Flood Insurance, Disaster Aid, and Economic Recovery in Europe *

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Abstract

We investigate the role of insurance regimes and disaster aid programs in recovery dynamics after flooding events in Europe from January 2014 to September 2023, covering 107 floods. We measure economic activity utilizing night lights data and find significant reductions in economic activity for four months after a major flooding event. Investigating economic recovery, we find evidence that economic recovery is faster under a flood insurance mandate for private property. We observe the highest reductions in night light intensity in the first four months after a flood in regions with an indirect mandate. Government aid crowds out insurance, indicating charity hazard. This interaction (partly) offsets the positive direct effect of insurance penetration on night light activity within the first four months after a flooding event. The findings highlight the effectiveness of a mandatory holistic approach for mitigating flooding risk and offering financial protection particularly in flood prone regions.

Keywords: flood insurance · disaster risk financing · economic recovery

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1 Introduction

Flooding is a significant risk worldwide and has far-reaching consequences for communities, the infrastructure, and the economy as a whole (Wahlstrom et al., 2015). As of 2022, 23% of the world population is at risk of severe flooding as discussed in Rentschler et al. (2022), including 145.9 million inhabitants of Europe and Central Asia. Climate change and coastal build-up aggravate the exposure to flooding worldwide. Flood insurance is usually available to private households in developed countries as one of the main tools to manage flooding risk. In addition to flood insurance, governments often enact ad-hoc government relief programs post major disasters to aid recovery. Naturally, we expect externalities between the (expected) availability of disaster aid and private insurance purchases, assuming that the expectation of disaster aid crowds out private insurance purchases. The literature refers to this phenomena as charity hazard (Tesselaar et al., 2022; Raschky and Weck-Hannemann, 2007). To address charity hazard, governments can decide to reduce or completely cut disaster aid programs or they can mandate individuals to purchase insurance. Our paper investigates the impact of these regulatory choices on the speed of recovery after major flooding events in Europe.

In this paper, we focus on a group of European countries that are relatively homogeneous in terms of flood exposure as well as economic development. Our study contributes to the understanding of efficient flood risk regulation globally as the vast literature on flood risk management has a U.S.-based focus (Browne and Hoyt, 2000; Raschky and Weck-Hannemann, 2007; Michel-Kerjan, 2010; Deryugina, 2017; Kousky, 2018; Hu, 2022; Collier et al., 2022). We exploit between-country variation in European countries to assess the impact of insurance regime and availability of government aid on the speed of recovery after a flooding event. In some European countries, flood insurance for residential buildings is mandatory, whereas others impose different forms of indirect mandates or leave flood insurance purchases entirely up to the individual. In addition to insurance regimes, European countries also vary with respect to ad-hoc disaster aid programs that interact differently with their insurance program. There are also countries that offer no ad-hoc disaster aid after flooding events.

We utilize the Emergency Events Database EM-DAT to severe flooding events and match this data to night light intensities measured from space. We use the difference in night lights intensity before and after a flood as a measure of reduction in economic activities due to flooding. This measure is impartial to potential endogeneity due to the prevalent insurance regime and disaster aid availability in the flooded region.[1] With these combined dataset, we investigate whether the insurance regime or the provision of government disaster aid lead to faster economic recovery after flooding events.

Our paper has three main results: First, we find evidence that a flood reduces the night light activity in the following four months of that event due to destroyed property and business disruptions in the affected region. We estimate recovery of economic activity to take four months. Second, our findings show that regions with mandatory insurance perform significantly better after a flooding event with regard to speed of recovery. Higher associated insurance propensities ensure (faster) access to insurance payments and therefore quicker recovery over the first four months after the flooding event took place. Third, the provision of government aid after flooding events is associated with lower insurance penetration in that region, indicating charity hazard. This interaction partly offsets the positive direct effect of insurance penetration on the night light activity within the first three months after flooding. Again, we find insurance penetration to have a positive effect on economic recovery.

This paper adds to a robust literature on disaster risk financing. Our novel contribution is to provide empirical evidence on whether and which insurance regime outperforms others with respect to economic recovery. Tesselaar et al. (2022) and Hudson et al. (2019) use simulation studies to approach this question while Charpentier and Le Maux (2014) analyze this question in a theoretical framework. Our empirical approaches aim to tackle the pressing question on how disaster risk and flooding losses can be best managed. Our findings can also inform debates about government's involvement in providing disaster insurance or relief programs.

This paper also highlights the importance of flood risk management in Europe. In recent years, the frequency and severity of flooding events have increased. The risk of flash flooding is one of the major natural hazards in Europe. The costs of floods to the European economy are substantial and have been estimated to be several billions of Euros each year. Given the growing risk of flooding in Europe, it is important for governments and communities to take proactive measures to reduce the likelihood and impact of these events, including investments in flood protection infrastructure, land-use planning, and emergency preparedness planning. Demand for flood insurance

[1] Utilizing actual loss amounts may be biased as moral hazard predicts an association between loss costs and insurance penetration.

in the European market has been studied by Surminski and Eldridge (2017) for the U.K., and Browne et al. (2015) for Germany. Whereas in this paper, we examine flood risk management programs across a list of European countries, providing a meaningful comparative study on best practices.

The paper is structured as follows: After this motivation, we first introduce the different flood risk management approaches in Europe. Section 3 then introduces the data we use in our analysis. Section 4 reports our empirical approach. We show our results in section 5. In section 6 we summarize our findings and conclude.

2 Flood risk management approaches in Europe

2.1 Insurance regimes

European countries can be divided into four different flood insurance regimes for residential property following to the approach from Tesselaar et al. (2022) and Hudson et al. (2019). We list them in the order of degree of regulatory rigor, starting with the lowest degree to the highest degree.
The first scheme (*Regime 1*) is a voluntary private market where purchases are not mandatory and underwriting is risk-based. Flood insurance is solely covered by the private sector in the following European countries: Austria, Netherlands, Germany, Italy, Greece, Slovakia, Luxembourg, Croatia, Bulgaria, Latvia, Estonia, and Lithuania. Insurance penetration of private households is usually between low and moderate, i.e. between 5%-35%.
The second scheme (*Regime 2*) includes mandated purchase requirements, through mortgage requirements and/or lease requirements for rental property. Insurance is offered by private insurers with risk-based premiums and insurance penetration rates are usually high. Hudson et al. (2019) estimate penetration rates of 75%-100% for buildings, while penetration is usually much lower for household contents. Sweden, Ireland, Hungary, Slovenia, Poland, Portugal, Czech Rep., Finland, and Denmark are regulating flood insurance as described in Regime 2.
The third scheme (*Regime 3*), i.e. public-private partnership (PPP), also includes mandated purchases by products offered by private insurers, yet, risk-based underwriting is limited. In addition, there is a government reinsurance program to support insurers financially in case of large flooding events. Penetration rates are higher than in Regime 2 as maximum premiums are capped. The U.K. is the only European country which

adheres to Regime 3 regulation for flood insurance. The National Flood Insurance Program in the United States would also be under Regime 3 and has been widely studied, as in Anderson (1974), Michel-Kerjan and Kunreuther (2011), and Kousky (2018). The fourth scheme (*Regime 4*) is mandatory insurance without risk-based underwriting. Coverage can be provided by public or private entities and there may be a government-paid reinsurance scheme operating in the background. Penetration rates can be expected to be close to 1. France, Belgium, Spain, and Romania operate under such a scheme. Table 1 provides an overview of the four different regimes in Europe.

Table 1: Flood insurance regimes in Europe

	Regime 1 (voluntary)	**Regime 2 (semi-voluntary)**	**Regime 3 (public-private partnership)**	**Regime 4 (direct mandate)**
Insurance mandate	No	Indirect	Indirect	Direct
Risk-based premiums	Yes	Yes	Partially	No
Countries	Austria, Germany, Netherlands, Italy, Croatia, Luxembourg, Latvia, Greece, Estonia, Lithuania, Slovakia, Bulgaria	Sweden, Ireland, Portugal, Poland, Slovenia, Czech Rep., Hungary, Finland, Denmark	U.K.	Spain, Belgium, France, Romania

Notes: This table gives a summary of flood insurance structures in European countries following the approach from Tesselaar et al. (2022) and Hudson et al. (2019). Romania fulfills many of the criteria associated with Regime 4, however, the insurance penetration rate remains quite low due to insufficient purchase enforcement.

The main research question of our paper is whether there are systematic differences in economic recovery depending on regulatory rigor. The first dimension of regulatory rigor we investigate is the choice of insurance regime. We aim to assess whether one of the regimes outperforms the others in terms of how fast a flooded area recovers.

In our analysis, we initially contrast Regime 4 (direct mandate) with all other insurance regimes. Regime 4 adopts the most rigorous regulatory approach, mandating coverage and prohibiting risk-based premiums. These measures result in the highest insurance penetration compared to all other regimes, thereby guaranteeing sufficient availability of financial compensation for disaster recovery. Accordingly, we expect quicker economic recovery in Regime 4 compared to all other regimes.

In additional analyses, we compare mandatory flood insurance and the indirect mandates to the voluntary approach. The comparison aims at assessing whether regions with indirect mandates also outperform regions without mandated flood insurance in terms of economic recovery after a flood. We include Regimes 2 and 3 together (indirect mandates) as well as separately in our analysis.

2.2 Ad-hoc disaster aid

In addition to investigating differences in insurance regimes, European countries also differ in how they provide access to ad-hoc disaster aid. Tesselaar et al. (2022) and Hudson et al. (2019) distinguish between four different ad-hoc disaster aids in Europe:

1. No ad-hoc disaster aid as in Latvia, Lithuania, Estonia, Croatia, and Slovenia.

2. Conditional disaster aid with uptake requirements to reduce charity hazard. The aim of uptake requirements are that anticipated disaster aid should not interfere with insurance demand for many individuals. Example countries are: the U.K., Ireland, Spain, Portugal, France, Belgium, and all Scandinavian countries.

3. Uncertain disaster aid as in Germany, the Netherlands, Italy, Greece, Albania, and Slovakia.

4. Certain disaster aid, which partially covers losses. Austria is the only European country that utilizes this approach.

Ad-hoc disaster aid immediately finances reconstruction in affected regions and should speed up recovery. At the same time, an indirect effect can offset (parts) of the direct effect: Ad-hoc disaster aid can crowd out public insurance as discussed in Raschky and Weck-Hannemann (2007) and Hinck (2024). This phenomena is known in the literature as charity hazard. If individuals have less coverage in the aggregate, the insurance sector supplies less capital for the required reconstruction of housing and public infrastructure.

In addition, disaster aid availability may not necessarily be associated with quicker recovery as government aid may take longer to be paid out than private insurance. Relief programs involve complex procedures including the assessment of damages and claims to initiate an appropriate and coordinated distribution of government aid. Therefore, we posit that government aid may slow down economic recovery as aid is typically not paid out in a speedy fashion.

One obstacle of understanding the effect of regulatory choices in economic recovery after floods is that choices on insurance regimes and disaster aid availability are not independently made. Also in our sample, we observe certain choice patterns of insurance regime and disaster aid programs: Countries with mandated flood insurance most commonly also have government disaster aid with uptake requirements. While countries which prohibit government disaster aid usually follow insurance regime 1. In addition, the choice of the financial response could be shaped by the flood exposure itself and needs to be taken into account. We address this by using mediator analyses to investigate recovery dynamics while accounting for interplays between different government disaster aid programs and insurance propensities. In the second part of our analysis we utilize insurance penetration as a proxy for the insurance regime to achieve higher heterogeneity in our data.

3 Data

3.1 Economic activity

We exploit the variation in economic recovery accounting for differences in flood risk management approaches using changes in night light activity as a proxy for economic activity. Our study relies on monthly time series from January 2014 to September 2023 ($t = 117$) as the night light configuration we use, only became available from 2014. We include 26 European countries which could be assigned to a flood insurance regime and aid program according to Tesselaar et al. (2022) and Hudson et al. (2019). We use a fine spatial resolution on GID 2 level[2] resulting in 7,130 unique grid-points for which we have monthly information on night light intensity, flooding events, and country specific information including gross domestic product. In total our sample comprises 834,210 grid-month observations. Table 2 below lists the countries in our sample. The data sources we compile are described in detail in this section.

[2] GID 2 corresponds to a granularity level of administrative districts in the included countries. Please find detailed information on GID-zones under: `https://gadm.org/maps.html`

Table 2: List of European countries

Country	ISO code	Grid points	Night lights	GDP per capita
Austria	AUT	94	1.99	51,019.93
Belgium	BEL	11	8.63	47,554.73
Bulgaria	BGR	263	0.76	20,820.14
Croatia	HRV	560	1.61	26,614.35
Czech Rep.	CZE	98	6.97	36,305.62
Denmark	DNK	99	3.36	51,974.38
Estonia	EST	223	1.90	32,609.27
Finland	FIN	21	1.46	44,712.80
France	FRA	96	3.62	41,743.80
Germany	DE	403	3.01	48,995.86
Great Britain	GBR	183	7.22	43,172.32
Greece	GRC	14	1.68	27,559.07
Hungary	HUN	168	1.09	30,146.03
Ireland	IRL	106	2.13	83,538.10
Italy	ITA	110	3.85	38,422.09
Latvia	LVA	26	0.65	27,651.12
Lithuania	LTU	48	1.00	33,174.18
Luxembourg	LUX	12	3.38	109,382.10
the Netherlands	NLD	355	10.79	52,762.06
Poland	POL	380	3.77	30,459.03
Portugal	PRT	308	4.73	31,783.28
Romania	ROU	2,939	0.92	25,411.81
Slovakia	SVK	79	2.31	32,114.64
Slovenia	SVN	192	1.08	34,990.05
Spain	ESP	52	4.37	36,214.55
Sweden	SWE	290	2.34	50,449.75
Total		7,130	2.44	33,242.46

Notes: This table shows the number of grid-points on county level (GID 2 level), monthly average radiance values that reflect the brightness of each grid-point at night, and GDP per capita for each country.

We measure economic disruptions and recovery by changes in night lights.[3] These data are collected by the Visible Infrared Imaging Radiometer Suite (VIIRS) instrument

[3] Night lights detected from space have been increasingly used to proxy economic activities. See for example, Henderson et al. (2012), Donaldson and Storeygard (2016), Del Valle et al. (2020), Nguyen and Noy (2020), Lin (2024).

on board the Suomi NPP and NOAA-20 satellite missions.[4] These satellite instruments detect electric lighting present on the earth's surface, most of which are from human settlements. The VIIRS night lights are measured in radiance values, with larger values representing more brightness. The raw data are processed and distributed by the Earth Observation Group (EOG) at the Payne Institute for Public Policy.[5] The initial processing procedure includes removing observations degraded by cloud cover or by solar or lunar contamination, and correcting for background radiance and features unrelated to electric lighting such as fires, flares, and volcanoes (Elvidge et al., 2017). The EOG-processed products consist of monthly files of average night lights radiance values and count of cloud-free observations, as well as a latest version of annual files produced by aggregating monthly files to further remove biomass burning, aurora, background noise, and outliers (Elvidge et al., 2021). All files have a geographic resolution of 15-arc-seconds (approximately 500m by 500m) covering the entire world from April 2012 to the present. We use the configuration that includes the stray-light corrected data because of higher data coverage toward the poles starting from the year 2014.

In table 2, the averages of night light intensity range from 0.65 in Latvia to 10.79 in the Netherlands with a mean of 2.44 on the aggregate. The comparably high night light values for example in the Netherlands, Belgium or Great Britain are consistent with high material stock densities and built-up volumes (Peled and Fishman, 2021). Figure 1 below shows average night lights from July in Europe from VIIRS.

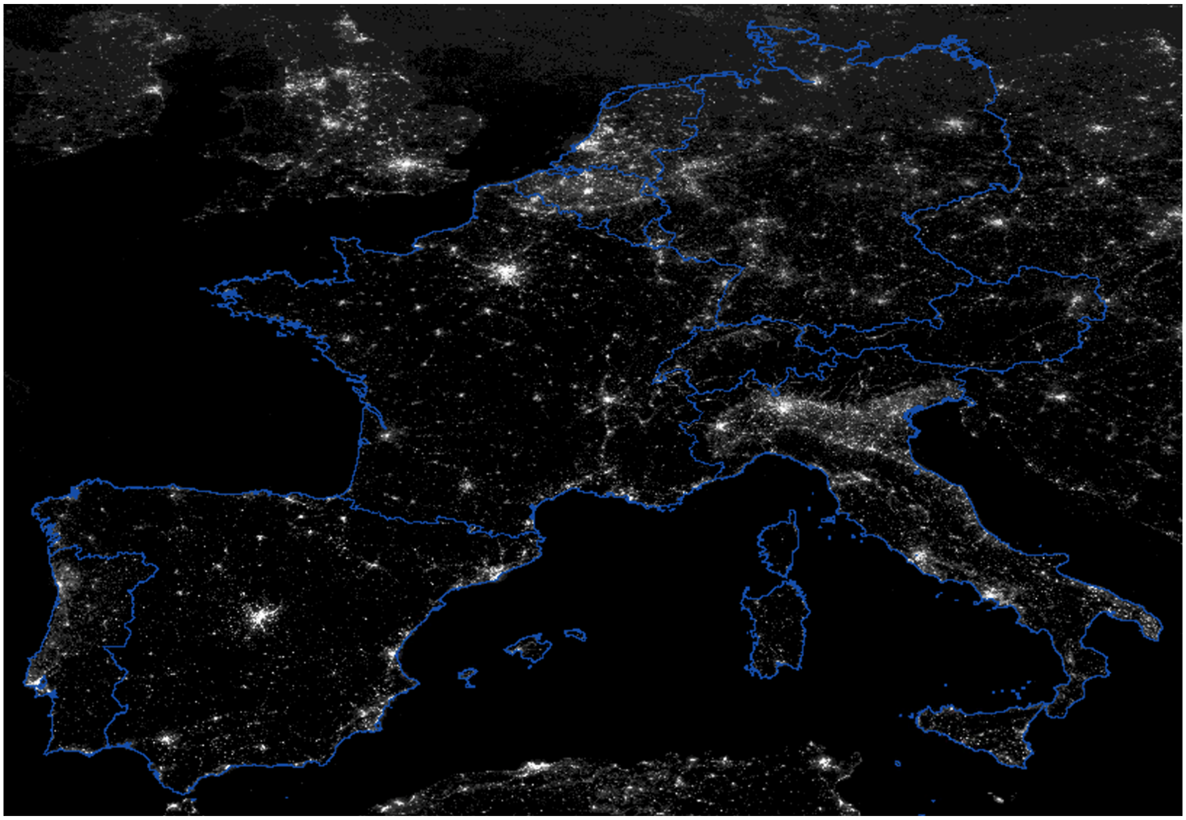
For our analysis we exclude observations for which no night light activity was observed due to measurement issues (1.3%), i.e. observations with an average night lights radiance value of zero.[6] Due to the skewness of night light values we then standardize the average night light values for each month to account for time trends and ease of comparability. Throughout our analysis we use the time-wise-standardized average radiance value as our measure of night light intensity which is approximately normally distributed.

[4] Another widely used night lights data – the predecessor of the VIIRS data – are collected under the US Air Force Defense Meteorological Satellite Program Operational Linescan System (DMSP-OLS), and are processed by the National Oceanic and Atmospheric Administration (NOAA) and the National Geophysical Data Center (NGDC). However, the DMSP-OLS night lights data have been discontinued since 2012. The DMSP-OLS data are only publicly available annually, and at a much coarser geographic resolution than its successor.

[5] `https://payneinstitute.mines.edu/eog/nighttime-lights/`

[6] Please note the possibility of the night light intensity being negative, especially for cells with typically little lights, due to airglow contamination.

Figure 1: Monthly average night lights from Europe (July 2021)



Notes: This figure shows the monthly average night lights activity across parts of Europe in July 2021. The data is derived from the Visible Infrared Imaging Radiometer Suite (VIIRS) instrument on board the Suomi NPP and NOAA-20 satellite missions. The data is sampled at 15 arc-second resolution (about 500m by 500m at the equator).

3.2 Insurance data

We derive our data on insurance penetration from Tesselaar et al. (2022) ranging from 0% (no insurance) to 100%. Table 3 provides an overview of the countries in our sample divided by flood insurance regime and government aid program. The table also shows the number of flooding events in the respective country in our sample.

Table 3: Insurance regime and government aid program by country

Country	**Insurance regime**	**Insurance penetration**	**Disaster aid**	**Floods**
Austria	Voluntary	20-30%	Certain	2
Belgium	Direct mandate	>75%	Conditional	2
Bulgaria	Voluntary	<10%	Uncertain	8
Croatia	Voluntary	N.A.	No Aid	7
Czech Rep.	Semi-voluntary	50%	Conditional	1
Denmark	Semi-voluntary	>90%	Conditional	.
Estonia	Voluntary	N.A.	No Aid	.
Finland	Semi-voluntary	86%	Conditional	.
France	Direct mandate	100%	Conditional	19
Germany	Voluntary	30-40%	Uncertain	3
Great Britain	PPP	>75%	Conditional	5
Greece	Voluntary	<10%	Uncertain	7
Hungary	Semi-voluntary	70-75%	Conditional	2
Ireland	Semi-voluntary	>90%	Conditional	1
Italy	Voluntary	<10%	Uncertain	17
Latvia	Voluntary	95%	No Aid	1
Lithuania	Voluntary	N.A.	No Aid	.
Luxembourg	Voluntary	5%	Uncertain	1
the Netherlands	Voluntary	<5%	Uncertain	1
Poland	Semi-voluntary	40-60%	Conditional	3
Portugal	Semi-voluntary	50%	Conditional	1
Romania	Direct mandate	20%	Conditional	10
Slovakia	Voluntary	30%	Uncertain	2
Slovenia	Semi-voluntary	50%	No Aid	2
Spain	Direct mandate	75%	Conditional	11
Sweden	Semi-voluntary	>95%	Conditional	1
Total				107

Notes: This table gives a summary of flood insurance and government aid structures in European countries following the approach from Tesselaar et al. (2022) and Hudson et al. (2019). Romania fulfills many of the criteria associated with Regime 4, however, insurance penetration rate remains quite low due to insufficient purchase enforcement. Data on insurance penetration is obtained from Tesselaar et al. (2022). Flooding event records are derived from the Emergency Events Database (EM-DAT) and cover flooding events from January 2014 to September 2023.

3.3 Disaster identification

We match the night lights data with flooding data from the widely used Emergency Events Database (EM-DAT) launched by the Centre for Research on the Epidemiology of Disasters (CRED). This database contains essential data on over 22,000 major flooding events in Europe since 1900.[7] The data covers three flood disaster groups: coastal floods, riverine floods, and flash floods. In addition to the date and location of the floods, EM-DAT provides information on casualties, economic damages, and insured losses for some flooding events. The database is compiled from various sources, including insurance companies or research agencies. In total, approximately 0.73% of the grid-month observations refer to a flooding period between January 2014 and September 2023 as recorded in EM-DAT, covering 107 different flooding events.

4 Empirical approach

We aim at analyzing whether there are differences in speed of recovery after major flooding events depending on the flood insurance regime in place in an affected region.

Let $Y_{i,t}$ denotes economic night light activity at time t and grid-point i. We estimate the following equation:

$$\begin{aligned} std(\mathrm{Y}_{i,t}) \quad &= \quad \beta_0 + \sum_{k=0}^{s} \beta_{1,k} \cdot \mathrm{Flood}_{i,t-k} + \sum_{k=0}^{s} \beta_{2,k} \cdot \mathrm{Insurance\ Regime}_i \times \mathrm{Flood}_{i,t-k} \\ &+ \quad \mathrm{Country\ Controls} + \mathrm{GID\ Effects} + \mathrm{Country\ Year\ Effects} + \mathrm{Time\ Effects} + \epsilon_{i,t}. \end{aligned} \tag{1}$$

We use the standardized average monthly night light activity as the dependent variable. $\mathrm{Flood}_{i,t-k}$ is a set of dummy variables being equal to one when a flood occurred at grid-point i at time $t-k$. k denotes the lag months after a flooding event, where $k=0$ indicating the current month. We vary the lag parameter k to determine how long flooding events impact economic activity, i.e. night light intensity, in the affected regions following the approach as in Lin (2024).

[7] Disaster events recorded in EM-DAT meet at least one of the following inclusion criteria: at least ten deaths (including dead and missing), at least 100 affected individuals, i.e. people affected, injured or homeless, or a call for international assistance or an emergency declaration.

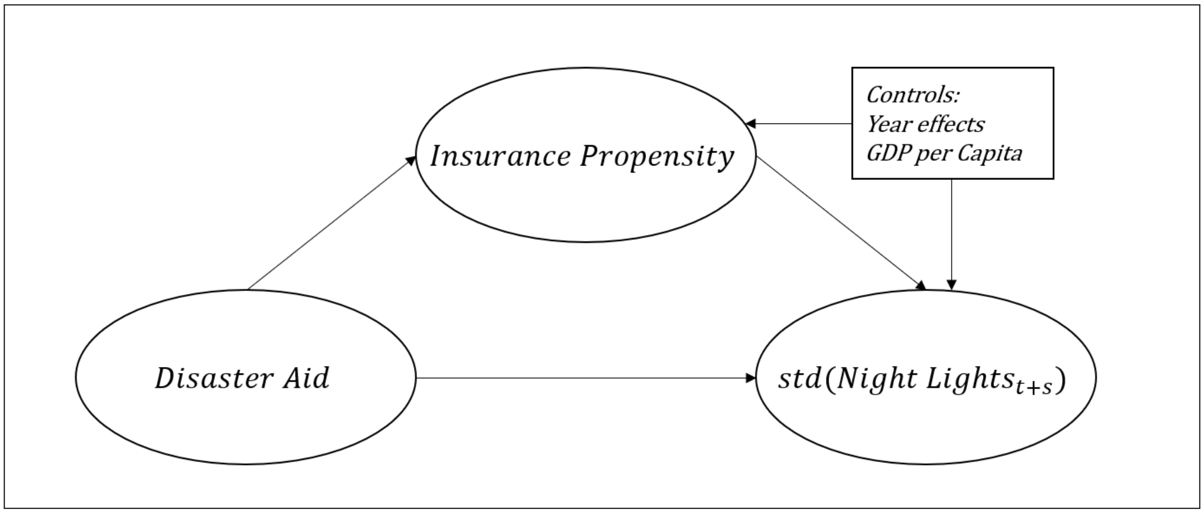
To assess whether there are significant differences across insurance regimes in economic recovery after a flood, we interact the set of dummy variables $\text{Flood}_{i,t-k}$ with the regime in place at the observation. Insurance regimes can be categorized in four groups as discussed above: voluntary private insurance (Regime 1), semi-voluntary insurance (Regime 2), public-private partnerships (Regime 3), and mandatory public insurance (Regime 4). Country controls include GDP per capita. We estimate a fixed-effects model on grid-point level and include country-year fixed-effects as well as time fixed-effects on a monthly level. Standard errors are clustered on grid-level.

Additionally, we include interaction variables with whether the region was hit by a flood or not, the insurance regime in place at that observation, and the insurance penetration which is obtained on country-level to assess potential differences of insurance penetration within insurance regimes. Again, we utilize the lags k which we obtained from determining recovery times and include the same controls as before. We therefore estimate:

$$\begin{aligned} std(Y_{i,t}) \;=\;& \beta_0 + \sum_{k=0}^{s} \beta_{1,k} \cdot \text{Flood}_{i,t-k} + \sum_{k=0}^{s} \beta_{2,k} \cdot \text{Insurance Regime}_i \times \text{Flood}_{i,t-k} \\ +\;& \sum_{k=0}^{s} \beta_{3,k} \cdot \text{Insurance Regime}_i \times \text{Flood}_{i,t-k} \times \text{Insurance Penetration}_i \\ +\;& \text{Country Controls} + \text{GID Effects} + \text{Country Year Effects} + \text{Time Effects} + \epsilon_{i,t}. \end{aligned} \tag{2}$$

To account for the interaction between insurance penetration and the provision of ad-hoc aid, we additionally perform mediator analyses where the effect of government aid is mediated by the insurance penetration in place at the affected region. We solely include observations for which a flood is recorded and investigate time lags of the monthly average night light activity as in the previous regressions. The mediator analysis is illustrated in figure 2 below. Additional payments through ad-hoc disaster aid can directly impact the speed of reconstruction, i.e. increase night light activity. At the same time, ad-hoc disaster aid can crowd out insurance and offset (parts) of the direct effect as a form of charity hazard. We use information on insurance penetration as in Tesselaar et al. (2022). Information on insurance penetration is available on country level. We control for year effects and GDP per capita in our mediator analyses.

Figure 2: Mediating effect of insurance penetration



Notes: This figure shows the concept of our mediator analysis where insurance penetration mediates the effect of disaster aid availability on (standardized) night lights. We use year effects and GDP per capita as control variables and investigate different time lags for the flooding event.

5 Results

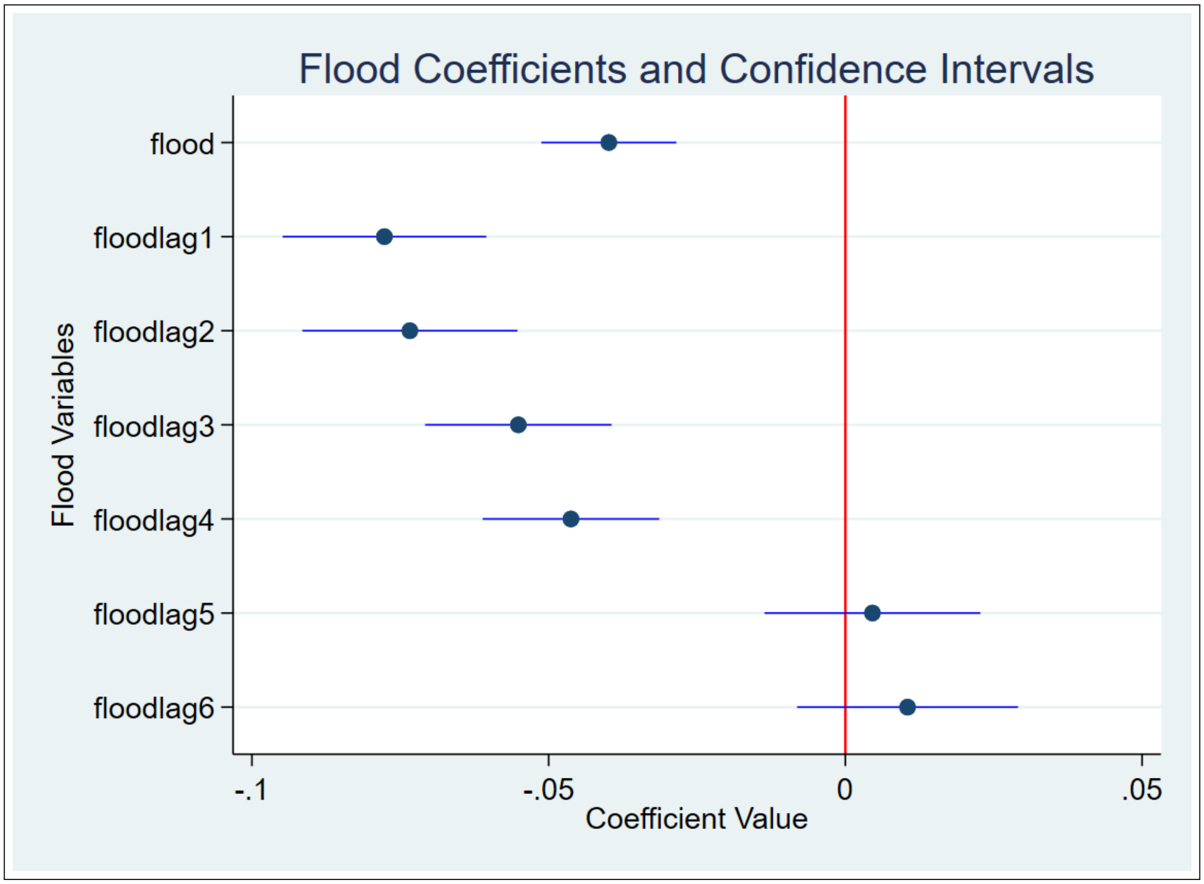
This section provides results with regard to the speed of recovery after flooding events measured as changes in night light activity for different insurance regimes. We use the time-wise standardized average value of VIIRS night lights in radiance values as the dependent variable. We estimate a fixed-effects model on GID 2 level. We also include country-year fixed-effects and time fixed-effects on a monthly level in all our model specifications. We control for the natural log of GDP per capita. Clustered standard errors on GID 2 level are shown in parentheses. We only include observations for which we have full information on the control variables in our model.

First, we estimate the speed of recovery after flooding events in our sample. Figure 3 shows results from equation (1) where we investigate different time lags for the flooding event with $s = 6$ months.

We find that a flood significantly reduces the monthly average night light intensity in the affected GID-zone in the following four months of that event. The coefficient estimates are highly significant at the 1% level for all flood dummies with a time lag of up to four months. This is intuitive as a flooding event destroys property and could cause an interruption of business in the affected area. Nevertheless, the countries in our sample are highly developed so that this effect diminishes steadily in magnitude over the recovery process and light intensity fully recovers after about five months.

There is no evidence that a flooding event negatively impacts the light intensity of an affected region after four months.[8] Therefore, we control for time lags of a flood of $s = 4$ throughout our further analyses.

Figure 3: Speed of recovery after flooding events



Notes: This figure shows coefficient estimates from our flooding dummy variables as in equation (1) where we test for a time lag of up to six months, $s = 6$. Coefficient estimates on the other variables are not shown but included in the model.

Column (1) and column (2) in table 4 show regression results from equation 1 and 2 respectively utilizing the time lags of $s = 4$ we obtained earlier. We use the group referring to no direct mandate as the omitted category. We compare the recovery process of regions with mandatory public insurance with regions with no direct mandate,

[8] The slightly smaller negative impact of the flood on night light intensity in the month of the flood can be explained by the fact that flooding events not necessarily occur on the first day of the months. As a result, night light intensity can remain at the original level in the days before the flood, affecting the average for the respective month.

i.e. voluntary private insurance (Regime 1), semi-voluntary private insurance (Regime 2), and public-private partnerships (Regime 3).

Consistent with our previous findings, a flood significantly reduces night light intensities in the affected regions in the following four months after the event. Night light reductions diminish steadily in magnitude over the recovery process and are no longer statistically significant after four months.

With regard to insurance regimes, regions with mandatory public insurance significantly (1%-level) perform better, i.e. faster recovery, after a flooding event than regions without a direct mandate in the first four months after the flooding event. Night light intensity recovers faster, starting from the month the flooding event took place. Column (2) in table 4 shows regression results of equation (2) where we test for differences in insurance penetration as an insurance mandate is not necessarily associated with a penetration rate of 100%. The results are rather mixed.

With regard to country specifics, we observe that higher GDP per capita increases the average night lights. The coefficient estimate is significant at the 1%-level. This is in line with the assumption that wealthier countries are associated with higher economic activity due to lighting from factories or buildings.

Table 4: Impact of floods and mandatory public insurance on economic recovery

	(1) FE: std(Night Lights)	(2) FE: std(Night Lights)
Flood_t	-0.040*** (0.006)	-0.044*** (0.007)
Flood_{t-1}	-0.078*** (0.009)	-0.091*** (0.010)
Flood_{t-2}	-0.074*** (0.009)	-0.087*** (0.011)
Flood_{t-3}	-0.055*** (0.008)	-0.068*** (0.009)
Flood_{t-4}	-0.048*** (0.008)	-0.061*** (0.009)
$\text{Flood}_t \times$Direct Mandate	0.014** (0.006)	0.026** (0.011)
$\text{Flood}_{t-1} \times$Direct Mandate	0.083*** (0.009)	0.077*** (0.013)
$\text{Flood}_{t-2} \times$Direct Mandate	0.074*** (0.009)	0.087*** (0.012)
$\text{Flood}_{t-3} \times$Direct Mandate	0.046*** (0.008)	0.069*** (0.011)
$\text{Flood}_{t-4} \times$Direct Mandate	0.056*** (0.008)	0.104*** (0.017)
$\text{Flood}_t \times$Direct Mandate$\times$Penetration		-0.047 (0.043)
$\text{Flood}_{t-1} \times$Direct Mandate$\times$Penetration		0.082** (0.036)
$\text{Flood}_{t-2} \times$Direct Mandate$\times$Penetration		-0.001 (0.015)
$\text{Flood}_{t-3} \times$Direct Mandate$\times$Penetration		-0.049 (0.031)

Flood_{t-4}×Direct Mandate×Penetration		-0.161** (0.070)
log(GDP per capita)	0.282*** (0.041)	0.433*** (0.065)
GID level effects	yes	yes
Country×year effects	yes	yes
Time effects	yes	yes
Constant	yes	yes
N	821,148	729,217
adj. R^2	0.875	0.875

Notes: This table shows fixed-effects regressions on GID 2 level, where we analyze the recovery process after flooding events for different flood insurance regimes. We compare regions with mandatory public insurance (Regime 4) and regions with no such mandate (Regime 1, Regime 2, Regime 3), with the latter being the reference group. The dependent variable is the time-wise standardized night light activity in grid-point i at month t. Flood_{t-k} is a set of flood dummy variables indicating whether a flood occurred at time $t-k$ at the respective grid-point, with k indicating monthly time lag. To account for differences across flood insurance regimes we interact our flood dummy with a dummy on the flood insurance regime in place at the observation. Interaction variables between our flood dummy, regime dummy, and insurance penetration account for variability of insurance penetration within regimes. We use the natural log of GDP per capita, country-year effects, and time effects as control variables. Fixed-effects on GID 2 level are included. Significance levels indicate the following: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors on GID 2 level are shown in parentheses. We report the adj. R^2 that accounts for the explanatory power of the GID fixed-effects.

Table 5 shows regression results where we differentiate for the insurance regimes separately. We group GID-zones with a semi-voluntary approach and public-private partnerships. Therefore, we compare the recovery process for regions with voluntary private insurance, an indirect mandate (semi-voluntary and PPP), and regions with a direct mandate (mandatory public insurance). The reference group in this setting is given by voluntary private insurance.

Table 5: Impact of floods, mandatory public insurance, indirect mandates, and voluntary insurance on economic recovery

	(1) FE: std(Night Lights)	(2) FE: std(Night Lights)
Flood_t	-0.010** (0.005)	-0.005 (0.007)
Flood_{t-1}	-0.022*** (0.006)	-0.027*** (0.008)
Flood_{t-2}	-0.021*** (0.007)	-0.032*** (0.009)
Flood_{t-3}	-0.008 (0.007)	-0.019** (0.009)

$Flood_{t-4}$	0.002 (0.007)	-0.007 (0.008)
$Flood_t$×Direct Mandate	-0.016*** (0.005)	-0.013 (0.011)
$Flood_{t-1}$×Direct Mandate	0.026*** (0.007)	0.013 (0.011)
$Flood_{t-2}$×Direct Mandate	0.021*** (0.007)	0.031*** (0.010)
$Flood_{t-3}$×Direct Mandate	-0.001 (0.007)	0.019* (0.011)
$Flood_{t-4}$×Direct Mandate	0.006 (0.007)	0.050*** (0.016)
$Flood_t$×Direct Mandate×Penetration		-0.047 (0.043)
$Flood_{t-1}$×Direct Mandate×Penetration		0.082** (0.036)
$Flood_{t-2}$×Direct Mandate×Penetration		-0.001 (0.015)
$Flood_{t-3}$×Direct Mandate×Penetration		-0.048 (0.031)
$Flood_{t-4}$×Direct Mandate×Penetration		-0.160** (0.070)
$Flood_t$×Indirect Mandate	-0.065*** (0.012)	-0.186*** (0.041)
$Flood_{t-1}$×Indirect Mandate	-0.121*** (0.018)	-0.337*** (0.063)
$Flood_{t-2}$×Indirect Mandate	-0.111*** (0.019)	-0.390*** (0.065)
$Flood_{t-3}$×Indirect Mandate	-0.100*** (0.016)	-0.309*** (0.054)
$Flood_{t-4}$×Indirect Mandate	-0.104*** (0.015)	-0.290*** (0.052)
$Flood_t$×Indirect Mandate×Penetration		0.197*** (0.061)
$Flood_{t-1}$×Indirect Mandate×Penetration		0.380*** (0.084)
$Flood_{t-2}$×Indirect Mandate×Penetration		0.497*** (0.085)
$Flood_{t-3}$×Indirect Mandate×Penetration		0.377*** (0.070)
$Flood_{t-4}$×Indirect Mandate×Penetration		0.333*** (0.072)
log(GDP per capita)	0.279*** (0.041)	0.430*** (0.065)
GID level effects	yes	yes
Country×year effects	yes	yes
Time effects	yes	yes
Constant	yes	yes
N	821,148	729,217
adj. R^2	0.875	0.875

Notes: This table shows fixed-effects regressions on GID 2 level, where we analyze the recovery process after flooding events for different flood insurance regimes. We compare regions with mandatory public insurance (Regime 4), regions with an indirect mandate (Regime 2, Regime 3), and regions with voluntary insurance (Regime 1), with the latter being the reference group. The dependent variable is the time-wise standardized night light activity in grid-point i at month t. Flood$_{t-k}$ is a set of flood dummy variables indicating whether a flood occurred at time $t-k$ at the respective grid-point, with k indicating monthly time lag. To account for differences across flood insurance regimes we interact our flood dummy with a dummy on the flood insurance regime in place at the observation. Interaction variables between our flood dummy, regime dummy, and insurance penetration account for variability of insurance penetration within regimes. We use the natural log of GDP per capita, country-year effects, and time effects as control variables. Fixed-effects on GID 2 level are included. Significance levels indicate the following: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors on GID 2 level are shown in parentheses. We report the adj. R^2 that accounts for the explanatory power of the GID fixed-effects.

The results highlight the outperforming effect with regard to speed of recovery after flooding events for regions with a mandatory holistic risk management approach. Again, the coefficient estimates on the interactions with the flood dummy and mandatory public insurance are highly significant at the 1%-level, while we find a negative effect on night light activity in the affected region in the same month of the flood of small magnitude. This can be attributed to the slower pay-out speed of claims from public insurance compared to payments from private insurers. Interestingly, regions with an indirect insurance mandate perform worse than regions with voluntary private insurance. While the recovery process is slowest in regions with an indirect mandate, higher insurance penetrations within indirect mandates increase the night light activity. This is in line with higher insurance penetrations ensuring (faster) access to insurance payments and therefore quicker recovery. Again, a higher GDP per capita significantly (1%-level) increases the night light activity.

We compare recovery dynamics explicitly distinguishing between all four insurance regimes in table 6 with voluntary private insurance as the omitted category.

Table 6: Impact of floods, mandatory public insurance, semi-voluntary insurance, public-private partnerships, and voluntary insurance on economic recovery

	(1) FE: std(Night Lights)	(2) FE: std(Night Lights)
Flood$_t$	-0.010** (0.005)	-0.005 (0.007)

Flood_{t-1}	-0.022*** (0.006)	-0.027*** (0.008)
Flood_{t-2}	-0.021*** (0.007)	-0.032*** (0.009)
Flood_{t-3}	-0.008 (0.007)	-0.019** (0.009)
Flood_{t-4}	0.002 (0.007)	-0.007 (0.008)
$\text{Flood}_{t}\times$Direct Mandate	-0.016*** (0.005)	-0.013 (0.011)
$\text{Flood}_{t-1}\times$Direct Mandate	0.026*** (0.007)	0.013 (0.011)
$\text{Flood}_{t-2}\times$Direct Mandate	0.021*** (0.007)	0.031*** (0.010)
$\text{Flood}_{t-3}\times$Direct Mandate	-0.001 (0.007)	0.019* (0.011)
$\text{Flood}_{t-4}\times$Direct Mandate	0.006 (0.007)	0.050*** (0.016)
$\text{Flood}_{t}\times$Direct Mandate$\times$Penetration		-0.047 (0.043)
$\text{Flood}_{t-1}\times$Direct Mandate$\times$Penetration		0.082** (0.036)
$\text{Flood}_{t-2}\times$Direct Mandate$\times$Penetration		-0.001 (0.015)
$\text{Flood}_{t-3}\times$Direct Mandate$\times$Penetration		-0.048 (0.031)
$\text{Flood}_{t-4}\times$Direct Mandate$\times$Penetration		-0.161** (0.070)
$\text{Flood}_{t}\times$Semi-Voluntary	-0.055*** (0.012)	-0.255*** (0.036)
$\text{Flood}_{t-1}\times$Semi-Voluntary	-0.118*** (0.020)	-0.387*** (0.060)
$\text{Flood}_{t-2}\times$Semi-Voluntary	-0.118*** (0.020)	-0.403*** (0.064)
$\text{Flood}_{t-3}\times$Semi-Voluntary	-0.107*** (0.017)	-0.305*** (0.052)
$\text{Flood}_{t-4}\times$Semi-Voluntary	-0.102*** (0.016)	-0.334*** (0.050)
$\text{Flood}_{t}\times$Semi-Voluntary$\times$Penetration		0.343*** (0.047)
$\text{Flood}_{t-1}\times$Semi-Voluntary$\times$Penetration		0.485*** (0.077)
$\text{Flood}_{t-2}\times$Semi-Voluntary$\times$Penetration		0.524*** (0.083)
$\text{Flood}_{t-3}\times$Semi-Voluntary$\times$Penetration		0.367*** (0.067)
$\text{Flood}_{t-4}\times$Semi-Voluntary$\times$Penetration		0.425*** (0.067)
$\text{Flood}_{t}\times$PPP	-0.159*** (0.038)	-0.164*** (0.039)
$\text{Flood}_{t-1}\times$PPP	-0.150*** (0.034)	-0.143*** (0.035)
$\text{Flood}_{t-2}\times$PPP	-0.050*** (0.016)	-0.041** (0.018)
$\text{Flood}_{t-3}\times$PPP	-0.030* (0.017)	-0.018 (0.018)
$\text{Flood}_{t-4}\times$PPP	-0.127*** (0.033)	-0.119*** (0.034)
log(GDP per Capita)	0.279*** (0.041)	0.429*** (0.065)
GID level effects	yes	yes
Country$\times$year effects	yes	yes
Time effects	yes	yes
Constant	yes	yes
N	821,148	729,217

adj. R^2	0.875	0.875

Notes: This table shows fixed-effects regressions on GID 2 level, where we analyze the recovery process after flooding events for different flood insurance regimes. We compare regions with mandatory public insurance (Regime 4), regions with a semi-voluntary approach (Regime 2), regions with a public-private-partnership (Regime 3), and regions with voluntary insurance (Regime 1), with the latter being the reference group. The dependent variable is the time-wise standardized night light activity in grid-point i at month t. Flood$_{t-k}$ is a set of flood dummy variables indicating whether a flood occurred at time $t-k$ at the respective grid-point, with k indicating monthly time lag. To account for differences across flood insurance regimes we interact our flood dummy with a dummy on the flood insurance regime in place at the observation. Interaction variables between our flood dummy, regime dummy, and insurance penetration account for variability of insurance penetration within regimes. We drop the interaction term for the public-private-partnership as this insurance approach applies to the UK only. We use the natural log of GDP per capita, country-year effects, and time effects as control variables. Fixed-effects on GID 2 level are included. Significance levels indicate the following: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors on GID 2 level are shown in parentheses. We report the adj. R^2 that accounts for the explanatory power of the GID fixed-effects.

With regard to risk management approaches, again we find evidence that economic disruptions are lower and recovery is faster in regions with an insurance mandate after a flood happened compared to territories with voluntary private insurance.

Interestingly, we find evidence that regions with a public-private partnership (Regime 3) are associated with a higher reduction in night light intensity along with a longer recovery process compared to regions with a voluntary market, i.e. territories with the lowest flood insurance regulation. This is surprising because of the relatively high insurance penetration related to Regime 3. In line with previous results, GID-zones with a higher GDP per capita are associated with significantly higher monthly night lights (1%-level) which is economically relevant. The high explanatory power of our regression model of about 87.5% in all our model specifications can be attributed to the explained variation in night light activity by the fixed-effects on grid-level.

In summary, we find evidence that economic recovery is fastest when the flooding risk is managed by public insurance mandates in the affected regions, while indirect mandates significantly perform worse than voluntary private insurance. This highlights the effectiveness of a mandatory holistic approach for mitigating flooding risk and offering financial protection particularly in flood prone regions.

While our results indicate a positive effect of public insurance mandates on night light activity within the first four months after a flooding event, we caution the reader to interpret our results as associations rather than causal inference as the choice of providing ad-hoc aid is not totally random and interacts with the insurance regime in place at the affected territory. Therefore, one could argue that the effect is rather (partly) driven by the underlying insurance regime, i.e. insurance penetration, in place at the affected region.

In a next step, we perform mediator analyses to account for the interaction between disaster aid and the insurance regime at place of the affected region for observations for which a flood is recorded. We investigate the impact of ad-hoc government aid on night light activity after flooding events. We therefore solely include observations for which a flooding event is recorded as insurance penetration itself is highly correlated with flood occurrence. We utilize time lags of $s = 3$. Table 7 shows results for the direct effects of our variables of interest on the monthly average night light activity and the indirect effect, where government aid is mediated by the insurance penetration in place at the affected region. We control for year effects and GDP per capita. We include time lags $s = 3$. The coefficient estimates on the insurance penetration are positive and highly significant in all our model specifications. Specifically, a higher insurance penetration significantly increases the night light activity within the first three months after flooding, supporting our previous findings. We find no significant direct effect for providing (at least some) disaster aid on the night light activity in the affected region within the first three months after the flooding event. This supports our hypothesis that government aid is not paid out in a very speedy fashion. Moreover, the anticipation of disaster aid seems to reduce the insurance penetration in the same region, indicating a form of charity hazard. The negative impact is significant at the 10%-level. Furthermore, a higher GDP per capita leads to both higher insurance penetrations and higher night lights within the first three months after flooding, as wealthier regions are associated with higher economic activities.

Table 7: Mediator analysis: disaster aid and night light activity

Dependent Variable: std(Night Lights$_{t+k}$)				
	(1)	(2)	(3)	(4)
	t	$t+1$	$t+2$	$t+3$
Main				
Insurance Penetration	0.402*** (0.139)	0.475*** (0.183)	0.435*** (0.160)	0.383** (0.150)
Disaster Aid	0.155 (0.191)	0.285 (0.278)	0.300 (0.230)	0.237 (0.274)

log(GDP per Capita)	0.408*** (0.055)	0.321*** (0.052)	0.310*** (0.049)	0.345*** (0.056)
Year effects	yes	yes	yes	yes
Constant	yes	yes	yes	yes
Insurance Penetration				
Disaster Aid		-0.288** (0.137)		
log(GDP per Capita)		0.407*** (0.022)		
Constant		yes		
N	5,919	5,919	5,919	5,919

Notes: The table shows mediator analysis with the insurance penetration as the mediator for disaster aid. We include observations only for which a flood is recorded. Significance levels indicate the following: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors on GID 2 level are shown in parentheses.

In summary, the outperforming effect with regard to recovery speed of some regions within the first three months after a flooding event is mainly driven by a higher insurance penetration. We find no significant effect of the provision of (at least some) disaster aid on night light activity within the first three months after flooding as aid payments by the government are usually not paid out very fast. Moreover, providing disaster aid seems to decrease the insurance penetration in the respective region, indicating a form of charity hazard.

6 Conclusion

With a further increase in temperature, the risk of flooding will become even more prominent in Europe as well as the rest of the world. In Europe, four different flood insurance regimes co-exist. The European countries also differ in how they provide ad-hoc aid by the government. We use the differences in regulatory schemes as a quasi-field experiment and posit the question how these financial responses perform in comparison to each other. We specifically investigate whether specific flood insurance regimes and aid programs fare in speed of economic recovery. This is highly relevant as the economic losses and disruptions show the burden of flooding risk to the society. In addition, economic recovery shows how quickly an economy can bounce back to previous activity levels.

Using monthly night lights data, we find evidence that mandatory insurance is associated with the fastest recovery after a flooding event. Interestingly, indirect insurance mandates perform worse than voluntary private insurance with regard to economic recovery. Some limitations should be mentioned. We have to account for potential endogeneity with regard to the choice of the insurance regime as the flood exposure itself may influence the design of the financial response to flooding risk. While some countries which use a voluntary insurance approach prohibit ad-hoc aid to reduce charity hazard, the interaction between a specific insurance regime and the provision of government disaster aid is crucial. To address potential endogeneity, we conduct mediator analyses where the insurance penetration mediates the effect of disaster aid on the monthly average night light activity in an affected region. Our results indicate no significant direct effect of government aid on night light activity within the first three months after a flooding event, while providing ad-hoc aid seems to reduce insurance penetration as a form of charity hazard.

Our results have important policy implications: Given that increasing flooding risk will subsequently lead to a higher financial burden to the society, choosing the most efficient insurance regime is a very promising risk management approach at this point. Specifically, the findings indicate that mandatory public insurance, as a way to manage flooding risks, can increase the speed of economic recovery compared to other insurance schemes.

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