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How do environmental shocks affect competitors in a supply chain? Evidence from a competitors' weighting matrix[*]

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Abstract

Quantifying the impact of supply shocks on global commodity trade networks is an increasing concern for researchers under the current threats of climate change and the lessons from the COVID-19 pandemic. This paper proposes a novel methodology to estimate these effects across the entire trade network: we create a weight matrix based on an index that captures the extent to which two coffee-producing countries compete within consumer markets. Using this matrix, we estimate the degree to which an adverse weather shock in a coffee-producing country influences the coffee production of its competitors. Our results show that this adverse shock has a negative direct effect on the country's coffee exports and, importantly, a positive effect on the quantities produced by its competitors.

Keywords: coffee, frosts, supply shocks, weighting matrix, spatial spillovers.

JEL Classification: E23, F1, Q02, Q17, Q56.

[*] The authors are grateful to Jaime Bonet, Karina Acosta and Gerson Pérez for their comments and suggestions.

¿Cómo afectan los shocks ambientales a los competidores en una cadena de suministro? Evidencia a partir de una matriz de competidores*

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Resumen

Cuantificar el impacto de los choques de oferta en las cadenas mundiales de comercio de productos básicos es una preocupación cada vez mayor para los investigadores ante las amenazas actuales del cambio climático y las lecciones de la pandemia del COVID-19. Este artículo propone una metodología novedosa para estimar estos efectos en toda la red comercial: creamos una matriz espacial de competidores basada en un índice que captura el grado en que dos países productores de café compiten dentro de los mercados de consumo. Utilizando esta matriz, estimamos el grado en que un choque climático adverso en un país productor de café influye en la producción y exportación de café de sus competidores. Nuestros resultados muestran que este choque adverso tiene un efecto directo negativo sobre las exportaciones de café del país y, más importante aún, un efecto positivo sobre las cantidades producidas por sus competidores.

Palabras clave: Café, heladas, choques de oferta, matriz de pesos espaciales, difusión espacial.

Clasificación JEL: E23, F1, Q02, Q17, Q56.

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1. Introduction

Quantifying the impact of supply shocks on global commodity trade networks is an increasing concern for researchers under the current threats of climate change and the COVID-19 pandemic in increasingly interconnected supply chains (Anderson, *et al,* 2016). These threats are even more significant in the case of agricultural supply chains, as crops are negatively affected by extreme and erratic weather conditions and agricultural products are perishable. In this paper, we study the case of the coffee supply chain, one of the most traded agricultural commodities, to empirically identify the effect of weather shocks on trade networks, and to answer the question: How does a negative weather shock in a competitor country impact the production and exports of coffee in a coffee-producing country?

The negative direct effect of adverse weather conditions has already been shown by several empirical studies. These studies have found that higher-than-usual temperatures negatively affect productivity (Nordhaus, 2006; Sayon *et al*., 2023), labor income (Dell, Jones & Olken, 2008; Partridge *et al.,* 2017), and exports (Jones & Olken, 2010; Li *et al.,* 2015) within countries affected by weather shocks. Kuwayama *et al.* (2019) find that droughts reduce crop yields in the U.S. but have no effect on farmers' income, as well as Birthal *et al*. (2015), who find that droughts significantly affect rice yields in India. The indirect effects of adverse weather conditions have been studied in the dyadic relationship between exporter and importer countries. For example, Dallman (2019) finds that temperature variations in the exporting country have a negative impact on bilateral trade and Ayala *et al*. (2022) show that floods and landslides in trading partners can affect local tax revenue. In the case of coffee, adverse weather conditions have been found to have a direct impact on productivity (Ceballos-Sierra & Dall'erba, 2021).

However, the indirect effect on competing countries has largely been ignored by these studies, which fail to recognize the interdependence between seemingly unrelated countries as they belong to interconnected supply chains (Fold, 2014). This could lead to biased estimates of the impact of climate change on global trade, as negative direct impacts of adverse weather conditions on the dyadic relationship between exporter and importer might be offset by increased production coming from competing countries as information is transmitted via prices (Lybbert *et al.,* 2014).

Further development in this literature has used shock propagation models to study supply networks beyond dyadic relationships. By simulating shocks across networks based on historical bilateral trade, they have shown that negative economic, environmental, and political shocks propagate through the supply networks singling out developing countries (Distefano, et al., 2021) and countries that are net importers or that import from more regions (Gephart, et al., 2016) as more susceptible to absorb the trade shocks.

We try to fill this gap in the literature by developing a novel weight matrix that captures the extent to which two countries, i and j, are competitors in the same supply network, in this case, the coffee supply network. We start by defining the potential demand of country i as the volume of coffee that all its competitors place in those markets where i sells coffee in any given year t. Then, to construct each competitor index, w_{ijt}, we look at the share of country j's predicted exports of country i's predicted potential demand. If country j is a fierce competitor of country i, our competitor index will approach 1, and 0 otherwise. We then estimate a spatial model, and through the competitor matrix, explore the spillover effect of adverse weather shocks on a country j over the production and export volume of country i. The results show that local frosts do not have a significant effect on local coffee production, exports, consumption, and stocks, while the frosts in competing countries have a positive effect on local coffee outcomes, both current and one-year lagged frosts.

These results imply that trade has the potential to compensate for the negative consequences of natural disasters. Countries seem to benefit from extreme weather shocks in competing economies. We believe that these results extend to other supply chains as anecdotal evidence seems to suggest. For instance, oil production by OPEC members has expanded since Russia's invasion of Ukraine and ensuing sanctions by Western countries[1]. Similar effects have been observed in the wheat market.[2] Future work will investigate how permanent these shifts in the supply chain are.

The outline of the paper is as follows: Section 2 presents an overview of the coffee trade network. Section 3 describes the methods used in building the competitor matrix and

[1] https://edition.cnn.com/2022/06/02/energy/oil-prices-opec-russia/index.html
[2] https://www.spglobal.com/commodityinsights/en/market-insights/latest-news/agriculture/060722-india-may-allow-up-to-500000-mt-of-wheat-exports-soon-in-second-tranche-since-ban

conducting the empirical estimations, as well as the data, and displays the descriptive statistics. Section 4 presents the results of the estimations. Finally, section 5 concludes and discusses the policy implications and the limitations of this study.

2. The coffee trade network

Coffee is one of the major commodities on the world market with around 75% of the production being exported in the 2018/2019 coffee year. World coffee exports have trended upwards over the period 1980-2009, rising from 3,7 million tons in 1980 to 9,3 million tons in 2009 (FAO, 2022). In 2016, five exporting countries accounted for 63.5% of total world exports from producing countries, with the largest exporters of coffee being Brazil (39.15%), Vietnam (34.22%), Colombia (14.95%), Indonesia (8.23%), and Ethiopia (3.45%). Brazil has increased its export levels during the period 1980-2019, dominating the market and maintaining adequate levels of competitiveness due to low production costs and its specialization in the robusta variety (FAO, 2022).

Similarly, five countries accounted for 57.7% of the total volume of coffee imports, with the main importers being the United States (20.8%), Germany (17.4%), Italy (7.6%), Japan (6.8%), and Belgium (5.2%). In relation to the imports of coffee in tons, an upward trend is observed between 1980 and 2009: imports surged from 3,713 thousand tons (t) in 1980 to 6,045 thousand tons (t) in 2009 (FAO, 2022). According to the International Coffee Organization (ICO), Europe accounted for 36.0% of world coffee consumption, North America 19.2%, South America 17.5%, Asia and Oceania 15.1%, Mexico and Central America 7.2%, and Africa 5.1%. The United States is the largest consumer with approximately 21.4 million bags per year, followed by Brazil (18.4 million), Germany (8.9 million), Japan (7.1 million), and Italy (5.8 million). The market concentration is also seen across private roasters. In fact, few transnational corporations control more than three-quarters of the world's coffee trade. These are Neuman Kafee (Germany), Volcafé (Switzerland), Cargill (United States), Esteve (Brazil-Switzerland), Aron (United States), Ed&F Man (United Kingdom), Dreyfus (France), and Mitsubishi (Japan), which control about 56% of the world market (Roldán, González and Salazar, 2003). Table 1 shows the market share of coffee producer countries for the 2019-2020 year.

Table 1. Market share of coffee producer countries. 2019/2020 Coffee year

Country	Species*	Market share (%)	Country	Species	Market share (%)
Brazil	(A/R)	35.27	Burundi	(A/R)	0.17
Viet Nam	(R/A)	18.47	Cameroon	(R/A)	0.16
Colombia	(A)	8.54	Guinea	(R)	0.11
Indonesia	(R/A)	6.93	Cuba	(A)	0.08
Ethiopia	(A)	4.45	Panama	(A)	0.07
Honduras	(A)	3.59	Timor-Leste	(A)	0.06
Uganda	(R/A)	3.34	Yemen	(A)	0.06
India	(R/A)	3.02	Bolivia	(A)	0.05
Mexico	(A/R)	2.41	The Central African Republic	(R)	0.03
Peru	(A)	2.32	Angola	(R/A)	0.03
Guatemala	(A/R)	2.18	Nigeria	(R)	0.03
Nicaragua	(A)	1.75	Togo	(R)	0.02
Côte d'Ivoire	(R)	1.17	Sierra Leone	(R)	0.02
Costa Rica	(A)	0.89	Sri Lanka	(R/A)	0.02
Tanzania	(A/R)	0.56	Jamaica	(A)	0.01
Kenya	(A)	0.51	Paraguay	0	0.01
Papua New Guinea	(A/R)	0.46	Malawi	(A)	0.01
El Salvador	(A)	0.40	Zambia	(A)	0.01
Venezuela	(A)	0.39	Ghana	(R)	0.01
Lao PDR	(R)	0.38	Trinidad & Tobago	(R)	0.01
Ecuador	(A/R)	0.34	Guyana	(R)	0.01
Thailand	(R/A)	0.31	Zimbabwe	(A)	0.01
Dominican Republic	(A/R)	0.24	Liberia	(R)	0.00
Democratic Republic of Congo	(R/A)	0.24	Congo	(R)	0.00
Madagascar	(R)	0.23	Nepal	(A)	0.00
Rwanda	(A)	0.21	Gabon	(R)	0.00
Haiti	(A)	0.21	Equatorial Guinea	(R)	0.00
Philippines	(R/A)	0.19			

Source: Authors' calculations based on the International Coffee Organization. Historical Data on the Global Coffee Trade. Total production. Retrieved from: https://www.ico.org/new_historical.asp. *A=Arabicas, R= Robustas.

In terms of per capita coffee consumption, The U.S. Food and Drug Administration shows relatively low domestic consumption of 4 to 6 Kg/person/year. In Europe, the largest consumers of coffee, in per capita terms, are in the Nordic countries with consumption ranging between 10 and 12 kg/person/year. They are followed by the Netherlands and Austria (8 to 10 kg/person/year) and Belgium and Germany (6 to 8 Kg/person/year). The influence of the West on Asian coffee consumption has been important; long-term trends show an increase in consumption in the market of Japan, Asian tigers (especially Hong Kong and Singapore), and China, despite competition from tea (J.Ganes Consulting, 2010).

In general, the increase in coffee consumption is not believed to be caused by decreases in price, given that the price elasticity of coffee demand is low and changes in coffee demand are mostly explained by changes in the population structure and preferences (Durevall, 2007; Grabs and Ponte, 2019). In addition, it has been shown that there is a close relationship between the growth in the income of OECD (Organization for Economic Development and Cooperation) countries and the increase in coffee imports. Coffee consumption is insensitive to income differences between individuals in the same country (Cartay and Ghérsi, 1996).

The world price of coffee is established in accordance with the conditions of supply and demand of the item on the world market; like other commodities, it is characterized by its volatility. Since there are different types of coffee, the ICO established a price system in 1965 to reflect the general or compound price of the different types of coffee, namely: soft Colombian Arabicas; other soft Arabicas; Brazilian Arabicas; other natural and robust Arabicas. Since 2000, the price of coffee is calculated with the average of the indicative prices of the groups, weighted according to their relative participation in international trade: Colombian softs: 12%; other softs: 23%; Brazilian naturals: 31%; robustas: 34% (ICO, 2012). In addition to the supply and demand factors, there are other adverse to coffee cultivation, such as climatic variations, and the presence of diseases and pests, among others.

The two main markets for coffee beans are in the New York and London Stock Exchanges. These operate under two modalities: current or physical markets and futures contracts. The latter do not involve physical transactions, since purchase and sale contracts are made specifying the aspects related to the quantities, the qualities required, and the delivery times. Historically, it has been important to stabilize prices in the world market for this item, limiting fluctuations in supply and their negative effects on coffee producing and exporting economies, through negotiations arising from the International Coffee Agreement created in 1962, made up of producer and consumer countries, its most recent renewal being in 2007, in which sustainable development was incorporated as a goal to be achieved in the world coffee economy.

From 2001 to 2011, the average price of coffee in real terms on the world market showed an increasing trend with an average growth annual rate of 14%. The strongest increase was observed in Colombian soft Arabicas, the other soft arabicas, and Brazilian natural Arabicas which increased by 12.0%, 13.1%, and 14.4%, respectively. For the same period, a more modest increase was observed in the robustas, of an average of 12.1% per year; these reached the highest price level in 2011 (US$ 109.21 cents per pound). According to the National Federation of Coffee Growers of Colombia (2010), the increase in coffee prices was based on excess demand or scarcity, which affected stocks. In addition, in 2010 and 2011, the prices of this item were linked to the expectations of the climate in the producing countries, especially the frost in the central zone of Brazil, the phenomenon of La Niña in Colombia, and Hurricane Karl in Mexico. The weather altered the quality and volumes of coffee from Brazil, as well as the slow marketing of the crop, which pushed coffee prices to levels above US$ 160 cents per pound.

3. Methodology and data

This paper follows a dynamic estimation to study how coffee production and exports are affected not only by frosts happening locally but also by those happening in trading competitors. First, to be able to capture this effect, we construct a time-varying weighting matrix, $\boldsymbol{W_t}$, where every w_{ijt} represents the degree of competition between countries i and j at time t. To the knowledge of the authors, there is no previous evidence of a weighting matrix measuring the degree of competition between countries that produce an arguably homogeneous product. In this case, geographical distance fails to be an appropriate way to assign weights that represent the strength of the relationship, since more distant countries can be stronger competitors if they sell to the same group of buyers.

The degree of competition between any pair of countries i and j is measured based on the predicted potential coffee demand from country i, $\widehat{PD}_{it}$. We define $\widehat{PD}_{it}$ as the difference between the total predicted coffee demand of the buyers of country i, $\widehat{D}_t$, and the total predicted coffee sales of country i at year t, that is, $\widehat{PD}_{it} = \widehat{D}_t - \widehat{D}_{it}$. The competing countries of i are the set of producers that also sell coffee to buyers from country i. In other words, we assume that coffee is a homogeneous product that can be easily substituted between producer countries. As a result, in the event of a negative shock that reduces the coffee production in country i, the buyer countries could get the coffee from competing countries.

To get the predicted demand, we rely on a gravity approach following a Pseudo Poisson Maximum Likelihood estimation (Santos Silva and Tenreyro, 2006, 2011). Gravity estimation allows to model bilateral trade flows for every pair of countries as a function of observable characteristics such as economic size and distance (Head and Mayer, 2014). With this approach, we address the potential endogeneity of $\boldsymbol{W_t}$ given that it depends on observed trade. The equation to estimate is the following:

$$T_{jit} = \exp\{\beta_1 + \beta_2 Shock_{jt} + \beta_3 Shock_{it} + \mathbf{X'}_{\mathbf{jt}}\boldsymbol{\gamma} + \mathbf{X'}_{\mathbf{it}}\boldsymbol{\eta} + \omega_{ji} + \lambda_t + e_{jit}\}. \quad (1)$$

T_{jit} is the value of total coffee exports or sales in dollars from country *j* to country *i* in year *t*. That is, the total coffee demand of country *i* from country *j* at time *t* ($T_{jit} = D_{ijt}$). $Shock_{jt}$ is the exogenous weather shock in exporting country and $Shock_{it}$ is the exogenous weather shock in the importing country. $\boldsymbol{X_{jt}}$ is a matrix of supply characteristics of the exporter, and $\boldsymbol{X_{it}}$ is a matrix of demand factors of the importer, ω_{ji} is a set of dyadic fixed effects controlling for time-invariant *ji*-specific characteristics such as geographical distance and tradition in the coffee production, λ_t are time fixed effects and e_{ijt} is the error term. The exogenous shock is defined as a dummy variable equal to one if the country experienced a frost in a specific year *t* on the areas suitable for coffee growth.

We obtain the predicted trade between countries *j* and *i*, $\hat{T}_{jit}$ which equals $\widehat{D}_{ijt}$. Next, for every country *i* and year *t*, we sum up the predicted coffee demand of all buyers for which $\widehat{D}_{ijt} > 0$. As a result, we have the predicted demand of all countries that sell coffee to the same set of buyers, $\widehat{D}_t = \sum_j \widehat{D}_{ijt}, \forall\, \widehat{D}_{ijt} > 0$. Then, the degree of competition between countries *i* and *j* at time *t*, w_{ijt} can be defined as follows:

$$w_{ijt} = \frac{\widehat{D}_{jt}}{\widehat{PD}_{it}},$$

Where $\widehat{D}_{jt}$ is the total predicted coffee sales by country *j* to all the buyers of country *i* at time t. The larger $\widehat{D}_{jt}$, the stronger the degree of competition between countries *i* and *j*. By construction, $\boldsymbol{W_t}$ is a row standardized weighting matrix. That is, $\sum_j w_{ijt} = 1$.

We offer an illustrative example on how we calculate the competitor's index: suppose that the global coffee market is made up of four exporters, labelled from A through D, and four importers labelled 1 through 4. The predicted flows of coffee between exporters and importers in year t are shown in Table 1:

Table 2. Trade flows, example

	Importer 1	Importer 2	Importer 3	Importer 4	Total Exports
Exporter A	25	28	50		103
Exporter B		21	58	50	129
Exporter C	44	45		31	120
Exporter D	22		60	72	154
Total imports	91	94	168	153	

The degree of competition between Exporter A and Exporter B is given by the formula:

$$w_{Exporter\ A,Exporter\ B,t} = \frac{D_{\widehat{Exporter\ B,t}}}{\widehat{PD}_{Exporter\ A,t}}$$

Where the predicted demand for Exporter A is given by the summation of the exports of countries B, C, and D to the importers 1, 2 and 3, which are A's buyers. On the other hand, the predicted demand for Exporter B would be given by the exports of countries A, C, and D to importers 2, 3, and 4, which are B's buyers, and so on. In turn, the predicted potential demand from Exporter A is 353 units minus 103. Therefore, the degree of competition between Exporter A and Exporter B is given by the expression:

$$w_{Exporter\ A,Exporter\ B,t} = \frac{21 + 58}{353 - 103} = 0.316$$

Carrying out the same procedure for all combinations of exporters yields the following competitor matrix:

Table 3. Competitor *W* matrix, example

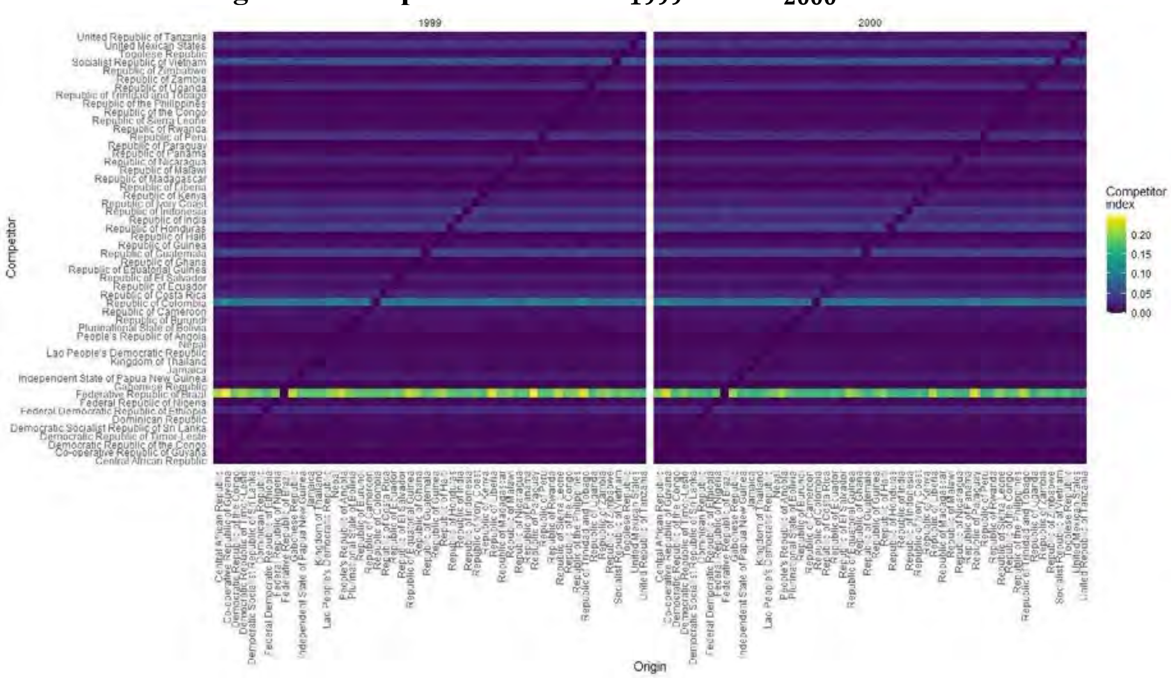
	Exporter A	Exporter B	Exporter C	Exporter D
Exporter A	0	0.316	0.356	0.328
Exporter B	0.273	0	0.266	0.461
Exporter C	0.243	0.326	0	0.431
Exporter D	0.291	0.419	0.291	0

Table 4 presents a subset of the actual weighting matrix, $\boldsymbol{W_{1995}}$, showing the competitor index for the five largest coffee producers, calculated through the procedure just described. For instance, the value of $w_{Brazil,Colombia,1995}$ is roughly 0.189, meaning that Colombia supplied 18.9 percent of Brazil's potential market in 1995, $PD_{Brazil,1995}$. In comparison, Ethiopia supplied only 2.7 percent of Brazil's potential market for that year. We argue that, were Colombia to have a hypothetical production setback in 1995, Brazil is better poised to fill in Colombia's deficit given its already strong competing relationship with Brazil. The dynamic nature of these matrices is of utmost importance to this study, as it captures the constantly changing strengths of the trading relationships of international supply chains. Figure 1 shows a heatmap plot of matrices $\boldsymbol{W_{1999}}$ **and** $\boldsymbol{W_{2000}}$ with lighter colors representing higher competitor indices. Among other things, Brazil was a weaker competitor of Paraguay, Liberia, and Guyana in 2000 than it was in 1999.

Table 4. Snippet of the $\mathbf{W_{1995}}$ matrix

Origin/Competitor	Brazil	Indonesia	Viet Nam	Colombia	Ethiopia
Brazil	0.000	0.076	0.085	0.189	0.027
Indonesia	0.195	0.000	0.074	0.164	0.023
Viet Nam	0.166	0.069	0.000	0.177	0.022
Colombia	0.232	0.064	0.078	0.000	0.026
Ethiopia	0.185	0.055	0.068	0.164	0.000

Figure 1. Comparison of the $\boldsymbol{W_{1999}}$ and $\boldsymbol{W_{2000}}$ matrices.



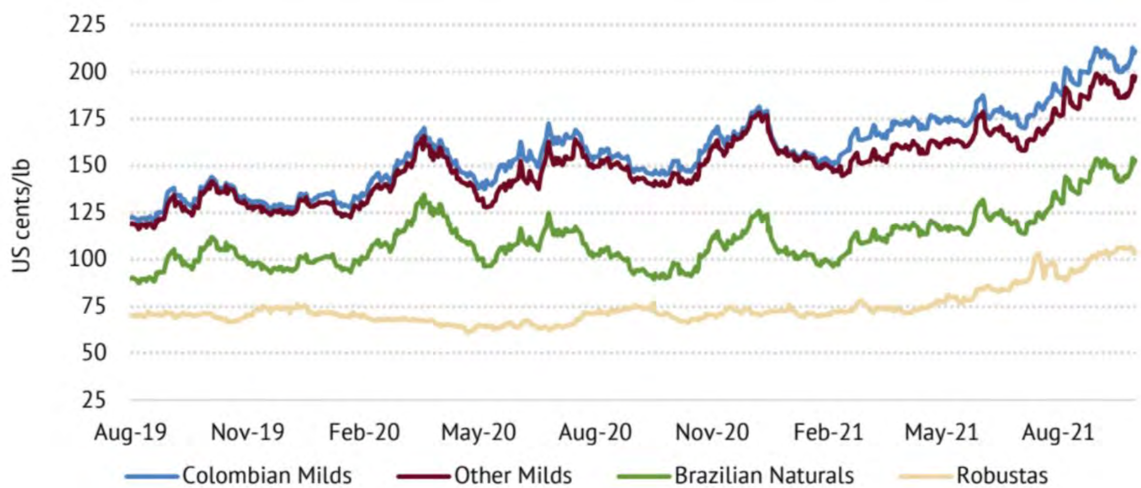
Second, after obtaining our **W** matrix, we estimate the following spatial lag of X (SLX) regression model:

$$Y_{it} = \alpha_i + \gamma_t + \beta_1 Y_{i,t-1} + \beta_2 D_{it} + \beta_3 D_{i,t-1} + \ \beta_4 \sum_j w_{ijt}\, ED_{jt} + \beta_5 \sum_j w_{ijt}\, ED_{i,t-1} + \boldsymbol{\lambda X_{it}} + \mu_{it}.$$

Y represents the volume of coffee produced, the volume of exports, consumption, or the level of stock, ED is a dummy variable equal to one if there was a frost in the country. We include current frosts and one-year lag frosts, as well as their spatial lag to capture the plausible lagged and spatial effects on coffee production. Every w_{ijt} represents the predicted share of exports of country j on the predicted potential demand of buyers of country i defined earlier. $\boldsymbol{X}$ is a matrix of control variables that includes demand and supply factors such as the Gross Domestic Product (GDP) per capita, population size, and measures of weather conditions such as temperature and precipitation. Standard errors, u, are clustered at the country level to allow for arbitrary serial correlations within countries.

As in Jones and Olken (2010), we consider an estimation with country fixed effects (α_i) that control for the fixed differences in the coffee production across countries as well as time fixed effects (γ_t) that account for the changes in coffee prices as well as common world time effects. Figure 2 presents the trends of prices for different coffee groups as they are traded in major commodity exchanges showing that the prices closely trace each other.

Figure 2. Trends in coffee prices for different groups, August 2019-August 2021

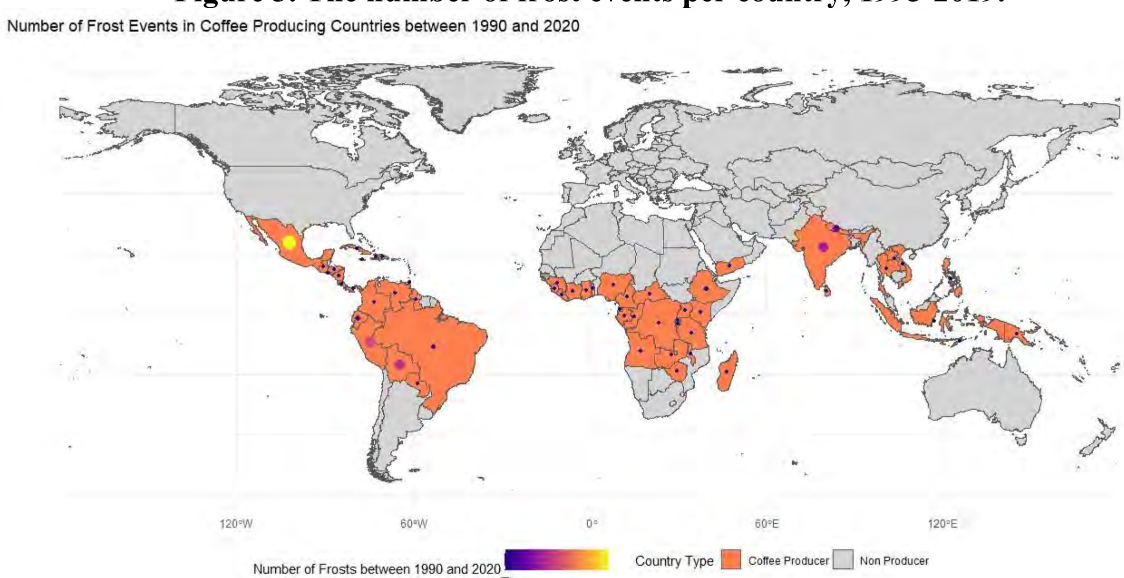


Source: adapted from The International ICO's August Coffee Market Report, retrieved from: https://www.ico.org/documents/cy2020-21/cmr-0821-e.pdf

We take advantage of the exogeneity of the occurrence of frosts across countries to arguably interpret the coefficients β_2 and β_3 as the impact of frosts happening locally on coffee production, and β_4 is the average effect of frosts in trading competitors on local coffee production, exports, consumption, and stock. Since we estimate a dynamic panel model, there is a plausible concern of endogeneity in our estimation because of the correlation in the error term that results from the inclusion of the lagged dependent variable as a regressor. However, this bias becomes negligible when the number of years increases, and we have a 25-year panel from 1995 to 2019, which should eliminate the concerns about the possibility that our results are suffering from this type of endogeneity.

Our data comes from different sources. The identification of occurrence of frosts was done through a two-step process. First, using the suitability maps estimated by Gruter *et al.* 2022, we narrowed down coffee production areas. We then superposed monthly minimum temperature rasters from 1995 to 2021, obtained from the Climatic Research Unit gridded Time Series (CRU TS) version 4.07 (Harris *et al.,* 2020), and extracted minimum temperature values for each cell representing areas suitable for coffee cultivation. If one or more pixels had temperatures below 4.1°C we identified the country as having suffered a frost event (Sentelhas *et al*., 1995).

Figure 3. The number of frost events per country, 1995-2019.



Source: the authors with data from the Climatic Research Unit gridded Time Series (CRU TS) version 4.07 (Harris et al., 2020).

The GDP and population information come from the World Bank, the weather information such as precipitation and temperature come from Harris *et al.* (2020), and coffee production and exports come from the International Coffee Organization. Figure 3 shows the number of frosts per country highlighting those that are classified as coffee producers. The most affected countries by frosts for the period 1995-2019 were Peru with 12 events, Thailand and Mexico (11), and Paraguay, Ethiopia and Brazil (10), while Equatorial Guinea, the Democratic Republic of Congo, Togo, Sierra Leone, and Ghana did not experience any frost event for the same period. The complete list of coffee producer countries considered in this study is displayed in Appendix 1.

4. Results

Table 5 shows the descriptive statistics of the variables used in our estimation for the 49 countries of our sample. We consider frosts happening locally and those occurring in competing countries, a relationship that is captured by our competitors' weight matrix $\boldsymbol{W}$. Competitors are countries that sell coffee to the same set of countries each year. This is possible under the assumption that coffee is a homogeneous product that can be easily substituted between producer countries. It is expected that local production is not only affected by extreme weather events happening locally but also by those that occur in competitor coffee producer countries. It can be seen in Table 5 that, on average, 18% of the country-year sample and 27% of competitors experienced at least one frost.

Table 5. Descriptive statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Frost	1,171	0.18	0.38	0	1
W*Frost	1,171	0.27	0.19	0	1
Production (tons)	1,171	152,799	441,982	0	3,907,860
Exports (tons)	1,171	116,962	307,703	0	2,430,643
GDP per capita (USD)	1,171	6,893	6,535	691.2	41,249
Temperature (°C)	1,171	23.91	1.98	18.0	28.2
Precipitation (mm)	1,171	141.40	51.01	42.9	301.9

Source: The authors with information from The World Bank, the BACI trade data, the authors with data from the Climatic Research Unit gridded Time Series (CRU TS) version 4.07, and Harris *et al*. (2020).

Table 6. Gravity estimation of coffee exports: PPML results.

Dependent variable	Exports
Population of origin	-2.458***
	(0.527)
Population of destination	0.673
	(0.522)
Ln(GDP per capita) origin	0.968***
	(0.172)
Ln(GDP per capita) destination	0.812***
	(0.222)
Frost at origin	-0.071***
	(0.024)
Constant	-5.970
	(14.118)
Observations	109,707
Pseudo R-squared	0.951

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The first step of our approach is to estimate $\boldsymbol{W}$ for every year. Table 6 shows the results of the gravity estimation. The value of exports is a function of origin and destination population and GDP per capita as supply and demand factors, as well as a dummy variable that captures the occurrence of a frost in the coffee area of the country of origin. The results indicate that countries with a larger population export less, and that both the economic size of countries of origin and destination are associated with a higher value of exports. Finally, as expected, frosts in the country of origin reduce the value of exports.

The gravity estimation coefficients will allow us to predict the bilateral trade flows for coffee producer countries to the rest of the world. The predicted bilateral trade flows are then used to create our $\boldsymbol{W_t}$, which will measure the economic dependance between competitor nations in the coffee trade network. This approach should eliminate any concern about the endogeneity of the weighting matrix since we do not use observed bilateral trade flows but predicted bilateral trade. In addition, it is important to point out that we consider origin, destination, and time fixed effects in the gravity estimation.

Table 7 shows the main results of our estimation. As we mentioned earlier, the main regression includes the volume of production, exports, consumption, and stocks as dependent variables. We consider current and one-year lag frost happening locally and in competing countries, given that coffee production may take some time to adjust after a frost. We also consider a set of control covariates that include the lagged dependent variable to capture the tradition of coffee producer countries, other weather measures such as average temperature and precipitation, and GDP per capita (in logs) to control for economic activity and development. We use the lagged GDP per capita to avoid the reverse causality problem with coffee production. In addition, we consider country-specific fixed effects and time fixed effects.

Table 7. Frosts and coffee production, consumption, exports, and stocks.

	Production	Exports	Consumption	Stocks
ln(production) (t-1)	0.66***			
	(0.09)			
ln(exports) (t-1)		0.85***		
		(0.03)		
ln(consumption) (t-1)			0.98***	
			(0.00)	
ln(stocks) (t-1)				0.87***
				(0.00)
Frost	-11.83	-25.16	-0.08	12.69
	(22.05)	(24.09)	(0.51)	(13.65)
Frost (t-1)	18.53	-5.57	0.09	-2.53
	(13.94)	(17.81)	(0.26)	(4.11)
W*Frost	2,631.93***	729.27***	-78.63***	-855.04***
	(497.75)	(217.09)	(17.58)	(169.83)
W*Frost (t-1)	611.66***	309.07***	-62.48***	389.08***
	(190.62)	(107.50)	(13.56)	(74.89)
Temperature	43.84	-5.92	0.45	12.33
	(47.56)	(30.08)	(3.58)	(16.00)
Temperature squared	-0.86	0.28	-0.02	-0.13
	(0.97)	(0.68)	(0.08)	(0.32)
Precipitation	-0.10	-0.08	0.00	0.03
	(0.21)	(0.13)	(0.01)	(0.13)
Precipitation squared	0.00	0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Ln (GDP per capita) (t-1)	28.71	6.92	0.53	2.99
	(20.10)	(6.42)	(0.74)	(3.42)
Constant	-1,839.04***	-360.16	33.82	42.90
	(655.56)	(347.84)	(44.13)	(199.32)
Observations	1,171	1,171	1,171	1,171
Adjusted R-squared	0.61	0.79	0.99	0.78

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: The authors with information from The World Bank, the BACI trade data, the authors with data from the Climatic Research Unit gridded Time Series (CRU TS) version 4.07, and Harris *et al*. (2020).

The results indicate that extreme weather events happening in competing countries significantly affect local coffee markets. Frosts happening locally do not affect total production, exports, consumption, nor stocks, whereas frosts happening in competing countries have a positive effect on production and exports, and a negative impact on local consumption and stocks. In addition, frosts happening in neighboring countries one year before increase local production, exports, and stocks, but reduce local consumption. The raise in local production after a contemporary frost may explain why the stock is larger in the next year. Specifically, a contemporary frost in all competing countries can increase local coffee production, in average, by 2,632 tons, exports by 729 tons, while reducing local consumption by 79 tons and stocks by 855 tons. One possible explanation is that countries decrease their stock after a negative production shock in competitors to capture the potential demand. Our findings are consistent with the inclusion of country and time fixed effects, and the residuals are clustered at the country level.

Ignoring this indirect effect would lead us to incorrect conclusions about the effect of natural disasters on coffee production and exports. The fact that frosts in competing countries affect local production and exports is another example of the potential compensating effect of trade after negative weather shocks (Ayala *et al*., 2022). Not surprisingly, the dependent variables show a very strong dependance on its lagged values, which is consistent with having a sample of coffee producing countries. In addition, there is no elasticity of coffee production, exports, consumption, nor stocks to per capita GDP, as well as no significant relationship with other weather control variables such as temperature and precipitation, possibly because we consider countries fixed effects in our regressions.

5. Conclusion

Coffee is one of the major commodities traded in the international markets, where the largest exporters for 2016 were Brazil (39.15%), Vietnam (34.22%), Colombia (14.95%) and the main importers being the United States (20.8%), Germany (17.4%), Italy (7.6%). This paper studies the impact of frosts on coffee production and exports considering frosts happening locally and in competing countries. We develop a method of estimation that allows us to consider producer countries and competing countries in the same regression, avoiding the omitted variable problem that can be a source of endogeneity.

Our approach consists of creating a row standardized weighting matrix of competitor countries, where the weights represent the market share of producer countries among all the producers facing the same international demand for the product each year. It is expected that a negative weather shock in a producer country that reduces local coffee production will also reduce the market segment of the same country in the international market. That segment will be captured by the closest competitors. As a result, this paper contributes to the literature by proposing a method for estimating this indirect effect of weather shocks applied to the coffee trade network.

We found that Brazil is the largest competitor for all countries, followed by Vietnam and Colombia, with small changes throughout the period 1995-2019. The results show that frosts in competing countries increase local coffee production and exports, and reduce consumption and stocks, although no direct effect was found. In addition, frosts in competing countries with one year lag increase local production, exports, and stocks. Our findings are robust to the inclusion of country and time fixed effects, as well as other control variables such as temperature, precipitation, and GDP. These results contribute to the literature studying the compensating effect of international trade to negative weather shocks. Ignoring the indirect impacts of natural disasters could lead to incorrect conclusions about the impact of extreme weather conditions.

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Appendix 1. List of coffee producing countries in our study

Countries	
Angola	Lao People's Democratic Republic
Bolivia	Liberia
Brazil	Madagascar
Burundi	Malawi
Cameroon	Mexico
Central African Republic	Nepal
Colombia	Nicaragua
Congo	Nigeria
Costa Rica	Panama
Democratic Republic of Congo	Papua New Guinea
Dominican Republic	Paraguay
Ecuador	Peru
El Salvador	Philippines
Equatorial Guinea	Rwanda
Ethiopia	Sierra Leone
Gabon	Sri Lanka
Ghana	Tanzania
Guatemala	Thailand
Guinea	Togo
Guyana	Trinidad and Tobago
Haiti	Uganda
Honduras	Viet Nam
Indonesia	Zambia
Jamaica	Zimbabwe
Kenya	