Natural Hazards, Growth and Risk-Transfer: An Empirical Comparison between Risk-Transfer-Mechanisms in Europe and the USA

Paul A. Raschky*

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Abstract

An analysis of the effects of natural hazards on society does not solely depend on a region's topographic or climatic exposure , but the region's institutional resilience to natural processes that ultimately determines whether these processes result in a natural hazard or not. The purpose of this paper is to provide an institutional comparison between different societal risk-transfer mechanisms against floods in Europe and the USA. In the short run, a major flood event in a European region reduces the regional GDP by 0.4-0.6%-points; an average flood event in the USA reduces the personal income by 0.3-0.4%-points. In addition, the results for the U.S. sample suggest that counties participating in the NFIP follow a less volatile growth path in subsequent years. Appropriate ex-ante risk-transfer policies can largely mitigate these effects, while ex-post governmental disaster relief tends to even enlarge the negative impact of natural hazards on income. These results provide useful implications for adaptation strategies against the adverse effects of climate change.

Keywords: Natural Hazards, Growth, Insurance, Dynamic Panel GMM

JEL classification: G22, Q54, R11

*Institute of Public Finance, University of Innsbruck, Universitaetsstrasse 15, A-6020 Innsbruck and alpS - Center for Natural Hazard Management, Innsbruck Austria. Tel.:+43-512-507-7160 13; Fax: +43-512-507-2970; Email:paul.raschky@uibk.ac.at (Currently visiting the Wharton School, Risk Management and Decision Process Center, University Of Pennsylvania, Philadelphia). The author would like to thank Michael Pfaffermayr, Michael Rinderer, Hannelore Weck-Hannemann and Hannes Winner for their useful comments.

1 Introduction

In the ongoing discussions on the effects of climate change on society numerous studies estimated the "economic" impact of changing climate conditions. One result of anthropogenic climate change could be an increase in the frequency of extreme weather events (IPCC 2007). So far, large natural catastrophes are like shocks to society and the economy, but more frequent events could mean that at least in some regions of the world natural catastrophes may become "normality" rather than rare shocks. In order to develop efficient adoption strategies a detailed analysis of the impact of natural hazards on society is needed. The analysis in this paper starts with a basic question: "How do Natural Hazards affect society?" If a river runs over the bank or an avalanche runs down a hill it is not a natural disaster *per se* it is just a natural process. The natural process becomes a "natural hazard" as soon as human beings, infrastructure or other forms of tangible or intangible capital is threatened and/or destroyed. Whether this natural process does not affect individuals at all or "evolves" to a natural disaster is not solely in the realm of the natural environment, but crucially depends on the behavior of human beings living in this environment. Human (economic) activity in general and thus human behavior in coping with natural processes is determined by the institutional framework they act in and the resulting incentives. Therefore, an analysis of the effects of natural hazards on society does not solely depend on a region's topographic or climatic exposure to natural processes, but the region's "societal exposure" to natural processes that ultimately determines whether natural processes result in a natural hazard or not. In addition, the institutional setting defines the channels through which natural hazards affect society. Hence, the primary purpose is to show that institutions do matter in natural hazard management and implement this thought both in a theoretical and empirical manner.

The purpose of this paper is to estimate the effects of flood events on regional economic development using GVA-data from 18 European countries - the EU-15 (excl. Ireland) Czech Republic, Hungary, Norway, Poland and Switzerland (an ultimate number of 199 NUTSII-regions) and 3,050 U.S. counties using dynamic panel methods. The European data shows variance in risk-transfer-mechanisms between countries; societal risk-transfer-mechanisms in the U.S. vary between counties as well as within counties. In comparison to a damage function, regional income is a more comprehensive indicator that encompasses both direct (decrease in the stock of human and physical capital) and indirect (e.g. decrease in production and consumption) effects. Risk-transfer-mechanisms have an influence on both effects. The direct effects could be lowered by ex-ante incentive that induces risk-reducing behavior (e.g. risk-based insurance premiums increase the costs of housing in hazard-prone areas and thus decreasing the concentration of wealth in these areas). After a disaster occurred, victims suffer from a loss of wealth and income. For example after the 2005 flooding in alpine areas in Europe, victims in the canton of Graubuenden, Switzerland (a country with mandatory insurance) obtained the full replacement value for their losses within 4-7 days. Flood victims in the bordering regions of Tirol and Vorarlberg in Austria (a country with governmental disaster assistance) had to wait on average for 51 days until they an average financial relief of 50% of the damage. Delayed an insufficient compensation for damages reduces the level of consumption and could have far reaching effects for the regional economy. Therefore an institutional analysis of societal risk-transfer-mechanisms demands an indicator that grasps all effects of flooding on society's well-fare. The hypothesis that ex-ante risk transfer policies are more efficient than ex-post disaster relief (Kunreuther & Pauly 2006) has not been rigorously tested so far. This study enlarges existing empirical work on the impact of flood events on economic development and quantifies the effects of different risk-transfer mechanisms.

2 Effects of Natural Hazards on Economic Development

Following natural disasters governmental sources and media publish estimates on the "economic losses" society has suffered. In general disasters affect economic stocks (direct effects) as well as economic flows (indirect effects). Damage on a company's production facilities is a decline in capital stock. The following business interruption leads to a reduction of output and service flows. Although the majority of loss reports focus on direct losses to stocks, flows tend to be a preferable measure for damage estimates (Rose 2004). First, flows give a wider picture of the effects of natural disasters. Machines in a factory may not be directly struck by a flood but production can still decrease or pause production because of shortages in intermediate goods, energy or natural resources due to the disaster. Second, losses to stocks might exaggerate damages due to natural disasters as only a fraction of the asset value translates into actual services and thus increases utility at a given point in time. Third, flows incorporate indirect effects of natural disasters in a more comprehensive manner.

The immediate effects of a natural disaster is a reduction of the amount of human and physical capital. Natural catastrophes can have direct effects on a nation's mortality rate (e.g. Anbarci, Escaleras & Register 2005, Kahn 2005) or increase outward migration flows to other countries (Halliday 2006). The pioneering work by Albala-Bertrand (1993) tried to estimate the direct capital losses through natural disasters. This direct destruction of input factors is followed by disruptions in production and output. The cross-country analysis by Tavares (2004) shows that natural disasters have a small, but negative effect on economic growth. Several studies concentrating on the macro-economic impacts of natural disasters on developing countries provide similar results. Rasmussen (2004) presents a comprehensive study of natural disasters in the Eastern Caribbean Currency Union. He concludes that disaster damages in this area amount to about 0.5 % of GDP. The panel study by Auffret (2003) also finds a decline in output due to natural disasters in Latin American and Caribbean economies.

The possible decline in national output in the aftermath of a disaster can lead to an increase in imports and a decrease in exports resulting in a deterioration in the balance of trade(Auffret 2003). The panel-econometric study by Gassebner, Keck & Teh (2006), however shows a general negative impact on trade (0.3% in imports and 0.1% in exports). The assumed effect of a deterioration in the balance of trade only applies for small exporting countries.

Another macro-economic effect of disasters is related to the level of investment. The impact on national investment levels is ambiguous. It mainly depends on the reconstruction effort and the efficiency of the risk-transfer regime in place. Private investment tends to decrease while governments tend to initiate more public spending. This might than lead to a higher budget deficit. The reduction in output and investment can also lead to a decrease in private consumption. The study by Auffret (2003) finds that natural disasters have a rather large negative impact on investment growth, as well as a negative effect on public and private consumption. Regarding international investment flows, Yang (2005) shows that following a major disaster, the national level of foreign lending, inward foreign direct investment as well as migrant's remittances increase.

After experiencing natural disaster individuals might accumulate a "buffer-stock" of capital as a form of self-insurance against future losses. Based on an intergenerational model, Skidmore (2001) showed that this form of risk-transfer might lead to an inefficient increase in aggregate savings. His cross-section analysis in 15 OECD countries showed that the number of natural disasters between 1965-1995 had a significant positive impact on the amount of aggregate net household savings.

In the medium to lung run, natural disasters can also have a positive effect on economic development, by boosting the economy's technology endowment. A recent study by Crespo-Cuaresma, Hlouskove & Obersteiner (2008) shows that a nation's exposure to catastrophic risk has a positive effect on knowledge spill-overs from foreign technology transfers. Skidmore & Toya (2002) find in a cross-country analysis that higher frequencies of climatic disasters are correlated with increases in total factor productivity and economic growth because disasters provide the impetus to update the capital stock and adopt new technologies in the medium to long run.

Existing empirical work analysing the growth effects of natural hazards show several deficits: From a methodological point of view one problem occurs by using cross-section data. Islam (1995) points out the drawbacks of cross-section analysis of economic growth. He argues that single cross-section regression ignore the country-specific aspects of the aggregate production function resulting in an omitted variable bias. His analysis shows "[...] that persistent differences in technology level and institutions are a significant factor in understanding cross-country economic growth." (Islam (1995) p.1128). As already suggested, country-specific institutional factors might be crucial in determining the effects of natural hazards on economic growth. Therefore existing studies might have obtained biased results. Islam (1995) provides a panel-econometric extension of the standard cross-section growth model developed by Mankiw, Romer & Weil (1992). The empirical analysis in the present paper takes its theoretical origin from these extensions.

A further point of critique stems from the spatial dimension of the existing studies. Both Tavares (2004) and Skidmore & Toya (2002) analyse the effects of natural disasters on country level using data from the EM-DAT database. Although, there is no doubt that large catastrophes such as Katrina in 2005 or the Tsunami in South-East-Asia in 2004 have large impacts on a nation's economy, other disaster events and "smaller", that are included in the EM-DAT database, might be "cushioned" by the institutional forces and a nation's aggregate economy. An analysis on regional level could therefore account for the spatial distribution of disaster effects. This might allow to identify the societal channels that determine the effects of hazards on economic growth in a more detailed manner. Existing empirical work was not able to identify certain characteristics regarding a country's exposure to natural hazards. This is simply due to the fact, that such data was not available so far. However, a recent project by the World Bank in collaboration with the Columbia University (Dilley, Chen, Deichmann, Lerner-Lam, Arnold, Agwe, Buys, Kjekstad, Lyon & Yetman 2005) identified global disaster hotspots. The underlying GIS-data is used to calculate a region's exposure to natural hazards. By creating an interaction term that accounts for this hazard exposure one can control whether a flood occurred in an already hazard-prone area or a region with actual low level of occurrence probability.

3 Institutional aspects of societal risk-transfer and Natural Hazards

Keeping in mind, that anthropogenic climate change could possibly increase the frequency of extreme weather events, the efficient allocation of resources in natural hazard management is essential to sustain a certain level of economic welfare. This allocation is incrementally influenced by the institutional framework defining the actors' incentives within the societal decision-making-process. Therefore the institutional design of natural hazard management and its effect on the relationship between natural disasters and economic development will be analysed. A comparison of alternative institutional designs in allows to examine the strengths and weaknesses of different systems and identify more efficient institutions. In this paper the focus lies on the institutional design of societal risk-transfer and natural hazards.

So far a wide range of theoretical and empirical literature already showed the positive effects of different institutions on economic development in general. The empirical work by Kahn (2005) shows that a number of broad institutional variables can have mitigating effects. He empirically assesses the impact of economic development and institutional quality on the death toll from natural catastrophes. In a first step he analyses the effects of GDP, a countries land area and geographic location on the probability that a disaster occurs. The probit estimates show that in general these variables do not have a significant effect on disaster probabilities[1]. Then he showed that the GDP per capita has a negative impact on both a nation's total death toll from natural catastrophes and a nation's death toll from earthquakes, extreme temperature, floods, landslides and windstorms separated. In a third step he evaluated the impact of institutions on the disaster death toll. He used a nation's level of democracy, income inequality, ethnic fragmentation and good governance indicators as proxies for institutional quality. Countries with better institutions, lower income inequality and a lower level of democracy experience more deaths. He argues that this might be explained that these nations do not properly enforce zoning laws and building codes, however calls for more research in this area. Anbarci et al. (2005) analyse the effects of a country's inequality (using the Gini coefficient) on earthquake fatalities. Their results suggest that a nation's inequality - as a proxy for the nation's institutional quality and ability to adopt preventive measures and policies (e.g. the creation and enforcement of building codes)- increases the number of earthquake fatalities (controlling for the earthquakes intensity).

3.1 Institutional design of risk-transfer

In this paper, the focus lies on more specific institutional variables that reduce the societal effects of natural disasters, namely risk-transfer-mechanisms. The market for insurance against flooding works imperfectly or fails completely. Adverse selection and moral hazard can only partly explain these market imperfections Jaffee & Russell (2003). Kunreuther (2000) defined the situation of distorted demand and insufficient supply on the market for natural hazard insurance as the *disaster syndrome*. Individuals tend to underinsure because of a) the underestimation of risk of low-probability high loss events and b) the expected financial relief by the government or private charity. This market failure has led to different forms of government intervention in the market for disaster insurance. In Europe several countries (France, Great Britain, Spain and Switzerland) have installed a system of

[1]GDP per capita only has a significant negative effect on the probability of a flood disaster

mandatory insurance, where every house-owner and company is obliged to purchase insurance coverage against natural-disaster-risks (for an overview of the different forms in each country see Von Ungern-Sternberg (2004)). The U.S. government has implemented the National Flood Insurance Program in 1968 in order to provide insurance cover against flooding at subsidized premiums. In participating counties, house owners in hazard-prone areas are obliged to purchase insurance coverage against floods. To other house owners flood insurance is available at reduced premiums. Depending on the extent of coverage, such an institutionalized insurance system should absorb some of the effects of a flooding on the economy.

In regions without institutionalized insurance regimes, risk-transfer against natural hazards is in the realm of the individuals and politicians. According to Skidmore (2001) individuals try to protect themselves against potential disaster damages by building up a capital buffer. This for of self-protecting is rather inefficient as the buffer stock is very often bigger than the actual losses. However, if self-insurance does not cover the disaster losses governments provide catastrophe assistance and financial relief. Governmental relief is either organized through a fund (e.g. Austria) or politicians provide ad-hoc financial assistance to the victims (e. g. Germany). Governmental disaster assistance can lead to the problem of *charity hazard*, the phenomenon that people underinsure or do not insure at all due to anticipated governmental assistance and/or private charity (Lewis & Nickerson 1989). In addition to an inefficient amount of insurance coverage, financial assistance from the government does rarely meet the needs of the disaster victims and leads to an inefficient allocation of public funds. An econometric study by Garrett & Sobel (2003) shows that almost half of FEMA's disaster payments are politically motivated. They show that disaster expenditure is significantly higher in election years (around $ 140 million as compared to non-election years) and that states with higher political impact haver on average a higher rate of disaster declaration (a requisite for financial assistance). Besley & Burgess (2002) find similar results using panel date from India on governmental food programs after crop flood damage. The work by Mustafa (2003) concluded that after the 2001 in Pakistan public support cheques where mainly distributed among family members and political supporters of local councilors coordinating the governmental assistance. Insufficient public relief and allocative inefficiencies should thus reduce the absorbing effect of governmental assistance. In comparison to an institutionalized ex-ante risk-transfer system, the mitigating effect of governmental disaster assistance should be smaller.

3.2 Disasters and mitigating institutions in an endogenous growth model

Albala-Bertrand (1993) provides a theoretical framework for the analyses of direct effects from disaster losses on the economy. His model defines an upper and lower bound for output fall from direct capital loss through natural disasters. The decrease in the economic growth rate is defined by the loss-to-output ratio. He also applied his theoretical model to estimate the economic losses from six major disasters events in Latin America. GDP of four out of six countries increased within the year the disaster occurred and the two following years. However, he did not use any further econometric methods to test his hypothesis. Ikefuji & Horii (2006) incorporated natural hazard risk into an endogenous growth model, where the frequency of natural disasters is linked to the amount of pollution. Natural hazards have an increasing effect on the depreciation rates of physical as well as human capital, although they assume that the damage on human capital is relatively lower compared to the damage on physical capital.

The analysis starts with a basic Solow model as used by Mankiw et al. (1992) and applies the assumptions made by Tol & Leek (1999) regarding investments in disaster management. In particular, the focus lies on the institutional design of the risk-transfer-mechanism as a mean of mitigating the effects of disasters on the economy. Assume the following Cobb-Douglas production function for production at time t

$$Y(t) = K(t)^{\alpha} \left[A(t) L(t)\right]^{1-\alpha}, \tag{1}$$

$$\text{where } 0 < \alpha < 1$$

According to the Solow-model it is assumed that L and A grow exogenously at the rates n and g

$$L(t) = L(0) e^{nt} \tag{2}$$

$$A(t) = A(0) e^{gt} \tag{3}$$

Hence, the number of effective labor $A(t) L(t)$, grows at a rate $(n+g)$. Taking s as the constant rate of saving and investment, k the stock of capital per effective unit of labor, K/AL, y as the level of output per effective unit of labor, Y/AL, and δ the constant rate of depreciation, the dynamics of k are given by

$$\dot{k} = sy_t - (n+g+\delta) k_t - D(F_t, \phi_t) k_t \tag{4}$$

$$= sk_t^{\alpha} - (n+g+\delta) k_t - D(F_t, \phi_t) k_t. \tag{5}$$

D_t represents the damage from hazard risks at time t, which is a function of F_t, a variable accounting for the magnitude of the disaster and ϕ_t, $0 \leq \phi \leq 1$, representing the fraction of losses covered by insurance..

$$D\left(F_t, \phi_t\right) = \begin{cases} D_t = 0 & if \quad F_t = 0, \phi_t = 0 \\ 0 < D_t \leq 1 & if \quad F_t = 1, \phi_t = 0 \\ 0 < D_t \leq 1 & if \quad F_t = 0, \phi_t = \phi^* \\ D_t = 0 & if \quad F_t = 1, \phi_t = \phi^* \\ 0 < D_t < 1 & if \quad F_t = 0, 0 < \phi_t < \phi^* \\ 0 < D_t < 1 & if \quad F_t = 1, 0 < \phi_t < \phi^* \end{cases}$$

Under the assumption of actuarially fair pricing, the amount of losses paid in disaster periods and the amount of insurance premiums paid during non-disaster periods depends on the level of insurance coverage ϕ. ϕ^* represents full coverage resulting in $D_t = 0$ if $F_t > 0$ and $\phi_t = \phi^*$. Risk management activity with insurance creates opportunity costs in the form of insurance premiums lowering consumption and investment, $D_t > 0$ if $F_t = 0$ and $0 < \phi_t < \phi^*$.

The steady state value of k is

$$\hat{k*} = \left(\frac{s}{(n+g+\delta) + D\left(F, \phi\right)}\right)^{\frac{1}{1-\alpha}} \tag{6}$$

Substituting equation 6 in the production function and taking the logarithm leads to the steady state income per capita:

$$\begin{aligned} \ln\left(y_t^*\right) = \ln(A_0) + gt + \frac{\alpha}{1-\alpha}\ln\left(s\right) \\ - \frac{\alpha}{1-\alpha}\ln\left(n+g+\delta\right) - \frac{\alpha}{1-\alpha}\ln\left(D\left(F_t, \phi_t\right)\right) \end{aligned} \tag{7}$$

Mankiw et al. (1992) now assume that the rate of technological progress is the same for all countries and in a cross-section regression t is a fixed number. Therefore, they suggest that

$$\ln(A_0) = \alpha + \epsilon, \tag{8}$$

where α is a constant and ϵ is a country-specific fixed term.

This cross-sectional framework assumes that TFP (A) is homogeneous across all countries and regions. However, several studies show that this does not apply. If TFP differs between regions and correlates with other variables, the estimates from the cross-section model are biased (Islam 1995). Islam (1995) proposed the following a panel-data framework that includes regional dummies as a control variable for different levels of technology.

Advancing the steady state a region's speed of convergence can be described by

$$\frac{d\ln(y_t)}{dt} = \lambda \left(\ln(y^*) - \ln(y_t) \right). \tag{9}$$

Where $\lambda = (1-\alpha)(n+g+\delta)$. Equation 9 leads to the log-linear adjustment process towards the steady-state.

$$\ln(y_t) - \ln(y_{t-1}) = \left(1 - e^{-\lambda t}\right) \left[\ln(y^*) - \ln(y_{t-1})\right] \tag{10}$$

Substituting y^* using equation 7 gives the following growth equation:

$$\begin{aligned} \ln(y_t) - \ln(y_{t-1}) = -\left(1 - e^{-\lambda t}\right) \ln(y_{t-1}) \left(1 - e^{-\lambda t}\right) \frac{\alpha}{1-\alpha} \ln(s) \\ -\left(1 - e^{-\lambda t}\right) \frac{\alpha}{1-\alpha} \ln\left(n+g+\delta\right) - \left(1 - e^{-\lambda t}\right) \frac{\alpha}{1-\alpha} \ln\left(D\left(F_t, \phi_t\right)\right) \\ + \left(1 - e^{-\lambda t}\right) \ln(A_0) + g\left(t - e^{-\lambda t} t\right) \end{aligned} \tag{11}$$

Adding $\ln(y_{t-1})$ to both sides of the equation results in an alternative expression of a panel data model

$$\begin{aligned} \ln(y_t) = e^{-\lambda t} \ln(y_{t-1}) \left(1 - e^{-\lambda t}\right) \frac{\alpha}{1-\alpha} \ln(s) \\ -\left(1 - e^{-\lambda t}\right) \frac{\alpha}{1-\alpha} \ln\left(n+g+\delta\right) - \left(1 - e^{-\lambda t}\right) \frac{\alpha}{1-\alpha} \ln\left(D\left(F_t, \phi_t\right)\right) \\ + \left(1 - e^{-\lambda t}\right) \ln(A_0) + g\left(t - e^{-\lambda t} t\right) \end{aligned} \tag{12}$$

4 Natural Hazards and Economic Growth - Empirical Evidence

4.1 Data

Empirical research on the macro-economic impact of natural disasters so far mainly happened at nation-level (e.g. Skidmore & Toya 2002, Auffret 2003, Rasmussen 2004). The advantage lies clearly in the comprehensive identification of high-order effects of disasters (Albala-Bertrand 1993). Pelling, Özerdem & Barakat (2002) and Rasmussen (2004) point out the importance of a country's size in connection with its vulnerability against natural hazards. Critical infrastructure and productive assets are more concentrated in smaller countries and the endowment with adaptive capacity of other infrastructure that could compensate temporary input shortages (e.g. in energy or water supply) is limited. Unfortunately there is hardly any data on the spatial extent or the intensity of the flood events available[2]. Analysing the effects of a major event on country level would suggest that one compares a flood for example in Austria (83.871 km^2) and with a flood in France (543.965 km^2). In addition, the consequences of an event might be absorbed by the nation's economy as a whole, in particular if the disaster took place early in the year. Therefore one cannot distinguish between the mitigating effects of the risk-transfer-mechanism in place and the absorptive capacity of the nation's economy. The study by Gassebner et al. (2006) supports the assumptions made above and shows that a correction of the number of natural disasters by country size leads to more reliable results.

An institutional comparison of different risk-transfer mechanisms might, thus demand an analysis at a lower aggregate level. Hence, the geographical level in this study is at the NUTSII-level for Europe and the county-level for the U.S.A. The specification for the European estimates are based on the regional dynamic panel analysis by Badinger, Mueller & Tondel (2004), while the specifications for the U.S. includes the major variables of the county-growth estimates by Higgins, Levy & Young (2006). The macro-data for Europe was provided by the European Regional Database from Cambridge Econometrics. Data for U.S. counties stems from U.S. Department of Commerce, Bureau of Economic Analysis as well as U.S. Census Bureau. For the flood hazards we use data on flood-disasters that took place in the territorial unit and spatial information on the flood-exposure of the region, based on GIS-data. The data on flood events are taken from the most comprehensive data set on disasters, the EM-DAT by the Centre for Research on the Epidemiology of Disasters (CRED) in Brussels. EM-DAT has collected around 12,000 reports of different disasters, such as flood, storms, earthquakes, volcanic eruptions, landslides as well as man-made disasters. The disaster has to fulfill at least one of the following criteria in order to be included in the database: 10 or more people reported killed, 100 people reported affected, declaration of a state of emergency, call for international assistance. Therefore, floods that occurred in thinly populated areas at the time are not included in the database and in the analysis. Based on this database, dummy-variables were created accounting for reported flood events in region j at time t. Normally, the dummy variable takes on the value 1 for the year (and region) in which the flood incident took place. Accounting for a flood event by using a dummy could be seen as a simplification of the problem (in particular by natural scientists). However there are three major reasons for this simplification: 1) From a methodological perspective this paper aims at estimating the effects of an *average* flood event on regional income. With respect to forecasting the effects of future flood events - in particular regarding

[2]Of course, single events received detailed evaluation, however such evaluations only took place for large-scale disasters. Including only floods that have been evaluated would substantially reduce the sample and make a thorough panel-data-analysis impossible.

a possible increase of such events due to climate change - the effects of an average historical flood might be more valuable than the effects of one specific historical flood (e.g. the "100-years flood in central Europe in 2002"). 2) The damage to human or physical capital is an endogenous variable (see section 3) and is therefore not an appropriate measure for a floods severity. For example, in his analysis of the extent of hurricane damages on international investment flows Yang (2005) used meteorological data on hurricanes as an instrument for hurricane damage, due to the potential endogeneity of disaster losses. However, in comparison to hurricanes it is hard to find variables for the extent of flood damage that are clearly exogenous.

There are 111 floods within the 199 European regions. 166 in the sample have all 26 years. The Czech Republic, Hungary and Poland (16 regions) have 16 years the former GDR-regions (6) have 15 years[3]. Figure 1 represents the number of floods per year that occurred in the sample within the NUTSII-regions.

- FIGURE 1 about here -

Flood data on historical events in the U.S. is obtained from the Sheldus flood database kindly provided by the Hazards and & Vulnerability Research Institute (2007). This database includes all flood events on county level between 1969 and 1995 that created more than U$ 50,000 in property or crop damage. From 1995 on it has also included events that created less than US$ 50,000 damage. Figures 2 and 7 show the number of floods per year in U.S. counties, Alaska and Hawaii.

- FIGURE 2 about here -

- FIGURE 7 about here -

Another issue concerning the flood dummy is related to the within-year occurrence of the flood. As the data on GDP and personal income is normally calculated at the end of the year, one can assume that the effects of floods that occurred early in a year might have been absorbed at end of the year. The problem in accounting for the month of the flood's occurrence is that it might lead to discretionarily setting the boundaries (e.g. First quarter or first half of the year) without any theoretical background. The number of floods are more or less equally distributed over the year both for Europe (see Figure 3) and the U.S.A (see Figure 4)

GIS-data on flood hazard areas is based on a study by the World Bank and Columbia University (Dilley et al. 2005) that identifies global natural disaster hotspots. Data on flood disasters from 1985 to 2003 has been

[3]Portugal Alentejo only has 2 periods, Portugal South has 24 years, Netherlands Flevoland has 20 years

collected and georeferenced by the Dartmouth Flood Observatory. These spatial historical data on flood events have then been combined in $1^\circ \times 1^\circ$ grid cells (see Figure 1 for Europe and Figure 2 for the U.S.). The attributes of the grid cells range form 0 to 10, depending on the amount of georeferenced flood events in the grid cell. The GIS-data has certain limitations: 1) Flood extent data identifies regions affected by floods and not the exact flooded areas. 2) Data on events in the early nineties are missing or of low spatial quality. However, this GIS-data is the best (publicly) available data on flood hazard area at such an aggregated level that has been collected and processed with a uniform method.

The data on flood exposure is only cross-section and can thus not be applied in the panel estimates. However, we use the GIS-data to construct an interaction term that accounts for flood-events in high, medium and low risk regions. An additional vector-file identifies the territorial boundaries of the NUTS II regions in Europe. The exposure to flood hazards in region j, h_j, is now obtained by combining the raster-data from the "Natural Disaster Hotspot" with the vector-layer and calculating the mean-value of the GIS grid cells, r, within the region:

$$\bar{h_j} = \frac{1}{n} \sum_{r=1}^{n} h_{jr} \tag{13}$$

Table 1 summarizes the results for mean flood exposure on nation-level. Luxembourg turns out to be the nation with the highest flood-exposure. The mean flood exposure of the European countries surveyed is 2.050.

- TABLE 1 about here -

The graphical representation of the regional flood exposure can be found in figures 5, 6 and 8.

- FIGURE 5 about here -

- FIGURE 6 about here -

- FIGURE 8 about here -

The data on mandatory insurance regimes in Europe is taken from Von Ungern-Sternberg (2004) and a treatment group is build. Great Britain is excluded from the mandatory insurance treatment group as it only shows an insurance density of about 62%[4]. In addition Portugal is included into the group due to a penetration of natural hazardinsurance of about 90 % (Schweizerische Rueckversicherungs-Gesellschaft 1998) that comes close

[4]For an explanation see Von Ungern-Sternberg (2004)

to the extent of a mandatory insurance system. Regarding risk-transfer-mechanisms in the U.S.A. the effects of the NFIP are examined. Counties are free to join the NFIP. The Federal Emergency Management Agency (FEMA) has issued a Community Status Book that indicates whether a county is participating in the NFIP Federal Disaster Management Agency (2007). The focus is on analysing the effects of the sole participation of a county in the Program. However, the Community Status Book as well as the institutional variations within the U.S. allows an in-depth examination of different program types and policies[5]. An additional examination focusses on the political economy of federal disaster assistance. Schwarze & Wagner (2004) argued that the massive financial assistance after the 2002 flooding in Germany augmented chancellor Schroeder's chances of re-election. An empirical study by Garrett & Sobel (2003) showed that almost two thirds of FEMA's disaster assistance is politically motivated and that the extent of disaster assistance is strongly correlated to presidential elections. Politicians can abuse these ad-hoc rubber-boots-policies[6] to gain votes in upcoming elections. Therefore federal election years in Europe and congressional and presidential election years in the U.S.A. are used as proxies for potential rubber-boots-policies.

4.2 Empirical Strategy

From equation 12 and the theoretical assumptions in section 3 the following specification for the econometric analysis can be derived:

$$\begin{aligned} \ln(y_{it}) = \gamma_t \ln(y_{i,t-1}) + \beta_1 \ln(s_{it}) + \beta_2 Agricult_{it} \\ +\beta_3 Service_{it} + \beta_4 Flood_{it} + \beta_5 F_{it} * Ins_{it} + \mu_i + \eta_t + \epsilon_{it} \end{aligned} \tag{14}$$

Taking $\mu_i = \left(1 - e^{-\lambda\tau}\right)\ln(A_i)$for regional fixed effects and η_t as time specific effects. $Agricult_{it}$ is the fraction of the primary sector in region i's economy at time t, $Flood_{it}$ is a dummy that switches to 1 if a flood event took place in region i at time t and $F_{it} * Ins_{it}$ is an interaction term representing whether the flood took place in a region with mandatory insurance (Europe) or a county that is a member of the National Flood Insurance Program (NFIP) (U.S.A.). For the U.S. personal income per capita is used (investment data is not available on county-level).

Equation 14 shows the presence of a lagged dependent variable $\ln y_{it-1}$ among the regressors, that is not strictly exogenous. In addition, the sample features a relatively large number of N (212 regions in Europe, 3,085 counties in the U.S.) in comparison to a relatively small number of T (on average 23 years in Europe, years in the U.S.). This constellation demands

[5]This is already part of the author's ongoing research activity.

[6]After natural catastrophes, politicians very often enter the disaster areas, wearing rubber boots, and promising immediate and unbureaucratic financial assistance to the victims.

the application of the dynamic panel data models. The analysis follows the suggestions made by Judson & Owen (1999). Their Monte-Carlo simulation reveal that the one-step GMM estimator proposed by Arellano & Bond (1991) performs well for unbalanced panels with $T = 20$ and that the Anderson-Hsiao estimator (Anderson & Hsiao 1981) outperforms other estimators if $T = 30$. Therefore we apply the one-step GMM estimator for the unbalanced European sample ($T = 24$ for most of the regions, $mean = 22.8$) and the Anderson-Hsiao estimator for the balanced U.S. sample ($T = 35$).

The set of instruments used in this specification follows the study on regional convergence in Europe by Badinger et al. (2004). Equation 6 states that the disaster function D actually affects the steady state capital stock and thus y_{it-1} in equation 12. Therefore lagged values of the flood variable $Flood_{i,t-n}$ and lagged values of the interaction term $(Flood*Insurance)_{i,t-1}$ are used as additional instruments for the lagged dependent variable $y_{i,t-1}$. The assumption that the first differences of the instruments are uncorrelated with the region specific fixed effects might not hold for the growth model and this specification. Therefore the system GMM estimator (Arellano & Bover 1995, Blundell & Bond 1998) cannot be used and equation 14 is estimated using the one-step difference GMM.

The empirical estimation for the U.S. sample is complicated by the fact that the relationship between income and the participation decision in the NFIP are subject to reversed causality. Raschky & Weck-Hanneman (2007) show that richer communities are more likely to participate in the NFIP. To circumvent this problem the endogenous treatment procedure provided by Heckman (1978) is applied. In a first step a standard probit regression describing the participation decision by a vector X of explanatory variables from the base equation and a vector Z of exogenous instruments. As additional instruments information of lagged flood events (e.g. occurrence, damage and fatalities) are used. This first stage regression is run for every year. In a next step the regression parameters are used to calculate the inverse Mill's ratio, which is the ratio between the probability density and the cumulative distribution function. The Mill's ratio and an interaction term between the Mill's ratio and the flood dummy are then used as additional instruments for the actual participation in the NFIP, $NFIP_{it}$, and the interaction term of participating in the program and the flood, $(Flood * Insurance)_{i,t-1}$,.

In addition, the Bureau of economic analysis has adjusted the income on county level for several major disasters (Bureau of Economic Analysis (BEA) 2006)[7]. We have accounted for this adjustment by simply including a dummy ($Corryear$) that switches to 1 for the years an adjustment took place.

[7]The adjustments relevant for this analysis are Hurricanes Andrew and Iniki in 1992, the Midwest flood and the East Coast storms in 1993, Hurricane Opal 1995, Hurricane Floyd in 1999, Tropical storm Allison in 2001 and the Hurricanes Charley, Frances, Ivan and Jeanne in 2004.

4.3 Results

The results for Europe and the U.S.A. should not be compared directly, as the samples differ in their flood and risk-transfer variables and the estimation methods applied. Therefore, the reader should compare similarities in the signs of the coefficients rather the absolute size of the coefficients. We first present the results of Europe and the USA for the baseline estimates and the estimates with mandatory insurance for Europe and NFIP for the USA. Then we examine the results of our robustness tests using an alternative flood measure. After that, the effect of the empirical proxy for governmental relief, election years, are shown. The section concludes with an examination of the effects of flood over time. For Europe solely the results of the Arellano-Bond estimates are presented, while for the U.S. , given the within variation in the risk-transfer mechanism, the results for Fixed effects (FE), instrumental fixed effects (IV-FE) and the Anderson Hsio first difference effects (AH-FD) are presented.

Table 2 summarize the results of the Arellano Bond dynamic panel-regression of the basic estimation for the European sample, where the effects of a flood on regional economic growth are estimated. If a flood occurred within a given year it has a negative effect on regional GDP in Europe of 0.4 % (column 2.1). The results of the baseline specification for U.S. counties also suggest that a flood decreases personel income by around 0.4 % (column 3.1). In the next step the variable accounting for ex-ante risk-transfer mechanisms was introduced. For the European sample this term is a interaction between the mandatory insurance dummy and the flood dummy, for the U.S. it is the interaction term between the participation in the NFIP dummy and the flood dummy. Let us first have a look on the effect of the flood variable. In both samples the flood variable increases. This means that the actual effect, after controlling for the risk-transfer measure, is higher in regions without ex-ante insurance systems. Both, mandatory insurance an the NFIP have a significant mitigating effect. The combined effect of the flood term and the interaction term are calculated in the Marginal Effect-section at the bottom of the respective tables. These effects suggest that mandaotry insurance regimes completly absorb the adverse effects of a regional effect in Europe (column 2.4). The NFIP reduces the effect by about 50 % (columns 3.2-3.4). These estimates clearly support the hypothesis in the theoretical model as well as the literature. However, the coefficients do not allow a decomposition of the mitigation effect into the fraction resulting from increasing protection and the fraction resulting from more efficient post-catastrophe relief. This decompostion should be part of future research. In contrast to the theory, the results of the fixed effect and fixed effect IV estimates for the U.S. signal a positve overall effect of participating in the NFIP on personal income. This result could be caused by the above mentioned endogeneity in the relationship between economic development and participation in the NFIP.

Accounting for this endogeneity (column 3.4) results in a negative sign, but a rather large effect on county-wide income.

- TABLE 2 about here -

- TABLE 3 about here -

In order to control for a region's general exposure to flood hazards and possible influences on the magnitude a robustness check is performed. Combining the flood-dummy with the GIS-data on the regional flood exposure leads to a smaller coefficient in both samples (column 2.3 for Europe and table 4 for the USA). Although the interaction term of flood and regional exposure is hard to interpret it suggests that our results are robust.

- TABLE 4 about here -

We now turn our focus on the ex-post risk-transfer through ad-hoc governmental relief. Once again it should be mentioned that these results only hold under the assumption that politician have a bigger generosity in election years and therefore election years are a good empirical proxy for governmental relief.

The estimates in tables 5 and 6 seem to support the theory that the floods that took place in years with federal elections have a larger negative impact on regional GDP in Europe than floodings in other years. For the USA we do not find these results. The effects of floodings in years with congressional elections do not clearly differ from those in other years. Presidential elections only slightly mitigate the disaster impact within the same year.

- TABLE 5 about here -

- TABLE 6 about here -

The last analysis examined the temporal patterns of a flood catastrophe and the varying risk-transfer systems. For the European sample the results can be found in table 2 and 5. The baseline estimates suggest no significant effect of a flood on growth in the subsequent year. However, controlling for mandatory insurance, a significant positive effect on growth can be found accounting for the expected reconstruction activity. Surprisingly, regions with mandatory insurance still experience a smaller growth rate. Estimates on subsequent years do not yield any significant results. Governmental relief in a flood year causes to diminish the positive reconstruction effect in the subsequent year. The effect of the interaction term is about -0.9%, while the coefficient for the lagged flood variable is 0.4% (column 5.3).

The U.S. sample allows a more profound analysis of the temporal patterns. The results are summarized in table 7 (NFIP) and table 8 (election years). Again, a positive effect on personal income in the subsequent year can be found. The positive effect, however, is smaller in counties participating in the NFIP. In order to get a better understanding, we estimated the effects over the subsequent 5 years.

Figure 8 provides a graphical representation of the deviations from the growth path given a flood and the different risk-transfer systems. At the beginning there is a large negative impact of flood, except for counties participating in the NFIP. The subsequent year experiences a large increase in growth, followed by volatile growth. Comparing the standard deviations of the marginal effects of the NFIP, congressional election and presidential elections reveals that the deviations are smaller in NFIP counties (0.0024) (compared to 0.0047 in non participating counties) and larger in both congressional (0.0035) and presidential election years (0.0038) (compared to 0.0033 and 0.0032 in respective years without elections).

5 Concluding Remarks

Natural disasters affect society in various ways. The purpose of this paper was to develop a theoretical an empirical framework for an institutional comparison of risk-transfer-mechanisms. This was implied by estimating the effects of flood events on regional economic growth both in Europe and the U.S.A. The results suggest, that flood events do have a negative impact on regional GDP in European NUTSII-regions and personal income in U.S. counties within the disaster-year and a positive effect in the preceding year. Regions that have implemented mandatory insurance regimes (Europe) or that take part in the National Flood Insurance Program (U.S.A) are clearly better off than regions without such a mechanism. Floodings that occurred during election years (an empirical proxy for governmental relief) have an even larger negative impact on regional economic development. Results from the U.S. sample further suggest that counties participating in the NFIP follow a less volatile growth path in the periods subsequent to a flood event.

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Figure 1: No. of floods per annum in NUTSII-regions in Europe

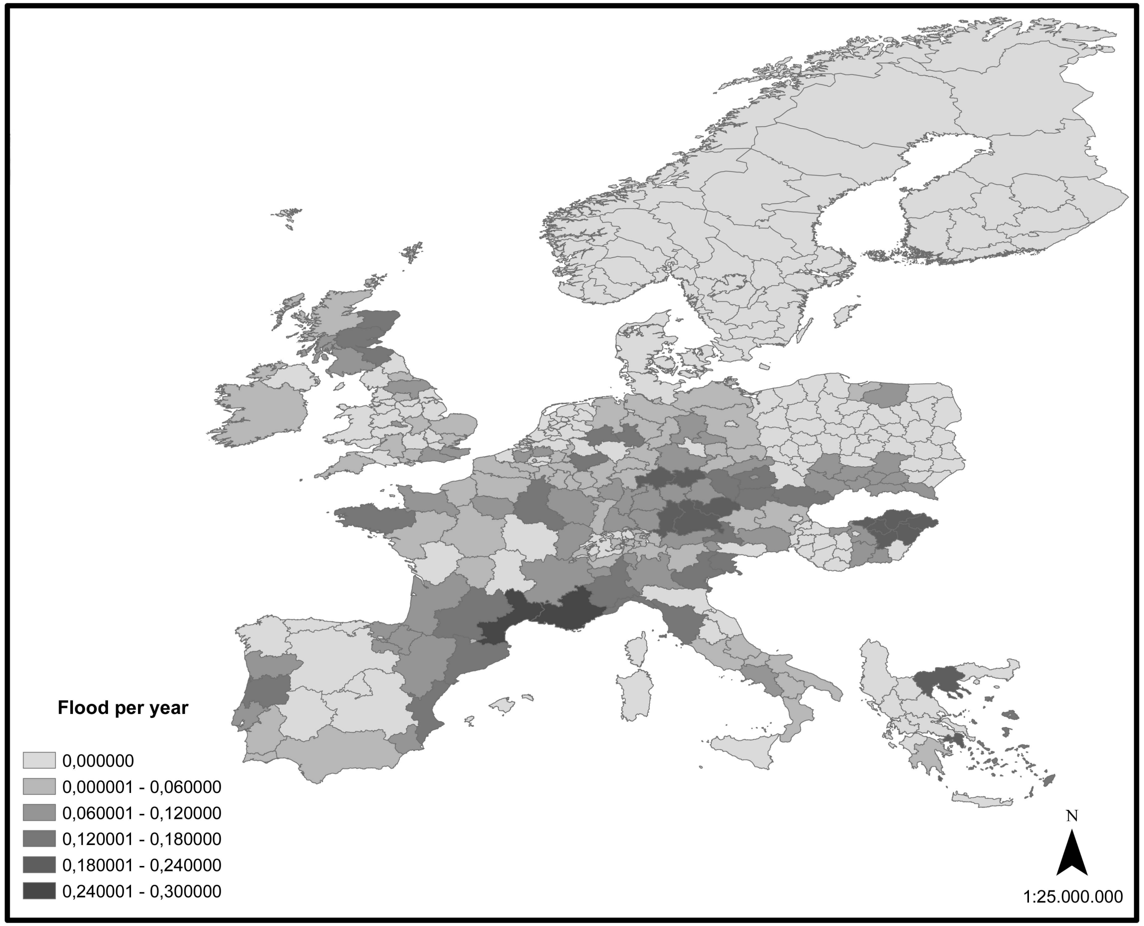

Figure 2: No. of floods per annum in U.S. counties

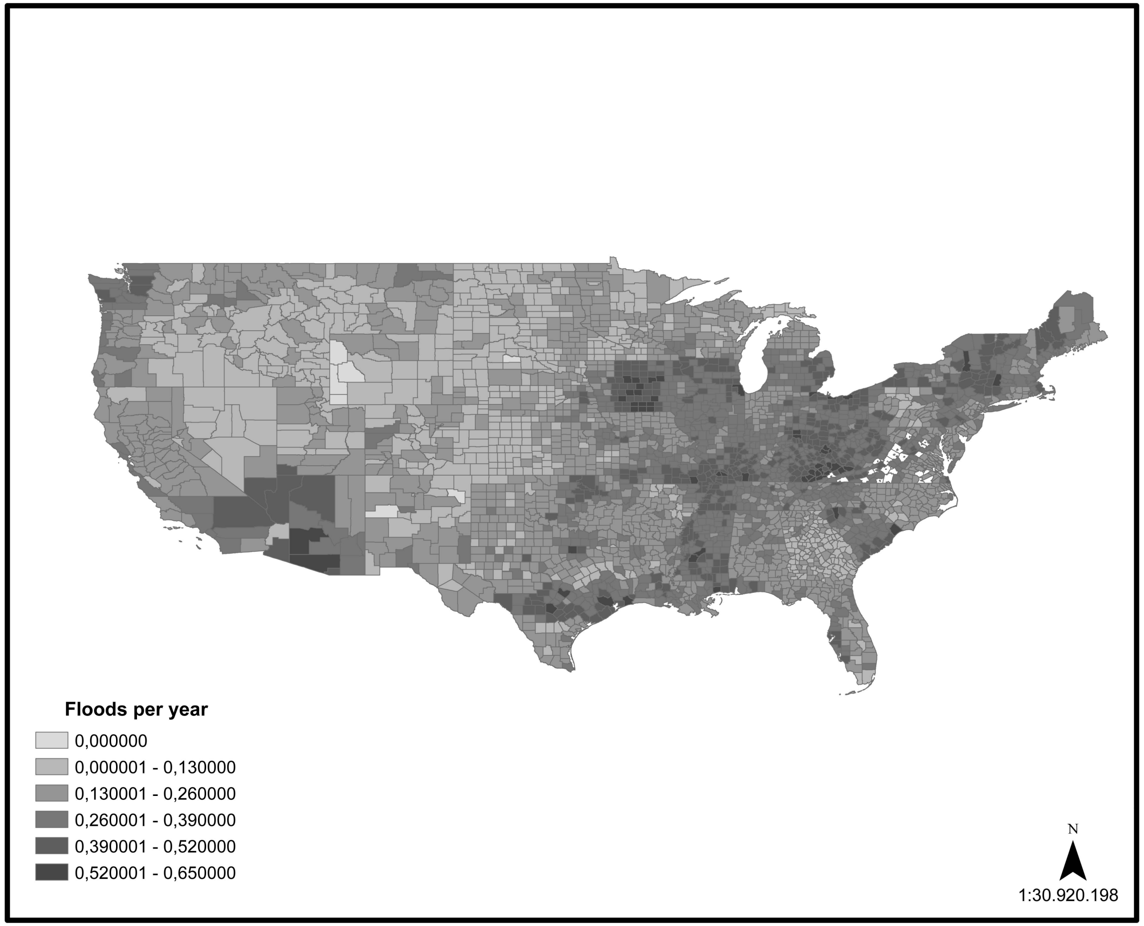

Figure 3: Frequency of Floods per month in Europe

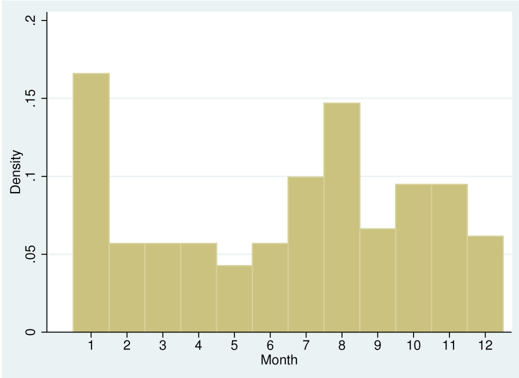

Figure 4: Frequency of Floods per month in U.S.A

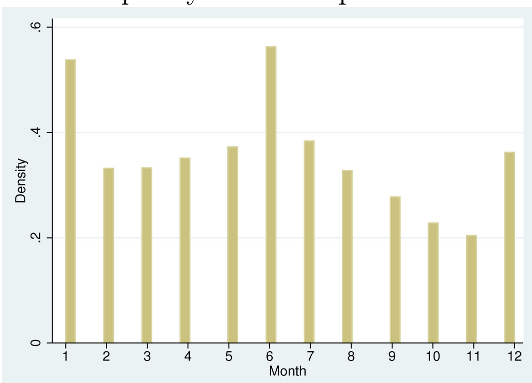

Figure 5: Regional flood exposure in U.S.A

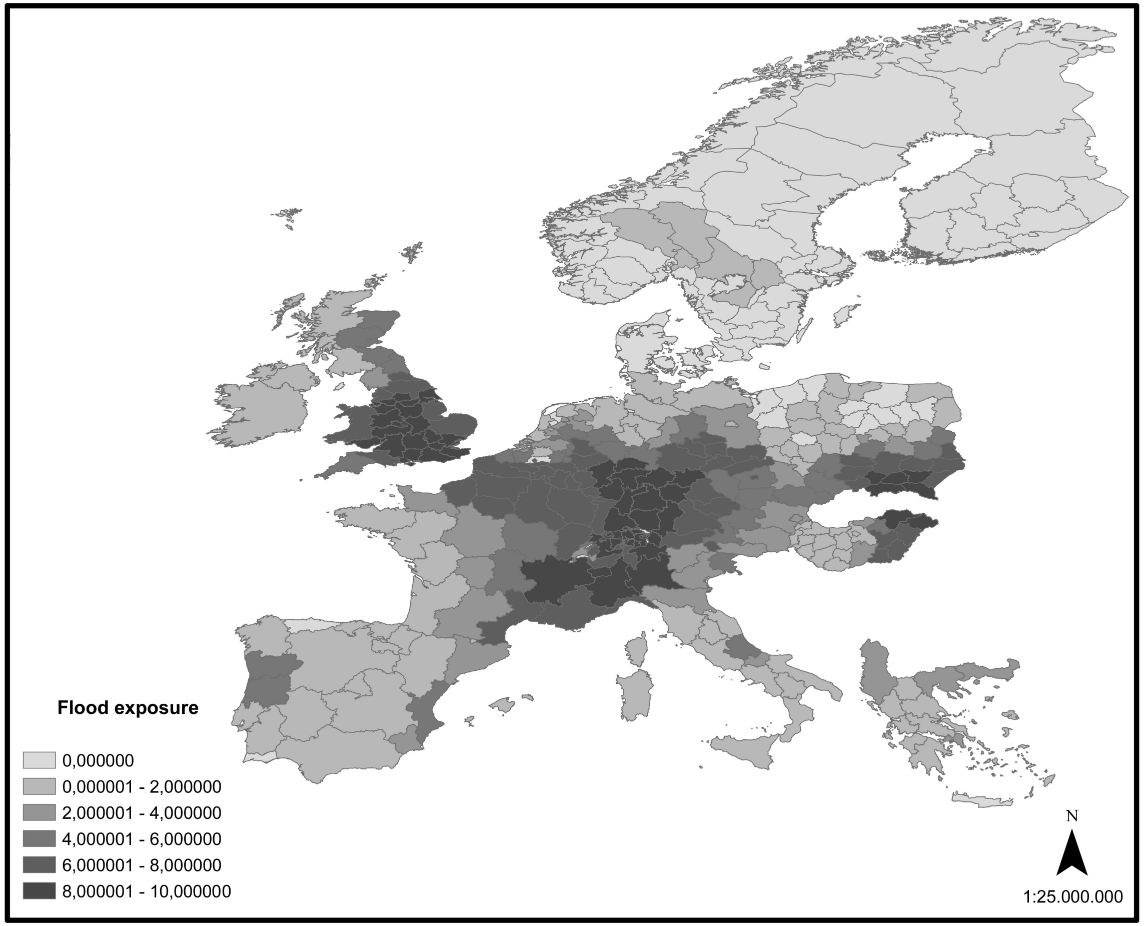

Figure 6: Regional flood exposure in U.S.A

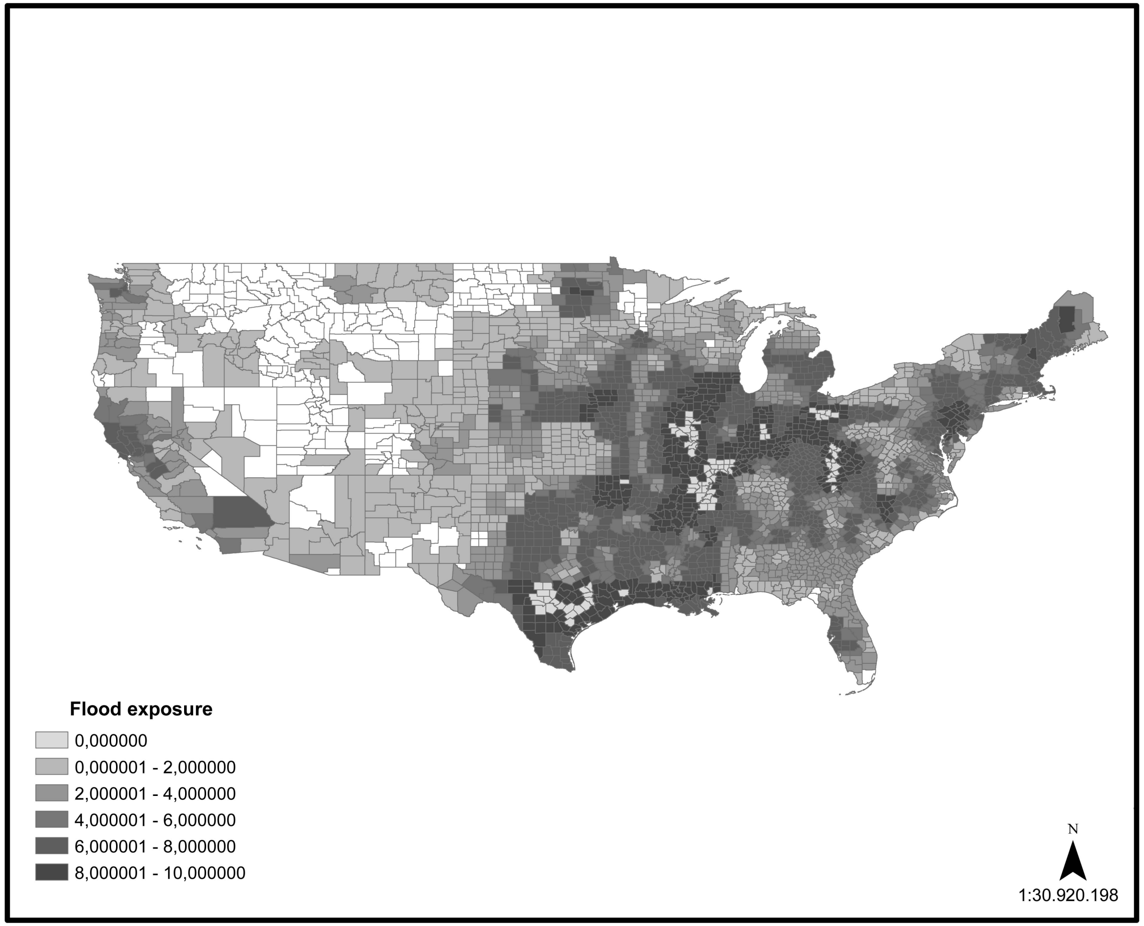

Figure 7: No. of floods per annum in counties in Alaska and Hawaii

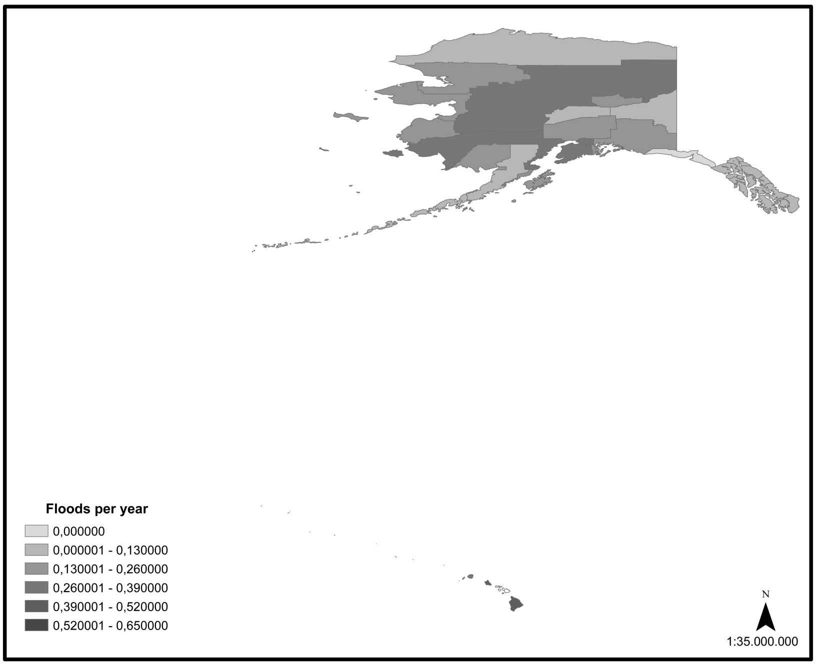

Figure 8: Regional flood exposure in Alaska and Hawaii

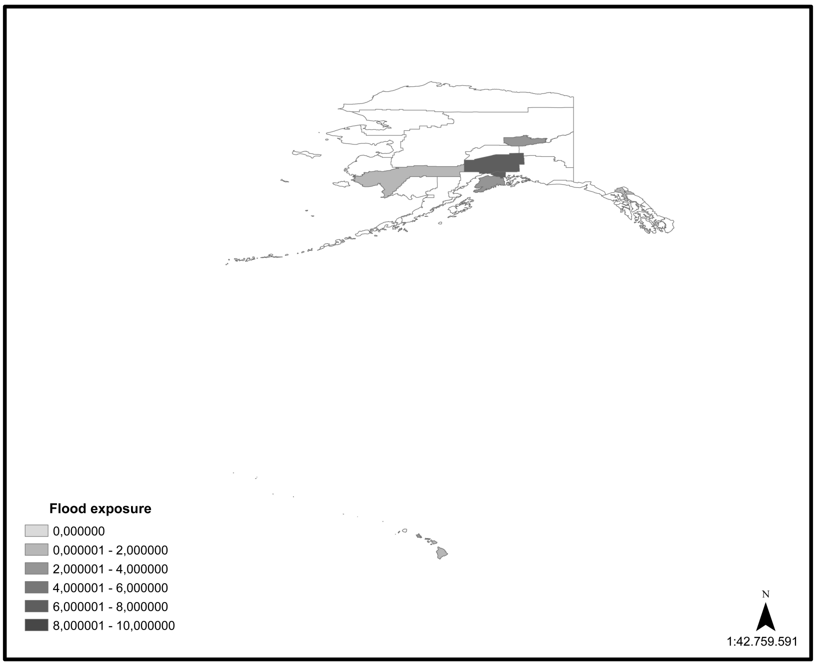

Table 1: Flood exposure in European nations - Summary statistics

Nation	**Mean**	**Std. Dev.**	**Total no. of flood disasters**	**Mean no. of regional floods**	**Std. Dev. of regional floods**	**Min.**	**Max.**
Austria	3.909	2.465	9	11	1.058	0	3
Belgium	5.879	1.990	13	1.091	0.516	0	2
Czech Republic	4.959	2.099	11	1.375	0.699	0	2
Denmark	0.000	0.000	0	0.000	0.000	0	0
Finland	0.000	0.000	0	0.000	0.000	0	0
France	4.363	3.581	42	1.476	1.792	0	6
Germany	5.368	3.591	21	1.124	1.063	0	4
Great Britain & Norther Ireland	5.505	3.741	21	0.733	0.965	0	4
Greece	1.238	1.588	9	1.000	1.706	0	5
Hungary	3.887	3.287	8	1.143	1.251	0	6
Italy	2.983	3.329	34	1.632	1.497	0	4
Luxembourg	7.587	0.493	1	0.000	0.000	0	0
Norway	0.061	0.140	0	0.000	0.000	0	0
Poland	2.428	3.307	7	0.500	0.614	0	2
Portugal	3.645	1.875	9	1.375	1.048	0	3
Spain	1.153	1.904	19	0.647	0.764	0	2
Sweden	0.013	0.112	0	0.000	0.000	0	0
Switzerland	7.486	2.693	5	0.714	0.703	0	2
The Netherlands	3.032	1.795	0	0.000	0.000	0	0

Table 2. The effects of flood on regional GDP in European - GMM-DIFF estimates

Dependent Variable	2.1^a	2.2^a	2.3^b	2.4^c	2.5^c
	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
$\ln y_{it}$	(t-value)	(t-value)	(t-value)	(t-value)	(t-value)
$\ln y_{i,t-1}$	0.438***	0.438***	0.442***	0.437***	0.435***
	(9.14)	(9.20)	(9.44)	(9.11)	(9.15)
$\ln s_{it}$	0.182***	0.180***	0.181***	0.188***	0.186***
	(6.42)	(6.37)	(6.33)	(6.57)	(6.56)
$Agriculture_{it}$	−0.097***	−0.096***	−0.096***	−0.098***	−0.096***
	(−5.71)	(−5.71)	(−5.44)	(−5.55)	(−5.51)
$Service_{it}$	0.136**	0.137**	0.160**	0.154**	0.165**
	(2.14)	(2.12)	(2.27)	(2.34)	(2.49)
$Flood_{it}$	−0.004*			−0.006**	
	(−1.78)			(−2.36)	
$Flood_{i,t-1}$		−0.000			0.003*
		(−0.08)			(1.76)
$(Flood * Exposure)_{it}$			−0.001***		
			(−3.09)		
$(Flood * Insurance)_{it}$				0.007*	
				(1.75)	
$(Flood * Insurance)_{i,t-1}$					−0.008***
					(−2.56)
Year dummies	Yes	Yes	Yes	Yes	Yes
Number of obs.	4,277	4,277	4,277	4,277	4,277
Number of Instruments	194	194	184	205	205
Prob >Chi^2	0.000	0.000	0.000	0.000	0.000
Sargan	0.208	0.147	0.191	0.264	0.301
AR(1)	0.000	0.000	0.000	0.000	0.000
AR(2)	0.244	0.246	0.246	0.242	0.231

Table to be continued.

Table 2. The effects of floods on regional GDP in Europe - GMM-DIFF estimates. *cont.*

Dependent Variable	2.1[a]	2.2[a]	2.3[b]	2.4[c]	2.5[c]
	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
$\ln y_{it}$	(t-value)	(t-value)	(t-value)	(t-value)	(t-value)
Marginal effect of	M.E.	M.E.	M.E.	M.E.	M.E.
flood disasters	(Std.Err.)	(Std.Err.)	(Std.Err.)	(Std.Err.)	(Std.Err.)
In regions without risk-transfer	−0.004*	−0.000	−0.001***	−0.006**	0.003*
mechanisms	(0.002)	(0.002)	(0.000)	(0.003)	(0.002)
In regions with risk-transfer				0.000	−0.005*
mechanisms				(0.003)	(0.003)

Notes: Numbers in parentheses are t-values. ***, **, * indicate significance at the 1, 5 and 10% level. One-step GMM difference estimators based on Arellano & Bond (1991).

[a] The third until the sixth lag of the lagged dependent variable ($y_{i,t-3}$ - $y_{i,t-6}$) and the first until the fifth lag of the flood variable ($Flood_{i,t-1}$ - $Flood_{i,t-5}$) were used as instruments for the lagged dependent variable $y_{i,t-1}$.

[b] The third until the sixth lag of the lagged dependent variable ($y_{i,t-3}$ - $y_{i,t-6}$) and the first until the fifth lag of the interaction term flood variable and flood exposure ($(Flood * Exposure)_{i,t-1}$ - $(Flood * Exposure)_{i,t-5}$) were used as instruments for the lagged dependent variable $y_{i,t-1}$.

[c] The third until the sixth lag of the lagged dependent variable ($y_{i,t-3}$ - $y_{i,t-6}$), the first until the fifth lag of the flood variable ($Flood_{i,t-1}$ - $Flood_{i,t-5}$) and the first and second lag of the interaction term flood variable and mandatory insurance ($(Flood * Ins.)_{i,t-1}$, $(Flood * Ins.)_{i,t-2}$) were used as instruments for the lagged dependent variable $y_{i,t-1}$.

Table 3: The effects of floods on personal income in U.S. counties

Dependent Variable	FE	FE	IV-FE	AH-FD
$\ln y_{it}$	3.1	3.2	3.3	3.4
$\ln y_{i,t-1}$	0.658***	0.658***	0.801***	0.127***
	(0.006)	(0.006)	(0.007)	(0.047)
$\ln(Agric.\ Inc._{it})$	0.025***	0.025***	0.023***	0.035***
	(0.001)	(0.001)	(0.001)	(0.001)
$\ln(Pop.\ density)_{it}$	0.014***	0.013***	−0.002	0.047
	(0.002)	(0.002)	(0.002)	(0.030)
BEA Corr.	0.012***	0.012***	−0.015***	0.009***
	(0.001)	(0.001)	(0.001)	(0.002)
$Flood_{it}$	−0.004***	−0.005***	−0.005***	−0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
$(Flood * Insurance)_{it}$		0.003***	0.002***	0.010***
		(0.001)	(0.001)	(0.003)
$(NFIP)_{it}$		0.002**	0.002**	−0.096***
		(0.001)	(0.001)	(0.007)
County FE	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes
Number of obs.	92,407	92,407	86.444	67,350
Prob $>\text{Chi}^2$	0.000	0.000	0.000	0.000
R^2	0.984	0.984		
Number of Instruments			38	34
Hansen J-Stat			0.662	0.213
Kleinbergen-Paap-Stat			0.000	0.000
1^{st}Stage F-Stat. $\ln y_{i,t-1}$			121.83***	116.03***
1^{st}Stage F-Stat. $(NFIP)_{it}$				178.00***
1^{st}Stage F-Stat. $(Flood * Ins.)_{it}$				1,845.43***
Marginal effect of	M.E.	M.E.	M.E.	M.E.
In regions without risk-transfer mechanisms	−0.004***	−0.005***	−0.005***	−0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
In regions with risk-transfer mechanisms		−0.002***	−0.002***	0.006***
		(0.001)	(0.001)	(0.002)

Notes: Robust standard errors in parenthesis. ***, **, * indicate significance at the 1, 5 and 10% level. First difference Anderson-Hsiao estimator based on Anderson & Hsiao (1981).

Table 4: The effects of floods on personal income in U.S. counties - Robustness Test

Dependent Variable	FE	FE	IV-FE	AH-FD
lny_{it}	4.1	4.2	4.3	4.4
ln$y_{i,t-1}$	0.658***	0.658***	0.801***	0.127***
	(0.006)	(0.006)	(0.003)	(0.049)
ln$(Agric.\ Inc._{it})$	0.025***	0.025***	0.023***	0.035***
	(0.001)	(0.001)	(0.002)	(0.001)
ln$(Pop.\ density)_{it}$	0.014***	0.014***	−0.002	0.039
	(0.002)	(0.002)	(0.002)	(0.029)
BEA Corr.	0.012***	0.012***	−0.005***	0.009***
	(0.001)	(0.001)	(0.002)	(0.002)
$(Flood * Exposure)_{it}$	−0.001***	−0.001***	−0.001***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
$(Flood * Exp * Ins)_{it}$		0.001***	0.001***	0.001***
		(0.000)	(0.000)	(0.000)
$(NFIP)_{it}$		0.001**	0.002**	−0.092***
		(0.001)	(0.001)	(0.007)
County FE	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes
Number of obs.	92,407	92,407	86.444	67,350
Prob >Chi^2	0.000	0.000	0.000	0.000
R^2	0.984	0.984		
Number of Instruments			38	34
Hansen J-Stat			0.384	0.212
Kleinbergen-Paap-Stat			0.000	0.000
1^{st}Stage F-Stat. ln$y_{i,t-1}$			118.57***	117.30***
1^{st}Stage F-Stat. $(NFIP)_{it}$				190.94***
1^{st}Stage F-Stat. $(Flood * Ins.)_{it}$				1,037.56***
Marginal effect of	M.E.	M.E.	M.E.	M.E.
In regions without risk-transfer mechanisms	−0.001***	−0.001***	−0.001***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.001)
In regions with risk-transfer mechanisms		−0.000	0.000***	
		(0.000)	(0.000)	(0.000)

Notes: Robust standard errors in parenthesis. ***, **, * indicate significance at the 1, 5 and 10% level. First difference Anderson-Hsiao estimator based on Anderson & Hsiao (1981).

Table 5. The effects of floods and federal elections on regional GDP in Europe (NUTSII) - GMM-DIFF estimates

Dependent Variable	5.1[a]	5.2[b]	5.3[b]
	Coefficient	Coefficient	Coefficient
lny_{it}	(t-value)	(t-value)	(t-value)
ln$y_{i,t-1}$	0.438***	0.463***	0.439***
	(9.14)	(11.80)	(9.28)
lns_{it}	0.182***	0.156***	0.178***
	(6.42)	(7.79)	(6.39)
$Agriculture_{it}$	−0.097***	−0.090***	−0.096***
	(−5.71)	(−6.51)	(−5.72)
$Service_{it}$	0.136**	0.057	0.38**
	(2.14)	(2.12)	(2.27)
$Flood_{it}$	−0.004*	−0.003	
	(−1.78)	(−1.06)	
$Flood_{i,t-1}$			0.004**
			(2.16)
$(Flood * Election)_{it}$		−0.004	
		(−1.09)	
$(Flood * Election)_{i,t-1}$			−0.014***
			(−3.07)
$(Election)_{it}$		−0.002**	
		(−1.96)	
$(Election)_{i,t-1}$			0.001
			(0.00)
Year dummies	Yes	Yes	Yes
Number of obs.	4,277	4,277	4,277
Number of Instruments	194	263	260
Prob >Chi^2	0.000	0.000	0.000
Sargan	0.208	0.901	0.841
AR(1)	0.000	0.000	0.000
AR(2)	0.244	0.204	0.243
Marginal effect of	M.E.	M.E.	M.E.
flood disasters	(Std.Err.)	(Std.Err.)	(Std.Err.)
In years without federal	−0.004*	−0.003	0.004**
elections	(0.002)	(0.003)	(0.002)
In years with federal		−0.007**	−0.009***
elections		(0.003)	(0.003)

Notes: Numbers in parentheses are t-values. ***, **, * indicate significance at the 1, 5 and 10% level. One-step GMM difference estimators based on Arellano & Bond (1991).

[a]The third until the sixth lag of the lagged dependent variable ($y_{i,t-3}$ - $y_{i,t-6}$) and the first until the fifth lag of the flood variable ($Flood_{i,t-1}$ - $Flood_{i,t-5}$)were used as instruments for the lagged dependent variable $y_{i,t-1}$.

[b]The third until the sixth lag of the lagged dependent variable ($y_{i,t-3}$ - $y_{i,t-6}$), the first until the fifth lag of the flood variable ($Flood_{i,t-1}$ - $Flood_{i,t-5}$), the first and second lag of the interaction term flood variable and election year ($(Flood* Election)_{i,t-1}$, $(Flood * Election)_{i,t-2}$) and the first and second lag of the election year ($(Election_)i, t-1$, $(Election)_{i,t-2}$,)were used as instruments for the lagged dependent variable $y_{i,t-1}$.

Table 6: The effects of floods on personal income and U.S. elections in U.S. counties

Dependent Variable	FE	AH-FD	FE	AH-FD
$\ln y_{it}$	6.1	6.2	6.3	6.4
$\ln y_{i,t-1}$	0.658***	0.130***	0.658***	−0.130***
	(0.006)	(0.045)	(0.006)	(0.045)
$Flood_{it}$	−0.004***	−0.002***	−0.005***	−0.002***
	(0.001)	(0.000)	(0.001)	(0.000)
$(Flood * Congressional$	−0.000	−0.000***		
$Elections)_{it}$	(0.000)	(0.000)		
$(CongressionalElections)_{it}$	−0.112***	−0.012***		
	(0.003)	(0.002)		
$(Flood * Presidential)$			0.000	−0.001**
$Elections)_{it}$			(0.001)	(0.000)
$(PresidentialElections)_{it}$			−0.022***	0.019***
			(0.001)	(0.002)
Other controls	Yes	Yes	Yes	Yes
County FE	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes
Number of obs.	92,407	67,350	92,407	67,350
Prob $>$Chi^2	0.000	0.000	0.000	0.000
R^2	0.984		0.984	
Number of Instruments		33		33
Hansen J-Stat		0.185		0.183
Kleinbergen-Paap-Stat		0.000		0.000
1stStage F-Stat. $\ln y_{i,t-1}$		138.79***		138.79***
Marginal effect of flood	M.E.	M.E.	M.E.	M.E.
In years without	−0.004***	−0.002***	−0.005***	−0.002***
election	(0.001)	(0.000)	(0.001)	(0.000)
In years with	−0.004***	−0.002***	−0.005***	−0.003***
election	(0.001)	(0.000)	(0.001)	(0.001)

Notes: Robust standard errors in parenthesis. ***, **, * indicate significance at the 1, 5 and 10% level. First difference Anderson-Hsiao estimator based on Anderson & Hsiao (1981).

Table 7: The effects of floods and the NFIP on personal income in U.S. counties over time (Anderson-Hsiao First-Diff estimator)

	Coefficients (Std. Err.)		ME (Std Err.)
$Flood_{it}$	−0.005***	No	−0.005***
	(0.001)	NFIP	(0.001)
$(Flood * Insurance)_{it}$	0.002*	NFIP	−0.003***
	(0.001)		(0.001)
$(NFIP)_{it}$	0.004***		
	(0.001)		
$Flood_{i,t-1}$	0.007***	No	0.007***
	(0.001)	NFIP	(0.001)
$(Flood * Insurance)_{i,t-1}$	−0.003***	NFIP	0.004***
	(0.001)		(0.001)
$(NFIP)_{i,t-1}$	−0.001		
	(0.002)		
$Flood_{i,t-2}$	−0.004***	No	−0.005***
	(0.001)	NFIP	(0.001)
$(Flood * Insurance)_{i,t-2}$	0.003***	NFIP	−0.002***
	(0.001)		(0.001)
$(NFIP)_{i,t-2}$	−0.000		
	(0.002)		
$Flood_{i,t-3}$	0.002***	No	0.002***
	(0.001)	NFIP	(0.001)
$(Flood * Insurance)_{i,t-3}$	−0.002**	NFIP	0.000
	(0.001)		(0.001)
$(NFIP)_{i,t-3}$	0.001		
	(0.002)		
$Flood_{i,t-4}$	−0.003***	No	−0.003***
	(0.001)	NFIP	(0.001)
$(Flood * Insurance)_{i,t-4}$	0.002***	NFIP	−0.001**
			(0.001)
$(NFIP)_{i,t-4}$	0.002**		
	(0.001)		
$Flood_{i,t-5}$	0.003***	No	0.003***
	(0.001)	NFIP	(0.001)
$(Flood * Insurance)_{i,t-5}$	−0.002**	NFIP	0.000
	(0.001)		(0.001)
$(NFIP)_{i,t-5}$	−0.001		
	(0.001)		
Std. Dev.			**0.0024**

Notes: Robust standard errors in parenthesis. ***, **, * indicate significance at the 1, 5 and 10% level.

Table 8: The effects of floods and election years on personal income in U.S. counties over time (Anderson-Hsiao First-Diff estimator)

Congressional Elections				Presidential Elections			
	Coefficients		ME		Coefficients		ME
$Flood_{it}$	−0.003***	No	−0.003***	$Flood_{it}$	−0.003***	No	−0.003***
	(0.001)	Elec	(0.001)		(0.001)	Elec	(0.001)
$(Flood * Elec)_{it}$	−0.001***	Elec	−0.004***	$(Flood * Elec)_{it}$	−0.001*	Elec	−0.004***
	(0.000)		(0.001)		(0.001)		(0.001)
$Flood_{i,t-1}$	0.005***	No	0.005***	$Flood_{i,t-1}$	0.005***	No	0.005***
	(0.001)	Elec	(0.001)		(0.001)	Elec	(0.001)
$(Flood * Elec)_{i,t-1}$	0.001*	Elec	0.006***	$(Flood * Elec)_{i,t-1}$	0.000	Elec	0.006***
	(0.000)		(0.001)		(0.000)		(0.001)
$Flood_{i,t-2}$	−0.003***	No	−0.003***	$Flood_{i,t-2}$	−0.003***	No	−0.003***
	(0.001)	Elec	(0.001)		(0.001)	Elec	(0.001)
$(Flood * Elec)_{i,t-2}$	0.000	Elec	−0.003***	$(Flood * Elec)_{i,t-2}$	0.001***	Elec	−0.004***
	(0.000)		(0.001)		(0.000)		(0.001)
$Flood_{i,t-3}$	0.002***	No	0.002***	$Flood_{i,t-3}$	0.001**	No	0.001**
	(0.001)	Elec	(0.001)		(0.001)	Elec	(0.001)
$(Flood * Elec)_{i,t-3}$	−0.001***	Elec	0.001***	$(Flood * Elec)_{i,t-3}$	0.001	Elec	0.002***
	(0.001)		(0.001)		(0.000)		(0.001)
$Flood_{i,t-4}$	−0.002***	No	−0.002***	$Flood_{i,t-4}$	−0.002***	No	−0.002***
	(0.001)	Elec	(0.001)		(0.001)	Elec	(0.001)
$(Flood * Elec)_{i,t-4}$	0.000	Elec	−0.002***	$(Flood * Elec)_{i,t-4}$	−0.001*	Elec	−0.003***
	(0.000)		(0.001)		(0.001)		(0.001)
$Flood_{i,t-5}$	0.002***	No	0.002***	$Flood_{i,t-5}$	0.002***	No	0.002***
	(0.001)	Elec	(0.001)		(0.001)	Elec	(0.001)
$(Flood * Elec)_{i,t-5}$	−0.000	Elec	0.002***	$(Flood * Elec)_{i,t-5}$	0.000	Elec	0.002***
	(0.000)		(0.001)		(0.000)		(0.000)
Std. Dev.			**0.0035**				**0.0038**

Notes: Robust standard errors in parenthesis. ***, **, * indicate significance at the 1, 5 and 10% level.

Figure 9: Deviation from growth path by risk-transfer system over time (U.S. sample, Flood Year - 5th lag)

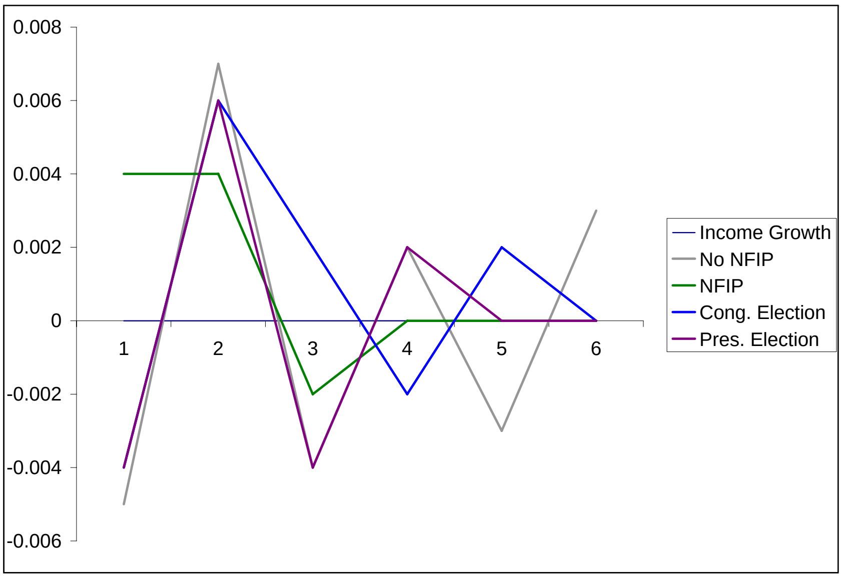

Table 9: Description and Sources of Data

Variable	Description	Source
Flood disasters	Data on flood disasters of certain extent in Europe, from 1970-1999	EM-DAT, Center for Research on the Epidemiology of Disasters (CRED), Brussels
	Flood events on U.S. county level	Sheldus database, Hazards & Vulnerability Research Institute, University of South Carolina
Flood hazard areas	GIS-Data; geo-referenced flood areas based on historical events in Europe using $1° \times 1°$ grid cells	Dilley et al. (2005)
GDP Europe	Gross Domestic Product in mio. €(1995 PPP) disaggregated on NUTSII-level	Cambridge Econometrics, European Regional Data, Cambridge
Investment Europe	Investment rate disaggregated on NUTSII-level	Cambridge Econometrics, European Regional Data, Cambridge
Personal Income USA	Personal income in USD (1995 PPP)	Regional Economic Information System (REIS), Bureau of Economic Analysis, U.S. Department of Commerce