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Master Thesis - International Economics

The effects of natural disasters on staple food prices in Sub-Saharan Africa: Does regional trade help?

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Abstract

In this paper I firstly investigate the effects of natural disasters on staple food prices in Sub-Saharan Africa by means of a panel data regression. Then I verify the extent to which intra-African trade helps mitigate the volatility of prices that arise after natural disasters. I focus on three types of disasters (floods, droughts, and storms), and six crucial staple foods (maize, wheat, rice, cassava, sorghum, millet). The database includes 30 Sub-Saharan African countries and spans over the period 1992 to 2017. The findings show that staple food prices are extremely sensitive to natural disasters and to trade in SSA. The effect is highly heterogeneous across the products, but also across the regions within SSA.

Acknowledgements

I would like to thank some of the people who supported me all along the process of this thesis, but also along my five years of university. First, I am grateful to my supervisor, Maarten Bosker, who brought insightful comments that have greatly helped develop my ideas and making this thesis happen. I also want to thank my family, who have supported me as they could, helping me to cheer up when I needed it and guiding me in the most important decisions of my student life. All of these from Madagascar. Last, I want to thank my closest friends, who have patiently listened to my complaints and helped me whenever they could and without hesitation. They have contributed enormously to this thesis just by being unconditionally present when I needed them the most.

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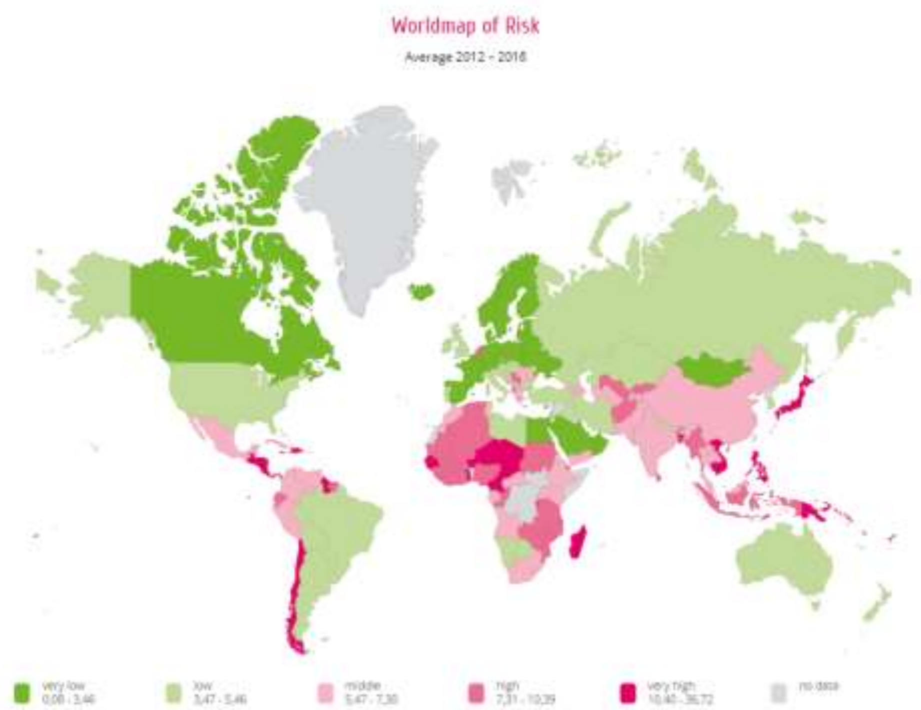
1. Introduction

The African continent has the highest prevalence of undernourishment in all regions of the world (FAO,2017). Moreover, the population is large and fast-growing, which adds to the challenge of solving food insecurity (Chauvin, Mulangu and Porto, 2012). Its population is expected to increase 2.5-fold by 2050, and some projections forecast that the demand for cereals will triple while the current levels of cereal consumption are for a substantial part imported (van Ittersum et al., 2016). If there has been a positive tendency in reducing undernourishment before 2015, the FAO (2017) reports that the progress has reversed and, since 2016, ongoing conflicts and natural disasters are worsening the situation.

In fact, natural disasters are one of the primary causes of the continuous food crisis in the SSA region. African countries are among the most vulnerable and the most severely affected by natural disasters. The World Risk Report assesses the vulnerability of each region to natural hazards, and their findings (summarized in Figure 1 below) clearly show the distress of SSA countries.



Source: World Risk Report 2016, from the United Nations University Institute for Environment and Human Security. Every year, the report assesses each country's exposure and vulnerability to natural disasters. The score reported in the map is a function of (1) the exposure or the chances to be affected by natural disasters, and (2) the ability of the country to respond to them (governance, disaster preparedness, early warning systems, medical services..), its ability to form long-term strategies against climate changes (education and research, environmental status, ecosystem protection, and adaptation strategies and investments) and the susceptibility of its population to the disasters measured by their socioeconomic condition such as the public infrastructures, the housing conditions, nutrition, poverty, economic capacity, or their income distribution. Higher scores refer to a higher risk level.

The Horn of Africa is a good example of a region characterized by food insecurity. The FAO (2015) estimates that the region alone absorbed 77% of all agricultural production losses caused by droughts worldwide between 2003 and 2013, amounting to USD 23.5 billion economic losses. In 2011, the region experienced its most severe drought in 50 years, which brought 3,1 million Somalis, i.e. a quarter of the country's population, into famine (Maxwell and Fitzpatrick, 2012). The failure of two successive rainfall seasons resulted in substantial livestock mortality and the lowest annual cereal crop production since the 1991–1994 civil war (Hillbruner and Moloney, 2012).

Natural disasters cause agricultural production losses and livestock destruction. A large proportion of the population in SSA is affected since 60% of the region's population is rural and lives off agriculture for subsistence, while the sector employs about 60% of the workforce (FAO, 2015c). The FAO (2015a) estimates that nearly 25% of the damages caused by natural hazards are borne by the agricultural sector worldwide. Hence, it becomes critical to try to determine how to alleviate the consequences of natural disasters in SSA. Adedeji, Gieck-Bricco, & Kehayova (2016) stress that the population in low-income countries are more vulnerable to disasters because of the poor infrastructure and their scarce resources which together limit their capacity to withstand natural disasters. Food prices are one channel through which disasters affect the population as it deters their access to food.

Regional integration, as a substitute of broad-based trade liberalization, is at the centre of the attention of policy-makers and it is believed to have the potential to foster development and economic growth across Africa. There are currently eight regional economic communities (RECs) and about thirty regional trade agreements (RTAs) (UNCTAD, 2015; Yang & Gupta, 2005). Recently, the African Union committed to building a Continental Free Trade Agreement (CFTA) by 2063. Those initiatives witness the will to deepen the economic integration of Africa.

Ensuring food security through more cooperation in agriculture is a priority on the agenda of African governments. In 2014, they signed the Malabo Declaration in which commit to triple intra-

African trade and to boost Intra-African trade in agricultural commodities and services by 2025 (African Union, 2014). The World Bank (2012) also believes that “Africa Can Help Feed Africa”. They argue that moving to open regional staple food markets within Africa can help to enhance food security. Moreover, they add that regional food imports can limit the exposure of domestic markets to the volatile international market for food.

Natural disasters, as argued earlier, are a major threat disrupting food supply and creating a large imbalance with the demand for food which leads to the increase in domestic food prices. Regional trade comes into play as a compensation for domestic losses when climatic changes and food shortage affect a single country. The difference in weather patterns across sub-Saharan African countries is expected to make regional production less variable than country-level production (World Bank, 2012). Hence, freer trade can link farmers and consumers across borders and compensate for the production losses following a severe natural disaster. Ultimately, price fluctuations are expected to be softened when shortfalls in one region can be compensated by surpluses in another region (Beekman and Meijerink, 2009).

The aim of this study is twofold: first to assess how natural disasters affect staple food prices in Sub-Saharan Africa (SSA), and secondly to understand whether more intra-African trade can help mitigate those effects. Through an empirical analysis based on a panel dataset on 30 countries of the African continent covering 25 years, I examine the short-term (one year) effect of three natural disasters-- droughts, floods and storms – on the prices of six products -maize, sorghum, millet, wheat, cassava and rice. I analyse this effect both at the SSA level and the regional level (for Eastern Africa (EA), Western Africa (WA), Southern Africa (SA) and Central Africa (CA)). Then I turn to the impact that intra-African trade could play both in normal times and in time of disaster, by interacting the disaster dummies with the quantity traded within Africa, controlling for the main effects of intra-African trade and of flows coming from the rest of the world between disasters and prices.

The main results show that the effect of natural disasters on food prices is highly heterogeneous across the products and across the regions. The dynamic of each disaster (timing, intensity) and the characteristics of each region (climate, production capacity, the diet of the population, regulations) are determinants in the effect of natural disasters on food prices. But overall, food prices are very sensitive to natural disasters in SSA. There is no clear evidence that intra-African trade can mitigate the effect of natural disasters, while I find a positive effect for wheat, rice and sorghum; maize seems to be a dangerous commodity to engage in for trade and there is no significant effect for millet and cassava. The same complex system of who produces what, who consumes what and what are the climatic conditions within a country still play an important effect and they are determinant for the impact of intra-African trade. Other external forces, such as the trade to the rest of the world and agricultural aid showed significant effects on the price of food as well.

The rest of the paper is organized as follows: Section 2 reviews the literature on the link between natural disasters and food prices and explores the evidence on the role of regional trade. Section 3 describes the datasets and their limitations, while section 4 presents my empirical methodology. Finally, section 5 presents the results of the regressions and Section 6 concludes.

2. Review of the literature

2.1. Why is it relevant to study the effect of disasters on food prices?

There are a large number of papers that attempt to quantify the impact of disasters on economic growth, and the effect of disasters on the economy have been discussed at length since the 1990s because of their political implications. But almost all existing research focuses on the overall GDP or on incomes; other impacts of disasters, such as the volatility and the level food-prices, have been under-investigated (Cavallo & Noy, 2010).

Albala-Bertrand (1993) is among the first to evaluate the effect of disasters on prices. Arguing that disasters do not negatively affect GDP growth, he received a notable attention for his critique of international disaster management initiatives. His economic approach has been later critized for being overly simplistic and his findings for lacking external validity. Indeed, he focuses on six Latin American countries, and because he uses simple correlation models which do not allow to account for shocks that can happen together with disasters (Raddatz, 2009). Over time, more data has been made available, which allowed for a broader geographical scope. Studying more countries seems to reverse the findings. For example, Skidmore and Toya (2002) use cross-country regressions to measure the effect of disasters on growth, and they find a positive effect of climatic disasters but a negative effect of geological disasters.

Noy (2009) examines the impact of 507 disasters on GDP over the period 1970-2003 and finds a significant negative coefficient. The effect is larger for smaller and less developed countries. His findings indicate that higher per capita income, literacy rates and institutional capacity help to mitigate the impact. Another strand of the literature finds that the impact of disasters depends on the type of disaster. Raddatz (2009) finds that climatic disasters (storms, floods, droughts and extreme temperatures) have a significant negative impact on GDP, mostly in the year of the disaster. Other disasters are not found to have a significant impact. Loayza et al. (2012) look even closer and compare the effect of various types of climatic disasters on the growth of different sectors of the economy. Their study concludes that droughts and storms have a strong negative impact on agricultural growth. The channels are rather intuitive: droughts negatively affect crops because water is critical for agriculture, and storms are expected to have destructive effects on harvests (Loayza et al., 2012).

Turning to the literature on the effect of natural disasters on prices, published studies are rather scarce, and this is even truer for Sub-Saharan countries. This gap is, however, critical because African populations are particularly affected by volatile and high food prices. Minot (2004) finds that food prices in SSA are more volatile than in other regions of the world and it is twice that of the global market. Those swings significantly affect the poor as food typically constitutes a large share of their spending and their income is close to the minimum subsistence level.

Small-scale studies exist, but most of them focus on regions where the effects are likely to differ from the case of interest. Cavallo, Cavallo and Rigobon (2014) for example study the daily behaviour of supermarket prices following two earthquakes, in Chile and in Japan respectively. Doyle and Noy (2015) study the Canterbury earthquakes of 2010 and 2011 and find no significant impact on prices in New Zealand. In both studies, the nature of the disaster and the structure of the market are different from that of SSA countries.

Again, natural disasters have more acute effects in SSA because a large part of its population depends on subsistence agriculture for their consumption or on agricultural activities for their income. Staatz, Haggblade, and Me-Nsope (2017) simulate a drought causing a reduction of 20% in the domestic production of sorghum and millet and other starchy staples by 20%, and using parameters based on the characteristics of the West African Sahel countries, he finds that the most vulnerable layer of the population, defined as the rural poor, would experience a 57% reduction in their calorie consumption.

The limitation of the existence of analysis of the effect on food prices directed me to use the findings of the studies of disaster on GDP in my analysis. As emphasized by Cavallo & Noy (2010), the research on the effect of domestic production (GDP) is rather extensive and many of the arguments that they use are valid in the context of my thesis. First, the key assumption of their models is the independence of the occurrence of a natural disaster from the GDP, and I believe that it also applies in the case of the effect on prices. I will give the reasons that support my beliefs when I describe my empirical model in Section 4. Secondly, the literature has described some of the mechanisms through which each disaster can affect agricultural production. For example, Loayza et al. (2012) find that floods have a positive effect because beyond the short-term destruction during their occurrence, there is a net positive effect on crops because of the abundant rainfall.

To my knowledge, the most comprehensive study on natural disasters and prices is conducted by Parker (2016). He focuses on the effect of natural disasters on the level and the persistence of inflation for 212 countries, and he measures the effect per level of development, per type of disasters and per sub-index including food prices. He finds that middle and low-income countries experience a significant and stronger food inflation (0.177 percentage point compared to 0.054 percentage point) compared to advanced countries. This effect is even stronger in the occurrence of a severe disaster, causing food price inflation to increase by 0.55 percentage point. Interestingly, he also finds that the level and the persistence of the inflation episode varies across disasters. If earthquakes do not significantly affect inflation, storms significantly increase food prices in the quarter of their occurrence and last up to three quarters later. Floods and droughts immediately and significantly increase headline price inflation in middle and low-income countries. Droughts have a longer effect, estimated to increase inflation by as much as 11.54 percentage points three years after the disaster. He also stresses that droughts may continue for several quarters and even years. Food price rise is one of the immediate impacts of natural hazards as it causes damages to livestock and the destruction of harvests, creating shortages and pushing up the price of remaining food (Parker, 2016).

2.2. Debates on food price stabilization policies

Food price stabilization policies are a rather historical debate and policymakers in Africa have tried to implement a wide range of price stabilization policies over time. In the seventies, state-owned grain enterprises were dominating the market and many African governments intervened in the food market through consumer price controls, subsidies to producers, or barriers to international trade. Food market interventions resisted the economic liberalization movement of the 1980s. The food market was slow to reform and many state-owned enterprises continued to regulate the market for staples across the continent. Some argue that state intervention in food markets is necessary for SSA because of the weakness of the private sector which is often constrained by the lack of credit and limited storage capacity. These enterprises, therefore, can and should operate like a buffer stock, buying when prices are low and selling when they are high (Poulton et al., 2006; Timmer, 2010). Others argue that unpredictable interventions by these enterprises are one of the see state-owned enterprises as the main constraints faced by private traders and they think that this exacerbates the instability of food prices (Chapoto and Jayne, 2009; Byerlee et al., 2006).

The uncertainty about the effectiveness of state price stabilization led researchers and policymakers to seek alternatives that do not involve direct intervention in grain markets. Trade comes as an appealing, although debatable, alternative. The global food price crisis of 2008, in particular, has raised vivid debates on trade policies to stabilize prices.

Trade insulation is often the path taken by governments to disconnect domestic prices from international fluctuations (FAO, 2015b). Demecke et al. (2008) surveyed government policies in 81 developing countries during the 2007/2008 food crisis and find that 25 of them either banned exports completely or increased export taxes. Net exporters can impose export taxes or bans to redirect local production to domestic markets, while net importers can decrease their tariffs, or subsidize imports, to buffer the impact of rising international food prices (Deason et al., 2014).

Another strand of the literature, however, opposes the idea that shielding the domestic economy from large food price shocks helps to stabilize prices. Giordani, Rocha and Ruta (2014) stand against trade insulation policies, arguing that it creates a multiplier effect of trade policies, as governments respond to each other with further trade insulation policies. They find that it worsens the price rise, particularly for food products. Measuring a deviation in global trade policy with the share of world trade covered by export and import measures, they find that one standard deviation leads to an increase in the range of 8% up to 42% of the price of staple food products during the global food crisis of 2008-2011. Martin and Anderson (2012) similar results, analysing the prices of rice and wheat in 1972-74 and 2006-08. Their results suggest that 45% per cent of the increase in rice prices in 2006-08, and 30% of the increase in wheat prices was due to insulating behaviour. The study of other staples yields the same result (Anderson, Ivanic and Martin, 2013). Jones and Kwieciński (2010) find a more mitigated answer, showing that the elasticity of price transmission and the movements of the exchange rate can switch the effect of trade insulation policies. India, China, and Indonesia, for example, were able to successfully insulate their domestic market during the period of rising international prices from 2006-08.

2.3. Food price stabilization after a natural disaster

When the source of price instability is natural disasters, the debate is different from the above. Opinions are rather unanimous in the economic literature, supporting the push of the international community and the African regional organizations to build a Continental Free Trade Area. The literature generally sees trade openness and regional integration as a potential source of stability. The rationale backing this belief is that increasing trade can help to compensate for the loss of agricultural production when natural disasters create a shortage of food supply and lead to unstable prices. In a compendium of the possible links between trade and food security, the FAO (2016) mentions that importing food can reduce the likelihood of shortages and ensure that food supply and prices are more stable.

Deason et al. (2014) show that a consolidated continental market has the potential to absorb the production volatility of single African countries. Computing the ratio of the domestic supply volatility on that of the African-wide market, the authors find evidence that the broader the area over which agricultural commodities are traded, the more stable the supply and the lower the food production volatility. Their results show that the domestic food supply of each single countries is much higher than that of the consolidated African supply. Guinea-Bissau’s domestic supply is close to 70 times more volatile than the Africa-wide market. Larger countries yield lower but still substantial volatilities, for example, they find that Nigeria’s local supply is 60% more volatile than the continental supply.

Regional trade is expected to have a compensation effect, where for example good rainfall and a successful harvest in one region can offset poor rains and a small harvest in another. Deason et al. (2014) explain that trade raises the availability of food as well as the ability of affected groups to access food. Thus, if there are no other interventions distorting the price, the imports should lower food prices or reduce the pace at which they rise when natural shocks create supply shortages. The idea is that trade reduces the risks incurred by vulnerable groups by keeping the domestic supply of food stable.

Azzarri et al. (2014) argue that there is a potential for increasing trade because of the high spatial distribution of cereal-production and the consumption patterns across Africa. They look at the distribution of the crops and their resilience to natural shocks, and they find that it is possible to compensate the production losses in one region by a surplus in another one as the crops are heterogeneously resilient.

Badiane, Odjo and Jemaneh (2014) assess whether trade integration of African markets can raise the capacity of domestic markets and absorb local price risks. They first find that integrating a regional economic community can indeed increase the intra-African trade in food and that it helps in growing more competitive domestic markets. They further show that regional markets can be a source of stability because (1) the stability of the regional-aggregated production is much higher than that of the single country members, domestic productions can be up to five times more volatile, and (2) the domestic fluctuations in production are only weakly correlated with that of its regional partner countries. A larger difference in the ratio of domestic to regional volatility combined with a low correlation with the volatility of the partner countries signal that RECs can absorb local risks. (Badiane, Odjo and Jemaneh, 2014).

The literature shows that the fluctuations in national production across the continent can offset each other in the occurrence of natural disasters and that the consolidated regional and continental markets can absorb the domestic risks. If what the literature finds is true, and if prices represent the dynamics of the supply and the demand for food, the compensation effect of trade should prevent large price movements when there is an exogenous natural shock. Staple food prices are critical for populations near the subsistence level for whom food represent a large part of their consumption. Hence, food prices are key to food security and ensuring their stability is important for food policies.

3. Datasets and their limitations

3.1. Food products

I use the most disaggregated food price data available from the FAO GIEWS Food Price Monitoring and Analysis (FPMA) tool. They track and regularly publish international and domestic agricultural prices to provide timely and transparent market information to decision makers and food security strategies. Their database is regularly used by international organizations, academia and researchers, and it is sourced from national statistics offices. The dataset covers 180 unique products in Sub-saharan Africa including fruits and vegetables, oil, livestock, dairy and cereals. I choose to focus my analysis on the five most common cereals, sorghum, millets, wheat, maize and rice; and one root crop: cassava.

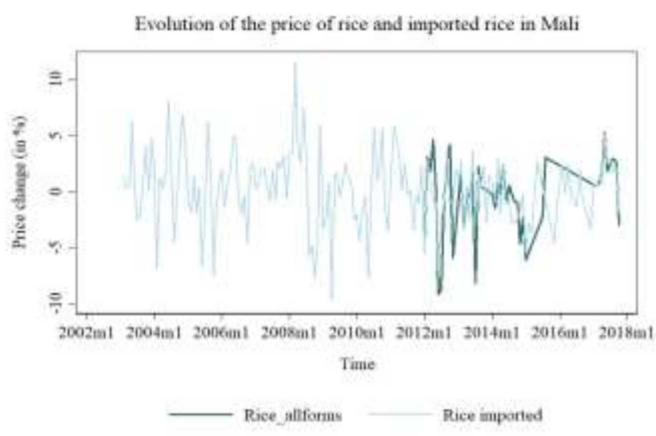
While cereals represent alone more than half of the caloric intake of African households (Berkum, Achterbosch and Linderhof, 2017), roots and tubers exhibit interesting nutritional and climate-resilient features that draw attention on their relevance for food security.

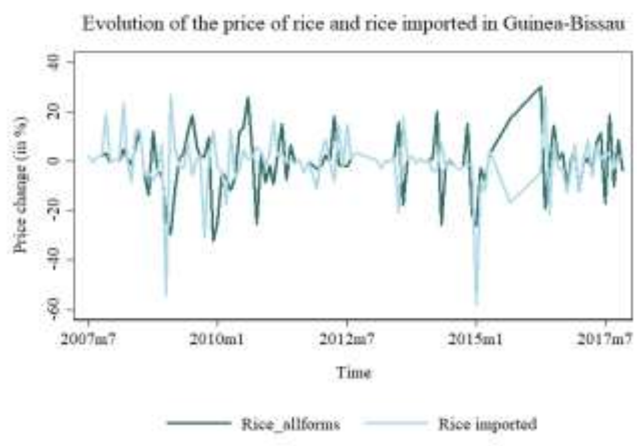
Cereals are also relevant to this study because their availability as well as their accessibility (through prices) are threatened by climate change. The population growth which is expected to lead to a 2.5-fold increase in the demand for cereals by 2050 aggravates the situation. Disasters cause large losses in cereal production, thus threatening food security by eroding the supply and pushing up the prices of the staple of many African households. In fact, the FAO (2015c) finds that 84% of the damage and losses caused by droughts is absorbed by the agriculture sector and that the total cereal losses in SSA amounted to USD 16 billion between 1991 and 2013. Another reason to use cereal prices is that they are traditionally used by the food security monitoring institutions. The FAO Committee on Food Security for example use observations from the global cereals market to monitor food security., acknowledging that cereals shed light on the global food situation due to their weight cereals in the overall food basket (FAO, 2003). The Famine Early Warning Systems Network is another important food monitoring organization, and they publish a monthly report on the trends of staple food that are key to food security including maize, rice, sorghum, millet and wheat.

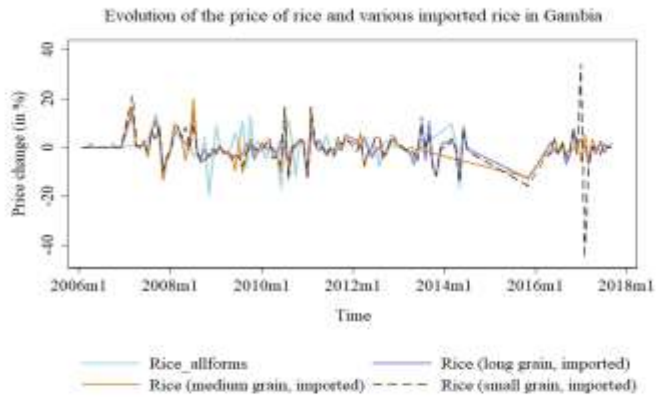
I also choose to look at the price behaviour of roots and tubers. They are increasingly seen as promising products to ensure stable food supply and food security. A working paper written for the African Development Bank emphasizes that, compared to other crops, roots and tubers produce more food per unit area of land, they have a superior nutritional quality relative to their price, and that they are far less susceptible to international market shocks (Sangina and Mbabu, 2015). The latter argument makes it an interesting case to evaluate the direct link between food prices and disasters and to investigate if more intra-African trade can lead to more stable food prices. However, the effect of natural disasters on roots and tubers prices are expected to be lower than for the other crops because they are more resilient to natural hazards. Lal, Gopikrishna, Ambily, & Amalraj (2014) conduct a study of the effect of natural hazards on tuber crops in Kerala, an Indian state that experiences drought, floods and other forms of climate anomalies, find that cassava outperforms other crops in term of resilience to climate shocks. Hartmann (2007) praises the importance of roots and tuber crops, calling them “insurance crops and safety shields in time of drought and other disturbances”.

The level of precision of the price data reported changes importantly across countries and across the regional markets within a country, depending on what is sold on the market. For instance, maize in reported under a general name in some countries/markets ("Maize"); but in others the data is more precise and the variety is reported ("Maize (white)" or "Maize (yellow)"); and other times there is data on the price of transformed forms of the product (for example " Maize meal (white, breakfast)" or " Maize meal (white, with bran)"). In my analysis, I choose to ignore the distinction between the varieties and the forms of the cereals. First, this heterogeneity considerably reduces the number of countries and the number of periods that can be analysed for each product. Hence, I aggregate “Maize(white)” and “Maize(yellow)” under “Maize”. Simply keeping the differentiation, on the other hand, would lead to a large imbalance of the number of country considered for each product. Taking the example of maize, there is only one country that reports the price of yellow maize, while 11 countries report the price of white maize. There are 12 other countries that report maize under the generic name (“Maize”) and 2 countries that report the price of “Maize (local)” with no mention of the variety. The FAO does not provide additional information on the composition of the generic “Maize” products, hence, it is not possible to assign them to any subgroups, and it is inconsistent to consider the variety of maize for some countries but not for others. Another reason to aggregate the products under a general name is that international food price monitoring platforms, such as the Agricultural Market Information System of the FAO, similarly ignore this distinction and consider the cereals under their generic name.

Thus, I average the price of the different varieties of the cereals and the root and tuber products at every period and for every country. It is important to note that this aggregation implies that the varieties of same products are equally sensitive to disasters and they are interchangeable products for the households, which drive their price in the same direction when the demand of one of the variety increases. In other words, I assume that all the subgroups of Maize, such as Maize yellow and Maize white, are affected in the same way by every natural disaster. I do not include imported products (such as "Rice (imported, Indian) or "Sorghum (food aid)", nor a transformed form of the products (such as "Maize meal" or reported as flour or meal in the dataset) in the aggregation. Imported products are not directly affected by the local disaster and including them in the aggregation could bias the effect of disasters on prices downward if international prices are more stable than local prices and upward if international price is more volatile than local food price. Minot (2004) finds that local food prices in SSA are twice as volatile as those in the global market. At a first glance, this tendency is not reflected in my sample, perhaps because I use even more aggregated values than Minot (2014) does. In the graphs below, I plot the price of local products together with their imported alternative for a few countries. We see that the prices of the imported alternatives of the products do not move together with the price of the local alternative, which reinforces the need to avoid the aggregation of the local with the imported products prices.







Source: Author's calculations

In my examples above, the price change of imported products is sometimes much larger than that of the local variety (referred to as "Rice_allforms" or "Maize_allforms" on the graphs above). More importantly, the price of imported products sometimes moves in opposite direction from the local product in the four graphs and averaging the price of the local products with that of the imported variety can attenuate the price movements and ultimately attenuating the effect natural disasters on prices. The price of the rice and the imported rice in Mali between 2015 and 2017 is a good illustration of such case: the local price goes up in 2015 and it decreases slowly until 2017 while the price of imported rice is rather unstable and moves up and down in the same period of time. The same case happens in Guinea-Bissau in 2015. Thus, I do not aggregate imported data with the local products. In the market for rice, imported products represent a large proportion of the sample and 54% of the price reported contain the mention "imported". It represents 6% of the maize data, less than 1% of the wheat data. For sorghum, 5.43% of the price data refers to food aid and I also exclude food aid from the analysis. As a support to my investigation, I will observe if imported products prices are affected by disasters and local supply disruption.

I do not include the transformed version of the products either (such as the various maize meals or the cassava meals). Their price depends on the other components of the meal and on the cost of processing, cooking, selling which can inflate the increase in price if, for example, they expand the quality of the products or hire more workforce to produce it. Therefore, accounting for the price of transformed products can bias the coefficient of the effect of disasters on prices upward if their price increase in the same period as a disaster, downward if they decrease. Moreover, the price of the transformed products must already include the price of the cereal or tuber base of the product.

3.2. Food prices

As mentioned above, I collect the food price data from the FAO GIEWS Food Price Monitoring and Analysis (FPMA) tool. The database includes over 1424 monthly price series with producer, retail and wholesale price series for major foods consumed in 89 countries. I restrict my analysis to the retail price products. First, because the bulk of the price series are retail prices and only 10 countries report either wholesale or producer prices.

Moreover, changes in retail prices reflect better the population's access to food as it refers to the price of the products at the end of the market chain between the seller and the final consumer. Retail prices are also generally used by organizations such as the World Food Program to estimate the consumer price indices[1] and the purchasing power of the population (World Food Program, 2013).

Because the purpose of my analysis is to study the effect of disasters on prices, I only include countries that have both food product prices and disaster data. My sample covers 30 African countries, with monthly prices for the different unit measures (400g, 500g, 3.5kg, 12.5kg, 50kg), but I construct the price per kilogram. While the sample period starts in January 1992 and ends in November 2017, ninety per cent of the prices reported cover periods after February 2007. Thus, I will first consider the whole period (1992 to 2017) and then conduct a robustness check on a subsample removing the years before 2007[2].

The data has been reported from regional markets. Ideally, I would compute an average country-level prices weighted in proportion to the size of the regions, as the prices in highly populated regions are more critical for the overall food security of the country. However, the availability of the regional level data is highly heterogeneous across countries and the number of periods available for the regional series is sometimes very small. Indeed, some countries have data on almost all of their official sub-regions, such as Benin which has price data for 11 over 12 of its official sub-regions; while others have a very few numbers of regions available, such as Cameroon for which

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[1] The Consumer Price Index (CPI) of the World Food Program computes t which is an index of retail prices measuring changes in the weighted average of prices of a basket of goods or services

[2] The 17 countries that have data before 2007 are Burkina Faso, Burundi, Cabo Verde Central African Republic, Chad, Côte d'Ivoire, Ethiopia, Gambia, Kenya, Liberia, Madagascar, Malawi, Mali, Mozambique, Niger, Senegal and Zambia.

the price data is available for only 2 regions over 10. Moreover, those regions are not necessarily representative of the population as they are not the most populated. Taking the same example of Cameroon, none of the two regions available is the most populated and together they account for 27% of the population of the country[3]. Lastly, the data has many gaps and many months or even years, are missing across the sub-regions. Hence, I decide to use a non-weighted average price across regions for every product, every country and every period to allow for a fair comparison across the countries.

3.3. Natural disasters

3.3.1. Source and possible limitations

The EM-DAT database is the most complete source and the most widely used database in the literature using natural disasters. It is collected by the Centre for Research on the Epidemiology of Disasters (CRED) at the Université Catholique de Louvain in Belgium. The database has been created to provide support to relief and recovery initiatives conducted by governments and other responsible agencies. It reports the occurrence of natural and technological disasters across the world, their human as well as their economic impact. The database includes disaster events which meet one of the following criteria: ten or more people killed; 100 or more people affected; declaration of a state of emergency; or call for international assistance. I focus on the three disasters that Parker (2016) found to have a significant effect on food prices: droughts, floods and storms. Moreover, the literature related to agriculture and food systems documents that hydro-meteorological disasters (especially droughts and floods) are the most common forms of natural hazards and are responsible for 70% of economic losses in SSA (Adhikari et al., 2015). Storms are relevant because the south-east African coast is one of the seven tropical cyclone basins[4].

The accuracy of the data on natural disasters and their impact is questionable, especially because national governments might have an interest in inflating their measured impact to receive more assistance and support from donor countries. If countries that are in a relatively worse economic

[3] The two regions available are the “Nord” and the “Extreme Nord” region, respectively accounting for 17,8% and 9,67% of the population of Cameroon in 2005. Neither Yaoundé, nor Douala, the two largest cities of Cameroon, are located in those regions.

[4] See the number of storms per year by basin here: http://www.aoml.noaa.gov/hrd/tcfaq/E10.html. Data collected from the World Meteorological organization shows that there have been, on average, 9.3 tropical storm per year in the West Indian Ocean basin (south east Africa).

situation tend to have higher prices and are more likely to report disasters, then this measurement error can bias the effect of disasters on prices upwards. Despite these caveats, the EM-Database is still the most accurate and comprehensive effort to collect cross-country data on natural disasters (Loayza et al., 2012)

3.3.2. The occurrence of the disasters

The database provides a starting date (day, month, year), which is necessary to track prices monthly. For every period and every country in which there is a price data available, I assign a dummy variable indicating whether in that month a drought, a flood or a storm has started. The availability of the month also allows looking at the effect on food prices 1 to 12 lags after the occurrence of a particular disaster which will help draw conclusions on the timing that different types of disasters might have. The duration of the disasters is not consistently provided, hence the end of the disasters is not taken into account in the analysis. In any case, this information would be of little use in my analysis as the objective is to investigate how long it takes for price changes to happen when a disaster is reported and how persistent such changes they are.

3.3.3. The difficulty of measuring the intensity of the disasters

In a compendium of the studies on the macroeconomic effects of natural disasters, Cavallo & Noy (2010) stress that the failure to find consistent results on the economic impact of natural disasters happens because the threshold used to record disasters by the EM-Database is rather low, which leads to the high incidence of small disasters in the sample. Hence, it is important to consider the magnitude of the disasters in my analysis when it is possible.

The literature (Loayza et al., 2012; Noy, 2009; Adedeji, Gieck-Bricco, & Kehayova, 2016) uses the total number of people affected which estimates the sum of injured, homeless and people requiring immediate assistance (basic survival needs such as food, water, shelter, sanitation and immediate medical assistance) during a period of emergency. In an analysis of the effect of disasters on the probability of the occurrence of a food supply crisis, Adedeji, Gieck-Bricco, & Kehayova (2016) use the total number of people affected as an independent variable, arguing that the more people are affected by a natural disaster, the higher the probability of a food crisis. Noy (2009) investigates the determinants of the macroeconomic impact of natural disasters and take into account the size of the economy. He computes a measure of disaster that takes into account its magnitude by dividing the number of people affected by the population size in the year prior to the disaster, and then he divides this further with the GDP of the year prior to the disaster.

Using the same proxy, i.e. the number of people affected to capture the intensity of the disaster, for the sub-Saharan African region leads to a very small number of intensity measures, which importantly reduces the sample included in the regression and results in omitted coefficients. In my sample, there are 56 observations of the number of people affected out of 240 drought events, 177 observations out of 1651 floods reported and 53 observations out of 253 storms. Hence, using the number of people affected would considerably reduce the sample of analysis[5].

3.4. Trade data

The trade data is collected from the UN Comtrade database which is the largest repository for international trade data. I collect yearly bilateral export, import trade flows for my 30 countries and for the 6 products I am analysing from 1992 to 2017. I use the quantity traded per kilo between my 30 countries and with 13 other Sub-Saharan African countries**.** My sample contains 2’787 yearly export observations and 3056 yearly import observations. I choose to only consider the trade of my 6 products of interest (Maize, Sorghum, Millet, Wheat, Cassava and Rice) to investigate if more trade of staple food products can contribute to reducing the effects of natural disasters on their prices. By excluding all the other products, I make sure that the trade effect that I find is only driven by the trade of one of the commodities I analyse.

All the countries do not necessarily trade all the 6 products and the data for sub-Saharan African countries is very inconsistent throughout the years and across the countries of my sample. Hence, I have to aggregate the trade of the 6 product per country to keep enough observations for my analysis. For example, Benin has 47 trade observations of maize, 83 observations for rice and 15 for wheat, while Botswana has respectively 6, 1 and zero observation for the same products. Taking the same example of countries, Benin has consistent observations from 1998 to 2017 on both imports and exports trade flows, while Botswana has only exports observations for 2012, 2015 and

[5] Before coming to this conclusion, I tried to run the regression using this data but I could not run a panel regression due to the lack of observations.

2017. Other limitations include the importance of informal trade[6] in SSA (Brenton et al., 2014) and the right for the countries to keep their trade flows confidential. The UN Comtrade database mentions the later and admits that countries have the right not to report some of its detailed trade. Despite those limitation, the UN Comtrade database remains the most comprehensive trade database for the 30 countries I am analysing, and it has the most complete data on disaggregated trade flows.

I will use the imports and the exports flows of the aggregation of maize, sorghum, millet, wheat, cassava and rice of each country with all their partners in sub-Saharan Africa to capture the effect of staple trade on the staple prices in the occurrence of a disaster. I also collect the quantity traded of those products with all the countries in the world, and I subtract the value of intra-SSA trade to have a measure of extra-SSA trade and to control for the possible variations in the prices that stem from the trade outside SSA. This way I can also compare how does the intra-African trade volumes affect the prices compared with extra-African trade volumes.

Of course, using the aggregation of the six products has some shortcomings as it makes the analysis of whether the price of a specific product increases when it is more traded. However, the interaction between the different product matters as well, and I will show in Section 5.1 that the products are all more or less produced in each region of SSA and that they are substitutes to each other, especially in times of disaster. For example, maize is highly sensitive to the lack of rainfall, and some populations turn to cassava which is more resilient and cheaper in times of droughts. Hence my aggregation can capture some of the interaction effect.

3.5. Control variables

3.5.1. Population size

I also collect the yearly population from the World Bank Development Indicators and control for the past-year population. The population size prior to the disasters can be determinant for the effects of the crop destruction on prices. A larger population could mean that there is a larger demand for the products, a larger risk for a disaster to create a food shortage which would increase prices. But

[6] Informal trade flows across African borders are movements that are not recorded by official national statistics, not inspected or taxed through official channels. Brenton et al. (2013) stress that informal trade is crucial to the livelihood of a large part of the population in Africa, and it contributes to regional food security.

on the one hand, a larger population could signal a larger capacity to recover from crop destruction as agriculture is labor intensive and in that case the coefficient would be negative.

3.5.2. Agricultural aid

Agricultural aid, which I expect to be higher in time of disasters and probably higher when there is a disaster, can also be an important determinant of the supply of staple products in SSA. Alabi (2014) studies the impact of agricultural aid on agricultural growth in SSA and finds that foreign agricultural aid has a positive and significant impact on agricultural GDP and agricultural productivity at 10% significance, and that disaster and conflict also have a positive and significant impact on aid receipt at 5% significance. If foreign agricultural aid responds to disaster, then its nature and amount can indeed play an important role after a disaster and even more after a strong disaster. Including this variable can maybe help to capture a part of the intensity effect as I would expect the value of the aid to correlates with the size of the disaster. I collect this data from the OECD database on official development aid and I aggregate the flows of various type of agricultural aid[7] that I believe to have the power to affect the supply and any variable related to the price of the six staple products I analyse I aggregate the flows coming from all donors to my 30 countries per year from 1995 to 2007. The flows are expressed in current dollar, which is more appropriate as I chose to use the nominal prices for the products. I include agricultural aid as a control.

3.5.4. Other important time-varying controls that I am not able to capture

What can also be determinant for the effect of disasters on crop prices, but for which I am not able to control for in my study, are the agricultural infrastructure and practices that determine whether the crops are more or less resilient from one country to another. Although there is a fixed country effect, those variables are time-varying and hence not fully captured in the country dummy as agriculture is a fast-changing sector and innovations happen at a micro level. The carry-over stock of each country can also determine whether there is going to be a shortage of food supply, but there is no data available on this

[7] Those flows are: Agricultural development, agricultural financial services, agricultural inputs, agricultural land resources, agricultural services, agricultural water resources, food crop production, Industrial crops/export crops, plant and post-harvest protection

Although the economic capacity of a population can matter in the resilience to food supply shocks, I cannot find an appropriate proxy. The economic capacity of the population can, for example, reduce their dependence on staple food and allow them to substitute for other products that were not affected by the shortage of cereals or cassava. However, because the dependent variable is the price level, using the GDP per capita is not the best way to capture this effect as prices should rise with GDP, and the mitigation effect would not be apparent.

4. Methodology

4.1. The effect of all type of disasters on food prices

The main identification assumption to all my regressions is that disasters are exogenous shocks and that they are independent from current or previous values of prices and from other determinants of the price level. The literature makes the same assumption and Raddatz (2009) refers to natural hazards as "The Wrath of God" to emphasize this exogeneity.

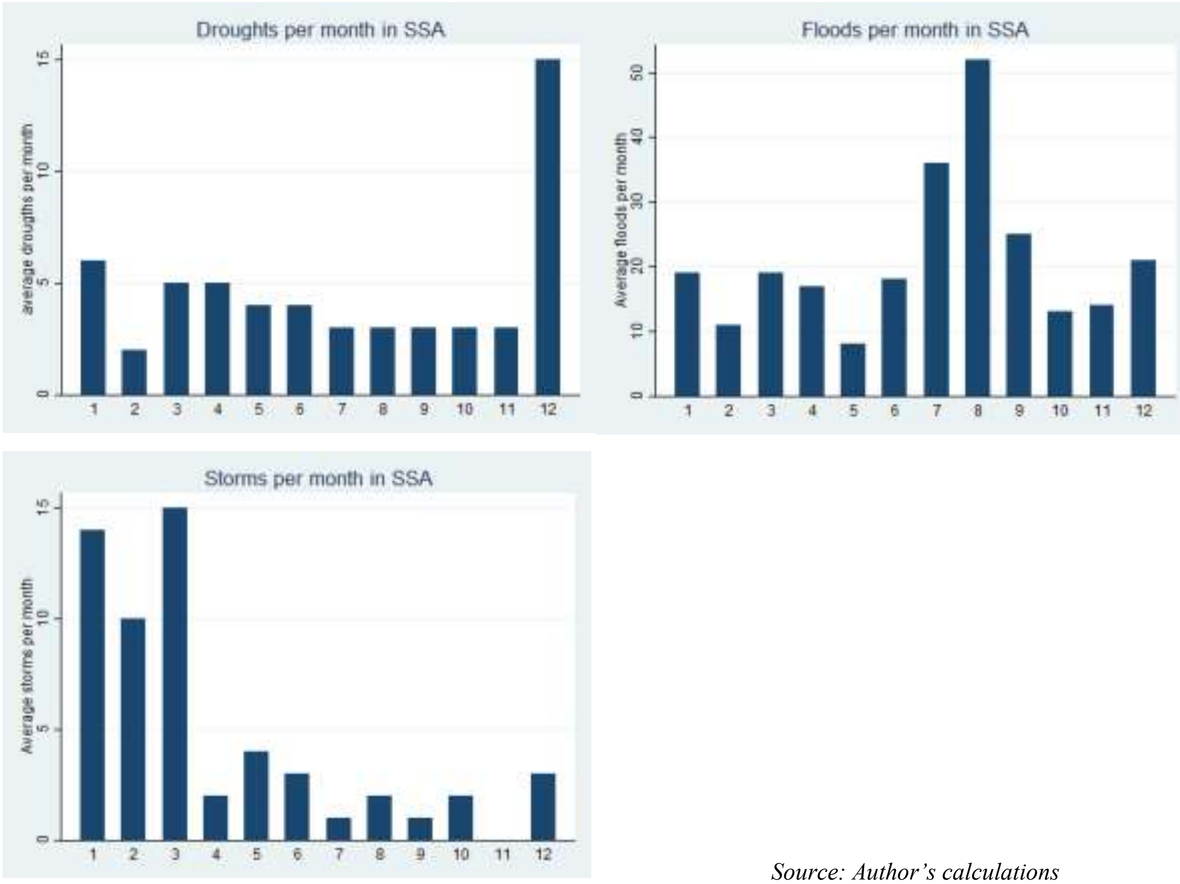
Indeed, although the disasters are rather seasonal (as shown in the plots that I add later, when I show the importance of seasonality in the occurrence of the disasters), the exact timing of the disasters and the reaction of the demand to the shortage of supply are not predictable. The farmers can have a knowledge of the approximate period at which a disaster might occur, but the best prediction they can do is to associate it to the seasons, for example, because they know that a flood can occur when the rainy season comes. Not knowing whether a flood will indeed occur, if they take precautions they would do it systematically at every rainy season, and this effect would be captured in the country fixed effect dummy. Even less predictable are the intensity of the disaster and the reaction and the food-buying behaviour of the households as a result. Those are, however, the key determinants of the movements of the price after a disaster.

As a starting point, I run a standard panel regression of the form:

$$P_{p,i,t} = \beta_0 + \sum_{j=1}^{12} \beta_{t-j} \, . D_{i,t-j} + \lambda_y + \lambda_i + \log(Pop_{i,t-13}) + \mu_{p,i,t} \quad \text{(Equation 1)}$$

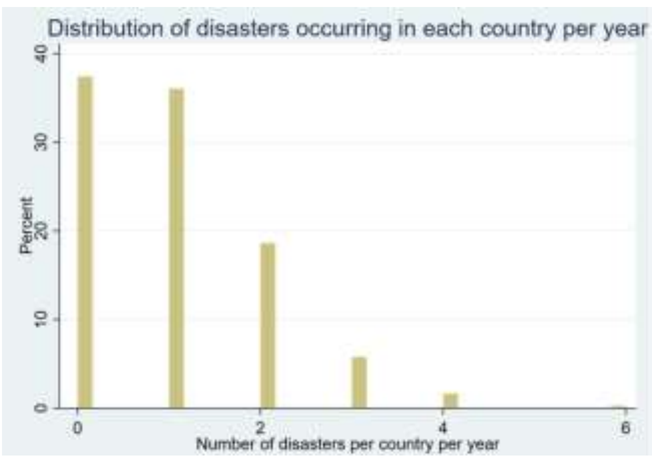
where the subscript p indicates the product of interest, i indicates the country and t represents the time period (monthly data). $P_{p,i,t}$ price of the product p in country i in period t, and $D_{i,t-j}$ is a dummy that takes a value of 1 if any type of disaster occurs in country i in period t-j. β_0 is the common intercept that capture the time-invariant determinants of the price of the product p, λ_i denotes the unobserved country-specific characteristics that define the long-run differences the price levels of the products such as the geographical location of the countries and the quantity of each variety that is produced on average or the diet of the population which defines the demand level for the products for example. λ_y captures global shocks that affect all the countries in year y, $\log(Pop_{i,t-13})$ captures the effect of an increase of 1% in the size of the population and finally $\mu_{p,i,t}$ is the error term.

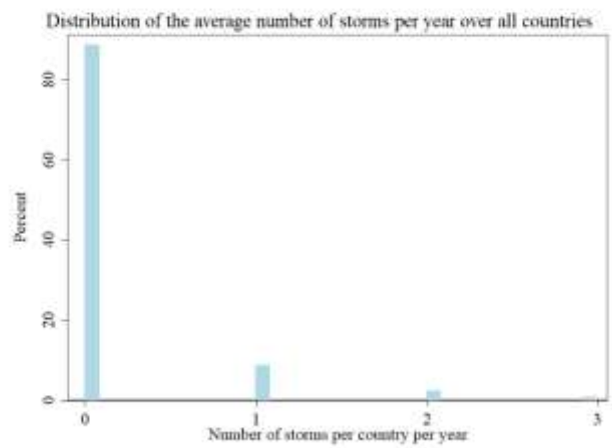
Although it is likely that there are seasonal patterns in prices, depending on the crop product and the country, I do not include seasonal dummies. First, because one same product might have different cropping season across the countries because of the climate and the country-specific soil conditions. Secondly, including seasonal dummies could absorb some of the true impacts of the disasters on prices if they are concentrated at certain periods of the year, every year. I plot the average number of disasters in each month, over all the years in my sample and the graph shows that there is a seasonal pattern in my data with droughts occurring mostly in December, floods in July-August and storms from January to March. In the appendix, I present the average number of each disaster per region. The plots per region show even more clearly that there is a seasonal pattern in the occurrence of the disasters. Floods, for example, occur mostly in March in Central Africa, June in Eastern Africa, July and August in Southern Africa and mostly August in Western Africa



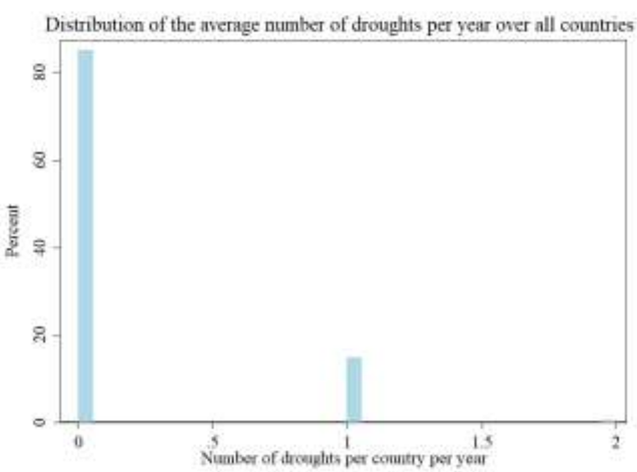
Source: Author's calculations

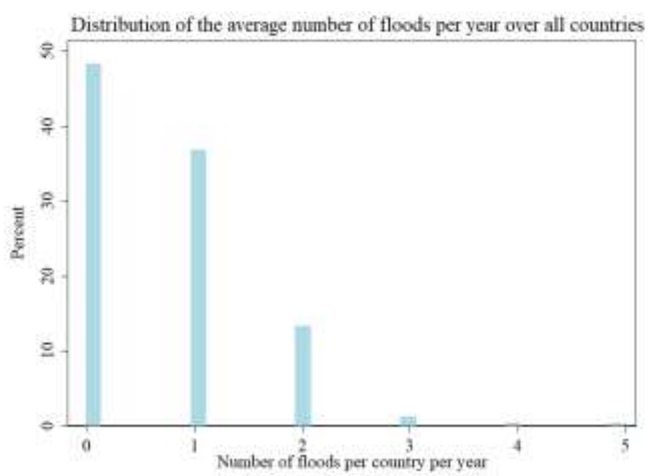
Back to the explanation of Equation (1), each β_{t-j} corresponds to the effect of the lag j of a disaster and takes $D_{i,t-j}$ takes a value of 1 when any type of disaster occurs in period t. I choose to consider the effect of several lags of the disasters because it is unlikely that the effect of a disaster to translate in a price rise in the same month. Indeed, the channel I investigate runs from the occurrence of a disasters to crop damages or destruction, which should translate into a product supply shortage on the market and a rise in price. Intuitively, it is unlikely that the destruction of the crops immediately translates into a price rise. The growth and the harvest of a crop takes several months before the product is sold on the market and includes several steps that are specific to each product and each country such as planting, irrigating, harvesting and marketing. Parker (2016) finds that the lags of disasters are jointly significant until up to 11 quarters, in other words three years, following a disaster, but I limit my analysis to one year. The main reason for my choice is that looking at more years requires to control for more factors that can affect the demand for food and the price of food over-time such as the crop productivity and the climate in the following year, the size of the population, the institutional and regulatory changes that can affect the price of one cereal, or expectations of the population. Over one year, I expect that the occurrence of one disaster will no longer be the sole effect of the disaster, but it will depend on the new disasters and how the population reacted to the past one. By choosing one year, I make the assumption that within one year those factors do not vary and the same type of disaster does not occur. But I believe that it is a reasonable assumption to make because in my data as in 72% of the years of my sample there is 0 or 1 disaster, considering the 30 countries and all types of disasters. The graph below shows that there are only 28% of the years in which there is more than 1 disaster per year reported, and it is likely to be even smaller when I consider the types of disasters separately. Investigating further what type of disaster occurs more than once a year, I find that mainly floods are concerned.





Source: Author's calculations





The tendency of floods to occur two times threaten my assumption, however, studies on the characteristics of floods have shown that the length of a flood spans over more than 6 months (Bischiniotis, et al., 2018) and heavy rain can already occur before the flood onset. The accumulation of rain lasts six months and continues up to one month after the peak of the flood (Bischiniotis, et al., 2018). Hence, I expect that what is reported as two floods within a year in the dataset can be driven by the fact that it is not clear when a flood really occurs, and in its pre-onset phase, the rain is increasingly heavier. In fact, the number of floods reported are likely to be the effect of one same flood.

I also make the assumption that the crops in all the regions of the country are affected similarly and that the price rise comes from a national shortage of cereal and tuber supply. Last, it is important to note that this choice means that the effect I investigate is the short-term effect of disasters on prices. If the rise in price occurs later than one year, because of carry-over stock of the products on the market for example, then it will not be captured in my analysis.

4.2. The effect of different types of disasters on food prices

My second key model considers the type of disasters separately. I use the same equation as in Equation (1), but I investigate separately the effect of a drought, a flood and a storm on the price of each product p.

$$P_{p,i,t} = \beta_0 + \sum_{j=1}^{12} \beta_{1,t-j} \ .Drought_{i,t-j} + \sum_{j=1}^{12} \beta_{2,t-j} \ .Flood_{i,t-j} + \sum_{j=1}^{12} \beta_{3,t-j} \ .Storm_{i,t-j} + \lambda_y + \lambda_i + \log(Pop_{i,t-13}) + \mu_{p,i,t} \quad \text{(Equation 2)}$$

where the dummies $Drought_{i,t}$, $Flood_{i,t}$ and $Flood_{i,t}$ take the value of 1 when one of the three disasters occurs in period t. β_0, λ_i, λ_t, $\log(Pop_{i,t-13})$ and $\mu_{p,i,t}$ can be interpreted in the same way as in Equation 1, and the coefficients $\beta_{1,t-j}$ $\beta_{2,t-j}$ and $\beta_{3,t-j}$ j correspond respectively to the effect of a drought, a flood and a storm in year t-j.

The literature emphasized the importance of differentiating the effect of the type of disasters when measuring the impact of natural hazards on the economy (see for instance Parker, 2016; Loayza et al., 2012; Raddatz, 2009). Loayza et al. (2012) find that different types of disasters have heterogeneous effects on the economic activity and their results reveal that droughts and storms negatively affect the GDP in the agricultural sector, while floods affect it positively. The authors explain that the positive effect of more rainfall, in the case of a flood, may outweigh the negative effect of the localised damage from flooding. When Parker (2016) evaluates the effect of different types of disasters on prices, he finds that storms have a significant impact on food price inflation during the first year following the disaster, flood has no significant impact on food price inflation, and drought has a positive but insignificant effect. Raddatz (2009) finds that droughts have the largest average impact on GDP per capita, together with extreme temperature shocks, reaching cumulative losses of 1 per cent of GDP and statistically significant at the 10% level. Windstorms and floods, on the other hand, have no significant effect in his estimation and he attributes this lack of significance to the possibility that the effect is heterogeneous across countries and strong only for some countries.

4.3. The effect of different types of disasters on food prices per region

Finally, I find interesting to look at the difference within the main geographical regions of sub-Saharan Africa as it can reveal the difference in the sensitivity of the price of my six products in each region. If a product represents a more important part of the diet in a specific region, then I would expect its price to increase more in that region, relative to the others.

I run Equation (2) for each official region of Africa based on the African Union's member geographical classification[8] (available in Annex 1), except for Northern Africa. For this regression, I construct a regional price using a weighted average of the price of each given product in each period (monthly). I use the size of the population of each country relative to the total population in the region in which the country is located. I regress this regional price average on the various lags of the three types of disasters as in Equation (2).

4.4. Including the interaction of the effect of trade with the disaster dummies and controlling for world trade and agricultural aid.

[8] The literature tends to change the countries in which regions, and there is no consensus on the geographical separation of the regions in Africa. Hence, I use the African Union's classification to be consistent in my analysis.

One of the key questions of my thesis was whether intra-African trade, compared to international trade, can mitigate the effect of the disasters on prices. I investigate this effect by interacting the total imports and the total exports of the six products from and to other SSA countries with the dummies representing the occurrence of one of the three disasters.

$$P_{p,i,t} = \beta_0 + \sum_{j=1}^{12} \beta_{1,t-j} \ .Drought_{i,t-j} + \sum_{j=1}^{12} \beta_{2,t-j} \ .Flood_{i,t-j} + \sum_{j=1}^{12} \beta_{3,t-j} \ .Storm_{i,t-j} + \sum_{j=1}^{12} \beta_{1,t-j} \ .\log(TotImp_{A,y}) * Drought_{i,t-j} + \sum_{j=1}^{12} \beta_{2,t-j} \ .\log\left(TotImp_{A,y}\right) * Flood_{i,t-j} + \sum_{j=1}^{12} \beta_{3,t-j} \ .\log\left(TotImp_{A,y}\right) * Storm_{i,t-j} + \sum_{j=1}^{12} \beta_{4,t-j} \ .\log\left(TotExp_{A,y}\right) * Drought_{i,t-j} + \sum_{j=1}^{12} \beta_{2,t-j} \ .\log\left(TotExp_{A,y}\right) * Flood_{i,t-j} + \sum_{j=1}^{12} \beta_{3,t-j} \ .\log(TotExp_{A,y}) * Storm_{i,t-j} + \lambda_y + \lambda_i + \log(Pop_{i,t-13}) + \log(TotImp_{W,y}) + \log(TotExp_{W,y}) + \log(TotImp_{A,y}) + \log\left(TotExp_{A,y}\right) + \log\left(aid_y\right) + \mu_{p,i,t} \quad \text{(Equation 3)}$$

The use of the log of the trade flows will allow tinterpreting the results as the change in price level when the trade increases by 1%.

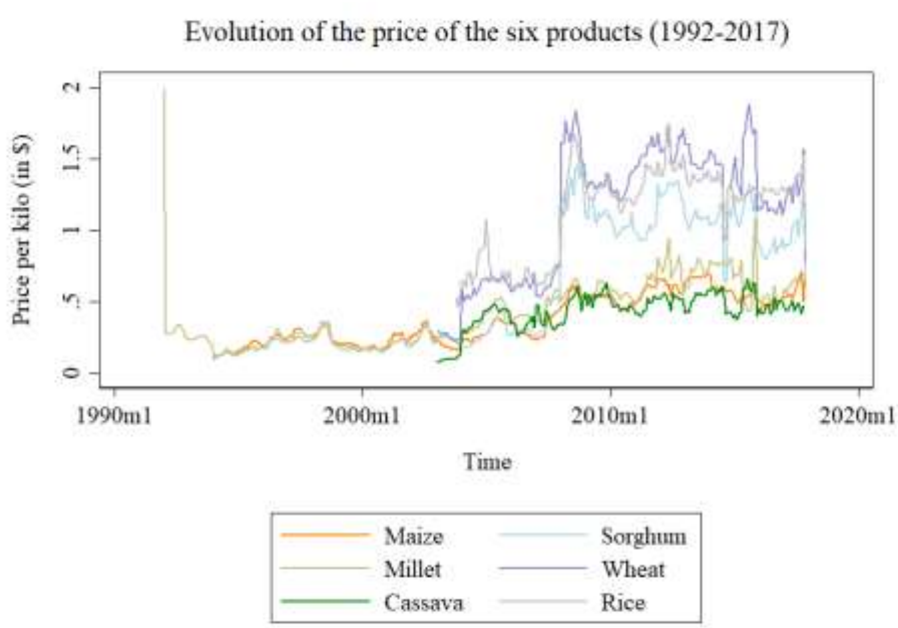
As mentioned and explained in the description of the data in Section 3.4, I use the aggregated trade of the six products I choose for my analysis to obtain the total imports and the total exports quantities with all SSA countries each year. I use the log of the total imports and the total exports with SSA in interaction with the occurrence of my three types of disasters. I further control for the main effect of the three disasters, as well as for the main effect of the total imports and the total exports to SSA countries as they both can affect prices independently from their interaction. Lastly, I control for the possible impact of flows from outside SSA: agricultural aid, $\log(aid_y)$, as well as the total imports $\log(TotImp_{W,y})$ and exports $\log(TotExp_{W,y})$ +and) to the world, which has been computed by deducting the intra-SSA trade values to the total imports and the total exports to the world. For example, each coefficient $\beta_{1,t-j}$ associated with the interaction term $\log\left(TotImp_{A,y}\right) * Drought_{i,t-j}$ can be interpreted as the effect of a 1% change in the total quantity of imports from SSA countries from its value in the period t-j in which a drought occurs, keeping the size of the population $Pop_{i,t-13}$, the quantity imported

$TotImp_W$ as well as the quantity exported $TotExp_W$ to the rest of the world fixed. Of course, the constant β_0, the country fixed effect λ_i and the year fixed effect λ_y remain the in my regression. One limitation of this regression is that I consider the log of the total trade, including my six products. Hence the effect is not necessarily due to an increase in the trade of a specific product but can also be caused by the trade of one of the six staples that I choose to analyse. However, it is certain that there are no other products included in it, and one could argue that the price of the staples are related anyways and that it is interesting to see how much any increase in trade can affect the price of a single product.

5. Results

5.1. Presentation of the key mechanisms causing variations in the effect of the disasters.

The description of the results will be organized by-products. The graph below shows the evolution of the price of the products, averaged over the 25 years (1992-2017) and over the 30 countries composing the sample. The graph shows that the magnitude of the change in price between the products can be highly heterogeneous, and the following results reinforce this argument as it reveals that disasters can affect the price of each of the products with different magnitudes and sometimes opposite directions. Indeed, the six products have different adaptability levels to the climate (temperature, moisture...).



Source: Author's calculations

Besides the difference in the products, there are other explanations that can justify the variation or the insignificance I find in the effect of disasters on staple prices. The following stand out from my results:

1) The diet of the population

The more important a crop in the diet of the population, the more its price is likely to increase with disasters (see the comparison of maize price in EA, SA and WA above);

2) The amount of production in the region

The supply should decrease after a disaster, but the price should increase only if there is a risk that the demand exceeds the supply. Hence, if a region is a large producer of millet for example, but the demand for millet is not very high in the same region, then I do not expect its price rise after a disaster. Indeed, it could even drop if the supply is much larger than the demand.

3) Regulations

Some African states intervene with no notice, and in a non-transparent way, in order to control the price of grains on the local market (Kent and Magrath, 2016). Price stabilization intervention can cause incoherence in the price movements that I observe as they disrupt the dynamics of the supply and the demand that usually sets the price.

4) Geography

Each region, and in fact each country and each sub-region within a country, experience different intensities of the disasters. Storms, for example, could be stronger in EA and SA where there are two countries from the 7th tropical cyclone basins: Mozambique (SA) and Madagascar (EA).

5) Crop destruction is not the only explanation for the short-term effect of the disasters

The results often show an immediate effect of a flood or a storm. Floods and storms can destroy farming and transportation infrastructure. Road damages, for instance, can disrupt the carriage of the supply to the demand. The expectation of a disruption in the supply, in time of disasters, can cause panic buying and a rapid increase in the price.

6) The effect of a disaster does not need to be unidirectional, and this is different across the disasters

Floods, for example, will often cause an increase in the prices close to the month of occurrence and a drop in prices after about 6 months. While the first increase can be caused by an immediate disruption in the delivery of the product from the producer to the end-consumer, the overall effect can be positive because of the excess rainfall on the crops. Loayza et al. (2015) explain that the overall increase in rainfall can be beneficial for the crops and the floods are usually concentrated in one region within a specific time, affecting only one specific region at a point in time and beneficial rainfall at the country level. Clearly, this is a feature that characterizes floods and does not apply, for instance, to droughts.

7) The interaction between the price of the products

There could be an interaction between the rise and the fall of the prices of the staple products within the same region as cereals are likely to be substituted to each other (and cassava tends to be a substitute for cereals).

I will describe those mechanisms in detail when I analyse the results for maize. To avoid redundancy, I will focus on mentioning if the results are in line with those mechanisms in the remainder of the paper. Furthermore, I will try to give an explanation when they do not align.

5.2. Summary statistics

Below I present two tables with the average price of each product in SSA and in each region. Those averages will be used as a benchmark in my description of the results, and I will interpret the coefficients of the changes in prices in terms of their importance relative to the average prices below.

	Mean price per kilo (in $)	Standard deviation	Max value	Min value
Maize	.4989079	.3844627	3.312349	.0970838
Sorghum	.8860178	1.755948	12.21272	.0912092
Millet	.5255313	.4104202	5.753026	.0939156
Wheat	1.339443	1.276809	8.311865	.2205784
Cassava	.472371	.264043	2.40678	.0047444
Rice	1.241135	1.461788	9.730466	.3213075
Total	.7984291	1.147675	12.21272	.0047444
N	11609			

Table A. Summary statistics of the price of each product in SSA. This table presents the average price of each product at the SSA level. *Source: Author's calculations*

	Maize	Sorghum	Millet	Wheat	Cassava	Rice
CA	0.590	0.325	0.577	1.721	0.466	1.096

	(0.340)	(0.106)	(0.231)	(0.770)	(0.156)	(0.409)
EA	0.451	0.505	0.715	0.640	0.501	0.707
	(0.127)	(0.180)	(0.125)	(0.167)	(0.0750)	(0.202)
SA	0.403	0.572	0.482	0.838	0.556	1.087
	(0.236)	(0.152)	(0.129)	(0.261)	(0.213)	(0.288)
WA	0.498	1.114	0.408	2.506	0.361	1.497
	(0.468)	(2.214)	(0.267)	(1.985)	(0.212)	(2.067)
Total	0.499	0.886	0.526	1.339	0.472	1.241
	(0.384)	(1.756)	(0.410)	(1.277)	(0.264)	(1.462)
N	3177	2165	1947	1359	978	1967

Table B. Average price per kilo of each product by region over the period 1992-2017 (in $). This table presents the average price of each of the six products of interest for this analysis and their standard deviation within the region in parenthesis. *Source: Author's calculations*

5.3. Results of the regressions

In order to improve the readability of my results, I will do the following:

1) I compare the rise or the drop in prices to the average price in the region of interest over the entire sample;
2) I present the results of the regressions in graphs where I only report the significant changes in prices from the month of occurrence of the disaster to the 12th subsequent month. I indicate the magnitude of the change next to each bar together with the significance level (the stars *, ** and *** respectively correspond to a 10%, 5% and 1% significance level). I do not report insignificant results, but all the tables are available in the Appendix;
3) At the SSA level, I structure the presentation of the results over two dimensions, i.e. the product and the type of disaster. When considering the different SSA regions, I will consider three dimensions: product, region and type of disaster.

5.3.1. Maize

Maize is the most widely cultivated staple crop in SSA and 77% of its production is consumed as food (Adhikari et al., 2015). Smale et al. (2011) show that SA populations are the largest consumers of maize, the figures are 85 kg/capita/year in SA, 27 kg/capita/year in EA and 25 kg/capita/year in WA and in CA (Smale et al., 2011). Maize is less crucial both in WA, where sorghum, millet and rice are preferred and in CA, where millet and sorghum are the predominant cereals and where their production is close to ten times the production of maize (Staatz et al., 2017; Honfoga and van den Boom, 2003).

Maize crops are predominantly rain-fed in SSA (Aylward et al., 2015) and there is a consensus that the reduction in rainfall decreases maize yields (Adhikari et al, 2015). Therefore, one could reasonably expect to see a negative impact of droughts on maize supply, and a consequent rise in prices.

When I consider my baseline model (Equation 1), in which I look at the effect of any type of disasters on the price of maize in the whole SSA region, I find no significant effect. Such insignificance, however, is possibly driven by heterogeneous effects between disasters and across different regions in SSA. After distinguishing between the types of disaster, it appears that droughts and floods have no effect on prices, but storms cause a significant cumulative increase of 0.19$ per kilo, or about 40% of the of the SSA average price of maize[9], in the third quarter after the storm (see Figure 1.1). This increase is strikingly large, and it is likely to deter the access to food of SSA households who consume maize as their staple. However, it is surprising that other disasters do not have an effect, in particular with respect to drought.

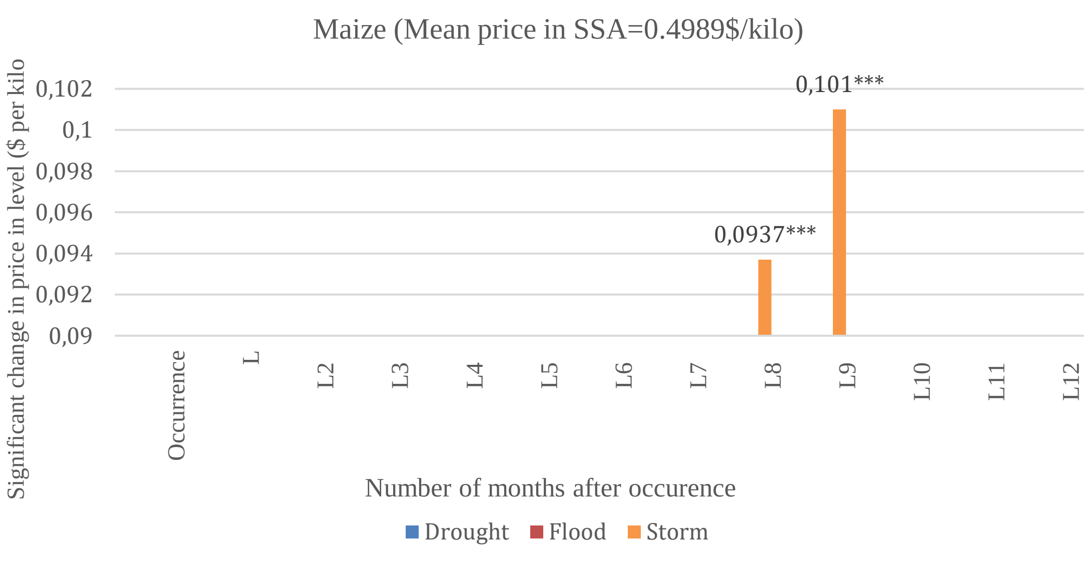


Figure 1.1: The effect of each type of disaster on the price of maize at the SSA level.

[9] To give the reader a measure of the importance of a rise or a drop in prices, I relate the values of the change (indicated on top of the bars in my figures) to the average price in the region of interest over the 25 years of my sample (indicated on top of each of the figures).

In order to understand the results better, I break down the analysis to the 4 macro-regions in SSA. The heterogeneity across regions seems to explain why I do not find any significant result at the SSA level: the sign, the magnitude, the timing and the significance of the three types of disaster differs a lot across the areas of SSA.

In EA, it appears that droughts and storms have a significant impact. Summing up the rise of the price occurring in the second quarter, i.e. lag 4 to 6, after the occurrence of a drought, I find that the price of maize increases by more than 100% of its average over EA countries and over the years of the sample (Figure 1.2). This effect is as expected given the large importance of maize in the diet of the EA region and given its sensitivity to the lack of water.

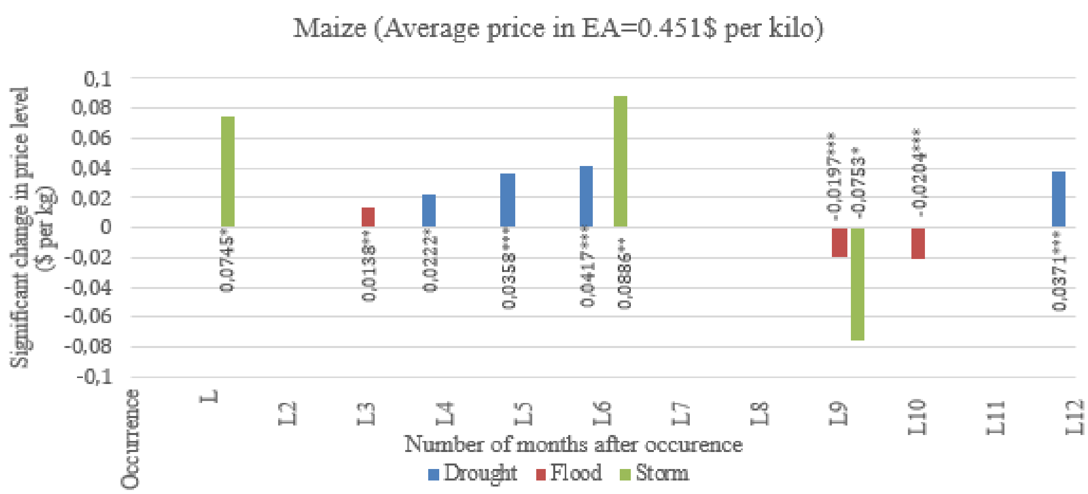


Figure 1.2: The effect of each type of disaster on the price of maize in EA

I find the opposite effect in WA, where droughts cause a net decrease in the price of maize. Although there is a significant rise two months after a drought, the price significantly drops by a larger magnitude in the last quarter of the year of occurrence of the drought (Figure 1.3) and the cumulative decrease is of the order of 30% of the WA maize price average. This result first comes as a surprise because I expected droughts to reduce the production of maize and to cause a shortage of the supply, which should, in theory, increase the price of maize. However, examining the characteristics of WA could explain this result. Smale et al. (2011) show that WA is the largest producer of maize in SSA between 1961 and 2008, and west African maize yields are of 1.7 ton per ha, against 1.5 in EA and 1.1 in SA. But maize is relatively less important for WA populations, and Macauley (2015) shows that maize represents 20% of the calories and protein consumed in West Africa, the figure is of almost 50% in EA and in SA. Even in times of droughts, the supply of maize in EA is more likely to fall short against its demand in EA than in WA. The large decrease in the price of maize could also result from an increase in the demand for sorghum, millet and other products that are more central to their diets after a disaster. In that case, the demand and the price of maize (not essential to their diet) would decrease.

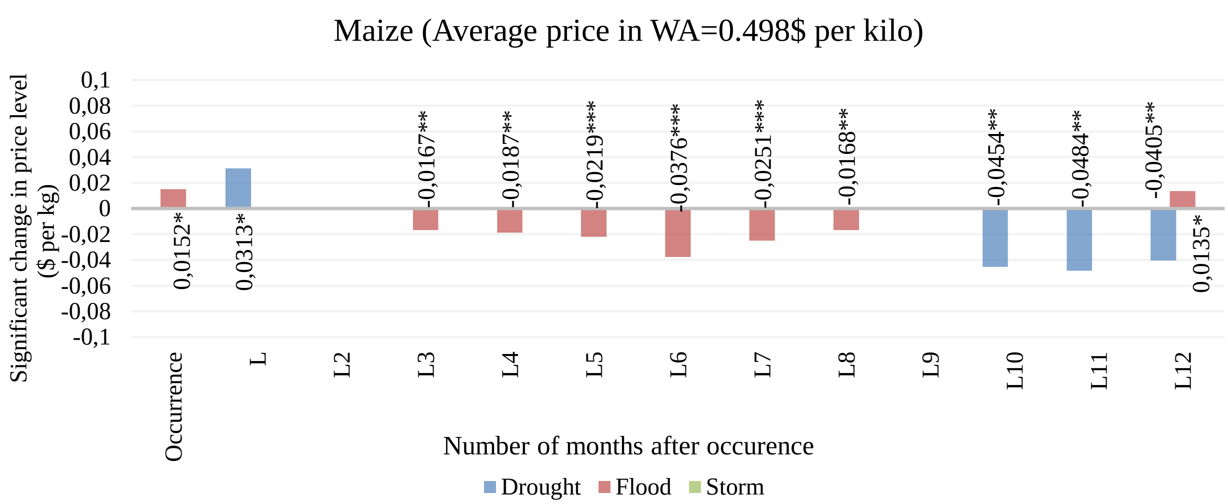


Figure 1.3: The effect of each type of disaster on the price of maize in WA

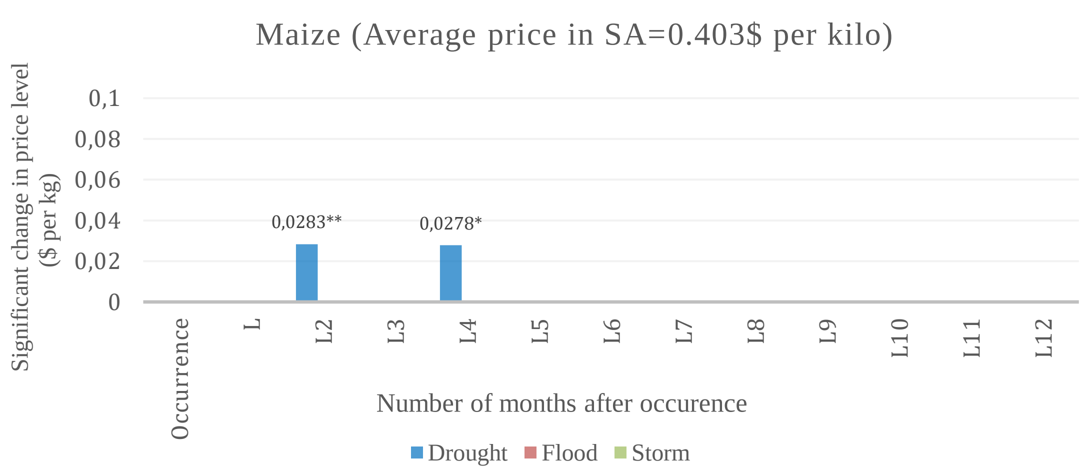


Figure 1.4: The effect of each type of disaster on the price of maize in SA

There is a curious smaller effect in SA: the total increase over a year is of 10% of the SA maize price average. This is surprising because the region is the largest consumer of maize and Smale et al. (2011) find that the consumption is of 85 kg/capita/year in SA, while it is 27% for EA (the second largest consumer of maize). A shortage of production in times of droughts should cause a much stronger effect than in EA and WA. But the regulation effect mentioned in Section 5.1 could be an explanation for this result. Maize is known for being a highly politicized commodity in SA because it is so crucial for the population. Kent and Magrath (2016) study the maize market in SA and stress that a key problem is that SA governments often intervene through price controls, trade barriers and subsidy programs. For example, in Zambia, the Food Reserve Agency (FRA) is historically the dominant buyer of maize. They purchase large shares in the maize market and offer cash on the spot to sellers at a high price to build local reserves and stabilize prices (Kent & Magrath, 2016; Sitko et al., 2017). The price is then not reflected in the dynamics of the supply and the demand anymore. Zambia is not the only SA country in which the state intervenes to stabilize prices. Other well-known examples are Zimbabwe through the Grain Marketing Board (GMB) or Malawi, with the Agricultural Development and Marketing Corporation (ADMARC) in Malawi (Sitko et al., 2017).

Finally, droughts have no significant effect in CA, which could be explained by the fact that both the production and the consumption of maize are low (Smale et al., 2011). For this reason, I do not report the graph. The table is available in the Appendix.

With respect to floods, it emerges that their effect on staple food prices typically changes over one year, and it is notably smaller compared to the effect of droughts. Both in EA and in WA, there is a first small rise (2% of the regional average in EA and 3% in WA). However, a decrease of 10% of the average in the third and fourth quarter following the drought outweighs this initial increase. I see a similar pattern in WA: after a small immediate rise effect, the kilo price of maize consistently decreases over the second and the third quarter following the flood (3rd to 8th month).

As explained in Section 5.1, the overall increase in rainfall can be beneficial for the crops in the long term. This could be particularly true for maize, which is the staple food that requires the most water to grow, compared to the other staples in the analysis. The rise right after the occurrence of a flood could be due to immediate damages to the infrastructure used to transport the supply to the end-consumer (from the farm to the market). I find no significant effect of floods in SA and in CA.

Finally, EA is the only region in which storms affect the price of maize. Although smaller than the effect of droughts, the results show that storms increase the price of maize by almost 40% of the average price over the year of their occurrence (Figure 1.2). Maybe this effect is driven by the centrality of maize in the EA diet and the fact that the EA region is home to one of the world's seven tropical cyclone basin. The southeastern coast of Africa, and more specifically, regions near the Indian Ocean such as Madagascar or Mozambique, are regularly affected by storms. The data collected by Fitchett and Grab (2014) shows that Madagascar, which is in the EA, experiences a tropical cyclone almost every year since 2000.

5.3.2. Sorghum

Sorghum is the second most important crop in SSA after maize in terms of quantity produced. Moreover, it covers 22% of the total cereal production area in SSA (Adhikari et al.,2015; Macauley, 2015). Sorghum is a cereal that is relatively more tolerant to droughts than maize, rice and wheat, but it is expected to be less resistant than millet (Adhikari, 2015). The effect of drought on sorghum should, therefore, be smaller in magnitude than for maize.

Results show no evidence of the effect of any disaster on the price of sorghum at the SSA level, hence I do not report the graph. Even looking at each type of disaster separately yields no significant results. This could be driven by the considerable heterogeneity of sorghum consumption across regions in SSA. Therefore, I continue the analysis by disaggregating the SSA area in the four regions.

The production and the consumption of sorghum are the largest in WA and CA. It is key to the diet of their population; thus, I expect a stronger effect of the disasters on the price of sorghum in those two regions. In EA and SA, the production sorghum is very small, and it accounts for only 7% of the cereal production in the region (Orr et al., 2016). However, in EA, there are still a few countries in which sorghum represents more than 25% of the country cereal production: in Sudan, it represents 66%, in Somalia represents 58%, and in Eritrea is 35%, for example. In SA, however, the cultivation of is negligible and sorghum only represents 2%[10] of the total cereal production of

[10] With the exception of Botswana, where sorghum represents 60% of its total cereal production.

the SA countries together (Orr et al., 2016). Hence, I expect a stronger effect of a disaster on the price of sorghum in the WA and CA relative to EA and SA.

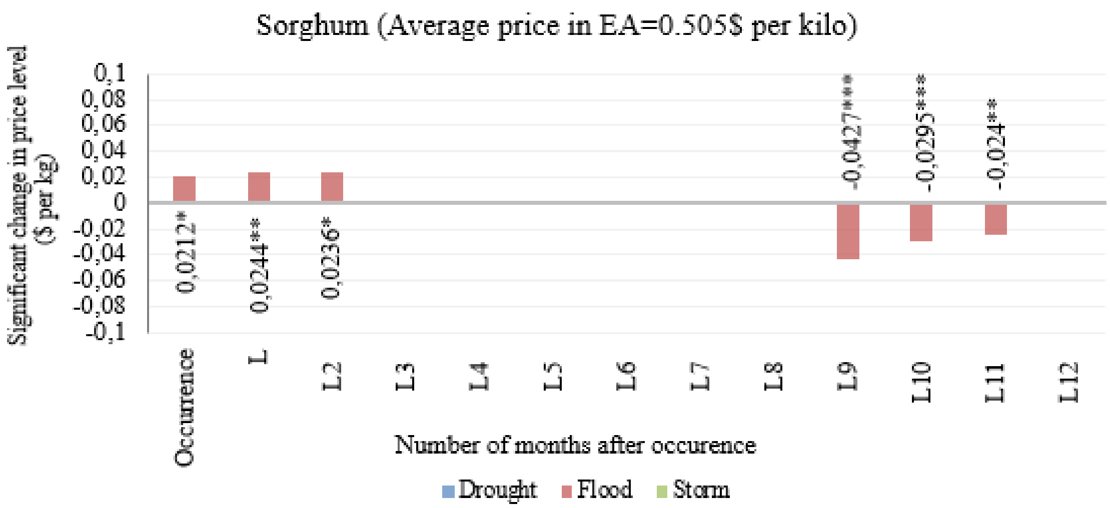


Figure 2.1: The effect of each type of disaster on the price of sorghum in EA

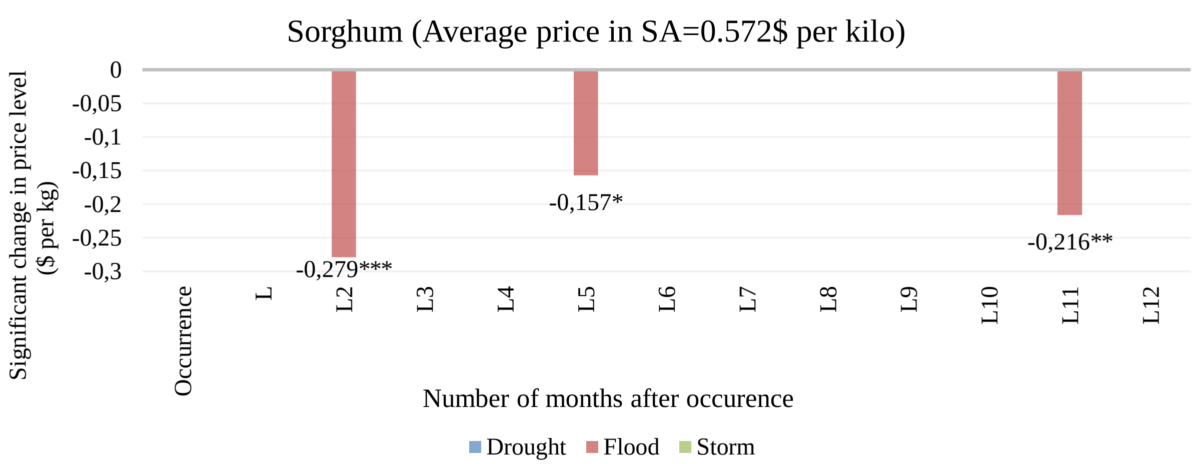


Figure The effect of each type of disaster on the price of sorghum in SA

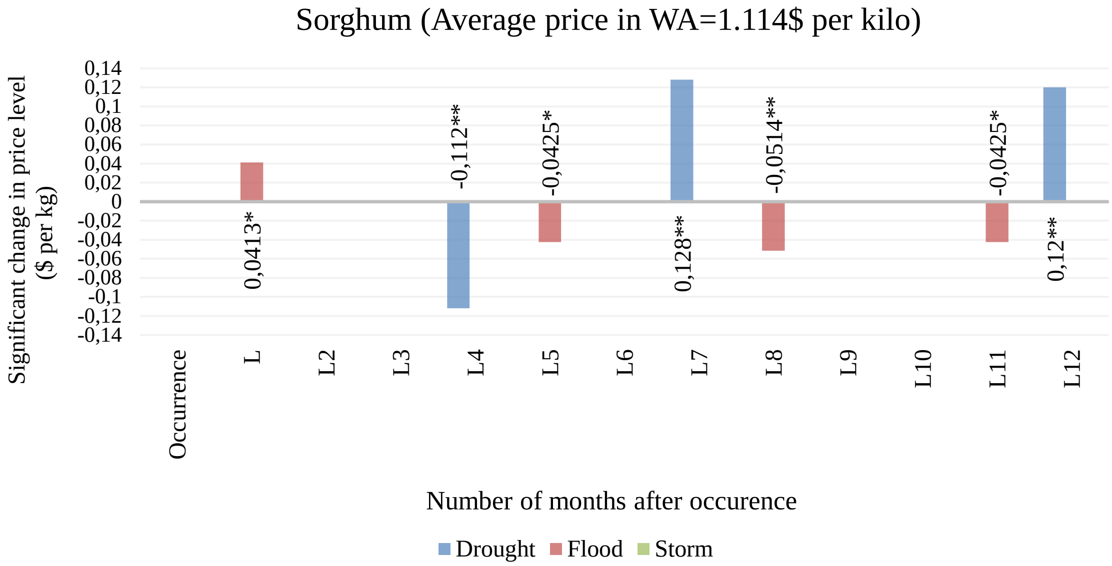


Figure 2.3: The effect of each type of disaster on the price of sorghum in WA

Droughts significantly affect the price of sorghum only in WA. The pattern of the change is unexpected, as the price first drops by 10% of the WA sorghum price average before it is outweighed by two increase episodes of the same order in the third quarter and in the last quarter after a drought. This might reflect the importance of sorghum in WA as its supply would rapidly fall short against its demand in the occurrence of a drought.

Floods affect the price of sorghum in a similar way to maize in EA and in WA. Floods first cause an immediate disruption of the supply, but the decrease that follows in the year outweighs the rise.

In SA, floods cause a large drop in the price of sorghum: it decreases by almost 50% of the regional average price in the quarter of occurrence of floods, and it continues to decrease in the 5th and the 11th month after by 27% and 38% of the regional average price, respectively. Given that the production and the consumption of sorghum are very small in SA (2% of the total cereal production in the region), the decrease could be driven a decrease in the demand of sorghum after a disaster as the population would prioritize the purchase of products that are more central to their diet.

Storms do no significantly affect the price of sorghum in any of the regions. Also, prices in CA region are not affected by any of the disasters, hence I do not include its graph.

5.3.3. Millet

Millet crops require few inputs and they are adaptable to drought and heat, Adhikari et al. (2015) even mention that they can grow in locations that are too hot and too dry for sorghum, which is already considered to be relatively more resistant to drought than the other cereals. Finally, millet can be stored for a very long time without significant losses. This is expected to make millet even less sensitive to disasters.

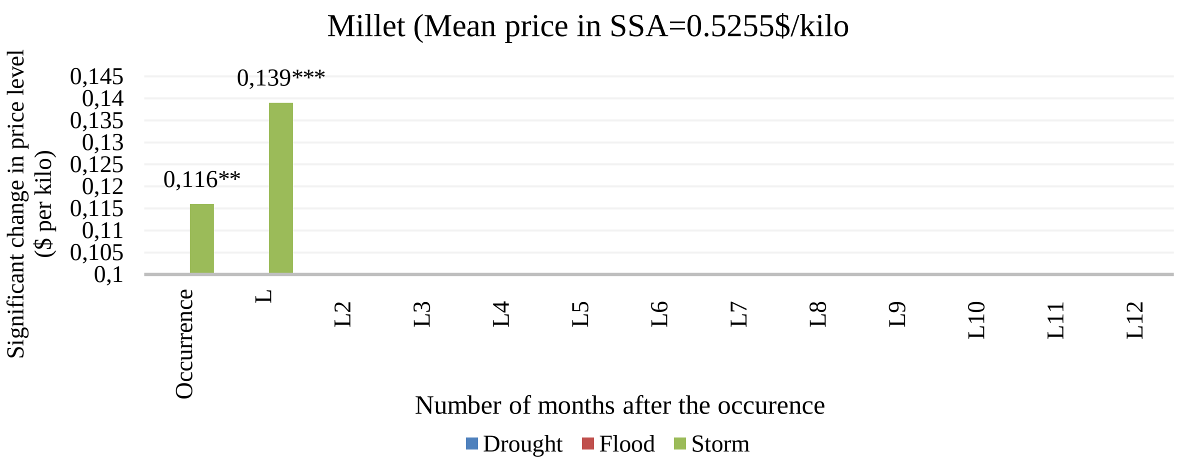


Figure 3.1: The effect of each type of disaster on the price of sorghum in WA

The aggregation of all disaster has no significant effect on the kilo price of millet. The results in the graph above show that when I differentiate between the types of disaster, there is a significant effect of storms, but no effect of droughts and floods. I find a strong and significant effect of storms on the kilo price of millet in the quarter of occurrence. In a similar way to floods, I would expect storms to have a direct effect through the destruction of the infrastructure that brings the supply to the market, or by flushing plantations that are growing.

However, I expect to find a significant variation in the effects of disasters on staple food prices across different regions in SSA. Indeed, in EA millet only represents 3% of the total crop production and in SA this figure is close to 1% (Orr et al., 2016). As mentioned in the description of the two previous products, it is one of the predominant crops in WA and CA, where, therefore, I expect to find the most relevant results.

There is no evidence of a significant impact of any of the three types of disasters on the price of millet in EA, the coefficients are omitted because there is a very little number of observations (91 price observations). This could be because millet represents only 3% of the production of cereal in EA and it is not key to the population's diet in the region. No results are reported for CA either because there are too few observations available to run a regression. Lastly, there is no significant effect either in SA. Hence, I only include the graph for the WA region.

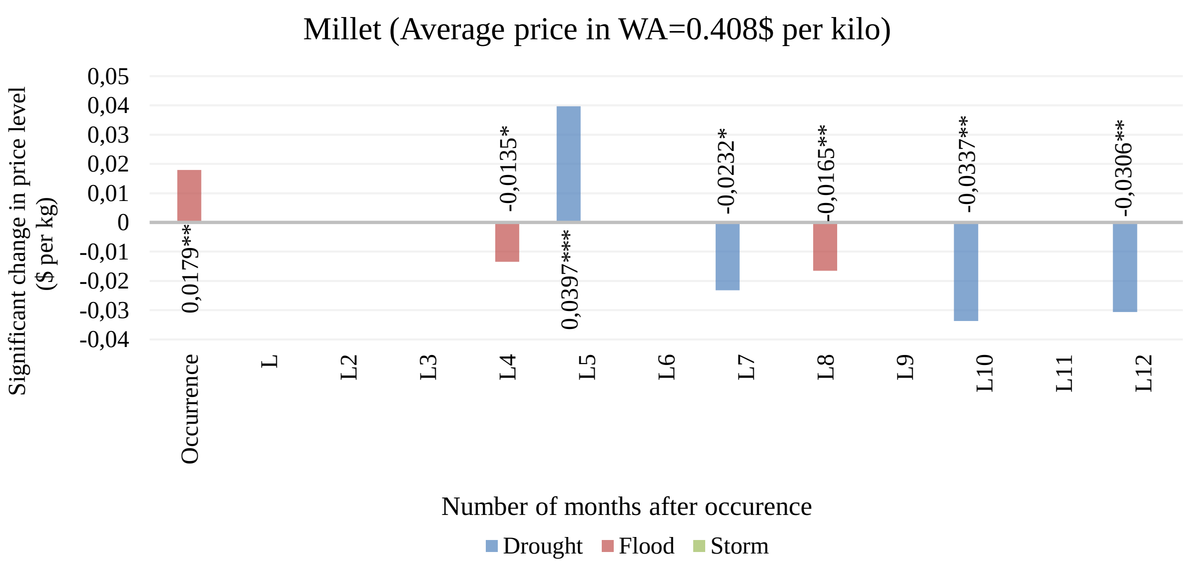


Figure 4.1: The effect of each type of disaster on the price of millet in WA

Given that millet is a key staple in WA, I would have expected the effect of the disasters to increase the price of millet. However, the results show the contrary and although the kilo price of millet first increases in the 5th month after a drought, it quickly starts decreasing in the second semester after the occurrence of a drought. It could be because millet is expected to be highly resilient to drought, and it is even expected to be more resilient than sorghum. In that case, it is possible that the millet crops are not affected by the lack of rainfall in times of drought. Again, the effect of drought is insignificant for the rest of the regions.

With respect to floods, I observe the same pattern as for maize and sorghum: there is an initial immediate increase followed by price decrease episodes. The same mechanism as for the other goods might apply here: prices increase due to the initial disruption of the supply, which is then followed by a good harvest given the abundance of rain.

5.3.4. Wheat

According to Adhikari et al. (2016), wheat is the cereal that is most sensitive to climate shocks in SSA because it requires low temperatures (the ideal temperature is between 15-20°C, which cannot be found in many regions) and abundance of water, i.e. high humidity and rain. However, wheat demand is on the rise all over the continent (Macneil, 2013), which is rapidly leading to a large supply-demand gap that has been mostly been filled with expensive imports. Therefore, wheat prices could be more responsive than other cereal prices in the occurrence of disasters as the demand already exceeds the supply in times of no disasters.

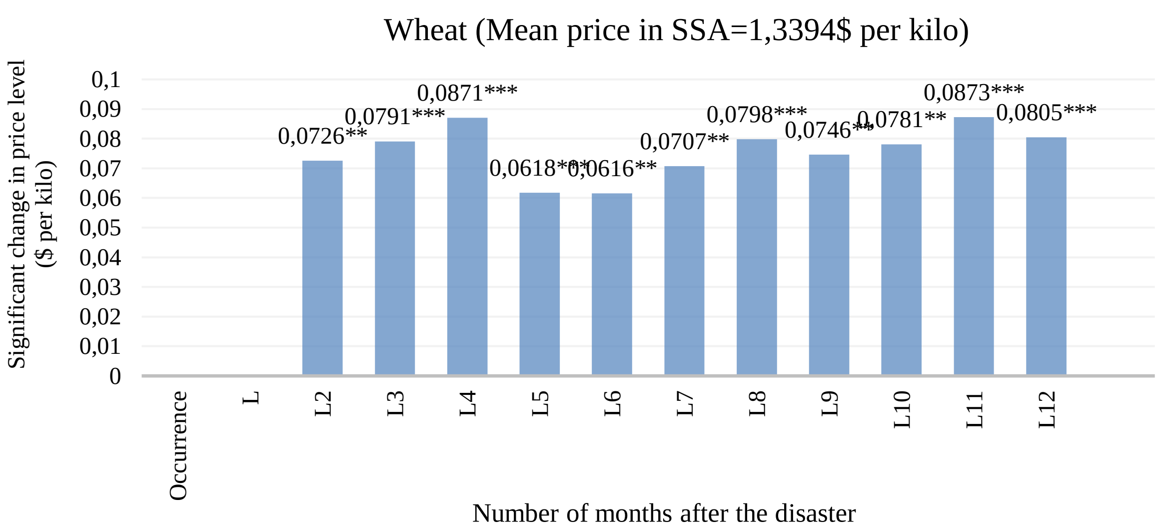


Figure 5.1: The effect of all disasters on the price of wheat in SSA

As expected, the price of wheat is strikingly sensitive to disasters, both at the SSA and the regional level. While for the other cereals it was difficult to find a significant effect when considering all types of disasters together at the SSA level, here one can immediately observe a strong and significant increase lasting ten consecutive months.

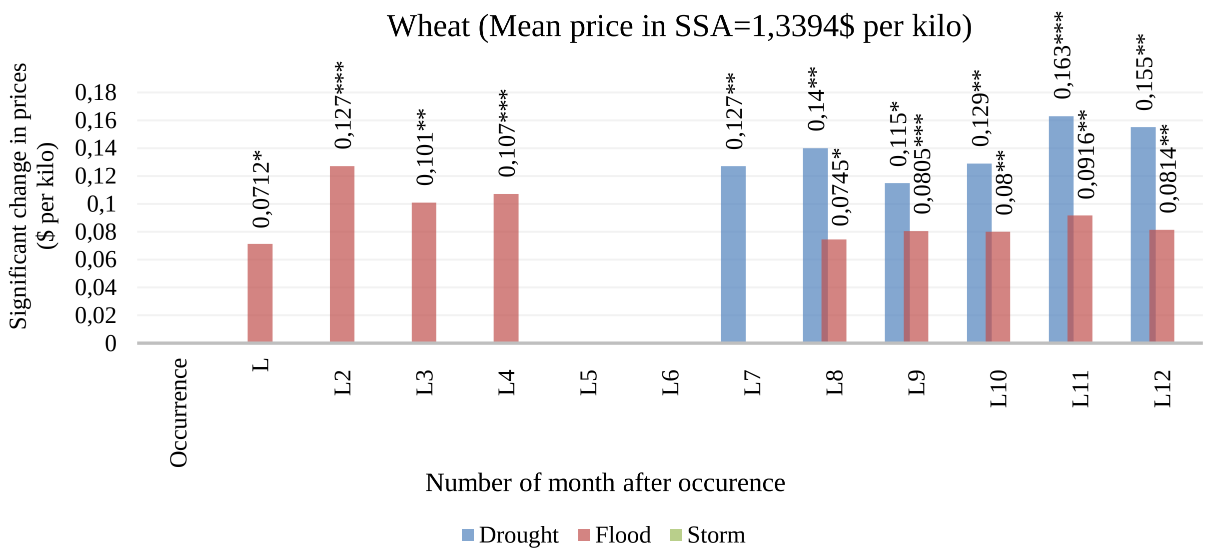


Figure 5.2: The effect of each type of disaster on the price of wheat in SSA

Separating the effect of the three disasters shows that droughts increase prices in the second half of the year in which they occur, while floods affect prices in almost every quarter, except for the second one after their occurrence, and storms have no effect on the price of wheat.

At the regional level, I would like to point out that the average wheat consumption is higher in EA and SA (30kg/year/capita) than in WA and CA (18kg/year/capita on average). But the growth in consumption has been higher in WA and CA: between 1996 and 2007, it has increased by 4,8% per year, while the increase has been of 2,2% per year on average in EA and SA (Negassa et al., 2013). The change is generally attributed to urbanisation, rising incomes and the convenience of cooking (Orr et al. 2016; Negassa et al., 2013; and Macneil, 2013).

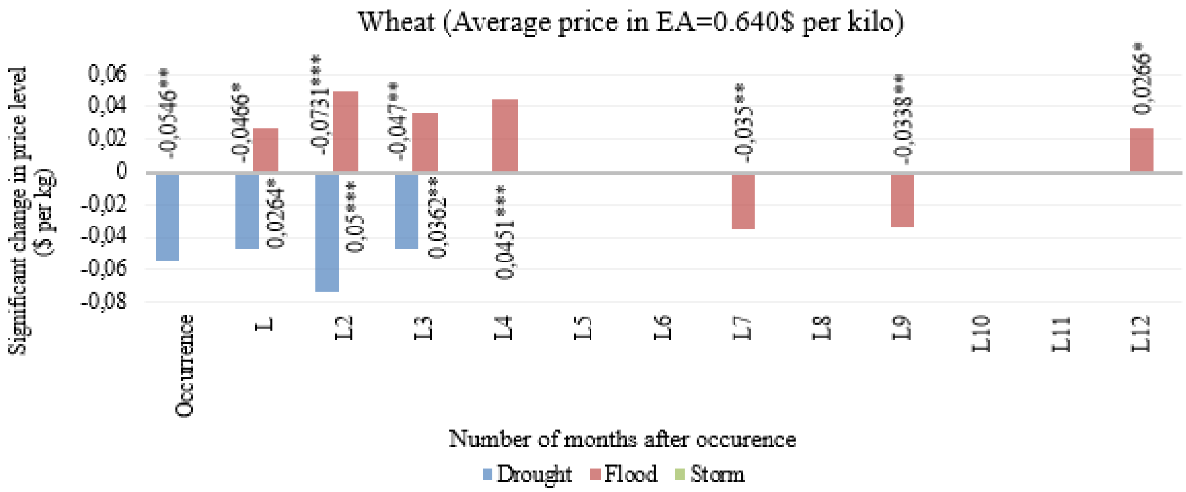


Figure 5.3: The effect of each type of disaster on the price of wheat in EA

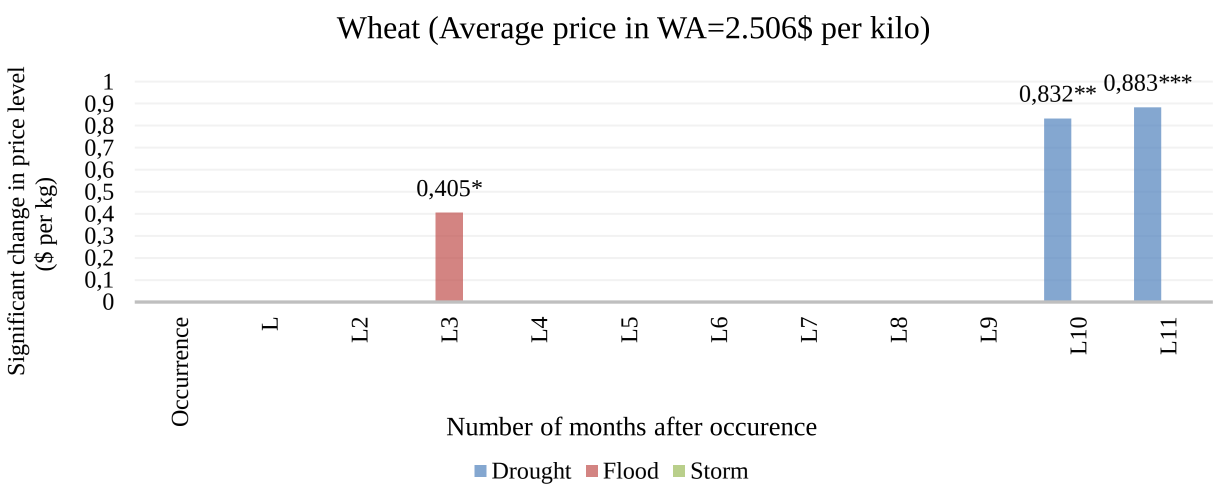


Figure 5.4: The effect of each type of disaster on the price of wheat in WA

In EA, droughts cause a significant decrease of an average of 0.055$ per kilo of wheat, or 4% of the EA's average price, for each of the four consecutive months starting from the occurrence of the drought. In WA, droughts significantly increase the price of wheat in the last quarter of the year of their occurrence with a rather strong effect (more than 30% of the regional average kilo price of wheat) during two consecutive months. The findings of Negassa et al. (2013) might explain the contrasting results: the authors estimate that the self-sufficiency ratio[11] in wheat is much lower in WA (11%) than in EA (83%). Hence, the likelihood of the demand to exceed the supply is much higher in WA and even more in time of disasters.

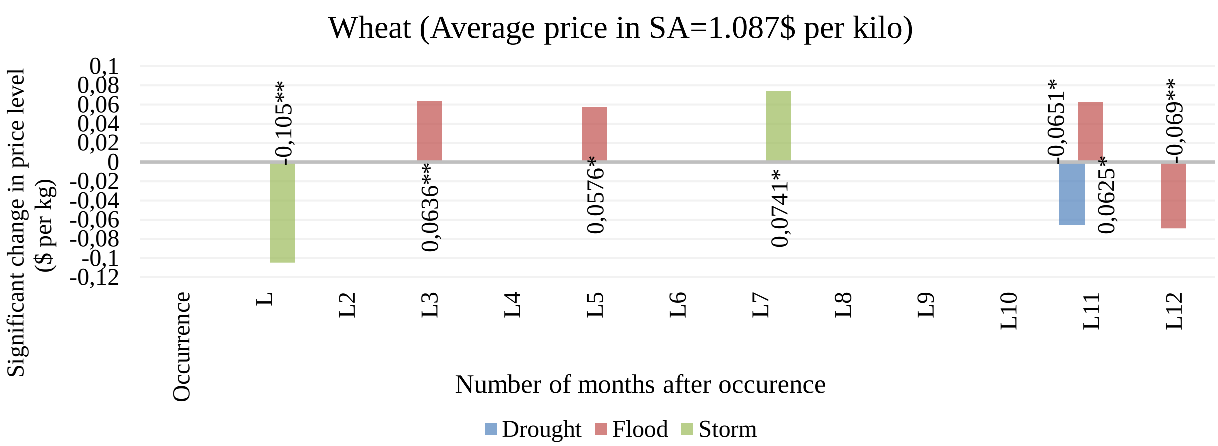


Figure 5.5: The effect of each type of disaster on the price of wheat in SA

In SA, there is a marginal decrease in the price of wheat in the last quarter of the year in which a drought occurs. For CA, there are not enough observations available in the sample.

In the same way as for the other products, floods cause a significant immediate increase in the price of wheat before turning into a price decreases both in SA and in EA. In WA, the pattern is different than in the other regions, and there is a net increase with no decrease episodes at all after a flood. This might be explained by the large gap between the supply and the demand in WA.

[11] The self-sufficiency ratio is computed as the ratio of domestic production to production plus imports minus exports expressed in percentage terms (Negassa et al., 2013)

Storms have a significant effect on the price of wheat only in SA, where there is an immediate decrease of 0.1$ per kilo and a decrease followed by an increase of 0.08$ in the 7th month. None of the channels that I have mentioned above seems to explain this result.

5.3.5. Cassava

Cassava is considered as a food security crop because of its high drought tolerance. Moreover, it is one of the cheapest sources of calories among all food crops. The IFAD (International Fund For Agricultural Development) and the FAO (Food and Agricultural Organization) investigate the incentives to grow cassava across SSA and find two important reasons driving the expansion of cassava's importance: it is used to fight famine hunger and drought, and it is resistant to pest and diseases (IFAD and FAO, 2015). Therefore, on one hand, I expect the supply of cassava to be relatively resilient to natural disasters, hence showing little impact on prices. On the other hand, the price of cassava should increase in time of disasters because its demand increases to secure the basic nutrition of the population.

In figure 6.1, I present the graph of the effects of natural disasters in the entire SSA region. It seems evident that, in general, the price of cassava is sensitive to disasters, even though the increases are not of great magnitude. The graph shows that there is an increase of the order of 5% above the region's average price in 4 months of the first semester after the disaster, accumulating to a 20% increase in price.

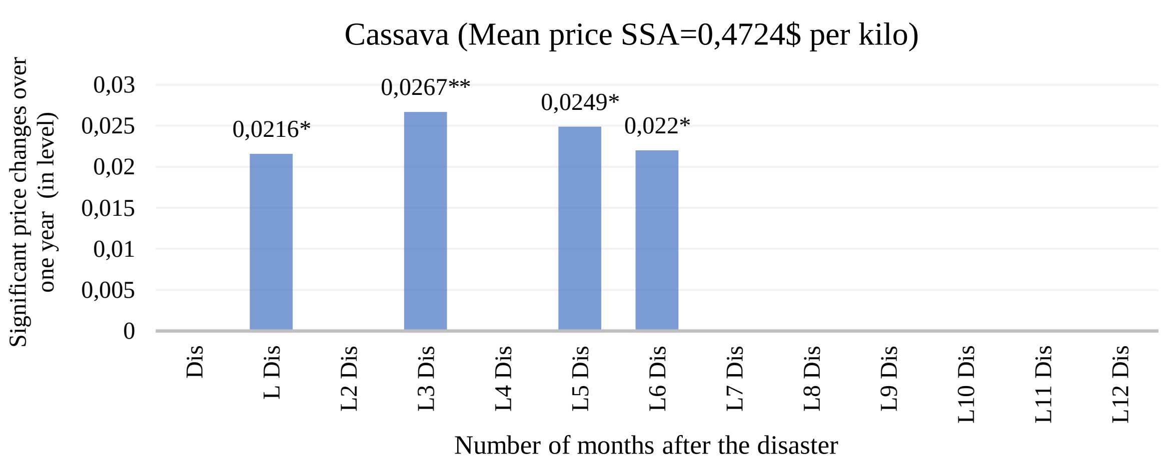


Figure 6.1: The effect of all of disasters on the price of cassava in SSA

Differentiating between the types of disaster, however, shows a marginal decrease after a drought, a marginal increase after a storm, and a continuous and significant increase after a flood. The high resistance of cassava to drought is confirmed by the fact that there is no price increase following a drought disaster. However, it is not immediately clear why the price should, instead, decrease.

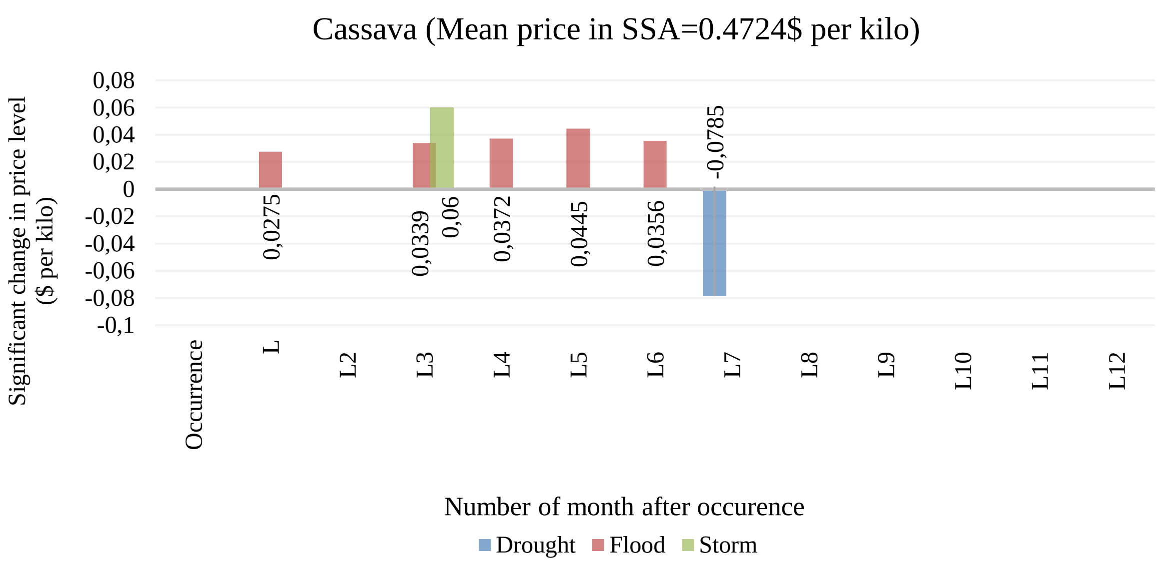


Figure 6.2: The effect of each disaster on the price of cassava in SSA

I continue with the analysis on the regional level. The study of the IFAD and the FAO (2015) on the cassava sector in Africa shows that the largest consumers of cassava are in WA and in CA, in particular in the Central African Republic, the Congo, the People's Republic of Congo, Ghana, and Nigeria. Confirming these statistics, I find no evidence of the effect of any type of disaster on the price of cassava in EA and in SA. I will, therefore, report the graphs for CA and WA only.

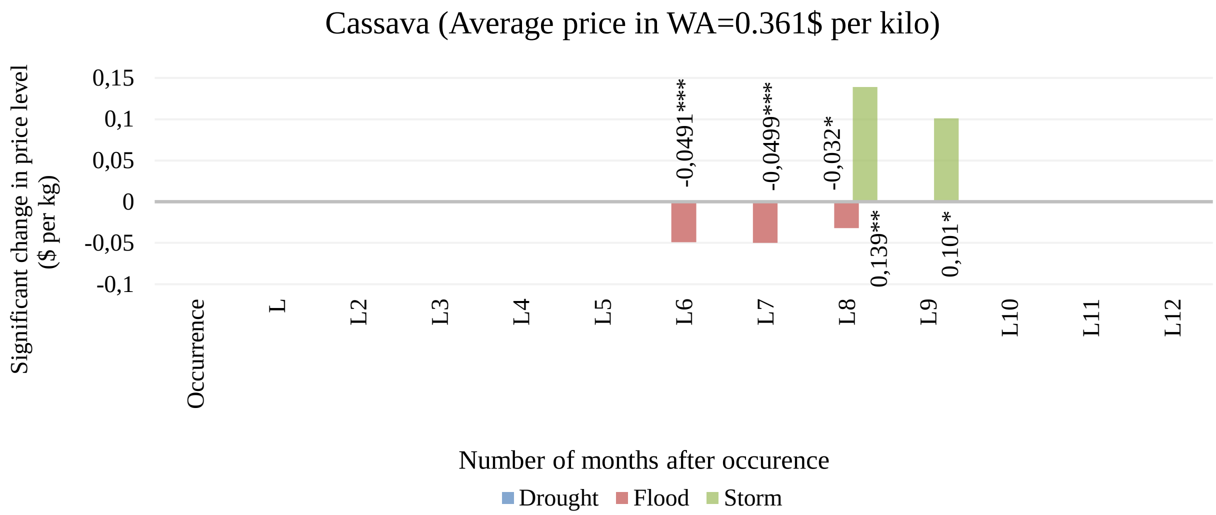


Figure 6.3: The effect of each disaster on the price of cassava in WA

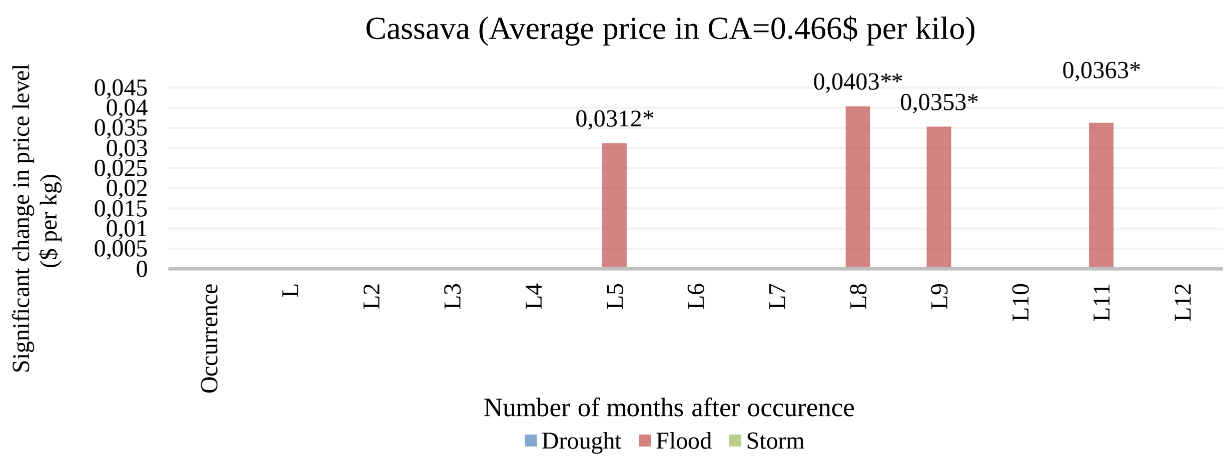


Figure 6.4: The effect of each disaster on the price of cassava in CA

It emerges that droughts have no significant effect in any regions. This strengthens the argument that cassava is more resistant to drought and the disaster does not cause significant disruptions in its supply. This is, however, in contrast with the negative effect of drought on cassava that I found when considering the effect at the SSA level. The contradiction might be driven by EA and SA together but not apparent when we taking the two regions apart.

Floods significantly decrease the kilo price of cassava in the third quarter after a flood (6th, 7th and 8th month after a flood) in WA. The decrease could be driven by the fact that WA's largest producer and consumers of cassava, Nigeria and Ghana, are self-sufficient (Coulibaly et al., 2014). On the contrary, floods significantly increase the price of cassava in CA. If the largest producers of cassava are in CA, it could be that the demand tends to exceed the supply in CA which is by far the biggest consumer of cassava among the regions of SSA (Aerni, 2006). My trade data supports this as CA is the second largest importer of cassava (the table showing the importance of each region in the import and the export flows is given in Appendix).

Storms only affect the kilo price of cassava rather strongly in WA in the third quarter after a storm with respectively 0.137$ and 0.107$ increase in the 8th and the 9th months following the disaster. There is no effect of storm in any of the other regions.

5.3.6. Rice

Because rice is highly sensitive to moisture stress and high temperatures, it is expected to be highly affected by droughts. Rice raises similar concerns as wheat, as its demand largely exceeds its production in most of the regions of SSA. Terdoo and Feola (2016) analyse the value chain of rice across Africa and stress that it is the most traded food product in term of quantities. All the regions of SSA import a large part of their rice consumption. WA is the first producer of rice, but its local production only insures 40% of its consumption. EA is the second largest producer, and it relies on imports for 15% of its consumption. SA is the largest consumer of rice, contradictorily, it is also the smallest producer forcing the region to rely on imports for almost all its consumption. The consumption of rice negligible in CA relative to the other regions (West Africa Rice Development Association, 2005).

There is no significant effect of any disaster at the SSA level when we do not differentiate between the type of disasters. Distinguishing the disasters, only droughts seem to have a significant effect, as shown in Figure 7.1. The price level of rice moves a lot following a drought, which has not been found in the other products. It decreases in the first quarter after a drought, then it increases in the second quarter before it drops again in the last quarter after a drought. Floods and storms have no significant effect.

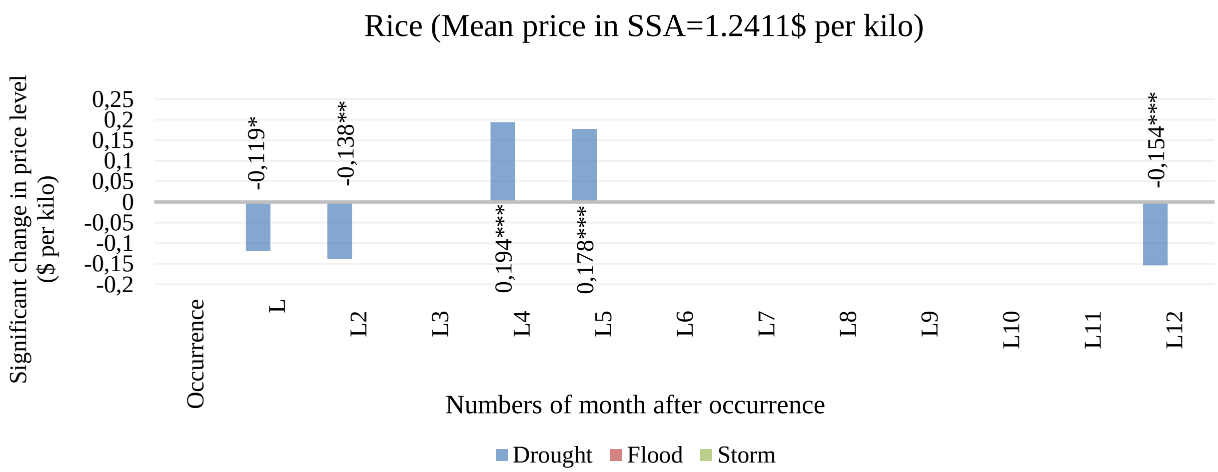


Figure 7.1: The effect of each disaster on the price of rice in SSA.

I will then turn to the analysis at the regional level. There are no significant effects of natural disasters in SA and in CA, hence I do not report the graph, which is likely due to the high share of rice that is imported in SA and the little rice consumption in CA. In EA, droughts cause a strong drop in the order of more than 30% of the regional price of rice in each month from the 2nd to the 4th following a drought. Given that EA, relative to the other regions, is rather self-reliant in rice, and because maize and wheat are more important in EA's population diet, it might be that the supply of rice still exceeds its demand, even in the occurrence of a drought. However, such reason is unlikely to be the only factor behind this strong result. Trade and regulation could be aspects that interfere with the analysis. I will look into trade more in detail later. A rather strong effect of droughts on rice prices can be found in the WA region as well, where the price of rice oscillates swiftly over the 12 months following the drought. This variation is difficult to understand and might be driven by the inflow of imports as we saw that WA only insures 40% of its consumption of rice (West Africa Rice Development Association, 2005).

In EA, floods cause a decrease in the 7th and the 8th months after their occurrence. Given that rice is highly sensitive to rainfall, it could be that floods generate an increase in production. If rice is not a priority in the consumption in EA, floods should not affect the supply of rice in the short term as it does for maize for example. The net effect then could be an excess in the supply of rice, compared to the demand. Despite the fact that the price of rice was expected to increase in the short term, as it is an important product in WA, floods actually had a negative impact on it during the entire third quarter after a drought. It could also be, however, that the country imports more in times of floods, which should lower the effect.

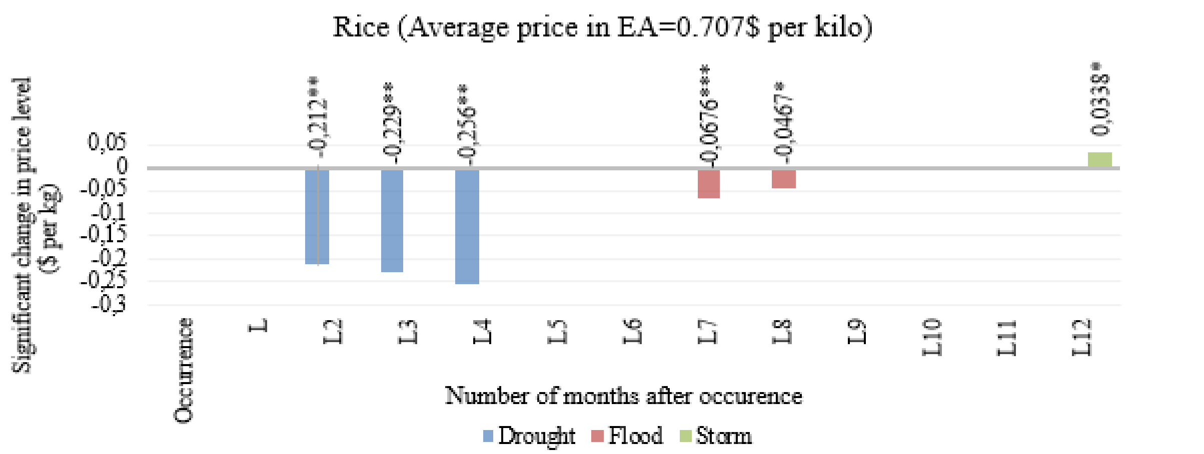


Figure 7.2: The effect of each disaster on the price of rice in EA.

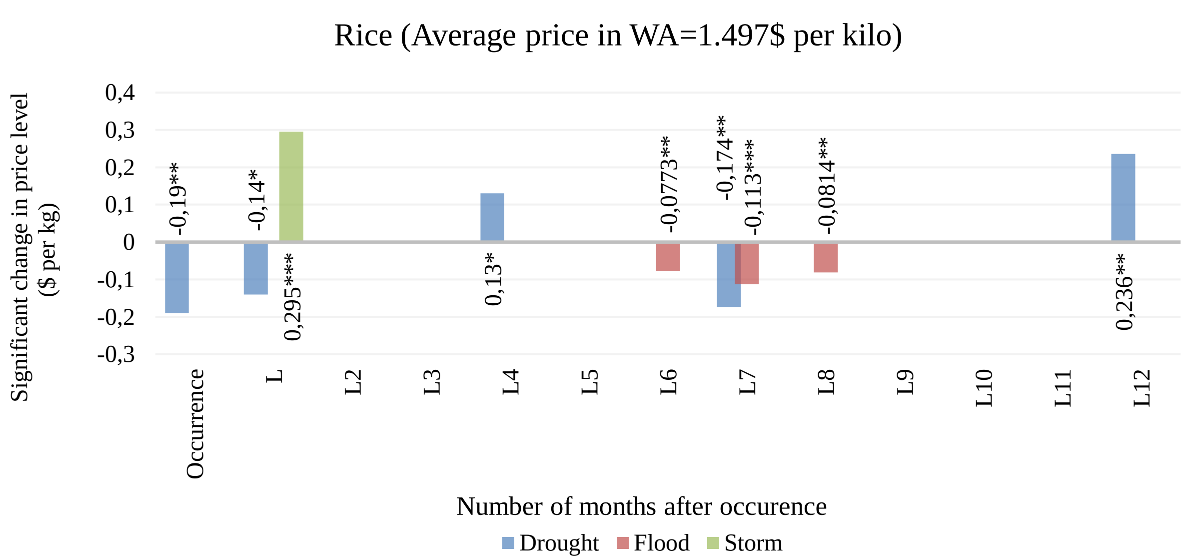


Figure 7.3. The effect of each disaster on the price of rice in WA

5.4 Is the quantity traded with other SSA countries determinant for the price of the staples?

The second key question of this thesis was to examine if intra-African trade over time significantly influenced the movements of staples' prices in the occurrence of a natural disaster. In the literature review, I showed that there is a political push to build an African common agricultural market, and an academic consensus that intra-African trade can benefit food security in SSA. Below, I investigate if the trading more of my six staple products affect their price and if yes, in which direction. I try to give an explanation based on the information that I gathered in the analysis of the effect of natural disasters on prices above.

In this section, I do not report the table, nor do I present it as I did in the section before. The reader can, however, find the detailed tables in the Appendix. I keep structuring the presentation of the results per product and per type of disaster. I also continue to interpret the results as a percentage of the average price of the product over the sample. Instead, I focus on three aspects of the results:

1) The direction of the significant changes in prices;
2) Whether it is an export or an import flow within SSA
3) The magnitude of the effect of intra-SSA trade relative to the coefficient of the extra-SSA trade

5.4.1. Maize

The results reported in Table 4, in Appendix, show that increasing imports to the rest of the world cause an increase the price of maize by 0.023$ per kilo, or 4.6% of the average price in SSA (significant at 1%). This effect is rather small compared to the magnitude of the effects of droughts that we found in Section 5.3.1. More exports do not significantly affect the local price, which is not surprising when looking at the composition of my trade data (see Appendix): the average quantity of maize that SSA countries exported to the rest of the world is small relative to the quantity imported ((8866487kg on average compared to 45'800'00kg of imports).

The increase in agricultural aid significantly decreases the price of maize by 0,017$ per kilo, or 3% of the average price of maize in the region. It could be that maize is a priority crop for development aid, especially because it is key for food security given the importance it has in the SSA diet (see the introduction to maize in Section 5.3.1).

Exporting more to SSA countries decreases the price of maize drops by 1.4% of its average price. However, this effect is small compared to the increase that is caused by increasing imports: I find a significant rise of 3,8% of the SSA average price. Nevertheless, the effect is slightly smaller than for extra-SSA imports (rise of 4.6% relative to the average price). In my dataset, the imported quantities of maize are much higher, on average, than the exported quantities. Which suggests that

The coefficient for drought alone, when we control for the interaction with intra-african trade, has a net negative effect on the price of maize. The coefficient of the effect of a drought alone changes to an important drop of almost three times the average price of maize in the last quarter of the year of its occurrence, while was insignificant at the SSA level in Section 5.3.1. Both the sign and the magnitude of this change are surprising, as maize an important staple in SSA and it has been documented that its production is highly sensitive to erratic rainfall, or droughts (see section 5.3.1). Thus, I suspect that this effect is driven by one or several countries in the sample. One possibility could be the countries which are subject to price stabilization policies and state interventions such as Zambia (see section 5.3.1 on Southern Africa).

Turning to the interaction coefficient, which captures the effect of trading more with SSA in the occurrence of a drought, shows that importing more with SSA in times of droughts causes an increase of the order of 23% of the average price when I sum the effect over a year. This result suggests that trading with other SSA countries in times of droughts is an important driver of the rise in price, while with no trade droughts should cause a large decrease in the price of maize. Because droughts usually affect a large area, and sometimes several countries, it is plausible that trading with other SSA countries in times of drought increases the local price. There could be a transmission of the distress from the neighbouring country who trades its maize.

I find the same pattern as for drought when I look at the effect of storms. Storms significantly decrease the price of maize (which opposes what we found in section 5.3.1), but importing more from SSA in time of storms increases its price and has no mitigating effect.

Finally, floods cause a strong rise of more than in the price of 300% of the average price in the first quarter of their occurrence. Interestingly, it seems like importing from other SSA countries in time of floods helps to mitigate the effect of the disaster. Although the effect is small relative to the striking increase (10% of the average price of maize) caused by the disaster term alone, it is significant at 1%.

5.4.2. Sorghum

Trading more outside Africa yields similar results than in the case of maize: importing causes a significant rise of 4.6% of its average price in SSA. However, the effect of agricultural aid is different and a 1% increase leads to a significant 7% increase from the average price of sorghum.

The most notable effect I find is that more intra-African trade in times of droughts decreases the price of sorghum by 20% of its average in the second quarter after a drought. However, importing or exporting more to SSA when there is no disaster does not significantly affect the price or sorghum. Other interactions of disasters with imports or exports have either a small or no significant results.

5.4.3. Millet

While importing more from the world also causes a positive effect (significant increase of 7% of the average price) like in the case of maize and sorghum, exporting more to the world can help reducing the average price of millet: I find that a 1% increase in exports outside SSA decreases the price of millet by 1.2% of its average price.

Droughts and floods both lead the price of millet to double over the year of their occurrence, but neither exporting nor importing more to SSA help decreasing the price when those disasters happen (interaction variable). Storms also leads to a net rise of over 100% of the millet price average in the year of their occurrence but importing more from SSA in times of storms seem to offset this effect, causing a decrease of a similar magnitude. We see that the mitigating effect can also depend on the disaster.

5.4.3. Wheat

More agricultural aid significantly increases the price of wheat by 36% of its average value in the region, or 0.483$ per kilo. If this finding is true, it can be concerning for policy making as it shows that an extreme case in aid has a strong and negative effect on local populations.

Even more striking is that I expected international trade to play an important role in setting the price of wheat, as it is a commodity that largely imported from the extra-SSA market. Orr et al. (2016) show for example that in EA and SA, wheat is one of the cereal with the largest trade deficit. This raises questions about the determinants of the price of wheat and whether my model is not missing another driver of the price of this product that would capture the effect of international trade.

Wheat is the first product for which importing more from SSA in normal times (no disasters) significantly reduces its price by 4,7% of its average for every percentage of imports from SSA. Conversely, exporting more increases the local price of wheat by 7.9% of its average. Trading seems to decrease the local price of wheat for the importer, but it can be costly for the exporter.

Yet this finding is still interesting because wheat has been the subject of debates because it is increasingly demanded on the SSA market (Orr et al., 2016) and, for now, it is largely imported from the international market (Negassa et al., 2013; Macneil, 2013). If importing more from SSA yields positive prospects for the price of wheat, and if one can identify why exporting to SSA increases the price, then intra-African trade could stand as a solution.

Now looking at the effect of the disasters alone, I find that droughts decrease the price of wheat by close to 10% of its average in the month that follows their occurrence. However, I find no further impact of any lag or of the other disasters.

I find no compelling significant effect of the interactions between the SSA-trade variables and the disaster dummies, except for a marginal increase of 3% of the average price of wheat (or 0.0436$ per kilo) in the month that follows the occurrence of a storm.

5.4.4. Cassava

None of my coefficients is significant in the case of cassava.

5.4.5. Rice

Analogously to the case of wheat, agricultural aid seems to be a threat to the local price of rice as more aid more than doubles the price of rice from its average (1.78$ per kilo against an average price of 1.24$ per kilo). Importing from the rest of the world has no effect on the price of rice, and this is as surprising as the case of wheat as rice is also a heavily imported product.

Importing more from SSA on average decreases the price of rice by up to 18% of its average. This result suggests a positive impact of intra-African trade, as the heavy imports of rice on the continent has also been the subject of worry from policy-makers. Exporting more from SSA countries, however, increases significantly the price of rice by 58% of its average, which is smaller than the increase incurred by agricultural aid but still very large compared to the encouraging effect from importing from SSA. This raises questions about why exporting costs so much to African countries.

Turning to the effect of the disasters, I find that floods significantly reduces the price of rice in SSA. This finding is in line with the results I find in Section 5.3.6 for WA in term of the direction of the effect, but the magnitude is remarkably high: every month after a flood the price of rice decreases by more than 100% of its average price and sometimes twice its average price and each of those months the effect is significant at 1%. However, I find that the price of rice within the regions in SSA is also highly variable (Section 5.2.2.), for example, the average price of rice in EA is 0.707$ per kilo while it is twice as expensive in WA (1.497$ per kilo).

Both importing and exporting more within SSA in times of flood increases the price of rice in every month after the occurrence of a flood, hence it seems that intra-African trade in rice is not recommendable and is responsible for a large part of the increase in the price of rice.

Those findings support the importance of floods, rather than droughts or storm which have no significant effect, on the rice market. It also suggests that trading between African countries decreases the price of rice in normal times, but it increases when trade occurs after a flood.

6. Concluding remarks

In this thesis, I have addressed the issue of natural disasters in SSA and their impact on food staple prices. In particular, I have focused on three types of disasters: floods, storms and droughts; and six staple foods: rice, cassava, sorghum, millet, wheat, maize. I started by trying to understand whether natural disasters have an impact on prices by running a regression of 12 lags of disasters on prices, then I turn to the impact that intra-African trade could play both in normal times and in time of disaster, by interacting the disaster dummies with the quantity traded within Africa, controlling for the main effects of intra-African trade and of flows coming from the rest of the world between disasters and prices.

The mechanisms behind the effect of natural hazards on staple food prices.

The results have shown that natural disasters do affect food prices, but the results were not always in line with my expectations. Looking closer into the most unexpected results revealed some of the mechanisms that could affect the effect of natural disasters on food prices.

First, I have found that there are important differences in how each product react to prices across the macro-regions of SSA. It is the case of maize and sorghum for instance. In the case of maize, it appeared that at the SSA level only storms led to an increase in prices. Breaking down the analysis to the regional level, I have found that droughts have a considerable impact in the EA region, where prices increase up to 100% over the 12 months following a drought. On the other hand, the WA region sees a decrease in prices of maize after a drought. I have argued that this might be due to the little importance that maize plays in the diet of the WA population.

I have also found a surprisingly small effect of droughts in SA, which is striking because the region is the largest consumer of maize. Exploring the literature on the price of maize in this region revealed that to the importance of maize in this region, governments might be prone intervene in the market to fight price volatility. State interventions and regulations can importantly distort the behaviour of prices, which, therefore, undermines the results I have obtained.

The pattern of the effect of floods was rather similar across the staples and the regions: there is an initial immediate increase followed by price decrease episodes. I suspect that prices increase due to the initial disruption of the supply, which is then followed by a good harvest gave the abundance of rain.

My results also confirmed that some products might be more resilient to the lack of moisture, and hence more or less sensitive to droughts, than others. Given that millet is a key staple in WA, I would have expected the effect of the disasters to increase their price. However, the results show the contrary and the kilo price of millet quickly starts decreasing in the second semester after the occurrence of a drought. Cassava also seems to be is very resistant to droughts across all regions, confirming the expectations.

Wheat is a cereal that seems to react to natural disasters quite consistently across regions, where in general it registers a strong and continuous price increase following droughts and floods. I have argued that this might arise from the relative difficulty of growing wheat across the whole SSA and the increasing importance of wheat in the diet of the populations across SSA.

Since rice is highly sensitive to moisture stress and high temperatures, it was expected to react strongly to droughts in particular. However, I find that the effect is unclear. I suspect that other factors that I have not been able to capture might lie behind this result.

In summary, the dynamic of each disaster (timing, intensity) and the characteristics of each region (climate, production capacity, the diet of the population, regulations) are determinants in the effect of natural disasters on food prices. But overall, food prices are very sensitive to natural disasters in SSA.

Does intra-African trade help mitigate this effect?

It is important to step beyond one assumption that I make in my first model: no African country produces everything it consumes and consumes everything it produces. In my second main model, I consider trade within Africa, keeping the effect of international (extra-SSA) trade, agricultural aid and population size fixed.

The results of this study show that trade within and outside SSA are determinant for the effect of natural hazards on food staples prices, as well as non-trade flows which are represented by agricultural aid in my model. However, there is no one-way effect and just like above, the results vary depending on the product, the disaster and the region.

Interestingly, I find that it can be beneficial for SSA countries to trade wheat and rice when there is no disaster. For instance, I find that importing more from SSA can significantly reduce the local price of rice and wheat by 18% and 4.7% of their average, respectively. In both cases, I find no significant effect of importing more from the rest of the world, which comes as a surprise since those are largely sourced from outside SSA. This reinforces the potential of producing and trading more of wheat and rice within Africa to lower their price. Moreover, these are two products that are currently imported in large quantities from the extra-SSA market.

It seems that the cost of trading falls harder on the exporting country, as exporting more to SSA significantly increases the local price of wheat and rice by 8% and 58% of their average price. This effect might be driven by the fact that, for now, the capacity to export wheat and rice is still very low in SSA. But reinforcing the production and supporting infrastructure for exports could help in this regard. The opportunities to produce more wheat and more rice are already investigated by academics and policy-makers (Negassa et al., 2013; Macneil, 2013). Large infrastructural projects to better connect African countries are also blooming, such as the Belt and Road Initiative.

However, this effect fades away in time of disaster. I find no significance of the interaction variables for wheat, which suggests no effect of trading more within SSA in time of disaster. For rice, both importing and exporting more from SSA in the occurrence of a flood caused a significant increase in the local price. Hence, I conclude that for wheat and rice, intra-African trade can help in decreasing their average price when there is no disaster, but when a natural hazard occurs, regional trade has no mitigating effect.

The prospects seem less positive for maize. Trading maize is always harmful, whether it is imported and exported to the world, or imported from within SSA. The effect is worsened in time of disaster and importing 1% more from SSA in times of droughts, for example, can cause an increase of about 23% of the average price of maize. The centrality of maize in the diet of SSA makes this result worrying, but it could also be the reason why trading maize costs such large increases in local prices.

Notably, intra-African trade seems to show the largest potential to mitigate the impact of disasters for sorghum. Importing and exporting more from and to SSA countries in times of droughts leads to a drop in the local price of sorghum, by as much as 20% and 8% respectively over the year of occurrence of a disaster. However, I find no effect for the other disaster and no effect of the trade when there is no disaster. Trading more with the world, however, increases the price of sorghum significantly by up to 7% of its average price in SSA.

Finally, the effect of agricultural aid is imbalanced. On one hand, more aid reduces the average price of maize by 3.5% of its average, and millet by 6.8%. On the other hand, it has an adverse effect on sorghum, wheat and rice by 7%, 36% and more than 100% respectively. This suggests that aid can distort prices and hinder the access to food by increasing local food prices. However, I could have captured this effect better by interacting this with the disaster dummies as the effect might be more positive (i.e. help decreasing local prices in times of distress), or by distinguishing between the different forms of aid in my variable (for example, direct food supply versus non-food aid such as research or land improvement). They certainly yield different effects on the price of staples. There is a body of literature on the effects of agricultural aid on food security, and it seems that the debate has been around the potential disincentive effect that receiving aid can cause among farmers in the recipient country (Gyimah-brempong and Adesugba, 2015).

Overall, it is clear that natural disasters affect the price of staples across Africa. However, the results indicate that there is no straightforward solution to mitigating them through intra-African trade. Understanding the dynamics of each disaster, the demand for each product and the costs of trading is crucial as we see that the prices of the products are extremely sensitive in general. The current interactions with the international market, and even official development aid, can also affect these dynamics. Hence, overlooking this complex interaction system in trade policies can lead to a further increase in food prices in the SSA region. Intra-African trade is definitely going to intensify, especially with the Continental Free Trade Area project slowly gaining the heart of politicians and investors across the world. My thesis warns about the risks of promoting more intra-African trade as the key to improve food security in SSA.

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APPENDIX

A.1. African Union Member States Geographical Classification

Central Region

Burundi, Cameroon, Central African Republic, Chad, Congo DR, Congo, Equatorial Guinea, Gabon, São Tomé and Príncipe

Eastern Region

Comoros, Djibouti, Ethiopia, Eritrea, Kenya, Madagascar, Mauritius, Rwanda, Seychelles, Somalia, South Sudan, Sudan, Uganda, Tanzania

Northern Region

Algeria, Egypt, Libya, Mauritania, Sahrawi, Republic Tunisia

Southern Region

Angola, Botswana, Lesotho, Malawi, Mozambique, Namibia, South Africa, Swaziland, Zambia, Zimbabwe

Western Region

Benin, Burkina Faso, Cape Verde, Côte d'Ivoire, Gambia, Ghana, Guinea Bissau, Guinea, Liberia, Mali, Niger, Nigeria, Senegal, Sierra Leone, Togo

A2. African Union REC's classification (https://au.int/en/organs/recs)

COMESA:

Burundi, Comoros, DR Congo, Djibouti, Egypt, Eritrea, Ethiopia, Kenya, Libya, Madagascar, Malawi, Mauritius, Rwanda, Seychelles, Sudan, Swaziland, Uganda, Zambia, Zimbabwe

EAC:

Burundi, Kenya, Rwanda, South Sudan, Tanzania, and Uganda.

ECOWAS:

Benin, Côte d'Ivoire, Gambia, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Niger, Nigeria, Senegal, Sierra Leone, Togo, Burkina Faso, and Cape Verde

SADC:

Angola, Botswana, Congo, Lesotho, Madagascar, Malawi, Mauritius, Mozambique, Namibia, Seychelles, South Africa, Swaziland, Tanzania, Zambia, Zimbabwe

ECCAS:

Angola, Burundi, Cameroon, Central African Republic, Chad, Congo, DR Congo, Equatorial Guinea, Gabon, and São Tomé and Príncipe

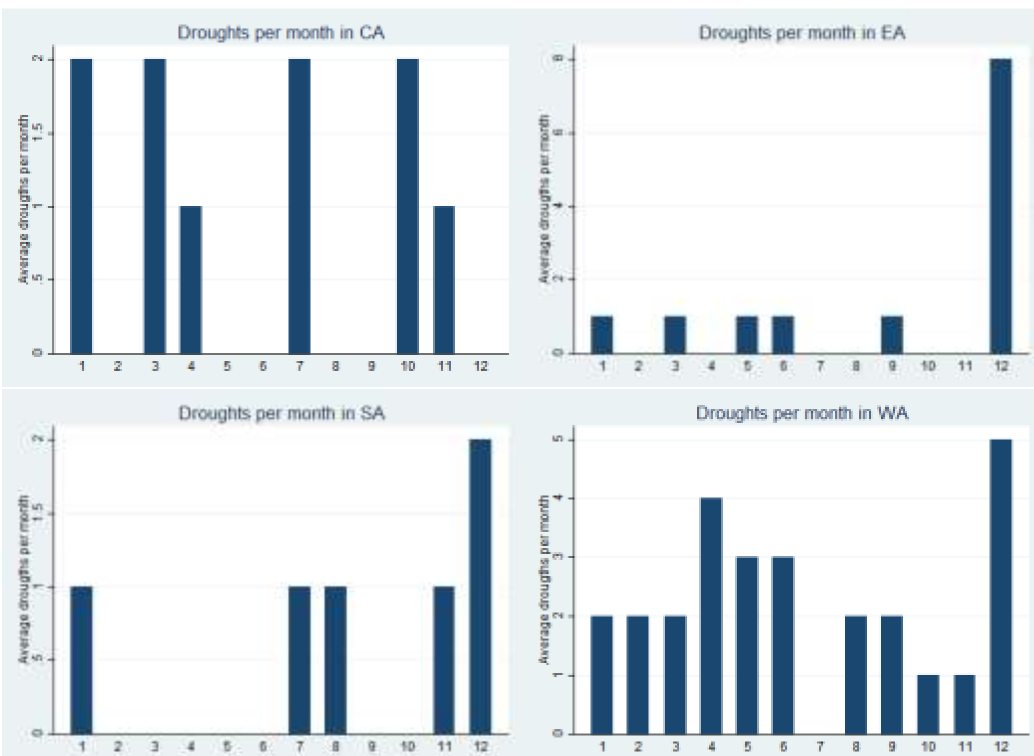
A3. Details of the products aggregation

Cassava	The variable Cassava_allforms comprises: Cassava, Cassava (chikwangue), Cassava (cossette), Cassava (dry) , Cassava (fresh), Cassava flour, Cassava leaves The following products are not included in the aggregation: Cassava meal, Cassava meal (attieke) Cassava meal (gari)
Maize	The variable Maize_allforms comprises: Maize, Maize (local), Maize (white), Maize (yellow), Maize flour The following products are not included in the aggregation: Maize meal, Maize meal (white, breakfast, Maize meal (white, first grade), Maize meal (white, fortified), Maize meal (white, roller, Maize meal (white, with bran), Maize meal (white, without bran), Maize (imported), Maize flour (imported)
Millet	The variable Millet_allforms comprises: Millet, Millet (white)
Potatoes	The variable Potatoes_allforms: Potatoes, Potatoes (Irish)
Rice	The variable Rice_allforms comprises: Rice, Rice (basmati, broken, Rice (high quality, local), Rice (local), Rice (long grain), Rice (low quality, local), Rice (mixed, low quality), Rice (paddy), Rice (paddy, long grain, local) The following products are not included in the aggregation: Rice (small grain, imported), Rice (white, imported) Rice (denikassia, imported), Rice (imported), Rice (imported, Indian), Rice

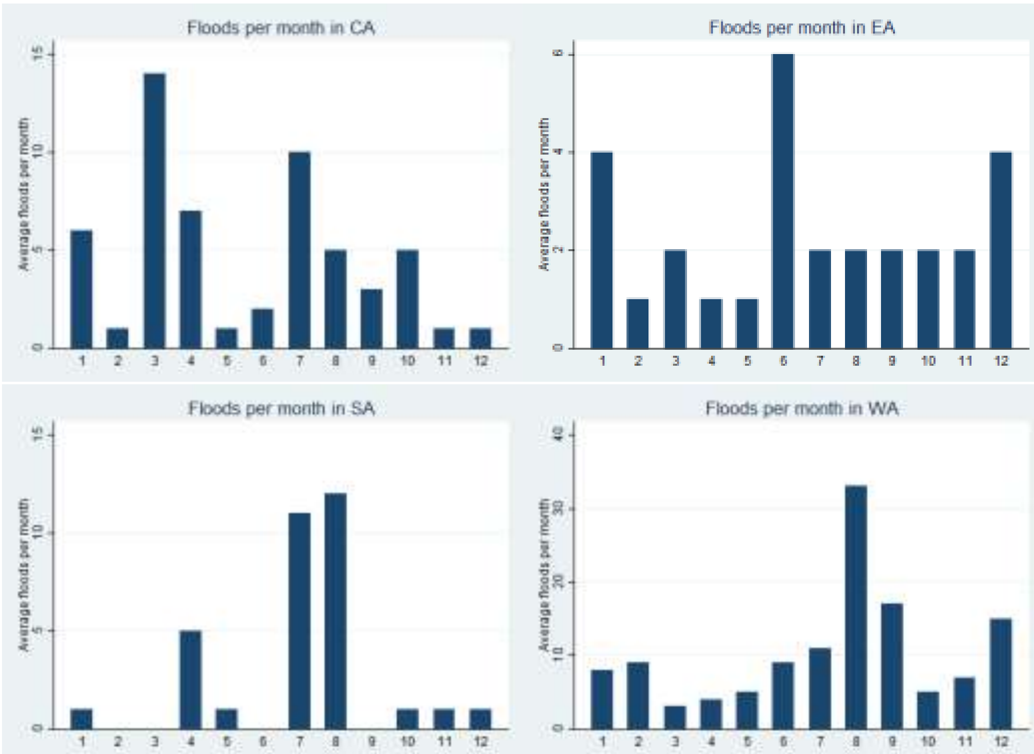
	(imported, Tanzanian, Rice (long grain, imported), Rice (medium grain, imported),
Sorghum	The variable Sorghum_allforms comprises: Sorghum, Sorghum (berbere), Sorghum (brown), Sorghum (red), Sorghum (taghalit), Sorghum (white), Sorghum flour The following product are not included in the aggregation: Sorghum (food aid)
Wheat	The variable Wheat_allforms comprises: Wheat , Wheat flour (fortified), Wheat flour (local) The following product are not included in the aggregation: Wheat flour (imported)

A4. The average number of each disaster per month per region.

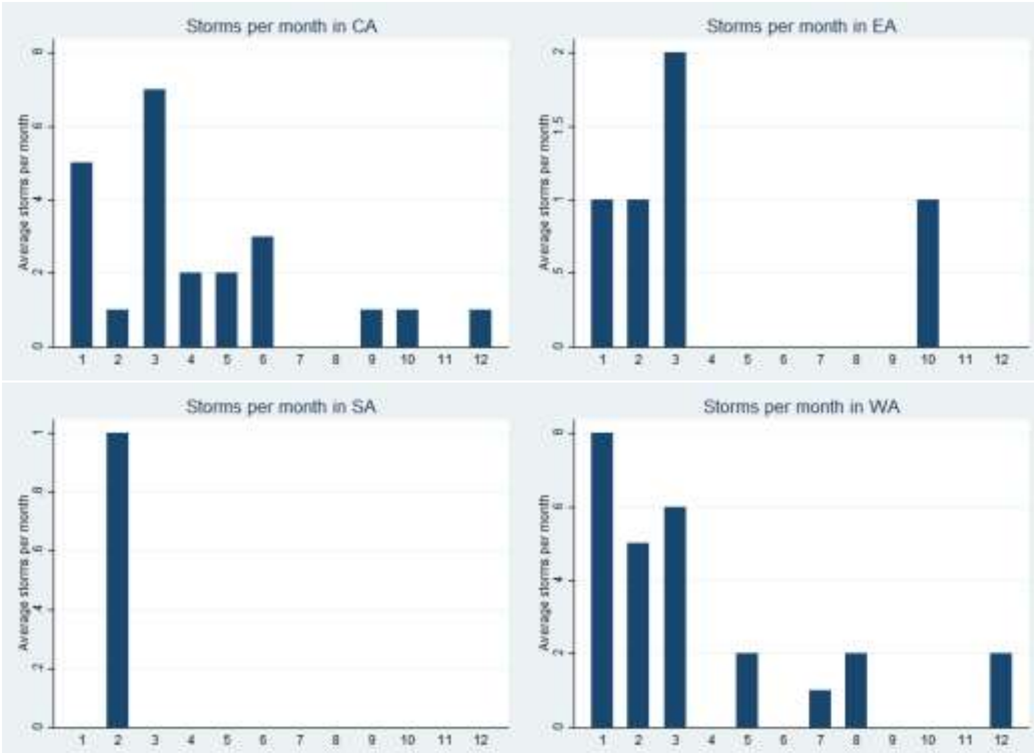
<u>Droughts</u>



Floods



Storms



A5. Distribution of the export and import flows by region

tradeflowcode = Export

region	Cassava	Maize	Millet	Rice	Sorghum	Wheat	Total
			Commodity Code				
SA	3.54	61.19	21.81	3.12	59.05	46.49	44.51
WA	0.37	9.30	73.59	77.22	11.04	32.54	28.87
EA	95.91	29.50	4.60	19.58	29.78	20.73	26.57
CA	0.19	0.01	0.00	0.08	0.13	0.24	0.05
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00

tradeflowcode = Import

region	Cassava	Maize	Millet	Rice	Sorghum	Wheat	Total
			Commodity Code				
SA	0.00	81.82	0.18	53.16	40.36	62.45	74.05
EA	80.59	11.18	26.70	18.69	39.57	15.23	14.18
WA	2.60	5.59	73.03	25.45	19.46	20.90	10.10
CA	16.80	1.41	0.09	2.70	0.62	1.41	1.67
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00

A6. Agricultural aid data: the sectors in my aggregation

Sector	Freq.	Percent	Cum.
Agricultural development	3,774	19.85	19.85
Agricultural financial services	1,118	5.88	25.73
Agricultural inputs	2,206	11.60	37.33
Agricultural land resources	2,430	12.78	50.11
Agricultural services	2,042	10.74	60.84
Agricultural water resources	2,261	11.89	72.73
Food crop production	2,787	14.66	87.39
Industrial crops/export crops	1,428	7.51	94.90
Plant and post-harvest protection and..	970	5.10	100.00
Total	19,016	100.00	

A7. Regression tables

Table 1: The effect of any type of disaster on the price level

	(1) Maize	(2) Sorghum	(3) Millet	(4) Wheat	(5) Cassava	(6) Rice
Dis	0.0192	0.0335	0.0266**	0.0388	0.0176	0.0171
	(0.111)	(0.412)	(0.039)	(0.186)	(0.180)	(0.483)
L.Dis	0.0127	0.0327	0.0152	0.0415	0.0198	-0.00142
	(0.289)	(0.428)	(0.248)	(0.158)	(0.126)	(0.952)
L2.Dis	0.00917	0.0223	-0.00785	0.0767**	0.0138	-0.0339
	(0.440)	(0.593)	(0.554)	(0.013)	(0.286)	(0.155)
L3.Dis	-0.00336	-0.00641	-0.00997	0.0813***	0.0260**	-0.0351
	(0.777)	(0.878)	(0.456)	(0.007)	(0.044)	(0.146)
L4.Dis	-0.00525	-0.0111	-0.0104	0.0899***	0.0186	0.0111
	(0.658)	(0.790)	(0.439)	(0.003)	(0.149)	(0.643)
L5.Dis	-0.00693	-0.00133	-0.00821	0.0661**	0.0191	0.00634
	(0.558)	(0.974)	(0.543)	(0.027)	(0.133)	(0.789)
L6.Dis	-0.00912	-0.00197	-0.0146	0.0634**	0.0194	-0.0307
	(0.439)	(0.961)	(0.272)	(0.033)	(0.129)	(0.183)
L7.Dis	-0.00140	0.0111	-0.00863	0.0734**	0.00535	-0.0155
	(0.906)	(0.783)	(0.513)	(0.015)	(0.666)	(0.500)
L8.Dis	0.0117	-0.000750	-0.00153	0.0851***	0.0180	-0.00291
	(0.322)	(0.985)	(0.907)	(0.005)	(0.153)	(0.899)
L9.Dis	0.0155	0.00904	-0.00359	0.0795***	0.0190	-0.00722
	(0.191)	(0.822)	(0.783)	(0.009)	(0.134)	(0.754)
L10.Dis	0.0141	0.0246	-0.000517	0.0816***	0.0153	-0.0117
	(0.229)	(0.539)	(0.968)	(0.009)	(0.213)	(0.612)
L11.Dis	0.0163	0.00758	0.00182	0.0888***	0.00628	-0.0244
	(0.163)	(0.849)	(0.888)	(0.004)	(0.605)	(0.286)
L12.Dis	0.0164	0.00961	0.00927	0.0819***	0.0000779	-0.0290
	(0.160)	(0.812)	(0.473)	(0.008)	(0.995)	(0.214)
L13.Population	-1.80e-09	2.08e-08***	3.10e-08***	1.17e-08***	-5.62e-08***	-1.77e-08
	(0.433)					(0.280)

		(0.003)	(0.000)	(0.000)	(0.000)	
Constant	0.237***	0.530***	0.260***	0.536***	0.657***	1.351***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
r2	0.176	0.155	0.442	0.418	0.432	0.127
chi2						
aic	-1903.4	1310.8	-2001.1	-426.0	-1127.0	-564.4
bic	-1700.1	1501.1	-1800.8	-297.3	-1013.5	-443.2

p-values in parentheses
* p<0.10, ** p<0.05, *** p<0.010

Table 2: The effect of droughts, floods and storms on the price level at the SSA level

	(1)	(2)	(3)	(4)	(5)	(6)
	Maize	Sorghum	Millet	Wheat	Cassava	Rice
(sum) Drought	-0.0129	0.0417	0.0344	0.0297	-0.0221	-0.0436
	(0.662)	(0.680)	(0.253)	(0.622)	(0.660)	(0.503)
L.(sum) Drought	-0.0160	0.0385	0.00795	-0.0206	-0.000143	-0.125**
	(0.581)	(0.704)	(0.794)	(0.718)	(0.998)	(0.041)
L2.(sum) Drought	-0.0204	0.0107	-0.00323	-0.0208	-0.0123	-0.140**
	(0.469)	(0.913)	(0.915)	(0.717)	(0.769)	(0.017)
L3.(sum) Drought	-0.0164	-0.0173	-0.00540	0.0220	-0.0275	-0.0966*
	(0.560)	(0.860)	(0.859)	(0.700)	(0.518)	(0.096)
L4.(sum) Drought	0.00102	-0.0753	0.00905	0.0621	-0.0287	0.189***
	(0.971)	(0.443)	(0.765)	(0.281)	(0.499)	(0.001)
L5.(sum) Drought	-0.00924	0.0230	-0.000170	0.0978*	-0.0458	0.176***
	(0.742)	(0.816)	(0.996)	(0.092)	(0.246)	(0.003)
L6.(sum) Drought	-0.00326	0.0365	-0.00170	0.0927	-0.0557	0.0209
	(0.908)	(0.719)	(0.955)	(0.110)	(0.155)	(0.720)
L7.(sum) Drought	-0.00648	0.180*	-0.000465	0.131**	-0.0713*	-0.0278
	(0.815)	(0.086)	(0.988)	(0.030)	(0.069)	(0.650)
L8.(sum) Drought	0.00256	0.141	0.000489	0.146**	-0.0257	-0.0141
	(0.926)	(0.181)	(0.987)	(0.016)	(0.513)	(0.809)
L9.(sum) Drought	0.00435	0.188*	-0.00166	0.120**	-0.00364	-0.0230
	(0.873)	(0.075)	(0.957)	(0.047)	(0.926)	(0.692)
L10.(sum) Drought	-0.000209	0.172	0.00247	0.136**	-0.00749	-0.0119
	(0.994)	(0.103)	(0.935)	(0.032)	(0.852)	(0.838)
L11.(sum) Drought	-0.00580	0.0835	-0.00830	0.163***	-0.00125	-0.0920*
	(0.835)	(0.444)	(0.785)	(0.009)	(0.972)	(0.100)
L12.(sum) Drought	-0.00311	0.124	-0.0129	0.151**	0.00444	-0.157***
	(0.912)	(0.273)	(0.681)	(0.015)	(0.902)	(0.008)
(sum) Flood	0.0214	0.0285	0.0144	0.0635*	0.0243	0.0435
	(0.124)	(0.545)	(0.339)	(0.099)	(0.110)	(0.144)
L.(sum) Flood	0.0161	0.0197	0.00602	0.0717*	0.0260*	0.0338
	(0.247)	(0.679)	(0.692)	(0.066)	(0.090)	(0.255)
L2.(sum) Flood	0.0136	0.0366	-0.0134	0.128***	0.0191	-0.0174
	(0.324)	(0.446)	(0.378)	(0.001)	(0.219)	(0.557)
L3.(sum) Flood	-0.000521	0.00107	-0.0153	0.0997**	0.0327**	-0.0196

	(0.970)	(0.982)	(0.318)	(0.013)	(0.035)	(0.521)
L4.(sum) Flood	-0.00670	0.00871	-0.0192	0.106***	0.0345**	-0.00193
	(0.625)	(0.856)	(0.212)	(0.009)	(0.026)	(0.949)
L5.(sum) Flood	-0.00695	-0.000802	-0.0132	0.0582	0.0333**	0.00482
	(0.612)	(0.987)	(0.395)	(0.148)	(0.030)	(0.871)
L6.(sum) Flood	-0.0135	-0.00338	-0.0230	0.0632	0.0282*	-0.0204
	(0.318)	(0.942)	(0.131)	(0.115)	(0.068)	(0.475)
L7.(sum) Flood	-0.00446	-0.00403	-0.0154	0.0635	0.0130	-0.00500
	(0.744)	(0.929)	(0.304)	(0.114)	(0.388)	(0.858)
L8.(sum) Flood	0.00202	-0.00812	-0.00462	0.0800**	0.0188	0.00661
	(0.883)	(0.857)	(0.756)	(0.048)	(0.212)	(0.814)
L9.(sum) Flood	0.00589	-0.00133	-0.00946	0.0875**	0.0196	-0.00171
	(0.667)	(0.977)	(0.525)	(0.030)	(0.192)	(0.951)
L10.(sum) Flood	0.0123	0.00932	-0.00692	0.0823**	0.0129	-0.00245
	(0.359)	(0.836)	(0.642)	(0.042)	(0.374)	(0.930)
L11.(sum) Flood	0.0184	0.00610	0.00105	0.0922**	0.00363	-0.00838
	(0.168)	(0.891)	(0.943)	(0.022)	(0.802)	(0.763)
L12.(sum) Flood	0.0174	-0.00137	0.0118	0.0827**	-0.00152	-0.0209
	(0.192)	(0.976)	(0.427)	(0.040)	(0.914)	(0.457)
(sum) Storm	0.0425	0.0870	0.0956**	-0.0299	0.0272	-0.0654
	(0.245)	(0.536)	(0.045)	(0.678)	(0.422)	(0.214)
L.(sum) Storm	0.0292	0.151	0.115**	0.0153	0.0215	-0.0492
	(0.423)	(0.284)	(0.025)	(0.839)	(0.501)	(0.333)
L2.(sum) Storm	0.0129	-0.0756	0.0373	0.0349	0.0321	-0.0356
	(0.723)	(0.617)	(0.508)	(0.693)	(0.309)	(0.493)
L3.(sum) Storm	-0.0123	-0.0592	0.0350	0.0627	0.0474	-0.0741
	(0.735)	(0.695)	(0.534)	(0.411)	(0.134)	(0.151)
L4.(sum) Storm	-0.00527	-0.0553	0.0254	0.0597	-0.00254	-0.0632
	(0.885)	(0.715)	(0.651)	(0.416)	(0.936)	(0.218)
L5.(sum) Storm	-0.00468	-0.0696	0.0189	0.0370	0.00222	-0.0670
	(0.898)	(0.646)	(0.737)	(0.587)	(0.945)	(0.191)
L6.(sum) Storm	0.00341	-0.00829	0.0446	0.0323	0.00155	-0.0479
	(0.925)	(0.956)	(0.427)	(0.635)	(0.962)	(0.348)
L7.(sum) Storm	0.0157	-0.0211	0.0504	0.0384	-0.0208	-0.0203
	(0.665)	(0.889)	(0.370)	(0.573)	(0.515)	(0.692)
L8.(sum) Storm	0.0948***	-0.0555	0.0216	0.0286	0.0109	-0.0134
	(0.009)	(0.714)	(0.700)	(0.677)	(0.730)	(0.795)
L9.(sum) Storm	0.104***	-0.0727	0.0303	0.0217	-0.00808	-0.00889
	(0.005)	(0.631)	(0.589)	(0.768)	(0.810)	(0.868)
L10.(sum) Storm	0.0391	-0.0432	0.0230	0.0225	0.0108	-0.0338
	(0.294)	(0.776)	(0.682)	(0.770)	(0.752)	(0.543)
L11.(sum) Storm	0.0235	-0.0826	0.00581	0.0208	0.00226	0.00573
	(0.531)	(0.580)	(0.908)	(0.789)	(0.946)	(0.917)
L12.(sum) Storm	0.0215	-0.0724	0.0304	0.0172	-0.0278	0.0391
	(0.578)	(0.651)	(0.546)	(0.825)	(0.412)	(0.476)
L13.Population	-1.94e-09	2.25e-08***	2.94e-08***	1.11e-08***	-5.71e-08***	-1.94e-08
	(0.400)					(0.237)

		(0.001)	(0.000)	(0.001)	(0.000)	
Constant	0.238***	0.519***	0.262***	0.536***	0.695***	1.362***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
r2	0.183	0.164	0.448	0.436	0.449	0.171
aic	-1869.9	1347.9	-1963.3	-397.1	-1090.0	-561.1
bic	-1519.8	1675.5	-1629.3	-149.0	-867.2	-313.8

p-values in parentheses
* p<0.10, ** p<0.05, *** p<0.010

Table 3: The effect of each disaster in EA, WA, SA and CA

East Africa: The effect of droughts, floods and storms on the regional price level

	(1) Maize	(2) Sorghum	(3) Millet	(4) Wheat	(5) Cassava	(6) Rice
(sum) Drought	0.00123	0.000270	0	-0.0546**	0.0275	0.00529
	(0.928)	(0.993)	(.)	(0.023)	(0.766)	(0.900)
L.(sum) Drought	-0.0177	0.0333		-0.0466*	0.102	-0.00471
	(0.185)	(0.294)		(0.052)	(0.271)	(0.911)
L2.(sum) Drought	-0.00688	0.0121		-0.0731***	0.129	-0.212**
	(0.585)	(0.627)		(0.002)	(0.166)	(0.026)
L3.(sum) Drought	0.00690	0.0267		-0.0470**	0.0688	-0.229**
	(0.601)	(0.284)		(0.047)	(0.456)	(0.015)
L4.(sum) Drought	0.0222*	0.0374		-0.0184	0.0533	-0.256**
	(0.093)	(0.140)		(0.446)	(0.564)	(0.013)
L5.(sum) Drought	0.0358***	0.0120		0.0189	-0.0472	-0.122
	(0.007)	(0.632)		(0.435)	(0.642)	(0.222)
L6.(sum) Drought	0.0417***	-0.00284		0.00389	-0.0125	-0.104
	(0.002)	(0.909)		(0.872)	(0.905)	(0.289)
L7.(sum) Drought	0.00608	-0.000579		0.00907	-0.0318	-0.0976
	(0.647)	(0.982)		(0.708)	(0.760)	(0.321)
L8.(sum) Drought	0.00865	-0.0134		0.00301	0.0493	-0.105
	(0.515)	(0.583)		(0.899)	(0.638)	(0.283)
L9.(sum) Drought	0.00196	-0.00642		0.0000326	0.0820	-0.106
	(0.883)	(0.794)		(0.999)	(0.435)	(0.286)
L10.(sum) Drought	0.00656	-0.0113		-0.0178	0.0424	-0.126
	(0.621)	(0.646)		(0.501)	(0.618)	(0.196)
L11.(sum) Drought	0.0193	-0.00395		-0.00323	-0.0289	-0.103
	(0.169)	(0.892)		(0.902)	(0.726)	(0.295)
L12.(sum) Drought	0.0371***	0.0453		0.0216	-0.0637	-0.118
	(0.008)	(0.108)		(0.393)	(0.441)	(0.222)
(sum) Flood	0.00489	0.0212*	-0.0101	0.0224	0.0263	0.0212
	(0.473)	(0.065)	(0.744)	(0.142)	(0.534)	(0.404)
L.(sum) Flood	0.0110	0.0244**	0.00930	0.0264*	0.0319	0.0135
	(0.117)	(0.049)	(0.801)	(0.092)	(0.528)	(0.570)
L2.(sum) Flood	0.0105	0.0236*	-0.00841	0.0500***	0.00563	0.00736

	(0.132)	(0.060)	(0.812)	(0.002)	(0.907)	(0.756)
L3.(sum) Flood	0.0138**	0.00612	-0.00762	0.0362**	0.0103	0.00247
	(0.047)	(0.621)	(0.832)	(0.023)	(0.836)	(0.917)
L4.(sum) Flood	0.00432	0.0127	0.0217	0.0451***	0.0445	0.00314
	(0.529)	(0.284)	(0.542)	(0.005)	(0.373)	(0.895)
L5.(sum) Flood	0.00108	-0.00453	0.0201	0.0176	0.0198	0.00759
	(0.873)	(0.703)	(0.594)	(0.276)	(0.706)	(0.749)
L6.(sum) Flood	0.00196	-0.00428	0.00434	-0.00739	0.0496	0.00818
	(0.773)	(0.709)	(0.903)	(0.646)	(0.341)	(0.730)
L7.(sum) Flood	0.000266	-0.00488	0.00944	-0.0350**	0.0477	-0.0676***
	(0.968)	(0.657)	(0.791)	(0.025)	(0.359)	(0.005)
L8.(sum) Flood	-0.00366	-0.00782	0.0203	-0.0190	0.0332	-0.0467*
	(0.585)	(0.474)	(0.563)	(0.212)	(0.470)	(0.051)
L9.(sum) Flood	-0.0197***	-0.0427***	-0.00857	-0.0338**	-0.0440	0.0425
	(0.004)	(0.000)	(0.806)	(0.036)	(0.325)	(0.176)
L10.(sum) Flood	-0.0204***	-0.0295***	-0.00102	-0.00701	-0.0254	0.0122
	(0.002)	(0.010)	(0.976)	(0.660)	(0.557)	(0.666)
L11.(sum) Flood	-0.00624	-0.0240**	0.0150	0.00675	-0.00478	0.0111
	(0.346)	(0.023)	(0.609)	(0.666)	(0.901)	(0.696)
L12.(sum) Flood	0.00249	-0.000403	0.0325	0.0266*	0.0206	0.00268
	(0.701)	(0.969)	(0.276)	(0.091)	(0.587)	(0.929)
(sum) Storm	0.0412	0	0	-0.0101	0	-0.0133
	(0.294)	(.)	(.)	(0.780)	(.)	(0.541)
L.(sum) Storm	0.0745*			-0.00571		-0.0117
	(0.058)			(0.874)		(0.597)
L2.(sum) Storm	-0.00230			-0.0115		0.00791
	(0.954)			(0.757)		(0.705)
L3.(sum) Storm	-0.0232			0.000646		-0.00910
	(0.562)			(0.985)		(0.655)
L4.(sum) Storm	-0.0244			0.0107		-0.00650
	(0.541)			(0.744)		(0.750)
L5.(sum) Storm	-0.00528			0.000797		-0.0107
	(0.895)			(0.981)		(0.600)
L6.(sum) Storm	0.0886**			0.00493		-0.00243
	(0.027)			(0.880)		(0.905)
L7.(sum) Storm	-0.0304			-0.00274		0.000660
	(0.449)			(0.934)		(0.974)
L8.(sum) Storm	-0.0521			-0.00380		0.000574
	(0.195)			(0.912)		(0.979)
L9.(sum) Storm	-0.0753*			0.0191		0.00679
	(0.061)			(0.598)		(0.743)
L10.(sum) Storm	-0.00645			-0.0434	-0.0302	-0.0140
	(0.865)			(0.304)	(0.715)	(0.503)
L11.(sum) Storm	0.0368	0.0359	0.104	0.0106	0.0709	0.00695

	(0.332)	(0.373)	(0.127)	(0.791)	(0.417)	(0.744)
L12.(sum) Storm	0.0573	0.0269	0.114*	-0.0112	0.0639	0.0338*
	(0.130)	(0.504)	(0.099)	(0.768)	(0.465)	(0.069)
L13.logpop	0.0668	-0.384	-0.215	0.0647	1.153	-0.176
	(0.575)	(0.130)	(0.759)	(0.800)	(0.278)	(0.702)
Constant	-0.843	6.767	4.074	-0.400	-18.46	3.656
	(0.670)	(0.104)	(0.709)	(0.923)	(0.288)	(0.616)
N	395	254	91	257	80	138
r2	0.767	0.826	0.443	0.692	0.552	0.664
aic	-1453.4	-916.9	-264.2	-810.0	-186.6	-483.2
bic	-1250.5	-779.0	-208.9	-632.5	-98.47	-348.5

p-values in parentheses
* p<0.10, ** p<0.05, *** p<0.010

Western Africa: The effect of droughts, floods and storms on the regional price level

	(1) Maize	(2) Sorghum	(3) Millet	(4) Wheat	(5) Cassava	(6) Rice
(sum) Drought	0.00615	0.0417	0.00728	-0.223	0	-0.190**
	(0.745)	(0.375)	(0.593)	(0.447)	(.)	(0.014)
L.(sum) Drought	0.0313*	-0.00923	-0.00201	-0.243		-0.140*
	(0.099)	(0.845)	(0.884)	(0.396)		(0.066)
L2.(sum) Drought	0.0298	-0.0153	-0.00214	-0.159		-0.122
	(0.116)	(0.746)	(0.877)	(0.576)		(0.111)
L3.(sum) Drought	0.0268	-0.0314	-0.0149	-0.119		-0.0805
	(0.158)	(0.506)	(0.281)	(0.670)		(0.291)
L4.(sum) Drought	0.00980	-0.112**	0.00390	-0.104		0.130*
	(0.604)	(0.018)	(0.777)	(0.708)		(0.090)
L5.(sum) Drought	0.0137	0.0143	0.0397***	-0.0383		0.101
	(0.469)	(0.763)	(0.004)	(0.910)		(0.202)
L6.(sum) Drought	-0.0124	0.0722	-0.00490	-0.156		-0.00818
	(0.513)	(0.145)	(0.723)	(0.643)		(0.918)
L7.(sum) Drought	0.0178	0.128**	-0.0232*	-0.117		-0.174**
	(0.349)	(0.013)	(0.093)	(0.729)		(0.039)
L8.(sum) Drought	0.0144	0.0546	-0.00308	-0.132		-0.113
	(0.449)	(0.290)	(0.824)	(0.696)		(0.178)
L9.(sum) Drought	0.00977	0.0574	-0.00605	-0.201		-0.103
	(0.607)	(0.266)	(0.663)	(0.559)		(0.220)
L10.(sum) Drought	-0.0454**	0.0570	-0.0337**	0.832**		-0.0115
	(0.017)	(0.270)	(0.015)	(0.013)		(0.891)
L11.(sum) Drought	-0.0484**	0.000338	-0.0358***	0.883***		-0.106
	(0.011)	(0.995)	(0.010)	(0.009)		(0.205)
L12.(sum) Drought	-0.0405**	0.120**	-0.0306**	0.926***		0.236**
	(0.043)	(0.027)	(0.032)	(0.009)		(0.013)
(sum) Flood	0.0152*	0.0236	0.0179**	0.0982	0.0141	0.0378
	(0.057)	(0.304)	(0.012)	(0.594)	(0.445)	(0.283)
L.(sum) Flood	0.00278	0.0413*	0.00263	0.195	0.0114	0.0233

	(0.725)	(0.072)	(0.713)	(0.291)	(0.527)	(0.514)
L2.(sum) Flood	-0.00367	0.0181	0.00132	0.270	0.00523	-0.0281
	(0.642)	(0.435)	(0.853)	(0.188)	(0.771)	(0.438)
L3.(sum) Flood	-0.0167**	0.00606	-0.00579	0.405*	-0.0168	-0.0448
	(0.035)	(0.796)	(0.423)	(0.056)	(0.348)	(0.234)
L4.(sum) Flood	-0.0187**	0.0134	-0.0135*	0.298	-0.0187	0.00332
	(0.020)	(0.568)	(0.063)	(0.156)	(0.302)	(0.929)
L5.(sum) Flood	-0.0219***	-0.0425*	-0.0254***	-0.0219	-0.00670	-0.00790
	(0.007)	(0.073)	(0.001)	(0.925)	(0.708)	(0.833)
L6.(sum) Flood	-0.0376***	-0.0648***	-0.0342***	0.00469	-0.0491***	-0.0773**
	(0.000)	(0.005)	(0.000)	(0.982)	(0.007)	(0.030)
L7.(sum) Flood	-0.0251***	-0.0648***	-0.0243***	0.0199	-0.0499***	-0.113***
	(0.001)	(0.004)	(0.001)	(0.925)	(0.005)	(0.001)
L8.(sum) Flood	-0.0168**	-0.0514**	-0.0165**	0.0755	-0.0320*	-0.0814**
	(0.031)	(0.023)	(0.018)	(0.725)	(0.062)	(0.020)
L9.(sum) Flood	-0.00395	-0.0786***	-0.00831	0.0738	-0.0201	-0.0239
	(0.611)	(0.001)	(0.240)	(0.731)	(0.240)	(0.492)
L10.(sum) Flood	0.00344	-0.0359	0.000783	0.0713	-0.0120	0.00405
	(0.656)	(0.110)	(0.912)	(0.740)	(0.472)	(0.908)
L11.(sum) Flood	0.00504	-0.0425*	0.00929	0.101	-0.00977	-0.00246
	(0.515)	(0.059)	(0.188)	(0.638)	(0.562)	(0.944)
L12.(sum) Flood	0.0135*	-0.0964***	0.0116	0.167	-0.0194	-0.0414
	(0.081)	(0.000)	(0.102)	(0.486)	(0.244)	(0.249)
(sum) Storm	0.0363	0.0750	0.0347	0.106	-0.0226	0.0673
	(0.227)	(0.279)	(0.171)	(0.847)	(0.694)	(0.546)
L.(sum) Storm	0.0236	0.0481	0.0356	0.317	-0.0563	0.295***
	(0.432)	(0.487)	(0.161)	(0.562)	(0.346)	(0.008)
L2.(sum) Storm	0.00437	0.0530	0.0228		-0.0415	0.159
	(0.884)	(0.484)	(0.369)		(0.485)	(0.236)
L3.(sum) Storm	-0.0269	0.0406	0.00333		-0.0568	0.0514
	(0.372)	(0.591)	(0.895)		(0.352)	(0.703)
L4.(sum) Storm	-0.0246	-0.0171	-0.00398		-0.0206	0.0636
	(0.415)	(0.820)	(0.875)		(0.734)	(0.636)
L5.(sum) Storm	-0.0152	0.0188	-0.00587		0.000640	0.133
	(0.615)	(0.805)	(0.817)		(0.992)	(0.324)
L6.(sum) Storm	0.0137	0.0139	0.0198		0.0304	0.0324
	(0.649)	(0.854)	(0.434)		(0.616)	(0.810)
L7.(sum) Storm	0.0219	0.0102	0.0193		0.0702	0.125
	(0.469)	(0.893)	(0.444)		(0.242)	(0.351)
L8.(sum) Storm	0.0305	0.0206	-0.00842		0.139**	0.0589
	(0.312)	(0.786)	(0.739)		(0.021)	(0.659)
L9.(sum) Storm	0.0325	0.0560	0.00547		0.101*	0.0719

	(0.282)	(0.461)	(0.829)		(0.092)	(0.590)
L10.(sum) Storm	0.0120	0.0547	0.000488		0.0825	0.0563
	(0.691)	(0.471)	(0.985)		(0.168)	(0.673)
L11.(sum) Storm	-0.000474	-0.00839	-0.00479		0.0673	-0.000360
	(0.987)	(0.912)	(0.849)		(0.258)	(0.998)
L12.(sum) Storm	-0.0135	0.00144	-0.00399		0.0444	-0.0179
	(0.656)	(0.985)	(0.875)		(0.456)	(0.893)
L13.logpop	0.0799	0.161	0.218**	3.393	0.181	1.058
	(0.506)	(0.657)	(0.042)	(0.537)	(0.690)	(0.124)
Constant	-1.031	-2.227	-3.081*	-46.82	-2.622	-15.44
	(0.577)	(0.685)	(0.059)	(0.542)	(0.719)	(0.139)
N	961	946	958	187	239	584
r2	0.838	0.910	0.889	0.718	0.588	0.648
aic	-2719.3	-704.4	-3009.1	237.4	-691.8	-317.0
bic	-2412.7	-403.5	-2692.8	366.7	-559.7	-94.16

p-values in parentheses
* p<0.10, ** p<0.05, *** p<0.010

Southern Africa: The effect of droughts, floods and storms on the regional price level

	(1)	(2)	(3)	(4)	(5)	(6)
	Maize	Sorghum	Millet	Wheat	Cassava	Rice
(sum) Drought	0.0124	0	0	-0.0141	0	0
	(0.470)	(.)	(.)	(0.786)	(.)	(.)
L.(sum) Drought	0.0113			-0.000159		-0.0609
	(0.487)			(0.997)		(0.646)
L2.(sum) Drought	0.0283*			0.0290		0.0238
	(0.083)			(0.517)		(0.857)
L3.(sum) Drought	0.0184			0.0160		-0.0126
	(0.257)			(0.713)		(0.924)
L4.(sum) Drought	0.0278*			-0.00822		-0.0195
	(0.085)			(0.844)		(0.883)
L5.(sum) Drought	0.00856			-0.0525		-0.0296
	(0.599)			(0.210)		(0.823)
L6.(sum) Drought	0.0101			-0.0488		-0.0141
	(0.534)			(0.244)		(0.915)
L7.(sum) Drought	0.0176			-0.0169		-0.0152
	(0.258)			(0.686)		(0.909)
L8.(sum) Drought	0.0239			0.00365		-0.0232
	(0.126)			(0.930)		(0.821)
L9.(sum) Drought	0.00855			-0.0422		-0.0385
	(0.566)			(0.313)		(0.712)
L10.(sum) Drought	0.00190			0.0212		0.0211
	(0.899)			(0.612)		(0.840)
L11.(sum) Drought	-0.0102			-0.0651*	0.0916	-0.0356
	(0.493)			(0.092)	(0.776)	(0.684)
L12.(sum) Drought	-0.00893			-0.0177	0.0478	0.000296
	(0.548)			(0.648)	(0.800)	(0.997)

(sum) Flood	0.0109	-0.0575	-0.0353	0.0310	-0.146	-0.0406
	(0.231)	(0.512)	(0.488)	(0.333)	(0.195)	(0.644)
L.(sum) Flood	-0.00460	0.00163	-0.00669	0.0399	-0.131	0.0330
	(0.613)	(0.985)	(0.895)	(0.233)	(0.521)	(0.780)
L2.(sum) Flood	-0.00584	-0.279***	-0.224	0.0300	-0.289	-0.00904
	(0.506)	(0.005)	(0.000)	(0.390)	(0.161)	(0.937)
L3.(sum) Flood	0.00993	-0.166*	-0.0238	0.0636**	-0.0539	0.0233
	(0.256)	(0.069)	(0.638)	(0.043)	(0.818)	(0.851)
L4.(sum) Flood	0.00533	-0.142	0.0239	0.0467	-0.129	-0.0247
	(0.540)	(0.117)	(0.637)	(0.137)	(0.584)	(0.844)
L5.(sum) Flood	-0.00449	-0.157*	0.0197	0.0576*	0.130	0.00450
	(0.606)	(0.084)	(0.697)	(0.063)	(0.581)	(0.970)
L6.(sum) Flood	-0.0123		-0.0153	0.0435	-0.127	-0.0323
	(0.163)		(0.762)	(0.169)	(0.672)	(0.787)
L7.(sum) Flood	0.00359	-0.00672	-0.00340	-0.00727	0.0299	-0.0298
	(0.691)	(0.939)	(0.946)	(0.817)	(0.888)	(0.796)
L8.(sum) Flood	0.00633	-0.122	0.0156	0.00494	-0.0615	-0.0201
	(0.486)	(0.173)	(0.757)	(0.883)	(0.738)	(0.859)
L9.(sum) Flood	0.0133	-0.0512	-0.0495	0.0265	-0.00399	-0.0586
	(0.138)	(0.559)	(0.334)	(0.409)	(0.982)	(0.622)
L10.(sum) Flood	0.0107	0.0837	-0.00533	-0.0179	-0.0196	-0.0680
	(0.226)	(0.343)	(0.916)	(0.596)	(0.905)	(0.527)
L11.(sum) Flood	0.0141	-0.216**	0.0328	0.0625*	-0.00398	-0.0684
	(0.102)	(0.022)	(0.518)	(0.059)	(0.983)	(0.554)
L12.(sum) Flood	0.0105	0.0187	0.0716	-0.0690**	-0.0548	-0.0555
	(0.223)	(0.830)	(0.169)	(0.022)	(0.739)	(0.497)
(sum) Storm	0.0240	-0.127	0.0286	-0.0156	-0.0473	0.0136
	(0.113)	(0.158)	(0.580)	(0.664)	(0.854)	(0.940)
L.(sum) Storm	0.00992	-0.0287	0.610	-0.105**	-0.306	-0.0202
	(0.507)	(0.807)	(0.000)	(0.012)	(0.248)	(0.909)
L2.(sum) Storm	-0.00677	-0.0952		-0.00594		0.0148
	(0.651)	(0.518)		(0.901)		(0.934)
L3.(sum) Storm	-0.00540	-0.0387		-0.00620	-0.0723	-0.0484
	(0.719)	(0.816)		(0.881)	(0.825)	(0.782)
L4.(sum) Storm	-0.0223	-0.0952		0.0395	-0.256	-0.0582
	(0.137)	(0.613)		(0.343)	(0.426)	(0.742)
L5.(sum) Storm	-0.0170	-0.0287		-0.0154	-0.236	0.0964
	(0.254)	(0.888)		(0.690)	(0.413)	(0.558)
L6.(sum) Storm	-0.0144	-0.0208		0.0327	-0.223	-0.0405
	(0.335)	(0.925)		(0.395)	(0.473)	(0.815)
L7.(sum) Storm	0.00530	0.0447		0.0741*	-0.312	-0.00741
	(0.724)	(0.849)		(0.054)	(0.334)	(0.965)
L8.(sum) Storm	-0.0202	-0.183		-0.0402	-0.219	-0.0269
	(0.180)	(0.469)		(0.305)	(0.440)	(0.885)
L9.(sum) Storm	0.0178	-0.0355		0.0134		
	(0.256)	(0.893)		(0.765)		
L10.(sum) Storm	0.0111	-0.184		0.0504		

	(0.476)	(0.509)		(0.236)		
L11.(sum) Storm	0.0155	0.135		0.0338		
	(0.328)	(0.641)		(0.424)		
L12.(sum) Storm	0.0123			0.0206		
	(0.465)			(0.629)		
L13.logpop	-0.109			-0.575	2.475	0.733
	(0.301)			(0.153)	(0.521)	(0.520)
Constant	1.793	0.623***	0.512***	9.315	-38.75	-9.752
	(0.262)	(0.000)	(0.000)	(0.109)	(0.527)	(0.560)
N	606	43	32	201	42	147
r2	0.877	0.724	0.926	0.843	0.720	0.596
aic	-1902.6	-83.16	-96.70	-507.6	-69.81	-178.9
bic	-1664.6	-39.13	-73.25	-345.8	-21.15	-47.37

p-values in parentheses
* p<0.10, ** p<0.05, *** p<0.010

Central Africa: The effect of droughts, floods and storms on the regional price level - insufficient data on sorghum, millet and wheat

	(1) Maize	(2) Cassava	(3) Rice
(sum) Drought	-0.125	0.0110	0.0721
	(0.669)	(0.795)	(0.805)
L.(sum) Drought	0.231	0.0252	0.120
	(0.580)	(0.605)	(0.773)
L2.(sum) Drought	0.162	0.0139	0.0633
	(0.581)	(0.781)	(0.874)
L3.(sum) Drought	0.0308	0.0255	-0.0442
	(0.907)	(0.626)	(0.909)
L4.(sum) Drought	0.0404	0.00684	0.116
	(0.880)	(0.898)	(0.755)
L5.(sum) Drought	0.0877	0.00381	0.131
	(0.733)	(0.946)	(0.727)
L6.(sum) Drought	0.0699	-0.0374	0.0528
	(0.786)	(0.491)	(0.888)
L7.(sum) Drought	0.0931	-0.0262	0.00328
	(0.718)	(0.627)	(0.993)
L8.(sum) Drought	0.0772	-0.00920	0.0116
	(0.765)	(0.861)	(0.975)
L9.(sum) Drought	0.0659	-0.0341	0.142
	(0.797)	(0.528)	(0.704)
L10.(sum) Drought	0.0878	-0.0120	0.101
	(0.738)	(0.827)	(0.788)
L11.(sum) Drought	0.0838	-0.0169	0.112
	(0.753)	(0.742)	(0.766)
L12.(sum) Drought	0.0608	-0.0117	0.143
	(0.818)	(0.799)	(0.704)
(sum) Flood	0.0156	-0.00829	-0.00676

	(0.812)	(0.638)	(0.934)
L.(sum) Flood	0.105*	0.00458	0.0911
	(0.092)	(0.777)	(0.229)
L2.(sum) Flood	0.106	-0.00497	0.0513
	(0.195)	(0.771)	(0.578)
L3.(sum) Flood	0.0753	-0.00514	-0.00716
	(0.296)	(0.769)	(0.926)
L4.(sum) Flood	0.0802	0.00135	-0.0662
	(0.308)	(0.938)	(0.459)
L5.(sum) Flood	0.0777	0.0312*	0.0119
	(0.296)	(0.076)	(0.888)
L6.(sum) Flood	0.0465	0.0159	-0.00162
	(0.538)	(0.352)	(0.985)
L7.(sum) Flood	0.124	0.0265	0.0599
	(0.137)	(0.140)	(0.498)
L8.(sum) Flood	0.0741	0.0403**	-0.00812
	(0.295)	(0.031)	(0.921)
L9.(sum) Flood	0.115	0.0353*	0.0644
	(0.164)	(0.074)	(0.504)
L10.(sum) Flood	0.0718	0.00202	0.0462
	(0.332)	(0.917)	(0.629)
L11.(sum) Flood	0.120	0.0363*	0.0595
	(0.122)	(0.051)	(0.538)
L12.(sum) Flood	0.107*	0.00292	0.0924
	(0.076)	(0.871)	(0.196)
(sum) Storm	-0.000846	-0.00356	0.0264
	(0.996)	(0.920)	(0.857)
L.(sum) Storm	0.0211	0.0161	-0.0957
	(0.889)	(0.633)	(0.517)
L2.(sum) Storm	0.0508	0.0156	-0.113
	(0.758)	(0.632)	(0.466)
L3.(sum) Storm	-0.156	0.0140	-0.219
	(0.541)	(0.714)	(0.423)
L4.(sum) Storm	-0.0479	0.0358	-0.165
	(0.812)	(0.300)	(0.403)
L5.(sum) Storm	-0.0178	0.0292	0.0394
	(0.893)	(0.412)	(0.742)
L6.(sum) Storm	-0.109	0.0246	0.0386
	(0.657)	(0.511)	(0.869)
L7.(sum) Storm	0.117	0.0227	0.214
	(0.538)	(0.540)	(0.283)
L8.(sum) Storm	0.0891	0.0407	0.178
	(0.624)	(0.351)	(0.309)
L9.(sum) Storm	0.0677	0.0156	0.0330
	(0.716)	(0.733)	(0.870)
L10.(sum) Storm	0.140	0.0219	0.00133
	(0.512)	(0.636)	(0.995)

L11.(sum) Storm	-0.0825	0.0237	-0.204
	(0.787)	(0.556)	(0.521)
L12.(sum) Storm	-0.123	-0.00526	-0.222
	(0.549)	(0.862)	(0.274)
L13.logpop	2.061	0.591	0.559
	(0.264)	(0.337)	(0.736)
Constant	-32.38	-9.007	-7.986
	(0.269)	(0.354)	(0.766)
N	83	131	74
r2	0.779	0.770	0.926
aic	-150.1	-401.6	-157.5
bic	-36.39	-252.1	-51.51

p-values in parentheses
* p<0.10, ** p<0.05, *** p<0.010

Table 4: Interactions with intra-African trade flows and controlling for world trade and agricultural aid

	(1) Maize	(2) Sorghum	(3) Millet	(4) Wheat	(5) Cassava	(6) Rice
logaid	-0.0174*	0.0628***	-0.0358***	0.483**	-0.157	1.782*
	(0.066)	(0.002)	(0.009)	(0.034)	(0.954)	(0.070)
logworldimp	0.0232***	0.0349***	0.0346***	-0.00793	-0.00252	0.0750
	(0.000)	(0.005)	(0.000)	(0.847)	(0.999)	(0.458)
logworldexp	0.000558	-0.00234	-0.00651***	0.0196	0.00676	-0.0363*
	(0.761)	(0.433)	(0.000)	(0.657)	(0.962)	(0.072)
logimp_A	0.0193***	0.00227	0.00328	-0.0633***	-0.0693	-0.226*
	(0.000)	(0.477)	(0.104)	(0.000)	(0.968)	(0.051)
logexp_A	-0.00736**	-0.00305	0.000136	0.106***	0.0937	0.720**
	(0.028)	(0.313)	(0.937)	(0.004)	(0.930)	(0.046)
(sum) Drought	-0.0379	1.242	0.686**	0.148	21.93	0.414
	(0.867)	(0.135)	(0.043)	(0.396)	(0.718)	(0.604)
L.(sum) Drought	-0.126	1.206	-0.0755	-0.147**	0.102	13.57
	(0.567)	(0.153)	(0.824)	(0.041)	(0.341)	(0.501)
L2.(sum) Drought	-0.219	1.337	-0.254		0.129	-0.775
	(0.324)	(0.115)	(0.455)		(0.231)	(0.405)
L3.(sum) Drought	-0.111	1.398*	-0.342		-0.112	-1.037
	(0.631)	(0.098)	(0.315)		(0.819)	(0.305)
L4.(sum) Drought	-0.0419	1.625*	-0.173		0.0259	-0.441
	(0.857)	(0.054)	(0.611)		(0.959)	(0.653)
L5.(sum) Drought	-0.0872	1.543*	-0.213		-0.124	-0.140
	(0.695)	(0.066)	(0.531)		(0.603)	(0.870)

L6.(sum) Drought	-0.0640	1.178	-0.270		-0.0614	-0.232
	(0.784)	(0.160)	(0.430)		(0.960)	(0.776)
L7.(sum) Drought	-0.0767	0.360	-0.289		-0.612	-0.508
	(0.741)	(0.569)	(0.299)		(0.640)	(0.555)
L8.(sum) Drought	-0.0857	0.0499	-0.116		-0.656	-0.725
	(0.701)	(0.897)	(0.584)		(0.613)	(0.353)
L9.(sum) Drought	-0.242	0.108	-0.151		-0.699	-0.683
	(0.244)	(0.782)	(0.504)		(0.684)	(0.417)
L10.(sum) Drought	-0.517**	0.238	0.0234		-0.625	-0.483
	(0.013)	(0.539)	(0.917)		(0.717)	(0.521)
L11.(sum) Drought	-0.484**	0.170	0.0282		6.412	-0.142
	(0.019)	(0.660)	(0.900)		(0.691)	(0.866)
L12.(sum) Drought	-0.347*	-0.0762	-0.139		6.437	-0.446
	(0.079)	(0.855)	(0.566)		(0.688)	(0.580)
(sum) Flood	0.315**	0.122	0.129	0.245	0.0590	-0.331
	(0.011)	(0.427)	(0.193)	(0.392)	(0.905)	(0.368)
L.(sum) Flood	0.343***	0.117	0.114	-0.479	-0.00169	-0.789*
	(0.006)	(0.432)	(0.238)	(0.152)	(0.997)	(0.050)
L2.(sum) Flood	0.282**	0.000197	0.0572	-0.416	-0.164	-1.708***
	(0.017)	(0.999)	(0.555)	(0.224)	(0.681)	(0.000)
L3.(sum) Flood	0.122	-0.0736	-0.0314	-0.172	0.0666	-2.940***
	(0.330)	(0.621)	(0.743)	(0.485)	(0.893)	(0.000)
L4.(sum) Flood	0.0620	-0.0640	-0.0383	0.0645	-0.500	-2.425***
	(0.620)	(0.669)	(0.692)	(0.770)	(0.290)	(0.000)
L5.(sum) Flood	0.0494	-0.145	-0.0905	0.0212	-0.412	-2.763***
	(0.710)	(0.376)	(0.400)	(0.924)	(0.397)	(0.000)
L6.(sum) Flood	0.0540	-0.0544	-0.0392	0.145	-0.144	-2.912***
	(0.639)	(0.716)	(0.684)	(0.477)	(0.720)	(0.000)
L7.(sum) Flood	0.0314	-0.0470	-0.0633	0.0188	-0.424	-2.922***
	(0.783)	(0.683)	(0.390)	(0.914)	(0.284)	(0.000)
L8.(sum) Flood	0.0243	-0.00959	-0.0714	-0.0514	-0.161	-2.976***
	(0.831)	(0.933)	(0.319)	(0.769)	(0.639)	(0.000)
L9.(sum) Flood	0.0886	0.0138	-0.000730	-0.170	-0.0180	-2.987***
	(0.423)	(0.909)	(0.992)	(0.479)	(0.960)	(0.000)
L10.(sum) Flood	-0.0332	0.0116	0.0138	0.134	-0.525	-2.779***
	(0.762)	(0.923)	(0.858)	(0.555)	(0.149)	(0.000)
L11.(sum) Flood	-0.0769	0.0702	-0.0230	0.0297	-0.183	-2.174***
	(0.480)	(0.548)	(0.756)	(0.360)	(0.606)	(0.000)
L12.(sum) Flood	-0.106	0.0569	-0.121	0.0295	0.155	-1.446***
	(0.370)	(0.635)	(0.113)	(0.257)	(0.681)	(0.002)
(sum) Storm	-0.0879	0.907	0.0843	-0.229	0.181	0.0237
	(0.839)	(0.202)	(0.841)	(0.216)	(0.709)	(0.965)
L.(sum) Storm	-1.113***	0.0394	0.0776	0.00933	0.0274	-0.0335
	(0.009)	(0.749)	(0.296)	(0.924)	(0.956)	(0.957)
L2.(sum) Storm	-0.696	0.0949	0.133*	-0.268	-0.00165	-0.254
	(0.105)	(0.443)	(0.075)	(0.253)	(0.994)	(0.720)
L3.(sum) Storm	-0.635	0.146	0.146*	0.0213	8.334	-0.178

	(0.130)	(0.246)	(0.053)	(0.813)	(0.838)	(0.792)
L4.(sum) Storm	-0.193	0.143	0.145**	-0.260	0.500	-0.273
	(0.644)	(0.210)	(0.034)	(0.275)	(0.702)	(0.734)
L5.(sum) Storm	-0.164	0.0897	0.139**	0.0350	0.609	-0.00905
	(0.693)	(0.427)	(0.039)	(0.664)	(0.639)	(0.989)
L6.(sum) Storm	-0.282	0.119	0.169**	-0.268	0.720	0.119
	(0.496)	(0.294)	(0.013)	(0.267)	(0.675)	(0.871)
L7.(sum) Storm	-0.580	0.147	0.195***	0.0502	0.614	-0.0720
	(0.158)	(0.195)	(0.004)	(0.476)	(0.721)	(0.911)
L8.(sum) Storm	-0.584	0.794	-0.0190	-0.259	-9.435	-0.0246
	(0.120)	(0.494)	(0.687)	(0.234)	(0.733)	(0.971)
L9.(sum) Storm	-0.629*	0.285	-0.00551	0.0339	-9.933	-0.0796
	(0.093)	(0.805)	(0.907)	(0.508)	(0.720)	(0.901)
L10.(sum) Storm	-0.302	0.372	-0.0129	-0.301	-0.436	1.677
	(0.421)	(0.748)	(0.784)	(0.230)	(0.777)	(0.429)
L11.(sum) Storm	-1.007**	1.249	6.015	0.0602	-0.378	0.453
	(0.011)	(0.414)	(0.255)	(0.661)	(0.806)	(0.306)
L12.(sum) Storm	-0.781*	0.0833	12.30**	-0.0236	-0.669	-0.247
	(0.065)	(0.957)	(0.021)	(0.616)	(0.652)	(0.732)
imp_A_D	0.0149*	-0.0417	-0.0184		-1.246	-0.0582
	(0.055)	(0.208)	(0.187)		(0.718)	(0.303)
L.imp_A_D	0.0199***	-0.0372	0.0146			-1.179
	(0.006)	(0.270)	(0.300)			(0.490)
L2.imp_A_D	0.0159**	-0.0461	0.0145			-0.0154
	(0.032)	(0.174)	(0.303)			(0.824)
L3.imp_A_D	0.0117	-0.0573*	0.0156			0.00665
	(0.126)	(0.091)	(0.268)			(0.932)
L4.imp_A_D	0.0111	-0.0685**	0.00663			0.0869
	(0.157)	(0.043)	(0.640)			(0.229)
L5.imp_A_D	0.0127*	-0.0648*	0.00697			0.0896
	(0.081)	(0.054)	(0.620)			(0.162)
L6.imp_A_D	0.00954	-0.0476	0.00956			0.0759
	(0.196)	(0.162)	(0.496)			(0.205)
L7.imp_A_D	0.00552	-0.0176	0.00953			0.0451
	(0.445)	(0.484)	(0.391)			(0.499)
L8.imp_A_D	0.00906	-0.00633	0.00698			0.0326
	(0.187)	(0.676)	(0.409)			(0.607)
L9.imp_A_D	0.00276	-0.0124	0.00251			0.0171
	(0.681)	(0.411)	(0.776)			(0.791)
L10.imp_A_D	0.0166**	-0.0177	-0.00347			0.0452
	(0.014)	(0.243)	(0.695)			(0.445)
L11.imp_A_D	0.0151**	-0.0108	0.000697		-0.420	0.00743
	(0.029)	(0.473)	(0.937)		(0.693)	(0.855)
L12.imp_A_D	0.0181***	-0.000789	0.0103		-0.420	0.0340
	(0.003)	(0.961)	(0.282)		(0.691)	(0.365)
imp_A_F	-	-0.00451	-0.00530	-0.0113	0.0176	0.0159
	0.0149***	(0.459)	(0.167)	(0.347)	(0.376)	(0.278)

	(0.005)					
L.imp_A_F	-0.0188***	-0.00524	-0.00770**	-0.00743	-0.000709	0.0189
	(0.000)	(0.374)	(0.038)	(0.554)	(0.973)	(0.166)
L2.imp_A_F	-0.0144***	-0.00238	-0.00600	-0.00339	-0.00777	0.0450***
	(0.004)	(0.686)	(0.106)	(0.786)	(0.687)	(0.002)
L3.imp_A_F	-0.00778	0.000909	-0.00459	0.00681	0.00845	0.0747***
	(0.153)	(0.876)	(0.210)	(0.578)	(0.716)	(0.000)
L4.imp_A_F	-0.00577	-0.000641	-0.00505	0.00235	0.0124	0.0653***
	(0.289)	(0.913)	(0.170)	(0.842)	(0.595)	(0.000)
L5.imp_A_F	-0.00406	0.00216	-0.000552	0.00144	0.0166	0.0667***
	(0.481)	(0.736)	(0.893)	(0.900)	(0.504)	(0.001)
L6.imp_A_F	-0.00565	-0.00173	-0.00148	-0.00744	0.0274	0.0619***
	(0.227)	(0.758)	(0.678)	(0.509)	(0.258)	(0.000)
L7.imp_A_F	-0.00331	-0.00156	-0.000348	0.00146	0.0245	0.0530***
	(0.476)	(0.724)	(0.899)	(0.890)	(0.306)	(0.000)
L8.imp_A_F	-0.00327	-0.00133	0.00105	0.00479	0.0244	0.0531***
	(0.480)	(0.762)	(0.698)	(0.649)	(0.274)	(0.000)
L9.imp_A_F	-0.00728*	-0.00247	-0.000582	0.0135	0.0130	0.0552***
	(0.098)	(0.610)	(0.844)	(0.386)	(0.574)	(0.000)
L10.imp_A_F	-0.00325	-0.00253	-0.00191	-0.00692	0.0254	0.0451***
	(0.445)	(0.599)	(0.520)	(0.636)	(0.259)	(0.000)
L11.imp_A_F	-0.000162	-0.00368	-0.000209		0.0260	0.0330***
	(0.969)	(0.438)	(0.943)		(0.208)	(0.001)
L12.imp_A_F	0.00447	-0.00111	0.00302		0.0106	0.0271**
	(0.335)	(0.821)	(0.317)		(0.670)	(0.021)
imp_A_S	0.0186	-0.0187	-0.000135	0.0144		-0.0380
	(0.201)	(0.168)	(0.987)	(0.148)		(0.451)
L.imp_A_S	0.0594***	-0.00194	-0.00602	-0.00359		-0.0267
	(0.000)	(0.837)	(0.283)	(0.677)		(0.240)
L2.imp_A_S	0.0500***	-0.00824	-0.0132**	0.0169		-0.0308
	(0.001)	(0.387)	(0.020)	(0.246)		(0.414)
L3.imp_A_S	0.0422***	-0.0144	-0.0139**	-0.00601	-0.476	-0.0368
	(0.005)	(0.136)	(0.015)	(0.457)	(0.842)	(0.203)
L4.imp_A_S	0.0214	-0.0148*	-0.0135**	0.0141		-0.0311
	(0.160)	(0.098)	(0.011)	(0.341)		(0.404)
L5.imp_A_S	0.0211	-0.00294	-0.00976*	-0.00894		-0.0311
	(0.163)	(0.737)	(0.053)	(0.237)		(0.280)
L6.imp_A_S	0.0211	-0.00562	-0.0104**	0.0142		-0.0249
	(0.160)	(0.522)	(0.040)	(0.349)		(0.508)
L7.imp_A_S	0.0301**	-0.00668	-0.0119**	-0.0104		-0.0272
	(0.041)	(0.446)	(0.020)	(0.135)		(0.343)
L8.imp_A_S	0.0272*	-0.0433			0.592	-0.0259
	(0.060)	(0.526)			(0.730)	(0.507)
L9.imp_A_S	0.0309**	-0.0139			0.617	-0.0288
	(0.033)	(0.839)			(0.719)	(0.315)

L10.imp_A_S	0.0116	-0.0196		0.0183	0.0245	0.0623
	(0.433)	(0.773)		(0.291)	(0.788)	(0.444)
L11.imp_A_S	0.0448***	-0.0626	-0.340	-0.00320	0.0206	0.00120
	(0.006)	(0.418)	(0.256)	(0.607)	(0.822)	(0.922)
L12.imp_A_S	0.0324*	-0.00804	-0.695**		0.0514	-0.00314
	(0.074)	(0.917)	(0.021)		(0.574)	(0.910)
exp_A_D	-0.0120	-0.0341	-0.0216**			0.0321*
	(0.239)	(0.119)	(0.017)			(0.053)
L.exp_A_D	-0.0114	-0.0363*	-0.0104			0.177
	(0.275)	(0.098)	(0.245)			(0.407)
L2.exp_A_D	-0.00181	-0.0369*	-0.000654			0.0676
	(0.863)	(0.095)	(0.942)			(0.313)
L3.exp_A_D	-0.00493	-0.0312	0.00332			0.0649
	(0.651)	(0.158)	(0.713)			(0.326)
L4.exp_A_D	-0.00794	-0.0343	0.00301			-0.0396
	(0.460)	(0.117)	(0.736)			(0.453)
L5.exp_A_D	-0.00813	-0.0339	0.00462			-0.0606
	(0.446)	(0.122)	(0.605)			(0.249)
L6.exp_A_D	-0.00578	-0.0270	0.00534			-0.0463
	(0.622)	(0.223)	(0.569)			(0.365)
L7.exp_A_D	-0.00165	-0.00638	0.00649			-0.00642
	(0.890)	(0.740)	(0.464)			(0.900)
L8.exp_A_D	-0.00334	0.00240	-0.00153			0.0159
	(0.775)	(0.867)	(0.843)			(0.750)
L9.exp_A_D	0.0120	0.00449	0.00523			0.0269
	(0.246)	(0.764)	(0.500)			(0.576)
L10.exp_A_D	0.0151	0.000913	0.000426			-0.00692
	(0.142)	(0.951)	(0.956)			(0.884)
L11.exp_A_D	0.0134	-0.00221	-0.00438			0.00248
	(0.187)	(0.882)	(0.569)			(0.944)
L12.exp_A_D	0.00226	0.00272	-0.00356			-0.00130
	(0.825)	(0.858)	(0.650)			(0.970)
exp_A_F	-0.00290	-0.00213	-0.00145	-0.00200	-0.0141	0.00800
	(0.501)	(0.689)	(0.681)	(0.881)	(0.579)	(0.538)
L.exp_A_F	-0.00193	-0.00185	0.00129	0.0436**	0.00688	0.0351*
	(0.655)	(0.725)	(0.712)	(0.043)	(0.773)	(0.064)
L2.exp_A_F	-0.00270	0.00275	0.00200	0.0359	0.0206	0.0695***
	(0.521)	(0.602)	(0.569)	(0.107)	(0.229)	(0.001)
L3.exp_A_F	-0.000203	0.00251	0.00535	0.00943	-0.00578	0.117***
	(0.961)	(0.633)	(0.122)	(0.631)	(0.819)	(0.000)
L4.exp_A_F	0.000974	0.00301	0.00585*	-0.00329	0.0207	0.0954***
	(0.815)	(0.575)	(0.099)	(0.834)	(0.384)	(0.000)
L5.exp_A_F	-0.000615	0.00575	0.00439	-0.000886	0.0128	0.114***
	(0.886)	(0.305)	(0.247)	(0.951)	(0.584)	(0.000)
L6.exp_A_F	0.000708	0.00329	0.00270	0.00155	-0.0121	0.126***
	(0.865)	(0.544)	(0.445)	(0.896)	(0.400)	(0.000)
L7.exp_A_F	0.000592	0.00283	0.00385		0.00509	0.135***

	(0.886)	(0.555)	(0.222)		(0.718)	(0.000)
L8.exp_A_F	0.00112	0.000674	0.00373		-0.00906	0.139***
	(0.785)	(0.886)	(0.217)		(0.515)	(0.000)
L9.exp_A_F	0.00103	0.000400	0.000249		-0.00416	0.138***
	(0.809)	(0.935)	(0.938)		(0.799)	(0.000)
L10.exp_A_F	0.00500	0.000543	0.000635		0.0124	0.133***
	(0.245)	(0.910)	(0.843)		(0.426)	(0.000)
L11.exp_A_F	0.00513	-0.00231	0.00218		-0.00831	0.106***
	(0.232)	(0.621)	(0.474)		(0.640)	(0.000)
L12.exp_A_F	0.00229	-0.00351	0.00562*		-0.0172	0.0661***
	(0.611)	(0.466)	(0.070)		(0.280)	(0.001)
exp_A_S	-0.0158	-0.0461	-0.00366			0.0289
	(0.360)	(0.204)	(0.864)			(0.732)
L.exp_A_S	0.00645					0.0177
	(0.709)					(0.784)
L2.exp_A_S	-0.0124					0.0399
	(0.474)					(0.613)
L3.exp_A_S	-0.00995					0.0362
	(0.554)					(0.642)
L4.exp_A_S	-0.0136					0.0412
	(0.413)					(0.642)
L5.exp_A_S	-0.0146					0.0142
	(0.377)					(0.859)
L6.exp_A_S	-0.00740					-0.00257
	(0.654)					(0.974)
L7.exp_A_S	0.00431					0.0239
	(0.794)					(0.756)
L8.exp_A_S	0.00875					0.0173
	(0.538)					(0.806)
L9.exp_A_S	0.00821					0.0244
	(0.562)					(0.749)
L10.exp_A_S	0.00881					-0.202
	(0.527)					(0.398)
L11.exp_A_S	0.0191	-0.0104		-0.00278		-0.0461
	(0.176)	(0.572)		(0.853)		(0.355)
L12.exp_A_S	0.0180	0.00327			-0.0139	0.0150
	(0.205)	(0.859)			(0.742)	(0.842)
L13.logpop	0.229	0.778**	-0.0702	0.120	-0.366	1.361
	(0.328)	(0.049)	(0.761)	(0.830)	(0.725)	(0.176)
Constant	-3.691	-13.33**	1.195	-11.07	8.840	-60.84**
	(0.313)	(0.030)	(0.741)	(0.369)	(0.756)	(0.018)
N	902	531	495	92	180	203
r2	0.665	0.589	0.866	0.958	0.605	0.882
aic	-1910.9	-1178.4	-1596.3	-417.8	-374.1	-586.0
bic	-1228.6	-614.1	-1062.3	-256.4	-93.07	-152.0

p-values in parentheses
* p<0.10, ** p<0.05, *** p<0.010