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Analysis

Spatial Distribution of the International Food Prices: Unexpected Heterogeneity and Randomness

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A B S T R A C T

Global food prices are typically analysed in a time-series framework. We complement this approach by focusing on the spatial price dispersion of the country-pair bilateral trade in the international food trade network (*IFTN*), for ten relevant commodities. The main purposes are to verify if the Law of One Price (*LOP*) holds and to investigate the emergence of randomness in the price-formation mechanism.

We distinguish between the "internal" variance, which indicates the magnitude of price discrimination, and the "external" variance, that is a measure of price dispersion. We find that, for some commodities, spatial price dispersion is remarkable and persistent over time (i.e., failure of the *LOP*) and that there exists a strict correlation between price spikes and peaks in spatial price variability.

We test whether the price distribution can be replicated through a stochastic process of extraction. Surprisingly, the actual distribution of prices, for several commodities, is well described by a random distribution. Then, the process of data aggregation is not neutral because the information at the micro-level scale might be lost at the macro-scale, due to the complexity of the *IFTN*. Finally, we discuss some possible economic explanations of these outcomes and the main methodological, environmental, and policy consequences.

1. Introduction

The end of hunger and the achievement of food security are global key issues explicitly included in the Sustainable Development Goals agenda (UN, 2015). The interest of the international community is justified by acknowledging the complex and interrelated environmental and social dimensions linked to food management, such as water resources (Generoso, 2015; Distefano and Kelly, 2017; Distefano et al., 2018b), energy and pollution (Carlsson-Kanyama et al., 2003; D'Odorico et al., 2018), land use and deforestation (Odegard and Van der Voet, 2014), and social security and health (Bellemare, 2015; Bush, 2010). Thus, a better understanding of food markets, especially in an era of globalisation (Duarte et al., 2014; Biewald et al., 2014; Suweis et al., 2015), is crucial to provide solid bases for food policies and resource management (Wang et al., 2016). This interest has been reinforced recently – after the two waves of world food price crises (2008 and 2011) – where economists analysed the aftermaths of price 'spikes' to assess the short-run effects (Piesse and Thirtle, 2009; Bellemare, 2015) and the main causes of *temporal* food price volatility (see Díaz-Bonilla, 2016, for a discussion). A common assumption behind these studies, and usual among agricultural economists, is the so-called *Law of One Price* (henceforth *LOP*): once prices are converted to a common currency (including transaction and transport costs), homogeneous goods should be sold for the same price in different countries (Miljkovic, 1999).[1] The *LOP* should hold when goods are highly traded, at least in spatially separated international markets (Baffes, 1991; Goldberg and Verboven, 2005).

On the contrary, *price dispersion* – namely, a homogeneous product being sold at different prices by different exporters – can emerge, for several reasons, such as entry barriers and geographical separation of markets (Krugman, 1991; Yang et al., 2017), different marginal costs (Crucini and Yilmazkuday, 2014; Yilmazkuday, 2016), variations in consumer preferences (Grebitus et al., 2013), and monetary illusion (Fehr and Tyran, 2001).[2] Following this branch of literature, we aim at testing the presence or not of *LOP* in the international food trade network (*IFTN*), extending the analysis to the price-formation mechanism. The existent literature empirically analysed spatial food-price dispersion only at the retail level (e.g., Anania and Nisticò, 2014) but, to our

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[1] Ancillary hypotheses are those concerning perfect competition: agents are price-takers, perfect information, no frictions on factor mobility, individual rationality, and so on.

[2] Monetary illusion indicates the psychological effect of making mistakes due to the use of different currencies.

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knowledge, no attempts have been done in the international market. Our study aims at filling this gap.

The following questions will be examined: (*i*) How large is the spatial variability around the average global price in a single period? (*ii*) How large is the magnitude of price discrimination? (*iii*) Is spatial food price dispersion due to deterministic mechanisms, or is the *IFTN* so complex to generate a seemingly random distribution of choice at the country-level scale? (*iv*) What are the possible environmental implications of the failure of the *LOP* in the *IFTN*? To shed light on these questions, we carry out an empirical analysis on the distribution of bilateral, importing, and exporting prices. These issues might have relevant consequences for a) the *modelisation* of the price-formation mechanism and selection of the scale of analysis (macro vs micro), b) the understanding of the *magnitude* of food crises and the shock propagation dynamics, c) the governments' *regulation* effectiveness, and d) the *resource management* under climate change (e.g., the "food, energy, and environment trilemma" Tilman et al., 2009). The last point deserves a particular attention. Indeed, although agricultural markets have usually been presented as a classical example of competitive markets (i.e., the *LOP* should hold), they are experiencing a drastic transformation due to higher concentration and vertical coordination (Sexton, 2012; Distefano et al., 2018a). This structural changes have important consequences on resource management as well. Indeed, the new competition for land, the use of food for energy purposes, and the water stress due to climate change (de Amorim et al., 2018) might not be properly incorporated in food prices (Debaere, 2014). Global food production comes from 1.5 billion hectares of cultivated land (Hanjra and Qureshi, 2010), irrigated agriculture accounts for about 70% of human water withdrawal of which almost a quarter is embodied in the international trade of food (Dalin et al., 2017). Neglecting these crucial issues in the international food market may lead to myopic policies that could exacerbate the over-exploitation of natural resources.

The current analysis is structured as follows: Section 2 explains the dataset and the main features of the selected commodities. Section 3 discusses the methodology and it shows the main outcomes. Section 4 describes the statistical analysis to test the randomness of the price distributions and the cross-commodity results. Section 5 discusses some drivers behind our results and the main environmental implications. Finally, Section 6 draws the main conclusions.

2. Data

Trade data are taken from the publicly-available Food and Agricultural Organization of the United Nations' on-line database (FAOSTAT),[3] which reports the trade flows among 254 countries[4] for several commodities, from 1986 to 2013. FAOSTAT provides the values of the bilateral trade exchanges from which we build the matrices whose entries are the amount of exchange between any single exporter and importer, both in tonnes (**F**) and US dollars (**V**).[5] Note that, in order to avoid inconsistencies, coming from different importer- or exporter-reported declarations, we apply an algorithm (inspired by Gehlhar and Pick, 2002) to build a consistent database of bilateral trade. Moreover, we subtract the *transaction costs* to properly test the *LOP*.[6] The interested reader can find a step-by-step description of the procedure followed to build the database in the Supplementary materials (*SM.1*).

We select four staple raw food products (wheat, maize, rice milled,[7] and soy-beans) because they cover more than 50% of the global calories intake (D'Odorico et al., 2014). We also add apples, potatoes, eggs, and luxury goods such as honey, coffee green, and cocoa beans. Our sample of commodities includes both staple and luxury aliments and different categories of food, such as cereals, fruit, vegetables, and animal derivatives. The heterogeneity of the sample (as reported in Table 1) generates results quite representative of the whole food market, making our methodology generalisable to other products. The main differences concern the 'length' of the chain of production, where some commodities are mostly intended for final consumption ('D.', e.g. apple) while other are characterized by longer processes of transformation ('Pr.', e.g. cocoa beans). The selected commodities are also heterogeneous in terms of number of trading relationships ($\overline{Link}$), number of countries involved ($\overline{N_E}$ and $\overline{N_M}$), and average flow in tonnes ($\overline{F_{jk}}$) of each exchange. We also report the last harmonised system code (*HS*2017) of each good included in each commodity-label that, together with the Grubel-Lloyd index (below), is useful to verify the presence of hidden quality. It appears that this issue is not relevant in our sample, in most of the cases.

To provide a wider picture, we also present additional indicators about the main features of our bundle of commodities (see Table 2):

- $\rho(P_{prod},P_{exp})$: is the correlation coefficient between the average exporting and production price[8] computed on all years pooled together;
- $\rho(P_{jk},Dist_{jk})$: is the correlation coefficient between the bilateral price and the reciprocal distance between the exporter j and the importer k;
- $\overline{Dist}$: is the average distance of the bilateral trade exchanges, averaged across all the period. In particular $\overline{Dist} = \sum_j \sum_k Dist_{jk} \frac{F_{jk}}{F_{tot}}$, where $Dist_{jk}$ is the geographical distance between the exporter j and importer k;
- Water Footprint (*WF*) represents the total amount of water to produce, along the whole supply chain, each commodity (Mekonnen and Hoekstra, 2011);
- *GLI*: is the standard Grubel-Lloyd index[9] that is a proxy of hidden quality; it compares the reciprocal cross-country trade. It takes value between 0 (if a country only exports or imports a given commodity) and 1 (if country's imports equal exports of a given commodity). The latter case should indicate the presence of hidden quality (i.e., categorical aggregation bias) because a country is both an importer and an exporter of the good with the same label.

[3] FAO, Statistics Division. FAOSTAT online database. Available at http://www.fao.org/faostat/en. Last update on December 11, 2015.

[4] The number of active countries changed over time due to political reasons. For example, the USSR is active only until 1991.

[5] We also use the World Bank Data to recover the global inflation to obtain real prices.

[6] See Appendix A for a detailed description of the data analysis and of the treatment of transaction costs. Note that here we assume idyiosyncratic transaction cost, while 'unobservable transaction costs' (e.g., risk premium) are not included due to lack of available data. However, since transaction costs are relatively low, we should expect the key messages of the present study still hold in case of a detailed treatment of 'unobservable transaction costs'.

[7] See http://faostat3.fao.org/home/E for a description of the conversion in milled equivalent.

[8] Data on production price are taken from FAOSTAT, see http://www.fao.org/faostat/en/##data/PP.

[9] The Grubel-Lloyd index is defined as

$$GLI_j^x = 1 - \frac{|E_j^x - M_j^x|}{E_j^x + M_j^x}$$

where E_j and M_j are the total export and import from j of the commodity x, respectively. Table 2 reports the global index, over all the time window, that is computed (omitting x) as a weighted average (by market shares) for each country, namely:

$$GLI = \sum_t^T \sum_j^N GLI_j(t) \cdot \frac{E_j(t) + M_j(t)}{2F_{tot}(t)}.$$

Note that we compute this indicator both in monetary and physical values, without observing significant differences; we opted to report the index computed on the monetary basis.

Table 1
Cross-commodity summary of the key features of each food category. *HS*2017 stands for the harmonised system and it indicates the sub-groups of products included in each label (source: http://www.findhs.codes/). 'Link', $\bar{F}_{jk}$, and $\bar{P}$ indicate the average number of exchanges, the average flow (in 1000 tonnes), and the average price (in \$/ton), respectively. $\bar{N}_E$ and $\bar{N}_M$ are the yearly average number of exporters and importers, while 'D.' and 'Pr.' stand for direct use and highly processed products.

Item	Kcal %	Description	HS2017	Link	$\bar{F}_{jk}$	$\bar{P}$	$\bar{N}_E$	$\bar{N}_M$
Wheat	20.4[a]	Cereal – staple (Pr.)	1001.11-.19-.91-.99	803	151	178	67.8	154.7
Rice	16.1[a]	Cereal – staple (D. - Pr.)	Milled Equivalent	708	34	402	72.6	162.5
Maize	12.8[a]	Cereal – staple (D. - Pr.)	1005.10-.90	537	167	906	74.0	135.7
Soy-beans	8.0[a]	Bean – staple (D. - Pr.)	1201.01	290	206	320	44.7	83.2
Potatoes	2.1[a]	Tuber – staple (D. - Pr.)	0701.10	780	11	906	87.4	159.6
Apple	< 1	Fruit – staple (D. - Pr.)	0808.10	787	7.5	614	73.0	147.0
Eggs	< 1	Animal – staple (D. - Pr.)	0407.11-.21-.90	727	1.5	1304	91.0	164.0
Honey	< 1	Animal – luxury (D.)	0409.00	696	0.5	1277	78.9	108.5
Coffee green	< 1	Seed – luxury (Pr.)	0901.11	981	5.5	2017	60.1	98.0
Cocoa-beans	< 1	Seed – luxury (Pr.)	1800.00	342	7	1632	59.4	57.4

[a] Refers to the global shares of calories intake, as reported in D'Odorico et al. (2014).

Table 2
Cross-commodity summary for additional indicators. The $\rho(P_{prod},P_{exp})$ is the correlation between the average exporting and production prices, *GLI* is the standard Grubel-Lloyd index, $\bar{Dist}$ is the average distance of bilateral exchanges, while $\rho(P_{jk},Dist_{jk})$ is the correlation between the bilateral price and the geographical distance. *WF* is the global average water footprint, as reported in Mekonnen and Hoekstra (2011).

Item	$\rho(P_{prod},P_{exp})$	*GLI*	$\bar{Dist}$ (10^3 km)	$\rho(P_{jk},Dist_{jk})$	*WF* (m^3 ton^{-1})
Wheat	0.144	0.12	5.81	−0.05	1827
Rice	0.243	0.14	5.26	−0.23	1673
Maize	0.146	0.11	6.54	−0.11	1222
Soy-beans	0.015	0.06	11.26	−0.08	2145
Potatoes	0.254	0.54	1.40	0.03	287
Apple	0.136	0.25	4.78	0.15	822
Eggs	0.455	0.37	1.76	0.13	3300
Honey	0.062	0.26	6.10	−0.03	N/A
Coffee green	0.284	0.08	7.83	0.05	15,897
Cocoa-beans	0.075	0.11	5.92	0.01	19,928

3. Spatial Price Dispersion in the *IFTN*

By following a complementary approach to standard economic analysis on temporal volatility, we introduce three measures of *spatial* price variability that are

(i) **total** variance (σ^2_{tot}) computed on the set of all bilateral trade relationships; it describes the price heterogeneity and if σ^2_{tot} is high it entails that the *LOP* does not hold in the product-specific *IFTN*;
(ii) **internal** variance (σ^2_{int}), that is the weighted average of the internal variability of the distribution of prices associated to a single *j*-th exporter ($\sigma^2_{int,j}$) to all its direct trade partners. If σ^2_{int} is high it indicates price discrimination; this might be due to dumping strategy[10] and/or asymmetric bargaining power;
(iii) **external** variance (σ^2_{ext}) evaluated from the distribution of the average prices set by every exporter. If σ^2_{ext} is high it indicates price dispersion possibly due to market segmentation and/or hidden quality.

Without loss of generality, we describe our procedure by omitting the time specification since each operation is repeated every year.

Given the matrix of product-specific bilateral trade price per ton (**P**)[11] – deflated by the global inflation rate in order to be comparable over time[12] – and tonnes (**F**), the yearly-average global price is computed as $\bar{P} = \sum_j^{N_E} \sum_k^{N_M} P_{jk} \cdot \frac{F_{jk}}{F_{tot}}$, where P_{jk} is the bilateral price per ton and F_{tot} is the overall physical flow traded on the network (in a given year). Note that $\bar{P}$ corresponds to a weighted average, where the weights are the market shares (F_{jk}/F_{tot}). The set of all the trade relationships generates the distribution of bilateral price from which we compute the total weighted variance of bilateral prices as

$$\sigma^2_{tot} = \sum_j^{N_E} \sum_k^{N_M} (P_{jk} - \bar{P})^2 \cdot \frac{F_{jk}}{F_{tot}}. \tag{1}$$

Let $\bar{P}_j = \sum_k^{N_M^j} P_{jk} \frac{F_{jk}}{F_j}$ be the weighted (by import share) average price of each exporter *j*, where N_M^j is the total number of importers from any generic exporter *j* and $F_j = \sum_k^{N_M^j} F_{jk}$ is the total export of *j*. We define the country-side internal variance ($\sigma^2_{int,j}$), for each exporter *j*, as the weighted (by import share) average of the quadratic distance of the bilateral price (P_{jk}) from $\bar{P}_j$. It is computed as $\sigma^2_{int,j} = \sum_k^{N_M^j} (P_{jk} - \bar{P}_j)^2 \cdot \frac{F_{jk}}{F_j}$. The aggregate *internal* variance (σ^2_{int}) is the weighted (by tonnes exported)[13] sum of any internal variance ($\sigma^2_{int,j}$), while the *external* variance is a measure of the quadratic distance of the average price fixed by each exporter ($\bar{P}_j$) with respect to the average global price ($\bar{P}$). Namely,

[10] We also refer to the "dumping strategy" to indicate the possibility, for a firm, of selling a homogeneous commodity by discriminating the price depending on the consumers. Classical theory suggests that perfect competition should prevent this opportunity.

[11] Note that in our case we should speak of yearly 'unitary average value' since we recover *P* as the ratio between nominal values (US dollar) and the physical flow (tonnes). For the sake of simplicity, and because the average values we found are close to the average prices of New York and Bremen/Hamburg markets and of the USDA database, we opt to keep the label "price". For a detailed description on the differences and implications of these two concepts see Gehlhar and Pick (2002). On the distinction between intra- and inter-annual variability of price, see Ott (2014).

[12] Note that given the presence of two partners, the exporter and the importer, the selection of the 'right' deflator might be ambiguous. Indeed, if one chooses, for instance, the Consumer (or Producer) Price Index of the exporter then all the values of the importers will be distorted, mostly in the case of a rich exporting country and a poor importing country with different food baskets of consumption (von Braun and Tadesse, 2012). For this reason, we opted to select a single yearly *global* deflator to reduce possible arbitrary distortions.

[13] We focus only on exporter side for two reasons: first, importers typically have only few partners (3 on average); second, the *IFTN* is usually dominated by few big exporters that cover most of the overall trade. The interested reader can find the results from the import side in the Supplementary materials (*SM.3*).

$$\sigma_{int}^2 = \sum_j^{N_E} \sigma_{int,j}^2 \cdot \frac{F_j}{F_{tot}} \qquad \sigma_{ext}^2 = \sum_j^{N_E} (P_j - \bar{P})^2 \cdot \frac{F_j}{F_{tot}}. \tag{2}$$

3.1. An Overview of Market Structure

For the sake of simplicity, here we only show the results for *wheat* and *coffee green*.[14] Fig. 1 shows the time-series of the average exporting price $\bar{P}_j$ (red lines) for the top two exporters which jointly cover about 33% of market sales (left and central panels), where the red band width indicates the internal standard deviation ($\sigma_{int,j}$). Some differences emerge. Firstly, the average price is much higher for coffee green, which ranges between \$1000 to \$4000 per ton (with a peak of ~\$6000 per ton for Colombia during the 2011 crisis), while the wheat price is within the interval \$100–\$300 per ton. Secondly, the wheat and coffee green markets reacted differently to the two recent world price food crises: wheat showed two remarkable spikes in those years, while coffee green was not affected by the crisis in 2008 but only by that occurred in 2011. Thirdly, the internal standard deviation (red band width) suggests a higher degree of price discrimination in the wheat market. In particular France showed, mostly until 1996, a remarkable variation of prices around the mean, meaning that the price differed depending on the importer's identity. Fourthly, the range of variation of exporter prices (i.e., σ_{ext}, red band width) is larger in case of coffee green, that presents a higher magnitude of price dispersion. These findings are confirmed by Table B.1 in Appendix B.

The green line in Fig. 1 shows the "scaled out-degree" of each exporter j, that is the weighted number of active links, computed as (neglecting the time specification): $\eta_j = \sum_k^{N_M^j} \eta_{jk}$, where $\eta_{jk} = F_{jk}/F_{jk}^{max}$ and F_{jk}^{max} is the maximum amount of single trade from exporter j to its top importer k. Note that in case of the world, η is computed over the whole set of importers in the *IFTN*. This index puts a minor weight to importers with a little share of imports, so that the indicator η_j is always lower than the simple out-degree($\eta_j < N_M^j$), unless all the importers have the same share. Then, η_j identifies the number of main players in each market; indeed, if $\eta_j \simeq m$, independently of the actual number of active links of j, it entails that most of the bilateral trade from j is concentrated toward m big importers. The main difference among the two commodities appears in the global values: wheat is experiencing a remarkable increase in the number of relevant agents that goes up to almost 20 in 2013; while in the case of coffee the market is concentrated, with few countries (~5) that dominate the international trade (see Table B.1 in Appendix B).

3.2. Empirical Evidence

At this point it is worth to investigate the three types of variance defined in Section 3, as shown in Fig. 2.

The σ_{tot} of wheat (panel 2a) is stable from 1986 to 2006 when it sharply increased with two peaks in correspondence of the food crises occurred in 2008 and in 2011. Afterwards, it returns on a stable path but on a higher level, showing a higher total variance than in the pre-shock period. This outcome confirms that a sudden rise in price level increases the temporal volatility (von Braun and Tadesse, 2012), suggesting that during the crises the spatial variance should increase as well. In line with the literature of temporal volatility (Maurice and Davis, 2011), we observe that spatial price dispersion of the coffee green market was higher, with two peaks in 1997 (due to an increase in energy, raw materials, and payroll costs (Talbot, 2004)) and in 2011. A confirmation of the higher variability of coffee green market is given by the average (over time) coefficient of variation of bilateral prices $(\overline{CV}_{jk}^{T})$[15] which is higher for coffee (0.33) than for wheat (0.25). In both cases, this result entails that the *LOP* fails in these two markets, as confirmed by the first column of Table B.1. Over time, one would guess that arbitrage and the process of globalisation (increasing number of countries and transactions) should smooth the range of variation because of a higher possibility to access the international market. However, as observed here, the *IFTN* shows a persistent and remarkable range of variation of bilateral prices within the same year for the same kind of commodity.[16]

When looking at σ_{int} and σ_{ext}, it emerges that the former is always slightly higher than the latter (except for 2002) in case of wheat; while in case of coffee green the opposite consideration holds ($\sigma_{int} < \sigma_{ext}$), suggesting that the coffee market is more segmented (i.e., price dispersion). This observation is supported by the average (over time) coefficient of variation (see Table B.1 in Appendix B): the $\overline{CV}_{int}^{T}$ of wheat is higher than for coffee (0.19 and 0.15, respectively); while the opposite holds for the $\overline{CV}_{ext}^{T}$ (0.14 and 0.25, respectively). Our analysis allows one to disentangle price dispersion and price discrimination, that not necessarily come out jointly (Kaplan and Menzio, 2015; Yoskowitz, 2002). In case of coffee, price dispersion could be due to hidden quality and/or higher bargaining power. However, the former hypothesis is not supported by the *GLI* of coffee green which is considerably low (see Table 2). Then, the hypothesis of asymmetric bargaining power seems more plausible, as the presence of buying cartel strategy should demonstrate (Hernandez et al., 2017). Instead, in case of wheat price discrimination might be explained by dumping strategies; indeed, when looking at the scale number of main traders it appears that only few exporters ($\eta_{exp} \sim 4$) faced the whole demand composed by a large number of big importers ($\eta_{imp} \sim 13$), as shown in Table B.1 in Appendix B.

Regarding the other commodities, similar results hold in most of the cases. The main exceptions are represented by soy-beans, cocoa-beans, and potatoes that reported low variances. The key message is that, when the *LOP* fails, the goods show a persistent and remarkable spatial price variability over time ($\overline{CV}_{jk}^{T}$). If confirmed, our finding suggests that, in most cases, the average global price should not be seen as a representative indicator of the value of bilateral exchanges worldwide, in contrast with a price reductionist approach. Before discussing some causes of these findings, we are interested in exploring the price-formation mechanism. In particular, could the country-pair *price-formation mechanism* in the *IFTN* be reducible by deterministic models or the system is so complex that can be replicated by a stochastic process, at the country-scale level? In this respect, we investigate the price-formation mechanism through a statistical perspective, as described below.

4. Food Price Formation: A Statistical Approach

The failure of the *LOP* posits a new challenge on the selection of the scale of analysis (Bergin et al., 2013) and on how to model heterogeneous prices of food commodities at the country-pair scale. The main purpose of this section is to infer from data a possible price-formation mechanism able to reproduce the heterogeneity of bilateral prices observed in the *IFTN*. We face this problem from a purely statistic viewpoint. The main idea is to test whether the actual price distribution may or not be replicated by a stochastic process of extraction. One may expect rational and random decisions generate very different distributions. In contrast, demand-side rational behaviour can be obtained on average even if consumers choose in a random way (Moscati and

[14] All the results for the other commodities are shown in the Supplementary materials (*SM.2*), the key messages hold in each case.

[15] The coefficient of variation is given by the ratio between the standard deviation (σ_{tot}) and the mean ($\bar{P}$).

[16] See the Supplementary materials (*SM.2*) for a description of spatial price distribution for the other commodities.

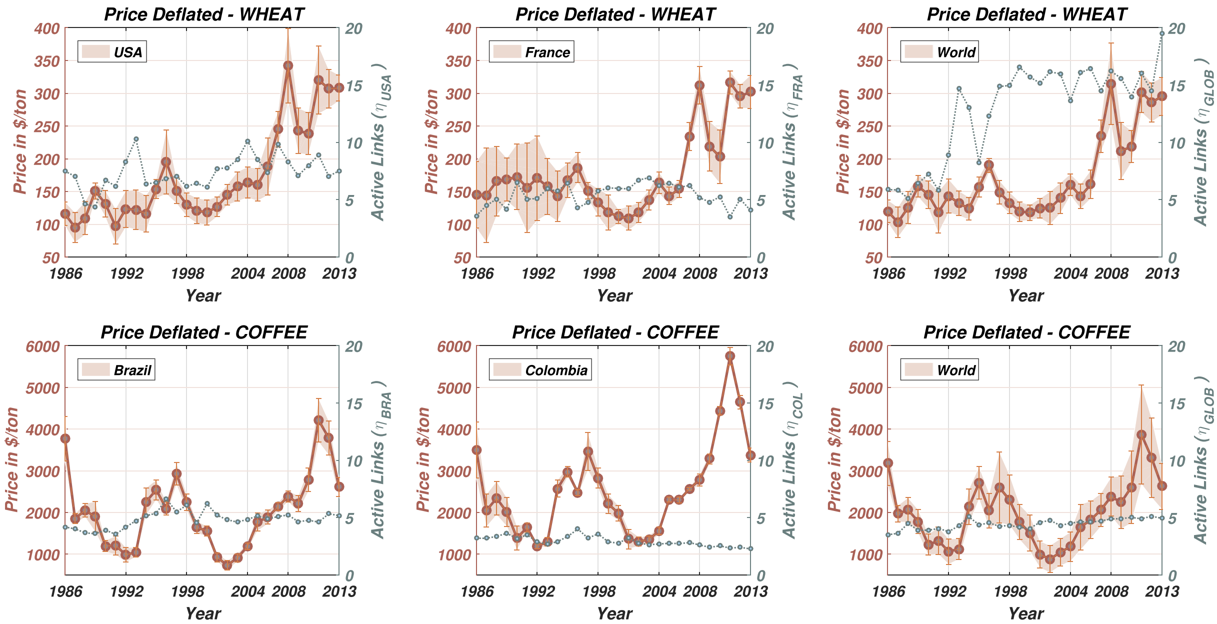
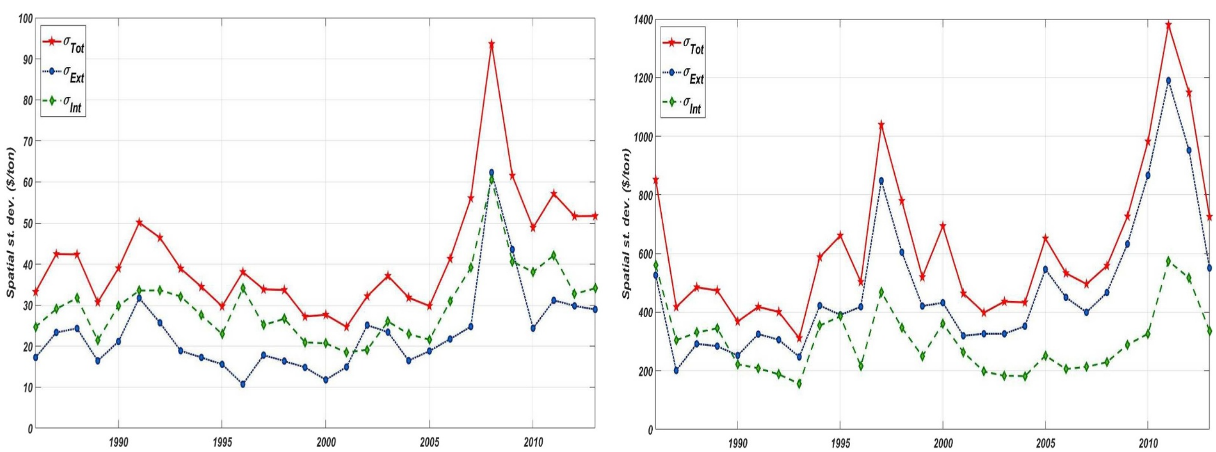


Fig. 1. Empirical time series of average price and variance. We report the average price – from 1986 to 2013 – of the top two exporters ($\bar{P}_j$) and global price ($\bar{P}$) for wheat (top) and coffee green (bottom). Red band width, around the red line, is proportional to the internal standard deviation of each country ($\sigma_{int,j}$), in case of single exporter, and to the external standard deviation in the global case (σ_{ext}). Green lines (right y-axes) are the 'scaled out-degree' (η).



(a) Wheat (b) Coffee

Fig. 2. Empirical time series of global spatial price dispersion. The graphs show, from 1986 to 2013, the square root of σ^2_{tot} (red line), σ^2_{ext} (blue line), and σ^2_{int} (green line) for (a) wheat and (b) coffee green.

Tubaro, 2011). Here we investigate the other way round, aiming at verifying whether a random distribution might emerge at higher scale of analysis in spite single choices of firms are (assumed to be) driven by rational decisions.

Before presenting the mathematical details, we briefly discuss the two key assumptions behind the process of random extractions that we test against real data, namely: (1) there exists a unique price distribution from which the prices are drawn, and (2) each country-level trade relation (F_{jk}) can be decomposed into homogeneous blocks of the same amount (in tons), representing the trade among firms. The logic behind our procedure is that the random sampling of the price distribution fixes the null hypothesis of the *stochastic versus deterministic* price formation: if the actual distribution (empirically measured) is similar to that of the null hypothesis we can conclude that – at the country level – there is no *collusive behaviour* from the buyers and/or sellers side. Section 4.2 shows that both conditions occur in the *IFTN* depending on the type of the commodity under assessment.

4.1. The Global Price Distribution

Here, we present the formal explanation of the statistical procedure to investigate the stochasticity of price distribution from our sample of foods. The available data include the bilateral price (P_{jk}, in $/ton) paid by the importer country k to the exporting country j. Clearly, P_{jk}, as well as the aggregate average values $\bar{P}_k$ and $\bar{P}_j$, will assume different values, depending on the specific countries considered. However, these empirical differences in price could be interpreted as the outcome of either specific price-formation mechanisms or sample variability of price.

We are therefore interested in defining a procedure to test

- the null hypothesis H_0: P_{jk} values are obtained by randomly sampling the price from a unique probability distribution;
- the alternative hypothesis H_1: *heterogeneities exist in the sampling procedure*, to say that the P_{jk} values have been sampled from different parent distributions.

If the null hypothesis turns out to be true, the price formation mechanism is a simple random sampling; otherwise, endogenous variables have an influence on the price formation (for example, export prices of a country are systematically larger than others because the cost of production in the country is higher than elsewhere).

Our understanding of the spatio-temporal price dynamics at the country-scale and our capacity to reproduce them are thus crucially determined by the test we are performing. However, formalizing a testing procedure is quite complicated, because price data refer to highly heterogeneous fluxes, which in turn impacts the statistical characterization of the price. For example, we expect a much higher sample variability of the price of a 10^2 tons flux compared to a 10^6 tons flux, because the latter is likely made up of a large number of smaller exchanges among the firms of the two countries (i.e., blocks), with random price fluctuations compensating with one another, thus reducing the variability of the aggregated price. We thus build up our testing procedure starting from the following ancillary assumptions:

(i) each edge F_{jk} is composed by a number N_{jk} of homogeneous blocks of size f (e.g., $f = 1000$ tons), representing the typical amount of food exchanged in a single economic transaction between two firms.[17] In formulas, $F_{jk} = f \cdot N_{jk}$ (the flux size is approximated to the closer multiple of f);

(ii) the price p of the block f is a *i.i.d* random variable with a distribution $g_{jk}(p)$. The distribution is the same for all blocks belonging to F_{jk}, but might be different for different fluxes;

(iii) the distribution $g_{jk}(p)$ is a Gamma distribution, with parameters θ_{jk} and λ_{jk}:

$$g_{jk}(p;\, \theta_{jk},\, \lambda_{jk}) = \frac{1}{\theta_{jk}^{\lambda_{jk}} \cdot \Gamma(\lambda_{jk})} \cdot p^{\lambda_{jk}-1} e^{-\frac{p}{\theta_{jk}}}. \tag{3}$$

Assumption (ii) corresponds to the hypothesis that price-formation is driven by a stochastic mechanism and that is not be present a collusive behaviour among agents. Note that price data are typically only available at the country scale, and thus these assumptions cannot be profitably verified with the available data. Verification of the null hypothesis H_0, however, entails an indirect verification of these ancillary assumptions too.

Under the assumptions (i)–(ii) the probability distribution of P_{jk} is obtained as the distribution of the average of N_{jk} independent random variables with common distribution $g_{jk}(p)$. Using the assumption (iv), and the fact that the sum of independent Gamma variables is again Gamma-distributed, one obtains$P_{jk} \overset{d}{\sim} \text{Gamma}[\theta_{jk}/N_{jk},\, N_{jk} \cdot \lambda_{jk}]$, where $\overset{d}{\sim}$ means 'distributed as'. Formally, the null hypothesis H_0 becomes$P_{jk} \overset{d}{\sim} \text{Gamma}[\hat{\theta}/N_{jk},\, N_{jk} \cdot \hat{\lambda}]$, namely $p \overset{d}{\sim} \text{Gamma}[\hat{\theta},\, \hat{\lambda}]$. Note that the subscripts have been dropped from the estimated parameters $\hat{\theta}$ and $\hat{\lambda}$ because we assume that they do remain the same for any considered couple of countries. Under H_0, the global parameters $\hat{\theta}$ and $\hat{\lambda}$ characterize, together with F_{jk}, the probability distribution of each and any of the food price at trade.

One can therefore calculate the probability value $q_{jk} = \gamma\left(\hat{\lambda},\, \frac{P_{jk}}{\hat{\theta}}\right)$ by calculating in P_{jk} the Gamma cumulative probability distribution with parameters $\hat{\theta}/N_{jk}$ and $N_{jk} \cdot \hat{\lambda}$. Under H_0 the q_{jk} values follow a uniform distribution, so that $q_{jk} \overset{d}{\sim} \text{Uniform}(0,\, 1)$.[18] Verification of H_0 can thus be performed through a standard uniform probability plot. If the points lie close to the bisector of the plot, the data are likely to be sampled from a uniform distribution, which in turns implies that the P_{jk} values are obtained by randomly sampling the single-block price from a unique global probability distribution, i.e. $p \sim \text{Gamma}(\hat{\theta},\, \hat{\lambda})$. We repeat the same procedure at a higher scale by including the average importing and exporting prices (see Appendix A for the mathematical details).

In summary, our randomness test is based on the following steps:

1. estimating the spatial price dispersion associated to each block (N_{jk}) and the aggregate spatial variance of the unique distribution of bilateral prices ($\hat{\sigma}_{tot}^2$);
2. estimating the cumulative probability (q) as if the bilateral prices were randomly picked from the unique global distribution;
3. repeating the same analysis for the aggregate level of import ($\bar{P}_k$) and export ($\bar{P}_j$) It allows us to verify the presence of asymmetric information among buyers and sellers;
4. performing a cross-commodity comparison of the actual distribution of prices with the one emerging from a random extraction.

4.2. Cross-commodity Comparison

Here we discuss the graphical results of testing randomness against causality in the distribution of prices per ton for all the ten commodities. Fig. 3 shows the cumulative[19] probability of q against the cumulative market share, that is the weight of each edge (composed by N_{jk} blocks). Given the stability of results over time, and in order to obtain a larger sample, we pool the results of all years together. For the sake of clarity, we recall that if the observed prices were actually extracted from the unique Gamma distribution, then it must be that the cumulative distribution of q is a Uniform(0,1), lying close to the bisector (black line). Hence, we compare the actual cumulative distribution of q (coloured lines) with the bisector, to assess if the distribution can be described by a stochastic process (at the macro-scale).

For the sake of clearness, we split the ten commodities in two categories: those that are well described by a stochastic process of extraction (top) and the others (bottom). This distinction is based on bilateral prices, although in some cases the results from importer and exporter side might differ. Based on the cross-commodity comparison, we found that in half of the cases (wheat, rice, soy-bean, honey, and eggs) the distribution of *bilateral* prices is well replicated by the process of random extraction from the global distribution, since the curves are close to the bisector. In the other cases, we observe a S-shaped curve, with either an under-estimation (cocoa beans and potatoes) or an over-estimation (coffee green and apples) of the variance.

When looking at the *importer* side, we observe that the price distributions of the first item category is still well approximated by the stochastic process in three cases (wheat, soy-beans, and rice), while honey shows a fatter lower tail and eggs have a distorted (non-randomic) price distribution. In the second item category, all the commodities continue to follow a systematic distorted (non-randomic) behaviour, with the exception of cocoa beans, whose distribution is well approximated by a random extraction. From the *exporter* side the picture changes and, in general, the prices do not seem to adhere in a satisfying way to the null hypothesis of a unique parent distribution.

[17] Indeed, the bilateral flow (F_{jk}), from an exporter (e.g., the USA) to an importer (e.g., Italy), is the overall sum of all the transactions occurred among the *firms* of the two countries. For example, if the USA sells 30,000 tons of wheat to Italy, then we assume that this bilateral flow is formed by, say, 30 single blocks, 'as if' 30 Italian firms are buying 1000 tons each from the American ones. Moreover, it can be shown that the block size does not alter the outcome from the random extraction.

[18] Note that our statistical procedure is mean-preserving because we compute the q probability for each observed price (computed for bilateral, importing, and exporting prices). What differs is the total spatial variance that provides us with the information about the randomisation of the prices observed, under H_0.

[19] The cumulation is based on market share. Indeed, for each value of q_{jk} we know the flow associated (F_{jk}) and the fraction with respect to the total trade (F_{jk}/F_{tot}). Then, we cumulate the percentage of trade associated to each value of q.

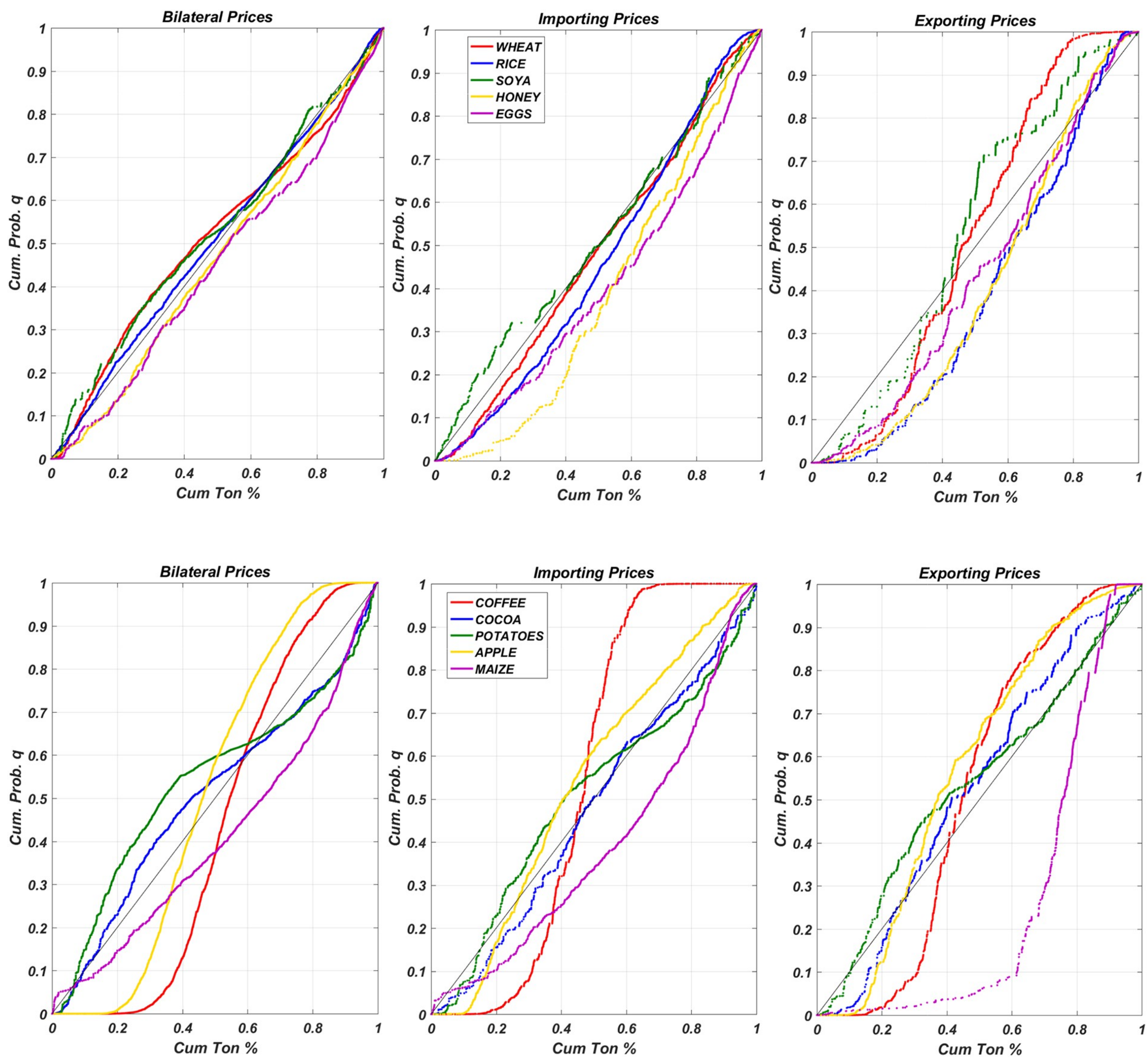


Fig. 3. Uniform probability plots, for all years pooled together, for all commodities. Left, center, and right panels refer to bilateral, aggregate import, and aggregate export, respectively. When the empirical points (coloured lines) lie close to the bisector (black straight line), price formation is well replicated by a stochastic process.

The differences observed between the importer and exporter side might be due the fact that the buyers have less information or a minor chance to properly compare all the alternatives (due to cost of research, time constraints, geographical and cultural distance, and so on), then showing a random behaviour at the country-level scale (macro).

Notably, the asymmetry between the import and export price distribution is confirmed by the recent literature (e.g., Gouel, 2016). Since staple food prices has positively skewed distributions (Deaton and Laroque, 1992), with more prices below than above the mean, then an exporting country has a greater incentive to deviate from a cooperative trade policy and to implement collusive behaviours, leading to a non-randomic distribution at the macro-scale.[20] The differences observed in the price distribution should not be simply reduced to the specific network properties of each item, because the commodities that fall in the first (random) and second category share common network features (see Table B.1 in Appendix B). In what follows we discuss some economic and environmental factors that play a role in the interpretation of these surprising outcomes.

5. Discussion

Here, we discuss the main factors that might affect the interpretation of our results, by including what emerged from Table 2.

(*I*) **Scale of analysis**. Our study, as most of the literature, is based on country (macro) level data that aggregate all the information related to the firms' behaviour (micro), which we are "mimicking" by decomposing the weight of each edge in many (identical) blocks of trade. Complex systems, as *IFTN* is, show the emergence of different properties when they are observed at different scales (Georgescu-Roegen, 1993; Malghan, 2010). In the current study, the emergent stochastic behaviour (at the macro scale) might be due to a complex interaction between firm's strategies (micro scale) and other extra-economic factors (policy reforms, environmental constraints, and so on). These results have relevant consequences in terms of modelisation and data collection: when the system does not present signals of complex behaviours and the *LOP* holds, then a price reductive analysis (based on average global prices) might still be meaningful and the data aggregation should not generate biased

[20] Note that, the presence of randomness tends to reduce when we move from the bilateral to the importer- and exporter-side. This might be due to a higher level of aggregation that reduces the number of observations.

results. In contrast, when micro-level structures interact in a complex way, the macro analysis can be useful per se but great caution is necessary to transfer processes detectable at the macro scale to the micro scale. The cross-commodity differences suggest a case-specific analysis on the possibility of the micro-foundation of the macro structure and dynamics of a specific market.

(*II*) **Market structure**[21] **and vertical price transmission** from farmers to retailers. Recent studies showed the relatively minor role played by food price in the world trade growth of food commodities (Serrano and Pinilla, 2010) due to the little value added in final production (Kim and Ward, 2013). In our context, farm-to-retail gap and imperfect vertical price transmission can explain the different results, in terms of stochastic distribution and price dispersion. From the importer side, many factors might determine a stochastic distribution at the macro-scale: (a) high farm-to-retail gap (Anania and Nisticò, 2014), (b) high price change frequency in food markets (Bils and Klenow, 2004), and (c) high consumers' search costs (Vavra and Goodwin, 2005). From the exporter side, the first column of Table 2 shows that, in all the cases (with the exception of eggs), the production price is weakly correlated with the exporting price suggesting that mark-up strategies might have an important role (Mayer et al., 2014; De Loecker et al., 2016).

(*III*) **Hidden quality**: in our case, other than the indication of the *HS*2017 (Table 1), we computed the Grubel-Lloyd index (third column of Table 2). It is low for the four major crops and coffee green, while it attains higher values for the animal derivatives, apple, and potatoes. Then, in the latter cases, hidden quality might explain the emergence of market niches and price discrimination (i.e., high $\overline{CV}_{int}^{T}$). However, we remark that this indicator might be biased in case of raw-food commodities because the possibility of exporting a good is strictly tied with the geographical and land characteristics that allow (or impede) the production of specific types of food. Indeed, the *GLI* is higher when the average distance of exchange is low, and *vice versa*, meaning that it includes information also on trans-boundary agreements, other than different quality (this might explain the behaviour of the potatoes market, which represents an exception).

(*IV*) **Counter-cyclical policy** intervention to stabilize the domestic food price (importer strategy) or to grasp higher price (exporter strategy). This implies that exporters may impose restrictions to obtain higher prices to importers, and conversely importers may limit the impact of low prices on their economy by applying tariffs. The asymmetric nature of the distributions of food commodity prices, with more prices below than above the mean but with occasional spikes (Gouel, 2016), might generate a series of un-coordinated country-level policies. Finally, the low correlation between bilateral price and geographical distance (column five of Table 2), might be a clue of international (bi- or multi-lateral) agreements, international aids, or import subsidies (Martin and Anderson, 2011).

(*V*) **Resource management and sustainability:** the failure of *LOP* and the complexity of the *IFTS* might undermine the key assumption that food prices reflect the scarcity of the natural resources used in the overall food production chain. In other words, our findings question whether food prices correctly include all the relevant information about the resources used (e.g., water, land, energy) and the potential damages (for instance due to pesticide and fossil fuels) along the whole food supply chain. If not, theoretical methodologies and policy decision making exclusively based on market reductionism (single indicator based on price) might lead to misleading choices, thus exacerbating environmental stress. These concerns are not just an academic curiosity, rather a vast literature is showing that climate change, land scarcity, and water stress might further constraint future food production (D'Odorico et al., 2018). A classical example of underestimated resource is water that, differently from other factor of production, has almost no impact on the pattern of exports (Sexton, 2012). The main cause is that water has usually a low (or null) economic value, and where it is scarce its pricing is not always clear and efficient (Debaere, 2014).

6. Conclusion

The current study focused on two relevant issues (i.e., spatial price dispersion and stochastic price distribution) that are, to the best of our knowledge, unexplored in the literature, but that provide a novel approach to the analysis of food price volatility. The first part was devoted to the evaluation of the *LOP*. In summary, the key findings are as follows:

(i) the spatial bilateral price dispersion (σ_{tot}) is large and persistent over time, implying that the *LOP* fails in most of the cases;
(ii) the distinction between the internal and external variability allows one to get insights about the *price discrimination* and *price dispersion*, respectively;
(iii) there is a strict correlation between price spikes and peaks in spatial σ_{tot} in most of the cases. It entails that during price crises the market is more fragmented and more opportunities for price discrimination (e.g., dumping strategy) might emerge.

Studying spatial price dispersion has noteworthy consequences, among other things, on the assessment of shock propagation. Methodologically, our approach is complementary with the current food price literature that defines a food crisis in correspondence of a price spike. However, we observed that if one had looked only at the global average price one would have not properly identified which countries were actually experiencing price spikes (mostly developing countries). Hence, price discrimination combined with the failure of the *LOP* might affect the mechanism of shock propagation during food crises, with asymmetric patterns. This observation might support the counter-cyclical political decision of developing countries – that are more sensible to price variations, since they show high income and price elasticities for staple foods (Cornelsen et al., 2015) – to mitigate adverse effects on domestic prices (Zorya et al., 2012). The take-home message is that there is no one-fits-all solution for all the countries; rather, future research might benefit from the inclusion of price spatial dispersion.

The second part of the current study was related to the issue of *randomness* in food price distributions at the country-scale. Our test indicated that, at the macro-scale (with no information on firms' strategy) the distribution of bilateral and importing prices (in half of the cases under assessment) were well replicated by a stochastic process of extraction, in half of the cases. This result has important consequences: first, the stochastic distributions (when observed) include both rich and poor countries, meaning that bargaining power, at least from the importing side, is not related to the level of affluence. Second, future models on price formation (at the macro-scale) should be product-specific and they should take into account the stochastic nature of the price formation mechanism (in some specific food commodity markets). In fact, since our results are time-independent, the presence of randomness entails that, predicting the future values of global mean and spatial variability, one can reconstruct the future distribution of bilateral prices.

Finally, high spatial food price variability and the presence of complex (and stochastic) behaviour suggest that price signals might not be always reliable. If so, the methodological and policy implications might have effects beyond food markets, involving resource management. Indeed, the price index might not correctly gather all the information about resource scarcity and exploitation. Thus, a deeper comprehension of the linkages among value, scarcity, and price is

[21] See Distefano et al. (2018a) for a detailed analysis of international food market structure.

required to properly address the complex interactions among food, energy, water, and climate change and to provide accurate evaluations of ecological systems.

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Appendix A. Mathematical Details of the Randomness Test

Here we describe the mathematical details that stand behind the construction of the randomness test, as explained in Section 4. In particular, we show how we estimate: (i) the parameters of the unique global Gamma distribution ($\hat{\theta}$, $\hat{\lambda}$), (ii) the moments of the distribution of each trade block (between firms), to say the mean (ψ_p) and the variance ($s^2_{\psi_{jk}}$), (iii) the moments of the unique global distribution, to say the mean (ψ) and the variance (s^2), and (iv) the probability density (q) associated to each price extraction.

The relations between parameters and moments for the Gamma distribution are

$$\theta = \frac{\sigma_p^2}{\mu_p} \qquad \lambda = \frac{\mu_p^2}{\sigma_p^2} \tag{A.1}$$

where μ_p is the average price of a block and σ_p^2 is its variance. Estimators of μ_p and σ_p^2 are obtained by considering that we may imagine the available data as belonging to a unique global sample of N_{tot} values of p, where

$$N_{tot} = \sum_j^{N_E} \sum_k^{N_M} \frac{F_{tot}}{f} \tag{A.2}$$

where F_{tot} is the total quantity traded in a year worldwide. The global sample is in turn made up of sub-samples of different size, where each sub-sample contains the same value, P_{jk}, repeated for N_{jk} times.

A different estimator of μ_p and σ_p^2 can be obtained from each sub-sample. The estimator of μ_p from the (j,k) sub-sample is $\psi_{jk} = P_{jk}$. A global estimator can be obtained as the weighted average of the sub-sample estimators, where the weight is the size of the sub-sample (larger samples produce more accurate estimators and should be provided with a larger weight):

$$\psi_p = \frac{1}{N_{tot}} \sum_j^{N_E} \sum_k^{N_M} N_{jk} \cdot \psi_{jk} = \frac{1}{N_{tot}} \sum_j^{N_E} \sum_k^{N_M} N_{jk} \cdot P_{jk} = \frac{1}{F_{tot}} \sum_j^{N_E} \sum_k^{N_M} P_{jk} \cdot F_{jk} \tag{A.3}$$

The variance of ψ_{jk} about the global average is $(P_{jk} - \psi_p)^2$ and can be related to the variance of a block in the sub-sample, s^2_{jk}, by the relation $s^2_{\psi_{jk}} = s^2_{jk}/N_{jk}$, which holds because ψ_{jk} is the average of N_{jk} independent elements. The estimator of σ_p^2 from the (j,k) sub-sample is thus $s^2_{jk} = N_{jk}(P_{jk} - \psi_p)^2$. A global estimator can be obtained again as the weighted average of the sub-sample estimators,

$$s^2 = \frac{1}{N_{tot}} \sum_j^{N_E} \sum_k^{N_M} N_{jk} \cdot s^2_{jk} = \frac{1}{N_{tot}} \sum_j^{N_E} \sum_k^{N_M} N^2_{jk} \cdot (P_{jk} - \psi_p)^2 = \frac{1}{f \cdot F_{tot}} \sum_j^{N_E} \sum_k^{N_M} F^2_{jk} \cdot (P_{jk} - \psi_p)^2 \tag{A.4}$$

The method-of-moments estimators of θ and λ, $\hat{\theta}$ and $\hat{\lambda}$, are obtained by setting $\mu_p = \psi_p$ and $\sigma_p^2 = s_p^2$. The last step toward the verification of the hypothesis H_0 entails using the information that, under H_0, $P_{jk} \overset{d}{\sim} \text{Gamma}(\hat{\theta}/N_{jk}, N_{jk} \cdot \hat{\lambda})$. One can therefore calculate the probability value $q_{jk} = \gamma\left(\hat{\lambda}, \frac{P_{jk}}{\hat{\theta}}\right)$ by calculating in P_{jk} the Gamma cumulative probability distribution with parameters $\hat{\theta}/N_{jk}$ and $N_{jk} \cdot \hat{\lambda}$, as

$$q_{jk} = G(P_{jk}; \hat{\theta}, \hat{\lambda}) = \int_0^{P_{jk}} g(P_{jk}; \hat{\theta}, \hat{\lambda}) du \tag{A.5}$$

Note that $\hat{\theta}$ scales with $1/f$ and $\hat{\lambda}$ scales with f; as a consequence, both $\hat{\theta}/Njk$ and $Njk \cdot \hat{\lambda}$ are independent of f, which means that the procedure produces the same results for any value of f.

Under H_0 the q_{jk} values follow a uniform distribution (because Eq. (A.5) is a probability integral transform), then $q_{jk} \overset{d}{\sim} \text{Uniform}(0, 1)$. Verification of H_0 can thus be performed through a standard uniform probability plot. If the points lie close to the bisector of the plot, the data are likely to be sampled form a uniform, which in turns implies that the P_{jk} values are obtained by randomly sampling the single-block price from a unique global probability distribution, $p \sim \text{Gamma}(\hat{\theta}, \hat{\lambda})$. We repeat the same procedure at a higher scale by including the average importing and exporting price.

To summarise, in the three cases we need to compute the incomplete gamma function as follows:

(i) $q_{jk} = G(P_{jk}; \hat{\theta}, \hat{\lambda})$ for bilateral trade, where

$$\hat{\sigma}^2_{jk} = \hat{\sigma}^2_{tot} \cdot \frac{f}{F_{jk}} \qquad \hat{\theta}_{jk} = \frac{\hat{\sigma}^2_{jk}}{\psi_p} \hat{\lambda}_{jk} = \frac{\psi_p^2}{\hat{\sigma}^2_{jk}} \tag{A.6}$$

(ii) $q_k = G(P_k; \hat{\theta}_k, \hat{\lambda}_k)$ for the importer side, where P_k is the average *importing* price of country k:

$$\hat{\sigma}^2_k = \hat{\sigma}^2_{tot} \cdot \frac{f}{F_k} \qquad \hat{\theta}_k = \frac{\hat{\sigma}^2_k}{\psi_p} \qquad \hat{\lambda}_k = \frac{\psi_p^2}{\hat{\sigma}^2_k} \tag{A.7}$$

(iii) $q_j = G(P_j; \hat{\theta}_j, \hat{\lambda}_j)$ for the importer side, where $\bar{P}_j$ is the average *exporting* price of country *j*:

$$\hat{\sigma}_j^2 = \hat{\sigma}_{tot}^2 \cdot \frac{f}{F_j} \quad \hat{\theta}_j = \frac{\hat{\sigma}_j^2}{\psi_p} \quad \hat{\lambda}_j = \frac{\psi_p^2}{\hat{\sigma}_j^2} \tag{A.8}$$

Appendix B. Empirical Evidence of Spatial Variability: All Commodities

In addition to the indicators computed in Section 3, we also present the results from the *temporal* variability of the yearly average price set by every exporter *j*. It is computed as the weighted standard deviation from the yearly average exporting price ($\bar{P}_j(t)$):

$$\sigma_{T,j}^2 = \sum_t^T (\bar{P}_j(t) - \bar{P}_{T,j})^2 \cdot \frac{F_j(t)}{F_{tot,j}},$$

where T is the overall time span (viz. 28 years), $\bar{P}_{T,j}$ is the average price of the *j*-th exporter during the time span, and $F_{tot,j}$ is the overall amount of exports from *j* during the entire period. The distribution of $\sigma_{T,j}^2$ provides further information about the external variability and the market competitiveness. Indeed, if most of the $\sigma_{T,j}^2$ values are concentrated within a narrow range, it follows that most of the exporters set a price close to each other over time. Conversely, a spread distribution implies that exporters can set different prices, suggesting (among other things) hidden quality (within the same category of commodity) that allows the creation of market niches. The right panels show the empirical distribution of the weighted standard deviation in the average price set by each exporter in the whole time span.

Table B.1 summarises the main outcomes for the other commodities (all the corresponding figures are shown in the Supplementary materials *SM.2*). In every cases (but potatoes) the average global price increased substantially over time.[22] In case of apple, honey, and eggs we observe that $\bar{CV}_{ext}^T > \bar{CV}_{int}^T$, which might be to hidden quality (as confirmed by high level of their *GLI* in Table 2) which can allow the emergence of market niches differentiated by quality. We also compute $\bar{CV}(\sigma_{int,j})$ as the product-specific average coefficient of variation of the internal variability of all the exporters ($\sigma_{int,j}$). In case of wheat it is low, showing that exporters follow similar strategy for price discrimination (or dumping strategy). The number of 'relevant' traders from both the exporter- (η_{exp}) and importer-side (η_{imp}) are extremely low, meaning that only few countries (around 3–4) are dominating the *IFTN*, with the exception of wheat and rice that show higher values ($\sim$ 13) from the importer-side. Moreover, the 'scaled' number of edges (η_{tot}) differs: in some cases most of the trade is concentrated in few links (about 6, for soy-beans, eggs, maize), while in other cases we find higher values (apples, coffee green, rice, and wheat, about 20).

Table B.1
Cross-commodity summary of spatial price dispersion. $\bar{CV}^T$ is the average coefficient of variation in the whole period computed on total (*jk*), external (ext), and internal (int) variances. CV_{tau} is the average temporal variances of exporting prices. In brackets, it is specified whether the distribution is concentrated around the mean ('con.') or not ('spread'). η is the average (over time) scaled degree – for the overall number of (relevant): links (η_{tot}), exporters (η_{exp}), and importers (η_{imp}), and $\bar{CV}(\sigma_{int,j})$ is the product-specific cross-country comparison of the selling strategy variability.

Item	$\bar{CV}_{jk}^T$	$\bar{CV}_{ext}^T$	$\bar{CV}_{int}^T$	$\bar{CV}(\sigma_{int,j})$	η_{tot}	η_{exp}	η_{imp}	$\bar{CV}_\tau$
Maize	0.42	0.26	0.27	0.18	6.9	2.1	5.7	0.37 (con.)
Wheat	0.25	0.14	0.19	0.09	23.2	4.3	13.3	0.38 (con.)
Soy-beans	0.16	0.08	0.11	0.07	6.6	2.1	3.4	0.40 (con.)
Rice	0.49	0.32	0.32	0.19	20.2	3.3	13.5	0.39 (con.)
Apples	0.46	0.34	0.28	0.12	19.9	6.9	6.8	0.30 (spread)
Potatoes	0.16	0.07	0.10	0.09	10.7	4.8	6.2	0.07 (con.)
Honey	0.58	0.37	0.33	0.08	10.5	4.2	3.8	0.43 (spread)
Eggs	0.69	0.45	0.42	0.13	5.4	3.6	4.0	0.31 (spread)
Cocoa beans	0.20	0.12	0.12	0.31	10.1	2.9	4.4	0.38 (con.)
Coffee green	0.33	0.25	0.15	0.29	19.2	4.3	4.5	0.39 (spread)

Last but not least, each category of food showed a persistent and not decreasing high spatial price heterogeneity over time ($\bar{CV}_{jk}^T$), confirming that the average global price is not a representative indicator of the value of bilateral exchanges when the *LOP* fails.

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolecon.2019.01.010.

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[22] See the Supplementary material for the graphical representation of the distribution of σ_j^T for each commodity.

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