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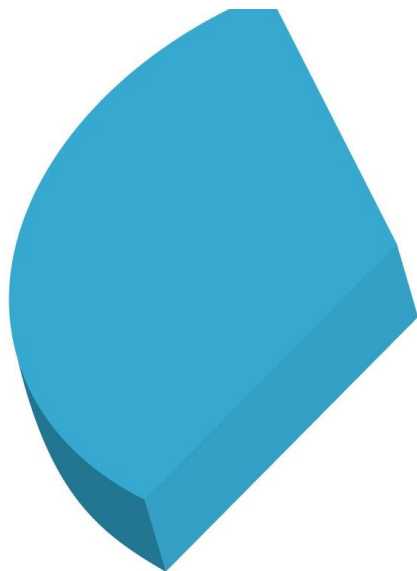
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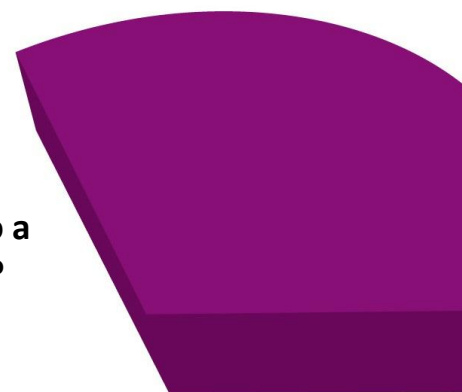
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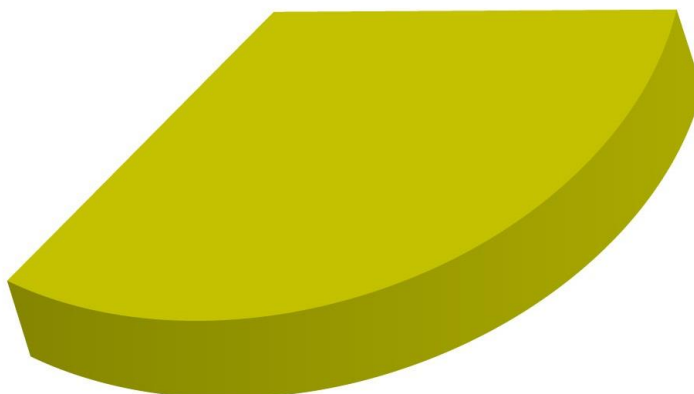
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**Why Natural Disasters Might Not Lead to a
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Why Natural Disasters Might Not Lead to a Fall in Exports in Developing Countries *

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Abstract

This paper tries to identify the different channels through which natural disasters affect exports of agricultural products in developing countries. It begins by presenting a first value added to the literature through drawing a simple theoretical set-up that highlights three different mechanisms at work: a shipment effect, a capability effect and a preference effect. It then takes the predictions of this set-up to the test. By matching different sets of disaster variables (occurrence and intensity) from EM-DAT and GeoMet datasets with trade data at the 6 digit-HS level, the first series of estimates point to a non-robust relationship between disasters and agricultural exports of developing countries. Following our theory set-up, we attribute this result to mixing three confounding effects with different magnitudes and opposing signs on trade. Using other sources of data, we could then identify two of the effects: a negative and statistically significant effect of disasters on exports when they occur in rural areas and at growing season times (the capability effect); and a positive and (very) robust relation with exports towards culturally close partners and where an important diaspora is settled (the preference effect). However, we could not show whether or not this 'solidarity'-consistent effect lasts over time. All in all, due to the limited physical impact on exports of most of the disasters via the capability effect and thanks to foreign demand through the pain relief provided by culturally close importers, natural disasters might not make small developing countries suffer that much economically.

Keywords: Natural Disasters, Trade and Environment, Agriculture in International Trade, Empirical Studies of Trade

JEL codes: Q54, F18, Q17, F14

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1 Introduction

An increasing literature from climate science mentions an important link between climate change and the frequencies of natural disasters but also those of some extreme events. This includes for instance events such as higher speed of cyclones, heat waves or a higher frequency of floods. These facts pose a series of questions regarding the economic future of small developing countries, specialized in agriculture. Following the world risk index figures, low and lower-middle income countries observe indeed a 10% risk of occurrence of a natural disaster each year, a figure twice as big as that of higher income countries. Besides, low and lower-mid income countries had respectively 50% and 20% of their GDP devoted to agriculture in 2012. Also, among these countries, half of the small economies had a revenue from their exports of agriculture that corresponds to at least 10% of their GDP.

Would these economies resist to a higher frequency of disasters in the years to come? And after all, are we sure there is an important impact of disasters on the revenues of these economies? In particular, what about their impact on the exporting activity? What are the mechanisms at play and how can we identify them?

Some research has been focusing on local and in particular macroeconomic outcomes of weather shocks and natural disasters. Dell, Jones and Olken (2014) survey the literature devoted to the New Climate-Economy. Among the cited works looking at the sectoral and macroeconomic impacts, Toya and Skidmore (2007), Noy (2009), Fomby, Ikeda and Loayza (2013), and Felbermayr and Gröschl (2014) provide examples. To synthesize the findings, agricultural output appears to be one of the sectors that is most hit in the economy. Further, industrial output, labor productivity, health, conflict and political stability happen to be affected, all of these ending-up curbing economic growth. Besides, small and poor countries, being often associated with poor quality of institutions and low education levels, appear to be much more sensitive to temperature shocks. Finally, the impact on outcomes appears to be more significant in general in the presence of severe disasters. Another strand of the literature focuses instead on the local effects of weather or disasters and do find again rather significant effects of disasters on local activity and especially on agriculture production at local levels. (Elliott, Strobl and Sun (2015) and Blanc and Strobl (2016) are two examples which look for instance at the local effects of Typhoons).

Nevertheless, the literature regarding the impact on trade flows has been relatively scarce. Dell, Jones and Olken (2014) had already highlighted the lack and need of studies on the link between trade and environmental related events. However, some studies have dealt with this aspect. Jones and Olken (2010) look at the impact of temperatures and precipitations on sectoral exports to the US and the World respectively, by using a cross-country database from 1973 to 2001. They find that temperatures – albeit not precipitations – reduce exports of poor countries: a 1 celsius degree warmer happen to reduce their exports by 2 to 5.7 percentage points. Agriculture happens to be however, much more affected than manufacturing. As for natural disasters, Oh and Reuveny (2010) rely on a gravity model to estimate their impact on international trade for 116 countries over the period 1985 to 2003. They find an induced reduction of both imports and exports following disasters. Besides, the higher the political risk and the stronger this decrease. Gassebner, Keck and Teh (2010) analyze the impact on trade of major natural and technological disasters. They rely on bilateral trade from 1962 to 2004 and use again a gravity equation *à la* Rose, while accounting for a series of fixed effects to control for multilateral resistance. In their first series of results, the impact of the number of disasters does not appear to be significant on bilateral imports. However the number of disasters adjusted for the surface of the country deters exports and imports. Besides, they find that the (negative) effect is stronger in autocratic and smaller countries. Dallmann (2018) studies the impact of weather variations on trade at the product level and finds an important heterogeneity across manufacturing and agricultural products: while temperature variations had more negative than positive impacts on product level trade (through a priori a reduction in output and labor productivity), variations in precipitations had on the opposite more positive and puzzling effects on product level trade. By studying the impact on changes in total exports after a shock, El Hadri, Mirza and Rabaud (2018) concentrate on the supply effects of disasters to find that the impact on supply of exports (a priori through changes in output and labour productivity) is low if not insignificant at the product level. Earthquake disasters were the only exception where one could identify a robust negative supply effect. However, the authors could obtain a negative impact on exports but only for (very) high intensity disasters.

This paper contributes to this strand of the literature. The first objective of our paper is to look more thoroughly at the relationship between natural disasters

and exports of agricultural products by developing countries – one of their major sources of revenues from abroad. In particular, the paper is among the first to offer a general trade set-up that emphasizes the different channels through which disasters might hurt trade, or in the contrary, sometimes encourage it. As it will be shown, the negative supply effects on agriculture expected from a natural disaster, usually documented in the studies mentioned above at local or macro levels, might be reduced or even compensated by a foreign demand effect, making the relationship with exports very ambiguous. We emphasize, in particular, three effects that a disaster could provoke on exports. The first one is what we shall call the capability-supply effect where an occurrence of a disaster might hurt in particular the capacity of some lands to produce, in the case of agriculture. We shall see that such an effect might not arise however, if the time by which a disaster occurs comes after the growing season period. The second effect that is flagged refers to what we shall call the supply of shipment effect. Here, the idea is that disasters might cause some disorder to the communication and transportation networks and/or hurt their corresponding infrastructure, which should result again in a reduction of access to world markets besides the national one. One would expect this effect to be significant on export flows in particular when urban areas are affected by disasters. Finally, our simple set-up shows how disasters might also produce distortions in the distributions of trade flows across trading partners through what we shall call a preference-effect channel. We conjecture here a change in the preferences of some importing countries after a catastrophe, for probably altruism/solidarity reasons. Such a change in the behaviour of importers is more likely to appear when the partner countries are culturally close to the victim one, or say host a significant diaspora that originates from the latter.

We use different datasets to try to identify better some of these mechanisms at play. The first series of data concerns natural disasters. Here, we employ in a systematic way two different databases: the Emergency Events Database (EM-DAT) from the University of Louvain and the recent GeoMet database produced by Felbermayr and Gröschl (2014). As for the exports data, we use essentially the BACI bilateral trade data from CEPII. As already mentioned, we focus our attention particularly on agricultural products observed at the 6 digits HS nomenclature and small developing countries' economies. Besides, if we are not able to find an effect on trade for these chosen products and countries, which are known to be sensitive

to disasters, it is very likely that we could not find an effect on trade in general for a broader set of products and countries. Incidentally, the choice of small countries happens to simplify the theory set-up we propose in the next section without loss of generality.

Also, we argue that the use of agricultural products offers a way to better identify the capability-supply effect. Indeed, we construct a new set of data where we add information about the type of area hit by a disaster in each observed country (rural or urban) and merge it with information regarding the growing seasons of each of the Top 5 products exported for a group of countries where the data is available on specialized internet websites and/or coming from the Food and Agriculture Organization (FAO). Finally, in order to identify the preference effect, we use different types of data that will be presented below, to capture the strengths of the cultural links between pairs of countries.

We run a series of regressions to see how disasters affect bilateral exports. Using the different sets of disaster variables (occurrence and intensity) at hand, our estimates point indeed to a negative but, in most cases, statistically non-robust relation between disasters and agricultural exports. Following our theory set-up, we attribute this result to mixing the three confounding effects with different magnitudes and opposite signs on trade. By using other new sources of data, we could then identify better two of those effects: a negative and statistically significant effect of disasters on exports when they occur in rural areas and at growing seasons times; and a positive and (very) robust relation with exports towards culturally close partners and where an important diaspora is settled. The latter result tends to show that disasters are redistributing trade across partners. In fact, for the neighbours we could identify changes in their preferences most probably through a solidarity act (altruism hypothesis) making them spend more on merchandise coming from a *close* country hit by a catastrophic event. Nevertheless, we could not show whether the 'solidarity'-consistent effect vanishes (or, on the contrary, persists) over time.

All in all, notably due to the limited physical impact of most of the disasters through the two supply channels and thanks to the pain relief provided by culturally close importers, natural disasters do not appear to make small developing countries suffer that much economically.

The outline of the paper is the following. Section 2 offers a new setup that disentangles the mechanisms through which disasters might be affecting trade flows.

Section 3 discusses how this set-up could be tested. Section 4 presents the data that are chosen to identify the channels highlighted by sections 2 and 3. Section 5 displays and discusses the econometric results. We conclude in section 6.

2 Natural disasters and exports: what are the mechanisms?

The objective of this part of the paper is to show the theoretical channels through which the occurrence of a disaster in a country can influence its exports and discuss how these channels can be retrieved empirically. Disasters have different effects on exports. Basically, they might affect exports to all countries in three ways: First through a shock on the capability of the hit country to produce and thus export to the rest of the world. Second, the impact might translate onto less exports via an increase in the barriers to trade. Third, one might think that the shock can change the preferences of importers from all countries, under the hypothesis that they are altruistic and equally care about the hit country. However, one would be tempted to expect some types of importers, not all of them, to change their demand behaviour to accommodate the shock. If so, disasters might be creating distortions in exports towards some countries and at the expense of others.

Thus, as we expect disasters to be associated with distortions in exports across partner countries, especially via the foreign demand channel, we choose to work with a gravity set-up which is the most suited to reveal those distortions, when they exist. Further, we show how one can derive econometric tests in such a set-up that allow to identify both, an expected impact of disasters on exports that is homogenous across partners on the one hand; together with an additional heterogenous impact, reallocating exports across countries on the other hand.

Assume a general set-up *à la* Head and Mayer (2014) whereby trade is undertaken between two countries i and j . However, we are interested in trade at the product level, k . Subscript k shall be made implicit in what follows to make easier the reading and comprehension of our equations but one should keep it in mind when interpreting the equations and variables. The bilateral trade equation can thus be represented by the following:

$$X_{ij} = S_i \frac{X_j}{\Phi_j} \phi_{ij} \quad (1)$$

where S_i represents the capability of a country i to export the product (implicitly k) to whichever destination. One can think of S_i to measure the competitiveness of a country in that product (through land or labor productivities and/or their costs). X_j is country's j expenditure related to the product. Besides, ϕ_{ij} represents the easiness of access of suppliers from i to market j . The variable $\Phi_j = \sum_l S_l \cdot \phi_{lj}$ stands for the average access of exporting countries to j , where each exporter's access is weighted by its respective capability in production of that product. It expresses the extent to which market j is accessible to all foreign suppliers. It is also a measure of set of opportunities consumers in j would have, thanks to the openness of j to all foreign suppliers.

For the purpose of this study, assume further that the bilateral access measure ϕ_{ij} can be represented by a combination of two other measures: a variable identifying the geographical and institutional difficulty to access some destination j by exporter i (τ_{ij}) and a measure of relative preference of consumers j towards the product coming from i (φ_{ij}). Hence, we define:

$$\phi_{ij} = \tau_{ij}^{-1} \cdot \varphi_{ij}$$

Now, the occurrence of a natural disaster in some given locality is typically an exogenous phenomenon. It is expected to have a negative effect on the capability to produce via a reduction in the productivity of land and labor (i.e. supply effect). Through infrastructure damages, it reduces further the capacity to ship products across space and countries (i.e. shipment effect). Further, as also already mentioned, preferences might change after the occurrence of a disaster, producing in turn a positive impact on exports of the victim country (i.e. foreign demand effect).

Let D_i represent any disaster variable one can think of. It can be a dummy to mention the occurrence of at least one disaster in country i at a particular time t . It might also be characterized by a continuous variable that is function of the number and/or strength of disasters observed at time t . Assume that the exporting country i we observe is small enough that any given change in its characteristics would not affect the multilateral easiness term, Φ_j . Then, transforming equation 1 in logs, applying simple comparative statics, and given that total expenditure of people in

j , X_j , will not be affected by a shock observed in i , one obtains the impact of a change in D_i through the following equation:

$$\frac{d \log X_{ij}}{dD_i} = \frac{\partial \log S_i}{\partial D_i} - \frac{\partial \log \tau_{ij}}{\partial D_i} + \frac{\partial \log \varphi_{ij}}{\partial D_i} \quad (2)$$

For ease of exposition, let us denote further the different elasticities to occurrence of disasters respectively by: $\frac{\partial \log S_i}{\partial D_i} = -\beta_S$, $\frac{\partial \log \tau_{ij}}{\partial D_i} = \beta_\tau$ and $\frac{\partial \log \varphi_{ij}}{\partial D_i} = \beta_\varphi^{ij}$.

From equation 2 and in the case of a small exporter, it is clear that the impact of disasters on exports translates via: 1) its expected impact on supply, i.e. β_S ; b) its expected impact on shipment costs, i.e. β_τ and c) its possible positive effect on preferences, i.e. β_φ^{ij} .¹

Equation 2 becomes:

$$\frac{d \log X_{ij}}{dD_i} = [-\beta_S - \beta_\tau + \beta_\varphi^{ij}] \quad (3)$$

Equation 3 provides a first view on how the occurrence of say, a disaster at some year t in some given country i might affect bilateral exports of the latter.

Now, to find the total net effect of disasters on trade, one needs to better characterize the expressions of the elasticities β_S , β_τ and β_φ^{ij} .

2.1 The capability-supply elasticity, β_S

One would expect the elasticity of trade to capability of supply of country i to be higher in absolute values, the closeness the occurrence of the disaster to the locality

¹Note however, that when the exporting country i is sufficiently big and performant to capture a significant size of the market j , a disaster that occurs in i could further affect indirectly exports from i to j through the multilateral easiness in accessing to country j term, i.e. $\frac{d \log \Phi_j}{dD_i}$. To see this, just consider that $\frac{\partial \log \Phi_j}{\partial D_i}$ can be approximated by $\frac{\partial \Phi_j}{\partial D_i} \cdot \frac{1}{\Phi_j}$. Through simple calculation of derivatives and some rearrangements one can find that

$$\frac{\partial \Phi_j}{\partial D_i} \cdot \frac{1}{\Phi_j} = \alpha_{ij} \left[\frac{\partial \log S_i}{\partial D_i} - \frac{\partial \log \tau_{ij}}{\partial D_i} + \frac{\partial \log \varphi_{ij}}{\partial D_i} \right]$$

where $\alpha_{ij} = \frac{S_i \cdot \tau_{ij}^{-1} \cdot \varphi_{ij}}{\Phi_j}$ represents the contribution share of country i to overall easiness of access into market j (Φ_j). This gives the following total impact on exports for a sufficiently big country:

$$\frac{d \log X_{ij}}{dD_i} = (1 - \alpha_{ij}) \cdot [-\beta_S - \beta_\tau + \beta_\varphi^{ij}].$$

The first term is always positive ($1 - \alpha_{ij}$). Hence, even when looking at big exporting economies the sign of the impact will still be the same as that when one looks at small ones as it is given by the second term $[-\beta_S - \beta_\tau + \beta_\varphi^{ij}]$. However, the intensity of the impact on exports should be smaller than in the case of small economies.

of production (or culture in the case of agricultural products). This is a necessary but not a sufficient condition in the case of agriculture however, as in order to curb production the timing of occurrence of a disaster needs to match the timing of growing seasons. Thus, let us express the capability-supply elasticity (expressed in absolute value) by :

$$\beta_S = m_{gs} \cdot m_r \cdot \beta'_S$$

with m_{gs} a variable indicating the extent to which the time of a sudden disaster meets the growing season one. Besides, consider m_r to be another variable that informs about whether the occurrence of the disaster takes place in a rural area where agricultural activity is likely to be observed. Both variables take values between 0 and 1. At one extreme, when $m_{gs} = 1$ and $m_r = 1$ the negative impact on capacity supply would be the highest and the negative effect on trade should be significant. However, at the other extreme (i.e. $m_{gs} = 0$ and $m_r = 0$) the impact on capacity supply and thus trade should be null.

2.2 The shipment-supply elasticity, β_τ

Transaction costs linked to shipments are expected to increase after an occurrence of a disaster (think about highways, ports or communication networks being damaged after an earthquake or a flood). Possible damages made to some of these equipments, like highways or telecommunication networks, should be affecting both intra-national and inter-national shipments alike. Besides, trade to foreign countries via international seaports or airports are likely to be further affected, if the gates to outside destinations (international seaports or airports) are also being hurt.

Because urban areas concentrate most of the telecommunication and highway networks, and because international seaports and airports are usually located there too, one would expect more damages to shipment supplies and thus a higher induced-impact of disasters on exports when they take place in urban areas. To fix ideas, recall that m_r is a dummy designating a disaster taking place in a rural area, then one that takes place in an urban place will be expressed by $m_u = (1 - m_r)$. Then, let us redefine the shipment supply elasticity (in absolute value) as:

$$\beta_\tau = \beta'_\tau + m_u \delta_\tau$$

where β'_τ designate the shipment-induced impact on exports when the disaster occurs in a rural area and δ_τ designates the additional effect when it happens to be located in an urban area.

2.3 The foreign preference elasticity, β_φ

A natural disaster might well induce a change in the preferences of some foreign consumers towards the goods provided by the home country. This possible change in behaviour of foreign consumers is related to what we shall call the altruism or solidarity hypothesis. If all foreign consumers change their behaviour in an equal fashion so as to import more from the victim countries' to express their solidarity, then the possible negative effects coming from the supply side (supply of production and shipments) might well be compensated, at least in part, by a change in the demand side coming from foreign consumers. It is unlikely however that foreign consumers from all countries would change their consumption behaviour. Actually, this behaviour is most likely to arise when consumers from outside are culturally close to the home country. In such a case, the catastrophe could have then a reallocative impact on trade: it favors relatively more exports to countries which are culturally close to the hit country (or in which an important diaspora of nationality i is settled). Hence, let us redefine

$$\beta_\varphi^{ij} = \delta_\varphi \cdot c_{ij}$$

where, in the case of a culturally close partner, say n , one would observe an induced effect of demand on exports through $\delta_\varphi \cdot c_{in}$, where δ_φ is a positive demand shifter and $c_{in} = 1$ standing for a dummy designating the importer j to be equal to n , whenever n is observed. On the opposite, whenever $j \neq n$, $c_{ij} = 0$ and thus $\beta_\varphi^{ij} = 0$.

3 Towards a testable equation

Plugging all of the above β expressions into equation 3 will give the total impact of disasters on bilateral exports, through

$$\frac{d \log X_{ij}}{dD_i} = \left[\underbrace{\underbrace{-m_{gs} \cdot m_r \cdot \beta'_S}_{\text{capability-supply effect}} - \underbrace{(\beta'_\tau + m_u \delta_\tau)}_{\text{shipment-supply effect}}}_{\text{total-supply effect}} + \underbrace{\delta_\varphi \cdot C_{ij}}_{\text{close country preference effect}} \right] \quad (4)$$

It is clear from the above equation that the total impact of natural disasters on exports is not necessarily negative. Indeed several cases are possible:

- The total effect on exports will be observed to be negative if the two supply effects (negative on trade) outweigh the preference effect (positive).
- The total effect of disasters might turn out to be positive on exports towards culturally close countries, however, if the preference effect is higher in absolute value than total-supply effect.
- Even in the absence of a preference effect, the impact might turn out to be non-significant on exports. If for instance natural disasters take place in a rural area at a time of non-growing seasons, the capability-supply effect would not be relevant and the shipment supply effect could be rather small (most of the network activity and connexions in transport and communication are in cities) making the coefficient that is estimated statistically non significant.
- Note finally that disasters which take place in a rural area might not be affecting negatively more exports than those hitting urban areas. Outside periods of cultural growth seasons, one would even expect an unambiguous higher negative effect when the shock attends urban areas.

Hence, in this section we wanted to show first how the link between bilateral exports and disasters variables can be actually ambiguous, whether in terms of sign or intensity. Thus, following our theoretical conclusion, if one runs a simple regression he or she would not be able to obtain a clearcut result, as the latter would be a mix of different and opposing effects. Nevertheless, from our data on trade and disasters and with the help of some other sources of information, one can show that at least two effects can be further identified, the capability-supply effect and the preference-effect (distortion effect).

To do so, and having all these mechanisms in mind, we go back to the equation to test 1, accounting for the expression of ϕ_{ij} , and transforming into logs one obtains:

$$\log X_{ij}^k = \log S_i^k + \log X_j^k - \log \tau_{ij} + \log \varphi_{ij} + \log \Phi_j^k \quad (5)$$

Let us consider further that $\log S_i^k = \alpha_S \log S_i'^k - \beta_S \log D_i$ where $\log S_i'^k$ represents a vector of variables that are expected to proxy the capability of i besides D_i . Also, let $\log \tau_{ij} = \alpha_\tau z_{ij} + \beta_\tau D_i$ where z_{ij} represents a vector of usual variables related to geography and institutions. Finally, let $\log \varphi_{ij} = +\alpha_\varphi z_{ij} + \beta_\varphi D_i$ with z_{ij} a similar vector of gravity variables capturing the preferences of consumers from j towards products coming from i other than D_i . By incorporating into equation 5 and adding a time subscript one would obtain:

$$\log X_{ijt}^k = \alpha_S \log S_{it}'^k + \log X_{jt}^k - \alpha z_{ij} + \log \Phi_{jt}^k + [\beta_\varphi^{ij} - \beta_S - \beta_\tau] \cdot D_{it} \quad (6)$$

with $-\alpha = -\alpha_\tau + \alpha_\varphi$, expected to be negative (the second term, α_φ is expected to be small compared to the transaction costs effect one, α_τ). It is then easy to see from equation 6 that encompassing the 3 coefficients related to the disaster variable into only one to be estimated, say β_{mix} , such that $\beta_{mix} = \beta_\varphi^{ij} - \beta_S - \beta_\tau$ might not lead to a very instructive information as to which of the effects are at work and by how much. One better way to identify the different channels is to recall that each of these channels can be revealed through some set of interactions with other variables mentioned in section 2 above. Hence if one replaces the β parameters by the corresponding expressions there, one would find the following type of equation that she would like ideally to test :

$$\begin{aligned} \log X_{ijt}^k &= \log S_{it}'^k + \log X_{jt}^k - \alpha z_{ij} + \log \Phi_{jt}^k \\ &\quad - \beta'_\tau \cdot D_{it} - \beta'_S m_{gs} \cdot m_r \cdot D_{it} - \delta_\tau \cdot (m_u) \cdot D_{it} + \delta_\varphi \cdot c_{ij} \cdot D_{it} \end{aligned} \quad (7)$$

In the next sections we test the above equations 6 and 7 and some of their variants. Especially, by interacting the disaster variable with others in the spirit of what is suggested above, it is then *a priori* possible to identify the different channels at work.

4 Data

We begin by presenting roughly the trade data we use, before detailing the disasters' data. In addition, we have built our own database to identify the growing season of crops for the top 5 exported agricultural products of each country of our sample and distinguish rural from urban areas. All these data and their sources are presented below.

4.1 Trade data

As we are interested in small developing countries, we have only kept the medium and low income countries according to World Bank definition, of less than 20 millions inhabitants. This corresponds to 74 exporting countries being selected (see Appendix A).

For those countries, we use the BACI database of the CEPII based on UN-COMTRADE, which reports bilateral trade flows in tons and values with around 200 potential partners, at product levels (6 digits harmonized system, HS92) over the period 1995 to 2010. We then extract all traded products related to agriculture and that are not transformed (grains, cereals, coffee, fruits, vegetables, animal live, wood, etc...) keeping about 270 agricultural products in our sample.² We work essentially with agricultural trade flows in tons rather than values, because we think that supply shocks should be more retrieved.³

Trade data at the product level is being used mainly to identify the capability-supply effect. In fact, one needs to associate each product at hand to the period of its growing season provided by other sources. Besides, and more generally, the use of an additional dimension increases variations in the data, within pairs of countries, which allows for better controls and should lead to more consistent point estimates in the econometrics part.

²Fisheries products figure were not used however. These were the only non-transformed agriculture products to be kept aside.

³After a disaster shock, prices could increase through less quantity supplied, thus biasing downward the pure quantity effect that we want to identify in the data. That being said, note that we have also run regressions in values and retrieved most of the results, probably because we are studying small price-taking countries. However, as expected, the coefficients related to the capability effect appeared to be smaller in magnitude, and sometimes non significant. Results are available upon request.

4.2 Disasters' Data

We use two datasets informing about natural disasters. To follow the literature we begin by using the Emergency Event Database (EM-DAT) delivered by the Center of Research on the Epidemiology of Disasters (CRED), University of Louvain (Guha-Sapir, Below and Hoyois, 2011). "*The database is compiled from various sources, including UN agencies, non-governmental organizations, insurance companies, research institutes and press agencies*" (Guha-Sapir, Below and Hoyois, 2011).⁴ We select only those which are qualified as natural disasters, thus covering droughts, earthquakes, epidemic, extreme temperature, famine, flood, insect infestation, landslide, volcanic eruption, wildfire, and windstorms.⁵ For each observed disaster, the EM-DAT dataset reports measures on the intensity of the damage like the number of persons killed or the amount of direct damages. It is well known from the literature however, that these data might not be sufficiently reliable (Oh and Reuveny (2010), and Noy (2009)) as the quality of reporting of damages and deaths is linked to the wealth of countries and thus endogenous to the level of development. We follow most of the recent literature and only consider from the EM-DAT dataset the information on occurrence of disaster events, that we use to compute the number of events in a year observed in a country.

The second dataset we consider is the Geophysical and Meteorological database (GeoMet), following Felbermayr and Gröschl (2014). This database reports the physical magnitudes of four particular types of disasters (earthquakes, extreme temperatures, floods and windstorms). Felbermayr and Gröschl (2014) measure the intensities related to each of the disasters at hand by applying the following measurement scales:

- floods: the deviation of total monthly rainfalls from the average monthly rainfalls of the entire period (1995-2010),
- extreme temperatures: the deviation of monthly maximum temperature from the average monthly temperatures of the entire period (1995-2010),
- earthquakes: the Richter scale in value for each earthquake observed,

⁴<http://www.emdat.be/>.

⁵For a disaster, at least one of the following criteria must be realized to be entered into this database: a- ten or more people reported killed, b- hundred or more people reported affected, c- declaration of the state of emergency, d- call for international assistance.

- storms: the wind speed in value for each storm observed.

From these monthly or event level observations, the authors then produce yearly aggregates at the country level, by selecting the corresponding maximum values observed each year and for each country. We replicate their method and also follow these authors to build a composite physical intensity index as the sum of each of the previous physical intensity measures weighted by the inverse of their standard deviation. Following Felbermayr and Gröschl, we call this additional variable Disaster Intensity Index.

4.3 Other important data for identification

4.3.1 Data to identify the supply-effects

As shown above, the supply effects can be decomposed into capability and shipment effects. First, the date of the cataclysm matters for identifying the capability-effect during the growing season. So, ideally, for each date of occurrence of a disaster in some country, one should look at whether it lies before or within the period of growing season for each of the products observed in that country.

However, because it is very costly and time consuming to identify the growing seasons for all of the agricultural products in all 74 countries, we have chosen to identify the growing season of the year for a sample restricted to the top 5 most exported products for each country at hand where the data could be observable (see details below). Besides, to ensure that our top 5 products are sufficiently representative of a country's total exports, we have only selected countries where they accounted for at least 50% of total agricultural exports. Also, to hold enough partner countries, we have kept further only the countries for which those top 5 products were at least exported towards ten different importers. At the end of the exercise, our new sub-sample that we use to identify the capability effect was then reduced from 74 to 26 exporting countries (See Appendix B for a list of these countries).

We use different sources of data, listed in Appendix C, to construct the growing season period of the year for each of the top 5 products and for each exporting country: national periodicals providing the period of crops, information from the Food and Agriculture Organization (FAO) or the U.S. Department of Agriculture (USDA) giving for some countries and products the calendar of harvests. We have also extracted data from national websites on specific crops for some products. Then,

armed with the data on the time of occurrence of natural disaster in EM-DAT, we were able to build a "crop growing season (grSeason)" variable, which indicates the proportion of catastrophes in a year that occur before or during the harvest.

Second, in order to capture the capability effect on the one hand and the shipment effect on the other, we still need to identify whether disasters occur in rural or urban regions. To do so, we use the FAO map "Global land cover distribution", by dominant land cover type FGGD (FAO Geonetwork Global Land cover Distribution). *"The FGGD global land cover map is a global raster datalayer with a resolution of 5 arc-minutes. Each pixel contains a class value representing the dominant land cover type found in the pixel"*⁶. The different types of surface observed can be either an artificial surface, a crop surface, a forest or a pasture surface. Each pixel provides either the dominant type observed (more than 75% of surface) or the dominant mix of two of these types (around 50 to 75%). Then, we associate FGGD information to EM-DAT's information on the localisation of catastrophe to identify the type of surface being hit by the disaster. For our study, we have coded a variable taking three values designating the extent to which the type of land is being rural for each of the observed disasters, based on the following classification:

- rural (value=1): when more than 75% of the dominant area is observed either to be a crop surface, a forest or a pasture surface. When a combination of these makes more than 75% the area is also considered to be rural;⁷
- urban (value=0): when more than 75% of the dominant area is observed to be artificial;
- mixed (value=0.5): when the area is observed to be mixed (around 50 to 75% being either crop, forest or pasture related surfaces, and the rest being an artificial area).

As we are interested in the types of land involved by disasters at a yearly level, we then define a variable that we call *rural* to be the share in total of rural zones hit by disasters, by summing the values of the above variable over all disasters for each year and each country. To stick to the theoretical specifications in section 1, and try to identify further a possible shipment effect, we also define a complement

⁶<http://www.fao.org/geonetwork/srv/en/main.home>

⁷Recall that we are considering wood products in our trade data which is why we consider forests surfaces as part of the rural area.

variable, *urban*, where $urban = 1 - rural$. The variable *urban* provides the share of disasters that are reported to be localized in an urban area.

4.3.2 Data to identify the preference changes

Our theoretical set-up states that one possible positive effect from disaster might come from a change in preferences of foreign based consumers. In particular, consumers in countries that are culturally close to that where the disaster has taken place might choose to import agricultural products from the victim country. One simple way to identify whether such effect is at work is to identify whether exports increase towards those countries where consumers are culturally close to the exporting country that has just experienced a disaster on its soil. We thus need information describing the extent to which each observed pair of countries is having a culturally close relationship. We adopt several definitions here for closeness. First, we begin by using an ex-ante and a priori exogenous measure of cultural closeness following De Souza, Mirza and Verdier (2018). These authors define the cultural closeness or what they call the (cultural) neighborhood among countries based on shared characteristics, i.e., a border, an official language, and a religion.⁸ Like these authors, we use different combinations of shared characteristics, e.g., two countries would be considered as neighbors when they share a border only or when, in addition, they also share a language and a religion. We simply argue that the more characteristics the countries share, the closer their neighborhood or cultural relationship. Second, we approximate cultural closeness by the diaspora originating from the victim country and living in the partner country. Using the World Bank Global Bilateral Migration Database, we extract the stock of migrants by nationality, residing in each country available, considering the figures of year 2000.⁹

4.3.3 Other control data

Finally, in addition to trade and natural disasters' data, we rely on usual gravity variables (geography and institutions) from:

- CEPII database of traditional gravity variables,

⁸We consider that two countries share a religion when a common religion is practiced by at least 50% of the population in each country.

⁹The data is provided every 10 years from 1960 to 2010 at <https://datacatalog.worldbank.org/dataset/global-bilateral-migration-database>.

- World Development indicator (WDI) for the countries' GDP per capita, and population.

5 Empirical analysis, results

We take our framework in section 2 and 3 to the test.

We first run a regression comparable to the theoretical equation (6) above. To do so, we begin by approximating $\log S'_{ik}$ (i.e. the part of supply independent from disaster shocks), by a series of controls including the value added in agriculture a year before $\log va_{i,t-1}$, population at date t $\log pop_{it}$, a (*product* \times *exporter*) fixed effect to account for some specialisation of countries across products and a (*product* \times *time*) fixed effect to control for any shift in technology of production of some products compared to others overtime. The log of total demand for product k by consumers from j , at time t (i.e. $\log X_{jkt}$) can be considered to be a linear function of the log size of population in j $\log pop_{jt}$ and that of its GDP per capita ($\log GDPcap_{jt}$) (i.e. purchasing power related variable), at time t . As already mentioned, z_{ij} can be approached by a series of standard transaction costs related variables such as logs of geographical distance ($\log dist_{ij}$), a dummy informing about a country that has ever been in a colony relationship with another partner (*colony*), another informing about a country having the same main language than the other (*language*), and whether or not partner countries are part of a free trade agreement (i.e. *FTA*). Finally, one can proxy the multilateral resistance term Φ_{jt}^k by a combination of (*product* \times *time*) and (*product* \times *importer*) fixed effects.

Then, the empirical counterpart to the theoretical equation (6), can be shown to take the following form¹⁰:

$$\begin{aligned} \log X_{ijt}^k = & \beta D_{it} + \alpha_1 \log va_{it-1} + \alpha_2 \log pop_{it} + \alpha_3 \log gdp_{jt} + \alpha_4 \log pop_{jt} \\ & + \alpha_5 \log dist_{ij} + \alpha_6 \text{adjacency}_{ij} + \alpha_7 \text{colony}_{ij} + \alpha_8 \text{language}_{ij} + \alpha_9 \text{FTA}_{ij} \\ & + \lambda_i^k + \lambda_j^k + \lambda_t^k + \epsilon_{ijt}^k \quad (8) \end{aligned}$$

¹⁰For more insights on specification of gravity equations, see Anderson and Van Wincoop (2003), Wooldridge (2003) and Head and Mayer (2014).

with, $\log X_{ijt}^k$, the logarithm of bilateral export of agricultural products and ϵ_{ijt}^k the error term.

The disaster variable D_{it} can take the following expressions:

- $\ln(\text{occurrence}_{it} + 1)$, the logarithm of one plus the number of major disasters in exporting country i in year t ; the data come from EM-DAT,
- index_{it} , the composite index, averaging the intensities of four types of natural disasters (earthquakes, extreme temperatures, floods and storms), analysed separately, for exporting country i in year t ; the data are taken from GeoMet,

As already suggested in section 3 above, we also run below a series of variants of the above specification where we try alternatively to concentrate on the shipment effect, the capability effect and the preference effect.

Table 1 provides the first results based on equation 9. Most of the usual gravity variables have the expected sign of boosting trade (population and GDP per capita of importer, value added in agriculture of exporter, FTA, common border, same language and colonial inheritance) or reducing it (distance).¹¹ More importantly, whether the occurrence of disaster or the index variables are considered, in columns 1 and 2 respectively, the related coefficient does not show up to be statistically significant. Following our theory set-up, we attribute this result to mixing the three confounding effects on trade.

5.1 Results: supply effects

We then consider identifying first the supply effects (i.e. shipment and capability effects). To do so, we already mentioned above that we needed information on the location of the disaster (i.e. urban or rural) and whether the timing of the shock overlaps with the growing seasons of our products' cultures. These information could be obtained for 26 countries and the top 5 most exported products by exporter.¹² Before trying to identify the supply effects we first run, as a benchmark, exactly the same specification above (eq. 9) but on the 26 countries instead of the full sample considered in columns 1 and 2. The objective is to see whether reducing the

¹¹The only two gravity-type variables that show up with an opposite sign to that expected are the population of the exporter and the common religion dummy. These variables are taken as controls however, and the reasons behind these negative signs are beyond the objectives of this paper.

¹²Wood products have not been considered here because the growth season does not apply.

sample to these countries would change or not the general statistically insignificant coefficient on the disaster's variables. Columns 3 and 4 produce again statistically insignificant coefficients on the two disaster's variables. Similar results are obtained when reducing further the sample to the top 5 products exported by country (see columns 5 and 6).

From there, we try now to identify the shipment effect. We thus introduce an additional interaction term in columns 7 and 8, where the two alternative disasters' variables are being interacted with the *urban* variable (i.e. a variable designating the proportion of disasters in the country taking place in urban areas each year). This new specification do not change the overall results concerning the effects of disasters: not only the statistical insignificance of the negative coefficient on disasters does not change, but also the interaction term does not appear with the expected negative sign and significance (see columns 7 and 8).

We then turn to a specification where the objective is to identify the capability effect. Columns 9 and 10 show the results of a specification where disasters variables in a year t double-interact with the *rural* variable and the crops' growing season variable. Interestingly, the coefficient on the double-interaction variable appears to be negative and statistically significant, whether one considers yearly disasters in numbers or in their intensity (i.e. index). On the other hand, the coefficient on the pure disaster's variable which used to be negative in a specification based on the same sample without these interactions (see columns 5 to 8) turn out now to become positive, *albeit* non significant. The results related to columns 9 and 10 are consistent with the view that what is driving the negative sign found on disasters in the earlier regressions is the impact of disasters' during the growing seasons. Once this effect is captured by the interaction term, the general impact of disasters on trade outside growing seasons turn out to be positive, while still statistically insignificant.

Columns 11 and 12 show the results of a demanding specification where we attempt to identify *both* a shipment effect and a capability effect. Again, the statistical insignificance of the coefficient on the first interaction term (i.e. with *urban* variable) does not change. The coefficient on the second interaction term (i.e. with growth season) is still negative and statistically significant when considering the number of disasters' related variable. But it turns out not to be so when considering the intensity of disaster variable (i.e. the index term). Because we could not obtain a clearcut statistically significant negative effect across the two employed disaster

variables, one can conclude from columns 9 to 12, that the identification of the capability effect while being very suggestive and relatively robust is not completely so, due to statistical insignificance of the result in column 12.¹³

5.2 Results: preference effects

Besides the supply effects shown in table 1, we try to test further whether or not disasters can also favor exports into some destinations through changes in preferences in these destinations in the aftermath of disaster events. More precisely, as already suggested in our theoretical set-up, we want to test here for the hypothesis that partner countries with a close culture to the exporting one, could reallocate their demand towards products originating from the latter when it is hit by a disaster.

To tackle this demand distortion effect, we augment our basic specification with interaction terms set between some dyadic gravity variables and the disaster variable as already shown by equation 7. In order to better understand what are the expected signs we present the empirical version of equation 7. One obtains :

$$\begin{aligned} \log X_{ijt}^k = & -\beta'_\tau \cdot D_{it} - \beta'_S m_{gs} \cdot m_r \cdot D_{it} - \delta_\tau \cdot (m_u) \cdot D_{it} + \delta_\varphi \cdot c_{ij} \cdot D_{it} \\ & + \alpha_1 \log va_{it-1} + \alpha_2 \log pop_{it} + \alpha_3 \log gdpcap_{jt} + \alpha_4 \log pop_{jt} \\ & + \alpha_5 \log dist_{ij} + \alpha_6 adjacency_{ij} + \alpha_7 colony_{ij} + \alpha_8 language_{ij} + \alpha_9 religion_{ij} + \alpha_{10} FTA_{ij} \\ & + \lambda_i^k + \lambda_j^k + \lambda_t^k + \epsilon_{ijt}^k \end{aligned} \quad (9)$$

One can recall that c_{ij} represents the closeness of culture variable. This theoretical variable can be then approached empirically by each of the gravity related variables dummies (religion, language, adjacency or colony) or a combination of these. We simply argue that the more characteristics the countries share, the closer their neighborhood or cultural relationship. As already mentioned in the data description section above, we also approximate c_{ij} by the length of the diaspora in the partner country. Then, the expected signs on the pure disaster variable ($-\beta_\tau$) and the two first interaction terms ($-\beta'_S$ and $-\delta_\tau$) should all be negative. On the opposite, the expected sign on the third demand term ($+\delta_\varphi$) is expected to be posi-

¹³Recall that the two interaction terms are correlated by construction in columns 11 and 12 and one effect is difficult to identify while holding the other constant. In fact, the proportion of disasters in urban regions and that related to rural regions sum up to unity ($urban = 1 - rural$).

Table 1: Exports and Disasters (Supply Effects)

Countries Products	All		All		26		All		26		Top 5		26		Top 5		26		Top 5	
	Disaster variable (1)	Occurrence (2)	Index (3)	Occurrence (4)	Index (5)	Occurrence (6)	Index (7)	Occurrence (8)	Index (9)	Occurrence (10)	Index (11)	Occurrence (12)								
Disaster _{it}	-0.00287 (0.0192)	-0.00300 (0.0057)	0.0236 (0.0231)	0.00634 (0.00733)	-0.0155 (0.0446)	-0.00629 (0.0103)	-0.0171 (0.0448)	-0.00913 (0.0108)	0.0169 (0.0514)	0.0165 (0.0169)	0.0155 (0.0520)	0.0140 (0.0203)								
Disaster _{it} * <i>urban_{it}</i>							0.0546 (0.113)	0.0352 (0.0299)				0.0294 (0.117)	0.0115 (0.0352)							
Disaster _{it} * <i>rural_{it}</i> * <i>growthseason_{it}^k</i>									-0.0751* (0.0443)	-0.0200** (0.0101)	-0.0737* (0.0447)	-0.0186 (0.0116)								
<i>lnDistance_{ij}</i>	-0.567*** (0.0187)	-0.567*** (0.0187)	-0.662*** (0.0216)	-0.662*** (0.0216)	-1.221*** (0.0912)	-1.221*** (0.0912)	-1.221*** (0.0912)	-1.221*** (0.0912)	-1.221*** (0.0912)	-1.221*** (0.0912)	-1.221*** (0.0912)	-1.221*** (0.0912)								
<i>Contiguity_{ij}</i>	0.364*** (0.0463)	0.364*** (0.0463)	0.414*** (0.0549)	0.414*** (0.0549)	0.988*** (0.190)	0.987*** (0.190)	0.988*** (0.190)	0.987*** (0.190)	0.986*** (0.190)	0.986*** (0.190)	0.986*** (0.190)	0.986*** (0.190)								
Common language _{ij}	0.215*** (0.0247)	0.215*** (0.0247)	0.350*** (0.0298)	0.350*** (0.0298)	-0.102 (0.0878)	-0.102 (0.0878)	-0.102 (0.0878)	-0.102 (0.0878)	-0.102 (0.0878)	-0.102 (0.0878)	-0.102 (0.0878)	-0.102 (0.0879)								
Colony _{ij}	0.389*** (0.0376)	0.389*** (0.0376)	0.151*** (0.0415)	0.151*** (0.0415)	1.114*** (0.138)	1.114*** (0.138)	1.114*** (0.138)	1.114*** (0.138)	1.115*** (0.138)	1.115*** (0.138)	1.115*** (0.138)	1.115*** (0.138)								
Religion _{ij}	-0.0875*** (0.0298)	-0.0875*** (0.0298)	-0.151*** (0.0375)	-0.151*** (0.0375)	-0.303*** (0.0870)	-0.303*** (0.0870)	-0.303*** (0.0870)	-0.303*** (0.0871)	-0.303*** (0.0870)	-0.303*** (0.0870)	-0.303*** (0.0870)	-0.303*** (0.0870)								
FTA _{ij}	0.234*** (0.0371)	0.234*** (0.0371)	-0.00433 (0.0503)	-0.00433 (0.0503)	0.221** (0.0965)	0.221** (0.0965)	0.221** (0.0965)	0.222*** (0.0966)	0.222*** (0.0965)	0.223** (0.0966)	0.223** (0.0965)	0.223** (0.0966)								
<i>lnagriculture value added_{it-1}</i>	0.541*** (0.0797)	0.542*** (0.0799)	0.467*** (0.0977)	0.461*** (0.0974)	0.777*** (0.148)	0.778*** (0.148)	0.776*** (0.149)	0.772*** (0.150)	0.766*** (0.148)	0.781*** (0.149)	0.765*** (0.149)	0.779*** (0.150)								
<i>lngdp_{it}</i>	0.254*** (0.0446)	0.254*** (0.0446)	0.0794** (0.0451)	0.0785* (0.0451)	0.424*** (0.0619)	0.424*** (0.0619)	0.424*** (0.0619)	0.424*** (0.0619)	0.424*** (0.0620)	0.425*** (0.0620)	0.425*** (0.0620)	0.425*** (0.0620)								
<i>lnpop_{jt}</i>	0.112 (0.131)	0.111 (0.131)	0.288** (0.131)	0.288** (0.131)	0.587*** (0.189)	0.587*** (0.189)	0.587*** (0.189)	0.587*** (0.189)	0.586*** (0.189)	0.588*** (0.189)	0.586*** (0.189)	0.588*** (0.189)								
<i>lnpop_{jt}</i>	-0.624*** (0.167)	-0.622*** (0.166)	-0.410* (0.226)	-0.397* (0.225)	-0.622 (0.572)	-0.618 (0.572)	-0.636 (0.574)	-0.649 (0.573)	-0.615 (0.573)	-0.680 (0.571)	-0.622 (0.576)	-0.686 (0.573)								
Years	1995-2010	1995-2010	1995-2010	1995-2010	1995-2010	1995-2010	1995-2010	1995-2010	1995-2010	1995-2010	1995-2010	1995-2010								
Exporter x Product FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes								
Importer x Product FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes								
Product x Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes								
Adjusted R-squared	0.608	0.608	0.632	0.632	0.702	0.702	0.702	0.702	0.702	0.702	0.702	0.702								
Observations	293,665	293,665	189,205	189,205	41,968	41,968	41,968	41,968	41,968	41,968	41,968	41,968								

Notes: Standard errors are clustered by exporter x time. Robust standard errors are in parentheses, with *** 1%, ** 5% and * 10% levels.

tive if one expects a solidarity effect to arise after the shock (i.e. change in demand towards people who resemble to us).

In what follows, we only provide the results regarding the number of disasters variable but the results are qualitatively similar with regard to the distortion effect estimations when one replaces the number of occurrence by the index variable.¹⁴ Table 2 shows the results on the 26 countries and Top 5 products subsample, where all distinct effects of disasters could actually be tested: supply (through shipments and capability) along with demand effects (changes in preferences). The different columns of table 2 provide the results of the different proxies of cultural closeness that were used to measure the latter. We begin by discussing the first supply terms and then turn to the demand effects.

Firstly, and consistently to what has been already shown in the prior table the impact of natural disasters through $-\beta_\tau$, remains not statistically different from 0. Second, the urban-shipment effect does not appear to be statistically significant neither. Third, the only negative effect that we could identify goes through the capability related parameter. An increase in 10% in the number of disasters reduces by 0.7% exports to a given partner, when these disasters happen to be located in a rural area ($m_r=1$) and when the timing of the shock corresponds to that of period of culture growth season $m_{gs} = 1$. But this figure provides a maximum negative effect: in a world where say, 50% of the shocks are located in urban areas and 25% of the shocks happen during the growth seasons then the impact would be around 0.08% which is actually a very small figure.

Now, let us turn to the preference effects that are estimated in the table. When each element of cultural closeness is taken separately and interacted to the disaster variable (either sharing a border, a religion, a language, or having been a colony of one another), the impact, although always positive (except for the colony interaction variable) does not appear to be statistically significant. The impact is significantly strengthened in value and becomes statistically significant and positive (see column 5, table 2), when partner countries share with the hit country the same language and the same border. The coefficient multiplies further by two when the countries share a common border, a language and a religion together (see column 6, coefficient on what is called the neighborhood variable as in ?). The positive and statistically significant result is corroborated when, instead of taking neighborhood, one opts for

¹⁴The results are available upon request.

the diaspora variable (see column 7, table 2). Hence, diasporas and neighborhood countries tend to support hit countries by increasing their bilateral imports in a way that is completely consistent with a demand effect.

All the data needed to identify the demand effect do actually exist for all our countries. In what follows, we then concentrate on identifying the demand effect using all the information available (74 countries and around 270 agricultural products). Table 3 provides the results. As the supply effects could not be dissociated and thus identified (recall that we do not have access to growth seasons for all products and countries), they are supposed to be captured by the coefficient on the first variable that appears in the table (pure disaster variable). Interestingly, one needs to note firstly that, compared to prior tables, most of the coefficients related to this variable turn now to be negative on trade although still statistically non significant. Next, more importantly, the demand effect found in the prior table through the interaction terms is now confirmed with the whole sample at hand. The demand effect is even now more robust across the different cultural closeness variables at hand. In this bigger sample, it appears to be negative and statistically significant when disaster are interacting with the same border, the same language and with their combination, along with their combinations with same religion variable (ie. neighborhood variable). The diaspora effect appears again to be positive and statistically significant, when a disaster hits a country.

To have a better quantitative idea of the effect of these interaction terms, let us consider again the neighborhood variable: being culturally very close to one hit country, makes the partner country increase its imports from the victim one by 2.4% on average when the number of disasters increase by 10%. We have computed the average standard deviation from the mean of disasters within countries over time to be around 30%. Then a representative increase in one standard deviation over the mean in the number of disasters increases exports to culturally close countries by around 7%.

In the last two columns, we concentrate uniquely on the demand effect while introducing a further set of fixed effects for exporter \times time and importer \times time that are supposed to wipe out all other supply effects. Strikingly, we still find that diaspora and neighbouring effects remain positive and statistically significant (columns 8 and 9, table 3).

Table 2: Exports and Disasters (Preference Effects)

Countries	26	26	26	26	26	26	26
Products	Top 5	Top 5	Top 5	Top 5	Top 5	Top 5	Top 5
Disaster variable	Occurrence (1)	Occurrence (2)	Occurrence (3)	Occurrence (4)	Occurrence (5)	Occurrence (6)	Occurrence (7)
Disaster _{it}	0.0228 (0.0527)	0.0101 (0.0559)	-0.0010 (0.0527)	0.0075 (0.0544)	-0.0027 (0.0523)	0.0001 (0.0525)	-0.0724 (0.0655)
Disaster _{it} * urban _{it}	0.0307 (0.117)	0.0283 (0.117)	0.0321 (0.117)	0.0335 (0.118)	0.0341 (0.117)	0.0351 (0.117)	0.0275 (0.118)
Disaster _{it} * rural _{it} * growthseason _{it} ^k	-0.0741* (0.0449)	-0.0733 (0.0448)	-0.0743* (0.0449)	-0.0755* (0.0447)	-0.0772* (0.0448)	-0.0844* (0.0452)	-0.0757* (0.0448)
lnDistance _{ij}	-1.220*** (0.0911)	-1.221*** (0.0911)	-1.219*** (0.0911)	-1.221*** (0.0911)	-1.254*** (0.0898)	-1.297*** (0.0869)	-1.101*** (0.0951)
Contiguity _{ij}	0.985*** (0.190)	0.987*** (0.190)	0.851*** (0.215)	0.986*** (0.190)			0.884*** (0.190)
Common language _{ij}	-0.104 (0.0881)	-0.111 (0.0901)	-0.102 (0.0878)	-0.103 (0.0878)			-0.188** (0.0903)
Colony _{ij}	1.190*** (0.157)	1.114*** (0.139)	1.119*** (0.138)	1.114*** (0.138)	1.054*** (0.105)	1.099*** (0.105)	1.051*** (0.138)
Religion _{ijt}	-0.300*** (0.0871)	-0.304*** (0.0869)	-0.302*** (0.0871)	-0.323*** (0.0948)	-0.297*** (0.0887)		-0.321*** (0.0859)
FTA _{ijt}	0.220** (0.0965)	0.222** (0.0966)	0.225** (0.0963)	0.222** (0.0965)	0.246** (0.0960)	0.252*** (0.0969)	0.174* (0.0951)
lnagriculture value added _{it-1}	0.766*** (0.149)	0.764*** (0.149)	0.766*** (0.150)	0.764*** (0.149)	0.769*** (0.150)	0.773*** (0.150)	0.757*** (0.148)
lngdp _{jt}	0.425*** (0.0619)	0.424*** (0.0620)	0.423*** (0.0619)	0.424*** (0.0620)	0.422*** (0.0618)	0.422*** (0.0620)	0.426*** (0.0628)
lnpop _{jt}	0.588*** (0.189)	0.584*** (0.189)	0.575*** (0.189)	0.586*** (0.189)	0.573*** (0.189)	0.569*** (0.189)	0.596*** (0.189)
lnpop _{it}	-0.626 (0.576)	-0.623 (0.576)	-0.627 (0.579)	-0.613 (0.577)	-0.637 (0.579)	-0.642 (0.581)	-0.600 (0.576)
Colony _{ij} * Disaster _{it}	-0.184 (0.121)						
Common language _{ij} * Disaster _{it}		0.0258 (0.0856)					
Contiguity _{ij} * Disaster _{it}			0.294 (0.194)				
Religion _{ij} * Disaster _{it}				0.0403 (0.0752)			
Contiguity _{ij} * Commonlanguage _{ij}					0.831*** (0.253)		
Contiguity _{ij} * Commonlanguage _{ij} * Disaster _{it}					0.494** (0.221)		
Neighborhood _{ij}						0.507 (0.0379)	
Neighborhood _{ij} * Disaster _{it}						0.819*** (0.274)	
Diaspora _{ij}							0.0588*** (0.0128)
Diaspora _{ij} * Disaster _{it}							0.0194** (0.0082)
Years	1995-2010	1995-2010	1995-2010	1995-2010	1995-2010	1995-2010	1995-2010
Exporter x Product FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Importer x Product FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product x Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.702	0.702	0.702	0.702	0.702	0.702	0.702
Observations	41,968	41,968	41,968	41,968	41,968	41,968	41,968

Notes: Standard errors are clustered by exporter x time. Robust standard errors are in parentheses, with *** 1%, ** 5% and * 10% levels.

Table 3: Exports and Disasters (All countries sample- Preference Effects)

Countries	All	All	All	All	All	All	All
Products	All	All	All	All	All	All	All
Disaster variable	Occurrence (1)	Occurrence (2)	Occurrence (3)	Occurrence (4)	Occurrence (5)	Occurrence (6)	Occurrence (7)
$Disaster_{it}$	-0.0039 (0.0197)	-0.0268 (0.0215)	-0.0303 (0.0187)	-0.0106 (0.0211)	-0.020 (0.0184)	-0.0214 (0.0184)	-0.123*** (0.0319)
$lnDistance_{ij}$	-0.567*** (0.0187)	-0.566*** (0.0187)	-0.567*** (0.0187)	-0.567*** (0.0187)	-0.593*** (0.0178)	-0.614*** (0.0176)	-0.486*** (0.0198)
$Contiguity_{ij}$	0.364*** (0.0462)	0.365*** (0.0462)	0.281*** (0.0539)	0.365*** (0.0463)			0.297*** (0.0477)
$Common\ language_{ij}$	0.215*** (0.0247)	0.192*** (0.0284)	0.214*** (0.0247)	0.215*** (0.0247)			0.152*** (0.0241)
$Colony_{ij}$	0.384*** (0.0452)	0.388*** (0.0377)	0.390*** (0.0373)	0.388*** (0.0378)	0.532*** (0.0339)	0.530*** (0.0339)	0.320*** (0.0385)
$Religion_{ijt}$	-0.0879*** (0.0298)	-0.0908*** (0.0300)	-0.0855*** (0.0298)	-0.103*** (0.0403)	-0.0471 (0.0302)		-0.129*** (0.0296)
FTA_{ijt}	0.234*** (0.0371)	0.235*** (0.0370)	0.236*** (0.0370)	0.235*** (0.0370)	0.250*** (0.0368)	0.256*** (0.0370)	0.176*** (0.0377)
$lnagriculture\ value\ added_{it-1}$	0.541*** (0.0797)	0.542*** (0.0792)	0.538*** (0.0797)	0.540*** (0.0796)	0.536*** (0.0796)	0.536*** (0.0795)	0.552*** (0.0795)
$lngdp_{jt}$	0.254*** (0.0446)	0.253*** (0.0445)	0.251*** (0.0446)	0.253*** (0.0445)	0.252*** (0.0444)	0.251*** (0.0445)	0.252*** (0.0442)
$lnpop_{jt}$	0.112 (0.131)	0.104 (0.130)	0.100 (0.131)	0.112 (0.131)	0.0976 (0.131)	0.0974 (0.131)	0.134 (0.129)
$lnpop_{it}$	-0.623*** (0.167)	-0.633*** (0.164)	-0.621*** (0.167)	-0.625*** (0.166)	-0.627*** (0.165)	-0.628*** (0.165)	-0.613*** (0.167)
$Colony_{ij} * Disaster_{it}$	0.0155 (0.0639)						
$Common\ language_{ij} * Disaster_{it}$		0.0750* (0.0452)					
$Contiguity_{ij} * Disaster_{it}$			0.182*** (0.0637)				
$Religion_{ij} * Disaster_{it}$				0.0309 (0.0506)			
$Contiguity_{ij} * Commonlanguage_{ij}$					0.381*** (0.0631)		
$Contiguity_{ij} * Commonlanguage_{ij} * Disaster_{it}$					0.167** (0.0780)		
$Neighborhood_{ij}$						0.267*** (0.0778)	
$Neighborhood_{ij} * Disaster_{it}$						0.240** (0.0935)	
$Diaspora_{ij}$							0.0451*** (0.0050)
$Diaspora_{ij} * Disaster_{it}$							0.0172*** (0.0043)
Years	1995-2010	1995-2010	1995-2010	1995-2010	1995-2010	1995-2010	1995-2010
Exporter x Product FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Importer x Product FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product x Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.608	0.608	0.608	0.608	0.608	0.608	0.609
Observations	293,665	293,665	293,665	293,665	293,665	293,665	293,665

Notes: Standard errors are clustered by exporter x time. Robust standard errors are in parentheses, with *** 1%, ** 5% and * 10% levels.

5.3 Robustness check: Altruism or high resilience?

In the previous section, we have identified a clear effect coming from interacting some bilateral variables proxying closeness of partners' culture with the disaster variables. The positive effect is perfectly consistent with our hypothesis of change in demand behaviours of close countries.

However, one can still think that these coefficients might also be consistent with another type of story, related to a cross-country heterogeneity in transaction cost changes that disasters might provoke. More precisely, one might argue that the routes and other means of communications that are used to trade with country i might be non-uniformly affected by disasters. In particular, they can be more resilient when they relate partners usually culturally close to i (better routes and communication infrastructures for some historical and/or institutional reasons). A simple way to discriminate between the two effects (high resilience or a change in preferences) is to look at *how disasters affect imports of victim countries rather than their exports*. As a matter of fact, if the high resilience explanation prevails then one should observe the same positive effect of disasters on imports of country i from its historical partners (i.e. a positive coefficient on the interaction term with closeness of culture variable). If the change in preferences prevails however, one should not observe any effect on that coefficient.

We thus run a bilateral *import regression* (based on an equation constructed in the same spirit as bilateral exports one) where now, the importer is the country where the disaster occurs. We want to see whether the interaction term $\text{disaster}_{jt} \times \text{close culture}_{ij}$, where the latter is approximated by variables related to transaction costs like the neighborhood variable, provides the same positive and statistically significant effect as in the previous table. In order to be sure about the robustness of our results, we show a series of specifications on both types of disasters' variables (number of disasters, at columns 1 to 3, and intensity of disasters, respectively shown in columns 4 to 6). Columns 1 and 4 are taken as benchmark regressions where the two disaster variables in i enter the regression respectively (without interactions). These show that *importers* (not exporters) hit by a disaster increase their demand for foreign agricultural products. While beyond the goal of this paper, this result is consistent with the view that disasters might reduce supply at home making consumers turn to products that they can find on world markets. More interestingly

though, through the interaction terms our table 4 provides some evidence in favor of the preference hypothesis: by considering either the number of occurrences or the intensity of disasters, we do not find any increase in imports coming from neighboring countries (see columns 2, 3 and 5 and 6, table 4). Note in passing that the result remains unchanged when we introduce, importer \times time and exporter \times time fixed effects (precisely columns 3 and 6).

Table 4: **Imports and Disasters (Altruism or high resilience ?)**

Countries	All	All	All	All	All	All
Products	All	All	All	All	All	All
Disaster variable	Occurrence (1)	Occurrence (2)	Occurrence (3)	Index (4)	Index (5)	Index (6)
Disaster _{it}	0.0596** (0.0256)	0.0528** (0.0258)		0.0134* (0.0070)	0.0126* (0.007)	
lnDistance _{ij}	-0.464*** (0.0174)	-0.558*** (0.0163)	-0.560*** (0.0159)	-0.464*** (0.0174)	-0.558*** (0.0163)	-0.561*** (0.0159)
Contiguity _{ij}	0.513*** (0.0349)			0.513*** (0.0349)		
Common language _{ij}	0.201*** (0.0278)			0.201*** (0.0278)		
Colony _{ij}	0.351*** (0.0371)	0.489*** (0.0383)	0.471*** (0.0376)	0.351*** (0.0371)	0.489*** (0.0383)	0.471*** (0.0376)
Religion _{ijt}	-0.171*** (0.0325)			-0.171*** (0.0325)		
FTA _{ijt}	0.105*** (0.0321)	0.122*** (0.0321)	0.190*** (0.0271)	0.106*** (0.0321)	0.124*** (0.0321)	0.190*** (0.0271)
lnagriculture value added _{it-1}	-0.0160 (0.0680)	-0.0198 (0.0677)		-0.0275 (0.0677)	-0.0299 (0.0674)	
lngdp _{jt}	0.247*** (0.0501)	0.244*** (0.0519)		0.246*** (0.0500)	0.246*** (0.0518)	
lnpop _{jt}	-0.0793 (0.150)	-0.0640 (0.150)		-0.0798 (0.150)	-0.0615 (0.150)	
lnpop _{it}	-0.0153 (0.231)	-0.0145 (0.230)		-0.0072 (0.231)	-0.0060 (0.231)	
Neighborhood _{ij}		0.176** (0.0733)	0.231*** (0.0561)		0.219*** (0.0642)	0.261*** (0.0473)
Neighborhood _{ij} * Disaster _{it}		0.0934 (0.0880)	0.0765 (0.0654)		0.0093 (0.0313)	0.0120 (0.0216)
Years	1995-2010	1995-2010	1995-2010	1995-2010	1995-2010	1995-2010
Exporter x Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Importer x Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Product x Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Exporter x Time FE	No	No	Yes	No	No	Yes
Importer x Time FE	No	No	Yes	No	No	Yes
Adjusted R-squared	0.537	0.535	0.551	0.537	0.535	0.551
Observations	382,949	382,949	389,118	382,949	382,949	389,118

Notes: Standard errors are clustered by exporter x time. Robust standard errors are in parentheses, with *** 1%, ** 5% and * 10% levels.

5.4 Testing for Persistence

In the last subsection, we finally ask whether the effects of disasters, where they are observed, persist overtime. We test the persistence by taking into account the effect of disasters occurring first in t and $t - 1$, then in the last 4 years including progressively (t to $t - 3$) in the regression. While the specification with t and $t - 1$ do produce results in favor of a non-persistence of the impact over time, those

specifications with more lags produce different results. Overall, one cannot conclude in a robust manner that the effect is temporary or whether it persists overtime.

6 Conclusion

With the rise in average temperatures every year, many developing countries are experiencing more extreme events. If the literature analyzes extensively the macroeconomic effects of climate change, there are only few papers studying their influence on trade.

In this paper, we have focused our analysis on the impact of natural disasters on exports of agricultural products of small developing countries (less than 20 millions inhabitants). In what we view as a value added to the literature, we have proposed a simple theory set-up that disentangles the different channels through which exports are being hit by disasters in a given country. In particular, three channels are highlighted: a shipment channel, a capability and a change in preference channel. More precisely, we conjecture that every thing being equal urban areas hit by disasters should be affecting more exports than rural areas through a destruction of infrastructure that are usely located in urban regions. Nevertheless, we also conjecture that disasters taking place in rural areas *during periods of growing seasons* should impact more negatively exports of agricultural products. Finally, we posit a third solidarity effect, neglected so far by the literature, that is positive not negative on trade but that still needs to be tested. We then take this set-up to the test by trying to identify each of these channels. By using data on the location of the disasters across urban and rural areas and by employing data on the period of growth season for each of the top 5 exported agricultural products by observed country, we could find a way to test for the two first channels respectively: shipment and capability channels. Besides, we employ a third series of data to identify the preference channel through the use of proxies regarding cultural neighborhood or closeness of partner countries to the exporting countries which experience the disasters.

Whereas we do not find a negative effect of disaster on trade when they happen to

Table 5: Exports and Disasters (Temporary or permanent phenomenon?)

Countries Products Disaster variable	All		All		All		All		All		All		All			
	Occurrence (1)	Occurrence (2)	Occurrence (3)	Occurrence (4)	Index (5)	Index (6)	Index (7)	Index (8)	Occurrence (1)	Occurrence (2)	Occurrence (3)	Occurrence (4)	Index (5)	Index (6)	Index (7)	Index (8)
Disaster _{it}	-0.0126 (0.0189)	-0.00168 (0.0205)	-0.103*** (0.0331)	-0.0860*** (0.0353)	-0.00120 (0.00335)	0.000160 (0.00355)	-0.0229*** (0.00671)	-0.0214*** (0.00694)								
Disaster _{it-1}	-0.00323 (0.0192)	0.00626 (0.0203)	-0.0888** (0.0353)	-0.0753*** (0.0364)	0.000163 (0.00349)	0.00120 (0.00345)	-0.0277*** (0.00656)	-0.0253*** (0.00669)								
Disaster _{it-2}		-0.0276 (0.0204)	-0.0918*** (0.0106)	-0.0918*** (0.0358)	0.00583 (0.0106)	0.00583 (0.0217)	-0.0292*** (0.00712)	-0.0292*** (0.00712)								
Disaster _{it-3}		-0.0178 (0.0194)	-0.0806*** (0.0360)	-0.0806*** (0.0360)	-0.00643 (0.0118)	-0.00643 (0.0118)	-0.0272*** (0.00773)	-0.0272*** (0.00773)								
lnDistance _{ij}	-0.612*** (0.0180)	-0.613*** (0.0198)	-0.487*** (0.0200)	-0.481*** (0.0213)	-0.516*** (0.0129)	-0.516*** (0.0144)	-0.415*** (0.0147)	-0.412*** (0.0157)								
Contiguity _{ij}			0.315*** (0.0490)	0.405*** (0.0499)		0.229*** (0.0317)	0.283*** (0.0337)	0.283*** (0.0337)								
Common language _{ij}			0.152*** (0.0244)	0.129*** (0.0254)		0.104*** (0.0201)	0.0985*** (0.0217)	0.0985*** (0.0217)								
Colony _{ij}	0.532*** (0.0356)	0.564*** (0.0378)	0.323*** (0.0401)	0.363*** (0.0420)	0.600*** (0.0288)	0.609*** (0.0311)	0.447*** (0.0325)	0.459*** (0.0356)								
Religion _{ij}			-0.126*** (0.0308)	-0.131*** (0.0337)		-0.125*** (0.0245)	-0.135*** (0.0261)	-0.135*** (0.0261)								
FTA _{ij}	0.265*** (0.0379)	0.285*** (0.0421)	0.181*** (0.0389)	0.193*** (0.0434)	0.193*** (0.0305)	0.201*** (0.0342)	0.133*** (0.0314)	0.134*** (0.0348)								
lnagriculture value added _{it-1}	0.523*** (0.0846)	0.503*** (0.0966)	0.540*** (0.0845)	0.518*** (0.0964)	0.313*** (0.0603)	0.333*** (0.0682)	0.322*** (0.0601)	0.347*** (0.0677)								
lnrdp _{it}	0.260*** (0.0471)	0.255*** (0.0509)	0.262*** (0.0469)	0.253*** (0.0505)	0.333*** (0.0323)	0.347*** (0.0355)	0.329*** (0.0316)	0.345*** (0.0347)								
lnpop _{it}	0.0889 (0.132)	-0.0155 (0.141)	0.116 (0.131)	-0.0106 (0.139)	-0.124 (0.105)	-0.137 (0.112)	-0.0970 (0.0995)	-0.121 (0.106)								
lnpop _{it}	-0.741*** (0.175)	-1.090*** (0.213)	-0.719*** (0.177)	-1.058*** (0.214)	0.210* (0.127)	0.0620 (0.149)	0.219* (0.126)	0.0823 (0.149)								
Neighborhood _{ij}	0.279*** (0.0906)	0.443*** (0.121)	0.279*** (0.0906)	0.443*** (0.121)	0.256*** (0.0470)	0.346*** (0.0575)	0.256*** (0.0470)	0.346*** (0.0575)								
Neighborhood _{ij} * Disaster _{it}	0.189* (0.0981)	0.0670 (0.0994)	0.189* (0.0981)	0.0670 (0.0994)	0.00241 (0.0109)	-0.00937 (0.0103)	-0.00937 (0.0103)	-0.00937 (0.0103)								
Neighborhood _{ij} * Disaster _{it-1}	0.0765 (0.0985)	-0.0213 (0.105)	0.0765 (0.0985)	-0.0213 (0.105)	0.00529 (0.0114)	-0.00739 (0.0112)	0.00529 (0.0114)	-0.00739 (0.0112)								
Neighborhood _{ij} * Disaster _{it-2}		0.0749 (0.0900)		0.0749 (0.0900)		-0.00115 (0.00343)		-0.00115 (0.00343)								
Neighborhood _{ij} * Disaster _{it-3}		-0.00278 (0.100)		-0.00278 (0.100)		0.00201 (0.00355)		0.00201 (0.00355)								
Diaspora _{ij}			0.0394*** (0.00542)	0.0330*** (0.00638)		0.0337*** (0.00423)	0.0259*** (0.0051)	0.0259*** (0.0051)								
Diaspora _{ij} * Disaster _{it}			0.0149*** (0.00446)	0.0125*** (0.00469)		0.00309*** (0.000934)	0.00293*** (0.000947)	0.00293*** (0.000947)								
Diaspora _{ij} * Disaster _{it-1}			0.0129*** (0.00465)	0.0111** (0.00480)		0.00403*** (0.000890)	0.00371*** (0.000935)	0.00371*** (0.000935)								
Diaspora _{ij} * Disaster _{it-2}				0.0100** (0.00457)			0.00416*** (0.000958)	0.00416*** (0.000958)								
Diaspora _{ij} * Disaster _{it-3}				0.00883* (0.00476)			0.00407*** (0.00101)	0.00407*** (0.00101)								
Years	1996-2010	1998-2010	1996-2010	1998-2010	1996-2010	1998-2010	1996-2010	1998-2010	1996-2010	1998-2010	1996-2010	1998-2010	1996-2010	1998-2010	1996-2010	1998-2010
Exporter x Product FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Importer x Product FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product x Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.612	0.624	0.613	0.625	0.615	0.622	0.616	0.623								

hit urban areas, we find a relatively robust negative effect of disasters when occurring in rural areas by the time of crops growing seasons. But the most robust effect is identified for the solidarity channel. We find a robust increase in exports to culturally closer countries, measured by an interaction term between disaster occurrence and dyadic similarities. The greatest effects come from the combined impact of common border, language and religion. So the more culturally similar the trading partner, the higher its increase in imports from hit countries. This impact is not persistent overtime, however. Therefore, we suggest that the demand effect observed is linked to temporary changes in preferences. Hence, it seems that temporary altruism is at play, in the aftermaths of natural disasters.

All in all, notably due to the limited physical impact of most of the disasters over time and space and thanks to the pain relief provided by culturally close importers, natural disasters do not appear to make small developing countries suffer that much economically.

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Appendix A: List of 74 countries

Albania	Jamaica
American Samoa	Jordan
Armenia	Kazakhstan
Azerbaijan	Kyrgyzstan
Belarus	Lao People's Democratic Republic
Belize	Lebanon
Benin	Liberia
Bhutan	Madagascar
Bolivia	Malawi
Bosnia and Herzegovina	Maldives
Bulgaria	Mali
Burkina Faso	Marshall Islands
Burundi	Mauritania
Cambodia	Mauritius
Cameroon	Micronesia
Cape Verde	Moldova, Republic of
Central African Republic	Mongolia
Chad	Mozambique
Comoros	Nicaragua
Congo	Niger
Costa Rica	Panama
Cuba	Paraguay
Dominica	Rwanda
Dominican Republic	Saint Lucia
Ecuador	Saint Vincent and the Grenadines
El Salvador	Sao Tome and Principe
Fiji	Senegal
Gabon	Sierra Leone
Gambia	Sri Lanka
Georgia	Suriname
Ghana	Tajikistan
Grenada	Togo
Guatemala	Tonga
Guinea	Tunisia
Guinea Bissau	Vanuatu
Honduras	Zambia
Ivory Coast	Zimbabwe

Appendix B : List of 26 countries

Belarus
Burkina Faso
Cameroon
Congo, Republic of
Costa Rica
Dominican Republic
Gabon
Guatemala
Honduras
Kazakhstan
Jordan
Lebanon
Madagascar
Malawi
Mali
Mauritius
Moldova , Republic of
Mozambique
Nicaragua
Panama
Paraguay
Senegal
Sri Lanka
Togo
Tunisia
Zimbabwe

Appendix C : Agricultural products and crop calendar : data sources
 Table C.0: Agricultural product and crop calendar : data sources

Country	Products	Sources
Belarus	Mushrooms & Truffles	https://fr.ruarjoseph.com/obspshestro/74117-grby-belarusi-opisaniie-i-foto.html
Belarus	Sugar beet	Konoplia, E.F. 1996: International conference "Ten years after the Chernobyl catastrophe". Minsk, Belarus, 7-12 October 1996 https://www.usda.gov/oc/weather/pubs/Other/MW/CACP/MinorWorldCropAreas.pdf
Cameroon	Bananas	http://www.fao.org/ag/cultiv/seed/cropcalendar/welcome.do
Cameroon	Coffee	https://fusiontables.google.com/DataSource?docid=1GUkizWpS6ZEQTUzdlPxpS19hWjB3BsnJLW6G6Nayrows:id=1
Cameroon	Cocoa beans	https://afafod.cirad.fr/en/content/download/4549/34434/version/1/file/Klaver,+Evolution+of+cacao-AFS+%26+effect+on+local+lively+ood+SW+Cameroon.pdf
Cameroon	Cotton	http://worldcottoncalendar.icac.org/
Sri Lanka	Coconuts	http://www.fao.org/3/a-an999e.pdf
Sri Lanka	Tea	http://crist.ac.lk/bisstream/handle/1/1998/COCOS-16-56.pdf?sequence=2&isAllowed=y
Sri Lanka	Cinnamon	http://www.pureeylontea.com/index.php/features/fine-eylon-tea/cultivation
Sri Lanka	Tobacco	http://blog.esmporium.com/post/tea-larvesting-times-of-the-main-tea-producing-countries.aspx http://www.ncdpsic.com/upload/docs/Harvest-calendar-full.pdf http://siteresources.worldbank.org/HEALTHNUTRITIONANDPOPULATION/Resources/281627-1095698140167/Annatlake-TheEconomicshole.pdf http://dailynews.lk/2010/10/07/business/95163
Congo, Rep.	Coffee	https://fusiontables.google.com/DataSource?docid=1GUkizWpS6ZEQTUzdlPxpS19hWjB3BsnJLW6G6Nayrows:id=1
Congo, Rep.	Sugar	http://news.lomelchono.com/?idnews=82992&t=Came-a-suce-au-Congo--une-production-de-677.549-tonnes-attendue
Costa Rica	Bananas	http://superfoods.com/pdf/crop-calendar.pdf
Costa Rica	Pineapples	http://www.nag.go.cr/bbioteva_virtual/cercia/tec-pina.pdf
Costa Rica	Melons (including watermelons)	https://daihet.unirioja.es/descarga/articulo/4835499.pdf
Costa Rica	Coffee	https://fusiontables.google.com/DataSource?docid=1GUkizWpS6ZEQTUzdlPxpS19hWjB3BsnJLW6G6Nayrows:id=1
Dominican Republic	Bananas	https://interordr.com/banana/
Dominican Republic	Avocados	https://interordr.com/el-aguacate/
Dominican Republic	sugar	https://www.cedaf.org.do/publicaciones/guias/download/cacao.pdf
Dominican Republic	Cocoa beans	https://archive.org/stream/tobacoindominic30alla/tobacoindominic30allaq7v.u.txt
Dominican Republic	Tobacco	https://procegar.org/news/tobacco-farming
Guatemala	Bananas	https://www.amcarde.org/gifs/index.php/Cultivo%20de%20Cosecha
Guatemala	Coffee	https://fusiontables.google.com/DataSource?docid=1GUkizWpS6ZEQTUzdlPxpS19hWjB3BsnJLW6G6Nayrows:id=1
Guatemala	Melons (including watermelons)	http://web.magr.aqob.gi/download/Epocas%20de%20siembra
Guatemala	Cardamoms	http://www.usaid.gov/pdf/gocs/P400K12.pdf
Guatemala	sugar	http://www.americeconomia.com/regiones-industrias/zafra-en-guatemala-concluye-con-un-crecimiento-de-11 http://www.prensa-latina.cu/index.php?o=mk&id=49631&SEO=marcha-a-buen-ritmo-zafra-azucarera-en-guatemala Robinson, J. C. & Galán Sando, V. 2013. Plátanos y bananas. Madrid: Prensa.
Honduras	Bananas	http://www.dole-espanol.com/dole-earth/videos/growing-stages.html
Honduras	Pineapples	http://www.dole-espanol.com/dole-earth/videos/growing-stages.html
Honduras	Melons (including watermelons)	https://www.dole-espanol.com/dole-earth/videos/growing-stages.html
Honduras	Coffee	https://fusiontables.google.com/DataSource?docid=1GUkizWpS6ZEQTUzdlPxpS19hWjB3BsnJLW6G6Nayrows:id=1
Honduras	Palm oil	https://bdigital.zamora.edu/bisstream/11036/5568/1/AGN-2005-T012.pdf
Kazakhstan	Melons (including watermelons)	http://www.advtour.com/kazakhstan/weather.htm
Kazakhstan	Durum wheat	http://www.fao.org/giews/countrybrief/country.jsp?code=KAZ
Kazakhstan	Wheat except durum wheat	http://www.fao.org/giews/countrybrief/country.jsp?code=KAZ
Kazakhstan	Barley	http://www.fao.org/giews/countrybrief/country.jsp?code=KAZ
Kazakhstan	Cotton	http://worldcottoncalendar.icac.org/
Jordan	Tomatoes	http://fscilister.org/sites/default/files/documents/Crop%20Calendar%20valley.WB.pdf
Jordan	Cucumbers and gherkins	http://fscilister.org/sites/default/files/documents/Crop%20Calendar%20valley.WB.pdf
Jordan	Aubergines (egg-plants)	http://fscilister.org/sites/default/files/documents/Crop%20Calendar%20valley.WB.pdf
Jordan	Peppers (Capsicum)	http://fscilister.org/sites/default/files/documents/Crop%20Calendar%20valley.WB.pdf
Lebanon	Potatoes	https://research.cip.cgiar.org/confluence/display/wpa/Lebanon
Lebanon	Oranges	https://archive.org/stream/studyofcitrusind88bunk/studyofcitrusind88bunk4.jvu.txt http://www.pressreader.com/
Lebanon	Grapes	http://homeguides.sfgate.com/orange-growing-season-63336.html http://pdf.usaid.gov/pdf/gocs/P400K51W.P.pdf
Lebanon	Apples	http://www.cawstedihiban.ir/BCPPlayer.asp?ID=1265518 http://blog.biominvestbank.com/wp-content/uploads/2016/11/Lebanese-Apples-Dehoned-as-the-King-of-Fruits.pdf http://www.harvesttable.com/2009/07/how-to-grow-apples/
Lebanon	Tobacco	http://isa-global-dialogue.net/cultivating-the-bitter-crop-in-a-lebanon-war-zone-2/

Appendix C : Agricultural products and crop calendar : data sources
 Table C.0: Agricultural product and crop calendar : data sources

Madagascar	Fruits and nuts	http://www.fao.org/agriculture/seed/cropcalendar/cropcalendar.do
Madagascar	Coffee	https://fusiontables.google.com/DataSource?docid=1GUKiZwpS6ZEQ7UzdPpSl9HWjB3BsnJLW6NaYrows:id=1
Madagascar	Vanilla beans	http://www.madagascar-guide.com/article/mag/reports/epicere-fine/la-vanille-de-madagascar_95.html
Madagascar	Cloves	http://www.trimeta-agrofood.com/sites/default/files/LES%20SPECIFICATIONS%20UI%20GROFLE%20DE%20MADAGASCAR1.pdf
Malawi	Tea	https://www.archive.org/stream/plantingharvesti90baum?ref=olpage/16/mode/2up
Malawi	Sugar	https://www.archive.org/stream/plantingharvesti90baum?ref=olpage/16/mode/2up
Malawi	Tobacco	https://www.archive.org/stream/plantingharvesti90baum?ref=olpage/16/mode/2up
Malawi	Cotton	https://www.archive.org/stream/plantingharvesti90baum?ref=olpage/16/mode/2up
Mali	Guavas	Chuhan-Pole, Punam; Angwafo, Manke. 2011. Yes Africa Can : Success Stories from a Dynamic Continent. World Bank.
Mali	Sugar	http://www.fao.org/agriculture/seed/cropcalendar/welcome.do
Mali	Cotton	http://worldcottoncalendar.icac.org/
Mauritius	Cut flowers	V.L Sheela 2008 .Flowers for Trade. New Delhi :New India Publishing Agency.
Mauritius	Sugar	http://www.omnicane.com/sugarcane-cultivation
Moldova, Rep.of	Walnuts	http://www.eurobroker.fr/noix-2/
Moldova, Rep.of	Sunflower seeds	http://www.deco.fr/jardin-jardinage/arbre-a-fruits/noyer/
Moldova, Rep.of	Sugar	http://f.li.lv/conference/proceedings2012/Papers/022_Kardakov_A.pdf
Moldova, Rep.of	Tobacco	http://mz.workspace.md/en/fermieri/cresterea-sfeclai-de-zahar/
Moldova, Rep.of	Cashew nuts	http://nest.ntua.gr/adapttoclimate/proceedings/fullpaper/Varanu_Moldova_Cashewnuts.pdf
Mozambique	Sugar	https://www.archive.org/stream/plantingharvesti90baum?ref=olpage/32/mode/2up
Mozambique	Tobacco	https://www.archive.org/stream/plantingharvesti90baum?ref=olpage/32/mode/2up
Mozambique	Cotton	http://worldcottoncalendar.icac.org/
Nicaragua	Bananas	Robinson, J. C. & Galán Saucó, V. 2013. Plátanos y bananas . Madrid : Mundi-Prensa.
Nicaragua	Coffee	https://fusiontables.google.com/DataSource?docid=1GUKiZwpS6ZEQ7UzdPpSl9HWjB3BsnJLW6NaYrows:id=1
Nicaragua	Ground-nuts	http://www.elnuevodiario.com.ni/economia/281507-nicaragua-vendera-mas-man/
Nicaragua	Sugar	http://www.nicaraguasugar.com/index.php?option=com_content&view=article&id=8&Itemid=175
Panama	Vegetables	http://www.mida.gob.pa/upload/documentos/calendariosiembrab%5B1%5D.pdf
Panama	Bananas	Robinson, J. C. & Galán Saucó, V. 2013. Plátanos y bananas . Madrid : Mundi-Prensa.
Panama	Melons (including watermelons)	http://www.mida.gob.pa/upload/documentos/calendariosiembrab%5B1%5D.pdf
Panama	Coffee	https://fusiontables.google.com/DataSource?docid=1GUKiZwpS6ZEQ7UzdPpSl9HWjB3BsnJLW6NaYcardid=2
Panama	Sugar	http://www.mida.gob.pa/upload/documentos/calendariosiembrab%5B1%5D.pdf
Paraguay	Wheat except durum wheat	http://www.world-grain.com/Departments/Country-Focus/Country-Focus-Home/Paraguay-2016.aspx
Paraguay	Maize except seed com	http://www.world-grain.com/Departments/Country-Focus/Country-Focus-Home/Paraguay-2016.aspx
Paraguay	Soya beans	https://www.usda.gov/oc/wheat/pub/Other/MWACAP/Graps/Paraguay/ParSoyProd0509.pdf
Paraguay	Cotton	http://worldcottoncalendar.icac.org/
Senegal	Tomatoes	http://www.fao.org/agriculture/seed/cropcalendar/welcome.do
Senegal	Beans	http://www.fao.org/agriculture/seed/cropcalendar/welcome.do
Senegal	Rice	http://www.fao.org/agriculture/seed/cropcalendar/welcome.do
Senegal	Ground-nut oil	http://www.fao.org/agriculture/seed/cropcalendar/welcome.do
Senegal	Cotton	http://worldcottoncalendar.icac.org/
Zimbabwe	Cut flowers	http://hpczim.co.zw/index.php/member-association/146-export-flowers-growers-association-of-zimbabwe-efgaz
Zimbabwe	Sugar	http://ec.europa.eu/development/body/publications/courier/courier176/fr/frp30.pdf
Zimbabwe	Tobacco	http://www.daff.gov.za/daffweb3/portals/0/brochures/20and%20production%20guidelines/sugar%20cane%20production%20%20guideline.pdf
Zimbabwe	Cotton	http://www.fao.org/agriculture/seed/cropcalendar/welcome.do
Zimbabwe	Coffee	http://www.fao.org/agriculture/seed/cropcalendar/welcome.do
Togo	Cotton seeds	https://fusiontables.google.com/DataSource?docid=1GUKiZwpS6ZEQ7UzdPpSl9HWjB3BsnJLW6NaYcardid=2
Togo	Cocoa beans	http://worldcottoncalendar.icac.org/
Togo	Cotton	https://www.icco.org/faq/58-cocoa-harvesting/131-what-time-of-year-is-cocoa-harvested.html
Tunisia	Dates	http://echebbi.chez.com/num1/dattes.html
Tunisia	Oranges	http://gsfruits.com/?page_id=1575&lang=fr
Tunisia	Olive oil	http://www.webmanagercenter.com/2015/10/26/166745/tunisie-agriculture-la-recolte-des-olives-estime-a-70-000-tonnes-a-medinine/
Tunisia	Maize oil	http://www.fao.org/agriculture/seed/cropcalendar/cropcal.do
Burkina Faso	Beans	http://www.fao.org/agriculture/seed/cropcalendar/welcome.do
Burkina Faso	Sesamum seeds	http://www.fao.org/agriculture/seed/cropcalendar/welcome.do
Burkina Faso	Raw sugar	http://www.vib.be/en/about-vib/Documents/vib_facts_uger_cane_E_N2017_006_L_Rs_iningle.pdf
Burkina Faso	Cotton	http://worldcottoncalendar.icac.org/