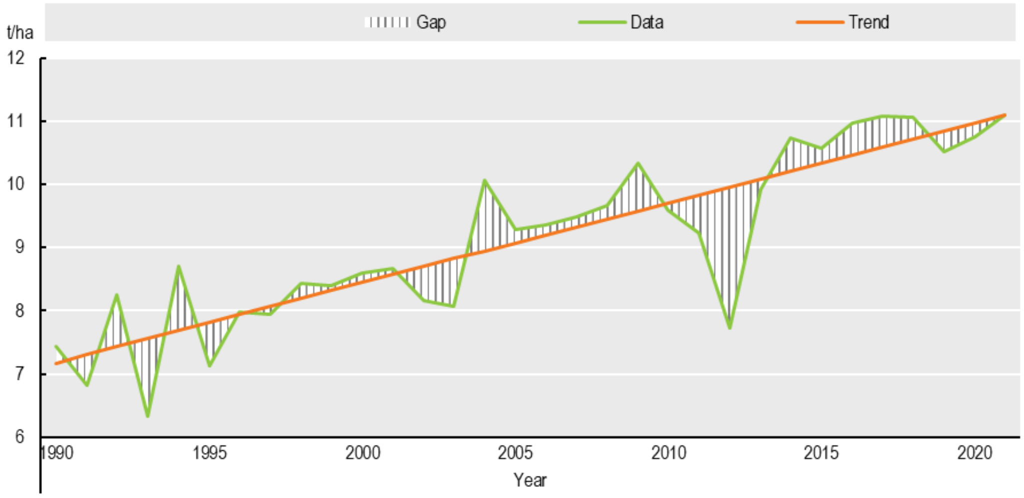
- *Country clusters*: uncertainty factors (i.e., the relative difference between observed yields and the trend estimate, as illustrated in Figure 2.1[8]) are now drawn for country clusters, rather than for all countries at the same time. Clusters have been chosen according to climatic zones (Table 2.1), assuming correlated climate variability within these zones.
- *Increased frequency of extreme yields*: the procedure to draw uncertainty factors for future years has been adjusted such that extreme yields have an increasing probability to be drawn over time.[9] Specifically, with the previous methodology, an extreme yield had a probability of 5% to be drawn for any future year. With the new methodology, this probability is gradually increased to between 10% and 23% in 2040, depending on the country cluster (Table 2.1).
- *Increased intensity of extreme yields*: while the previous methodology did not allow for uncertainty factors to fall below their lowest historical value this has been changed to model increased intensity of extreme weather events. A gradual increase from the first to the final simulation year was implemented so that by 2040, crop yields can be 10% below their historical minimum.

[8] The yield trend is estimated here through a cubic polynomial functional form. One drawback is that it does not guarantee future yields to be positive if the function is extended.

[9] Extreme yields are defined as historical variations from the trend that fall into the 5th percentile of the yield distribution (i.e. all yields for which the uncertainty factor is lower or equal to the 5th percentile).

Figure 2.2 illustrates adjustments 2) and 3). The grey distribution of wheat yields in the European Union is based on the previous methodology. This distribution is independent of the year from which the uncertainty factors are drawn. With the new methodology, the yield distribution changes for each simulation year so that the probability of extreme yields increases, and the value of these extreme yields decreases over time.[10]

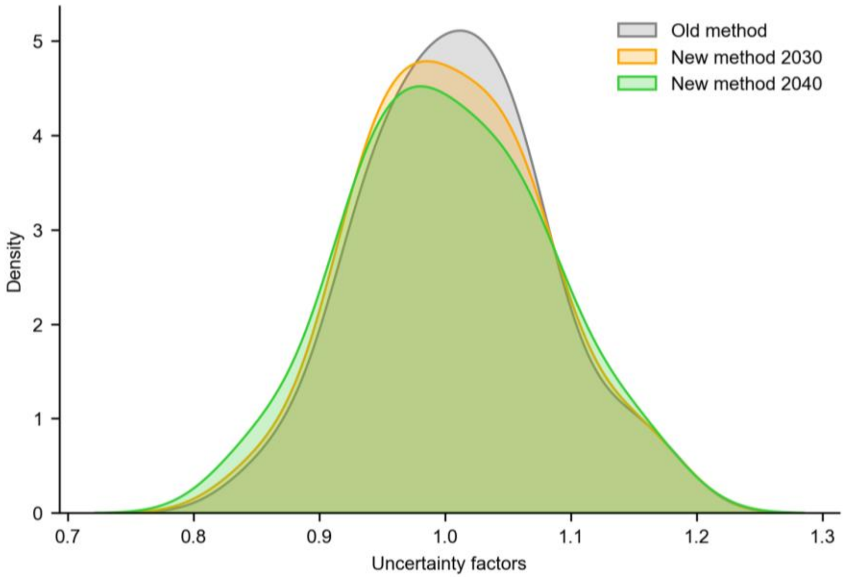
Figure 2.1. Historical maize yields in the United States



Note: Uncertainty factors are the vertical grey lines (the gap) divided by the trend value.
Source: Aglink-Cosimo database.

Figure 2.2. Distribution of uncertainty factors, previous versus new methodology

Wheat yields in the European Union



Note: Kernel density plots with bandwidth = 0.8. The distribution of the old method is applicable for all simulation years and for the first simulation year of the new method.
Source: Authors.

[10] This methodology is based on simplified considerations and lacks an empirical connection of a weather distribution with extreme yields. It also only captures the effect that increased weather events have on the variability of yields, but not their effect on mean yields (Ummenhofer and Meehl, 2017[46]). This could be improved by generating different baseline projections for the two cases. However, the general findings of this study are not sensitive to this simplification, but the magnitude of effects might change.

The probability of extreme weather events in 2040 for the 15 country clusters have been derived from the IPCC special report on extreme events (IPCC, 2012[13]). The report provides regionally averaged data on the annual frequency of extreme temperature and precipitation events for three time periods (i.e.,1981-2000, 2046-2065 and 2081-2100), and 26 regions. The projections are based on twelve global circulation models and are available for three emissions scenarios.

The probabilities of extreme temperature and precipitation events in 2046-2065 were averaged across the three emission scenarios for each of the 26 regions. A simple rule was then applied to be able to reflect these regional variations in the scenario assumptions. Specifically, the following calculations were made on the IPCC data:

- The average frequencies of extreme temperature and precipitation events in 2046-65 were divided by 2 and 4, respectively, and then summed.
- This scaling down reflects the fact that not every extreme weather event leads to an extreme yield.
- This also puts a stronger weight on extreme temperature events than on precipitation events, to reflect empirical evidence that temperature-related extremes have a stronger impact on yields than precipitation-related extremes (Vogel et al., 2019[41]).
- This number was then divided by 1.5 to reflect the shorter time period of our projections (until 2040) compared to IPCC projections (until 2046-2065)
- Finally, the resulting annual probabilities of extreme weather events were allocated to the model country clusters, by selecting the corresponding IPCC region or by taking an average across several IPCC regions.

Table 2.1 presents the projected regional probabilities of extreme weather events in 2040 that have been considered in this scenario analysis.[11]

Table 2.1. Scenario assumptions on the probability of extreme weather events in 2040, by country cluster

Clusters	Cluster members	Probability of extreme weather events in 2040
Cluster 1	Canada, United-States	11%
Cluster 2	Mexico	20%
Cluster 3	Brazil, Paraguay	19%
Cluster 4	Columbia, Peru	15%
Cluster 5	Chile, Argentina	10%
Cluster 6	Rest of South America and the Caribbean	18%
Cluster 7	European Union-27, United Kingdom, Norway, Russian Federation, Ukraine, Switzerland, Rest of Europe	11%
Cluster 8	Indonesia, Malaysia, Philippines, Asia least developed	22%
Cluster 9	India, Thailand, Viet Nam	15%
Cluster 10	Kazakhstan, China, Korea, Japan, Rest of Asia	16%
Cluster 11	Iran, Türkiye, Pakistan, Egypt, Israel, Rest of Near-East, Rest of North Africa	22%
Cluster 12	Saudi Arabia, Ethiopia, Least Developed North Africa	23%
Cluster 13	Sub-Saharan Africa, Nigeria	21%
Cluster 14	South Africa	21%
Cluster 15	Australia, New Zealand, Rest of Oceania	12%

[11] Numerical example: for the Central America/Mexico region, the average annual probability of extreme temperature and precipitation events (across the 3 emission scenarios) in 2046-65 are 0.56 and 0.07, respectively (IPCC, 2012[13]). We first divided the probabilities of extreme temperature and precipitation events by 2 and 4, respectively, and then summed them up, which gives 0.30 (0.56/2 + 0.07/4=0.30). We then divided this number by 1.5 and multiplied it by 100, which gives a probability of 20% (0.30/1.5*100=20). Therefore, for Mexico, we considered that the probability of extreme weather event increase from 5% in the base period (2019-21) to 20% in 2040. The multipliers (2,4 and 1.5) used in this calculation are chosen arbitrarily to avoid overestimating the yield effect associated with an extreme weather event.

To better understand how the Aglink-Cosimo model responds to a crop yield shock, the specification of yield equations in the recursive dynamic setting of Aglink-Cosimo deserves a closer look. Yields in region *r* for commodity *c* and year *t* are of this general form:

$$\log(YLD_{r,c,t}) = \alpha + \beta_1 * \log\left(\frac{PP_{r,c,(t-1)} + EPY_{r,c,(t-1)}}{\gamma_c * CPCI_{r,c,(t-1)} + (1-\gamma_c) * CPCI_{r,c,t}}\right) + \beta_2 * TRD_{r,c,t} + \log(R_{r,c,t}) \quad (1)$$

Where:

PP =	Producer price (in local currency/t)
EPY =	Policy variable (in local currency/t)
CPCI =	Cost of production index (2008 = 1)
γ_c =	Share of production cost occurring in the previous marketing year
TRD =	Trend
R=	Calibration factor

Box 2.1. The OECD-FAO Aglink-Cosimo model of global agricultural markets

Aglink-Cosimo is an economic model of global agricultural markets which can be used to analyse supply and demand of major agricultural commodities, as well as biodiesel and ethanol. It is managed by the Secretariats of the OECD and the Food and Agriculture Organization of the United Nations (FAO). The model is used to generate the annual *OECD-FAO Agricultural Outlook* and for scenario analysis (OECD/FAO, 2022[40]).

Aglink-Cosimo is a recursive-dynamic partial equilibrium model used to simulate development of annual market balances (production, consumption, exports, imports and stocks) and prices for major agricultural commodities: cereals (maize, wheat, rice and other coarse grains), oilseeds and oilseed products (protein meal and vegetable oil), sugar, meat (beef and veal, poultry, pig meat, and sheep meat), dairy (fresh dairy products, cheese, butter and milk powders), biodiesel, ethanol, cotton, pulses, and roots and tubers.[1] As a recursive-dynamic model, outcomes for one year influence those for the following years (e.g. through herd size dynamics).

The model has a global coverage.[2] World markets for agricultural commodities are assumed to be competitive, with buyers and sellers acting as price takers. Market prices are determined through global and regional equilibrium in supply and demand. Domestically produced and traded commodities are assumed to be perfect substitutes from the point of view of buyers and sellers. However, the model own- and cross price elasticities do not account for isocaloric compensation with other agricultural commodities. This implies that consumers do not have food calorie targets and likely over- or underestimate market impacts of shocks in food markets. Aglink-Cosimo includes exports and imports but does not track bilateral trade flows.

More information (including detailed model documentation of Aglink-Cosimo) is available at www.agri-outlook.org.

Note: 1. The model does not consider highly processed foods which account for 30% of food consumption.
2. Specifically, the Aglink component of the model consists of 14 modules: ten OECD countries and regions (Australia, Canada, European Union (EU), Norway, Japan, Korea, Mexico, New Zealand, Switzerland, the United Kingdom and the United States) and four non-OECD countries (Argentina, Brazil, China and the Russian Federation). The Cosimo component of the model completes the world coverage and consists of 42 endogenous modules: three OECD countries (Chile, Israel and Türkiye), a further 27 single countries, and 12 regional aggregates.

Yield shocks are implemented as changes to the calibration factor R. The double-log nature of the equation guaranties that any multiplier to R is the same multiplier to the yield itself. Therefore, reducing the R-factor in a given year is equivalent to shifting the yield function to the left. However, the endogenous model reaction does not allow for yields to adjust in the same year as most endogenous variables on the right-hand side of the equation are lagged by one year.[12]

With domestic production being fixed, which variables can adjust in case of a supply shortfall? Demand can go down but is relatively inelastic. Therefore, most of the adjustments must come from stocks and international trade. Stocks are represented with a speculative motive (sell more when prices are high) and a transaction motive (stock more when production is high). Therefore, a shortfall in domestic production will drive stocks down, partly compensating for the supply shortfall. International trade in Aglink-Cosimo responds to changes in domestic prices relative to international prices. Rising relative domestic prices will thus reduce exports and increase imports.

In theory, if a country has a high level of trade integration, it should be able to adjust to domestic market fluctuations more easily and thus reduce domestic price volatility and stabilise domestic consumption. However, with multiple countries experiencing yield shocks simultaneously, this outcome is less clear as the domestic effects in country A could be offset by the effects of country B on international markets. A global market model like Aglink-Cosimo can help to assess the overall effects of trade openness on the variability of international and domestic prices as well as on domestic demand.

3. Trade scenarios

This section introduces the deterministic trade scenarios underlying the stochastic analysis. It first specifies the scenario assumptions and then compares outcomes under the trade scenarios with outcomes under the baseline.

3.1. Scenario definition

In order to assess the potential for trade to mitigate the impact of extreme weather events on agriculture, the stochastic framework of the Aglink-Cosimo model is applied to two trade specifications:

- The *Restricted Trade scenario* in which border protection is increased.
- The *Integrated Trade scenario* in which border protection is reduced.

Both scenarios are compared to the *Baseline* of the OECD-FAO Agricultural Outlook 2022-2031 where policy measures are usually kept at their current level unless legislation foresees any change in the next decade. Non-Tariff Measures (NTMs) and other barriers to trade, such as limited port access in developing countries, are not explicit in Aglink-Cosimo.

Simple rules are used to define the trade specifications in the *Restricted Trade* and *Integrated Trade* scenarios, as this scenario analysis has an illustrative character. Table 3.1 presents the trade assumptions for all commodities in the model under both scenarios (relative to the baseline specifications). The scenarios only consider changes in import restrictions.

[12] Only the cost of production index of the current year enters the equation, but the endogenous variables entering this index are all lagged as well. Therefore, there is no adjustment possibility for domestic production in the year when the shock appears, as land allocation is based on lagged incentives as well. However, as low yields in year t will drive domestic prices up, the yield equation in year t+1 will use these higher prices. This naive price expectation is probably unrealistic because farmers may know very well if a price spike was due to a bad harvest in the past year. In case of area allocation this naive effect is dampened by using three-year average lagged prices and yields to compose the incentive per ha that drives allocation. However, the challenge remains and has not been overcome yet: How to distinguish a price signal from noise.

Table 3.1. Scenario trade specifications compared to the baseline

	Restricted trade scenario	Integrated trade scenario
Tariffs	Doubled but at least plus 10% *ad valorem*	Cut in half
TRQs	Cut in half	Doubled
Import parameters	Cut in half	Doubled

Import parameters (last line of Table 3.1) in Aglink-Cosimo are a measure of trade integration. A high value corresponds to a high level of trade integration, meaning that domestic and international prices move in parallel, while prices decouple in case of low trade integration. Annex A explains this link in more detail.

It is important to note that the shock to the model is larger in the *Restricted Trade* scenario because trade restrictions that do not exist in the baseline are introduced by applying at least 10% *ad valorem* tariff on import prices, while in the *Integrated Trade* scenario only existing trade restrictions are reduced.

3.2. Scenario impacts

This section briefly compares outcomes under the *Integrated Trade* and the *Restricted Trade* scenarios with outcomes under the baseline. Although not the focus of this study, changes to trade specifications also alter the reference path for the stochastic analysis. This comparison will help to distinguish between the effects of the trade scenarios and the effects of the stochastic shocks.

The implementation of the trade scenarios acts as demand shock on world agricultural markets. A change in trade restrictions translates into a domestic price shock. For importing countries, domestic prices increase in the *Restricted Trade* scenario as international supply becomes more expensive while domestic prices decline in the *Integrated Trade* scenario. Therefore, demand on international markets decreases compared to the baseline in the *Restricted Trade* scenario and increases in the *Integrated Trade* scenario. For exporting countries, the domestic price effect follows the world price effect, which goes in the opposite direction than the one described for importing countries.

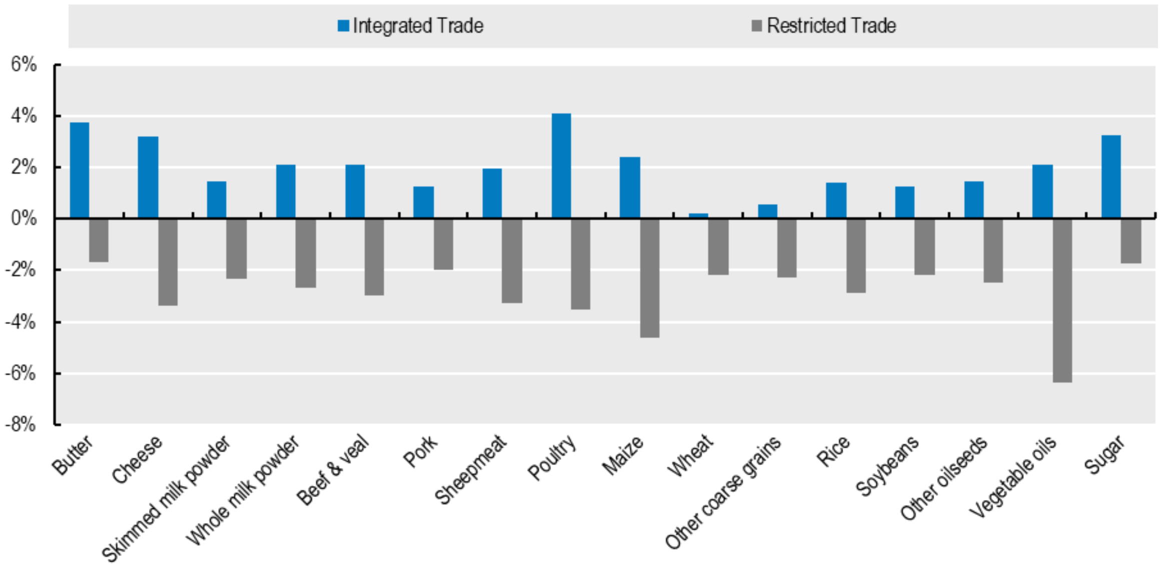
The world price variable in Aglink-Cosimo is based on representative export prices. In simulations, these prices are used to clear world markets, and the link to the representative price becomes less clear as all countries have a different level of price transmission between world and domestic markets (Annex A).

International prices increase with higher levels of trade integration due to the rise in demand on international markets (Figure 3.1). They are found to be between 0.2% and 4% above baseline levels in the *Integrated Trade* scenario, and between 1.5% and 6% below baseline levels in the *Restricted Trade* scenario.

Domestic and international prices tend to go in opposite directions following a change in trade restrictions. However, there are exceptions to this general trend. First, the decline in international prices in the *Restricted Trade* scenario can, in some cases, offset the increase in domestic prices. Domestic prices in the *Restricted Trade* scenario increase by 3.5%, on average, compared to the baseline, but with prices ranging between -8% and +40% (compared to baseline levels) in 2040. Overall, 75% of domestic prices are found to be above baseline levels and 25% below.

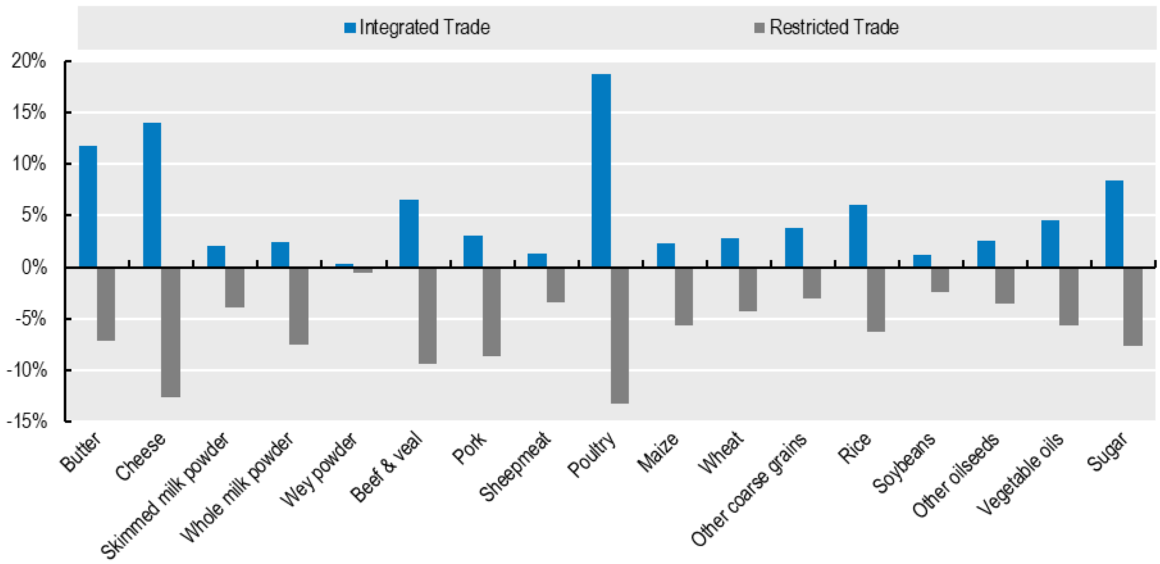
This effect also exists in the *Integrated Trade* scenario but is further influenced by the initial level of trade protection. Domestic prices only decline when border protection measures are in place in the baseline. If this is not the case, the shock only comes from increasing international prices and thus domestic prices increase as well. In the *Integrated Trade* scenario, domestic prices are found to be 0.4% below baseline level, on average. However, domestic prices range between -35% and +10% compared to the baseline; with 65% of prices being above baseline levels.

Figure 3.1. International commodity prices, % change compared to the baseline (2040)



Source: Simulation results.

Figure 3.2. International trade volumes, % change compared to the baseline (2040)

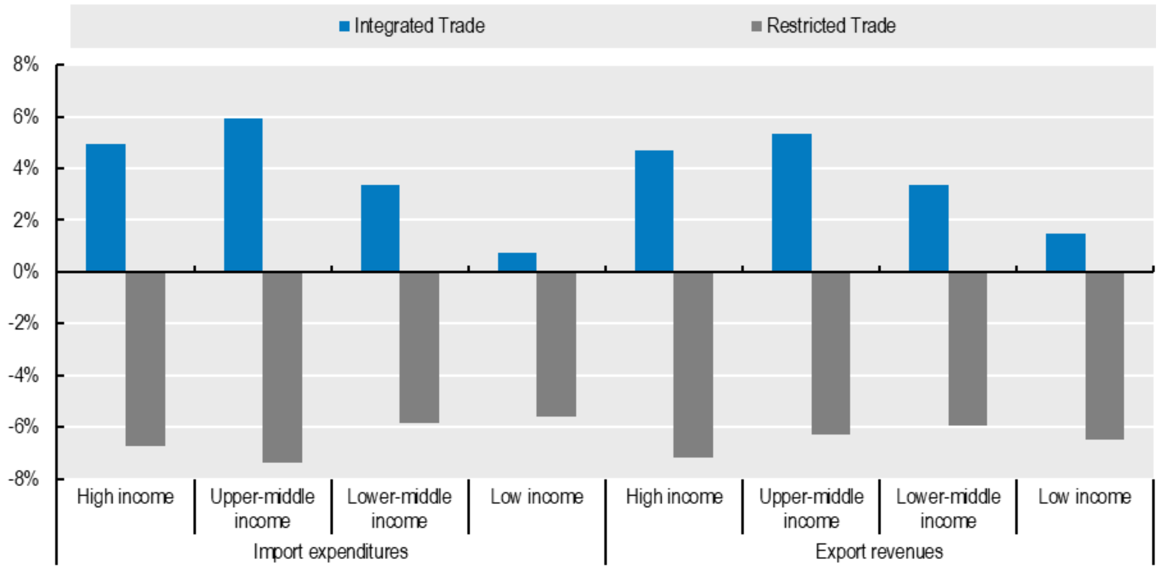


Source: Simulation results.

Global trade volumes also increase with higher levels of trade integration (Figure 3.2). However, the extent to which trade increases differs among commodities. Trade in cheese, butter and poultry increases more strongly than trade in other commodities in the *Integrated Trade scenario*. This is mainly due to growing imports from the European Union and the United States, where imports are relatively protected, and trade is regulated by TRQs in the baseline. The tariff reduction applied in the *Integrated Trade scenario* makes imports competitive at the out-of-quota tariff.

Larger traded quantities at higher international prices result in an increase in import expenditures and export revenues in the *Integrated Trade* scenario (Figure 3.3Figure 3.3). While the *Restricted Trade* scenario has a similar impact on import expenditures and export revenues across different country income groups (around -6% compared to baseline level), in the *Integrated Trade* scenario these impacts increase with country income level. This is because low-income countries tend to be less protective on the import side, so the reduction in trade barriers in the *Integrated Trade* scenario has a smaller effect on their import expenditures. Higher income countries, on the other hand, usually have well-established export industries and thus benefit more from trade liberalisation in terms of export revenues.

Figure 3.3. Import and export values, % change compared to the baseline (2040)



Note: Trade values only include commodities explicit in Aglink-Cosimo and are calculated as imports/exports volumes multiplied by the world market price (OECD/FAO, 2022[42]).
Source: Simulation results.

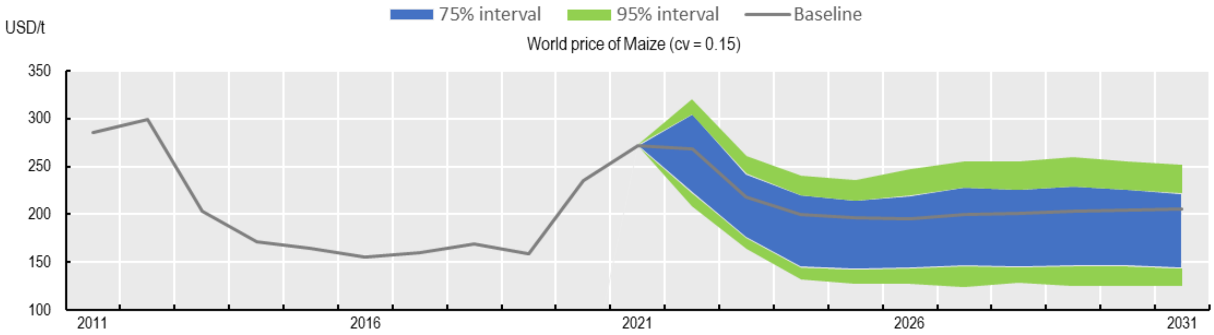
4. Stochastic scenario analysis

The stochastic scenarios, in which the model is executed 500 times for both trade scenarios with stochastic annual crop yields, can shed light on the variability of market variables around the results of the deterministic scenarios discussed above. This section first introduces the indicators used to analyse the stochastic scenario results before presenting the results in detail.

4.1. Indicators

There are different ways of presenting results from stochastic simulations. First, fan charts can be used, as in the *OECD-FAO Agricultural Outlook*, where the 75th and the 95th percentiles are drawn around the baseline value (Figure 4.1). The 95th percentile can be interpreted as follows: every year there is a 5% chance that the maize price will fall outside the green range (2.5% chance to be lower and 2.5% chance to be higher). Although this might seem like a low probability, over a period of ten years, there is a cumulated probability of 40% that the price will fall outside this range in at least one of those years.

Figure 4.1. Baseline and stochastic intervals for the international maize reference prices



Source: OECD/FAO (2022[40]).

However, using this graphical analysis for several variables and across different scenarios is challenging. This analysis requires that impacts on variables can be compared across different scenarios. The coefficient of variation, whose value is shown in Figure 4.1, is one of the measures that can be used to describe a distribution of scenario results. A higher coefficient of variation indicates a wider distribution of the variable.

Given the range of impacts examined in this study, attention can be given to one side of the distribution, e.g. for prices, consumers are more concerned about the risk of high prices rather than low ones. For stocks, it is the other way around. Therefore, a first indicator that is applied in the result section is the semi variance, which is defined as the variance of all observations above or below the mean of the distribution:

$$\text{Semivariance} = \frac{1}{n} * \sum_{r_i < mean}^{n} (r_i - mean)^2 \qquad (2)$$

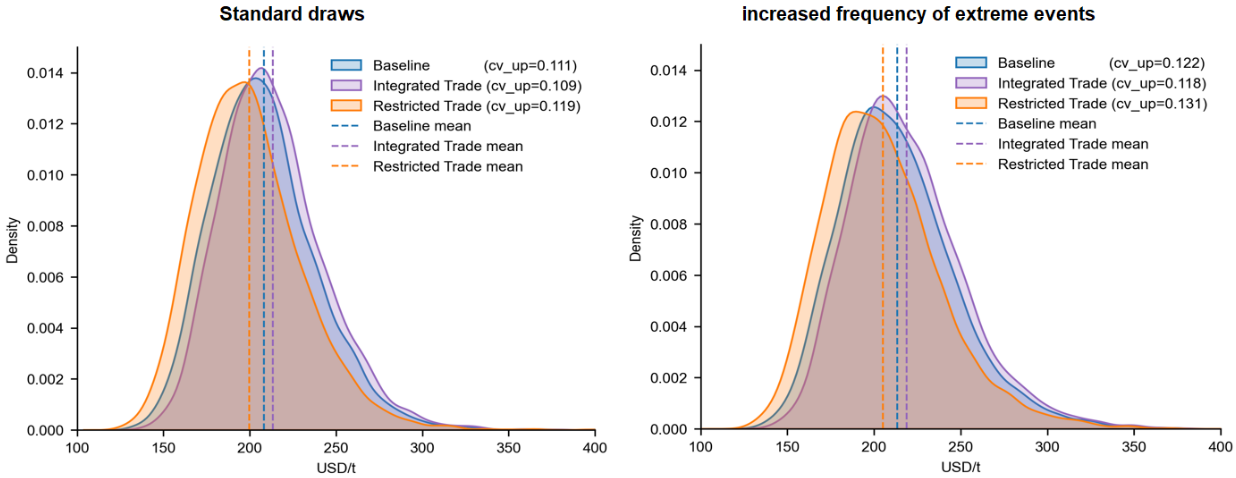
Where *n* is the number of observations below the mean of the full distribution. Equation (2) gives the formula for downside variance. The corresponding formula for the upside variance is straightforward. The semi variance is then translated into coefficients of upside and downside variation by taking the square root and dividing the result by the mean of the distribution. These coefficients are used to compare the stability of market variables between the *Restricted Trade* and the *Integrated Trade* scenarios.

Figure 4.2 illustrates how the upside variation can be used to assess changes in the upside risk of a variable, here the world maize price, under the different trade scenarios. The figure gives the density functions of the maize price for the baseline and the two trade scenarios as well as the mean values. As shown in Figure 3.1 the mean value of the maize price is higher in the *Integrated Trade scenario* and lower in the *Restricted Trade scenario*, compared to the baseline.

However, since the three distributions do not have the same mean, it is difficult to visually assess if the right tail of the distribution is longer or shorter in the *Integrated Trade* scenario. The upside variation, referred to in the legend as cv_up, is used as a condensed measure to answer this question. The higher the level of protection, the higher the simulated upside variation.

Figure 4.2 also illustrates the importance of factoring in increased frequency of extreme weather events in the yield draws (Section 2). With the previous methodology, the right tail of the distribution was shorter than with the new methodology, indicating that an increase in the frequency of extreme maize yields leads to an increase in the frequency of extreme maize prices. The upside variation is higher with the new methodology, as well as the difference in the upside variation between the *Restricted Trade* and *Integrated Trade* scenarios, indicating that the benefits of open markets in terms of price stability are larger when considering increased frequency of extreme weather events.

Figure 4.2. Distribution of world maize prices across 500 simulations and projection years (2022-2040)



Source: Simulation results.

A second indicator used in this analysis is *market vulnerability*. Originally proposed by Van Oijen et al (2013[43]) for ecosystems, a simple yet consistent method of probabilistic risk analysis was applied to agricultural commodity markets by Chatzopoulos et al. (2021[4]). The method can be conceptually summarised as follows: in a system at risk, a risk factor affects the elements at risk through a hazard condition. In this report, 'system at risk' refers to agricultural commodity and food markets; (extremely low) crop yields are the 'risk factor'; 'elements at risk' are commodity market balances and prices; and the hazard condition is given by an arbitrarily selected threshold.

The probability distributions of yield, P(YLD), and of the elements at risk, P(•), are linked through the law of total probability:

$$\mathrm{P}(\bullet) = \int \mathrm{P}(\mathrm{YLD})\mathrm{P}(\bullet \mid \mathrm{YLD})\mathrm{dYLD} \tag{3}$$

Normal agro-climatic conditions lead to the expected state of the agricultural and food system that is represented by baseline yields, E(YLD), and baseline projections of the market variables at risk, E(•). Hazard can generally be defined as:

$$\mathrm{H} = \mathrm{P}(\mathrm{YLDscen} < \mathrm{YLDbase}) \tag{4}$$

Vulnerability, then, is the difference in simulated model behaviour under hazardous (leading to YLDscen < YLDbase) and non-hazardous conditions (leading to YLDscen ≥ YLDbase), thus reflecting the general sensitivity of the system to the risk factor.

$$\begin{aligned} \mathrm{V}(\bullet) = \mathrm{E}(\bullet \mid \mathrm{YLD_{scen}} < \mathrm{YLD_{base}}) - \mathrm{E}(\bullet \mid \mathrm{YLD_{scen}} \geq \mathrm{YLD_{base}}) = \\ \int \bullet\, \mathrm{P}(\bullet \mid \mathrm{YLD_{scen}} < \mathrm{YLD_{base}})\mathrm{d}\bullet - \int \bullet\, \mathrm{P}(\bullet \mid \mathrm{YLD_{scen}} \geq \mathrm{YLD_{base}})\mathrm{d}\bullet \end{aligned} \tag{5}$$

As interest often lies on extremely low yields, an arbitrarily selected threshold for the risk factor can be used to define extreme hazard (XH). This study uses a 5% probability threshold, which is equivalent to assuming that one yield out of 20 is considered too low, which in turn implies that:

$$\mathrm{XH} = \mathrm{P}\left(\mathrm{YLD}_{\mathrm{scen}} \leq \mathrm{YLD}_{\mathrm{p5}}\right) \tag{6}$$

Therefore, the domestic vulnerability of any market element (denoted with a placeholder) attributable to extremely low yields can be defined as:

$$\begin{aligned} \mathrm{V}(\bullet) = {} & \mathrm{E}\left(\bullet \mid \mathrm{YLD}_{\mathrm{scen}} \leq \mathrm{YLD}_{\mathrm{p5}}\right) - \mathrm{E}\left(\bullet \mid \mathrm{YLD}_{\mathrm{scen}} > \mathrm{YLD}_{\mathrm{p5}}\right) \\ & - \int \bullet \, \mathrm{P}\left(\bullet \mid \mathrm{YLDscen} \leq \mathrm{YLD}_{\mathrm{p5}}\right) \mathrm{d}\bullet - \int \bullet \, \mathrm{P}\left(\bullet \mid \mathrm{YLD}_{\mathrm{scen}} > \mathrm{YLD}_{\mathrm{p5}}\right) \mathrm{d}\bullet \end{aligned} \tag{7}$$

Depending on the expression of conditional expectations, V(•) can be expressed in levels or relative terms. Since this report focuses on extremely low yields, V(•) values imply a reduction in domestic production, exports and ending stocks and an increase in imports and prices. Figure 4.3 illustrates this calculation with the maize price in the United States in the *Integrated Trade* and *Restricted Trade* scenarios. The figure shows all simulated prices as a cloud of points and the blue line is an estimated response function (linearised) of maize prices to maize yields.

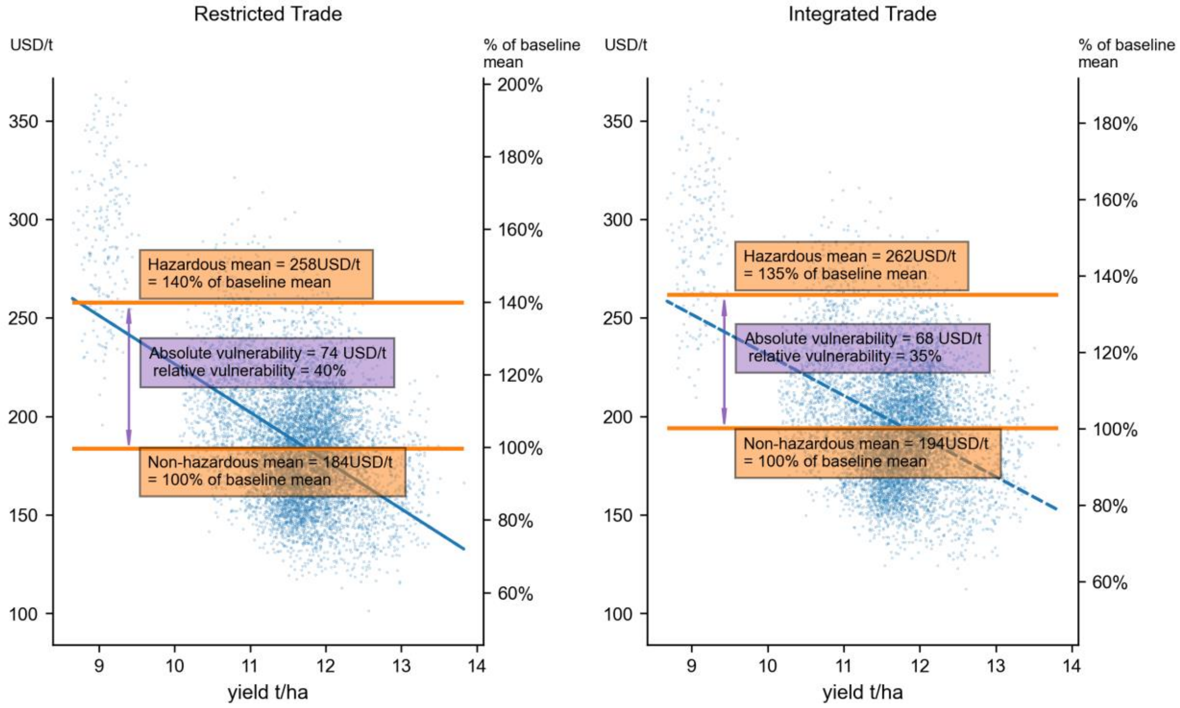
In the *Restricted Trade* scenario, the hazardous mean (i.e. the mean of all simulations for which maize prices in the United States are above the 95^{th} percentile) is equal to USD 258/t. The non-hazardous mean (i.e. the mean of all simulations for which prices are below this threshold) is equal to USD 184/t. The resulting absolute market price vulnerability (referred to as "price vulnerability"' in the rest of the report) is the difference between the hazardous and the non-hazardous means, which is USD 74/t.

The relative market vulnerability can then be calculated by dividing the absolute market price vulnerability by the average maize price in the baseline. The relative vulnerability is equal to 40% and 35% in the *Restricted Trade* and *Integrated Trade* scenarios, respectively, and is the basis for the indicator used in Section 4.2, where the difference between these two values is calculated. The difference between the relative market vulnerability under the *Restricted Trade* and the *Liberalization* scenario is equal to 5 percentage points and these 5 percentage points are plotted in Figure 4.3 for maize in the United States.

The same calculations can be done for the stochastic runs that used the standard method of draws. In this case the difference in the relative price vulnerability is equal to 4 percentage points. This indicates once again that the gains from liberalised trade with respect to price stability are larger when considering increased frequency and intensity of extreme yield events. As this can be confirmed for most of the analysed variables, the rest of the report only present results derived from the new method of drawing uncertainty.

This crop and market variable-specific indicator can be used to measure the vulnerability of the selected variable in a country to extreme domestic yields as presented in Figure 4.3. This indicator can also be used to explore the vulnerability of country A to extreme yields in country B, and thus help assess whether country A imports variability from country B – a major concern in some countries – increases with higher level of trade integration. However, as there are many commodity and country combinations, it is labour intensive to compare all countries with each other for each crop. This method is therefore applied with respect to the aggregate of the top five exporters of each commodity (Table 4.2).

Figure 4.3. Calculation of price vulnerability to domestic maize yield extremes in the United States (2022 – 2040)



Source: Authors based on Chatzopoulos et al (2021[4])

4.2. Results

This section compares the impact of extreme yield shocks on selected indicators under the *Restricted Trade* and the *Integrated Trade* scenarios. In most cases, outcomes under the baseline fall between the two trade scenarios but tend to be located closer to the *Integrated Trade* scenario.

4.2.1. Trade openness generally reduces countries' vulnerability to domestic yield shocks

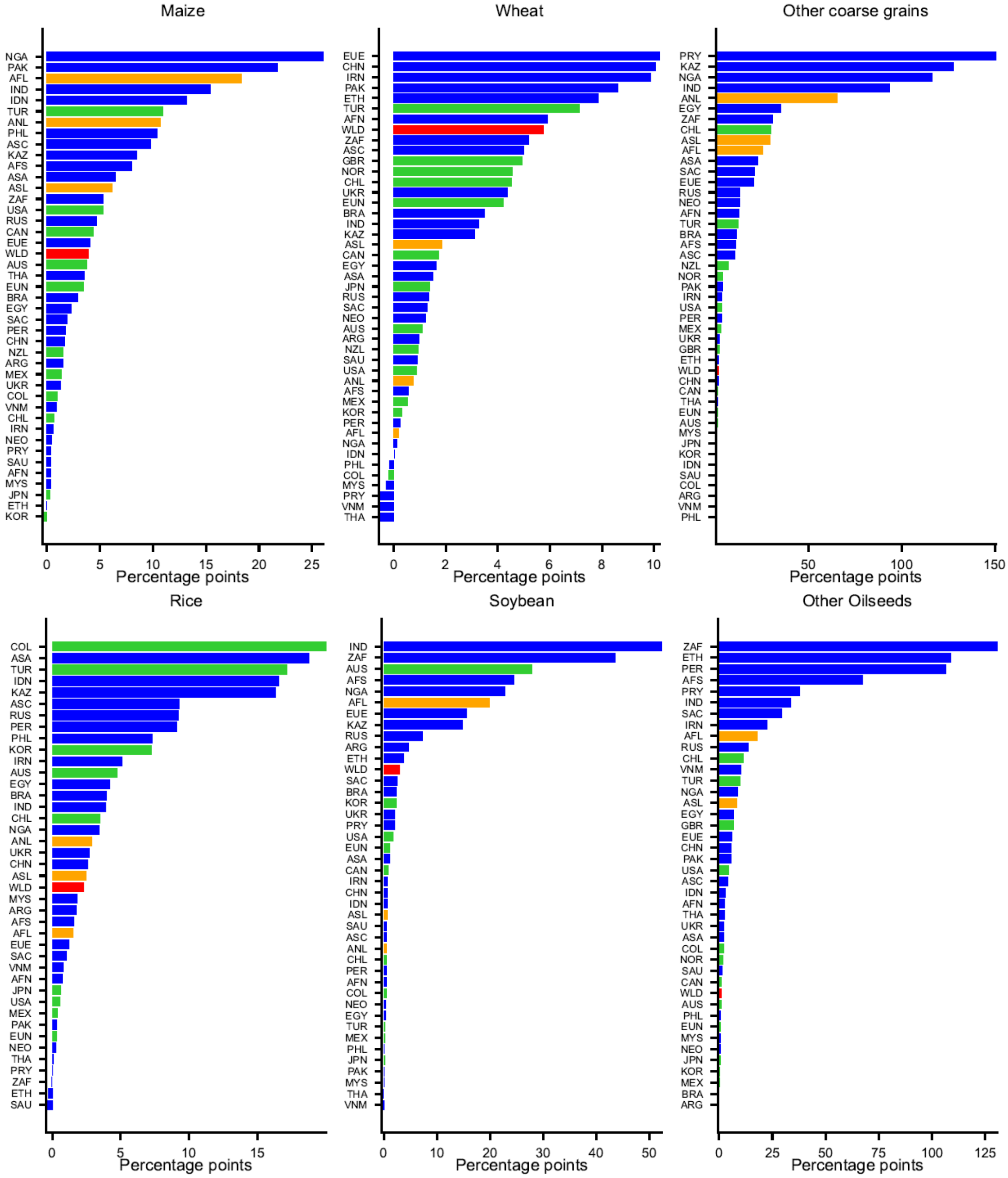
As mentioned, higher trade openness could help to cushion the impacts of yield shocks on consumers, by increasing the flexibility with which purchases can be made on the international market to offset domestic supply shortfalls (Section 1.3). The difference of the relative price vulnerability under the *Restricted Trade* and the *Integrated Trade* scenarios can be used to test this assumption. If this difference is positive, it indicates that vulnerability is higher under the *Restricted Trade* scenario, while a negative value indicates higher vulnerability in the *Integrated Trade* scenario.

Figure 4.4 shows this difference for cereals and oilseeds prices for all countries and regions represented in Aglink-Cosimo. In the vast majority of cases, price vulnerability to domestic yield extremes is reduced with a higher level of trade integration.

Differences between countries in terms of price vulnerability to domestic yields shocks (Figure 4.4) are the result of two opposing effects. On the one hand, countries' vulnerability to domestic yield extremes decreases the more connected a country is to international markets. On the other hand, trade liberalisation increases the price transmission from the international market, which can lead to higher domestic price variability. Although the first effect dominates in most cases, the second effect can dominate, especially when domestic production accounts for a small share of total consumption. This is the case for instance for wheat production in the Asian countries found at the bottom of Figure 4.4, where trade liberalisation is associated with higher price vulnerability.

Figure 4.4. Price vulnerability to domestic yield extremes

Difference in vulnerability between the Restricted Trade and Integrated Trade scenarios



Note: OECD countries are shaded in green, the 3 least developed countries (LDC) aggregates in orange, the world average in red and the remaining countries in blue. Figure use relative vulnerability to the average variables across the time horizon 2022-2040. Positive values indicate higher vulnerability under the *Restricted Trade* scenario. Country/region codes can be found in Annex C.
Source: Simulation results.

4.2.2. Trade openness generally reduces countries' vulnerability to yield shocks occurring in key exporters

Vulnerability was also calculated as countries' vulnerability to extreme yields occurring in the top five exporters of each commodity (Table 4.2). As the group of major exporters are expected to dominate price effects on international markets (at least from a supply perspective), this measure gives an indication of the vulnerability of a country to yield extremes happening in other countries if it increases its reliance on imports.

Figure 4.5 shows that countries tend to be less vulnerable to extreme yield shocks happening in the top 5 exporters when they have higher level of trade integration, although the correlation is less strong than in the case of domestic yield shocks (Section 4.2.1).

There are two opposing effects impacting countries' vulnerability to extreme yields in key exporters. On the one hand, countries become more vulnerable to supply volatility in major exporters when they are more dependent on imports. On the other hand, the *Integrated Trade* scenario assumes that trade becomes more flexible for all commodities at the same time, which results in increased substitutability among products on the demand side. For most countries, the second effect dominates the first, therefore vulnerability decreases with trade liberalisation. Even for countries for which vulnerability increases in the *Integrated Trade* scenario this does not imply that trade protection is a superior strategy, as this is only a partial indicator. Indeed, for most countries found at the bottom of Figure 4.5 their vulnerability to domestic yield extremes is significantly higher in the *Restricted Trade* scenario (Figure 4.4) and so is the overall effect on food prices (Figure 4.7).

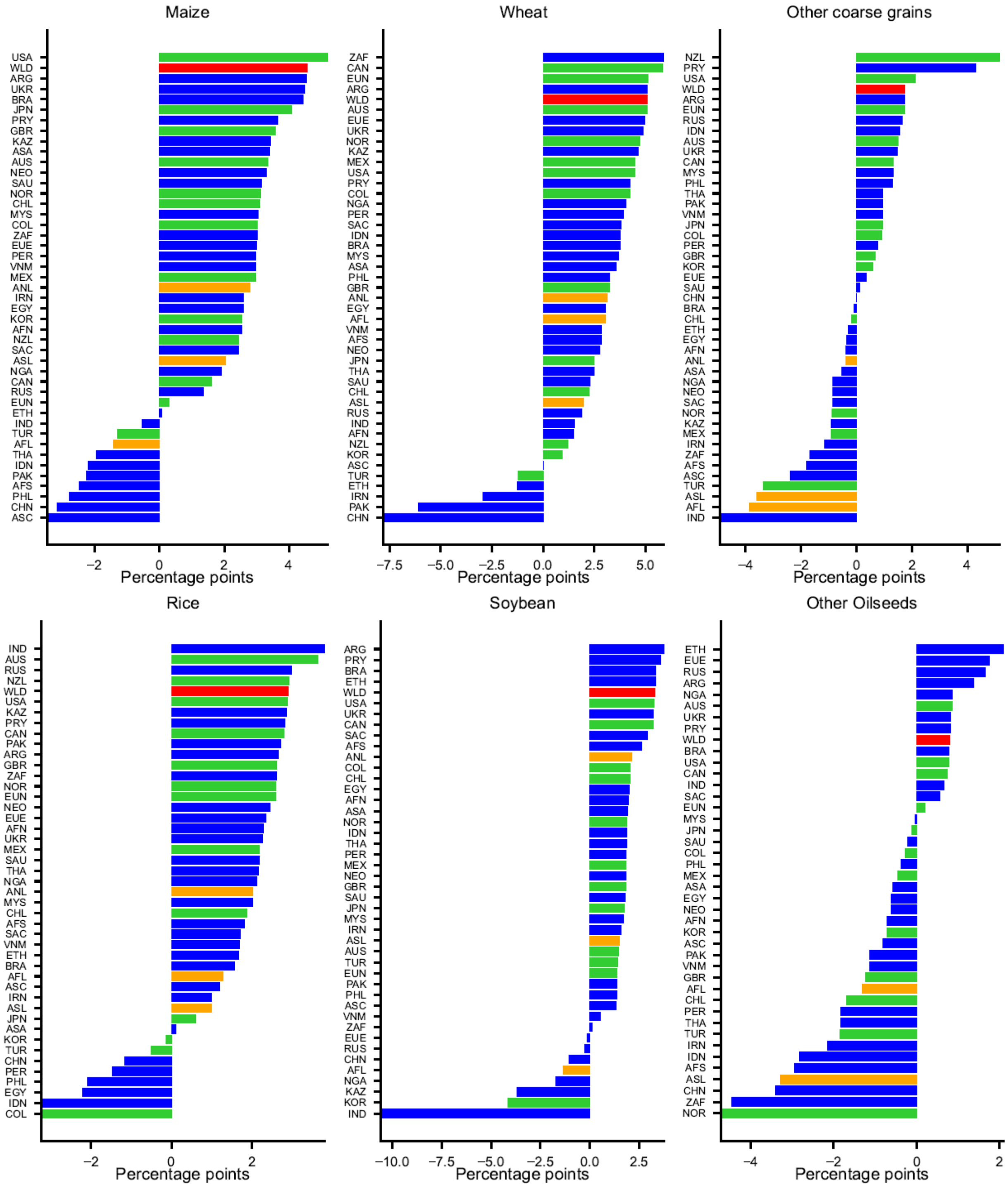
Table 4.1. Top five exporters for food commodities

Commodity	Top 5 exporting countries
Maize	United States, Brazil, Argentina, Ukraine, Russia
Wheat	Russia, EU27, United States, Canada, Australia
Other coarse grains	EU27, Australia, Russia, Canada, United States
Rice	India, Thailand, Viet Nam, Pakistan, United States
Soybeans	Brazil, Argentina, United States, Canada, Paraguay
Other oilseeds	Canada, Ukraine, Australia, Russia, India

Note: Calculated for 2030
Source: (OECD/FAO, 2022[40])

Figure 4.5. Price vulnerability to yield extremes in TOP five exporters

Difference in vulnerability between the *Restricted Trade* and *Integrated Trade* scenarios



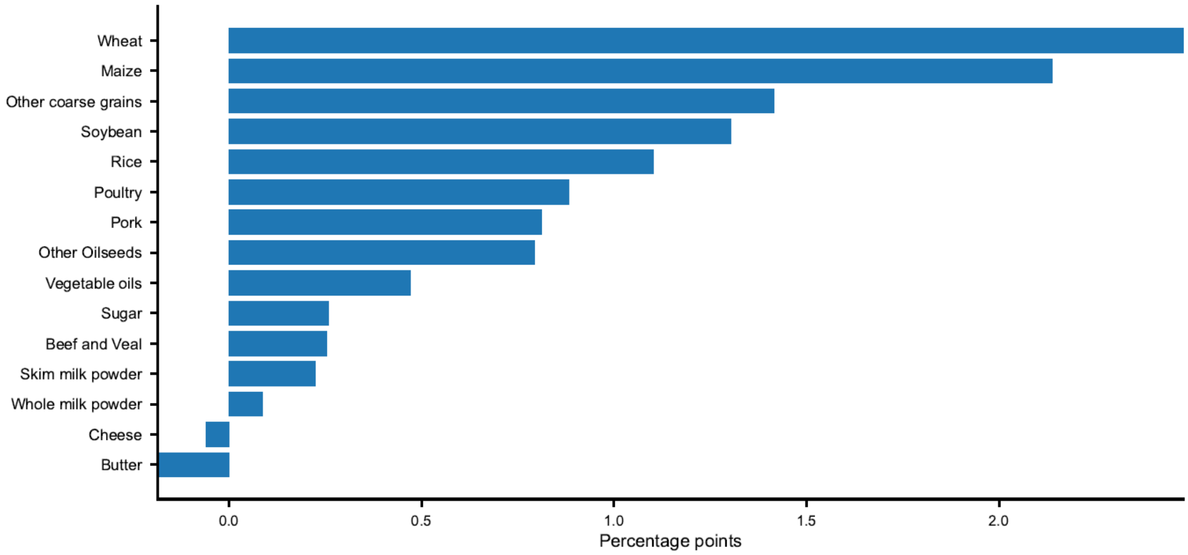
Note: OECD countries are shaded in green, the 3 least developed countries (LDC) aggregates in orange, the world average in red and the remaining countries in blue. Figure uses relative vulnerability to the average variables across the time horizon 2022-2040. Positive values indicate higher vulnerability under the *Restricted Trade* scenario. Country/region codes can be found in Annex C.
Source: Simulation results.

4.2.3. Trade openness reduces the risk of extreme world market prices

Market vulnerability, as defined in Section 4.1, is a good measure for assessing the vulnerability of one variable (e.g. prices) to a shock on crop yields. However, this comparison can only be performed for commodities whose yields have been shocked stochastically i.e. crop commodities in this study. As several crop products are used as animal feed, it is also of interest to explore the impact of a crop yield shock on the price of animal products under the two trade scenarios. For this assessment, the upper semi variance defined in Section 4.1 is used.

Figure 4.6. World price upper variability

Difference between the *Restricted Trade* and *Integrated Trade* scenarios



Note: Figure uses upper semi-variation coefficient of average world prices across the time horizon 2022-2040. Positive values indicate higher vulnerability under the *Restricted Trade* scenario.
Source: Simulation results.

Figure 4.6 shows that the risk of high world market prices is generally higher in the *Restricted Trade* scenario, suggesting that trade liberalisation can help to stabilise international food commodity markets. Butter and cheese are the two exceptions. One explanation could be the segmented structure of dairy markets. While skimmed and whole milk powders are largely produced for international markets (more that 50% of global production is traded), this share is much lower for butter and cheese where a large percentage of global trade occurs within global or bilateral TRQs. At the same time, export supply for dairy products is highly concentrated, with more than 60% of dairy trade originating in New Zealand, the European Union, and the United States. Moreover, the production of different dairy products is coupled. Therefore, more flexibility on international dairy markets for one product could constrain the supply of another product.

These findings do not contradict those in Figure 3.1 showing that world prices are generally lower in the *Restricted Trade* scenario. Figure 4.6 looks at the (relative) upper variation around the mean of all 500 model runs. The variation around the lower average prices in the *Restricted Trade* scenario is found to be higher than around the average prices in the *Integrated Trade* scenario.

4.2.4. Trade openness reduces volatility of domestic prices

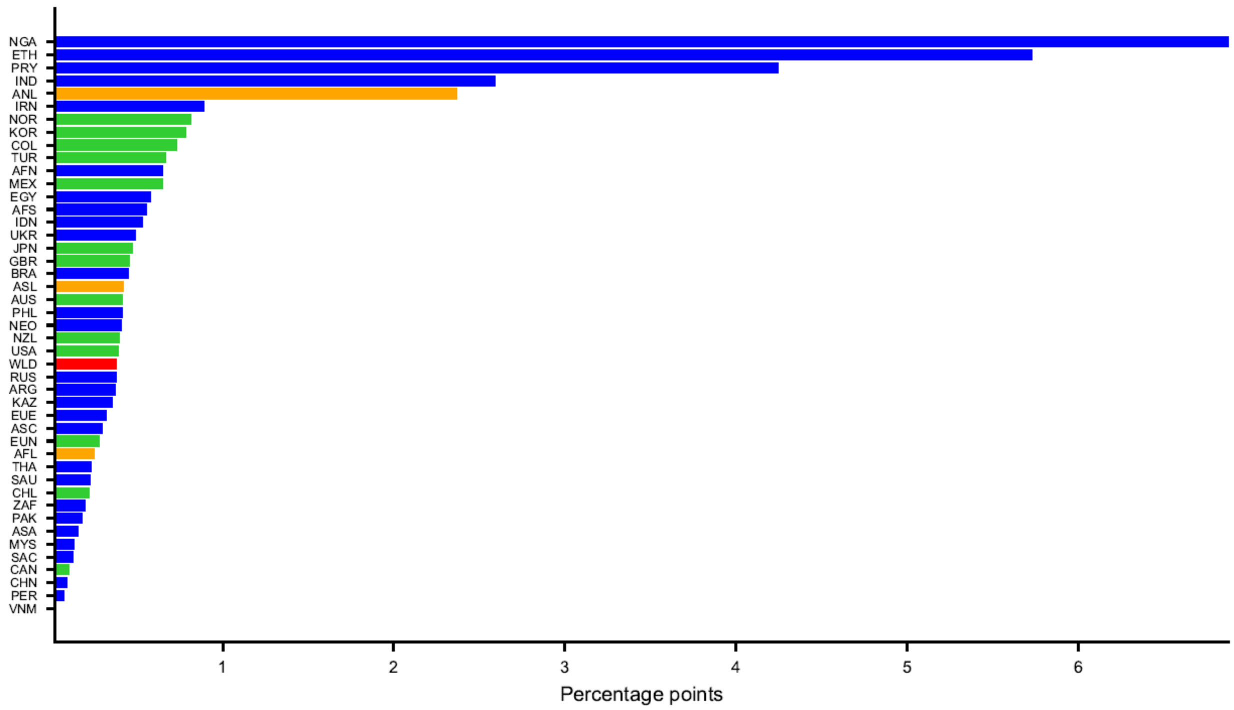
As countries are more interested in their domestic price developments, this section explores whether increased stability of world market prices following trade liberalisation also translates into more stable domestic prices. Figure A B.1 in Annex B shows that the risk of high single commodity prices has a clear tendency to decrease with higher level of trade integration. There are exceptions for some commodity-country combinations, but overall, the positive effect of trade liberalisation is dominating.

This finding is supported by Figure 4.7, which shows the difference in the variability of a national food price index between the *Integrated Trade* and the *Restricted Trade* scenarios. This index is calculated in a similar manner as the FAO food price index, but instead of trade weights, the average food demand quantity for the years 2014-2016 is used as weight. Overall, for most countries the risk of high domestic food prices decreases with trade integration. Trade integration is thus found to improve food affordability in case of extreme yield shocks.

Despite exceptions for some country-commodity combinations, trade integration is thus found to have an overall positive effect on the stability of both domestic (Section 4.2.4) and international food prices (Sections 4.2.1 and 4.2.2) in case of extreme yield shocks.

Figure 4.7. Upper variability of national food price index

Difference between the *Restricted Trade* and *Integrated Trade* scenarios



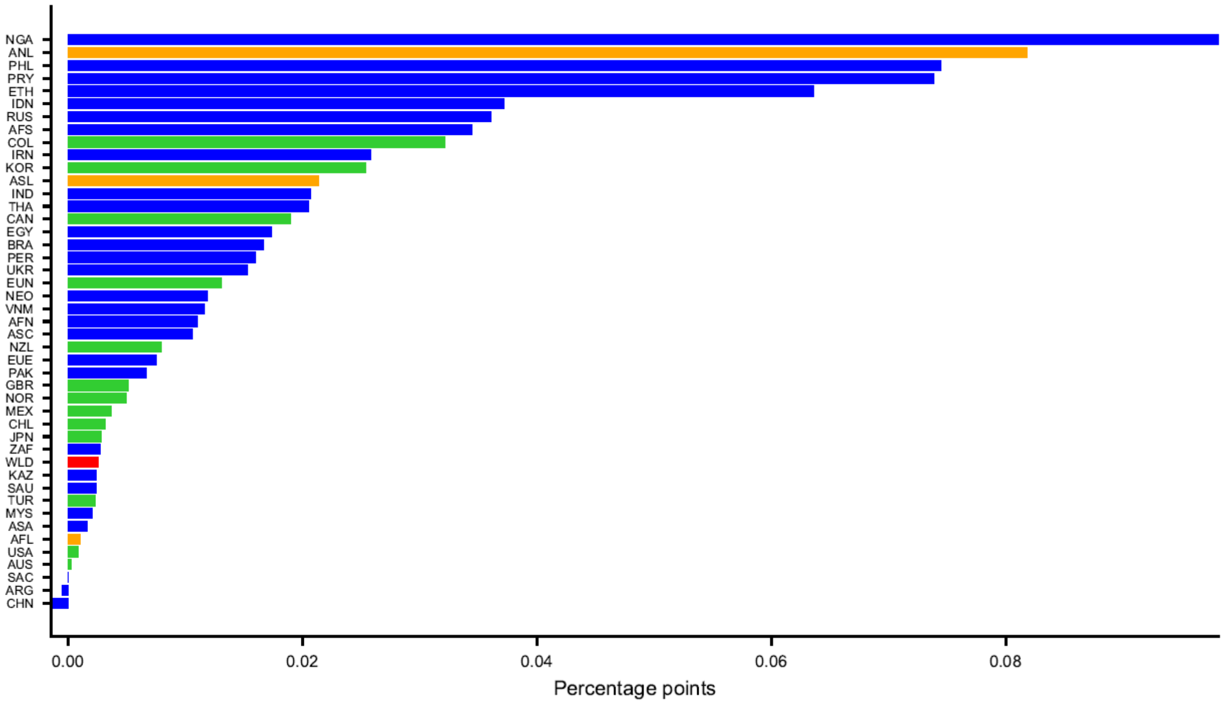
Note: OECD countries are shaded in green, the three least developed countries (LDC) aggregates in orange, the world average in red and the remaining countries in blue. Figure uses upper semi-variation coefficient of average national food price index across the time horizon 2022-2040. Positive values indicate higher vulnerability under the *Restricted Trade* scenario. Country/region codes can be found in Annex C.
Source: Simulation results.

4.2.5. Trade openness helps stabilise food supply

Food availability is one of the four dimensions of food security. As the risk of high food prices is reduced in the *Integrated Trade* scenario, the decline in food availability is also less severe in the *Integrated Trade* scenario than in the *Restricted Trade* scenario, suggesting that trade integration stabilises food supply in case of extreme yield shocks (Figure 4.8). The risk of lower food availability might increase for some commodities in some countries in the *Integrated Trade* scenario, but the overall effect of trade integration on food availability is found to be positive.

Figure 4.8. Downside variability of national food availability

Difference between the *Restricted Trade* and *Integrated Trade* scenarios



Note: OECD countries are shaded in green, the three least developed countries (LDC) aggregates in orange, the world average in red and the remaining countries in blue. Figure uses lower semi-variation coefficient of average food availability across the time horizon 2022-2040. Positive values indicate higher vulnerability under the *Restricted Trade* scenario. Country/region codes can be found in Annex C.
Source: Simulation results.

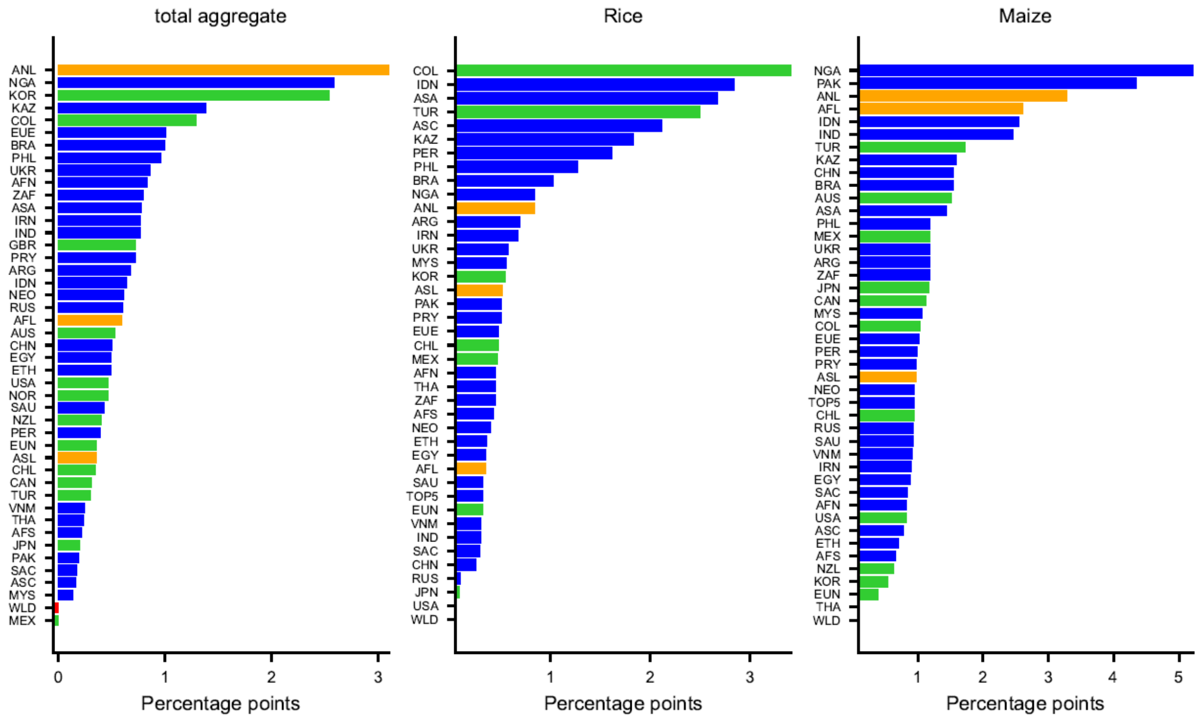
Trade integration thus ensures more stable food availability and prices if an extreme weather event occurs, but it also requires more flexibility, especially from traders. Countries must be able to swiftly adjust the volumes they trade on international markets in order to deliver food to where it is needed. As Aglink-Cosimo does not include bilateral trade flows, the scenario results can only tell parts of the story.

4.2.6. Trade openness takes pressure off stocks

Stocks are included for several products in Aglink-Cosimo, mainly for cereals, and can also act as a buffer in case of domestic price shocks. Higher trade integration takes some of this buffer function over so that in the *Integrated Trade* scenario the risk of very low stock levels is reduced as shown in Figure 4.9 for wheat and maize.

Figure 4.9. Downside variability of domestic stocks

Difference between the *Restricted Trade* and *Integrated Trade* scenarios



Note: OECD countries are shaded in green, the 3 least developed countries (LDC) aggregates in orange, the world average in red and the remaining countries in blue. Figure uses lower semi-variation coefficient of average stock levels across the time horizon 2022-2040. Positive values indicate higher vulnerability under the *Restricted Trade* scenario. Country/region codes can be found in Annex C.
Source: Simulation results.

5. Discussion

With climate change, and an increased frequency and intensity of extreme weather events, the risk pooling effect of trade is likely to become more important. There is thus a case for further trade liberalisation to “thicken” international markets and to enable trade to play its balancing and stabilising role.

This scenario analysis highlights the potential for trade to cushion the negative impacts of extreme weather events on food prices and food availability. The results clearly indicate that food security concerns increase in less integrated trading systems.

As mentioned, however, the shock to the model is stronger in the *Restricted Trade* scenario than in the *Integrated Trade* scenario. Therefore, moving from today’s trading system to a more liberalised one would show smaller benefits than those suggested by this analysis. Nonetheless, this scenario clearly shows that although countries may wish to restrict trade, one of the costs of doing so is reduced stability in domestic markets.

Greater participation in global trade is a necessary part of most countries’ national food security strategies. However, the process and consequences of opening to trade are more complex than can be captured by a model. Trade liberalisation thus needs to be part of a wider coherent policy package to enhance food security.

The FAO (2015[44]) highlights that the relationship between the level of engagement in trade and food security is influenced by the way food markets work, by the ability and willingness of producers to respond to the changing incentives that trade can bring, and by the geography of food insecurity. The FAO also emphasises that the likelihood of price spikes, even if episodic, needs to be factored into longer-term decisions related to the management of trade in food and agricultural products. The present study finds that trade integration reduces the risk of price spikes, which should therefore also be factored into longer-term decisions.

As for any model-based analysis, this study is subject to several limitations. First, Aglink-Cosimo is a partial equilibrium model therefore it does not provide any feedback of the economy to the agricultural sector. Second, Aglink-Cosimo does not feature bilateral trade flows, so specific trade relations between countries are not captured, and the model assumes that the international trading system can, in all situations, respond flexibly to changing conditions. Third, the analysis assumes that all countries make changes to their trading systems at the same time and with the same consistency. The impact of this assumption on the potential for trade to mitigate the effects of extreme weather events could be assessed in future scenario analyses. Nonetheless, several scenario implementations have been tested and the general messages did not change, indicating the robustness of these results.[13]

A fourth limitation is related to the interaction between trade and domestic policies. While they are often interlinked, this scenario analysis does not adjust domestic policies for changes in border protection (e.g. trade measures for wheat and rice in China should not been treated independently from domestic Minimum Support Price policies). Furthermore, bilateral frictions that may arise from market protection measures that could be implemented in the context of extreme events are not reflected in this study. Finally, the analysis explores the impact of extreme crop yields on agricultural markets that are attributed to extreme weather events. However, these events also have significant effects on pasture yields, which in turn impact pasture-based animal production. This study did not take into consideration impacts on grass-based animal production systems.

The analysis presented in this report could be complemented in several ways. First, the trade policy scenarios could be sharpened by decomposing the impact of the different trade measures (i.e. import parameters, import tariffs and TRQs) on vulnerability, instead of altering them simultaneously. The effects of unilateral trade liberalisation (i.e. by one country at the time) could also be explored to get a better understanding of the issue. Moreover, although this study focuses on extreme yield events, it could be extended to analyse the impact of extreme trade events such as those resulting from the COVID-19 pandemic or from Russia's war of aggression against Ukraine.

Finally, further research could be conducted to explore the impacts of different types of policies in a stochastic environment, including domestic subsidies and stockholding policies. Analysing the impacts of trade restricting measures implemented by major exporters as a response to extreme weather events would also be a good addition to the literature.

[13] For example, the same scenarios were evaluated without altering the trade parameters. The results would come to the same conclusions, but naturally the magnitude of effects was lower.

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Annex A. Technical annex

Trade parameters in Aglink-Cosimo – a sensitivity Analysis

This section explains how trade parameters work in Aglink-Cosimo in order to justify their handling as scenario parameters in this analysis.

Trade equations in Aglink-Cosimo are of this general type:

$$\log\left(\mathrm{IM}_{\mathrm{r,c,t}}\right) = \alpha + \beta * \log\left(\frac{\mathrm{PP}_{\mathrm{r,c,t}}}{\mathrm{IMP}_{\mathrm{r,c,t}} * \left(1 + \mathrm{TAVI}_{r,c,t}/100\right)}\right) + \log\left(\mathrm{R}\right) \tag{65}$$

$$\log\left(\mathrm{EX}_{\mathrm{r,c,t}}\right) = \alpha + \beta * \log\left(\frac{\mathrm{PP}_{\mathrm{r,c,t}}}{\mathrm{EXP}_{\mathrm{r,c,t}} * \left(1 - \mathrm{TAVE}_{r,c,t}/100\right)}\right) + \log\left(\mathrm{R}\right) \tag{66}$$

Where:

IM =	Quantity imported (in kt)
EX =	Quantity exported (in kt)
PP =	Producer price (local currency/t)
IMP =	Import price (local currency/t)
EMP =	Export price (local currency/t)
TAVI =	Import tariff (or subsidy) in *ad valorem* equivalent
TAVE =	Export tax (or subsidy) in *ad valorem* equivalent

The beta parameters in the import and export equations define the responsiveness of trade to the wedge between border prices and domestic prices. They are negative for exports and positive for imports. If the parameter is small, the wedge must increase more in order to result in similar traded quantities than it is the case when the parameter is high. In other words, with a low parameter, domestic and international prices are more likely to decouple, indicating that the domestic market is not well integrated into the international market.

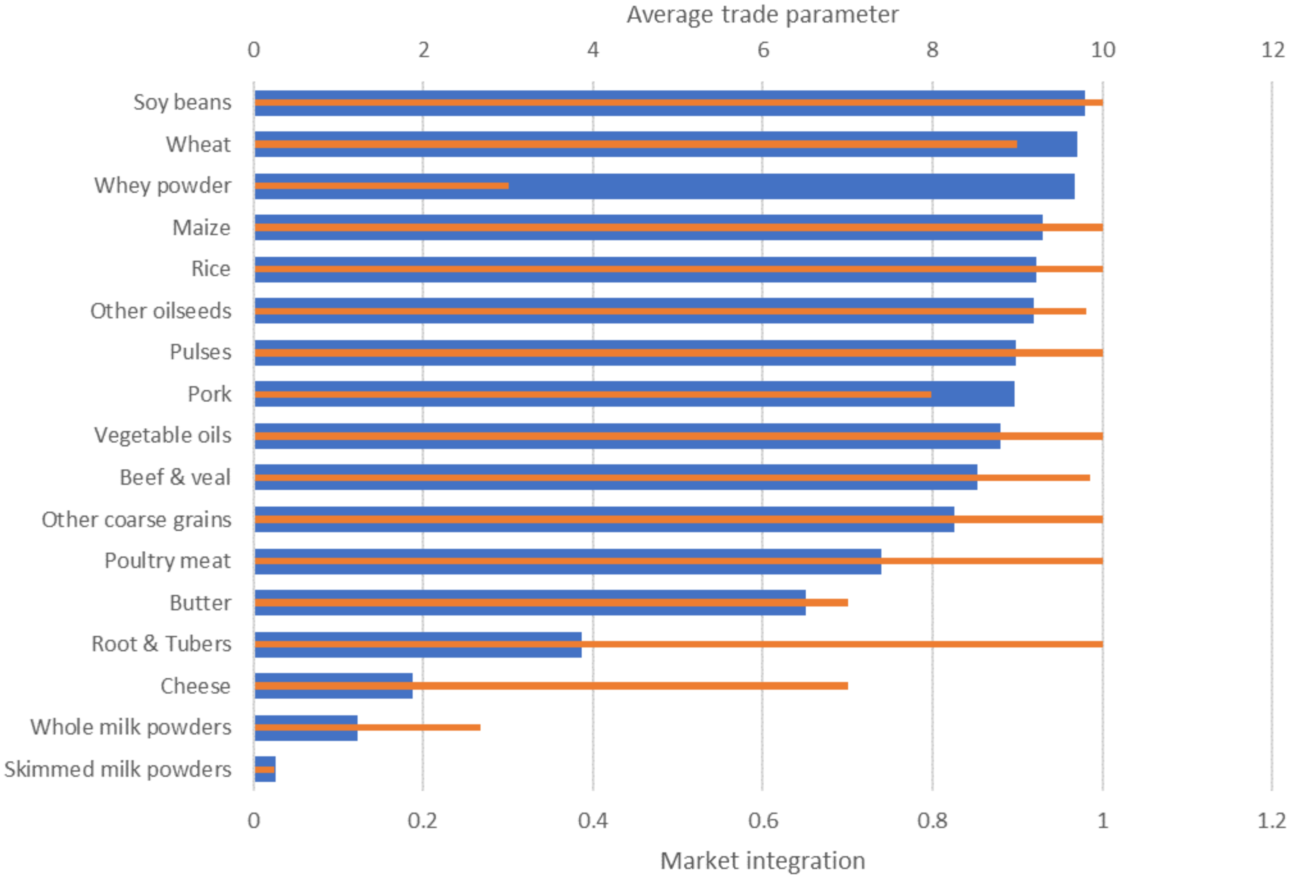
The level of trade integration has not been measured so far for the different commodity markets in Aglink-Cosimo. A possible indicator is the elasticity of domestic prices to border prices. This has been computed for the Brazil module by shifting the different world market prices ceteris paribus by 10% in 2030. The result of this sensitivity analysis is shown in Figure A A.1.In many cases, the size of the trade parameter is strongly correlated with the level of market integration. Two commodities stand out in Figure A A.1. The first one is Whey powder (WYP) where a relative low trade parameter of 3 has a trade integration of above 90%. This is because Whey powder in Brazil is not produced domestically therefore imports are the only source of supply and the domestic price will follow the world market price even with a low trade parameter. The opposite example is the roots and tubers (RT) market. A relatively high parameter of 10 leads to a market integration of only 0.4. The reason is that trade only accounts for a small fraction of domestic consumption. Therefore, even with a high trade parameter, international markets have limited influence on domestic markets.

Trade integration is therefore not only a function of explicit trade policies (like tariffs or TRQs) but also depends on the level of the trade parameters as well as the share of trade in domestic markets (e.g. calculated as (imports + export)/(supply + demand)).

Increasing the import parameter as it is done in this study therefore increases trade integration, but if the initial trade level is small the effect on trade integration will also be small.

Figure A A.1. Market integration and trade parameters in Brazil

Orange bars are trade parameters (upper axis), blue bars give market integration (lower axis)

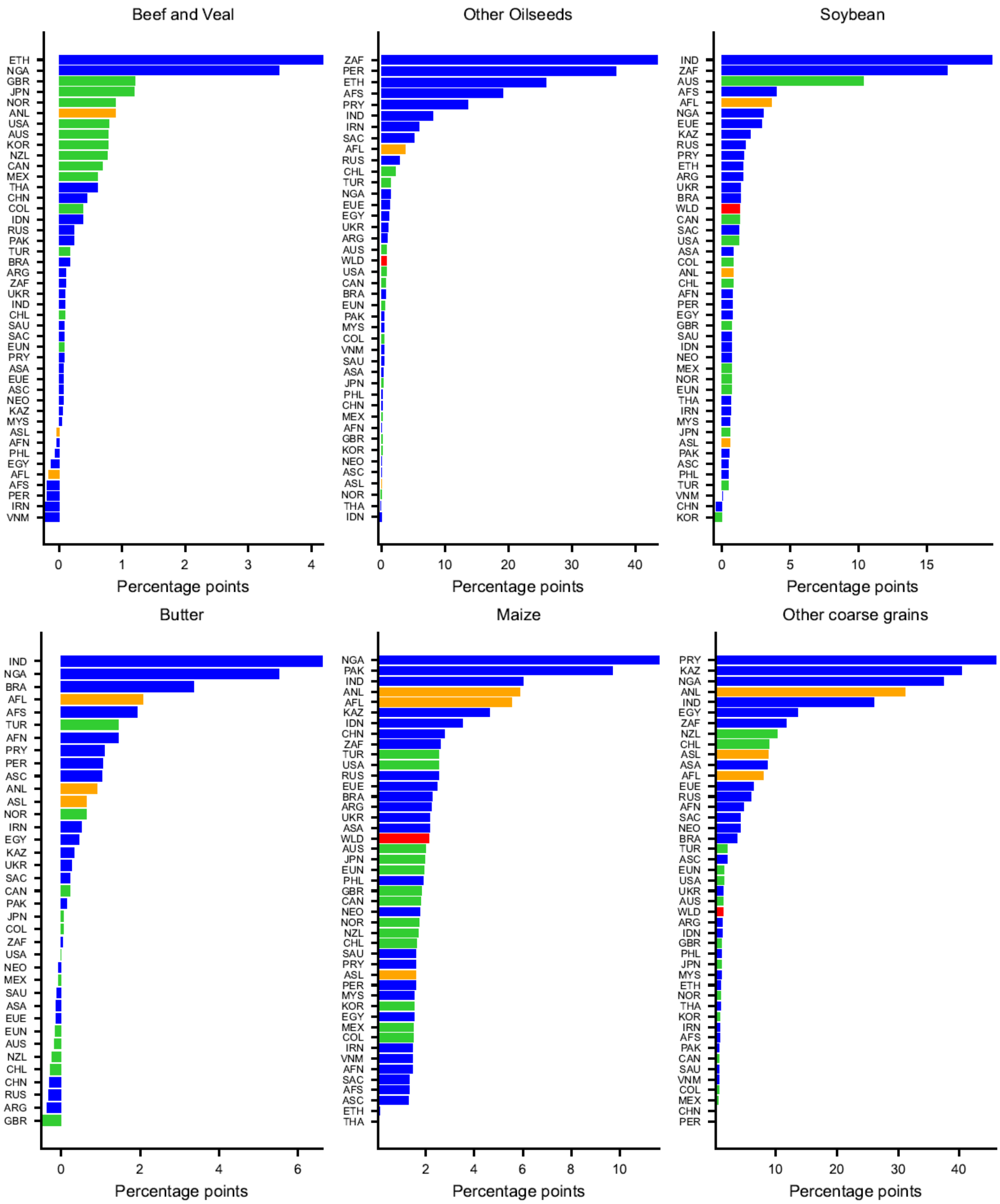


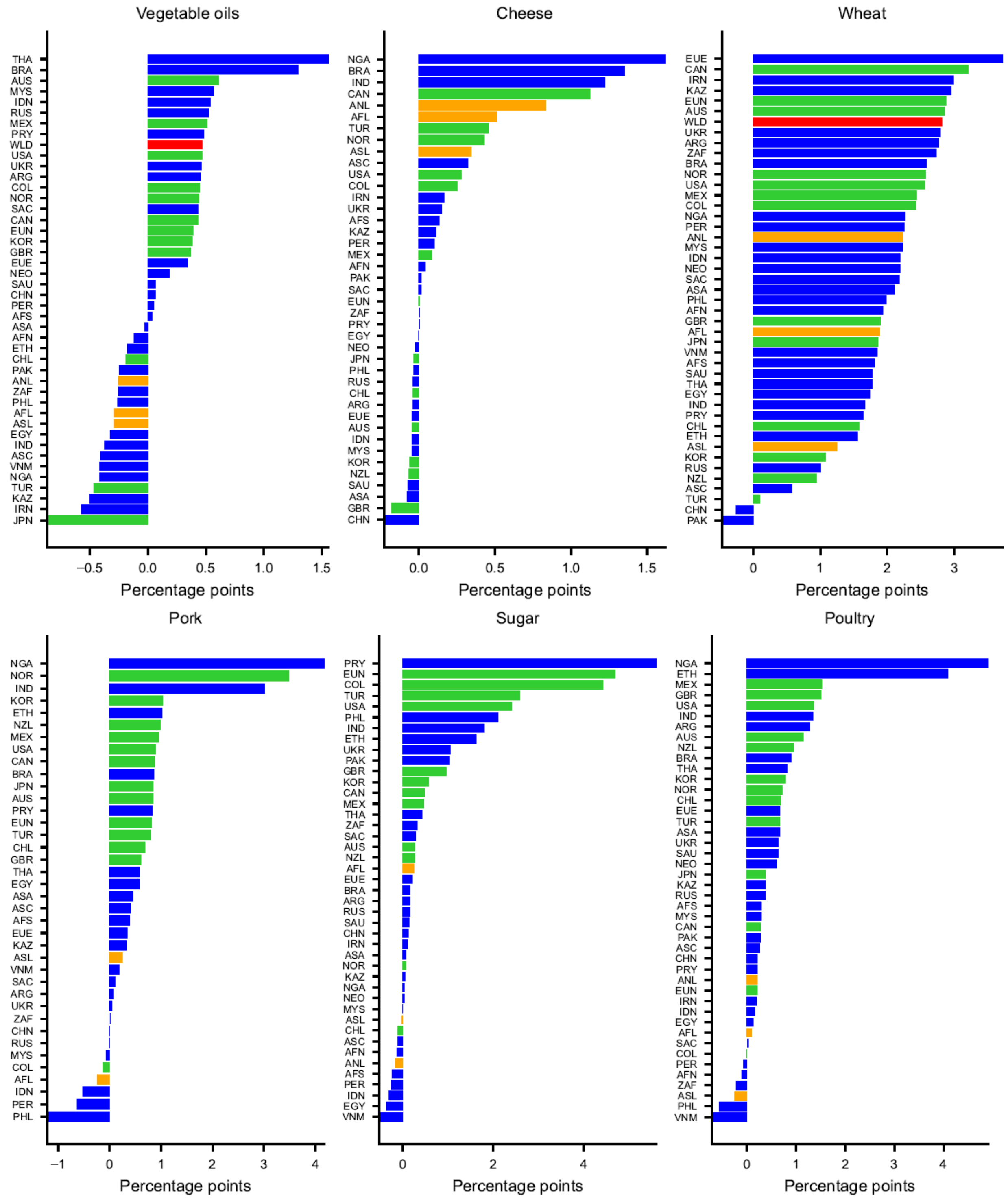
Note: Average trade parameters are weighted averages between import and export parameters
Source: Own illustration.

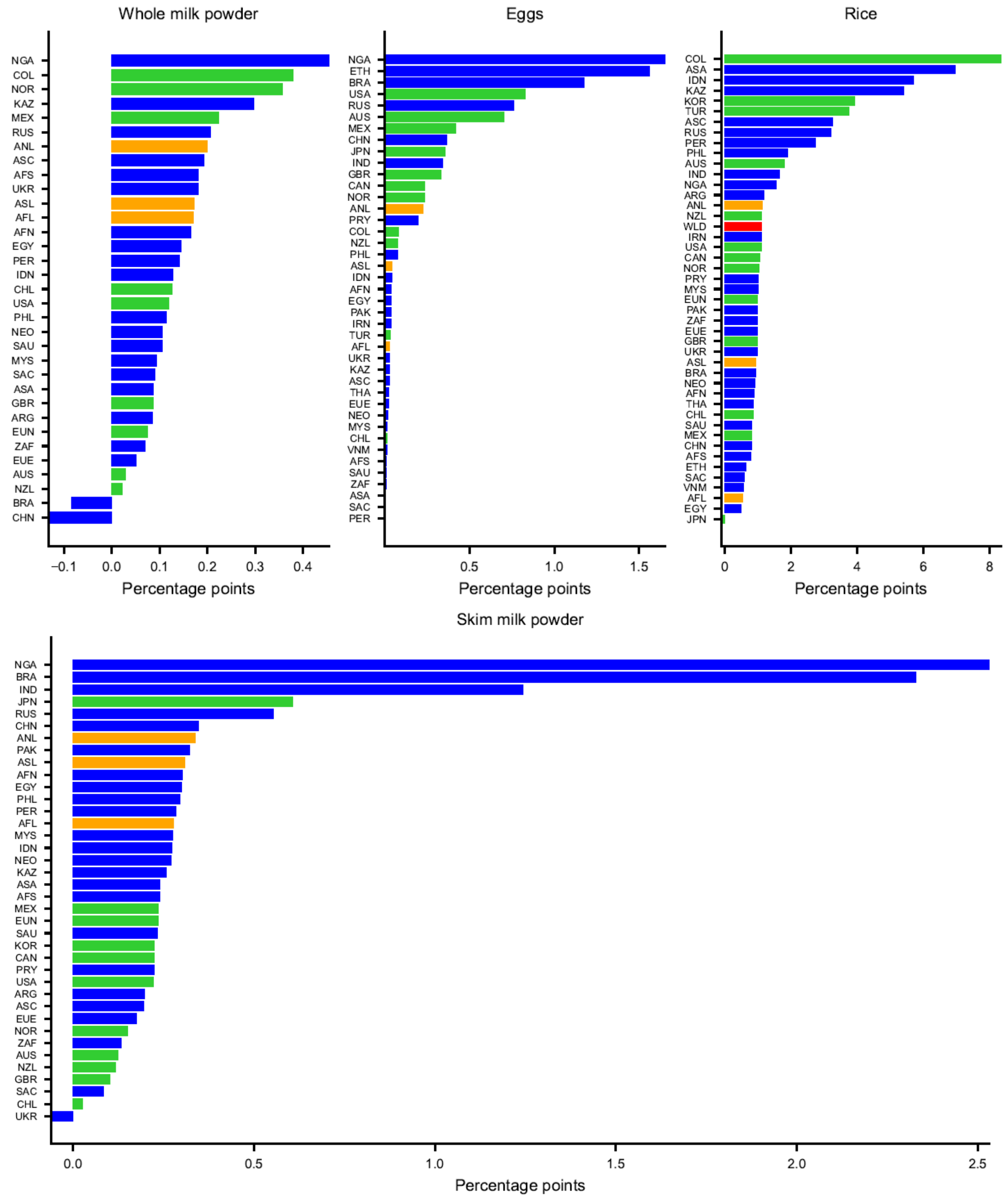
Annex B. Extended results

Figure A B.1. Upper variability of national food prices

Difference between the *Restricted Trade* and *Integrated Trade* scenarios




Vegetable oils
THA BRA AUS MYS IDN RUS MEX PRY WLD USA UKR ARG COL NOR SAC CAN EUN KOR GBR EUE NEO SAU CHN PER AFS ASA AFN ETH CHL PAK ANL ZAF PHL AFL ASL EGY IND ASC VNM NGA TUR KAZ IRN JPN
−0.5 0.0 0.5 1.0 1.5
Percentage points
Cheese
NGA BRA IND CAN ANL AFL TUR NOR ASL ASC USA COL IRN UKR AFS KAZ PER MEX AFN PAK SAC EUN ZAF PRY EGY NEO JPN PHL RUS CHL ARG EUE AUS IDN MYS KOR NZL SAU ASA GBR CHN
0.0 0.5 1.0 1.5
Percentage points
Wheat
EUE CAN IRN KAZ EUN AUS WLD UKR ARG ZAF BRA NOR USA MEX COL NGA PER ANL MYS IDN NEO SAC ASA PHL AFN GBR AFL JPN VNM AFS SAU THA EGY IND PRY CHL ETH ASL KOR RUS NZL ASC TUR CHN PAK
0 1 2 3
Percentage points
Pork
NGA NOR IND KOR ETH NZL MEX USA CAN BRA JPN AUS PRY EUN TUR CHL GBR THA EGY ASA ASC AFS EUE KAZ ASL VNM SAC ARG UKR ZAF CHN RUS MYS COL AFL IDN PER PHL
−1 0 1 2 3 4
Percentage points
Sugar
PRY EUN COL TUR USA PHL IND ETH UKR PAK GBR KOR CAN MEX THA ZAF SAC AUS NZL AFL EUE BRA ARG RUS SAU CHN IRN ASA NOR KAZ NGA NEO MYS ASL CHL ASC AFN ANL AFS PER IDN EGY VNM
0 2 4
Percentage points
Poultry
NGA ETH MEX GBR USA IND ARG AUS NZL BRA THA KOR NOR CHL EUE TUR ASA UKR SAU NEO JPN KAZ RUS AFS MYS CAN PAK ASC CHN PRY ANL EUN IRN IDN EGY AFL SAC COL PER AFN ZAF ASL PHL VNM
0 1 2 3 4
Percentage points



Note: OECD countries are shaded in green, the 3 least developed countries (LDC) aggregates in orange, the world average in red and the remaining countries in blue. Figure uses upper semi-variation coefficient of the average domestic prices across the time horizon 2022-2040. . Positive values indicate higher vulnerability under the *Restricted Trade* scenario. Country/region codes can be found in Annex C

Source: Simulation results.

Annex C. Aglink-Cosimo country and product codes

Table A C.1. Aglink-Cosimo country/region codes

Code	Country / region
WLD	World
NOA	North America
CAN	Canada
USA	United States of America
LAC	Latin America aggregate
ARG	Argentina
BRA	Brazil
CHL	Chile
COL	Colombia
MEX	Mexico
PRY	Paraguay
PER	Peru
SAC	Other South America
EUR	Europe
EUN	European Union
E14	EU-14
NMS	New EU Member States (later than EU15)
GBR	United Kingdom
NOR	Norway
CHE	Switzerland
RUS	Russian Federation
UKR	Ukraine
EUE	Other Europe
OCD	OCEANIA DEVELOPED
AUS	Australia
NZL	New Zealand
OCE	Other Oceania
AFR	AFRICA
ANL	Least Developed North Africa
AFN	Other North Africa
EGY	Egypt
ETH	Ethiopia
NGA	Nigeria
ZAF	South Africa
AFS	Other Sub-Saharan Africa
AFL	Africa Southern Least Developed
ASP	Asia Pacific
JPN	Japan
KAZ	Kazakhstan
ISR	Israel
ASC	Central Asia
CHN	China, mainland
IND	India
IDN	Indonesia

Code	Country / region
KOR	Korea
MYS	Malaysia
PAK	Pakistan
PHL	Philippines
THA	Thailand
VNM	Viet Nam
ASA	Other Asia
ASL	LDC-Southern Asia
NEO	Other Near East
IRN	Iran (Islamic Republic of)
SAU	Saudi Arabia
TUR	Türkiye
LIC	Low-income countries
LMC	Low-middle income countries
UMC	Up-middle income countries
HIC	High income countries

Source: Aglink-Cosimo modelling system.

Table A C.2. Aglink-Cosimo Product codes

Code	Product / product aggregate
TOT	Total aggregate
ANM	Animals
MT	Meat
BV	Beef and Veal
PK	Pork
PT	Poultry
SH	Sheep
DY	Dairy
MK	Milk
BT	Butter
CH	Cheese
SMP	Skim milk powder
FDP	Fresh dairy products
WMP	Whole milk powder
WYP	Whey powder
CA	Casein
EG	Eggs
FH	Fish
OAP	Other animal products not modelled
VGT	Vegetal
CE	Cereals
MA	Maize
WT	Wheat
RI	Rice
OCG	Other coarse grains
OPL	oilseeds and oil palm
SB	Soybean
OOS	Other Oilseeds
PL	Palm oil
OSPR	Processed oilseed products
VL	Vegetable oils
PM	Total Protein Meal
SCR	Sugar crops
SBE	Sugar beet
SCA	Sugarcane
SW	Sweetener
SU	Sugar
SUR	Raw sugar
SUW	White sugar
HFCS	High fructose corn syrup
RT	Roots and tubers
PS	Pulses

Source: Aglink-Cosimo modelling system.

This report was approved and declassified by the Working Party of Agricultural Policies and Markets in March 2023 and was prepared for publication by the OECD Secretariat.

Comments are welcome and can be sent to tad.contact@oecd.org.