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Natural disasters over France a 35 years assessment

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ABSTRACT

Using an exhaustive administrative database, we assess the impact of extreme weather events over French cities between 1982 and 2017. We identify numerous non-catastrophic disasters, thereby improving coverage wrt. the existing literature. Counting residents of cities stricken by a disaster, we find that in the long run, there were 22 residents affected every month per thousand population. This risk factor has been falling by 5 fewer people with every passing decade. France has thus improved its preparedness to natural disasters even though the seaboard regions fare worse than the northern region, most likely because of heightened urban pressure in hazardous areas by the seaside. Tropical territories are more at risk than the temperate European mainland, from a different mix of events. The full economic cost of natural disasters is estimated at 22 € per capita per year and represent a small fraction of property insurance premiums. Residents from safer areas currently subsidize those living in riskier areas. To be more effective, preventive investments should be directed towards the main cities.

1. Introduction

Since time immemorial, human societies have sought protection from natural disasters by settling in safe areas and later, by building safeguarding infrastructures such as dikes, canals, and walls. A natural disaster may then be an *exceptional* weather event battering a *well prepared* community or simply a *strong* event striking *defenseless* people. As an illustration, the 2010 Haiti earthquake generated more casualties and damage (relative to GDP) than the stronger one in Chile a month later. Preparedness has been discussed ever since the dreadful 1755 Lisbon earthquake. Whereas Voltaire lamented the devastating natural events for which no reasonable justification could be found, Rousseau responded in anthropogenic fashion that “the majority of our physical misfortunes are also our work”; he was alluding to urban density and people's obsession with their property as root causes for the elevated number of casualties.[1]

The recurrence of natural disasters warrants studying their socio-economic impact. Ideally, one would identify the more pressing risks, with a view to discriminate among possible cost-effective adaptations such as zoning, protection, prevention or education, to name a few. The SREX-IPCC (2012) report however states that “data on disasters and disaster risk reduction lack at the local level, which can constrain improvements in local vulnerability reduction”.[2] Contributing to this task, we exploit an almost exhaustive French database of natural disasters to infer whether the country is preparing adequately to withstand these calamities. To disentangle the respective roles of nature and man, we shall assume *a stable distribution of extreme weather events over France over the 1982–2017 period*. This claim, statistically corroborated by our data (cf. §4), is in line with the conclusion of §3.5 of the SREX report for Europe, namely that the low quality of extreme weather records, their geographical limitation and the overall short duration of surveys make it virtually impossible to identify with statistical confidence any change of the climate over modern times.

The inter-temporal evolution of global losses from catastrophes is clearly rising but mostly due to socioeconomic factors such as wealth, population, and urban pressure (cf. Mohleji and Pielke (2014) or Hoeppe (2016)). Regarding macroeconomic impact, the meta-analysis of Klomp and Valckx (2014) concludes to a negative short-run effect beyond the direct destruction losses and a negative drag on long-run growth, although this latter finding is disputed. Focusing on exposure, Park et al. (2015) assemble atmospheric and economic data to show that South Korea's preventive investments have reduced vulnerability to

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[1] cf. Dynes (2005) or Deléage (2005) for the original French quotes (§1 and §13). Today people die while trying to salvage their cars from underground parkings during flash floods, as analyzed by Arrighi et al. (2016).

[2] In the conclusion to a recent update, Hay et al. (2016) note ‘ongoing challenges with data availability and quality, the ability to monitor and report extreme events consistently and the capacity to develop and apply the complex statistical methods to undertake rigorous analyses.”

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tropical cyclones. Mechler and Bouwer (2015) obtain a likewise result for Bangladesh.

Whereas these two studies use precise readings from weather stations, their socioeconomic information is limited to national or regional GDP and damages estimates. In this article, we go down to the city level to obtain a finer characterization of the impact of natural disasters upon the territory which, we believe, constitutes a novelty in the literature. Our findings are in line with those cited above but for a country, France, whose socioeconomic development is more advanced and where floods dominate the natural disasters mix. In line with the theoretical prediction of Schumacher and Strobl (2011) for a developed country, we observe that, on average, the French population is becoming less exposed to natural disasters over the last 35 years. A qualification is nevertheless in order for seaboards where the positive trend is partially countered by population pressure into risk-prone areas; as a result, the individual exposure risk is stable over the last decade (2008–2017) as opposed to decreasing in the other regions. We also study the French overseas islands finding that people living under the tropics are affected with a higher frequency but by a surprisingly small margin. This outcome carries two messages, firstly that mainland risk might have been underestimated by studies only looking at major catastrophes and secondly, that tropical island nations can achieve a reasonable level of natural disaster protection if they manage to fund and implement preventive structures and zoning rules like the French government did.[3]

The rest of the paper is divided as follows. Section 2 highlights the semantic difference between catastrophes and disasters with a call to focus on the latter lesser known category. Section 3 describes the legal context leading to our disaster database, a few descriptive statistics and the method by which it is exploited, as well as some crucial assumptions. Section 4 clarifies the relationship of our work with climate change which is needed to proceed safely. Section 5 covers the socioeconomic impact and is further divided into subsections. The first looks at the temporal evolution over continental france, the second at variations across four climatic French regions. A third part aims to identify an impact of natural disasters upon classical economic measures of well being. Lastly, we put the cost of natural disasters into perspective with the French insurance market. Section 6 increases the geographic granularity to discuss what general policy objective might be best. Section 7 offers a critical discussion and provides some comparisons with neighboring countries as well as policy recommendations for France. Section 8 concludes.

2. From catastrophes to disasters

As detailed in Boccard (2018), the natural disaster rosters featuring prominently in the literature, namely EM-DAT and MunichRe, focus on major disasters (aka catastrophes), eschewing hundreds of less dramatic events that are no less consequential for their victims.[4] At issue is the small sample size since natural catastrophes are unfrequent events. Over the last decade, MunichRe and EM-DAT report no more than 72 and 32 catastrophes, respectively, per month for the entire world. This forces authors to set the entire planet as their research universe to perform a meaningful statistical analysis. The downside of this choice is the resulting large variance of climates, economics regimes and levels of development for the country sample. It is then difficult to relate econometrically natural disasters to economic variables. Even for the US where data collection regarding extreme weather events is extensive, Gall et al. (2009) reveal a series of inconsistencies and limitations that may lead to misinterpretation and fallacies.[5]

To progress in our understanding of the roots and consequences of natural disasters, we believe that two criteria should be fulfilled. Firstly, one should adopt a fixed basis e.g., a single country of appreciable geographical extent, to allow for the recording of many events. Secondly, to avoid selection biases, one should establish a set of inclusion criteria that are exogenous, stable across time and low enough to include smaller natural disasters. Recall indeed that from a socioeconomic point of view, a natural disaster is any severe alteration of community life. As such, it may feature an absence of casualties or be confined to a remote valley with a low population count; it should nevertheless be accounted for. We shall argue that our French administrative database meets these requirements, being exhaustive, independent of insurance coverage and proof to statistical recording artifacts.

3. Data and method

This section presents the French legal framework for insurance against natural disasters and how the associated database is used. In 1981, the newly elected socialo-communist government created a commission on *major natural risks* headed by famed vulcanologist Haroun Tazieff. Subsequent to the 1981 Christmas major flood episode that left scores of citizens with uninsured losses, a dedicated law was voted the next year (1982), mandating the inclusion of a guarantee against natural disasters within insurance contracts as retold by Decrop and Gilbert (1993). Under this framework, the interior ministry may declare a *state of disaster* for a township after the occurrence of an extreme event at the mayor's request. Insurance companies can then compensate their clients for unconventional risks such as *floods, mudslides, drought induced ground movements, avalanches, earthquakes, waves action, landslides, volcanism or cyclonic winds*.[6] Traditional insurance still covers the losses resulting from forest fire, stormy wind, hail, weight of snow and frost. Extreme temperature phenomena (cold spells and heatwaves) are absent from our study since they strike people rather than the insurable assets covered by the French disaster scheme. In any case, these events lack an ex-ante definition since they are only identified ex-post by comparing long term death rates to those of the suspicious period, thus making attribution arduous.

The French natural disaster scheme is currently funded by a compulsory 12% fee levied upon the nearly universal private property insurance contracts.[7] It is conservatively managed with a view to withstand a future major catastrophe such as the flooding of the entire Paris region (which is bound to return at some point in the future). Given this overriding goal, we may expect authorities to apply strict criteria for disaster declarations, thereby limiting frivolous claims (cf. Neumayer et al. (2014) on the political economy of natural disaster damage). We shall then assume stability of the criteria used to declare a natural disaster, thereby eliminating any selection bias (which could otherwise distort our results).

The July 2018 update of the CATNAT (aka “catastrophe naturelle”) database contains over 160 000 entries starting in August 1982, each recording a township, a date, a disaster type and its duration. The minimum number of yearly declarations is 452, the median 2 832 and the maximum 31 150. Floods take up 68% of declarations followed by droughts with 15% and storms (inc. hurricane, tornado) with 10%. Some disasters, typically drought induced ones, are sometimes proclaimed up to one year after the facts; this leads us to exclude the year 2017 in order to avoid an artificial reduction in the incidence of disasters. Based on the date featured in each declaration, we identify 3 676 eventful days across 35 years i.e., *two natural*

[3] Obviously, a catastrophic storm such as Irma over the Caribbean in September 2017 will always cause havoc.

[4] The literature employs also the distinction intensive vs. extensive natural disasters.

[5] Referring to studies about the Lisbon earthquake, Aguirre (2012) warns of a

(*footnote continued*)
tendency by researchers to inflate the socio-economic impact to mythical proportions.

[6] Wind speed above 145 km/h for at least 10 min or gust over 215 km/h (cf. CCR (2017)).

[7] A 0.5% rate is also levied upon general car insurance to cover the automobile losses due to natural disasters.

Table 1
Major climatic events in France between 1900 and 2017.

Tragedies (5) if > 1000 casualties or > 3 bn€ loss
- Two Volcanic Eruptions in the West Indies: 1902, 30 000 casualties
- Double Storm over mainland: Xmas 1999, 100 casualties, 15 bn€ loss
- Heat Waves over mainland: 2003 & 2006: 15 000 and 2 000 casualties

Major catastrophes (41) if > 100 casualties or > 0.3 bn€ loss
- Earthquake in South-East: 1909, 46 casualties
- Floods: 1910, 30, 40, 58, 77, 83, 88, 92, 93, 94, 95, 99, 2002, 03, 10 (2), 11,16
- Droughts: 1976, 89, 92, 96, 2003, 11, 17
- Fire: 1949, South-West, 82 casualties
- Tropical Storms in Reunion: 1932, 48, 62, 80, 87, 89, dozens of casualties
- Tropical Storms in West Indies: 1966, 70, 89, 2017, dozens of casualties
- Continental Storms: 1982, 87, 90, 2009, 10, dozens of casualties

Catastrophes after 1950 (88) if > 10 casualties or > 30M€ loss
- 41 floods on the continent
- 1 tsunami, 1 fire and 2 cold snaps
- 3 land slides overseas and 5 on the continent
- 8 earthquakes and 8 avalanches
- 11 tropical storms and 8 continental ones

disasters per week. As there are sometimes more than one disaster on a given day, we identify 4 939 extreme weather events; the distribution across categories is floods (59%), landslides (27%), droughts (9%) and 5% for the remaining categories. As a matter of comparison with catastrophes, as defined officially by DGPR (2008), France has suffered a little more than one yearly catastrophe since 1900 as we show in Table 1.[8] The CATNAT database therefore proves that catastrophes are only the tip of the iceberg whenever one talks about natural disasters.

Result 1. Whereas natural **catastrophes** occur less than twice a year in France, a natural **disaster** impacts the country twice a week.

To quantify the socio-economic impact of natural disasters, one would ideally look into the CATNAT fund for the individual claims lodged by victims. It appears however that even the pool of insurance companies cannot perform this task as their own studies rely on samples. In a second best world, one would count the claims issued after each disaster but the ministerial declaration only refers to the township where the disaster took place. We thus proxy the number of victims by the population (of the city), implicitly assuming that the following assumption holds identically for a village or a metropolis:

Assumption 1. The proportion of residents victims of a natural disaster is constant, independent of time, location or the nature of events.

This is obviously a crude approximation. For a limited number of major disasters, we were able to compute this ratio: one in 16 people affected by storm Xynthia (2010) made a claim and one in 8 did so after storm Klaus (2008). For a sample of major floods (including the latest one in 2016), we find a ratio ranging from 30 to 75. The many errors we are bound to make by ignoring the victims' information should nevertheless *even out* at country level thanks to the law of large numbers when applied to our thousands of records. Summarizing, our study will not count *victims* but people *affected* or *impacted* by natural disasters i.e., living in a stricken township at the time of events. We compute the ratio of impacted people to population (for a given area and a given month) i.e., affected people over a month per thousand residents (‰).

To compute our impact ratio, we use five historical INSEE censuses (1982, 1990, 1999, 2006, 2010) and the modern continuous census for the more than 36 500 French townships. This detail is needed to account for population growth and the migrations that took place between regions, mostly from the North towards the Western (Atlantic) and Southeastern (Mediterranean) seaboards, together with the continuing exodus from the countryside towards urban centers.[9] The population of a township at a specific date is obtained by linearization of the surrounding censuses population counts.

4. On climate change

Before we may study the evolution of the socioeconomic impact of natural disasters, we need to assess whether the natural phenomena at stake is governed by a stable inter-temporal distribution. There is indeed the suspicion that the phenomenon is becoming more acute, namely that climate change is already noticeable in the frequency of natural disasters. This possibility is worthy of consideration as our timespan lies at the threshold between weather and climate (30 years for the IPCC vs. 50 for the WMO). Two avenues are considered, which, at any rate, do not contribute to the study of climate in France or its evolution but to understand better the relationship with the distribution of natural disasters.

For this assessment, we first select floods over continental France which account for a large majority of all disaster records (over 100 000 declarations). A province (aka département) is an area of no more than 80 km × 80km; it is therefore highly unlikely that two distinct floods would strike it on the same day. We let $\mathbb{D}$ be the set of départements and $\mathbb{M}$ the set of months, starting in August 1982 and ending in December 2017 and let $f_{i,m}$ count the days where at least one city from province $i \in \mathbb{D}$ is awarded a disaster declaration during month $m \in \mathbb{M}$. We believe this to be a good measure of the monthly incidence of floods over that province but we must be cautious that the straight summation will double count any river rise involving the several provinces that cover the basin of the river under study. To derive a coherent national measure, we develop a proximity algorithm to identify clusters of connected provinces which are flood stricken on the same day. We then assume that a different flood stroke each isolated cluster that day. The monthly score f_m sums all the disasters found this way; it may well be greater than the number of days within a month. Over the entire period, the database contains 2 704 flooding days but once we bunch together those belonging to the same event but declared on a different date and separate the distinct events occurring on the same day (because lofted in different river basins), we obtain 2 746 occurrences of flooding.

Since the intensity and extension of a flood, whether a flash or riverine one, is often impacted by embankments and derivations, urban pressure must be accounted for. Consider indeed a known flooding area that was historically covered by fields and pastures. In such a context, no flooding would lead to a natural disaster declaration but once buildings and infrastructures start encroaching upon the area, the possibility becomes real. It therefore makes sense to construct a second measure taking this anthropogenic factor into account. Along side the *raw* score f_m, we compute a monthly population index $h_m = \frac{p_m}{p_0}$ from the continental France population count p_m where the initial date is August 1982. The *net* score is then defined as $g_m = \frac{f_m}{h_m}$. To eliminate seasonality, we apply a 12-months moving average to both series and obtain $\tilde{f}_m$ and $\tilde{g}_m$. We regress these seasonally adjusted scores on a linear date variable and an intercept with the model

$$\tilde{f}_m = \alpha_1 + \beta_1 \, \text{date}_m + \varepsilon_m \qquad \tilde{g}_m = \alpha_2 + \beta_2 \, \text{date}_m + \xi_m$$

Additionally, we perform the non-parametric Mann-Kendall test of association to identify a trend in the series (statistic τ). The regression estimates are shown in Table 2.

We observe that the raw flood count is statistically flat since parameter β_1 cannot be distinguished from zero. The Kendall-τ_1 statistic likewise fails to be conclusive regarding the existence of a monotonic trend. Once we account for the increased population pressure, results change clearly as parameter β_2 becomes statically negative and likewise the Kendall-τ_2 statistic indicates a downward trend. These findings are

[8] Continental France refers to the part belonging to the European continent, including the island of Corsica.

[9] The change in the distribution of city populations between 1982 and 2017 induces a 10% fall in the coefficient of variation and a 23% fall in the kurtosis

(*footnote continued*)
revealing that nowadays less of the variance lies on very large cities.

Table 2
Regression of monthly flood count against time.

(1) raw count	Estimate	Standard Error	t-Statistic	P-Value
α	51.112	20.1951	2.53091	0.0117936
β	−0.0218193	0.010093	−2.16181	0.0312783
τ	−0.0769665			0.0281633
(2) corrected	**Estimate**	**Standard Error**	**t-Statistic**	**P-Value**
α	112.461	18.7241	6.00621	$4.5725*10^{-9}$
β	−0.0527924	0.00935791	−5.64147	$3.37343*10^{-8}$
τ	−0.196889			$1.63848*10^{-8}$

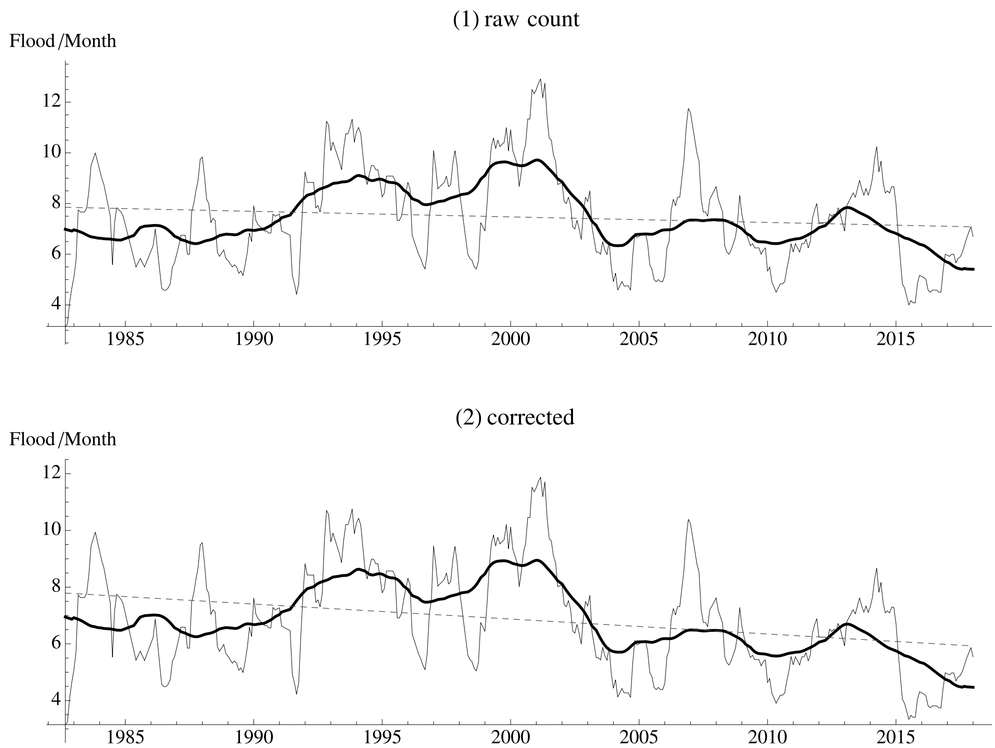

Fig. 1. Mainland French Monthly Flood count.

observable on the two panels of Fig. 1 displaying the seasonally adjusted monthly flood scores as well as the 48 months moving average smoothed version and the linear trend.

Result 2. The raw incidence of floods over mainland France is stable over the last 35 years. Once we account for the heightened population pressure, it displays a negative trend.

The second avenue to assess a possible impact of climate change upon the distribution of natural disasters in France is forest fires caused by nature i.e., lighting. The endangered mediterranean seaboard has been monitored since 1973 by the "Délégation à la Protection de la Forêt Méditerranéenne" (DPFM)[10] whereas the European Forest Fire Information System (EFFIS) provides more rudimentary information regarding the entire French forest between 1985 and 2013. The correlation between the two series reaches 96% so that the mediterranean section appears to be a very good proxy of the fire issue for the entire continental French territory. According to IGN (2017), the continental French forested area grew from $S_{1985} = 14.1$ million hectares (MHa) to $S_{2017} = 16.9$ MHa. At such a growth rate, the initial forest area was about $S_{1973} = 13.2$ MHa. As of 2016, the mediterranean forest extension M_t represented 42% of the continental forest S_t. Matching this background information ($M_t = 0.42 \times S_t$) with the extension burned every year due to lightning (nature) N_t and human behavior (accidental as well as malevolent) H_t, we compute the yearly rate of destruction of the mediterranean forest due to nature $\mu_t = \frac{N_t}{M_t}$ and man $\nu_t = \frac{H_t}{M_t}$. It must be noted firstly that humans are one hundred times more dangerous than nature when it comes to forest fires. Secondly, the 54% correlation between the two series also reveals that hot and dry weather conditions make all fire triggers more likely. To test the existence of a trend, we study the econometric equations $\nu_t = \alpha_1 + \beta_1 \text{year}_t + \varepsilon_t$ and $\mu_t = \alpha_2 + \beta_2 \text{year}_t + \varepsilon_t$. The results are reported in Table 3 allow to conclude that both rates of forest fire destruction display a significative downward trend, the anthropogenic rate ν_t fell from about 5‰ to 2‰ (over the period 1973–2017) while the natural rate μ_t is about one hundred times smaller and likewise falling. The latter fact proves that the incidence of natural forest fires over the French mediterranean seaboard is receding over the last 44 years.

At the outset of this section, we may say that on the basis of two unrelated natural risk, flood and fire, the perception that nature is striking France harder than before is misconstrued. We shall therefore pursue our study under the hypothesis of a stable distribution of the underlying natural phenomena.

[10] Although three quarters of French forest land are private property, forest fires are excluded of the CATNAT scheme.

Table 3
Forest Fires in France (‰ of forest area burned).

β	Estimate	Standard Error	t-Statistic	P-Value
natural	−0.0853911	0.0301864	−2.82879	0.00707029
human	−54.8433	11.1497	−4.91882	0.0000132

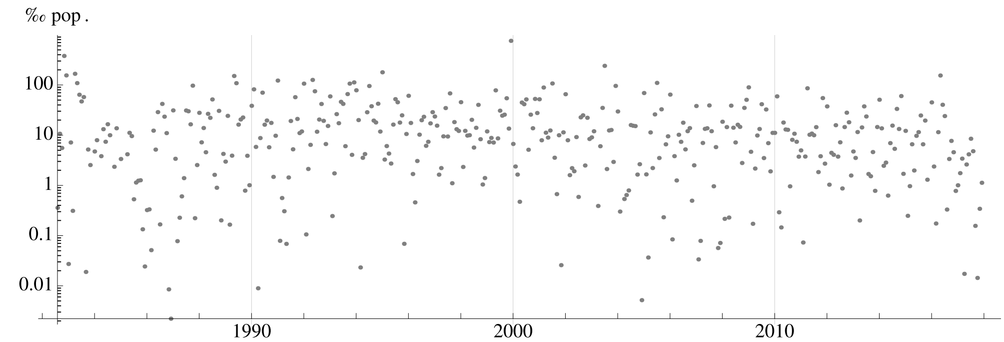

Fig. 2. Continental French People affected every month The time series $x_{0,m}$ is shown from August 1982 until December 2017 in ‰ scale.

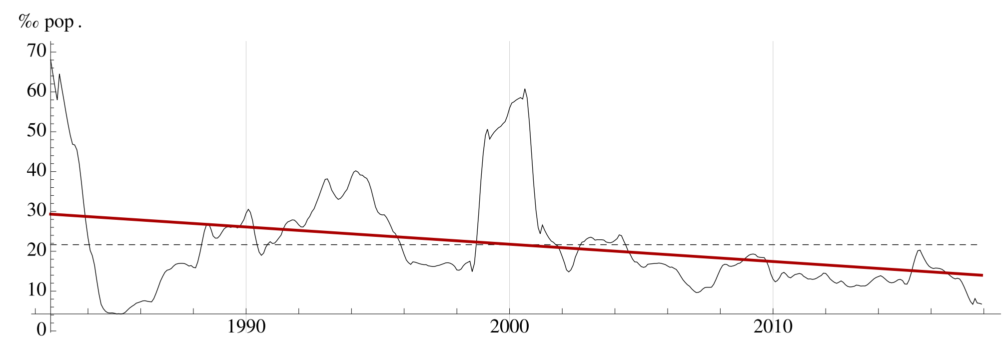

Fig. 3. Continental French People affected every month The smoothed time series $z_{0,m}$ is shown from August 1982 until December 2017 in ‰ scale.

5. Socioeconomic impact of natural disasters

5.1. Evolution of the impacted population in France

We denote $\mathbb{C}$ the set of all 36 500 french townships ("communes"), $\mathbb{T}$ the set of days (August 1982–December 2016) and $p_{i,t}$ the city's population on that day (computed by interpolation from the censuses). From the natural disasters database, we extract a (long) list $\mathbb{K}$ of spatiotemporal pairs (i, t) whereby city i was stricken by a natural disaster on day t. We group cities into large regions $\mathbb{J}$ using index $j = 0$ for mainland France, $j = 1$ for the northern region, $j = 2$ for the western one, $j = 3$ for the southeastern one and $j = 4$ for the overseas territories. For $j \in \mathbb{J}$, $m \in \mathbb{M}$, let $K_{j,m} \subset \mathbb{K}$ be the list of cities within region j stricken by a natural disasters during month m. We define $q_{j,m} = \sum_{(i,t)\in K_{j,m}} p_{i,t}$ the total population residing in area j impacted by a natural disaster during month m (equal to zero in some rare occasions). The risk rate is then defined as

$$x_{j,m} = \frac{q_{j,m}}{p_{j,m}}$$

where $p_{j,m} = \sum_{i\in j,t\in m} p_{i,t}$ is the region's population during month m. Fig. 2 displays the time series $x_{0,m}$ for continental France; a logarithmic scale is made necessary by the distance between extremes. There are indeed a few month free from any disasters while the impact of storms Lothar and Martin around Christmas 1999 is plainly visible since $\frac{3}{4}$ of the population was living in a township that declared a state of emergency in December 1999.

Given that recurring natural disasters such as floods and storms have a strong seasonal pattern, we study the 12 month moving average

$$y_{0,m} = \frac{1}{12}\sum_{i=0}^{11} x_{0,m-i}$$

An additional smoothing is used on Fig. 3 which displays the time series

$$z_{0,m} = \sum_{k=-4}^{4} \omega_k y_{0,m+k}$$

a version of $y_{0,m}$ smoothed with a 9-points Savitzky-Golay filter ω. The flat dashed line displays the overall mean

$$\mu_0 = \frac{1}{|\mathbb{M}|}\sum_{m\in\mathbb{M}} x_{0,m}$$

indicating that over the long run *22‰ of the continental French population is impacted every month by a natural disaster*. The linear trend line, shown in red, is markedly sloping down: with every passing decade, there are 4‰ fewer residents affected by disasters every month.

To derive more precise results, the seasonally adjusted impact $y_{0,m}$ is regressed[11] on a linear date variable and an intercept with the model

$$y_{0,m} = \alpha_0 + \beta_0 \text{ month}_m + \varepsilon_0$$

Table 4 shows the parameters obtained as well as the Mann-Kendall test (statistic τ_0). Both tests confirm the existence of a downward

[11] By de-trending the original time series, the P-value is improved by 7 orders of magnitude.

Table 4
Regression parameters for the risk rate.

Mainland	Estimate	Standard Error	t-Statistic	P-Value
α	1000.53	157.122	6.36789	$5.00099*10^{-10}$
β	−0.4893	0.0785468	−6.22941	$1.13152*10^{-9}$
τ	−0.209116			$1.19544*10^{-10}$

tendency for the share of the French population impacted by natural disasters every month.

Result 3. On the basis of the affected populations, and assuming a stable climate over the 1982–2017 period, continental France has improved its preparedness to natural disasters.

If one insists on using the general evidence of a worsening climate (through not corroborated by our limited data), then the government's risk management policy becomes even more laudable: although disasters might be more frequent, citizens are better protected than ever. Our finding agrees with Mechler and Bouwer (2015) who show that vulnerability has been scaled down in Bangladesh as the GDP losses to floods fell from 7.5% to 3.3% over three decades (1974–2006) i.e., a decadal reduction of 14‰, similar to our figures. Likewise, Park et al. (2015) study disasters over South Korea and observe a smaller but still significant reduction in vulnerability to tropical storms.

5.2. Variations across climatic regions

The 12 continental administrative regions of France (as newly defined in 2016) are shown on Figure XXX with 3 color schemes indicating their climate influence: continental over the *North* (green), Atlantic over the *West* (blue), mediterranean over the *Southeast* (orange). The French Overseas territories located in the Caribbean and Indian ocean are under the influence of a tropical climate. As these four climatic regions feature distinct distributions of extreme events (shown in Table 5 in terms of affected populations), we are warranted to rerun our analysis on a regional basis.

The northern region contains one half of the mainland population ($\approx 33M$) and thus displays a profile close to the national average. As before, we use the monthly count of northern population impacted by natural disasters $q_{1,m}$ to build the regional risk rate $x_{1,m}$ and its seasonally adjusted version $y_{1,m}$ (with a 12-month moving average). Fig. 4 displays $z_{1,m}$ the smoothed version of $y_{1,m}$, the long term average $\mu_1 = \frac{1}{|\mathbb{M}|}\sum_{m\in\mathbb{M}} y_{1,m}$ and the

Table 5
Disaster Distribution among regions.

Area (%)	South-East	North	West	Overseas	Mainland
Flood	58.3	65.3	64.7	58.2	59.3
Landslide	23.4	25.8	19.6	15.9	27.6
Drought	13.1	7.8	10.4	0.	8.8
Waves	2.1	0.8	3.9	13.7	2.4
Storm	0.2	0.1	0.5	9.3	0.2
Earthquake	0.7	0.2	0.4	2.7	0.5
Avalanche	2.2	0.1	0.6	0.	1.3
# days	2411	2420	1320	182	4773

regression model $y_{1,m} = \alpha_1 + \beta_1\,\text{month}_m + \varepsilon_1$. We find highly significant statistics for parameters β_1 and τ_1 which are thus statistically negative as shown in Table 6. The Kendall-τ_1 statistic is likewise conclusive regarding the existence of a monotonic downward trend.

Nearly the entire northern population suffered the Christmas 1999 storms but overall the north has a more benign climate than the entire country since only 18‰ of its population is impacted on average every month over the long run. The preparedness improvement is also in line with the nation as the decadal change is − 5‰. Taking a snapshot of the last decade, the risk factor is now down to one half of the national figure at 7.6‰ vs. 14.4‰ (for the mainland).

The western region, host to some 13 million people faces the Atlantic ocean and thus suffers more from storms and droughts. Most of the population suffered the Christmas 1999 storms which stands as the major event (heavy forest destruction and 27 casualties in the region). The other historically significant event is Cyclone Xynthia in February 2010 which caused 59 casualties on the Atlantic seaboard but only ranks twelfth in terms of population affected.[12] This region has a profile very much like the national one with a long term risk factor of 21‰, an improvement rate of − 4‰ per decade and a risk of 15‰ over the last decade. The temporal evolution of the risk factor is shown on Fig. 5. We find highly significant statistics for parameters β_2 and τ_2 which are thus statistically negative as shown in Table 7.

The southeastern Mediterranean region, home to some 19 million people, includes Nice, the city with the greatest number of disaster declarations (almost twice a year). As can be seen with the smoothed seasonally adjusted risk rate $z_{3,m}$ shown on Fig. 6, the impact of the Christmas 1999 storms is much smaller than elsewhere whereas the November 1982 flood stands clearly as the major event.[13] The long term mean is the highest in mainland France at 31‰, falling at a rate of − 4‰ per decade. The trend parameter in the linear time regression is significative as seen from Table 8 while the Kendall association test fails to be conclusive, thus indicating a more feeble trend (compared to the other continental regions).

The disaster history in this region is however heavily influenced by the catastrophic floods of November 1982. If we eliminate this outlier, the long run mean falls to 28‰ and crucially, the regional profile ceases to display a long term trend (statistically speaking). At any rate, the southeastern region displays an average risk factor of 26‰ over the last decade which is three times greater than in the north. This higher risk incidence is possibly due to the ever greater population density in the mountainous valleys leading to the Mediterranean coast, which are host to most major cities. As noted by the sustainable planning commission in CGDD (2009), urban development forces ever more people to live

[12] As revealed by the Court of Audit (2012), population pressure on the seaboard induced a lax application of zoning rules in order to allow for the construction of additional dwellings in seaside areas prone to flooding and wave action.

[13] With 15 casualties in France and 12 in Andorra (a tiny country of the Pyrenees), the episode on 6/11 qualifies as a catastrophe due to the heavy destructions. There was also another major flood on 26/11 which explains the high count for that particular month.

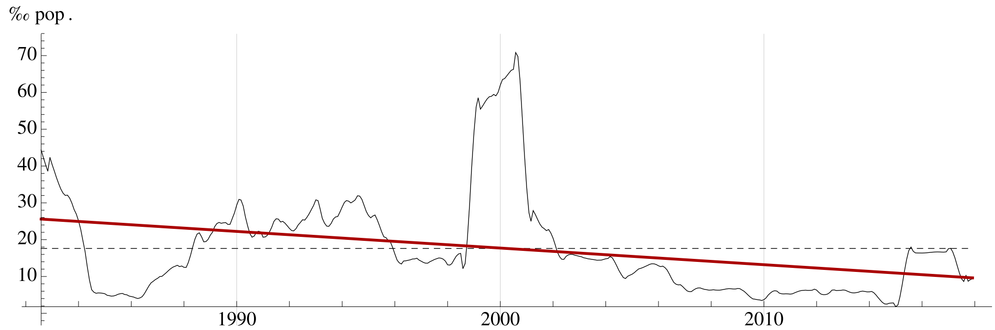

Fig. 4. Northern French People affected every month The smoothed time series $z_{1,m}$ is shown from August 1982 until December 2017 in ‰ scale.

Table 6
Regression parameters for **Northern** France.

North	Estimate	Standard Error	t-Statistic	P-Value
α	1018.04	166.885	6.10023	$2.39302*10^{-9}$
β	−0.50013	0.0834277	−5.99478	$4.36983*10^{-9}$
τ	−0.309992			$1.35395*10^{-21}$

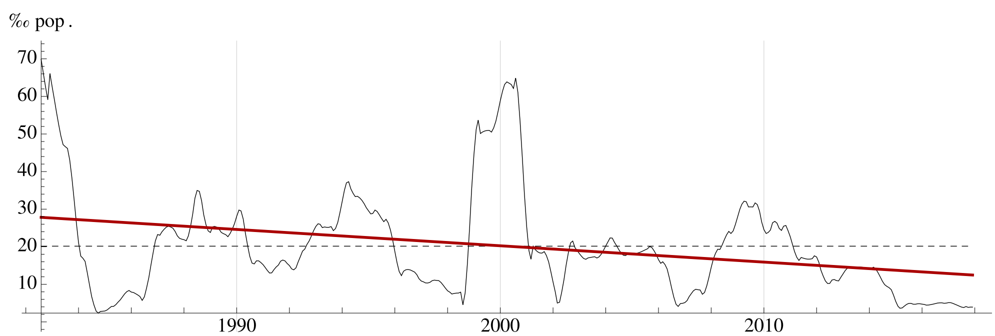

Fig. 5. Western French People affected every month The smoothed time series $z_{1,m}$ is shown from August 1982 until December 2017 in ‰ scale.

Table 7
Regression parameters for **Western** France.

West	Estimate	Standard Error	t-Statistic	P-Value
α	980.937	185.122	5.29887	$1.87931*10^{-7}$
β	−0.480214	0.0925444	−5.18901	$3.28762*10^{-7}$
τ	−0.179917			$3.0314*10^{-8}$

Table 8
Regression parameters for **Southeastern** France.

South-East	Estimate	Standard Error	t-Statistic	P-Value
α	1058.59	215.865	4.90397	$1.34161*10^{-6}$
β	−0.514044	0.107913	−4.7635	$2.61896*10^{-6}$
τ	−0.0676153			0.0373184

into risky areas (regarding flash floods).

Result 4. Mediterranean France suffers a higher than average hazard risk, not falling of late, as opposed to the safer continental northern region whose current risk is less than half the long term average. The western region presents intermediate values in line with country mean.

We now assess the impact of natural disasters on the overseas French islands in the Caribbean and the Indian Ocean whose population

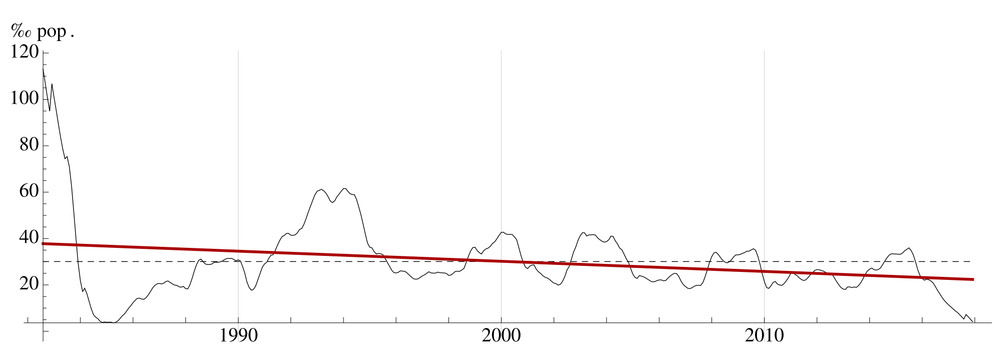

Fig. 6. Southeastern French People affected every month The smoothed time series $z_{1,m}$ is shown from August 1982 until December 2017 in ‰ scale. Beware that the vertical scale goes to a maximum of 120‰.

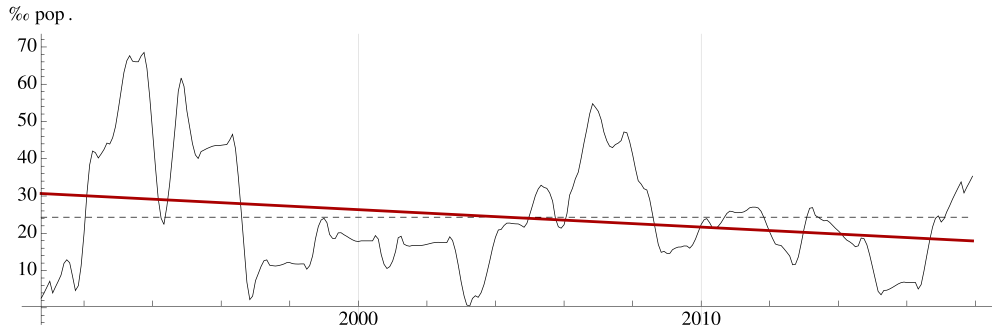

Fig. 7. Overseas French People affected every month The smoothed time series $z_{1,m}$ is shown from January 1990 until December 2017 in ‰ scale.

Table 9
Regression parameters for **Overseas** France.

Overseas	Estimate	Standard Error	t-Statistic	P-Value
α	1052.87	334.168	3.15073	0.00178007
β	− 0.512722	0.166714	− 3.07545	0.0022802
τ	− 0.036865			0.323834

Table 10
Disaster risk parameters for France.

Region	Pop	LT risk	last decade	Decadal Change
South-East	19.4	30.5	26.8	− 5.1
North	33.	17.5	7.9	− 5.
West	13.3	20.3	15.3	− 4.8
Overseas	1.9	25.3	27.4	− 5.1
Mainland	65.7	21.7	14.9	− 4.9

has passed the 2 million mark, having grown 40% since 1990 when the disaster records started. Due to their tropical climate, a different distribution of events is observed: floods only represent 51% of the affected people, sea-rise 19%, storms 16%, landslides 8% and telluric activity 5%. Because these islands have a small geographic extension, they suffer fewer climatic events (128 vs 3000+) but their population density is thrice the mainland one, making exposure to storms more pronounced. Those two effects however cancel out as the long term risk rate is even lesser than the European one (computed over the same period): 18 vs. 22‰. The small number of records spreading over more than two decades produces an irregular risk profile, as can be seen with the smoothed seasonally adjusted risk rate $z_{4,m}$ shown on Fig. 7.

The overseas seasonally adjusted risk rate $y_{4,m}$ is falling at a rate of − 4‰ per decade. The trend parameter β_4 in the linear time regression is significative as seen from Table 9 while the Kendall association test fails to be conclusive, also indicating here a weak trend (Table 10).

The long term risk factor is 24‰ versus 22‰ for the mainland (over the same shorter 26 years period). This small difference is surprising given the contrast between the mild European climate and the wilder tropical one. Intuitively, although small islands are unlikely to be on the course of tropical storms, once they are stricken, the damages are major and most, if not all, of the population is affected. We would therefore expect a higher long term risk exposure than on the European continent where such storms are unusual and cannot damage the entire country. The resolution of the paradox might come from the old continent. By looking beyond catastrophes, we uncover hundreds of natural disasters, impacting millions of people every year. The European risk factor may then be higher than what our preconceptions lead us to anticipate because non catastrophic amplitude flooding as well as summer flash floods are rather frequent (at least once a week in mainland France). We must however note that, even on islands benefitting from the funding of a rich metropolis to build public infrastructures, the risk of enduring a natural disaster is greater than on the temperate Europe landmass. Over the last decade the risk factors are respectively 23‰ and 14‰.

Result 5. Tropical French islands suffer a greater natural hazard risk than the mainland but it is commensurate with the risk faced by the European seaboard regions.

The following table sums-up our main findings.

5.3. Individual well being

Having identified how frequently the French population is affected by natural disasters, the next step is to inquire about a possible socio-economic impact. As we show in the next section, the total damages, both to public and private assets, inflicted by natural disasters upon France over the last decades are tiny compared to the nation's wealth. This absence of a meaningful effect of disasters upon global economic performance leads us to inquire about local impacts.

Subnational economic statistics are sparse and limit our ability to take advantage of the geographic finesse of our database. We use the quarterly unemployment rate U over 1983–2016 for the 96 mainland provinces, extracted from the French statistical institute INSEE. We denote $\mathbb{T}$ the set of trimesters. For département $j \in \mathbb{D}$ and quarter $t \in \mathbb{T}$ (made of months m_1, m_2, m_3), we build $x_{j,t} = \frac{q_{j,m_1} + q_{j,m_2} + q_{j,m_3}}{p_{j,m_2}}$ the natural disaster risk rate (total impacted population over mean population) and the unemployment rate of change[14] $V_{j,t} = \frac{U_{j,t} - U_{j,t-1}}{U_{j,t-1}}$. We regress the change in unemployment, an indicator of the on-going economic activity, against disaster risk, both measured a the provincial and quarterly level. Our panel regression model uses fixed effects to allow for intrinsic regional differences[15]

$$V_{j,t} = \alpha_j + \beta\, x_{j,t} + \gamma \text{pop}_{j,t} + \varepsilon$$

As detailed in Table 11, we find an unexpected but significant negative association ($\beta < 0$ with a t-statistics of − 6) between the risk rate and the evolution of the jobless rate, meaning that disasters could possibly generate employment (in the short run). A back of the envelope calculation using U as dependent variable in the regression, the mean levels for x, U, active population and total population reveals possibly one new job per 200 impacted people.[16]

The second strategy to relate disaster risk and wellbeing is coarser as it relies on yearly regional GDP per capita $Y_{j,t}$ (in region j and year t). The same panel regression technique is applied to the 22 mainland

[14] This variable has many zeroes as the original data has only one digit precision so that minimal changes over a quarter are not reflected in the variable U.

[15] Fixed effects regression uses panel data, in which there are observations from two or more time periods for each entity, to control for omitted variables that vary across entities but not over time.

[16] We do not emphasize this result because the regression $U_{j,t} = \alpha_j + \beta \ln(x_{j,t}) + \gamma \text{pop}_{j,t} + \varepsilon$ displays a significative positive relationship possibly meaning that extremely severe disasters spur a higher unemployment.

Table 11
Unemployment vs. Disaster Risk.

	Estimate	Standard Error	t-Statistic	P-Value
α	136	33.462	4.060	0.000
β	−0.011	0.002	−6.530	0.000
γ	$2e^{-4}$	$5e^{-5}$	−2.940	0.003

Table 12
Per capita GDP growth vs. Disaster Risk.

	Estimate	Standard Error	t-Statistic	P-Value
α	560	101	5.55	0.000
β_0	0.0032	0.0028	1.13	0.258
β_1	0.0072	0.0027	2.66	0.008
γ	$-2e^{-4}$	$3e^{-5}$	− 4.35	0.000

administrative regions.[17] The fixed effect regression model yielding the most interesting results, shown in Table 12, involves the *lagged* risk indicator applied to economic growth $Z_{j,t} = \frac{Y_{j,t} - Y_{j,t-1}}{Y_{j,t-1}}$ rather than real GDP per capita Y with

$$Z_{j,t} = \alpha_j + \beta_0 \text{ risk}_{j,t} + \beta_1 \text{ risk}_{j,t-1} + \gamma \text{pop}_{j,t} + \varepsilon$$

Finding a significative and positive β_1 could indicate that regional economic activity accelerates after a year intensive in disasters, thus reinforcing our fist result. At any rate, the low magnitude of the economic parameters found[18] means that any effect of natural disasters exposure would be confounded by the other more powerful drivers of economic growth. In hindsight, it is probably because preparedness keeps improving and maintains the hazard rate on the seaboards at an acceptable level that families wishing to move around France can safely concentrate on the socioeconomic factors and ignore environmental risk.

Result 6. There is no discernible impact of natural disaster risk upon economic activity.

5.4. *The cost of natural disasters*

This section uses parsimonious estimates of the private and social cost of natural disasters to complement our previous results and put them into the wider economic context of the country. As revealed by the insurance pool CCR (2017), in order to support 29 millions households and 6 millions business assets against natural disasters, the CATNAT fund collects a levy upon 41 millions cars and another 41 millions private properties. The total market value of the covered assets is 6 times over the annual French GDP or almost a quarter million € per inhabitant. Between 1982 and 2016, the compulsory contribution to the fund has risen (in real terms) from 13 € to 23 € per capita[19] because the underlying insured basis has grown and the additional premium rate has been raised from 5.5% to 12% as the fund was initially running a deficit. At the same time, payments for natural disaster losses have a random nature, having achieved a maximum of 50 € per capita in 2003; over the 1982–2016 period, each French resident has contributed 14.4 € (in real terms of 2017) per year to compensate victims of natural disasters. These figures are however small compared to the overall French insurance market where each resident spends over 3 000 € every year (including 300 € on car, 250 € on property and 2 000 € on life products). Similar global figures are reported in Germany and Spain (cf. GDV (2017) & CCS (2017)). Although rising, the yearly per capita payment to cover natural disaster losses are 19 € in Germany and 7.5 € in Spain on average over the last decade.

[17] A reform in 2016 merged several regions but since GDP data is only available until 2014, we had anyway to use the jobless rate at the department level in 2015 and 2016 to estimate GDP at the "old region" level over these years.

[18] Another quick calculation indicates a gain of 5€ per capita.

[19] On average each insurance taker pays a premium of 18 € to the fund.

Table 13
Insured cost per capita for major disasters.

unit	M€11	M	€
Drought	Loss	Affected	p.c.
1989	5041.00	2 0.67	243.88
2003	1996.00	1 4.75	135.32
2004	1001.00	8.19	122.22
2011	822.00	7.31	112.43
2012	250.00	3.02	8 2.75
Total/Mean	9110.00	5 3.94	**168.89**
Earthquake	Loss	Affected	p.c.
1996	95.00	0.60	158.33
2004	74.00	0.60	123.33
2007	54.00	0.29	185.00
Total/Mean	128.00	0.89	**143.52**
Floods	Loss	Affected	p.c.
1988–2016	10,504.30	6 5.18	**161.16**

unit	M€11	M	€	
Storm	Loss	Affected	p.c.	Name
1987/10	1214.02	3.16	3 84.18	87J
1990/02	340.00	0 .64	5 35.43	Vivian
1999/10	75.00	0.50	1 50.00	José & Lenny (Gua.)
1999/12	1 0,246.00	4 8.30	2 12.13	Lothar & Martin
2009/02	220.00	0.40	5 50.00	Quinten
2007/08	218.00	1.50	1 45.33	Dean (Gua.)
2008/08	67.00	1.00	67.00	Hautmont
2009/01	1743.00	5.80	3 00.52	Klaus
2010/02	1480.00	7.40	2 00.00	Xynthia
2011/12	180.00	0.50	3 60.00	Joachim
2013/12	44.00	0.44	1 00.00	Dirk
2014/01	45.00	0 .99	45.32	Bejisa (Réunion)
Total/Mean	1 5872.02	7 0.63	**224.73**	

To learn more about the economic cost of natural disasters in France, we draw from FFSA (2017) who reports on a variety of major disasters having stricken France since 1987. Using the population of the townships affected by these major events, we compute a cost per capita in 2011€ (denoted p. c.) reported in Table 13. The letter M stands for millions of people or euros. Beware that we count populations impacted by disasters not the actual victims. The real claims average about 10 k€ for flood or sea-rise and 17 k€ for drought (cf. CGDD (2010)).[20]

Regarding floods, each episode impacts on average two million people at a per capita cost that is relatively stable.[21] Unexpectedly, storms are more violent than floods or droughts, thus generate greater losses upon insured property. The fact that mean losses are close enough between the various disasters categories is a sign of robustness of our approach.

In DGPR (2013), the French ecology ministry estimates the total nationwide economic damage for a few large catastrophes. The uninsured losses from floods are found to make up 50% of the insured losses while for storms the share rises to 100% due to the destruction of public forests and equipment such as roads, public lighting or electrical poles. For the other event categories, information is missing which leads us to equate earthquakes with storms (100% uninsured losses) but only assign

[20] The 2015 drought lead to less than 200M€ losses.

[21] Note however that our limited sample ranges from a low 40 €/p.c. to a high 1 600€/p.c. for the Draguignan flash flood of June 2010 (27 casualties and 1 bn€ of losses) which affected less than half a million people. The figure for Lourdes in 2013 is even higher given the lower population involved.

a 20% premium for droughts as they mostly strike crops and private buildings which are covered by their own (non-disaster) insurance schemes. Aggregating over all categories while accounting for their differential frequencies, we find that the social cost of a natural disaster is 53% greater than its private cost. Expressed in per capita terms, natural disasters thus imposed each year an additional 7.7 € of damages per capita for uninsured public property. The total social cost of natural disasters is thus $14.4 + 7.7 = 22.1$ € per capita and year. When compared to the average amount paid for home insurance, we obtain:

Result 7. The full economic cost of natural disasters for France, measured over 35 years, represents 9% of the private property insurance premiums and less than 1% of the overall insurance market.

It could be said that such a result holds only for a rich country like France with a long bureaucratic tradition. However, the smallness of the figures (similar to what takes place in neighboring countries of Europe) indicates that a national scheme of protection against natural disasters, possibly mixing private and public insurance, can be managed even for a developing country, as soon as its insurance market is mature enough to get most of the population onboard for basic property insurance.

At the world level, only 28% of losses are covered by insurers and even in the mature US market this ratio does not go beyond 53%. A very significant insurance gap thus remains which, from a business perspective, is an investment opportunity. Aon Benfield (2017) notes indeed that the insurance industry is over-capitalized with traditional insurance products offering a low profitability and investors looking for new insurance vehicles, disconnected from the economic cycle such as products linked to natural disasters. Specifically, the reinsurance capital covering catastrophes has surpassed 600 bn$ in 2017 (growing at a CAGR of 5% over the last decade) which is four times over the extremely large insured losses of the exceptional year 2017. But to grow the portfolio of insurable items and increase the (economic) protection against disasters, the insurance industry must work hand in hand with authorities to upgrade the legal insurance framework without which the market cannot deliver. The French case is telling in this respect of a close cooperation that has allowed natural disaster insurance to penetrate into almost every house and thus avoided the tragic aftermath of Hurricane Caterina in the US.

6. Geography vs. the people

In this section, we increase the geographic granularity down to the county level (3790 so-called cantons) to identify where and how much natural disasters affect residents, with a view to discuss policy options. The geographical distribution of natural disaster impacts may be focused on *geography*, *intensity* or *density*. The first option, used by the insurance pool and the media (cf. LeMonde newspaper), concentrates solely on the geographical location of natural disasters. Since the 36 500 French townships split the territory into a density knitted grid, the counting of events per township amounts to draw a spatial density mapping. By its very construction, this approach focuses solely on nature (geography) and completely ignores inhabitants. This approach thus prohibits any meaningful socioeconomic study of natural disasters and shall not be pursued.

Per the 1946 French Constitution, the government has a duty to “protect citizens against natural calamities”. Policies therefore ought to level off their risk of facing a natural disaster. The adequate county measure for such an *intensity* objective is then the ratio of affected people during the 35 years of observation to the average county population during that period. Recall that we count affected people as $q_{i,m} = p_{i,m}$ if and only if township i was stricken by a natural disaster during month m for otherwise $q_{i,m} = 0$. For a county j, we have $q_{j,m} = \sum_{i \in j} q_{i,m}$ and over the entire period August 1982–December 2017 of n month, the average number of affected people is $q_j = \frac{1}{n}\sum_m q_{j,m}$. The decadal intensity ratio is thus $\eta_j = 10\frac{q_j}{p_j}$ where $p_j = \frac{1}{n}\sum_m p_{j,m}$ is the average county population. The mean of η over continental France is 2.3, meaning that each resident will see two natural disasters take place in his/her city during a decade.

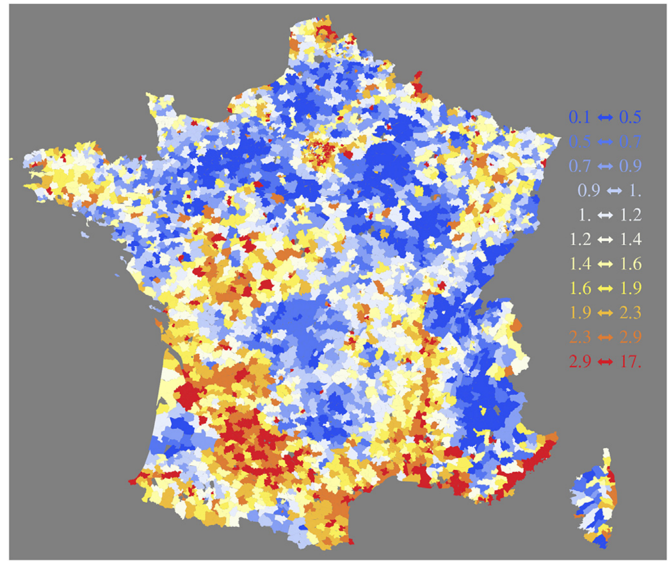

Fig. 8. Relative Disaster Intensity The average number of natural disaster declarations per decade and per capita η_j is shown for each county j of continental France using a temperature coloring scheme going from a minimum of 0.1 in dark blue to a maximum of 17 in dark red. The overall mean is 2.3. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Plotting η_j with a coloring scheme for all counties, we observe on Fig. 8 an arc of elevated intensity all over southern France, from Bordeaux to Italy with an emphasis over the mediterranean seaboard and the greater Rhone valley which features a high prevalence of floods. There are also large swaths of western inland counties that are regularly stricken by drought. It is over those darker red areas that natural disasters are most violent, thus calling for more preventive action.

As time passes, those stricken areas have received more reconstruction and prevention funding, thereby creating a strong subsidization from the more quiet parts of the country (further inland and up north). This is because the law mandates all French people to contribute more of less equally to the super fund. Many of those impacted counties are however located in the rural countryside with low population density. We thus arrive at the following, already noted by Poussin et al. (2013).

Result 8. Application of the principle of “equality against the natural hazard risk” has lead to heavy subsidization of many risky areas with a low population density.

An alternative policy objective dubbed the *density* approach seeks to reduce the impact of natural disasters over the aggregate country population,[22]: the adequate county measure is now the product of the previous intensity measure η_j by the population density of the county $\delta_j = \frac{p_j}{\sigma_j}$ where σ_j is the county area. This product simplifies into the ratio $\psi_j = \frac{q_j}{\sigma_j}$ of mean affected people over the period 1982–2017 per hectare. The overall mean for continental France is 9.6. The high ranking counties observable with a dark red shade on Fig. 9 are now the inner areas of the main French population centers. The mediterranean arc still stands out but is much thinner as it only cover cities. It is now joined by areas from the populous north and east, nearby Belgium and Germany respectively. A novel view thus emerges:

[22] This *density* vs. *intensity* dichotomy is an exact translation of the classical economic policy dilemma of maximizing growth (measured by GDP) vs. minimizing income inequality.

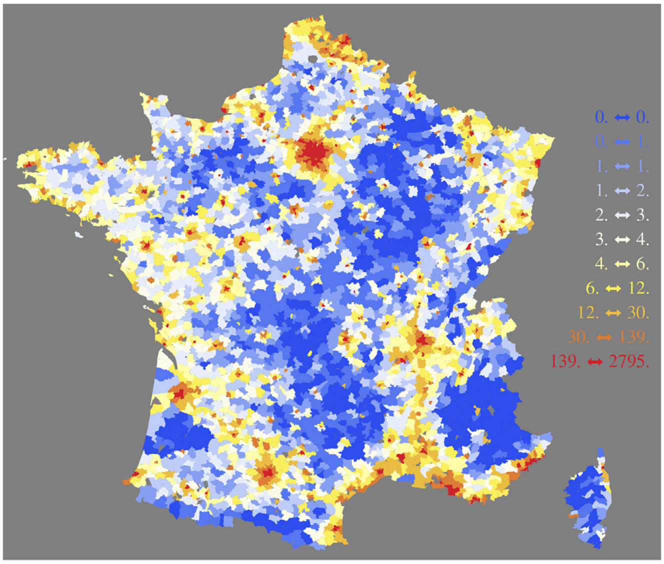

Fig. 9. Relative Disaster Density The average number of affected people per hectare is shown for each continental French county using a temperature coloring scheme going from a minimum of 0 in dark blue to a maximum of 2795 in dark red. The overall average is 9.6. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Result 9. If one seeks to reduce natural hazard risk for the entire population, protection is most effective in the urban centers and away from the countryside.

Should the government follow the *density* approach, it would have to direct its effort at the large urban centers where millions of people are at moderate risk (as opposed to hamlets at high risk). Table 14 illustrates a middle ground between *intensity* and *density* by showing the counties where disaster intensity is high but at the same time there is a large population density; it turns out that they are all regional capital cities, southeastern mediterranean cities as well as many suburbs of Paris.

7. Discussion and policy recommendations

We have shown that, on the basis of the affected populations, France has improved its preparedness to natural disasters. Schumacher and Strobl (2011) offer a theoretical reading of our empirical finding with a microeconomic behavioral model where only rich people (and by extension countries) find it worthwhile to undertake prevention expenditure against small hazard risk. Intuitively, France fits into the category of advanced economies facing a low frequency of extreme weather events (due to its mild climate). Then, as the economy grows, so do protective investments; ultimately the country reaps the benefits of weaker impacts from recurring natural disasters. However, as shown by Poussin et al. (2013) in a survey of victims, the high financial security provided by CatNat decreases the willingness of homeowners to take flood protection measures. The literature (e.g., Suykens et al. (2016)) is of the opinion that institutional responses are needed to improve preparedness. In the French case, additional protective investments and legislative measures were voted after major catastrophes to avoid their repetition.[23] For instance, townships must draw an atlas of natural hazards and design a prevention plan against knowledgeable natural risks (fulfillment is however notoriously slow) and contingency plans for post-disaster restoration. The latter are pitted against socio-economic development to determine a zoning level ranging from total prohibition to none as well as some modifications to existing buildings and infrastructures. Novel actions to reduce risk in already developed zones are also financed from the disaster fund.

Under the current scheme, natural disaster damages to public assets befall the central state (the last resort insurer), thus accentuating the aforementioned subsidization of riskier areas (as local communities do not face all the consequences of their urban development choices). Within a context of sustainable finance, it becomes desirable for each community to bear a greater share of the disaster cost but obviously without losing the national insurance umbrella. This can be achieved by transferring ownership of public assets to local communities and (initially) subsidize the market premium for insurance against natural disaster (cf. Linnerooth-Bayer and Hochrainer-Stigler (2015)). As premiums are based on the underlying risks and the efforts undertaken to mitigate those, communities would be motivated to act responsibly when faced with potentially high premiums for projects under a significant risk of disaster. Indeed, like all the expenses generated by public asset maintenance, insurance premiums have to be recovered either through local taxes or usage fees upon which voters are notoriously sensitive. The latter would thus discipline their local governments into prudent investment and ultimately, this would push down further the hazard risk faced by public assets. France is already considering similar ideas at the individual level with a view to reduce the high degree of subsidization that currently exists between risky and safe areas of the country (cf. EC (2013)). With a similar objective in mind, Suykens et al. (2016) have studied the legal frameworks of Belgium, France, the Netherlands and the UK. They come to the conclusion that linking high risk locations to exclusion from recovery schemes or to premium hikes are most likely to trigger reaction from households. They also recommend to establish clear and transparent criteria for natural disaster declaration that would for instance allow to distinguish two levels, local and global, whereby in the first case, regional authorities would bear the weight of the losses. Such a first step towards localizing financing of damages among the 14 regions of France would be both ethical and incentivizing since low risk regions would cease to finance the losses of other places that are mostly due to excessive urbanization and at the same time, burdened regional governments would have a more direct incentive to legislate. Whenever, an event triggers a major natural disaster, national solidarity would be called upon, as it is currently the case at any level of losses.

Looking ahead, the approach followed in this article may be applied to other countries where similar administrative rosters of extreme weather events are maintained by the insurance industry. For the future, it would be desirable to identify whether the improving preparedness of the country is due to more resilient constructions (wherever they may be build) and/or a better zoning policy (building outside risky areas). The raw information at our disposal points towards the latter possibility as the 1.5 million population of the 5% safest counties has grown thrice faster than the 10 million population living in the 5% riskiest counties.

8. Conclusion

Our study of natural disasters over France leverages a (quasi) exhaustive administrative database of disaster declarations at the township level. Assuming firstly, that the criteria for declaring a natural disaster has remained unaltered and secondly, that proxying township victims by the residents count is adequate, we obtain a number of results.

Firstly, the frequency of natural disasters is fifty times over that of catastrophes collected by traditional rosters, thereby unearthing the many smaller disasters that impact millions of people's lives. Regarding

[23] The original 1982 law was strengthened in 1987, 1995, 2003 and 2010 (to transpose the 2007 European Floods Directive). Today, 12% of the premiums going to the CATNAT fund are used to finance preventive investments. In a related fashion, Hoeppe (2016) notes how Hamburg, Germany, invested into defenses after a deadly and costly sea-surge and has since been protected from 9 occurrences, each more severe than the original one.

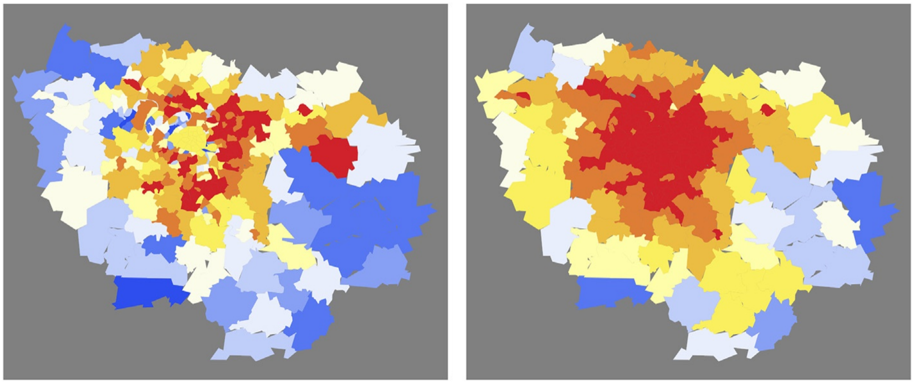

Fig. 10. Intensity vs. Density around Paris The previous measures shown in Fig. 8 and 9 are displayed with the same scale for a close-up of the Île de France region containing Paris and its suburbs.

Table 14
Cities with both great intensity and density of natural disasters.

City	Intensity	Density
Nice	17.1	2654
Cagnes-Sur-Mer	13.0	1107
Antibes	12.1	1135
Marseille	11.2	1337
Cannes	11.1	1301
Bordeaux	10.3	1674
Toulouse	8.7	1123
Saint-Laurent-Du-Var	8.6	895
Metz	6.4	613
Le Mans	6.3	581
Le Havre	6.0	607
Boulogne-Sur-Mer	5.6	1028
Montpellier	5.5	866
Tours	5.5	753
Talence	5.5	932
Antony	5.5	1181
Argenteuil	5.4	1091
Fresnes	5.3	1309
Rosny-Sous-Bois	5.1	1199
Rouen	5.0	883
L'Hay-Les-Roses	4.9	1301
Toulon	4.9	607
Gagny	4.5	839
Garges-Les-Gonesse	4.5	1124
Livry-Gargan	4.5	861
Sarcelles	4.5	1017
Lyon	4.4	1532
Lille	4.4	970
Brunoy	4.3	566
Caen	4.3	611

climate change, the incidence of floods over mainland France is found to be stable over the last 35 years and even falling once we account for the heightened population pressure. Next, we find that France has improved its preparedness to natural disasters even though the seaboard regions fare worse than the northern continental region, most likely because of heightened urban pressure in risky areas by the seaside. French tropical territories are found to suffer a slightly greater hazard risk in the long run when compared to the temperate climate of mainland France. This finding warrants the insistence of tropical islander nations to tackle urgently the risks associated with climate change, particularly regarding prevention and resilience. However, the very fact that exposure in tropical France is commensurate with the “rich and safe” mainland part of the country means that the task awaiting islander nations is achievable (which the examples of Bangladesh and South Korea also demonstrate). Moving to economic considerations, we find that the occurrence of natural disasters does not impact meaningfully either employment or growth. The estimated full economic cost of natural disasters is a small fraction of current expenses for private property insurance, making the management of a disaster risk scheme quite manageable even for developing countries. Regarding fairness, the current principle of equalizing natural hazard risk among French citizens sees the majority, living in safe areas, subsidizing a minority living in riskier areas both for compensation and for preventive investments. Under the alternative principle of protecting the greatest number of people, investment would be directed at the main cities under a significant risk. This view would likely be the one favored by cash-constrained developing countries (and is gaining traction in France itself).

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