Weather Shocks and Agri-Food Imports

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Abstract:

Food security is threatened by weather shocks. I estimate how weather shocks in destination affect imports, both in value, volume, and average price. Using aggregate trade data, on agri-food products, and destination-specific yearly degree-days, from 1995 to 2017, I estimate a gravity equation. Countries facing adverse weather shocks do not import more in value, but import less in quantity, and with larger prices. Results are consistent with the idea that weather shocks deter revenues, expenditures and import demand. Overall, imports do not allow to cope with negative agri-food production shocks.

Keywords: Agri-food, Trade, Imports, Weather.

JEL codes: F14, Q17.

Highlights:

- Countries facing adverse weather shocks do not import more in value, but import less in quantity, and with larger prices.
- Imports do not allow to cope with negative agri-food production shocks.
- Results are consistent with the idea that weather shocks deter revenues, expenditures and import demand.

Note: All data and code can be provided to replicate the analysis.

1. Introduction

Global food security is threatened by weather shocks. Indeed, agricultural and food production may be deterred by adverse weather shocks. In a climate change context, the increased occurrence and intensity of weather shocks reinforces threats to global food security (FAO, 2016). In this context, agri-food imports may act as a substitute for deterred domestic production.

In this note, I estimate how weather shocks in destination affect imports. When a country is hit by adverse weather shocks, how large are the effects on imports? Using aggregate trade data, on the universe of agri-food products, from 1995 to 2017, I estimate a state-of-the-art gravity equation, in which the main variable of interest is the occurrence of weather shocks in the destination, measured in yearly degree-days. As these shocks are exogenous to trade flows and decisions, estimates can be considered as causal from weather to trade.

Three main results emerge. First, I find no significant effect of weather shocks on import values. Second, weather shocks significantly deter imported quantities and significantly increase unit values (as proxy of prices), hence leading to unchanged trade values. Countries facing adverse weather shocks hence do not import more in value, import less in quantity, and with larger prices. Third, results are consistent with the idea that weather shocks deter revenues, expenditures and import demand. On the contrary, I find no evidence in favor of increased imports to cope with potentially negatively affected production.

Overall, imports do not allow to cope with negative agri-food production shocks. International trade does not reduce threats to food security in presence of weather shocks. This result complements the existing literature in two ways. First, present results build upon recent articles focusing on weather as trade shifters (Dallmann, 2019; Jones and Olken, 2010; Li et al., 2015). To the best of my knowledge, no study explicitly focuses on shocks in destination. Second, this study complements existing evidence on determinants of agri-food trade (Gaigné and Gouel, 2022) and its implications regarding food security (Brooks and Matthews, 2015).

2. Data and Method

Sample and Measures

We combine (i) trade information with (ii) a dataset of weather shocks in each destination and (iii) with destination-specific controls. As for trade, we rely on the BACI dataset (Gaulier and Zignago, 2010), informing on flows (both values and quantities) at the origin country o- destination d – HS6 chapter s– year t level. Using this dataset, I restrict sample to agri-food products, i.e., HS2 chapters 01 to 24. I then define unit values as the ratio between inflation-corrected traded values and trade volumes. The main analysis is performed at the HS2 level, hereafter denoted as sectors.

Second, to measure weather shocks, we rely on NOAA Global Historical Climatology Network, Daily (GHCN-D) (Menne et al., 2012), providing averaged temperatures at the weather station (w)-country (d) - day (j) -year (t) level, $\mathrm{T_{wdjt}}$. We aggregate the data into a measure at the country-year level: first, by averaging temperatures (over weather stations) at the country-day-year ($\mathrm{T_{jdt}}$), and then by aggregating the daily measures into destination-year (t) degree-days (Degree $\mathrm{Days_{dt}}$) using the following computation:

$$\text{Degree Days}_{\mathrm{jdt}} = \begin{cases} 0 & \text{if } \mathrm{T_{jdt}} < 8 \\ \mathrm{T_{jdt}} - 8 & \text{if } 8 < \mathrm{T_{jdt}} < 32 \\ 24 & \text{if } \mathrm{T_{jdt}} > 32 \end{cases}$$

and $\text{Degree Days}_{\mathrm{dt}} = \sum_{\mathrm{j \in t}} \text{DegreeDays}_{\mathrm{jdt}}$.

This measure captures the cumulative number of days of with temperatures larger than 8°C and the intensity of the temperatures (pairwise correlation with average temperature= 0.875). Note that it is not a measure of extreme heat, as extreme temperatures (above 32°C) are neutralized by the exercise. This measure has been used in many economy-wide analyses (such as Jessoe, Manning, and Taylor (2018)).

Third, I complement this sample by using country-year specific data from World Development Indicators (World Bank, 2016): GDP, population, real effective exchange rate, and other macroeconomic variables. I also use bilateral distance data from CEPII (Mayer and Zignago, 2011).

Empirical models

I estimate the impact of weather shocks in destination on incoming trade flows. I hence estimate gravity models (Head and Mayer, 2014) at the origin-destination-sector-year level.

Model 1: Average effects

In formal terms, I first estimate:

$$\text{Outcome}_{\mathrm{odst}} = \lambda_{\mathrm{ods}} + \lambda_{\mathrm{ost}} + \alpha\, \text{DegreeDays}_{\mathrm{dt}} + \beta_1 \text{GDP}_{\mathrm{dt}} + \beta_2\, \text{Popu}_{\mathrm{dt}} + \beta_3\, \text{REER}_{\mathrm{dt}} + \varepsilon_{\mathrm{odst}}$$

in which $\text{Outcome}_{\mathrm{odst}}$ is either log import value ($\mathrm{X_{odst}}$), log import quantity ($\mathrm{Q_{odst}}$) or log import unit value ($\mathrm{UV_{odst}}$). The specification includes two sets of fixed effects to absorb unobserved heterogeneity. First, λ_{ods} denotes a set of origin-destination-sector fixed effects, that control for bilateral distance between countries, and preferences (assumed to be fixed) in both countries, as well as specialization. This set also absorbs most of the variance in export outcomes at the extensive margin, i.e., changes in export status over time. Hence, all results can be interpreted as evidence at the intensive margin of trade. Second, λ_{ost} is a set of origin-sector-year fixed effect, that absorb potential supply shocks in exporting countries. Note also it accounts for weather shocks in the origin country. These fixed effects more generally control for the so-called outward "multilateral resistance terms" (Anderson and van Wincoop, 2003). Armed with these fixed effects, the identifying variation is across years within an exporter-importer-product group, across years. The main variable of interest ($\text{DegreeDays}_{\mathrm{dt}}$)

captures the weather shock in destination x year of interest. In this estimation, α is the main parameter of interest and is the elasticity of trade flows to weather shocks. Beyond trade shifters in the origin (subsumed in the fixed effects), the specification controls for trade shifters in destination, including GDP, total population (Head and Mayer, 2014), and real effective exchange rate.

Model 2: Heterogeneity

We also estimate a set of models allowing for an interaction between weather shocks and destination-year specific variables, to capture the heterogeneous response of import flows across destinations:

$$\begin{aligned}\mathrm{Outcome_{odst}} = {} & \lambda_{\mathrm{ods}} + \lambda_{\mathrm{ost}} + \alpha\ \mathrm{DegreeDays_{dt}} + \beta\ \ \mathrm{Dest.Caracteristic}_{dt} \\ & + \gamma\ \ (\mathrm{DegreeDays_{dt}} \times\ \mathrm{Dest.Caracteristic}_{dt}) + \varepsilon_{\mathrm{odst}}\end{aligned}$$

in which $\mathrm{Dest.Caracteristic}_{dt}$ can be GDP, population, Agricultural GDP, … In this specification, the main coefficient is γ: it captures the differential effect of the destination characteristics on the weather-import relationship. For instance, if both α and γ are negative, it implies that the destination characteristic included in specification amplifies the negative impact of weather shocks on trade outcome.

All models are estimated using OLS. Standard errors are clustered at the destination-year level, which is also the level of the weather shocks.

3. Results

Effects of weather shocks

Table 1 provides the estimated effects of weather shocks on imports. Colum 1 shows that foreign weather shocks, on average, do not deter total imports value. As import value is the combination of quantities and of unit price, this insignificant result could be the result of two opposite forces. Column 2 on the contrary supports that the same weather shocks deter import quantities: when hit by weather shocks, a country reduces its imports in volume. A 10% increase in the degree-days in destination implies a 1.3% decrease in import quantities. Results do not support that imports act as a substitute for local production: when hit by a weather shock, countries do not seem to increase imports to cope with potentially affected production. This result can be explained by the negative impact of weather shock on import demand, thus lowering realized imports.

Colum 3 finds a positive association between unit value and weather shocks: the larger the weather shock, the larger the price increase. A 1% increase in the degree-days in destination implies a 0.09% increase in average price.

Heterogeneity across sectors

Figure 1 plots the estimated elasticity of quantities (panel A) and unit values (panel B) for each HS2 chapter separately. On average, weather shocks do not deter import volumes but increase prices for animal products

(HS2 01 to 05), decrease volume and increase price for foodstuff (HS2 16 to 24), as well as for cereals and oil seeds (HS2 10 to 12). Estimates always confirm an opposite effect of weather shocks on import volumes and prices, although not always significant.

Heterogeneity across destinations

Tables 2 and 3 investigate the heterogeneous effects of weather shocks across destinations. Indeed, weather shocks at home may interact with the country characteristics to shape the import response, both regarding import demand and import price. The model includes an interaction term between weather shock and (i) country characteristics, such as GDP or access to credit, and (ii) bilateral distance.

Table 2 shows that import volumes are even more deterred by weather shocks in destination with lower GDP (col. 1), and with lower access to credit (col.3) independently of the importance of agricultural GDP (col. 2). Indeed, credit may act as a risk management tool, and could absorb revenue shocks. As a result, importing countries with lower levels of development are more negatively affected by weather shock. Results also imply that the distance does not magnify the negative impact of weather shocks.

Table 3 shows that the positive association between weather shocks and import price is shaped by GDP: the larger the GDP, the lower the import price increase. We however find no effect of agricultural GDP (export supply), total credit, and distance (hardly significant) on the weather-unit value relationship.

4. Conclusions

A few interpretations can be made from the analysis. First, weather shocks seem to affect imported quantities though aggregate import demand. On the one hand, weather shocks may deter total import demand, captured by relatively lower GDP: from the exporter side, the destination market (hit by the weather shocks) is less attractive, and thus exporters reduce their sales (in volumes). On the other hand, as this market is less attractive, competition is lower on this market, and thus exporters (on average) can charge larger prices, ceteris paribus. We find evidence of this "reduced sales – larger unit value" relationship, potentially leading to insignificant effect of weather shocks on import values (Dallmann, 2019; Li et al., 2015).

Second, deterred local production does not determine the import patterns. Indeed, we find no significant role played by agricultural GDP, capturing the potential production-deterring effect of weather shocks. In the case of large agri-food production losses, we do not find evidence in favor of increased imports to cope with this negative shock. Rather, these production shocks seem to transmit to aggregate expenditure and hence affect import pattern through an expenditure channel only.

Finally, weather shocks in destinations affect import patterns *within* an exporter-importer-sector relationship, whereas most of the existing literature –performed at the aggregate level– focuses on adjustments of imports *across* exporting and importing countries. As for future research, the impact of weather shocks and the subsequent changes (quantities and price) could hence be estimated across importing and exporting *firms*, within importing and exporting countries.

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Table 1- Effects of Degree-Days in destination on trade outcomes

Dep Variable:	Log X	Log Q	Log UV
	(1)	(2)	(3)
Degree-Days in Dest.	-0.049	-0.138*	0.089***
	(0.063)	(0.071)	(0.032)
GDP	1.100***	0.998***	0.102***
	(0.055)	(0.061)	(0.025)
Population	0.084	0.150	-0.065
	(0.111)	(0.128)	(0.081)
Real Eff. Exch. Rate	0.493***	0.330***	0.162***
	(0.069)	(0.070)	(0.021)
Observations	1112559	1112559	1112559
R^2	0.848	0.842	0.737

All estimations include origin-destination-sector and origin-sector-year fixed effects. Clustered standard errors in parentheses. Cluster: by Destination-Year. * p<0.1, ** p<0.05, *** p<0.01

Table 2: Heterogeneity across destinations (Quantities)

Dep Variable:	Log Quantities			
	(1)	(2)	(3)	(4)
Degree-Days in Dest.	-2.341***	-1.580	-0.613***	0.672
	(0.770)	(1.158)	(0.152)	(0.587)
GDP	0.309	0.985***	0.976***	0.996***
	(0.257)	(0.062)	(0.059)	(0.061)
Degree-Days x GDP	0.084***			
	(0.030)			
Popu.	0.055	0.061	0.115	0.158
	(0.132)	(0.140)	(0.125)	(0.128)
Real Eff. Exch. Rate	0.329***	0.332***	0.293***	0.331***
	(0.069)	(0.069)	(0.069)	(0.070)
Agri. GDP		-0.478		
		(0.423)		
Degree-Days x Agri. GDP		0.064		
		(0.052)		
Total credit			-0.713***	
			(0.239)	
Degree-Days x Total credit			0.102***	
			(0.031)	
Degree-Days x Distance				-0.099
				(0.071)
Observations	1112559	1112559	1112559	1112559
R^2	0.842	0.842	0.842	0.842

All estimations include origin-destination-sector and origin-sector-year fixed effects. Clustered standard errors in parentheses. Cluster: by Destination-Year. * p<0.1, ** p<0.05, *** p<0.01

Table 3: Heterogeneity across destinations (Unit Value)

Dep. Variable	Log Unit Value			
	(1)	(2)	(3)	(4)
Degree-Days in Dest.	1.219***	0.257	0.077	-0.248
	(0.380)	(0.461)	(0.090)	(0.178)
GDP	0.456***	0.088***	0.101***	0.103***
	(0.118)	(0.028)	(0.025)	(0.025)
Degree-Days x GDP	-0.043***			
	(0.014)			
Popu.	-0.017	-0.087	-0.064	-0.069
	(0.083)	(0.080)	(0.081)	(0.081)
Real Eff. Exch. Rate	0.163***	0.165***	0.160***	0.162***
	(0.021)	(0.021)	(0.021)	(0.021)
Agri. GDP		0.096		
		(0.166)		
Degree-Days x Agri. GDP		-0.007		
		(0.020)		
Total credit			-0.010	
			(0.138)	
Degree-Days x Total credit			0.002	
			(0.018)	
Degree-Days x Distance				0.041*
				(0.022)
Observations	1112559	1112559	1112559	1112559
R^2	0.737	0.737	0.737	0.737

All estimations include origin-destination-sector and origin-sector-year fixed effects. Clustered standard errors in parentheses. Cluster: by Destination-Year. * p<0.1, ** p<0.05, *** p<0.01

Figure 1- Effect of foreign temperatures on quantities (panel A) and unit values (panel B) for each HS2 chapter.