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The adverse consequences of global harvest and weather disruptions on economic activity

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Extreme weather events are expected to increase with climate change. Such events are detrimental for local economic activity but could also affect countries that are not directly exposed through global agricultural production shortfalls and price surges. Here, estimations for 75 countries show that increases in global agricultural commodity prices caused by harvest or weather disruptions in other regions of the world significantly curtail economic activity. The impact is considerably stronger in advanced countries, despite relatively lower shares of food in household expenditures. Effects are weaker when countries are net exporters of agricultural products, have large agricultural sectors and/or are less integrated in global markets for non-agricultural trade. Once we control for these characteristics, the relationship between the country's income per capita and the economic repercussions becomes negative. Overall, these findings suggest that the consequences of climate change on advanced countries, particularly through food prices, may be larger than previously thought.

There is ample evidence that climate change has increased the variance and frequency of extreme weather conditions[1–3]. Studies project, in the coming decades, a further rise in the frequency, duration and intensity of extreme weather events such as droughts, heatwaves, tropical cyclones and heavy rainfall[4,5]. Since temperature and precipitation are key inputs in agricultural production, the economic consequences are considered to be most important for agriculture. In particular, low-income countries are projected to suffer because poorer countries already have hotter climates, as well as higher shares of agriculture in economic activity[6–11].

An element that has received little attention is the possible indirect impact of climate change on economic performance of countries through fluctuations in global agricultural (food) commodity prices. Since global production of the most important crops comes from a small number of major producing regions, severe weather conditions in these regions could lead to substantial swings in global prices of agricultural commodities. For example, extreme droughts in Russia and Eastern Europe were the primary reason for the rise in prices by more than 30% in 2010 (Fig. 1)[12–14]. Such swings in global food prices could even curtail economic activity in countries that are not directly exposed to the weather conditions.

The rise in the frequency and intensity of extreme weather events, as well as distributions of pests and diseases due to climatic changes, are projected to result in greater risks of global food system disruptions, including agricultural production shortfalls and price surges[4,5,15]. An event that would have been called a 1-in-100 yr extreme adverse food production shock over the period 1951–2010 may become as frequent as 1-in-30 yr before the middle of the century[16]. Economic models also project a 1–29% average cereal price increase by 2050 compared to a 'no climate change' scenario[5,16–20]. Given the high proportion of food in household expenditures, this could augment the costs of climate change for poor countries. Moreover, these indirect effects may also affect rich economies, which also have non-negligible shares of food expenditures.

Here, we provide empirical evidence for the impact of disruptions in global agricultural markets on economic activity of 75 advanced and developing countries. We (1) estimate the effects of changes in global agricultural commodity prices that are caused by harvest disturbances and/or weather shocks in other regions of the world on real gross domestic product (GDP), (2) examine whether there are differences between high- and low-income countries and (3) explore the correlation with other relevant country characteristics. Such evidence is not only useful to assess possible consequences of climate change. For example, the results should also help to evaluate the repercussions of policies that may influence food prices, such as agricultural trade policies, ethanol subsidies or food security programmes.

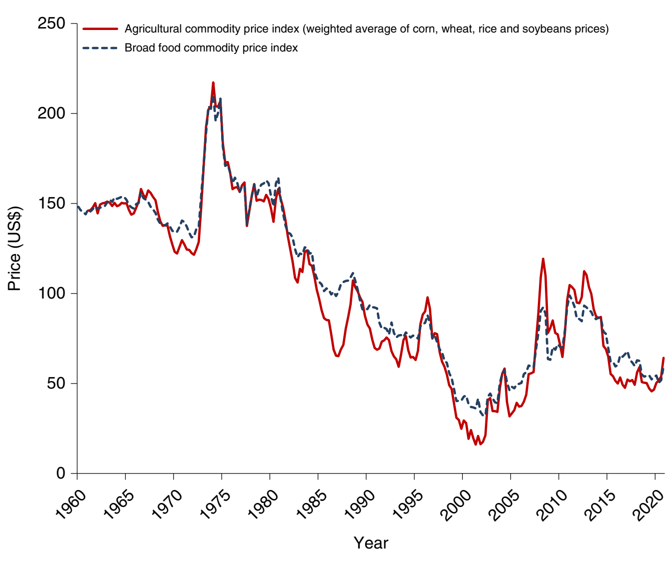

Fig. 1 | Evolution of global real agricultural commodity prices over time. The agricultural commodity price index is a trade-weighted average of the prices of corn, wheat, rice and soybeans. The broad food commodity price index is a trade-weighted average of benchmark food prices for cereals, vegetable oils, meat, seafood, sugar, bananas and oranges. All prices are in US$ and measured as 100 times the natural log of the index, deflated by US CPI. Data from the IMF (https://data.imf.org/).

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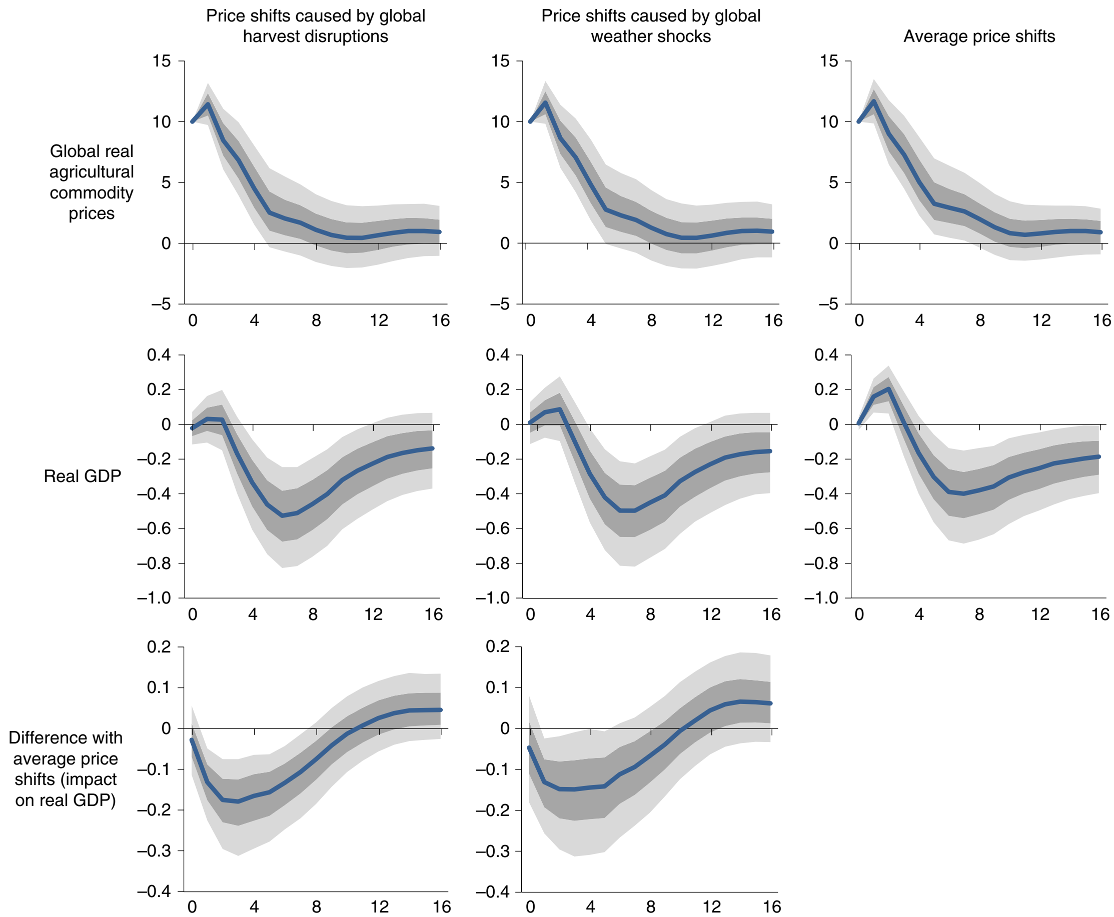

Fig. 2 | Dynamic effects of global agricultural commodity market disruptions. Impulse responses (mean group panel SVAR-IV estimator) to a 10% increase in global agricultural commodity prices (US$) triggered by the shocks, with 68 and 95% bootstrapped CIs that account for correlation of the residuals across countries. The impulse is at period 0, while all other determinants are kept constant. Horizon of the responses (*x* axes) is quarterly. The first column isolates, for each country, price changes that are caused by unfavourable harvest disruptions in other regions of the world. The second column isolates price changes that are caused by weather shocks (temperature and precipitation) in other regions of the world. The third column shows the effects of average (all) price innovations. Results are based on 75 advanced and developing countries, covering the period 1970Q1–2016Q4.

Previous research has shown that the effects of global agricultural production shortfalls on economic activity of the United States turn out to be a multiple of its share in household consumption[14]. However, there are no studies that have estimated the effects of global food production shocks on economic activity of other economies, nor studies that have conducted cross-country comparisons. There exist studies that have estimated the macroeconomic consequences of changes in agricultural prices but these studies assume that (all) changes in international commodity prices are exogenous for individual countries[21–23]. This assumption is controversial and we will show that such estimates are distorted. Specifically, reverse causality between economic activity and agricultural prices is probably present[24,25]. To establish causal relationships and to assess the consequences of climate change, it is important to identify shifts in prices that are caused by exogenous agricultural market disturbances rather than endogenous responses to global economic conditions. Even for small countries that do not affect global demand, this distinction is important because these countries may also be directly affected by global economic developments, for example, through trade. In addition, our main research question requires that the price shifts are triggered by agricultural disruptions in other regions of the world. To achieve identification, we construct two sets of instrumental variables for each country that fulfil these conditions.

We use two quarterly series of exogenous global harvest disruptions, as proposed by us previously[14]. The first instrument is a generic series of unanticipated shocks to the aggregate harvest volumes of the four most important staple food commodities: corn, wheat, rice and soybeans. To obtain shocks in other regions of the world for each country, we systematically exclude the harvests of the country itself, the entire subregion in which the country is located and the harvests in the neighbouring subregions. The second instrument is episodes of major global agricultural commodity supply disruptions, which have been identified with narrative methods. More details are provided in the Methods.

As an alternative set of instrumental variables for agricultural market disruptions, and to capture more explicitly the link with climatic factors, we construct global weather shocks for a quadratic in average temperature as well as total precipitation. By combining temperature and precipitation data on a 0.5° grid for the entire world with grid-level planting and harvest dates for the four major crops, and the fraction of each grid cell that is used for the crops, we calculate global monthly agricultural-weighted weather conditions. The shocks are the deviations of the weather outcomes from their historical averages and long-term trend. Again, for each country we exclude the weather conditions of the entire subregion in which the country is located and the neighbouring subregions. For details, refer to the Methods.

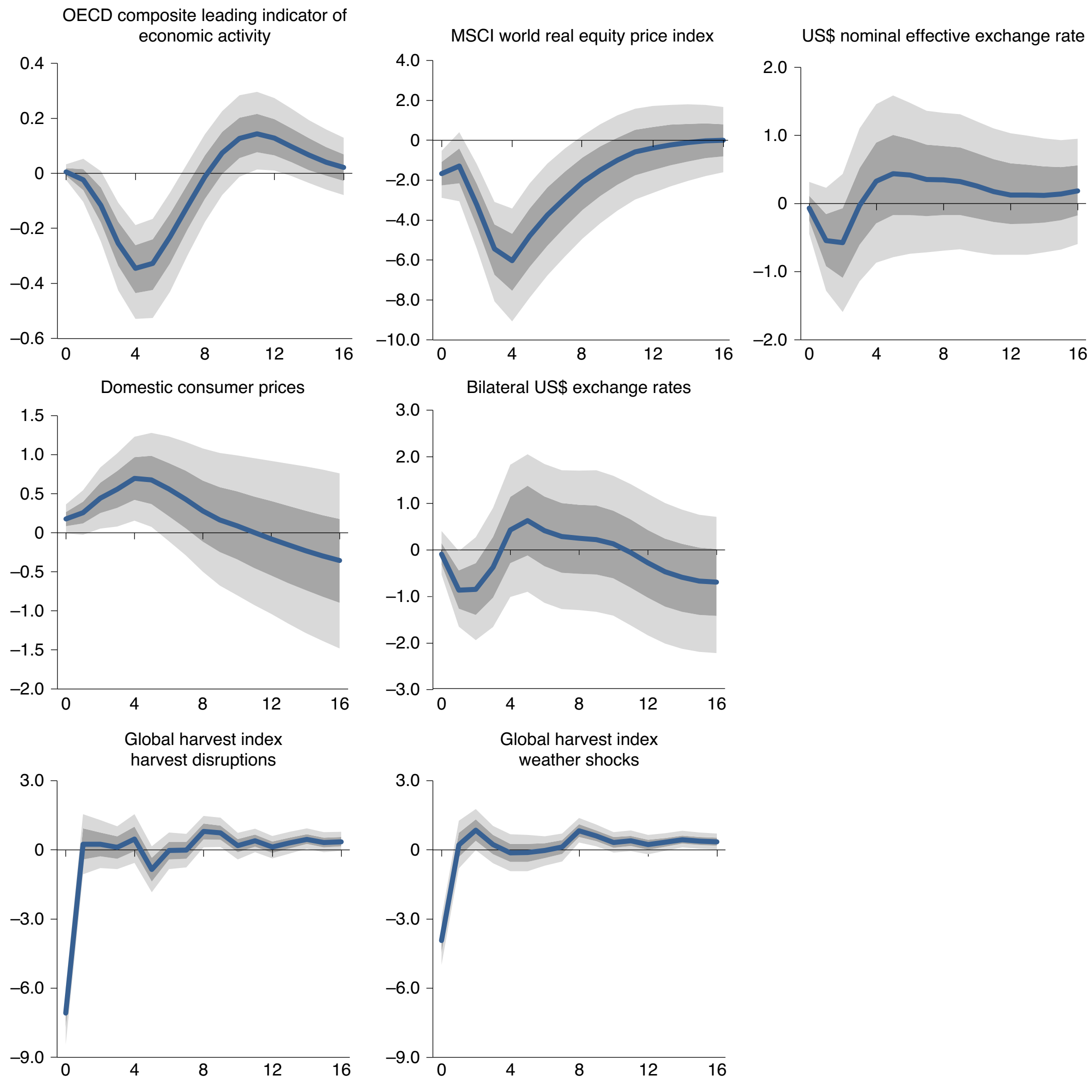

Fig. 3 | Effects of global agricultural commodity market disruptions on other variables. Impulse responses to a 10% increase in global agricultural commodity prices caused by harvest disruptions in other regions of the world, with 68 and 95% bootstrapped CIs that account for correlation of the residuals across countries. Horizon of the responses (*x* axes) is quarterly. The first row shows the effects on the other variables of the baseline SVAR-IV model. The second and third rows show the effects on variables that are added one-by-one to the baseline model. Consumer prices and bilateral exchange rates are individual-country data. The bottom row also includes the effects of the weather shocks on the global harvest index.

In the next step, we use the two sets of instruments to estimate the dynamic effects of global harvest disruptions and weather shocks that raise global real agricultural commodity prices by 10% on impact. As the baseline, we estimate individual-country and panel structural vector autoregression models with external instruments (SVAR-IV)[26,27]. To examine several country characteristics simultaneously, we conduct panel IV regressions with local projection methods (LP-IV)[28]. A battery of robustness checks is discussed in the Methods.

Effects of global agricultural commodity market disruptions

The harvest disruptions trigger significant shifts in global prices and can be considered as strong instrumental variables for most of the countries (Supplementary Information Table 4). At the panel level, the *P* value of each instrument is <0.0001 and the adjusted R^2 is 0.22. The weather shocks also have a significant impact on global agricultural prices in the first stage of the estimations for most countries but are less efficient instruments, in particular for North and Central American countries. The panel adjusted R^2 is 0.10. We therefore discuss the estimations based on the harvest disruptions as the baseline.

A rise in global agricultural commodity prices caused by unfavourable harvest disruptions returns to the baseline (that is, the level without the shock) after ~2 yr (Fig. 2). The price shift leads on average to a significant fall in real GDP. Specifically, GDP starts to fall after about two quarters, reaches a maximal decline of 0.53% after six quarters and then gradually returns to the baseline (Fig. 2, second row). The sluggish and persistent response of economic activity to exogenous shocks is a standard finding in theoretical and empirical studies and is typically explained by the presence of capacity adjustment costs, habit persistence of households, financial acceleration effects and/or sticky prices[29–31].

The effects of agricultural price shifts induced by weather shocks in other regions of the world are very similar to price changes caused by harvest disruptions (Fig. 2, second column). This applies to all results reported here. The results are also not sensitive to the choice and construction of the instrumental variables,

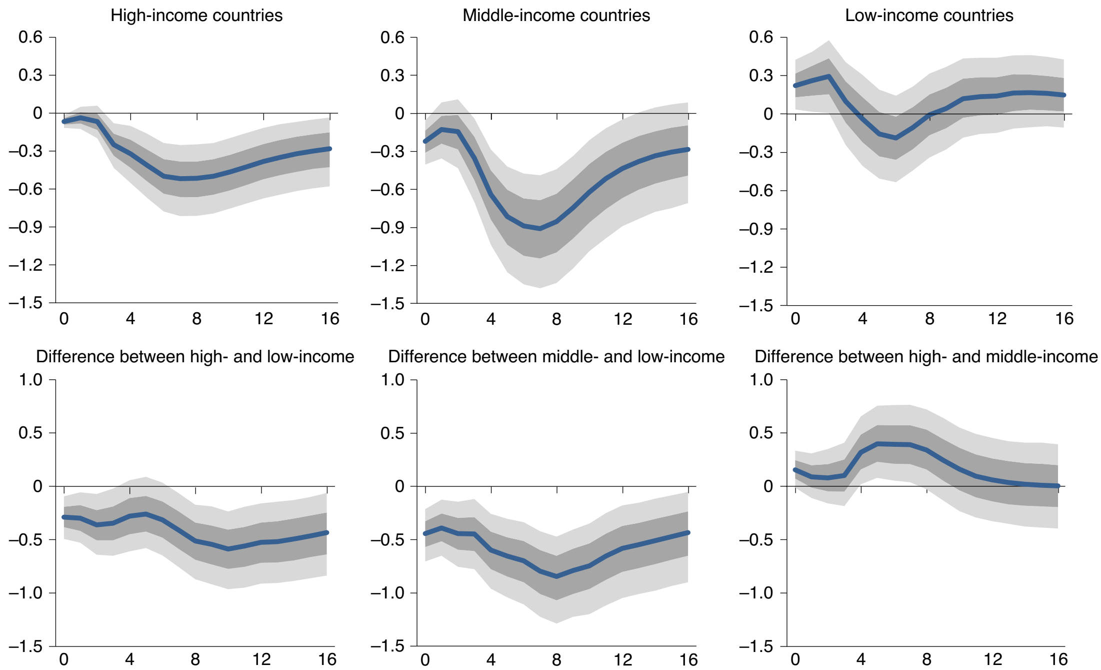

Fig. 4 | Effects of global agricultural commodity market disruptions in advanced versus poor countries. Average impulse responses of each group of countries to a 10% increase in global agricultural commodity prices caused by harvest disruptions in other regions of the world, with 68 and 95% bootstrapped CIs that account for correlation of the residuals across countries. Horizon of the responses (*x* axes) is quarterly. High-income countries are the top tertile (top-25) of countries according to purchasing power parity (PPP)-adjusted real GDP per capita over the period 2000–2015. Low-income countries are the bottom tertile (51–75) and middle-income countries are the remaining countries (26–50). The bottom row shows the difference between country groups, together with CIs.

several perturbations to the SVAR-IV model and when we allow for nonlinear relationships between the shocks and agricultural prices (Supplementary Information, section C1–3).

The magnitudes are economically important. A way to illustrate this are the episodes that are used to construct the narrative shocks. For example, in the summer of 2010, global agricultural prices increased by >30%, which was predominantly the consequence of the worst heatwave and drought in more than a century in Russia and Eastern Europe. According to the estimates, this has lowered average annual real GDP growth by ~0.8 percentage points for two subsequent years (that is, cumulative 1.6 percentage points). As a reference: actual real GDP growth over the two subsequent years was on average 2.6%. Similarly, the unfavourable shocks in 2002 and 2012 have reduced real GDP cumulative by 1.0 and 0.8 percentage points, respectively. On the other hand, the two most recent favourable agricultural market shocks (1996 and 2004) have boosted economic activity each time by 1.2 percentage points.

The results shown in Fig. 2 further demonstrate that it is important to isolate price shifts that are truly exogenous to estimate the macroeconomic effects properly. Specifically, when it is assumed that all global price changes are exogenous shocks (that is, when instrumental variables are not used for identification), the effects on real GDP are significantly positive in the short run, while the peak decline is only 0.40%. The differences relative to the IV-estimations are statistically significant. Note that we also find biased estimates for small countries.

Several indicators of (expected) global economic activity decline as a result of agricultural market disruptions, whereas consumer prices increase significantly (Fig. 3). The US$ exchange rate remains constant. Furthermore, the dynamic response of global harvests suggests that production shortfalls in one region are almost inconceivably compensated by more production in other regions afterwards. This suggests that farmers' decisions are not based on observations of current and previous prices (that is, the so-called cobweb theorem or pork cycles)[32,33]. Instead, together with the persistent rise of agricultural prices, this pattern is consistent with rational expectations models of commodity markets with speculation[34].

Finally, the effects are considerably different across the 75 individual countries (Supplementary Information Fig. 3). Several countries experience substantial declines in real GDP, which contrasts with a temporary rise in other countries.

Differences in effects between rich and poor countries

To begin with, we compare the effects for the top, middle and bottom tertiles of the countries according to income per capita. The top tertile are all advanced economies according to the International Monetary Fund (IMF) World Economic Outlook country[35] classification, while the low-income countries are all classified as emerging market or developing economies. High- and middle-income countries are much more affected by agricultural market disruptions in other regions of the world (Fig. 4). In high-income countries, real GDP declines by 0.52%. For middle-income countries, the peak decline is even 0.91%. In contrast, low-income countries experience a rise of GDP in the first year after the shock. Even though the effects become negative after 1 yr, the peak decline is only 0.19% and statistically insignificant. Overall, the differences with both other groups are significant.

The stronger effects in high-income countries are surprising. First, it has been shown that food market disruptions affect the economy mainly through their impact on consumer spending, while the share of food (commodities) in household expenditures is much lower than in low-income countries[14]. Second, high-income countries typically have more effective government institutions. It is hence less likely that food price increases trigger conflicts such as food riots which, in turn, could have negative effects on real GDP[36].

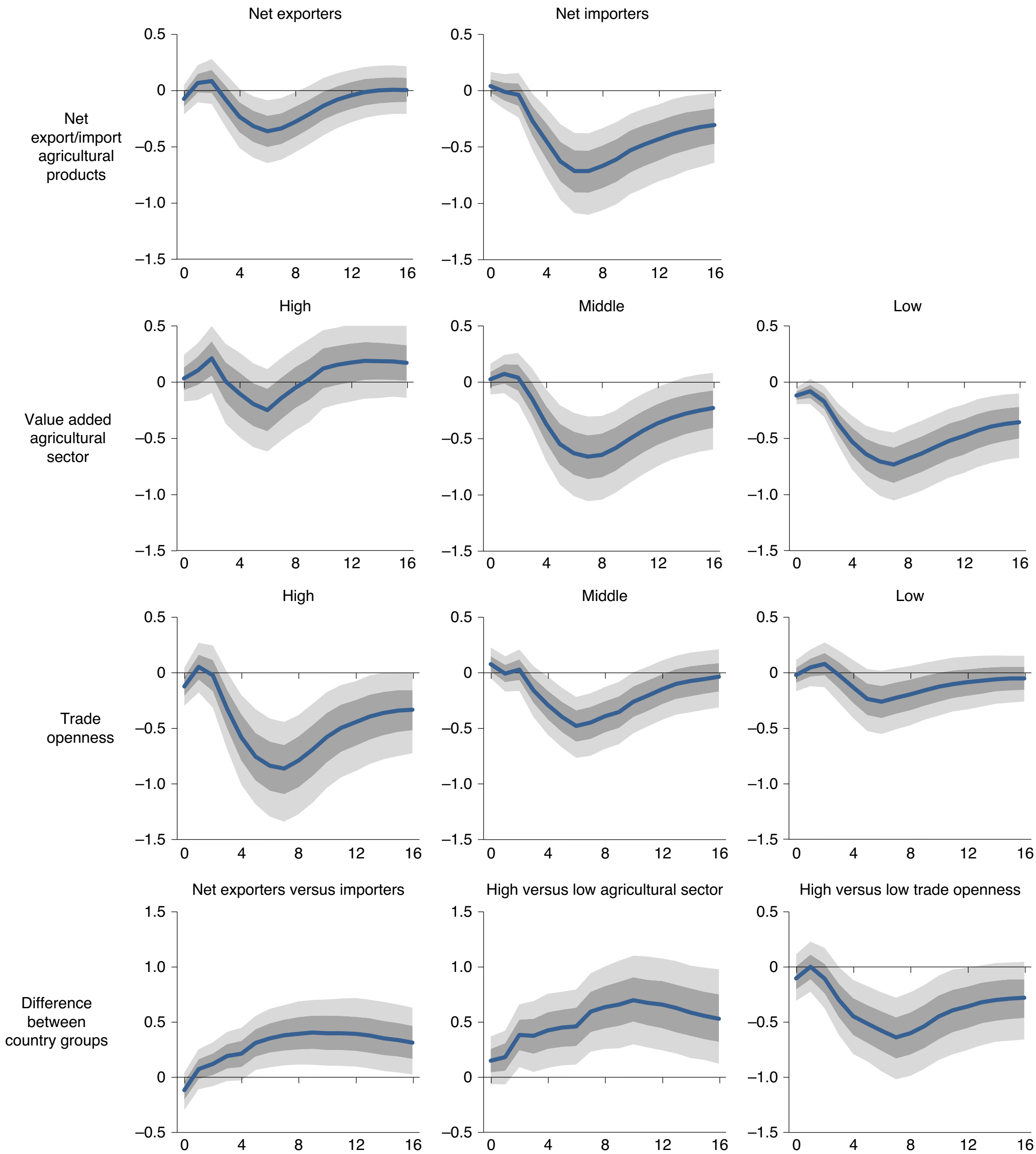

Fig. 5 | Effects of global agricultural commodity market disruptions on country groups according to other characteristics. Average impulse responses of each group of countries to a 10% increase in global agricultural commodity prices caused by harvest disruptions in other regions of the world, with 68 and 95% bootstrapped CIs that account for correlation of the residuals across countries. Horizon of the responses (*x* axes) is quarterly. High/middle/low are top, middle and lowest tertiles of countries on the basis of the characteristics. The characteristics are calculated on the basis of the period 2000–2015.

Finally, high-income countries are financially more developed, which allows households to smooth consumption and firms to smooth production when they experience income shocks[37,38].

Relationship with other country characteristics

Next, we examine whether there is a relationship between the effects and three relevant characteristics that are typically different between high- and low-income countries (Fig. 5). Note that, in contrast to the dynamic consequences of agricultural market shocks reported in the paper, these characteristics do not necessarily imply causal mechanisms. Studies that investigate the transmission mechanisms conclude that these are very complex[14]. Nevertheless, this analysis could provide stylized facts to guide future research.

First, since net food commodity exporters typically also benefit from higher international prices because of a possible favourable terms of trade effect, the macroeconomic repercussions might be more subdued[39]. We therefore split the countries according to their net export position of agricultural commodities: 40 countries are net exporters and 35 net importers. The effects are on average indeed weaker in countries that are net agricultural exporters. The difference between both groups is significant.

Countries that have relatively large agricultural sectors may be more isolated from changes in global prices because more households are self-sufficiency farmers, while a lot of agricultural commodities are traded on local markets only because of higher food transportation costs in rural areas compared to urban economies[24,40].

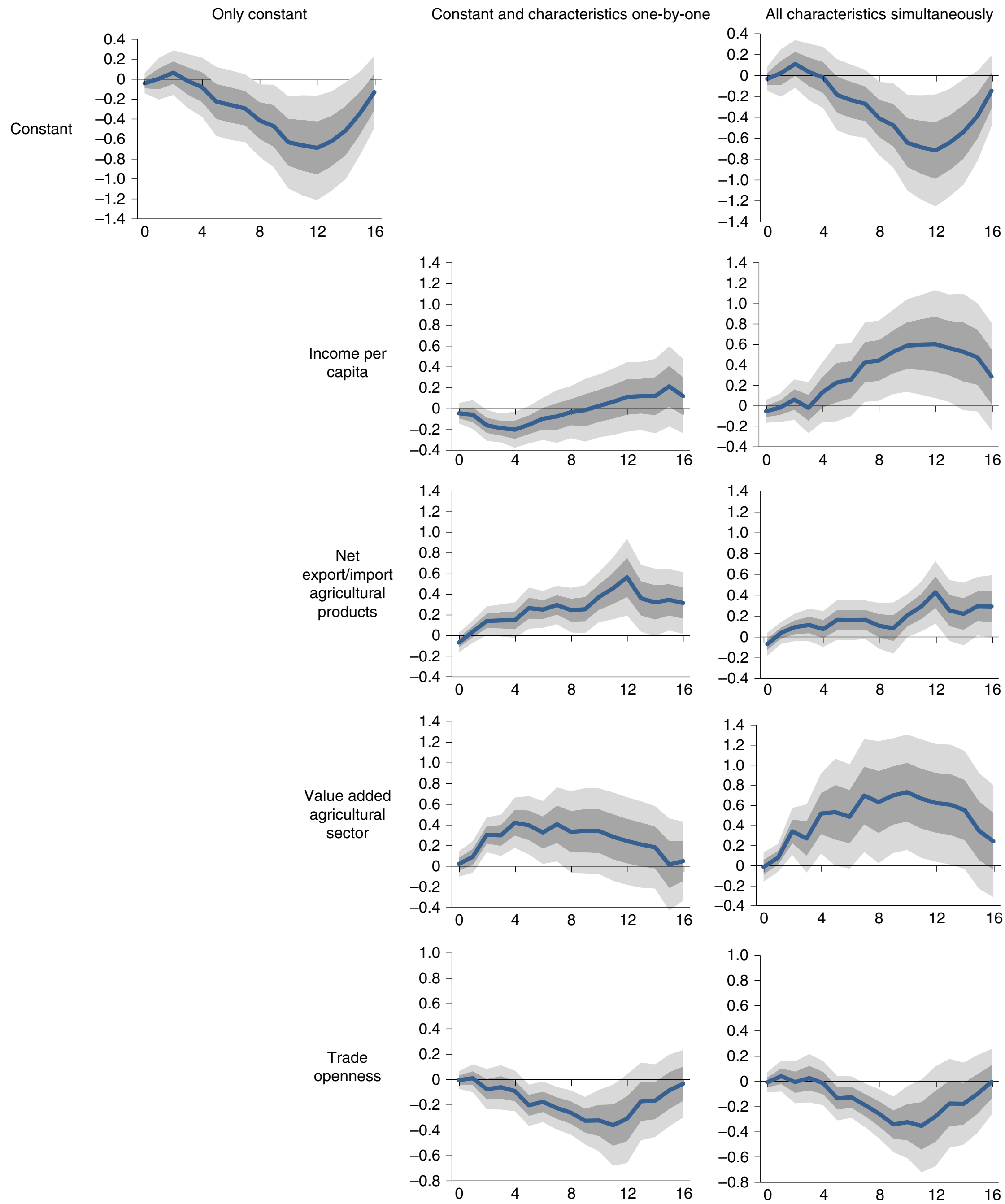

Fig. 6 | Influence of country characteristics on the magnitudes of the macroeconomic consequences of global agricultural market disruptions. Impulse responses to a 10% increase in global agricultural commodity prices caused by harvest disruptions in other regions of the world estimated with pooled mean group panel LP-IV methods, with 68 and 95% CIs that are adjusted for correlations between residuals across countries and serial correlation over time. Horizon of the responses (*x* axes) is quarterly. The constant reflects the average effects on real GDP for all countries, while the other panels show the additional effects when a country characteristic deviates by 1 s.d. from the sample mean.

There are insufficient data available to estimate the pass-through to domestic food prices but this hypothesis is supported by the insignificant pass-through to (overall) consumer prices in countries with large agricultural sectors, which is shown in Supplementary Information Fig. 11. The results in Fig. 5 reveal that the decline in real GDP is on average smaller in countries that have a large agricultural sector.

Finally, various studies have shown that enhanced trade integration increases the correlation of business cycles among countries[41–43]. Since the shocks have a significant impact on worldwide economic activity, countries that are more integrated with the rest of the world via trade may be more affected. Indeed, the effects are significantly greater in countries with higher shares of trade in GDP: real GDP decreases by 0.86% in the top tertile, compared to 0.26% in the lowest tertile.

Simultaneous analysis of country characteristics

The correlations between income per capita and net exports of agricultural products, the share of agriculture in GDP and the share of non-agricultural trade in GDP over the period 2000–2015 are −0.11,

−0.71 and 0.35, respectively. It is not clear if this can explain why advanced economies are more affected than low-income countries. We use panel LP-IV methods to analyse this, which are less efficient than panel SVAR-IV models but allow the impulse responses to be a linear function of several characteristics simultaneously.

Looking at the average effects across countries, there is a peak decline of real GDP by 0.71%, which is larger than the baseline SVAR-IV estimates (Fig. 6, first column). The relationships between the impact on real GDP and each country characteristic (as a continuous variable) one at the time are consistent with the SVAR-IV results for country groups: the repercussions are stronger when the country's income per capita or trade openness are higher, while the effects are weaker when the share of agriculture or the net exports share of agricultural commodities in GDP are larger.

Most importantly, when all characteristics are considered simultaneously, there is a sign-switch for income per capita. In particular, the effects on real GDP are more subdued when countries are richer. The relationship is statistically significant and economically relevant: once we control for the other characteristics, the peak decline is roughly 0.6 percentage points less when income per capita is 1 s.d. above the sample mean. The sign-switch suggests that the stronger average effects in high-income countries are related to the other characteristics. Particularly the size of the agricultural sector seems to be important to explain cross-country heterogeneity. When this share is 1 s.d. above the sample mean, the total impact on real GDP becomes negligible.

Implications

There are several implications that are relevant for policy-makers and future research. First, it is often argued that poor countries have to bear the bulk of the climate change burden, which acts as a disincentive for rich countries to mitigate their GHG emissions[44]. However, our results suggest that the repercussions on rich countries are probably larger than previously thought. Specifically, if there is a rise in the frequency and intensity of extreme weather events such as droughts and heatwaves that induce global agricultural production shortfalls, there will be more frequent and greater downturns in economic activity compared to a 'no climate change' scenario through increases in global food prices. Our findings also imply that enhanced variation in harvest volumes due to climatic changes will, in itself, generate welfare losses for households because of a corresponding rise in macroeconomic volatility. In particular, according to standard macroeconomic models, positive as well as negative fluctuations in economic activity that are caused by external shocks rather than changes in, for example, household preferences imply welfare losses[45].

Second, the weaker effects in low-income countries approves the scepticism about the idea that higher food prices are unambiguously harmful for the poor[24,46]. In particular, the world's poor have high shares of food expenditures but are also highly dependent on farming or are employed in sectors that are related to agricultural production. Accordingly, our macro evidence complements microeconomic studies, which conclude that we need a nuanced debate on the welfare effects of changes in food prices[47–51]. Yet, since the methods that we use require sufficiently long quarterly time series, a caveat of our analysis is that it does not include extremely poor countries, which could behave differently.

Third, swings in global agricultural prices are important for economic activity in many countries. Scholars studying business cycle fluctuations should hence consider accommodating agricultural markets in their models. This also applies to the analysis of policies that may affect agricultural prices, such as public food security programmes, agricultural export bans, import tariffs, ethanol subsidies or carbon offset programmes.

Finally, additional research is needed to improve our understanding of the transmission mechanisms. There are several channels that could influence the vulnerability of economies to rising food prices that are not captured in the analysis. Examples are the pass-through of global price shifts to local prices or the composition of food production and consumption. Furthermore, the monetary policy response to the inflationary consequences or the presence of government policies aimed at mitigating price increases are probably important for the macroeconomic effects. Overall, a better understanding of the mechanisms is crucial to implement policies that could mitigate the adverse consequences of extreme weather conditions on economic activity of countries through shifts in global agricultural prices that we have documented.

Online content

Any methods, additional references, Nature Research reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at https://doi.org/10.1038/s41558-021-01102-w.

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Methods

Panel SVAR-IV models. The baseline methodology are SVAR models, which capture the dynamic relationships between a set of macroeconomic variables within a linear system and allow measurement of the causal effects of structural shocks on all the variables in the model controlling for other developments in the economy that may influence the variables[52]. We estimate the effects of disruptions in global agricultural markets on real GDP for a panel of 75 countries. The selection of the countries is determined by the availability of quarterly macroeconomic data. An overview is provided in Supplementary Information Table 3.

For each country i, the macroeconomic dynamics are described by the following VAR model of linear simultaneous equations:

$$Y_{i,t} = \alpha_i + A_i(L)\,Y_{i,t} + u_{i,t} \tag{1}$$

$Y_{i,t}$ is a vector of endogenous variables representing the economy in quarter t, α_i is a vector of constants and linear trends, while $A_i(L)$ is a polynomial in the lag operator L. Parameter $u_{i,t}$ is a vector of reduced-form residuals, which are related to the structural shocks by

$$u_{i,t} = B_i \epsilon_{i,t} \tag{2}$$

where B_i is a non-singular (invertible) matrix. For the baseline estimations, $Y_{i,t}$ contains four global variables; that is, global real agricultural commodity prices (US$), the US$ nominal effective exchange rate, the Organisation for Economic Co-operation and Development (OECD) Composite Leading Indicator (CLI) and the MSCI index of world real equity prices, as well as the individual country's real GDP.

Global agricultural commodity prices are the weighted average of the benchmark prices of the four most important staples: corn, wheat, rice and soybeans. We choose these commodities because they closely resemble the instrumental variables, account for ~75% of the caloric content of food production worldwide, are relatively close substitutes that can be aggregated in a single index, are significantly affected by weather conditions and have been traded in integrated global markets for many decades, while the prices of other food commodities are also typically strongly related to these four staple food items[53]. The prices are collected from IMF[54] Statistics Data. In Supplementary Information Fig. 5, we also show results based on the broad food commodity price index that is shown in Fig. 1. Since prices are in US$, the nominal price index has been deflated by the US Consumer Price Index (CPI) to retrieve real prices and the model includes the US$ nominal exchange rate. The CLI and world equity prices capture fluctuations in (expected) global economic activity, which should help to isolate exogenous agricultural price changes from demand-induced price shifts[55]. In addition, it could capture transmission and spillovers across countries via the global business cycle. Finally, the vector of endogenous variables includes chain-weighted real GDP of each country. For details about the data, see section A1–5 in the Supplementary Information and also section C3 for the robustness of the results when we include additional global and/or country-specific variables in the VAR model.

The coefficients of α_i, $A_i(L)$ and the reduced-form residuals $u_{i,t}$ in equation (1) can simply be estimated by ordinary least squares. Because we are only interested in one structural shock; that is, shifts in real agricultural commodity prices caused by harvest disturbances or weather shocks in other regions of the world, only the elements of one column of B_i have to be identified. To do this, let $Z_{i,t}$ be a vector of instrumental variables of such disturbances for country i. These instruments can be used for identification of the first column of B_i if:

$$E\left[Z_{i,t}\epsilon^{1\prime}_{i,t}\right] \neq 0 \tag{3}$$

$$E\left[Z_{i,t}\epsilon^{2\prime}_{i,t}\right] = 0 \tag{4}$$

where $\epsilon^1_{i,t}$ is a shock to real agricultural prices caused by harvest (or weather) disturbances in other regions of the world and $\epsilon^2_{i,t}$ a vector of all other structural shocks. Equation (3) postulates that the instruments are correlated with the target shocks (instrument relevance condition), while equation (4) requires that the instruments are uncorrelated with all other shocks (exogeneity condition). For more technical details, see refs. [26,27] or ref. [56]. Below, we propose two sets of instruments that fulfil these conditions.

The VAR models are estimated in log levels, which gives consistent estimates while allowing for possible co-integration relationships between the variables[57]. This is the safest approach since pretesting and imposing the co-integration relationships could lead to serious distortions in the results when regressors have almost unit roots[58]. Note that the conclusions also hold when we estimate the VAR models in first differences (Supplementary Information Fig. 5).

The VARs are estimated for all 75 individual countries. To obtain panel estimates, which are the results shown in the figures, we average the impulse response functions of the individual countries. In contrast to fixed effects panel estimations, a mean group estimator allows for cross-country heterogeneity and does not require that the dynamics of the economies in the VAR are the same.

In the estimations, we include five lags of the endogenous variables, which is the maximum number suggested by the Akaike information criterion across all countries. The results are, however, not sensitive to the lag order choice. Supplementary Information Table 3 reports the sample period for each country. The start of the sample, which is 1970Q1 (where Q is quarter) the earliest due to the availability of the global equity price index, varies across countries. This can be explained by data availability and obvious historical reasons. For example, the samples of several Eastern European countries only start in the 1990s. The end of the sample is always 2016Q4, which is determined by the availability of the harvest indicators.

To check the validity and strength of the instruments, Supplementary Information Table 4 shows, for each country, the first-stage adjusted R^2, F statistics and robust F statistics allowing for heteroskedasticity. The figures always show the impulse responses for a global agricultural market shock that raises agricultural commodity prices by 10% on impact. We construct 68 and 95% confidence intervals (CIs) using the recursive (Rademacher) wild bootstrap procedure of ref. [27], whilst taking into account the correlation of the VAR residuals across countries (that is, for each draw the reshuffle of the residuals is the same for all countries). Note that a recursive block bootstrap based on a random reshuffle of the residuals with replacement would be problematic because the reshuffle has to be same across countries to account for cross-country correlation of the residuals, while the panel is unbalanced. In addition, since the narrative instrument contains many zero observations, a drawing procedure with replacement would produce zero vectors with positive probability. It is hence more convenient to apply the Rademacher procedure. A caveat is that this could underestimate the uncertainty when instruments are relatively weak[59]. We use 5,000 replications to calculate the CIs. To obtain the CIs of the panel VARs, we calculate the average impulse responses of the individual countries for each replication.

Panel LP-IV approach. If the SVAR-IV model adequately captures the data-generating process, this method is most efficient to estimate the dynamic effects[56]. Another popular method in empirical macroeconomics uses local projections with instrumental variables (LP-IV). An advantage of LP-IV is that it is possible to estimate the relationship between the dynamic effects and several country characteristics simultaneously, which is not possible with panel SVAR-IV models[60]. A disadvantage is that structural impulse responses tend to have higher bias, larger variance and lower coverage accuracy of CIs in small samples compared to VAR estimations. Note that local projections also suffer a loss of observations at the end of the sample (depending on horizon h), while some countries have relatively short sample periods.

For each horizon h we estimate the following panel LP-IV model:

$$\begin{aligned} y_{i,t+h} = {} & \alpha_{i,h} + \beta_{i,h} t + \sum_k \vartheta_{k,h} \mathrm{char}\,(k)_i + \delta_{i,h}\,(L)\, y_{i,t} + \rho_{i,h}\,(L)\, X_{i,t} \\ & + \left[\gamma_{0,h} + \sum_k \gamma_{k,h} \mathrm{char}\,(k)_i\right] \mathrm{RACP}_t + \epsilon_{i,t+h} \end{aligned} \tag{5}$$

where $y_{i,t+h}$ is real GDP of country i at horizon h. Parameters $\alpha_{i,h}$ and $\beta_{i,h} t$ are country fixed effects and time trends, respectively, while $\delta_{i,h}\,(L)$ and $\rho_{i,h}\,(L)$ are polynomials in the lag operator ($L = 5$) that could vary across countries. Parameter $X_{i,t}$ is a set of control variables determined before date t. This vector includes all the variables of the SVAR-IV model. Parameter $\mathrm{char}\,(k)_i$ is a vector of k country characteristics; that is, for each country the average values of the characteristic over the period 2000–2015. Before the estimations, the characteristics are demeaned by the (cross-country) sample mean and divided by the standard deviation. Accordingly, $\gamma_{0,h}$ represents the average response of real GDP at horizon h to a change in global agricultural commodity prices (RACP_t) at time t, while $\gamma_{k,h}$ is the additional effect on a country's real GDP when the characteristic is 1 s.d. larger/smaller than the sample mean. For agricultural commodity prices, we use the two instrumental variables discussed below. In essence, the approach is similar to the pooled mean group (PMG) model[61]. Specifically, the PMG estimator allows all coefficients and error variances to differ across countries but constrains the average effects of the shocks on real GDP ($\gamma_{0,h}$) and the parameters of the country characteristics ($\gamma_{k,h}$) to be the same across countries. Finally, the standard errors of the estimates are adjusted for correlations between the residuals across countries and serial correlation between the residuals over time. These are calculated as discussed in ref. [62].

Global harvest disruptions. We use two instrumental variables for harvest disruptions. The first instrument is a generic series of unanticipated harvest shocks in other regions of the world. The construction explores the fact that there is a time lag of at least one quarter (3–10 months) between the planting of the four staples and the harvest. Accordingly, harvest volumes cannot (endogenously) respond to changes in the state of the economy within one quarter; that is, one could realistically assume that a possible influence of food producers on the volumes during the quarter of the harvest itself is meagre. For example, it is not realistic to postulate that farmers increase food production by raising fertilization activity during the harvesting quarter in response to improving economic conditions, since several studies have shown that in-season fertilization strategies are inefficient and often even counterproductive for the staples that we consider[63,64]. At the same time, harvest volumes are in the final quarter still subject to exogenous disturbances, such as changing weather conditions or crop diseases, which are isolated as harvest shocks. Overall our previous work[14] shows that global harvests do not convey relevant endogenous responses to macroeconomic conditions within one quarter.

In a first step, we elaborate on ref. [14] to construct quarterly indexes of global harvest volumes. Specifically, the Food and Agriculture Organization of the United Nations (FAO) publishes annual harvest data for each of the four major staples for 192 countries. In ref. [14] we combine the annual harvest data of each individual country with that country's planting and harvesting calendars for each of the four crops, to allocate the harvest volumes to a specific quarter. Since most countries have only one relatively short harvest season for each crop, it is possible to assign two-thirds of world harvests to a specific quarter. The four crops of all countries are then aggregated to construct a quarterly composite global agricultural commodity production index. We use the same principium but, for each country, we aggregate the harvest volumes of all countries in the world, except the harvests of the country itself, the entire subregion in which the country is located and the harvests in the neighbouring subregions. For example, for Italy, we exclude the harvests of all countries in South Europe, West Europe, East Europe and North Africa. The reason is that we do not want to measure direct effects of extreme weather events on the local economy, which would distort the results. The harvests of the other countries in the region are also excluded because weather variation might be correlated across neighbouring countries. We use the United Nations definitions of subregions. After aggregating, the series are seasonally adjusted using the Census X-13 ARIMA-SEATS Seasonal Adjustment Program (method X-11). The results of this exercise are 75 indicators of harvest volumes in other regions of the world.

In the next step, we use the indicators to estimate unanticipated harvest shocks. In essence, the shocks are quarterly prediction errors of the harvest volumes conditional on past harvests and a set of information variables that may influence harvests:

$$q_{i,t} = c_i + \beta_i t + C_i(L) X_t + D_i(L) q_{i,t} + v_{i,t} \tag{6}$$

where $q_{i,t}$ is the natural logarithm of the aggregated harvest volumes in other regions of country i. Parameter X_t is the vector of control variables that may affect harvest volumes with a lag of one or more quarters: the natural logarithms of global real agricultural commodity prices, the OECD CLI, world real equity prices and real crude oil prices. Although agricultural prices should capture all relevant information in efficient markets, we also include indicators of expected global economic activity to capture possible additional information about demand for food commodities. The oil price is included because food commodities can be considered as a substitute for crude oil to produce energy, while oil is used in the production, processing and distribution of agricultural commodities. Parameter c_i is a constant, t a time trend, while $C_i(L)$ and $D_i(L)$ are polynomials in the lag operator. We set $L = 6$ but the results are robust when we choose an alternative number of lags or include more control variables.

For all countries, we estimate equation (6) over the period 1970Q1–2016Q4. If we assume that the information sets of local farmers are no greater than equation (6), the residuals $v_{i,t}$ of this estimation can be considered as unanticipated harvest shocks in other regions. Note that anticipated harvest innovations before t should be reflected in the control variables, in particular agricultural commodity prices, because an arbitrage condition ensures that changes in futures prices also affect spot prices of storable commodities[65].

As the second instrument, we use the major exogenous global agricultural commodity market shocks that have been identified with narrative methods in ref. [14]. More precisely, in ref. [14] we rely on newspaper articles, FAO reports, disaster databases and other online sources to identify 13 historical episodes of substantial movements in agricultural commodity prices that were unambiguously caused by events in agricultural markets and unrelated to the state of the economy. An overview and brief description of these episodes is included in Supplementary Information Table 1. Six episodes are unfavourable shocks, while seven episodes have been characterized as favourable. These episodes are converted to a quarterly dummy variable series, which is equal to 1 and −1 for unfavourable and favourable shocks, respectively. To minimize correlation of the shocks with domestic agricultural production, for each country we exclude an episode when the growth of domestic harvests deviated more than 1 s.d. from its mean over the period 1965–2016. Accordingly, about 30% of the episodes are excluded.

In the estimations, we assume that the impact of the harvest disruptions on agricultural prices is linear. There exist, however, studies that have documented that the effects of agricultural output shocks on prices are conditional on the amount of stocks and that there may be asymmetries between positive and negative production shocks[66,67]. In Supplementary Information section C2, we examine the sensitivity of the results when we allow for such extensions. Even though we confirm some nonlinearities, this does not affect the results reported in the paper.

Weather shocks. Since weather may not be the only determinant of exogenous harvest disruptions, we also consider a set of instruments that are directly linked to climatic factors. Following previous studies that have used quadratic specifications to capture nonlinear (concave) relationships between weather outcomes and crop yields, we construct four instruments: an agricultural-weighted quadratic in both average temperature and total precipitation at the global level[53,68]. To do this, we use the global gridded weather dataset of the Climate Research Unit at the University of East Anglia, which provides monthly estimates of temperature and precipitation on a 0.5° grid for the entire world covering the period 1901–2019[69]. Similar to Roberts and Schlenker[53], who construct annual global weather shocks, we weight the weather in a country over the areas a crop is grown and the time during which it is grown. Specifically, the weather outcome for a specific crop in a country is the area-weighted average of all grids that fall in a country over the growing season. The fraction of each grid cell (harvest area) that is used for each of the four major crops that compose the agricultural price index is obtained from ref. [70], while the growing season for each crop in the grid cell is collected from ref. [71]. Both datasets are on a 5-min grid. We assume a linear evolution of planting and harvesting. For example, if the harvest season is between days 70 and 100 of the year, we assume that half of the harvest has been realized at day 85, while the other half is exposed to the weather conditions on that day. Accordingly, the way that crops in the grid are exposed to the monthly weather outcomes varies between 0 and 1.0 over the year. To obtain global agricultural-weighted weather conditions, we then aggregate the weather outcomes on the basis of the average export share of the country in global exports over the period 1992–2016 and the weight of the crop in the global agricultural price index. Overall, the weather outcomes cover 95% of global export and production of the four crops.

This calculation is done for temperature, squared temperature, precipitation and squared precipitation, respectively. Again, for all countries, we construct global weather indicators excluding the weather outcomes of the entire subregion in which the country is located and the neighbouring subregions. We then regress the global weather indicators over the period 1901–2019 on 12 monthly dummies to capture seasonal effects, as well as a linear, quadratic and cubic time trend to capture climatic trends. The quarterly averages of the monthly residuals of this estimation are the weather shocks that are used as four instrumental variables. In contrast to the harvest shocks, a caveat of the weather shocks is that there is some weak higher order serial correlation present in the series. In section A3 of the Supplementary Information, we explain the construction in more detail and show several robustness checks, such as nonlinear relationships and alternative weather data. The results turn out to be robust.

Data availability

The datasets used for this paper are available at: https://doi.org/10.5281/zenodo.4665886.

Code availability

The codes to reproduce the results of the paper are available at: https://doi.org/10.5281/zenodo.4665886.

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