WORKING paper

BANQUE DE FRANCE
EUROSYSTÈME

Decomposing the Inflation Response to Weather-Related Disasters[1]

Erwan Gautier, Christoph Grosse-Steffen, Magali Marx & Paul Vertier[2]

December 2023, WP #935

Abstract

This paper provides empirical evidence on the compositional effect of weather-related disasters on consumer prices. We combine data on monthly granular inflation for 12 CPI product categories with data on extreme weather events for four French overseas territories sporadically hit by large weather-related disasters. We find that disasters lead to a maximum rise in consumer prices of 0.5 percent with substantial heterogeneity in the price response. An immediate strong surge in the prices of food, and notably of fresh products, is partially offset by a decline in the prices of manufactured products and services. The effects of weather-related disasters dissipate after four months and differ along the income distribution, notably raising inflation for low-income households by more. Price controls dampen the price response on impact, but lead to similar adjustments in the price level after six months.

Keywords: Natural Disasters; Extreme Weather; Inflation; Disaggregate Inflation; Inequality; Price Gouging

JEL classification: E31, Q54

[1] We would like to thank Eric Strobl for an excellent discussion, and seminar participants at Toulouse School of Economics, University of Marseille, EEA-ESEM Congress 2023, T2M Conference 2023, Banque de France and IEDOM (Institut d'Emission des Départements d'Outre-Mer) for useful comments and suggestions.The views expressed in this paper are those of the authors and do not necessarily represent those of the Banque de France or the Eurosystem.

[2] Banque de France, erwan.gautier@banque-france.fr, christoph.grossesteffen@banque-france.fr, magali.marx@banque-france.fr, paul.vertier@banque-france.fr

NON-TECHNICAL SUMMARY

How do weather-related disasters affect consumer prices? In times when central banks consider climate risks in their operational frameworks, this becomes a relevant monetary policy question. The existing empirical literature has focused mostly on the aggregate price effect. However, natural disasters are a complex mix of supply disruptions driving up prices in the short run, combined with a shock to the composition of aggregate demand, with differing effects in sign and magnitude across types of goods and services. Aggregate price effects of natural disasters will depend on the relative strength of these supply and demand effects over time.

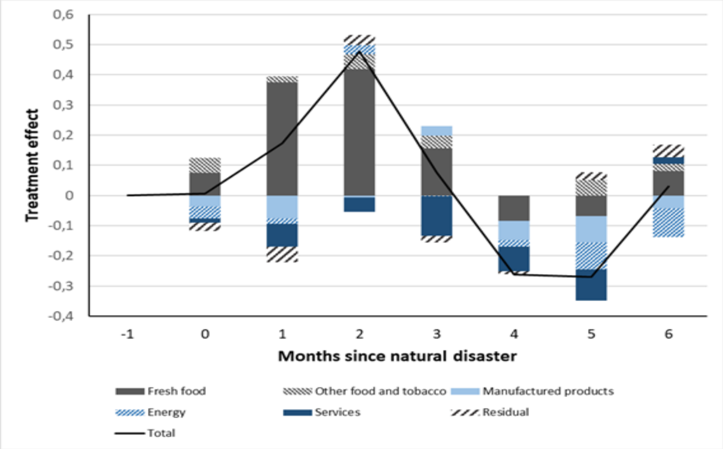
This paper documents how prices of granular CPI product categories respond to weather-related natural disasters. We focus our empirical analysis on prices in four French overseas territories (DCOM, *Départements et Collectivités d'Outre-Mer*), which are regularly exposed to significant weather-related disasters and located in different places of the world. For each of these small territories, the French statistical office (Insee) produces harmonized price indices at a disaggregate product level and available at a monthly frequency between 1999 and 2018. We identify weather-related disasters by combining administrative and meteorological data sets. While administrative databases detect disasters with significant economic consequences, they may suffer from different reporting biases: for instance, the probability to declare the state of emergency is positively correlated with the insurance coverage in the community, and the intensity of natural disasters reported in news-driven and insurance-based data is correlated with GDP per capita. Conversely, an approach only relying on the intensity of meteorological data imperfectly takes into account the heterogeneity in regional vulnerabilities. Overall, these data limitations to measure economic consequences of natural disasters are likely to generate both attenuation biases and omitted variable biases. To reduce these biases, we rely on an instrumental variable approach where we use meteorological records of wind speed and rainfall to predict the occurrence of extreme weather events that imply significant economic damage as reported by administrative data. We then measure the impact of these disasters on the evolution of prices for up to six months after the shock, using a local projection method. We compute the price responses at the product and aggregate level.

We find that weather-related disasters induce a temporary but statistically significant rise in headline consumer prices, with a peak at 0.5 percent two months after the disaster occurrence. The overall observed effect is driven by an immediate strong surge in the prices of fresh food products of 11 % after two months, which vanishes after four months. Prices of other food products also increase, but more moderately and in a more sustained manner (+0.3 %). By contrast, the prices of services and manufactured products decline moderately (and in a less statistically significant way), by about -0.2 %. The positive effects on food prices are likely to reflect negative supply shocks, as we observe a simultaneous decrease in agricultural employment. To the contrary, the negative effects on the prices of manufactured products and services are likely to reflect negative demand shocks.Our results point to small and temporary effects on headline inflation, mainly related to distortions of relative prices.

These effects translate into distributional effects through the heterogeneity in household consumption structure. Overall, the weather-related disasters increase temporarily inflation inequality, with a difference of up to 0.2 pp between the bottom and upper quintiles of the household income distribution. The rise in inflation inequality is primarily due to the fact that the weight of food in the consumption basket is higher for low income households.We also analyse the effects of the introduction of price cap policies, namely the *Bouclier Qualité-Prix* introduced in 2013. Price caps lower the impact response of price reactions to weather-related disasters in the sample period. However, cumulated over six months, price reactions are not significantly affected by the introduction of price cap policies, implying that the adjustment in the price level is just spread over the horizon of six months.

Finally, this paper documents the importance of controlling for region-specific seasonality for the unbiased estimation of inflationary effects, which affects both the occurrence of disasters and price variations. This matters in particular, but not only, for fresh-food prices.

Figure: Decomposition of the reaction of total inflation to a weather-related disaster



Note: Decomposition of the cumulative impulse response of headline CPI to a natural disaster in the baseline specification. The contribution of each component is computed as the cumulative response of the CPI of this component times its average weight in the consumer baskets of the four DCOMs between 1999 and 2018. Treatment effects are expressed in percent.

Décomposition de la réponse de l'inflation aux catastrophes météorologiques

RÉSUMÉ

Cet article fournit une quantification de l'effet de composition des catastrophes météorologiques sur les prix à la consommation. Nous combinons des données mensuelles sectorielles d'inflation pour 12 catégories de produits de l'IPC avec des données sur les événements météorologiques extrêmes pour quatre territoires français d'outre-mer sporadiquement touchés par des catastrophes météorologiques. Nous montrons que les catastrophes entraînent une hausse maximale des prix à la consommation de 0,5 %, avec une hétérogénéité significative dans la réaction des prix. Une forte hausse des prix des produits alimentaires, et notamment des produits frais, est partiellement compensée par une baisse des prix des produits manufacturés et des services. Les effets des catastrophes météorologiques se dissipent après quatre mois et diffèrent selon la distribution des revenus, augmentant notamment davantage l'inflation pour les ménages à faible revenu. Les contrôles de prix atténuent la réaction des prix à l'impact, mais conduisent à des ajustements similaires du niveau des prix après six mois.

Mots-clés : catastrophes naturelles ; conditions météorologiques extrêmes ; inflation ; inflation désagrégée ; inégalité ; gonflement des prix

1. Introduction

How do natural disasters affect consumer prices? In times when central banks consider climate risks in their operational frameworks, this becomes a relevant monetary policy question (e.g. Schnabel, 2021). The existing empirical literature has focused mostly on the aggregate price effect. However, natural disasters are a complex combination of supply disruptions driving up prices in the short run, combined with a shock to the composition of aggregate demand, with differing effects in sign and magnitude across types of goods and services. Aggregate price effects of natural disasters will depend on the relative strength of these supply and demand effects over time. This paper documents how prices of granular CPI product categories respond to weather-related natural disasters. The full decomposition across product categories helps to sharpen our understanding of the overall inflation response to extreme weather events, which are projected to become more frequent because of climate change.

We focus our empirical analysis on prices in four French overseas territories, namely Guadeloupe, Martinique, Guyane and La Réunion, which we refer to as DCOM (*Départements et Collectivités d'Outre-Mer*). These data come with two benefits. First, these territories are regularly exposed to significant weather-related disasters and they are located in different places of the world, which allows studying shocks that are de-synchronized across territories. To measure weather-related disasters, our analysis rely on several data sets: two administrative data sets reporting natural disasters at the local level and three sources collecting meteorological records (wind-speed, rainfalls and extreme weather events), Second, for each of these four relatively small territories, we also use highly harmonized price indices produced by the French statistical office (Insee), at a disaggregate product level and available at a monthly frequency over the period 1999-2018. Since these territories are rather small and isolated (three of them are small islands), we can identify precisely the effects of extreme weather events on prices by matching information on natural disasters and product-level price indices for these four territories.

We identify natural disasters induced by extreme weather events by combining both administrative and meteorological data sets in our empirical approach. The ideal measure of natural disasters would report the direct economic damages resulting from a natural disaster due to asset damage and business interruptions. However, in practice, the existing literature usually relies on two sources of data to approximate this ideal measure. One approach is to use administrative databases that detect an event based on *ad hoc* criteria. Administrative databases have the advantage of detecting disasters with significant economic damage with a relatively high accuracy. However, they are also known to be subject to various reporting biases (Felbermayer and Gröschl 2014, Grislain-Letremy 2018), which are likely to generate both attenuation biases and omitted variable biases. Another approach uses meteorological and geophysical data and approximates the severity of the disaster event by the intensity expressed in the quantity of precipitation, wind speed or Richter scale of earthquakes. Unfortunately, this approach only imperfectly predicts hazardous incidents, as events of similar physical amplitude are associated with different levels of destruction depending on regional vulnerabilities.[2] To overcome these empirical issues, we follow a two-step procedure. First, we combine the two types of data sources for French DCOMs: we use the emergency events database (EM-DAT) measuring natural disasters in several countries and regions in the world and a French administrative data set collecting local information on natural disasters (*Gestion Assistée des Procédures Administratives relatives aux Risques*, or GASPAR). In a second step, we use meteorological records as reported by weather stations, as collected by remote sensing systems based on satellites, and extreme weather events as reported by the French national weather service (Météo-France). We rely on an instrumental variable approach where we use this meteorological information as an instrument for the occurrence of events reported by administrative data. Doing so, we select economic disasters that we can directly connect to extreme meteorological events. To assess the inflation effects of natural disasters, we then relate the economic disasters as predicted by the first-step equation to the evolution of prices for different time horizons after the shock using a local projection method *à la* Jordà (2005). We are thus able to derive the price response both at the product level for different product categories and at the aggregate level following a given natural disaster shock.

Our main results are the following. First, we find that weather-related disasters induce a temporary but statistically significant rise in headline consumer prices, with a peak at 0.5 percent two months after the disaster occurrence. The overall observed effect is driven by an immediate strong surge in the prices of fresh food products of 11 % after two months, which vanishes after four months. Prices of other food products also increase, but more moderately and in a more sustained manner (+0.3 %). This positive inflation effect coincides with a negative impact of natural disasters on agricultural employment, pointing to a negative supply shock with a displacement of labour supply from agricultural sector to other low-skilled occupations (as also found by Kirchberger, 2017).[3] Our

[2] The extent of economic damages is affected by geological features such as the shape of the continental shelf or coast (Bertinelli and Strobl, 2013) or land use in the affected area. Damage from an incident of similar geophysical strengths can be dampened through adaptation measures, which themselves are a function of a number of determinants such as the ex-ante exposure to risks (Schumacher and Strobl 2011), the quality of institutions (Kahn 2005), and economic development (Felbermayer and Gröschl 2014).

[3] We do not find other evidence of effects on employment for other sectors, except for a negative effect in the construction sector.

findings on food products are consistent with the response of retail prices following typhoons in China. Bao, Sun and Li (2022) document that fresh products are driving the overall response in food prices, in particular vegetables.

By contrast, the prices of services and manufactured products decline moderately (and in a less statistically significant way), by about -0.2 %. Overall, our results point to small and temporary effects on headline inflation, mainly related to distortions of relative prices. Finally, we show that results obtained using a damage function approach relying only on meteorological data are in line with the ones we can obtain using an IV approach.

We also find distributional effects from natural disasters across income groups. To measure these distributional effects, we first measure household-specific consumption structure for different income groups relying on household survey data and then using these weights by income group, we aggregate the product-level price responses to natural disasters to obtain heterogeneous price responses by income group (Hobijn and Lagakos 2005, Hobijn et al 2009). Since the effect on fresh food prices is positive and much stronger than any other product category, the effect on total inflation strongly depends on the share of fresh food in the consumption basket. We find that the upward effect on headline prices after two months is of 0.6 percent in the bottom quintile of the income distribution, i.e. 0.1 pp above the average effect. The upper quintile, in contrast, experiences a rise in consumer prices of 0.4 percent, i.e. 0.1 pp below the average effect. Overall, the natural disasters have a positive effect on inflation inequality across income groups, but this impact is only transitory.

We also document that public policies limiting price gouging have an effect on the shape of the price response: after the implementation of a price cap on a set of first necessity goods in 2013 (*Bouclier Qualité-Prix,* BQP), the increase of fresh products prices following a natural disaster was much smaller in magnitude. The stronger reaction of prices before the BQP points towards the existence of price gouging in the absence of regulation. However, consistently with a large literature we find that price gouging is unlikely to explain all of the observed effect. Indeed, after six months, the cumulated price response before and after the BQP are close (as price increases after the BQP are more persistent), suggesting that even in the presence of regulation, retailers increase their prices after a natural disaster but in a more staggered way in presence of price cap policies.[4]

Our main contribution to the existing literature is twofold.

[4] See also the large literature on price gouging during crises, which generally finds limited effects (Cabral and Xu, 2021, Beatty et al., 2021, Gagnon and Lopez-Salido, 2020; Neilson, 2009; Culpepper and Block, 2008).

First, the rather small aggregate effects of weather-related natural disasters on headline inflation can be the result of quite heterogeneous price responses across products. Parker (2018) and Kabundi et al. (2023) have probably provided the most comprehensive analysis on the effect of natural disasters on inflation. In both papers, the authors use data from the international disaster database EM-DAT and relate these events to CPI inflation covering about 200 countries. These two studies find strong heterogeneity in the impact of disasters on inflation across disaster types and the country-level of development. They also both emphasize the specific effect of natural disasters on food product inflation. Our contribution is a focus on small territories frequently exposed to extreme weather events and for which we can estimate precisely the price response to natural disasters for all product categories of CPI inflation. Focusing on smaller territories as well, Heinen et al. (2018) estimate the impact of hurricanes and floods on prices on Caribbean islands. They inspect total headline CPI and three sub-categories, namely food, housing and utilities, and all other items. Their baseline result is an inflationary effect of disasters, lasting for one month in response to floods and two months in response to storms. In line with our findings, food prices is the sub-component that reacts most strongly to disasters. However, no offsetting effects are observed in product sub-categories, possibly due to the still high level of aggregation of the category 'other goods'. Our contribution is to provide a fully exhaustive and detailed analysis of compositional effects (as our data contain information on both indices and weights of different components of headline CPI), at a more granular level (as our data cover 12 types of goods and services). A highly balanced panel allows us to interpret our findings as compositional effects of headline inflation, and the availability of weights helps us to decompose product by product the effect on headline CPI. Finally, integrating specific sectoral economic dynamics enables us to provide plausible narratives for shifts in sectoral supply and demand, which is not frequently discussed in the existing literature.

Our second contribution to the existing literature is more methodological on the way we identify weather-related disasters. Most of the existing literature measuring the price effects of weather related disasters relies on either administrative data or on meteorological records. Both sources have pros and cons. When relying on administrative data sets like EM-DAT or the French administrative data set GASPAR, the treatment of natural disasters as exogenous is problematic, as these data sources are subject to reporting biases (Felbermayer and Gröschl 2014). Another approach consists of using meteorological and geophysical data only. Heinen et al. (2018) build a damage function, which is a complex non-linear combination of meteorological records to estimate the economic damages caused by extreme weather events and then related this damage function to prices. However, this method is more prone to specification errors since it depends on thresholds above which wind and rain generate physical damages (sometimes based on laboratory simulations or calibrated on specific economies) and more generally, on the assumption that the economic damages generated by extreme meteorological records are not linear in wind speed and rainfalls (Emanuel, 2011). However, in a context in which countries adapt to the consequences of climate change, the relationship between meteorological records and economic damages might not only differ across economies, but also evolve over time. Since we rely on both types of data, we propose in this paper a new methodological approach where we instrument the occurrence of administrative events using meteorological records, in particular taking into account non-linear effects of meteorological records in the first stage. It allows us to identify natural disasters due to extreme events that do not suffer the reporting bias. We further compare the results obtained with the different methodologies and find that using administrative data only in a simple OLS framework tends to underestimate the price effects of extreme weather events. Using a damage function with meteorological records leads to consistent results but requires assuming specific thresholds regarding the relationship between the physical intensity of economic destructions and meteorological data (Auffhammer 2018, Kolstad and Moore 2020).

Finally, we also document new results regarding the treatment of seasonal effects when estimating the effect of weather-related disasters on prices. Most empirical contributions evaluating the impact of natural disasters on inflation control for average time-specific fixed effect but do not take into account for the fact that the seasonality of extreme weather events can vary across territories, and can be correlated with the inflation seasonality. This is in particular a concern for products locally produced. In our baseline methodology, we include month-year fixed effects (controlling for common DCOMs shocks) but also monthly dummies, which are specific to each DCOM. We therefore capture the “surprise” component of extreme wind and rainfall compared to usual seasonal patterns, which is likely to be particularly important in a context in which the frequency and timing of extreme weather events is evolving due to climate change. We show that the treatment of seasonality can affect significantly the estimated response of prices to natural disasters and we argue that a region-specific treatment of seasonality is crucial to identify precisely the price response.

The paper also relates to the literature studying the consequences of natural disasters for inflation dynamics. Cavallo et al. (2014) and Doyle and Noy (2015) analyze the reaction of prices to large earthquakes in the form of event studies. Parker (2018) and Kabundi et al. (2023) use a variety of natural disasters, ranging from geophysical events to extreme weather events, distinguishing the intensive margin of disaster-types on prices. A few papers study only weather-related disasters, as we do. One specific strand of papers focuses on temperature variations (Faccia et al. 2021, Ciccarelli et al. 2023, Kotz et al. 2023). Finally, our findings closely relate to papers focusing on inflation dynamics of fresh food items in response to wind storms in China (Bao, Sun and Li 2022) and the study by Heinen et al. (2018) discussed in detail above.

The paper is structured as follows. Section 2 describes the data and the estimation strategy. Section 3 describes the estimation results. Section 4 describes distributional effects. Section 5 presents robustness checks. Section 6 concludes.

2. Data on inflation and weather-related disasters in French overseas territories

In this section, we describe how we combine detailed information on natural disasters and prices for French overseas territories, for the period January 1999 to April 2018.

2.1 Product-level inflation data

We use the Consumer Price Index produced at a monthly frequency by Insee for each of the four French DCOMs. In France, there is no regional price index available. French overseas territories are the only subnational regions for which price indices are specifically calculated using price quotes collected in each overseas territory. These consumer price indices have been computed since 1967 in Guadeloupe, Martinique and La Réunion, and since 1969 in Guyane. The methodology used to compute them is similar to that of the metropolitan CPI since 1993 and is part of the CPI for France since 1998. Price indices are published at a monthly frequency at a granular level for 12 CPI components, along with their annual weight in the consumption basket. Table A.1 in the Appendix displays the summary statistics of price indices used.

There are some specificities of consumer prices in DCOMs, where prices are set in a distinctive manner compared to the metropolitan territory. First, price levels are generally higher in DCOMs, notably because of food prices, and the price gap remained broadly constant between 1985 and 2010 (Berthier et al. 2010). Second, as documented in Table A.2 in Appendix, even though inflation in DCOMs is significantly correlated with inflation in the metropolitan area[5], this

[5] Several factors can explain this positive correlation. First, the consumption structure of DCOMs converged progressively to that of the metropolis (with a decrease in food consumption and an increase in services consumption), partly reflecting a catch-up policy linked to the *départementalisation* of these four territories (i.e. their transformation into French *départements* starting from 1946). Second, price-setting mechanisms are to a large extent jointly determined between DCOMs and the metropolis: the minimum wage in DCOMs is aligned with that of the metropolis since 1996, public compensations are identical (albeit with a premium compensating for the distance to the metropolis), and so are quality norms and rent setting mechanisms.

correlation is lower for food inflation (Hugounenq and Chauvin 2006), and especially for fresh products.

Second, the heterogeneous correlation of CPIs between metropolitan France and the DCOMs is likely to reflect heterogeneous trade prevalence across types of goods and services. Indeed, according to Hugounenq and Chauvin (2006) about 45 percent of DCOMs' final household consumption was imported in 1999 (of which 60 percent came from the metropolis). The share of imported goods was as high as 70 percent for manufactured products and 90 percent for durables and fuels. In stark contrast, the food sector depends much more on local production. In 1995, between 55 and 63 percent of food needs were covered by local products. In general, coverage ratios are higher for fresh products than for *all food* products (combining fresh and processed food), reflecting a higher prevalence of imports for processed food.[6]

Third, DCOMs benefit from specific fiscal schemes to compensate for their distance with the metropolis: VAT is lower and a specific tax on imported products (*octroi de mer*), protects local production against external competition. Tobacco and petroleum products are also taxed differentially in the DCOMs and in the metropolis: no VAT is imposed on petroleum products, and taxes on tobacco are decided by local authorities. Furthermore, prices of petroleum products are set by local authorities.

2.2 Weather-related disasters data

This section presents the data sources on natural disasters and extreme weather events.

2.2.1 Administrative databases for natural disasters

In this paper, we use two different data sets collecting administrative information on economic losses due to natural events.

First, we use a French administrative dataset collecting information about the assisted management of administrative procedures related to risks (*Gestion Assistée des Procédures Administratives relatives aux Risques*, or GASPAR), assembled by the French Ministry of Ecological Transition. This dataset lists all natural disasters by municipality since 1990. In this data set, a disaster refers to the declaration by the French government of a state of "natural disaster", after the consultation of an inter-ministerial commission. Importantly, the declaration of state of natural disaster conditions the eligibility of households to an insurance compensation. The GASPAR dataset contains various

[6] Table A.3 in Appendix A reports coverage ratios based on data from the *Observatoire des économies agricoles ultramarines*.

information, such as the starting date and the ending date of the event, the code of the municipality, the localization, and the label of the risk. In this setting, we identify as natural disasters events that include labels floods, tropical storms or cyclones.[7] By aggregation of daily information, we build a monthly indicator variable per oversea territory. In the empirical analysis, we consider the month of the natural disaster corresponding to the beginning date of the disaster.

We complement this data with information coming from the international disaster database EM-DAT, a database produced by the Center for Research on the Epidemiology of Disasters (CRED) with a global coverage. The events recorded in the database are aggregated from several sources, namely insurance companies, UN agencies, NGOs, research institutes and press agencies. Events recorded in EM-DAT must respect at least one of three criteria: (i) 10 or more people killed, (ii) 100 or more people affected/injured/homeless, (iii) declaration by the country of a state of emergency and/or an appeal for international assistance. Only disasters of type 'storm' and 'flood' are considered here, from which we obtain monthly indicator variable per oversea territory if there was at least one natural disaster reported during a month.

Combining these two data sets, we have full information on natural disasters hitting one of the four French oversea territories DCOM as reported by administrative authorities. Table A.7 in the Appendix documents that most of the events in EM-DAT are also reported by in GASPAR, but a smaller proportion of GASPAR events are reported in EM-DATA. This latter observation is due to the fact that GASPAR reports a significantly higher total number of events, which are as a result associated with lower intensity of economic losses.

Both data sources have well-documented reporting biases. A heterogeneous insurance pattern across French oversea territories likely leads to misreporting in the GASPAR database due to a charity hazard. Grislain-Letrémy (2018) shows that the probability that local authorities declare the state of emergency depends on the insurance coverage of households in their community. If this coverage is large, authorities have an incentive to declare an emergency, a pre-requisite in French law for insurance payouts. If the coverage is low, however, local communities might be better off by calling for direct financial assistance from the French government. This imposes a misreporting bias into the GASPAR database. For EM-DAT, Felbermayr and Gröschl (2014) find a different bias. They conclude that news-driven and insurance-based data sets generally pose the problem of

[7] These types of events include tropical phenomena, storms, cyclones, damages due to waves or tidal waves, floods. A natural disaster can combine several events of this type at the same time. The events we focus on notably excludes volcanic eruptions, damages due to lava, landslides, earthquakes, snow storms and avalanches, which are also reported in GASPAR.

selection bias and a correlation of intensity measures with error terms in growth regressions. Such a selection bias would also most likely affect our results on inflation responses.

To overcome these potential biases, we complement our data sets on natural disasters with data on meteorological records. This will allow using an IV approach where natural disaster events are instrumented by extreme weather events (see the empirical specification below).

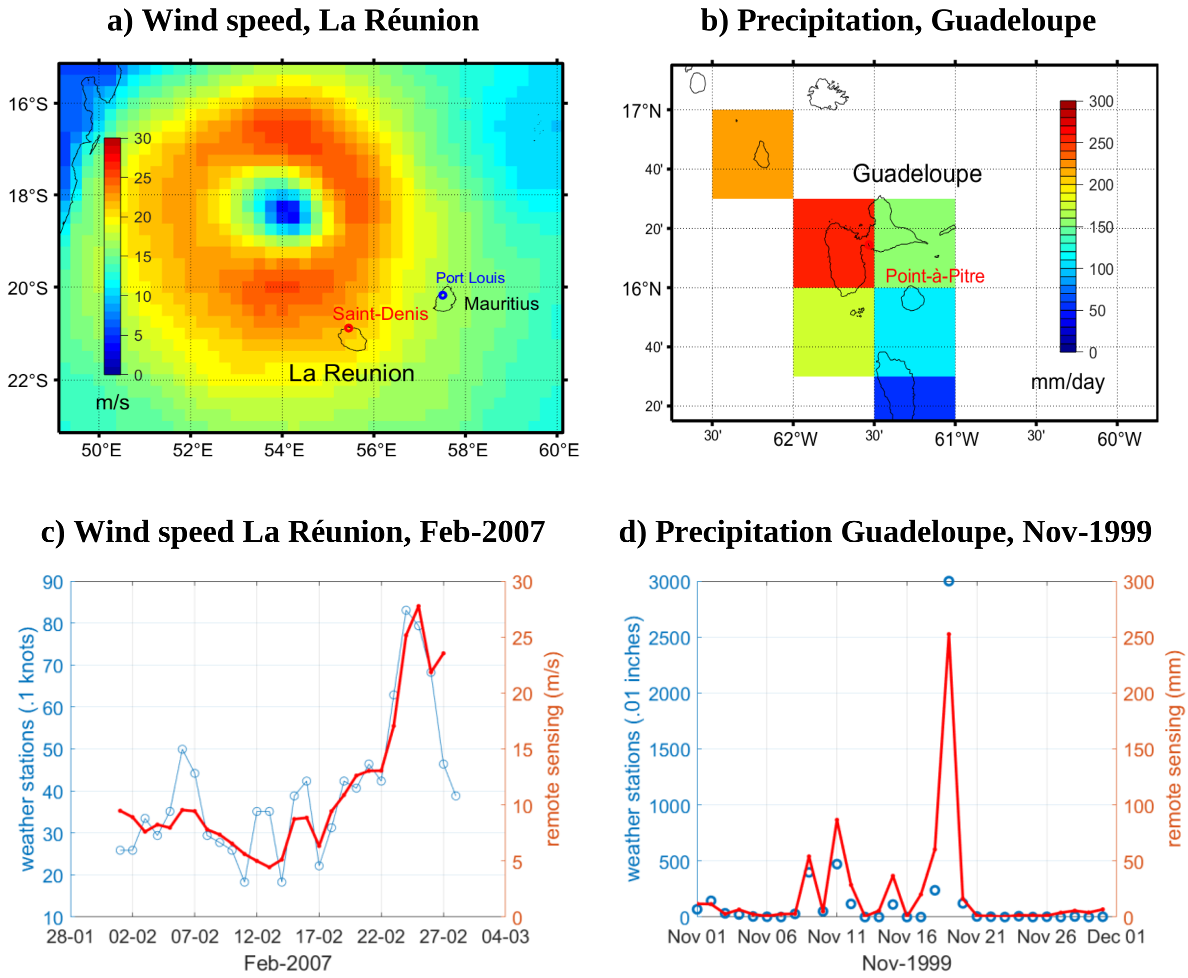
2.2.2 Meteorological records

We use three types of meteorological information: meteorological records as (i) reported by weather stations, or (ii) collected by remote sensing systems based on satellites, and (iii) extreme weather events as reported by the French national weather service (Météo-France).

Meteorological records from weather stations are obtained from the *Global Surface Summary of the Day* (GSOD), a database derived from the Integrated Surface Hourly dataset. This source provides data for over 9,000 stations around the world beginning in 1929, of which two to three match to each of the regions in our analysis (see Figure A.2 in the Appendix). Each weather station provides data on precipitation in 0.01 inches in cumulative terms per day and the maximum wind speed measured for one minute during the day in tenths of knots.

We combine these data with meteorological records obtained via remote sensing. Wind speed is taken from the NOAA's *Cross-Calibrated Multi-Platform* (CCMP) wind vector analysis that allows computing wind speed over the ocean surface in meters per second. Each vector summarizes the average wind speed in a cell of 0.25 degrees of latitude longitude coordinates within a 6 hours interval. Figure 1a provides an illustration of the data for the case of cyclone "Gamède" passing La Réunion in February 2007. Precipitation data is taken from the NOAA's *Climate Prediction Center* (CPC) database, which provides daily cumulative precipitation in millimeters per square meter at a resolution of 0.5 degrees of latitude longitude coordinates. Figure 1b illustrates an episode of extreme precipitation on Guadeloupe in November 1999 (see also Figures A.3 and A.4 in the Appendix). The data within each cell/day-observation or station/day-observation are aggregated to a region-month observation x_{it} using the maximum daily precipitation and wind speed observation, or $x_{it} = \max[x_{i1}, x_{i2}, \dots, x_{iN}]$, where *N* denotes the last day or the last 6 hour interval of month *t* in region *i*.

Figure 1. Data from remote sensing

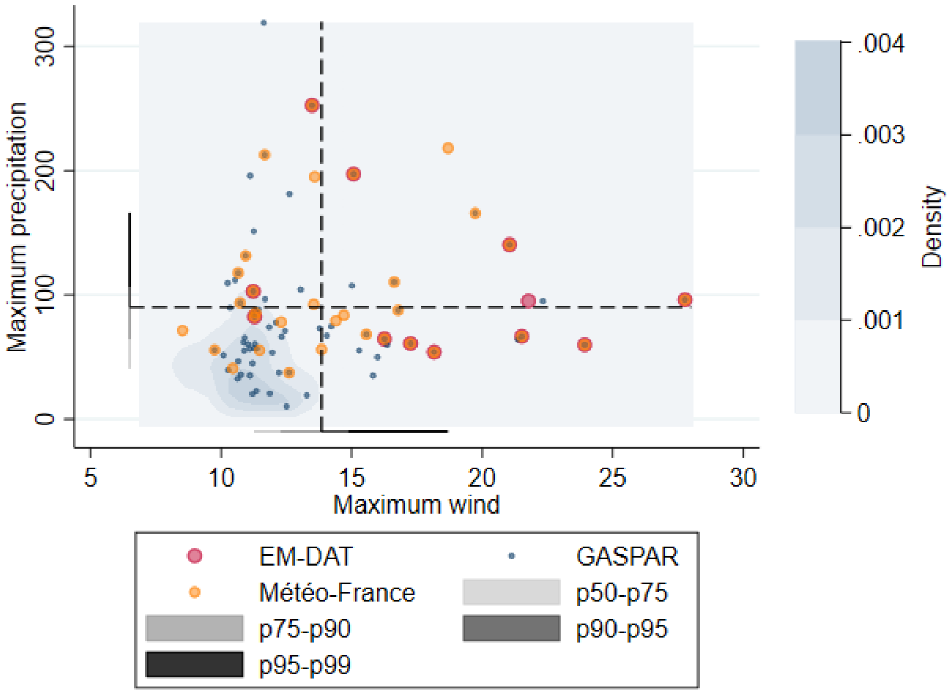


Note: Panel a) Wind speed via remote sensing from the NCAR Cross-Calibrated Multi-Platform (CCMP), measured on a 0.25-degree grid in meters per second on a range from 0 to 30. The panel shows the maximum average wind speed in a 6h interval on La Réunion in the sample, which amounts to 27.76 m/s on 2007-Feb-25 (12AM) when cyclone "Gamède" passed the island. Panel b) Precipitation via remote sensing is taken from the NOAA Climate Prediction Center (CPC), measured on a 0.5-degree grid in millimeters per day. The panel shows the maximum daily precipitation on Guadeloupe in the sample, which amounts to 252.59 mm on 19.11.1999. Panel c) Wind speed records from remote sensing are plotted alongside maximum for 1 minute sustained wind speed from weather stations as documented in the Global Surface Summary of the Day (GSOD) database in .1 knots. Panel d) Precipitation records from remote sensing are plotted alongside precipitation from weather stations as documented in GSOD in .01 inches.

Compared to weather stations data, remote sensing data has the advantage of providing an almost full coverage with relatively long historical data. However, the remote sensing data is also less reliable for extreme events, e.g. high wind speed (>15m/s). Table A.9 in the Appendix reports summary statistics calculated using the two different sources: overall, remote sensing data report lower precipitation levels than weather stations, and exhibit a lower variability. The opposite is true for wind speed data: remote sensing data reports higher wind speed and higher variability compared to weather stations. However, despite the different scales of remote sensing and weather stations data, a direct comparison of records obtained through the wind speed event on La Réunion in February 2007 (Figure 1c) and for rainfall in Guadeloupe during November 1999 (Fig. 1d) shows that both measures detect the same day as an extreme event. Both types of records indicate that La Réunion is the region with the highest average measure of wind speed, and that Guyane is the region with the highest average measure of rainfall.

Lastly, we combine this continuous weather data with a dummy variable for all extreme weather events identified by the French national weather service ("Météo France"), which lists 32 extreme meteorological events. 31 percent of events are located in Martinique, 25 percent in Guadeloupe, 25 percent in La Réunion and 19 percent in Guyane (see Table A.10 in the Appendix).

Figure 2. Administrative shocks and joint distribution of precipitation and wind speed



Note: Events from EM-DAT, GASPAR and Météo France are illustrated as discrete events and plotted against the distributions of physical intensity of wind speed in meters/second from CCMP (x-axis) and rainfall in cumulative millimeters per day from CPC (y-axis). Dotted lines represent the median value of wind speed and precipitation across all four regions.

Figure 2 illustrates the correlation between administrative disaster data and physical intensity of rainfall and wind. Specifically, it displays the occurrences of administrative events against the joint distribution of maximum monthly precipitation and wind speed, for data from remote sensing. Comparing discrete events with physical intensity of wind and precipitation, it appears that a large number of events are located in the upper parts of the distribution. More specifically, EM-DAT and Météo France events are almost systematically located above the median of either wind or precipitation records, and most of them are in the top quartile. To the contrary, GASPAR events are mainly located in the center of the distribution. This reveals one of the main difficulties for empirical economic analysis of extreme weather events, which is rooted in the imperfect correlation between physical intensity of a meteorological event and economic damages. [8]

This suggests that events in the EM-DAT data set are related to natural disasters with significant physical intensity, while this is not necessarily the case for many events from the GASPAR data set.

3. Empirical strategy

In this section, we describe our baseline empirical methodology to relate price dynamics to weather-related disasters due to extreme events and incurring significant economic damages. We proceed in two steps. First, we relate economic disasters as reported by administrative data to meteorological data, which helps to select economic disasters that we can directly connect to extreme meteorological events. In a second step, we relate prices to these events using a local projection method to estimate the effect of natural disasters on inflation dynamics.

3.1 First-stage regression

When we relate inflation to weather-related disasters as measured from administrative datasets, our estimates could eventually suffer from two types of biases. First, an attenuation bias can arise: for instance if some natural disasters are reported while there is no substantial economic damage, or no underlying extreme meteorological event. Similarly, an omitted variable bias is also possible if reporting biases are systematic. Furthermore, the use of dummy variables alone does not allow a direct interpretation of the effects with respect to the intensity of the natural disasters. In our baseline empirical approach, we therefore instrument our weather-related disaster events using meteorological data as exogenous shocks. The implicit assumption is that the intensity of rainfalls or wind speed is correlated with economic damages incurred by meteorological events, but these weather-related extreme events affect prices only through the economic damages they create.

[8] This discussion also helps to distinguish between weather and climate. Following the literature, we would refer to climate as moments of the distribution underlying longer periods of realizations of weather data. Our focus is on extreme weather realizations in the tails of the distribution of precipitation and wind speed data recovered via remote sensing techniques, and not in effects of changes in the moment of this distribution, see e.g. Dell et al. (2012) for the latter.

In a first step, we regress our binary variable of administrative natural disasters $\omega_{i,t}$ on meteorological data $X_{i,t}$ for DCOM i at date t (year-month) using the following specification:

$$\omega_{i,t} = \alpha + \beta X_{i,t} + \delta_t + \mu_m + \gamma_i + \mu_m \times \gamma_i + \varepsilon_{i,t} \qquad (1)$$

where γ_i is a DCOM fixed effect, δ_t is a time (year-month) fixed effect, μ_m is a calendar month fixed effect. The motive for interacting regional fixed effects with a monthly dummy is that seasonality of weather shocks can differ across DCOMs.

Table 1. First stage: Regressing administrative disasters on meteorological data

	Remote sensing data				Weather stations data			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Wind	**0.026***** **(3.53)**	0.009 (0.30)	-0.047 (0.41)	-0.014 (0.43)	0.011 (0.69)	0.025 (0.38)	0.198 (0.65)	0.031 (0.42)
Rain	**0.002***** **(4.28)**	0.002* (1.90)	0.002* (1.74)	0.002** (2.28)	0.001*** (4.32)	0.000 (1.06)	0.001 (1.30)	0.001** (2.07)
Wind^2		0.001 (0.51)	0.004 (0.57)	0.002* (1.66)		-0.002 (0.21)	-0.062 (0.61)	0.000 (0.04)
Rain^2		0.000 (0.26)	-0.000 (0.65)	0.000 (0.45)		0.000 (1.16)	-0.000 (0.58)	0.000 (1.07)
Wind^3			-0.000 (0.49)				0.006 (0.61)	
Rain^3			0.000 (0.80)				0.000 (0.90)	
Météo France event	**0.426***** **(5.25)**	0.420*** (5.02)	0.425*** (4.99)		0.485*** (6.18)	0.485*** (6.16)	0.499*** (6.14)	
R^2	**0.35**	0.35	0.35	0.29	0.33	0.33	0.32	0.24
N	**928**	928	928	928	928	928	928	928
F-Stat	**39.68**	23.35	18.96	21.19	29.68	17.55	9.85	14.76

Note: Estimation results for first-stage model (2) with dependent variable all natural disasters reported in EM-DAT and Gaspar as binary variable. All wind speed variables are expressed in m/s and all precipitation variables are expressed in mm. *Wind* in columns 1-4 corresponds to the maximum wind speed from the CCMP database per region and month. *Rain* in columns 1-4 is the maximum of daily precipitation in a region as reported by the Climate Prediction Center (CPC). *Wind* in columns 5-8 corresponds to the monthly maximum of sustained wind speed per region and month from GSOD. *Rain* in columns 5-8 is the maximum of daily precipitation amount per month and region taken from GSOD. *MF* is a dummy variable for a noticeable event reported by the French national meteorological service Météo-France. T-stats are reported in parentheses. Significant at ***0.01, **0.05, *0.10.

Table 1 reports the results of first stage regressions using as exogenous variables meteorological data collected via remote sensing (columns 1 to 4) or data collected via weather stations (columns 5 to 8). In the different regressions, we consider linear (columns 1 and 5), square (columns 2 and 6) and cubic (columns 3 and 7) specifications of wind speed and precipitation. Non-linear terms for wind speed and precipitation are considered since there is evidence that economic damage from wind speed is best captured by a cubic relationship (Emanuel 2011). Note that non-linearity is explicitly taken into account in all our specifications since we include Météo-France events as dummy variables in equation (1). In order to assess the impact of this dummy on the coefficient of remote sensing and weather station, we also present the square specification without including the Météo-France events (columns 4 and 8).

Some novel results emerge from this table. First, all specifications show a very strong first stage relationship, with F-statistics typically above 20 for remote sensing data and above 10 for data from weather stations. Second, overall, remote sensing data appear to have a higher predictive power (with F-statistics and R-squared systematically higher than for weather stations). This is a surprising result, as data from weather stations are known to be more precise for high wind speed and precipitation levels. However, the better coverage in terms of geography of remote sensing data and the uninterrupted availability at daily frequency make more than up for this. When it comes to the prediction of an extreme weather event, the data quality is sufficient, as confirmed by Figure 1c and Figure 1d. Third, in all specifications, dummies for Météo-France events predict strongly and significantly the probability of an economically significant event. Removing dummies for Météo-France, as we do in columns (4) and (8), entails slightly more significant coefficients for non-linear terms (for instance, the square term of wind speed for remote sensing data becomes significant at the 10 % level), but a lower adjusted R^2. Therefore, modeling the non-linearity between meteorological data and economically significant events through the inclusion of Météo-France dummies is favored over the inclusion of non-linear meteorological data.[9]

Based on these results, our preferred specification is the one of column (1) from which we compute fitted values $\widehat{\omega}_{i,t}$. Since the dependent variable is an indicator variable associated with weather-related disaster events with large economic damages, we interpret $\widehat{\omega}_{i,t}$ as the predicted probability of an economically significant natural disaster as a function of meteorological data.[10] A one-standard deviation increase in wind speed (for an average standard deviation across DCOMs of 1.7 meters per second) increases by 4.4 pp the probability of observing a natural disaster according to administrative datasets. Conversely, a one-standard deviation increase in precipitation level (for an average standard deviation across DCOMs of 95.2 mm)

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[9] However, for applications in which the Météo-France data is unavailable, column (4) still highlights that the inclusion of non-linear terms is recommended.

[10] As we are in a linear setting, some predicted probabilities $\widehat{\omega}_{i,t,m}$ lie below zero and above 1, as illustrated by Figure B.1 in Appendix B.

increases by 19.0 pp the probability of observing a natural disaster according to administrative datasets. As a matter of comparison, the average predicted probability of a shock conditional on observing no shock is 3 %, while it is equal to 57 % conditional on observing a shock (the figures are the same if we condition only on GASPAR shocks, but they are respectively 6 % and 86 % if we condition on the occurrence of an EM-DAT shock).

Figure B.1 in Appendix B shows the distribution of predicted probability, and Figures B.2 to B.4 decompose the latter conditionally on actual administrative natural disasters, based on the specification of column (1). While the distribution of predictive probabilities is strongly skewed to the right, we observe that, the distribution conditional on an observed administrative shock is shifted to the right compared to the distribution when there is no administrative shock.

In the rest of the paper, we present results based on the specification of column (1), and compare it with alternative specifications (notably using weather stations data and different choices of time fixed effects).

3.2 Second-stage regression

Our estimation for the second stage relies on a local projection method (Jordà, 2005). We relate the log of the price index evolution between date *t-1* where *t* corresponds to the date (year-month), and date $t+h$ where h=*0,...,6* months to the estimated probability of a natural disaster $\widehat{\omega}_{i,t}$ recovered from equation (1). The index i is for the different DCOMs, $i = 1, \dots, 4$. Our baseline equation is the following:

$$\log\left(\frac{P_{i,t+h}}{P_{i,t-1}}\right) = \tau_h + \theta_h \widehat{\omega}_{i,t} + \gamma_{i,h} + \delta_{t,h} + \mu_{m,h} + \mu_{m,h} \times \gamma_{i,h} + \varepsilon_{i,t,h} \qquad (2)$$

where $\widehat{\omega}_{i,t}$ is the predicted probability of a natural disaster at date *t* in DCOM *i* according to administrative datasets. Time (year-month) fixed effects are denoted by $\delta_{t,h}$, while $\mu_{m,h}$ denote calendar month fixed effects. DCOM fixed effects are denoted by $\gamma_{i,h}$, while $\varepsilon_{i,t,h}$ is an i.i.d residual. This equation is estimated separately for each horizon h, and the parameters of interest are θ_h, which capture the cumulative effect on prices of a natural disaster for each horizon h. $\mu_{m,h} \times \gamma_{i,h}$ is an interaction term to capture DCOM-specific monthly seasonal variations.

In our main specification, we estimate equations (1) and (2) using a 2SLS estimator. We also compare the 2SLS estimates with OLS specifications in which we directly regress prices variations on $\omega_{i,t}$, i.e. the dummy variable capturing the occurrence of an administrative shock.

Given the descriptive statistics presented on natural disasters, we expect the estimated price reactions to be stronger under the instrumental variable estimation than under the OLS estimation. The 2SLS estimate gives the variation of price reaction to the continuous linear predicted probability of an administrative shock that ranges from 0 to 1. Put differently, it gives estimates of prices reactions for administrative shocks that are triggered by extreme meteorological events, but not for those that are unrelated to the latter.

Our parameter of interest θ_h should be interpreted as the effect on inflation of an increase in the probability of observing the *average* discrete administrative shock triggered by an increase in an extreme meteorological event. However, since our approach relies on a continuous instrumental variable in the first stage, it also captures the intensive margin of a weather-related disaster. Even though the treatment is binary, the probability of observing the average treatment is increasing in the continuous meteorological records, and thus embeds some intensity effects (see also Section 5 for a more complete discussion).

Another important question related to this estimation strategy is how it compares with other methodologies used in the literature, and notably to the damage function approach. One potential concern about our IV approach is indeed that it might substitute biases of administrative data with measurement biases due to meteorological data. Besides, since their effects on economic activity are highly non-linear, the accuracy of the results depends on how well non-linearities are captured by our available measures of wind speed, rainfall and the extreme event dummy variable reported by *Météo France*. In order to compare our IV approach with an alternative existing empirical strategy, we have also run an OLS regression where the exogenous variable is a standard damage function, as described in Heinen et al. (2018) (see section 4.2 for details).

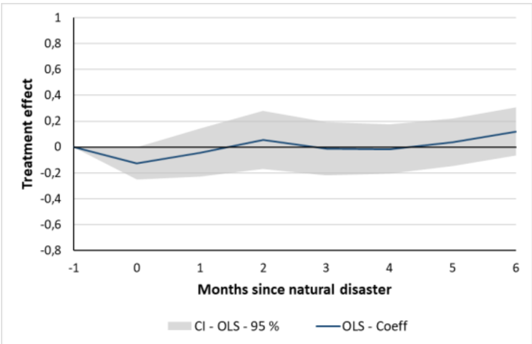
4. Main results

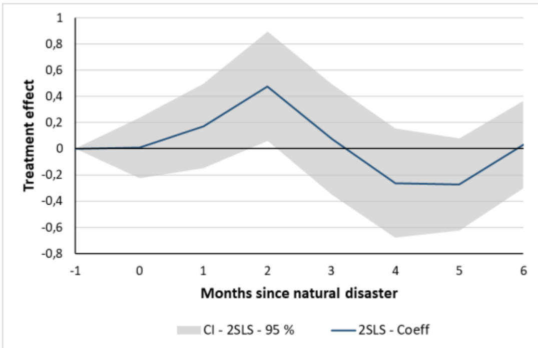
In this section, we present results of our baseline estimation strategy, both for the OLS and IV results, and compare them to alternative specifications.

4.1 Baseline specification

In Figure 3, we present the main results from our baseline estimations (OLS and IV settings) for headline CPI. Based on the IV estimation, our first main finding is that total CPI is on average affected by weather-related disasters. It first increases moderately and temporarily by about 0.5 percent after two months. The effect rapidly narrows down to zero. The OLS estimate exhibits broadly the same pattern, but with much smaller coefficients (reaching a maximum of 0.06 percent after two months). These estimates for total CPI are in the range of those found in the existing literature. Heinen et al. (2018) find that an average hurricane or flood causes a temporary rise of CPI by about 0.1pp. Parker (2018) finds that a natural disaster among the top quantile leads to an increase of total CPI by about 0.6 pp after a year, and 0.9 pp after two years[11].

Figure 3: Main results – Headline CPI





Note: The figures plot the cumulated impulse response function for headline CPI, in our baseline OLS and IV specification. Treatment effects are expressed in percent. 95 percent confidence intervals with robust standard errors in shaded areas.

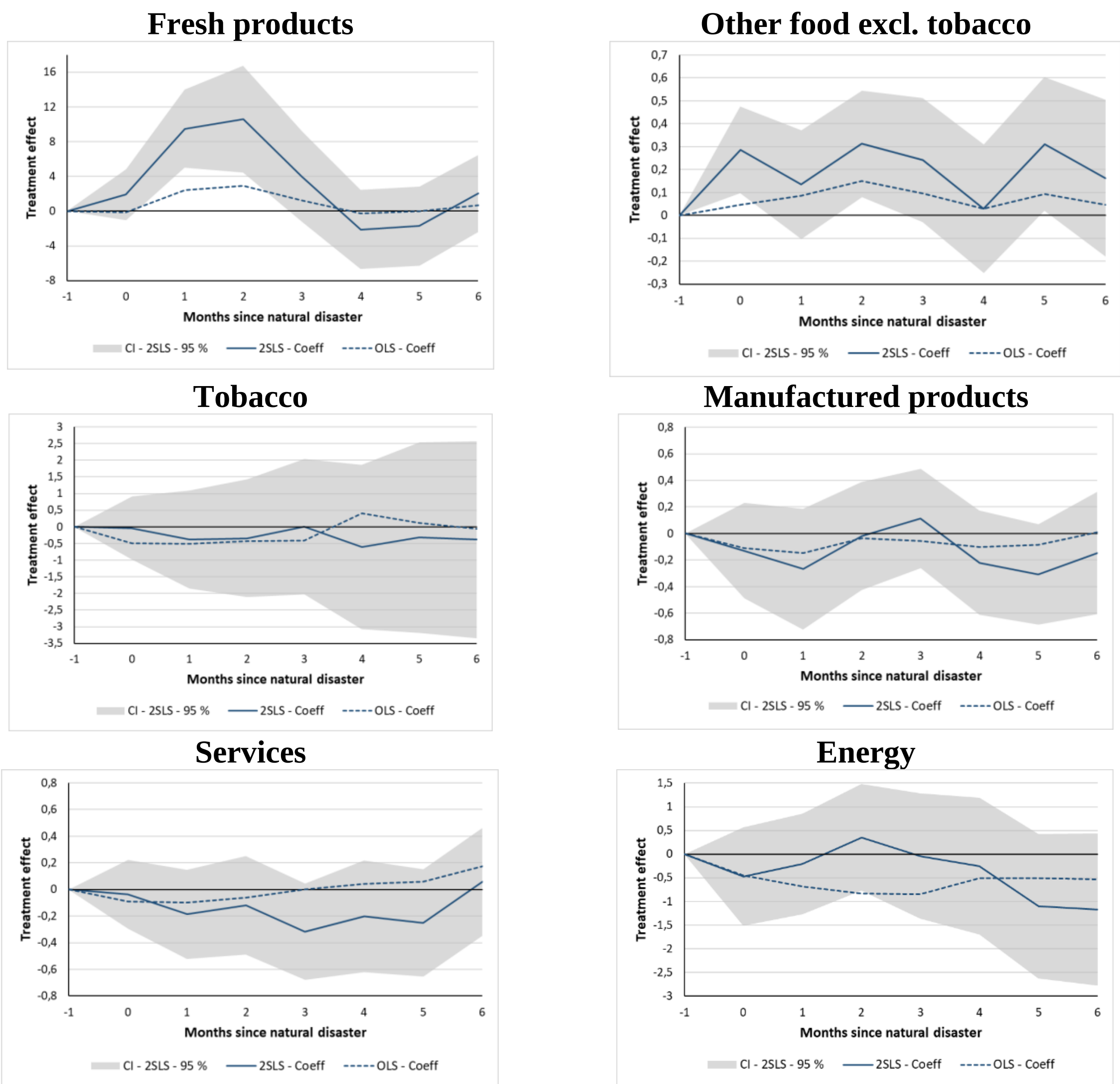
Our second main result is that composition effects drive the impact on aggregate inflation, which vary over time. Figure 4 displays the estimated coefficients for the six main components of headline CPI, comparing our baseline 2SLS estimate with OLS estimates. [12] On the one hand, inflation of fresh products increases strongly and rapidly, up to 11 percent after two months. This effect is particularly strong, as it typically represents about 2.2 standard deviations of fresh food CPI on average across the four overseas territories. This positive effect then decays progressively, until reaching zero after six months. Weather-related disasters have also a positive effect on prices of other food items, but the magnitude of the effect is much smaller (+0.3 percent). On the other hand, prices of services and manufactured products decrease moderately by 0.2 percent. These effects are marginally significant (at the 10 % level), slightly

[11] Both papers find that positive effects are stronger for food, and that the effects are generally negative for other components (such as housing). However, contrarily to our estimates, the effects cannot be decomposed as data on consumption weights are not available (Heinen et al., 2018) and data coverage is not homogenous across countries (Parker, 2018). Parker (2018) also finds that upward effects are more persistent for droughts and to a lesser extent for floods, but not for storms.

[12] The full set of estimated coefficients in the baseline 2SLS, both for headline CPI and its 12 subcomponents, is presented in Table B.1 in Appendix. Figure B.5 and Table B.2 in Appendix present the cumulated price response for OLS with confidence intervals. Finally, while we do not present results regarding pre-trends in our baseline results, we find them to be of small magnitude and largely insignificant see Figure B.8 in Appendix for the baseline results of fresh products with pre-trends up to 3 months).

more persistent than those observed for fresh food products, and broad-based across their subcomponents. Finally, prices of energy or tobacco do not react significantly to the natural disaster shocks, which is expected since they are strongly administered. In all specifications, 2SLS estimation yields higher estimates than the OLS estimation. In the case of fresh products, the maximum effects estimated in the OLS are positive and significant, but about 3.5 times smaller than those estimated in the 2SLS setting. This confirms that using only administrative shocks tends to underestimate the effects of disasters on inflation since many of these natural disasters (in particular as reported by the GASPAR dataset) do not correspond to extreme meteorological events and are therefore likely to be related to lower real economic damages.

Figure 4: Main results – CPI components - IV



Note: The figures plot the cumulated impulse response function for headline CPI and its different subcomponents, in our baseline IV specification (solid blue) and for the OLS specification (dotted blue). 95 percent confidence intervals for the 2SLS specification with robust standard errors in shaded areas. Treatment effects are expressed in percent.

Turning to the interpretation of these results, the positive effects on the prices of food are likely to be driven by supply-side factors, while the negative effects on other CPI items are likely to be driven by demand factors. To shed light on these mechanisms, we estimate reactions of sector-level employment in overseas territories to natural disasters, results are reported in Table B.3 in Appendix.[13] Our main finding is a sustained decrease in agricultural employment following a natural disaster (reaching a maximum effect of - 3 % after two months, but remaining around -1 to -2 % after 6 months). This suggests that the price increase in food results from a negative supply shock related to the destruction of crops in fields. In parallel, we also observe an increase in the level of employment in other low-skilled jobs increases, such as in interim (reaching a maximum of 16 % after 4 months, but remaining above 5 % over the projection horizon), and in car repair (+1 % after 5 to 6 months), suggesting some worker reallocation effects from agricultural sector to these sectors. This finding is in line with previous studies documenting a drop in agricultural labor supply after natural disasters (Kirchberger, 2017). This also suggests a stronger negative supply effect for fresh food products, which are more likely to be produced locally than for other food products which are often imported. The supply of other items is likely to be less responsive to weather-related disasters, since these products are largely imported (manufactured products, tobacco and energy[14]) or produced through the public sector (services). Unsurprisingly, employment in these sectors does not react to natural disasters.[15] There is one exception, which is a significant drop of employment in the construction sector for three months, reaching up to -1.4 pp before fading out. However, it is difficult to map this sectoral drop in employment with inflation data by product type, as costs related to owner occupied housing are systematically excluded from HICP inflation in the euro area. Some home related expenses fall under the two categories "Other manufactured products" and "Other services" (Table A.4), both product categories with falling inflation rates in response to weather-related disasters. This is consistent with potentially lower activity in the construction sector due to weather-related business interruptions. The combination of these factors with a downward price reaction points towards the predominance of negative

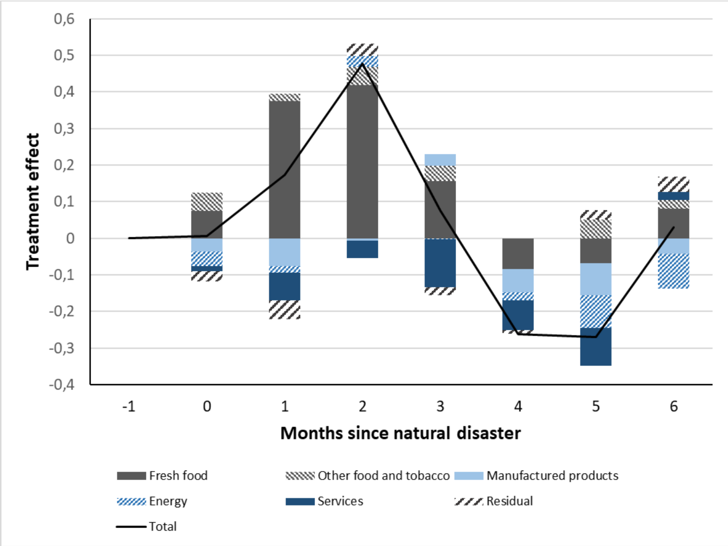
[13] We describe available measures of sectoral employment in overseas territories in Appendix, Table B.3. These results should be considered as more exploratory than those on consumer prices, as they are based on quarterly data and are available for a shorter period of time.

[14] Regarding energy, the prediction is however, that supply and demand effects are less relevant than for other components of the CPI. First, in France, oil prices quickly follow the international prices of crude oil (Gautier et al. 2023), making unlikely that local supply or demand effects affect the general price dynamics. On the other hand, in the specific case of DCOMs, oil prices are set administratively, which might mute the effects of any existing supply or demand effect. The negative effect of natural disasters on energy prices is therefore hard to interpret.

[15] Relatedly, we did not find any effect of natural disasters on the value or volume of imported goods.

demand effects.[16] This result is in line with recent contributions showing that natural disasters decrease demand, notably through higher risk aversion (Cantelmo et al. 2023, Cassar et al. 2017).

Figure 5: Decomposition of the reaction of total inflation in the baseline specification



Note: Decomposition of the cumulative impulse response of headline CPI to a natural disaster in the baseline IV local projection. The contribution of each component is computed as the cumulative response of the CPI of this component times its average weight in the consumer baskets of the four DCOMs between 1999 and 2018. Treatment effects are expressed in percent.

Figure 5 decomposes the effect on total inflation based on the observed effect for the five main components (namely fresh food, other food including tobacco, services, manufactured products and energy) using the results of the IV estimation. Each contribution is computed as the observed pass-through multiplied by the average weight of the component over 1999-2018. The "residual" contribution corresponds to the difference between the estimated reaction of headline inflation and the sum of estimated contributions of the five components. The response of inflation to weather-related disasters is heterogeneous across CPI components both in terms of timing and amplitude, with a quick and positive response of food inflation (especially fresh food), and a negative contribution of inflation in services and manufactured products.

[16] In the case of services, comparing the variation of economic activity in the tourism sector with prices of accommodations and restaurants would be particularly useful. However, while we observe employment and activity in the accommodations/restaurants sector, we do not observe the CPI of accommodations and restaurants (which is part of the "other services" aggregate). Interestingly, we observe no employment variation in the tourism sector, but find an immediate increase of about 10 % in the number of overnight hotel stays, which progressively vanishes. This points to a positive demand shock, which could be driven by relatives coming to help their family in the aftermath of the disaster (in a context where a majority of tourism flows in DCOMs are due to affinity motives). Another explanation could be that hotels were used as temporary accommodation for households who lost their homes.

4.2 Comparison with results from damage functions

In this section, we compare our baseline results to two different sets of estimates obtained with damage functions. In a first step, we construct damage functions from remote sensing data in close analogy to Heinen et al. (2018). Damage functions represent a mapping from weather or climate into economic outcomes in the sense of a ‘dose response function’ (Auffhammer 2018).

For the wind destruction index, we follow Strobl (2012), who builds a hurricane destruction index. We adjust his approach for the use of remote sensing data of wind in order to obtain a time-series of wind damage for each region. Specifically, for gridded cell *j* of weather data in one of our four regions *i* and within a day *d*, we compute the monthly wind-destruction as

$$H_{it} = \max\left[\sum_{j=1}^{J} \xi_{ij} \sum_{d=1}^{D} \left(W_{ijd}^{max}\right)^3 \times \mathbb{1}_{\left\{W_{ijd}^{max} > W_i^*\right\}}\right]_{d \in t}, \tag{2}$$

where ξ_{ij} are exposure weights for grid cell *j* in region *i*, which aggregate to one at the regional level, W_{ijd}^{max} is the maximum sustained wind speed for one minute in an intraday window *d* of six hours from CCMP, and $\mathbb{1}_{\{W > W_i^*\}}$ is an indicator variable that takes the value of one if the recorded wind speed exceeds a threshold value W_i^*. Maximum sustained wind speed enters the damage function in cubic form, as it is found that the local destructive power of wind is roughly in cubic form related to wind speed (Emanuel 2011).

Exposure weights ξ_{ij} are constructed from satellite nighttime light data. Nighttime light has a high predictive power for economic activity and can usefully complement official statistical data (Henderson et al. 2012). Pérez-Sindín et al. (2021) show that nighttime light is a good proxy for regional GDP patterns in Colombia independent from the level of urbanization, which ranges in their study from rural areas with less than 5,000 habitants to cities of more than 500,000 habitants. Chen & Nordhaus (2019) show that satellite nighttime light data is better at predicting cross-sectional GDP than time-series evolution of GDP, which makes it particularly suited for the construction of weights in our application, as we are only interested in detecting areas of relatively higher economic activity.

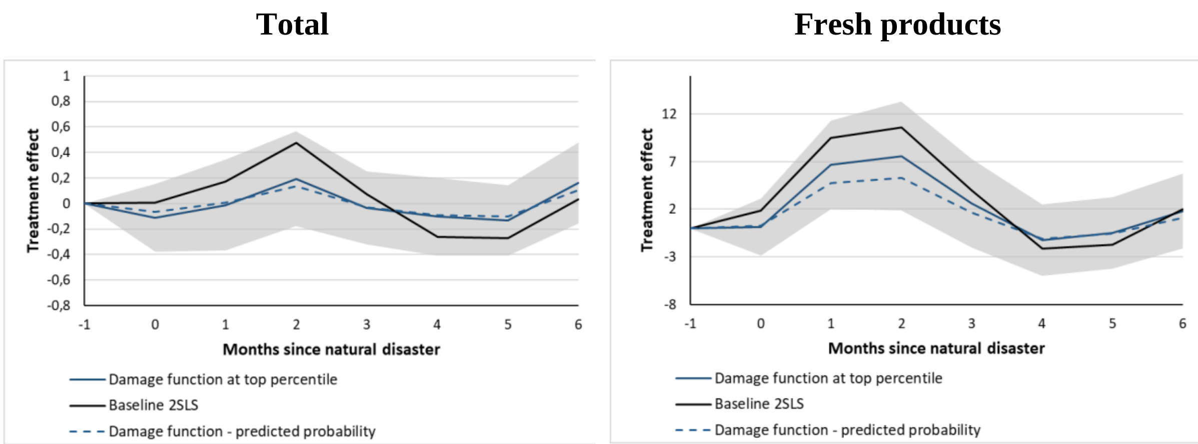
Regarding possible economic destruction due to excessive rainfalls, we also follow Heinen et al. (2018) and define region specific flood destruction as

$$F_{it} = \max\left[\sum_{j=1}^{J} \xi_{ij} \times r_{ijdt} \times \mathbb{1}_{\{r_{ijdt}>r_i^*\}}\right]_{d\in t}, \tag{3}$$

where r_{ijdt} is the cumulative sum of rainfall in millimeters over a three-day window in region i, weather cell j, on day d, in month t. The exposure weights ξ_{ij} follow the same logic as above and are also constructed from satellite nighttime light data (see Appendix C for details on the calibration of region-specific threshold values r_i^*).

In Figure 6, we compare our baseline estimates for total CPI and fresh products CPI to estimates using damage functions. Since the units of the damage function are not directly comparable to those of the explanatory variable in the second stage of our baseline 2SLS (which is a predicted probability), we present predicted price responses for two distinct variations of damage functions. The first one corresponds to the slope of the regression of the predicted probability on the damage functions, i.e. the variation of damage functions associated to a predicted probability going from 0 to 1. In that case, the inflation response is directly comparable to our baseline 2SLS. The second case does not use the predicted probability, and corresponds simply to the difference between the top percentile of damage function and the first percentile, i.e. the price response when damage functions shift from their 1 % lowest value to their 1 % top value. In both cases, the plotted predicted price response is the cumulative predicted price responses for each damage function.

Figure 6: Damage functions for total and for fresh products



Note: The figures plot the cumulated impulse response function for damage functions evaluated using the predicted probability of shock (dotted blue) or at the top percentile of damage function (sold blue), compared to our baseline 2SLS (black line). Shaded areas represent 95 percent confidence intervals with robust standard errors for damage functions evaluated at the top percentile of shocks. Treatment effects are expressed in percent.

The results using this specification are very coherent with those of our baseline 2SLS methodology. Both estimated reactions appear to be close, and the price reaction using the damage function appears slightly smaller than the one obtained in our baseline specification. In particular, the price reaction in our baseline 2SLS is higher than the price reaction of damage function estimated at its top percentile: this suggests that our estimation is unlikely to underestimate price reactions compared to damage functions. In Figures B.6 and B.7 in Appendix, we report results of separated regressions for wind damage function and rain damage function, both evaluated at the top percentile. Results appear to be mainly driven by wind damage function, with only limited effects for rain damage function, a result that is similar to those obtained by Heinen et al. (2018).

4.3 Controlling for regional seasonality

Weather-related extreme events are quite seasonal in overseas territories. We discuss here how the treatment of this seasonality can affect our results.

Seasonality in weather extreme events but also in inflation differs a lot across the territories since La Réunion, is located in the southern hemisphere whereas Guadeloupe, Martinique and Guyane are located in the northern hemisphere. Table A.8 in the Appendix highlights that weather-related disasters in La Réunion are predominantly concentrated during the first half of the year, while extreme weather events in the remaining DCOMs are concentrated in the second half of the year. Besides, while Guadeloupe, La Réunion and Martinique have comparable number of administrative shocks (both in GASPAR and in EM-DAT), Guyane has a much smaller number of shocks (all based on GASPAR data), which are mainly concentrated in the month of May (Tables A.7 and A.8).

Similarly, seasonal patterns in inflation differ across overseas territories. Figure A.1 in Appendix plots the average monthly variations for the main components of CPI across DCOMs. Seasonal variations in La Réunion appear to be distinct from those of other DCOMs, both in terms of timing and in terms of magnitude. The difference of timing can largely be explained by the fact that La Réunion is the only DCOM of our sample located in the southern hemisphere. The differences in the magnitude of seasonal variations between La Réunion and other DCOMs are particularly salient for fresh food and services, the latter likely driven by seasonality in the tourism sector.

Taking this seasonality into account is important since the economic impact of natural disasters might depend on whether their occurrence was expected or not. Strong wind and rainfalls occurring in a season known to be traditionally hit by extreme weather events might be less harmful to economic activity than if they occur in a season generally spared by such events. Additionally, during the season when natural disasters are more frequent, economic damages due to a specific event might depend on the deviation between this event and the average events occurring during this season.

Table 2 – Alternative specifications for the 2SLS strategy

	T=0	T=1	T=2	T=3	T=4	T=5	T=6
(A) Baseline							
Headline	0,01	0,17	0,48**	0,08	-0,26	-0,27	0,03
Fresh products	1,89	9,48***	10,60***	3,96	-2,11	-1,72	2,03
Other food excl. tobacco	0,29***	0,13	0,31***	0,24*	0,03	0,31**	0,16
Manufactured products	-0,13	-0,27	-0,02	0,11	-0,22	-0,31	-0,15
Services	-0,03	-0,19	-0,12	-0,32*	-0,20	-0,25	0,06
Energy	-0,48	-0,20	0,35	-0,04	-0,25	-1,10	-1,17
Tobacco	-0,04	-0,38	-0,35	0,00	-0,60	-0,32	-0,38
(B) No seasonal effect							
Headline	0,00	0,19	0,48**	0,26	0,17	0,16	0,22
Fresh products	7,66***	18,34***	20,86***	13,32***	3,56	-1,51	-2,46
Other food excl. tobacco	0,17**	0,07	0,19*	0,13	0,04	0,32**	0,25
Manufactured products	-0,59***	-1,11***	-1,26***	-1,13***	-1,00***	-0,72***	-0,69**
Services	-0,21	-0,24	0,13	0,51**	1,21***	1,36***	1,53***
Energy	-0,69	-0,99**	-1,00*	-1,65***	-1,84***	-2,15***	-1,98***
Tobacco	-0,10	-0,45	-0,72	-0,65	-1,01	-0,13	0,44
(C) No month-year FE							
Headline	-0,01	0,18	0,52**	0,25	-0,04	0,01	0,22
Fresh products	1,37	8,99***	11,40***	4,60	-0,23	0,18	2,62
Other food excl. tobacco	0,07	0,06	0,18	0,07	-0,16	0,22	0,07
Manufactured products	-0,04	-0,26	-0,06	0,17	-0,14	-0,23	-0,04
Services	-0,16	-0,37**	-0,20	-0,27	-0,26	-0,31	-0,10
Energy	0,04	0,82	1,50	1,54	2,18*	2,17	2,07*
Tobacco	0,41	-0,19	0,03	0,38	-0,31	-0,54	-0,93

***Note*:** The table shows alternative specifications of local projections of consumer prices in a 2SLS setting. Panel (A) shows results for our baseline specification, panel (B) shows results for a 2SLS specification controlling for year-month fixed effects, but not for DCOM-specific month fixed effect and panel (C) shows results for a 2SLS specification controlling for DCOM-specific month fixed effect, but not for year-month fixed effect.
*p < 0.10; **p < 0.05; *** p < 0.01.

In our baseline regression, we have included month fixed effects interacted with regional fixed effects to capture these seasonal effects specific to each overseas territories. In this section, we compare our baseline 2SLS specification with alternative 2SLS specifications controlling differently for seasonal patterns. Table 2 reports the results. Panel (A) reports our baseline estimates. Panel (B) reports results from a specification excluding monthly DCOM-specific fixed effects (but including month-year fixed effects common to all DCOMs). Panel (C) reports results from a specification excluding month-year fixed effects (but including monthly DCOM-specific fixed effects and year fixed effects common to all DCOMs). While the effects for headline CPI remain very comparable across specifications (with a maximum estimated effect of 0.5 percent after two months), the product-level price reactions differ substantially. In particular, not controlling for DCOM specific monthly-seasonality yields much stronger effects for fresh food products (which go up to 21 % after two months). This stronger effect for fresh food products is driven by the distinct seasonality of la Réunion, which is the only DCOM located in the southern hemisphere, and for which the magnitude of seasonal variations of fresh food prices is higher than in other areas. These stronger effects for fresh food products are offset by stronger negative effects for manufactured products (down to a minimum of -1.3 % after two months), and on energy (down to -2,1 % after 5 months). Additionally, the prices of services increase more substantially in the end of the horizon (up to 1.5 % after 6 months).[17] Controlling for seasonal effects (but not for time fixed effects), yields results closer to our baseline specification (with a maximum reaction of fresh food products of 11 %, and a more significantly negative reaction of services prices after two months). However, it implies a positive reaction of energy prices, which is hard to reconcile with the fact that energy products are imported.

Overall, these results imply that controlling for region-specific seasonal patterns is quite important to identify precisely the effect of weather-related extreme events on prices.

5. Distributional effects of natural disasters

5.1 Which households are hurt the most by natural disasters?

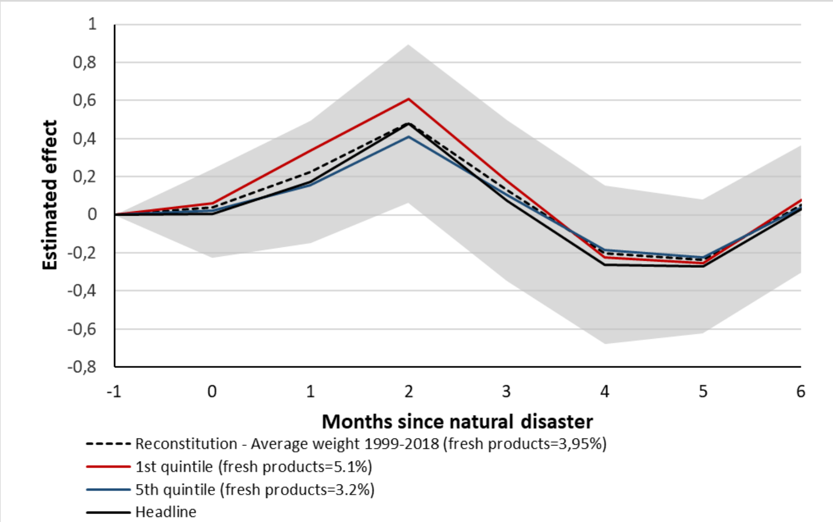
In this section, we investigate whether the effects of natural disasters on consumer prices vary across different types of households. Indeed, given that the main positive effects on inflation are channeled through fresh food products, and to the extent that the weight of food is generally higher for households with a lower income, we expect that the effects on total inflation is higher for the latter. To test this hypothesis, we use data from a survey produced by Insee for the year 2017 (*Budget des familles*). This survey gives a decomposition of the consumption basket of households, both across overseas territories and across quintiles of household.[18] We combine these data with our estimated impulse-response functions, in order to derive an estimated impulse-response function of total CPI for each quintile (see Appendix D for the detailed methodology).

[17] This specific effect appears to be entirely driven by the disasters and price seasonality of Guyane, in which 60 % of shocks occur in the month of May.

[18] Table D.1 in Appendix reports the share of food in the consumption basket for each of the four DCOMs we focus on, and confirms that the share of food decreases strongly when income rises.

In Figure 7, we plot our estimated impulse response function of total CPI for each quintile, compared to the reconstitution of the impulse response function under average weights of fresh products between 1999 and 2018. Our results suggest that the maximum reaction of CPI in the first two quintiles is higher than the maximum reaction of CPI by about 0.1 percent for households, reaching about 0.6 percent after two months, against 0.5 percent in the effect estimated based on average weights. On the contrary, the reaction is more muted for households in the top of income distribution, notably those in the last quintile (maximum of 0.4 percent).

Figure 7 – Baseline and alternative effects on CPI inflation by income quintile

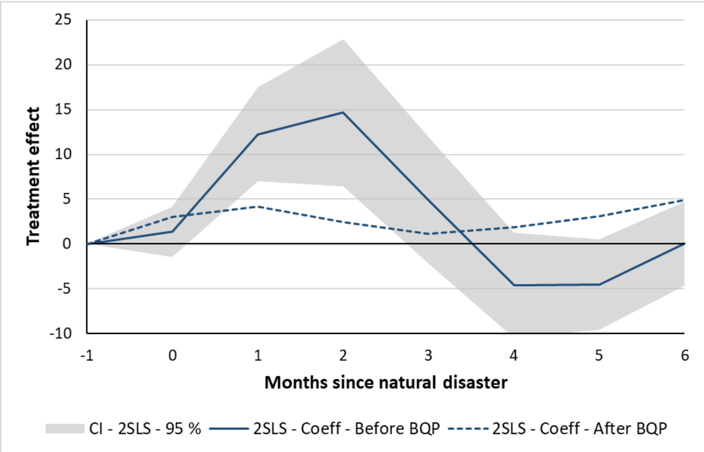


Note: Baseline 2SLS estimate for headline CPI in solid black, with its 95 % confidence interval in shaded area. The black dotted line is the reconstitution of the effect on headline CPI using a linear combination of estimated effects on fresh products and total excluding fresh products using average weights between 1999 and 2018. The blue and red lines are the reconstitutions using estimated weights of fresh products for the top and bottom quintiles of income. Treatment effects are expressed in percent.

5.2 Do price controls help?

The extent of administered prices and local price control policies can affect the effect of natural disasters on prices. As argued above, one of the potential reasons behind the insignificant reaction of energy prices, beyond the fact that they are largely driven by international prices of crude oil, is that they are partly controlled by local authorities. However, more interestingly in our context, the extent of price regulation regarding food prices has also evolved over time. In November 2012, following protests against the cost of living in several DCOMs, a price cap called *Bouclier Qualité Prix* (BQP) was implemented for a selected basket of elementary consumer products. The BQP, which was eventually implemented in March 2013, states that the total price for this basket of selected products cannot be higher than a fixed ceiling. The selection of products and the overall price cap are renegotiated annually, and can differ across DCOMs. For example, in 2018, the BQP in La Réunion contained 109 products for an overall price cap of 288 euros. 78 of these 109 products were food products, and among them, 48 were locally produced. The BQP can therefore be interpreted as a form of regulation preventing price gouging.

Figure 8: Reaction of the fresh products CPI before and after the implementation of the BQP



Note: Impulse response functions of fresh food products for shocks occurring before the implementation of the BQP (until December 2012) and after the implementation of the BQP (since January 2013 onwards). 95 percent confidence intervals with robust standard errors in shaded areas. Treatment effects are expressed in percent.

In Figure 8, we document cumulative impulse response functions for the prices of fresh products before and after the implementation of the BQP. In this case, we consider that pre-BQP period is until December 2012, and that post-BQP period starts in January 2013.[19] Before the implementation of the BQP, the price reaction of food products was immediate and strong, reaching 12 percent after 2 months, and then decreased until reaching zero after four months. After the implementation of the BQP, the price reaction of fresh food products was much more sluggish, reaching 4 percent after one month and remaining between 0 and 5 percent over the whole projection horizon. As a result, the price reaction after the implementation of the BQP is significantly lower in the first few months, but significantly higher in the following months. Eventually, after 6 months, the cumulative price responses before and after the BQP are close (24 percent in the former case, and 20 percent in the latter), suggesting that the overall effect is similar in the long run, but the adjustment is smoother and more persistent with BQP than without this policy. Overall, these effects therefore suggest that some amount of price gouging is likely to drive the price reaction in our baseline specification (as the maximum price variation is higher without regulation), but that it is unlikely to drive all of the price reaction. In the longer

[19] This evaluation is imperfect since it only compares two periods, during which several confounding could occur. However, the predictive power of the first stage is strong in both cases (F-statistic of 32.8 before the BQP and 13.0 after the BQP), and the number of shocks occurring annually in the DCOMs during the two periods is very close (about 0.9 on average every year).

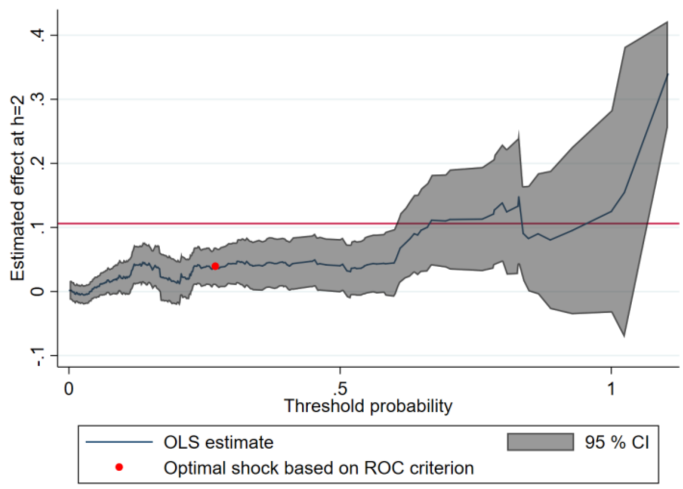
run, the cumulative price variations are identical with or without regulation, suggesting that retailers are constrained to increase their prices.

6. Robustness analysis

6.1 Quantifying the intensive margin in an IV setup

In this section, we present an approach to capture intensity effects in an IV setup. To do so, we implement the following strategy: we estimate the price response to a set of discrete shocks, where the shock is equal to one if the estimated probability based on equation (1) is above a certain threshold, and zero otherwise. We estimate these equations for a set of 928 evenly-spaced thresholds going from the minimum to the maximum values of estimated probabilities, and plot the estimated coefficient at horizon *h=2* for each regression against the threshold probabilities. We compare these results with the one obtained in our baseline specification, and highlight the result based on an optimal discrete threshold according to a ROC criterion (i.e. a discrete shock based on a threshold probability that maximizes the share of true positives and minimizes the share of false positive).[20] Figure 9 plots the results for fresh food products.

Figure 9: Price reactions of fresh products for a set of discrete shocks based on varying thresholds of estimated probabilities



Note: Maximum estimated effect of OLS regressions for fresh product prices with shocks based on discretized probabilities estimated from first-stage regression (1), with threshold varying from 0 to 1. Confidence intervals at the 95 % level in grey. The red dot represents the estimate based on a threshold derived from a ROC curve. The red line corresponds to our baseline estimated effect.

[20] See Appendix E for a description of how we derive this optimal discrete shock and its properties.

Several conclusions can be derived from this figure. First, the maximum estimated effect based on discrete shocks derived from estimated shock probabilities are increasing in the threshold. The effect goes from about 0 when the threshold is equal to 0 (meaning that virtually all observations are defined as a "shock") to about 35 % when the threshold is equal to 1 (meaning that only observations with the highest shock probability are treated as shock). Second, the estimated effect based on an optimal threshold derived from a ROC curve is of only 4 %. This comes from the fact that, while the predicted shock correctly identifies the majority of actually observed administrative shocks, a majority of predicted shocks actually do not correspond to an extreme weather event. Third, our baseline estimate is about 2.5 times the value of the estimate under the optimal threshold, and it is located in the upper part of the distribution (Figure E.2, Appendix). Indeed, even though it is largely below the maximum estimated value (35 %), the number of estimations for which we observe an effect higher than our baseline is actually small (5.6 %). Finally, we find that when the threshold of the predicted probability is set a little above 50%, the impact of natural disasters on prices of fresh food products varies around the value estimated in our baseline regression (about 10%).

6.2 Placebo regressions

In this section, we present results of different placebo regressions where we have randomized weather-related disaster shocks in both equations of our two-step model. We have run three distinct exercises.

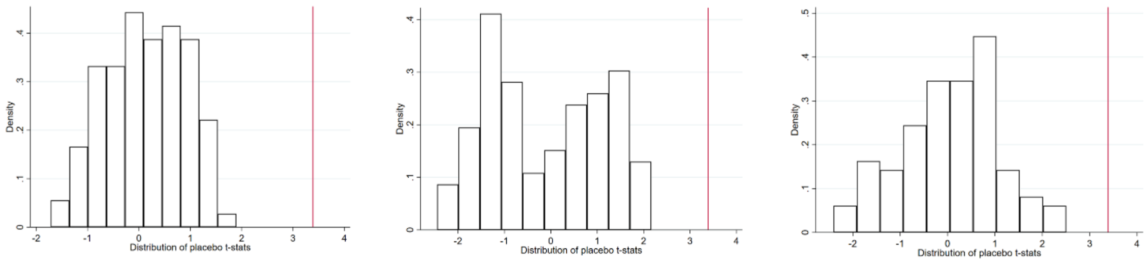
In a first exercise, we have randomized the instrumental variables. Namely, we simulate rainfalls and wind data from Gumbel laws of distribution (whose parameters are derived from the empirical distribution of rainfall and wind records across DCOMs) since the Gumbel law is well suited to replicate the distributions of extreme events. We also simulate Météo-France shocks from a uniform distribution, drawing as many shocks as the actual number of observed Météo-France shocks in our data, but without allocating them to DCOMs proportionally to their observed frequency of shocks. We run 100 2SLS estimations, each based on a distinct set of simulated data for instruments and using the actual observations for the treatment variable.

In a second exercise, we keep the actual values of the instrumental variables, but we randomize the treatment, drawing randomly 69 shocks from a uniform distribution. As in the previous exercise, we do not allocate them to DCOMs proportionally to their observed frequency of shocks. We run 100 2SLS estimations, each based on a distinct set of simulated data for the treatment, but keeping the actual observations of the instrumental variables (see Appendix F for further methodological details).

In a third exercise, we keep the actual values of the instrumental and treatment variables, and we compute the correct predicted probability of treatment in the first stage, but we randomly allocate this predicted probability across DCOMs and over time between the first and second stage. We run 100 OLS estimations of the second stage, each based on a distinct set of randomization of the predicted probability.

Figure 10: Distribution of T-stats of placebo regressions

a) Randomization of instrumental variables	**b) Randomization of treatment variable**	**c) Randomization of predicted probabilities**



Note**:** The figures plot the distributions of T-stats of placebo tests. In Figure 10a, the randomized variables are the instrumental variables. In Figure 10b, the randomized variable is the treatment variable. In Figure 10c, the predicted probability is randomly allocated across DCOMs between the first and the second stage. The red vertical lines correspond to the t-stat of the baseline estimation.

Figure 10 plots the distributions of T-statistics for local projections of fresh food prices at horizon $h=2$, as well as the T-statistics from our baseline estimate (red vertical line). While the T-stat of the baseline estimate is equal to 3.4, 95 % of those in the placebo estimates with randomization of instrumental variables are below 1.3 (Panel a), 95 % of those in the placebo estimates with randomization of treatment are below 1.7 (Panel b), and 95 % of those in the placebo estimates with randomization of predicted probabilities are below 1.8 (Panel c).

6.3 Robustness to alternative specifications

In this section, we present several robustness exercises for headline CPI and the CPI of fresh products. Our robustness tests show that our main results hold and are robust to the chosen specification or to the definition of the shock, even if the exact magnitude of the effect can vary. The results are summarized in Table 3. Table B.4 in the Appendix presents results for the other components.

First, La Réunion might play a specific role because the volatility of fresh food inflation is much higher there than in the other DCOMs, and also because extreme weather events are also in La

Réunion more frequent than in the other DCOMs. When we estimate our baseline 2SLS without La Réunion ("2SLS – Baseline – no Réunion"), the effect on headline CPI is still positive but insignificant, with a maximum of 0.2 percent after two months. The effect on prices of fresh products is much smaller than in the baseline (2.9 percent), but significant at the 5 % level. Importantly, the identification power in the 2SLS setting is comparable to the baseline (the F-statistic of the first stage is of 21.6), which suggests that the lower estimated effect is not due to a lower quality of the model. This exercise suggests that most of the inflation effect of weather-related disasters comes from La Réunion where extreme weather events are more frequent than in other DCOMs.

Table 3 – Robustness analysis

	T=0	T=1	T=2	T=3	T=4	T=5	T=6
(A) Total							
2SLS - Baseline	0,01	0,17	0,48**	0,08	-0,26	-0,27	0,03
2SLS – Baseline – not including la Réunion	0,10	0,18	0,13	-0,09	-0,21	-0,29	-0,17
2SLS – Baseline, 3 lags shock	0,00	0,21	0,52**	0,15	-0,11	-0,12	0,18
2SLS – 3 lags CPI	-0,02	0,09	0,35*	-0,06	-0,41**	-0,39**	-0,10
2SLS – Baseline excl. shock < 6months	0,02	0,24	0,63**	0,10	-0,34	-0,35	0,04
2SLS – 6 lags forward	-0,07	0,13	0,42*	0,04	-0,34	-0,34*	-0,09
2SLS – Baseline, Weather station data	-0,10	0,02	0,30	-0,01	-0,26	-0,33*	0,00
(B) Fresh products							
2SLS - Baseline	1,89	9,48***	10,60***	3,96	-2,11	-1,72	2,03
2SLS – Baseline – not including la Réunion	0,74	2,85**	2,53	0,38	-1,55	-1,08	0,35
2SLS – Baseline, 3 lags shock	2,16	8,93***	9,90***	3,39	-1,95	-1,17	2,60
2SLS – 3 lags CPI	2,37	9,78***	10,14***	2,82	-3,12	-2,70	1,14
2SLS – Baseline excl. shock < 6months	2,57	12,48***	13,91***	5,20	-2,70	-2,18	2,78
2SLS – 6 lags forward	2,17	9,87***	11,31***	4,08	-2,86	-2,13	2,02
2SLS – Baseline, Weather station data	0,66	7,13***	9,19***	4,11	-0,77	-1,13	2,23

***Note*:** The table shows alternative specifications of local projections of consumer prices. Panel (A) shows results for total CPI, panel (B) shows results for the CPI of fresh products. "2SLS baseline" is our baseline 2SLS specification. "2SLS – Baseline – no Réunion" is the baseline specification excluding La Réunion. "2SLS – Baseline; 3 lags shock" controls for up to 3 lags of the shock (instrumented by relevant lags of the instrumental variables). "2SLS – 6 lags forward" controls for up to 6 forward lags of the shock. "2SLS – 3 lags CPI" controls for 3 lags of monthly variations of CPI. "Baseline excl. shock < 6 months" is the baseline specification, excluding shocks which occur less than 6 months after a previous shock. "2SLS – Baseline, Weather station data" is the baseline specification, but with instruments taken from weather station data rather remote sensing data.
*p < 0.10; **p < 0.05; *** p < 0.01.

Second, we present alternative specifications in which we control differently for lags of the shocks and of the dependent variable. In a first specification, we control for up to three lags of the shock ("2SLS – Baseline, 3 lags shock"), instrumenting them with their respective lags of meteorological data. The estimated effect for fresh products is very close to our baseline specification, with a maximum effect of 10 percent after 2 months. In another exercise ("2SLS – 3 lags CPI"), we implement a lag-augmented local projection, as advised by Montiel-Olea and Plagborg-Møller (2021), by controlling for up to three lags of CPI. Here again, the results remain very close to our baseline estimate.

Third, we run specifications taking into account the fact that shocks might occur at close intervals. In such a setting, our specification (which entails two-way fixed effects and prolonged treatment effects) might wrongly identify heterogeneous effects over time (as documented by De Chaisemartin and d'Haultfoeuille, 2020). In a robustness exercise, we first run a specification in which we do not define as a shock any event that is occurring less than 6 months after a preceding shock ("2SLS – Baseline excl. shock < 6months"). Doing so, we find effects for fresh products that are of similar magnitude as in the baseline specification, but slightly higher (12.5 percent after two months). Alternatively, in order to further rule out the risk that our results are potentially driven by compound effects, we control for up to 6 forwards of the shock. Here again, the results are robust, and if anything slightly stronger than in the baseline specification (effect of 11 % after two months).

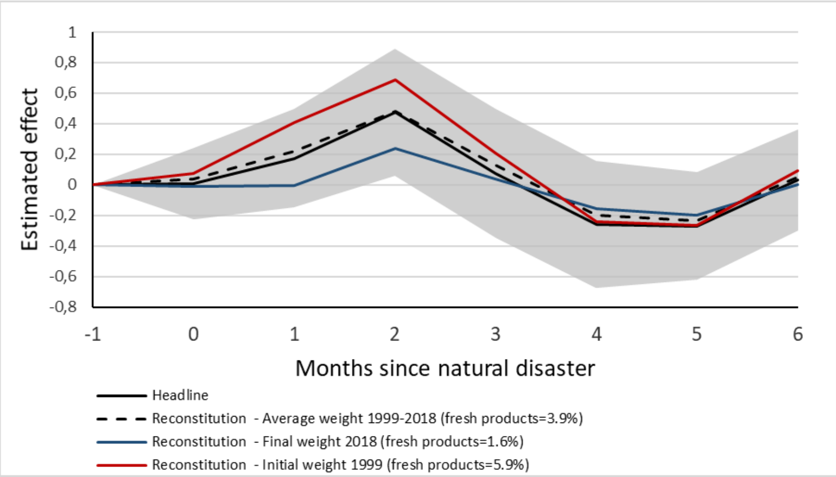
In a final exercise ("2SLS – Baseline, Weather station data"), we present results using meteorological observations from weather stations in the first step. The maximum estimated effect on fresh products (7 percent) is very close to the baseline effect, yet slightly smaller, which confirms the lower identification power of data coming from weather stations.

6.4 Varying the share of fresh food

The overall positive effect of natural disasters on inflation is mainly driven by the large effect on prices of fresh food products, which represent a small fraction of the CPI basket of goods (4 percent on average between 1999 and 2018). The share of fresh food products has continuously decreased over our sample period from 5.9 percent in 1999 to 1.6 percent in 2018 (Table A.5 in Appendix). In this robustness exercise, we estimate the overall effect on inflation of natural disasters when we vary the share of fresh products.

In Figure 11, we show counterfactual effects on headline inflation, assuming different weights for fresh products. The dark solid line represents the effect estimated in the baseline specification for total CPI, as estimated in Figure 3. The dark dashed line represents a reconstitution of the effect on total CPI, computed as a linear combination of effects estimated on fresh products and total excluding fresh products, using their average weight over the estimating sample. This reconstitution is close to the estimated effects, though not exactly identical: this reflects the fact that the estimated shocks are not uniformly distributed over the estimating sample. The blue line represents an aggregated effect on total CPI, still using a linear combination of effects estimated on fresh products and total excluding fresh products, but using their *end-of-sample* weight in 2018. In this case, the estimated effect on total CPI is lower than in the baseline specification, with a maximum response of 0.2 percent after two months. Finally, the red line represents the same aggregation of effects, but using the weights of fresh products and total excluding fresh products as measured at the *beginning-of-sample* in 1999: in this case, the effect is much stronger than in the baseline, reaching up to 0.7 percent after two months.

Figure 11 – Baseline and alternative effects on CPI inflation



Note: Comparison of the baseline IV estimation of total CPI (solid black line) with a reconstitution of the effect using a linear combination of estimated effects on fresh products and total excluding fresh products with average weights between 1999 and 2018 (solid dotted line), weights as of 1999 (red line) and weights as of 2018 (blue line). Treatment effects are expressed in percent.

7. Conclusion

This paper estimates the sectoral effects on prices of weather-related natural disasters in the four French overseas territories (DCOMs) between 1999 and 2018. It thereby contributes to a better understanding of the inflationary impact of physical risks that are likely to increase in the future because of climate change. We find a small positive and transitory effect on total consumer prices after two months (+0.5 percent). The granularity of the data, which is split into 12 product categories with available weights according to the respective expenditure shares, allows for a full decomposition of the total effect. The response of inflation to weather-related disasters is heterogeneous across CPI components both in terms of timing and amplitude, with a quick and positive response of food inflation (especially fresh food), which is partly offset by a negative contribution of inflation in services and manufactured products. We provide complementary evidence on real activity. Significant reductions in employment in the agricultural and construction sector provide a plausible narrative for the transmission channels at play, separating between dominant supply versus demand forces, which is relatively rare in this literature. While lower employment in the agricultural sector points toward dominant supply effects in the price response of fresh food, lower demand for housing-related goods and services in conjunction with lower employment in the construction sector are likely to contribute to the negative price response of services and manufactured goods.

Two interesting related findings are worth highlighting. First, we document and quantify the consequences of weather-induced natural disasters for inflation inequality. The distributional effects depend primarily on the differing weight of fresh food in the consumption basket of households, which is decreasing along the income distribution. Second, we document and quantify how the introduction of price regulation in 2012 affects price-gouging behavior. While the immediate impact is significantly lower after the introduction of a *Bouclier Qualité-Prix*, price responses a few months after the disaster shock are higher, leading to a similar total effect after six months. This result is interesting for policymakers during times of high inflation, in which price regulation is actively discussed again in academia and among policy circles (Neely 2022).

Finally, the paper makes two smaller methodological contributions of interest for follow-up empirical work. First, it shows that an IV approach leads to comparable results as the calibration of weather-related damage functions. Second, the findings underline the importance of a careful modeling of seasonality, as inflation and weather-induced disaster might share common seasonality patterns that potentially bias the estimator.

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ONLINE APPENDIX

DECOMPOSING THE INFLATION RESPONSE

TO WEATHER-RELATED DISASTERS

Erwan GAUTIER, Christoph GROSSE-STEFFEN, Magali MARX, Paul VERTIER

Appendix A. Data

A.1 Consumer prices in French DCOMs

Table A.1 – Descriptive statistics of inflation data

	Guadeloupe		Guyane		La Réunion		Martinique		DCOMs		France	
Component	m-o-m	sd	m-o-m	sd	m-o-m	sd	m-o-m	sd	m-o-m	sd	m-o-m	sd
Headline	0.12	0.47	0.11	0.31	0.12	0.60	0.12	0.36	0.12	0.43	0.12	0.31
Fresh products	0.22	3.45	0.30	3.41	0.71	9.21	0.26	2.92	0.37	4.75	0.25	3.49
Other food	0.15	0.47	0.12	0.30	0.16	0.38	0.15	0.37	0.14	0.38	0.12	0.21
Tobacco	0.77	2.81	0.67	3.00	0.73	3.90	0.77	2.82	0.73	3.14	0.49	1.72
Manufactured products	0.04	0.93	-0.03	0.26	0.04	0.89	0.02	0.66	0.02	0.68	0.01	1.04
Energy	0.21	1.94	0.24	2.12	0.22	1.81	0.23	1.91	0.22	1.94	0.30	1.66
Services	0.13	0.59	0.14	0.50	0.13	0.80	0.13	0.46	0.13	0.59	0.15	0.41

Note: Moments computed from the first-difference in the logarithm of monthly price indices over the period 1999m01 to 2018m04. DCOMs refers to the unweighted average across all four overseas territories.

Table A.2 – Correlations between main CPI in DCOMs and in France (1999m01-2018m04)

Component	**Guadeloupe**	**Guyane**	**La Réunion**	**Martinique**	**DCOMs**
Headline	0.22 [0.001]	0.12 [0.06]	-0.04 [0.51]	0.12 [0.06]	0.14 [0.04]
Fresh products	0.05 [0.46]	0.02 [0.76]	0.02 [0.76]	-0.12 [0.06]	0.00 [0.95]
Other food	0.09 [0.18]	0.21 [0.00]	0.37 [0.00]	0.27 [0.00]	0.36 [0.00]
Tobacco	0.25 [0.00]	0.10 [0.13]	0.28 [0.00]	0.14 [0.00]	0.34 [0.00]
Manufactured products	0.31 [0.00]	0.38 [0.00]	-0.21 [0.00]	0.36 [0.00]	0.23 [0.00]
Energy	0.31 [0.00]	0.27 [0.00]	0.21 [0.00]	0.37 [0.00]	0.35 [0.00]
Services	0.41 [0.00]	0.59 [0.00]	0.58 [0.00]	0.44 [0.00]	0.70 [0.00]

Note: p-values between brackets

Headline CPI is significantly correlated between DCOMs and France with an average correlation of 0.14, except for La Réunion. The correlation is on average strong and positive for services (0.7) but smaller for manufactured products and energy (0.2 to 0.3), and this holds true for all DCOMs except for La Réunion in which the CPI of manufactured products is negatively correlated with that of France. While the CPI of other food products and tobacco is positively correlated between DCOMs and France, this is not the case for the CPI of fresh food products which is not correlated between DCOMs and France (0.00 on average).

Table A.3 – Coverage ratio of local production

	Fruits		Vegetables	
	Fresh	**All**	**Fresh**	**All**
Guadeloupe	44 %	16 %	55 %	43 %
Martinique	31 %	13 %	39 %	26 %
Guyane	94 %	79 %	90 %	81 %
La Réunion	62 %	34 %	68 %	48 %

Note**:** The table shows the coverage ratio of local production for fruits and vegetables in the 4 DCOMs, both for fresh products (Fresh) and the sum of fresh and non-fresh products (All).
Source: *Observatoire des économies agricoles ultramarines* (2021)– La couverture des besoins alimentaires dans les DCOM

Table A.4 Composition of CPI aggregates

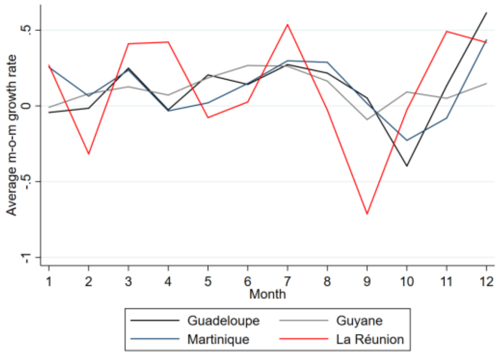
Fresh food	01131	Fresh or chilled fish
	+ 01133	Fresh or chilled seafood
	+ 01161	Fresh or chilled fruit
	+ 01171	Fresh or chilled vegetables other than potatoes and other tubers
	+ 011741	Fresh or conserved potatoes
Other food	0111	Bread and cereals
	+ 0112	Meat
	+ 01132	Frozen fish
	+ 01134	Frozen seafood
	+ 01135	Dried, smoked or salted fish and seafood
	+ 01136	Other preserved or processed fish and seafood-based preparations
	+ 0114	Milk, cheese and eggs
	+ 0115	Oils and fats
	+ 01162	Frozen fruit
	+ 01163	Dried fruit and nuts
	+ 01164	Preserved fruit and fruit-based products
	+ 01172	Frozen vegetables other than potatoes and other tubers
	+ 01173	Dried vegetables, other preserved or processed vegetables
	+ 011742	Processed potatoes (excluding crisps)
	+ 01175	Crisps
	+ 01176	Other tubers and products of tuber vegetables
	+ 0118	Sugar, jam, honey, chocolate and confectionery
	+ 0119	Food products n.e.c.
	+ 012	Non-alcoholic beverages
	+ 021	Alcoholic beverages
Footwear and garments	0311	Clothing materials
	+ 0312	Garments
	+ 0313	Other articles of clothing and clothing accessories
	+ 0321	Shoes and other footwear
Pharmaceutical products	0611	Pharmaceutical products
	+ 06131	Corrective eye-glasses and contact lenses
	+ 06132	Hearing aids
	+ 06139	Other therapeutic appliances and equipment
Other manufactured products	0431	Materials for the maintenance and repair of the dwelling
	+ 0511	Furniture and furnishings
	+ 05121	Carpets and rugs
	+ 05122	Other floor coverings
	+ 05201	Furnishing fabrics and curtains
	+ 05202	Bed linen
	+ 05203	Table linen and bathroom linen
	+ 05209	Other household textiles
	+ 0531	Major household appliances whether electric or not
	+ 0532	Coffee machines, tea makers and similar appliances
	+ 054	Glassware, tableware and household ustensils
	+ 05511	Motorised major tools and equipment
	+ 05521	Non-motorised small tools
	+ 05522	Miscellaneous small tool accessories
	+ 0561	Non-durable household goods
	+ 0612	Other medical products
	+ 071	Purchase of vehicles
	+ 0721	Spare parts and accessories for personal transport equipment
	+ 07224	Lubricants

	+ 08201	Fixed telephone equipment
	+ 08202	Mobile telephone equipment
	+ 08203	Other equipment of telephone and telefax equipment
	+ 0911	Equipment for the reception, recording and reproduction of sound and picture
	+ 0912	Photographic and cinematographic equipment and optical instruments
	+ 0913	Information processing equipment
	+ 0914	Recording media
	+ 0921	Major durables for outdoor recreation
	+ 0922	Musical instruments and major durables for indoor recreation
	+ 0931	Games, toys and hobbies
	+ 09321	Equipment for sport
	+ 09322	Equipment for camping and open-air recreation
	+ 0933	Gardens, plants and flowers
	+ 093421	Products for pets
	+ 095	Newspapers, books and stationery
	+ 121211	Electric appliances for personal care
	+ 1213	Other appliances, articles and products for personal care
	+ 123111	Jewellery
	+ 123121	Clocks and watches
	+ 123211	Travel goods
	+ 123221	Articles for babies
	+ 123291	Other personal effects n.e.c.
Energy	0451	Electricity
	+ 0452	Gas
	+ 0453	Liquid fuels
	+ 0454	Solid fuels
	+ 07221	Diesel
	+ 07222	Petrol
	+ 07223	Other fuels for personal transport equipment
Petroleum products	04522	Liquefied hydrocarbons (butane, propane, etc.)
	+ 0453	Liquid fuels
	+ 07221	Diesel
	+ 07222	Petrol
	+ 07223	Other fuels for personal transport equipment
Rents	0411	Actual rentals paid by tenants
	+ 0441	Water supply
	+ 0442	Refuse collection
	+ 0443	Sewage collection
	+ 0455	Heat energy
	+ 05204	Repair of household textiles
	+ 05523	Repair of non-motorised small tools and miscellaneous accessories
Health services	062	Out-patient services
Transportation services	0731	Passenger transport by railway
	+ 0732	Passenger transport by road
	+ 0733	Passenger transport by air
	+ 0734	Passenger transport by sea and inland waterway
	+ 0735	Combined passenger transport
Communication services	081	Postal services
	+ 083	Telephone and telefax services
Other services	0314	Cleaning, repair and hire of clothing
	+ 032201	Repair and hire of footwear
	+ 0432	Services for the maintenance and repair of the dwelling
	+ 0444	Other services relating to the dwelling n.e.c.

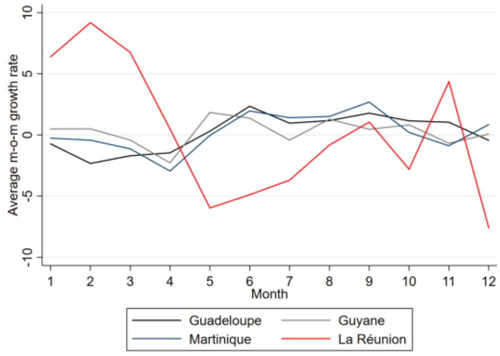
	+ 05123	Services of laying of fitted carpets and floor coverings
	+ 0513	Repair of furniture, furnishings and floor coverings
	+ 05204	Repair of household textiles
	+ 0533	Repair of household appliances
	+ 05404	Repair of glassware, tableware and household utensils
	+ 05512	Repair, leasing and rental of major tools and equipment
	+ 05523	Repair of non-motorised small tools and miscellaneous accessories
	+ 0562	Cleaning services
	+ 0723	Maintenance and repair of personal transport equipment
	+ 0724	Other services in respect of personal transport equipment
	+ 0736	Other purchased transport services
	+ 08204	Repair of telephone or telefax equipment
	+ 0915	Repair of audiovisual, photographic and information processing equipment
	+ 0923	Maintenance and repair of other major durables for recreation and culture
	+ 09323	Repair of equipment for sport, camping and open-air recreation
	+ 09341	Purchase of pets
	+ 0935	Veterinary and other services for pets
	+ 094	Recreational and cultural services
	+ 096	Package holidays
	+ 10	Education
	+ 11	Restaurants and hotels
	+ 1211	Hairdressing salons and personal grooming establishments
	+ 121221	Repair of electric appliances for personal care
	+ 123131	Repair of jewellery, clocks and watches
	+ 123231	Repair of other personal effects
	+ 124	Social protection
	+ 125	Insurance
	+ 126	Financial services n.e.c.
	+ 127	Other services n.e.c.

Figure A.1. Seasonal variations of monthly CPI inflation in DCOMs

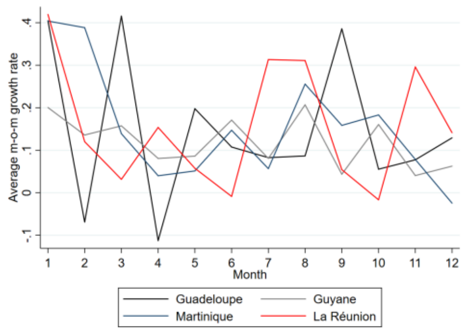
Headline



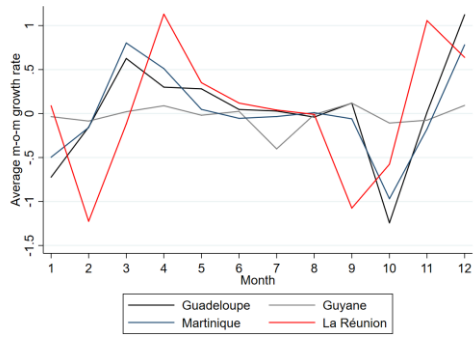
Fresh food products



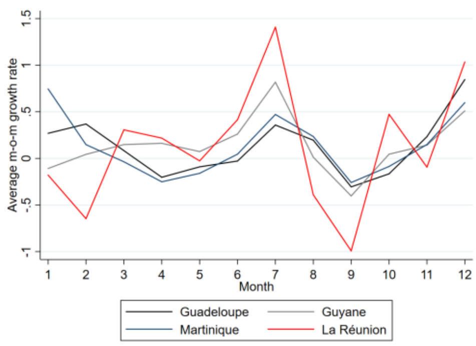
Other food



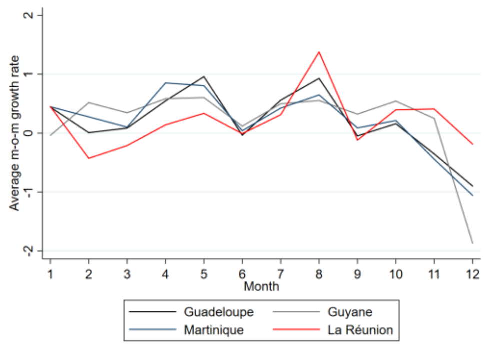
Manufactured products



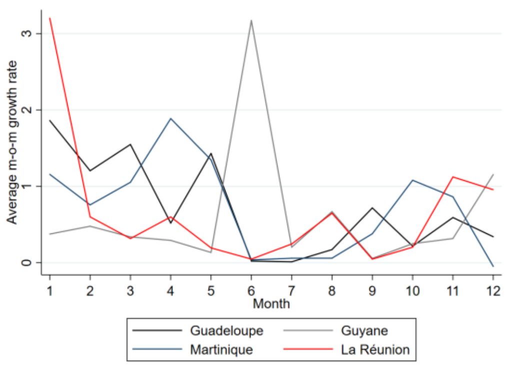
Services



Energy



Tobacco



Note: Average monthly variation (in %) of CPI for each component

A.2 Composition of consumer baskets across DCOMs

The composition of consumption baskets is heterogeneous across French territories and varies over time. Table A.5 reports the weights of each aggregate according to the French statistical office (Insee) over our sample period, in each territory, and the unweighted mean over the sample. Food including tobacco represents about 18% of the consumer basket in the considered territory at the end of the sample, with a weight that is declining over time. Fresh products represent roughly 10% of the food basket in 2018 (1.6% of CPI basket), and its weight strongly decreased over time from 5.9% in 1999. Services represent about 45% of the consumer basket at the end of the sample, with a maximum weight of 47% in La Reunion and a minimum weight of 43% in Guadeloupe. Contrary to food, the weight of services increases over time in all territories. The main component is other services (see Table A.4 for details about the composition of this aggregate), which represents about 22% of the total basket in 2019, and whose weight increased over time. Manufactured products represent 29.9% of the CPI basket in 2019, only slightly above the sample mean.

Table A.5 – Weight of the main aggregates of Consumer Price Index

	Guadeloupe		**Guyane**		**La Réunion**		**Martinique**		**DCOMs**		**France**	
Aggregate	**Weight 2018**	**Weight 1999-2018**	**Weight 2018**	**Weight 1999-2018**	**Weight 2018**	**Weight 1999-2018**	**Weigh 2018**	**Weight 1999-2018**	**Weight 2018**	**Weight 1999-2018**	**Weight 2018**	**Weight 1999-2018**
Food	1709	2226	1757	2359	1812	2181	1897	2140	1794	2226	1820**	1849**
Fresh products	179	453	162	402	121	263	180	463	160	395	243	218
Other food	1441	1698	1434	1847	1523	1748	1601	1623	1500	1729	1384	1460
Tobacco	89	75	161	110	168	172	116	55	133	103	193	193
Manufactured products	3344	3025	2930	2535	2748	3058	2871	2850	2973	2867	2594	2949
Footwear and garment	482	626	663	616	506	641	483	676	533	640	416	477
Other manuf. products	2290	2101	1850	1705	1932	2208	1924	1925	1999	1985	1753	2029
Pharmaceutical products	572	298	417	214	360	209	464	249	453	242	425	443
Energy	694	903	789	733	642	748	791	858	729	810	777	776
Petroleum products	498	691	572	507	464	532	592	645	531	594	408	454
Services	4253	3847	4524	4372	4748	4013	4441	4152	4491	4096	4809	4404
Transportation*	223	428	304	440	256	426	163	236	236	382	282	246
Communication*	409	287	390	387	374	445	425	351	399	367	223	257
Health	714	367	566	236	968	387	657	348	726	334	617	534
Rents	774	820	1239	1618	907	988	904	1014	956	1110	764	750
Other services	2132	2063	2025	1878	2243	1970	2292	2258	2173	2042	2923	2617

* Data available only since 2010 for all DCOMs.

Note**:** The table shows the weight of the main components of CPI in the four DCOMs, and in France, for 2018 and for the period 1999-2018. The average for the four DCOMs is an unweighted mean.

Comparing, the weights in DCOMs to those in metropolitan France, three facts stand out. First, the weight structure is more stable over time in metropolitan France. Second, the weights in DCOMs and in France differ mainly with respect to food excluding fresh products (which is higher in DCOMs) and service (which is lower in DCOMs). Thirdly, the composition of consumption baskets in DCOMs are converging to the one measured in metropolitan France.

A.3 Real activity

2.1.2 Data on economic activity

Table A.6 – Descriptive statistics on real activity

	Guadeloupe	Guyane	La Réunion	Martinique	DCOMs
Employment (share in total, in %)*					
Agriculture (AZ)	1,48	0,74	1,12	3,75	1,77
Food manufacturing (C1)	2,47	1,13	2,58	2,20	2,09
Extractive industry (C2)	1,83	2,77	1,47	2,14	2,05
Manufacturing – machines (C3)	0,19	0,16	0,29	0,17	0,20
Manufacturing – transports (C4)	0,02	0,27	0,04	0,02	0,09
Manufacturing – other (C5)	2,62	3,93	2,62	2,43	2,90
Construction (FZ)	4,88	6,25	5,69	4,94	5,44
Car repair (GZ)	12,64	9,30	13,10	11,47	11,63
Transports (HZ)	4,69	5,12	4,79	4,68	4,82
Accomodation – restaurants (IZ)	3,90	3,40	2,96	4,00	3,56
Information – communication services (JZ)	1,82	1,20	1,65	1,70	1,59
Finance – insurance (KZ)	2,79	1,17	2,32	2,92	2,30
Real estate (LZ)	0,56	0,62	0,79	0,67	0,66
Scientific – administrative (MN)	8,22	6,51	8,23	8,89	7,96
Public administration (OQ)	44,55	51,12	42,35	41,14	44,79
Other services (RU)	6,21	4,33	8,96	7,92	6,85
Interim	1,09	2,13	1,10	1,02	1,34
Number of overnight stays in hotels (thousands)**	90,74	28,81	87,83	102,75	77,53

Note: The table shows average values of real activity variables used in the main analysis, from the beginning of data availability until April 2018. * Data since 2010; ** Data since 2011

We complement our empirical analysis with some sectoral data on real activity. We include sectoral employment data at quarterly frequency, available since 2010. Employment in DCOMs is dominated by services: non-commercial services (public administration) represent about 45 percent of employment, and commercial services represent about 39 percent of employment. In contrast, the manufacturing industry represents only about 7 percent of total employment, the construction sector about 5 percent, followed by the agricultural sector with 2 percent (Table A.6).

To assess the effect of natural disaster on the tourism sector, we also include monthly hotel overnight stays in our analysis. They amount to 77 000 on average every month, which roughly corresponds to 15 percent of the average population of DCOMs.

A.4 Administrative disaster databases

Table A.7 – Overlap between the administrative measures of shocks

		Number (%) in		**Number (%) in**			
	N	**GASPAR**	**EM-DAT**	**Guadeloupe**	**Guyane**	**La Réunion**	**Martinique**
GASPAR	68	-	11 (16.2%)	21 (30.9%)	5 (7.3%)	22 (32.3%)	20 (29.4%)
EM-DAT	12	11 (91.7%)	-	3 (25%)	0 (0%)	5 (41.7%)	4 (33.3%)
All admin.*	**69**	**-**	**-**	**21 (30.4%)**	**5 (7.2%)**	**23 (33.3%)**	**20 (30%)**

Note: The table shows descriptive statistics on the distribution of natural disasters in four French oversea territories. "All admin"is the union between GASPAR and EM-DAT events.

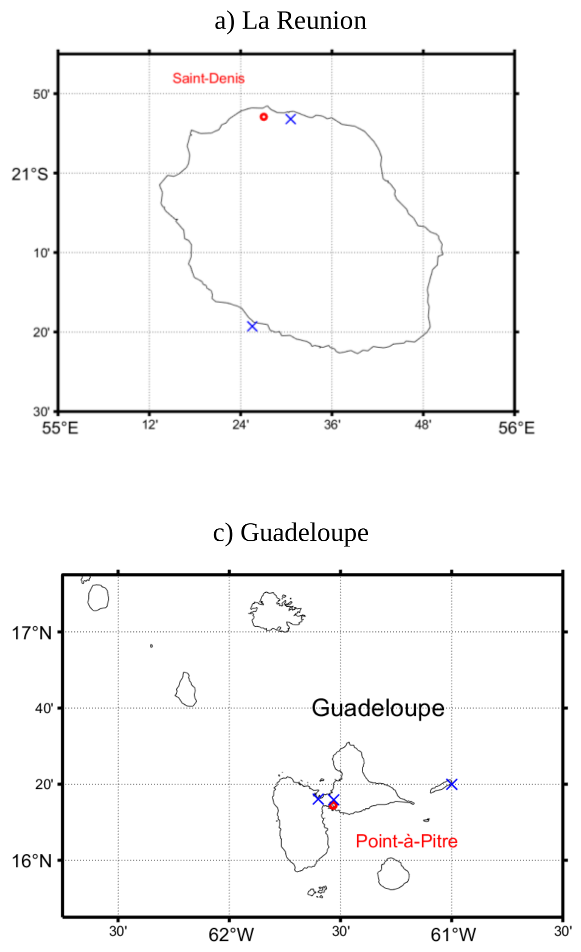
Table A.8 - Share of total administrative shocks by month of the year

Month	**La Réunion**	**Guadeloupe**	**Martinique**	**Guyane**
1	26.09	9.52	0	20,00
2	34.78	0	0	0
3	8.70	4.76	0	0
4	21.74	0.00	10.00	20,00
5	4.35	14.29	10.00	60,00
6	0	4.76	0	0
7	0	0	5.00	0
8	0	4.76	10.00	0
9	0	19.05	20.00	0
10	0	14.29	20.00	0
11	0	19.05	15.00	0
12	4.35	9.52	10.00	0

Note: The table shows the share of total number of administrative shocks occurring during each calendar month, in the different DCOMs. 34.78 % of all shocks in La Réunion occurred during the month of February.

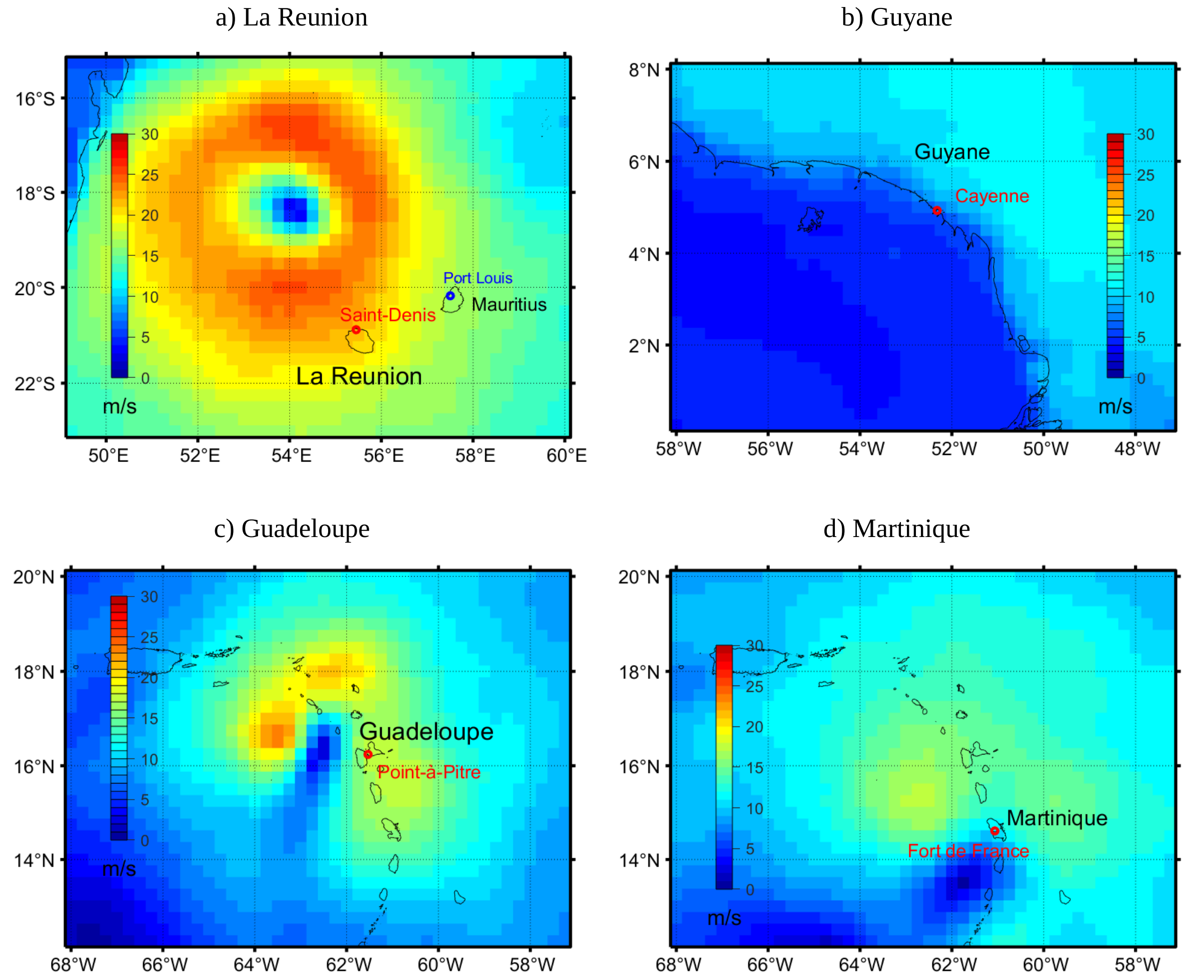
A.5 Meteorological data

Figure A.2. Location of weather stations



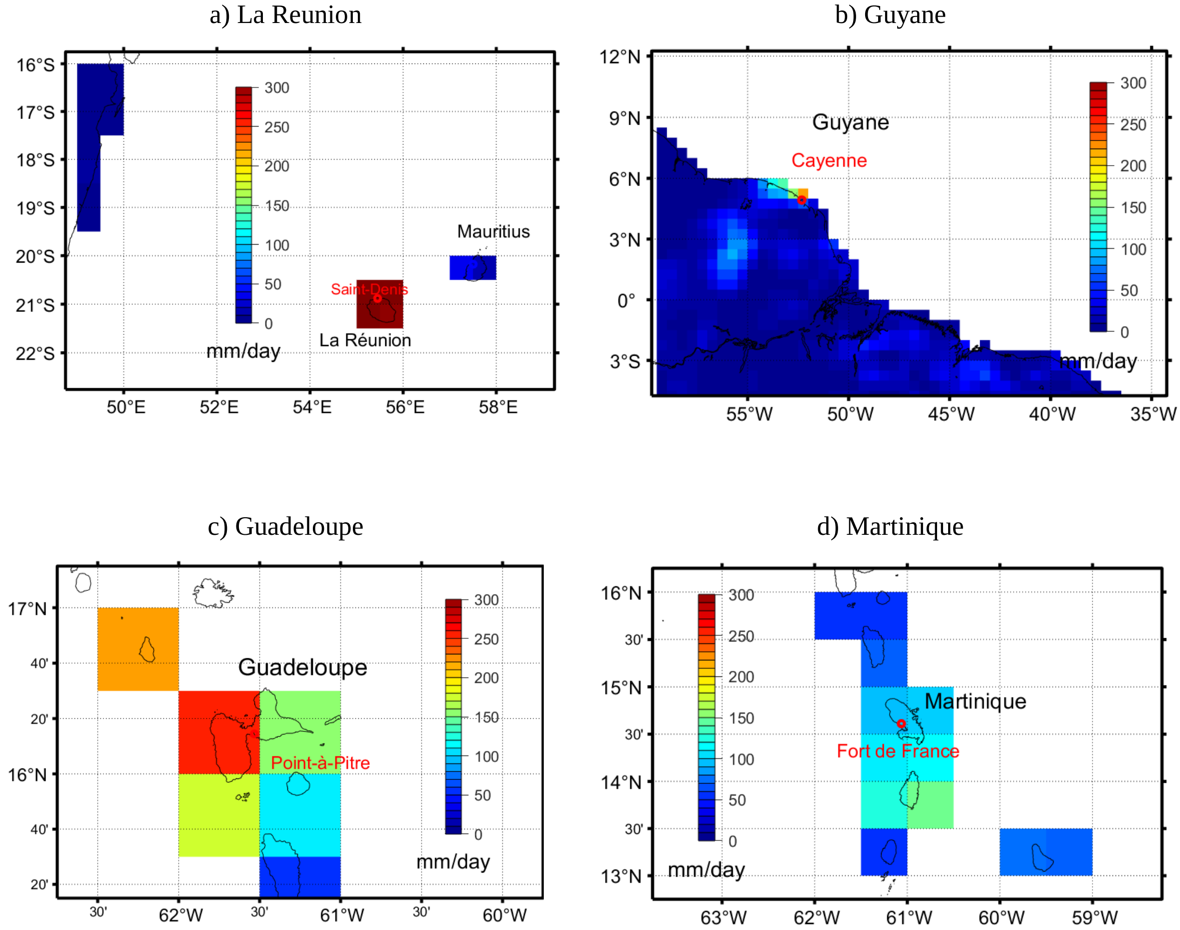
Note: Weather stations from the Global Summary of the Day (GSOD) database on La Reunion (*St Denis Gillot, St Pierre Pierrefonds*), Martinique (*La Lamentin, Martinique Aime Césaire International Airport, Trinité Caravelle*), Guadeloupe (*La Desirade, Le Raizet, Point-à-Pitre International Airport*), and Guyane (*Maripasoula, Rochambeau, St Laurent du Maron*).

Figure A.3. Wind speed via remote sensing



Note: Wind speed via remote sensing from the Cross-Calibrated Multi-Platform (CCMP), measured on a 0.25-degree grid in miles per second on a scale between zero and 30. Panels a) to d) show the maximum 6h average wind speed, which amount to 27.76 m/s 2007-Feb-25 (12AM) on La Reunion (cyclone Gamede), 17.26 m/s 17-Aug-2007 (6PM) on Martinique (hurricane Dean), 21.52 m/s 19-Sep-2017 (6PM) on Guadeloupe (hurricane Maria), and 13.52 m/s 10-Mar-2015 (12 PM) in Guyane.

Figure A.4. Precipitation via remote sensing



Note: Precipitation via remote sensing from the Climate Prediction Center (CPC), measured on a 0.5-degree grid in millimeters per day. Panels a) to d) show the maximum daily precipitation, which are 319.11 mm, 29.01.2011on La Reunion, 141.06 mm, 28.09.2016 on Martinique, 252.59 mm, 19.11.1999 on Guadeloupe, and 212.79 mm, 08.04.2000 in Guyane.

Table A.9 Summary statistics of meteorological data

	Precipitation				Wind speed			
	Remote sensing (CPC)		**Weather stations (GSOD)**		**Remote sensing (CCMP)**		**Weather stations (GSOD)**	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
La Reunion	43.25	45.92	110.08	122.48	13.12	2.55	2.75	0.46
Guyane	69.82	30.97	142.67	86.21	10.06	1.31	1.62	0.35
Guadeloupe	36.67	25.10	89.03	92.81	11.61	1.58	1.99	0.58
Martinique	40.36	23.98	97.32	79.19	11.17	1.26	2.45	0.70
Unweighted average	47.53	31.49	109.78	95.17	11.49	1.68	2.20	0.52

Note: All data was harmonized for comparability. Precipitation is measured in cumulative millimeters per day (conversion: .01 inches = 0.254 mm). Wind speed is measured in meters/second (conversion: .1 knots = 0.0514444 m/s).

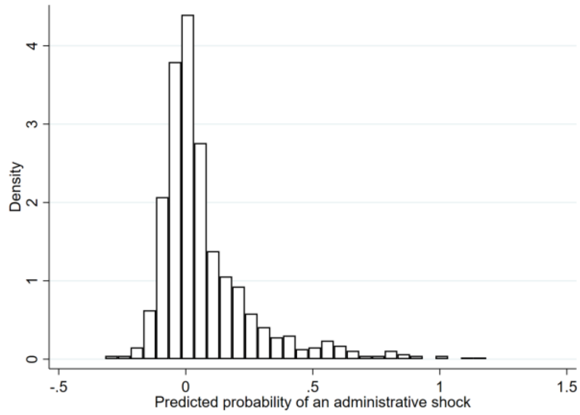
Table A.10 Météo France events

Region	Date	Event name	Event type
La Réunion	24-Feb-2007	Gamede	cyclone
La Réunion	3-Mar-2006	Diwa	cyclone
La Réunion	21-Jan-2002	Dina	cyclone
La Réunion	3-Jan-2018	Ava	cyclone
La Réunion	9-Mar-1999	Davina	cyclone
La Réunion	4-Mar-2018	Dumazile	cyclone
La Réunion	1-Jan-2014	Bejisa	cyclone
La Réunion	7-Mar-2015	Haliba	cyclone
Guyane	15-May-2013	-	extreme rain
Guyane	24-Jan-2010	-	extreme rain
Guyane	1-Jun-2008	-	extreme rain
Guyane	8-May-2006	-	extreme rain
Guyane	30-Apr-2000	-	extreme rain
Guyane	17-May-2000	-	extreme rain
Guadeloupe	10-Nov-2018	-	extreme rain
Guadeloupe	18-Sep-2017	Maria	hurricane
Guadeloupe	12-Oct-2012	Rafael	hurricane
Guadeloupe	3-Jan-2011	-	extreme rain
Guadeloupe	30-Aug-2010	Earl	hurricane
Guadeloupe	17-Aug-2007	Dean	hurricane
Guadeloupe	18-Nov-1999	Lenny	hurricane
Guadeloupe	21-Oct-1999	Jose	hurricane
Martinique	16-Apr-2018	-	extreme rain
Martinique	31-Dec-2017	-	extreme rain
Martinique	28-Sep-2016	Matthew	hurricane
Martinique	6-Nov-2015	-	extreme rain
Martinique	12-Oct-2012	Rafael	hurricane
Martinique	1-Aug-2011	Emily	hurricane
Martinique	30-Oct-2010	Tomas	hurricane
Martinique	4-May-2009	-	extreme rain
Martinique	17-Aug-2007	Dean	hurricane
Martinique	18-Nov-1999	Lenny	hurricane

Note : Events obtained from Météo France websites documenting extreme events in the four regions:
http://pluiesextremes.meteo.fr/lareunion/Le-club-des-500-mm.html,
http://pluiesextremes.meteo.fr/guyane/-Evenements-memorables-.html
http://pluiesextremes.meteo.fr/antilles/-Evenements-memorables-.html

Appendix B. Additional results

Figure B.1 – First stage fitted values: Predicted probability of a significant natural disaster



Note: The figure shows the density plot of fitted values $\widehat{\omega}_{it}$ of model (1). Since the dependent variable is an indicator variable associated with natural disaster events with large economic damages, we interpret $\widehat{\omega}_{it}$ as the predicted probability of an economically significant natural disaster as a function of meteorological data.

Figure B.2 – First stage fitted values: predicted probability conditional on the occurrence of GASPAR shocks

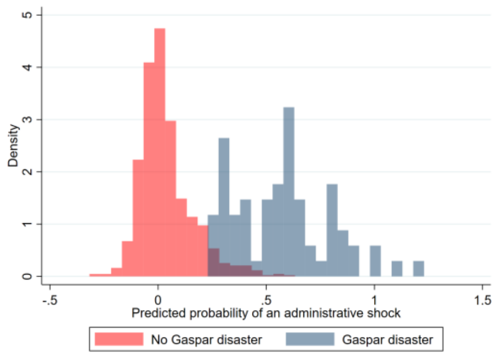


Figure B.3 – First stage fitted values: predicted probability conditional on the occurrence of EM-DAT shocks

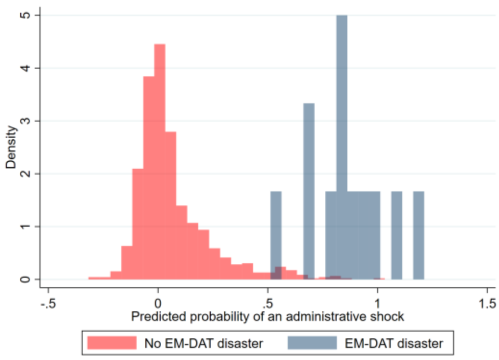


Figure B.4 – First stage fitted values: predicted probability conditional on the occurrence of adminitrative shocks

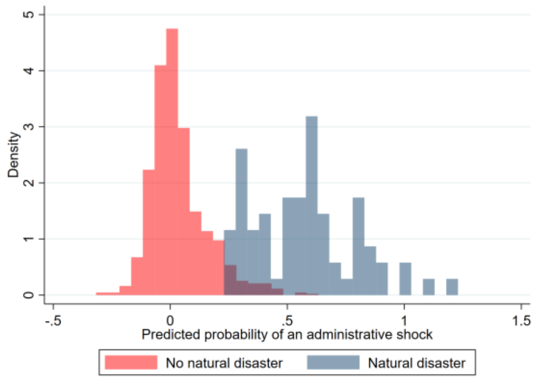
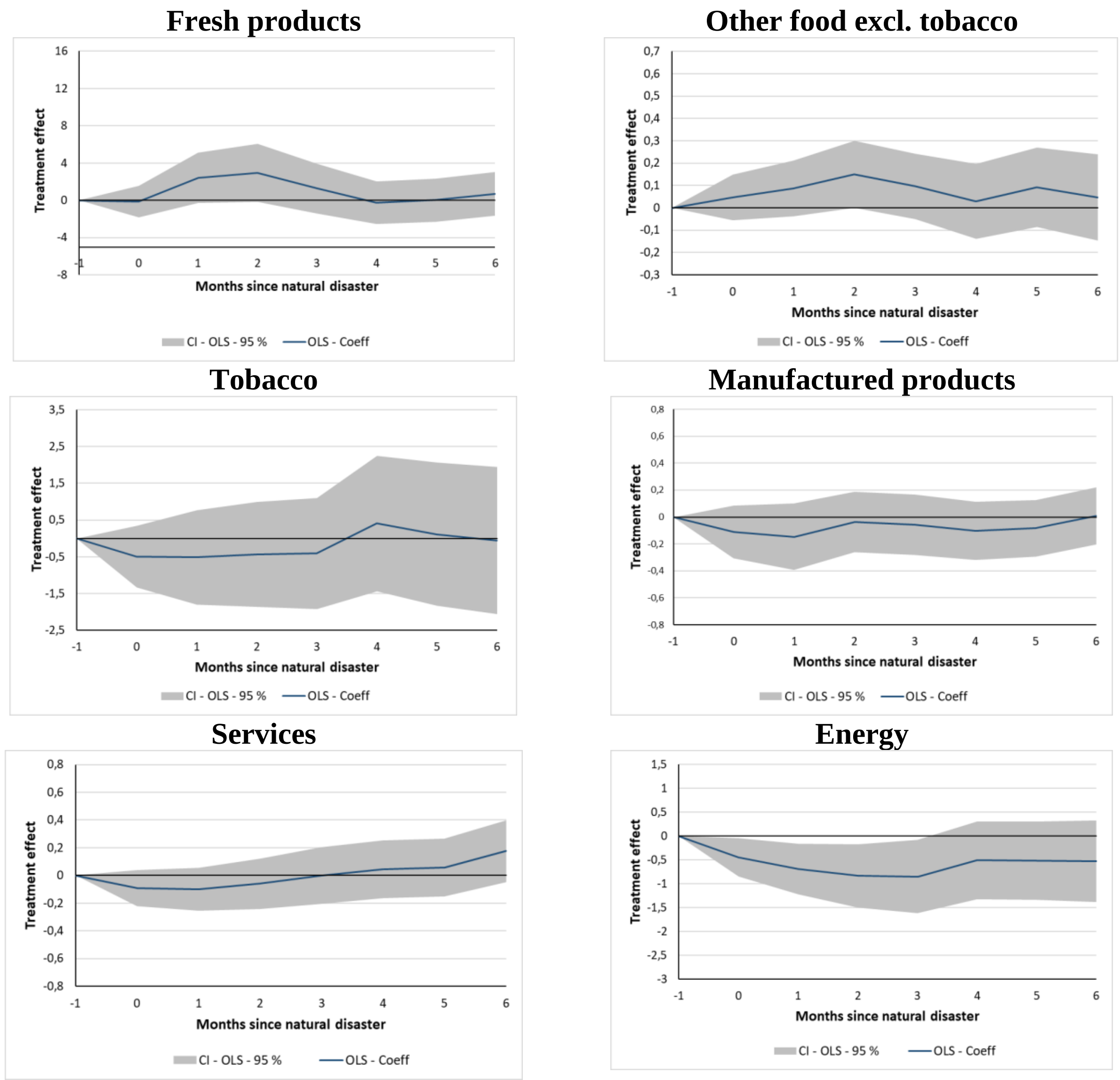


Figure B.5: Main results – CPI components - OLS



Note: The figures plot the cumulated impulse response function CPI components, in our baseline OLS specification. Treatment effects are expressed in percent. 95 percent confidence intervals with robust standard errors in shaded areas.

Table B.1 – Baseline effects on CPI inflation for all available aggregates

	T=0	T=1	T=2	T=3	T=4	T=5	T=6
Food excl. tobacco	0.39	1.62***	2.28***	0.86	-0.38	0.02	0.57
	(0.24)	(0.42)	(0.63)	(0.57)	(0.50)	(0.43)	(0.41)
Other food	0.29***	0.13	0.31***	0.24*	0.03	0.31**	0.16
	(0.10)	(0.12)	(0.12)	(0.14)	(0.14)	(0.15)	(0.17)
Fresh products	1.89	9.48***	10.60***	3.96	-2.11	-1.72	2.03
	1.49	2.29	3.13	2.65	2.32	2.32	2.25
Tobacco	-0.04	-0.38	-0.35	0.00	-0.60	-0.32	-0.38
	(0.48)	(0.75)	(0.90)	(1.04)	(1.26)	(1.46)	(1.51)
Energy	-0.48	-0.20	0.35	-0.04	-0.25	-1.10	-1.17
	(0.53)	(0.54)	(0.58)	(0.67)	(0.74)	(0.78)	(0.82)
Petroleum products	-0.69	-0.35	0.43	-0.13	-0.49	-1.68	-1.74
	(0.73)	(0.75)	(0.79)	(0.92)	(0.99)	(1.04)	(1.08)
Manufactured products	-0.13	-0.27	-0.02	0.11	-0.22	-0.31	-0.15
	(0.18)	(0.23)	(0.21)	(0.19)	(0.20)	(0.19)	(0.24)
Other manuf	0.00	-0.11	-0.02	-0.04	-0.12	-0.20*	-0.28*
	(0.08)	(0.10)	(0.11)	(0.10)	(0.12)	(0.11)	(0.15)
Footwear and garments	-0.28	-0.95	-0.27	0.87	-0.75	-1.03	0.10
	(0.79)	(0.92)	(0.81)	(0.75)	(0.78)	(0.79)	(0.83)
Pharmaceutical products	-0.07	-0.01	0.02	-0.15	0.00	-0.03	-0.26
	(0.12)	(0.15)	(0.16)	(0.16)	(0.21)	(0.23)	(0.28)
Services	-0.03	-0.19	-0.12	-0.32*	-0.20	-0.25	0.06
	(0.13)	(0.17)	(0.19)	(0.18)	(0.21)	(0.20)	(0.21)
Other services	-0.16	-0.18	-0.12	-0.21	-0.27	-0.45*	-0.22
	(0.16)	(0.18)	(0.21)	(0.22)	(0.25)	(0.26)	(0.27)
Rents	-0.05	-0.20**	0.11	0.07	0.20	0.18	0.33
	(0.07)	(0.10)	(0.15)	(0.17)	(0.20)	(0.21)	(0.23)
Communication services	-0.35**	-0.50	-0.66*	-0.61*	-0.64*	-0.31	0.04
	0.18	0.34	0.38	0.37	0.37	0.36	0.44
Health services	-0.28**	-0.17	-0.20	-0.29	-0.37	-0.27	-0.41
	(0.13)	(0.18)	(0.20)	(0.23)	(0.25)	(0.28)	(0.32)
Transportation services	-0.22	0.27	1.26	0.31	-0.61	3.59	3.74
	(2.02)	(2.04)	(2.05)	(1.93)	(2.57)	(2.42)	(3.47)
Total	0.01	0.17	0.48*	0.08	-0.26	-0.27	0.03
	(0.12)	(0.16)	(0.21)	(0.21)	(0.21)	(0.18)	(0.17)
N	926	926	926	926	926	926	926

***Note*:** Cumulative impulse response functions of consumer prices in the 4 DCOMs estimated between 1999m01 and 2018m04, using a 2SLS local projections. Robust standard errors in parentheses.
*p < 0.10; **p < 0.05; *** p < 0.01.

Table B.2: Main results – CPI components - OLS

	T=0	T=1	T=2	T=3	T=4	T=5	T=6
OLS estimates							
Total	-0,13**	-0,04	0,06	-0,01	-0,02	0,04	0,12
	(0.06)	(0.09)	(0.11)	(0.11)	(0.10)	(0.09)	(0.10)
Fresh products	-0,11	2,41*	2,94*	1,27	-0,25	0,02	0,69
	(0.86)	(1.37)	(1.59)	(1.37)	(1.17)	(1.18)	(1.18)
Other food excl. tobacco	0.05	0,09	0.15*	0,10	0,03	0,09	0,05
	(0.05)	(0.06)	(0.08)	(0.07)	(0.09)	(0.09)	(0.10)
Manufactured products	-0,11	-0,15	-0,04	-0,06	-0,10	-0,08	0,01
	(0.10)	(0.13)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
Services	-0,09	-0,10	-0,06	0,00	0,04	0,06	0,18
	(0.07)	(0.08)	(0.09)	(0.10)	(0.11)	(0.11)	(0.11)
Energy	-0,45**	-0,69**	-0,83**	-0,85**	-0,51	-0,51	-0,53
	(0.20)	(0.27)	(0.34)	(0.39)	(0.41)	(0.42)	(0.44)
Tobacco	-0,49	-0,52	-0,43	-0,41	0,40	0,11	-0,05
	(0.43)	(0.66)	(0.73)	(0.77)	(0.94)	(0.99)	(1.02)

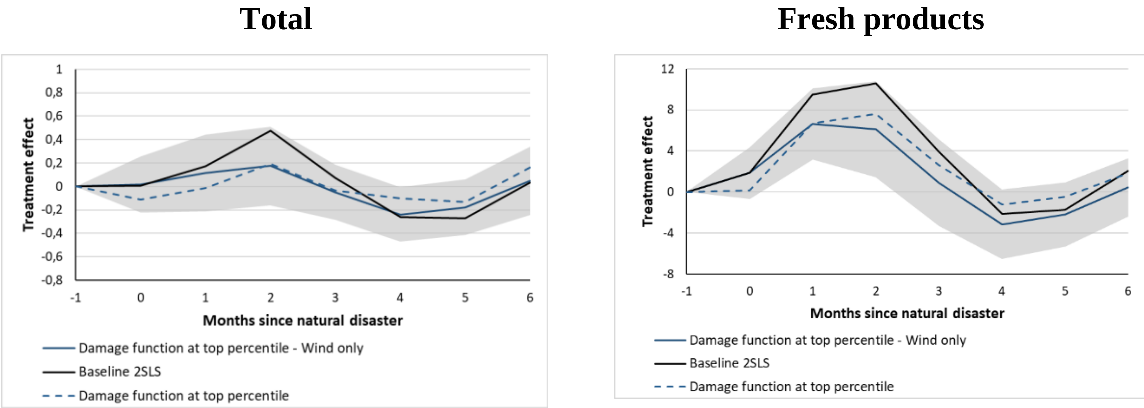
***Note*:** Cumulative impulse response functions of consumer prices in the four DCOMs estimated between 1999m01 and 2018m04, using OLS local projections. Robust standard errors in parentheses.
*p < 0.10; **p < 0.05; *** p < 0.01.

Table B.3 - Main effects of meteorological extreme events on sectoral employment and on hotel stays (2SLS)

	T=0	T=1	T=2	T=3	T=4	T=5	T=6
Hotel stays							
Overnight hotel stays	-0,23	10,54**	7,88*	7,64	3,52	1,56	-0,21
	(3,59)	(4,66)	(4,52)	(5,07)	(5,78)	(4,99)	(3,82)
Employment							
Total	-0,37*	-0,33	-0,18	-0,16	0,23	0,16	0,13
	(0,21)	(0,27)	(0,28)	(0,36)	(0,37)	(0,39)	(0,39)
Agriculture (AZ)	-1,08	-2,29*	-3,22**	-1,27	-1,55	-1,90	-1,88
	(0,86)	(1,26)	(1,30)	(1,59)	(1,73)	(1,69)	(2,18)
Food manuf. (C1)	-0,03	-0,35	-1,41	0,40	-0,79	-0,91	-1,14
	(0,58)	(0,78)	(0,89)	(1,13)	(1,27)	(1,31)	(1,26)
Extractive industry (C2)	-0,29	0,20	-0,94	-1,02	-1,43	-1,25	-0,40
	(0,37)	(0,70)	(0,78)	(0,86)	(1,06)	(1,02)	(1,39)
Manuf. – machines (C3)	0,46	1,01	-0,10	0,42	0,96	3,52	3,06
	(1,21)	(1,78)	(2,01)	(1,87)	(2,06)	(2,15)	(2,38)
Manuf.-transports (C4)	5,73	1,49	7,29	3,79	-4,57	-8,42	-12,24
	(5,64)	(8,90)	(8,70)	(8,05)	(11,26)	(10,83)	(10,26)
Manuf. – others (C5)	-0,23	-0,05	0,18	-0,04	0,14	0,20	1,20
	(0,27)	(0,46)	(0,51)	(0,62)	(0,68)	(0,77)	(0,80)
Construction (FZ)	-0,72*	-1,06*	-1,38*	-0,80	0,11	0,19	0,23
	(0,41)	(0,62)	(0,75)	(1,02)	(1,23)	(1,27)	(1,44)
Car repair (GZ)	-0,12	-0,39	-0,01	0,49	0,94*	1,16**	1,03*
	(0,27)	(0,35)	(0,44)	(0,44)	(0,50)	(0,56)	(0,58)
Transports (HZ)	-0,28	-0,03	0,17	0,10	0,02	0,64	-0,03
	(0,32)	(0,55)	(0,61)	(0,64)	(0,78)	(0,69)	(0,73)
Accom. – restaurants (IZ)	0,32	0,68	0,36	0,23	0,03	0,25	-0,15
	(0,39)	(0,55)	(0,64)	(0,75)	(0,82)	(0,86)	(0,81)
Info. – comm (JZ)	-1,03*	-0,88	1,04	1,55	1,97	1,20	2,37**
	(0,53)	(0,85)	(1,21)	(1,26)	(1,38)	(1,22)	(1,20)
Finance – insurance (KZ)	0,12	0,47	0,15	0,54	-0,40	0,28	-0,14
	(0,61)	(0,73)	(0,76)	(0,70)	(0,74)	(0,76)	(0,68)
Real estate (LZ)	-0,40	-1,14	-0,87	-0,59	-1,71	-0,91	0,30
	(0,58)	(0,83)	(0,97)	(1,03)	(1,35)	(1,34)	(1,36)
Scientific – admin (MN)	-0,49	-0,11	0,40	0,47	0,37	0,69	0,09
	(0,40)	(0,59)	(0,63)	(0,83)	(0,98)	(1,08)	(1,15)
Public admin (OQ)	-0,44*	-0,35	-0,12	-0,48	0,22	-0,13	0,09
	(0,24)	(0,33)	(0,34)	(0,41)	(0,41)	(0,45)	(0,47)
Other services (RU)	-0,15	-0,21	-0,58	-1,20	-0,73	-1,01	-0,95
	(0,41)	(0,63)	(0,69)	(0,84)	(0,98)	(0,97)	(0,91)
Interim	5,57	9,22	7,02	15,53**	7,97	15,97*	5,89
	(5,46)	(6,85)	(7,10)	(7,26)	(8,17)	(8,40)	(7,86)

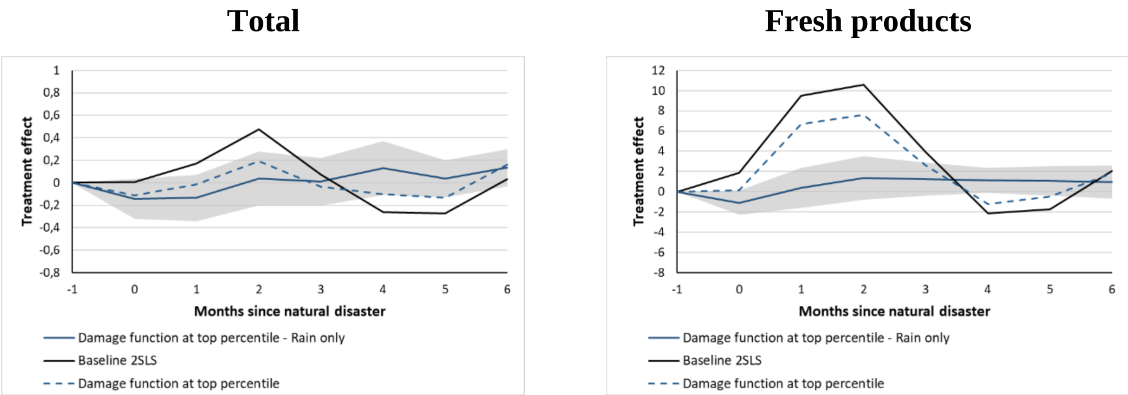
***Note*:** Cumulative impulse response functions of real activity data in the 4 DCOMs estimated between 1999m01 and 2018m04, using a 2SLS local projections. T-stat with robust standard errors in parentheses.
*p < 0.10; **p < 0.05; *** p < 0.01.

Figure B.6: Comparison of baseline damage functions with wind-only damage functions, at top percentile



Note: The figures plot the cumulated impulse response function for headline CPI and fresh products CPI, for wind damage function (in solid blue), compared to our baseline 2SLS (in black) and to our combined wind and rain damage function (dotted blue). The damage functions are evaluated at the top percentile of shocks, and shaded areas represent 95 percent confidence intervals with robust standard errors for wind-only damage functions. Treatment effects are expressed in percent.

Figure B.7: Comparison of baseline damage functions with rain-only and rain-only damage functions, at top percentile



Note: The figures plot the cumulated impulse response function for headline CPI and fresh products CPI, for rain damage function (in solid blue), compared to our baseline 2SLS (in black) and to our combined wind and rain damage function (dotted blue). The damage functions are evaluated at the top percentile of shocks, and shaded areas represent 95 percent confidence intervals with robust standard errors for rain-only damage functions. Treatment effects are expressed in percent.

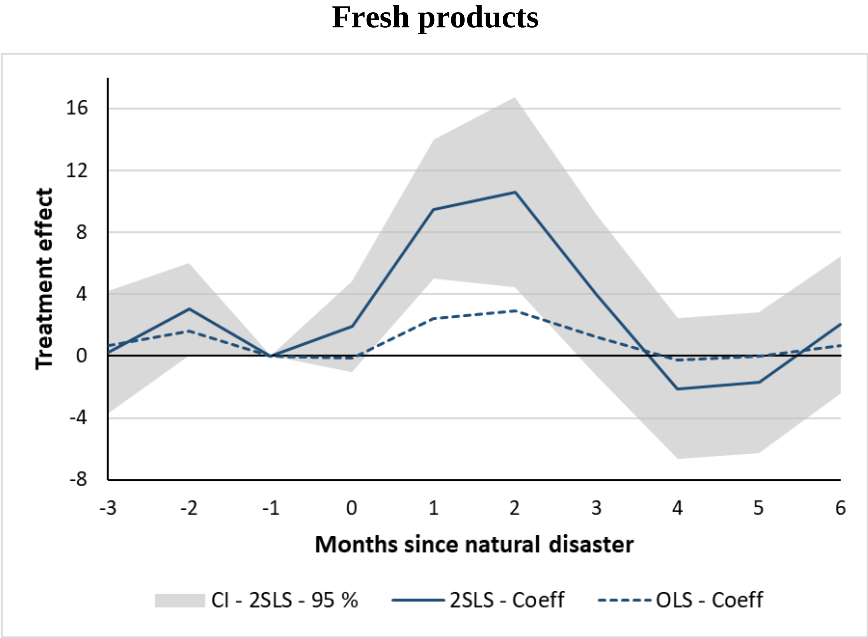
Table B.4 – Robustness analysis for other components

	T=0	T=1	T=2	T=3	T=4	T=5	T=6
(A) Other food excl. tobacco							
2SLS - Baseline	0,29***	0,13	0,31***	0,24*	0,03	0,31**	0,16
2SLS – Baseline – no Réunion	0,27**	0,16	0,21	0,20	-0,01	0,40*	0,31
2SLS – Baseline, 3 lags shock	0,24***	0,15	0,33***	0,24*	0,04	0,29**	0,13
2SLS – Baseline 3 lags CPI	0,24***	0,08	0,26**	0,19	0,01	0,29**	0,14
2SLS – Baseline excl. shock < 6months	0,37***	0,17	0,40**	0,30	0,02	0,39**	0,20
2SLS – 6 lags forward	0,23**	0,18	0,31***	0,28**	0,10	0,29*	0,19
2SLS – Baseline, Weather station data	0,23**	0,09	0,26**	0,19	0,02	0,31**	0,21
(B) Manufactured products							
2SLS - Baseline	-0,13	-0,27	-0,02	0,11	-0,22	-0,31	-0,15
2SLS – Baseline – no Réunion	-0,09	0,04	-0,07	-0,11	-0,35	-0,47*	-0,40
2SLS – Baseline, 3 lags shock	-0,16	-0,23	0,05	0,14	-0,08	-0,11	0,08
2SLS – Baseline 3 lags CPI	-0,17	-0,32*	-0,03	0,04	-0,32*	-0,37**	-0,21
2SLS – Baseline excl. shock < 6months	-0,17	-0,35	-0,03	0,15	-0,29	-0,39	-0,19
2SLS – 6 lags forward	-0,11	-0,35	0,00	0,08	-0,23	-0,29	-0,07
2SLS – Baseline, Weather station data	-0,18	-0,34	-0,32	-0,16	-0,44**	-0,52**	-0,38
(C) Services							
2SLS - Baseline	-0,03	-0,19	-0,12	-0,32*	-0,20	-0,25	0,06
2SLS – Baseline – no Réunion	0,00	-0,19	-0,16	-0,22	-0,09	-0,28	-0,09
2SLS – Baseline, 3 lags shock	-0,03	-0,16	-0,10	-0,31*	-0,15	-0,22	0,12
2SLS – Baseline 3 lags CPI	-0,08	-0,20	-0,17	-0,35**	-0,25	-0,30	0,01
2SLS – Baseline excl. shock < 6months	-0,04	-0,25	-0,16	-0,41*	-0,26	-0,33	0,07
2SLS – 6 lags forward	-0,18	-0,27	-0,30	-0,37**	-0,28	-0,27	-0,11
2SLS – Baseline, Weather station data	-0,05	-0,15	-0,07	-0,19	-0,09	-0,17	0,24
(D) Energy							
2SLS - Baseline	-0,48	-0,20	0,35	-0,04	-0,25	-1,10	-1,17
2SLS – Baseline – no Réunion	-0,45	0,14	0,16	-0,33	-0,03	-0,74	-1,26
2SLS – Baseline, 3 lags shock	-0,46	-0,06	0,46	0,51	0,30	-0,71	-1,00
2SLS – Baseline 3 lags CPI	-0,51	-0,30	0,20	-0,25	-0,44	-1,34*	-1,38*
2SLS – Baseline excl. shock < 6months	-0,61	-0,25	0,44	-0,05	-0,34	-1,45	-1,57
2SLS – 6 lags forward	-0,81	-0,54	-0,04	-0,54	-0,65	-1,45*	-1,70**
2SLS – Baseline, Weather station data	-0,48	-0,40	0,06	-0,44	-0,67	-1,56**	-1,97**
(E) Tobacco							
2SLS - Baseline	-0,04	-0,38	-0,35	0,00	-0,60	-0,32	-0,38
2SLS – Baseline – no Réunion	0,34	0,99	0,70	1,35	-0,06	0,22	-0,56
2SLS – Baseline, 3 lags shock	-0,37	-0,87	-0,15	0,43	0,43	0,58	0,47
2SLS – Baseline 3 lags CPI	0,02	-0,51	-0,58	-0,19	-0,78	-0,60	-0,60
2SLS – Baseline excl. shock < 6months	-0,10	-0,53	-0,45	0,00	-0,75	-0,49	-0,58
2SLS – 6 lags forward	0,50	0,77	0,90	1,00	1,22	1,46	1,53
2SLS – Baseline, Weather station data	-1,03**	-1,56**	-1,07	-0,06	-0,92	-1,37	-1,78

***Note*:** The table shows alternative specifications of local projections of consumer prices. Panel (A) shows results for total CPI, panel (B) shows results for the CPI of fresh products. "2SLS baseline" is our baseline 2SLS specification. "2SLS – Baseline – no Réunion" is the baseline specification excluding La Réunion. "2SLS – Baseline; 3 lags shock" controls for up to 3 lags of the shock (instrumented by relevant lags of the instrumental variables). "2SLS – 6 lags forward" controls for up to 6 forward lags of the shock. "2SLS – 3 lags CPI" controls for 3 lags of monthly variations of CPI. "Baseline excl. shock < 6 months" is the baseline specification, excluding shocks which occur less than 6 months after a previous shock. "2SLS – Baseline, Weather station data" is the baseline specification, but with instruments taken from weather station data rather remote sensing data.

*p < 0.10; **p < 0.05; *** p < 0.01.

Figure B.8: Baseline for fresh products CPI, including pre-trends up to 3 months



Note: The figure plots the cumulated impulse response function for the CPI of fresh products in our baseline IV specification (solid blue) and for the OLS specification (dotted blue). 95 percent confidence intervals for the 2SLS specification with robust standard errors in shaded areas. Treatment effects are expressed in percent.

Appendix C. Constructing wind and rain damage functions

This section provides complementary information on the construction of damage functions. For the calibration of wind speed threshold value W^*, we follow Emanuel (2011) and set it to 50 knots. More specifically, we follow a two-step approach. Since remote sensing data is less precise for extreme values, we compute in a first step the percentile of wind speed above 50 knots from ground station recordings available through GSOD. In a second step, we apply the percentile to the remote sensing data from CCMP in order to obtain a threshold value $\widehat{W}_i^*$ for each region and expressed in meters per second.

The calibration of region-specific rainfall threshold values r_i^* follows Heinen et al. (2018), The threshold is based on precipitation of 112 mm, cumulative over a three-day window, which Heinen et al. (2018) calibrated to an intensity duration flood model and actual flood event data for Trinidad. Given the heterogeneity of regions in our sample, with likely differing threshold values, we proceed in two steps. First, we compute the percentile of 112 mm over three-day windows for the closest region to Trinidad in our sample, i.e. Martinique. We then applied this percentile value to rainfall data of the remaining regions in our data sample to obtain regional threshold values in millimeters. The resulting threshold values are 229 mm for La Réunion, 52 mm for Guadeloupe and 74 mm for Guyane.

Exposure weights ξ_{ij} are constructed from satellite nighttime light data from the U.S. Air Force Defense Meteorological Satellite Program (DMSP), obtained via the Earth Observation Group (Baugh et al 2010). We use the version cleaned by background noise, averaged across the calendar year and corrected for percent frequency of light detection. Figure C.1, panel a) visualizes the data for the case of La Réunion. Fig. C.1 panel b shows nighttime light observations that are cleaned from observations above ocean surface. We use geographic information system software and freely available shape files on ocean surface by *Natural Earth* to do so. The main motivation is to take into account noise from coastal areas, such as ships or other coastal activities. We compute a proxy of economic activity in a weather cell *j* in region *i* as

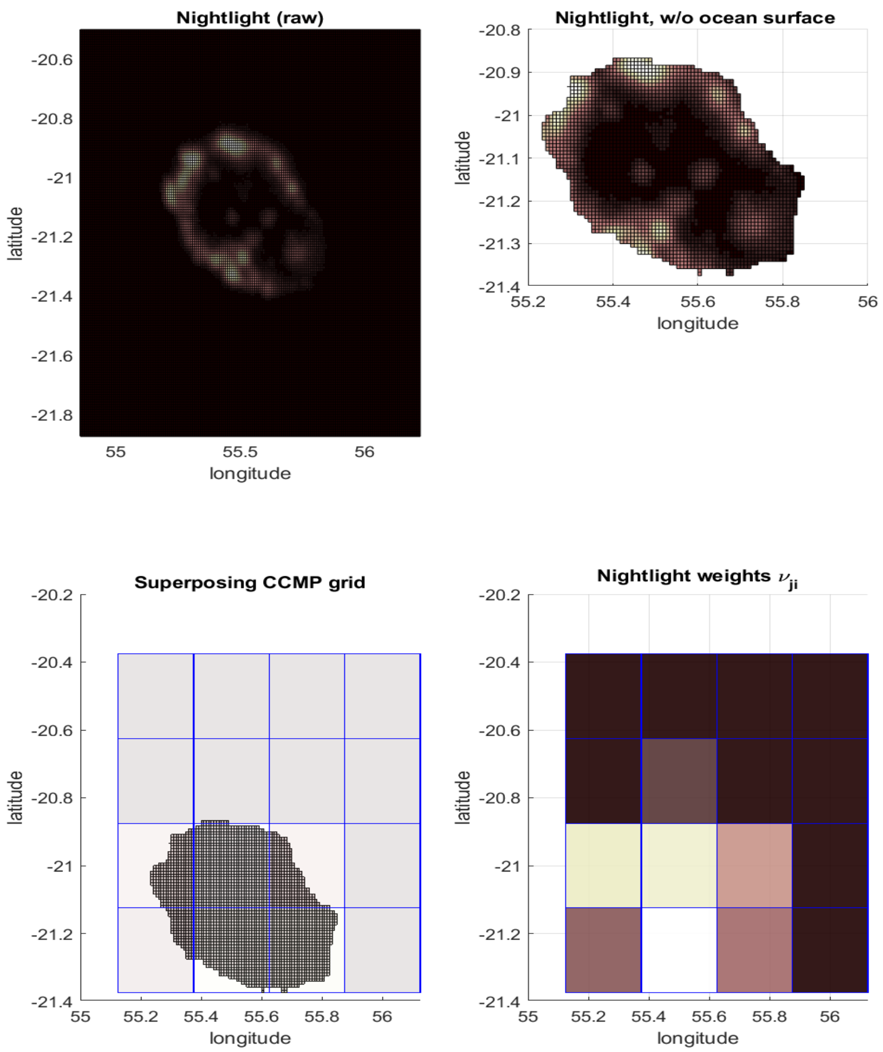
$$v_{ij} = \sum_{n=1}^{N} NTL_{ijn} \times \mathbb{1}_{\{O_{ijn}=0\}} \tag{C.1}$$

where NTL_{ijn} denotes nighttime light in region *i* in weather cell *j* and nighttime light grid cell *n*, and $\mathbb{1}$ denotes an index variable which takes the value one if the nighttime light is recorded above land. Fig. C.1 panel c illustrates that the number of nighttime light observations *N* per weather cell j can vary substantially. The final weights are obtained by dividing nighttime light intensity in each weather cell j by total nighttime light intensity in region i:

$$\xi_{ij} = \frac{\nu_{ij}}{\sum_j \nu_{ij}} \tag{C.2}$$

Figure C.1 panel d illustrates the final result, while brighter areas indicate higher values of ξ_{ij}.

Figure C.1. Night time light weights for La Réunion



Note: Panel a) Satellite nighttime lights are from the Defense Meteorological Satellite Program (DMSP), average light for the calendar year 2000 times the percentage percent frequency of light detection. Panel b) Nighttime light w/o ocean surface makes use of the ocean surface shape file from *Natural Earth*. Panel c) Weather cells are from the *Cross-Calibrated Multi-Platform* (CCMP). Panel d) Brighter cells of the final nightlight weights indicate higher share of total detected nighttime light, which is the proxy for regional economic activity.

Appendix D. Constructing an IRF for each quintile of income

The main difficulty to merge the CPI data with the *Budget des familles* is that the *Budget des familles* consumption basket and the CPI aggregates we considered, though they are based on the same underlying classification (COICOP), have differing compositions. This prevents from mapping perfectly the two sets of items. We therefore focus on the item that reacts the most strongly in our estimation, namely food. However, reconciling the two dataset is not straightforward. Indeed, while Insee publishes the CPI of fresh products and total excluding fresh products, the share of fresh products in the consumption baskets is not observed in the *Budget des familles* survey. Conversely, while the *Budget des familles* survey gives weight for total food (including tobacco), the food CPI published by Insee excludes tobacco. We therefore resort to the following simple approximation. First, in the *Budget des familles* survey, for each quintile of income, and on average across the four departments, we compute the percent deviation in the share of food (including tobacco), compared to the average share. Second, we apply these percent deviations to the average weight of fresh product observed in our sample. This gives us estimated weights of fresh products for each quintile. We therefore implicitly assume that the deviation of weights of fresh products between the quintiles and the average is the same as the observed deviation of weights of food including tobacco, and that the deviation of weights of food products observed in 2017 between the quintiles and the average is representative of the deviations which occurred between 1999 and 2018. Finally, we combine the estimated baseline impulse response functions for fresh products and total excluding fresh products with these set of weights for fresh products (and their respective counterparts, corresponding to the weights of total excluding fresh products for the different quintiles) to derive an estimated impulse response function of total CPI for each quintile.

Table D.1: Share of food (incl. tobacco) in the household consumption basket, by quintile of income (2017)

	Guadeloupe	**Martinique**	**Guyane**	**La Réunion**	**Average**
Total	15.8	16.0	15.8	17.0	16.2
1st quintile	19.8	19.9	21.2	23.3	21.1
2nd quintile	20.1	18.0	20.7	21.9	20.2
3rd quintile	16.5	16.5	16.2	17.2	16.6
4th quintile	15.8	15.3	15.2	15.7	15.5
5th quintile	12.4	13.9	12.2	14.5	13.3

Note: This table presents the share of food (including tobacco) in the household consumption basket, according the *Enquête Budget des Familles* of 2017. The average across the 4 DCOMs is computed as an unweighted mean.

Appendix E. Deriving an optimal shock based on estimated shock probability using a ROC curve

We derive an optimal shock based on estimated shock probability using a ROC curve. To build the ROC curve, we discretize the range of observed values of predicted shock probability based on equation (1) (i.e. $\widehat{\omega}_{i,t,m}$) into 928 evenly-spaced values, ranging from a minimum of -0.32 and a maximum of 1.18. For each value T among these 928 values, we define a discrete shock variable equal to one if $\widehat{\omega}_{i,t,m}$ is above T, and zero otherwise. For each of these discrete shocks, we compute a true positive rate (TPR, sensitivity) and a false positives rate (FPR, 1-specificity) using the following formulas:

$$TPR = \frac{True\ positive}{True\ positive + False\ negative}$$

$$FPR = \frac{False\ positive}{False\ positive + True\ negative}$$

True positive corresponds to the number of observations classified as a shock based which indeed are observed shocks; *false negative* is the number of observations which are not classified as a shock while there is actually a shock; *false positive is* the number of observations classified as a shock while there is actually no shock; *true negative* is the number of observations which are not classified a shock when there is actually no shock.

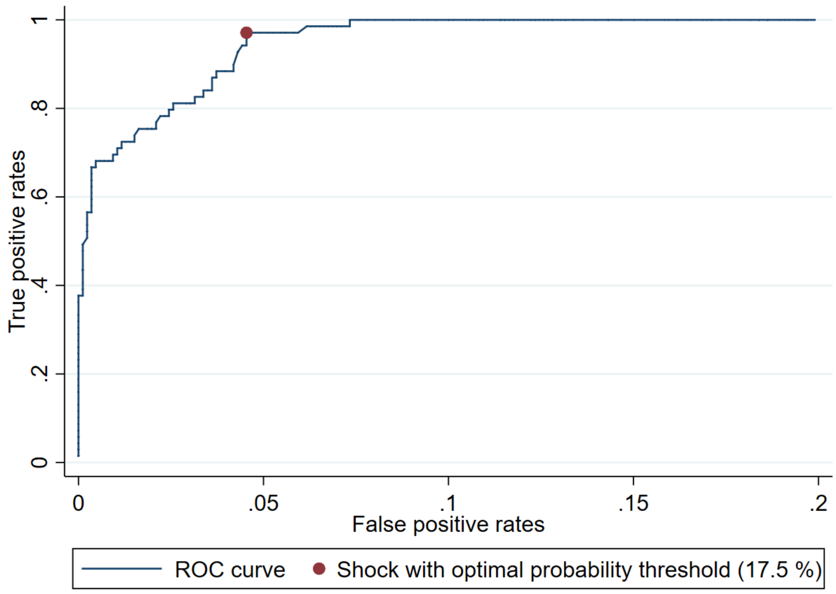
The ROC curve in Figure E.1 plots TPR against FPR for all of the 928 discrete shocks defined above. The further the ROC line is from the diagonal line, the more successful is the model at identifying shocks.

We define the optimal threshold as the one which maximizes the following formula:

$$\sqrt{TPR \times (1 - FPR)}$$

The optimal threshold is of 17.5 %: we then define an observation as shock when its underlying estimated probability of an administrative shock is higher than 17.5 %. The confusion matrix of shocks derived under the optimal threshold is depicted in Table E.1. It shows that all of actual administrative shock are correctly classified as shock, but that observations classified as a shock represent less than the half of the total number of observations classified as a shock (69 out 177, 40 %).

Figure E.1. ROC curve based on linear probability models with varying thresholds for shock discretization



Note: The curve represents the share of true positive shocks (i.e. the number of true positive divided by the sum of true positive and false negative) against the share of false positive (i.e. the number of true positive divided by the sum of false positive and true negative), for all of the 928 thresholds of predicted probability between 0 and 1. The red dot corresponds to the threshold maximizing the true positive rate while minimizing the false positive rate, and corresponds to a threshold of 17.5 %.

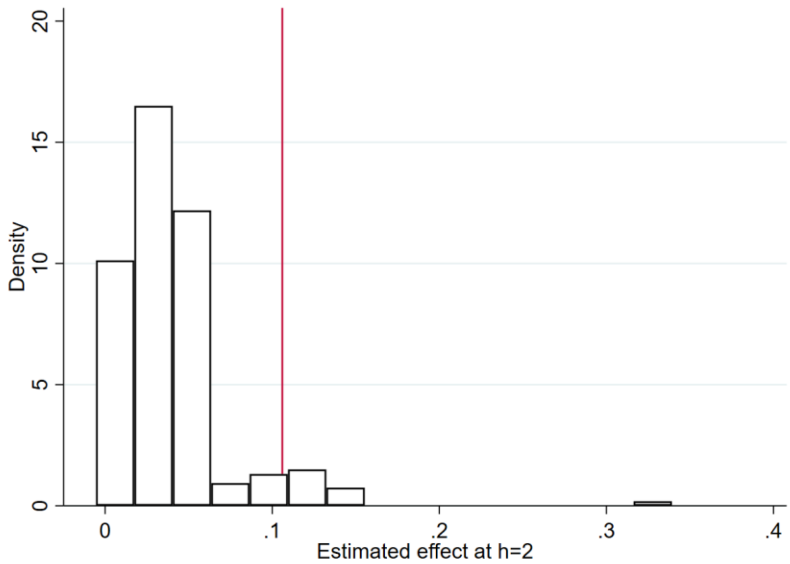
Table E.1. Confusion matrix for the optimal shock based on the ROC curve

	Pred. shock=0	**Pred. Shock=1**
True shock=0	751	108
True shock=1	0	69

Results from the regressions presented in Figure 9 are based on the following OLS specification for each of the 928 values of T:

$$\log\left(\frac{P_{i,t,m+h}}{P_{i,t,m-1}}\right) = \tau_h + \theta_h \mathbb{1}(\widehat{\omega}_{i,t,m} > T) + \gamma_{i,h} + \delta_{t,h} + \theta_{m,h} + \theta_{m,h} \times R_{i,h} + \varepsilon_{i,t,m,h}$$

Figure E.2. Distribution of estimated effects on fresh products in the discrete shocks against the baseline effect



Note: Distribution of estimated coefficients represented in Figure 9. The red line corresponds to the baseline 2SLS effect.

Appendix F. Drawing random weather shocks for placebo estimations

In this section, we describe how we draw random weather shocks for our first placebo estimation (in which we instrument the actual administrative shocks by randomly generated). We model the maximum observed monthly rainfalls and wind speed using Gumbel distributions. The latter are part of generalized extreme values distributions, which are well suited to model extreme phenomena, such as the ones we focus on.

For wind and rain, we generate 100 random draws from Gumbel distributions whose parameters match the empirical moments of the maximum wind and rain distributions. More specifically, the expected value and variance of a random variable following a Gumbel distribution of location parameter μ and of scale parameter β are defined as:

$$E(X) = \mu + \beta\gamma$$

$$V(X) = \frac{\pi^2}{6}\beta^2$$

Where γ is Euler-Mascheroni constant (approximated by the value 0.5772156649). We therefore define $\hat{\beta}$ and $\hat{\mu}$ as:

$$\hat{\beta} = \sqrt{6} \times \frac{\widehat{sd(X)}}{\pi}$$

$$\hat{\mu} = \widehat{E(X)} - \hat{\beta}\gamma$$

Where $\widehat{sd(X)}$ and $\widehat{E(X)}$ are empirical standard deviation and expected values observed for the variable X in our full sample of observations. Empirically, $\hat{\beta}$ and $\hat{\mu}$ are similar to the parameters estimated in Stata using the package *extremes.* Using these sets of parameters, computed both for observed maximum records of wind speed and rainfall, we randomly generate placebo values of maximum records of wind speed and rainfall these values, defining them as:

$$Max_{placebo} = \max(\hat{\mu} - \hat{\beta} \times \ln(-\ln(\mathrm{U})), 0)$$

Where U is a random draw in a uniform distribution [0,1]. Since random draws in a Gumbel distribution can take negative values, we truncate them at zero, in order to match the fact that maximum rainfall and wind speed cannot have negative values.

In Figures F1 and F2, we plot the densities of placebo records (in grey), the density of observed records (in red), and the density of a random draw of a normal distribution with parameters of expected value and standard deviation equal to the empirical moments of maximum wind speed and rainfalls (in blue). In Figures F3 and F4, we plot the QQ plots of our random draws against the observed distributions. Overall, our random draws match reasonably well the distribution of observed maximum wind speed and rainfall, and are better suited to such data than a normal distribution.

Table F.1. Empirical moments of maximum wind and rainfall and computed parameters of Gumbel distribution

	$\widehat{E(X)}$	$\widehat{sd(X)}$	$\hat{\mu}$	$\hat{\beta}$
Maximum wind speed	11.49	2.07	10.56	1.61
Maximum rainfall	47.53	35.16	31.70	27.41

Figure F.1. Placebo and observed maximum wind speed

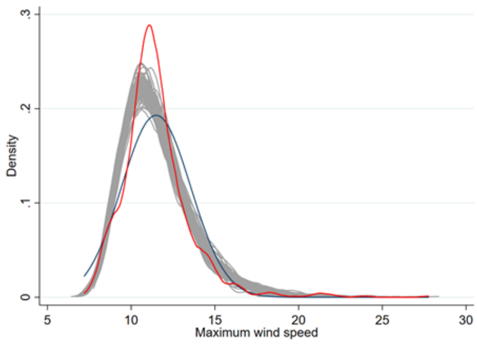
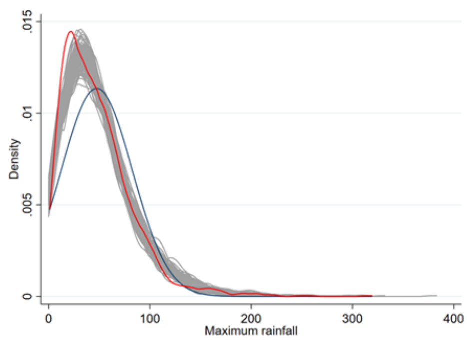


Figure F.2. Placebo and observed maximum rainfall



Note: The grey curves represent 100 densities of random draws in a Gumbel distributions matching the observed moments of maximum wind speed and maximum rainfalls. Blue curves correspond to a random draw in a normal distribution. Densities of actual maximum wind speed and rainfalls are plotted in red.

Figure F.3. QQ plots of placebo and observed maximum wind speed

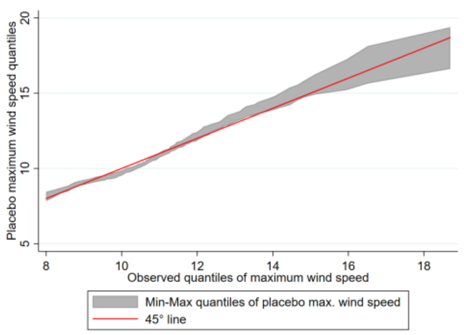
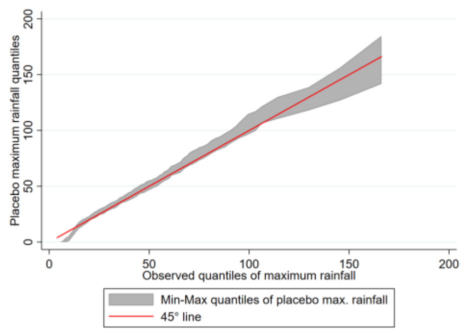


Figure F.4. QQ plots of placebo and observed maximum rainfall



Note: The graphs plot the range of quantiles of placebo maximum wind speed (resp. placebo maximum rainfall) against the respective quantiles of observed maximum wind speed (resp. observed maximum wind speed).