Global Agricultural Value Chains and Food Prices[*]

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June 5, 2023

Abstract

We study the relationship between global agricultural value chains (GAVCs) and food prices. Using longitudinal data on a sample of 138 countries for the period 2000 to 2015 and a Bartik shift-share instrumental-variable design, we study how participation in GAVCs at the country level relates to consumer food price levels and volatility. We find that participation in GAVCs is associated with a decrease in consumer food price levels and an increase in food price volatility, suggesting that participation in GAVCs involves a mean-variance trade-off. This trade-off is more pronounced among low-income countries, especially sub-Saharan African countries. We show that association between participation in GAVCs and food price volatility is likely due to a lack of diversification among suppliers, which can be expressed as an externality from the profit-maximization behavior of individual firms. Decomposing participation in GAVCs into upstream and downstream linkages, we find that food price volatility is associated more strongly with downstream participation than with upstream participation. We explore some policy options aimed at increasing the resilience of GAVCs.

Keywords: Global Value Chains, Agricultural Value Chains, Food Prices

JEL codes: F14, Q17, O19, E31

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[*]We are grateful to Michele Mancini, Daria Taglioni, Aleks Schaefer, and Andrew Schmitz and to seminar audiences at Göttingen, Iowa, Kiel, Minnesota, OARES, and Purdue, as well as conference participants at the International Agricultural Trade Research consortium and the SCC-76 Economics and Management of Risk in Agriculture and Natural Resources group meeting for useful comments and suggestions. All remaining errors are ours.

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1 Introduction

In recent years, some of the economic emergencies induced by the global COVID-19 pandemic and the Russian attack on Ukraine were amplified by historically high degrees of market integration and participation in global value chains (GVCs). In 2020, for instance, some parts of the world faced mask and ventilator shortages as producing regions were unable to export enough—or to export at all. On the supply side, Ukraine could not ship wheat out in 2022 because of the Russian blockade on the Black Sea, resulting in a global grain supply decrease of about 8 percent and subsequent grain price increases on global markets. On the demand side, a COVID cluster in the port of Los Angeles put many stevedores out of commission for a few weeks and led to backed up supply chains on the import side in the same year.

Do longer GVCs and a greater dependence on international trade mean more or less exposure to global shocks? A substantial body of literature, both theoretical and empirical, shows that trade reduces long-term consumer prices in both exporting and importing regions—those are the well-known grains from trade—and helps reduce price volatility because of the buffering function of trade (e.g. Alessandria et al., 2021; Solingen et al., 2021; Sposi et al., 2021; Melitz and Redding, 2014; Arkolakis et al., 2012). Another strain of theoretical (Turnovsky, 1974; Batra and Russell, 1974; Feder et al., 1977; Newbery and Stiglitz, 1984) and empirical (e.g. Novy and Taylor, 2020; Appelbaum and Kohli, 1998) literature argues that trade can fuel domestic price uncertainty, emphasizing the exposure-increasing effect.[1] Thus, while the effects of international trade on exposure to global shocks are likely to be country- and commodity-specific, whether trade increases or decreases price volatility remains an empirical question.

We study the relationship between participation in global agricultural value chain (GAVCs) on the one hand and price levels as well as volatility on the other hand. We focus on the agricultural and food sectors because food (i) is a necessity that is consumed by every

[1]For the remainder of this paper, we use the terms "price volatility" and "price uncertainty" interchangeably.

consumer in all countries at comparable rates, (ii) is traded by all countries, (iii) is often perishable and thus has limited storage potential, and (iv) is the subject of widely available data.[2] For our analysis, we rely on data from FAOSTAT for food prices and from the Eora database for data on GAVCs. We calculate real food price levels and the coefficient of variation of annual consumer food price indices as measures of the first and second moments of the food price distribution—food price levels and food price volatility, respectively. Our empirical strategy exploits the longitudinal nature of the data and adopts a Bartik shift-share instrument to identify the relationship between the extent of participation in GAVCs at the country-year level and food price levels and volatility in the same country-year. This allows quantifying (i) the overall relationship between participation in GAVCs and prices, but also (ii) the relationship between of different types of GAVC linkages (i.e. upstream and downstream) and food prices, and (iii) how those relationship vary among groups of countries (i.e., low-, middle-, and high-income countries) and regions.

Four distinct findings emerge from our analysis. First, and unsurprisingly given the extensive literature on the gains from trade, we find that participation in GAVCs is associated with lower food prices on average. This is consistent across GAVC directions (i.e., upstream or downstream), regions, and income groups. Second, participation in GAVCs is associated with higher price volatility, a finding which is more pronounced in low- and lower middle-income countries, especially sub-Saharan Africa. Third, countries with downstream-producing sectors (e.g., food processing) are much more likely to see higher food price volatility than countries with upstream-producing sectors (e.g., agriculture). Finally, it looks as though participation in GAVCs is associated with increases in food price volatility because it leads to lower levels of diversification via greater reliance on fewer suppliers.

Our findings have a number of implications for policy. Most importantly, national and international trade policy must recognize the heterogeneity in the strength of the apparent

[2]While the recent literature has referred to the two sectors—agriculture on the one hand, and food and beverages on the other hand—combined as "agri-food" (Barrett et al., 2022), we use "agricultural value chains" to refer to value chains encompassing both sectors.

trade-off between food price levels and volatility across types of GAVCs and groups of countries. Relying on foreign-sourced critical intermediate inputs to produce at the higher end of value chains is riskier for industries located in low-income countries than for those located in high-income countries. Policy options to reduce price volatility while expanding the gains from GAVCs include supply diversification and strengthening the institutional frameworks that govern trade relations while avoiding suppliers in bad institutional environments. Our contribution is fourfold. First, while previous theoretical contributions (Turnovsky, 1974; Batra and Russell, 1974; Feder et al., 1977; Newbery and Stiglitz, 1984) suggest that trade and market instability may correlate both negatively or positively, there are only a few empirical applications in the trade uncertainty literature. Second, while most previous applied work on trade and uncertainty focuses on aggregated trade flow levels (e.g. Novy and Taylor, 2020; Appelbaum and Kohli, 1997), we take the analysis one step further by using data on GVCs to assess the relationship between global sourcing and prices. Third, we add to an emerging body of literature on GVCs in the agricultural and food sectors (Lim and Kim, 2022; Montalbano and Nenci, 2022; Ndubuisi and Owusu, 2021; Balié et al., 2019). Fourth, because our application uses data on food and agriculture, we add to the literature on trade policy and food market stability (e.g. Berger et al., 2021; Gouel, 2016; Pieters and Swinnen, 2016; Rude and An, 2015; Anderson et al., 2013; Jayne et al., 2006; Josling and Tangermann, 1999).

The remainder of this paper proceeds as follows. In Section 2, we present a theoretical framework relating GVCs and volatility. Section 3 presents in turn our estimation and identification strategies. In Section 4, we discuss the data we use in our analysis. We present our results in Section 5, where we also present the results of a number of robustness checks and explore treatment heterogeneity. Section 6 discusses the potential mechanisms behind our findings as well as the welfare and policy implications of our results. We summarize and offer concluding remarks in Section 7.

2 Conceptual Framework

Our theoretical framework builds up on the observation of Arkolakis et al. (2012) that the gains from trade can be expressed as

$$\widehat{W} = \widehat{\lambda}^{\frac{1}{\varepsilon}}, \tag{1}$$

where the change in welfare $\widehat{W} = \frac{W'}{W}$ for a country is determined by change in the share of expenditure on domestic goods, $\widehat{\lambda} = \frac{\lambda'}{\lambda}$, and on the elasticity of imports with respect to trade costs ε. The parameter λ is equal to 1 minus the import penetration ratio of the economy, which is itself the percentage of imports in total domestic consumption and measures the extent to which a country's domestic market is supplied by imports. This measure is closely related to GVC participation, which describes the degree to which a country is integrated into the global production and distribution networks of goods and services. The standard GVC participation definition is the percentage of a country's gross exports that are made up of imported inputs.

We modify equation 1 in three significant ways. First, we decompose import penetration into (i) GVC value generation and (ii) imports. Under the assumption that production P is domestic consumption D plus exports X and there is no storage, i.e. $P = D + X$, the import penetration ratio can be expressed as

$$\lambda = 1 - (\frac{M_p}{P} - \frac{M_x}{X}), \tag{2}$$

where imports dedicated for export M_x are a subset of imports in total production M_p. The share of imports in exports $\frac{M_x}{X}$ is the standard measure of the participation in global value chains (Cigna et al., 2022). Thus, equation 1 may be rewritten as

$$\frac{W'}{W} = \left(\frac{\left(1 - \frac{M_p}{P} + \frac{M_x}{X}\right)'}{1 - \frac{M_p}{P} + \frac{M_x}{X}} \right)^{\frac{1}{\varepsilon}}. \tag{3}$$

Simplifying $\frac{M_x}{X} = GVC$ and letting $1 - \frac{M_p}{P}$ equal a constant δ yields

$$\frac{W'}{W} = \left(\frac{(\delta + GVC)'}{\delta + GVC} \right)^{\frac{1}{\varepsilon}}. \tag{4}$$

We highlight the part of import penetration that constitute GVC participation, i.e., imports used to generate exports. Imports that contribute to production destined for domestic consumption are included in δ.

Second, we argue that a country's welfare from trade is also dependent on trade that occurs between other countries at an earlier stage of the value chain, and that each each link generates welfare as in equation 1. We can simply model this by expressing the GVC value generation of a country as the share ϕ of the sum of the values generated (r) along the entire value chain:

$$GVC_i = \phi \sum_{i=1}^{I} r_i, \tag{5}$$

where I is the length of the GVC, and each country's welfare gain from GVC participation can be expressed as a share ϕ of total value generation along the value chain.

Third, we consider the fact that each GVC link is subject to random supply or domestic demand shocks. Following other theoretical and empirical studies on trade and uncertainty (e.g. Turnovsky, 1974; Batra and Russell, 1974; Feder et al., 1977; Newbery and Stiglitz, 1984; Novy and Taylor, 2020), we introduce uncertainty by including a probability p for each trade connection to occur and thus express the welfare gains-from-trade as

$$\frac{W(r,p)'}{W(r,p)} = \left(\frac{\left(\delta + \phi \sum_{i=1}^{I} r_i p_i\right)'}{\delta + \phi \sum_{i=1}^{I} r_i p_i} \right)^{\frac{1}{\varepsilon}}. \tag{6}$$

The implications of equation 6 are that the welfare derived from GVC participation depends first on the conventional gains form trade—which are often measured as changes in prices—and secondly on the probability that individual GVC links occur. With regards to the latter, we note that ideally, individual probabilities are uncorrelated. In practice, however, linkages are not independent from previous linkages. That is, if a shock affects one GVC connection, all subsequent connections of the GVC are affected as well, and so probabilities are not uncorrelated.

3 Empirical Framework

In this section, we first discuss the estimation strategy we adopt to study the link between participation in GAVCs and food prices. We then turn to the identification strategy we rely on to identify the relationship between participation in GAVCs and food price levels or volatility.

3.1 Estimation Strategy

As the welfare changes resulting from GVC participation can be expressed as a function of the gains from trade and the uncertainty of individual GVC link occurrence, our empirical setup expresses each of the consumer price level and consumer price volatility of consumer prices as a linear function of participation in GAVCs. Moreover, we restrict our empirical application to food and agriculture because food (i) is a necessity good that is consumed in all countries at comparable rates, (ii) is traded in all countries, (iii) is often perishable and has limited storage potential, and (iv) GVC data are widely available including at the sub-sector level, which enables the shift-share design we rely on for identification.

Specifically, we estimate the relationship between participation in GAVCs and (i) food price levels as well as (ii) volatility over time within a given country. To do so, we estimate the following baseline equation:

$$p_{it} = \beta_1 GAVC_{it} + \gamma_1' X_{it} + \delta_{1i} + \eta_{1t} + e_{1it}, \tag{7}$$

where p_{it} is the real consumer price level for food in county i in year t, $GAVC_{it}$ is the GAVC participation rate in the same country in the same year, and X_{it} is a vector of control variables that includes time-variant country-level characteristics listed in Appendix Table A.1 and described in Section A.1. We also include country fixed effects δ_i to control for time-invariant factors for each country as well as year fixed effects η_t to control for shocks affecting all countries similarly in each given year. Lastly, e_{it} is an error term with mean zero. The parameter of interest is β_1, which captures the relationship between participation in GAVCs and the real food price level in equation 7.

Similarly, to estimate the relationship between participation in GAVCs and food price volatility, we estimate the following equation

$$CV_{it}^{p} = \beta_2 GVC_{it} + \gamma_2' X_{it} + \delta_{2i} + \eta_{2t} + e_{2it}, \tag{8}$$

where CV_{it}^{p} is the coefficient of variation of monthly prices in a year calculated as the mean-normalized standard deviation over a given year t (i.e., $CV_{it}^{p} = \frac{\sigma_p}{\mu_p}$), which we use as our measure of price volatility, and every other variable is as in equation 7. The parameter of interest is β_2, which captures the relationship between participation in GAVCs and food price volatility in equation 8.

Although our baseline estimation strategy helps to account for potential sources of endogeneity by means of country and year fixed effects and a number of control variables, participation in GAVCs is likely to remain endogenous to both price levels and volatility. In the next section, we explain the Bartik shift-share instrumental variable design we deploy in an effort to identify the relationship between participation in GAVCs and food prices.

3.2 Identification strategy

To address the issue of endogeneity in the relationship between participation in GAVCs and food prices, we deploy a shift-share instrumental variable (IV) design proposed by Bartik (1991) (Bartik, 1991). This allows isolating the plausibly exogenous variation in participation in GAVCs. Bartik shift-share IVs are designed to mitigate endogeneity concerns in panel-data settings with unit and time fixed effects. These designs draw on the sub-dimension-specific (here, country-specific) share at a given point in time (i.e., the "share") and the overall variation in a sub-dimension-specific variable over time (i.e., the "shift") to predict treatment variation.[3]

Here, the use of a Bartik shift-share IV allows reducing the bias stemming from the endogeneity of participation in GAVCs to price levels or volatility. Our research design thus decomposes country-level participation in GAVCs into sub-dimensions of the two sectors we study, viz. agriculture as well as food and beverages, the former pertaining to activities closer to raw materials, the latter pertaining to value generation at the processing stage.

We thus exploit the identity whereby shocks to GAVCs are the sum of individual country- and sector-level shocks. We thus modify equations 7 and 8 by using the Bartik shift-share IV to instrument for $GAVC_{it}$. Our IV is such that

$$IV_{it} = \frac{1}{gexp_{it}} \sum_{k} \left(w_{ik,t-1} e_{kt} \right), \tag{9}$$

where $\frac{1}{gexp_{it}}$ weights the instrument by gross exports from country i at year t. The variable $w_{ik,t-1}$ represents the initial sector-specific share ($w_{ik,t-1} \geq 0$), which defines the exposure of each observation i to the global shock in the previous year $t-1$. It is calculated as the ratio of sector-specific GAVC for observation i in year $t-1$ to the sum of GAVC across all observations, i.e., $w_{ik,t-1} = \frac{GAVC_{ik,t-1}}{\sum_i GAVC_{ik,t-1}}$. This value represents the share of the sector's contribution by country i within the total GAVC. Finally, e_{kt} is the sum over all countries' sector-specific participation in GAVCs (i.e., the shift).

The *relevance* of our IV is determined by the relationship between the initial exposure of a subsector to a global shock in a given country and the actual change in GAVC partici-

[3]See Goldsmith-Pinkham et al. (2020) for a review of the Bartik IV method. For notable examples of its application, see Card (2009); David et al. (2013); Nakamura and Steinsson (2014); Acemoglu and Restrepo (2020).

pation in the same country. As with the relevance of any IV, this is testable, and we show the results of relevance tests in our analysis.

When it comes to the *validity* of our IV, Goldsmith-Pinkham et al. (2020) show that the Bartik IV can be expressed as a GMM estimator where the shares are used as instrumental variables. Thus, the exclusion restriction requires that the shares of the initial sector distribution be independent from the outcomes and other unobserved drivers. Here, we argue that the initial global distribution of agricultural as well as food and beverages sectors are driven by climate, soil quality, land availability, and other natural endowments that are exogenous to food prices.

4 Data

We use data on participation in GAVCs, food prices, and control variables for 138 countries for the period 2000-2015. The data come from three sources. First, data on participation in GAVCs comes from the EORA Global Value Chain Database. Second, consumer food price indices come from FAOSTAT. To obtain real food price levels by country and compute the coefficient of variation of monthly food price changes by year, we multiply these indices by purchasing power parity exchange rates obtained from the World Development Indicators (WDI) database. Third, our control variables also come from the WDI database.

4.1 Global Agricultural Value Chains

The Eora MRIO database offers country-level tracking of participation in GVCs for 26 sectoral classifications for the period 2000-2015. Using a multi-region input-output (MRIO) table, it provides national estimates of value-added in trade (Casella et al., 2019). Am MRIO table provides a comprehensive overview of all value-added activities across industries within a country that participate in global production (Hummels et al., 2001; Johnson and Noguera, 2012; Johnson, 2018). This distinguishes it fundamentally from national input-output account data, which primarily depict value-chain linkages within industries confined to a country's boundaries. Borin and Mancini (2019) use MRIO database to construct GVC participation data, capturing all sources of value-added activities across multiple countries. They introduce an empirical method to extract value-added exports from gross exports, allowing researchers to account for each value-added activity using cross-country input-output data.[4]

The foregoing allows capturing measuring participation in GAVCs across countries. The data developed by Borin and Mancini (2019) provides an important advantage compared to other country-level GVC data sources, such as the Trade in Value Added (TiVA) data set and the World Input-Output Database, which only covers a subset of high-income countries.[5] Moreover, the data allows decomposing GVC participation into upstream and downstream linkages.

More specifically, gross exports can be disaggregated into three primary value-added activities: domestic value-added (DVA), foreign value-added (FVA), and domestic value-added embedded in other countries' exports (DVX) (Koopman et al., 2014; Los and Timmer, 2018; Wang et al., 2017; Belotti et al., 2020). DVA represents the value of a country's exports that is generated by domestic production factors, contributing to its GDP. FVA, on the other hand, refers to the value of a country's exports that originates from imported inputs–the use of imported intermediate inputs in the production process of exported products. FVA serves as a measure of upstream GVC participation, capturing *downstream linkages* within the production network. Lastly, DVX signifies the domestic value-added in intermediate goods that are further re-exported by a trading-partner country. It represents exported raw materials that are subsequently used in another country and are exported again to a third country. DVX measures downstream GVC participation, encompassing *upstream linkages*.

Following Koopman et al. (2014) and Borin and Mancini (2019), three value-added ac-

[4]For similar analytical frameworks that have been developed to measure intermediate sourcing contributions of countries and sectors in GVC network, see Koopman et al. (2014); Los and Timmer (2018); Wang et al. (2017).

[5]The Eora MRIO data set offers coverage of the largest number of countries compared to other data sets. For example, the TiVA data set covers 64 countries and the World Input-Output Database covers 43 countries, respectively.

tivities yield our GAVC participation measure for country i in year t:

$$GVC\ Participation_{it} = \frac{DVX_{it} + FVA_{it}}{Gross\ Export_{it}} \tag{10}$$

Similar to Lim (2021) and Lim and Kim (2022), we employ the "Agriculture and Fishing" industry classification to assess participation in agricultural-sctor GVCs and the "Food and Beverage" industry classification to measure participation in food-sector GVCs, respectively. The agricultural sector encompasses production related to agriculture, hunting, forestry, and fishing, as defined by the International Standard Industrial Classification, Rev. 3, divisions 01, 02, and 05. The food sector encompasses activities related to food and beverages, as specified by ISIC, Rev. 3, divisions 15 and 16. By incorporating both the agricultural and food sectors, we construct the comprehensive measure of total participation in GAVCs, defined as

$$GAVC\ participation_{it}^{Total} = \frac{DVX_{it}^{agr} + DVX_{it}^{food} + FVA_{it}^{agr} + FVA_{it}^{food}}{Gross\ Export_{it}^{agr} + Gross\ Export_{it}^{food}}, \tag{11}$$

where agr and $food$ respectively denote the agriculture and food and beverage industries. We then measure upstream participation, $\frac{FVA_{it}^{j}}{Gross\ Export_{it}^{j}}$, and downstream participation, $\frac{DVX_{it}^{j}}{Gross\ Export_{it}^{j}}$, where $j \in \{agr, food\}$. The range of all GVC participation is between 0 and 100. [6]. Again, we do this for 138 countries for the period 2000 to 2015.[7]

4.2 Food Prices

The food price data are retrieved from the FAOSTAT monthly food consumer price index (CFPI) database.[8]. The FAOSTAT monthly food CPI data capture the change in the cost of food overall over time (i.e., annual year-over-year inflation for the corresponding month

[6] We generate GAVC data using the STATA module `icio` following (Belotti et al., 2020)

[7] We exclude 47 countries from the UNCTAD-Eora dataset due to inadequate GVC data availability and a significant absence of national employment data from the WDI database.

[8] Data are from https://www.fao.org/faostat/en/#data/CP

of the previous year). The FAO food CPI data set contains a complete set of time series from January 2001 to December 2015 which matches the span of our GAVC data.

To obtain real food price levels, we weigh the food price data with PPP exchange rates from the WDI database. We measure the annual food price level by averaging the monthly food price levels in a year. For the price variability measure, we calculate the coefficient of variation (CV) of monthly consumer food price indices in a year.

4.3 Control Variables

We include an extensive set of country-level, time-varying covariates to control for features of (i) the agricultural sector, (ii) socio-economic conditions, (iii) demographic conditions, and (iv) trade policy. For the first three categories, we use data from the WDI database, spanning the period from 2000 to 2015. For trade policy variables, we use Mario Larch's Regional Trade Agreements Database which includes all multilateral and bilateral regional trade agreements as notified to the World Trade Organization (WTO) from 1950 to 2019 (Egger and Larch, 2008). Table A.1 in Appendix A.1 provides detailed descriptions of all variables included in our empirical analysis.

5 Results

In this section, we first present baseline results for equations 7 and 8 and a number of robustness checks on those core results. We then present results by sector and by type of linkage (i.e., upstream or downstream) before presenting results that explore treatment heterogeneity by region and by income.

5.1 Baseline

Table 1 shows estimation results for equation 7. Here we find evidence that increased participation in GAVCs is associated with lower real food prices—a relationship that is robust to including control variables as well as country and year fixed effects, and to instrumenting participation in GAVCs with our shift-share variable. In terms of economic significance, the estimated coefficients imply that a one percentage point increase in participation in GAVCs is associated with a decrease in real food prices of 1.7 to 5 percentage points.

TABLE 1: GAVCs and Food Price Levels

Dependent Variable	Log food price level					
Model	OLS	Bartik IV				
	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
GAVC share	-1.650**	-5.035***	-3.582***	-3.066***	-3.012***	-2.331***
	(0.6636)	(1.183)	(1.072)	(0.9326)	(0.8716)	(0.7855)
Agriculture	Yes		Yes	Yes	Yes	Yes
Economy	Yes			Yes	Yes	Yes
Demography	Yes				Yes	Yes
Trade Policy	Yes					Yes
Fixed-effects						
Country	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	2,179	2,171	2,171	2,171	2,171	2,171
F-test (1st stage), GAVC share		1,310.5	1,152.7	1,074.3	1,080.8	1,013.0
R^2	0.94718	0.91585	0.93047	0.93694	0.94187	0.94943
Within R^2	0.47110	0.10774	0.26285	0.33145	0.38369	0.46387

Notes: Clustered (country & subregion) standard-errors in parentheses. ***: 0.01, **: 0.05, *: 0.1. Outcome variable is the log of the real food price level. Treatment is measured as the share of GVC participation ranging between 0-1. The models include 33 control variables relating to agriculture, the economy, trade and trade policy, and demography. Appendix A.1 provides a full list of the controls.

Table 2 shows estimation results for equation 8. Here, we find evidence that increased participation in GAVCs is associated with more price instability—a relationship absent from the naïve OLS specification in column 1, but which is revealed by our shift-share design, and which is robust to including control variables as well as country and year fixed effects. In terms of economic significance, the estimated coefficients imply that a one percentage point increase in participation in GAVCs is associated with an increase in food price volatility of 9 to 12 percentage points.

TABLE 2: GAVCs and Food Price Volatility

Dependent Variable:	CV of food price index					
Model	OLS	Bartik IV				
	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
GAVC share	0.0123	0.1175***	0.0876*	0.0892*	0.0873*	0.0882*
	(0.0374)	(0.0409)	(0.0443)	(0.0469)	(0.0482)	(0.0478)
Agriculture	Yes		Yes	Yes	Yes	Yes
Economy	Yes			Yes	Yes	Yes
Demography	Yes				Yes	Yes
Trade Policy	Yes					Yes
Fixed-effects						
Country	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	2,174	2,174	2,174	2,174	2,174	2,174
F-test (1st stage), GAVC share		1,312.2	1,154.1	1,075.4	1,080.5	1,012.7
R^2	0.58808	0.36167	0.37826	0.57533	0.57837	0.58497
Within Adjusted R^2	0.33939	-0.00648	0.01431	0.32506	0.32720	0.33439

Notes: Clustered (country & subregion) standard-errors in parentheses. ***: 0.01, **: 0.05, *: 0.1. Outcome variable is the within-year coefficient of variation of the CFPI. Treatment is measured as the share of GVC participation ranging between 0-1. The models include 33 control variables relating to agriculture, the economy, trade and trade policy, and demography. Appendix A.1 provides a full list of the controls.

The association between participation in GAVCs and lower food prices is in line with the theoretical trade and GVC literatures and constitutes additional evidence in favor of the gains from trade (Alessandria et al., 2021; Antràs and de Gortari, 2020; Antràs, 2020; Melitz and Redding, 2014; Arkolakis et al., 2012, e.g.). Moreover, the magnitude of the association is reasonable considering real food price differentials among countries. For instance, in high-income countries, which usually host agricultural and food sectors that are more integrated into GAVCs, consumers spend less than 15 percent on their income on average while the national average of food expenditure in less GAVC-integrated economies can be above 50 percent (Roser and Ritchie, 2021). These results highlight the important role GAVCs can play in increasing consumer welfare and improving food insecurity. The estimated relationship seems to come at the cost of increased price uncertainty, however. In that regard, economies seem to be trading-off the mean and variance of food prices when strengthening their participation in GAVCs.

5.2 Robustness Checks

Appendix A.2 assesses the robustness of our core results that greater participation in GAVCs is associated with lower but more volatile food prices. Here, we provide a brief summary of the evidence in that appendix.

On the instrument relevance front, the seeming price-decreasing and volatility-increasing effects of participation in GAVCs hinge upon the relevance of the Bartik shift-share IV. The large F-Statistics which we observe in all models provide evidence that the instrument is relevant.

On the instrument validity front, with regards to exclusion restriction, recall that our identifying assumption is that the distribution of agricultural industry shares is driven by natural endowments, and not by food price levels, volatility, or other confounders. We perform several tests and robustness checks to buttress that claim, as proposed in Goldsmith-Pinkham et al. (2020).

First, we estimate the model using the limited information maximum likelihood (LIML) (Anderson and Rubin, 1949) and a modification of bias-corrected two-stage least squares (MBLS) (Kolesár et al., 2015), and cross-check our inference against Ecker-Huber-White heteroskedasticity robust standard errors (SEs) and information matrix-based SEs (IM-SE). Both the estimators and standard errors are similar, providing no reason to suspect that the models are misspecified.

Second, we run a Sargan overidentification test of from a TSLS model where we use industry shares as instruments. Goldsmith-Pinkham et al. (2020) show that for the exclusion restriction to hold, the industry shares are required to be exogenous. The test provides evidence that the error term is not correlated with the industry-share IVs.

Third, we examine the correlation between our observable country correlates and initial industry shares. The results are depicted in Table A.3. The models explain between 36 and 52 percent of the variation, which is relatively low given the extensive set of country-level controls. We observe strong coefficients and correlations between initial industry shares and land variables which supports our identifying assumption. Moreover, trade policy variables also correlate with industry shares, which constitutes the mechanism under investigation. That said, we also observe loading with population and the food production index. While the food production index could still mask mostly natural endowments, it could also capture other supply-side confounders. Similarly, population could inherit demand-side confounders. While both of these could imply some leakage of the exogeneity assumption, both coefficients are small in magnitude.

5.3 Positioning in GAVCs

Thus far, we found that the seeming global uncertainty exposure effect of GAVC participation seems to dominate the seeming local uncertainty protection effect given that participation in GAVCs is associated with more volatile food prices. To shed more light on this result, we estimate our core equations by GAVC linkage type (i.e., upstream vs. downstream) and split the sample by sector (i.e., agriculture vs. food and beverages). Table A.5 of the Appendix provides further evidence that our estimated relationships are qualitatively similar across sectors, and not driven asymmetrically by either the agriculture or the food and beverages sector.

Table 3 shows results for equation 8 where treatment is a country's GAVC position upstream or downstream. That variable is an index ranging from -1 to 1, where -1 describes a sector that is exclusively engaged in upstream-type GAVC, i.e. producing and exporting raw materials, while 1 describes a sector that exclusively imports intermediate inputs and exports final goods. In other words, the index proxies the position of a sector along the value chain.

TABLE 3: GAVC Positioning and Food Price Volatility (OLS)

Dependent Variable	CV of food price index				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
GAVC - Position	0.2230***	0.1566*	0.1815*	0.1807*	0.1719*
	(0.0703)	(0.0750)	(0.0890)	(0.0945)	(0.0891)
Agriculture		Yes	Yes	Yes	Yes
Economy			Yes	Yes	Yes
Demography				Yes	Yes
Trade Policy					Yes
Fixed-effects					
Country	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	2,174	2,174	2,174	2,174	2,174
R^2	0.35613	0.38439	0.57151	0.57314	0.58110
Within R^2	-0.01471	0.02982	0.32471	0.32728	0.33982

Notes: Clustered (country & subregion) standard-errors in parentheses. ***: 0.01, **: 0.05, *: 0.1. Outcome variable is the within-year coefficient of variation of the CFPI. Treatment is measured as an indicator ranging between -1 and 1 where -1 designates full upstream positioning and 1 full downstream positioning. The models include 33 control variables relating to agriculture, the economy, trade and trade policy, and demography. Appendix A.1 provides a full list of the controls.

We find that downstream-type GAVC activity is more strongly associated with price uncertainty than upstream-type activity. Conversely, table 4 provides evidence that the relationship between price levels and participation in GAVCs also stems from downstream-type GAVC participation instead of upstream activity.

TABLE 4: GAVC Positioning and Food Price Levels (OLS)

Dependent Variable	Log food price level				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
GAVC - Position	-9.558***	-6.405**	-6.248**	-6.228**	-4.587**
	(2.706)	(2.288)	(2.420)	(2.322)	(1.828)
Agriculture		Yes	Yes	Yes	Yes
Economy			Yes	Yes	Yes
Demography				Yes	Yes
Trade Policy					Yes
Fixed-effects					
Country	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	2,171	2,171	2,171	2,171	2,171
R^2	0.86281	0.90881	0.91368	0.91746	0.93628
Within R^2	-0.45454	0.03316	0.08478	0.12490	0.32440

Notes: Clustered (country & subregion) standard-errors in parentheses. ***: 0.01, **: 0.05, *: 0.1. Outcome variable is the log of the real food price level. Treatment is measured as an indicator ranging between -1 and 1 where -1 designates full upstream positioning and 1 full downstream positioning. The models include 33 control variables relating to agriculture, the economy, trade and trade policy, and demography. Appendix A.1 provides a full list of the controls.

Splitting our results by sector shows that the relationship between participation in GAVCs and increased food price volatility for downstream-type GAVC participation is stronger in the food and beverages sector than in the agricultural sector. The interpretation of these coefficients, however, warrants some caution since they are at the sub-sector level, and thus do not allow calculating a shift-share. Thus, they are subject to bias stemming from endogeneity which—as revealed by the Bartik IV models—can be quite substantial.

TABLE 5: GAVC Positioning and Food price Volatility (OLS)

Dependent Variable	CV of food price index		
Sector	Agriculture	Food & Beverages	Total
Model:	(1)	(2)	(3)
Variables			
GAVC position	0.035	0.055***	0.059**
	(0.025)	(0.018)	(0.024)
Fixed-effects			
Country	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	2,182	2,182	2,182
R^2	0.59786	0.59900	0.59907
Within R^2	0.36937	0.37115	0.37125

Notes: Clustered (country & subregion) standard-errors in parentheses. ***: 0.01, **: 0.05, *: 0.1. Outcome variable is the within-year coefficient of variation of the CFPI. Treatment is measured as an indicator ranging between -1 and 1 where -1 designates full upstream positioning and 1 full downstream positioning. The models include 33 control variables relating to agriculture, the economy, trade and trade policy, and demography. Appendix A.1 provides a full list of the controls.

5.4 Treatment Heterogeneity by Region

In Table 6, we report results for equation 8 by splitting the sample by region. We observe stronger estimated relationships for sub-Saharan Africa. The estimated coefficient for participation in GAVCs there is more than five times larger than in the aggregate. That said, the coefficient for participation in GAVCs in the price level equation, detailed in Table 6, is strong in all regions, but not in sub-Saharan Africa, where the estimated coefficient is not significantly different from zero. By contrast, it is most pronounced in Latin America and the Caribbean. An implication of this is that sub-Saharan African countries may not really face a mean-variance trade-off when increasing their participation in GAVCs, which appears to leave price levels unchanged but leads to higher price volatility.[9] In Table A.12 and Table A.15 of the Appendix A.3.3, we show results by income group. Although statistical power there is low, the magnitude and sign of the estimated coefficients suggest that the trade-offs become stronger by income group. These results are in line with recent findings of heterogeneous channels of the impact of GVCs across countries at different levels of development (Montalbano and Nenci, 2022; Ndubuisi and Owusu, 2021).

In summary, our key findings are twofold: participation in GAVCs is associated with (i) lower food prices, and (ii) higher food price volatility. This suggests that, on average, countries are facing a mean-variance tradeoff as a result of increased participation in GVCs when it comes to food prices. This trade-off is particularly pronounced for downstream-type GAVCs, i.e., in sectors closer to consumers, as opposed to upstream-type GAVCs, which are closer to producers. Finally, we also find that the severeness of the mean-variance trade-off differs by region and income group: in high-income countries, the cost of lower real food prices in the form of food price instability is moderate, but in lower-income countries, and in sub-Saharan Africa in particular, the seeming food price instability effect is larger at comparable lower price reductions.

[9] Moreover, the welfare effects of decreasing food prices in developing countries is more ambiguous. Decreasing food prices worsen producer rents and the share of population dependent on agricultural production is often higher in lower-income countries (e.g. Swinnen and Squicciarini, 2012). We explore this in Section 6.2.

TABLE 6: GAVCs and Food Price Volatility by Region (Bartik IV)

Dependent Variable	CV of food price index					
Continent	All	EA & P	E & CA	LA & C	ME & NA	SSA
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
GAVC share	0.0857	0.0293	-0.0416	-0.0856	-0.3222	0.5846*
	(0.0510)	(0.0941)	(0.0305)	(0.1198)	(0.2231)	(0.2274)
Agriculture	Yes	Yes	Yes	Yes	Yes	Yes
Economy	Yes	Yes	Yes	Yes	Yes	Yes
Demography	Yes	Yes	Yes	Yes	Yes	Yes
Trade Policy	Yes	Yes	Yes	Yes	Yes	Yes
Regional Dummies						
Fixed-effects						
Country	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	2,046	290	654	357	252	493
F-test (1st stage), GACV share	909.35	235.92	208.83	328.52	34.085	61.852
R^2	0.60371	0.69287	0.60362	0.59452	0.69876	0.70701
Within R^2	0.37175	0.36526	0.30890	0.31900	0.30852	0.59470

Notes: Clustered (country & subregion) standard-errors in parentheses. ***: 0.01, **: 0.05, *: 0.1. Outcome variable is the within-year coefficient of variation of the CFPI. Treatment is measured as the share of GVC participation ranging between 0-1. The models include 33 control variables relating to agriculture, the economy, trade and trade policy, and demography. Appendix A.1 provides a full list of the controls.

TABLE 7: GAVCs and Food Price Levels by Region (Bartik IV)

Dependent Variable	Log food price level					
Contintent	All	EA & P	E & CA	LA & C	ME & NA	SSA
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
GAVC share	-2.503***	0.1924	-2.688*	-5.482	-3.683**	-2.622
	(0.8635)	(0.7196)	(1.281)	(2.055)	(0.9906)	(1.306)
Agriculture	Yes	Yes	Yes	Yes	Yes	Yes
Economy	Yes	Yes	Yes	Yes	Yes	Yes
Demography	Yes	Yes	Yes	Yes	Yes	Yes
Trade Policy	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
Country	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	2,043	290	654	354	252	493
F-test (1st stage), GAVC share	908.33	235.92	208.83	339.86	34.085	61.852
R^2	0.94877	0.98297	0.97720	0.97391	0.98515	0.92665
Within R^2	0.47796	0.80576	0.73971	0.67073	0.87135	0.44378

Notes: Clustered (country & subregion) standard-errors in parentheses. ***: 0.01, **: 0.05, *: 0.1. Outcome variable is the log of the real food price level. Treatment is measured as the share of GVC participation ranging between 0-1. The models include 33 control variables relating to agriculture, the economy, trade and trade policy, and demography. Appendix A.1 provides a full list of the controls.

6 Discussion

In this section, we first discuss how a lack diversification in value chain participation can lead to higher price volatility. Second, we discuss the welfare implications of participation in GAVCs considering the objective functions of various actors in a stylized economy. Finally, we discuss political economy issues pertaining to participation in GAVCs and international trade, and point to various ways of increasing the resilience of GAVCs.

6.1 Why Does GAVC Participation Lead to Higher Price Volatility?

One of our core findings is that participation GAVCs is associated with more price volatility. To some extent, this finding contradicts the idea that global sourcing allows for more resilience as inputs are more diversified. Returning to equations 3 and 4, which state that GVC participation is measured by imports in exports ($\frac{M_x}{X}$), this implies that imports will come from multiple origins. That is,

$$\frac{M_x}{X} = \frac{\sum_{i=1}^{N} M_{xi}}{X} \tag{12}$$

where N is the number of countries of origin, or sources of imports. For GVCs to be diversified requires large N, while concentrated GVCs have low N.

Figure 1 depicts the problem from a firm-level perspective. In GVCs, firms source inputs (x_i) from N sources (N countries) and sell outputs q_i, which in turn serve as inputs x_j for firms j. For profit maximization, firms firms minimize $\sum x_{ij} p_{ij}$. If firms care about uncertainty in supplies, they additionally hedge supplies by maximizing N and minimizing $Cov(\sigma_{i,j}\sigma_k)$ for $j \neq k$ and $i \neq k$. From a macro perspective, however, $Cov(\sigma_j \sigma_i)$ is always non-zero because of the sequencing. Uncertainty at one stage of the value change will thus affect all subsequent stages. Thus, for value chains to be resilient to shocks, the number of suppliers should be large and the correlation of input price uncertainty should be low.

As a first assessment of N (i.e., the number of sources) in GAVCs, we consider tradi-

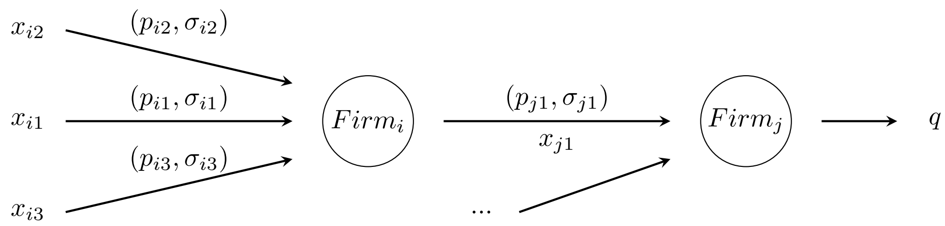

FIGURE 1: Diversification of GVCs. x are inputs, p input prices, σ the associated probability of input delivery, and the subscripts i and j describe two subsequent stages in a value chain.

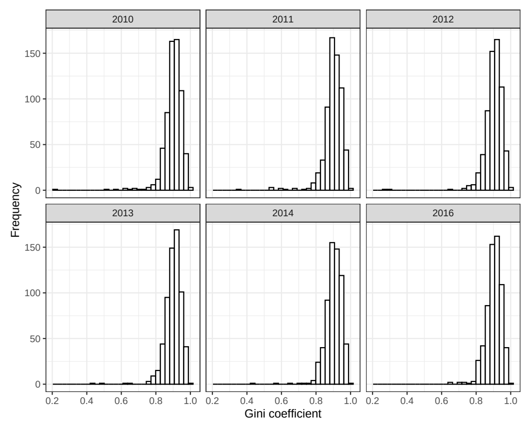

FIGURE 2: Frequency of Gini coefficients of agri-food commodities. We use UN COMTRADE data and select commodities at the 6-digit level Harmonised System (HS) code. We subset to chapters 01 - 24 (Food and Agriculture) and calculate Gini coefficients of origins for 649 commodities for the years from 2010-2015. The higher the coefficient the more concentrated (unequal) are supply countries.

tional trade data. We use UN COMTRADE data and select commodities at the six-digit level harmonised system HS code. We subset to chapters 01 - 24 (Food and Agriculture) and calculate Gini coefficients of origins for 649 commodities for the period 2010-2015. A coefficient of one implies that 100 percent of the supply of a good originates in 1 percent of countries. A value of 0 implies that all origins contribute equally to global supply. Thus, the higher the coefficient, the more concentrated (i.e., unequal) are supplier countries.

Figure 2 shows the frequency of resulting Gini coefficients. Here, we observe rather high Gini coefficients, with an average exceeding 0.8. The implication of this is that global agri-food value chains are more concentrated than they are diversified. For most commodities, there are only a few countries that export those commodities.

The observation of concentrated rather than diversified agri-food supply chains finds confirmation in national-level studies. Stevens and Teal (2023), Ma and Lusk (2021), Hadachek et al. (2023), and Wahdat and Lusk (2022) find that US agri-food value chains are concentrated, which compromises resilience to national-level shocks in those studies.

6.2 Participation in GAVCs and Welfare

In order to discuss the welfare gains from GAVC participation, we proceed as follows. Our framework consists of three agents, viz. consumers, producers, and the government. In the absence of government intervention and with a closed economy, consumers and producers interact on markets, and their optimizing behavior determines the relative price of labor w/p. When the government intervenes by opening the economy, the behavior of consumers and producers responds in part to the policy adopted by the government. The government, for its part, either adopts a policy of trade openness or not on the basis of each type of agent's indirect utility function. The solution concept thus adopted here is that of sub-game perfection: The government (correctly) anticipates how each type of agent will respond to policy, and it downstream inducts to set a policy that will ensure political stability. Whether "political stability" means a lack of social unrest or re-election of the current government is an empirical question Bellemare (2015), and thus beyond the scope of our analysis.

In what follows, we first present each agent type's optimization problem along with associated first-order conditions. We then set up the government's own maximization problem. There is little here that is new relative to textbook models when it comes to our three agent types. What is new to our knowledge is how the government will set different policies according to (i) each agent type's indirect utility function and (ii) the importance (i.e., proportion, or measure) of each agent type in the overall economy, which maps into weights for each agent type in the government's objective function.

Before proceeding with the remainder of this section, we note that we will be reusing some of the notation used in prior sections. As such, this section "resets" notation. While we realize this could confuse unsuspecting readers, we also wish to use conventional notation in this section, which we view as standing on its own.

6.2.1 Primitives

We are concerned with two goods: food, which we denote by $x \geq 0$, and leisure, which we denote by $\ell \geq 0$. Each good has associated prices $p > 0$ and $w > 0$. We discuss preferences and technology in the next two sections, which are dedicated respectively to the consumers and the producers that make up our stylized economy. While we could add a third, composite nonfood good to our model, doing so is not necessary, and so we err on the side of parsimony by considering only food and leisure.

6.2.2 Consumers

Consumer preferences $\succsim$ are represented by the utility function $u(x_i, \ell_i)$ for consumer i, which is such that $u_x > 0$, $u_\ell < 0$, $u_{xx} < 0$, $u_{\ell\ell} < 0$, and $u_{x\ell} = u_{\ell x} > 0$. We further impose Inada conditions on food such that $u_x(0) = \infty$ and $u_x(\infty) = 0$. In other words, any consumer must consume a positive amount of food, but she can only consume so much food.

Each consumer i has an endowment of time equal to E_i^L, which she can spend either in labor L_i or leisure ℓ_i, such that $E^L = L_i + \ell_i$.

Consumer i's maximization problem is such that

$$\max_{x_i, \ell_i} u(x_i, \ell_i) \text{ s.t.} \tag{13}$$

$$px_i + w\ell_i \leq y_i + wL_i. \text{ and} \tag{14}$$

$$E_i^L = L_i + \ell_i \tag{15}$$

where y_i denotes consumer i's independent income.

Combining Equations 14 and 15, we can rewrite the budget constrain as a Beckerian full-income constraint, such that

$$px_i + w\ell_i \leq y_i + w(E_i^L - \ell_i), \tag{16}$$

where the LHS of Equation 16 denotes the consumer's expenditures on food and leisure and the RHS denotes her full-income, i.e., her labor income wL_i as well as her independent income y_i.

The FOCs of the consumer's maximization problem are such that

$$u_f - \mu_i p = 0, \tag{17}$$

$$u_\ell - 2\mu_i w = 0, \text{ and} \tag{18}$$

$$\mu_i \cdot [px_i + w\ell_i - y_i - w(E_i^L - \ell_i)] = 0, \tag{19}$$

where μ_i denotes the Lagrange multiplier on the budget constraint (and thus the marginal utility of income), whose value is equal to zero given that the budget constraint holds with equality as a result of the utility function being increasing in both of its arguments.

From Equations 17 to 19, we recover the consumer's Marshallian (or Walrasian) demand functions for food and leisure $x_i^*(p, w, y_i)$ and $\ell_i^*(p, w, y_i)$, consumer i's supply of labor $L_i^* = E_i^L - \ell_i^*(p, w, y_i)$, as well as the marginal utility of the consumer's income $\mu_i^*(p, w, y_i)$

Plugging these Marshallian demand functions back into the consumer's utility function $u(x_i, \ell_i)$ then yields the consumer's indirect utility function, which measures the consumer's welfare, such that

$$V(p, w, y_i) = u[x_i^*(p, w, y_i), \ell_i^*(p, w, y_i)]. \tag{20}$$

We are interested here in what happens when the food price level p and food price volatility σ_p change. Signing the former is relatively straightforward, since indirect utility functions are decreasing in the price of consumption goods.[10] In other words, $V_p < 0$, and an increase (decrease) in the price of food makes the consumer worse (better) off.

What about the effect of a change in food price volatility on welfare? This is captured by the curvature of the indirect utility function in the space defined by p, w, and y, such that

$$V_{pp} = \begin{bmatrix} V_{pp} & V_{pw} & V_{py} \\ V_{wp} & V_{ww} & V_{wy} \\ V_{yp} & V_{yw} & V_{yy} \end{bmatrix}, \tag{21}$$

where, as in Bellemare et al. (2013), the diagonal terms capture the curvature of the indirect utility function with respect to a given parameter, which is related to the individual's preferences relative to the variance that parameter (e.g., V_{pp} is related to an individual's preferences over the variance of the price of food, or food price uncertainty), and the off-diagonal terms capture the curvature of the indirect utility function with respect to two parameters, which is related to the individual's preferences relative to the covariance between those two parameters (e.g., V_{yw} is related to an individual's preferences over the covariance between her individual income and the wage).

The question as regards the effect of food price uncertainty (or food price volatility), then, has to do with the sign of V_{pp}, since a consumer's coefficient of absolute price uncertainty aversion A_{pp} (Bellemare et al., 2013) is such that

$$A^i_{pp} = -\frac{V_{pp}}{V_y} = , \tag{22}$$

which, from Barrett (1996) and Bellemare et al. (2013), we know is equal to

$$A^i_{pp} = \frac{x_i}{p}[\beta(\eta - R) + \epsilon], \tag{23}$$

[10]Signing the effect of a change in the wage w would be more difficult, however, given that w figures in both the consumer's expenditures as well as her income, and so unlike an increase in p, an increase in w does not have an unambiguous effect on her welfare.

where x_i and p are the consumer's demand for and the price of food, respectively, and where β is the consumer's budget share of food, $\eta > 0$ is the income elasticity of her demand for food, R is her Arrow-Pratt coefficient of relative (income) uncertainty aversion, and η is the own-price elasticity of her demand for food. By analogy to Arrow-Pratt income risk aversion $-\frac{u''}{u'}$, A^i_{pp} is positive when a consumer is risk loving over p, it is zero when a consumer is risk neutral over p, and it is negative when a consumer is risk loving over p.

Whether A^i_{pp} is positive, negative, or neither depends on the relationship between the parameters on the RHS of Equation 23. Both $\frac{x_i}{p}$ and β will be positive for pure consumers, and following Barrett (1996), R (which usually ranges anywhere from 1 to 3 in empirical studies; see Bellemare et al. (2013)) will usually exceed η for food overall (which is less than unity given that food is a normal good). Since ϵ is negative for food (i.e., the own-price elasticity of food is negative), then the RHS of Equation 23 will be negative, which suggests that food consumers are price risk-loving when it comes to food. This result, which runs counter to conventional wisdom, goes back to Waugh (1944), who demonstrated that (pure) consumers would be made worse off by a policy stabilizing a price at its mean. For producers, things are different. We now turn to them.

6.2.3 Producers

The only good produced in our stylized economy is food, and so the only type of producer we encounter are producers of food. Given the nature of farming in all but the most industrialized economies, we assume that the firms in this stylized economy are sole proprietorships. In other words, while a firm j's objective is to maximize profit, that profit directly feeds into individual j's (i.e., the sole proprietor of firm j) income, which determines how much individual j can consume. We further assume that firm owners are pure capitalists. That is, they do not supply any labor to the economy.

Firm j's maximization problem is such that

$$\max_{L_j} pF(L_j) - wL, \tag{24}$$

with associated FOC

$$pF_{L_j} - w = 0. \tag{25}$$

From Equation 25 we can derive the firm's labor demand function $L^*(w, p)$ as well as its profit function, which is such that

$$\pi_j^*(w, p) = pF(L^*(w, p)) - wL^*(w, p). \tag{26}$$

The textbook model of the firm typically stops here. But since we are considering firms—that is, farms—that are sole proprietorships, we further note that the firm owner's utility maximization problem is such that

$$\max_{x,\ell} u(x_j, \ell_j) \text{ s.t. } px_j + w\ell_j \leq \pi_j^* + y_j, \tag{27}$$

where π_j^* is the profit derived from ownership of firm j and y_j denotes consumer j's independent income. This is consistent with the way Sandmo (1971) setup his study of the impacts of output price risk on profit maximization behavior.

Given that all relevant markets (i.e., food and labor) exist and are not fragmented, this is akin to an agricultural household model with separability of the profit- and utility-maximization decisions (Singh et al., 1986; Bardhan and Udry, 1999), and so the problem is recursive. What this means in practice is that individual j maximizes profit on her farm, and she then maximizes her utility, which depends in part on her farm profits. This makes the problem more tractable.

The FOCs of the producer's maximization problem are the familiar

$$u_f - \mu_j p = 0, \tag{28}$$

$$u_\ell - \mu_j w = 0, \text{ and} \tag{29}$$

$$\mu_j \cdot (\pi_j^* + y_j - p x_j - w\ell_j) = 0, \tag{30}$$

where μ_j denotes the Lagrange multiplier on the budget constraint (and thus the marginal utility of income), whose value is again equal to zero given that the budget constraint holds with equality as a result of the utility function being increasing in both of its arguments. From Equations 28, 29, and 30, we recover the consumer's Marshallian demand functions for food and leisure $x_j^*(p, w; \pi_j^* + y_j) = x_j^*(p, w, y_j)$ and $\ell_j^*(p, w; \pi_j^* + y) = \ell_j^*(p, w, y_j)$ since $\pi_j^* = \pi_j^*(w, p)$.

Plugging these Marshallian demand functions back into the consumer's utility function $u(x_j, \ell_j)$ then yields the consumer's indirect utility function, which measures the consumer's welfare, such that

$$V(p, w, y_j) = u(x_j^*(p, w, y_j), \ell_j^*(p, w, y_j)). \tag{31}$$

Increases in p cause the producer's welfare to increase via her production, but also to decrease via her consumption, and so whether her welfare increases or decreases in response to an increase in p will depend on her marketed surplus $M_j = F(L^*(w, p)) - x_j$ (Deaton, 1989). In other words, the welfare effect of an increase in p depends on whether j is a net seller (i.e., $M_j > 0$) or net buyer (i.e., $M_j < 0$ of food), or whether she is autarkic with respect to food (i.e., $M_j = 0$).

When it comes to food price volatility, a logic similar to that of the consumer prevails, and Bellemare et al. (2013) have derived a coefficient of absolute price risk aversion for agricultural households whose production and consumption decisions are separable, which are identical to the producers in our stylized economy. That coefficient is such that

$$A_{pp}^j = -\frac{M_j}{p}[\beta(\eta - R) + \epsilon], \tag{32}$$

and whose sign depends on the relationship between the constituent variables and parameters. If the parameters β, η, R, and ϵ are similar to those for consumers (i.e., Equation 23), then $A^j_{pp} > 0$ for net sellers (a result consistent with the theoretical findings of Baron (1970) and Sandmo (1971), and with the empirical results in Bellemare et al. (2013)), $A^j_{pp} < 0$ for net buyers (a finding consistent with our results in the previous section), and $A^j_{pp} = 0$ for households who are autarkic with respect to food.

6.2.4 The Government

We consider only the role of the government in allowing for the trade of food, which is the only tradable commodity in our model. As borders are opened to the international trade of food, p either decreases or stays the same (i.e., it only makes sense to import food in cases where the foreign price of food is cheaper, and exporting food does not cause the price of food to rise).

The government maximizes a social welfare function which adds indirect utility functions of pure food consumers (λ_1), households that both produce and consume food but who are net sellers of food (λ_2), households that both produce and consume food but who are net buyers of food (λ_3), and households that both produce and consumed food but who are autarkic with respect to food (λ_4), such that

$$\max_{p,\sigma_p} W = \lambda_1 E[V_1] + \lambda_2 E[V_2] + \lambda_3 E[V_3] + (1 - \lambda_1 - \lambda_2 - \lambda_3) E[V_4]. \tag{33}$$

This implies that governments choose between (i) trade openness and high integration in GVCs or (ii) no trade and low integration in GVCs, which results in p and σ regimes that have different welfare impacts depending on the composition of the economy. In other words, the government compares the LHS and RHS of the following equation

$$W_o(p_o, \sigma_{po}) \lesseqgtr W_c(p_c, \sigma_{pc}), \tag{34}$$

and chooses whichever state of trade openness (o) or no trade (c) and GVC integration that yields the highest social welfare. All welfare states have specific uncertainty in their realization of price levels, which in turn determine individual utility functions of the agents. The measures through which government set trade and GVC integration include trade policies, trade agreements, subsidies and other instrument that incentivize (or disincentivize) participation in agri-food GVCs by producers.

Given that, considering only the food price level, consumers and producers who are net buyers of food will benefit, producers who are net sellers of food will lose out, and producers who are autarkic will neither benefit nor lose out from the international trade of food.

Our empirical results have two implications for the political economy of participation in GAVCs. First, consumers benefit from lower prices while producers do not. In addition, consumers might even draw utility from higher price volatility, while producers do not. As our empirical results suggest that greater participation in GAVCs results in lower consumer prices and higher volatility, consumers benefit more from participation in GAVCs participation than producers do.

Second, the social welfare gains from low or high prices hinges upon the share of producers and the average budget share dedicated to food purchases in a country. Our results suggest that in low-income countries, where the proportion of net sellers of food is higher than in high-income countries, trade openness tends to hurt those net sellers both by lowering price levels and increasing price volatility. Given that, it is perhaps no surprise that low-income countries have been especially reticent to liberalizing their agricultural sector.

6.3 Policy Implications

The results of this paper generate a number of policy implications. While we find support for the long-standing hypothesis that participation in GAVCs leads to lower consumer prices, our results also challenge the conventional wisdom according to which participation in GAVCs stabilizes prices.

Concentration in GVCs is an intuitive result on the basis of trade theory. Trade openness and GVC participation lead to gains from trade, but also specialization. Specialization in turn creates vulnerabilities to shocks that stem from natural events, but also from policy uncertainty. Economists as early as Adam Smith observed that "defence ... is more important than opulence" (Book IV, Chapter II, p. 465), and highlighted that specialization stands at odds with diversification. Both are standard results in trade theory.

Consequently, policies that reduce uncertainty in GVCs come at the cost of gains from trade, or lower prices. Thus, the resilience of value chains should be traded off against lower prices. Lack of GAVC diversification can be seen as an externality problem: individual firms' marginal benefits from diversification are likely much lower than the social marginal benefit from diversification. To wit, a number of governments have intervened in GVCs to source critical inputs in times of shortages in the past.

Thus one policy solution could lie in internalizing the divergence between industry marginal benefits and social marginal benefits are tariff quotas that increase with increasing concentration such that when trade ties become more concentrated other, less competitive origins become more competitive. This could ensure a higher number of supply chain links. A similar mechanism could be adopted for origins with political uncertainty. Such tariffs are only applied after the import share of a given country exceeds a certain threshold and rises progressively with increasing import shares. This enables other supplier's competitiveness and contributes to diversify supply structures. (Grossman et al., 2023) provide further analysis on GVC diversification from a subsidy perspective.

Another way to increase resilience is to support some level of domestic supply (e.g. Solingen et al., 2021; Blumenschein et al., 2017). The extent of domestic supply in various stages of value chains is hard to quantify, and also comes with higher inefficiency and loss of gains from trade, viz. higher prices. Finding an equilibrium between local and global sourcing is a tall order and warrants more research.

We find that trade-offs between lower food prices and higher food price volatility differ by income group (i.e., low-, middle-, or high-income countries) and by type of supply chain participation (i.e., upstream or downstream). The most severe trade-off is induced by downstream-type GAVCs in sub-Saharan Africa countries, and given our findings, it is no surprise that those countries have been reticent to liberalizing agricultural trade. Thus, one key policy implication of our paper is that participation in GAVCs is likely to have heterogeneous effects across sectors, value chains, and countries, which is consistent with the conclusions of Montalbano and Nenci (2022) and Ndubuisi and Owusu (2021), for instance. National policy and international governance should take into account the production stages, as well as macroeconomies when designing trade policies and recommendations.

Another volatility-reducing strategy relates to managing trade relationships. This relates to the political economy of trade and, most importantly, constitutes a reduced dependency on sectors that operate in unfavorable institutional environments. Here, another trade-off emerges—one between supporting sectors in lower-income countries, which often suffer from bad institutional environments, and keeping supply flows stable. Policy could focus on supporting strong private partnerships and building long-term business relationships among agribusinesses. At a certain extent of governance uncertainty, however, supplies from such countries are likely to impose substantially higher uncertainty than the short-term welfare effects. These are countries with autocratic governments or dictatorships. Cases in point are, for instance, the energy import concentration of some European countries that rely heavily on natural gas from Russia, or the future supply of phosphorus, a necessary nutrient for crop production, which is expected to be concentrated in Western-Sahara by the end of the century, a region claiming independence, but controlled by Morocco since 1979—a situation that has led to a state of quasi permanent civil unrest (Egan, 2023).

Downstream-oriented supply chain activities in developing countries are facing the largest uncertainty for the lowest consumer benefits. These are sectors that are heavily affected by supply chain bottlenecks or other international market risks that curb or slow down trade. One explanation here could be that existing trade relationships between low-income and SSA countries are to a relatively greater extent with countries with unstable institutions, including autocracies, and also otherwise characterized by social and political instability (Osakwe et al., 2018). Moreover, with regards to trade ties with higher-income countries, downstream-type sectors in developing countries are often subject to oligopoly power (e.g. Lee et al., 2012). In the event of extraordinary supply shocks in import regions or elsewhere contracts with businesses in low-income countries are often prioritized low and are the first to be cut off from shipments[11]. Relying on foreign-sourced critical intermediate inputs to produce at the higher end of the value chain is riskier for industries located in low-income countries than for those operating out of higher-income countries.

Aside from diversifying suppliers, one general policy recommendation concerns the institutional framework that governs trade relationships. More precisely, contracts and agreements between buyers and suppliers could be strengthened with regard to risk sharing to minimize supply chain back-ups (e.e. Guo et al., 2017; Zhao et al., 2010). One reason why prices become unstable is when demand is price-inelastic, as in the case of goods such as food and energy, buyers begin hoarding during an upward market shock and sellers try to sell at the highest possible prices. Such events can be planned for in binding legal agreements, and contracts can have similar provisions, perhaps in the form of quotas that need to be fulfilled before free market price trade.

7 Conclusion

Recent disruptions in GVCs and price volatility have had serious consequences on welfare and trade policy. While the trade literature predicts that increased GVC participation drives down the prices of traded commodities, ever-increasing numbers of trade ties and shipment legs are also likely to increase market and price uncertainty in value chains because of uncertainty in various parts of the world.

[11] A recent point in case is when Ukraine—a traditional source of wheat for many countries in Africa—started shipping grains during the Ukraine-Russia war. As markets were tight and prices high, only 17 percent of the shipments were destined to Africa but instead to Europe and Asia. See https://www.un.org/en/black-sea-grain-initiative

We have empirically analyzed the relationship between participation in GAVCs and (i) food prices price levels and (ii) food price volatility. Our main results suggest that participation in GAVCs involves a trade-off between the mean and variance of the food price distribution. That is, greater participation in GAVCs is associated with lower food prices, but it is also associated with more food price volatility. While lower food prices are a reflection of the gains from trade, higher price volatility seems to stem from low diversification in GAVCs. As trade leads to specialization, many GAVCs are characterized by a low number of exporters, which leads to there being less resilience of GAVCs toward shocks.

Moreover, we find that the mean-variance trade-off in food prices is heterogeneous across regions, income groups, and value chain types. High-income countries benefit most from lower consumer prices while suffering the lowest uncertainty impacts through GVC participation. By contrast lower-income countries, in particular economies in sub-Saharan Africa, experience the lowest reductions in prices associated with GVC participation while incurring the largest increases in price uncertainty. Downstream linkages of GVC and food processing sectors inflict a stronger trade-off than upstream positioning in GVC and agricultural sectors.

Donwstream industries in GAVCs—those closer to consumers, such as the food processing and retail sectors—rely on a greater number of trade ties and goods exchanged, each of which is subject to some level of uncertainty. Low-income countries' trade relationships are relatively more subject to unstable institutional environments while they are often cut off from supplies from sectors in higher-income countries in case of extraordinary supply and demand shocks. Both of these factors are likely to contribute to low income-countries benefiting less from GAVCs than high-income countries.

The lack of diversification of GAVCs might constitute an externality problem. The marginal benefit of firms of diversifying is likely lower than the social marignal benefit of diversified GAVCs. Thus policy makers could address the problem by implementing Pigou-type and progressive tariff quotas that reduce concentration at the cost of lower gains from trade.

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Appendix

A.1 Descriptives

Figure A.1 provides an account of food price volatility across countries in 2008—a year during which food prices were unstable because of a surge over several months—and 2013—a year during which prices were relatively stable.

Figure A.2 and Figure A.3 depict the coefficient of variation of real food prices as averages by income group and by region, respectively.

Table A.1 lists all variables employed in the analysis and their sources.

Figures A.4 depicts the global distribution of GAVC participation in 2015.

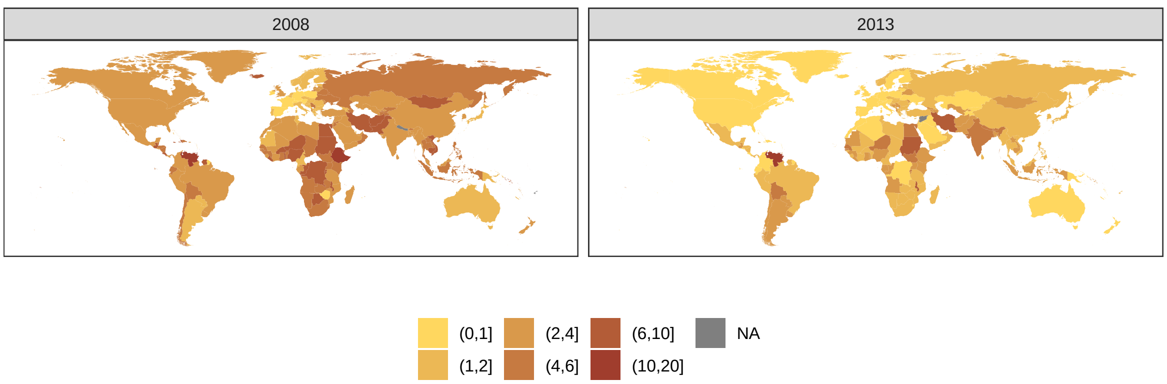

FIGURE A.1: Global within-year food price variation in 2008 and 2013 in %

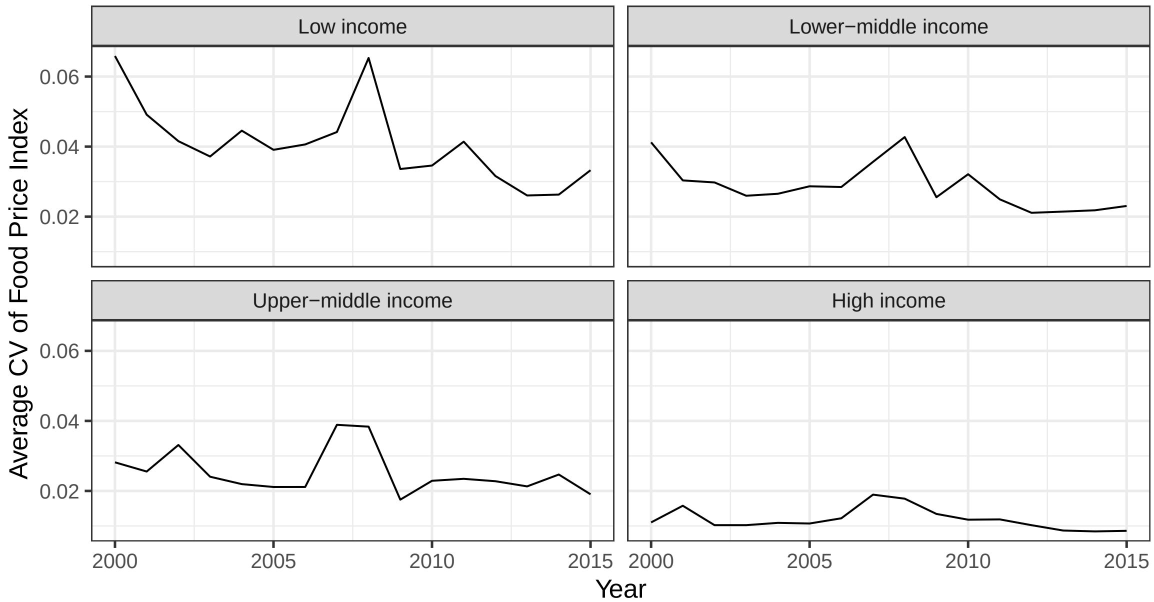

FIGURE A.2: Average within-year coefficient of variation of food price index by income group

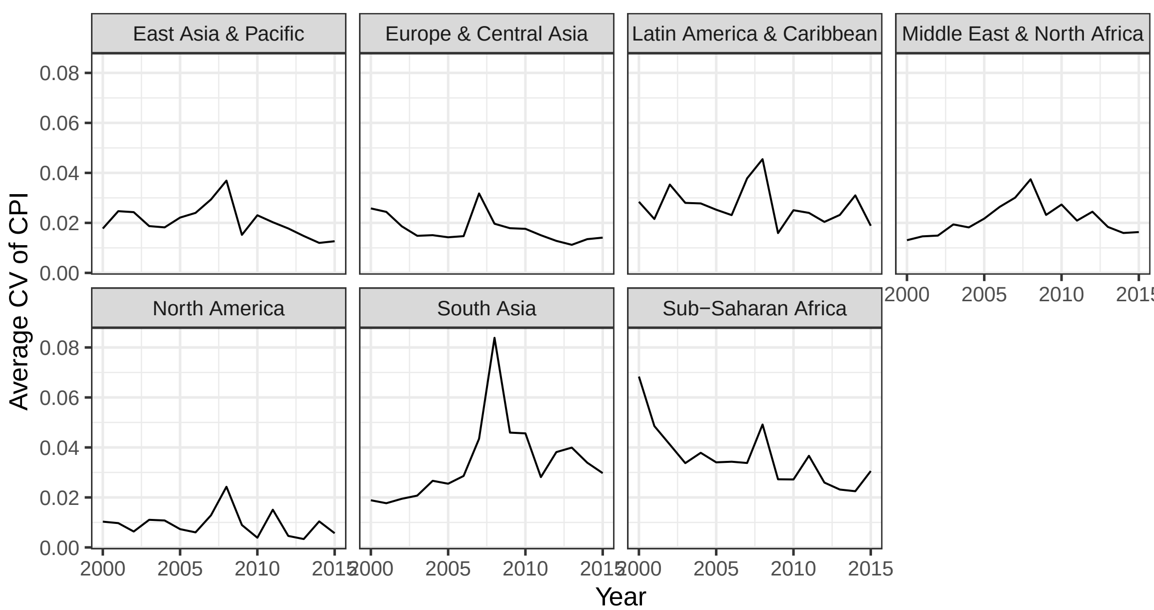

FIGURE A.3: Average within-year coefficient of variation of food price index by contintent

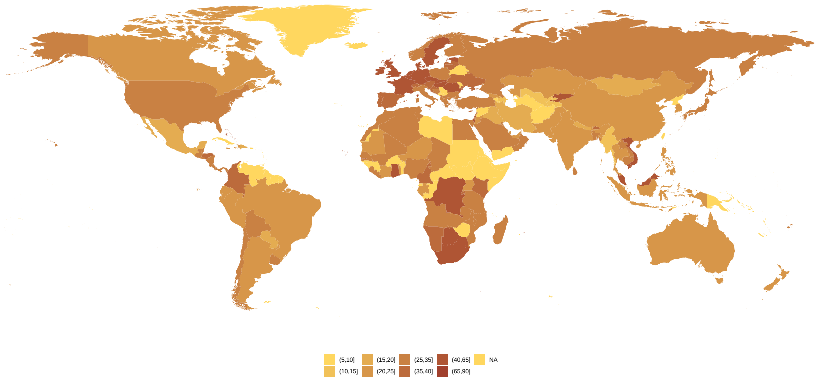

FIGURE A.4: AGVC participation in % of exports by country in 2015

TABLE A.1: List of variables and data sources

Description	Source
Consumer prices, food indices (2015 = 100)	FAOSTAT
GVC participation (%) by sector	UNCTAD-Eora
GVC downstream participation (%) by sector	UNCTAD-Eora
GVC upstream participation (%) by sector	UNCTAD-Eora
Population ages 0-14 total	World Development Indicators
Population ages 15-64 total	World Development Indicators
Population ages 65 and above total	World Development Indicators
Population density (people per sq. km of land area)	World Development Indicators
Population growth (annual %)	World Development Indicators
Population female	World Development Indicators
Population male	World Development Indicators
Population total	World Development Indicators
Rural population	World Development Indicators
Urban population	World Development Indicators
Price level ratio of PPP conversion factor (GDP) to market exchange rate	World Development Indicators
GDP growth (annual %)	World Development Indicators
Inflation GDP deflator (annual %)	World Development Indicators
GDP (constant 2010 US$)	World Development Indicators
Agriculture forestry and fishing value added (% of GDP)	World Development Indicators
Exports of goods and services (% of GDP)	World Development Indicators
Imports of goods and services (% of GDP)	World Development Indicators
Total fisheries production (metric tons)	World Development Indicators
Land under cereal production (hectares)	World Development Indicators
Cereal production (metric tons)	World Development Indicators
Capture fisheries production (metric tons)	World Development Indicators
Food production index (2004-2006 = 100)	World Development Indicators
Livestock production index (2004-2006 = 100)	World Development Indicators
Arable land (hectares)	World Development Indicators
Agricultural land (sq. km)	World Development Indicators
Land area (sq. km)	World Development Indicators
Number of Regional Trade Agreements (RTA) by country	MLRTA Database
Number of Customs Unions (CU) by country	MLRTA Database
Number of Free Trade Agreements (FTA) by country	MLRTA Database
Number of Economic Integration Agreements (EIA) by country	MLRTA Database
Number of Partial Scope Agreements (PSA) by country	MLRTA Database
Country Region category	the UN Standard Country Codes

[H]
Notes: For MLRTA database, see https://www.ewf.uni-bayreuth.de/en/research/RTA-data/index.html.

A.2 Robustness Checks

Our identification strategy relies on a shift-share instrumental variable. Our identifying assumption is that the within-country distribution of industry shares is independent from food prices, food price volatility, and unobservables. We argue the distribution between the agricultural and food and beverages sectors is driven by natural endowments, and thus exogenous to both.

To help establish the claim that this assumption is valid, we conduct several robustness checks. We follow the tests proposed in Goldsmith-Pinkham et al. (2020) to assess the validity of our exclusion restriction. This entails estimating alternative models where we check for homogeneity in estimates across sectors,[12] testing for overidentification, and assessing the correlation between various correlates and industry shares.

A.2.1 Alternative Models under Homogeneity

One way to assess the validity of the Bartik IV to alternative estimators by estimating by limited information maximum likelihood (Anderson and Rubin, 1949), by modification of bias-corrected two-stage least square (MBTSL; see Kolesar et al., 2015), and the information matrix-based standard errors (IM-SE) as a first check of the specification of our models. Table A.2 shows the respective estimates and regular SEs, Ecker-Huber-White heteroskedasticity-robust SEs and IM-SE. Both the estimators and standard errors are similar to our core results, providing no reason to assume that the models are misspecified.

TABLE A.2: Alternative IV Estimators (TWFE and Country Correlates)

	β	SE	EHW-SE	HTE-robust SE	IM-SE
OLS	0.012310	0.020506	0.021629		
Bartik TSLS	0.088224	0.034570	0.045442	0.045442	
LIML	0.087524	0.034570	0.046798		0.036188
MBTSL	0.089327	0.034589	0.046846	0.046856	
TSLS	0.013935	0.029141	0.022237		
	Overidentification (Sargan) test: $p = 0.919357$				

A.2.2 Test of Overidentification

Another way to test the validity of multiple IVs is by conducting a Sargan test of overidentification. While our research design consists of only one Bartik IV, our shares-driven

[12] As our application does not look at an intervention, or a dichotomous treatment that turns on, we cannot construct pretrends

identification strategy requires the industry shares to be exogenous. We estimate a model with individual industry shares as separate IVs by two-staged least squares to assess the exogeneity of industry shares. The test results are detailed at the bottom of Table A.2.

A.2.3 The Relationship between Sector Shares and Observable Correlates

One way to assess the validity of the exclusion restriction is to examine how sector composition correlates with observable covariates that could be linked to participation in GAVCs, just like potential unobservable confounders. The relationships between observable location characteristics and industry shares offers suggestive evidence on mechanisms that could compromise the exclusion restriction. It is worth highlighting that the empirical strategy is still valid if the covariates of the shares and outcomes are correlated in levels, but not if the levels of share covariates predict *changes* in the outcome variable.

Table A.3 provides OLS regression results for individual sector shares and our Bartik IV for baseline year 2001 on all control variables used in the analysis in 2010. As a first observation, we find that the R^2 is rather low given the vast set of variables and their fundamental nature. The variables describing agriculture, the economy, trade, demographics and trade policy respectively only account for 36 percent and 52 percent of variation in the agriculture and food and beverages sectors. We argue that the sector distribution is mainly dependent on exogenous natural circumstances such as fertile land endowment. The significant and strong correlation of the land variables supports this hypothesis and thus gives no reason to suspect the exclusion restriction to not hold. Moreover, trade variables and in particular trade policy variables are correlated with sector shares, which, however, will be exogenous to prices.

More worrisome regarding our exclusion restriction is that the food production index as well as population growth are statistically significant correlates of the sector shares. While the food production index could reflect mostly natural endowments, this opens up the channel of supply and demand side shocks to influence both sector shares and food price changes not exclusively through participation in GAVCs.

TABLE A.3: Relationship between industry shares and country characteristics

Dependent Variable	Agriculture	Food and Beverages	Bartik IV
Model:	(1)	(2)	(3)
Variables			
Agricultural land (sq. km)	2.47×10^{-8} (2.26×10^{-8})	2.99×10^{-8}* (1.75×10^{-8})	5.89×10^{-7} (3.91×10^{-7})
Arable land (hectares)	-1.47×10^{-9} (2.45×10^{-9})	3.21×10^{-9} (1.98×10^{-9})	8.79×10^{-8}** (4.1×10^{-8})
Land under cereal production (hectares)	-8.8×10^{-9}** (4.1×10^{-9})	-6.59×10^{-9}* (3.6×10^{-9})	-6.64×10^{-7}*** (1.01×10^{-7})
Land area (sq. km)	1.58×10^{-8} (9.83×10^{-9})	-5.85×10^{-9} (8.03×10^{-9})	6.11×10^{-7}*** (1.85×10^{-7})
Cereal production (metric tons)	1.59×10^{-9} (1.15×10^{-9})	-1.67×10^{-9} (1.11×10^{-9})	2.98×10^{-8} (1.94×10^{-8})
Food production index (2004-2006 = 100)	0.0016*** (0.0006)	0.0014*** (0.0004)	0.0740*** (0.0129)
Livestock production index (2004-2006 = 100)	-9.67×10^{-5} (0.0005)	-0.0008* (0.0005)	-0.0229* (0.0126)
Population density (people per sq. km of land area)	-4.09×10^{-6} (1.19×10^{-5})	-3.41×10^{-5}** (1.51×10^{-5})	0.0013*** (0.0004)
Capture fisheries production (metric tons)	-1.15×10^{-8} (2.63×10^{-8})	-3.36×10^{-8} (2.17×10^{-8})	-1.17×10^{-6}*** (2.88×10^{-7})
Total fisheries production (metric tons)	-6.31×10^{-9} (1.93×10^{-8})	2.56×10^{-8}* (1.53×10^{-8})	5.52×10^{-7}*** (2.1×10^{-7})
Agriculture forestry and fishing value added (% of GDP)	-0.0004 (0.0011)	-0.0010 (0.0009)	0.0319 (0.0221)
Exports of goods and services (% of GDP)	0.0014** (0.0006)	0.0014** (0.0006)	0.1233*** (0.0161)
Imports of goods and services (% of GDP)	0.0004 (0.0006)	0.0013** (0.0006)	0.0760*** (0.0185)
Inflation GDP deflator (annual %)	-0.0013 (0.0010)	-0.0008 (0.0008)	0.0043*** (0.0009)
GDP (constant 2010 US$)	-1.17×10^{-14} (3.1×10^{-14})	6.07×10^{-14}** (2.9×10^{-14})	1.16×10^{-12}** (5.83×10^{-13})
GDP growth (annual %)	0.0019 (0.0023)	0.0017 (0.0019)	-0.0818* (0.0437)
Population ages 0-14 total	-0.0001 (9.97×10^{-5})	-6×10^{-5} (7.22×10^{-5})	0.0013 (0.0009)
Population ages 15-64 total	-0.0001 (9.97×10^{-5})	-6×10^{-5} (7.22×10^{-5})	0.0013 (0.0009)
Population ages 65 and above total	-0.0001 (9.97×10^{-5})	-6×10^{-5} (7.22×10^{-5})	0.0013 (0.0009)
Population growth (annual %)	-0.0179*** (0.0053)	-0.0066 (0.0049)	-0.6255*** (0.1228)
Population female	2.16×10^{-8} (1.53×10^{-8})	2.21×10^{-8} (1.38×10^{-8})	-0.0012 (0.0009)
Population total	0.0001 (9.97×10^{-5})	6×10^{-5} (7.22×10^{-5})	
Rural population	1.46×10^{-9} (1.43×10^{-9})	3×10^{-9}** (1.24×10^{-9})	-9.8×10^{-5}*** (9.92×10^{-6})
Regional Trade Agreements (RTA)	-0.0012** (0.0006)	9.34×10^{-5} (0.0006)	0.0687*** (0.0148)
Customs Unions (CU)	0.0065*** (0.0021)	0.0052*** (0.0017)	0.4819*** (0.0478)
Free Trade Agreements (FTA)	0.0023*** (0.0008)	0.0006 (0.0006)	0.0349* (0.0194)
Partial Scope Agreements (PSA)	0.0011 (0.0009)	-0.0004 (0.0011)	-0.0056 (0.0254)
Economic Integration Agreements (EIA)	0.0035** (0.0015)	0.0013 (0.0014)	-0.0089 (0.0712)
Regional Trade Agreements (RTA) (i)	0.0660 (0.0401)	0.0892** (0.0386)	16.21*** (0.9485)
Customs Unions (CU) i	-0.0154 (0.0231)	-0.0184 (0.0205)	-2.585*** (0.5646)
Free Trade Agreements (FTA) i	-0.0456** (0.0210)	-0.0197 (0.0212)	-1.908*** (0.4925)
Partial Scope Agreements (PSA) i	-0.0269 (0.0300)	-0.0068 (0.0298)	-3.443*** (0.7780)
region	0.0045 (0.0086)	0.0022 (0.0075)	0.0421 (0.2170)
subregion	0.0025** (0.0012)	0.0021* (0.0011)	0.1410*** (0.0288)
Population male			-0.0012 (0.0009)
Urban population			-9.82×10^{-5}*** (9.92×10^{-6})
Economic Integration Agreements (EIA) i			3.368* (1.867)
Fit statistics			
Observations	136	136	2,174
R^2	0.37142	0.52444	0.50491
Adjusted R^2	0.16806	0.37058	0.49680

Heteroskedasticity-robust standard-errors in parentheses
****: 0.01, **: 0.05, *: 0.1*

Each column reports results of a single regression of a 2001 industry share on 2010 characteristics. The final column is the Bartik instrument constructed using the growth rates.

A.3 Further Results

In this section, we present further results for our analysis of treatment heterogeneity.

A.3.1 Results by Sector

Table A.5 shows OLS estimates of the relationship between participation in GAVCs and food price volatility where the sample is split by the agriculture and food and beverages sectors. The results show that neither sector seems to be driving the results individually. Instead, the main results in the paper are driven by both sectors jointly.

TABLE A.4: GAVCs and on real price levels and price instability, by sector (OLS)

Dependent Variables:	CV of food price index		Log food price level	
Sector	Agriculture	Food & Beverages	Agriculture	Food & Beverages
Model:	(1)	(2)	(3)	(4)
Variables				
GAVC share	0.0102	0.0121	-1.503***	-1.032
	(0.0383)	(0.0297)	(0.4339)	(0.7183)
Agriculture	Yes	Yes	Yes	Yes
Economy	Yes	Yes	Yes	Yes
Demography	Yes	Yes	Yes	Yes
Trade Policy	Yes	Yes	Yes	Yes
Fixed-effects				
Country	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	2,182	2,182	2,179	2,179
R^2	0.59719	0.59721	0.94701	0.94645
Within R^2	0.36831	0.36833	0.46945	0.46385

Clustered (Country & subregion) standard-errors in parentheses
****: 0.01, **: 0.05, *: 0.1*

A.3.2 By Type of GAVC

Here, we provide results from models in which the variable of interest is constructed such that it contains only downstream or upstream linkages of participation in GAVCs.

TABLE A.5: GAVCs and on food price volatility, by sector (OLS)

Dependent Variable	CV of food price index		
Sector	Agriculture	Food & Beverages	Total
Model:	(1)	(2)	(3)
Variables			
GAVC share	0.0102	0.0121	0.0060
	(0.0383)	(0.0297)	(0.0411)
Agriculture	Yes	Yes	Yes
Economy	Yes	Yes	Yes
Demography	Yes	Yes	Yes
Trade Policy	Yes	Yes	Yes
Fixed-effects			
Country	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	2,182	2,182	2,182
R^2	0.59719	0.59721	0.59716
Within R^2	0.36831	0.36833	0.36826

Clustered (Country & subregion) standard-errors in parentheses
****: 0.01, **: 0.05, *: 0.1*

TABLE A.6: GAVCs and on food price level, by sector (OLS)

Dependent Variable	Log food price level		
Sector	Agriculture	Food & Beverages	Total
Model:	(1)	(2)	(3)
Variables			
GAVC share	-1.503***	-1.032	-1.650**
	(0.4339)	(0.7183)	(0.6625)
Agriculture	Yes	Yes	Yes
Economy	Yes	Yes	Yes
Demography	Yes	Yes	Yes
Trade Policy	Yes	Yes	Yes
Fixed-effects			
Country	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	2,179	2,179	2,179
R^2	0.94701	0.94645	0.94716
Within R^2	0.46945	0.46385	0.47094

Clustered (Country & subregion) standard-errors in parentheses
****: 0.01, **: 0.05, *: 0.1*

TABLE A.7: Downstream GAVCs and food price volatility by sector (OLS)

Dependent Variable	CV of food price index		
Sector	Agriculture	Food & Beverages	Total
Model:	(1)	(2)	(3)
Variables			
downstream - GAVC share	0.035	0.037*	0.043*
	(0.026)	(0.021)	(0.022)
Agriculture	Yes	Yes	Yes
Economy	Yes	Yes	Yes
Demography	Yes	Yes	Yes
Trade Policy	Yes	Yes	Yes
Fixed-effects			
Country	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	2,182	2,182	2,182
R^2	0.59759	0.59792	0.59797
Within R^2	0.36894	0.36946	0.36953

Clustered (Country & subregion) standard-errors in parentheses
****: 0.01, **: 0.05, *: 0.1*

TABLE A.8: Upstream GAVCs and food price volatility by sector (OLS)

Dependent Variable	CV of food price index		
Sector	Agriculture	Food & Beverages	Total
Model:	(1)	(2)	(3)
Variables			
Upstream - GAVC share	-0.031	-0.141**	-0.092
	(0.053)	(0.055)	(0.072)
Agriculture	Yes	Yes	Yes
Economy	Yes	Yes	Yes
Demography	Yes	Yes	Yes
Trade Policy	Yes	Yes	Yes
Fixed-effects			
Country	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	2,182	2,182	2,182
R^2	0.59740	0.59940	0.59865
Within R^2	0.36865	0.37178	0.37060

Clustered (Country & subregion) standard-errors in parentheses
****: 0.01, **: 0.05, *: 0.1*

TABLE A.9: Downstream GAVCs and food price level, by sector (OLS)

Dependent Variable	Log food price level		
Sector	Agriculture	Food & Beverages	Total
Model:	(1)	(2)	(3)
Variables			
Downstream - GAVC share	-0.254	-0.676	-0.766
	(0.525)	(0.521)	(0.637)
Agriculture	Yes	Yes	Yes
Economy	Yes	Yes	Yes
Demography	Yes	Yes	Yes
Trade Policy	Yes	Yes	Yes
Fixed-effects			
Country	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	2,179	2,179	2,179
R^2	0.94595	0.94622	0.94620
Within R^2	0.45888	0.46151	0.46137

Clustered (Country & subregion) standard-errors in parentheses
****: 0.01, **: 0.05, *: 0.1*

TABLE A.10: Upstream GAVCs and food price level, by sector (OLS)

Dependent Variable	Log food price level		
Sector	Agriculture	Food & Beverages	Total
Model:	(1)	(2)	(3)
Variables			
Upstream - GAVC share	-2.27***	-0.792	-2.24**
	(0.593)	(1.89)	(1.06)
Agriculture	Yes	Yes	Yes
Economy	Yes	Yes	Yes
Demography	Yes	Yes	Yes
Trade Policy	Yes	Yes	Yes
Fixed-effects			
Country	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	2,179	2,179	2,179
R^2	0.94736	0.94601	0.94685
Within R^2	0.47294	0.45947	0.46781

Clustered (Country & subregion) standard-errors in parentheses
****: 0.01, **: 0.05, *: 0.1*

TABLE A.11: GAVCs and position on food price level, by Sector (OLS)

Dependent Variable	Log food price level		
Sector	Agriculture	Food & Beverages	Total
Model:	(1)	(2)	(3)
Variables			
GAVC position	0.683	-0.494	-0.005
	(0.453)	(0.526)	(0.560)
Fixed-effects			
Country	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	2,179	2,179	2,179
R^2	0.94620	0.94609	0.94595
Within R^2	0.46130	0.46022	0.45879

Clustered (Country & subregion) standard-errors in parentheses
****: 0.01, **: 0.05, *: 0.1*

A.3.3 By Income Group

In Table A.12 we report results by income group (e.g., low-, middle-, or high-income countries). We make reference to these results in the text. While the statistical power of the coefficients is limited, probably owing to the relatively low number of observations with a large number of independent variables in the sample split models, the magnitude of the coefficients is in line with results from previous models and we observe a similar progression of trade-offs along income levels of economies. Namely, the uncertainty increasing GAVCs and participation in low-income countries is strongest in low income countries and weakest in high-income countries. In upper-middle income countries the estimated coefficient is negative, but closest to zero among all estimated coefficients.

That said, Table A.15 shows that the seeming price reducing effects of GAVCs is strongest in upper-middle income countries, followed by high-income countries. By contrast, low- and lower-income countries experience comparably lowest gains—and possibly even losses, in the case of lower-middle-income countries—from GAVC participation. Table A.13 and Table A.14 detail the estimates by GVC-type and sector.

TABLE A.12: GAVCs and on food price volatility, by income group (Bartik IV)

Dependent Variable	CV of food price index			
Income group	Low	Lower-middle	Upper-middle	High
Model:	(1)	(2)	(3)	(4)
Variables				
GAVC share	0.5739	0.0872	-0.0217	0.0306
	(0.3148)	(0.0503)	(0.0234)	(0.0606)
Agriculture	Yes	Yes	Yes	Yes
Economy	Yes	Yes	Yes	Yes
Demography	Yes	Yes	Yes	Yes
Trade Policy	Yes	Yes	Yes	Yes
Regional Dummies				
Fixed-effects				
Country	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	365	563	591	655
F-test (1st stage), GAVC share	55.591	355.77	149.49	460.22
R^2	0.64333	0.65031	0.53908	0.50560
Within R^2	0.54747	0.47217	0.25027	0.13307

Clustered (Country & subregion) standard-errors in parentheses
****: 0.01, **: 0.05, *: 0.1*

TABLE A.13: Agriculture sector: GAVCs and on food price volatility, by income group (OLS)

Dependent Variable	CV of food price index			
Income group	Low	Lower-middle	Upper-middle	High
Model:	(1)	(2)	(3)	(4)
Variables				
GAVC share	0.1676	0.0805**	-0.1599**	-0.0427
	(0.1134)	(0.0316)	(0.0670)	(0.0429)
Agriculture	Yes	Yes	Yes	Yes
Economy	Yes	Yes	Yes	Yes
Demography	Yes	Yes	Yes	Yes
Trade Policy	Yes	Yes	Yes	Yes
Fixed-effects				
Country	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	367	564	591	660
R^2	0.65640	0.76729	0.54458	0.50821
Within R^2	0.56649	0.65091	0.25922	0.15042

Clustered (Country & subregion) standard-errors in parentheses
****: 0.01, **: 0.05, *: 0.1*

TABLE A.14: Food and Beverages sector: GAVCs and on food price volatility, by income group (OLS)

Dependent Variable	CV of food price index			
Income group	Low	Lower-middle	Upper-middle	High
Model:	(1)	(2)	(3)	(4)
Variables				
GAVC share	0.1076	-0.0262	-0.1220	-0.0248
	(0.0589)	(0.0267)	(0.1269)	(0.0329)
Agriculture	Yes	Yes	Yes	Yes
Economy	Yes	Yes	Yes	Yes
Demography	Yes	Yes	Yes	Yes
Trade Policy	Yes	Yes	Yes	Yes
Fixed-effects				
Country	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	367	564	591	660
R^2	0.64641	0.76410	0.53061	0.51142
Within R^2	0.55389	0.64613	0.23649	0.15596

Clustered (Country & subregion) standard-errors in parentheses
****: 0.01, **: 0.05, *: 0.1*

TABLE A.15: GAVCs and on food price level, by income group (Bartik IV)

Dependent Variable	Log food price level			
Income group	Low	Lower-middle	Upper-middle	High
Model:	(1)	(2)	(3)	(4)
Variables				
GAVC share	-1.005	-0.3532	-8.256***	-3.932***
	(1.119)	(0.7375)	(2.083)	(1.128)
Agriculture	Yes	Yes	Yes	Yes
Economy	Yes	Yes	Yes	Yes
Demography	Yes	Yes	Yes	Yes
Trade Policy	Yes	Yes	Yes	Yes
Fixed-effects				
Country	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	365	563	588	655
F-test (1st stage), GAVC share	55.591	355.77	149.49	460.22
R^2	0.95705	0.94701	0.93725	0.97377
Within R^2	0.46471	0.58806	0.36709	0.68031

Clustered (Country & subregion) standard-errors in parentheses
****: 0.01, **: 0.05, *: 0.1*