University of Innsbruck

Working Papers
in
Economics and Statistics

Estimating the effects of risk transfer mechanisms against floods in Europe and U.S.A.: A dynamic panel approach

Paul Raschky

2007-05

University of Innsbruck
Working Papers in Economics and Statistics

The series is jointly edited and published by

- Department of Economics (Institut für Wirtschaftstheorie, Wirtschaftspolitik und Wirtschaftsgeschichte)
- Department of Public Finance (Institut für Finanzwissenschaft)
- Department of Statistics (Institut für Statistik)

Contact Address:
University of Innsbruck
Department of Public Finance
Universitaetsstrasse 15
A-6020 Innsbruck
Austria
Tel: +43 512 507 7151
Fax: +43 512 507 2970
e-mail: finanzwissenschaft@uibk.ac.at

The most recent version of all working papers can be downloaded at
http://www.uibk.ac.at/fakultaeten/volkswirtschaft_und_statistik/forschung/wopec

For a list of recent papers see the backpages of this paper.

Estimating the Effects of Risk Transfer Mechanisms against floods in Europe and U.S.A.: A Dynamic Panel Approach.

Paul A. Raschky[1]

March 27, 2007

[1]Institute of Public Finance, University of Innsbruck, Universitaetsstrasse 15, A-6020 Innsbruck and alpS - Centre for Natural Hazard Management, Innsbruck Austria. Tel.:+43-512-507-7160 13; Fax: +43-512-507-2970; Email:paul.raschky@uibk.ac.at. The author would like to thank Michael Pfaffermayr, Michael Rinderer, Hannelore Weck-Hannemann and Hannes Winner for their useful comments.

Abstract

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 institutional resilience to natural processes that ultimately determines whether natural processes result in a natural hazard or not. An appropriate method for an international institutional comparison in the field of natural hazard management is still missing. The focus in this paper is on the institutional comparison of societal risk transfer mechanisms mitigating the effects disasters. Dynamic panel estimates using growth data from a) 199 European regions (NUTSII) between 1990-2004 and b) 3.050 U.S. counties between 1970-2003 reveal a significant negative impact of historical flood events on regional economic development. The application of GIS-data on the spatial distribution of flood events further allows to control for a regions exposure to floods. In the short run, a major flood event in a European region reduces the regional GDP by 0.4%-0.6%; an average flood event in the U.S.A reduces the personal income by 0.3%-0.4%. Mandatory insurance regimes in Europe absorb the negative short-run effect of a flood, while the National Flood Insurance Program in the U.S.A. mitigate the effects of a flood by about 50%. The results provide empirical foundation for the proposition that ex ante risk transfer policies are more efficient than ex post disaster relief.

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

JEL classification: G22, Q54, R11

1 Introduction

In the ongoing discussions on the effects of climate change on society numerous studies estimated the "economic" impact of changing climatic conditions. One result of anthropogenic climate change could be an increase in the frequency of extreme weather events (IPCC 2001). 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 adopation 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 environmental, but crucially depends on the behaviour of human beings living in this environment. Human (economic) activity in general and thus human behaviour 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. In particular 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 will be estimated by using dynamic panel methods. 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 behaviour (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 occured, victims suffer from a loss of wealth and income. For example after the 2005 flooding in alpine areas in Europe, victims in the canton fo 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 ressources 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. Rose (2004) identifies three comprehensive approaches to estimate economic losses due to natural disasters: Computable General Equilibrium Models (CGE), Input-Output Models (I-O) and econometric analysis.

Computable general equilibrium models (CGE) can simualte individual optimization behaviour in the context of e.g. business interruptions or ressource shortages resulting from natural disasters. Rose & Liao (2005) applied this technique to estimate the regional economic impacts of disruptions in the water services of the Portland (Oregon, US) metropolitan area. The simulation yiels in overall (direct and indirect) losses in output from water outage between 30,5% (with pre-event mitigation) and 41% (without any pre-eventmitigation) within the first week after an earthquake of magnitude 6.1 took place. This implicates between $418 mill. and $561 mill. of losses to the gross output of the Portland metropolitan area within this period. It is important to note, that these studies only measure a small fraction of actual effects of disasters on the economy and focussing on macroeconomic variables can thus deliver a broader picture. Auffret (2003) developed a simple framework to perform such an assesment on the aggregate level.

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 Caribean 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 ambigous. 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 consumtion. 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 technolgoy endowment. A recent study by Crespo-Cuaresmo, Hlouskove & Obersteiner (2007) 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 ingore the country-specific aspects of the aggregate production function resultin in an omitted variable bias. His analysis shows "[...] that persistent differences in technology level and institutions are a signifcant 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 Kathrina 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 characterisitcs regarding a country's exposure to natural hazards. This is simply due to the fact, that such data was not availlable 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 occured in an already hazard-prone area or a region with actual low level of occurence 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 ressources 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 institional design of natural hazard management and its effect on the relationship between natural disasters and economic development will be analysed. A comparison of alternative instituional designs in natural hazard management allows to examine the stengths and weaknesses of different systems and identify more efficienct insititutions. In this paper the focus clearly 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 seperated. In a third step he evaluated the impact of instituions 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 expereince 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 inequaltiy (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 sitution 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 underestimatation of risk of low-probability high

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

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 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, houseowners in hazard-prone areas are obliged to purchase insurance coverage against floods. To other houseowners flood insurance is available at reduced premiums. Depending on the extent of coverage, such an instiutionalized 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-protectiong 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 phenomenom that people underinsure or do not insure at all due to anticipated governmental assistance and/or private charity (Raschky & Weck-Hannemann (2006) Schwarze & Wagner (2004)). 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 fo 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 governmemental 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 occured 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 endgenous 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 phyiscal 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

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

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 effecive labour $A(t) L(t)$, 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 labour, K/AL, y as the level of output per effective unit of labour, Y/AL, and δ the constant rate of depreciation, the dynamics of k are given by

$$\begin{aligned} \dot{k} &= sy_t - (n+g+\delta) k_t - D(F_t, \phi_t) k_t & (4) \\ &= sk_t^{\alpha} - (n+g+\delta) k_t - D(F_t, \phi_t) k_t. & (5) \end{aligned}$$

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..

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

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

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

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

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

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 homogenous 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

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

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

The macro-data for Europe was kindly 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 Epidemology of Disasters (CRED) in Brussels. EM-DAT has collected around 12,000 reports of different disasters, such as flood, storms, earthquakes, volcanic erruptions, 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 occured 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 a possible increase of such events due to climate change - the effects of an average historical flood might be more valuble 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 apporpriate 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 endogenity 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[2]. Figure 1 represents the number of floods per year that occured 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 occurence 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 occured early in a year might have been absorbed at end of the year. The problem in accounting for the month of the flood's occurence 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 collected and georeferenced by the Dartmouth Flood Obsrevatory. 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

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

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) availlable 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%[3]. 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 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[4]. 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[5] 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.

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

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

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

5 Empirics

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

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

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 wether 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 availlable 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 the application of the dynamic panel data models. The analysis follows the suggestions made by **?**. 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, Mueller & Tondel (2004). Equation 6 states that the disaster funtion 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 (**?**, **?**) cannot be used and equation 14 is estimated using the one-step difference GMM.

5.1 Preliminary Empirical Results

The results for Europe and the U.S.A. cannot be compared directly, as the samples differ in their flood variables as well as the risk-transfer varialbes. In addition, the Bureau of economic analysis has adjusted the income on county level for several major disasters (Bureau of Economic Analysis (BEA) 2006)[6]. We have accounted for this adjustment by simply including a dummy ($Corryear$) that switches to 1 for the years an adjustment took place.

Therefore the reader should compare similarities in the signs of the coefficients rather the absolute size of the coefficients. Table 2 (Europe) and table 3 (U.S.A) summarize the results of the Arellano Bond dynamic panel-regression of the basic estimation, where the effects of a flood on regional economic growth are estimated. If a flood occured within the same year it has the expected negative effect on regional GDP in Europe (column 2.1) and county level personal income in the U.S. (column 3.1). The coefficient of the flood-dummy for the European estimates is larger than the coefficient for the U.S. This can be explained that the Sheldus database, the source for the U.S. flood-dummy, records nearly all flood events while the EM-DAT-database (Europe) only files major flood events. The sign of the lagged flood-dummy (column 2.2 for Europe and column 3.2 for the U.S.) is almost 0 for Europe and positive and significant for the U.S. estimates. Combining

[6]The adjustments relevant for this analysis are Hurricans 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.

the flood-dummy with the GIS-data on the regional flood exposure leads to a smaller coefficient in both samples (columns 2.3 and 3.3).

- TABLE 2 about here -

- TABLE 3 about here -

The next step consisted of the inclusion of institutional variables. As already mentioned, it is not solely the natural process of flooding, but the process in combination with the institutional settings that might result in a disaster. The interaction-term accounting for a flooding in a region endowed with mandatory insurance absorbs the entire negative effect of the disaster dummy(column 2.4). In the U.S. sample the interaction term for a flood in a county participating in the NFIP mitigates the effect by about 50%. Estimating the effects of risk-transfer mechanisms in the following year the results show a different picture. In Europe as well as in the U.S. the risk-transfer regimes have a significant negative effect on regional income and the effect is even bigger than the positive effect of the lagged flood-variable. This means a negative net-effect of risk transfer mechanisms in the following year.

- TABLE 4 about here -

- TABLE 5 about here -

The estimates regarding the effects of election years and the assumed bigger generosity of politicians seem to support the theory. Floods that took place in years with federal elections have twice the negative impact on regional GDP in Europe than floodings in other years. In the following year the effect of the interaction term is about -0.9%, while the coefficient for the lagged flood variable is 0.4%. Thus, the positive effect of a flood in the follow-up year is completly diminished through inefficiencies created by governmental assistance. For floodings in election years in the U.S.A. apply similar 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 disasterimpact within the same year and decrease the positive effect in the following year.

6 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. Additionally the impact of instituional resilience was brought forward. Regions that have implemented mandatory insurance regimes (Europe) or take part in the National Flood Insurance Program (U.S.A) are clearly better off than regions without such a mechanism. Floodings that occured during election years (as an empirical proxy for governmental relief) have an even larger negative impact on regional economic development.

References

Albala-Bertrand, J. M. (1993), 'Natural disaster situations and growth: A macroeconomic model for sudden disaster impacts', *World Development* **21**(9), 1417–1434.

Anbarci, N., Escaleras, M. & Register, C. A. (2005), 'Earthquake fatalities: the interaction of nature and political economy', *Journal of Public Economics* **89**(9-10), 1907–1933.

Anderson, T. W. & Hsiao, C. (1981), 'Estimation of dynamic models with error components', *Journal of American Statistical Association* **76**, 589–606.

Arellano, M. & Bond, S. (1991), 'Some tests of specification for panel data: Monte carlo evidence and an application to employment equations', *Review of Economic Studies* **58**, 277–297.

Arellano, M. & Bover, O. (1995), 'Another look at the instrumental variables estimation of error-components models', *Journal of Econometrics* **68**, 29–51.

Auffret, P. (2003), High consumption volatility: The impact of natural disasters?, World bank policy research paper 2962, World Bank.

Babcock, M. & Mitchell, B. (1980), 'Impact of flood hazard on residential property values in galt (cambridge), ontario', *Water Resources Bulletin* **16**(3), 532–537.

Badinger, H., Mueller, W. G. & Tondel, G. (2004), 'Regional convergence in the european union, 1985-1999: A spatial dynamic panel analysis', *Regional Studies* **38**(3), 241–253.

Besley, T. & Burgess, R. (2002), 'The political economy of government responsiveness: Theory and evidence from India', *The Quarterly Journal of Economics* **117**(4), 1415–1451.

Blundell, R. & Bond, S. (1998), 'Initial conditions and moment restrictions in dynamic panel data models', *Journal of Econometrics* **87**, 11–43.

Bureau of Economic Analysis (BEA) (2006), Local area personal income and employment methodology, Methodology working paper series mp-5, U.S. Department of Commerce,Bureau of Economic Analysis.

Crespo-Cuaresmo, J., Hlouskove, J. & Obersteiner, M. (2007), 'Natural disasters as creative destruction: Evidence from developing countries', *Economic Inquiry* **forthcoming**.

Dilley, M., Chen, R. S., Deichmann, U., Lerner-Lam, A. L., Arnold, M., Agwe, J., Buys, P., Kjekstad, O., Lyon, B. & Yetman, G. (2005), Natural disaster hotspots: A global risk analysis, Disaster risk management series no. 5, The World Bank and Columbia University.

Federal Disaster Management Agency (2007), The national flood insurance program community status book, Technical report, FEMA Publications.

Garrett, T. A. & Sobel, R. S. (2003), 'The political economy of FEMA disaster payments', *Economic Inquiry* **41**(3), 496–509.

Gassebner, M., Keck, A. & Teh, R. (2006), Shaken, not stirred: The impact of disasters on international trade, Kof working ppaper no. 0-139, Swiss Institute for Business Cycles (KOF), Swiss Federal Institute of Technology Zurich (ETH).

Halliday, T. (2006), 'Migration, risk, and liquidity constraints in el salvador', *Economic Development and Cultural Change* **54**(4), 893–925.

Hazards & Vulerability Research Institute (2007), The spatial hazard events and losses database for the united states (version 5.1 - online database), available from "http://www.sheldus.org", University of South Carolina.

Ikefuji, M. & Horii, R. (2006), Natural disasters in a two-sector model of endogenous growth, mimeo, Graduate School of Economics, Osaka University.

Intergovernmental Panel on Climate Change (IPCC) (2001), *Climate Change 2001: The Scientific Basis*, Cambridge University Press.

Islam, N. (1995), 'Growth empirics: A panel data approach', *The Quarterly Journal of Economics* **110**(4), 1127–1170.

Jaffee, D. & Russell, T. (2003), Markets under stress: The case of extreme event insurance, *in* R. Arnott, B. Greenwald, R. Kanbur & B. Nalebuff, eds, 'Economics of an Imperfect World', MIT Press, pp. 35–52.

Judson, R. A. & Owen, A. L. (1999), 'Estimating dynamic panel data models: a guide for macroeconomists', *Economics Letters* **65**, 9–15.

Kahn, M. E. (2005), 'The death toll from natural disasters: The role of income, geography and institutions', *The Review of Economics and Statistics* **87**(2), 271–284.

Kunreuther, H. (2000), Strategies for dealing with large-scale and environmental risks, *in* H. Folmer, L. Gabel, S. Gerking & A. Rose, eds, 'Frontiers in Environmental Economics', Edward Elgar, pp. 293–318.

Kunreuther, H. & Pauly, M. (2006), 'Rules rather than discretion: Lessons from Hurricane Katrina', *Journal of Risk and Uncertainty* **33**, 101–116.

Mankiw, G. N., Romer, D. & Weil, D. N. (1992), 'A contribution to the empirics of economic growth', *The Quarterly Journal of Economics* **107**(2), 407–437.

Mustafa, D. (2003), 'Reinforcing vulnerability? disaster relief, recovery and response to the 2001 flood in Rawalpindi, Pakistan', *Environmental Hazards* **5**, 71–82.

Raschky, P. A. & Weck-Hannemann, H. (2006), 'El riesgo de caridad. Análisis económico de la ayuda gubernamental tras las catástrofes naturales', *Gerencia de riesgos y seguros* **93**, 17–31.

Rasmussen, T. N. (2004), Macroeconomic implications of natural disasters in the Caribean, Imf working paper 04/224, International Monetary Fund.

Rose, A. (2004), Economic principles, issues, and research priorities in hazard loss estimation, *in* Y. Okuyama & S. E. Chang, eds, 'Modeling Spatial and Economic Impacts of Disasters', Springer-Verlag, pp. 13–36.

Rose, A. & Liao, S.-Y. (2005), 'Modeling regional economicresilience to disasters: A computable general equilibrium analysis of water service disruptions', *Journal of Regional Science* **45**(1), 75–112.

Schwarze, R. & Wagner, G. G. (2004), 'In the aftermath of dresden: New directions in german flood insurance', *The Geneva Papers on Risk and Insurance* **29**(2), 164–168.

Schweizerische Rueckversicherungs-Gesellschaft (1998), Ueberschwemmungen: Ein versicherbares risiko? - eine marktuebersicht, Technical report, Swiss Re Publications.

Skidmore, M. (2001), 'Risk, natural disasters, and household savings in a life cycle model', *Japan and the World Economy* **13**, 15–34.

Skidmore, M. & Toya, H. (2002), 'Do natural disasters promote long-run growth?', *Economic Inquiry* **40**(4), 664–687.

Tavares, J. (2004), 'The open society assesses its enemies: shocks, disasters and terrorist attacks', *Journal of Monetary Economics* **51**, 1039–1070.

Tol, R. S. J. & Leek, F. P. M. (1999), Economic analysis of natural disasters, *in* T. E. Downing, A. A. Olsthoorn & S. J. Tol, Richard, eds, 'Climate, Change and Risk', Routledge, pp. 308–327.

Von Ungern-Sternberg, T. (2004), *Efficient Monopolies: The Limits of Competition in the European Property Insurance Market*, Oxford University Press.

Yang, D. (2005), Coping with disasters: The impact of hurricanes on international financial flows, 1970-2001, Ford school of public policy working paper no. 2005-003, Ford School of Public Policy and Department of Economics University of Michigan.

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

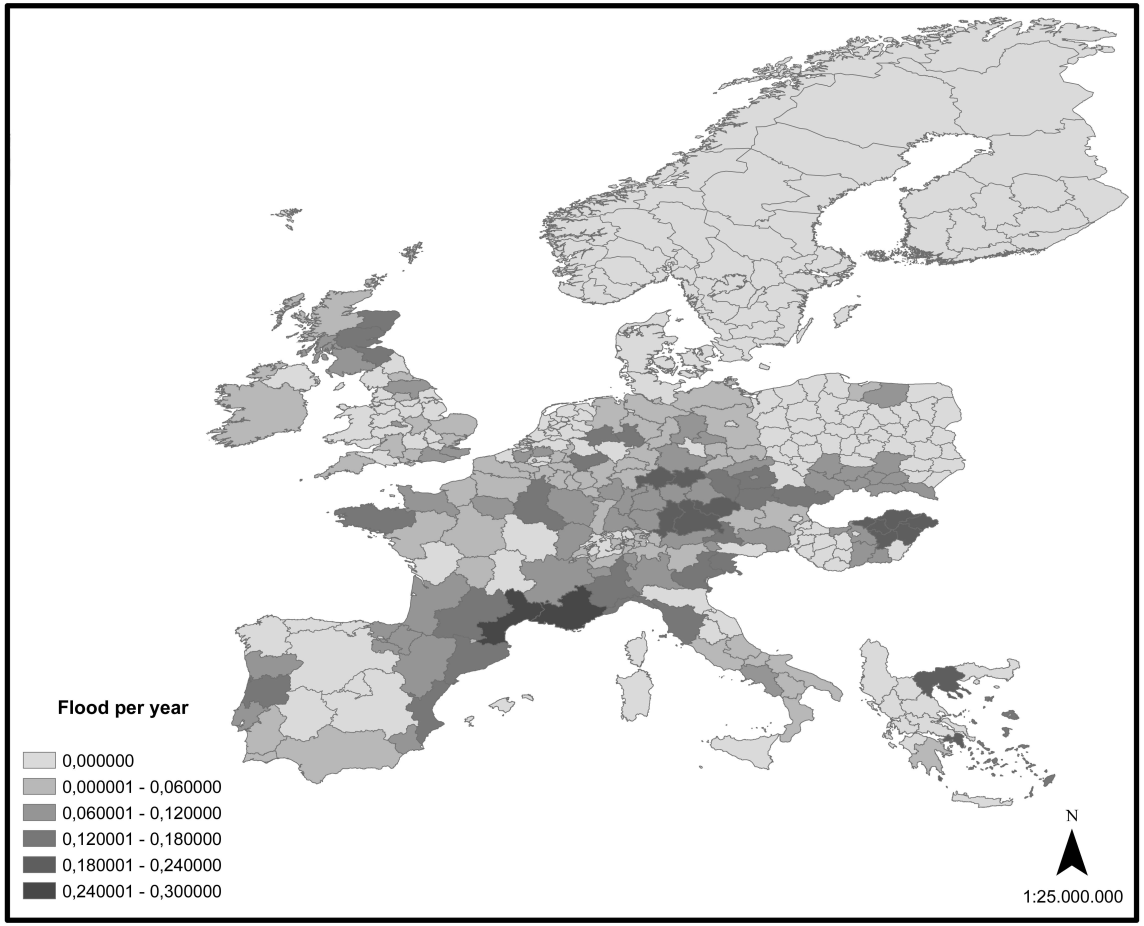

Figure 2: No. of floods per annum in U.S. counties

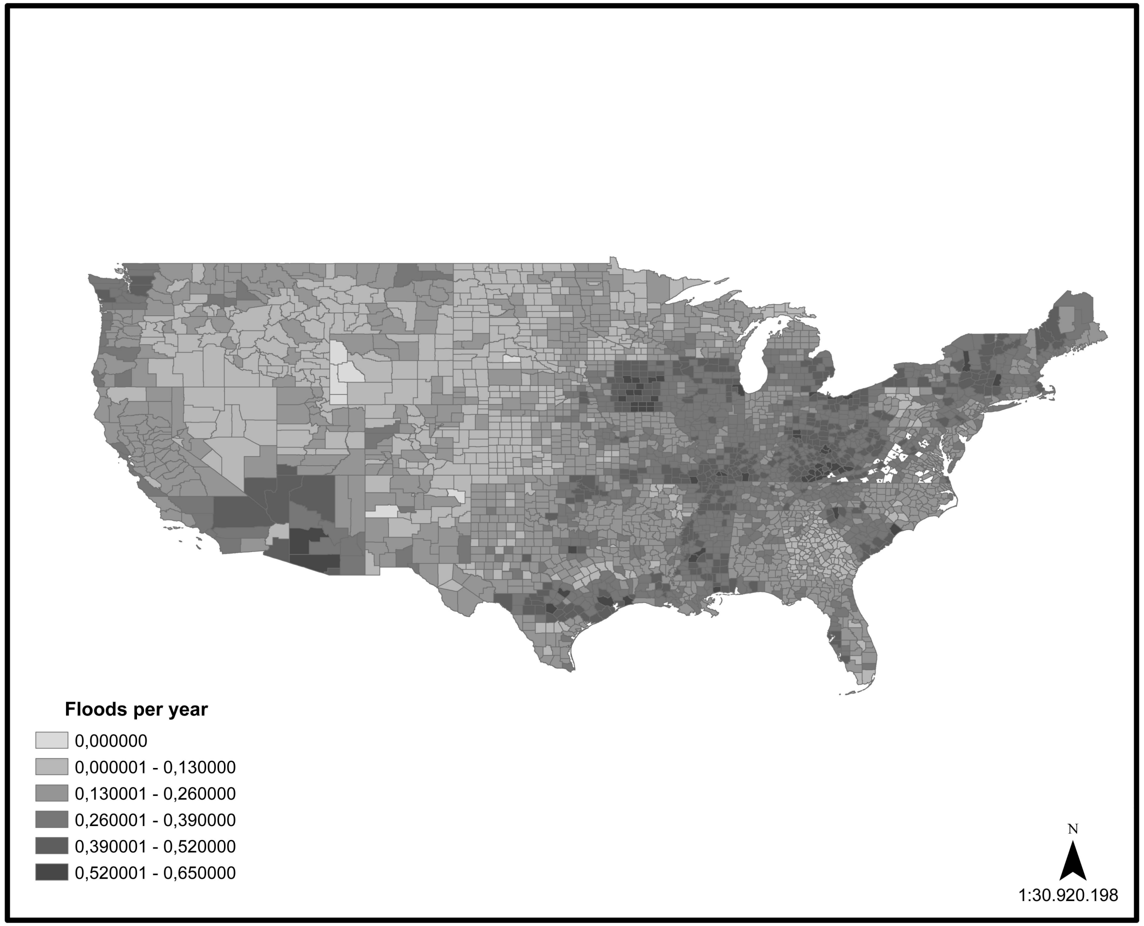

Figure 3: Frequency of Floods per month in Europe

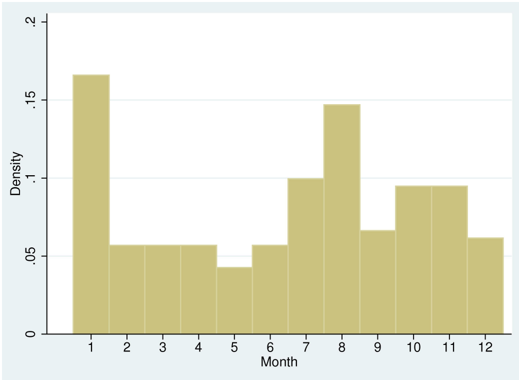

Figure 4: Frequency of Floods per month in U.S.A

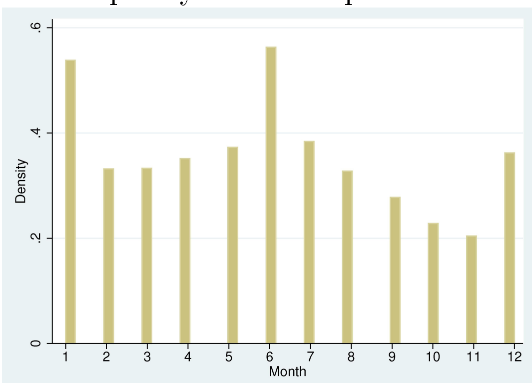

Figure 5: Regional flood exposure in U.S.A

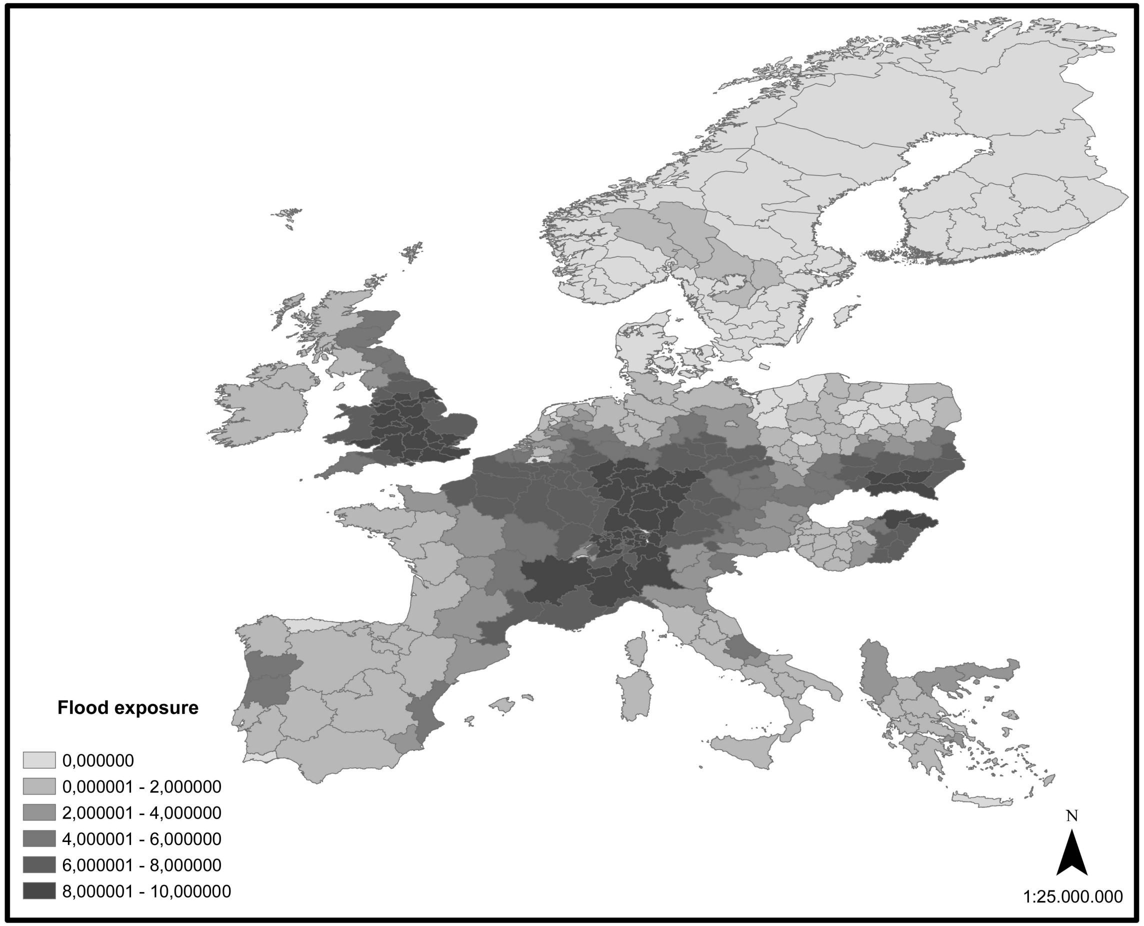

Figure 6: Regional flood exposure in U.S.A

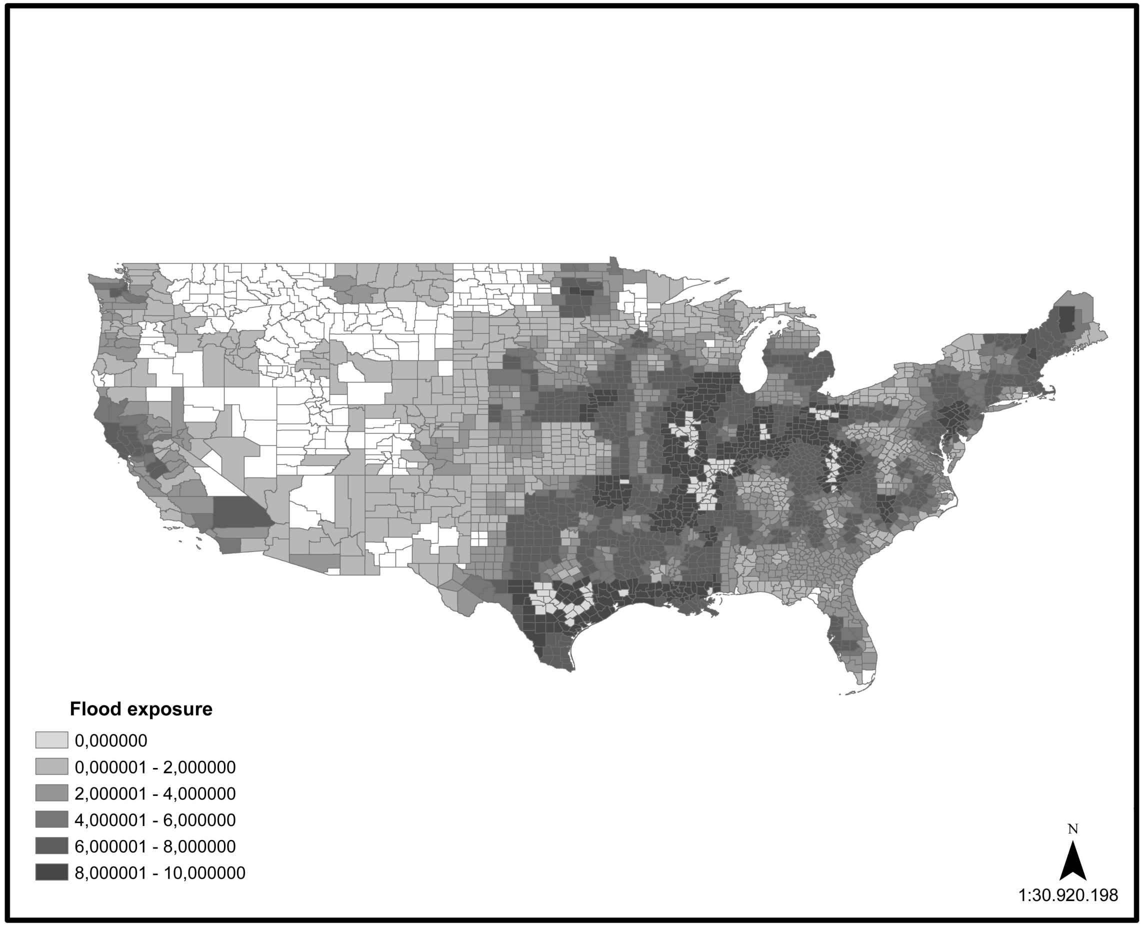

Figure 7: No. of floods per annum in counties in Alaska and Hawaii

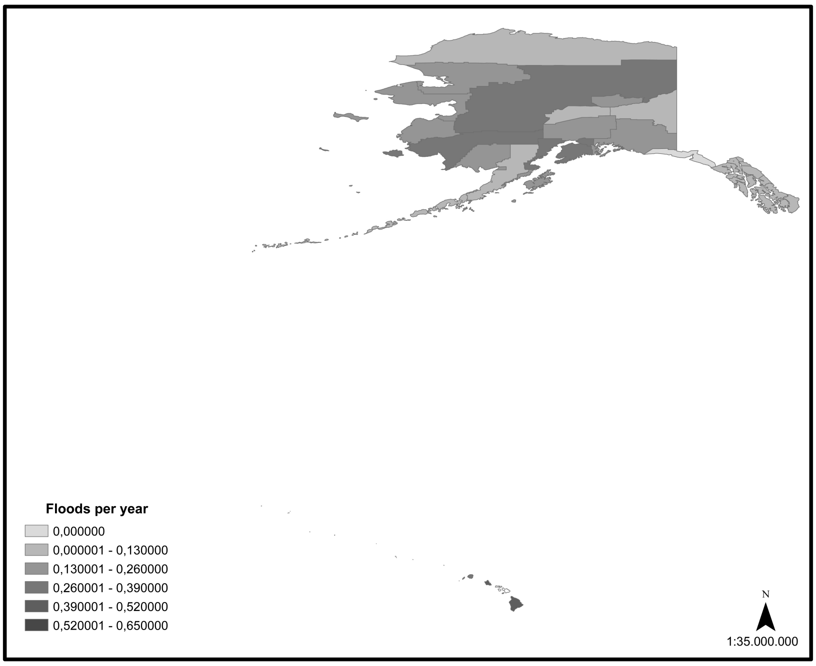

Figure 8: Regional flood exposure in Alaska and Hawaii

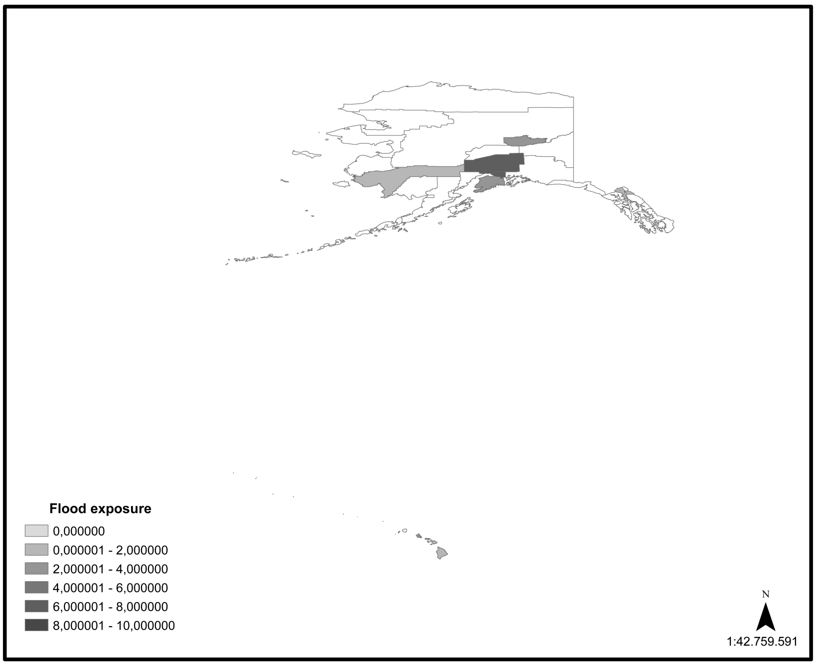

Table 1: Flood exposure in European nations - Summary statistics

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)	
$(MandatoryInsurance)_{it}$				0.005	
				(0.84)	
$(Flood * Insurance)_{i,t-1}$					−0.008***
					(−2.56)
$(MandatoryInsurance)_{i,t-1}$					0.006
					(0.89)
Year dummies	Yes	Yes	Yes	Yes	Yes

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)
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
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 $y_{i,t-1}$.

Source: Regional database Cambridge Econometrics, EM-DAT Centre for Research on Epidemology of Disasters (CRED); Global Natural Disaster Hotspots (Dilley et al. 2005)

Table 3. The effects of floods on personal income in U.S. counties - Anderson-Hsiao estimates.

Dependent Variable	3.1[a]	3.2[a]	3.3[b]	3.4[c]	3.5[c]
	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
$\ln y_{it}$	(t-value)	(t-value)	(t-value)	(t-value)	(t-value)
$\ln y_{i,t-1}$	0.356***	0.361***	0.933***	0.361***	0.367***
	(4.99)	(5.02)	(5.72)	(5.08)	(5.12)
$Agriculture_{it}$	0.044***	0.044***	0.065***	0.044***	0.044***
	(36.36)	(36.15)	(20.42)	(36.51)	(36.34)
$\ln(Population$	−0.351***	−0.353***	−0.446***	−0.353***	−0.354***
$density)_{it}$	(−15.51)	(−15.48)	(−9.27)	(−15.60)	(−15.58)
$Flood_{it}$	−0.003***		−0.004***		
	(−7.02)		(−3.27)		
$Flood_{i,t-1}$		0.003***			0.004***
		(5.88)			(6.28)
$(Flood * Exposure)_{it}$			−0.001***		
			(−6.61)		
$(Flood * Insurance)_{it}$			0.001*		
			(1.76)		
$(NFIP)_{it}$			0.001		
			(−0.50)		
$(Flood * Insurance)_{i,t-1}$					−0.002***
					(−2.65)
$(NFIP)_{i,t-1}$					−0.002
					(−1.06)
Year dummies	Yes	Yes	Yes	Yes	Yes
Number of obs.	75,525	75,525	50,709	75,525	75,525
Number of Instruments	27	27	27	29	29

Table to be continued.

Table 3. The effects of floods on personal income in U.S. counties - Anderson-Hsiao estimates. *cont.*

Dependent Variable	3.1^a	3.2^a	3.3^b	3.4^c	3.5^c
	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
$\ln y_{it}$	(t-value)	(t-value)	(t-value)	(t-value)	(t-value)
Prob $>$Chi^2	0.000	0.000	0.000	0.000	0.000
Sargan	0.678	0.647	0.196	0.532	0.587
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	−0.003***	0.003***	−0.001****	−0.004***	0.004***
mechanisms	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
In regions with risk-transfer				−0.002***	0.001***
mechanisms				(0.001)	(0.001)

Notes: Numbers in parentheses are t-values. ***, **, * indicate significance at the 1, 5 and 10% level. First difference Anderson-Hsiao estimator based on Anderson & Hsiao (1981).

[a] The third until the sixth lag of the lagged dependent variable ($y_{i,t-3}$ - $y_{i,t-6}$) and the first and second lag of the flood variable ($Flood_{i,t-1}$ - $Flood_{i,t-2}$) 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 ($(Flood * Insurance)_{i,t-1}$, $(Flood * Insurance)_{i,t-2}$) and ($NFIP_{it}$) were used as instruments for the lagged dependent variable $y_{i,t-1}$.

Source: Regional Economic Information System (REIS), Bureau of Economic Analysis; Sheldus database, Hazards & Vulnerability Research Institute; Global Natural Disaster Hotspots (Dilley et al. 2005)

Table 4. The effects of floods and federal elections on regional GDP in Europe (NUTSII) - GMM-DIFF estimates

Dependent Variable	4.1^a	4.2^b	4.3^b
	Coefficient	Coefficient	Coefficient
$\ln y_{it}$	(t-value)	(t-value)	(t-value)
$\ln y_{i,t-1}$	0.438***	0.463***	0.439***
	(9.14)	(11.80)	(9.28)
$\ln s_{it}$	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 $y_{i,t-1}$.

Source: Regional database Cambridge Econometrics, EM-DAT Centre for Research on Epidemology of Disasters (CRED).

Table 5. The effects of floods and elections on personal income in U.S. counties - Anderson-Hsiao estimates.

Dependent Variable	5.1[a]	5.2[b]	5.3[b]	5.4[b]	5.5[b]
	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
$\ln y_{it}$	(t-value)	(t-value)	(t-value)	(t-value)	(t-value)
$\ln y_{i,t-1}$	0.356***	0.356***	0.356***	0.360***	0.363***
	(4.99)	(5.02)	(5.02)	(5.04)	(5.06)
$Agriculture_{it}$	0.044***	0.044***	0.044***	0.044***	0.044***
	(36.36)	(36.52)	(36.52)	(36.32)	(36.26)
$\ln(Population$	−0.351***	−0.351***	−0.351***	−0.352***	−0.353***
$density)_{it}$	(−15.51)	(−15.57)	(−15.57)	(−15.54)	(−15.53)
$Flood_{it}$	−0.003***	−0.003***	−0.003***		
	(−7.02)	(−7.20)	(−7.39)		
$Flood_{i,t-1}$				0.003***	0.003***
				(6.42)	(6.46)
$(Flood * Congressional$		0.000*			
$Elections)_{it}$		(1.84)			
$(CongressionalElections)_{it}$		−0.033***			
		(−11.91)			
$(Flood * Presidential)_{it}$			0.001***		
$Elections)_{it}$			(2.77)		
$(PresidentialElections)_{it}$			−0.014***		
			(−6.59)		
$(Flood * Congressional$				−0.001***	
$Elections)_{i,t-1}$				(−2.87)	
$(CongressionalElections)_{i,t-1}$				−0.064***	
				(9.94)	

Table to be continued.

Table 5. The effects of floods and elections on personal income in U.S. counties - Anderson-Hsiao estimates. *cont.*

Dependent Variable	5.1[a]	5.2[b]	5.3[b]	5.4[b]	5.5[b]
	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
$\ln y_{it}$	(t-value)	(t-value)	(t-value)	(t-value)	(t-value)
$(Flood * Presidential$					-0.001***
$Elections)_{i,t-1}$					(-3.35)
$(PresidentialElections)_{i,t-1}$					-0.073***
					(-7.10)
Year dummies	Yes	Yes	Yes	Yes	Yes
Number of obs.	75,525	75,525	75,525	75,525	75,525
Number of Instruments	24	28	28	28	28
Prob $>$Chi^2	0.000	0.000	0.000	0.000	0.000
Sargan	0.678	0.691	0.653	0.689	0.614
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 years without	-0.003***	-0.003***	-0.003***	0.003***	0.003***
elections	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
In years with		-0.003***	-0.002***	0.003***	0.002***
elections		(0.000)	(0.000)	(0.000)	(0.001)

Table to be continued.

Table 5. The effects of floods and elections on personal income in U.S. counties - Anderson-Hsiao estimates. *cont.*

Dependent Variable	5.1^a	5.2^b	5.3^b	5.4^b	5.5^b
	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
$\ln y_{it}$	(t-value)	(t-value)	(t-value)	(t-value)	(t-value)

Notes: Numbers in parentheses are t-values. ***, **, * indicate significance at the 1, 5 and 10% level. First difference Anderson-Hsiao estimator based on Anderson & Hsiao (1981).

[a] The third until the sixth lag of the lagged dependent variable ($y_{i,t-3}$ - $y_{i,t-6}$) and the first and second lag of the flood variable ($Flood_{i,t-1}$ - $Flood_{i,t-2}$) 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 ($(Flood * Insurance)_{i,t-1}$, $(Flood * Insurance)_{i,t-2}$) and ($NFIP_{it}$) were used as instruments for the lagged dependent variable $y_{i,t-1}$.

Source: Regional Economic Information System (REIS), Bureau of Economic Analysis; Sheldus database, Hazards & Vulnerability Research Institute; Global Natural Disaster Hotspots (Dilley et al. 2005)

Table 6: 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

University of Innsbruck – Working Papers in Economics and Statistics
Recent papers

2007/05 **Paul Raschky:** Estimating the effects of risk transfer mechanisms against floods in Europe and U.S.A.: A dynamic panel approach.

2007/04 **Paul Raschky and Hannelore Weck-Hannemann:** Charity hazard - A real hazard to natural disaster insurance.

2007/03 **Paul Raschky:** The overprotective parent - Bureaucratic agencies and natural hazard management.

2007/02 **Martin Kocher, Todd Cherry, Stephan Kroll, Robert J. Netzer and Matthias Sutter:** Conditional cooperation on three continents.

2007/01 **Martin Kocher, Matthias Sutter and Florian Wakolbinger:** The impact of naïve advice and observational learning in beauty-contest games.

University of Innsbruck

Working Papers in Economics and Statistics

2007-05

Paul Raschky

Estimating the effects of risk transfer mechanisms against floods in Europe and U.S.A.: A dynamic panel approach

Abstract
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 institutional resilience to natural processes that ultimately determines whether natural processes result in a natural hazard or not. An appropriate method for an international institutional comparison in the field of natural hazard management is still missing. The focus in this paper is on the institutional comparison of societal risk transfer mechanisms mitigating the effects disasters. Dynamic panel estimates using growth data from a) 199 European regions (NUTSII) between 1990-2004 and b) 3.050 U.S. counties between 1970-2003 reveal a significant negative impact of historical flood events on regional economic development. The application of GIS-data on the spatial distribution of flood events further allows to control for a regions exposure to floods. In the short run, a major flood event in a European region reduces the regional GDP by 0.4%-0.6%; an average flood event in the U.S.A reduces the personal income by 0.3%-0.4%. Mandatory insurance regimes in Europe absorb the negative short-run effect of a flood, while the National Flood Insurance Program (NFIP) in the U.S.A. mitigate the effects of a flood by about 50%. The results provide empirical foundation for the proposition that ex ante risk transfer policies are more efficient than ex post disaster relief.

ISSN 1993-4378 (Print)
ISSN 1993-6885 (Online)