DECOMPOSING THE INFLATION RESPONSE TO NATURAL DISASTERS

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Abstract: This paper provides empirical evidence on the compositional effect of natural disasters on consumer prices based on monthly inflation data covering 12 types of goods and services in four French overseas territories. While disasters lead to a maximum rise in consumer prices of 0.5 percent, substantial heterogeneity characterizes the price response. An immediate strong surge in the prices of fresh food products of 12 percent is partially offset by a decline in the headline price index excluding fresh food products by 0.2 percent. Natural disasters have a persistent inflationary effect for six months, since services prices pick up after four months. While the highest income quantile experiences a mild increase of inflation by 0.2 percent, the rise for households in the lower quantile is with 0.7 percent more than three times as large.

JEL: E31, Q54

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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 disasters will depend on the relative strength of these supply and demand effects over time.

This paper contributes to closing this gap in the literature by providing a disaggregate analysis of price dynamics that contribute to an inflation surge observed in response to natural disasters. By focusing on the compositional effect, we also shed light on the distributional consequences of natural disasters with respect to consumption heterogeneity across income groups. We study natural disasters generating extreme wind speed and rainfall between 1999 and 2018 in four French overseas departments and regions (DCOM, for *Départements et Collectivités d'Outre-Mer*)*:* Guadeloupe, Guyane, Martinique and La Réunion. The territories are regularly exposed to significant natural disasters and are located in different places of the world, which allows studying shocks that are de-synchronized across territories. Our setting is unique in that it can leverage highly harmonized inflation records produced by the French statistical institute (Insee), with a high level of detail and frequency (monthly indicator for 12 components) that we match with two other datasets. First, combining price data with data on sectoral economic activity allows us to draw plausible conclusions about shifts in sectoral supply and demand. Second, we employ expenditure survey data available at the level of overseas regions that quantifies differing spending patterns across income groups over time. We compute income-group specific inflation rates per cohort to measure distributional- and welfare effects from disasters over time.

Our study also innovates in the way we identify natural disasters. The literature is confronted with a twofold measurement problem. The first best measure would report the direct economic damages resulting from a natural disaster due to asset damage and business interruptions. Since such data does not exist, in practice two sources of data are employed. One approach is to use administrative databases that detect an event based on criteria, for example a declared state of emergency by local authorities. Administrative databases have the advantage of detecting disasters with significant economic damage at a relatively high accuracy. However, they are also known to be subject to various reporting biases (Felbermayer & Groeschel 2014, Grislain-Letremy 2018). Therefore, another approach uses meteorological and geophysical data, which reports the severity of the disaster event objectively 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.[1] We combine administrative and meteorological data in an IV (instrumental variables) approach to overcome reporting biases and improve the detection of relevant extreme weather events. Specifically, we estimate a damage function by regressing the occurrence of administrative emergency events on wind speed and precipitation data from various sources and use the linear prediction in the second stage model to elicit the effect of natural disasters on prices.

Our main results are threefold. First, we find that natural disasters induce a rise in headline consumer prices with a first peak at 0.5 percent two months after disaster occurrence, and another peak at 0.5 percent six months after the disaster. The overall effect observed in the first two months can be decomposed into an immediate strong surge in the prices of fresh food products of 12 percent after two months, which dies out after four months. The gets partially offset by an immediate moderate decline in the headline price index excluding fresh food products of 0.2 percent after one month. The decline is especially due to manufactured products that drop by 0.6 percent after one month. After three months, even though the effect on manufactured products remains negative and broadly stable, the effect on the headline price index excluding fresh food products fades out, and even turns positive after four months, until reaching 0.5 percent after six months. This is due to prices of services, which increase markedly after four months. This positive effect on services in the longer-run is driven by the category “other services”, the main component of services which notably includes accommodation, restaurants, and transportation. This difference across products in the timing of price response could be related to differences in the degree of price rigidity between goods and services (Gautier et al., 2022). Overall, our results point to small and temporary effects on headline inflation, but strong distortions of relative prices.

Second, we find significant distributional effects from natural disasters across income groups from diverging product inflation rates. We follow the standard approach by using microdata to measure household-specific consumption bundles at the income-group level, to which we apply the

[1] 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 & Strobl 2011), the quality of institutions (Kahn 2005), and economic development (Felbermayer and Groeschl 2014).

disaggregate price dynamics (Hobijn and Lagakos 2005, Hobijn et al 2009). This allows us to compute an income-group specific inflation rate conditional on a natural disaster. 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 0.65 percent in the bottom quintile of the income distribution, i.e. about 30 percent higher than the average effect. The upper quintile, in contrast, experiences a rise in consumer prices of 0.4 percent, i.e. about 20 % lower than the average effect. Furthermore, the effect of natural disasters on inflation is estimated to be about 50 percent higher at the beginning of our sample period (1999) than in our baseline, which is due to the steady decline of the share of fresh food in the consumption basket.

Finally, we document the effect of natural disasters on economic quantities, to shed light on supply versus demand effects in disaggregate inflation. Disasters have no significant effect on total employment, but sectoral effects turn out significant. On the one hand, there is a decrease in agricultural employment, which would suggest that the price increase in food results from a negative supply shock related to the destruction of crops in fields, which no longer need care or being harvested. Further, we find that the number of overnight stays drops temporarily during the month of the disaster. This is broadly in line with very short-lived negative effects found by Granvorka & Strobl (2013) for hurricanes in the Caribbean. The impact turns significant and positive from months two to six. Rosselló et al. (2020) also find positive effects of storms and floods over a 6 month and 12 month horizon. They rationalize their finding by a rise in the number of people coming to support friends or relatives for reconstruction.

The paper provides novel empirical insights to the literature that studies the effects of natural disasters on prices. Earlier contributions in this field are predominantly case studies. Cavallo et al. (2014) examine the impacts of the 2010 Chile and the 2011 Japan earthquakes on product availability and prices. They use price data collected from website of international supermarkets at daily frequency and find that prices adjust only mildly despite immediate and persistent effects on product availability. This finding is in line with Gagnon and Lopez-Salido (2020) who document weak effects of snowstorms and cyclones on prices in US supermarkets despite strong variations in demand. A possible explanation for small price effects in scanner data are in pricing models in which retailers fear customer anger or have fairness concerns. Small effects on consumer price inflation at the macroeconomic level are typically found for natural disaster episodes in advanced economies (Doyle and Noy 2015, Kamber et al. 2013), contrasting with larger effects in emerging economies (Laframboise and Loko 2012). In this paper, we argue that effects in headline inflation often average out the forceful disaggregate price dynamics in response to natural disasters.

Our paper is most closely related to two papers that analyze components of consumer price inflation in a cross-section of countries. Parker (2018) analyses a panel of 223 countries using consumer price data at quarterly frequency with information on sub-indices for food, housing, energy and all remaining items. Natural disaster events are taken directly from the emergency events worldwide database EM-DAT. The study finds strong heterogeneity in the impact of disasters on inflation across all sub-categories of prices, disaster type and the level of development. While headline inflation responds by an increase of 0.6 percentage point in the first year, food prices are positive only in the first two quarters and turn negative thereafter, leaving food price inflation insignificant in the year following the shock. Housing and energy prices tend to decrease by 0.4 percentage points each. While these results point into the direction of potentially off-setting sectoral price dynamics, the estimated coefficients cannot be interpreted as compositional effects due to the unbalanced nature of the panel. Heinen et al. (2018) focus on the impact of cyclones and floods on prices in 15 Caribbean Islands. They inspect total headline CPI and three sub-categories, namely food, housing and utilities, and all other items. Effects of natural disasters are obtained from a destruction index for hurricanes and floods. 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 off-setting effects are observed in product sub-categories, possibly due to the still high level of aggregation of the category 'other goods'. Our paper contributes to this literature by providing a more granular analysis, covering 12 types of goods and services prices. A highly balanced panel allows us to interpret our findings as compositional effects of headline inflation. Integrating specific sectoral economic dynamics enables us to provide plausible narratives for shifts in sectoral supply and demand, which is absent in the existing literature.[2]

Our findings also contribute to the literature on inflation inequality. There is a long literature documenting differences of inflation rates across households due to structural variation across consumption baskets. Such household-level inflation inequality is particularly well documented for the United States (Michael 1979, Hobijn et al 2009), while more recent work adds a layer of inflation inequality arising from actual prices paid using scanner data (Kaplan and Schulhofer-Wohl 2017). Argente and Lee (2021) track income-specific price indexes from 2004 to 2016 and

[2] Another related contribution is Faccia et al. (2021), which relates consumer prices to extreme temperatures for 48 advanced and emerging economies, and find positive and non-linear impacts of extremely hot temperatures in the short-term on inflation (particularly for food inflation, during summers, and in emerging economies), which turn negative in the medium-term.

document rising inflation differences during the Great Recession. Our paper contributes to this literature by showing that natural disasters amplify inflation inequality across income groups, but with only transitory effects.

The paper is structured as follows. Section 2 describes the data and the estimation strategy. Section 3 describes the estimation results and Section 4 concludes.

2. Data and empirical strategy

In this section, we describe how we combine detailed information on natural disasters and prices for French overseas territories, for the period 1999m1 to 2018m4.

2.1 Data on prices and economic activity

2.1.1 Consumer price index

We use the Consumer Price Index produced by Insee for each of the four French DCOMs. In France, there is no available regional price index. French overseas territories are the only subnational regions for which price indices are specifically calculated using price quotes collected in each of the French 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 French CPI since 1998. Price indices are published at a monthly frequency by Insee at a detailed level for 12 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 way 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, even though inflation in DCOMs is significantly correlated with inflation in the metropolitan area[3], this correlation is lower for food inflation (Hugounenq and Chauvin 2006).

[3] 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.

Second, the heterogeneous correlation of CPIs between 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 importations for processed food.[4]

Third, DCOMs benefit from specific fiscal schemes to compensate for their distance with the metropolis: VAT is reduced and the *octroi de mer*, a specific tax on imported products, hedges 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.

Such characteristics bear important implications for the interpretation of the effects we observe, that we discuss in Section 3.

2.1.3 Data on economic activity

The analysis is complemented with data on real activity. We include sectoral employment data at quarterly frequency. 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 (see Table A.5 in the Appendix).

To assess the effect of natural disaster on the tourism sector, we 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.

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

2.2 Natural disasters data

This section discusses the administrative and meteorological data sources and how we treat the data before using them in the IV approach.

2.2.1 Emergency databases for natural disasters

A first type of data source on natural disasters collect administrative information on economic losses due to natural events. In this paper, we will use two data sets collecting administrative information.

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, where a disaster corresponds 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 information, such as the beginning and end 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[5]. The data are aggregated to obtain a monthly indicator variable per oversea territory. As a convention, it is considered that the month of the natural disaster corresponds to the beginning date of the disaster.

We complement this data with information coming from the emergency events database EM-DAT, a worldwide database produced by the Center for Research on the Epidemiology of Disasters (CRED). 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

[5] 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.

administrative authorities. Table 1 describes the degree of overlap between our discrete administrative measures as well as their geographical distribution.

Table 1 – 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.

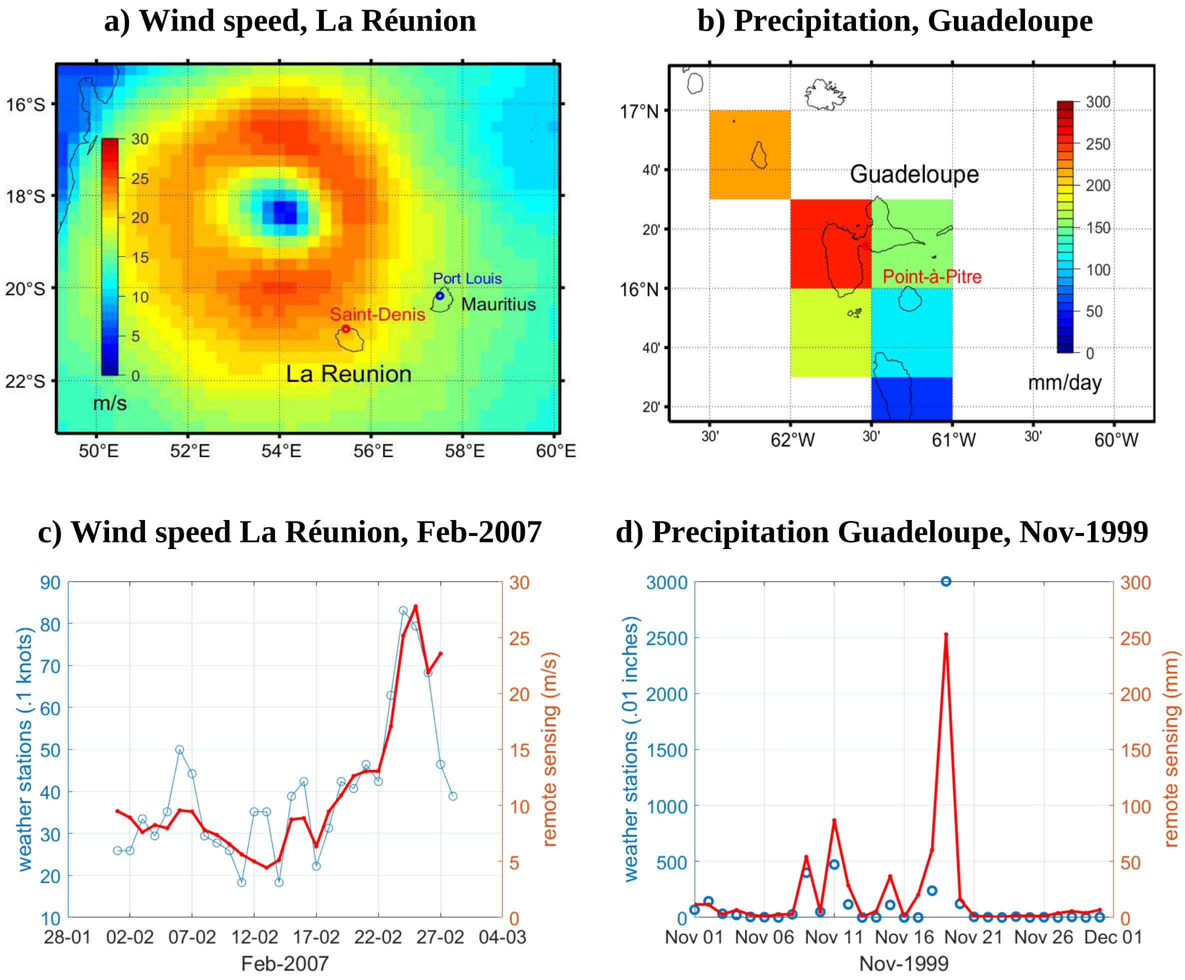
There is a distinct seasonality of shocks between La Réunion, which is located in the southern hemisphere, and Guadeloupe, Martinique and Guyane, which are located in the northern hemisphere. Table A.8 in Appendix A highlights that shocks in La Réunion are predominantly concentrated during the first semester, while shocks in the remaining DCOMs are concentrated in the second semester.

Both data sources have well-known 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 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, which is why we propose an IV approach below: heuristically, we want to correct the potential bias by crossing administrative data with meteorological features.

2.2.2 Meteorological records

To overcome the selection biases in the two administrative databases, we use meteorological data in three forms: (i) reported in weather stations, (ii) collected by remote sensing systems based on satellites, and (iii) extreme weather events reported by the French national weather service (Météo-France).

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 Gamede 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.

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 9000 stations around the world beginning in 1929, of which two to three match to each of the regions in our analysis (see Figure A.1 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.

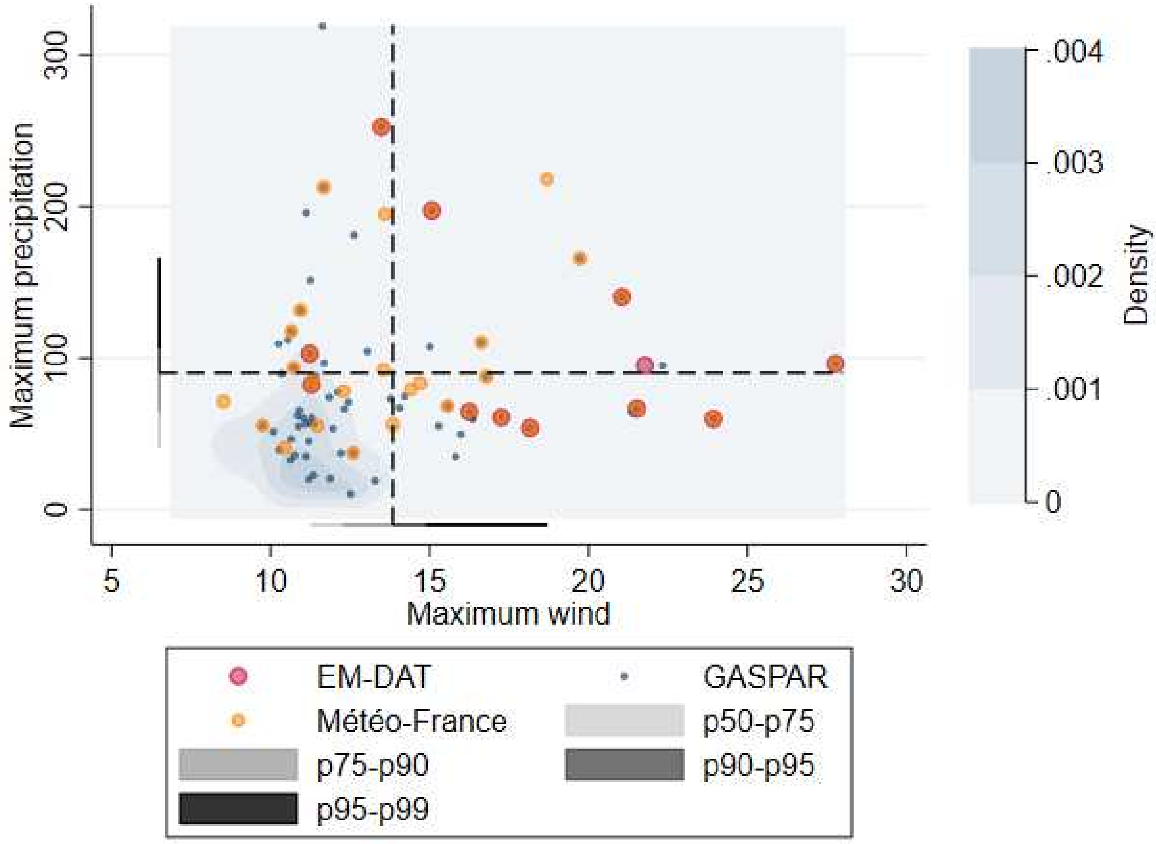
We combine these data with meteorological records obtained via remote sensing. Wind speed is taken from the NCRA *Cross-Calibrated Multi-Platform* (CCMP) wind vector analysis that allows computing wind speed over the ocean in meters per second. Each vector summarizes the average wind speed in a cell 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 Gamede 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.2 and A.3 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*.

In general, while remote sensing data provide a nearly complete coverage across time and geographic location with respect to weather stations data, they are said to be less precise concerning extreme events. Table A.7 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.

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"). According to this source, 32 months are indicated as extreme meteorological event, of which 31 percent are located in Martinique, 25 percent in Guadeloupe, 25 percent in La Réunion and 19 percent in Guyane (see Table A.6 in the Appendix).

Figure 2 illustrates the relationship 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 suggests that EM-DAT is related to natural disasters with significant physical intensity, while this is not necessarily the case for many events from GASPAR.

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.

2.3 Estimation strategy

In this section, we describe our empirical methodology to relate price dynamics to economic disasters due to extreme meteorological events that incurred significant economic damages. We proceed in two steps. In a first equation, 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 local projection technique to estimate the effect of natural disasters on inflation dynamics.

2.3.1 First-stage regression

As argued above, administrative shocks are likely to be subject to several biases and while they reflect situations of severe economic damages, they might not be exogenous to the economic conditions. Estimates could eventually suffer from a bias if we employ the dummy variables from administrative databases directly in our model. We therefore instrument our natural disaster events of storms and flooding events using meteorological data. The implicit assumptions for unbiased estimation are that (i) physical intensity is correlated with the economic damage (*relevance restriction*) and (ii) weather phenomena affect prices only through the economic damages they create (*exclusion restriction*). Specifically, we regress meteorological data $X_{i,t,m}$ for DCOM i during month m of year t on a binary variable of administrative natural disasters $\omega_{i,t,m}$ using the following specification:

$$\omega_{i,t,m} = \alpha + \beta X_{i,t,m} + \gamma_i + \delta_t + \theta_m + \theta_m \times R_i + \varepsilon_{i,t,m} \quad (1)$$

where γ_i is a DCOM fixed effect, δ_t is a year fixed effect, θ_m is a calendar month fixed effect and R_i is a dummy indicating whether DCOM i is La Réunion. The motive for interacting calendar month fixed effect with a dummy for La Réunion is that the seasonality of its shocks is markedly different compared to that of the remaining three regions.[6]

We present the results of the first stage in Table 2, for meteorological data collected via remote sensing and weather stations, respectively. For each set of data, we include linear (columns 1 and 5), square (columns 2 and 6) and cubic (columns 3 and 7) specifications of wind speed and precipitation. Non-linear relationships are considered since there is evidence that economic damage from wind speed is best captured by a cubic relationship (Emanuel 2011). Note, however, that non-linearity is already present in all specifications as we include Météo-France events as dummy variables in model (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 as dummy variables (columns 4 and 8).

[6] In a robustness exercise, we estimate the model without this interaction term and discuss more on the identification issues related to the seasonality of extreme metrological events.

Table 2. 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*** **	-0.016	-0.136	-0.033	0.022	0.070	-0.062	-0.080
	(3.53)	(0.52)	(1.27)	(1.01)	(1.47)	(1.12)	(0.24)	(1.01)
Rain	**0.002*** **	0.001	0.002	0.001*	0.001***	0.000	0.000	0.000*
	(4.28)	(1.58)	(1.44)	(1.71)	(4.34)	(0.70)	(1.05)	(1.95)
Wind^2		0.002	0.010	0.003**		-0.008	0.038	-0.006
		(1.28)	(1.31)	(2.22)		(0.80)	(0.45)	(0.46)
Rain^2		0.000	-0.000	0.000*		0.000**	-0.000	0.000
		(1.13)	(0.29)	(1.90)		(2.10)	(0.36)	(2.49)**
Wind^3			-0.000				-0.005	
			(1.10)				(0.56)	
Rain^3			0.000				0.000	
			(0.64)				(0.83)	
MF	**0.411*** **	0.387***	0.388***		0.476***	0.474***	0.482***	
	(4.71)	(4.26)	(4.05)		(5.52)	(5.49)	(5.42)	
A.R^2	**0.31**	0.32	0.32	0.26	0.29	0.29	0.29	0.20
N	**928**	928	928	928	928	928	928	928
F-Stat	**39.66**	22.42	20.54	21.70	29.57	19.32	8.70	21.09

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.

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 appears 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 and rain for remote sensing data becomes significant at least 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.[7]

Based on these results, our preferred specification is the one of column (1) from which we compute fitted values $\widehat{\omega}_{i,t,m}$. Since the dependent variable is an indicator variable associated with natural disaster events with large economic damages, we interpret $\widehat{\omega}_{i,t,m}$ as the predicted probability of an economically significant natural disaster as a function of meteorological data.[8] 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) 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 5 %, while it is equal to 40 % conditional on observing a shock (the figures are the same if we condition only on GASPAR shocks, but they are respectively 7 % and 75 % if we condition on the occurrence of an EM-DAT shock). Figure B1 in Appendix B shows the distribution of predicted probability, and Figures B2 to B4 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 a 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). In Section 3.4, we present alternative results where the instrument is based on weather stations data, and using alternative specifications (notably for time fixed effects).

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

[8] 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.

2.3.2 Second-stage regression

Our estimation for the second stage relies on the local projection method (Jordà 2005). We estimate the evolution of the log of the price index between the month before the disaster and $h=0,...,6$ months after the disaster, with respect to the estimated probability of a natural disaster $\widehat{\omega}_{i,t,m}$ recovered from equation (1). The index i represents the different possible DCOMs, for $i = 1,..4$. Our baseline equation is the following:

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

where $\widehat{\omega}_{i,t,m}$ is the predicted probability of a natural disaster during month m of *year* t in DCOM i according to administrative datasets. Month-year fixed effects are denoted by $\delta_{t,h}$, and local fixed effects by $\gamma_{i,h}$, while $\varepsilon_{i,m,t,h}$ 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. $\theta_{m,h} \times R_{i,h}$ is an interaction term to capture seasonal differences between La Réunion and the three other overseas regions.

In our main estimation, we estimate equations (1) and (2) using a 2SLS estimation. We also compare the 2SLS estimates with OLS specifications in which we directly regress prices variations on $\omega_{i,t,m}$, 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 slightly above 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.

3. Main results

In this section, we present results of our baseline estimation strategy, both for the OLS and IV results.

3.1 Inflation

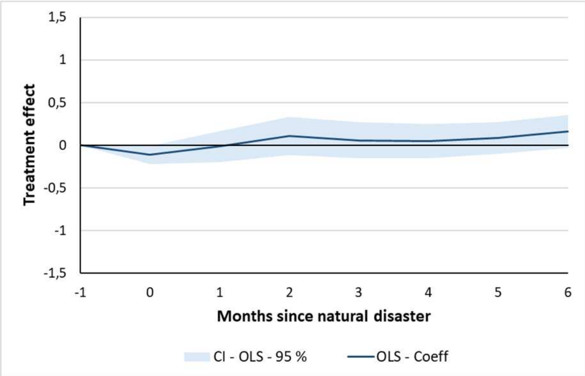
In Figure 3, we present the main results from our baseline estimation, both in the OLS and the IV setting. Based on the IV estimation, our first main finding is that total CPI is on average moderately affected by natural disasters. It first increases moderately and temporarily by about 0.5 percent after two months. The effect rapidly narrows down to zero, before increasing again after five to six months, until reaching 0.5 percent at six months. However, and this is our second main finding, this aggregate effect is driven by composition effects which vary over time. On the one hand, the prices of fresh products increase strongly and rapidly, up to 12 percent after two months. This effect is particularly strong, as it typically represents about 2.5 standard deviations of fresh food CPI on average across the four regions, and about 1.3 standard deviations of fresh food CPI in La Réunion. This positive effect then decays progressively, until reaching zero after six months. On the other hand, the prices of items other than fresh products first decrease moderately by 0.2 percent after one month. These negative effects also dissipate quickly and turn positive after four months, peaking at 0.5 percent after six months. Therefore, while the first spike in headline CPI is driven by fresh products, the second is rather driven by the components excluding food products. Our third main finding is that the 2SLS estimation yields much 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 four 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, as a significant part of them do not reflect extreme meteorological events. Further, the 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 lead to an increase of total CPI by about 0.6 pp after a year, and 0.9 pp after two years[9].

[9] 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., 2019) 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.

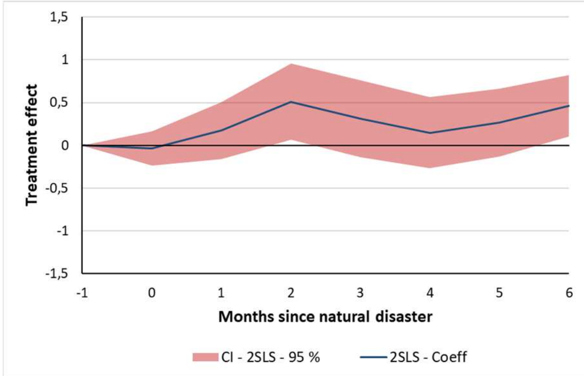
Figure 3: Main results – Total and fresh food

a) Total

OLS

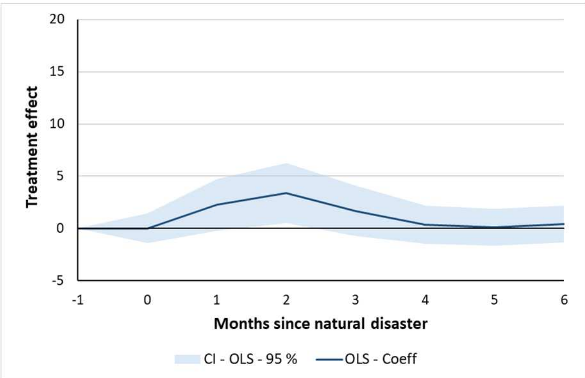


IV

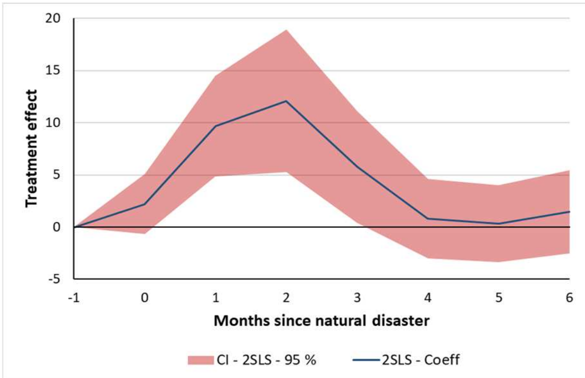


b) Fresh products

OLS

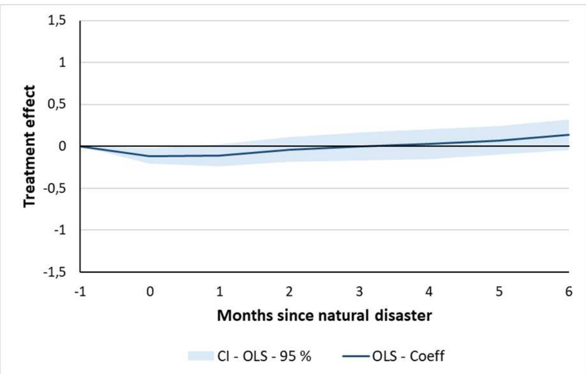


IV

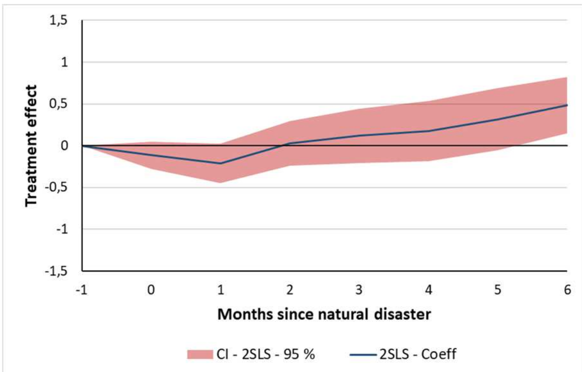


c) Total excluding fresh products

OLS

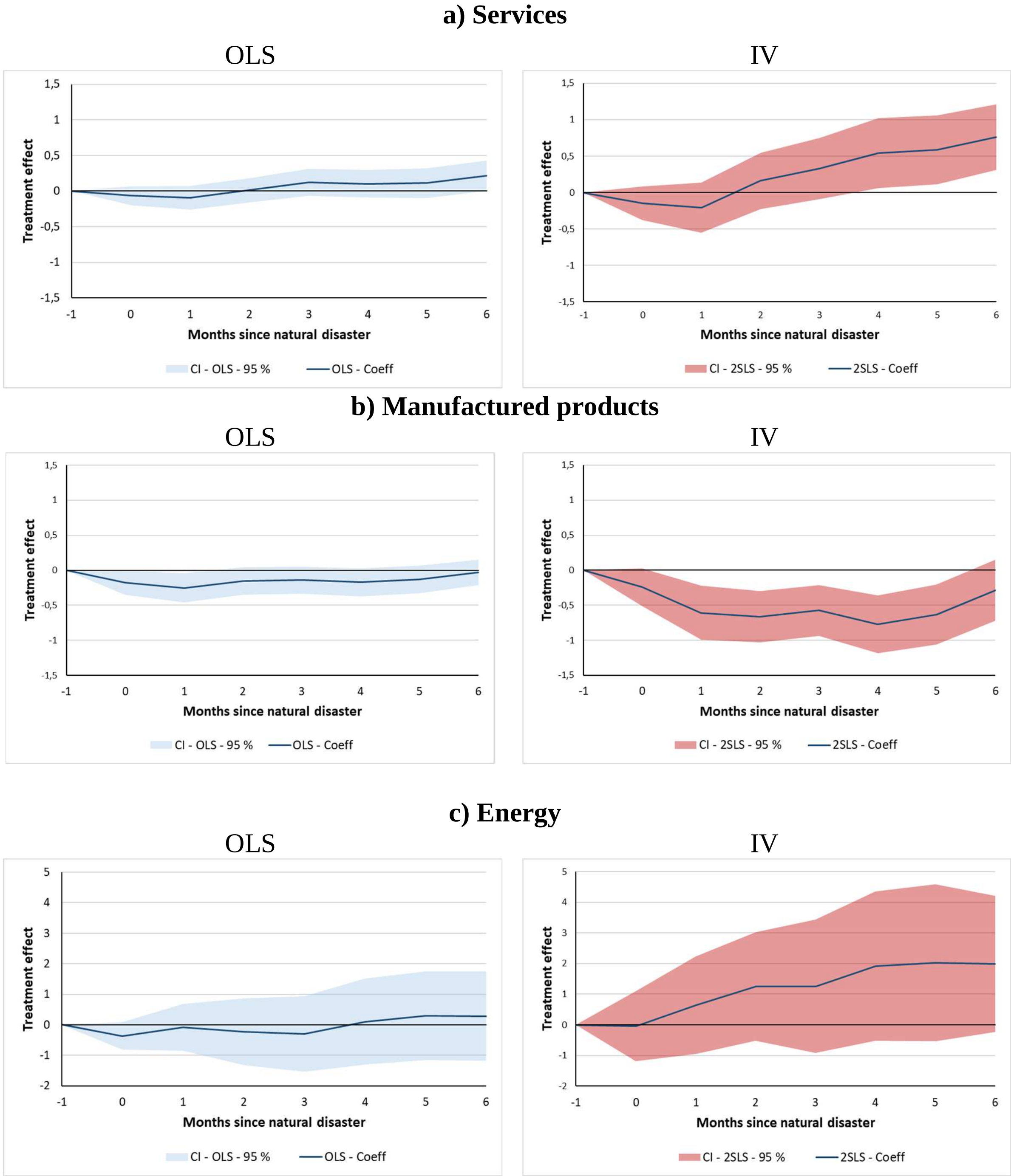


IV



Note: The figures plot the cumulated impulse response function for headline CPI, CPI of fresh products and headline CPI excluding fresh products. The left panel represents results from OLS estimations, while the right panel represents results from IV estimations. Treatment effects are expressed in percent. 95 percent confidence intervals with robust standard errors in shaded areas. Treatment effects are expressed in percent.

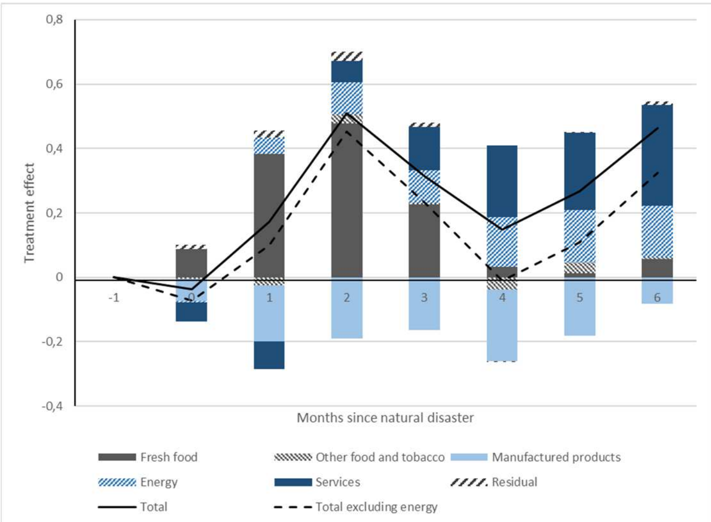
Figure 4: Main results – Services, manufactured products and energy



Note: The figures plot the cumulated impulse response function for the CPI of services, manufactured products and energy. The left panel represents results from OLS estimations, while the right panel represents results from IV estimations. 95 percent confidence intervals with robust standard errors in shaded areas. Treatment effects are expressed in percent.

In Figure 4, we highlight the effects obtained for the main other components than fresh food, and in Table B.1 in Appendix B, we present estimated coefficients for all available components. In the months immediately following the shock, we first find negative effects for manufactured products and services, albeit with different levels of statistical significance. The effects on manufactured products immediately drops down to -0.6 percent after one month, and remain below -0.8 percent until five months after the shock. This negative effect is mostly driven by a strong decrease in the prices of footwear and garment, by about 3 percent. The effect on the prices of services reaches a minimum of -0.1 percent in services (after one month), which is however not significant at traditional confidence levels. This negative effect after one month is primarily driven by moderate but significant decreases in the prices of health services (-0.3 percent in the month of the shock) and rents (-0.2 percent one month after the shock). The prices of services quickly recover and after four months, they even surpass the prices observed in the absence of a shock, by about 0.08 percent. This longer-run increase is driven both by other services, which is the main component of services and includes notably accommodation and restaurants (+0.6 percent after 6 months), and by transportation services, which increases sizably until reaching about 10 percent in the outer ranger of the horizon. This difference in the speed of adjustment of prices in food and services could be related to a difference in the degree of price stickiness. It is a well known fact that food prices are much more flexible than services prices and so react more quickly to shocks (see Gautier et al. 2022 for recent euro area evidence). Finally, while we observe positive coefficients of one to two percent for the prices of energy, they are overall imprecisely estimated and not significant. The absence of significant effect on energy prices is in line with the fact that energy prices are largely administered in DCOMs.

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.

In Figure 5 we decompose 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), under the IV estimation. Each contribution is computed as the observed pass-through multiplied by the average weight of the component over 1999-2018.[10] The "residual" contribution corresponds to the difference between the estimated reaction of total prices and the sum of estimated contributions of the five components. The heterogeneity of reaction between fresh food and other components is clearly visible. We also report the effect on total inflation excluding energy, as the effect on the latter component is imprecisely estimated. The patterns across the two measures of total inflation are similar, but while the effect on total inflation excluding energy is close to that on total in the first three months, it is a bit smaller in the outer years of the projection horizon (as the estimated effect on energy is imprecisely estimated but positive after 6 months).

3.2 Supply or demand effects?

The sectoral effects we observe are likely to be explained by a mix of supply and demand effects. In turn, whether the consumed goods and services are produced locally or imported is likely to affect the supply and demand channels. Regarding fresh food, which is largely produced domestically, one can assume that the observed increase in prices is largely due to a negative supply shock. Regarding goods that are more often imported, such as manufactured products, one can expect that natural disasters rather represent a negative demand shock, with no specific shock on the supply side, therefore leading to a negative effect.[11] Finally, regarding services, the channels are likely to be more mixed. On the one hand, services are largely produced locally. They represent a larger share in the VAT than in Metropolitan France and than in comparable small-island economies. We therefore conclude that a natural disaster is likely to represent a negative supply shock. Yet, natural disasters might also affect the demand for services, especially in the tourism sector: effects on demand could be negative, e.g. due to reputation effects, or positive if part of tourism is related to affinity motives, which can push people to come support family or relatives.

[10] Except for the component "food including tobacco and excluding fresh food", for which we do not have a CPI: this contribution is computed as difference between the contribution of total food including tobacco (for which we do observe a CPI) and the contribution of fresh food).

[11] 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. 2022), making unlikely that local supply or demand effects affect the general price dynamics. On the other hand, in the specific case of DROMs, 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.

To explore whether these hypotheses hold true, we estimate the effects of natural disasters on sectoral economic activity, to characterize the extent to which the effects on prices are driven by supply or demand effects. Because the data we employ give information on local economic activity, they are better suited to provide information on items largely produced locally, namely fresh products and services; for this type of product, we could expect a close connection between local activity and consumption. They are likely to be less informative about the channels affecting the prices of manufactured products or energy; for these products which are mostly imported, there would be a small correlation between local activity and local consumption.[12] Importantly, 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[13].

In Figure 6, we present the main significant reactions of real activity variables. All estimated cumulated responses of real activity are presented in Table B.2 in the Appendix. Figure 6a shows that employment in the agricultural sector decreases strongly after a shock, falling by 4 percent after two months. This negative effect progressively narrows after three months, until reaching zero after six months. This large negative effect on agricultural employment suggests that the effect of natural disasters on fresh food prices is mostly a *negative supply shock,* which destroys crops in the fields which do no longer need care or need to be harvested. Thus, employment falls and prices rise. This interpretation is reinforced by the fact that the prices of fresh products react strongly to natural disasters, while those of other types of food do not: indeed, since the former are more reliant on local producers than the latter, this suggests that effects on fresh products is mainly driven by the effect that natural disasters have on local production.

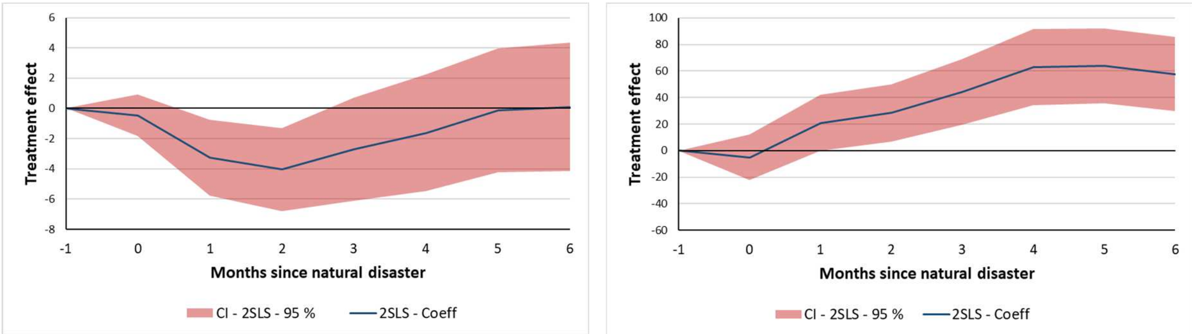
Figure 6b documents a strong increase in the number of overnight stays after six months, with a maximum effect of about 60 percent reached after four months. This strong increase mirrors the increase observed in the prices of services, suggesting the existence of a positive demand shock. Such a result can appear at odds with the existing literature, which ends to document a negative, despite short-lived impact of natural disasters on tourist flows (Hsiang, 2010; Granvorka and Strobl 2013). However, Rosselló et al. (2021) also find positive effects of storms on tourism.

[12] High frequency data on local consumption by product is not available to us.
[13] However, the first stages of the estimations for employment and overnight hotel stays remain largely valid, as the F-Statistic are respectively equal to 16.9 and 15.3.

One possible explanation could be the effects arising out of humanitarian motives, such as friends and relatives visiting affected regions to help and support.

Figure 6. Reaction of agricultural employment and number of overnight stays to a natural disaster

a) Agricultural employment **b) Number of overnight stays**



Note: The figures plot the cumulated impulse responses of agricultural employment (left panel) and number of overnight stays (right panel) to the occurrence of a natural disaster in the baseline IV local projection. Treatment effects are expressed in percent.

Finally, we do not find significant effects of natural disasters on employment in the manufactured sector. However, because manufactured products are largely imported in the DCOMs, it is more likely than the observed decrease in prices comes from a negative demand shock than from a positive supply shock, even though such effects cannot be identified in our data.[14]

3.3 Distributional effects of natural disasters

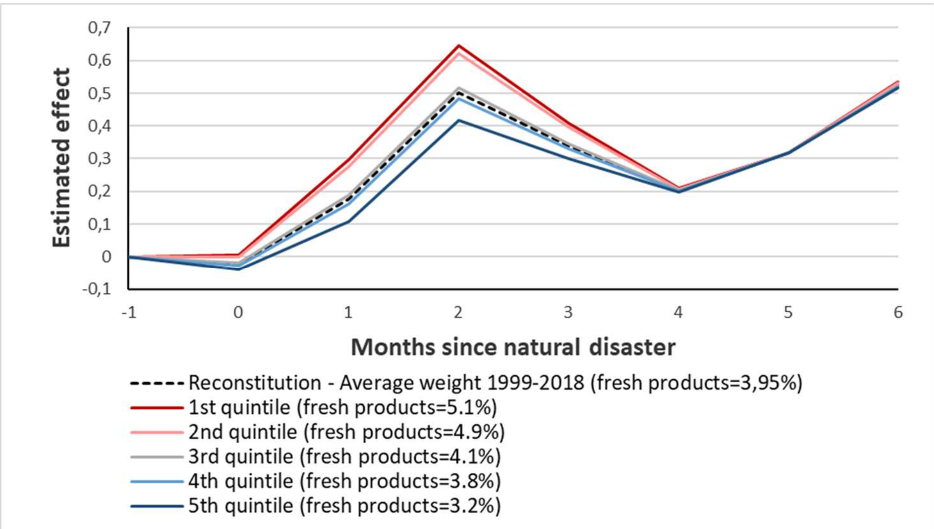
In this final section, we investigate whether the effects of natural disasters on consumer prices differ across different types of households. Indeed, given that the main positive effects are channeled through the fresh food and to the extent that the weight of food is generally higher for households with lower income, we expect that the effects on total inflation is higher for the latter. To test this hypothesis, we exploit the *Budget des familles* survey, produced by Insee for the year 2017. This survey gives a decomposition of the consumption basket of households, both across overseas territories and across quintiles of household. We combine these data with our estimated impulse-response functions, in order to derive an estimated impulse-response

[14] In alternative specifications, we tested whether natural disasters affected the quantities of goods imported quarterly in the DCOMs (sources?), but we did not find any significant effect in these specifications.

function of total CPI for each quintile. The methodology used to reconstruct an impulse-response function for each quintile of household is described in Appendix C.

Table C.1 in Appendix represents the share of food in the consumption basket for each of the 4 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 0.4pp).

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

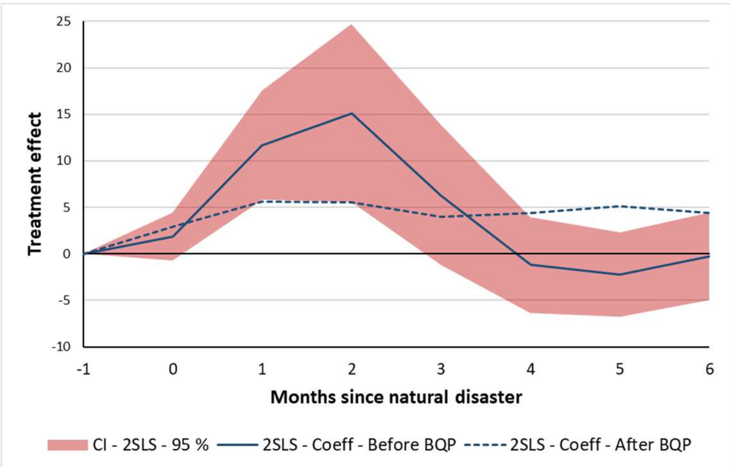


Note: Comparison of the reconstitution of effect on headline CPI using a linear combination of estimated effects on fresh products and total excluding fresh products using average weights between 1999 and 2018 (solid dotted line), with reconstitutions using estimated weights of fresh products for the 5 quintiles of income (blue, red and grey lines). Treatment effects are expressed in percent.

3.4 The role of administered prices

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 (Gautier et al. 2022), is that they are partly controlled by local authorities. But more interestingly in our context, the extent of price regulation regarding food prices has evolved over time across our sample. Indeed, in November 2012, following protests against the cost of living in several DCOMs, a price cap called *Bouclier Qualité Prix* (BQP) was voted for a selection of base products. The BQP, which was eventually implemented in March 2013, states that the total price for the considered selection of products cannot be higher than a fixed threshold. The selection of products and the overall price cap are renegotiated annually, and can differ between DCOMs. As a matter of 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 came from local production. 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).[15] Before the implementation of the BQP, the price reaction of food products was immediate and strong, reaching 15 percent after 2 months, and then decreased until reaching zero after 4 months. After the implementation of the BQP, the price reaction of fresh food products was much more sluggish, reaching 5 percent after one month and remaining there over the whole projection horizon. Therefore, 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 sum of cumulative price responses is equivalent between with or without the BQP, 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.

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



[15] 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 32.6 before the BQP and 14.4 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).

***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.

4. Sensitivity

4.1 Robustness to alternative specifications

In this section, we present several alternative results for the three main aggregates under scrutiny, namely total, fresh food and total excluding fresh food. Our robustness tests show both that our main qualitative results are robust to the chosen specification or to the definition of the shock, but that the exact estimated magnitude can vary along these dimensions. The results are summarized in Table 4.

Table 4 – Robustness analysis

	T=0	T=1	T=2	T=4	T=6
(A) Total					
2SLS - Baseline	-0.000	0.002	0.005**	0.001	0.005**
2SLS – Year x Month FE	0.000	0.002	0.005**	0.002	0.002
2SLS – Baseline, 3 lags shock	-0.001	0.001	0.003	0.001	0.003*
2SLS – Baseline, Weather station data	-0.001	0.001	0.004*	0.002	0.005***
2SLS – Baseline – no Réunion	0.000	0.002	0.003*	0.003	0.006***
2SLS – Baseline excl. shock < 6months	-0.000	0.002	0.007**	0.002	0.006**
OLS	-0.001**	-0.000	0.001	0.000	0.002
Jan – Feb – La Réunion	-0.001	-0.002	0.002	0.001	0.002
(B) Fresh products					
2SLS - Baseline	0.022	0.097***	0.121***	0.008	0.015
2SLS – Year x Month FE	0.077***	0.183***	0.209***	0.036	-0.025
2SLS – Baseline, 3 lags shock	-0.001	0.047*	0.064*	-0.024	-0.018
2SLS – Baseline, Weather station data	0.013	0.082***	0.112***	0.024	0.025
2SLS – Baseline – no Réunion	0.022**	0.055***	0.061***	0.010	0.001
2SLS – Baseline excl. shock < 6months	0.030	0.127***	0.158***	0.012	0.022
OLS	0.000	0.023*	0.034**	0.004	0.004
Jan – Feb – La Réunion	0.098***	0.205***	0.268***	0.168***	0.065***
(C) Total excl. fresh products					
2SLS - Baseline	-0.001	-0.002	0.000	0.002	0.005***
2SLS – Year x Month FE	-0.003***	-0.005***	-0.003***	0.001	0.003**
2SLS – Baseline, 3 lags shock	-0.001	-0.001	0.001	0.003*	0.005***
2SLS – Baseline, Weather station data	-0.001	-0.002*	-0.000	0.002	0.005***
2SLS – Baseline – no Réunion	-0.001	-0.002	-0.000	0.003	0.007***
2SLS – Baseline excl. shock < 6months	-0.001	-0.003*	0.000	0.002	0.006***
OLS	-0.001**	-0.001	-0.000	0.000	0.001
Jan – Feb – La Réunion	-0.004***	-0.010***	-0.009***	-0.005***	-0.001

Note: The table shows alternative specifications of local projections of consumer prices for 0, 1, 2, 4 and 6 months following a natural disaster. Panel (A) shows results for total CPI, panel (B) shows results for the CPI of fresh products, and panel (C) show results for total CPI excluding fresh products. "2SLS baseline" is our baseline 2SLS specification; "2SLS – Year x Month FE" replace the baseline fixed effects with country and year x month fixed effects; "2SLS – Baseline; 3 lags shock" controls for up to 3 lags of the shock (instrumented by relevant lags of the instrumental variables); "2SLS – Baseline, Weather station data" is the baseline specification, but with instruments taken from weather station data rather remote sensing data; "2SLS – Baseline – no Réunion" is the baseline specification excluding La Réunion; "2SLS – Baseline excl. shock < 6 months" is the baseline specification, excluding shocks which occur less than 6 months after a previous shock; "OLS" is the baseline OLS

regression; “Jan-Feb. – La Réunion” is an OLS local projection where the “shock” is a dummy equal to one for the months of January or February in La Réunion and zero elsewhere.
*p < 0.10; **p < 0.05; *** p < 0.01.

First, the seasonality of extreme events could raise specific identification issues. In particular, month fixed effects but also interacting them with La Réunion could capture part of the effect of extreme events on prices if these events mostly occur in some specific months. With this respect, our baseline regression where we include both monthly dummies which are specific to La Réunion located in the Southern hemisphere and the other 3 regions which are located in the Northern hemisphere is pretty conservative. As a robustness check, we relax this constraint in our specification and we include only DCOM and year-month fixed effects (“2SLS – Year x Month FE”) and not the interaction term between La Réunion and month fixed effects. The latter only capture effects that are common to all 4 DCOM, and therefore does not absorb seasonality effects specific to La Réunion, as we do in the baseline specification. Doing so, while the effect on headline CPI is overall unchanged (+0.5 percent after two months), we estimate much stronger effects on the prices of fresh products than in the baseline, up to +21 percent after two months, and much lower effects on headline CPI excluding fresh products (- 0.5 percent after one month). This comes from the fact that the natural disasters we study occur with strong seasonal patterns that are quite different between La Réunion and the other DCOMs. As a matter of comparison, in the last specification of each panel (“Jan – Feb – La Réunion”), we estimate the effect of dummies equal to one in La Réunion in January and February (months in which natural disasters are the most concentrated) and zero otherwise: the effect is close in magnitude to the estimated effect in the alternative specification without seasonal effects, confirming the need to control for DCOM specific seasonal patterns in the baseline specification.

Second, we present alternative specifications in which we control for up to 3 lags of the shock (“2SLS – Baseline, 3 lags shock”). The estimated effect for fresh products is slightly smaller than in the baseline specification. This might come from two effects. First, a better control of the dynamic effect of the shock. Second, given that the results vary only in the 2SLS setting (and not in the OLS), this is also likely to reflect a weaker identification of the 2SLS when we include lags: indeed, in this setting, the shock and its 3 lags are all instrumented by the baseline instruments and 3 lags of the latter (increasing the share of non-significant instruments in the first stages). Yet, even though the results are slightly smaller than in the baseline, the peak of the effect on fresh products remains high (6.4 percent), and the effect on total excluding fresh products is close to the baseline specification.

In a third exercise ("2SLS – Baseline, Weather station data"), we present results using weather stations. The maximum estimated effect on fresh products (11.2 percent) is very close to the baseline effect, yet slightly smaller, which confirms their lower identification power.

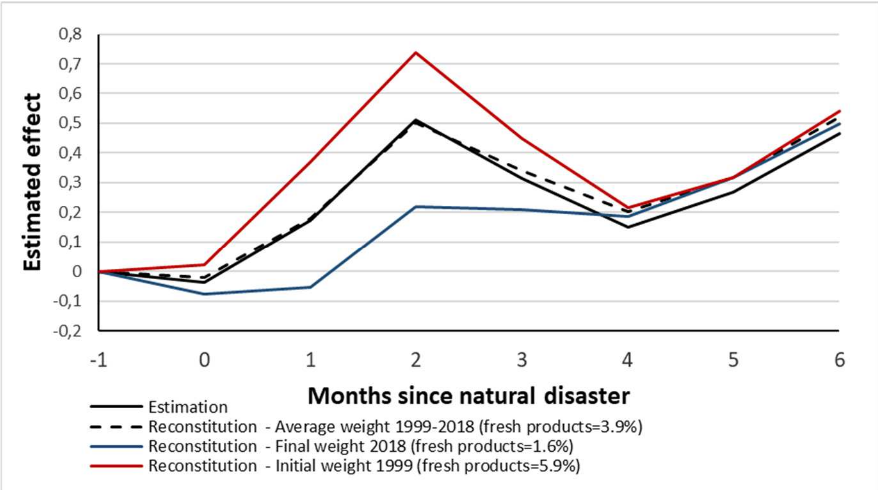
We then present results of a 2SLS equation excluding La Réunion (2SLS – Baseline – no Réunion), which is characterized both by a higher frequency of shocks and by a higher volatility of fresh products. Excluding La Réunion, the maximum estimated effect for fresh products (6.1 percent) is sizably lower than in the baseline specification, though it remains highly significant. This is likely to be explained by the distinct features of La Réunion in terms of both natural disasters and fresh food prices, as the identification power in the 2SLS setting is comparable to the baseline (the F-statistic of the first stage is of 32.7).

Finally, we 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. This is to prevent the risk of wrongly identifying heterogeneous effects over time, which can occur in a panel setting with twoway fixed effects and prolonged treatments, as has been documented by De Chaisemartin and d'Haultfoeuille (2020). Doing so, we find effects for fresh products that are of the same magnitude than in the baseline specification, but slightly higher (15.8 percent after two months).

4.2 Varying in the share of fresh food

Since the largest effects are observed for fresh products, the effect on total inflation depends on the weight of fresh products in the total consumption basket. In order to evaluate how sensitive our results on total CPI are to a variation in the weight of fresh products, we estimate different effects on total inflation depending on the latter. On average, between 1999 and 2018, the average weight of fresh food was of 4 percent. However, this average value hides a strong downward trend, as the average weight of fresh food prices decreased from 5.9 percent in 1999 to 1.6 percent in 2018. In Figure 9, 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 observed 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 were not distributed uniformly over the estimating sample. The blue line represents a reconstitution of the effect on total CPI, still using a linear combination of effects estimated on fresh products and total excluding fresh products, but using their *final* weight (as of 2018). In this case, the estimated effect on total CPI is lower than in the baseline specification, and is even negative in the month of the shock (by -0.1 percent). Finally, the red line represents the same reconstitution, but using the *initial* weights of fresh products and total excluding fresh products: in this case, the effect is much stronger than in the baseline, reaching up to 0.07 percent after two months, i.e. about 45 percent above the maximum baseline effect. The effect on total inflation would therefore be maximal for a weight of fresh products equal to that observed in the beginning of the estimating sample, and minimal for a weight of fresh products equal to that observed in the end of the estimating sample.

Figure 9 – 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.

5. Conclusion

This paper estimates the sectoral effects on prices of natural disasters in the 4 French DCOMs between 1999 and 2018. We find a small positive effect on total consumer prices after two months (+0.5 percent), which can be decomposed into a strong positive effect on fresh products, and a negative effect on all other components. While the effect on fresh products vanishes rapidly, we observe a positive effect on the prices of services in the longer run, which induces a second spike of headline prices at +0.5 percent after 6 months. Additional evidence on real activity point toward the existence of negative supply effects in the agricultural sector, but to potentially positive demand effects in services. We also show that the positive effect on fresh products is less steep after the implementation of the *Bouclier Qualité-Prix* in 2012, which imposes a ceiling on a basket of essential goods, but that it does not revert back to zero as in the baseline effect. We also document that the effect of natural disasters on inflation strongly depend on the weight of the most affected components (namely fresh food): had the weight of fresh food remained equal to its high value observed in the beginning of the sample, the effect on total inflation would have been 45 percent higher than the one estimated in the baseline specification. This also implies that households for which the weight of food is the highest in the consumption basket (namely households with the lowest level of income) are the most affected by natural disasters.

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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
Headline excluding fresh products	0.11	0.46	0.11	0.29	0.12	0.53	0.11	0.34	0.11	0.4	0.12	0.31
Food	0.18	0.87	0.17	0.72	0.22	1.47	0.19	0.72	0.19	0.94	0.17	0.47
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
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.

Do inflation rates co-move across French territories? We find that total CPI is significantly correlated between DCOMs and France with an average correlation of 0.14, except for La Réunion (Table A.2). 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. The CPI of food is not-significantly correlated between DCOMs and France (0.11 on average), with zero correlation for fresh products. In section 2.1.2, we discuss some of the channels that might explain these heterogeneous correlations between types of goods and services.

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

Component	Guadeloupe	Guyane	La Réunion	Martinique	DCOMs
Headline	0.22	0.12	-0.04	0.12	0.14
	[0.001]	[0.06]	[0.51]	[0.06]	[0.04]
Headline excluding fresh products	0.28	0.16	-0.05	0.24	0.19
	[0.000]	[0.02]	[0.43]	[0.000]	[0.003]
Food	0.10	0.09	0.08	-0.07	0.11
	[0.12]	[0.16]	[0.22]	[0.26]	[0.11]
Fresh products	0.05	0.02	0.02	-0.12	0.00
	[0.46]	[0.76]	[0.76]	[0.06]	[0.95]
Manufactured products	0.31	0.38	-0.21	0.36	0.23
	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]
Energy	0.31	0.28	0.21	0.37	0.35
	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]
Services	0.41	0.59	0.58	0.44	0.70
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Note: p-values between brackets

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.

A.2 Real activity

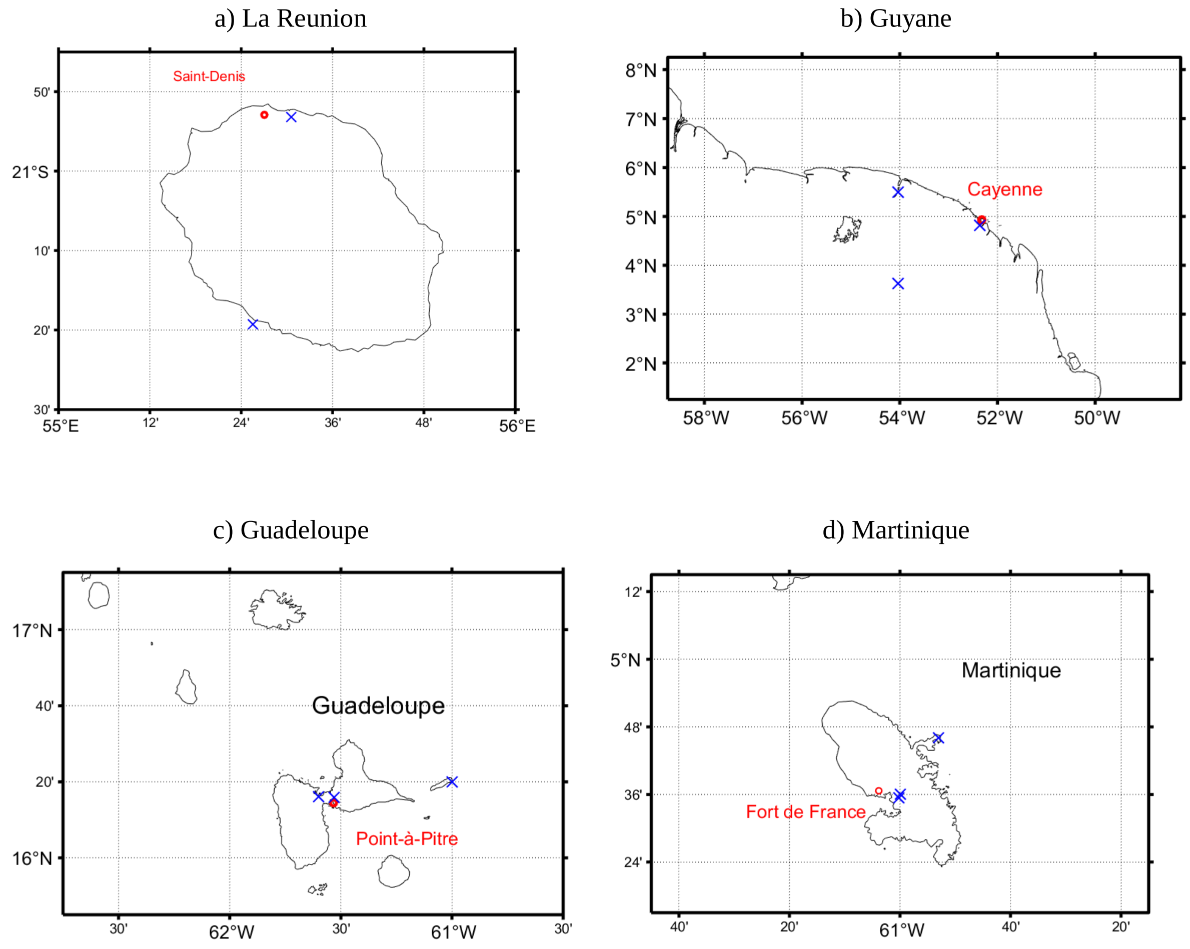
Table A.5 – Descriptive statistics on real activity

	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; ***Data since 2000

A.3 Meteorological data

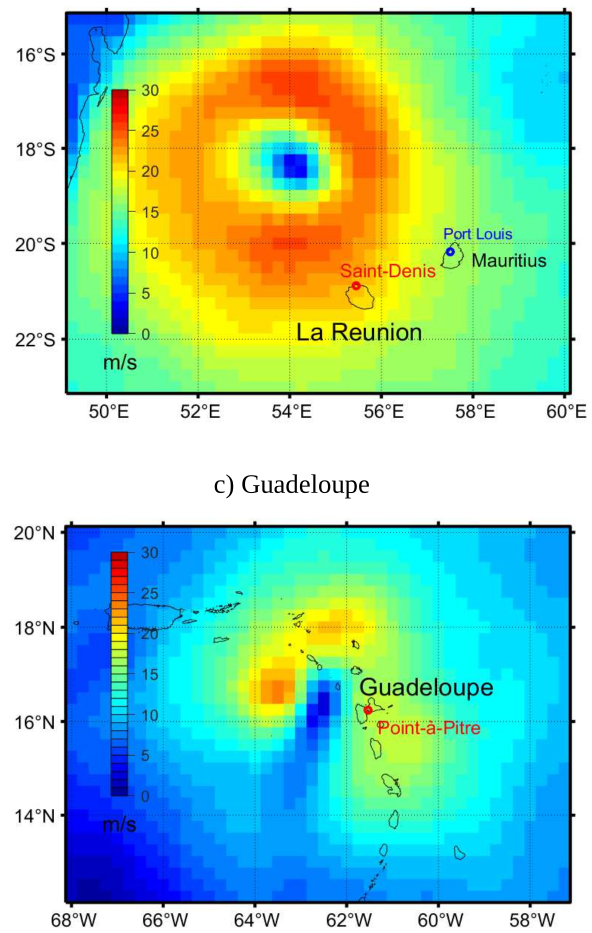
Figure A.1. Location of weather stations



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*).

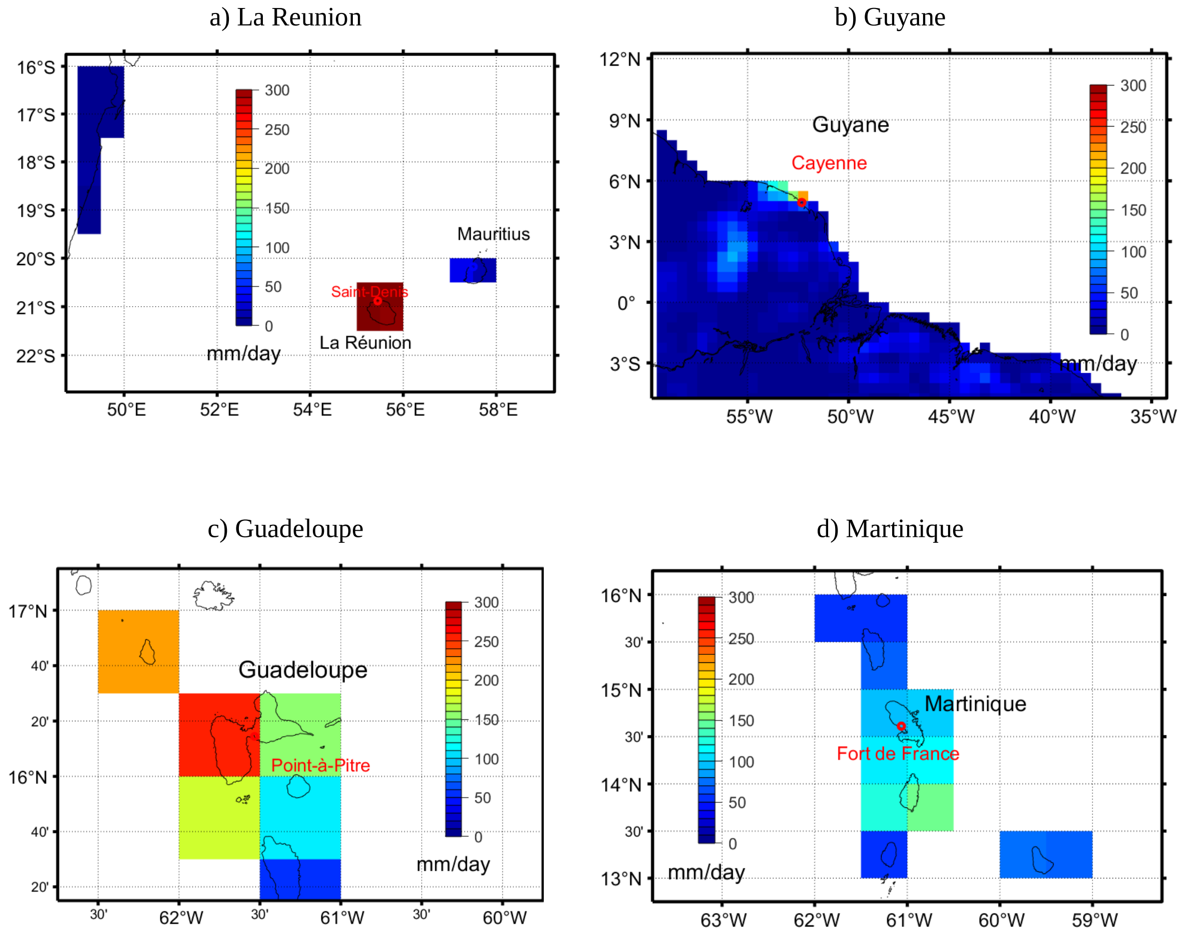
Figure A.2. Wind speed via remote sensing

a) La Reunion b) Guyane



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.3. 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.6 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

Table A.7 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).

A.4 Administrative disaster databases

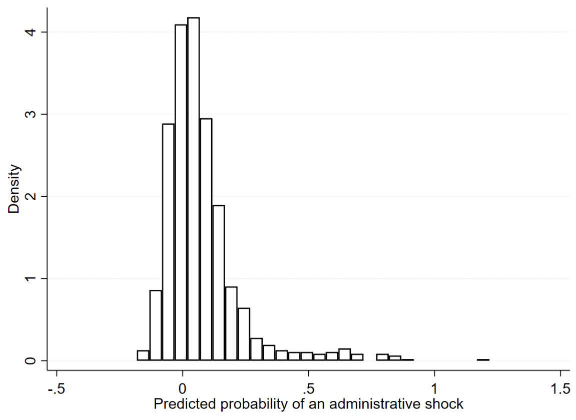
Table A.8 - Share of total administrative shocks occurring in each month

Month	La Réunion	Guadeloupe – Martinique – Guyane
1	26,09	6,52
2	34,78	0
3	8,7	2,17
4	21,74	6,52
5	4,35	17,39
6	0	2,17
7	0	2,17
8	0	6,52
9	0	17,39
10	0	15,22
11	0	15,22
12	4,35	8,7

Note: The table shows the share of total number of administrative shocks occurring during each calendar month, decomposing between La Réunion (located in the southern hemisphere) and the three other DCOMs (located in the northern hemisphere). 34.78 % of all shocks in La Réunion during the month of February.

Appendix B. Additional results

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

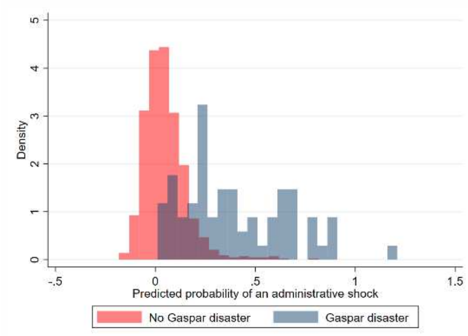


Figure B.3 – First stage fitted values: predicted probability conditional on the occurrence of EM-DAT shocks

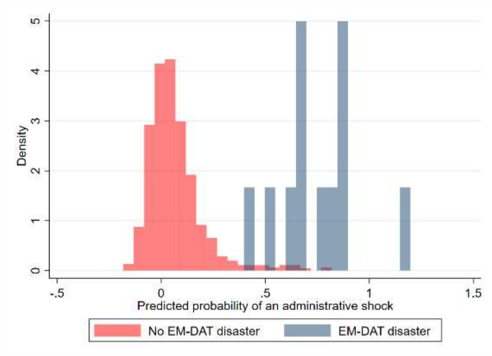


Figure B.4 – First stage fitted values: predicted probability conditional on the occurrence of adminsitrative shocks

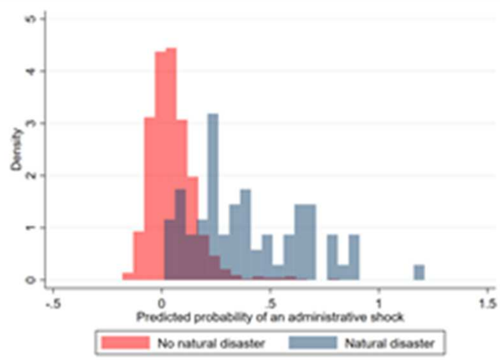


Table B.1 – Baseline effects on CPI inflation for all available aggregates

	T=0	T=1	T=2	T=3	T=4	T=5	T=6
Food excl. tobacco	0.004	0.017***	0.024***	0.011*	-0.000	0.002	0.003
	(1.48)	(3.55)	(3.29)	(1.79)	(0.08)	(0.46)	(0.66)
Other food	0.001	0.001	0.002*	0.002	-0.000	0.003**	0.002
	(0.58)	(0.58)	(1.81)	(1.08)	(0.19)	(2.17)	(1.06)
Fresh products	0.022	0.097***	0.121***	0.058**	0.008	0.003	0.015
	(1.51)	(3.95)	(3.47)	(2.10)	(0.41)	(0.16)	(0.72)
Tobacco	-0.001	-0.004	-0.000	0.006	0.004	0.007	0.008
	(0.14)	(0.69)	(0.00)	(0.59)	(0.35)	(0.58)	(0.61)
Energy	-0.000	0.006	0.012	0.013	0.019	0.020	0.020*
	(0.08)	(0.79)	(1.38)	(1.13)	(1.55)	(1.55)	(1.75)
Petroleum products	-0.002	0.008	0.017	0.016	0.025	0.026	0.026*
	(0.20)	(0.71)	(1.35)	(1.03)	(1.46)	(1.48)	(1.71)
Manufactured products	-0.002*	-0.006***	-0.007***	-0.006***	-0.008***	-0.006***	-0.003
	(1.75)	(3.10)	(3.57)	(3.09)	(3.65)	(2.90)	(1.28)
Other manuf	-0.000	-0.001	-0.002	-0.002	-0.002	-0.001	-0.002
	(0.57)	(1.58)	(1.32)	(1.46)	(1.40)	(1.06)	(1.13)
Footwear and garments	-0.007	-0.026***	-0.031***	-0.020***	-0.031***	-0.028***	-0.008
	(1.07)	(3.20)	(3.89)	(2.72)	(3.37)	(2.77)	(1.08)
Pharmaceutical products	-0.001	-0.001	0.000	-0.003*	-0.002	-0.002	-0.004*
	(0.45)	(0.36)	(0.14)	(1.77)	(1.17)	(0.87)	(1.73)
Services	-0.001	-0.002	0.002	0.003	0.005**	0.006**	0.008***
	(1.26)	(1.18)	(0.81)	(1.54)	(2.21)	(2.42)	(3.31)
Other services	-0.001	-0.001	0.002	0.004**	0.006**	0.004*	0.006**
	(0.75)	(0.54)	(1.06)	(2.16)	(2.52)	(1.72)	(2.32)
Rents	-0.001	-0.002**	0.001	0.001	0.003	0.003	0.004*
	(0.73)	(2.40)	(0.54)	(0.74)	(1.18)	(1.32)	(1.65)
Communication services	-0.002	-0.003	-0.002	-0.004	-0.003	-0.002	0.001
	(1.02)	(0.92)	(0.58)	(1.15)	(0.81)	(0.53)	(0.14)
Health services	-0.003**	-0.002	-0.002	-0.002	-0.002	-0.001	-0.001
	(2.21)	(0.93)	(0.99)	(0.70)	(0.81)	(0.18)	(0.44)
Transportation services	-0.017	-0.011	0.025	0.061**	0.059*	0.097**	0.078*
	(0.63)	(0.35)	(0.97)	(2.26)	(1.67)	(2.47)	(1.95)
Total	-0.000	0.002	0.005**	0.003	0.001	0.003	0.005**
	(0.36)	(1.02)	(2.24)	(1.37)	(0.70)	(1.32)	(2.54)
Total excluding fresh products	-0.001	-0.002*	0.000	0.001	0.002	0.003*	0.005***
	(1.37)	(1.76)	(0.19)	(0.71)	(0.96)	(1.68)	(2.83)
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. T-stat with robust standard errors in parentheses.
*p < 0.10; **p < 0.05; *** p < 0.01.

Table B.2 - 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	-0.051	0.208*	0.285***	0.442***	0.628***	0.639***	0.577***
	(0.58)	(1.93)	(2.59)	(3.51)	(4.30)	(4.45)	(4.06)
Employment							
Total	-0.001	-0.002	-0.003	-0.004	-0.004	-0.002	-0.002
	(1.12)	(1.00)	(1.30)	(1.09)	(1.03)	(0.57)	(0.50)
Agriculture (AZ)	-0.005	-0.033**	-0.041***	-0.027	-0.016	-0.001	0.001
	(0.65)	(2.55)	(2.91)	(1.55)	(0.82)	(0.06)	(0.04)
Food manuf. (C1)	-0.003	-0.004	-0.005	0.010	0.001	0.003	-0.004
	(0.57)	(0.49)	(0.51)	(0.78)	(0.09)	(0.19)	(0.33)
Extractive industry (C2)	-0.000	0.001	-0.008	-0.008	-0.015	-0.011	0.001
	(0.12)	(0.09)	(0.94)	(0.89)	(1.24)	(0.98)	(0.05)
Manuf. – machines (C3)	-0.001	0.015	0.009	0.018	0.035	0.061**	0.055**
	(0.11)	(1.08)	(0.53)	(0.99)	(1.64)	(2.42)	(1.97)
Manuf.-transports (C4)	0.017	-0.027	-0.046	-0.043	-0.134	-0.146	-0.155
	(0.35)	(0.38)	(0.54)	(0.47)	(1.07)	(1.19)	(1.30)
Manuf. – others (C5)	-0.003	0.000	-0.004	-0.004	-0.000	0.002	0.006
	(0.97)	(0.08)	(0.57)	(0.54)	(0.03)	(0.23)	(0.74)
Construction (FZ)	-0.005	-0.004	-0.017	-0.017	-0.009	-0.010	-0.009
	(1.25)	(0.72)	(1.93)*	(1.63)	(0.77)	(0.79)	(0.58)
Car repair (GZ)	-0.004	-0.002	-0.004	-0.004	-0.004	-0.005	-0.005
	(1.24)	(0.53)	(0.94)	(0.94)	(0.82)	(0.81)	(0.74)
Transports (HZ)	-0.001	0.001	0.004	0.003	0.005	0.008	0.003
	(0.32)	(0.30)	(0.61)	(0.47)	(0.72)	(1.14)	(0.34)
Accom. – restaurants (IZ)	-0.000	0.006	0.003	0.002	0.007	0.008	0.002
	(0.05)	(1.02)	(0.47)	(0.26)	(0.95)	(0.91)	(0.19)
Info. – comm (JZ)	-0.008	-0.014	-0.013	-0.013	-0.012	-0.008	0.009
	(1.04)	(1.32)	(1.01)	(1.20)	(1.12)	(0.67)	(0.58)
Finance – insurance (KZ)	0.004	0.012**	0.014**	0.011*	0.003	0.004	0.002
	(1.20)	(1.99)	(2.15)	(1.85)	(0.52)	(0.56)	(0.25)
Real estate (LZ)	0.003	-0.006	-0.006	-0.004	-0.016	-0.007	0.006
	(0.44)	(0.70)	(0.60)	(0.41)	(1.27)	(0.59)	(0.46)
Scientific – admin (MN)	-0.003	-0.003	-0.006	-0.006	-0.004	0.000	-0.004
	(1.17)	(0.50)	(1.03)	(0.85)	(0.53)	(0.01)	(0.34)
Public admin (OQ)	-0.001	-0.005	-0.004	-0.006*	-0.007*	-0.007	-0.003
	(0.28)	(1.45)	(1.30)	(1.74)	(1.89)	(1.47)	(0.70)
Other services (RU)	0.000	-0.006	-0.014*	-0.023**	-0.035***	-0.034***	-0.032***
	(0.09)	(1.03)	(1.77)	(2.34)	(3.28)	(3.21)	(2.84)
Interim	0.015	0.079	0.062	0.117**	0.077	0.133	0.030
	(0.33)	(1.32)	(0.97)	(2.04)	(1.26)	(2.10)**	(0.47)

***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.

Appendix C. 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 C.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 D. Composition of consumer baskets across DCOMs

The composition of consumption baskets is heterogeneous across French territories and changes over time. Table D.1 reports the weights of each aggregate according to the French statistics institute (Insee) over the period of interest, 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. Contrarily to food, the weight of services is increasing over time in all territories. The main component is other services (see Appendix A.1 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 D.1 – 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 4DCOMs, and in France, for 2018 and for the period 1999-2018. The average for the 4 DCOMs is an unweighted mean.

Comparing, the weights in DCOMs to those in metropolitan France, three facts stand out. First, the structure of weights 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 that of France.